

Towards a More Complete Understanding of Adverse Impact: Examining Issues of Minority
Availability

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TOWARDS A MORE COMPLETE UNDERSTANDING OF ADVERSE IMPACT:
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(ABSTRACT)

Selection research often examines whether adverse impact can be reduced/eliminated from employment practices. Such research, however, largely ignores the influence of minority availability issues (i.e., the number of minorities who apply and the number of minorities who accept a job offer); three general factors comprise minority availability: the missing applicant problem, targeted recruitment and job refusal rates. As minority availability issues have not been systematically addressed in the broader literature, the purpose of this study was twofold: 1) to highlight the importance of and explicate a comprehensive description of their potential effects on adverse impact and 2) to demonstrate such effects through monte carlo simulations. Specifically, simulations were used to examine issues related to the level effects and covariance effects of minority availability on adverse impact. Therefore, an iterative process was used whereby minority availability factors were manipulated to produce combinations that meaningfully affect adverse impact; the goal was to conduct as many simulations as necessary to establish a reliable pattern of the effects of minority availability on adverse impact. Simulation results suggest minority availability issues can influence the detection of adverse impact. In fact, minority availability issues may hinder efforts to reduce adverse impact in some selection contexts. Implications of these results are discussed.

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Introduction

In countries like the United States, where equal employment laws exist (see Title 42 of the U.S. code), organizations have a vested interest in the legal context surrounding their employment decisions. Federal law explicitly states employment practices cannot discriminate on the grounds of race, color, religion, sex or national origin (Title VII, 1964). Regardless, employment discrimination occurs. Discrimination can be intentional, where employees are treated differently due to being in any of the five protected classes (i.e., race, color, religion, sex or national origin), and is referred to as disparate treatment (EEOC, 1978). Alternatively, employee discrimination can be unintentional and is referred to as disparate impact. Organizations may have seemingly non-discriminatory employment practices in place that nonetheless negatively impact members of a protected class (EEOC, 1978). Therefore, disparate impact highlights a dilemma; organizations can design systems to produce high quality employment decisions, and yet those practices produce statistically different selection ratios across subgroups, i.e., adverse impact (e.g., Hough, Oswald & Ployhart, 2001).

The detection of adverse impact, however, does not automatically indicate discrimination on the part of the organization. Adverse impact becomes a legal issue when 1) the selection practices that cause adverse impact are not properly validated, 2) the qualifications that differentiate selected employees from not selected employees are not bona fide occupational qualifications (BFOQ)¹ or a business necessity, or 3) there exists equally valid selection practices that produce less adverse impact (see EEOC, 1978; Title 42 of the U.S. Code). The potential legal implications that accompany adverse impact ensure it is a legitimate concern for organizations: evidence of adverse impact is, in fact, the basis of a disparate impact court case (see Title 42 of the U.S. code). The question then becomes, can organizations reduce/eliminate

adverse impact in their employment practices?

To help answer this question, researchers of employee selection often investigate the effects of different selection practices on adverse impact (Guion, 1998). For instance, research has examined the effect of minority applicant recruitment strategies on adverse impact (e.g., Collins & Han, 2004; Newman & Lyon, 2009), the effect of different predictors, combination of predictors and the various weighting schemes of combined predictors on adverse impact (e.g., Potosky, Bobko, & Roth, 2005; De Corte, 1999), and the effect of different selection methods on adverse impact (e.g., De Corte, Lievens, & Sackett, 2006; Sackett & Roth, 1991). Much of this research comes to the same conclusion: it is difficult to reduce adverse impact if the selection system includes a measure of cognitive ability or a measure closely related to cognitive ability. The goal of increasing diversity and the goal of maximizing productivity are typically incompatible (Gottfredson, 1988; Pyburn, Ployhart & Kravitz, 2008; Sackett, Smith, Ellingson, & Kabin, 2001).

When cognitive ability scores are included in a selection battery, attempts to simultaneously achieve both maximized performance and increased diversity results in a compromise between the two goals (De Corte, Lievens, & Sackett 2007, 2008; Newman & Lyon, 2009; Potosky et al., 2005; Sackett & Roth, 1991). In fact, adverse impact typically remains after attempts to reduce it; selection situations that provide the best balance between performance and diversity goals often result in unacceptable levels of adverse impact (cf., Finch, Edwards, & Wallace, 2009).

Much of this research, however, has focused extensively on strategies intended to reduce the standardized race differences on predictor/predictor composite scores that in turn result in

reduced adverse impact (e.g., De Corte et al., 2007, 2008; Potosky et al., 2005); the effect of minority availability on adverse impact has been largely ignored. Minority availability refers to both the number of minority applicants who apply and the number of minority applicants who accept a job offer. To date, minority availability has not been comprehensively examined in relation to the detection of adverse impact. Although some researchers have highlighted the importance of minority availability in influencing adverse impact ratios (e.g., Dunleavy, Stuebing, Campion & Glenn, 2008; Newman & Lyon, 2009; Tam, Murphy & Lyall, 2004), only individual aspects of minority availability (e.g., targeted recruitment or job refusal rates) have been considered; minority availability issues have not been systematically addressed in the broader literature. In reality, the influence of minority availability issues may further complicate attempts to reduce adverse impact. Therefore, the purpose of the current research is twofold. I will 1) highlight the importance of and explicate a comprehensive description of the potential effects of minority availability on adverse impact and 2) further demonstrate such effects through monte carlo simulations.

Literature Review

Research on employee selection has primarily focused on the reduction of adverse impact through the examination of standardized race effects on predictor/predictor composite scores (e.g., Hough et al., 2001; Ployhart, & Holtz, 2008). Therefore, this research has indicated a multitude of topics that inform changes to standardized race effects: the formation of predictor composites, especially in regards to concerns of predictor intercorrelations (e.g., Schmitt, Rogers, Chan, Sheppard, & Jennings, 1997); the use of various weighting schemes in predictor composite formation (e.g., De Corte, 1999; Potosky, et al., 2005); and issues related to multiple hurdle selection situations, such as the effect of predictor order (e.g., De Corte et al., 2006;

Finch et al., 2009). Below is an overview of the substantive findings from this research.

Traditional Adverse Impact Studies

Predictor composite: formation. Much of the research regarding predictor composites focuses on determining the validity, or potential benefit, of using predictor composites over that of individual predictors (e.g., Cascio, Valenzi, & Silbey, 1980; Schmidt & Hunter, 1998; Schmitt et al., 1997). For example, cognitive ability is commonly used as a predictor in selection and has a validity of 0.5 in predicting job performance (Schmidt & Hunter, 1998). Research has indicated that the inclusion of another predictor, such as work samples ($r=0.54$), can actually increase validity of the predictor composite above that of the two individual predictors, i.e. $R=0.63$ (Potosky et al., 2005). Research has been less clear in regards to predictor composite effects on adverse impact. Nevertheless, there has been support for the view that adding a predictor to cognitive ability will reduce adverse impact, namely by reducing standardized race effects (e.g., Pulakos & Schmitt, 1996). In fact, researchers have indicated an expectation that including predictors with smaller group differences into predictor composites reduces adverse impact (e.g., Campbell, 1996); yet little research has directly assessed this supposition. Notable exceptions, however, have attempted to test the veracity of these claims (e.g., Sackett & Ellingson, 1997; Schmitt et al., 1997; Potosky et al., 2005).

For example, Sackett and Ellingson (1997) attempted to determine the changes to the magnitude of group differences when employing predictor composites. Therefore, they were able to examine how predictor intercorrelations and predictor race effects influenced adverse impact. Their results indicated that reducing adverse impact through predictor composite formation is a complex issue: standardized race effects do not necessarily lessen as predictors with small race

effects are included into the composite. In fact, standardized race effects may even increase beyond that of the two individual predictors alone (also see Schmitt & Quinn, 2010). Similarly, Potosky, Bobko, and Roth (2005) indicated that adding another predictor to cognitive ability generally increased predictive validity (i.e., average increase in $R=0.05$); it did not, however, guarantee a reduction in adverse impact.

Predictor composite: weighting schemes. In response to the increased use of predictor composite scores, researchers began examining how adverse impact was affected by composite formations (e.g., De Corte et al., 2008; Potosky et al., 2005), i.e., how different weighting schemes, used to combine predictors, inform adverse impact decisions. In essence, weighting schemes that maximize validity, like regression weighting, tend to maximize standardized race effects, increasing the likelihood of adverse impact. On the other hand, weighting schemes that reduce standardized race effects, like optimal weighting, tend to reduce the likelihood of adverse impact (De Corte et al., 2008). This reduction in standardized race effects, however, usually comes at a cost: predicted mean job performance decreases. Moreover, when predictor composites include measures of cognitive ability, reductions to adverse impact are often low and costs to predicted job performance are likely high (e.g., Finch et al., 2009).

De Corte and Lievens (2003) highlight these issues as weighting schemes for predictor composite formation often produce a trade-off between increasing diversity and maximizing performance. Until recently, organizations had to decide which weighting scheme best represented their diversity and performance goals. In response to this, De Corte et al., (2007) developed a technique to determine predictor composites that optimized the trade-off between the organizational goals of diversity and performance, i.e., pareto optimal weighting. Although it is clear that maximizing either one of these goals separately will negatively impact the other (i.e.,

diversity and performance), parteo optimal equations inform practitioners how decisions regarding predictor composite formation will impact their competing goals of diversity and performance.

Multi-stage selection. Organizations commonly use multi-stage selection systems if it is not feasible to administer all predictor/predictor composites to all applicants at once. In many cases, this is due to the increased cost and logistical concerns involved with single-stage selection systems (cf., Sackett & Roth, 1996). Instead, organizations may implement multiple stages of selection that include different predictors/predictor composites to determine which applicants move on in the selection process. In essence, the concerns of multi-stage selection are similar to those of predictor composites mentioned above: the chosen predictors, as well as the way in which the predictors are used together, influence adverse impact decisions (e.g., Finch et al., 2009). Results regarding multi-stage selection indicates that issues of adverse impact are quite complex.

For example, De Corte et al. (2006) focused on the effect of predictor order in the selection process on selection outcomes. Situations where the predictor with the largest race effect was administered first produced the best adverse impact ratio, as long as the selection ratio associated with that stage was equal to or higher than the selection ratio associated with the subsequent stage. The lowest levels of adverse impact were associated with those selection situations where the predictor with the largest race effects also had the smallest selection ratio. Similarly, Finch et al. (2009) reiterated much of what is in the literature: attempting to maximize performance and maximize diversity results in a compromise between the two goals. Furthermore, Finch et al. (2009) indicate that the use of multi-selection techniques can reduce the effects of adverse impact; however, these effects are dependent on a number of factors, i.e.,

weights given to lower impact predictors, predictor intercorrelations, selection ratios, etc.

In short, the issue of reducing adverse impact is complicated. Although Finch et al. (2009) indicate situations that produce no adverse impact, none of these conditions included a measure of cognitive ability. The goal to reduce race differences on predictor/predictor composites enough to substantially reduce adverse impact is near impossible when measures of cognitive ability are involved.

Summary. Regardless of the methods used to examine selection outcomes or the avenues by which researchers attempt to reduce standardized race effects, the results are similar: organizations are faced with a difficult situation as the goals of maximizing both diversity and job performance tend to compete. Attempts to reduce adverse impact likely reduce predicted job performance (De Corte et al., 2008; Hough et al., 2001; Ployhart & Holtz, 2008). Furthermore, few attempts to increase diversity completely eliminate adverse impact (cf., Finch et al., 2009), especially when a measure of cognitive ability is used in the predictor composite. This has led to some researchers wondering “just how likely it is for organizations to actually avoid adverse impact in selection systems” (p. 311, Potosky et al., 2005). Nevertheless, this may only be half of the picture: much of the research overlooks minority availability issues. Under present conditions, research suggests it is near impossible for organizations to reduce adverse impact without suffering, often sizeable, reductions in validity (e.g., De Corte et al., 2006; Potosky et al., 2005). The inclusion of minority availability issues may compound the issue; in some situations it may, in fact, be impossible for organizations to easily influence adverse impact at all.

Minority Availability Issues

There are three general factors that affect minority availability: the “missing applicant

problem,” targeted recruitment and job refusal rates. The missing applicant problem is a label used to describe the common situation where there are too few qualified minority applicants. Targeted minority recruitment has the opposite effect of the missing applicant problem in that targeted recruitment increases the number of minimally qualified minorities in the applicant pool. Whereas the missing applicant problem and minority recruiting affect minority availability prior to job offers, job refusal affects minority availability in terms of actual employment in the organization.

In relation to adverse impact, each of these minority availability factors can be further partitioned into level and covariance effects. For both the missing applicant problem and targeted recruiting, level effects simply refer to the impact that these factors have on the percentage of minimally qualified minorities in the applicant pool. The level effect of refusal rate refers to the overall percentage of refused job offers, which can be separated by applicant race.

The term covariance effect refers to the relationship between each minority availability factor and the predictor composite scores. As will be explained, if cognitive ability is measured directly or indirectly in the assessments used to make the hiring decision, then it is likely that minority availability factors covary with predictor composite scores. These covariance effects can affect the level of adverse impact.

Level Effects

Level Effects of Job Refusal Rates. Job refusal rates refer to the likelihood that an applicant will refuse a job offer during the selection process (e.g., Tam et al., 2004). Given that minority applicants are more likely than majority applicants to withdraw from the selection process (e.g., Avery, Gordon, Massengill, & Mussio, 1975; Bretz & Judge, 1998; Ployhart,

McFarland, & Ryan, 2002; Schmit & Ryan, 1997), it is important to understand the effects of these differential refusal rates job on adverse impact. Most adverse impact research, however, assumes all job offers are accepted (e.g., Bobko & Roth, 2004; De Corte & Lievens, 2003; De Corte et al., 2006; Finch et al., 2009; Newman & Lyon, 2009; Potosky et al., 2005).

Tam et al. (2004) simulated the effects of various minority refusal rates on adverse impact across multiple selection scenarios (i.e., manipulation of overall selection ratios, race effects on the predictor scores, minority refusal rates, etc.). Not surprisingly, their results indicated that detection of adverse impact was more likely as minority refusal rates increased. The effect of job refusal rates is straightforward: as more minority applicants withdraw from the selection system, the likelihood of detecting adverse impact increases because subsequent job offers are more likely to be made to a majority applicant than a minority applicant. (Assuming there are more majority applicants and minority applicants.)

However, Tam et al. (2004) did not vary the percentage of minority applicants when simulating the effects of job refusal rates. They held minority percentage constant at 13 percent – based on census data and ‘real-world’ data from another study. Moreover, their study used top-down selection. In doing so, Tam et al. (2004) failed to provide a comprehensive assessment of the effects of job refusal rates on rates of adverse impact. Specifically, they did not examine the extent to which the percentage of minorities in the applicant pool moderates job refusal rates and minority preference hiring in the detection of adverse impact. The current study extends Tam et al.’s (2004) study by assessing the effects of job refusal rates in a selection context where minority preference is given and the percentage of minority applicants varies.

Level Effects and the Missing Applicant Problem. Level effects of the missing

applicant problem are primarily attributable to labor market issues. Minority availability in the relevant labor market can be scarce (abundant) due to local demographics; as the base rate of minorities in the local population decreases (increases), it is likely that the availability of qualified minorities also decreases (increases). Moreover, local demographics may also influence the recruitment of qualified minorities from outside of the local area. A larger (smaller) base minority population may attract (discourage) qualified minorities to apply for a position. Therefore, the relevant labor market can be impacted through the racial composition of particular locales.

Adverse impact researchers commonly use labor statistics or general population averages to reference the racial composition of the applicant pool. However, these referent points may not provide an accurate representation of the relevant labor market (e.g., Lerner, 1979). Adverse impact research that assumes that the applicant pool reflects the national average of African-Americans does not generalize to locales where the minority population differs meaningfully from the national average.

For example, Phoenix, AZ has a population comprised of 71.1% Caucasian and 5.1% African American (U.S. Census Bureau, 2006b). Conversely, Philadelphia, PA has 45% Caucasian and 43% African American (U.S. Census Bureau, 2006a). The use of national demographics in adverse impact research does not adequately reflect the variability in minority availability. As the disparity between the percentage of minority and majority applicants in the applicant pool increases, it is expected that more Caucasians will be hired (Dunleavy, et. al., 2008).

In terms of diversity, the limited availability of minority applicants is a negative force on

achieving affirmative action goals. However, by itself, the missing applicant problem due to labor market demographics is a “neutral force” on *adverse impact*. The classic operational definition of adverse impact compares selection ratios between the majority group members and the protected group members. For example, the four-fifths rule indicates adverse impact if the protected class selection ratio is less than 80% the majority selection ratio. For a given selection decision process, *assuming top-down selection*, increasing or decreasing the percentage of minimally qualified minority applicants will *not* affect adverse impact ratios.

However, if minority preference is used in the hiring process (e.g., banding), then the effectiveness of minority preference hiring in terms of adverse impact is a function of the percentage of qualified minority applicants. That is, decreases in minority applicants due to the missing applicant problem limits the effectiveness of minority preference hiring strategies for reducing adverse impact.

Level Effects and Targeted Recruitment. Recruiting refers to organizational practices designed to affect who applies for a given job (Rynes, 1991). Organizations can influence the racial composition of the qualified applicant pool through recruiting. Newman and Lyon (2009) highlighted the potential use of targeted recruitment on adverse impact. Organizations can design targeted recruitment strategies to meet needs regarding minority representation in the applicant pool.

However, as with the missing applicant problem, targeted recruiting does not directly affect adverse impact. Instead, targeted recruiting improves the effectiveness of minority preference hiring because it increases the percentage of potentially hireable minorities. Whereas the level effects of the missing applicant problem limits the effectiveness of minority preference

hiring on adverse impact, increasing the percentage of minority applicants through targeted recruiting increases the effectiveness of the minority preference hiring practices.

Summary of Level Effects. To summarize, job refusal rates are a negative force on adverse impact because it is more likely that a minority applicant who refuses a job offer will be replaced by a majority group member. In contrast, the level effects associated with the missing applicant problem and targeted recruiting does not directly affect adverse impact. Rather, the level effects due to missing applicant problem and targeted recruiting increase or decrease the effectiveness of a minority preference as a tactic for reducing adverse impact. As the percentage of minority applicants decreases due to the missing applicant problem, minority preference hiring will be less effective in reducing adverse impact. Alternatively, as the percentage of minority applicants increases due to targeted recruiting, minority preference hiring will be more effective in reducing adverse impact.

The interesting question is how the level effects of the minority availability factors jointly affect the detection of adverse impact. More specifically, when using minority preference hiring, modeling adverse impact as a function of both variations in race-based differences in job refusal rates and variations in the percentage of minorities in the applicant pool. The variations in the percentage of minorities in the applicant pool reflect the negative effects of the missing applicant problem and the positive effects of targeted recruitment. Alternatively stated, for level effects, the primary issue is to evaluate the extent to which increases and decreases in the percentage of minimally qualified applicants (due to the missing applicant problem and/or targeted recruitment) ameliorate or exacerbate the negative effect of race differences in refusal rates on adverse impact.

Covariance Effects

Minority availability issues may also increase adverse impact as a function of race effects on the predictor composite scores, i.e., covariance effects.

Covariance Effects and the Missing Applicant Problem. It is unlikely that the entire relevant labor market, between the ages of 25 and 65, meet the minimum qualification to apply for specific jobs. In fact, organizations commonly use pre-screening devices to initially restrict the number of qualified applicants (Buster, Roth, & Bobko, 2005). In doing so, organizations often alter the racial composition of the applicant population (i.e., the relevant labor market) by restricting who is classified as a qualified applicant (cf., Lerner, 1979; Wollack, 1994). These pre-screening devices can be licensures/certifications, GPA, work experience/educational/task requirements, etc. (e.g., Buster et al., 2005; Roth & Bobko, 2000; Berry, Gruys, & Sackett, 2006). Once the applicant pool is screened for minimally qualified applicants, organizations typically use other assessments to determine who is hired for the job (i.e., interviews, cognitive ability tests, etc.). This initial screening can often alter the racial composition of the applicant population and potentially influence adverse impact. Research on minimum qualifications has focused on criterion-related validity (e.g., Buster et al., 2005). It is likely that race moderates the relationship between a given minimum qualification and cognitive ability in that increasing levels of the minimum qualifications will likely manifest as increased race effects on the predictor composite scores. Explication of the likely moderating effect of minimum qualifications on the race-predictor composite score relationship is detailed below, using educational requirements.

It is likely that educational requirements moderate the race – predictor composite score

relationship such that race effects on the predictor composite increase as minimum education requirements increase. Cognitive ability is related to educational attainment (Berry et al. 2006); reported correlations between cognitive ability and degree level range between 0.34 and 0.63 (Berry, et. al., 2006; Plag & Goffman, 1967; Waldman & Avolio, 1991). Berry et al. (2006) compared adverse impact when using cognitive ability versus degree requirements. Both selection techniques produced greater adverse impact as selection ratios decreased, but degree requirements produced less overall adverse impact than cognitive tests. However, Berry et al. (2006) did not examine the effect of using degree requirements as a pre-screening in selection system that used cognitive ability tests.

Additional research suggests that race differences on cognitive ability tests increase as level of degree attainment increases. For example, Roth and Bobko (2000) highlighted this possibility in their examination of race effects and college GPAs. They found that the race effect on GPAs increased as a function of class rank. Race effects favoring Whites increased from $d = 0.21$ to $d = 0.49$ to $d = 0.78$ for the sophomore, junior and senior class ranks. Roth and Bobko (2000) surmised the observed race effects on GPA could be due to university efforts to reduce African American drop-out rates. In effect, if the university initializes tutoring and other support available for African American students, then fewer African-Americans will drop-out. Without the same support systems, those Caucasians who perform poorly will end up leaving the university. This explanation suggests a relatively stable mean grade-point average for African American students and a rising mean grade-point average for Caucasian students, which is the pattern the found. Caucasian students averaged a 0.285 grade-point increase from sophomore to senior year while African American students averaged 0.100 grade-point increase (Roth & Bobko, 2000). The unstated implication of the Roth and Bobko's finding is that race effects on

cognitive ability scores for African-Americans and Caucasians will follow the same pattern.

Incoming college students exhibit roughly a one standard deviation (SD) race effect on cognitive ability scores (i.e., SAT scores, Sackett & Shen, 2010). If low-performing African American students remain in college and low-performing Caucasian students drop out, the race effect on cognitive ability scores for college graduates is expected to increase, assuming the low-performing Caucasian student who drops out of college also had the lower cognitive ability scores. Other research has indicated that standardized race effects on cognitive ability scores on entrance exams may increase as degree level increases. For instance, a GRE board report (Pennock-Roman, 1993) indicated the race effect on SAT quantitative scores (i.e., for entry into college) was 1.04 SD, with Caucasian test takers scoring higher. This is similar to the standard 1 SD used in the literature. However, the race effect on GRE quantitative scores (i.e., for entry into graduate school) was 1.20 SD. More recently, the College Board (Camara & Schmidt, 1999) examined group differences across a host of standardized tests. Their findings were similar to the GRE board report; standardized race effects on SAT scores were approximately 0.83 SD to 0.92, where standardized tests into higher education (i.e., GRE, LSAT, GMAT and MCAT) produced larger race effects that ranged from approximately 0.96 SD to 1.14 SD.

