No. 13-1371

IN THE

Supreme Court of the United States

TEXAS DEPARTMENT OF HOUSING
AND COMMUNITY AFFAIRS, *et al.*,

Petitioners,

v.

THE INCLUSIVE COMMUNITIES PROJECT, INC.,

Respondent.

ON WRIT OF CERTIORARI TO THE UNITED STATES COURT OF APPEALS FOR THE FIFTH CIRCUIT

BRIEF OF IAN AYRES AS *AMICUS CURIAE* IN SUPPORT OF RESPONDENT

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STATEMENT OF INTEREST OF *AMICUS CURIAE*[1]

I am an economist and lawyer who has dealt extensively with statistical analysis of disparate impact and disparate treatment. I am the William K. Townsend Professor at Yale Law School and a Professor at Yale's School of Management. I was the editor of the Journal of Law, Economics, and Organization from 2002 to 2009. In 2006, I was elected to the American Academy of Arts and Sciences. I received a B.A. in Russian Studies and economics from Yale University, a J.D. from Yale Law School, and a Ph.D. in economics from M.I.T.

Over the last 25 years, I have published more than a dozen statistical studies testing for disparate treatment or disparate impact in a variety of settings: from bail setting and taxicab tipping to kidney transplantation and eBay baseball card

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[1] No counsel for a party authored any part of this brief and no counsel or party made a monetary contribution intended to fund the preparation or submission of the brief. The cost of this brief was paid for entirely by the *amicus* and/or his counsel. Pursuant to this Court's Rule 37.3(a), all parties have consented to the filing of this brief.

auctions.[2] In addition, my 2002 book, *Pervasive Prejudice?: Unconventional Evidence of Race and Gender Discrimination* develops and tests for unjustified disparate racial impacts and disparate treatment in a variety of non-conventional settings. I have also developed and applied theories of (i) what constitutes a "business justification" for disparate impact purposes, and (ii) how to use regressions to test for unjustified disparate impacts.[3]

I have statistically tested for racial disparities in policing practices as an expert witness for the

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[2] *See, e.g.*, Ian Ayres, Fred Vars & Nasser Zakariya, *To Insure Prejudice: Racial Disparities in Taxicab Tipping*, 114 Yale. L. J. 1613 (2005); Ian Ayres, *Three Tests for Measuring Unjustified Disparate Impacts in Organ Transplantation: The Problem of "Included Variable" Bias*, 48 Pers. Biology S68 (2005).
I have also published dozens of econometric tests in non-discrimination settings. *See, e.g.*, Ian Ayres & Quinn Curtis, *Beyond Diversification: The Pervasive Problem of Excessive Fees and "Dominated Funds" in 401(k) Plans*, Yale L. J. (forthcoming 2014).

[3] *See* Ian Ayres, *Market Power and Inequality: A Competitive Conduct Standard for Assessing When Disparate Impacts are Justified*, 95 Calif. L. Rev. 669 (2007); Ian Ayres, Testing for Discrimination and the Problem of "Included Variable Bias," unpublished working paper (2010).

Justice Department and have served as an expert witness in more than a dozen matters concerning tests of racial disparate impact in lending.[4] Additionally, I served as a consultant to the Justice and Commerce Department in developing statistical methods to test whether an affirmative program is narrowly tailored to remedy discrimination.[5]

Consistent with my sustained efforts to improve the analysis of disparate impact testing in a wide variety of settings, I have a strong interest in ensuring that the Court's treatment of this case is informed by a sound understanding of pertinent statistical issues. In particular, I write to correct the misunderstandings and misapprehensions contained in James P. Scanlan's amicus brief.

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[4] *See, e.g., Adkins v. Morgan Stanley*, No. 1:12-cv-7667-VEC (S.D.N.Y.); *Saint-Jean v. Emigrant Mortgage Co.* (2013) No. 1:11-cv-02122-SJ (E.D.N.Y.); *Guerra v. Guerra v. GMAC LLC, No. 2:08-cv-01297-LDD (E.D. Pa.).*

[5] *See, e.g.*, Ian Ayres, Written Statement, Disparity Studies as Evidence of Discrimination in Federal Contracting, U.S. Commission on Civil Rights (May 2006); *Rothe Dev. Corp. v. United States Dept. of Defense*, 545 F.3d 1023 (Fed. Cir. 2008).

