Gender representation and the adoption of hiring algorithms: Evidence from MBA students and executives*

Patryk Perkowski

Columbia Business School

Job Market Paper

Click here for the latest version

January 9, 2023

Abstract

I examine how job performance and diversity considerations shape recommendations for adopting algorithms in hiring. Between 2019 and 2022, around 400 business managers and executives coded up and evaluated algorithms aimed at improving hiring at a firm. Although these algorithms would lead to large performance improvements for most, managers were unlikely to recommend adoption. Instead, their adoption recommendations were strongly shaped by the demographic impacts of the algorithm, particularly in regard to gender. Algorithms that decreased the number of female hires were half as likely to be adopted as those that had no impact or increased it. These results hold while controlling for the algorithm's impact on job performance, and are not present for two other protected classes, age and country of origin. I rule out that this behavior was driven by fear of illegal discrimination. Instead, using a regression discontinuity design, I provide causal evidence that even marginal decreases in the number of female hires leads managers to reject hiring algorithms. I conclude by discussing the implications of these results for our understanding of algorithmic aversion, algorithmic bias, and the returns to algorithmic decision-making in business.

Keywords: hiring algorithms, algorithmic aversion, gender, algorithmic decision-making, people analytics
JEL Classification: M5, J7, M15

*Patryk Perkowski (PPerkowski22@gsb.columbia.edu). I thank Erica Bailey, James T. Carter, Bo Cowgill, Fabrizio Dell'Acqua, Jorge Guzman, Don Green, Bruce Kogut, Stephan Meier, Jean Oh, Katherine Sun, and Jordan Lionell Weatherwax for helpful feedback. I thank Nicole Hawro for excellent research assistance, and Angela Ryu for help accessing the data. All errors are my own.

1 Introduction

Rather than rely on human intuition, firms are increasingly delegating decision-making authority to algorithms. Rapid changes in data collection, storage, and processing technologies have led to the rise of data-driven decision making in businesses (Brynjolfsson et al. 2003; Brynjolfsson and McElheran 2016a,b), whereby firms rely less on human intuition and more on data. In some instances, firms have moved from using data to influence decision making to completely delegating decision-making authority to algorithms. Evidence from the past decade indicates that algorithms can outperform humans in settings as diverse as chess (Hassabis 2017), medical diagnoses (Rajpurkar et al. 2018), and speech detection (Assael et al. 2016). Such developments have coincided with algorithmic adoption in business domains such as service operations, product development, and marketing and sales. Overall, the rise of algorithms in business will have fundamental impacts on how businesses compete and operate.

At first blush, algorithms appear prime for adoption in the field of recruitment. First, hiring is inherently a prediction problem, whereby a firm tries to forecast a given applicant's on-the-job performance, usually using information obtained from the application process such as a resume or interview.[1] Given that recent developments in machine learning and artificial intelligence are advances in statistical prediction (Agrawal et al. 2019), hiring seems well suited to the use of algorithms. Indeed, recent empirical evidence suggests that algorithms are more effective at identifying top job performers than humans (Kuncel et al. 2014; Chalfin et al. 2016; Cowgill 2020; Li et al. 2021). Second, the rise of human capital management platforms, such as worker and applicant tracking systems, has increased the quality and quantity of data that firms have about their workers and job applicants (Aral et al. 2012). Increased data helps improve prediction accuracy, which would thus increase the returns to algorithmic hiring. Third, technological advancements have increased the returns to selective hiring, making it more important to have accurate predictions of potential hires' job performance (Cowgill and Perkowski 2022). Fourth and finally, the rise of job search platforms like Indeed and LinkedIn has increased application volumes, thereby increasing firm screening costs (Cappeli 2001); algorithmic approaches offer a solution with lower marginal costs than human screening. Overall, improvements in prediction technology, increased data availability, and higher firm screening costs favor algorithms playing a prominent role in hiring.

[1] Firms may also try to forecast other information about a candidate, such as their desired salary. This is also inherently a prediction problem for the firm.

Still, firm adoption of algorithms in hiring has lagged behind algorithmic adoption in other business functions. McKinsey's Global Survey of AI in 2021, for example, found that while over half of respondents reported using analytics in at least one business function, only eight percent reported using it in talent management.[2] Firms were around three times as likely to use algorithms for product and service development, or service operations, and twice as likely to use it for customer service analytics than talent analytics.[3] These survey results suggest that despite the benefits to algorithms in hiring, there are meaningful barriers to adoption.

One reason why adoption lags in hiring is that it presents statistical challenges that other business settings do not. Perhaps the most salient of these challenges is the difficulty of obtaining an outcome measure for the algorithm to maximize (Tambe et al. 2019). Job performance is notoriously difficult to measure (Levinson 2003), and managers may seek to optimize outcomes other than job-performance (such as retention, salary requirements, or a combination of these measures). This increases the difficulty of deploying algorithms in hiring, compared to other business domains where the outcome measure is more easily measurable (for example, ad clicks). Additionally, analytics done in the personnel arena suffer from issues regarding smaller sample sizes and significant sample selection issues.[4] These obstacles increase the difficulty of prediction, are less pressing in other business applications, and depress the usefulness of algorithms in hiring. Overall, these statistical challenges create significant obstacles to algorithmic adoption in hiring.

In addition, algorithmic hiring raises ethical concerns regarding bias, discrimination, and distributional outcomes, which are paramount to business and society. Articles in scholarly journals and in the public press document many instances of algorithmic bias, whereby algorithmic approaches either codify or introduce new bias against under-represented candidates.[5] These concerns are front and center for policymakers, firms, and employees, alike. In 2019, United States Senator Ron Wyden introduced the Algorithmic Accountability Act, which would require that companies perform audits of

[2]This percent includes firms using algorithms for recruiting and for retention, so the percent using algorithms in hiring is almost certainly lower. See https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021 for more information.

[3]This may reflect the results in Bhatia and Meier (2022), who find that executives show a bias towards customers rather than employees using data from earnings calls and board composition.

[4]For example, suppose that an organization trains an algorithm to maximize job performance. However, the organization does not have data on the job performance of individuals it does not hire. This is an important sample selection bias that the organization must deal with. This refers to the "selective labels problem" in computer science. For more information on the selective labels problem, see Kleinberg et al. (2017); Lakkaraju et al. (2017); Cowgill (2020); Rambachan and Roth (2020).

[5]See, for example, https://hbr.org/2019/05/all-the-ways-hiring-algorithms-can-introduce-bias.

their algorithmic systems and report the findings to the Federal Trade Commission.[6] In New York City, a new law will require that employers conduct independent audits of their automated tools to test for bias.[7] Meanwhile, firms have begun partnering with academics to audit their algorithmic approaches to hiring. The startup pymetrics, which offers a machine-learning pre-employment assessment, teamed up with a series of academic researchers to run audits to evaluate their system for bias (Wilson et al. 2021). The start-up HireVue also participated in such an audit by working with Richard N. Landers, a prominent Industrial-Organizational Psychologist.[8] Such concerns are also commonly held amongst the general population. A Pew Research survey, for example, found that 42 percent of American adults believe that hiring algorithms would do a worse job than humans when it comes to hiring candidates from diverse backgrounds (compared to 27 percent who thought they would do better) and 58 percent belief algorithms would do worse than humans at evaluating candidates with non-traditional work experience.[9] In sum, business and society are skeptical that algorithms can provide unbiased predictions. And, these concerns have compelled firms and policymakers alike to pay special attention to the distributional consequences of hiring algorithms across racial, gender, and other demographic lines.

To be sure, the rise of algorithms has increased the codifiability and testability of the impact on hiring policies on demographic representation. Algorithms have given decisionmakers the ability to carefully measure the impacts of the algorithm and any distributional shifts in the diversity of hires.[10] Even black-box algorithms, which obscure how inputs are combined, can be audited and tested for demographic impacts.[11] The use of these tools will require that executives decide between algorithms of varying effects (for example, choosing to implement an algorithm that will increase the female representation but decrease the number of workers above the age of 50 by six percent distribution, versus one that has the opposite effect). Understanding how these tradeoffs influence algorithmic adoption decisions has important consequences for our understanding of hiring, human resource strategy, and worker careers more generally.

[6] See https://www.congress.gov/bill/116th-congress/house-bill/2231 for the text of the bill.

[7] https://news.bloomberglaw.com/daily-labor-report/new-york-city-ai-bias-law-charts-new-territory-for-employers

[8] For more information, see https://www.hirevue.com/press-release/independent-audit-affirms-the-scientific-foundation-of-hirevue-

[9] See https://www.pewresearch.org/internet/2017/10/04/americans-attitudes-toward-hiring-algorithms/.

[10] It is interesting to note that several papers find that algorithms can improve diversity, relative to human decision makers who are more biased. For example, an number of papers, including Cowgill (2020), Li et al. (2021), Pisanelli (2022b) and Pisanelli (2022a), present evidence that the use of algorithms in hiring increased the number of hires that were female or were racial minorities compared to the status quo approach of humans. However, the extent to which this is true in broader settings is unclear.

[11] See, for example, https://www2.deloitte.com/us/en/pages/advisory/articles/black-box-artificial-intelligence.html.

I examine these tensions using four years of data from an assignment in a People Analytics course at a top business school in the United States. From 2019 to 2022, over 400 MBA and Executive MBA (EMBA) students (collectively referred to as "managers" and "participants") were tasked with writing hiring algorithms in order to improve hiring practices at an anonymous (and fictitious) company (referred to, in this manuscript, as "Firm F"). The managers received data concerning approximately 2,000 workers, 689 of whom were currently employed by the company, and 1,258 of whom were not currently employed but were eligible to be hired. Managers had access to workers' demographic characteristics (such as gender, age, and education), employment characteristics (such as work status), and current employer characteristics (such as firm size and workplace flexibility). For the 689 hired workers, the managers had a measure of job performance that was unbiased and without noise. This data represents data that is collected by human capital management systems such as ADP and Workday, albeit with a smaller sample and fewer covariates.

The assignment asked managers to analyze this data and develop an algorithm to improve hiring practices at this firm. This occurred through a series of five steps. First, the managers were asked to determine the predictors of being hired by the firm, and of job performance at the firm. Second, the managers were asked to formulate hypotheses on how the firm could improve its hiring practices using the results of their analysis. Third, the managers quantified and translated their hypotheses into hiring algorithms that they then used to select (i) 20 workers in the applicant pool whom the firm should have hired if it used the algorithm, and (ii) 20 workers who were currently employed by the firm but who should never have been hired if the algorithm was used.[12] Fourth, after making their hiring recommendations, the managers were given performance data for all 1,258 potential workers and had to evaluate the proposals' impact on job performance and workplace diversity. Finally, managers asked whether they would recommend that the firm adopt their proposals or maintain the status quo of hiring by humans. The exercise was designed to resemble a typical task conducted by a People Analytics team or by human resource management consultants, with a special focus on relating the adoption recommendation to the performance and demographic representation impacts.[13]

[12] In theory, the use of algorithms in hiring may also change the number of employees who are hired (for example, if the algorithm selects workers who have lower salary requirements or have a higher willingness to supply for the firm. In this setting, I hold constant the number of employees influenced by the change. However, it is possible to simulate the impact of the algorithm across the size threshold.

[13] The task was designed in a way to limit many of the statistical issues mentioned above. The setting features a job-performance measure that is unbiased, and managers were instructed to ignore other outcome variables such as salary demands. The aim was to focus attention on relating the adoption recommendation and the performance and demographic representation impacts, and not the other challenges that would depress adoption recommendations.

There are a number of reasons why this task presents a natural setting to study how the demographic representation impacts of algorithms shape their adoption recommendation rates. First, the setting allows me to hold constant other factors that may impact algorithmic adoption (such as the amount of training data or the existence of a measurable job performance outcome) and thereby to zero in on how demographic representation shapes algorithmic adoption. Second, the setting provides a unique measure of algorithmic adoption. It is notoriously difficult to get data on firm technology adoption decisions; my setting contains a measure of algorithmic adoption recommendations, which I can then relate to the performance outcomes of algorithms. Third, the setting allows me to bypass the Fundamental Problem of Causal Inference and estimate the causal impact of algorithms on firm outcomes. Understanding how the effects of an algorithm impact adoption rates requires an unbiased measure of how the algorithm changes job performance and demographic representation. While it is possible to estimate how a given algorithm would influence demographic diversity (for example, by using algorithmic audits as described earlier), such audits are more difficult for job performance since this measure is only collected conditional on having been hired. Although no proposal was ever implemented, I can assuage this concern using a simulation method described in Section 3.2 that uses the forty workers whose employment status is changed by the adoption of algorithms. Overall, the task presents a creative setting that bypasses many of the difficulties in studying algorithmic adoption decisions.

My analysis proceeds in the following steps. First, I estimate the causal impact of adopting a hiring algorithm on the firm's outcomes by comparing outcomes for the forty candidates whose hiring status changes as a result of the algorithm. I am particularly interested in the impacts on job performance and the demographic distribution of hires, both on average and across the distribution of managers.[14] Second, I estimate how these impacts are related to the adoption recommendation given by the manager. I regress the adoption recommendation on the performance and demographic impacts of the algorithm to understand the predictors of recommending algorithmic adoption. Lastly, I investigate whether there is support for various mechanisms that could be driving the adoption decisions I observe, such as fear of illegal discrimination.

My results indicate that if implemented, the hiring algorithms would lead to hires with much higher job performance scores than the status quo of human decision-making. The 20 recommended hires

[14] In a sense, this second analysis mirrors recent papers that give a team of analysts the same data and study the distribution of conclusions that the group comes to. See, for example, Silberzahn et al. (2018)'s study of bias in soccer.

had a job performance score that was on average around 470 points higher than the twenty that the algorithms suggested to fire. The 20 recommended fired candidates had a job performance score of 2,345, indicating that the algorithm would lead to a 20 percent improvement in job performance of the firm's hires. This is true not just for the average candidate recommended by the algorithm, but also throughout the performance distribution of recommended candidates. Results from quantile regressions reveal that the algorithms increase the performance of the bottom 10 percentile of workers by 30 percent, and the top 10 percentile of workers by 15 percent. Moreover, over 80 percent of managers wrote a hiring algorithm that increased the job performance of hires, with an average increase of 32 percent. Those whose algorithms decreased job performance did so by 11 percent on average. Overall, the subject population was effective in writing algorithms that improved the quality of hires as measured by job performance.

Although the algorithms would on average increase the job performance of new hires, managers were wary of recommending adoption. Although over 80 percent of managers wrote algorithms that would increase job performance, only 54 percent recommended adoption. Algorithms that led to larger increases in job performance were more likely to be recommended for adoption, but there are many algorithms that would increase job performance that are not recommended, and others that decrease it and are recommended.

My results indicate that the demographic impacts of my algorithms played a special role in adoption recommendations. I examine the impacts across three characteristics: gender, age, and region of origin. My results indicate that the algorithms had negative impacts on the proportion of female, older, and Latin American hires, reducing their numbers by 13, 40, and 90 percent, respectively. Meanwhile, the hiring algorithms led to hires that skewed male, younger, and were more likely to be from Asia. While the average impact on the gender diversity of new hires is negative, this effect features substantial heterogeneity. Around half of managers increase the number of female hires, and they do so by 30 percent on average, while the other half decrease it, and they do so by 39 percent on average. Thus, while adopting the hiring algorithm would have increased job performance for the majority of managers, it would also lead to large changes in the demographics of hired workers.

I then relate these performance and demographic impacts to the adoption recommendation. Algorithms that reduce the number of female hires are 30 percentage points less likely to be recommended for adoption, or a 45-percent decline relative to the control mean of 68 percent. This holds true even

controlling for the algorithm's impact on job performance, and on the other demographic categories. Meanwhile, managers are less responsive to the impacts on other demographic characteristics, highlighting the unique role played by gender diversity considerations in shaping algorithmic adoption recommendations.

To add a causal interpretation to these results, I estimate a regression discontinuity design that compares adoption recommendations for hiring algorithms that marginally decrease the number of female hires, versus those that marginally do not (i.e., they keep the gender distribution of the firm the same or marginally increase the number of female hires). I first show that hiring algorithms to the right versus left side of this cutoff exhibit no systematic differences in their impacts on job performance or demographic characteristics other than gender. I then examine how crossing this threshold impacts rates of adoption recommendations. Algorithms to the left of this cutoff were much less likely to be recommended for adoption: managers were around 28 percent less likely to recommend the adoption of hiring algorithms that marginally decreased the number of female hires, and this effect remains once I control for the other impacts of the algorithm, and for participant covariates.

Moreover, I rule out that manager behavior is driven by fear of illegal discrimination. I conduct an empirical exercise using the EEOC's Four-Fifths rule in hiring, which states that disparate impact exists in a selection rule if the selection rate for a group is less than four-fifths of the rate for the group with the highest selection rate.[15] For example, an algorithm that accepts ten percent of male applicants but only three percent of female applicants would violate the Four-Fifths rule. I code up the average selection rate for men and for women for each algorithm, and tag the ones that violate the rule. I find that participants were as likely to not recommend adoption for algorithms that illegally decreased the number of female hires versus ones that did so legally. In other words, passing or failing the Four-Fifths test had no impact on adoption rates conditional on the overall direction of the gender impact, offering evidence that participant behavior was not driven by fear of illegal discrimination.

Overall, my paper highlights the unique considerations facing algorithmic adoption decisions in the domain of hiring. By doing so, I extend the literature on algorithmic adoption and aversion and illustrate the important role played by demographic considerations, particularly gender, in algorithmic adoption recommendations. I also contribute to the growing literature on the causes and consequences of algorithmic bias by identifying the role played by modeling approaches in predicting adverse impact in my domain. Finally, I extend the literature on the relationship between human resource management

[15] For more information, see https://www.eeoc.gov/laws/guidance/questions-and-answers-clarify-and-provide-common-interpretation-u

practices and the returns to algorithmic decision making by providing empirical evidence of a complementarity between algorithmic decision-making, and hiring for workers with technical degrees and with machine learning skills. I further explore these links in the next section.

