Recent Contributions to Theories of Discrimination

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May 2023

Abstract. This paper surveys the literature on theories of discrimination, focusing mainly on new contributions. Recent theories expand on the traditional taste-based and statistical discrimination frameworks by considering specific features of learning and signaling environments, often using novel information- and mechanism-design language; analyzing learning and decision making by algorithms; and introducing agents with behavioral biases and misspecified beliefs. This survey also attempts to narrow the gap between the economic perspective on “theories of discrimination” and the broader study of discrimination in the social science literature. In that respect, I first contribute by identifying a class of models of discriminatory institutions, made up of theories of discriminatory social norms and discriminatory institutional design. Second, I discuss issues relating to the measurement of discrimination, and the classification of discrimination as bias or statistical, direct or systemic, and accurate or inaccurate.

1. Introduction

Traditionally, economic theories of discrimination are categorized either as taste-based or as statistical discrimination. In the context of labor markets, taste-based discrimination roughly corresponds to differential treatment of individuals due to employers’ preferences: two equally productive individuals may be valued differently by a discriminating employer based on their identity traits. On the other hand, theories of statistical discrimination highlight that discrimination can arise even when employer preferences are independent of employees’ identities. In that case, discrimination arises because worker’s payoff-irrelevant identities can serve as signals of their underlying productivities. As such, discrimination is not due to employers’ preferences over identities themselves, but rather their preferences over employee productivity, which is at least to some extent conveyed by their identity.

The profession has put much effort towards understanding these classical theories of discrimination, and empirically validating one or both of them in the context of labor, housing and credit markets, and beyond. Much of this work is addressed in detail by excellent surveys, such as Arrow (1998), Fang and Moro (2011), Lang and Lehmann (2012), and Lang and Spitzer

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I provide a short treatment of these traditional theories, but this survey mainly aims to document recent theoretical contributions to the literature on discrimination.\(^1\)

Section 2 starts with a presentation of taste-based and statistical discrimination models, as in Phelps (1972) and Arrow (1973). In Sections 2-4, I discuss developing literatures that build on traditional models of statistical discrimination, considering specific details of learning environments, and modeling agents’ behavioral biases and misspecified beliefs. We see that models that consider these institutional details and biased behaviors lead to novel theoretical insights and empirical predictions regarding discrimination and its consequences. See subsection 1.2 and 1.3 below for more details.

Beyond discussing new theories of statistical discrimination, this survey also aims to establish a bridge between the approaches to discrimination in the economics and sociology literature. In a paper published in the *Journal of Economic Perspective* in 2020, sociologists Mario Small and Devah Pager criticize the economic research agenda on discrimination, arguing that it misses “what sociologists and others have called ‘institutional discrimination,’ ‘structural discrimination,’ and ‘institutional racism,’ which are all terms used to refer to the idea that something other than individuals may discriminate by race.”

In their essay, they define *institutional discrimination* as “differential treatment that may be caused by organizational rules or by people following the law,” and say that it need not result from personal prejudice or from rational guesses on the basis of group characteristics.

Indeed, in all the contributions I review in sections 2, 3, and 4 discrimination is either rooted on personal prejudices or based on rationally (or irrationally) biased beliefs. In contrast, in Sections 5 and 6, I discuss theories that do not rely on either of those two traditional pillars. I refer to these theories as broadly relying on “discriminatory institutions,” alluding to institutional discrimination as defined in Small and Pager (2020). Despite this allusion, I do not believe these economic theories to fully (or even to a large extent) describe the sociological perspective on institutional discrimination. Rather, they are some notable examples of economic theories of discrimination that come closer to that approach.

Another way to compare and contrast the economic approach to discrimination to other sociological theories is by proposing ways to measure discrimination and decompose that measure into its various components due to different causes. By doing so, one is able to evaluate whether and how much of differential treatment is due to bias, or statistical discrimination.

\(^1\)I draw heavily on these surveys for the discussion of these traditional theories of discrimination in Section 2.

\(^2\)Much of the recent literature on discrimination has been empirical, but that is not the focus of this survey. For a recent treatment on the empirical literature, see Lang and Spitzer (2020).
components, and how much is due to other — maybe institutional or systemic — components. In this vein, a recent paper by Bohren, Hull and Imas (2023) help contextualize economic perspective on “theories of discrimination”, and propose a method to measure the importance of different theories. In section 7, I briefly survey the recent literature on the measurement of discrimination, amongst other things connecting Bohren, Hull and Imas’ (2022) categorization of discrimination as direct and systemic discrimination to other definitions of discrimination in the economic and other social sciences literatures.

1.1. What is Discrimination?. For the purposes of this survey, I understand discrimination to be differential treatment that is attributed to ostensibly “equal” agents, based solely on their observable identities. This definition is very broad, and it is often necessary to specify what we mean by “ostensibly equal agents” – in what ways should agents be “equal” in order to merit equal treatment? Are these characteristics observable? – and also what we mean by “differential treatment” – at each instance? On average? At the individual or group-level?

At times, it will be important to clarify and contrast these potential definitions. However, I want to first be clear about what I do not mean by the word discrimination. Routinely, when we talk about discrimination, we attribute some motive to the differential treatment. For example, we talk about discrimination by race, or by gender, or discrimination of minorities. In general, I find that the theoretical economic literature has little to offer as means to explain what groups are discriminated against, and what are the characteristics that make some identities salient while others non-salient. Accordingly, the theories I review in this survey should not be read as relating to or as explanations for discriminatory behavior against any particular group.

A few papers do point to the differential size of groups prompting discrimination, so that one should expect minority groups to be treated differently from majority groups. However, most papers are silent when it comes to the reasons why some identities are salient, and usually point to historically relevant characteristics.

1.2. Learning and Discrimination. Chambers and Echenique (2021) and Escudé, Onuchic, Sinander and Valenzuela-Stookey (2022) – discussed in Section 2 – consider the traditional model of Phelpsian statistical discrimination through the lens of information design. In that language, the authors characterize environments where populations with the same skill distribution, but different skill-signaling technologies, receive different wages on average. Their results indicate that specific features of the technology through which employers learn about
workers’ skills determine whether discriminatory outcomes arise. Accordingly, Section 3 considers papers that study details of employers’ skill-assessment problems and relate them to the existence and implications of discrimination.

In section 3.1, I present papers that study the dynamic learning environments in which employers learn about workers’ qualities. In these environments, depending on the learning technology, employers may end up in discriminatory learning traps, where they ineffectively learn about the skills of workers with disfavored identities. For example, Bardhi, Guo and Strulovici (2023) show that, when employers learn about workers’ skills by observing “good news,” early-career discrimination is self-correcting and, over time, similarly qualified workers receive equal treatment on average. Contrastingly, in “bad news” learning environments, early-career discrimination is spiralling, and workers who are almost equal ex-ante have very different expected career paths. Similar discriminatory learning dynamics also arise when worker performance is assessed by myopic learning algorithms – in Section 3.2, I review a short literature on discrimination by learning algorithms.