INTRODUCTION AND SUMMARY OF ARGUMENT

James P. Scanlan has submitted an amicus brief claiming that "standard statistical analyses of discrimination are unsound." He is wrong, and his contention is not consistent with well-accepted science. Additionally, Scanlan appears to misunderstand the legal question in a disparate impact case: whether a defendant's policies produced an unjustified disparate impact. His analysis is predicated entirely on the notion that a plaintiff must show that race *caused* a defendant to make certain employment decisions. Scanlan's arguments are inapplicable even on their own terms under the correct legal standard.

Even under the incorrect standard used by Scanlan, moreover, his analysis is deeply flawed. Scanlan focuses on descriptive statistics instead of rigorous statistical regression and hypothesis testing, and he wholly ignores the concept of statistical significance. Notably, his claim that disparate impact measures are mutually inconsistent (depending on whether the disparity is framed in terms of applicant failure or success) is simply false. Even using the very numerical example suggested by Scanlan, it is plain that a properly specified regression—one that includes controls for factors that are plausibly business justified—can robustly test for unjustified disparate impacts (regardless of whether the inquiry is framed in terms of the likelihood of failure or the likelihood of success).

Amicus respectfully asks this Court to give no weight to Scanlan's arguments: they are unscientific and misleading.

ARGUMENT

A. Scanlan Misleadingly Focused On Descriptive Statistics.

1. Statisticians Rely on Rigorous Statistical Techniques.

Scanlan's central claim that the "standard statistical analyses of discrimination are unsound" is fatally flawed. The standard, rigorous, and well-accepted method uses what is known as multivariate statistical regressions. Scanlan essentially fails to address this methodology at all.

Scanlan instead argues that what are known as summary statistics (i.e., descriptive statistics) should not be used to identify disparate impact.[6] This may be true in certain cases, but it is also something of a non-sequitur because it fails to discuss the actual tools used by statisticians, who utilize "inferential statistics" and hypothesis testing to infer whether the disparity observed in a sample is merely a product of chance. Scanlan, moreover, entirely fails to confront how multivariate regressions can test for the significance of disparities after accounting for non-race influences.[7]

[6] The four measures that he claims are the standard measures of disparity are merely "descriptive statistics"—chiefly conditional means—that fail to assess whether the disparities are statistically significant.

[7] The four descriptive statistics that feature prominently in Table 1 of Amicus Scanlan's, Advantaged Group to Disadvantaged Group pass ratio, Advantaged Group to Disadvantaged Group fail ratio, Percentage Point Difference between pass rates, and odds ratios, do not incorporate information conveyed by business-justified

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Although Scanlan mentions in passing that analysts attempting to estimate disparities in terms of odds ratios might use logistic regressions, he does not discuss the statistical techniques underlying the regression. *Cf., e.g.*, *ATA Airlines, Inc. v. Fed. Express Corp.*, 665 F.3d 882, 889-90 (7th Cir. 2011) (Posner, Easterbrook, Wood, JJ.) (discussing the difference between proper and improper statistical regressions). Yet regression analysis of historic decision-making is *the* central tool by which statisticians test whether the race of the plaintiffs influenced the defendant's decision making. *See, e.g.*, *Garcia v. Johanns*, 444 F.3d 625, 635 (D.C. Cir. 2006) (discussing the importance of regression analysis).[8] A regression can simultaneously control for a variety of potential influences and estimate the

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covariates that should inform the relationship between the outcome of interest and race.

[8] Regression analysis is a statistical method for determining the relationship that exists in a set of data between a variable to be explained—called the "dependent variable"—and one or more "explanatory variables."

size and statistical significance of the individual influences. *See* D. James Greiner, *Causal Inference in Civil Rights Litigation*, 122 Harv. L. Rev. 533 (2008).

This is not a minor omission. Proper regressions analysis can produce robust indicators of disparity that avoid the claimed inconsistencies of his descriptive statistic measures. Indeed, this brief, below in Part C, provides an example using the data contained in Scanlan's brief.

At bottom, using summary statistics alone to identify the disparate impact of a policy is not a standard practice among statisticians and econometricians. *See, e.g.*, *Garcia*, 444 F.3d at 635. Thus, Scanlon's entire brief attempts to refute a false premise. It cannot provide support for the notion that disparate impacts are not cognizable under the Fair Housing Act.