This paper proceeds as follows. Section 2 describes the background and related literature, and highlights this paper's contribution to the literature on algorithmic adoption, the literature on the causes and consequences of algorithmic bias, and the literature on algorithmic decision-making and human resource management practices. Section 3 describes the setting, including the task, participants, and data. Section 4 outlines the empirical strategy while section 5 displays the empirical results. Section 6 discusses the implications of the results for algorithmic adoption and for firm hiring strategies, and section 7 concludes.

2 Background and related literature

This paper is related to three interconnected literatures: the literature on algorithmic adoption in hiring, the literature on the causes and consequences of algorithmic bias, and the literature on the returns to algorithmic decision-making. I begin by providing some background information and describe how my paper contributes to our understanding of these literatures.

2.1 The adoption of algorithms in hiring

This paper concerns the adoption of algorithms in hiring. A 2020 survey of human-resource managers found that the proportion of human resource departments that used predictive analytics jumped four-fold from 2016 to 2020.[16] Part of this growth is likely driven by an increasingly large ecosystem of start-ups that offer algorithmic services in hiring, such as Eightfold AI, Beamery, and FindEm.[17] Such startups (and tools developed in-house) have allowed organizations to use algorithmic tools in hiring throughout the organizational hierarchy, including C-suite executives.[18] These adoption decisions are likely driven by the benefits that algorithms offer relative to human and non-algorithmic approaches regarding quality and cost.

[16] https://www.mercer.com/content/dam/mercer/attachments/private/global-talent-trends-2020-report.pdf
[17] See Raghavan et al. (2020) for an analysis of the claims and practices of such startups with regard to bias.
[18] See, for example, https://hbr.org/2015/04/hiring-c-suite-executives-by-algorithm.

A number of empirical papers provide evidence that algorithmic hiring leads to better quality hires than traditional human approaches. For example, Chalfin et al. (2016) illustrates how machine learning can improve predictions of worker productivity in police officer hiring and teacher promotion decisions. Cowgill (2020) shows that the use of algorithms helps improve performance on various productivity measures including the likelihood of passing an interview, the likelihood of accepting a job offer, and on-the-job productivity when employed. Li et al. (2021) illustrates how a hiring algorithm that values exploration improves the eventual hiring rates of candidates selected for an interview relative to the firm's existing practices. These results suggest that algorithmic hiring can lead to hired candidates that are more productive than those brought about through human approaches.

Despite the evidence that suggests that algorithms can improve hiring outcomes, there are meaningful barriers to algorithmic adoption. First and foremost, there is a growing literature on algorithmic aversion, which seeks to unpack why human decision makers often ignore algorithmic recommendations, even when those recommendations outperform humans.[19] This literature has argued that a variety of factors influence the presence and size of algorithmic aversion, including being more responsive to algorithmic errors (Dietvorst et al. 2015), perceived capabilities of the algorithm (Longoni et al. 2019; Hertz and Wiese 2019), having a desire for human coworkers (Dell'Acqua et al. 2022), task characteristics (Castelo et al. 2019; Hertz and Wiese 2019) and financial incentives and framing (Greiner et al. 2022).[20] This literature has documented the human tendency to distrust and avoid algorithmic recommendations, even if they outperform human ones. Concerns regarding algorithmic aversion are also larger in hiring than in other domains. For example, the Pew Research Center's survey on automation in everyday life found that almost 70 percent of US adults say the development of hiring algorithms makes them feel somewhat or very worried, compared to 54 percent for driverless cars, and 47 percent for robot caregivers for older adults.[21] For these reasons, algorithmic aversion likely depresses adoption rates in the domain of hiring.

In addition to general algorithmic aversion, there are also statistical barriers that impede algorithmic adoption in hiring, especially relative to other business domains. One barrier is obtaining a dependent

[19] See for Burton et al. (2020) and Mahmud et al. (2022) for systematic literature reviews of algorithmic aversion in human-machine decision-making. See Glikson and Woolley (2020) for a review of the empirical literature on human trust in artificial intelligence.

[20] This is also a literature on algorithmic appreciation, whereby humans are more likely to follow recommendations given by an algorithm. See, for example, Logg et al. (2019).

[21] See https://www.pewresearch.org/internet/2017/10/04/automation-in-everyday-life/. Part of this is due to skepticism that algorithms could do better than humans in the hiring process. 60 percent think algorithms would do worse in hiring candidates who fit well with a company's culture.

variable for the algorithm to predict. While dependent variables in other business domains are clearer (for example, ad clicks or product buys in marketing), obtaining such a measure in the hiring context is difficult. In theory, an algorithm can seek to maximize the expected job performance of new hires, but measuring job performance is notoriously difficult (Levinson 2003; Tambe et al. 2019). Moreover, even if one can get a measure of job performance, managers likely have other concerns such as salary requirements and retention. An algorithm that maximizes the job performance of new hires may fail in an organization where retention concerns are important; instead, an algorithm that maximizes the product of job performance and expected retention may fare better. A second barrier is limited data, both with respect to the unit of analysis and observability of the outcome. While an advertising or marketing team may have daily or even hourly sales data for a product, job performance outcomes (however measured) are measured in more aggregate time periods (for example, quarterly performance reviews for workers), which limits the predictive accuracy of algorithms. A third limitation is time lag; it takes a while to observe job performance outcomes, which makes the programming difficult.[22] These issues have made it difficult to adopt off-the-shelf machine learning and algorithmic approaches into the hiring domain.

In addition to these statistical barriers, there are also ethical and normative challenges to algorithmic adoption in hiring. Bias, discrimination, and demographic representation present pressing issues for algorithmic adoption in hiring. A Pew Research survey, for example, found that 42 percent of American adults believe that hiring algorithms would do a worse job than humans when it comes to hiring candidates from diverse backgrounds (compared to 27 percent who thought they would do better).[23] Moreover, 58% believe that algorithms are worse than humans at evaluating job applicants with non-traditional work experience. These results highlight that humans are skeptical that algorithms are better than humans at screening candidates from diverse backgrounds and non-traditional work experiences. There are also concerns about algorithmic bias, whereby algorithms codify existing biases. Many articles in the popular press document the existence of algorithmic bias. Indeed, Cowgill et al. (2020a) provides experimental evidence that providing business leaders with prompts about the unavoidable nature of algorithmic bias depresses algorithmic adoption intentions. Overall, algorithmic impacts on diversity and bias are front and center when confronting algorithmic adoption decisions.

In this paper, I examine how these considerations shape algorithmic adoption intentions. In the

[22] There are, of course, some empirical workarounds to these problems. For example, practitioners may use a surrogate index (Athey et al. 2019) to come up with the predicted value of a long-term outcome given short-term outcomes.

[23] See https://www.pewresearch.org/internet/2017/10/04/americans-attitudes-toward-hiring-algorithms/.

empirical exercise, managers evaluate the performance of their algorithms in terms of on-the-job performance and demographic representation. I study how the decision to use algorithms or maintain the status quo of human decision-making is related to these effects. Both job performance and diversity considerations, including tradeoffs between various protected categories like gender, age, and national origin, shape the perceived performance of hiring systems, and digitization makes the codifiability of these tradeoffs possible. I study how the presence of algorithms in the decision-making process shifts outcomes along these dimensions, and how these outcomes shape adoption recommendations. I do so in an environment where many of the statistical issues described above are controlled for through the design of the task. Moreover, I show that avoiding a decrease in the number of female hires is a unique contributor to algorithmic aversion in the domain of hiring, and that this is an important phenomenon shaping the managerial decision-making process.

2.2 Algorithmic bias

My paper also contributes to a burgeoning literature on algorithmic bias, which uses tools from computer science, economics, and management to examine what leads algorithms to make unfair and systematic errors against certain groups (Kirkpatrick 2016; Kleinberg et al. 2018; Cowgill and Tucker 2020; Rambachan et al. 2020). Understanding what causes algorithmic bias. and potential solutions to mitigate these concerns, is of utmost importance. This literature generally considers three broad sources of algorithmic bias: (i) biased input data, (ii) biased modeling approaches, and (iii) biased programmers.

First, algorithmic bias can stem from biased input data (Rambachan and Roth 2020; Cowgill et al. 2020c; Cowgill and Tucker 2020; Choudhury et al. 2020). Algorithms require input data to make predictions; if this input data does not represent the broader population, the predictions from this algorithm may lead to biased predictions. Perspectives regarding biased input data are captured by the popular phrase "bias-in, bias-out" and can manifest themselves in various ways. One example is sample selection bias, whereby an algorithm is trained on a dataset that is unrepresentative of the population at hand. Another is the problem of selective labels, whereby observed outcomes (for example, job productivity) are only observed for a subset of the population, which can be influenced by bias from humans (Kleinberg et al. 2017; Lakkaraju et al. 2017; Cowgill 2020; Rambachan and Roth 2020). If algorithmic bias is due to biased input data, then two solutions have been proposed:

(i) having humans impute labels or outcome variables in regions of high confidence (De-Arteaga et al. 2018); or (ii) using representative data (Cowgill et al. 2020c). However, such solutions may be difficult in the context of hiring. For example, it is difficult to predict job performance, which may make imputation unreliable. Moreover, organizations are unlikely to experiment with their hiring processes (Oyer and Schaefer 2010), which makes gaining representation data more difficult. These issues make the biased input data problem more pronounced in the domain of hiring.

Second, algorithmic bias can stem from the modeling approach that translates inputs into algorithmic predictions. While the approach described in the previous paragraph examines the observations available for prediction (and how they are related to outcomes), this one focuses on the variables that go into an algorithmic prediction, and how those variables are combined to lead to a recommendation (see, for example, Pope and Sydnor 2011). Prior work has examined how the inclusion or exclusion of specific characteristics, including gender (Goldin and Rouse 2000), criminal history (Agan and Starr 2017; Doleac and Hansen 2020; Cullen et al. 2022), and salary history (Agan et al. 2021; Hansen and McNichols 2020), influences outcomes across demographic groups. Some proponents argue that excluding information about demographic characteristics in algorithms can decrease bias. For example, LinkedIn's algorithm excludes the name, age, gender, and race of individuals to avoid bias in its job matching algorithm.[24] In this domain, algorithmic bias can be mitigated by paying careful attention to the variables that are allowed to enter the prediction. Similarly, a line of thinking argues that the quantitative level of sophistication of programmers can curtail algorithmic bias. For example, machine learning tools allow for not only more flexible functional forms, but also for programmers to hold out and test their algorithms before implementation, which are difficult for humans to do non-algorithmically. Overall, these approaches pay careful attention to the modeling approach that translates inputs into outputs, in order to reduce algorithmic bias.

Finally, algorithmic bias may be due to bias in the sample of computer programmers. The technology sector in the United States is one of the least diverse[25] Bias here can arise because the population of computer programmers is not representative of the population of those who will be impacted by the algorithm (Cowgill et al. 2020c; Cowgill and Tucker 2020). White and male programmers may not pay enough attention to issues regarding bias and discrimination, and their algorithms may feature

[24] See https://www.technologyreview.com/2021/06/23/1026825/linkedin-ai-bias-ziprecruiter-monster-artificial-intelligence/ for more information.

[25] See, for example, the EEOC's special report on diversity in high tech. https://www.eeoc.gov/special-report/diversity-high-tech.

more algorithmic bias than algorithms written by non-white and female programmers. In such cases, improving the demographic representation of programmers should decrease algorithmic bias.

This paper contributes to this literature by investigating which of these hypotheses are responsible for algorithmic bias in my setting. While I cannot test whether biased input data influences algorithmic bias because my setting features no variation in the sample data that is given, I differentiate between the "biased modeling strategy" versus "biased programmer" hypotheses above. I code up which algorithms would fail the EEOC's Four-Fifths test, and examine whether modeling approaches or programmer demographic characteristics predict failing the Four-Fifths test. I find support for the former. Algorithms that used machine learning methods and tested multiple models were much less likely to lead to an adverse impact on gender, suggesting that focusing on algorithmic approaches may be an effective way to curtail algorithmic bias. Meanwhile, my results find limited support for the "biased programmer" hypotheses: I observe no differences by the gender, technical background, or educational institution of the manager who wrote the algorithm, which lines up the results in Cowgill et al. 2020c. Although the modeling approaches used are not randomized, these results provide suggestive evidence that mitigating algorithmic bias is more effective through studying modeling approaches.

2.3 The returns to algorithmic decision-making

Finally, this paper is related to the literature on the returns to algorithmic decision making. One particular focus has been the human resource management practices that are complementary to algorithmic decision making and analytics. Tambe (2014) shows that the returns to big data technologies require significant data assets and labor markets where many workers have the required big data technology skills. Using U.S. Census Bureau data on manufacturing establishments, Brynjolfsson et al. (2021) illustrates that the returns to prediction technology are larger for organizations with more educated workers and with better managerial capacity. Rock (2021) shows that having hired workers with AI skills increased the returns to deep-learning technology by using Google's open-source launch of TensorFlow as a natural experiment. Overall, these papers have illustrated that the returns to algorithmic decision making and analytics depend critically on the human resources that a firm has.

My paper contributes to this literature by examining whether and how various human resource management strategies are complementary to algorithmic decision-making. My set-up allows me to generate an estimated treatment effect of algorithmic decision making on job performance for

each participant in my sample. I can then relate this treatment effect to a few human resource characteristics, including whether the participant has a technical degree, machine learning skills, and comes from an elite undergraduate university. I show that a technical background and machine learning skills are complementary to algorithmic decision making: Technical workers with machine learning skills vastly outperform technical workers without these skills, likely due to the increase in the predictive accuracy of their algorithms. Meanwhile technical workers with machine learning skills do better than non-technical workers with machine learning skills, likely by being more careful with implementation. Meanwhile, selective hiring and technical hiring have no individual impact on the returns to algorithmic adoption, nor a complementary one. Instead, algorithms written by programmers with technical backgrounds and machine learning skills see the largest gains in job performance. These results point to an important complementarity between hiring for technical workers and for machine learning skills, and suggest that organizational redesign in the age of algorithms will require firms simultaneously screen for both. More broadly, it suggests that organizations that adopt data driven decision making will shift their job demand characteristics toward workers with more technical skills and more technical backgrounds.

3 Setting

The task occurred as a mandatory assignment in a People Analytics course at a top MBA program. The course was held eight times from 2019 to 2022.

3.1 Task

The task involved managers designing their own hiring algorithm to improve hiring at a firm. The managers received data on around 2,000 workers, 689 of whom were currently employed at the company, and 1,258 of whom were who were not currently employed but were eligible to be hired. Managers had access to worker's demographic variables (such as gender, age, and education), employment characteristics (such as work status), and current employer characteristics (such as firm size and workplace flexibility). For the 689 hired workers, the managers had a measure of job performance that was unbiased and without noise. The task required managers to analyzing this data to generate recommendations for the company to improve its hiring.

The task consisted of two parts. In the first part, the managers had to examine the workforce data and make recommendations on how the company could improve its hiring practices. The managers first had to examine the predictors of being hired at firm F (P1Q1) and of job performance (P1Q2). Participants were not required to use a specific type of analysis, but most used linear and logistic regression (see section 5.1 for analysis of the methods used). Question three then asked participants to formulate a hypotheses, using their previous analysis, regarding how the firm could improve its hiring practices (P1Q3). For example, if a manager found that men were more likely to be hired but there were no gender differences in job performance, they could argue that the firm could improve its hiring practices by placing no weight on gender in allocating interviews. Similarly, they could use propose using the predicted values from the job performance regression to select candidates to interview. In this question, managers generated a set of rules to be followed in determining which candidates to hire. In the final question of part one, the managers had to use this rule to come up with two lists of 20 workers (P1Q4). First, they had to generate a list of 20 workers who were hired by the firm, but would have been rejected if the firm was using the hiring algorithm from P1Q3. Second, they had to generate a list of 20 applicants from the applicant pool who were not initially hired, but would have been hired had the firm used the hiring algorithm from P1Q3.

In the second half of the assignment, participants had to evaluate the performance of their algorithms and make a recommendation for or against adoption. Following the submission of all parts of part 1, the managers received performance data for all applicants (not just those initially hired by the firm). They then tested whether the twenty applicants they proposed selecting performed better or worse than the twenty workers they proposed rejecting (P2Q1). They then examined the impact of their proposal on workplace diversity (P2Q2). For example, they could analyze whether their hiring algorithm increased or decreased gender diversity at the firm. The prompt was intentionally kept broad so that the managers could examine diversity across their desired dimension. Finally, the manager was asked whether they would recommend that the firm adopt this algorithm, assuming there were no alternatives besides their algorithm and continuing with the status quo (P2Q4). The manager then had up to 300 words to describe their reasoning for their decision. Appendix A.3 displays a copy of the instructions that participants received. The data that managers received came from the PIAC dataset (Cowgill et al. 2020b), an international survey that measures cognitive and workplace skills in over 40 countries.

3.2 Benefits of the setting

There are a number of reasons why this task presents a natural setting to study how the job performance and demographic impacts of algorithms shape their adoption. First, the setting allows me to hold constant other factors that may impact algorithmic adoption. In the previous paragraphs, I documented that various factors influence the rate of algorithmic adoption, such as the amount of training data available or the existence of a measurable job performance outcome. My setting holds the input data factors that increase the benefits of algorithmic adoption, while providing a task where the statistical challenges are already dealt with. This allows me to zero in on how demographic representation shapes algorithmic adoption recommendations, which would be difficult in settings that feature variation in data inputs or differences in statistical measures.

Second, the setting provides a way to study and measure differences in algorithmic adoption. It is difficult to obtain data on firm technology adoption decisions, and relate them to performance outcomes. Such studies have either use protected Census data (see, for example, Brynjolfsson and McElheran 2016a,b; Brynjolfsson et al. 2021), large sample surveys initiated by researchers (see, for example, Hitt and Brynjolfsson 1997; Bresnahan et al. 2002; Brynjolfsson et al. 2003), or case studies in narrowly-defined industries (see, for example, Ichniowski et al. 1997; Bartel et al. 2007; Berman and Israeli 2021). My setting complements these approaches by allowing for a clean measure of algorithmic adoption recommendations, which I can then relate to the performance outcomes of algorithms. Although these are adoption recommendations and not decisions, they are still important inputs into algorithmic adoption, and can shed light on how demographic considerations shape managerial decision making.