While statistical discrimination may result from exogenous characteristics of the learning environment, it can also be enhanced by endogenously chosen learning technologies. A recent literature studies learning with rational inattention, where employers choose the precision of the signal they wish to observe about a worker’s quality, subject to some “attention cost.” Specifically, an employer can learn the employee’s skill with any desired precision, but signal precision is costly. Section 3.3 discusses models of discrimination by rationally inattentive employers. In one such environment, Bartoš, Bauer, Chytilová, and Matějka (2016) find that rational inattention may amplify existing quality disparities between workers with different group memberships.

Most of Section 3 considers models where employers learn about passive workers. Contrastingly, Section 3.4 considers models where workers signal their productivity to employers, à la Spence. In a recent contribution, Onuchic and Ray (2023) study signaling through team formation, and find that discriminatory outcomes may arise, where team members that belong to different identities may systematically receive different credit for team outcomes.

1.3. Discrimination with Misperceptions. A common feature of models introduced in sections 2 and 3 is that employers are assumed to hold correct beliefs. A nascent literature points to the importance of incorporating potential agent misperceptions, or failures of rational expectations, into models of discrimination – I consider this literature in Section 4.
Section 4.1 introduces models that generalize the standard Phelps (1972) and Coate and Loury (1993) models to allow for misspecified beliefs and dynamic considerations. For example, Bohren, Imas and Rosenberg (2019) propose a model of inaccurate statistical discrimination. In it, an agent performs a sequence of tasks that generate signals about their underlying ability. In each period, a short-lived evaluator learns about the agent’s ability both through direct observation of their task performance, but also by observing reports made by previous evaluators, who may be biased. Bohren, Imas and Rosenberg (2019) study the implications of evaluators’ misspecified beliefs – about the distribution of agent types and about the beliefs of other evaluators – on the dynamics of discrimination.

In Section 4.2, I discuss models that incorporate behavioral heuristics to interpret individual outcomes, potentially generating group-dependent interpretations. Bordalo, Coffman, Gennaioli and Shleifer (2016) study stereotypes based on a representativeness heuristic that anchors itself on salient identity traits, such as gender or racial identity. Heidhues, Köszegi and Strack (2019) consider an alternative learning heuristic. They study a model where an agent wishes to learn the true discrimination pattern in a society, based on observed outcomes. But the agent is stubbornly overconfident: they hold a point belief about their own ability, which is above the correct one. They find that adding this one behavioral element to an otherwise “standard” model generates a series of empirically verified patterns in social beliefs.

1.4. Discriminatory Institutions. Small and Pager (2020) recognize that research in economics – both empirical and theoretical – has traditionally adopted either the taste-based or the statistical discrimination perspectives, focusing substantially on assessing which approach is a more appropriate description of discrimination as a sociological phenomenon. They go on to criticize this economic research agenda, arguing that it misses “what sociologists and others have called institutional discrimination”, meaning “differential treatment that may be caused by organizational rules or by people following the law.”

To talk about the economic perspective on discriminatory institutions, we must first understand how economists (and economic theorists) view institutions. The Nobel-prize-winning economist Douglass North, in his Journal of Economic Perspectives article in 1991, titled “Institutions,” writes (emphases and cuts are my own):

Institutions are the humanly devised constraints that structure political, economic and social interaction. They consist of both informal constraints (sanctions, taboos, customs, traditions, and codes of conduct), and formal rules (constitutions, laws, property rights). (...) Together with the standard constraints of economics they define the choice set and therefore determine transaction and
production costs and hence the profitability and feasibility of engaging in economic activity. (...) Institutions provide the incentive structure of an economy; as that structure evolves, it shapes the direction of economic change towards growth, stagnation, or decline.

The articles I survey in Sections 5 and 6 exactly speak to the two types of institutions referred to by North – models of informal constraints (social norms) in the former and formal rules (institutional design) in the latter.

The first class of models I consider in section 5 are roughly embedded in Kandori’s (1992) environment, and view discrimination as a social norm enforced in communities. In these models, the discriminatory social norm is sustained by a society’s desire to coordinate, and by society members’ fear of being sanctioned.

Take, for example, Pęski and Szentes (2013). In their model, agents continuously and randomly match in pairs, and each pair has the opportunity to form a profitable partnership. Agents belong to different identity groups, but are otherwise homogeneous. They show that discriminatory equilibria exist, where agents form partnerships with other agents with their own group identity, but never with members of other groups. This type of discriminatory behavior is supported by agents beliefs that, if they form cross-identity partnerships, they will be refused partnerships in the future by members of their own group.

In that model, discrimination stems from and is reinforced by the existing discriminatory social norm. In other words, agents act discriminatorily because it is the social norm to discriminate; and the social norm is upheld by agents’ fears of being punished for not conforming.

Still on the topic of discriminatory social norms, in section 5.4, I briefly comment on a literature stemming from Akerlof and Kranton (2000), which proposes that group-dependent behavior stems from people’s desire to conform with socially-determined identity-norms.

Section 6 considers a different approach to institutional discrimination, whereby discrimination stems from organizations that are designed asymmetrically, potentially benefitting some groups and harming other identities. I survey a few papers that argue that institutional designers – managers, or regulators, for example – may optimally design discriminatory mechanisms when they have efficiency or some other considerations as their goal. These papers are part of a more extensive literature on mechanism design that discusses the optimality of asymmetric mechanisms. I remain agnostic as to whether these discriminatory mechanisms speak to the

\[\text{Kandori's (1992) model of community-enforced social norms is not the only economic approach to modeling social norms. For other seminal contributions, see for example Young (1993) and Bernheim (1994).}\]
“sociological” question of discrimination, and choose to discuss only a few more immediately relevant contributions.

1.5. The Economic Perspective. Relative to research in other social sciences, the economic perspective on discrimination is sometimes seen as “justifying discriminatory behavior.” One view of Phelps’ (1972) theory of statistical discrimination is that the learning technology is given and, in making the “efficient” statistical inference about workers’ abilities, a firm will act discriminatorily. A cynical reader may then think that “it is unfortunate that the learning process is biased, but such is the world; and there is no point in trying to fight against ‘efficient’ discrimination.”

As a final note in this introduction, I hope to clarify that, even if we take the economic perspective and write models of interactions between rational agents, there are various mechanisms that lead to discriminatory outcomes. Some, but definitely not all, of these perspectives can be seen as “justifying” discrimination as an unfortunate, but efficient outcome.

For example, many of the models in Section 3, which are newer developments in the literature of statistical discrimination, regard discriminatory outcomes as (often inefficient) learning traps. Some of these papers also view the learning technology itself as a choice variable, which invalidates the cynical approach described above. Among seminal contributions, statistical discrimination as in Arrow (1973) is an inefficient outcome due to a coordination failure. Finally, models of discriminatory social norms, considered in Section 5, further illuminate the discriminatory mechanism stemming from coordination failures between rational agents in a community.

Furthermore, even if one does side with the cynical reading of Phelpsian theories of statistical discrimination, these theories are almost entirely silent about what identity traits define the groups that are/“should be” treated differently. The economic treatment provides little to no theory on what defines a salient identity.

The papers on discriminatory institutional design, discussed in Section 6 show that discriminatory organizational rules can be a chosen outcome when institutional designers have efficiency, or some other considerations, as their goal. (But again, are silent as to what groups should be “discriminated against”.) In my view, one of the contributions of this sub-literature lies in

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4Tilcsik (2021) contends that the idea that statistical discrimination, rather than simply providing an explanation, can lead people to view social stereotyping as useful and acceptable and thus help rationalize and justify discriminatory decisions.