The current adverse impact literature uses the aggregate finding that Caucasians score 1 SD higher than African-Americans (Gottfredson, 1988; Hunter & Hunter, 1984) as the benchmark for race differences on the predictor composite scores (e.g., De Corte et al., 2006; De Corte et al., 2007; Finch et al., 2009). The assumption of a fixed 1 SD difference overlooks the likelihood that educational requirements moderate the relationship between race and the predictor composite scores. The implication of this moderating relationship is that educational requirements produce a covariance effect on adverse impact. That is, as degree requirement

increase, fewer minorities are minimally qualified. Furthermore, the increasing degree requirements likely increase race differences on predictor composite scores that assess cognitive ability (either directly or indirectly). More generally, such a moderating effect will occur in any selection context where minimum qualifications are related to cognitive ability and cognitive ability is measured directly or indirectly in the predictor battery.

Covariance Effects and Targeted Recruitment. To further reduce adverse impact, Newman and Lyon (2009) argue for targeted recruiting of highly qualified minorities. Targeted recruiting can be based on abilities, combinations of race and abilities, or combinations of some other desired qualities. Recruiting practices are not considered to be selection procedures; therefore, they are not susceptible to adverse impact claims (EEOC, 1978). Organizations can implement general recruitment strategies to increase minority applicants or targeted recruitment strategies to increase only highly qualified minorities.

Newman and Lyon (2009) examined the effects of various recruitment strategies on expected adverse impact and expected performance of hires. They were interested in understanding “how various recruitment strategies might interfere with each other in the effort to increase diversity within organizations while maintaining high performance levels” (p. 301, Newman & Lyon, 2009). Their results indicated that targeted recruitment of highly qualified minority applicants, i.e., recruitment based on cognitive ability within the minority group, recruitment based on conscientiousness within the minority group, and the combination of the two, produced the largest reductions in adverse impact (i.e., adverse impact ratio=0.45, 0.45 and 0.65, respectively, compared to the adverse impact ratio=0.32 for no recruitment, for the largest selection ratio). This reduction was above that of minority recruitment not based on targeted attributes (i.e., adverse impact ratio=0.32).

It is important to note, however, that Newman and Lyon (2009) did not give minority preference in hiring; they used mathematical equations to estimate the effects of recruitment on adverse impact and job performance. This could be one reason why similar adverse impact ratios were indicated for the no recruitment condition and the minority recruitment, not based on targeted attributes, condition. Although they did not explore the impact of recruitment strategies on standardized race effects, it is clear that adverse impact is reduced when recruitment is designed to attract qualified minority applicants.

Using cognitive ability scores to target minorities in the relevant labor market will likely decrease standardized race differences on predictor composite scores, resulting in lower levels of adverse impact (i.e., targeted recruiting will have an indirect effect on adverse impact).

Covariance Effects and Job Refusal Rates In simulation research, job refusal rates are typically not considered or are held constant across applicants. However, the likelihood an individual refusing a job likely covaries with the predictor composite scores; more qualified applicants are more likely to refuse a job offer than less qualified applicants (Tam et al., 2004). Furthermore, race likely moderates the relationship between the job refusal probability and predictor composite scores (cf., Tam et al., 2004). First, African American applicants, on average, are more likely than Caucasian applicants to withdraw from the selection system (Tam et al., 2004). Second, organizations likely compete for highly qualified minority applicants thereby lowering the likelihood any one organization will successfully hire any given highly qualified minority. The end result of this competition is greater observed race differences on predictor scores and an associated increase in adverse impact for those applicants actually hired into the organization.

Summary of Covariance Effects. The aforementioned level effects assume that minority availability factors are *independent* of scores on the predictor composite used to make hiring decisions. The reality is that this assumption of independence is not tenable in most selection contexts because minority availability factors likely affect the observed race differences on predictor composite scores. Any increase in observed race differences will increase adverse impact (due to decreases in the numerator of the minority selection ratio) and any decrease in observed race differences will decrease adverse impact (due to increases in the numerator of the minority selection ratio).

Minimum qualifications, used in combination with a predictor composite that includes a measure of cognitive ability, exemplify a negative covariance effect on adverse impact. As minimum qualifications increase, observed race differences (favoring the majority applicants) on the predictor composite scores likely increases, thereby exacerbating adverse impact. In contrast, targeted recruitment of the most qualified minority applicants likely has a positive effect on adverse impact (Newman & Lyon, 2009). Assuming a fix number of minority applicants, increasing the percentage of highly qualified minorities will decrease race differences on the predictor composite scores, thereby decreasing adverse impact. For example, if an organization that requires a bachelor's degree for entry level managers successfully recruits minority applicants from only the most selective universities, then this targeted recruitment should reduce observed race differences on cognitive ability test scores, resulting in less adverse impact.

Job refusal rates are also likely to produce an indirect effect on adverse impact. More highly qualified applicants are more likely to refuse a job offer than less highly qualified applicants (Tam et al., 2004). Furthermore, it is likely that race moderates the relationship between the likelihood of refusal and predictor composite scores. It is clear that organizations

have difficulty attracting highly qualified minorities (Newman & Lyon, 2009; Ployhart & Holtz, 2008). This implies greater competition among organizations for the best minority candidates than for the best majority candidates. Increased competition for highly qualified minority applicants implies that the correlation between likelihood of job refusal and cognitive ability is stronger for African-Americans than Caucasians. The end result of such a moderating relationship is an increase in adverse impact because observed race differences on predictor composite scores for those applicants who accept job offers will be larger than the predictor composite race differences for applicants offered a job.

In summary, minority availability issues have both level and covariance effects on adverse impact. For level effects, the missing applicant problem and targeted recruitment (manifested in the percentage of minority applicants) are neutral in terms of effects on adverse impact; whereas job refusal rates are a negative force. For covariance effects, the correlation between the missing applicant problem and predictor composite scores and the correlation between the job refusal rates and predictor composite scores are both negative forces on adverse impact; the correlation between targeted recruitment of only highly qualified minorities and predictor composite scores is a positive force on adverse impact. To date, research has not recognized the complexity of minority availability in regards to adverse impact. The primary purpose of the current study is to empirically examine both level and covariance effects of minority availability on adverse impact.

Overview

Organizations have a vested interest in increasing the diversity of their workforce. One reason for this interest is the legal implications associated with employment discrimination (see

Title 42 of the U.S. Code). Though discrimination can be intentional, this study focuses on unintentional discrimination and the unique challenge it presents: employment practices, designed to make quality employment decisions, can inadvertently produce statistically different selection ratios across subgroups, i.e., adverse impact (e.g., Hough et al., 2001). To guide organizations with their employment decisions, research in employee selection has examined the effects of many selection practices on decisions of adverse impact (cf., Guion, 1998; Hough et al., 2001). Much of this research, however, suggests organizations aimed at reducing adverse impact (i.e., increasing diversity) will have a difficult time doing so; often, the reduction of adverse impact is at the cost of a reduction in predicted job performance (Gottfredson, 1988; Sackett et al., 2001). In fact, organizations may still be faced with adverse impact issues even after their attempts to reduce it (cf., Finch et al., 2009).

Purpose

I use monte carlo simulations to examine specific issues related to both level effects and covariance effects of minority availability on adverse impact. For level effects, the specific issue is the interplay between job refusal rates and the effectiveness of minority preference hiring as a function of the percentage of minimally qualified minority applicants.

For covariance effects, there are several negative forces on adverse impact, including the covariance effect due to increasing minimum qualifications, the level effects of overall refusal rates, the covariance effect of overall refusal rates, and race moderating the covariance effect of overall refusal rates (i.e., the minority applicants exhibit a stronger positive correlation between job refusal rates and predictor composite scores than majority applicants). Against all these negative forces, the only covariance positive force on adverse impact is targeted recruiting of the

most highly qualified minorities.

Given that predictor composite scores saturated with cognitive ability produce adverse impact, it is pointless to simulate the negative covariance effect of minimum qualifications. Simulating a positive correlation between minimum qualifications and race differences on the predictor composite scores will only increase adverse impact beyond that produced by the predictor composite score alone.

As such, the foci of the covariance simulations are on the positive effects of targeted recruiting of highly qualified minorities. In essence, the question of interest is how strong must the negative correlation between the percentage of minority applicants and the predictor composite scores be to meaningfully reduce adverse impact. This issue is examined in relation to the presence/absence of two negative forces, the level of refusal rates (both when majority applicant refusal rate is equal to and less than minority group applicant rate) and a positive correlation between overall job refusal rates and predictor composite scores (both when majority applicant refusal rate is equal to and less than minority applicant refusal rate).

Although there are no formal hypotheses for these simulations, I have expectations regarding the results. For level effects simulations, there will be contexts where increasing or decreasing the percentages of minority applicants will change the effects of refusal rates on adverse impact. My expectations are best couched in terms of the effectiveness of minority preference hiring on adverse impact. It is established that refusal rates cause adverse impact (i.e., Tam, et al., 2004). Obviously, minority preference hiring will offset the negative effects of refusal rates to a degree. The important question is the extent to which minority preference hiring will offset the negative effects of refusal rates, which will be dependent on the percentage of

minority applicants (representative of the level effects of the missing applicant problem and targeted recruiting). Because race differences on the predictor composite are more powerful than minority availability level effects, running simulations that assume race differences on the predictor will obfuscate conclusions about level effects. As such, the level effects simulations are run assuming no race difference on the predictor composite scores.

For the covariance effects simulations, the primary focus is the extent to which targeted recruiting of highly qualified minorities/reducing the “missing applicant problem (i.e., increasing the percentage of minorities) and a positive correlation between the percentage of minorities and predictor composite scores can offset adverse impact in the presence/absence of other negative forces on adverse impact (i.e., the level of minority job refusal rates and the correlation between minority job refusal rates and predictor composite scores) . For these covariance simulations, I assume a “baseline” observed race difference on the predictor composite scores. However, I am not optimistic that targeted recruiting will significantly offset adverse impact unless the negative correlation between the percentage of minorities and predictor composite correlations is strong, especially when all the negative effects (both level and covariance) of refusal rates are included.

Method

Simulation Decision Criteria

Fully simulating the effects of minority availability requires eight parameters: four level effects and four covariance effects. The four key parameters that represent the level effects are: 1) the percentage of minority applicants due to missing applicant problem, 2) the percentage of minority applicants due to recruitment, 3) the majority applicant refusal rate, and 4) the minority applicant refusal rate. Correlations of each of these key parameters with the predictor composite

scores are needed to model the covariance effects. In essence, the full model of minority availability is an eight-way design producing 255 combinations of variables to simulate (starting with each main effect for each variable and then working to the eight-way interaction), and that is for just one selection ratio and applicant pool n-size combination.

It is not feasible to conduct simulations of the full array of minority availability variables that affect adverse impact. Therefore, I developed a set of decision criteria to guide which combinations of variables to simulate. The first decision criterion is the issue of race differences on the predictor composite scores. I decided to simulate level effects of minority availability only in contexts where there were no race differences on the predictor composite scores.

It is possible to envision a situation where predictor composite scores show no race differences (e.g., making hiring decisions using only personality predictors) and where the predictor composite scores correlate with the missing applicant issue, recruitment effects and/or refusal rates (i.e., variables representing the covariance effects). However, such correlations are more likely when a measure of cognitive ability is included in the test battery, thereby producing race differences where African-American applicants score lower than Caucasian applicants. As such, when race differences on the predictor composite were assumed, I simulated the full effects (i.e., level and covariance effects) of minority availability searching for those situations where targeted recruiting of highly qualified minority applicants meaningfully reduced adverse impact.

The second decision criterion was to hold variables of less interest constant. Since the focus of the study is the effects of minority availability on adverse impact, the level of the majority refusal rate and the correlation between the majority refusal rate and the predictor composite were both held constant.

The third decision criterion was to strategically confound the level effects for both the missing applicant problem and targeted minority recruitment. As previously mentioned, recruiting is a countervailing force to the missing applicant problem. Modeling these two variables separately does not add to understanding; rather the results when modeling the parameters separately are a function of the magnitude of each individual parameter. Therefore, I systematically increased or decreased the percentage of minority applicants in the simulations to simultaneously represent the ultimate effects of both the missing applicant problem and targeted recruitment.

Veridical Simulation Program

I created a simulation program to examine how minority availability issues effect adverse impact. The ideal goal for the simulation program was to model the hiring process as it might occur in an organizational setting. However, a complicating issue is that modeling the level effects requires preference used in the hiring criterion. Therefore, the core simulation program is designed to mimic the hiring outcomes when using sliding bands. These bands are created using the standard error of measurement of the predictor composite test, or more specifically the standard error of the difference between test scores, assuming a test reliability of 0.85 (i.e., $1.96 * 1.141 * \text{test score standard deviation} * \text{square root of } (1 - \text{test score reliability})$). By placing a band around the highest predictor composite score, much like a confidence interval, equally qualified applicants are identified for hire. These bands provide the opportunity for a level of minority preference during the selection process. Therefore, minority applicants are hired first and majority applicants are hired in a top-down fashion. Once the top-scorer is selected for hire, the band shifts down around the next highest scorer and the hiring process repeats until a desired number of hires are selected.

Initially, I created a program that exactly simulates hiring decisions using sliding bands process. However, the modeling of minority availability factors using this program requires extraordinary amounts of computing power (see Appendix A for a copy of SAS code to simulate sliding bands). The iterative nature of the sliding-band selection technique results in the program using large amounts of processing time searching for applicants to hire.

Therefore, I created a simulation program that mimics selection outcomes when using sliding bands, but does so with fewer computer processing requirements (i.e., less hunting and pecking for hires). In this program the hiring sequence is executed as follows:

1. The program selects hires in a top-down fashion until a pre-set number of hires are selected (i.e., the applicant pool size*the overall selection ratio).
2. A band is then created around the highest remaining applicant. All of the minorities present in this band are selected for hire.

The key difference between the veridical simulation program and the one that I use is the manner in which hires are selected. The simulation program rank orders applicants based on predictor composite scores and then selects the desired number of hires in a top-down fashion. Then, the band is created and placed around the top-scorer not selected for hire. In doing so, additional minority hires can be made from this band to ensure the number of minority hires from this simulation program is similar to the number of hires from the veridical simulation of sliding bands.

To ensure that my program produced similar outcomes as the veridical program, I first used the full sliding-band program to identify the number of minority hires that would occur

under the sliding-band selection method, assuming a predictor composite reliability of 0.85. In generating the sliding-band selection data, I assumed 100% minority preference within the band, with top-down selection for majority applicants, until the target number of hires was acquired (i.e., the applicant pool size*overall selection ratio). However, it is unlikely that minorities would be given 100% preference during the selection process; therefore, this number was adjusted. Instead of using the full 100%, I only used 75% of the minority hires indicated by the sliding-band selection method. This adjusted number becomes the target number of minority hires for the simulation program in this study.

I then tested the new simulation program to ensure a similar number of minority hires was selected. For example, in the full effects models, where the overall selection ratio equals 0.15, the target number of minorities hired from the veridical program was nine (i.e., 75% of the 12 minorities hired). To obtain a similar number of minority hires from the new simulation program, I manipulated the size of the band in the new program until the target number was achieved. As the original band was created using the standard error of the difference between test scores (i.e., $1.96 * 1.141 * \text{test score standard deviation} * \text{square root of } (1 - \text{test score reliability})$), I manually adjusted the size of the band by dividing by a constant. In the above selection situation, the band was divided by two to indicate minority hires of roughly nine. This process was repeated for each of the baseline model conditions.

This banding process approximated the target overall selection ratios; however, it also inflated the overall selection ratios slightly as minority percentages increased. This is a limitation to using the new simulation in place of the veridical simulation. However, the actual selection ratios generally were close to the target selection ratio (a couple of percentage points in most cases). The simulations did not inflate the overall selection ratio more than 5% points when

minority percentage was less than 50%.

Simulation Program

A SAS program was constructed to create population data for the use in 1) determining the qualified applicant pool, 2) selecting hires from the qualified applicant pool and 3) examining adverse impact. (Detailed discussions of the parameters to be used in the simulation are discussed below.) The simulations are created through seven steps.

Step one. A vector of 100,000 scores representing standardized predictor composite scores is generated. These predictor composite scores are normally distributed with a mean of zero and standard deviation of one. These 100,000 cases represent the population of minimally-qualified applicants.

Step two. The composition of majority and minority sub-group membership are delineated by randomly selecting a predetermined number of cases to be classified as majority and minority members. This predetermined number is based on the proportion of minorities available due to the missing applicant problem/targeted recruitment.

Step three. For the full effects simulations, step three adjusts the predictor composite scores by 1 SD for Caucasian applicants.

Step four. In step four, the simulation selects the applicant pool based on a specified percentage of minority applicants.

Step five. Each applicant is coded as either a 1 or a 0 (1 indicating they will reject a job offer and 0 indicating that they will accept a job offer), depending on the level job refusal rate. In

the level effects model, this is based on the level of job refusals. Therefore, when job refusal rates are 0.20, approximately 20% of the applicant pool is identified as likely to reject a job offer. In the full effects model this is based on the both the level and correlation of job refusals with predictor composite scores. Therefore, when job refusal rates are 0.20 and the correlation between job refusal rates and predictor composite scores is 0.30, approximately 20% of the applicant pool is still identified as likely to reject a job offer. The difference, however, is that the likelihood of an applicant refusing a job offer increases as their predictor composite score increases.

Step six. Based on the overall selection ratio, step five selects applicants for hire, using the proxy banding procedures, and any selected applicants identified as refusing a job offer are replaced with the next qualified applicant.

Step seven. In step seven, the average adverse impact for the selection situation. Evidence of adverse impact is examined using the 4/5th rule and the Z_{IR} significance test (see EEOC, 1978; Esson & Hauenstein, 2006).

Triangulation Process

To reiterate, the goal of the level effects simulations was to assess the extent to which increasing/decreasing the percentage of minimally qualified applicants increases/decreases the effectiveness of minority preference hiring in reducing adverse impact, across different levels of job refusal rates. The goal of the full effects simulations was to assess the percentage of minorities and the level of the negative correlation between the percentage of minority applicants and predictor composite scores necessary to mitigate adverse impact in the presence (and absence) of other negative forces on adverse impact (i.e., the level and covariance effects of

minority job refusal rates).

To accomplish these goals I did not use the traditional approach to simulation research whereby each factor was manipulated at different fixed levels (e.g., high, medium, and low) and each factor is crossed with every other factor in the design. Instead, I manipulated factors as needed to find those points that indicate meaningful changes in adverse impact.

I first ran the normative simulations assuming a sample size of 1,000 applicants. From these baseline analyses, I used an iterative process whereby I deviated minority availability factors from the normative models searching for those combinations that meaningfully affect adverse impact. The implication of this triangulation process was that there were not a fixed a priori number of simulations to run. Rather, the goal was to conduct as many simulations as necessary so as to establish a reliable pattern of the effects of minority availability on adverse impact.

For the level effects simulations, the normative baseline model assumed 13% minority applicants to reflect the aggregate population, a 15% level of job refusals for majority applicants and a 0 SD race differences on the predictor composite score. The 13% minority applicants were based on the aggregate population breakdown, and the 15% level of majority refusals was based on the findings of Tam et al. (2004). I then increased the minority job refusal rates from 15% and manipulated the percentage of minority applicants. The latter represented the manifestation of the level effects for the missing applicant problem and targeted recruitment.

For the full effects simulations, the normative baseline model assumed 13% minority applicants, 15% (20%) level of job refusals for the majority (minority) applicants, a 0.1 (0.2) correlation between the likelihood of a majority (minority) applicant refusing a job offer and the

predictor composite scores, and a 1 SD difference on the predictor scores favoring majority applicants.

From this baseline full effects simulation, the level of the minority job refusal rate was reduced to equal the level of the majority refusal rate (i.e., 0.15), the correlation between the likelihood of minority applicants refusing a job offer and the predictor composite score was decreased to the 0.15 baseline correlation for majority applicants, the percentage of minority applicants was increased from the 13% baseline, the strength of the positive correlation between the percentage of minority applicants and the predictor composite score was strengthened from a zero correlation.

Through these simulations, this study explicated how minority availability issues influence the understanding and detection of adverse impact, alone (i.e., the level effects models) and in conjunction with traditional simulations that focus only on race differences on predictor composite scores (i.e., the full effects models).

Selection ratios. The overall percentage of applicants hired (i.e., the selection ratio) also affects adverse impact. When hiring is based on the top-down criterion, the more selective the organization, the more likely adverse impact is detected. However, when minority preference is used and the level effects of the minority availability factors are included, a decreasing selection ratio does not necessarily result in greater levels of adverse impact. Therefore, I triangulated minority availability factors using two selection ratios that correspond to organizational contexts where the selection ratio is small (0.15) and moderate (0.30).

Applicant Pool Sample Size. Throughout the simulations a sample size of 1,000 is used to determine the qualified applicant pool. This is, in part, due to needing a sample size where the

Z_{IR} significance test has adequate power. As noted by Morris and Lobsnez (2000), it is suggested to use a sample size that produces a frequency of at least five in the smallest expected cell based on the following equation: $(N * SR_T * P_{MIN})$, where N is the total sample size, SR_T is the overall selection ratio and P_{MIN} is the proportion of minorities in the applicant pool. A sample size of 1000 produces a frequency of approximately 6, i.e., $(1000 * .15 * .04)$, in the smallest expected cell for this simulation. This should ensure that the overall sample size is sufficiently large enough to justify the usage of significance tests in the detection of adverse impact. I set the minimum proportion of minorities in the applicant pool to 4%. With an applicant pool of 1000, a 4% minority representation results in 40 minority applicants. Once minority representation is too low, it is difficult to determine what adverse impact statistics mean, if anything. Therefore, instances where minority representation falls below 4% are not simulated. Additionally, this sample size (i.e., 1000) would mimic situations for larger organizations. In situations where sample sizes are small, very small changes to the composition of hires (i.e., changing the race of one hire) can flip an indication of no adverse impact to one of adverse impact, and vice versa (Hauenstein & Tison, 2010).

Adverse Impact Assessment

For each combination of parameters, the assessment of adverse impact is replicated 1,000 times. The dependent variables of interest are the percentage of adverse impact ratios (i.e., 4/5th rule) greater than or equal to the 0.80 standard and the percentage of time adverse impact is indicated using the Z_{IR} significance test, with a 0.05 Type I error rate.

Results

The purpose of this study was to explicate how minority availability issues (i.e., the

missing applicant problem, targeted minority recruitment and job refusal rates) impact decisions of adverse impact in the selection context. More specifically, these simulations examined how minority availability issues influence the detection of adverse impact in selection contexts with and without race effects on the predictor composite (i.e., covariance and level effects). For clarity, results are presented for the level and full (i.e., level and covariance) effects simulations separately.

Level Effects

The level effects simulations assessed the extent to which increasing/decreasing the percentage of minimally qualified applicants increased/decreased the effectiveness of minority preference hiring in reducing adverse impact, across different levels of job refusal rates.

Overall Selection Ratio=0.30. Figures 1 and 2 depict the effects of minority job refusal rates (i.e., the x-axis) and the percentage of minorities in the applicant pool (i.e., categories in the legend) on the detection of adverse impact. Majority job refusal rates were held constant at 0.15 and the overall selection ratio equals 0.30. In Figure 1, the y-axis represents the proportion of Z_{IR} significance tests, across the 1,000 iterations of the simulation program, indicating a statistical difference between the selection ratios of minority and majority applicants.

In general, Figure 1 represents the rate of detecting adverse impact as minority job refusal rates and the percentage of minorities change – there is a U-shaped pattern to the findings. Minority job refusal rates below 0.30 and above 0.35 results in increasingly greater percentages of significant differences between the selection ratios. However, below 0.30, the significant differences are due to the minority selection ratio being greater than the majority selection ratio. It is only above 0.35 where the significant differences reflect the traditional adverse impact

situation where the minority selection ratio is less than the majority selection ratio. For example, when minority job refusal rates are 0.40 and the percentage of minorities is 0.04, significant differences between minority and majority selection ratios will be indicated 0.092 or 9.2% of the time. Increase the percentage of minorities to 0.50 and a significant difference between the selection ratios will be indicated .209 or 20.9% of the time (i.e., a difference of approximately 0.117 or 11.7% between the two percentages of minorities). When minority job refusal rates are 0.50, a significant difference in selection ratios is indicated 26.4% (i.e., 0.264) and 91.5% (i.e., 0.915) of the time for minority percentages of 0.04 and 0.50, respectively (i.e., a difference of approximately 0.651 or 65.1%).