Third and finally, this setting offers a way to bypass the Fundamental Problem of Causal Inference and estimate the unit-level causal impact of algorithms on firm outcomes. Understanding how the effects of an algorithm impact adoption recommendation rates requires an unbiased measure of how the algorithm would change job performance and demographic representation. While it is possible to estimate how a given algorithm would influence demographic diversity (for example, by using algorithmic audits as described earlier), such audits are more difficult for job performance since this measure is only collected conditional on having been hired. Doing so for job performance runs into the Fundamental Problem of Causal Inference (Rubin 1974; Holland 1986), which states that researchers can never observe unit-level causal effects because we can only observe one potential outcome per unit.

For example, if we wanted to make a statement about the causal impact of adopting a hiring algorithm on job performance, we only observe one potential outcome: we observe the treated potential outcome if the firm adopts the algorithm, and we observe the control potential outcome if the firm does not adopt. The task allows me to avoid this problem by simulating each managers' potential outcomes when algorithmic hiring is implemented versus when it is not. More specifically, each manager's potential outcome under the status quo (without algorithmic hiring) is the average outcome Y across the 689 employees who are employed at the firm at the start of the assignment. Meanwhile, the managers' potential outcome under algorithmic hiring is the average Y across the 689 workers, after removing the 20 workers who the manager's algorithm determined should have never been hired, and adding the 20 workers who the manager's algorithm determined should have been hired. I can then compare outcomes across these two pools to measure the causal impact of algorithmic hiring for each manager in my sample, for various outcome measures including job performance and worker representation. Although no proposal was ever implemented, I can estimate a unit-level causal effect of adopting a hiring algorithm on firm outcomes. For these reasons, the task presents a creative setting that bypasses many of the difficulties in studying algorithmic adoption decisions, albeit with some important limitations.

3.3 Participants

Overall, 397 participants completed the assignment across eight sections from 2019 to 2022. Appendix A.1 displays the number of participants who completed the assignment by section. In Table 1, I examine summary statistics of this population. 41% were female. In terms of education, 87% completed their undergraduate degree in the US, with 14% earning a BS. Ten percent went to a top–25 undergraduate institution. Around a third were in the EMBA program. The industry distribution was 26% in finance, 19% in technology, 17% in business services, 12% in social services, 9% in arts, 5% in real estate, and 12% in other industries. These numbers line up with the backgrounds of managers in the United States.

3.4 Data

My data consists of a few sources. First, I have data on the background of participants. This was collected directly from resumes that were submitted prior to the first week of class. This includes their educational background and work experience. Second, I have data on each participants' assignment submission. This includes the method and analysis conducted for P1Q1 and P1Q2, the hiring recommendation from P1Q3, the proposed candidates to hire/not hire from P1Q4, and the decisions to incorporate their proposal or not from P2Q3. Finally, I have the raw data that participants received to conduct the assignment. This allows me to merge manager hiring recommendations with candidate performance and demographic information to study the exact nature of tradeoffs that the managers were facing.

4 Empirical strategy

The goal of this paper is to examine the impact of various hiring algorithms on the kinds of candidates that are hired, and then examine how these impact whether the algorithm are recommended for adoption. To that end, the specifications in this paper come in one of a few forms.

First, I want to understand how each manager's hiring algorithm impacted the job performance and the demographic makeup of new hires. In order to do this, I run the following regression:

$$y_{m,c} = \beta_0 + \beta_1 * Accepted_{m,c} + \delta * X_m + \epsilon_{s,c} \quad (1)$$

where m indexes managers and c indexes job candidates. $Accepted_{s,c}$ is a binary indicator that equals one if manager m's algorithm accepted job candidate c, and is zero if it rejected this candidate. $y_{s,c}$ represents various outcome measures, including job performance, gender identity, age, education and region of origin. X_m is a matrix of manager-level controls including their gender, education, and prior industry, and programming method used. In some of the results, I estimate equation 1 but replace X_m with M_m, a set of manager-level fixed effects. This looks for variation within each manager, comparing the twenty candidates their algorithm accepted versus the twenty candidates their algorithm said to rejected. I estimate equation 1 with robust standard errors clustered at the manager

level. The coefficient of interest is β_1, which measures the average difference in outcomes for candidates hired versus rejected by the algorithm.

In my second analysis, I model how the impacts of the hiring algorithm affect whether or not it is adopted by the manager. To do so, I estimate various versions of the following model:

$$Adopt_m = \alpha_o + \alpha_1 * Impact_m^{jobperformance} + \alpha_2 * Impact_m^{gender} + \alpha_3 * Impact_m^{age} + \alpha_4 * Impact_m^{region} + \theta * A_m + \epsilon_m \quad (2)$$

where m indicates managers. $Adopt_m$is a binary indicator that equals one if manager m recommending adopting their hiring algorithm, and zero otherwise. $Impact_m^{jobperformance}$ is a variable that captures the percent improvement in job performance that is caused by participant m's hiring algorithm. $Impact_m^{gender}$ is a variable that captures the impact of participant m's hiring algorithm on gender at the firm. I include one of two function forms. First, I estimate a version where $Impact_m^{gender}$ captures the change in female hires at the organization that is induced by algorithmic adoption, going from -20 to $+20$. The coefficient here would capture the change in adoption recommendation rates given one more female hire that is caused by algorithmic adoption. Second, I estimate a version where $Impact_m$ is a binary indicator that equals one if the hiring algorithm would reduce the number of female hires at the firm, and zero otherwise; this version measures the difference in adoption recommendation rates for an algorithm that decreases the number of female hires, versus increases it or keeps the gender profile the same. $Impact_m^{age}$ amd $Impact_m^{region}$ are defined similarly for age and country of origin, respectively, while A_m is a vector of participant controls. The coefficients of interest are α_1, α_2, α_3, and α_4, which capture how adoption recommendations vary with the job performance and demographic impacts of algorithms.

In my final analysis, I use a regression discontinuity design to examine whether an aversion to decreasing female hires has a causal impact on managerial adoption recommendations. To do so, I estimate various versions of the following model:

$$Adopt_m = \alpha_o + \alpha_1 * DecreaseFemaleHires_m + \theta * A_m + \epsilon_m \quad (3)$$

where m indicates managers. $Adopt_m$ is a binary indicator that equals one if manager m suggested adopting their hiring algorithm, while $DecreaseFemaleHires_m$ is a binary indicator that equals one if participant m's hiring algorithm would decrease the number of female hires at the firm, and zero otherwise. I subset my sample with a bandwidth that I obtained using the procedures in Calonico et al. (2014b) and Calonico et al. (2014a).

5 Empirical results

In the empirical results below, I begin by providing an overview of the modeling approaches used by my sample of managers, and their adoption recommendation decisions. I then estimate the impact of algorithmic adoption on the job performance and demographic make-up of hires. Next, I relate the adoption recommendation to the impacts of the algorithm, and provide evidence that an aversion to decreasing female representation plays a special role in these decisions. Finally, I rule out several alternative explanations for my findings.

5.1 Overview of modeling approaches and adoption recommendations

5.1.1 Modeling approaches

I begin by examining the content of the hiring algorithms that were created. The bottom of Table 1 examines the distribution of modeling strategies across the whole sample.[26] The most popular approach, used by over 80 percent of managers, was linear regression. These managers regressed job performance on various candidate covariates, and then used the predicted values from this regression to generate predicted job performance values for all job candidates. The second most common approach was tabulation, which was used by 13 percent of managers. Managers who used this approach examined average job performance across different values of the demographic variables. For example, a manager would look at average job performance across different education categories and form a hypothesis to accept candidates from the bucket with the highest average job performance. A few (four percent) used machine learning techniques such as a random forest or having a training and testing set. The managers also differed in their use of demographic variables, and their predictions. Fewer than 30

[26] In Appendix Section A.2, I display examples of the modeling approaches used.

percent were mindful of using sensitive demographic data such as gender, age, and geographic region. Managers also differed in the number of empirical models they considered. Around half of the managers considered multiple models in their approach (for example, running multiple regression models and choosing the one with the highest R^2). Overall, the subject population used relatively strong empirical techniques in the design of their hiring algorithms, and mirrors the analytical methods used in many people analytics applications.

5.1.2 Algorithmic adoption recommendations

In Figure 2, I examine manager adoption recommendations across my entire sample of managers. Overall, 54 percent of managers recommended adopting the algorithm, while 46 percent recommended keeping human decision making.

5.2 The impacts of algorithmic hiring

In this section, I estimate the causal effect of algorithmic hiring in my setting. Recall that each manager's algorithm generated a sample of 20 candidates who were rejected by the firm but should have been hired if the algorithm was used, and a sample of 20 candidates who were hired by the firm but should have been rejected according to the algorithm. The impact of adopting the algorithm can thus be examined by comparing average outcomes for the 20 accepted candidates versus the 20 rejected candidates using Equation 1.

5.2.1 Job performance

Table 2 displays the results of equation 1 using job performance as the outcome measure. Column 1 compares accepted versus rejected candidates, while column 2 adds manager controls such as the gender, education, and prior industry of the manager. Meanwhile, columns 3 replaces the manager controls with manager fixed effects.

My results indicate that the hiring algorithms on average led to large increases in the job performance of accepted candidates. The twenty accepted candidates had a job performance score that was over 470 points higher on average than rejected candidates. This difference is large and economically significant: The average job performance of the rejected candidates was 2,328, indicating that the algorithm led

to a 20 percent improvement in job performance relative to the control group.[27] This is also true not just for the average candidate but also throughout the performance distribution of recommended candidates. In Appendix B.1.1, I run quantile regressions to examine the impact of the hiring algorithm throughout the distribution. Results from quantile regressions reveal that the algorithms increases the performance of the bottom 10 percentile of hires by over 30 percent, and the top 10 percentile of hires by around 13 percent.

In addition to examining the average impact of the hiring algorithm on job performance, I can also estimate treatment effects across the distribution of managers in my sample. This allows me to understand the extent to which all managers were able to improve performance, or whether there was large heterogeneity in their treatment effects on job performance. I do so by estimating equation 1 for each manager, and then converting the estimated treatment effect into a percent improvement (by dividing the estimated coefficient by the average performance of rejected candidates for each manager). I plot these treatment effects and confidence intervals in Figure 1, sorting the effects from largest to smallest. The figure illustrates that most were able to improve performance outcomes. Over 80 percent of managers wrote a hiring algorithm that increased the job performance of hires; among these, the average increase was 32 percent. Those whose algorithms decreased job performance did so by, on average, 11 percent.[28]

However, although over 80 percent of managers wrote algorithms that would increase job performance, only 54 percent recommended adoption. This suggests that the algorithm's impact on demographic representation may play a special role in adoption recommendations.

5.2.2 Demographic representation

I next examine the impact of the hiring algorithm on the demographic profile of the firm's hires. I focus on three demographic variables: gender, country of origin, and age. First, Panel A of Table 3 displays the results of equation 1 using a binary indicator for being a female candidate as the outcome measure. The coefficient captures the percentage point change in the number of female hires: a positive number signifies that the algorithm will lead to more female hires than the status quo. The results in Panel A of Table 3, however, show that the hiring algorithms on average have no impact on the gender

[27] If I compare the size of this treatment effect to the entire pool of hired workers, it represents an effect of 17 percent (= 478.1/2832.6).

[28] In Appendix Section B.1.3, I examine time trends in the average impact on job performance. I find that algorithms written in 2022 led to larger increases in job performance than those written in 2019.

representation of hires. In fact, the point estimate is negative, signifying that the hiring algorithms, if anything, reduce the number of female hires, though this effect is not statistically significant at conventional levels. Although the algorithms contain no impact on the gender of hires, this conceals vast heterogeneity by manager. Figure 3 examines the impact by manager. This is similar to Figure 1 except the X-axis displays the impact on the raw number of female hires rather than the percent change. Slightly over half of the hiring algorithms increase the number of female hires, while the other half decrease it.[29]

The hiring algorithm also led to changes in the distribution of hires relative to two other demographic categories: age and region of origin. Table 3 also displays the results of equation 1 for various age (Panel B), and region (Panel C) brackets. The algorithm shifted the age distribution of the firm downward. Hired workers were 40 percent less likely to be aged 50–65, while the proportion of workers between the ages of 16 and 24 doubled. The hiring algorithms also shifted the regional allocation of hires. There were large increases in the number of hires from Asia, and fewer hires from Latin America.[30]

5.2.3 Summary of algorithmic impacts

Overall, algorithmic adoption would increase the job performance of hires, but lead to meaningful changes in the demographic profile of hires. Overall, a substantial majority of managers were effective in writing hiring algorithms that improved the job performance of hires. However, adoption recommendation rates lagged: while over 80 percent of managers wrote algorithms that would increase the job performance of hires, just over half recommended adoption. In the following section, I examine how these considerations impacted adoption.

[29] Appendix Section B.1.3 examine time trends in the percentage of algorithms that decrease the number of female hires. I find that algorithms written in 2022 were much less likely to decrease the number of female hires than those written in 2019. This may suggest an increased attention toward gender diversity in my sample, especially because I do not observe such patterns for the likelihood of decreasing age and region of origin diversity.

[30] In Appendix Section B.1.5, I examine correlations between the performance impacts of the algorithms and their demographic impacts. The results indicate no relationship between the impact on job performance and the impact on gender diversity. However, algorithms with larger increases in job performance, were more likely to decrease the number of hires aged 50-65 and from Latin America.

5.3 What predicts algorithmic adoption recommendations?

In this section, I examine how the job performance and demographic impacts of hiring algorithms are related to managers' adoption recommendations. To do so, I regress a binary indicator for recommending adoption on various measures of the job performance and demographic impacts of the algorithm using various forms of Equation 2.

The results in Table 4 indicate that adoption recommendations are related to not only the job performance impacts of algorithms, but also their demographic impacts. Column 1 examines the relationship between the job performance impact of the algorithm and the subsequent adoption recommendation, and finds unsurprisingly that algorithms that lead to larger job performance increases are more likely to be recommended for adoption. Meanwhile, column 2 examines how the demographic impacts of an algorithm are related to adoption recommendations. Managers are more likely to recommend adoption if the algorithm has a larger (more positive) impact on the number of female hires. Meanwhile, the impacts on age and country of origin have no relationship with adoption recommendations. These demographic impact results hold when controlling for job performance (column 3) and also manager controls (column 4), suggesting a robust relationship between algorithmic adoption recommendations and the demographic impacts of algorithms.

To provide further evidence on this link, I also test for whether managers are responsive to aggregate decreases in under-represented groups. The final three columns of Table 4 replace the demographic count predictors from the first four columns, with binary indicators for whether the algorithm decreased the number of hires from each group. These coefficients estimate the difference in adoption recommendation rates for algorithms that decrease the number of hires from each demographic group, versus increase or have no effect. The results in column 5 indicate that algorithms that decreased the number of female hires were 30 percentage points less likely to be adopted. This effect size is large and statistically meaningful: since 68 percent of hiring algorithms that do not decrease the number of female hires are recommended for adoption, this effect translates into a 45 percent decrease ($= 0.302/0.677$). Meanwhile, the results confirm a limited relationship between adoption recommendations and the age and country of origin demographic impacts./footnoteThe results in column 6 provide some evidence that managers are more likely to adopt hiring algorithms that decrease the number of hires from Latin America. However, this coefficient loses significance once I control for manager characteristics in column 7. These results provide compelling evidence that algorithmic adoption recommendations are

strongly related to the gender impacts of algorithms, and that managers are wary of recommending algorithms that would decrease the number of female hires.

5.4 Regression discontinuity design evidence

One drawback of Table 4 is that it presents correlational evidence of a link between the gender impacts of an algorithm and algorithmic adoption recommendations. The nature of the empirical strategy does not allow me to claim a causal link between the two. For example, it may be the case that individuals who exhibit more algorithmic aversion, are more likely to write algorithms that decrease the number of female hires. In such a case, my adoption recommendation results are not driven by the impacts of the algorithm, but rather the beliefs of the manager. While the manager controls in columns 4 and 7 should partially mitigate these issues, I cannot fully control for this concern and claim causality using Table 4.

In order to add a causal interpretation to these results, I estimate a regression discontinuity design (Angrist and Lavy 1999; Hahn et al. 2001; Lee and Lemieux 2010) that compares adoption recommendations around the gender impact threshold of zero. If an aversion to decreasing the number of female hires was driving managerial adoption recommendations, then I would expect that managers are less likely to adopt hiring proposals that marginally decrease the number of female hires, versus algorithms that do not change the gender distribution of the firm or marginally increase the number of female hires. In Figure 4, I plot the regression discontinuity effect of decreasing the number of female hires on algorithmic adoption recommendations using the procedures from Calonico et al. (2014b) and Calonico et al. (2014a). The figure provides evidence that algorithms to the left of the cutoff are less likely to be adopted than those to the right.

In order to more credibly estimate the difference in algorithmic adoption recommendations along the cut-off, I estimate Equation 3 and display the results in Table 5. Doing so requires selecting a bandwidth around the cut-off for which to estimate the equation. In order to get this bandwidth, I follow the procedure in Calonico et al. (2014b) and Calonico et al. (2014a), which returns an optimal bandwidth of 4.18; I therefore limit my regression to algorithms that increased or decreased the number of female hires by up to four.

The results in Table 5 provide support for a causal link between the gender impact of an algorithm

and the subsequent adoption recommendation. The results in column 1 indicate that algorithms that marginally decreased the number of female hires were 16 percentage points less likely to be recommended for adoption than those that had no impact or marginally increased the number of female hires. Given that two-thirds of algorithms with no marginal decrease in female hires are adopted, this represents a 24 percent decrease in the likelihood of recommendation relative to the control mean (= 0.162/0.670). Meanwhile, these results hold while controlling for the job performance impacts of the algorithm, for the impacts on other demographic measures, and for manager controls.