5In Bardhi, Guo and Strulovici (2023), if given the chance, the employer would choose to learn with the “good news technology,” which does not induce the spiralling discriminatory outcome.
showing that sometimes there is a tension between “fairness” and efficiency (and also that sometimes there is not). From this precise understanding, some new literature strands are currently developing in mechanism and algorithmic design, studying design by principals with redistributive/fairness, as well as efficiency, as their goals – these are briefly commented on in sections 6.3 and 6.4.

2. Taste-Based and Statistical Discrimination

2.1. Taste-Based Discrimination. The basic taste-based model is proposed in Becker (1957). His model assumes that employers derive some disutility from the number of Black employees they hire, despite there not being productivity differences between Black and white workers. The disutility level varies across potential employers and, absent any frictions, the market settles on an equilibrium where almost all firms are completely segregated: at the equilibrium wages, the less discriminatory firms optimally hire only Black workers and the more discriminatory firms hire only white workers. This observation is one of the many implications of Becker’s theory that do not fit empirical observations – Lang and Lehmann (2012) discuss the model’s empirical merits at length.

From a theoretical perspective, the main criticism to the taste-based theory, as put by Arrow (1998), is that it neglects Darwinian principles. Supposedly, in a market where employers are not uniform in their discriminatory tastes, non-discriminatory employers would run more profitable businesses. In that case, a competitive market should be fully taken over by non-discriminatory employers over time. Taken seriously, this theory should then predict wage differentials and segregation between Black and white workers to be only transitory.

Later models of taste-based discrimination attempt to address this criticism. Their main extra ingredient is that labor markets are frictional. In Black (1995), job search is random and time-consuming. Workers sequentially search for jobs and, in equilibrium, accept jobs whenever the offered wage and match quality yield greater value than the expected payoff of continuing the search. This condition endogenously determines a reservation wage above which a worker accepts a job offer.

In such a job market, if some employers are prejudiced and unwilling to hire Black workers, or only willing to hire them at a discounted wage, then the expected value of additional search to Black workers is lowered. Consequently, the reservation wage used by Black workers also decreases. Finally, understanding that it is “cheaper” to attract Black workers, even non-prejudiced firms then have an incentive to offer them lower wages. In a frictional labor
market, it is then possible to have discriminatory equilibria where, due to the presence of *some* employers with discriminatory taste, *all* employers strategically make distinct job offers to equally productive individuals of distinct identities. Moreover, in these discriminatory equilibria, biased employers are not necessarily “competed out” of the market.

2.2. Phelpsian Statistical Discrimination. Phelps (1972) proposes a simple problem of statistically inferring workers’ productivities based on imperfectly informative productivity signals, and workers’ payoff-irrelevant identities. Each worker has an identity \( j \in \{B, W\} \) and a productivity type \( p \) which is drawn from a normal distribution \( N(\mu_j, \sigma_j^2) \). An employer wants to hire this worker and is willing to pay a wage equal to the worker’s productivity. However, the employer only observes the worker’s identity and an imperfect productivity signal, given by \( \theta = p + \epsilon \), where \( \epsilon \) is distributed according to \( N(0, \sigma_\epsilon^2) \).

Given an identity and signal observation, the employer’s inference of the worker’s expected productivity is

\[
E(p|\theta, j) = \frac{\sigma_j^2}{\sigma_j^2 + \sigma_\epsilon^2} \theta + \frac{\sigma_\epsilon^2}{\sigma_j^2 + \sigma_\epsilon^2} \mu_j
\]

Of course, if the productivity signal is perfectly informative (\( \sigma_\epsilon^2 = 0 \)), then the employer fully observes the worker’s type and there is no scope for discrimination. If instead the signal is imperfect, the inferred productivity of a worker may depend on their group identity.

At this point, it is useful to formally define (statistical) discrimination.\(^6\)

**Individual Level Discrimination.** One possible approach is to define discrimination at an *individual level*: statistical discrimination arises when two individuals with the same observable outcome (signal realization \( \theta \)), but different identities, receive different productivity inferences – and therefore different wages – from the employer.

Equation (1) implies that such individual-level discrimination occurs when populations \( B \) and \( W \) differ, either in their underlying productivity distributions (\( \mu_B \neq \mu_W \) or \( \sigma_B^2 \neq \sigma_W^2 \)), or in the accuracy of their productivity signal (\( \sigma_\epsilon_B \neq \sigma_\epsilon_W \)). Suppose \( \mu_B < \mu_W \), so that population \( B \) is on average less productive than population \( W \). Then the inferred productivity of two workers who draw the same signal realization \( \theta \) will be different if they belong to different identities, because a worker’s identity is effectively an additional signal of their productivity. Specifically, the worker who belongs to \( B \) will be expected to be less productive.

\(^6\)See Aigner and Cain (1977) for a thorough discussion of alternative definitions of statistical discrimination.
Otherwise, suppose groups have identical productivity distributions, with \( \mu_B = \mu_W \) and \( \sigma^2_B = \sigma^2_W \), but different productivity signaling technologies. For example, let \( \sigma^2_{\epsilon_B} > \sigma^2_{\epsilon_W} \), so that the signal is more noisy for group \( B \) individuals. The productivity inference made by the employer is therefore more responsive to the signal for group \( W \) than it is for group \( B \). Specifically, a group-\( B \) person who draws an above average signal realization is interpreted as having a lower expected productivity than a \( W \)-group person with the same signal realization. Conversely, a \( B \) person with a lower than average signal realization is seen as more productive than if they belonged to group \( W \).

**Group-Level Discrimination.** In this last exercise, where only the signaling technology differs across groups, individual-level statistical discrimination occurs, but on average both groups receive the same wage. To see this, take \( \mathbb{E}(p|\theta, j) \) from equation (1), and average it with respect to the distribution of signal realizations \( \theta \) generated by each group \( j \in \{B, W\} \), to find that \( \mathbb{E}[\mathbb{E}(p|\theta, j)] = \mu_j \), which is the same across groups.

Based on this observation, Aigner and Cain (1977) qualify that Phelps’ (1972) model of discrimination “does not constitute economic discrimination, statistical or otherwise.” Instead, they propose an alternative definition of statistical discrimination, referring to a group-level phenomenon, rather than Phelps’ individual-level assessment: *Group-level* statistical discrimination arises when two groups with the same underlying productivity distribution, but different productivity-signaling technologies, receive different wages on average.

Phelps (1972) assumes that the employer offers employees wages equal to their expected productivity, given the observed signal. This crucial assumption excludes the possibility of group-level statistical discrimination, even when more general productivity distributions and signaling technologies are allowed.\(^7\) Generally, if the wage payment equals the posterior mean productivity induced on the employer – or is an affine function of this posterior mean – then two groups with the same prior productivity distribution must receive the same expected payment. This result follows directly from the martingale property of posteriors: the expected posterior mean must equal the prior mean.