In Figure 2, the y-axis indicates the proportion of adverse impact ratios (AIR), across the 1,000 iterations of the simulation program, greater than or equal to 0.80, which indicates the proportion of simulation iterations that did *not* indicate adverse impact using the AIR statistic (i.e., the 4/5th rule). For instance, when minority job refusal rates are 0.40 and minority percentage is 0.04, 70.9% (i.e., 0.709) of the time no adverse impact will be indicated using AIR.

The general trend of Figure 2 is not surprising, as minority job refusal rates increase indications of adverse impact also increase (i.e., the proportion of AIR greater than or equal to 0.80 decreases). On the left hand side of Figure 2 (i.e., data points where minority refusal rates are less than 0.35) the majority of the data points indicate adverse impact less than 10% of the time (i.e., proportion of AIR greater than or equal to 0.80 are 0.90 or larger). In contrast, once minority job refusal rates are equal to or greater than 0.40, larger percentages of minorities in the applicant pool generally result in more instances of adverse impact.

Summary for Overall Selection Ratio=0.30. These results indicate that minority refusal

rates can produce meaningful levels of adverse impact, when the overall selection ratio 0.30. However, in this simulation, meaningful levels of adverse impact occurred when the minority refusal rate was greater than 0.45, i.e., when the minority refusal rate was approximately 30% greater than the majority refusal rate. The results for selection ratio=0.30 indicate that the effects of the percentage of minorities on adverse impact is counter-intuitive. Decreasing the percentage of minorities *decreases* the likelihood that a higher minority rejection rate increases adverse impact. For any given minority job refusal rate > 0.35 , increasing the percentage of minorities increases the likelihood of detecting adverse impact. This is primarily due to the fact that larger percentages of minority applicants provide more opportunities for minorities to refuse job offers.

Overall Selection Ratio=0.15. Figures 3 and 4 present the level effects results for selection ratio = 0.15. Relative to Figure 1, the curves in Figure 3 are flatter. Adverse impact is only detected above 10% of the time when the minority refusal rate is approximately 0.40. Moreover, adverse impact does not reach a 50% significance rate until the minority refusal rate is approximately 0.50 (and only when the percentage of minority applicants is 13% or greater).

The results in Figure 4 (i.e., 0.15 overall selection ratio) mirror Figure 2 (i.e., 0.30 overall selection ratio). In both Figures, the curves (representing different percentages of minority applicants) tend to intersect at the 45% minority refusal rate. The difference is that the slopes of the curves in Figure 4 are less steep than the slopes of Figure 2, indicating that adverse impact is less likely when the overall selection ratio is 15% than when the overall selection ratio is 30%.

Summary for Overall Selection Ratio=0.15. The results for the two different overall selection ratios are similar. The major difference is the steepness of the trend lines, where the more selective selection context (i.e., overall selection ratio of 0.15) flattens the overall trends.

The flatter curves for the selection ratio = 0.15 indicate that greater organization selectivity reduces the numbers of contexts where job refusal rates and minority representation will produce adverse impact. Figures 1 and 3 both “bottom-out” when minority job refusal rates range between 0.30 to 0.35, indicating that little adverse impact is detected in these situations. Due to the more flattened trend in Figure 3, this “bottom-out” region extends from 0.25 to 0.40. Moreover, Figures 2 and 4 both have a point of inflection around minority job refusal rates of 0.45 – beyond this point, greater minority representation results in more indications of adverse impact.

Manipulation of Majority Job Refusal Level. In the above level effects simulations, it was assumed that the majority refusal rate was always 15%. The issue with holding the majority selection rate constant is that it is impossible to determine if the pattern of adverse impact detection was due solely to the difference between majority-minority selection ratios, or if the pattern was attributable to both the level of refusal rates for both groups *and* the difference between the two refusal rates.

Therefore, I ran additional simulations (overall selection ratio=0.15) where the majority refusal rate was set to zero (See Figure 5 and Figure 6). Relative to Figure 3, the curves in Figure 5 have shifted to the left, indicating that points where the curves in both figures “bottom-out” is a function of approximately a 0.15 difference between the majority and minority refusal rates. Similarly, in Figure 6, the curves intersect at approximately the 35% minority refusal rate as opposed to the curves intersecting at approximately the 45% minority refusal rate in Figure 4. The results of these additional simulations indicate that the effect of refusal rates on adverse impact is primarily dependent on the magnitude of the difference between the majority-minority refusal rates, not the absolute level of the minority refusal rate.

Full Effects

The purpose of the full (i.e., level and covariance) effects simulations was to determine if targeted recruiting of highly qualified minorities can reduce race differences on the predictor composite to the point that adverse impact is meaningfully reduced. Alternatively stated, these simulations aimed to determine the strength of the negative correlation between the percentage of minorities and predictor composite scores necessary to mitigate the negative influence from other covariance effects (i.e., level of minority job refusal rates and the correlation between job refusal rates and predictor composite scores). These simulations began with a baseline model that assumed:

1. A 1 SD race effect on the predictor favoring the majority,
2. 13% minority representation,
3. A zero correlation between percent of minority applicants and predictor composite scores,
4. A 0.1 between job refusal rates and predictor composite scores for majority applicants and, a 0.2 correlation job refusal rates and predictor composite scores for minority applicants,
5. An average job refusal rate of 0.15 for majority applicants and 0.25 for minority applicants.

All full effects simulations assume the level of majority job refusal rate and the correlation between majority job refusal rate and predictor composite scores are constant (i.e., 0.15 and 0.2, respectively).

Across simulations, however, the level of minority job refusal rates and the correlation between majority job refusal rate and predictor composite scores are manipulated from a level

that is greater than the majority level (i.e., 0.25 for the job refusal rate and 0.20 for the correlation) to a level that is equal to the majority level (i.e., 0.15 for the job refusal rates and 0.10 for the correlation). As mentioned above, both of these values are greater for minority applicants than majority applicants in the baseline model and represent the presence of two additional negative forces on adverse impact (beyond predictor composite score differences). Subsequent simulations systematically remove the negative effects of refusal rates by either equating the level of refusal rate of the majority applicants and minority applicants and/or equating the correlation between refusal rate and the predictor composite score for both majority and minority applicants.

I have included a decision tree to explain what parameter values are included in each of the figures (see Figure 7). For each overall selection ratio (i.e., 0.30 and 0.15), each figure is based on a correlation between minority job refusal rate and predictor composite scores (i.e., 0.20 or 0.10) and a level of minority job refusal rates (i.e., 0.25 or 0.15). Recall that the majority job refusal rate is held constant at 0.10 and the correlation between majority job refusal rate and predictor composite scores is held constant $r = 0.15$.

Within each simulation condition explained above, the detection of adverse impact is examined across varying minority percentages and levels of the correlation between minority percentages and predictor composite scores. To reflect the effects of targeted recruiting of only highly qualified applicants, the correlation between minority percentages and predictor composite scores is assumed to be negative, i.e., increasing minority percentages beyond the 13% national average decreases the standardized race effect on the predictor composite. To better explicate this effect, Figure 8 represents the resulting standardized race effect on the predictor composite (i.e., y-axis), given the minority percentage in the applicant pool (i.e., x-

axis) and the correlation value (i.e., legend categories) examined in the simulation. Therefore, when the correlation is zero, the standardized race effect on the predictor composite is 1 SD, regardless of the minority percentage. Increases to the correlation value, however, result in lower standardized race effects on the predictor composite as minority percentage increases.

Below are the results for the full effects simulations in two selection contexts: situations where the overall selection ratios are 0.30 and 0.15.

Overall Selection Ratio=0.30. In Figures 9 thru 12, the y-axis represents the proportion of Z_{IR} significance tests, across the 1,000 iterations of the simulation program, indicating a statistical difference between the selection ratios of minority and majority applicants. Therefore, for a given percentage of minorities and correlation between minority percentage and predictor composite scores, one can determine the proportion of Z_{IR} significance tests that indicate adverse impact. Across the four selection contexts (i.e., Figures 9 thru 12), there are very few differences.

For instance, increasing the percentage of minorities does very little to reduce adverse impact (i.e., reduce the proportion of Z_{IR} significance tests) when there is no correlation between minority percentage and predictor composite scores. In fact, adverse impact is detected almost 100% of the time when no correlation is present, regardless of the percentage of minorities in the applicant pool. Similarly, the proportion of Z_{IR} significance tests remains above 90% (i.e., 0.90) when the correlation between minority percentage and predictor composite scores is -0.30 or less and minority percentage is less than 65% (i.e., 0.65). Moreover, all four selection contexts indicate that a correlation between minority percentage and predictor composite scores greater than -0.50 is the most favorable, in terms of indicating adverse impact. Minority percentage must

be roughly 50% (i.e., 0.50) or greater when the correlation is around -0.50 and 40% (i.e., 0.40) or greater when the correlation is around -0.70, before adverse impact is indicated less than 90% of the time, i.e., the proportion of Z_{IR} significance tests < 0.90 .

No selection context, however, indicates adverse impact less than 10% of the time (i.e., proportion of Z_{IR} significance tests < 0.10) when minority percentages are less than 0.65 and the correlation between minority percentage and predictor composite scores are less than or equal to -0.70. In fact, even the most favorable conditions, when minority percentages are less than 0.65, adverse impact is detected 30% of the time (i.e., the proportion of Z_{IR} significance tests is, on average, 0.30, across the selection contexts when the correlation between minority percentage and predictor composite scores is -0.70).

Figure 12 represents the most favorable of the selection contexts where race effects on the predictor composite are included: the correlation between job refusal rates and predictor composite scores and the level of job refusal rates are equal for minority and majority applicants and their values are low (i.e., 0.10 and 0.15, for the correlation and level respectively). Given this “favorable” selection context, minority percentages were extended to 75% (i.e., 0.75) to determine if there were selection situations where adverse impact was detected less than 10% of the time (i.e., the percentage of Z_{IR} significance tests < 0.10). Although the proportion of Z_{IR} significance tests did drop below 0.10, minority percentage and the correlation between minority percentage and predictor composite scores needed to be high, i.e., 0.70 and -0.70, respectively. No other selection condition meaningfully reduced adverse impact.

Figures 13 through 16 present the AIR statistics for the corresponding conditions presented in Figures 9 through 12. Once again, the results suggest that targeted recruiting is

unlikely to reduce adverse impact when starting from a 1 SD race difference on cognitive ability without targeted recruiting. For example, when there is little (i.e., -0.10) to no correlation between minority percentage and predictor composite scores, increasing the percentage of minorities does little to reduce adverse impact (i.e., increase AIR tests greater than or equal to 0.80); the proportion of AIR tests greater than or equal to 0.80 never rises above 10% (i.e., 0.10). All four selection contexts indicate that a correlation between minority percentage and predictor composite scores greater than -0.50 is the most favorable, in terms of reducing adverse impact. Minority percentages must be roughly 45% (i.e., 0.45) or greater when the correlation is around -0.50 and 35% (i.e., 0.35) or greater when the correlation is around -0.70, to see adverse impact indicated less than 90% of the time, i.e., the proportion of AIR tests greater than or equal to 0.80 above 0.10. No selection context, however, indicates adverse impact less than 10% of the time (i.e., proportion AIR tests greater than or equal to 0.80 above 0.90) when minority percentages are less than 0.60 and the correlation between minority percentage and predictor composite scores are less than or equal to -0.70. Even the most favorable conditions still indicate adverse impact upwards of 20% of the time when minority percentages are less than 0.65 (i.e., the proportion of AIR tests greater than or equal to -0.80 is, on average, 0.20, across the selection contexts when the correlation between minority percentage and predictor composite scores is -0.70).

Figure 16 represents the most favorable of the selection contexts where race effects on the predictor composite are included. As with Figure 12, the correlation between job refusal rates and predictor composite scores and the level of job refusal rates are equal for minority and majority applicants, which are low values (i.e., 0.10 and 0.15, for the correlation and level respectively). This “favorable” selection context was extended to include minority percentages

up to 75% (i.e., 0.75) to determine if there were selection situations where adverse impact was detected less than 10% of the time (i.e., the proportion of AIR tests greater than or equal to 0.80 above 0.90). Although this result was satisfied, minority percentage and the correlation between minority percentage and predictor composite scores needed to be high, i.e., 0.65 and -0.70, respectively. No other selection condition meaningfully reduced adverse impact.

Overall Selection Ratio=0.15. Figures 17 thru 24 represent the same information provided in Figures 9 thru 16 with one exception: the overall selection ratio is 0.15. Reducing the selection ratio from 0.30 to 0.15 had little effect on the detection of adverse impact. There primary effect of reducing smaller selection ratio was to flatten the curves. These flatter curves for the 0.15 selection ration indicate that, relative to the 0.30 selection ratio, a larger percentage of minority applicants is needed to reduce adverse impact. For instance, in Figure 20, when the correlation between minority percentage and predictor composite scores is -0.70, minority percentage needs to be roughly 0.75 before adverse impact is indicated less than 10% of the time (i.e., proportion of ZIR tests < 0.10). However, the same correlation value of -0.70, in a selection situation where the overall selection ratio is 0.30, requires a minority percentage of roughly 0.70 to indicate adverse impact less that 10% of the time (see Figure 12).

Similarly, the interpretation of Figures 21 thru 24 is comparable to Figures 13 thru 16: an increase in minority percentage and/or an increase in the correlation between minority percentage and predictor composite scores results in a decrease in adverse impact (i.e., an increase in the proportion of AIR tests greater than or equal to 0.80). However, as mentioned above, the entire trend is flattened – instances where adverse impact decreases for each of the correlation values require a larger percentage of minorities in the applicant pool. Another notable difference is the fact that the largest reduction in adverse impact still detects it roughly 30% of

the time (i.e., correlation value of -0.70 and minority proportion of 0.75).

Manipulation of Majority Job Refusals (Level and Correlation). It is clear in the above results that an overall selection ratio of 0.30 provides the most favorable conditions in which to reduce adverse impact. However, even in the most favorable selection situations (i.e., equal minority and majority job refusal ratios and correlations between job refusal ratios and predictor composite scores) adverse impact is not readily reduced. In fact, to ensure adverse impact is detected less than 10% of the time, minority percentage and the correlation between minority percentage and predictor composite scores must be 0.70 and -0.70, respectively (see Figure 12). Therefore, I decided to also examine a selection situation that was even more “favorable” to examine any reduction in adverse impact. I re-ran the full effects model (with an overall selection ratio of 0.30) where the majority job refusals and the majority correlation between job refusals and predictor composite scores were larger than the minority values. Therefore, majority and minority job refusals were 0.25 and 0.15, respectively, whereas the majority and minority correlation values were 0.20 and 0.10, respectively. These results are presented in Figures 25 and 26.

Figures 25 and 26 are interpreted the same as Figures 12 and 16, respectively. In fact, there are few differences between them. The overall trend remains the same: increasing minority percentage and/or the negative correlation between minority percentage and predictor composite scores reduces the detection of adverse impact. Regardless, in Figure 25, minority percentages around 0.40 are required to meaningfully decrease the detection of adverse impact (i.e., percentage of Z_{IR} values dip below 90%) and minority percentages around 0.70 are required to reduce the detection of adverse impact below 10% (and this is only in instances where the correlation value is -0.70). Similar results are found in Figure 26. Minority percentages around

0.40 improve AIRs; however, minority percentages around 0.65 – 0.70 are required to indicate AIRs greater than or equal to 0.80 more than 90% of the time.

Discussion

Organizations are often interested in reducing adverse impact in their employment practices. This not only stems from the legal implications associated with employment discrimination (see Title 42 of the U.S. Code) but also from organizational goals to increase diversity in the workplace. Research in employee selection aims to guide organizations with their employment decisions and has examined the effects of many selection practices on adverse impact (cf., Guion, 1998; Hough, et al., 2001). Much of this research, however, highlights the difficulty associated with the reduction of adverse impact. Not only do reductions of adverse impact commonly result in declines of predicted job performance (Gottfredson, 1988; Sacket, et al., 2001), but attempts to reduce adverse impact are often an act of futility. Organizations are often still faced with adverse impact issues even after their attempts to reduce it (cf., Finch, et al., 2009).

The main focus of this employee selection research, however, is on the reduction of race effects on the predictor composite (e.g., De Corte, et al., 2007; De Corte, et al., 2008; Potosky, et al., 2005). This overlooks an important influence on adverse impact: minority availability issues, i.e., the “missing applicant” problem, targeted recruitment and job refusal rates. Although some researchers acknowledge that these issues may affect adverse impact (e.g., Tam, et al., 2004; Newman & Lyon, 2009), research has not presented a comprehensive, systematic examination of minority availability. Without this consideration, it is unclear how these issues exacerbate/ameliorate the detection of adverse impact in the selection context. Examining these

effects in selection situations void of standardized race effects on predictor composite scores highlight the potency of their individual influence (both on adverse impact ratios via job refusal rates and on facilitating diversity goals (i.e., increasing minority percentage through targeted recruiting and the missing applicant problem) through minority preference. In contrast, considering the full effects (i.e., level and covariance effects) of minority availability in selection contexts *with* race effects on predictor composite scores, highlights how these issues influence organizational attempts to reduce adverse impact. A full account of minority availability issues within selection contexts provides a more realistic understanding of adverse impact, even if this understanding compounds the difficult position in which organizations are placed when reduction of adverse impact is the goal.

The purpose of this study was to explore how the level and covariance effects of minority availability issues impact decisions of adverse impact. More specifically, this study sought to determine the 1) conditions under which minority availability issues exacerbate adverse impact, void of any race effects on the predictor composite (i.e., level effect models) and 2) conditions under which minority availability issues reduce adverse impact, when race effects on the predictor composite exist in the selection context (i.e., full effect models). Monte carlo simulations were used to model detection of adverse impact in each of these selection contexts.

Level Effects

The level effect simulations sought to determine if minority availability issues can produce adverse impact, even when there are no race effects on the predictor composite. The results indicated that the detection of adverse impact increases as 1) as the minority applicant refusal rate increased from the majority applicant refusal rate, 2) the percentage of minority

applicants reached a certain threshold (approximately 40% in the simulations) and 3) the selection ratio increased. Obviously, these results reflect general trends as opposed to specific probabilities of detecting adverse impact due to level effects associated with job refusal rates and minority availability.

It is clear that minority availability can produce adverse impact when there are no race differences on the predictor composite. What is not apparent is whether these selection contexts where adverse impact is likely to be detected are realistic in an organizational setting. One reason for this uncertainty is the paucity of descriptive research on minority availability. Descriptive research is needed regarding race differences on refusal rates, the effectiveness of targeted recruiting in terms of both increasing the percentage of minority applicants and the percentage of highly qualified minorities, and the effects of labor market variables on the percentage of minority applicants. Without this descriptive information, it is difficult to draw firm conclusions regarding the extent to which minority availability produces adverse impact in the selection systems.

However, it appears that the selection contexts where minority availability produces adverse impact are atypical. First, the missing applicant problem only influences adverse impact when minority preference hiring is used. Selection systems that formally include a minority preference hiring criteria are difficult to defend from a legal standpoint (Sackett et al., 2001). However, organizations are clearly sensitive to achieving affirmative action goals, and they likely engage in unstated hiring practices that result in a form of minority preference hiring. Second, in the current simulations, reaching a 0.50 probability of detecting adverse impact required that the minority job refusal rate be at least 30% greater than the majority job refusal rate, and that the percentage of minority applicants be greater than the 40%.

In summary, it appears unlikely that minority availability routinely causes adverse impact in organizational hiring systems. The need for a high percentage of minority applicants appears to be the most likely reason that minority availability does not routinely cause adverse impact. However, there may well be organizational contexts where adverse impact is solely due to minority availability issues. Awareness of the extent to which these organizational contexts exist requires the aforementioned descriptive research efforts.

Full Effects

The goal of the full effect simulations was to determine the extent to which targeted recruiting might reduce race differences on predictor composite, thereby reducing adverse impact. However, the mitigating effects of targeted recruiting also were examined in relation to the negative effect of race differences on job refusal rates. Results of the simulation indicated that targeted recruiting did little to reduce adverse impact, regardless the presence/absence of race differences on job refusal rates. To meaningfully reduce adverse impact in the simulations required that the percentage of minority applicants reach at least 65% *and* that the correlation between minority percentage and predictor composites scores reach at least -0.70.

It is reasonable to consider how the simulations of the full effects might be modified to present a less pessimistic view of targeted recruitment and adverse impact when race differences exist on the predictor composite score. First, reducing the magnitude of the starting point for the race effects on the predictor composite score from 1 SD would increase the effectiveness of targeted recruiting. If targeted recruiting reduces the race difference on the predictor composite score from the baseline race difference without targeted recruiting, then the smaller the baseline race difference, the greater the beneficial effects of targeted recruiting. Second, the starting point

of a 1 SD race difference on the predictor composite score was yoked to the 13% minority applicant. Raising or lowering the minority percentage yoked to the race difference starting point on the predictor composite would also affect the detection of adverse impact. Of these two issues, the reducing the magnitude of the race difference starting point clearly has the greatest potential to demonstrate the benefits of targeted recruiting.

Descriptive research regarding refusal rates and targeted recruiting is also needed to assess the generalizability of the full effects simulations. Specifically, the correlation between job refusal rates and predictor composite scores, the extent to which race moderates the refusal rate-predictor composite relationship, the effectiveness of targeted recruiting in the sense of increasing the percentage of qualified minority applicants, and the extent to which targeted recruiting reduces race differences on the predictor composite scores. Without knowledge of the strengths of these relationships, it is unclear how much of a positive influence targeted recruiting will have on the detection of adverse impact. In the simulations, the correlation between minority percentage and predictor composite scores was assumed to be negative due to the positive influence of targeted recruitment. However, there is no research to guide the choice of the strength of this negative relationship. Moreover, it is possible that race differences on the predictor composite score increase as the percentage of minority applicant increase. That is, the “negative” influence of the “missing applicant problem” may well be stronger than the “positive” influence of targeted recruitment. If this is so, larger percentages of minorities would lead to larger race effects on the predictor composite and, thus, a higher likelihood of indicating adverse impact. Furthermore, the negative influences of job refusals (i.e., its correlation with predictor composite scores) may be worse (or better) than examined in these simulation contexts. Without research to understand these values, it is unclear how much of an influence minority availability

issues have in the reduction of adverse impact.

The reality is these full effect models present a bleak picture. As mentioned above, even the assumption of a negative correlation between percentage of minorities and predictor composite scores, indicated that efforts to reduce/eliminate adverse impact are extremely difficult; if additional research, examining real world manifestations of minority availability issues, discover this correlation to instead be positive, reductions in adverse impact could be near impossible. Therefore, the current study highlights the influential role minority availability issues can play in regards to the detection of adverse impact. On the other hand, the current study also highlights ways in which organizations can use minority availability to aid efforts to reduce the detection of adverse impact - attempts to reduce adverse impact are most responsive to situations where there are more qualified minorities in the applicant pool and the overall selection ratio is high. This translates into increasing targeted recruitment efforts, lowering minimum qualifications and increasing overall selection ratios.