The validity of the regression discontinuity design depends on whether algorithms to the left versus right of this cut-off do not vary in other dimensions besides their gender impact. I provide two pieces of evidence that this is the case. First, I provide visual evidence in Appendix Section B.2.1, whereby I recreate Figure 4 but for placebo outcomes that should not vary along this cut-off. Second, I rerun Equation 3 with these placebo outcomes and display the results in Appendix Section B.2.2. Both of these analyses illustrate limited differences across the threshold for placebo outcomes, and thereby provide further support for the validity of the regression discontinuity design. Overall, these results indicate that even marginal decreases in female representation have a causal impact on algorithmic adoption recommendations.

5.5 Alternate explanations

In this section, I rule out various alternate explanations for the results documented in this paper, including avoiding algorithms that discriminate against protected classes, and managerial incentives.

5.5.1 Avoiding algorithms that discriminate against protected classes

The first alternate explanation is that managers do not adopt these algorithms because they fear legal repercussions for discriminating on the basis of a protected class. According to this theory, managers are weary of adopting algorithms that lead to adverse impacts on protected categories because they fear the repercussions of legal action.

However, a few patterns in the data hint that legal fears are not the primary driver of adoption decisions. First, if legal concerns regarding discrimination were the primary reason why these algorithms are not adopted, then managers would be unlikely to adopt hiring algorithms that discriminate against

any protected class. However, as the results in Table 3 show, this is not the case. Although age is a protected class, managers are not less likely to recommend adoption for algorithms that decrease the number of hires aged 50–65.

There is a second and more direct test that can rule out legal concerns as the primary motivation. The U.S. Equal Employment Opportunity Commission (EEOC) has a rule of thumb to determine whether adverse impact exists within a given selection device: the Four-Fifth's Rule.[31] This rule states that a selection rate for any group that is less than four-fifths of that for the group with the highest rate constitutes evidence of adverse impact (also called 'disparate impact'), that is, discriminatory effects on a protected group. If managers were concerned of legality, they would be particularly wary of adopting hiring algorithms that violate the Four-Fifth's Rule versus those that do not violate the Four-Fifth's Rule (but still decrease the number of female hires).

In order to investigate this possibility, I conduct an adverse impact analysis for each manager's algorithm.[32] Adverse impact exists if the ratio of the female-to-male selection ratios is under 0.80, or if the male-to-female selection ratio is under 0.80. Appendix B.3 displays the a histogram of these adverse impact coefficients and shows that 78 percent of algorithms failed the Four-Fifth's rule. In Appendix Figure B.14, I display the average recommendation rates for algorithms based on whether they (i) decrease female representation or not, and (ii) would pass or fail the four-fifths test. If fear of illegal behavior were driving my results, I would expect to see that algorithms with an impact ratio of less than 0.80 are less likely to be adapted than those with an impact ratio of 0.80 or more. However, this is not the case. The results indicate that passing or failing the Four-Fifth's test has no bearing on the likelihood of adoption Instead, my results indicate that decision-makers adopt algorithms that increase female representation, regardless of whether they would be legal or not, and avoid algorithms that decrease female representation, regardless of whether they would be legal or not. For these reasons, my results are unlikely to be driven by legal fears.[33]

[31] See https://www.eeoc.gov/laws/guidance/questions-and-answers-clarify-and-provide-common-interpretation-uniform-guidelines for more information.

[32] I calculate an average selection rate for men and for women using the 20 candidates they recommended, and the 1,258 candidates in the applicant pool (704 women and 554 men). The selection rate for female candidates is given by $\frac{N_F^{Selected}}{N_F^{Available}} = \frac{N_F^{Selected}}{704}$, where $N_F^{Selected}$ measures the number of female candidates selected by the manager, while the selection rate for men is given by $\frac{N_M^{Selected}}{N_M^{Available}} = \frac{N_M^{Selected}}{554}$.

[33] In Appendix Section B.4, I examine whether participant demographic characteristics or programming practices predict whether or not a given algorithm would fail the Four-Fifth's test. I find no impact of demographic characteristics. Instead, there is a complementarity between using machine learning and testing multiple models– those who use machine learning and test and iterate are much less likely to fail the Four-Fifth's test. This provides support for the "biased modeling strategy" hypothesis in Section 2.2.

5.5.2 Incentives

A second alternate explanation is that the managers in my sample were incentivized, either explicitly or through social pressures, to consider the demographic impact of an algorithm in their adoption recommendations. There are a variety of ways that this could occur. For example, if the managers were primed to arguments or discussions of algorithmic bias and its inescapability, they may be more likely to avoid using the algorithm.[34] This could also occur through the grading incentives managers faced; those in my sample may be less likely to suggest algorithmic adoption if they believed doing so would risk a high-quality grade. Finally, there may be social pressures to respond in support of considering the demographic impacts of algorithms (for example, if fellow classmates would see their responses). Overall, these concerns would suggest that the results in this paper are due to unique features of the task and setting, rather than a more general decision-making process.

There are various aspects of the task and setting that mitigate these concerns. First, the course included a balanced discussion of the merits and drawbacks of algorithms and bias, and a case study where algorithmic hiring improved diversity at an organization.[35] Second, the instructions made clear that the evaluations would be based on the quality of the argument for or against adoption, and not the actual recommendation decision. Third, managers were not told of the specific recommendations of others. Instead, results from the assignment were only shared in aggregate. For these reasons, it is unlikely that incentivization through unique features of the setting drove the impacts I observe.[36]

6 Discussion

In this paper, I documented that algorithmic adoption recommendations are shaped by not only job performance considerations but also demographic representation ones. Using four years of data from an assignment that resembles a "People Analytics" task, I showed causal evidence that the gender impact of an algorithm has a substantial impact on adoption recommendations. In my setting, managers

[34] Indeed, Cowgill et al. (2020a) provide evidence that decision-makers are less likely to suggest algorithmic use when given arguments regarding the inescapability of algorithmic bias.

[35] If anything, it seems like the bias here would go in the opposite direction. The course emphasized that while concerns about algorithmic bias are legitimate, human decision makers are oftentimes more biased. Meanwhile, algorithms enable auditability, which is much more difficult for human decision makers. This would lead decision-makers to favor algorithms over human decision-making if they were concerned about the distributional impacts of selection processes.

[36] One limitation of the study is that the managers were not incentivized. No cost to them (outside of these described above) in selecting a course of action. There is also an interesting question of how managers would make adoption recommendations where they incentivized for their decision. These likely feature cost considerations. However, I believe this would still happen here in the real-world. Give some examples.

were wary of recommending algorithms that would decrease the number of female hires, even if these algorithms would lead to improved job performance. Such algorithms were 28 percent less likely to be adopted than similar algorithms without a negative impact on female hires. Overall, these results illustrate that demographic considerations, particularly surrounding gender, play a key role in the algorithmic adoption decision-making process.

The results in this paper open up the question of why managers were unlikely to recommend the adoption of algorithms that would decrease the number of female hires. Broadly speaking, managers may gain value through not decreasing the number of female hires through two ways. On the one hand, managers may derive instrumental value from not decreasing the number of female hires. Managers may view not decreasing the number of female hires as instrumental for achieving certain organizational outcomes. For example, they may fear that decreasing the number of female hires will lead to lower financing access or increased difficulty in attracting and retaining new talent. Through this mechanism, not decreasing the number of female hires leads to important organizational outcomes, and managers view it as a means to an end. On the other hand, managers may derive intrinsic value from not decreasing female hires. Through this mechanism, managers have a preference for not decreasing gender diversity that goes above and beyond any gain to the organization; instead, they view not decreasing the number of female hires as an end, and not a means to an end.

In my setting, it is likely that managerial recommendation decisions are influenced by both instrumental and intrinsic preferences for diversity. Implementing an algorithm that decreases female representation may cause organizations to face criticism and potential consequences from investors for not having a diverse or inclusive workplace, or may decrease the benefits that accrue to diverse workforces. On the other hand, the productivity benefits that accrue because of algorithmic adoption were unlikely to sway managers into recommending it. In fact, there were some managers who rejected algorithms that would lead to large increases in the job performance of new hires, suggesting intrinsic motivation may play a role in their decision making process.

Differentiating between instrumental versus intrinsic value is notoriously difficult. Doing so in my setting would require an experimental design that holds constant the various organizational considerations at play, and varies the demographic profile of new hires.[37] In this paper, I provided a setting that

[37] A study like this would need to signal to decision-makers that implementing the algorithm would have no impact on organizational outcomes such as the recruitment of new hires or retention of existing workers, but doing so may struggle with realism considerations.

captured a core instrumental value for organizations (job performance), and asked decisionmakers to consider this and ignore other organizational outcomes such as salary or retention. However, it is likely that the managers in my sample had other instrumental means in mind that went beyond job performance. Separating these two goes beyond the scope of the paper, but presents an exciting avenue for future work.[38]

The results in this paper also permit speculation into complementarities between human resource management practices and algorithmic decision-making. A key concern has been the human resource management practices that are complementary to algorithmic decision making and analytics (Tambe 2014; Brynjolfsson et al. 2021; Rock 2021). Overall, these papers have illustrated that the returns to algorithmic decision making and analytics depend critically on the human resources that a firm has.

The data in my paper allow me to relate the job performance impacts of an algorithm to the demographic profile of the coder. The structure of the assignment allows me to generate an estimated treatment effect of algorithmic decision making for each manager in my sample. This is the difference in job performance scores for the forty candidates whose employment status changes as a result of the move from human screening to algorithmic screening. I can then relate how various manager covariates are related to the returns to algorithmic decision-making. I focus on three attributes: (i) whether or not the manager went to a selective undergraduate university; (ii) whether or not the manager has a technical undergraduate degree; and (iii) whether or not the manager uses machine learning methods. I then compare the job performance impacts of algorithms written by participants with these various attributes.

I examine the complementarity between human resource management practices and algorithmic adoption in Appendix Section B.1.2. The results indicate that workers with technical backgrounds and with machine learning skills are complementary to algorithmic adoption. Technical workers with machine learning skills outperform not only technical workers without these skills, but also non-technical workers with machine learning skills. I posit that the former is likely due to the increase in the predictive accuracy of their algorithms, while the latter is driven by more careful algorithmic implementation. Meanwhile, selective hiring and technical hiring have no individual impact on the returns to algorithmic adoption, nor a complementary one.

[38] For example, Bartling et al. (2014) presents a novel experimental design for estimating the intrinsic value of decision rights. Such an experiment may be adopted to help measure how managers consider the instrumental versus intrinsic values of not reducing the number of female hires in their hiring procedures.

These results point to an important complementarity between hiring for technical workers and for machine learning skills, and suggest that organizational redesign in the age of algorithms will require firms simultaneously screen for both in their search for programmers. More broadly, it suggests that organizations that adopt data-driven decision making will change their job demand characteristics toward workers with more technical skills and more technical backgrounds.

7 Conclusion

This paper is motivated by the rise of algorithms in hiring. Various business and labor market trends have led to a secular rise in the demand for algorithmic screening. These include improved prediction power driven by advances in machine learning, rising application volumes due to job search platforms and the internet, and increasing returns to selective hiring. Each of these trends has increased the relative attractiveness of using algorithms to sort and select potential workers.

This paper examines how business managers consider the benefits and drawbacks of algorithmic adoption in the domain of hiring. It examines four years of data from a "People Analytics" assignment, whereby participants wrote hiring algorithms to improve hiring at an organization. I relate the estimated impact of these algorithms (on job performance and on demographic representation) to algorithmic adoption recommendations. While I find that algorithms that lead to larger job performance increases are more likely to be recommended, gender diversity considerations also play an important role in the algorithmic adoption decision-making process. I find that algorithms that decreased the number of female hires were much less likely to be recommended for adoption, and present causal evidence that this effect is driven by even marginal decreases in the number of female hires. Meanwhile, I rule out that this behavior is due to legal considerations regarding discrimination; instead, the managers in my sample exhibit an aversion to even minor decreases in the number of female hires. Overall, the paper highlights the unique role played by gender diversity in shaping algorithmic adoption decisions.

A focal concern for researchers and business leaders alike is understanding how algorithms will influence hiring outcomes and employee-employer matching. In this paper, I use a setting that allows me to estimate the impact of algorithmic adoption on two key hiring measures: job performance and demographic representation. Algorithmic adoption in my setting holds constant the applicant pool and each candidate's job performance, so that the switch from human screening to algorithmic

screening only changes which candidates' potential outcomes are revealed. However, the switch to algorithmic screening will likely lead to other important changes in the hiring and selection process. Understanding these presents a series of exciting future directions to build on a much-needed literature on how algorithmic tools are reshaping employee-employer matching.

First, algorithmic adoption may shift the types of workers in a firm's applicant pool. There is a growing literature that examines how firm attributes impact employee labor supply (see, for example, Burbano 2016 and Abraham and Burbano 2022). If workers draw a disutility from being screened algorithmically, shifting from human screening to algorithmic screening may alter the set of workers available to select from. Indeed, a recent Pew survey indicates that only 22 percent of U.S. adults say they would be comfortable applying for a job where an algorithm would make hiring decisions.[39] There may be some candidates who only apply if they are screened by humans and not by machines, and others who only apply if they are screened by machines but not humans. The Pew survey presents interesting demographic differences in willingness to be screened by an algorithm. Men and younger workers were more likely to support algorithmic hiring, suggesting that algorithmic hiring may skew a firm's applicant pool to be predominantly young and male. Moreover, to the extent that workers gain a non-pecuniary benefit (Cassar and Meier 2018) from being screened by a human, firms may need to design incentives to increase applications to jobs with algorithmic screening. An open question is to study whether algorithmic hiring influences who applies to jobs, and the willingness of candidates to provide labor at a given salary level. Such questions will have important implications for the adoption of hiring algorithms. For example, if algorithmic hiring shifts the pool of applicants to lower-quality workers, or applicants need to be compensated for being screened by a machine, the returns to algorithms in hiring may be more limited such that adoption is disadvantageous.

Second, algorithmic hiring may alter the available information about each candidate that is used during selection. In my set-up, the change from human to machine screening does not impact the type of information that is available about each candidate; instead, the algorithm changes the relative weights placed on the candidate inputs. However, algorithmic adoption may change what firms know about potential employees. Many start-ups in this space offer algorithmic assessment tools that collect new forms of data that are difficult to collect with human screening. For example, HireVue offers game-based psychometric assessments that are made possible by algorithms. If algorithmic screening enables the collection of more detailed job candidate information, then it can increase the quality of

[39] https://www.pewresearch.org/internet/2017/10/04/americans-attitudes-toward-hiring-algorithms/

hiring decisions that are made. Thus, the returns to algorithmic hiring will depend, in part, on the new information it reveals about candidates, and the validity and consistency of this data.

Third, algorithmic hiring may change employee-employer matching by altering how workers act on the job. In my empirical set-up, each worker has a job performance measure that does not vary depending on the screening method, and the switch from human to algorithmic screening only changes which workers' job performance measure is observed. However, it is likely that the method by which a worker is screened leads to changes in their observed job performance. For example, the same worker screened by an algorithm may exert less effort at work than if he was screened by a human because they have less identification with the employer and its mission. Algorithmic screening may also be demotivating; indeed, Dell'Acqua et al. (2022) presents experimental evidence that being randomly assigned to work alongside an automated co-worker leads human workers to decrease their own effort. Thus, understanding the behavioral responses of workers under different hiring methods will be necessary for understanding how the use of algorithms is transforming employee-employer matching.

Finally, algorithmic hiring is only one of the many changes to hiring that is a result of digitization and advancements in information technologies. For example, digitization and job platforms have also led to outbound recruiting, whereby firms seek out candidates directly rather than waiting for them to apply (Carrillo-Tudela et al. 2015; Black et al. 2022; Kim and Pergler 2022). Additionally, online labor markets have made it easier for firms to outsource and delegate hiring decisions to (human) third-party specialists (Cowgill and Perkowski 2022; Kolhepp and Aleksenko 2022). Firms thus have new strategic options when compiling their applicant pools (through inbound recruiting or outbound recruiting) and evaluating those pools (in-house by a human, in-house by an algorithm, outsourced to a human, or outsourced to a machine). An exciting avenue for future research is to relate a firm's broader hiring strategy choices to its internal structure, and characteristics about the job and pool of applicants.[40] For example, firms may be more likely to use algorithms in jobs with many applicants (where evaluating each applicant by a human is too costly) and more measurable performance metrics (where algorithms can do well at predicting who will be a good hire). Formalizing and testing these and other hypotheses will further our understanding of firm screening and hiring in the digital age. Doing so will require not only an understanding of the benefits and drawbacks of human versus machine

[40]There is also likely variation in the types of algorithms that are deployed (for example, using algorithms to scrape data from resumes, versus using facial analysis to collect data from online interviews).

prediction, but also an appreciation of behavioral responses by job candidates and workers alike.

References

Abraham, Mabel and Vanessa Burbano, "Congruence Between Leadership Gender and Organizational Claims Affects the Gender Composition of the Applicant Pool: Field Experimental Evidence," *Organization Science*, 2022, *33* (1), 393–413.

Agan, Amanda and Sonja Starr, "Ban the Box, Criminal Records, and Racial Discrimination: A Field Experiment*," *The Quarterly Journal of Economics*, 08 2017, *133* (1), 191–235.

Agan, Amanda Y, Bo Cowgill, and Laura K Gee, "Salary History and Employer Demand: Evidence from a Two-Sided Audit," Working Paper 29460, National Bureau of Economic Research November 2021.

Agrawal, Ajay, Joshua S. Gans, and Avi Goldfarb, "Exploring the impact of artificial Intelligence: Prediction versus judgment," *Information Economics and Policy*, 2019, *47*, 1–6. The Economics of Artificial Intelligence and Machine Learning.

Angrist, Joshua D. and Victor Lavy, "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement," *The Quarterly Journal of Economics*, 1999, *114* (2), 533–575.

Aral, Sinan, Erik Brynjolfsson, and Lynn Wu, "Three-Way Complementarities: Performance Pay, Human Resource Analytics, and Information Technology," *Management Science*, 2012, *58* (5), 913–931.

Assael, Yannis M., Brendan Shillingford, Shimon Whiteson, and Nando de Freitas, "LipNet: End-to-End Sentence-level Lipreading," 2016.