Aigner and Cain (1977) note, instead, that group-level discrimination arises if employers offer a non-linear wage schedule – for example, due to the employer being risk-averse. In the model of normally distributed signals in the previous section, if the wage offered by the employer is a convex function of the induced posterior mean, then the group with higher signal accuracy receives higher wages on average. Formally, let \( w : \mathbb{R} \to \mathbb{R} \) be a convex wage schedule, and

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\(^7\)As opposed to the model presented above, which assumes that productivity and productivity signals are normally distributed.
suppose $\sigma^2_B > \sigma^2_W$. Then, using Jensen’s inequality, we have

$$\mathbb{E} \left[ w \left( \mathbb{E} ( p | \theta, B ) \right) | \sigma^2_B \right] < \mathbb{E} \left[ w \left( \mathbb{E} ( p | \theta, W ) \right) | \sigma^2_W \right],$$

because the distribution of posterior means induced by group $W$’s signal is a mean-preserving spread of the distribution of posterior means induced by group $B$’s signal – or, equivalently, because group $W$’s productivity signal is Blackwell more informative than that of group $B$.\(^8\)

**A New Characterization of Phelpsian Statistical Discrimination.** Chambers and Echenique (2021) use the recently-developed language of information design\(^9\) to characterize production and signaling technologies that are conducive to statistical discrimination, at the group level. In this language, a population is defined by an underlying productivity distribution (a prior) and a signaling technology. A signaling technology (or a signal) is a (perhaps non-deterministic) map between productivity and signal realizations. For example, a signal realization could be a grade at a test, and a signaling technology is the map which specifies a distribution of grades that is attained by people of each productivity level.

Often, the information design literature, including Chambers and Echenique (2021), equates a signal realization with the posterior distribution that is induced by an observer who sees that signal realization. Under this equivalence, the concept of *individual-level* statistical discrimination is moot: two workers with the same signal realization would necessarily induce equal productivity inferences on the employer, and would therefore receive equal wages. That being the case, Chambers and Echenique (2021) propose a characterization of *group-level* statistical discrimination.

In their model, a firm observes a worker’s signal realization, as well as their group membership, and forms a posterior about the worker’s productivity. The firm has a technology, defined by a set of available tasks and, given their posterior about the worker’s productivity, the firm matches the worker with a task, and pays them their productive outcome at the chosen task. This worker-task matching problem performed by the firm yields potentially nonlinear worker-payment schedules.

As a variation of Aigner and Cain’s (1977) definition, Chambers and Echenique (2021) say statistical discrimination takes place when there is some firm technology such that two populations with the same skill distribution, but different signaling technologies, receive on average different payments. This definition clarifies that the average payments to a population depend

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\(^8\)This argument is not the product of Aigner and Cain’s (1977) model with a risk-averse employer, but rather a simpler illustration of how non-linearity in the wage schedule – of unmodeled origin – can yield group level statistical discrimination.

\(^9\)Mainly the literature following Kamenica and Gentzkow (2011).
not only on the signaling technology, but also on the firm technology. With respect to the latter aspect, it takes a conservative approach in defining discrimination to be present if there is any firm technology that yields an average payment difference.

Chambers and Echenique’s (2021) results formalize two aspects already hinted at by the discussion above. First, they characterize properties of signals that yield discrimination. Interestingly, they show that two productivity signals do not need to be ordered in their informativeness (in the Blackwell order) in order for discrimination to arise. There may be statistical discrimination even when the information structure of one population is not more informative than the other. (More on this below.) Second, they connect discrimination to a notion of linearity of wage payments.

In the first result, they argue that, rather than Blackwell ordering, the relevant characterization of Phelpsian statistical discrimination is an identification property – they say that a set of signals is identified “if it is possible to uniquely identify the signal structure observed by an employer from a realized empirical distribution of skills.” In a follow-up paper, Escudé, Onuchic, Sinander and Valenzuela-Stookey (2022) propose another interpretation: identification holds if “there are no two distinct populations with the same skill distribution.”

Under that interpretation, Chambers and Echenique’s (2021) result is a dismal one, as it implies that discrimination is inevitable. More specifically, whenever there are distinct populations with the same skill distribution, there will be discrimination between them.

Escudé, Onuchic, Sinander and Valenzuela-Stookey (2022), also show how Blackwell’s Theorem characterizes statistical discrimination in terms of statistical informativeness, and that Chambers and Echenique’s (2021) equivalence between discrimination and identification is a corollary of this rewriting of Blackwell’s Theorem. Further, Escudé, Onuchic, Sinander and Valenzuela-Stookey (2022) provide some finer-grained properties of statistical discrimination which are also implied by this rewriting.

2.3. Equilibrium Statistical Discrimination. The models described in the previous section regard discrimination as purely a problem of statistical inference, where identical populations receive unequal treatment due solely to their access to different technologies to communicate their talents to potential employers. Contrastingly, Arrow (1973) points out that people’s ability to convey their productivity to employers influences their choice to invest in their productivity in the first place. Following this reasoning, he argues that two ex-ante identical populations, with access to distinct signaling abilities, may choose different productivity investments, and attain distinct productivity levels at an ex-interim stage.
This section introduces the literature following Arrow (1973), which studies equilibrium models of statistical discrimination. The core message is that unequal treatment across identities can arise from “self-fulfilling prophecies,” whereby employers conjecture that employees’ identities meaningfully signal some information about their productivity, and, understanding this preconception, employees are incentivized to behave in a way that confirms the initial discriminatory conjecture.

To fix ideas, take the model in Coate and Loury (1993). Firms wish to hire a continuum of workers to perform either a simple or a complex task. Workers are either skilled or unskilled, and also belong to one of two identities (B or W). Any worker that is allocated to a simple role receives a wage of 0 and also yields to the firm a payoff of 0. On the other hand, if a worker is allocated to the complex task, then they receive a strictly positive wage, regardless of their skill type. The firm, on the other hand, receives a strictly positive payoff if the worker in the complex position is skilled and a strictly negative payoff if not.

At an initial stage, all workers are unskilled and draw a random cost that they can choose to pay to become skilled. The distribution of costs does not differ across identities, so that, ex-ante, all workers are equally able to become skilled. Importantly, the firm does not see the workers’ skill investments. Like in Phelps (1972), they only observe an imperfect signal about whether this worker is skilled, as well as the workers’ payoff-irrelevant identity.

To calculate the Bayesian posterior probability that a worker is skilled, the firm uses the observed signal realization as well as a prior, which is given by the firm’s conjecture of the overall proportion of workers that chose to invest in acquiring the skill. This conjectured prior may also depend on the worker’s identity – for instance, the firm may think that W workers invest in skill-acquisition in a greater proportion than B workers. This is where the self-fulfilling nature of the model comes in: Because the prior conjectured by the firm affects their interpretation of the imperfect skill signal, the incentives to invest in acquiring skill are themselves affected by the firm’s conjecture.

In equilibrium, the firm’s conjecture is required to be accurate. However, because of the complementarity between the firm’s prior and the workers’ actions, there may be multiple equilibria, with different investment levels. Indeed, Coate and Loury (1993) show that, under some assumptions on the distribution of investment costs, there are at least two such equilibria. Moreover, the multiple equilibria are Pareto-ranked, so both firms and workers are better off in equilibria where firms (correctly) conjecture that a larger proportion of workers acquire skill.