2. Scanlan Wrongly Ignores Statistical Significance.

In light of Scanlan's arguments, it bears emphasis that regression approaches can be, and have been, widely used to appraise the statistical significance of disparate impact. *See, e.g.,* Ian Ayres, *Pervasive Prejudice? Unconventional Evidence Of Race And Gender Discrimination* 100-105 (2003) (reporting regressions from Atlanta car dealership data); Mark A. Cohen, *Imperfect Competition in Auto Lending: Subjective Markups, Racial Disparity, and Class Action Litigation*, 8 Rev L. Econ. 21 (2012). Amicus respectfully submits that this Court should be reluctant to embrace any statistical argument (such as Scanlan's) that ignores this fundamental statistical concept. *Cf., e.g.*, *In re Elec. Books Antitrust Litig.*, No. 11 MD 2293, 2014 U.S. Dist. LEXIS 42537, at *80 (S.D.N.Y. Mar. 28, 2014) (discussing the importance of considering statistical significance).

To provide just one example, what are known as t-tests are used to determine whether the relationship between two variables is due to chance alone at a 90, 95 or 99th percent confidence level. This inferential approach was first developed nearly a century ago. *Cf. South Dakota Public Utilities Com. v. Federal Energy Regulatory Com.*, 643 F.2d 504, 513 n.13 (8th Cir. 1981) ("The 't'-test produces a significance level which measures the validity of using the relationships between variables to support a hypothesis."). It is inappropriate for Scanlan to have opined on the validity of statistical analyses in ways that wholly ignore the central contribution of this learned art, hypothesis testing.

B. Scanlan's Analysis Purports To Apply To Claims Regarding Disparate Treatment, But This Is A Case About Disparate Impact.

Scanlan's analysis should be disregarded by this Court for another, independently sufficient reason: he concedes that he is not actually focusing on disparate impact. In particular, he writes:

> In discussing these subjects, *I do not usually draw distinctions between disparate impact and disparate treatment*. The measurement issues pertaining to both subjects involve determining the strength of an association between group membership and likelihood of experiencing some favorable or adverse outcome. Issues as to the strength of that association, which I will commonly refer to here as

> the strength of the forces causing the outcome rates to differ, are essentially the same whether disparate treatment or disparate impact is alleged.

(Scanlan Br. at 4 (emphasis added)). But a claim for disparate treatment requires intent—i.e., it requires that discriminatory motives "cause" discrimination, while *intent is not an element in* a disparate impact analysis. *See, e.g.*, *Watson v. Fort Worth Bank & Trust*, 487 U.S. 977, 987 (1988) ("The factual issues and the character of the evidence are inevitably somewhat different when the plaintiff is exempted from the need to prove intentional discrimination."). *Ricci v. DeStefano*, 557 U.S. 557, 577 (2009) (addressing disparate impact).[9] In disparate impact employment litigation, to establish a prima facie case, Title VII plaintiffs first must show that their employer uses "a particular employment practice that causes a disparate impact on the basis of race,

[9] This is not to suggest that the same statistical models are not probative of both types of claims, depending on the model and on the facts of the case, or to ignore that in many instances ongoing, unmonitored, uncorrected disparate impact can lead to an inference of disparate treatment.

color, religion, sex, or national origin." 42 U.S.C. § 2000e-2(k)(1)(A)(i). An employer may then defend against liability by demonstrating that the challenged employment practice is "job related for the position in question and consistent with business necessity." 42 U.S.C. § 2000e-2(k)(1)(A)(i).[10]

And because a plaintiff need not show that race played any role in the employer's decision to implement the race-neutral employment practice in disparate impact litigation, *a statistical approach that is geared toward testing whether a plaintiff's race caused an employer to behave differently has no necessary relation to the core elements in a disparate impact claim*. Scanlan's claim that "the strength of the forces causing the outcomes to differ" is "essentially the same whether disparate treatment or disparate impact is alleged" is misdirection in

[10] Even if the employer meets that burden, plaintiffs may succeed if they can show that the employer has refused to adopt an available alternative employment practice that would reduce the level of disparate impact while still serving the employer's legitimate needs. *Id.* §§ 2000e-2(k)(1)(A)(ii)(C).

disparate impact analysis: race need not be a force that causes outcomes to differ.