Athey, Susan, Raj Chetty, Guido W. Imbens, and Hyunseung Kang, "The Surrogate Index: Combining Short-Term Proxies to Estimate Long-Term Treatment Effects More Rapidly and Precisely," NBER Working Papers 26463, National Bureau of Economic Research, Inc November 2019.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw, "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills*," *The Quarterly Journal of Economics*, 11 2007, *122* (4), 1721–1758.

Bartling, Björn, Ernst Fehr, and Holger Herz, "THE INTRINSIC VALUE OF DECISION RIGHTS," *Econometrica*, 2014, *82* (6), 2005–2039.

Berman, Ron and Ayelet Israeli, "The Value of Descriptive Analytics: Evidence from Online Retailers," *Working paper*, 2021.

Bhatia, Nandil and Stephan Meier, " Are Customers 10x More Important to Firms than Employees? Empirical Analysis of Imbalance in Emphasis Between Two Stakeholders," *Working paper*, 2022.

Black, Ines, Sharique Hasan, and Rembrand Koning, "Hunting for Talent: Firm-driven Labor Market Search in the United State," *Working paper, Available online at* https://www.hbs.edu/ris/Publication%20Files/Hunting_for_talent-3_91b04534-b543-485b-91bd-732c8d030efd.pdf, 2022.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt, "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *The Quarterly Journal of Economics*, 2002, *117* (1), 339–376.

Brynjolfsson, Erik and Kristina McElheran, "Data in Action: Data-Driven Decision Making in U.S. Manufacturing," Working Papers 16-06, Center for Economic Studies, U.S. Census Bureau January 2016.

_ **and** _ , "The Rapid Adoption of Data-Driven Decision-Making," *American Economic Review*, May 2016, *106* (5), 133–39.

_ **, Lorin M. Hitt, and Kim Heekyung Hellen Kim**, "Strength in numbers: How does data-driven decisionmaking affect firm performance?," *Working paper*, 2003.

_ **, Wang Jin, and Kristina McElheran**, "The power of prediction: predictive analytics, workplace complements, and business performance," *Business Economics*, October 2021, *56* (4), 217–239.

Burbano, Vanessa C., "Social Responsibility Messages and Worker Wage Requirements: Field Experimental Evidence from Online Labor Marketplaces," *Organization Science*, 2016, *27* (4), 1010–1028.

Burton, Jason W., Mari-Klara Stein, and Tina Blegind Jensen, "A systematic review of algorithm aversion in augmented decision making," *Journal of Behavioral Decision Making*, 2020, *33* (2), 220–239.

Calonico, S., M. D. Cattaneo, and R. Titiunik, "Robust data-driven inference in the regression-discontinuity design," *Stata Journal*, 2014, *14* (4), 909–946(38).

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik, "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 2014, *82* (6), 2295–2326.

Cappeli, Peter, " Making the most of on-line recruiting," *Harvard Business Review*, 2001, *79* (3), 139–166.

Carrillo-Tudela, Carlos, Bart Hobijn, Patryk Perkowski, and Ludo Visschers, "Majority of Hires Never Report Looking for a Job," *FRBSF Economic Letter, Available online at https://www.frbsf.org/economic-research/publications/economic-letter/2015/march/labor-market-turnover-new-hire-recruitment/*, 2015.

Cassar, Lea and Stephan Meier, "Nonmonetary Incentives and the Implications of Work as a Source of Meaning," *Journal of Economic Perspectives*, August 2018, *32* (3), 215–38.

Castelo, Noah, Maarten W. Bos, and Donald R. Lehmann, "Task-Dependent Algorithm Aversion," *Journal of Marketing Research*, 2019, *56* (5), 809–825.

Chalfin, Aaron, Oren Danieli, Andrew Hillis, Zubin Jelveh, Michael Luca, Jens Ludwig, and Sendhil Mullainathan, "Productivity and Selection of Human Capital with Machine Learning," *American Economic Review*, May 2016, *106* (5), 124–27.

Choudhury, Prithwiraj, Evan Starr, and Rajshree Agarwal, "Machine learning and human capital complementarities: Experimental evidence on bias mitigation," *Strategic Management Journal*, 2020, *41* (8), 1381–1411.

Cowgill, Bo, "Bias and Productivity in Humans and Algorithms: Theory and Evidence from Resume Screening," *Working paper; Available online at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3584916*, 2020.

_ **and Catherine E. Tucker**, "Algorithmic fairness and economics," *Working paper, Available online at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3361280*, 2020.

_ **and Patryk Perkowski**, "Delegation in hiring: Evidence from a Two-Sided Audit," *Working paper; Available online at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3584919*, 2022.

_ **, Fabrizio Dell'Acqua, and Sandra Matz**, "The Managerial Effects of Algorithmic Fairness Activism," *AEA Papers and Proceedings*, May 2020, *110*, 85–90.

_ , _ , **Sam Deng, Daniel Hsu, Nakul Verma, and Augustin Chaintreau**, "Replication Data (A) for 'Biased Programmers or Biased Data?': Individual Measures of Numeracy, Literacy and Problem Solving Skill – and Biographical Data – for a Representative Sample of 200K OECD Residents," 2020.

_ , _ , **Samuel Deng, Daniel Hsu, Nakul Verma, and Augustin Chaintreau**, "Biased Programmers? Or Biased Data? A Field Experiment in Operationalizing AI Ethics," in "Proceedings of the 21st ACM Conference on Economics and Computation" EC '20 Association for Computing Machinery New York, NY, USA 2020, p. 679–681.

Cullen, Zoe B, Will S Dobbie, and Mitchell Hoffman, "Increasing the Demand for Workers with a Criminal Record," Working Paper 29947, National Bureau of Economic Research April 2022.

De-Arteaga, Maria, Artur Dubrawski, and Alexandra Chouldechova, "Learning under selective labels in the presence of expert consistency," *CoRR*, 2018, *abs/1807.00905*.

Dell'Acqua, Fabrizio, Bruce Kogut, and Patryk Perkowski, "Super Mario Meets AI: Experimental Effects of Automation and Skills on Team Performance and Coordination," *Working paper; Available online at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3746564*, 2022.

Dietvorst, B. J., J. P. Simmons, and C. Massey, "Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err," *Journal of Experimental Psychology: General*, 2015, *144* (1), 114–126.

Doleac, Jennifer L. and Benjamin Hansen, "The Unintended Consequences of "Ban the Box": Statistical Discrimination and Employment Outcomes When Criminal Histories Are Hidden," *Journal of Labor Economics*, 2020, *38* (2), 321–374.

Glikson, Ella and Anita Williams Woolley, "Human Trust in Artificial Intelligence: Review of Empirical Research," *Academy of Management Annals*, 2020, *14* (2), 627–660.

Goldin, Claudia and Cecilia Rouse, "Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians," *American Economic Review*, September 2000, *90* (4), 715–741.

Greiner, Ben, Philipp Grunwald, Thomas Lindner, Georg Lintner, and Martin Wiernsperger, "Incentives, Framing, and Trust in Algorithmic Advice: An Experimental Study," *Working paper*, 2022.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw, "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 2001, *69* (1), 201–209.

Hansen, Benjamin and Drew McNichols, "Information and the Persistence of the Gender Wage Gap: Early Evidence from California's Salary History Ban," Working Paper 27054, National Bureau of Economic Research April 2020.

Hassabis, Demis, " Artificial Intelligence: Chess match of the century," *Nature*, 2017, *544*, 413–414.

Hertz, Nicholas and Eva Wiese, " Good advice is beyond all price, but what if it comes from a machine?," *Journal of Experimental Psychology: Applied*, 2019, *25* (3), 386–395.

Hitt, Lorin M. and Erik Brynjolfsson, "Information Technology and Internal Firm Organization: An Exploratory Analysis," *Journal of Management Information Systems*, 1997, *14* (2), 81–101.

Holland, Paul W., "Statistics and Causal Inference," *Journal of the American Statistical Association*, 1986, *81* (396), 945–960.

Ichniowski, Casey, Kathryn Shaw, and Giovanna Prennushi, "The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines," *The American Economic Review*, 1997, *87* (3), 291–313.

Kim, Danny and Mike Pergler, "Startup Hiring through Firm-Driven Search: Evidence from VFA," *Working paper*, 2022.

Kirkpatrick, Keith, "Battling Algorithmic Bias: How Do We Ensure Algorithms Treat Us Fairly?," *Commun. ACM*, sep 2016, *59* (10), 16–17.

Kleinberg, Jon, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan, "Human Decisions and Machine Predictions*," *The Quarterly Journal of Economics*, 08 2017, *133* (1), 237–293.

_ , Jens Ludwig, Sendhil Mullainathan, and Ashesh Rambachan, "Algorithmic Fairness," *AEA Papers and Proceedings*, May 2018, *108*, 22–27.

Kolhepp, Jacob and Stepan Aleksenko, "Delegated Recruitment and Hiring Distortions," *Working paper, Available online at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3905019*, 2022.

Kuncel, Nathan R., Deniz S. Ones, and David M. Klieger, "In Hiring, Algorithms Beat Instinct," *Harvard Business Review*, 2014, *May Print Issue.*

Lakkaraju, Himabindu, Jon Kleinberg, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan, "The Selective Labels Problem: Evaluating Algorithmic Predictions in the Presence of Unobservables," in "Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining" KDD '17 Association for Computing Machinery New York, NY, USA 2017, p. 275–284.

Lee, David S. and Thomas Lemieux, "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*, June 2010, *48* (2), 281–355.

Levinson, Harry, "Management by Whose Objectives?," *Harvard Business Review*, 2003, *January.*

Li, Danielle, Lindsey Raymond, and Peter Bergman, "Hiring as Exploration," *Working paper, available online at https://danielle-li.github.io/assets/docs/HiringAsExploration.pdf*, 2021.

Logg, Jennifer M., Julia A. Minson, and Don A. Moore, "Algorithm appreciation: People prefer algorithmic to human judgment," *Organizational Behavior and Human Decision Processes*, 2019, *151*, 90–103.

Longoni, Chiara, Andrea Bonezzi, and Carey K Morewedge, "Resistance to Medical Artificial Intelligence," *Journal of Consumer Research*, 05 2019, *46* (4), 629–650.

Mahmud, Hasan, A.K.M. Najmul Islam, Syed Ishtiaque Ahmed, and Kari Smolander, "What influences algorithmic decision-making? A systematic literature review on algorithm aversion," *Technological Forecasting and Social Change*, 2022, *175*, 121390.

Oyer, Paul and Scott Schaefer, "Personnel Economics: Hiring and Incentives," Working Paper 15977, National Bureau of Economic Research May 2010.

Pisanelli, Elena, "A new turning point for women: artificial intelligence as a tool for reducing gender discrimination in hiring," *Working paper*, 2022.

_ , "Your resume is your gatekeeper: Automated resume screening as a strategy to reduce gender gaps in hiring," *Economics Letters*, 2022, p. 110892.

Pope, Devin G. and Justin R. Sydnor, "Implementing Anti-discrimination Policies in Statistical Profiling Models," *American Economic Journal: Economic Policy*, August 2011, *3* (3), 206–31.

Raghavan, Manish, Solon Barocas, Jon Kleinberg, and Karen Levy, "Mitigating bias in algorithmic hiring," in "Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency" ACM jan 2020.

Rajpurkar, Pranav, Jeremy Irvin, Robyn Ball, ..., and Matthew Lungren, " Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists," *PLoS Med*, 2018, *15* (11).

Rambachan, Ashesh and Jonathan Roth, "Bias In, Bias Out? Evaluating the Folk Wisdom," in Aaron Roth, ed., *1st Symposium on Foundations of Responsible Computing (FORC 2020)*, Vol. 156 of *Leibniz International Proceedings in Informatics (LIPIcs)* Schloss Dagstuhl–Leibniz-Zentrum für Informatik Dagstuhl, Germany 2020, pp. 6:1–6:15.

_ , Jon Kleinberg, Jens Ludwig, and Sendhil Mullainathan, "An Economic Perspective on Algorithmic Fairness," *AEA Papers and Proceedings*, May 2020, *110*, 91–95.

Rock, Daniel, "Engineering Value: The Returns to Technological Talent and Investments in Artificial Intelligence," *Working paper*, 2021.

Rubin, Donald B., "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies," *Journal of Educational Psychology 66(5): 688-701*, 1974.

Silberzahn, R., E. L. Uhlmann, D. P. Martin, P. Anselmi, F. Aust, E. Awtrey, Š. Bahník, F. Bai, C. Bannard, E. Bonnier, R. Carlsson, F. Cheung, G. Christensen, R. Clay, M. A. Craig, A. Dalla Rosa, L. Dam, M. H. Evans, I. Flores Cervantes, N. Fong, M. Gamez-Djokic, A. Glenz, S. Gordon-McKeon, T. J. Heaton, K. Hederos, M. Heene, A. J. Hofelich Mohr, F. Högden, K. Hui, M. Johannesson, J. Kalodimos, E. Kaszubowski, D. M. Kennedy, R. Lei, T. A. Lindsay, S. Liverani, C. R. Madan, D. Molden, E. Molleman, R. D. Morey, L. B. Mulder, B. R. Nijstad, N. G. Pope, B. Pope, J. M. Prenoveau, F. Rink, E. Robusto, H. Roderique, A. Sandberg, E. Schlüter, F. D. Schönbrodt, M. F. Sherman, S. A. Sommer, K. Sotak, S. Spain, C. Spörlein, T. Stafford, L. Stefanutti, S. Tauber, J. Ullrich, M. Vianello, E.-J. Wagenmakers, M. Witkowiak, S. Yoon, and B. A. Nosek, "Many Analysts, One Data Set: Making Transparent How Variations in Analytic Choices Affect Results," *Advances in Methods and Practices in Psychological Science*, 2018, *1* (3), 337–356.

Tambe, Prasanna, "Big Data Investment, Skills, and Firm Value," *Management Science*, 2014, *60* (6), 1452–1469.

_ , Peter Cappelli, and Valery Yakubovich, "Artificial Intelligence in Human Resources Management: Challenges and a Path Forward," *California Management Review*, 2019, *61* (4), 15–42.

Wilson, Christo, Avijit Ghosh, Shan Jiang, Alan Mislove, Lewis Baker, Janelle Szary, Kelly Trindel, and Frida Polli, "Building and Auditing Fair Algorithms: A Case Study in Candidate Screening," in "Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency" FAccT '21 Association for Computing Machinery New York, NY, USA 2021, p. 666–677.

Tables

Table 1: **Summary statistics**

	Mean	Std. Dev	Min	Max	N
Female	0.41	0.49	0	1	397
Education					
Undergraduate degree in the US	0.87	0.33	0	1	397
BS degree	0.14	0.34	0	1	397
Top 25 undergraduate institution	0.10	0.30	0	1	397
EMBA student	0.32	0.47	0	1	397
Previous industry					
Finance	0.26	0.44	0	1	397
Technology	0.19	0.40	0	1	397
Business Services	0.17	0.38	0	1	397
Real Estate	0.05	0.22	0	1	397
Services	0.12	0.32	0	1	397
Arts	0.09	0.28	0	1	397
Other	0.12	0.32	0	1	397
Modeling approach used					
Uses cross-tabs	0.13	0.34	0	1	397
Uses regression	0.83	0.38	0	1	397
Uses machine learning	0.04	0.20	0	1	397
Uses sensitive covariates	0.90	0.30	0	1	397
Considers multiple models	0.60	0.49	0	1	397

Notes: This table displays summary statistics at the manager level.

Table 2: **Impact of the hiring algorithm on job performance**

	Job performance		
	(1)	(2)	(3)
Accepted by algorithm	493.5***	493.5***	492.0***
	(25.74)	(25.74)	(26.10)
R^2	0.177	0.177	0.306
Observations	15585	15585	15585
Mean of rejected candidates	2324	2324	2324
Effect size (%)	21.2	21.2	21.2
Participant controls	No	Yes	No
Participant fixed effect	No	No	Yes

Notes: This table examines the impact of adopting the hiring algorithm on job performance. It display the results of a regression of job performance on an indicator for being accepted by the algorithm (relative to rejected candidates). Column 1 includes no controls, column 2 includes manager controls including their gender, education, and prior industry, and programming method used, and column 3 includes manager fixed effects. All regressions include robust standard errors clustered at the manager level.

Table 3: **Impact of the hiring algorithm on gender, age, and region**

Panel A: Gender

	Female candidate		
	(1)	(2)	(3)
Accepted by algorithm	-0.0284	-0.0284	-0.0275
	(0.0216)	(0.0216)	(0.0219)
R^2	0.001	0.001	0.069
Observations	15585	15585	15585
Mean of rejected candidates	0.470	0.470	0.470
Effect size (%)	-6.1	-6.1	-5.9
Participant controls	No	Yes	No
Participant fixed effect	No	No	Yes

Panel B: Age

	Candidate age			
	16-24	25-34	35-49	50-65
	(1)	(2)	(3)	(4)
Accepted by algorithm	0.0763***	0.0732***	-0.0320**	-0.1170***
	(0.010)	(0.010)	(0.013)	(0.010)
R^2	0.104	0.064	0.062	0.071
Observations	15585	15585	15585	15585
Mean of rejected candidates	0.060	0.141	0.504	0.295
Effect size (%)	126.7	52.0	-6.4	-39.8

Panel C: Region

	Candidate region				
	Central & Eastern Europe	Asia	Latin America & the Caribbean	North America & Western Europe	Africa
	(1)	(2)	(3)	(4)	(5)
Accepted by algorithm	0.0033	0.1860***	-0.2000***	0.0143	-0.0042
	(0.011)	(0.016)	(0.014)	(0.017)	(0.003)
R^2	0.062	0.133	0.278	0.132	0.062
Observations	15585	15585	15585	15585	15585
Mean of rejected candidates	0.19	0.12	0.22	0.45	0.01
Effect size (%)	1.8	150.8	-89.1	3.2	-28.6

Notes: This table examines the impact of adopting the hiring algorithm on gender, age, and region diversity. Panel A display the results of a regression of a binary indicator for being a female candidate on an indicator for being accepted by the algorithm (relative to rejected candidates). Column 1 includes no controls, column 2 includes manager controls including their gender, education, and prior industry, and programming method used, and column 3 includes manager fixed effects. Meanwhile, Panel's B and C reproduce Column 3 of Panel A for age and region. All regressions include manager fixed effects and robust standard errors clustered at the manager level.