In Coate and Loury (1993), and more broadly in the literature following Arrow (1972), statistical discrimination arises because workers of different identities play different equilibria.
For example, $B$ workers may invest less in skill acquisition relative to their $W$ counterparts precisely because firms correctly conjecture they will do so – in this case, $B$ workers play a Pareto-worse equilibrium, and $W$ workers a Pareto-better one. Group inequality would be eliminated if somehow $B$ workers and firms could coordinate on the good equilibrium.

Importantly, in this model, there is no interaction between $B$ and $W$ workers and their interests are not in conflict: if $B$ workers were to coordinate on a better equilibrium, $W$ ones would not at all be affected. Later models, such as Moro and Norman (2004), relax Coate and Loury’s (1993) assumption of exogenous wages. They propose a general equilibrium model of statistical discrimination, where wages offered to workers of different identities are interdependent. Among other results, the authors show that the dominant identity may benefit from the discriminatory treatment of the disadvantaged group.

Since Arrow’s (1972) contribution, and early formalizations as in Coate and Loury (1993), an extensive literature has developed, proposing various models of equilibrium statistical discrimination in the labor market. Most models highlight the importance of information and job-search frictions, and their interplay, in yielding discriminatory outcomes. For earlier work featuring the effects of search frictions, see Rosén (1997), or Mailath, Samuelson, and Shaked (2000). For a detailed survey, please refer to Fang and Moro (2011). More recent contributions include Jarosch and Pilossoph (2019) and Gu and Norman (2020).

3. Learning and Discrimination

Theories of statistical discrimination rely on the basic assumption that, at the time of hiring, employers imperfectly observe the aptitude of different candidates for the job position being offered. Recent contributions take a deeper look into the details of employers’ productivity-assessment problems.

Section 3.1 considers a developing literature that relates Phelpsian statistical discrimination to features of employers’ learning environments. In section 3.2, I discuss two papers that study the discriminatory implications of screening done by myopic algorithms. Section 3.3 examines worker screening by rationally inattentive employers. Finally, in section 3.4, I introduce a model where workers signal their underlying productivity through their choice to work in teams or alone.

3.1. Learning Traps and Discrimination. Bardhi, Guo and Strulovici (2023) propose a model where time is continuous and, at each instant, a firm assigns to a task at most one of two workers of unknown skill. Each worker $i \in \{A, B\}$ is either of high or low quality, with
being the commonly held prior probability that worker \( i \) is of high quality. Worker \( A \) is assumed to have ex-ante higher expected quality, so that \( p_A > p_B \), but the paper is mainly interested in the case where workers are almost equal, so that \( p_B \uparrow p_A \).

The firm wishes to employ either worker if and only if they are of high quality. More specifically, the firm receives a positive flow payoff \( v \) at any instant when a high-quality worker is performing the task and a zero flow payoff when a low-quality worker is employed. If no worker is assigned to the task at a given point, then the firm receives a flow payoff strictly between 0 and \( v \). The overall firm payoff is only realized at the end of the time horizon.\(^{10}\)

If a worker is employed at the time interval \([t, t + dt]\) and their type is \( \theta \in \{h, l\} \), then a public signal arrives with probability \( \lambda_\theta dt \). The authors study two baseline learning technologies: breakthrough learning, where \( \lambda_h > 0 = \lambda_l \), so that an observed signal reveals that the worker is of the high type; and breakdown learning, where \( \lambda_l > 0 = \lambda_h \), so a signal reveals a worker’s low type.

These scenarios represent inherent properties of the type of task performed at a given firm. For example, scientific research can be thought of as a breakthrough learning environment, where most observed news – say, a new published paper or an awarded grant – are positive news about the researcher’s underlying type. On the other hand, a nightwatch or an airline pilot work in breakdown environments, where publicly observed news are usually negative – for example, a successful robbery attempt or an emergency landing.

The main result in Bardhi, Guo and Strulovici (2023) is that, depending on the underlying learning environment, a small difference in ex-ante expected quality between worker \( A \) and worker \( B \) can lead to large differences in career trajectories and, consequently, payoff.

First focus on a breakthrough learning technology. Because \( p_A > p_B \), at the beginning, the firm allocates worker \( A \) to the task. If a breakthrough is observed, then the firm learns that worker \( A \) has high quality and allocates them to the task forever. Otherwise, at each instant where no breakthrough is observed, the firm’s posterior that worker \( A \) is of high type is updated downwards. This happens until some time \( t^* \), where this posterior equals to the prior on worker \( B \). From that point onwards, \( A \) and \( B \) are treated symmetrically, so that their expected career paths and payoffs coincide.

Under the main case of interest, where workers are almost equal (\( p_B \uparrow p_A \)), \( t^* \) is very small, which also implies that the probability of a breakthrough for worker \( A \) in the interval \([0, t^*]\) becomes negligible. Thus, even from an ex-ante perspective, worker \( A \) and \( B \) have almost

\(^{10}\)This guarantees that the firm does not learn each worker’s type after an arbitrarily small employment period.
equal expected career paths. In this sense, the breakthrough learning environment is such that early-career discrimination is self-correcting.

Now take the breakdown learning scenario. Equally, the firm starts by allocating worker $A$ to the task, but in case of a breakdown, $A$ is revealed to be of low type and is never again employed by the firm. At that point, the firm optimally starts to employ worker $B$. Otherwise, the firm’s posterior on $A$’s quality is updated positively and they remain employed. Unless $A$ signals a breakdown, worker $B$ is never employed and no learning about their type ever takes place.

In this case, early-career discrimination is spiralling: even when workers are almost equal ($p_B \uparrow p_A$), $A$ and $B$ have very different expected career paths, and the ratio between the expected payoffs of workers $A$ and $B$ does not approach 1.

This result shows that discrimination can be a path-dependent and cumulative process. Despite both employees being symmetric, the employer fails to learn, or delays learning, about the worker with a dis-favored identity until they are “done” learning about the favored employee. In this model, the equilibrium learning dynamics hurt the dis-favored employee. However, they do not hurt the favored one or the firm, and are not inefficient.\footnote{The discriminatory equilibrium is “constrained efficient,” because, given the learning technology, a planner could not improve on the equilibrium play. However, the model still yields interesting policy implications. Suppose we regard the learning technology as a choice, rather than a fixed environment characteristic. In that case, we would find that, given the choice, both the firm and the planner would prefer learning through the non-discriminatory “good news” process, rather than the discriminatory “bad news” process.}

In other contexts, explored below, learning traps can be discriminatory, and also inefficient. Che, Kim and Zhong (2019) study statistical discrimination in markets where ratings and recommendations facilitate social learning among users. They introduce a model in which long-lived buyers and sellers wish to trade, but, in each period, their meetings are subject to search frictions. There is a platform that provides buyers with ratings that are informative about the quality of the goods provided by each of the sellers. The sellers can provide high or low quality goods, but also differ in their payoff-irrelevant identities.

The platform is assumed to be unbiased in the sense that, given some information about a seller’s quality, it generates the same rating regardless of that seller’s identity. However, discrimination may still arise due to the platform’s data-acquisition process. Information about a seller’s quality is acquired whenever they transact with a buyer, who then reports to the platform whether the good they received was of low or high quality.
Because data is sampled only when transactions occur, and because buyers wish to transact with the sellers they believe are of high quality – those with good ratings – then much data is generated about sellers who already have high ratings, and little data is observed about low-rated sellers. A discriminatory feedback loop may ensue: if sellers of a dis-favored identity are seldom sampled by buyers, despite their good ratings, then a good rating becomes a less informative signal about their quality. Which, in turn, encourages buyers in the next period not to transact with positively-rated sellers of the dis-favored identity.

