Review of Wiggins, Benjamin. 2020. *Calculating Race: Racial Discrimination in Risk Assessment*. Oxford.

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Racist algorithms have drawn increasing attention in the past few years. In June 2021, the National Football League agreed to stop using race in its calculations of brain functioning which made it more difficult for Black players to claim monetary damages for traumatic brain injuries caused by repeated concussions.¹ That same month, *Slate* ran a long expose about racism in algorithms that determine whether a patient's kidney disease is severe enough to merit a transplant. One version of this calculation makes Black patients look less sick, and thus ineligible for a transplant, based on a small, outdated study and justified by the assumption that Black people are more muscular on average.² A broader conversation across academic fields has identified the tendency for algorithms to produce racist results even when race itself is not a variable.³

As historian Benjamin Wiggins' new book shows, these sorts of algorithms have a long history. Across three tightly-written chapters, Wiggins documents the history of the use of race in risk assessments in life insurance, criminal justice, and real estate in the United States. The fourth and final substantive chapter looks at what happens to risk assessments when the explicit use of race is replaced with proxies: variables that are formally race-neutral but which correlate very strongly with race. Wiggins provides a sociological approach to this historical material, framing the book explicitly in terms of Michael Omi and Howard Winant's racial formation theory and Ulrich Beck's risk society.

The interior chapters then dig into the historical narratives surrounding key moments and calculative techniques in each context: late 19th century debates about the use of race in life insurance (as connected to broader debates around scientific racism), criminal identification and parole prediction in the early 20th century (including discussions of the explicit use of race in a parole violation prediction system devised by sociologist Ernest Burgess in the 1920s), and the use of the racial composition of neighborhoods in underwriting standards used by the Federal Housing Administration (FHA) in the 1930s-1940s ("redlining"). Most of this material is based on existing secondary sources, but Wiggins brings this history to life with plenty of narrative detail and some additional primary source work, including a novel analysis of changes in the FHA underwriting manuals to increasingly emphasize race in the 1930s. The final chapter looks at more recent periods and how (with some exceptions like those noted in the beginning of this review) risk assessments increasingly eschew the explicit use of race (often as a result of successful changes by the Civil Rights Movement and other anti-racist activists), but instead deploy variables that amount to much the same thing. Perhaps most infamously, predictive algorithms in criminal justice routinely use criminal history as a key predictive variable. Given systemic racism in the criminal justice system, this variable ends up serving as a proxy for race.

¹ <https://www.npr.org/2021/06/02/1002627309/nfl-says-it-will-halt-race-norming-and-review-brain-injury-claims>

² <https://slate.com/technology/2021/06/kidney-transplant-dialysis-race-adjustment.html>

³ Noble, Safiya. 2018. *Algorithms of Oppression*. Benjamin, Ruha. 2019. *Race After Technology*.

Together, these chapters provide a readable, succinct historical primer useful for anyone interested in understanding how debates over the relationship between risk and race have played out over the past century, including useful links to the contemporary conversations over fairness in machine learning. The book's strengths are also its weaknesses. One cost of brevity is that connections between these domains are made very quickly and sometimes are not entirely compelling (on the other hand, these chapters would be easy to use as standalone readings in a variety of contexts). A second cost is that the stories sometimes feel incomplete: the narrative zooms in on a particular historical moment but does not bring the story up to the present. As a result, it can be hard to evaluate the ultimate consequences of, for example, the elimination of race as an explicit variable in life insurance. Did this ultimately decrease racial inequality in access to life insurance? Or simply transform it into some form of "predatory inclusion" as we see in other contexts, like student loan debt and subprime mortgages?⁴

Perhaps the more important limitation, though, is one that the book shares with much of the contemporary debate over algorithms: the frustrating tendency to conflate how algorithms may be unfair (in the sense of treating similarly situated people differently based on their race, as in the case of the kidney function calculation) and how they may accurately detect existing forms of disadvantage (albeit not always correctly attributing or contextualizing the source of those disadvantages). Actuarial techniques will tend to reinforce social inequality because they will accurately register historical disadvantage and discrimination and naturalize it as risk. But how much do the techniques deserve blame for this as opposed to the conditions that created and perpetuated those risks? Take the example of Burgess's parole prediction system. Burgess failed to elucidate *why* race and crime were correlated (that is, he did not write about the role of structural racism in policing practices, the labor market, and so on). Race and crime are correlated now, and likely were correlated then. The problem is not the algorithm here, or not primarily the algorithm, but the racist institutions whose logic it accurately detects. As Ben Green (2021) puts it: "if data accurately depicts a social reality that is the product of oppression, the algorithm will reproduce those unjust conditions."⁵

This dynamic also shapes the books' final recommendations. Returning to the concept of the risk society, Wiggins argues that we should aim to use risk assessment to "share risk equitably" (100) and that engaging the history of risk assessment will help us do so. This is a limited vision - the vision of *more accurate* risk classification. It assumes that the relevant risks are in some sense fixed and inescapable, albeit perhaps redistributable. But what if we could instead imagine a world where many risks are *eliminated*? Precarity is a political choice. Mass incarceration is a political choice. Our goal cannot be simply to redistribute risk so that, say, white and Black men are equally likely to be, but rather we should seek a world where incarceration is much less common than it is now. Risk assessments may play a role in this process, but I fear that our collective focus on such assessments - and especially our focus on their fairness and accuracy rather than their "ideological effects"⁶ - may ultimately distract us from much of the work needed to undo systemic racism and create a better, more just society.

⁴ Seamster, Louise, and Raphaël Charron-Chénier. 2017. "Predatory Inclusion and Education Debt: Rethinking the Racial Wealth Gap." *Social Currents* 4(3):199-207. doi: [10.1177/2329496516686620](https://doi.org/10.1177/2329496516686620).

⁵ Green, Ben. 2021. "Impossibility of What? Formal and Substantive Equality in Algorithmic Fairness." *ArXiv:2107.04642 [Cs]*.

⁶ Simon, Jonathan. 1988. "The Ideological Effects of Actuarial Practices." *Law & Society Review* 22(4): 772-800.