Table 4: **The predictors of algorithmic adoption recommendations**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Recommended algorithmic adoption (=1)						
Impact on job performance, %	0.002**		0.004***	0.004***		0.001	0.001
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Impact on # of female hires		0.017***	0.017***	0.017***			
		(0.003)	(0.003)	(0.003)			
Impact on # of hires aged 50-65		0.004	0.007	0.006			
		(0.006)	(0.006)	(0.006)			
Impact on # of hires from Latin America		-0.002	0.009	0.009*			
		(0.005)	(0.005)	(0.005)			
Decreased # of female hires (=1)					-0.302***	-0.302***	-0.292***
					(0.048)	(0.048)	(0.049)
Decreased # of hires aged 50-65 (=1)						-0.053	-0.038
						(0.056)	(0.057)
Decreased # of hires from Latin America (=1)						0.123*	0.101
						(0.063)	(0.065)
Constant	0.495***	0.554***	0.512***	0.315**	0.677***	0.598***	0.435***
	(0.034)	(0.033)	(0.035)	(0.138)	(0.032)	(0.056)	(0.147)
R2	0.011	0.082	0.104	0.131	0.091	0.113	0.132
Observations	393	393	393	393	393	393	393
Manager controls	No	No	No	Yes	No	No	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Notes: This table examines the predictors of algorithmic adoption recomments. It displays the results of a regression of a binary indicator for recommending algorithmic adoption, on various job performance and demographic impacts, plus manager controls. All regressions include robust standard errors.

Table 5: **Regression discontinuity design estimates of the impact of decreasing female representation on algorithmic adoption recommendations**

	Recommended algorithmic adoption (=1)			
	(1)	(2)	(3)	(4)
Decreased female	-0.199**	-0.183**	-0.182**	-0.157*
representation (=1)	(0.079)	(0.079)	(0.080)	(0.082)
R2	0.038	0.053	0.054	0.094
Observations	167	166	166	166
Mean of rejected candidates	0.670	0.670	0.670	0.670
Effect size (%)	-28.1	-27.3	-27.1	-23.4
Job performance control	No	Yes	Yes	Yes
Other demographic controls	No	No	Yes	Yes
Manager controls	No	No	No	Yes

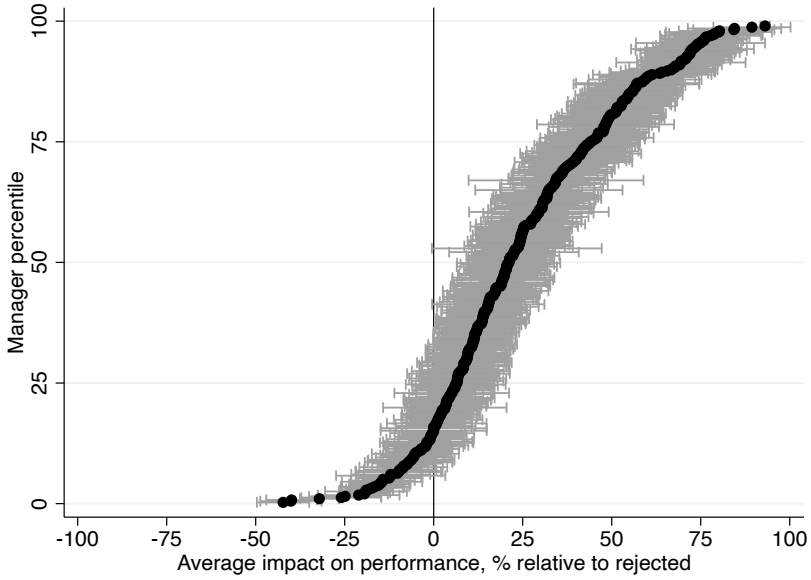
Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Notes: This table presents regression discontinuity evidence that the gender impact of an algorithm has a causal effect on algorithmic adoption recommendations. I follow the bandwidth selection procedure in Calonico et al. (2014b) and Calonico et al. (2014a), which returns an optimal bandwidth of 4.18; I therefore limit my regression to algorithms that increased or decreased the number of female hires by up to four. All regressions include robust standard errors.

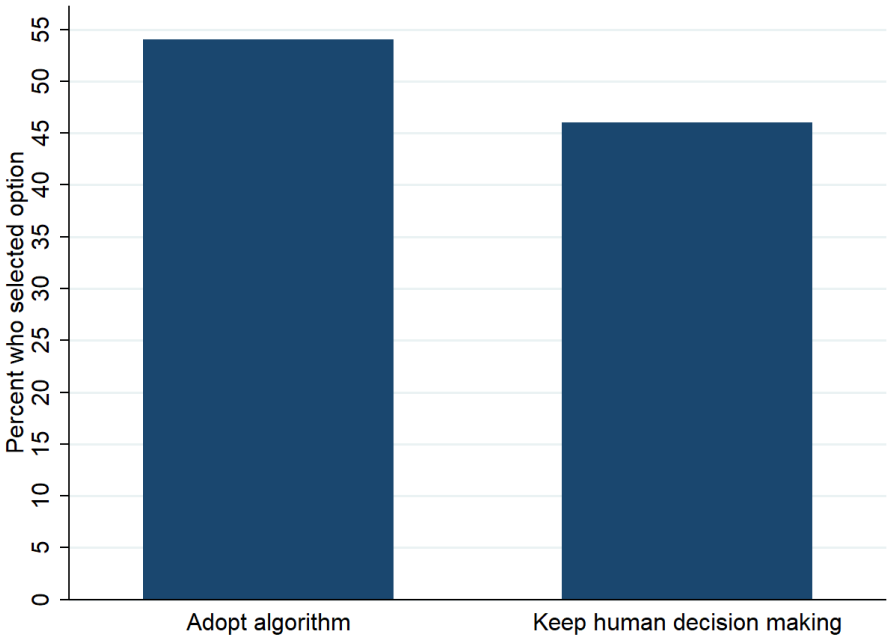
Figures

Figure 1: **Impact of the hiring algorithm on job performance, by manager**



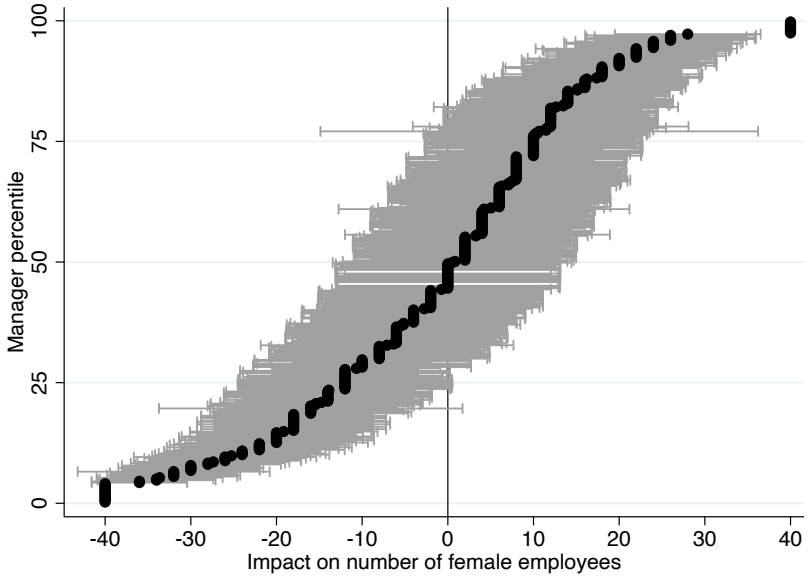
Notes: This figures examines the impact of adopting the hiring algorithm on job performance for each manager. It display the results of a regression of job performance on an indicator for being accepted by the algorithm (relative to rejected candidates), subsetting the sample to each manager. The treatment effects are sorted by largest to smallest.

Figure 2: **Manager adoption recommendations**



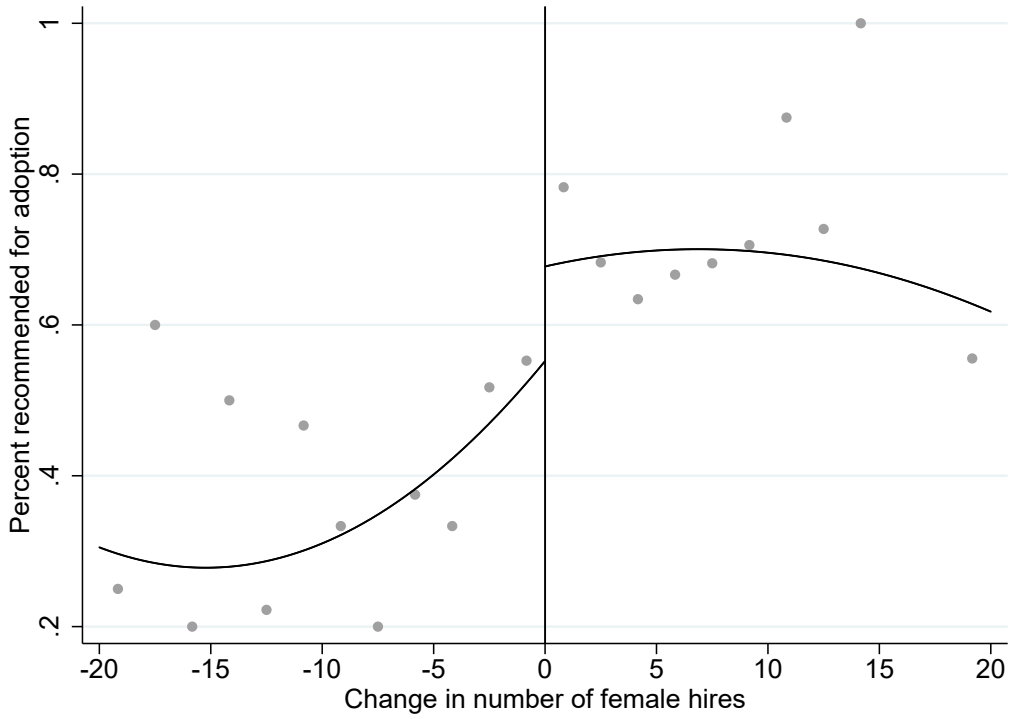
Notes: This figure examines recommendation decisions given by the managers in my sample.

Figure 3: **Impact of the hiring algorithm on workforce gender, by manager**



Notes: This figures examines the impact of adopting the hiring algorithm on candidate gender for each manager. It display the results of a regression of an indicator of female on an indicator for being accepted by the algorithm (relative to rejected candidates), subsetting the sample to each manager. The treatment effects are sorted by largest to smallest.

Figure 4: **Regression discontinuity effect of decreasing the number of female hires on algorithmic adoption recommendations**



Notes: This figures displays algorithmic adoption recommendations by the algorithm's impact on gender diversity using the regression discontinuity plot procedure from Calonico et al. (2014b) and Calonico et al. (2014a) The x-axis displays the aggregate change in the number of female hires due to algorithmic adoption, while the y-axis displays the percent of algorithms that are adopted.

Appendix: For Online Publication Only

A Additional experimental details

A.1 Participants by section

Table A.1: Number of participants per section

Section	Date	Type	Number of students
1	Summer 2019	MBA	49
2	Spring 2020	MBA	56
3	Spring 2020	EMBA	18
4	Summer 2020	MBA	50
5	Summer 2020	EMBA	21
6	Summer 2021	MBA	62
7	Summer 2021	EMBA	25
8	Spring 2022	MBA	60
9	Summer 2022	EMBA	56
Total			397

Notes: This table displays the number of students that completed the assignment in each section.

A.2 Example of modeling approaches

In this subsection, I display examples of the modeling approaches used by the participants. Figure A.1 displays an example of the responses from a participant who used regression, Figure A.2 for tabulations, and Figure A.2 for machine learning.

Figure A.1: Example of modeling approach using regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.51699188
R Square	0.26728061
Adjusted R Square	0.26248436
Standard Error	0.41156062
Observations	2000

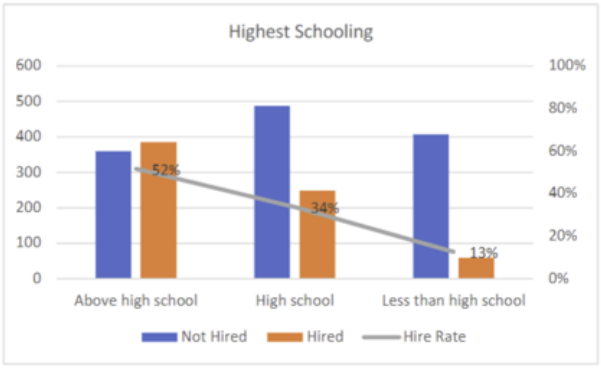
ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	13	122.709062	9.43915859	55.7269991	5.887E-124
Residual	1986	336.392938	0.16938214		
Total	1999	459.102			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.05113688	0.0217356	2.35267833	0.01873583	0.0085099	0.09376385	0.0085099	0.09376385
Above HS	0.16241061	0.02021539	8.03400754	1.6015E-15	0.12276501	0.20205622	0.12276501	0.20205622
Employed or self employed	0.17009895	0.02521318	6.74642843	1.9812E-11	0.12065188	0.21954602	0.12065188	0.21954602
Public	-0.06175	0.02819792	-2.1898788	0.02864898	-0.1170506	-0.0064494	-0.1170506	-0.0064494
Female	-0.0509851	0.01899494	-2.6841406	0.00733206	-0.0882372	-0.013733	-0.0882372	-0.013733
Employee, supervising more than 5 people	0.20210208	0.03569221	5.66235846	1.7105E-08	0.13210398	0.27210018	0.13210398	0.27210018
Self-employed, supervisor	0.25904931	0.05426158	4.77408342	1.9372E-06	0.15263371	0.36546491	0.15263371	0.36546491
251-1k	0.0590907	0.03489857	1.69321268	0.09057182	-0.009351	0.12753235	-0.009351	0.12753235
>1k	0.16698559	0.04806498	3.47416311	0.00052344	0.07272251	0.26124867	0.07272251	0.26124867
North America and Western Europe	0.05842867	0.0188115	3.10600755	0.00192312	0.02153632	0.09532102	0.02153632	0.09532102
To a high extent	0.15272336	0.03169428	4.81864065	1.555E-06	0.09056583	0.2148809	0.09056583	0.2148809
To a very high extent	0.12505709	0.03479977	3.5936181	0.00033406	0.0568092	0.19330498	0.0568092	0.19330498
Satisfied	0.15141197	0.02501145	6.05370692	1.688E-09	0.10236054	0.2004634	0.10236054	0.2004634
Extremely satisfied	0.17993769	0.03052367	5.89502052	4.3913E-09	0.1200759	0.23979947	0.1200759	0.23979947

Notes: This figure displays an example of the modeling approach used by a participant using regression.

Figure A.2: Examples of modeling approaches using tabulations

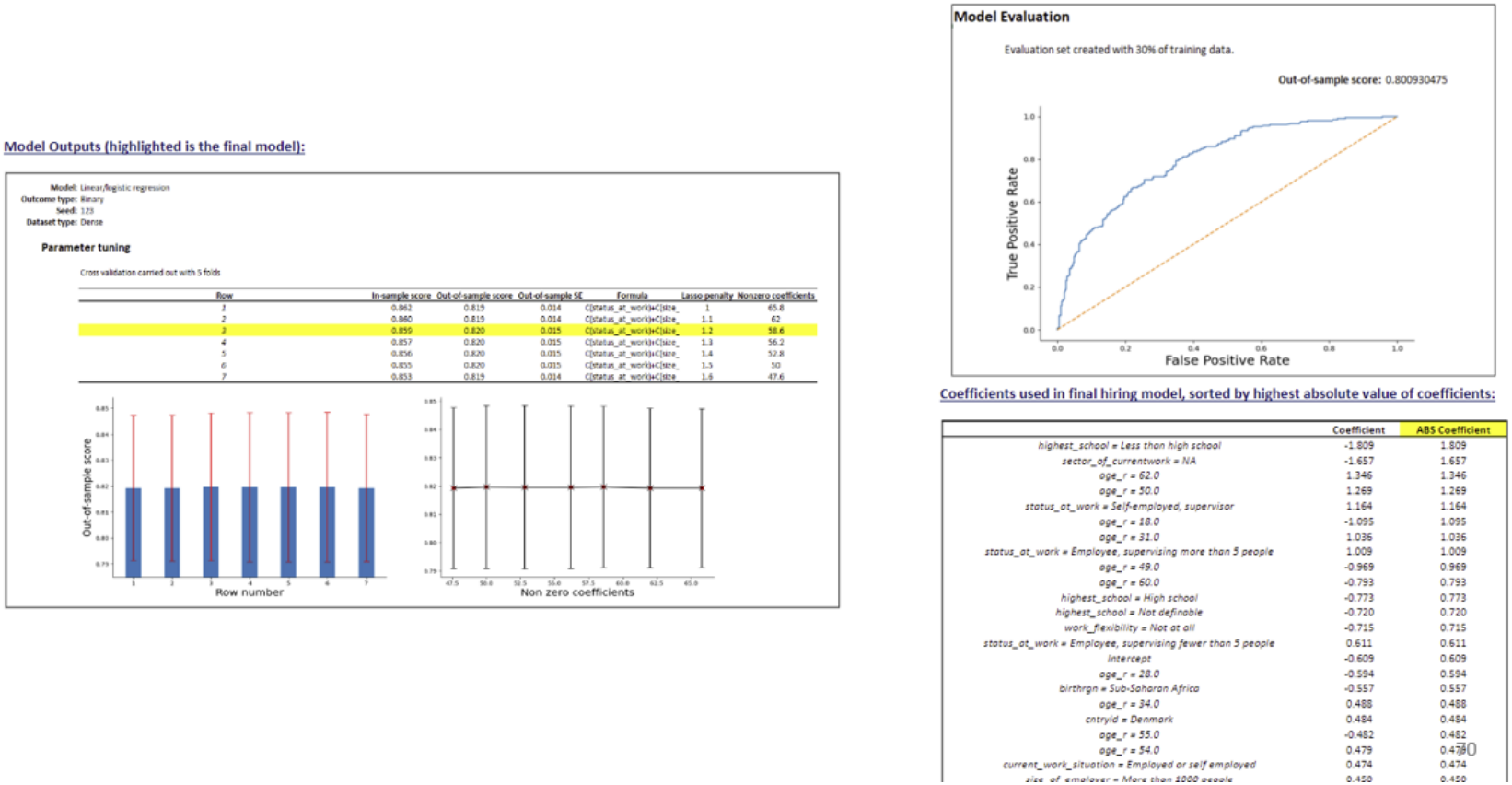


Hired?	1	
"highest_highschool"		
Row Labels	**Count o**	**%**
Above high school	385	54%
High school	249	35%
Less than high school	59	8%
Not definable	10	1%
(blank)	11	2%
Grand Total	**714**	100%

Highest Schooling	1000-1500	1500-2000	2000-2500	2500-3000	3000-3500	3500+
Above high school	0%	1%	12%	39%	42%	7%
High school	1%	5%	21%	43%	27%	2%
Less than high school	5%	14%	29%	46%	5%	2%

Notes: This figure displays examples of the modeling approaches used by participants using tabulations.