3.2. Myopic Learning Algorithms. Che, Kim and Zhong’s (2019) model describes an instance of statistical discrimination as a “learning trap,” where a society is stuck in an equilibrium with little learning about the underlying quality of members of a dis-favored identity. A similar type of learning trap is studied in Komiyama and Noda (2021), who propose a model of statistical discrimination as a failure of social learning.

Komiyama and Noda (2021) propose a multi-armed bandit model of social learning. Their model features a sequence of myopic (short-lived) firms that make hiring decisions. In each round, one firm hires a worker from a set of candidates, who constitute the multiple bandit arms. The firm wishes to hire the most skilled worker, which they infer from some observable worker characteristics, which include the worker’s identity. At first, no firm knows precisely how to interpret these characteristics. Rather, firms learn the statistical association between characteristics and skills using data pertaining to past hiring cases – they are frequentists, rather than Bayesian learners.

Each worker belongs to either a minority or a majority identity. Suppose that, at some point in the stochastic learning process, workers with a minority identity have their skill underestimated. Once the minority identity is undervalued, it is difficult for one of its members to appear to be the best candidate, and the firm prefers to instead hire a majority worker. At this point, a learning trap ensues: as long as firms only hire majority workers, society cannot learn about the minority group, and the imbalance persists in the long run. This phenomenon is labeled perpetual underestimation.

Perpetual underestimation arises due to each firm’s myopic behavior. In each period, the myopic firm chooses the safe arm and hires a worker with the best record given the current information. By doing so, the firm forgoes exploring the risky arm, which would generate

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Vellodi (2021) studies a model with this same mechanism, i.e., where information about well-regarded, established, sellers is generated more quickly than about incoming sellers with no previous reputation. He argues that platform rating design can be used to counteract this force and incentivize new sellers to enter the market. While his model is not applied to study discrimination, similar ratings design results may also apply when a platform’s objective is to minimize the scope for statistical discrimination.
more information about the minority population, to be used by future firms. In this sense, the societal learning follows a *greedy algorithm*.

From this societal learning perspective, Komiyama and Noda (2021) show that statistical discrimination via perpetual underestimation is not only unfair, but can be inefficient. The authors find that either using a exploration-subsidy mechanism or temporarily using the Rooney rule, which requires each firm to interview at least one minority candidate as a finalist for each job opening, can effectively mitigate discrimination caused by insufficient data, as well as improve welfare.\(^{13}\)

Li, Raymond and Bergman (2021) similarly view hiring as a multi-armed bandit problem: to find the best workers over time, firms can exploit the safe bandit arm, by selecting from groups with proven track records, or explore the risky arm by selecting from under-represented groups to learn about their quality. Like Komiyama and Noda (2021), Li, Raymond and Bergman (2021) highlight that incorporating exploration incentives in developing decision-making algorithms can lead to more efficient and more equitable outcomes.

Finally, Lepage (2022) and Benson and Lepage (2023) propose models with similar “learning trap” discrimination dynamics, and test their predictions using a labor market experiment (the former paper) and administrative records from a large national US retailer (the latter paper). Lepage’s (2022) results illustrate the formation of biased beliefs based on employer’s experience with previous workers. And Benson and Lepage’s (2023) results suggest that managers develop biased beliefs from endogenous learning about racial groups, thereby systematically disadvantaging minority workers.

### 3.3. Learning with Costly Information Acquisition

In all models introduced in sections 3.1 and 3.2, information about a worker’s quality is only produced when that worker is hired. Two recent papers instead propose models where employers can observe a potential employee’s quality with any desired precision. However, employers incur in *attention costs* which are increasing in the precision of the chosen quality signal.\(^{14}\)

Bartoš, Bauer, Chytílová, and Matějka (2016) study a simple model where a candidate is considered for a job. Accepting this candidate’s application is profitable to the employer if and only if the candidate is of high-enough quality. As mentioned, this employer is *rationally inattentive*: they can learn the candidate’s quality to any degree of precision, but at some increasing

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\(^{13}\)Fershtman and Pavan (2020) use a different model to argue that “soft” affirmative actions such as the Rooney rule may backfire if the evaluation of minority candidates is noisier than that of non-minorities.

\(^{14}\)See also Cavounidis, Lang and Weinstein (2022), which proposes a screening model where firms discriminate in the acquisition or use of productivity-relevant information.
attention cost. For example, they can gather a lot of information before making a decision, by calling the candidate’s previous employers, reading their resumé carefully, and having many people interview the applicant. Alternatively, they could simply skim the provided resumé before making an, admittedly less informed, decision.

The candidate belongs to either identity $A$ or identity $B$, and identity $A$ is assumed to contain candidates that are on average more qualified than those of identity $B$. The candidate’s identity is observed by the employer before they decide how much attention to put towards screening – think of an employer seeing the candidates’ names right at the beginning of a selection process for a job. The main result in this paper argues that the employer’s rational inattention often amplifies the expected outcome differences between individuals of the two identities. More specifically, this amplification arises through different mechanisms depending on the selectivity of the hiring process.

Suppose first that the hiring process is highly selective; without observing any extra information, the employer would choose not to accept an application from either a candidate of identity $A$ or a candidate of identity $B$. The authors call this a cherry-picking market. In this case, the rationally inattentive employer optimally pays more attention to an application from a candidate of identity $A$ than one from a candidate of identity $B$. Consequently, candidates of identity $A$ who are of high-enough quality are often recognized as such, and accepted by the employer. Conversely, a candidate of identity $B$ with the same, high-enough, quality is less likely to be properly identified, and thus more often assigned the default rejection.

In other words, the optimal attention assignment implies that the probability of type-2 errors, wherein a good candidate is not hired, is lower for identity $A$ than for identity $B$. This mechanism amplifies the difference between the ex-ante hiring probability of candidates of identities $A$ and $B$, relative to the benchmark where the same attention level is paid to applications coming from both identities.

Instead consider a lemon-dropping market, where absent any extra information, the employer’s default action is to accept a candidate from both identities. The rationally inattentive employer now optimally pays more attention to applications from identity $B$ than to those coming from members of identity $A$. As a consequence, candidates of identity $B$ who are not of high-enough quality, are more likely than their identity-$A$ counterparts to be recognized and accordingly rejected. In this case, the probability of type-1 errors, wherein a bad candidate is

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15Bartoš, Bauer, Chytilová, and Matějka (2016) also conduct field experiments and find that, in various contexts, the attention decisions of potential employers and landlords are consistent with their model’s predictions.
hired, is lower for identity $B$ than for identity $A$. Once again, this mechanism is discriminatory, in that it amplifies existing differences between the two identities.

Fosgerau, Sethi, and Weibull (2021) study a similar environment with a rationally inattentive screener. They observe that the attention decision of the screener itself determines the incentives for workers of different identities to invest in acquiring skill in the first place. The codetermination of skill-choice and screening-attention imply that there are multiple equilibria – similarly to Coate and Loury (1993) – and ex ante identical categories can receive asymmetric equilibrium treatment.