As applied to the lending context, while broader testing is often done, *disparate impact tests need only include controls for attributes that are plausibly business justified*. Thus, and depending on context, it may be appropriate to include fewer non-race control variables in such disparate impact testing than in disparate treatment testing. In a disparate treatment test, the central statistical concern is often "omitted (or excluded) variable bias"—the worry that the statistical estimates of disparate treatment are biased because the regression inappropriately *excludes* necessary non-race variables. If a test fails to control for a relevant non-race factor that may have prompted an employer's adverse decision with regard to a particular plaintiff, then the test may falsely attribute the adverse decision to the applicant's race.

In disparate impact testing, however, a primary statistical concern is "included variable bias" – the worry that the statistical estimates of disparate impact are biased because the regression inappropriately *includes* certain non-race variables.[11]

Scanlan's mistaken conflation of different kinds of discrimination is confounded by the fact that his descriptive statistic measures, unlike the more standard regression measures used in both disparate impact and disparate treatment testing, do not control for *any* non-race factors. Yet a crucial part of regression analysis turns on the appropriate list of non-race controls to include in multivariate regression.

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[11] This is not to suggest that the law countenances a decision-maker's speculative assertion or invocation of variables that had no actual relevance in real time simply for the purpose (or with the effect) of obscuring the relevant statistical relationships. The fact that there are "more" control variables in disparate treatment analysis does not itself signify any greater robustness, rather, it underscores that one must consider that there may be factors used in decision-making that, although not business justified, are nonetheless actually used and may provide an alternative explanation to intentional discrimination. It is also true that the use of too many similar variables raises its own scientific concerns such as overfit or multicollinearity.

To use the seminal example of *Griggs v. Duke Power Company*, even putting aside that under the facts of that case the high school degree was likely a pretext for intentional discrimination, if having a high school diploma is not a business justified condition of employment, then it is inappropriate to separately control for diploma status in a disparate impact test to show the hiring shortfall. 401 U.S. 424 (1971).[12] The degree to which an unjustified variable explains away (reduces) any hiring shortfall is not harmful to, but in fact helps, the plaintiffs' case because it shows the impact of the employment of the unlawful practice. Indeed, Table 2 in the following section undertakes precisely this analysis.

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[12] In *Griggs*, this Court found that Duke Power's requirement of a high school diploma or use of an aptitude test to screen applicants for certain jobs resulted in a disparate impact violation because (1) the requirements caused African-American applicants to be disproportionately rejected, and (2) the requirements were not reasonable measures of job performance.

C. Scanlan Mistakenly Characterizes Disparate Impact Measures as Mutually Inconsistent, When Well-Specified Regressions Produce Robust Results that are Independent of Whether the Disparity is Framed in Terms of Applicant Failure or Success.

Scanlan argues that the example illustrated in Table 1 of his brief, as well as in his own cited work, that standard measures of disparate impact disparities depend crucially on the relative frequencies of disadvantaged and advantaged groups in ways that make it impossible to reach conclusions as to even the *direction* of a policy's disparate impact. *See* James P. Scanlan, *The Mismeasure of Discrimination, Faculty Workshop, the University of Kansas School of Law* (Sept. 20, 2013), available at http://jpscanlan.com/ (last visited Dec 19, 2014). In other words, he argues that it is not possible to determine whether a policy favors or disfavors a particular group. He is wrong.

The example central to Scanlan's argument, presented in Table 1 of his brief, demonstrates that a proper, statistically valid regression produces robust, frame invariant, findings of disparate impact.

Consider the following example: suppose that one is interested in whether an employer's hiring policy for maintenance workers that categorizes applicants as either "high" or "low" quality applicants has a disparate impact. Assume that high-quality applicants have both a high school diploma and some additional attributes, but, as in *Griggs*, having a high-school diploma is not a job-related qualification for the positions. Assume further that "low-quality" applicants possess all the requisite job-related qualifications but lack a high-school diploma. (For simplicity, think of what Scanlan terms the "Advantaged Group," as comprising white applicants, and the "Disadvantaged Group" as comprising black applicants.) Finally, assume that there are 1,000 applicants: 200 black and 800 white and that these applicants are randomly assigned as specified in Scanlan's Table 1.[13]

Using these assumptions, the dataset—generated by Amicus—exactly reproduces Scanlan's Table 1:

Table 1: Pass and Fail Rates of Advantaged Group (White) and Disadvantaged Group (Black)

Cut-off	AG Pass	DG Pass	AG Fail	DG Fail	AG/DG Pass	DG/AG Fail	Percent-age Point Diff	Odds
High	0.80	0.63	0.20	0.37	1.27	1.85	0.17	2.35
Low	0.95	0.87	0.05	0.13	1.09	2.6	0.08	2.84

[13] In particular, this dataset randomly assigns 640 (80%) of the white subpopulation of applicants to the high group, 120 (15%) of the white subpopulation of applicants to the low group, and the remaining 40 (5%) to either a high school graduate only group or a neither graduate nor qualified group.
To reproduce the subpopulation proportions that match Scanlan's Table 1, Amicus assumed a 95% probability of white applicants being qualified, an independent 84% probability of white applicants having a diploma, a 87% probability of black applicants being qualified and an independent 72% probability of black applicants having a diploma

The table above confirms that the constructed dataset reproduces the summary statistics from Scanlan's example. While Scanlan motivates his examples by imagining a test with either a high or low qualifying cutoff, amicus' re-creation shows that these assumed proportions are also amenable to a *Griggs* interpretation. In other words, Scanlan asks whether an employer moving from a low to a high qualifying cutoff produces a disparate impact, *but the actual question is whether the low or high qualifications are business justified*—in this example (and in *Griggs*) whether having a high school diploma is actually related to an employee's job performance.

Using Sclanlan's data, moreover one can estimate the ordinary least squares (OLS) regressions to test for whether the employer's policy of only hiring "high quality" applicants causes an unjustified disparate racial impact. Table 2 contains the results of these regressions.

Table 2: Example of Regression Analysis

Specification	Included Variable Bias (1)	Unjustified Disparate Impact (2)	Adjusted Outcome (3)
VARIABLES	Offer	Offer	Offer2
Black	0.00368	-0.106***	-0.110***
	(-0.009)	(-0.032)	(-0.032)
Qualified	0.805***	0.798***	0.798***
	(-0.045)	(-0.016)	(-0.016)
Diploma	0.930***		
	(-0.015)		
Constant	-0.748***	0.0418***	0.0418***
	(-0.055)	(-0.014)	(-0.014)
Observations	1,000	1,000	1,000
R-squared	0.946	0.241	0.242

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The "Included Variable Bias" specification, reported in column 1, regresses the employer offering decision (equal to 1 if employer offers the applicant a job and 0 if the employer rejects the applicants) on whether the applicant is qualified, whether the applicant has a diploma, and whether the applicant is African-American. As argued above, this specification suffers from "included variable bias," in that it produces a biased estimate of whether the employer's diploma requirement causes a disparate impact. It is simply impossible to test whether a diploma requirement causes a racially disproportionate impact in a specification that simultaneously controls for both the diploma and the applicant race.

To test for whether the employer's decision-making produces unjustified disparate racial impacts it is necessary (as argued above) to exclude from the specification any variables that are not plausibly business-justified. In this example by assumption, this means excluding the control indicating whether a particular applicant has a high-school diploma. The "Unjustified Disparate Impact" specification, reported in column 2, does just this. After controlling for plausibly business-justified qualifications, this specification estimates that the decision-making process produces a disparate racial impact. Specifically, the estimated Black coefficient indicates for this dataset that black applicants who are similarly situated with regard to business justified qualifications were 10.6% percentage points less likely to be offered employment. Moreover, the regression estimates that this unjustified disparate racial impact is statistically different than zero (p-value < 0.01).

As one moves from the first to the second column of regression results, the Black coefficient estimate exhibits just the kind of adverse movement in the race coefficient that is indicative that the employer's diploma requirement caused the disparate impact in question. The third specification, reported in column 3, finds that this adverse movement of the race coefficient is in fact statistically significant,[14] which is evidence that

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[14] The specification in column (3) separately tests whether any adverse movement in the race coefficient is statistically significant, by estimating an alternative form of column (2) which by regressing an "Adjusted Defendant Decision" onto the column (2) controls, where Adjusted Defendant Decision = Defendant Decision - $ß_{1(\text{column 1})}$ * Minority and $ß_{1(\text{column 1})}$ is the estimated coefficient from the column (1) regression that includes the unjustified diploma policy control. By first subtracting the estimated race coefficient from a regression which includes an unjustified policy control, and then re-regressing this adjusted decision variable on

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employer's diploma policy is a statistically significant cause of an unjustified disparate racial impact.