Figure A.3: Example of modeling approach using machine learning



Notes: This figure displays examples of the modeling approaches used by participants using machine learning.

A.3 Task Instructions

A.3.1 Background

On Canvas, you will find Excel data containing the personal characteristics of about 2,000 workers who are eligible to be hired by a company. Note: This is a real dataset. However, we have anonymized the company and refer to it as "ACME Corp." ACME is a large diversified multinational who extensively utilizes strategy and management consultants and often hires their consultants into headquarters staff and executive roles. ACME employs mostly mid-skill workers in developed countries. Their jobs require intermediate math literacy. Suppose that you're a recent MBA graduate asked to help optimize ACME's employment practices. You can think of yourself either as a junior executive at ACME, or as one of the consultants hired by ACME. For your homework assignment, analyze the data and answer the questions below. This is a very small scale-exercise. In the real world, your data will probably include more than 2,000 candidates and more than 14 variables per candidate. The goal of this exercise is to give you experience working on the underlying concepts in larger-scale analysis of strategy (and discussed in class).

A.3.2 Part One

Answer Part 1 questions 1-3 using up to 300 words for each question. Defend your answers with analysis of this data. You may utilize tables and/or charts as part of your explanation.

- What variables are the best predictors of being hired by ACME?
- What variables are the best predictors of job performance for workers who were hired?
- Formulate a hypothesis about how ACME could improve its hiring. Justify your reasoning.[1]
- Using your hypothesis above, list the CandidateIds of:
  - The top 20 rejected workers ACME should have hired under your hypothesis.
  - The 20 hired workers ACME should have rejected.

[1] Your dataset does not include estimates of how much each worker would cost to hire (i.e., their salary requirements) or their probability of accepting an offer. Obviously this would be an important component to a hiring strategy. For the purposes of this assignment, assume that workers demand the same salary and be equally likely to accept the offer. That is: Focus on the worker-quality issues, and assume that cost considerations will be someone else's job later.

Upload your answers to Part 1 on Canvas. After you do, we'll share more data with you about the job performance of the 20 CandidateIds you listed in 4a.

A.3.3 Part Two

Using the new data emailed to you, evaluate your hypothesis in Part 1, Questions 3 and 4. Answer all Part 2 questions using up to 300 words for each question. Defend your answers with analysis of this data. You may utilize tables and/or charts as part of your explanation.

- Are your 20 proposed hires better or worse than the 20 you rejected?
- Did your make ACME's workforce more diverse? Or better in other ways that aren't captured by job performance?
- Combining your answers to Part 2, Q1 and Q2. Assume there are no alternatives besides your proposal and continuing with the status quo. Do you recommend that ACME adopt your proposal?

B Additional empirical results

B.1 Miscellaneous empirical results

B.1.1 Quantile regression impact on job performance

In Table B.1.1, I examine the impact of the hiring algorithm on candidate job performance using quantile regression.

Table B.2: Quantile regression results for job performance

	Job performance				
	Quantile:				
	10	25	50	75	90
	(1)	(2)	(3)	(4)	(5)
Accepted by algorithm	756.1***	650.3***	483.8***	412.2***	320.3***
	(21.39)	(6.58)	(13.30)	(7.45)	(9.91)
Observations	15585	15585	15585	15585	15585
Mean of rejected candidates	1498	1900	2336	2751	3074
Effect size (%)	32.5	28.0	20.8	17.7	13.8

Notes: This table examines the impact of adopting the hiring algorithm on job performance. It display the results of a quantile regression of job performance on an indicator for being accepted by the algorithm (relative to rejected candidates) with manager controls. The quantiles cutoffs are 10, 25, 50, 75, and 90. All regressions include robust standard errors.

B.1.2 Manager predictors of the job performance impacts of algorithms

In this subsection, I investigate the predictors of the job performance impacts of algorithms in my setting. Although the average impact of algorithms is often positive in my setting, Figure 1 illustrates that this estimate conceals a lot of heterogeneity. Understanding the source of this heterogeneity (and which participants write better algorithms) can help determine how algorithmic decision-making is related to a firm's broader human resource management strategy.

In this subsection, I examine whether the use of algorithms in decision-making is complementary to three different human resource strategies: (i) selective hiring (whereby the firm only seeks to hire candidates from top universities); (ii) technical hiring (whereby the firm only seeks to hire candidates who have an undergraduate degree in a B.S. field); and (iii) machine learning hiring (whereby the firm only seeks to hire candidates who have machine learning skills).

My goal is to relate these features to the returns of algorithmic decision-making. An ideal study

would randomize algorithmic decision-making across firms that also vary in the extent to which they rely on selective and/or technical and/or machine learning hiring (possibly also through random assignment). However, this is not possible. Using data from managers in my sample, meanwhile, is complicated by two factors. First, no hiring algorithms were ever adopted in my setting given that this was a class assignment. Second, my data is at the manager, and not the firm level, which makes it difficult to make strong statements regarding the impact of various hiring strategies on the returns to algorithmic decision-making.

I assuage these concerns in the following way. First, it is possible to use the data at hand to estimate the causal impact of algorithmic adoption if it were adopted at Firm F. Recall that it is possible to estimate a manager-level treatment effect of algorithmic adoption on the job performance. In the introduction and empirical strategy, I discuss how I can simulate each manager's treated potential outcome (average outcomes at the firm if they implement algorithmic hiring) and their control potential outcome (average outcomes at the firm if they maintain the status quo). The impact of algorithmic hiring for manager m is simply the difference between these two quantities, or:

$$\tau_m = E[Y_m|UsesAlgorithms] - E[Y_m|KeepsStatusQuo].$$

For each manager in my sample, I thus have a measure of τ_m, or the causal impact of adopting the hiring algorithm written by manager m.

Second, in order to make inferences about complementarities between firm hiring policies and the impact of algorithmic hiring τ_m, I assume that each manager m corresponds to a hypothetical firm with the set of hiring practices that lead the firm to hire manager m. I index firms by (S_m, T_m, M_m), where $S_m = 1$ if the firm has a selective hiring policy (so that manager m went to an elite university if $S_m = 1$) and 0 if they do not (when manager m did not go to an elite university). Similarly, $T_m = 1$ if the firm hires technical talent (so that manager m has a B.S. degree if $T_m = 1$) and 0 if they do not (when manager m does not have a BS), with a similar definition using $M_m = 1$ if the firm screens for machine learning skills, and 0 otherwise. I can then estimate the relationship between τ_m and (S_m, T_m, M_m) to understand whether there are complementarities between firm screening practices and the returns to algorithmic decision-making.

Table B.3 studies these complementarities by relating τ_m to various functional forms of (S_m, T_m, M_m). The results indicate that hiring for machine learning skills has a large impact on the performance of

hiring algorithms. Algorithms written using machine learning outperform those using regression and tabulations by around six percentage points. Meanwhile, selective hiring and technical hiring have no impact on the returns to algorithmic adoption, and there is also no complementarity between selective hiring and technical hiring. Instead, I do find some evidence of a complementarity between technical hiring and hiring for machine learning skills (columns 4 and 5).These estimates show that technical workers with ML skills outperform both technical workers without ML skills, and non-technical workers with machine learning skills. These results illustrate that hiring for technical workers and for machine learning skills is complementary to algorithmic adoption.

Table B.3: **Complementarities in the impact of HRM practices**

	Performance improvement from algorithm, percent				
	(1)	(2)	(3)	(4)	(5)
Selective hiring	6.105	11.21	4.684		10.57
	(5.787)	(7.582)	(5.695)		(7.901)
Technical hiring	-3.721	0.339		-3.760	-1.973
	(3.952)	(4.200)		(3.748)	(4.281)
Hiring for ML	6.083		4.105	-1.781	-4.610
	(7.232)		(7.552)	(7.796)	(8.022)
Selective X Tech		-16.66			-13.81
		(10.74)			(11.01)
Selective X ML			15.44*		18.08
			(9.350)		(11.16)
Tech X ML				28.62**	30.41**
				(12.56)	(12.90)
Selective X Tech X ML					.
					.
R2	0.006	0.012	0.005	0.008	0.019
Observations	395	395	395	395	395

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

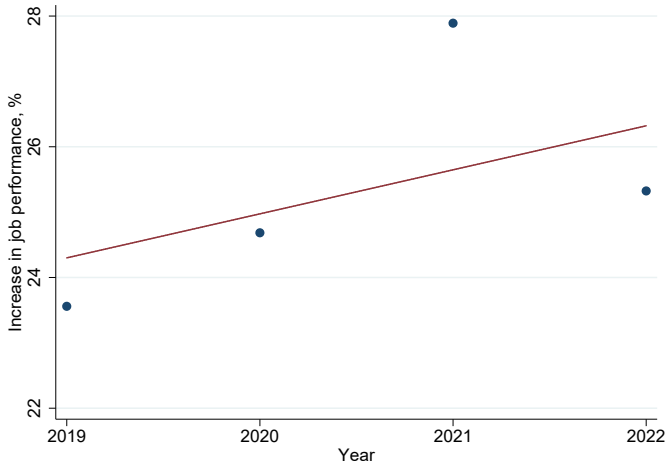
Notes: This table examines complementarities in the impact of HRM practices on the increase in job performance. Selective hiring is a binary variable that equals one if the programmer went to a top-15 undergraduate program, and zero otherwise. Technical hiring is a binary variable that equals one if the programmer received a BS degree or equivalent, and zero otherwise. ML hiring is a binary variable that equals one if the programmer has machine learning skills, and zero otherwise. All regressions include robust standard errors.

B.1.3 Trends in algorithmic impacts over time

In this subsection, I examine trends in the impacts of algorithms over time. The goal is to understand whether those in my sample improve the quality of their algorithms over time.

In Figure B.4, I display the average performance increase for algorithms, broken up by year. The results indicate a steady increase in the job performance impact of algorithms: those written by managers in the 2019 classes improve job performance by 23.6 percent on average, while those in the 2022 classes improved job performance by 25.3 percent on average. This represents over a 7 percent increase in job performance. Meanwhile, Figure B.5 shows the corresponding figure for the likelihood of decreasing the number of female hires. The results indicate that managers are now less likely to write algorithms that decrease the number of female hires. 67 percent of algorithms written by those in 2019 classes decreased the number of female hires, versus 41 percent in the 2022 classes.

Figure B.4: Time trends in the average change in job performance

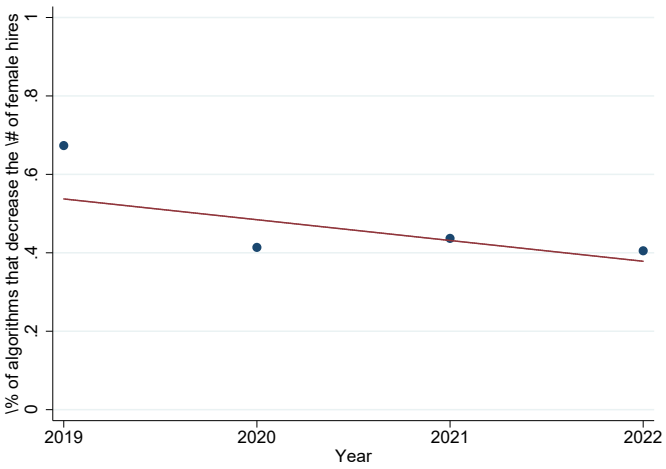


Notes: This figure displays a binned scatter plot of the average job performance increase due to algorithmic adoption by year.

B.1.4 Individual-level impacts on demographic characteristics

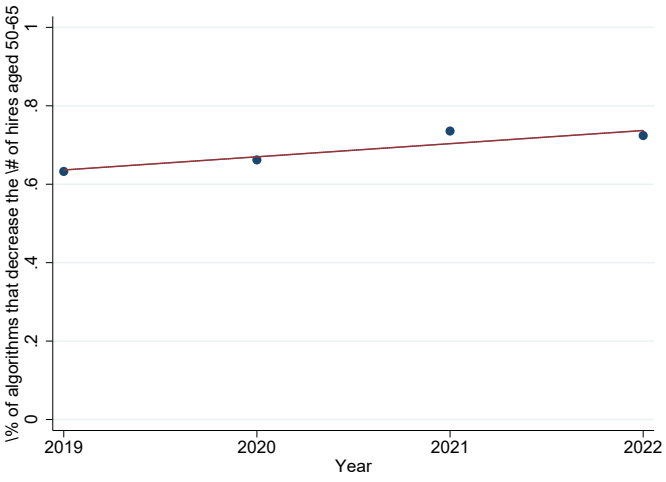
In the main text, I show the individual-level impact of each manager's hiring algorithm on firm performance (Figure 1) and the change in female employees (Figure 3). In this section, I reproduce the same analysis except for region (Figure B.8), and age (Figure B.9).

Figure B.5: Time trends in the likelihood of decreasing female hires



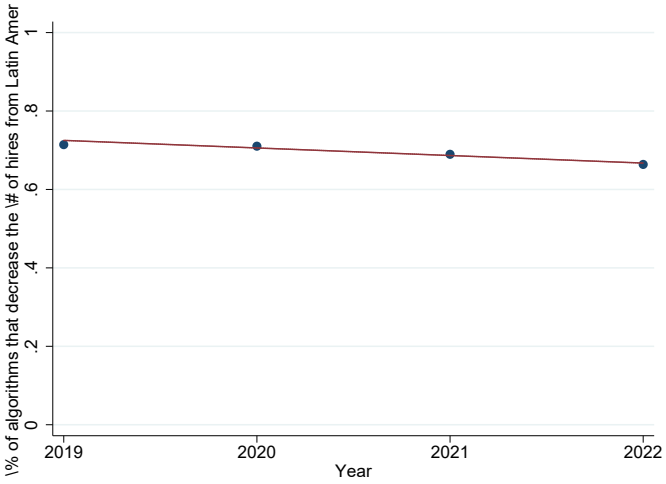
Notes: This figure displays a binned scatter plot of the average percent of algorithms that decrease the number of female hires, by year.

Figure B.6: Time trends in the likelihood of decreasing hires aged 50-65



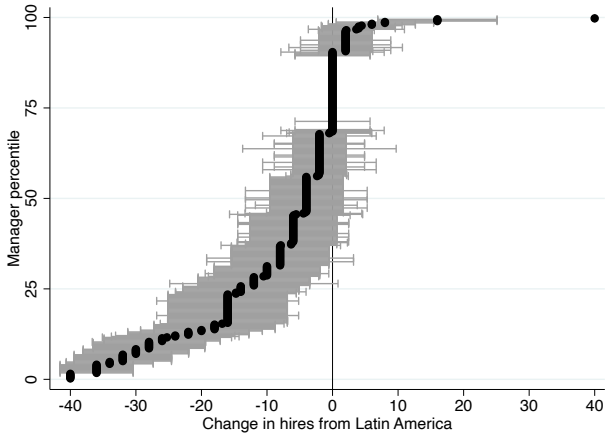
Notes: This figure displays a binned scatter plot of the average percent of algorithms that decrease the number of hires aged 50–65, by year.

Figure B.7: Time trends in the likelihood of decreasing hires from Latin America



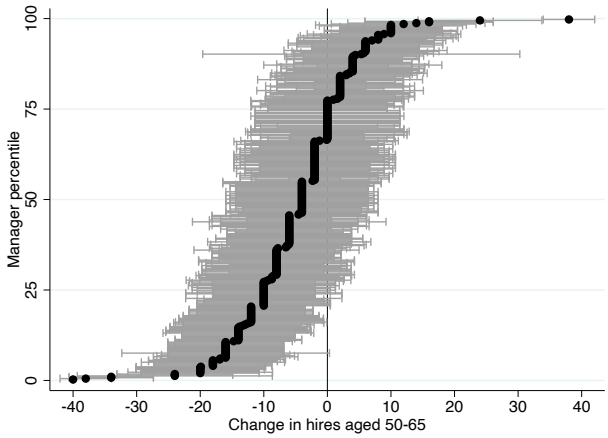
Notes: This figure displays a binned scatter plot of the average percent of algorithms that decrease the number of hires from Latin America, by year.

Figure B.8: Impact of the hiring algorithm on number of hires from Latin America , by manager



Notes: This figures examines the impact of adopting the hiring algorithm on candidate region for each manager. It display the results of a regression of an indicator for Latin America on an indicator for being accepted by the algorithm (relative to rejected candidates), subsetting the sample to each manager. The treatment effects are sorted by largest to smallest.

Figure B.9: Impact of the hiring algorithm on number of hires aged 50–65 , by manager



Notes: This figures examines the impact of adopting the hiring algorithm on candidate age for each manager. It display the results of a regression of an indicator for age 50–65 on an indicator for being accepted by the algorithm (relative to rejected candidates), subsetting the sample to each manager. The treatment effects are sorted by largest to smallest.