Echenique and Li (2022) also propose a model where a principal rationally acquires information about the skills of agents in majority and minority groups. By rationally allocating scarce attention between the groups, the principal may create incentives for majority agents to invest in skill acquisition, and for minority agents not to do so. Interestingly, Echenique and Li (2022) show that as the attention cost decreases, the difference in skill acquisition (and payoff) between the majority and minority groups may increase; thereby highlighting that “statistical” discrimination may indeed worsen as information becomes more readily available.

In a way, the models of myopic learning algorithms (in 3.2) and the just mentioned models with costly information acquisition rely on roughly the same mechanism. In both cases, discrimination arises (and is reinforced) because it is costly to experiment with members of the ex-ante less appealing group. The main difference is that, in myopic learning models, this cost takes the form of an opportunity cost, while in the “rational inattentive” firms models, the learning cost is explicitly given by an information cost function.

3.4. Signaling in Groups. So far, Section 3 considered discriminatory mechanisms inherent to employers’ learning problems. A complementary approach is to study discrimination in models where workers signal their productivity to employers, à la Spence (1978).

In broad strokes, Spence’s (1978) model of signaling is itself a model of equilibrium discrimination. In it, workers with different productivity levels invest in some costly activity that has no inherent benefit. The cost of investing in this activity satisfies a single crossing property, meaning that investment is more costly to workers with lower productivity. In equilibrium, higher productivity workers disproportionally invest in the costly activity, which then emerges as a signal of a worker’s underlying quality. Effectively, this costly activity serves as means for an employer to discriminate between high- and low-productivity workers.

So far in our discussion, we defined discrimination as differential treatment of agents that are inherently equal. Contrastingly, the “discriminatory” equilibrium in Spence (1978), described
above, involves disparate treatment of agents that indeed have different underlying productivity. Fang’s (2001) model of signaling through a cultural activity inches closer (though not fully) to our notion of discrimination.

In Fang (2001), agents can perform some costly and unproductive cultural activity prior to investing in skill acquisition, and prior to being considered by an employer. Importantly, the cost of the cultural activity and the cost of skill acquisition are independent, in contrast with Spence’s (1978) single crossing assumption. Fang (2001) shows that, despite this independence, an equilibrium exists where individuals with low cost of skill investment disproportionately join the cultural activity. That equilibrium is “discriminatory,” in the sense that those who perform the unproductive cultural activity receive preferential treatment from employers.

More recently, Onuchic-Ray (2023) propose a signaling model where, in discriminatory equilibria, agents’ ability to signal their type is itself affected by their payoff-irrelevant identity. There is discrimination in the interpretation of costly signals: signals sent by inherently equal agents are interpreted differently, depending on the agents’ identities.

Onuchic-Ray (2023) study a model of team formation, where workers’ outputs in teams, as well as their choices to work in teams in the first place, serve as signals of their underlying productivity. In a team outcome, the joint output is a signal of the productivity of both team members. To interpret it, an observer who does not see individual contributions to that outcome must conjecture them based on team members’ identities. This identity-based interpretation creates scope for equilibrium discrimination in credit attribution.

In the model, there are two potential partners, who each have an idea for a project. The quality of a worker’s project idea is a signal of their underlying ability. Agents see their own and their prospective partner’s ideas, and choose to work together or separately, based on a combination of projects’ direct value and the reputational value. In terms of direct project value, combining individual ideas is assumed to be always preferable to solo work. More importantly, a project’s reputational value is a function of the posterior inference made by an observer about the partners’ types, after seeing either their solo or joint project outcomes.\[16\]

If agents work alone, the outside observer sees the separate project outcomes and calculates Bayesian posteriors mechanically. If instead partners combine their ideas, then the observer sees the joint project outcome, but not each individual contribution, and thus forms a conjecture about which pairs of ideas might have led partners to this collaborative outcome. That conjecture is coupled with Bayesian updating to assign posteriors to the two partners. In

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\[16\] Alluding to the partners’ career concerns, as in the literature following Holmström (1999).
equilibrium, the observer’s conjectures about individual contributions, and the partners’ collaboration strategies are codetermined, and such codetermination is the main mechanism that allows for the existence of discriminatory equilibria.

To understand, suppose that the observer conjectures that partner 1 contributes better ideas to joint projects than partner 2 does, and so, upon seeing a certain collaborative outcome, understands that more credit for that outcome should be assigned to the former than to the latter. In that case, if collaboration takes place, partner 1 receives a higher posterior than partner 2. Anticipating this credit assignment, partner 1 is indeed more willing to share good ideas with partner 2, while partner 2 is more likely to keep good ideas to themselves.

This strategic response, in turn, can justify the observer’s initial conjecture, yielding an equilibrium where partner 1 is favored in terms of credit assignment, while partner 2 is “discriminated against.” This discriminatory credit assignment is an equilibrium outcome, rather than an exogenous bias on the part of the observer – it is self-fulfilling, as in Arrow (1973).

Onuchic and Ray (2023) characterize productive environments where stable equilibria feature self-fulfilling discrimination – for example, careers where reputational outcomes are very important, relative to the direct value of projects, are relatively more susceptible to the discriminatory mechanism. An empirical prediction of their model is that an agent with the disfavored identity is more likely than a favored agent to attain a certain target posterior if that target is either very high or very low.

To see this, note that, in a discriminatory equilibrium, the disfavored agent is more inclined to keep better ideas for solo work, relative to their favored counterpart. Consequently, when they draw a very good idea, they pursue it in a solo project and attain a very high posterior, while a favored identity would pursue a collaboration and receive a more moderate posterior instead. As a converse, an agent with the favored identity is relatively more likely to attain moderate target posteriors. In this sense, the disfavored agent faces relatively riskier career prospects.

Baumann and Dutta (2022) also study a model where agents signal their types to a principal as a group. Specifically, in Baumann and Dutta (2022) there is a population of agents that are connected to each other via some given network. Each agent has an ability (either good or bad), which is drawn independently across agents from an identical distribution. Moreover, agents may have some hard evidence about their own ability type, as well as about any agents to whom they are connected through the given network. This piece of hard evidence is such that, if seen by the principal, it perfectly conveys the true ability of the agent to which it refers, as in Dye (1985). Also as in Dye (1985), there is some probability that the agent does not
have hard evidence about their own type, or about the types of the individuals to whom they are connected.

Given their evidence realization (about own-type and types of agents they are connected to), an agent chooses whether to disclose these pieces of information to the principal or not. After disclosure (or not disclosure) happens, the principal forms beliefs about all agents’ abilities and chooses one or more agents to receive a divisible prize. The principal’s payoff structure is such that they wish to allocate prizes to the agents most likely to be of the good ability type.

Baumann and Dutta (2022) main result is to characterize an equilibrium in which agents reveal evidence about themselves if and only if they are of the good type (thereby conveying such good news to the principal), and reveal evidence about people they are connected to if and only if these connections are of the bad type (thereby conveying the bad news about the connections to the principal). In this equilibrium, if the principal sees any hard evidence about an agent’s type, that type is learnt. More interestingly, if the principal sees no evidence about an agent’s type, then they form a posterior which depends on the number of connections that agent has. Specifically, if that agent has many connections and the principal observes no evidence, then it is very likely that the agent is of the good type, and therefore other individuals did not wish to convey the evidence to the principal. Conversely, if an agent has very few connections, then it is very likely that none of their connections had any evidence to disclose.