To most organizations, the most palatable of these options is targeted recruitment, especially since lowering minimum qualifications and increasing overall selection ratios may negatively influence job performance. Therefore, organizations can implement targeted recruitment strategies to assist in their efforts to reduce adverse impact. This, however, is not new; recruitment strategies are commonly employed (see Taylor & Collins, 2000, for a review of recruitment strategies). Nevertheless, if every organization implements targeted recruitment strategies, no single organization will benefit from their efforts. Why not? Simply put, there are only so many qualified minorities to recruit. If every organization is recruiting the same qualified minorities, the same problem exists – high competition; organizations are still vying for the same applicants.

Another alternative is to increase the number of available qualified minorities. For example, if there are only 100 qualified minorities available for recruitment, targeted recruitment may raise the number of qualified minorities in a particular applicant pool from 30 to 50; regardless of the increase, an organization cannot recruit more than the 100 available minorities. An alternative is to focus was on increasing the number of qualified minorities. Efforts to recruit, hire and retain more minorities may be more fruitful. This, however, requires investments into the community: investments to ensure more minorities are acquiring the skills necessary to become qualified applicants and investments to create more desirable locales to aid in the recruitment and retention of qualified minorities. Investments of this magnitude are likely to require policy changes that incentivize and encourage such behavior.

Conclusion

The reality is that researchers and practitioners need to better understand minority availability issues within the selection context, as it is clear that these issues can influence the detection of adverse impact. For instance, the level effect models of minority availability can indicate adverse impact over 90% of the time, when there are no race effects on the predictor (see Figures 1 thru 6). And, the full effect models of minority availability do very little to reduce the detection of adverse impact, in realistic selection situations – organizations must have upwards of 70% minorities in the applicant pool before minority availability meaningfully reduces adverse impact (see Figures 9 and 23). Without a better understanding of how these minority availability issues manifest themselves in the real-world, researchers and organizations are likely to underestimate the severity of their adverse impact problem. Researchers already acknowledge the difficulties in reducing adverse impact; the inclusion of minority availability may further compound this issue.

References

- Avery, R.D., Gordon, M.E., Massengill, D.P. & Mussio, S.J. (1975). Differential dropout rates of minority and majority job candidates due to 'time lags' between selection procedures. *Personnel Psychology*, 28, 175-180.
- Berry, C.M., Gruys, M.L. & Sackett, P.R. (2006). Educational attainment as a proxy for cognitive ability in selection: effects on levels of cognitive ability and adverse impact. *Journal of Applied Psychology*, 91, 696-705.
- Bobko, P. & Roth, P.L. (2004). Personnel selection with top-score-referenced banding: on the inappropriateness of current procedures. *International Journal of Selection and Assessment*, 12, 291-298.
- Bretz, R.D. & Judge, T.A. (1998). Realistic job previews: a test of the adverse self-selection hypothesis. *Journal of Applied Psychology*, 83, 330-337.
- Buster, M.A., Roth, P.L. & Bobko, P. (2005). A process for content validation of education and experienced-based minimum qualifications: an approach resulting in federal court approval. *Personnel Psychology*, 58, 771-799.
- Camara, W.J. & Schmidt, E. (1999). Group differences in standardized testing and social stratification (College Board Report No. 99-5). Retrieved from the College Board website: http://professionals.collegeboard.com/profdownload/pdf/rr9905_3916.pdf.
- Campbell, J.P. (1996). Group differences and personnel decisions: validity, fairness and affirmative action. *Journal of Vocational Behavior*, 49, 122-158.

- Cascio, W.F., Valenzi, E.R., & Silbey, V. (1980). More on validation and statistical power. *Journal of Applied Psychology*, 65, 135-138.
- Collins, C.J. & Han, J. (2004). Exploring applicant pool quantity and quality: the effects of early recruitment practice strategies, corporate advertising, and firm reputation. *Personnel Psychology*, 57, 685-717.
- De Corte, W. (1999). Weighting job performance predictors to both maximize the quality of the selected workforce and control the level of adverse impact. *Journal of Applied Psychology*, 84, 695-702.
- De Corte, W. & Lievens, F. (2003). A practical procedure to estimate the quality and the adverse impact of single-stage selection decisions. *International Journal of Selection and Assessment*, 11, 89-97.
- De Corte, W., Lievens, F. & Sackett, P.R. (2006). Predicting adverse impact and mean criterion performance in multistage selection. *Journal of Applied Psychology*, 91, 523-537.
- De Corte, W., Lievens, F. & Sackett, P.R. (2007). Combining predictors to achieve optimal trade-offs between selection quality and adverse impact. *Journal of Applied Psychology*, 92, 1380-1393.
- De Corte, W., Lievens, F. & Sackett, P.R. (2008). Validity and adverse impact potential of predictor composite formation. *International Journal of Selection and Assessment*, 16, 183-200.
- Dunleavy, E.M., Stuebing, K.M., Campion, J.E. & Glenn, D.M. (2008). Using the 4/5ths rule as

an outcome in regression analyses: a demonstrative simulation. *Journal of Business Psychology*, 23, 103-114.

Esson, P. L., & Hauenstein, N. M. A. (May, 2006). *Adverse impact: four-fifths rule versus statistical significance testing in the courtroom*. Paper presented at the 21st annual conference of the Society for Industrial and Organizational Psychology, Dallas, Texas.

Equal Employment Opportunity Commission (EEOC), Civil Service Commission, Department of Labor, and Department of Justice. (1978). Uniform guidelines on employee selection procedures. *Federal Register*, 43, 38290 – 38315.

Finch, D.M., Edwards, B.D., & Wallace, J.C. (2009). Multistage selection strategies: simulating the effects on adverse impact and expected job performance for various predictor combinations. *Journal of Applied Psychology*, 94, 318-340.

Gottfredson, L.S. (1988). Reconsidering fairness: a matter of social and ethical priorities. *Journal of Vocational Behavior*, 33, 293-319.

Griggs v. Duke Power Co., 401 US 424 (1971).

Guion, R.M. (1998). *Assessment, measurement, and prediction for personnel decisions*. Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Hauenstein, N. & Tison, E.B. (2010). *Detecting adverse impact: the four-fifths rule versus significance testing*. Manuscript in preparation.

Hough, L.M., Oswald, F.L., & Ployhart, R.E. (2001). Determinants, detection and amelioration of adverse impact in personnel selection procedures: issues, evidence and lessons learned.

International Journal of Selection and Assessment, 9, 152-194.

Hunter, J.E. & Hunter, R.F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin*, 96, 72-98.

Lerner, B. (1979). Employment discrimination: adverse impact, validity and equality. *The Supreme Court Review*, 1979, 17-49.

Morris, S.B., & Lobsenz, R.E. (2000). Significance tests and confidence intervals for the adverse impact ratio. *Personnel Psychology*, 53, 89-112.

Murphy, K.R. (1986). When your top choice turns you down: effect of rejected offers on the utility of selection tests. *Psychological Bulletin*, 99, 133-138.

Murphy, K.R. & Tam, A.P. (2004). The decisions job applicants make: insights from a bayesian perspective. *International Journal of Selection and Assessment*, 12, 66-74.

Murphy, K.R., Osten, K. & Myors, B. (1995). Modeling the effects of banding in personnel selection. *Personnel Psychology*, 48, 61-84.

National Association of System Heads (NASH) – Educational Trust (2009). Charting a necessary path: the baseline report of public higher education systems in the access to successful initiative. Retrieved from Educational Trust website:
<http://www.edtrust.org/sites/edtrust.org/files/publications/files/NASH-EdTrust.BaselineReport.pdf>

Newman, D.A. & Lyon, J.S. (2009). Recruitment efforts to reduce adverse impact: targeted recruiting for personality, cognitive ability and diversity. *Journal of Applied Psychology*,

94, 298-317.

- Pennock-Roman, M. (1993). Differences among racial and ethnic groups in mean scores on the GRE and SAT: cross-sectional comparisons (GRE Board Professional Report N. 86-09aP; ETS Research Report 91-13). Retrieved from the Educational Testing Service website: <http://www.ets.org/Media/Research/pdf/RR-91-13-Pennock-Roman.pdf>
- Plag, J.A. & Goffman, J.M. (1967). The armed services qualifications test: its validity in predicting military effectiveness for naval enlistees. *Personnel Psychology*, 20, 323-340.
- Ployhart, R.E. & Holtz, B.C. (2008). The diversity-validity dilemma: strategies for reducing racioethnic and sex subgroup differences and adverse impact in selection. *Personnel Psychology*, 61, 153-172.
- Ployhart, R.E., McFarland, L.A. & Ryan, A.M. (2002). Examining applicants' attributions for withdrawal from a selection procedure. *Journal of Applied Social Psychology*, 32, 2228-2252.
- Potosky, D., Bobko, P., & Roth, P.L. (2005). Forming composites of cognitive ability and alternative measures to predict job performance and reduce adverse impact: corrected estimates and realistic expectations. *International Journal of Selection and Assessment*, 13, 304-315.
- Pulakos, E.D. & Schmitt, N. (1996). An evaluation of two strategies for reducing adverse impact and their effects on criterion-related validity. *Human Performance*, 9, 241-258.
- Pyburn, K.M., Ployhart, R.E. & Kravitz, D.A. (2008). The diversity-validity dilemma: overview

- and legal context. *Personnel Psychology*, 61, 143-151.
- Roth, P.L. & Bobko, P. (2000). College grade point average as a personnel selection device: ethnic group differences and potential adverse impact. *Journal of Applied Psychology*, 85, 399-406.
- Roth, P.L., Bobko, P. & Switzer, F.S. (2006). Modeling the behavior of the 4/5ths rule for determining adverse impact: reasons for caution. *Journal of Applied Psychology*, 91, 507-522.
- Rynes, S.L. (1991). Recruitment, job choice, and post-hire consequences: a call for new research directions. In M.D. Dunnette & L.M. Hough (Eds.), *Handbook of industrial and organizational psychology: Vol. 2* (2nd ed., pp. 399-444). Palo Alto, CA: Consulting Psychologists Press.
- Sackett, P.R. & Ellingson, J.E. (1997). The effects of forming multi-predictor composites on group differences and adverse impact. *Personnel Psychology*, 50, 707-721.
- Sackett, P.R. & Roth, L. (1991). A monte carlo examination of banding and rank order methods of test score use in personnel selection. *Human Performance*, 4, 279-295.
- Sackett, P.R. & Roth, L. (1996). Multi-stage selection strategies: a monte carlo investigation of effects on performance and minority hiring. *Personnel Psychology*, 49, 549-572.
- Sackett, P.R., Schmitt, N., Ellingson, J.E., & Kabin, M.B. (2001). High-stakes testing in employment, credentialing, and higher education: prospects in a post-affirmative action world. *American Psychologist*, 56, 302-318.

- Sackett, P.R. & Shen, W. (2010). Subgroup differences on cognitive tests in contexts other than personnel selection. In J.L. Outtz (Ed.), *Adverse impact: implications for organizational staffing and high stakes selection* (pp. 323-346). New York, NY: Taylor and Francis Group.
- Schmidt, F.L. & Hunter, J. (1998). The validity and utility of selection methods in personnel psychology: practical and theoretical implications of 85 years of research findings. *Psychological Bulletin*, 124, 262-274.
- Schmit, M.J. & Ryan, A.M. (1997). Applicant withdrawal: the role of test-taking attitudes and racial differences. *Personnel Psychology*, 50, 855-876.
- Schmitt, N. & Quinn, A. (2010). Reductions in measured subgroup mean differences: what is possible? In J.L. Outtz (Ed.), *Adverse impact: implications for organizational staffing and high stakes selection* (pp. 425-451). New York, NY: Taylor and Francis Group.
- Schmitt, N., Rogers, W., Chan, D., Sheppard, L. & Jennings, E. (1997). Adverse impact and predictive efficiency of various predictor combinations. *Journal of Applied Psychology*, 82, 719-730.
- Tam, A.P., Murphy, K.R. & Lyall, J.T. (2004). Can changes in differential dropout rates reduce adverse impact? A computer simulation study of a multi-wave selection system. *Personnel Psychology*, 57, 905-934.
- Taylor, M.S. & Collins, C.J. (2000). Organizational recruitment: enhancing the intersection of research and practice. In C.L. Cooper & E.A. Locke (Eds.), *Industrial and Organizational Psychology: Linking Theory with Practice* (pp. 304-334). Oxford, UK :

Blackwell Publishers Inc.

Title VII of the Civil Right Act (1964). 42 U.S.C. § 2000d et seq.

Title 42 of the U.S. Code § 2000a et seq.

U.S. Census Bureau. (2006a). *State and county quickfacts: Philadelphia, PA*. Retrieved March 5, 2010, from <http://quickfacts.census.gov/qfd/states/42/4260000.html>.

U.S. Census Bureau. (2006b). *State and county quickfacts: Phoenix, AZ*. Retrieved March 5, 2010, from <http://quickfacts.census.gov/qfd/states/04/0455000.html>.

U.S. Census Bureau. (2008a). *Annual estimates of the resident population by sex, race and hispanic origin for the united states: April 1, 2000 to July 1, 2008*. Retrieved March 5, 2010, from <http://www.census.gov/popest/national/asrh/NC-EST2008/NC-EST2008-03.xls>.

U.S. Census Bureau. (2008b). *Educational attainment of the population 18 years and over by age, sex, race and hispanic origin: 2008*. Retrieved March 5, 2010, from <http://www.census.gov/population/www/socdemo/education/cps2008.html>.

Waldman, D.A. & Avoilio, B.J. (1991). Race effects in performance evaluations: controlling for ability, education and experience. *Journal of Applied Psychology*, 6, 897-901.

Wollack, S. (1994). Confronting adverse impact in cognitive examinations. *Public Personnel Management*, 23, 217-224.

Footnotes

¹Race or color can never be considered a BFOQ, unlike religion, sex, national origin and age (Title VII, 1964).

Appendix A

Veridical Sliding-Band Simulation Code for SAS

```

dm 'log;clear;output;clear;';
options mprint mlogic pageno=1 nodate formdlim="=" notes source;
data temp;
run;
filename junk dummy;
proc printto log=junk;
run;
ods listing close;
ods results=off;
%macro research(nsim=1000);
%let SR=0.15;
%let N=1000;
%let MinR=0.13;
%let RaceEffect=0;
%do index = 1 %to &nsim;
  data _null_;
    call symput("Nmin",&MinR*&N);
    call symput("Nmaj",&N.-(&MinR.*&N));
    call symput("AppPool",&N*&SR);
  run;

  data graduation&index;
    do i=1 to 100000;
      x=rannor(0);
      race = 'White';
      if i gt (100000*(1-&MinR)) then race='Black';
      if race='White' then x = x + &RaceEffect;
      output;
    end;
  run;
  proc sort data=graduation&index;
    by race;
  run;
  proc surveyselect data=graduation&index method=sys sampsize=(&Nmin &Nmaj)
    out=applicantpool&index;
    strata race;
    id x;
  run;
  proc freq data=applicantpool&index;
    table race;
    ods output OneWayFreqs = OrigCounts&index;
  run;
  proc sort data=applicantpool&index;
    by descending x;
  run;

  data applicantpool&index;
    set applicantpool&index;
    i = _n_;
    c=0;

```



```

        output;
run;
proc means data=graduation&index var;
    var x;
    ods output summary=popvar&index(rename=(x_Var=sig2x));
run;
data popvar&index;
    set popvar&index;

    do i = 1 to &N;
        bandwidth = sqrt(8*sig2x*(1-0.85));
        output;
    end;
    drop sig2x;
run;
%do j = 1 %to &AppPool;
    proc sort data=applicantpool&index (keep=race x Sel: samp: i c);
        by c descending x;
    run;

    data rank&index;
        set applicantpool&index;
        by c descending x;
        if first.c and first.x then xmax=x;
        else delete;
run;
data xmax&index;
    set rank&index(keep=xmax);
    do i = 1 to &N;
        xmax=xmax;
        output;
    end;
run;
data applicantpool&index;
    merge applicantpool&index (in=a) popvar&index xmax&index;
    by i;
    Band = ((xmax-x)<=bandwidth);
    if a;
run;
proc freq data=applicantpool&index;
    where band=1;
    tables race;
    ods output OneWayFreqs = racecheck&index;
run;
proc transpose data=racecheck&index out=racecheck&index;
run;
proc means data=applicantpool&index n;
    where band=1;
    var band;
    ods output Summary=BandSize&index;
run;
data _null_;
    set bandsize&index;
    call symputx("bandsize",band_n,'L');
run;
data racecheck&index;
    set racecheck&index;

```

```

where _name_ eq "Frequency";
if coll=&bandsize then do;
    WhiteApps = Coll;
    BlackApps = 0;
end;
else do;
    WhiteApps=&bandsize.-Coll;
    BlackApps=Coll;
end;

drop col: _label_;
call symputx("BlackApps",BlackApps,'L');
call symputx("WhiteApps",WhiteApps,'L');
run;
%if &BlackApps ne 0 %then %do;
proc surveysselect data=applicantpool&index method=sys sampsize=1
out=tempf&index;
    where race="Black" and band=1;
    id i x race;
run;
%end;
%else %do;
proc surveysselect data=applicantpool&index method=sys
sampsize=1 out=tempf&index;
    where race="White" and band=1;
    id i x race;
run;
%end;
data _null_;
set tempf&index;

call symputx("newsel",i,'L');
run;
proc datasets library=work;
append base=selected&index data=tempf&index;
run;
data applicantpool&index;
set applicantpool&index;
where i ne &newsel;
run;
%end;
proc sort data=selected&index;
by race;
run;
proc means data=selected&index n;
ods output summary=FirstRoundPicks&index;
run;
data FirstRoundPicks&index;
set FirstRoundPicks&index;
call symputx ("firstroundpicks", i_N, 'L');
run;
data FirstRound&index;
set selected&index;
if race='White' then reject = ranbin (0,1,0.10);
else reject = ranbin (0,1,0.10);
keep race x reject;

run;

```

```

proc means data=FirstRound&index mean;
    var reject;
    by race;
    ods output summary=RejectRate&index;
run;
%if &index = 1 %then %do;
    data overallreject;
        set RejectRate&index;
    run;
%end;
%else %do;
    data overallreject;
        set overallreject RejectRate&index;
    run;
%end;
data FirstRound&index;
    set FirstRound&index;
    if reject = 1 then delete;
run;
proc freq data=FirstRound&index;
    tables race;
    ods output OneWayFreqs = hires&index;
run;
data hires&index;
    set hires&index;
    where race eq "White";
run;
proc transpose data=hires&index out=hires&index;
run;
data hires&index;
    set hires&index;
    where _name_ eq "CumFrequency";
    NewHires=(&AppPool.-Coll);
    drop col: _label_;
    call symputx("NewHires",NewHires,'L');
run;
data applicantpool&index;
    set applicantpool&index;
    i = _n_;
run;
proc means data=graduation&index var;
    var x;
    ods output summary=popvars&index(rename=(x_Var=sig2x));
run;
data popvars&index;
    set popvars&index;
    do i = 1 to (&N.-&firstroundpicks.);
        bandwidth = sqrt(8*sig2x*(1-0.85));
        output;
    end;
    drop sig2x;
run;
%do k = 1 %to &NewHires;
    proc sort data=applicantpool&index (keep=race x Sel: samp: i c);
        by c descending x;
    run;

```

```

data tempx&index;
  set applicantpool&index;
  by c descending x;
  if first.c and first.x then xmax=x;
  else delete;
run;
data xmaxs&index;
  set tempx&index(keep=xmax);
  do i = 1 to (&N.-&firstroundpicks.);
    xmax=xmax;
    output;
  end;
run;
data applicantpool&index;
  merge applicantpool&index (in=a) popvars&index xmaxs&index;
  by i;

  Band = ((xmax-x)<=bandwidth);
  if a;
run;
proc freq data=applicantpool&index;
  where band=1;
  tables race;
  ods output OneWayFreqs = racechex&index;
run;
proc transpose data=racechex&index out=racechex&index;
run;
proc means data=applicantpool&index n;
  where band=1;
  var band;
  ods output Summary=BandSizes&index;
run;
data _null_;
  set bandsizes&index;
  call symputx("bandsize",band_n,'L');
run;
data racechex&index;
  set racechex&index;
  where _name_ eq "Frequency";
  if coll=&bandsize then do;
    WhiteApps = Coll;
    BlackApps = 0;
  end;
  else do;
    WhiteApps=&bandsize.-Coll;
    BlackApps=Coll;
  end;
  drop col: _label_;
  call symputx("BlackApps",BlackApps,'L');
  call symputx("WhiteApps",WhiteApps,'L');
run;
%if &BlackApps ne 0 %then %do;
  proc surveysselect data=applicantpool&index method=sys sampsize=1
out=temp&index;
    where race="Black" and band=1;
    id i x race;
  run;

```

```

%end;
  %else %do;
    proc surveyselect data=applicantpool&index method=sys
sampsiz=1 out=temps&index;
      where race="White" and band=1;
      id i x race;
    run;
  %end;

data _null_;
  set temps&index;
  call symputx("newsel",i,'L');
run;
%put newsel=&newsel;
proc datasets library=work;
  append base=SecondRound&index data=temps&index;
run;
data applicantpool&index;
  set applicantpool&index;
  where i ne &newsel;
run;
%end;
data finalpool&index;
  set FirstRound&index SecondRound&index;
  keep race x;
run;
proc sort data=finalpool&index;
  by race;
run;
proc freq data=finalpool&index;
  table race;
  ods output OneWayFreqs = FinalCounts&index;
run;

data results&index;
  set OrigCounts&index FinalCounts&index;
run;
proc transpose data=results&index out=results&index;
run;
data results&index;
  set results&index;
  where _name_="Frequency";
  BlackApps = Col1;
  WhiteApps = Col2;
  if col3=&AppPool then do;
    WhiteHires = Col3;
    BlackHires = 0;
  end;
  else do;
    WhiteHires=Col4;
    BlackHires=Col3;
  end;
  AI = (blackhires/blackapps) / (whitehires/whiteapps);
  PropAI = AI >= 0.80;
  ZIR = log(AI) / sqrt((1-&SR) / (&SR) * (1/&Nmaj + 1/&Nmin));
  drop _label_ coll-col4;
run;

```

```

%if &index = 1 %then %do;
    data all;
        set results&index;
            where _name_ ne "";
    run;
%end;
%else %do;
    data all;
        set all results&index;
            where _name_ ne "";
    run;
%end;
proc datasets library=work;
    save Overallreject All;
quit;
run;
%end;
data all;
    set all;
    ZIRpval = cdf("normal",-abs(ZIR))*2;
    ZIRlogic = ZIRpval < 0.05;
run;

dm 'log;clear;output;clear;';
quit;
proc printto;
run;
%mend;
%research(nsim=1000);
ods listing;
ods results=on;
proc means data=all n mean std min max median;
    title "No Race effects equal job refusals=0.10 selection ratio=0.15
minority proportion=0.13 ";
    var PropAI AI ZIR ZIRpval ZIRlogic;
run;
proc sort data=overallreject;
    by race;
run;
proc summary data=overallreject mean;
    title "overall job refusal rates";
    by race;
    var reject_mean;
    output out=meanjobrefusal;
run;

```

Figure Captions

Figure 1. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across minority job refusal rates and proportions of minorities in the applicant pool (i.e., 0.04, 0.13, 0.25, 0.40 and 0.50). This selection context assumes an overall selection ratio of 0.30, a majority job refusal rate of 0.15 and no race effects on predictor composite scores.

Figure 2. The proportion of adverse impact ratios (AIR) greater than 0.80 (i.e., the 4/5th rule), across minority job refusal rates and proportions of minorities in the applicant pool (i.e., 0.04, 0.13, 0.25, 0.40 and 0.50). This selection context assumes an overall selection ratio of 0.30, a majority job refusal rate of 0.15 and no race effects on predictor composite scores.