Most importantly, the results of these regressions are independent of whether the employer's decision is framed as a decision to offer employment or a decision to reject an application. The foregoing example establishes that well-specified regressions have three core advantages ignored by Scanlan's analysis of proportions: (a) the regressions can estimate whether disparate impacts persist after controlling for business justified influences; (b) the regressions can estimate whether these unjustified disparate impacts are statistically significant; and (c) the regressions produce estimates of disparate impact that are, counter to Scanlan, frame invariant.

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a specification that is identical except which excludes the unjustified, one can estimate whether the exclusion causes a statistically significant an adverse movement in the race coefficient.

D. Scanlan's Suggestion that Courts Should Deny a Disparate Impact Cause of Action Because of the "Difficulty" and "Uncertainty" of the Determination Should be Rejected Out of Hand.

Scanlan suggests that courts should deny granting a disparate impact claim under the Fair Housing Act because, according to Scanlan, "appraising the size of a disparate impact, and determining whether one practice has a less discriminatory effect than another, are matters of great difficulty and considerable uncertainty." (Scanlan Br. at 2-3.) This suggestion flies in the face of common court practice. Courts in a variety of settings routinely admit regression analysis to aid jurors in sussing out questions of causation. *See, e.g.*, *In re: Neurontin Mktg. & Sales Practices Litig.*, 712 F.3d 60, 69 (1st Cir. 2013) ("[R]egression analysis is a widely accepted method of showing causation . . . ."); Daniel L. Rubinfeld, "Reference Guide on Multiple Regression," in Reference Manual on Scientific Evidence, 2nd ed., Federal Judicial Center

(2000), pp. 179-227.[15] Scanlan's implication is that because an evidentiary element is "difficult" to determine, courts should not recognize a legal theory at all that uses such evidence. This is without basis. *Cf., e.g.*, *ATA Airlines*, 665 F.3d at 889-90 (discussing the distinction between a regression analysis that is scientifically valid and one that is not).

Indeed, triers of fact, guided by courts in their gatekeeping role, assisted by expert witnesses, and vetted through the adversarial process are often called upon to decide difficult evidentiary issues. There is absolutely nothing in Scanlan's analysis to suggest that the "difficulty" or "uncertainty" of

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[15] "Multiple regression analysis is a statistical tool for understanding the relationship between two or more variables." *Id.* at 181. As the Reference Guide discusses, regression analysis is used in a variety of contexts, is valuable scientific evidence, and, when coupled with empirical evidence of a causal relationship, is instructive on questions of causation. *Id.* at 182-185. *See also* Joshua Angrist & Jorn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion* 133 (2009) ("Causal inference has always been the name of the game in applied econometrics.").

determining disparate impact questions are any different in the employment context.

All of Scanlan's core examples, moreover, are motivated by the potential disparate impact of a qualifying test for employment. But Congress has unequivocally determined that a disparate impact cause does lie in the employment context. *See, e.g.*, *Lewis v. City of Chicago*, 560 U.S. 205, 208 (2010). It is for this reason that testing for and identifying the presence of an unjustified disparate impact is frequently less difficult than proving "intentional discrimination": it does not call upon fact finders to establish *mens rea* of animus or race consciousness.

As much to the point, while statistically testing for unjustified disparate impacts often requires the aid of expert witnesses, there is nothing inherently more difficult or uncertain about undertaking this kind of analysis than statisticians and courts encounter in a variety of other contexts. Degree of difficulty is not a persuasive ground for denying this cause of action.

CONCLUSION

Well-accepted and rigorous arguments support the conclusion that statistical methods exist to test for disparate impacts. Properly specified regressions controlling for plausible business justified influences on an organization's decisions can be used to identify when specific practices cause unjustified disparate impacts. Amicus James P. Scanlan's failure to engage the questions of statistical significance, hypothesis testing or the appropriate set of control variables render his conclusions unpersuasive and contrary to the weight of expert statistical opinion. He is wrong to argue that "standard statistical analyses of discrimination are unsound." Regression analysis provides a sound and statistically robust method of analyzing and testing for unjustified disparate impacts.

December 23, 2014

Respectfully submitted,

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