B.1.5 Correlation between algorithmic impacts

In Table B.4, I display the correlation between various impacts of the algorithms.

Table B.4: **Correlations**

		Algorithmic impacts on		
	Job performance	Female hires	Hires aged 50-65	Hires from Latin America
Algorithmic impacts on				
Job performance, %	1			
# of female hires	−0.0544	1		
# of hires aged 50-65	−0.303***	−0.00722	1	
# of hires from Latin America	−0.633***	0.0699	0.284***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table examines correlations between the job performance and demographic impacts of algorithms.

B.2 Regression discontinuity design tests

In Section 5.4 of the main text, I show evidence using a regression discontinuity design that marginally decreasing the number of female hires leads to a lower likelihood of algorithmic adoption. The validity of this design depends on algorithms not exhibiting any differences other than their gender impact along the cutoff. In this section, I run two tests to provide evidence that this is the case. First, I provide visual evidence in Section B.2.1 that placebo outcomes do not vary across the gender cutoff. Second, I rerun Equation 3 with these placebo outcomes in Section B.2.2 and show that the threshold has no impact on these outcomes.

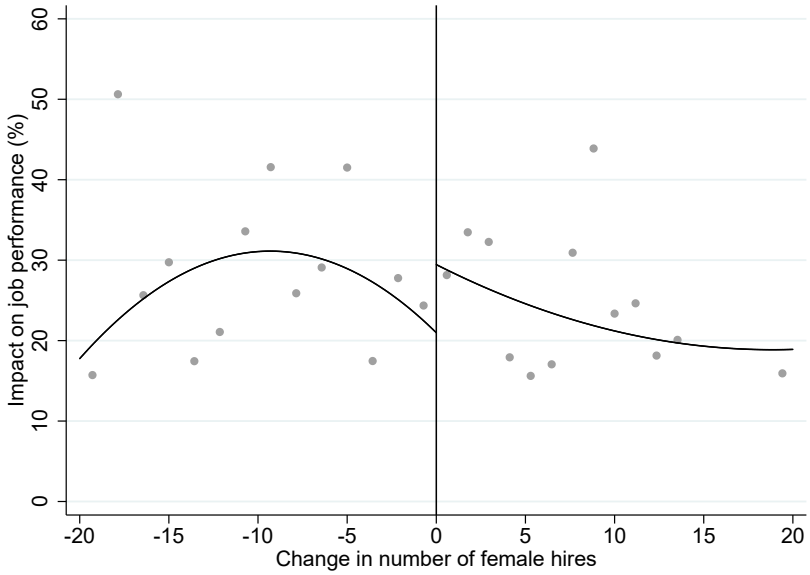
B.2.1 Visual evidence

In Figure 4 of the main text, I plot the regression discontinuity effect of decreasing the number of female hires on algorithmic adoption recommendations using the procedures from Calonico et al. (2014b) and Calonico et al. (2014a). The figure provides evidence that algorithms to the left of the cutoff are less likely to be adopted than those to the right. In this subsection, I estimate the same discontinuity effect design but use other algorithmic outcomes as my dependent variable. These include the job performance impact of the algorithm (Figure B.10), the impact on the number of hires aged 50-65 (Figure B.11), and the impact on the number of hires from Latin American (Figure B.12). These figures show limited discontinuities around this threshold, illustrating limited differences in algorithmic impacts to the right versus the left of the gender threshold (except for the change in the number of female hires). This analysis illustrates that units on either side of the threshold are comparable, and provides support for the validity of the regression discontinuity design employed.

B.2.2 Regression-based evidence

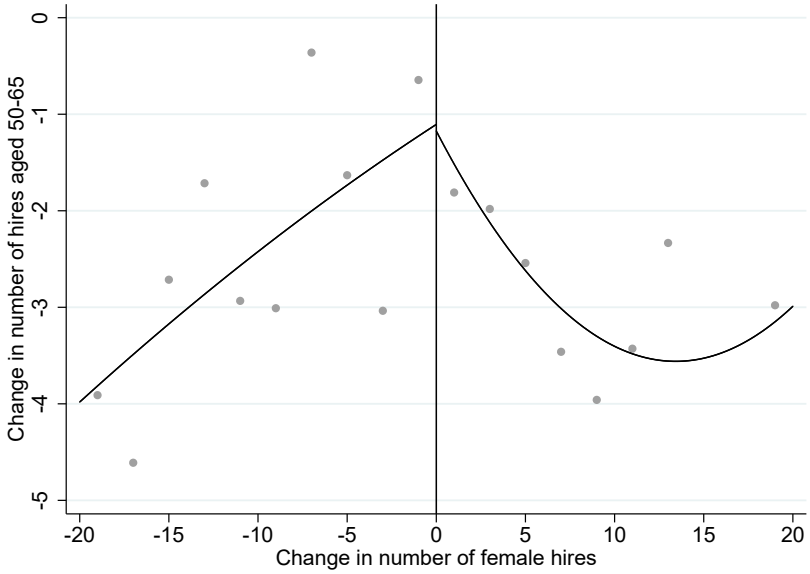
The second test of the validity of the regression discontinuity design re-runs Equation 3 from the main text (from Column 1 of main text Table 5, but using placebo outcomes. I display the results in Table B.5. The results show that algorithms to the left versus right of the cutoff do not differ in observable characteristics, further adding credibility to the regression discontinuity design.

Figure B.10: Average change in job performance, by impact on female representation



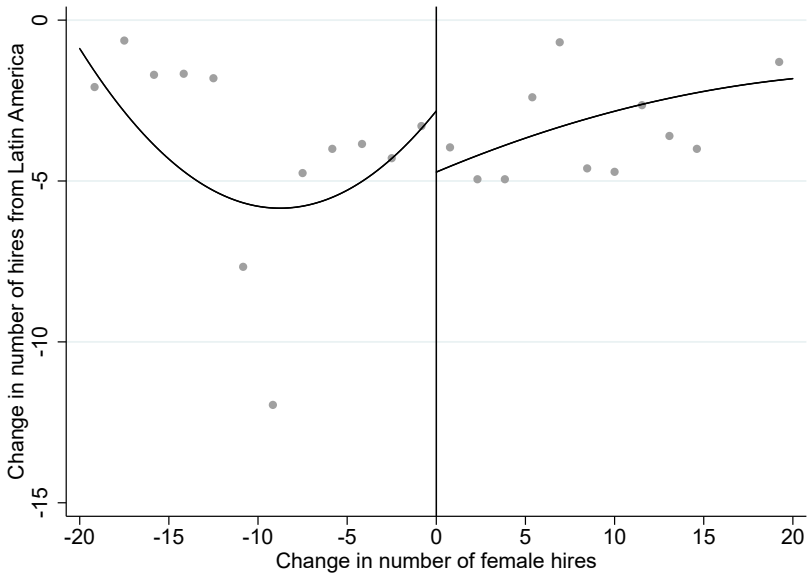
Notes: This figure displays the average job performance impact by the algorithm's impact on gender diversity using the regression discontinuity plot procedure from Calonico et al. (2014b) and Calonico et al. (2014a).

Figure B.11: Average change in number of hires aged 50-65, by impact on female representation



Notes: This figure displays the average impact on the number of hires aged 50-65, by the algorithm's impact on gender diversity using the regression discontinuity plot procedure from Calonico et al. (2014b) and Calonico et al. (2014a).

Figure B.12: Average impacts on the number of Latin American hires, by impact on female representation



Notes: This figure displays the average impact on the number of hires from Latin America, by the algorithm's impact on gender diversity using the regression discontinuity plot procedure from Calonico et al. (2014b) and Calonico et al. (2014a).

Table B.5: **Regression discontinuity design estimates of other (placebo) outcomes**

	Impact on:		
	Decreased hires aged 50-65, (=1)	Decreased Latin American hires, (=1)	Change in job performance, percent
	(1)	(2)	(3)
Decreased female count (=1)	0.121	-0.0656	-6.059
	(0.0765)	(0.0777)	(4.652)
R2	0.014	0.004	0.010
Observations	167	167	166

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Notes: This table examines the impact of the gender change of an algorithm on various placebo outcomes. I follow the bandwidth selection procedure in Calonico et al. (2014b) and Calonico et al. (2014a), which returns an optimal bandwidth of 4.18; I therefore limit my regression to algorithms that increased or decreased the number of female hires by up to four. All regressions include robust standard errors.

Table B.6: Adoption rates by legality and direction of impact

		Total	Accepted	
		N	N	%
		(1)	(2)	(3)
Failed $\frac{4}{5}^{th}$'s rule	$N_{F,old} > N_{F,new}$	167	63	38
Failed $\frac{4}{5}^{th}$'s rule	$N_{F,old} \leq N_{F,new}$	142	98	69
Passed $\frac{4}{5}^{th}$'s rule	$N_{F,old} > N_{F,new}$	9	4	44
Passed $\frac{4}{5}^{th}$'s rule	$N_{F,old} \leq N_{F,new}$	74	47	64

B.3 Four-Fifth's Rule analysis

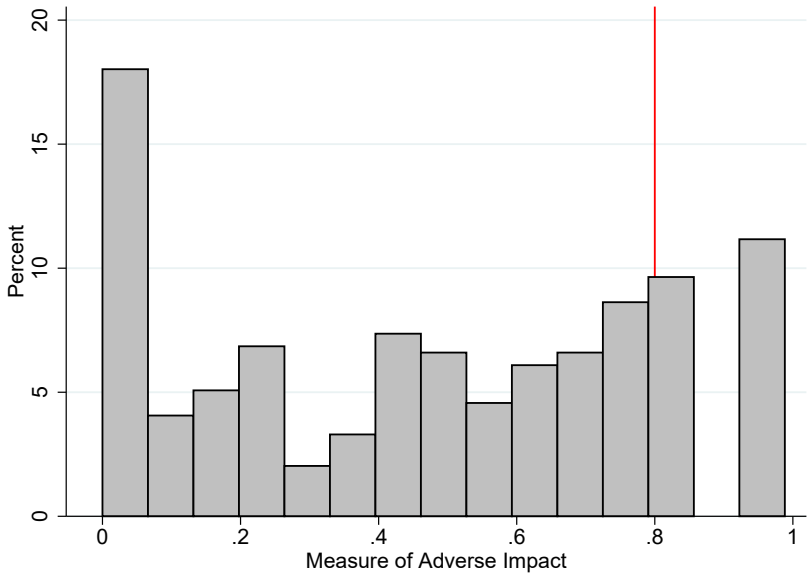
Figure B.13 displays the ratio of selection rates for my adverse impact analysis. I display $\frac{SelectionRate_W}{SelectionRate_M}$ for algorithms where $SelectionRate_W < SelectionRate_M$, and $\frac{SelectionRate_M}{SelectionRate_W}$ for algorithms where $SelectionRate_M \leq SelectionRate_W$. The figure shows that 80 percent of hiring algorithms would fail the $\frac{4}{5}^{th}$'s rule. Out of these, 54 percent had an adverse impact for women, while the remaining 46 percent had an adverse impact for men. Table B.6 displays the number of algorithms in each bucket and their average adoption rate.

Meanwhile, Figure B.14 displays the average recommendation rates for algorithms based on whether they (i) decrease female representation or not, and (ii) would pass or fail the four-fifths test. If fear of illegal behavior were driving my results, I would expect to see that algorithms with an impact ratio of less than 0.80 are less likely to be adapted than those with an impact ratio of 0.80 or more. However, this is not the case. The results indicate that passing or failing the four-fifths test has no bearing on the likelihood of adoption ($p = 0.69$ and $p = 0.42$ for algorithms that decrease vs increase female representation, respectively). Instead, my results indicate that decision-makers adopt algorithms that increase female representation, regardless of whether they would be legal or not, and avoid algorithms that decrease female representation, regardless of whether they would be legal or not ($p = 0.01$ and $p = 0.28$ for algorithms that fail the four-fifths test, and for algorithms that pass it, respectively). For these reasons, my results are unlikely to be driven by legal fears.

B.4 Predictors of failing the Four-Fifth's test

In Table B.7, I examine what predicts whether a given algorithm would fail the Four-Fifths test. I code up the algorithms as having failed or passed the test following the procedure described in Appendix

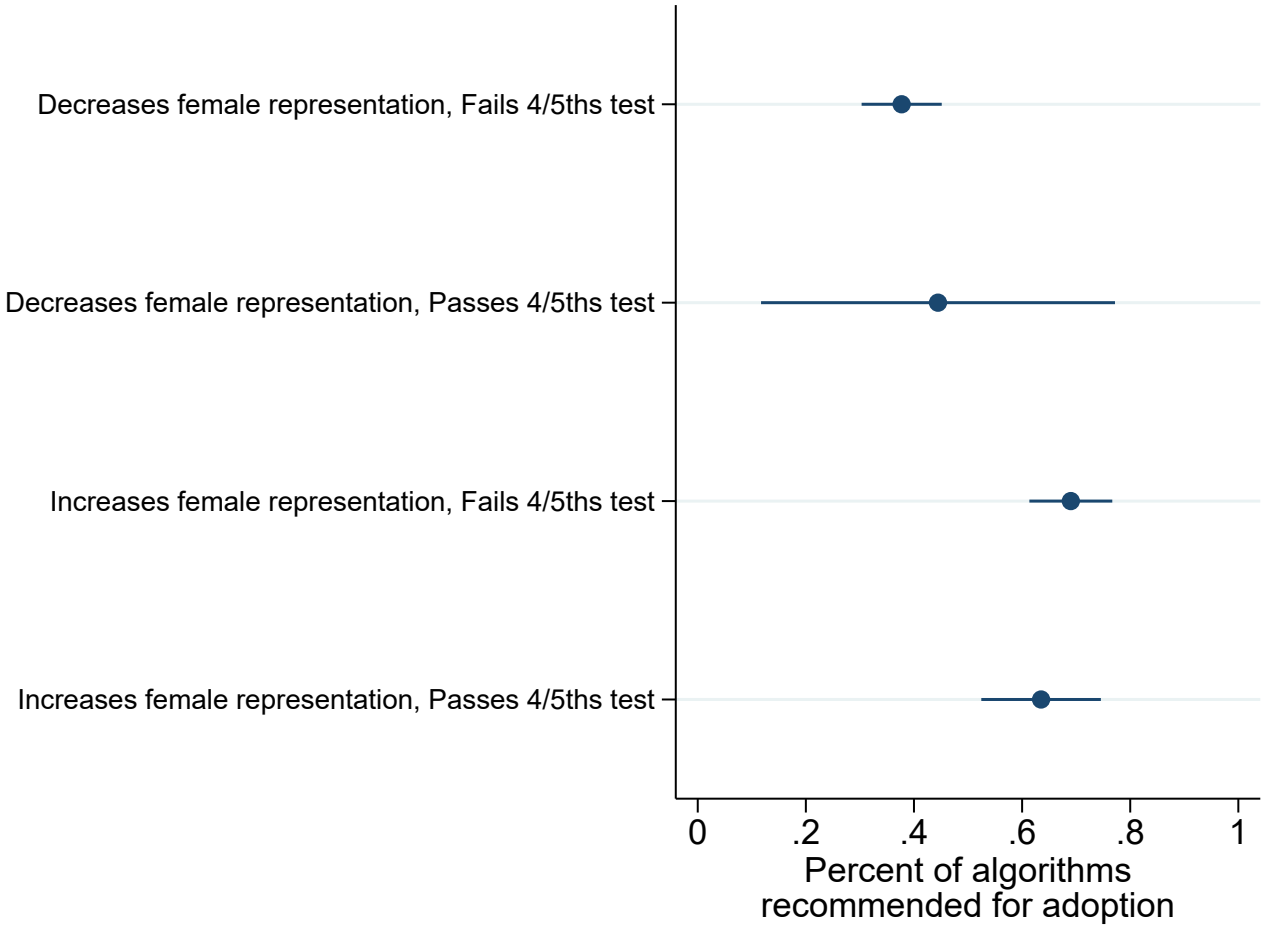
Figure B.13: Distribution of Ratio of Selection Rates



Notes: This figure displays the ratio of selection rates for my adverse impact analysis. I display $\frac{SelectionRate_W}{SelectionRate_M}$ for algorithms where $SelectionRate_W < SelectionRate_M$, and $\frac{SelectionRate_M}{SelectionRate_W}$ for algorithms where $SelectionRate_M \leq SelectionRate_W$.

Section B.3. The results indicate that the demographic impact of the participant has no impact on the likelihood of having an adverse gender impact. Instead, there is a complementarity between using machine learning and testing multiple models– those who use machine learning and test and iterate are much less likely to fail the Four-Fifth's test.

Figure B.14: Average recommendation rates, by algorithm demographic impact and adverse impact ratio



Notes: This figure displays the average adoption recommendation rate for algorithms by whether or not they decrease female representation, and whether or not they would pass the EEOC's four-fifths rule.

Table B.7: **The predictors of failing the Four-Fifths test**

	(1)	(2)	(3)	(4)
	Failed Four-Fifths test (= 1)			
Female	0.010			0.009
	(0.050)			(0.052)
Executive	0.035			0.037
	(0.053)			(0.054)
BS degree	-0.024			-0.018
	(0.066)			(0.066)
Selective undergraduate	-0.021			-0.030
	(0.070)			(0.071)
Uses ML		-0.067	0.199***	0.221***
		(0.136)	(0.032)	(0.044)
No sensitive demographic		-0.026	-0.024	-0.003
covariates		(0.045)	(0.045)	(0.048)
Uses multiple models		-0.019	-0.008	-0.006
		(0.041)	(0.042)	(0.044)
Uses ML X Uses multiple models			-0.420**	-0.439**
			(0.193)	(0.198)
Uses ML X No sensitive			(.)	(.)
demographic covariates			(.)	(.)
R2	0.002	0.002	0.008	0.010
Observations	371	395	395	370
controls				

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Notes: This table examines what algorithmic and managerial covariates predict whether a given algorithm would fail the Four-Fifth's test. All regressions include robust standard errors.