Figure 3. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across minority job refusal rates and proportions of minorities in the applicant pool (i.e., 0.04, 0.13, 0.25, 0.40 and 0.50). This selection context assumes an overall selection ratio of 0.15, a majority job refusal rate of 0.15 and no race effects on predictor composite scores.

Figure 4. The proportion of adverse impact ratios (AIR) greater than 0.80 (i.e., the 4/5th rule), across minority job refusal rates and proportions of minorities in the applicant pool (i.e., 0.04, 0.13, 0.25, 0.40 and 0.50). This selection context assumes an overall selection ratio of 0.15, a majority job refusal rate of 0.15 and no race effects on predictor composite scores.

Figure 5. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across minority job refusal rates and proportions of minorities in the applicant pool (i.e., 0.04, 0.13, 0.25, 0.40 and 0.50). This

selection context assumes an overall selection ratio of 0.15, a majority job refusal rate of 0 and no race effects on predictor composite scores.

Figure 6. The proportion of adverse impact ratios (AIR) greater than 0.80 (i.e., the 4/5th rule), across minority job refusal rates and proportions of minorities in the applicant pool (i.e., 0.04, 0.13, 0.25, 0.40 and 0.50). This selection context assumes an overall selection ratio of 0.15, a majority job refusal rate of 0 and no race effects on predictor composite scores.

Figure 7. This outlines the parameter values represented in Figures 9 thru 24. Each figure represents an overall selection ratio, a correlation between minority job refusal rate and the predictor composite, and a level of minority job refusal rate. The level of majority job refusal rate and the correlation between majority job refusal rate and the predictor composite are held constant (i.e., 0.15 and 0.10, respectively). Within each figure, the detection of adverse impact, across percentage of minorities in the applicant pool and the correlation between the percentage of minorities and the predictor composite, is examined.

Figure 8. This represents the magnitude of the standardized race effect on the predictor composite, as a function of the percentage of minorities in the applicant pool and the correlation between minority percentage and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7).

Figure 9. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across the percentage of minorities in the applicant pool and correlations between minority percentage and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 10. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 11. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 12. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 13. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across the percentage of minorities in the applicant pool and correlations between minority percentage and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal

rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 14. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 15. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 16. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 17. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores

(i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 18. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 19. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 20. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 21. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between

proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 22. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.20.

Figure 23. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.25 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 24. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.15, majority and minority job refusal rates of 0.15 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.10 and 0.10.

Figure 25. The proportion of Z_{IR} significance tests indicating a statistical difference between the selection ratios of minority and majority applicants, across proportions of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.25 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.20 and 0.10.

Figure 26. The proportion of adverse impact ratios (AIR) greater than or equal to 0.80 (i.e., the 4/5th rule), across proportion of minorities in the applicant pool and correlations between proportion of minorities and predictor composite scores (i.e., 0, -0.1, -0.3, -0.5 and -0.7). This selection context assumes an overall selection ratio of 0.30, majority and minority job refusal rates of 0.25 and 0.15 and correlations between majority and minority job refusal rates and predictor composite scores of 0.20 and 0.10

Figures

Figure 1

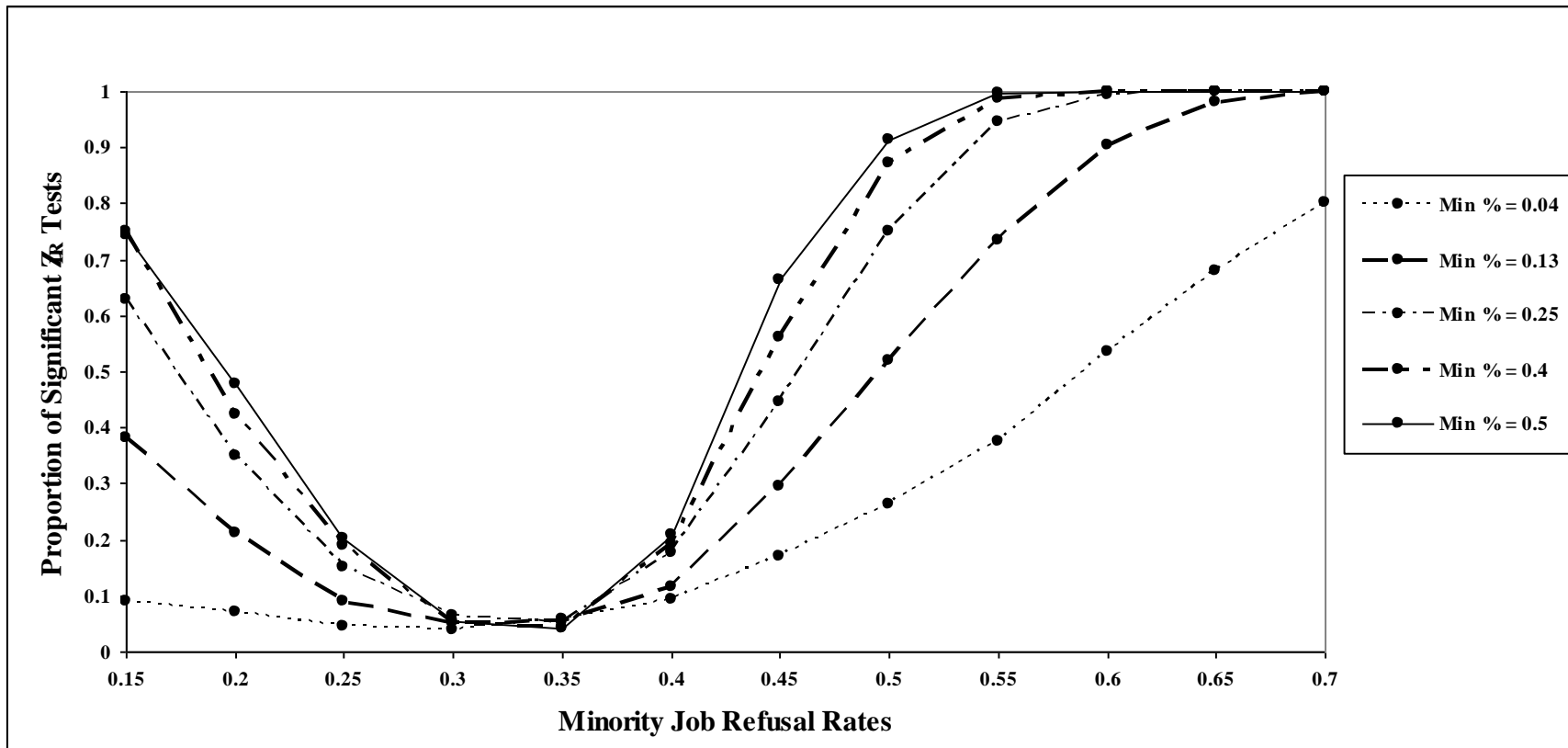


Figure 2

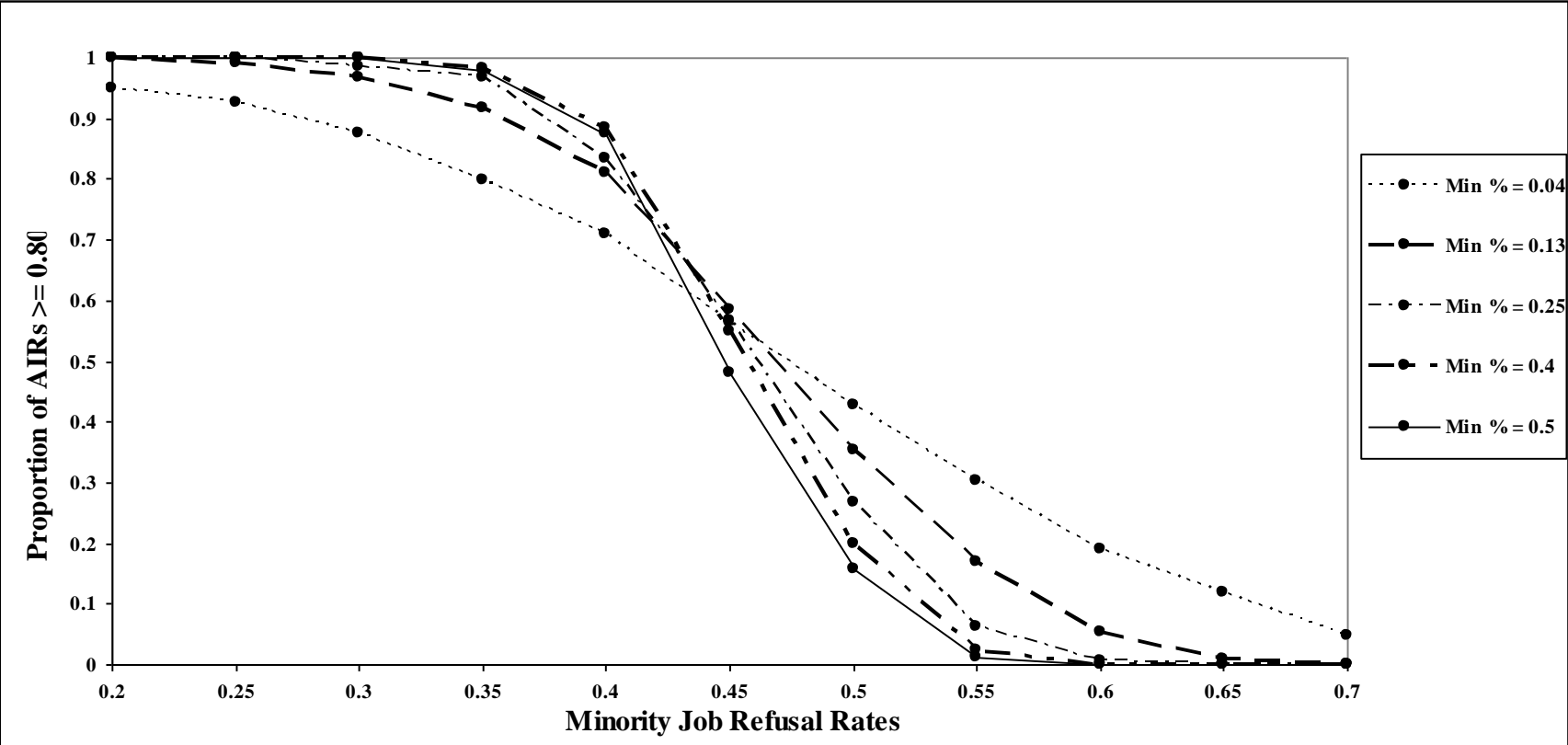


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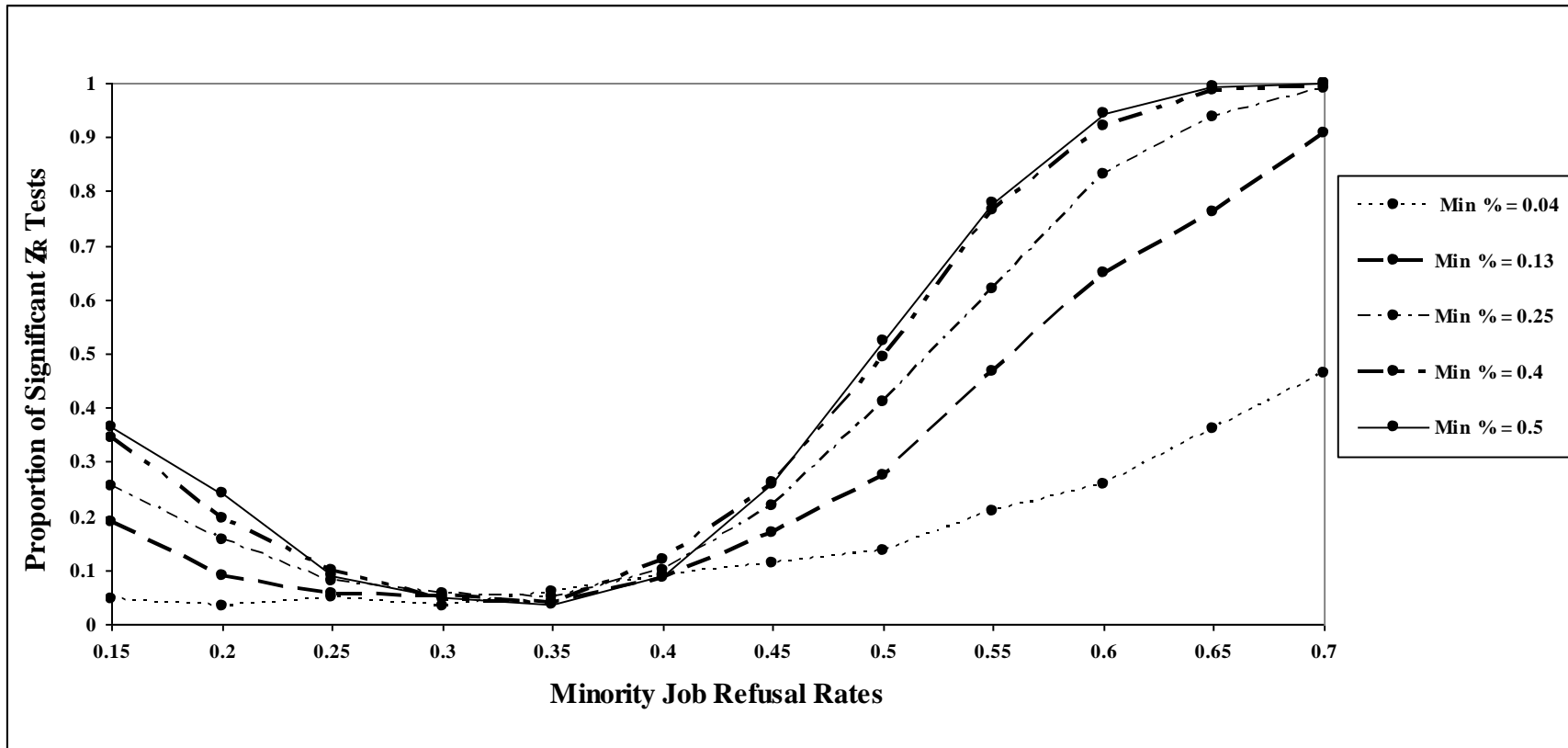


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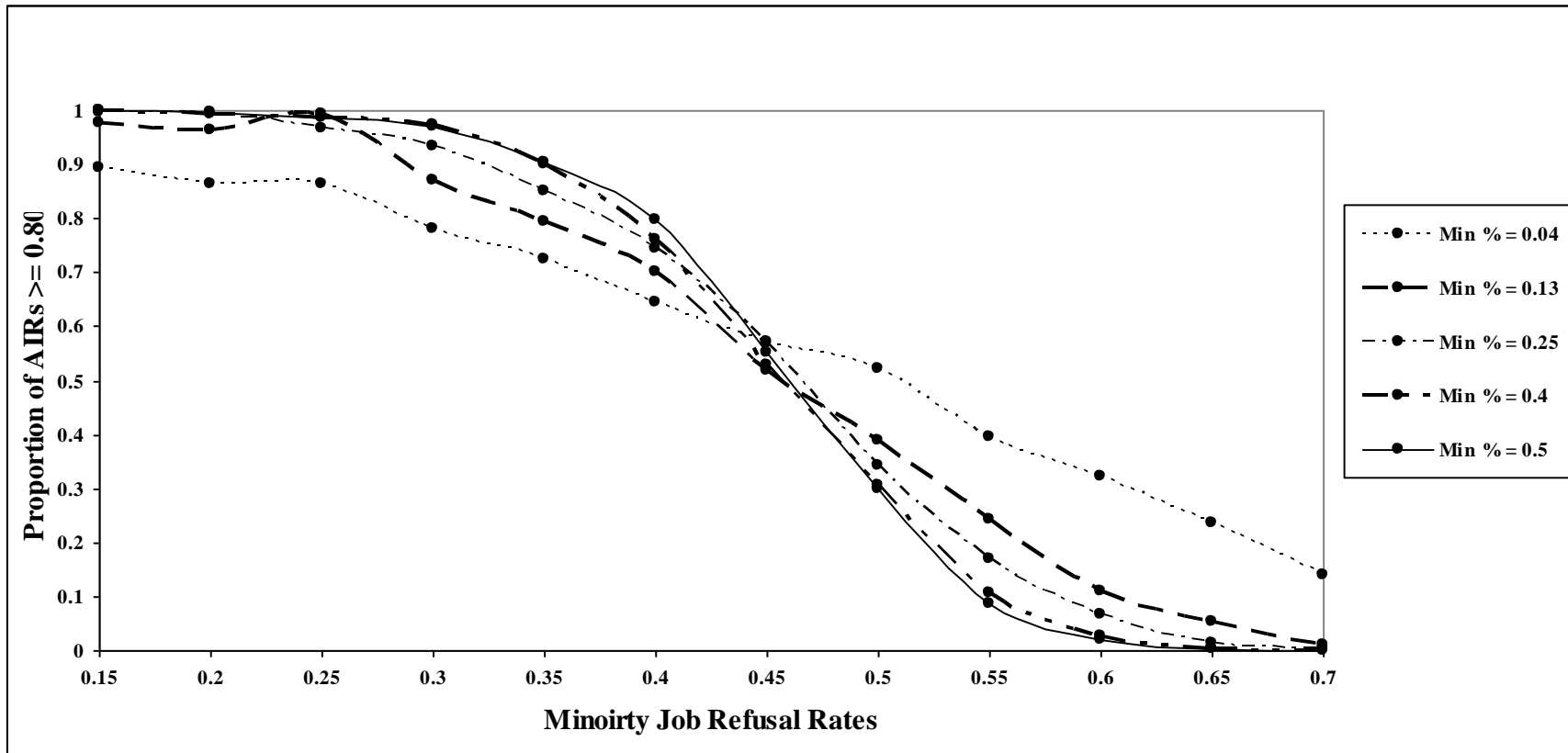


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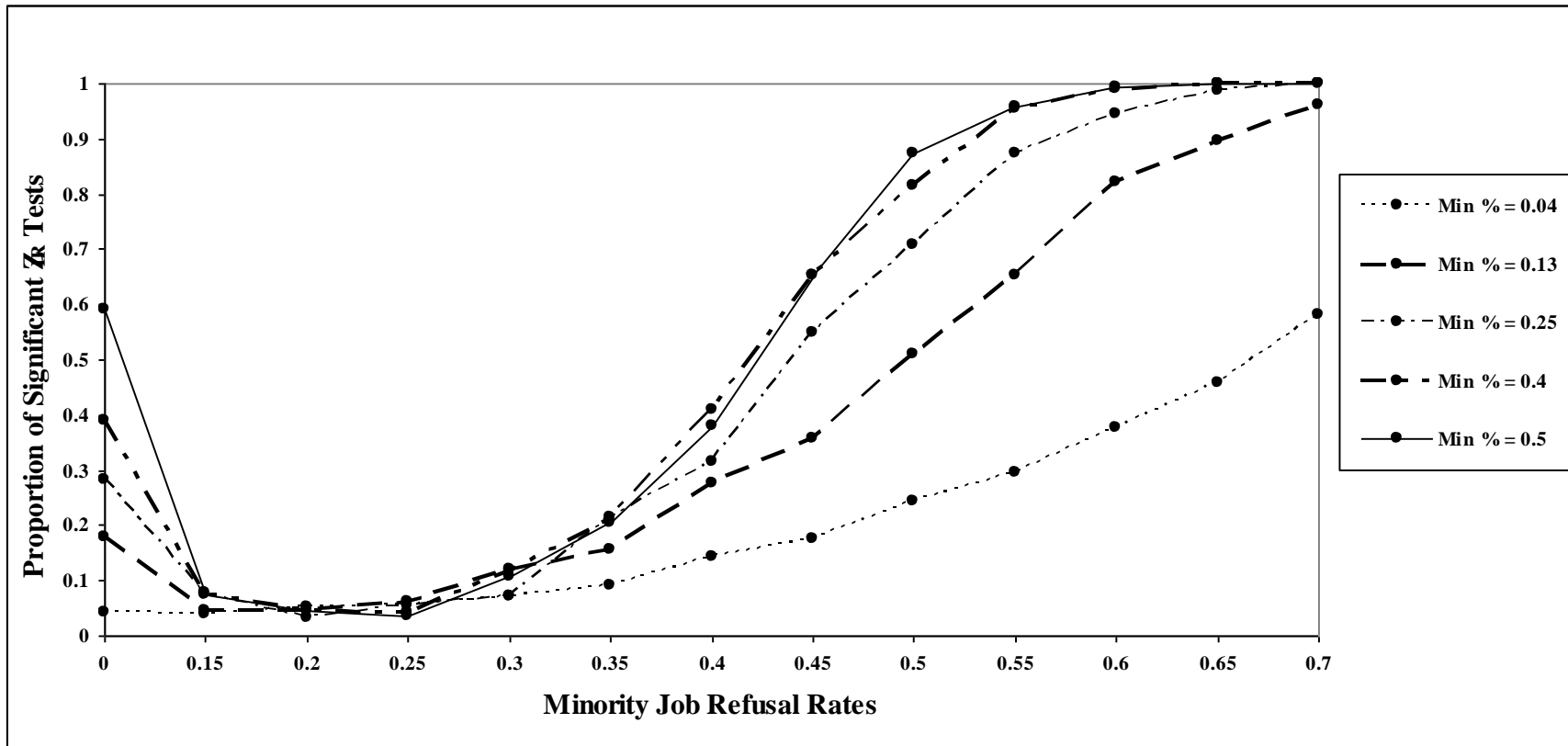


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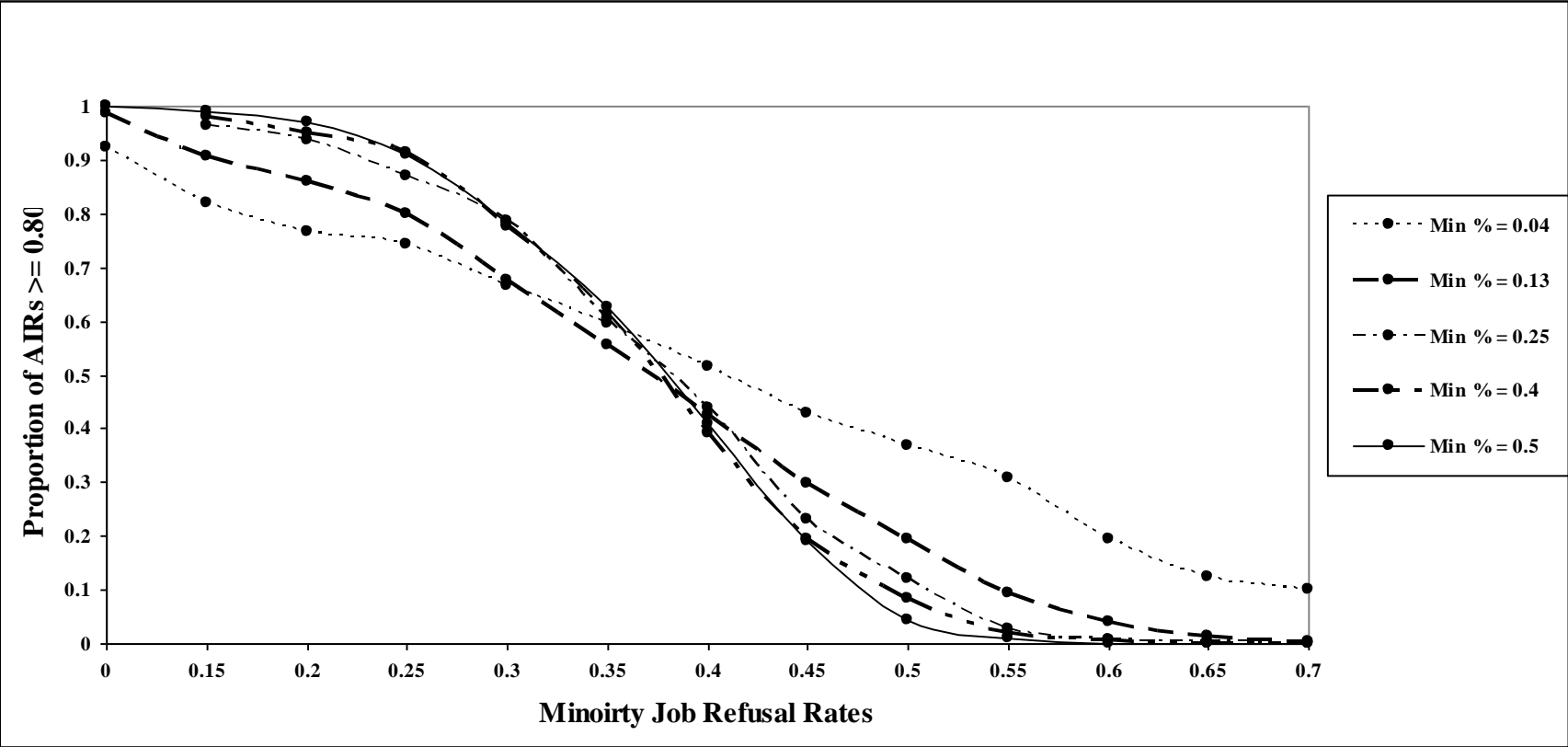


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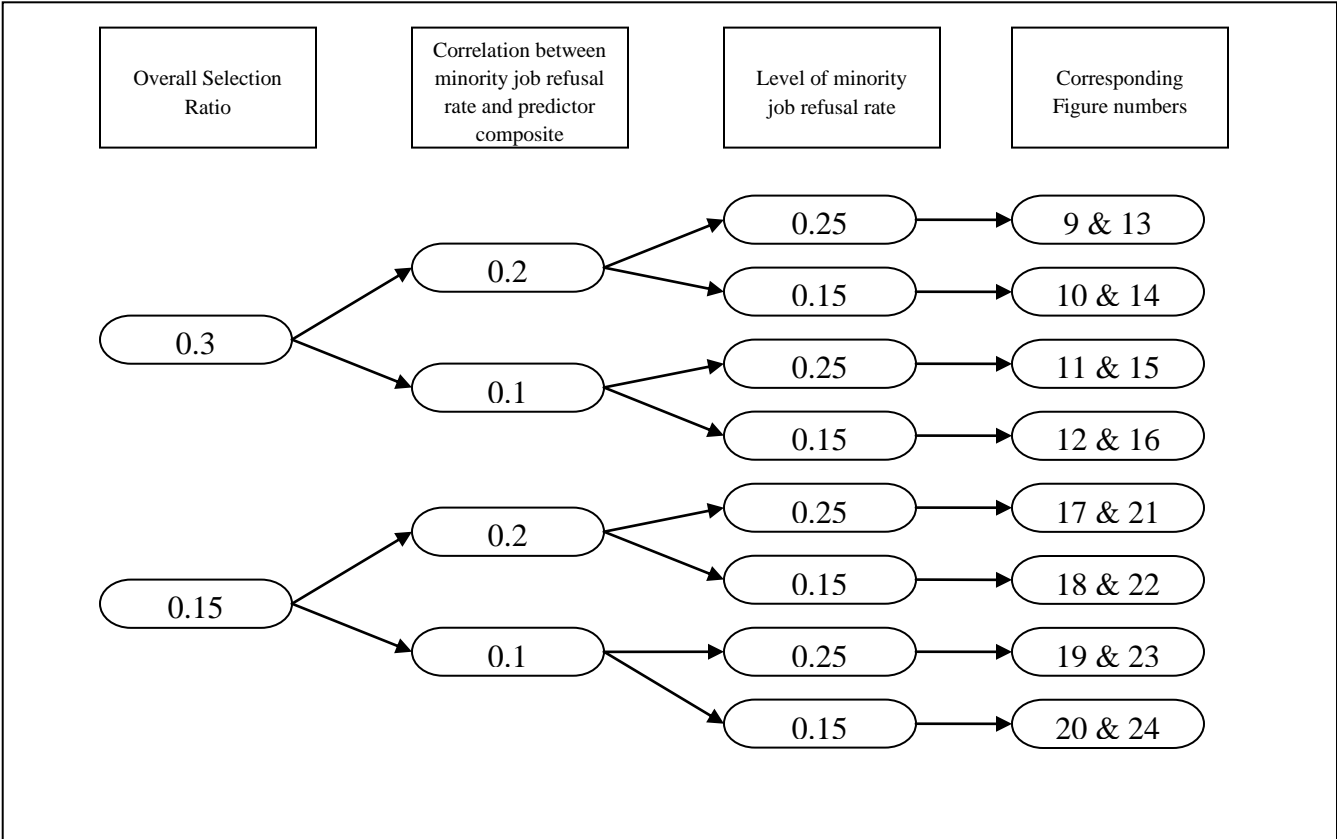


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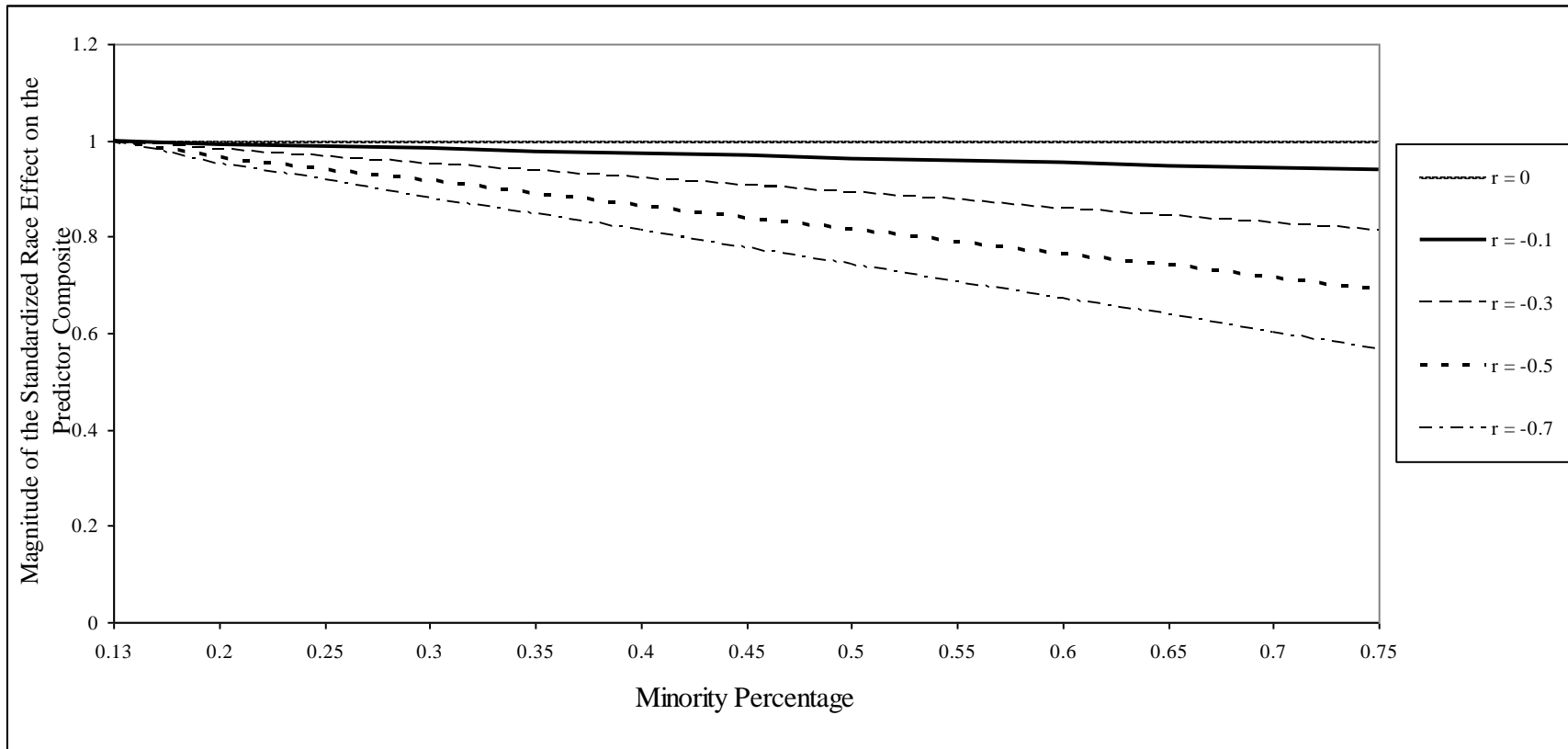


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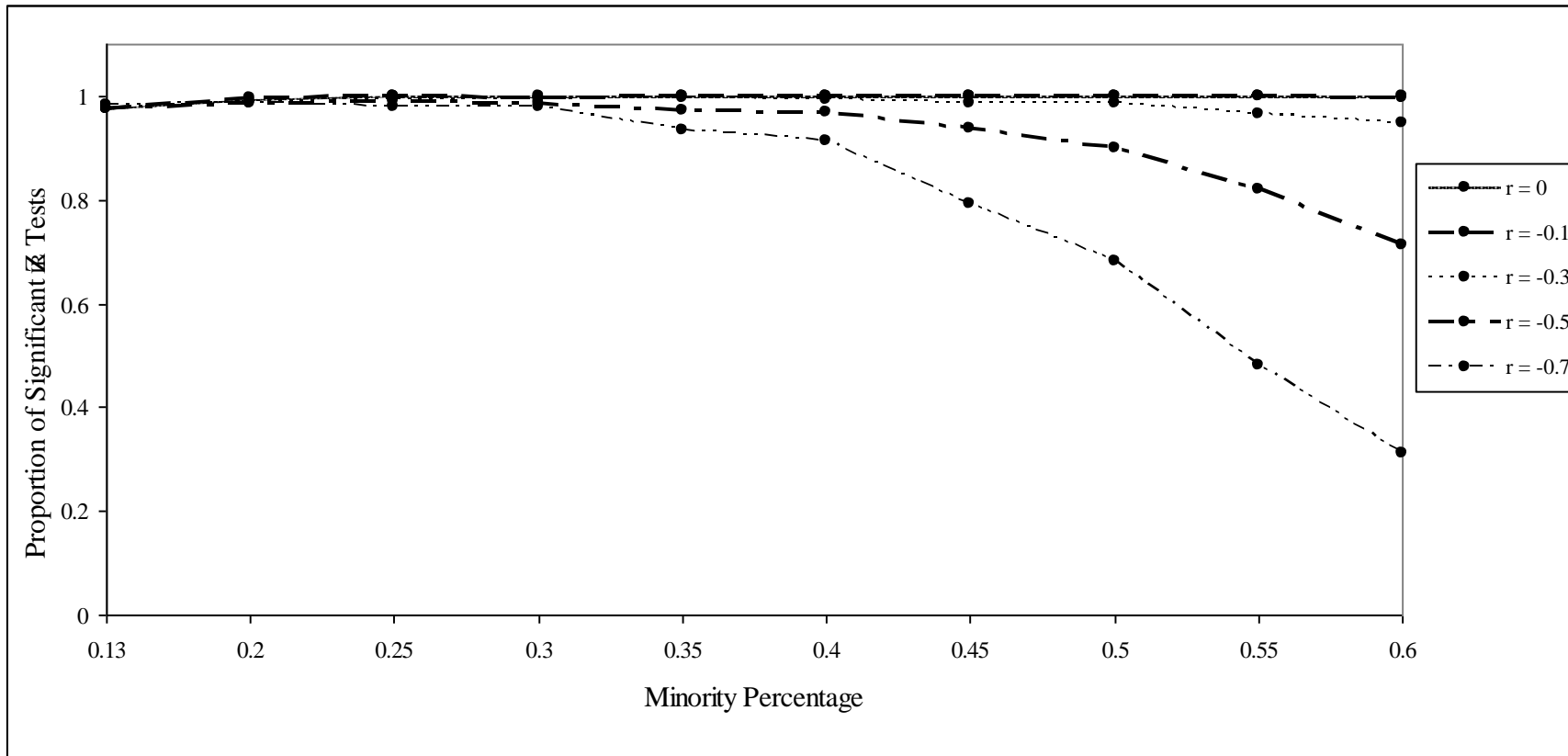


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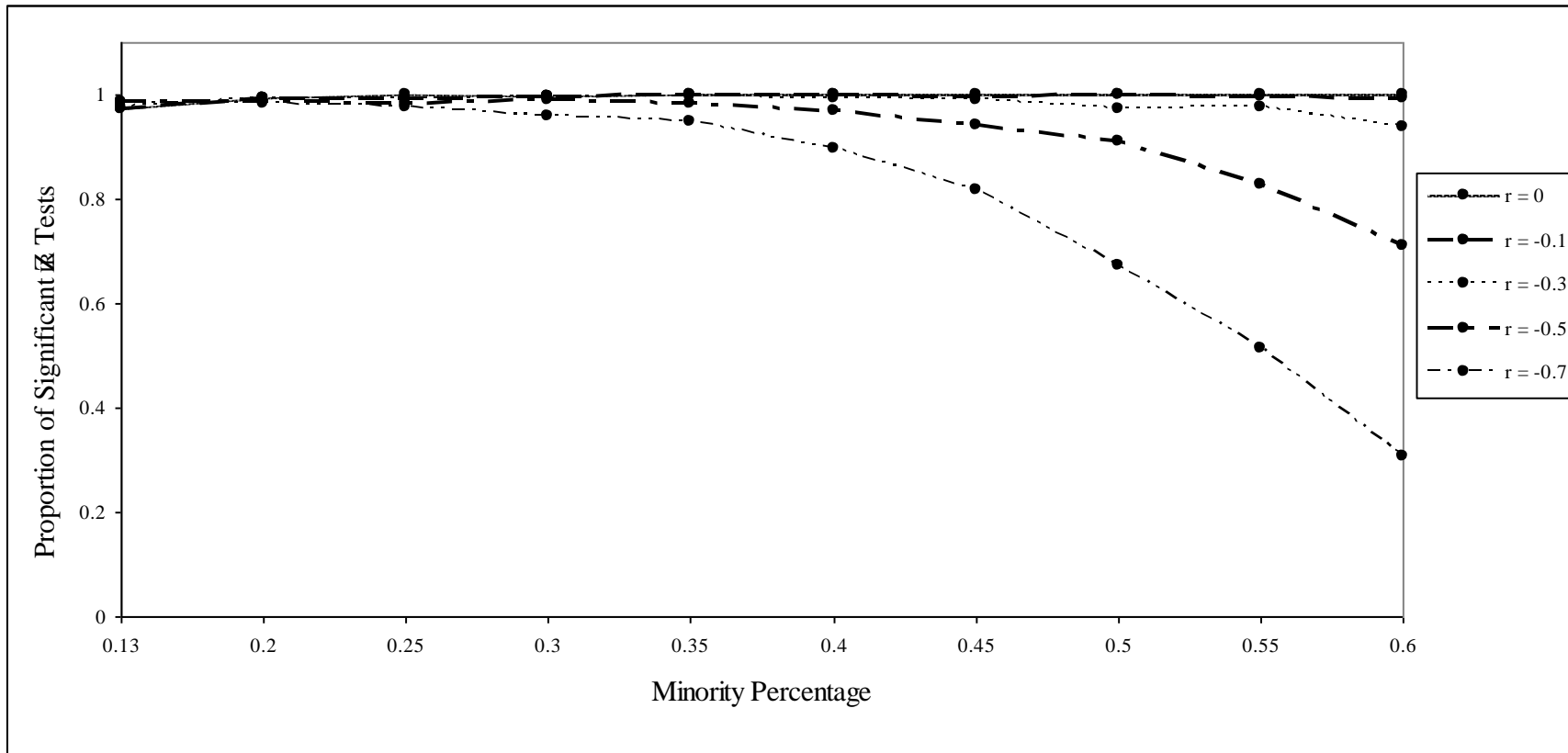


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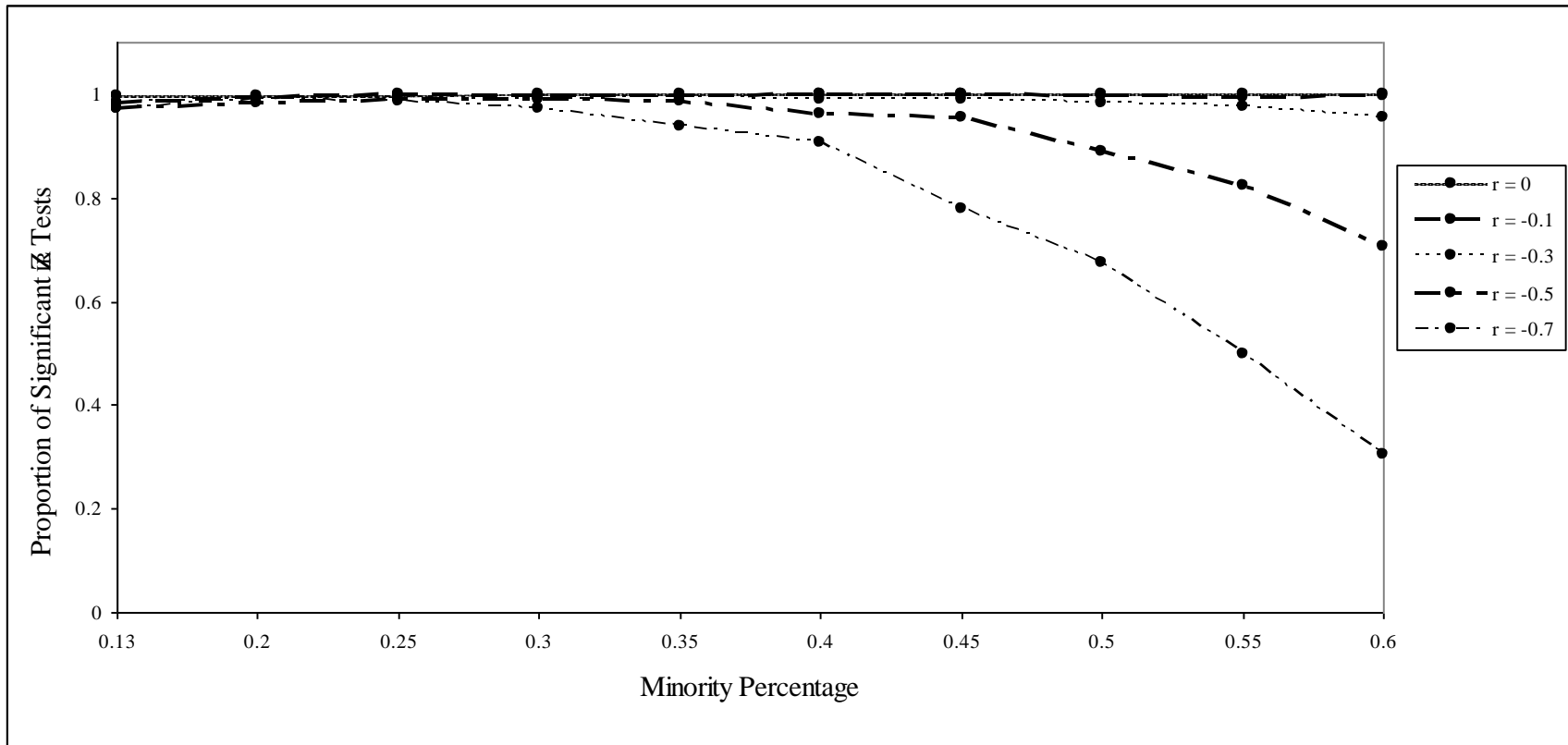


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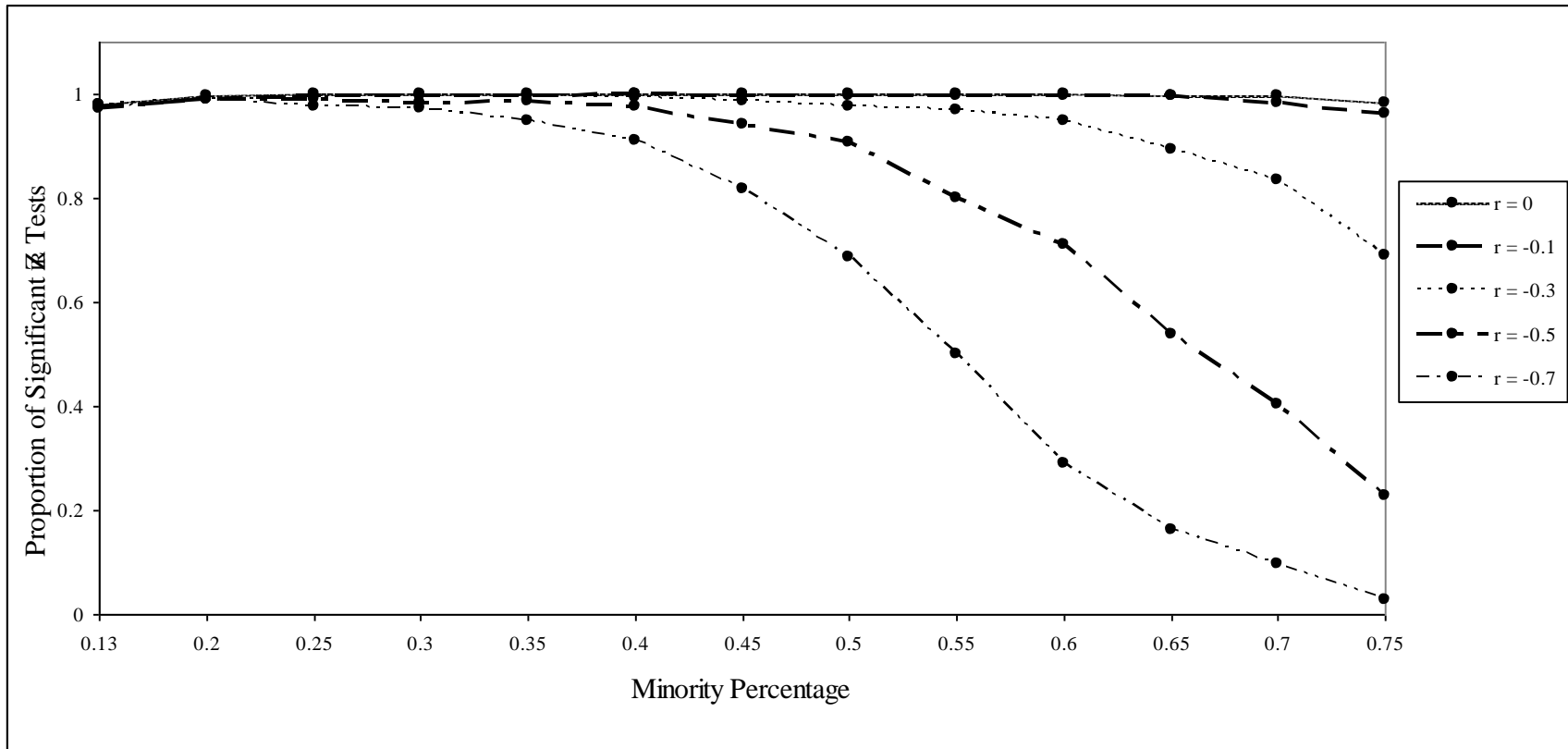


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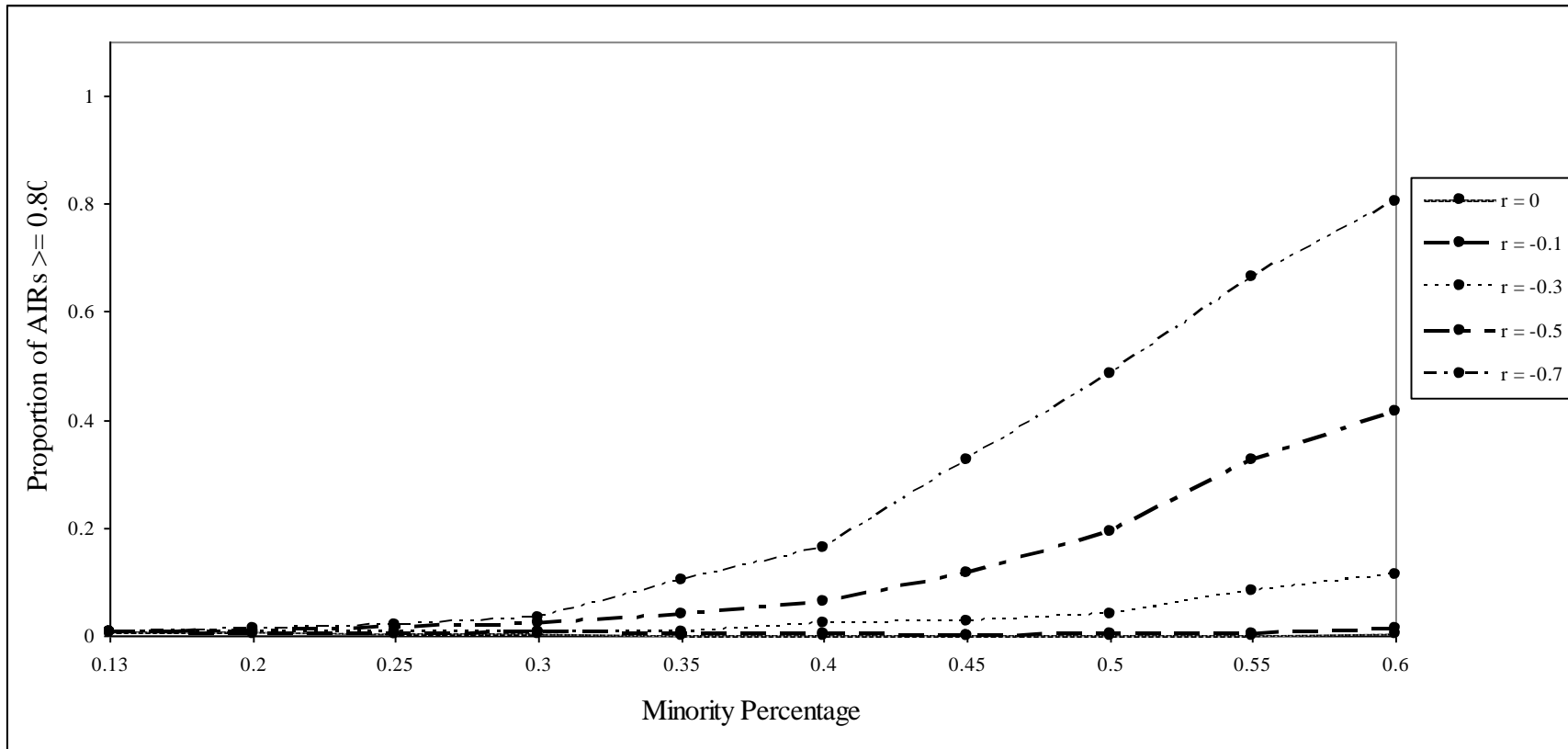


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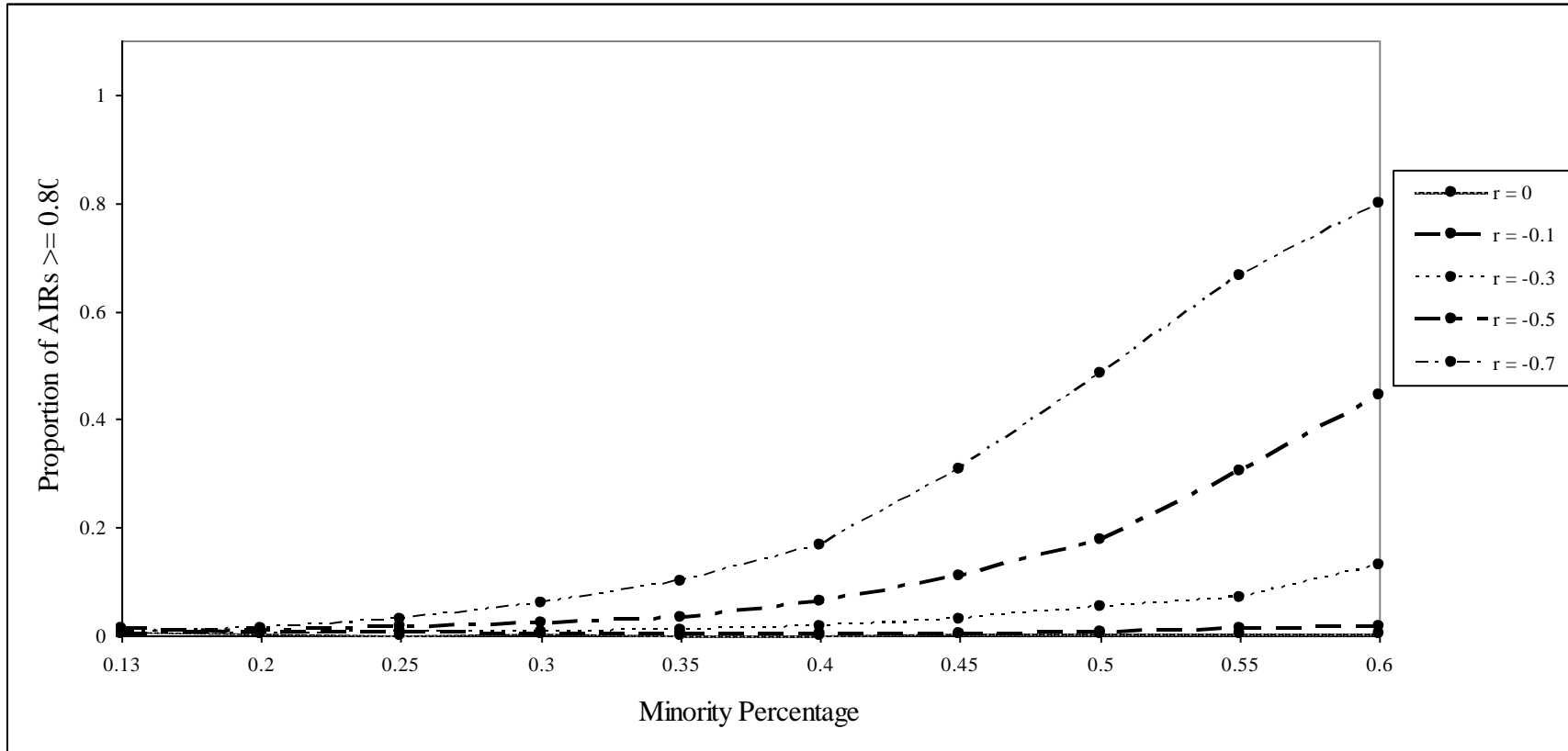


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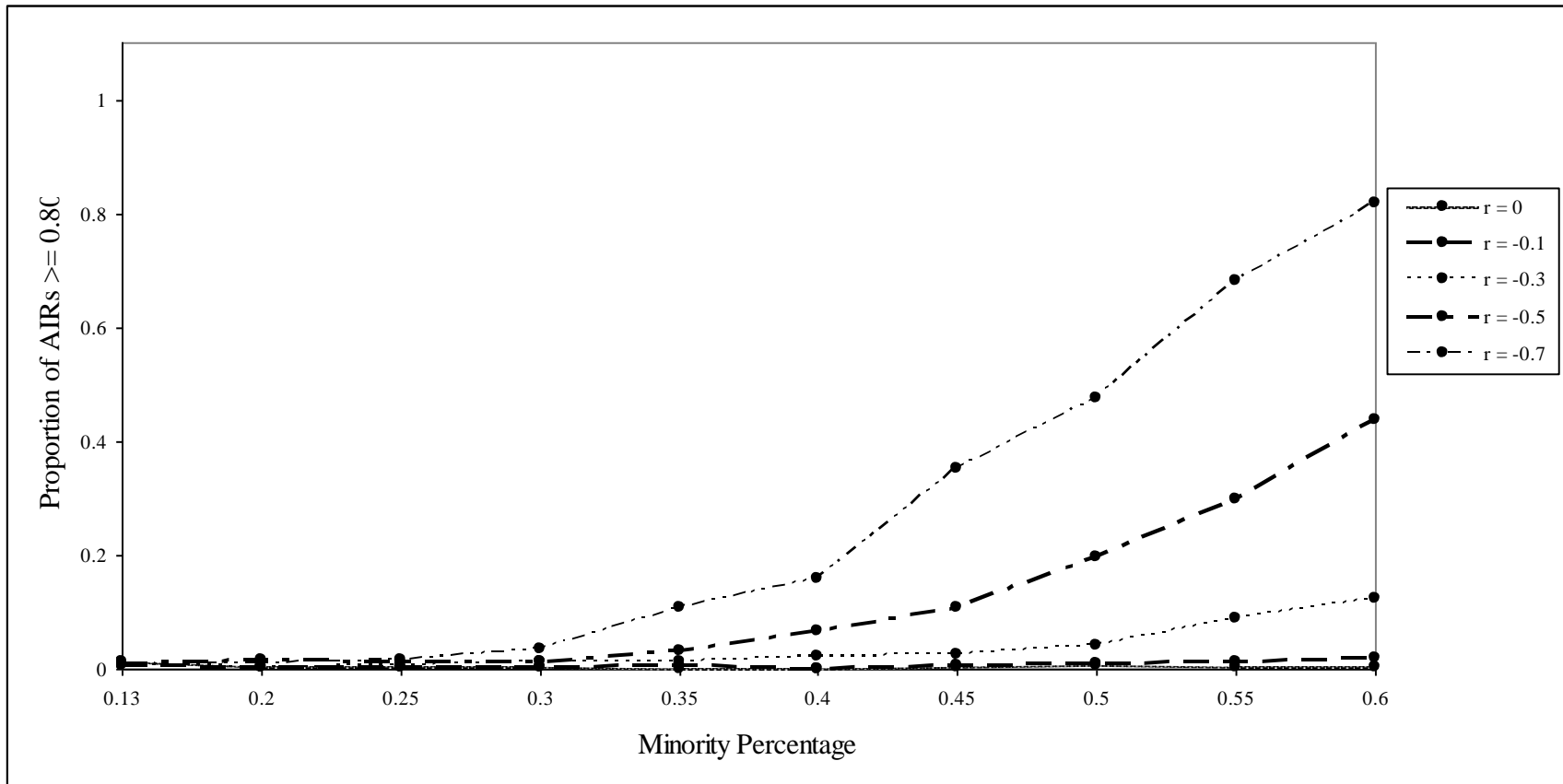


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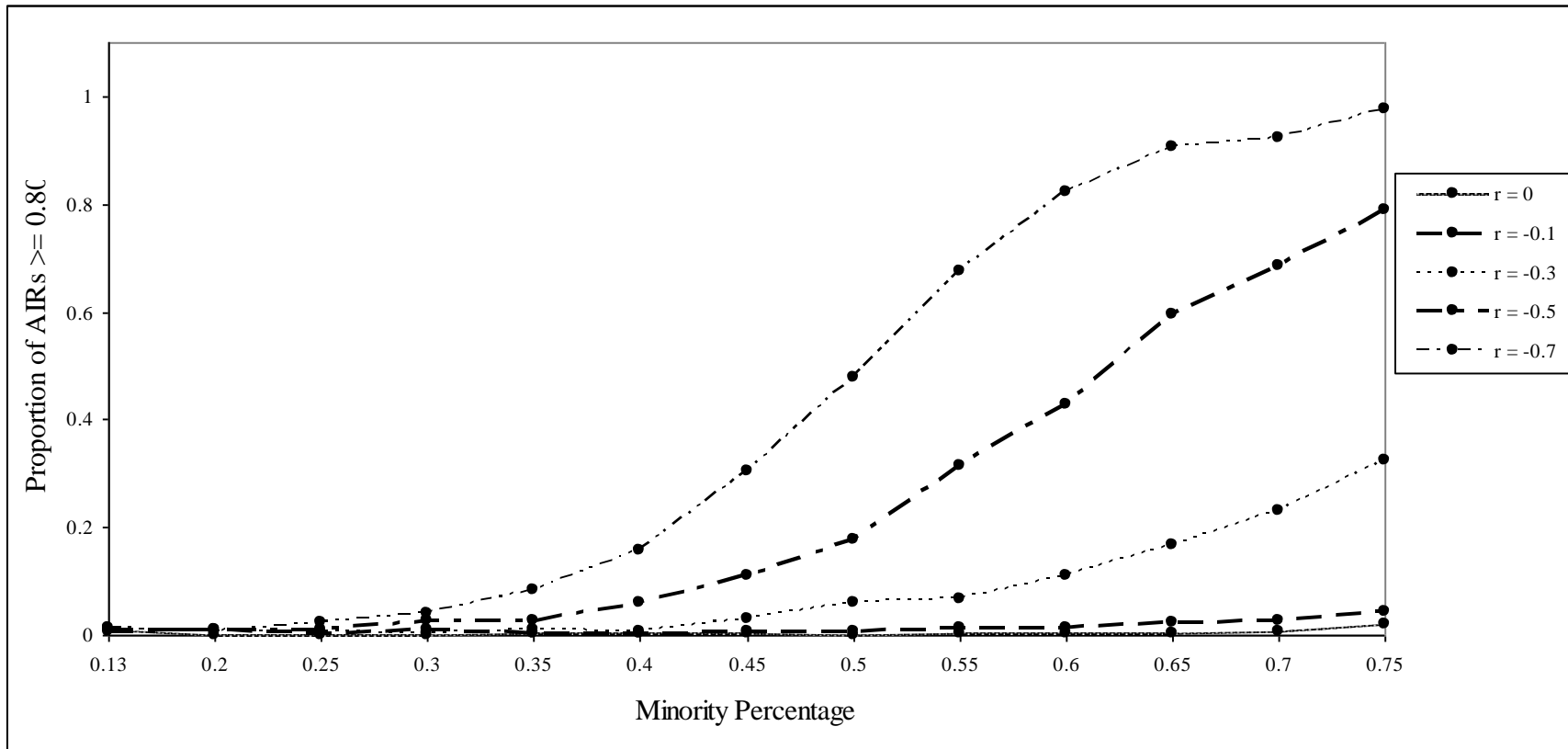


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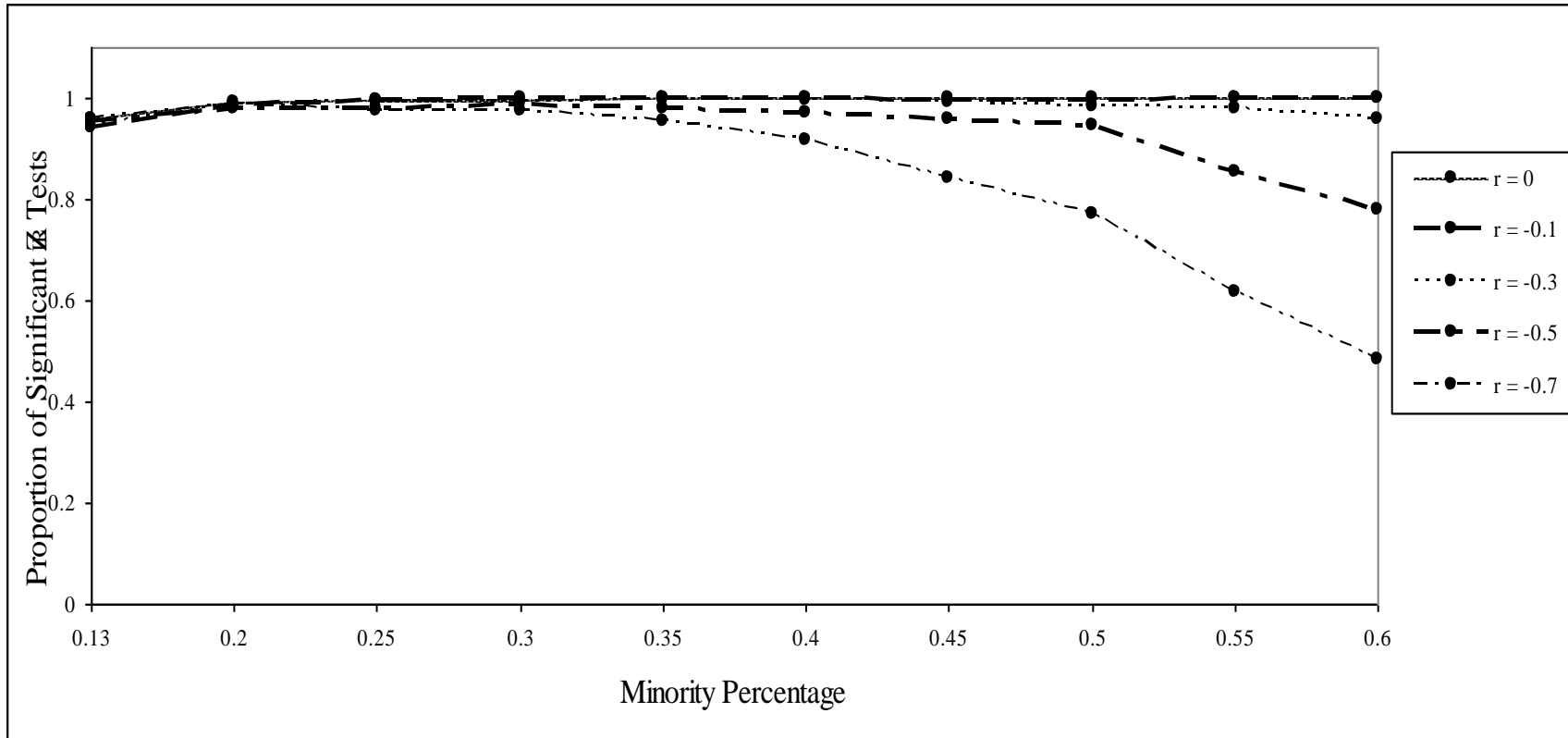


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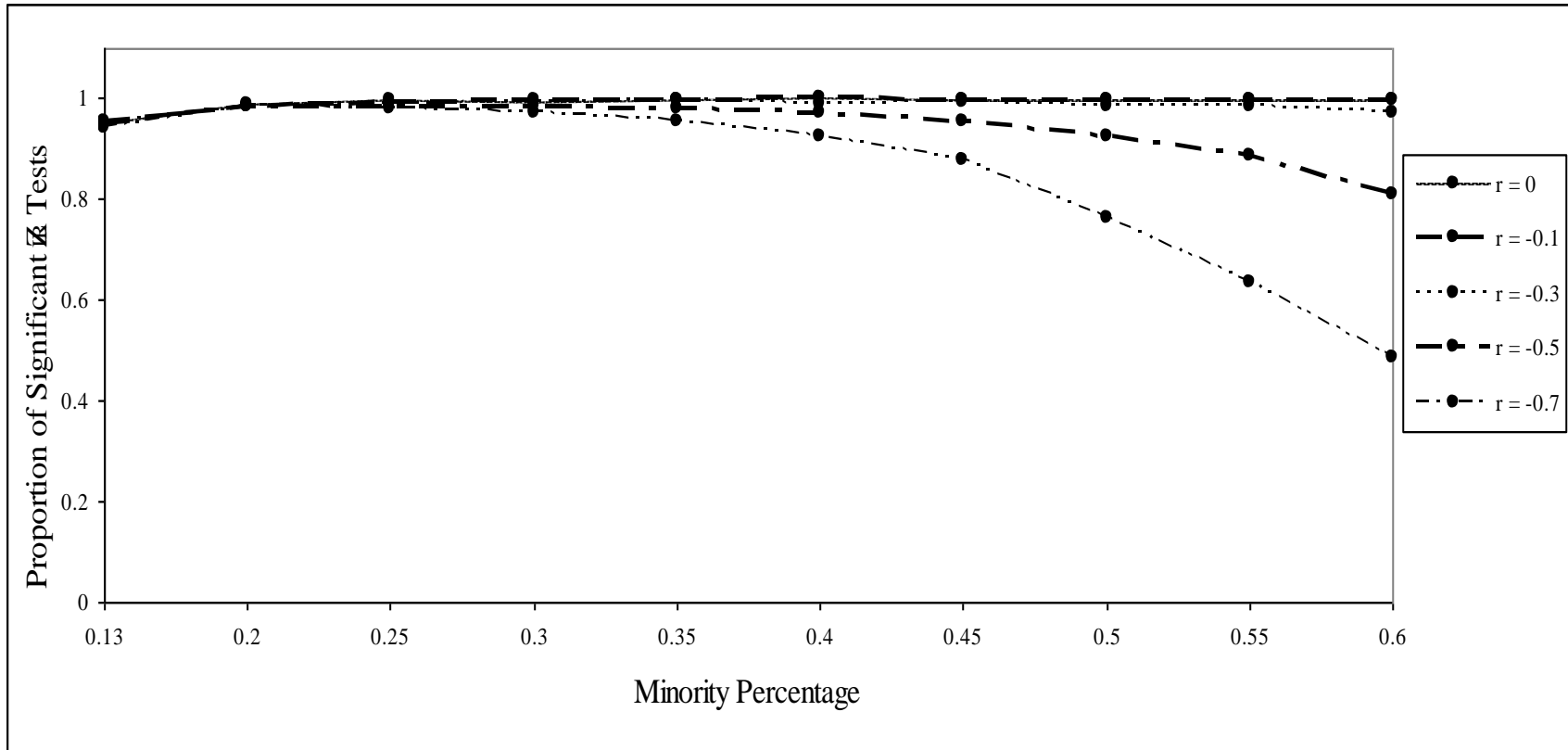


Figure 19

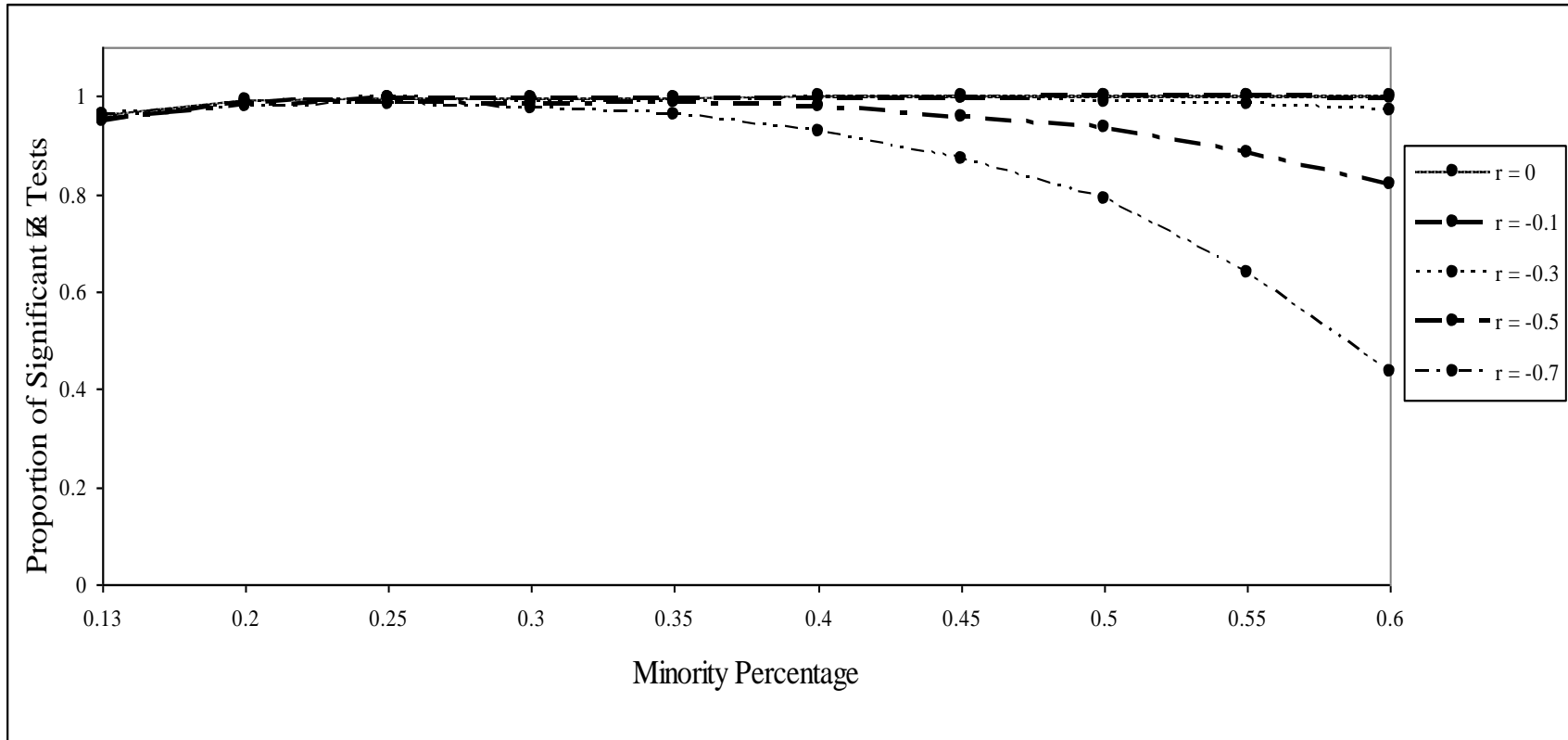


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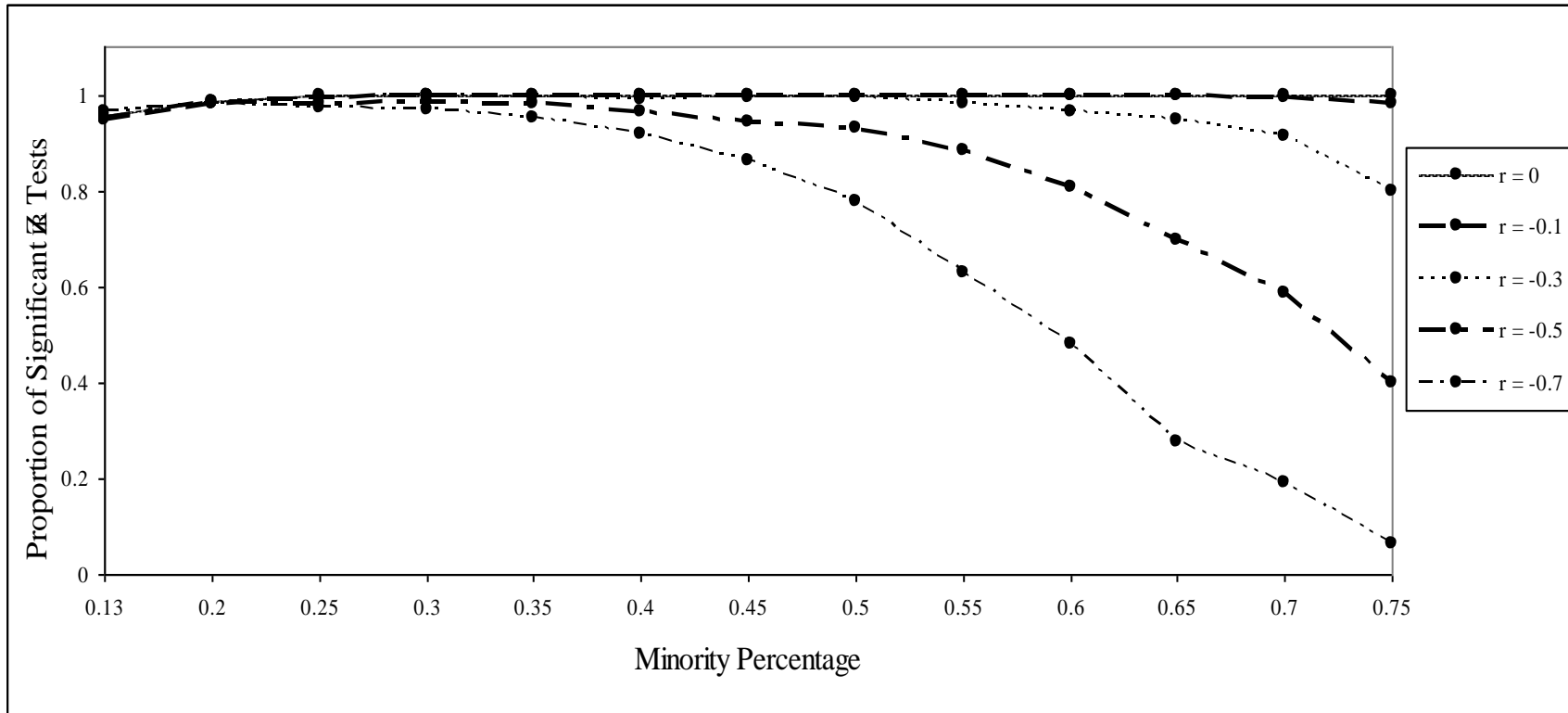


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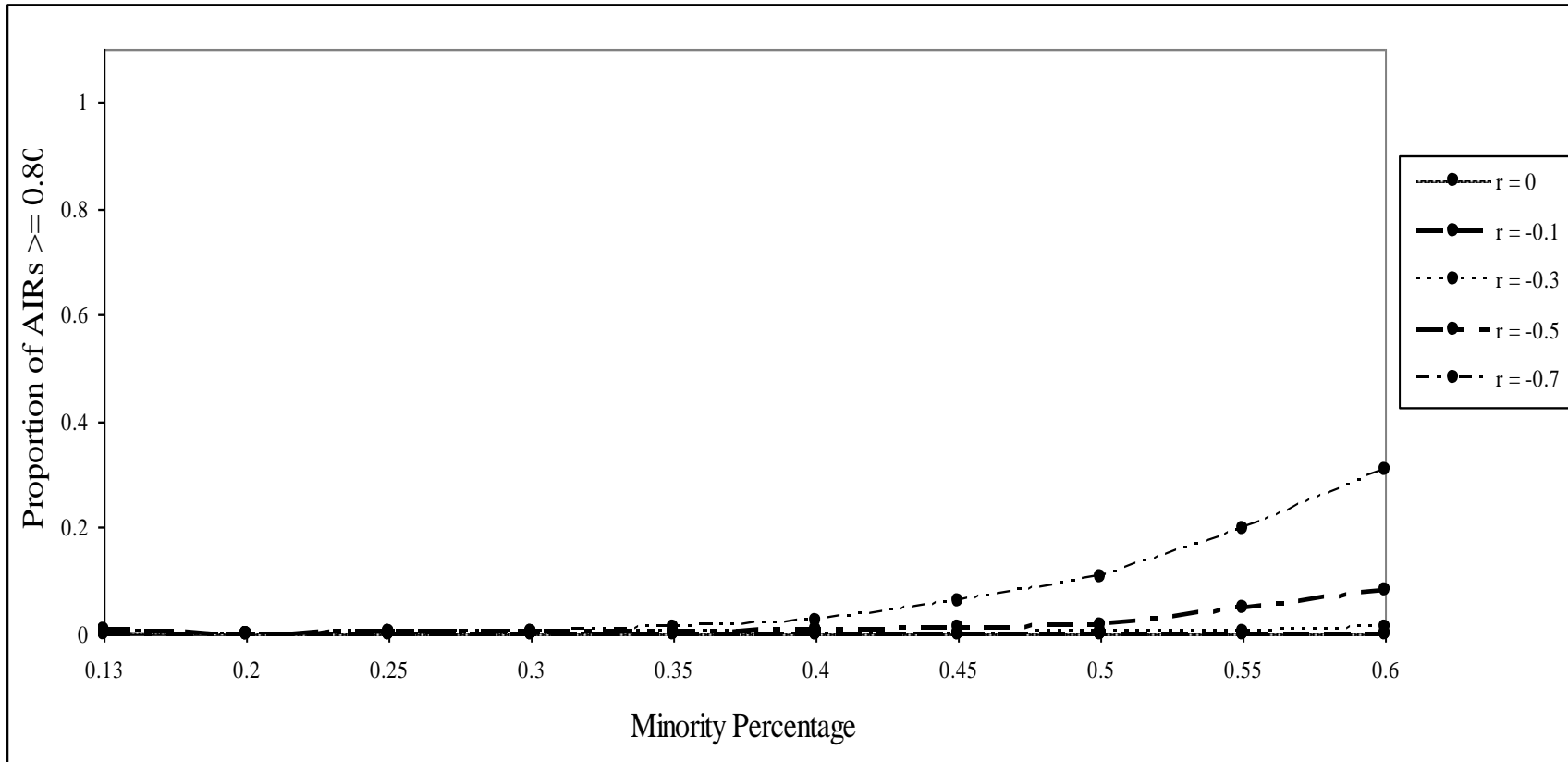


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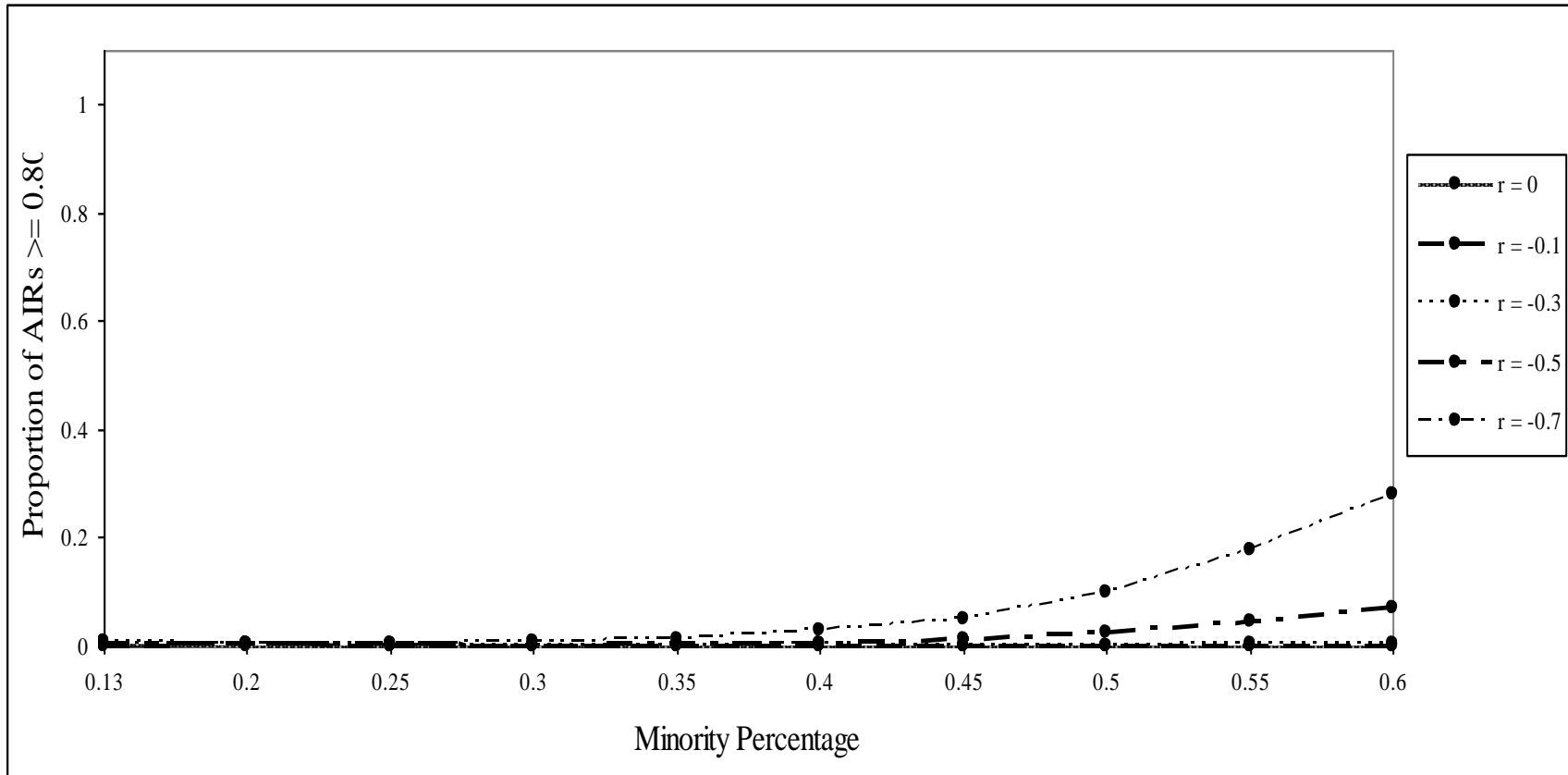


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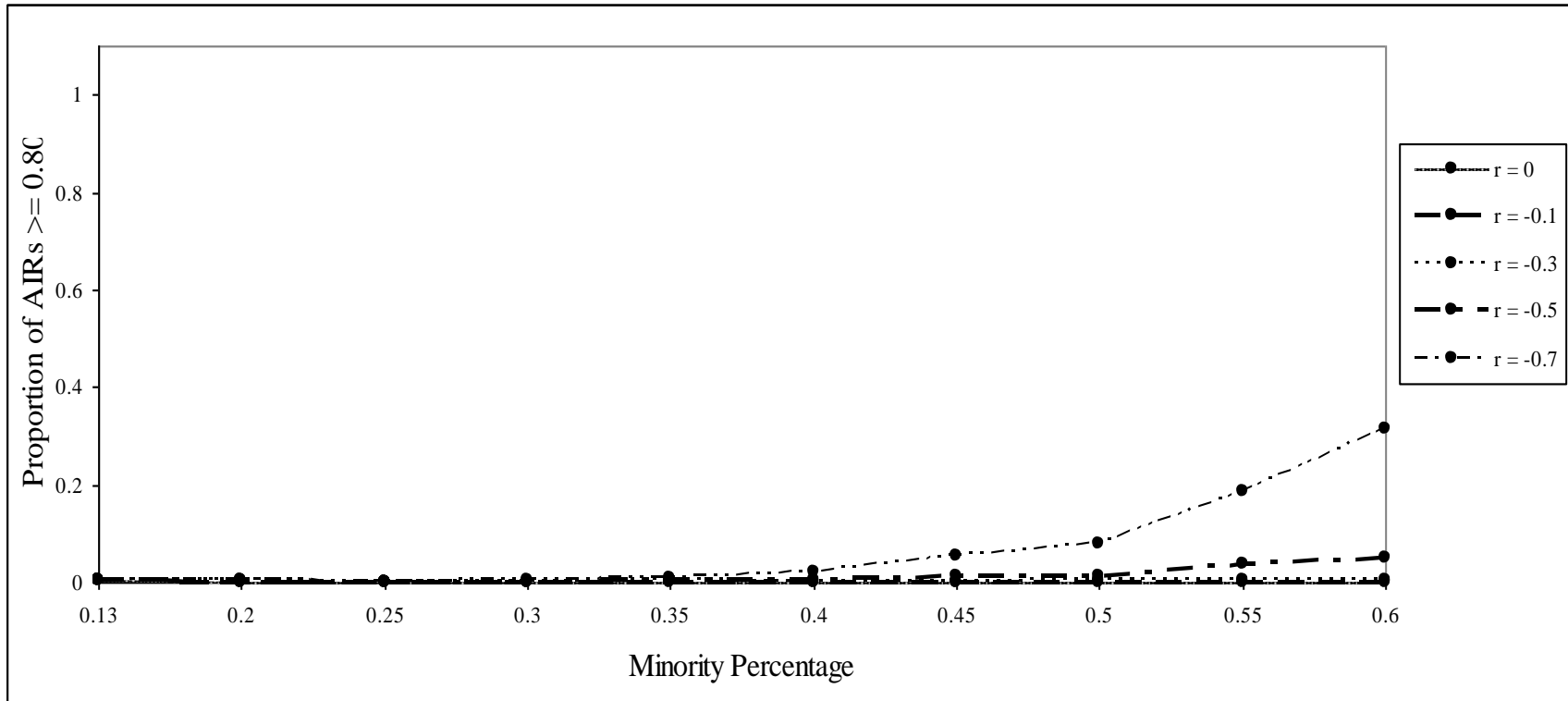


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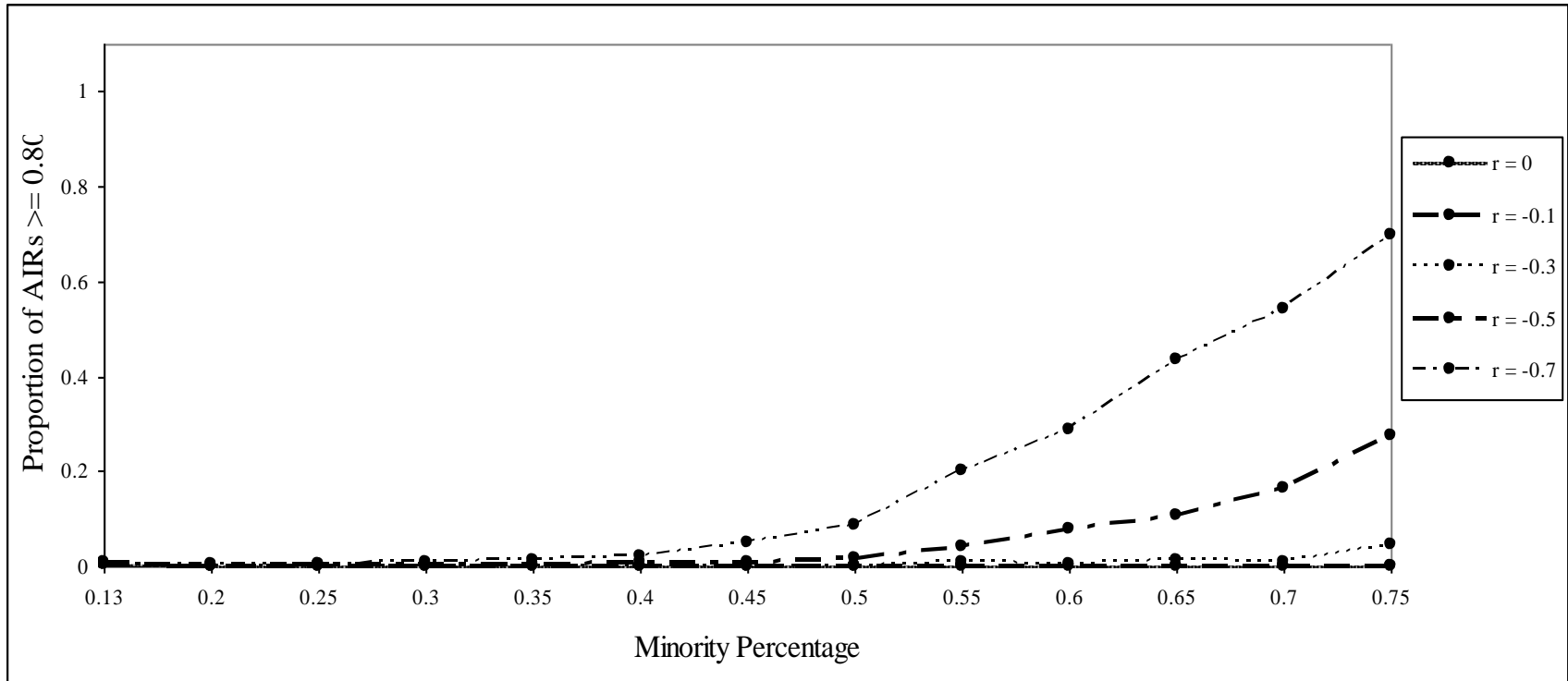


Figure 25

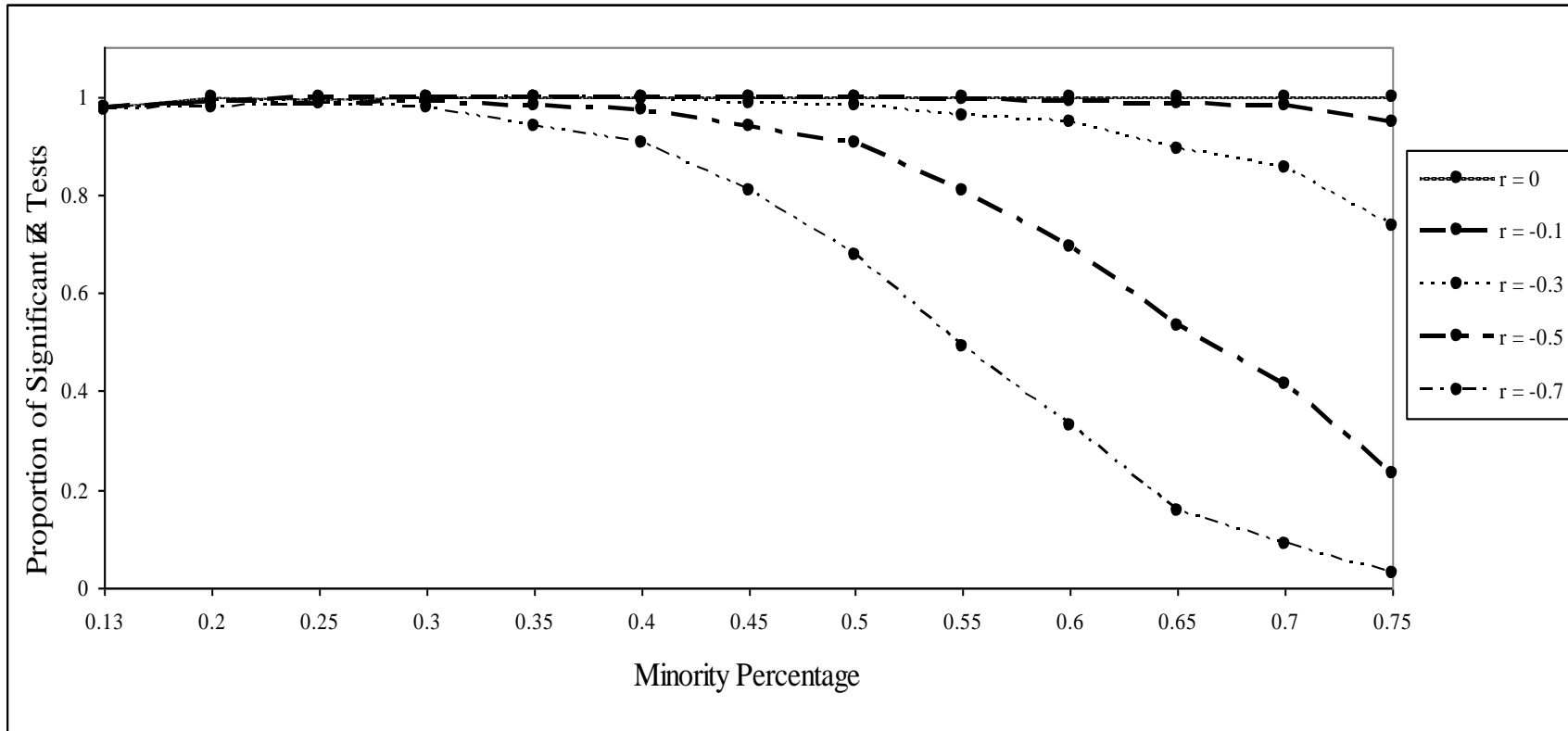


Figure 26