The authors highlight that this equilibrium is discriminatory, in the sense that signals about highly connected agents are interpreted more favorably than signals about less connected agents – there is discrimination in favor of high-degree agents. Baumann and Dutta (2022) also show that, despite this “ex-post” discrimination in favor of connected individuals, it may be that highly connected individuals are “ex-ante” less likely to win a prize. To see this, note that, conditional on no bad evidence being generated about them, highly connected individuals are better off than their less connected counterparts. However, the probability that no bad evidence is generated also decreases as the agent’s degree increases. Such a discrimination reversal result across the ex-ante and ex-post perspective is also highlighted in Onuchic Ray (2023): they show that agents with identities that are favored in terms of credit assignment in an equilibrium may actually receive a lower ex-ante expected payoff.
4. Discrimination with Misperceptions

A common feature of models introduced in sections 2 and 3 is that employers are assumed to hold correct beliefs.\textsuperscript{17} A nascent literature has pointed to the importance of incorporating potential agent misperceptions, or failures of rational expectations, into models of discrimination. Section 4.1 introduces models that generalize the standard Phelps (1972) and Coate and Loury (1993) models to allow for misspecified beliefs and dynamic considerations. In section 4.2, I discuss models that incorporate behavioral heuristics to interpret individual outcomes, potentially generating group-dependent interpretations.

4.1. Dynamics of Inaccurate Discrimination. Bohren, Imas and Rosenberg (2019) propose a model where a sequence of evaluators tries to learn about an agent’s underlying ability based on their reported performance on a series of tasks (reported by previous evaluators), as well as on their group identity. I now describe a simplified version of their model.\textsuperscript{18}

An agent belongs to a group $g \in \{A, B\}$ and has unobserved ability $a$, drawn from a Normal distribution, with mean potentially distinct across groups, and some group-independent precision. The agent sequentially performs two tasks (in periods 1 and 2, say), each of which generates a performance outcome equal to $a$ plus some normally distributed, mean-zero, error.

In each period, a short-lived evaluator makes a report, assessing the agent’s ability. In period 1, the first evaluator observes only the agent’s performance outcome generated by that period’s task before making their report. In period 2, the second evaluator sees period 2’s task performance, as well as the first evaluation. In making their reports, evaluators wish to precisely estimate the agent’s underlying ability.

Each of the evaluators is “mostly Bayesian” when estimating the agent’s underlying ability, with two caveats. First, they might discriminate against one of the groups because of some animus. Like in Becker’s (1957) taste-based discrimination, an evaluator may simply have a preference for underestimating the ability of a member of a certain group. In this case, they

\textsuperscript{17}With two caveats: First, Komiyama and Noda (2021) are a notable exception, modeling firms as frequentist, rather than Bayesian, learners. As discussed, firms may end up in a learning trap, where they misunderstand the relation between characteristics and productivity. Second, even in the mentioned models of Bayesian learning, it is not important that the prior belief held by the firm be correct, and certainly there would be no major implications of assuming that priors are wrong in the presented models. Rather, the more relevant assumption was that the firms’ learning processes were “correct” Bayesian learning processes. Contrastingly, we will see that in Bohren, Imas and Rosenberg (2019), agents’ misperceptions make them “inaccurate Bayesian learners.”

\textsuperscript{18}This description skips some details about the learning process. Moreover, in Bohren, Imas and Rosenberg (2019), there is a (potentially infinite) sequence of evaluators. In my brief description, I consider the case with only two tasks and two evaluations, which is enough to describe the main results.
choose to report an evaluation that is worse than their true ability estimate when the agent belongs to a group they are biased against.

The second caveat is that the evaluator may have a misspecified model of the world. There are two potential misspecifications: (i) an evaluator may hold a wrong belief about the average ability in a group; and (ii) an evaluator may be wrong about the distribution of evaluator beliefs. The second potential misspecification is relevant to the period 2 evaluator who must interpret the report made by the evaluator in period 1 before making their own assessment of the agent’s quality. The evaluation environment is described by a distribution of evaluator types – their beliefs and taste-biases.

Group \( g \in \{A, B\} \) is said to be discriminated against \textit{in period 1 after a certain performance outcome} if the average report made by period-1 evaluators after seeing the outcome for an agent in group \( g \) is smaller than the average report made after seeing that same outcome coming from an agent of the other group. This average is taken with respect to the distribution of evaluators.\(^{19}\)

Group \( g \in \{A, B\} \) is said to be discriminated against \textit{in period 2 after a given period-1 evaluation and a given period-2 performance outcome} if the average report made by period-2 evaluators after seeing this history for an agent in group \( g \) is smaller than the average report made after seeing that same history coming from an agent of the other group.

The two main theoretical results allow an analyst (an observer outside of the model) to assess the presence of discrimination, as well as its driving force – whether it is taste-based, belief-driven, but correctly specified, or driven by incorrectly specified beliefs – based on observational data. Suppose period-1 discrimination takes place against some group, say \( A \). The first result shows that, if discrimination is belief-driven, then period-1 discrimination is decreasing in the accuracy of the period-1 performance outcome. The same is not true if discrimination is taste-based.

The second result concerns the dynamics of discrimination. Suppose there is period-1 discrimination against group \( A \), and suppose it is belief-driven. If all period-2 evaluators have correctly specified models, then there cannot be any period-2 discrimination against group \( B \) – that is, there is \textit{no discrimination reversal}. If, otherwise, some (but not too many) evaluators

\(^{19}\)In the paper, the authors first define discrimination by a particular evaluator (a particular set of beliefs and taste biases), and then define \textit{average discrimination} as the expected value with respect to the distribution of evaluator types in the population. Their main results refer to average discrimination.
hold wrong beliefs and underestimate the average ability in group $A$, then there may be period-2 discrimination against group $B$. That is, the presence of some misspecified evaluators can generate *discrimination reversal* between periods 1 and 2.

To understand this result, first note that the period-1 discrimination against group $A$ is straightforwardly driven by the presence of some evaluators who underestimate group $A$’s average ability. More interestingly, the period-2 reversal happens because period-2 impartial evaluators, after seeing a period-1 report about a group-$A$ member, understand that it may have been made by a misspecified evaluator, who would have under-reported. As such, the period-2 impartial evaluator interprets a period-1 report about a group-$A$ member more favorably than if it referred to a group-$B$ member. Consequently, then the impartial period-2 evaluator will discriminate against group $B$, and if there are enough impartial period-2 evaluators, then there will be period-2 discrimination against group $B$ on average.

While these theoretical results are valuable in their own merit, a large contribution of the paper lays in using these predictions to empirically test, in a particular experimental context, whether discrimination is driven by animus, correct beliefs, or misspecified beliefs. Their online experiment is run in a platform where users post content that is evaluated by other users on the platform. They assign posts to accounts that exogenously vary by gender and evaluation histories. With no prior evaluations, women face significant discrimination. However, following a sequence of positive evaluations, the direction of discrimination reverses: women’s posts are favored over men’s. This is consistent with the discrimination reversal posited by their model of discrimination driven by misspecified beliefs.

An earlier paper, Fryer (2007), also points out that discrimination reversal may take place in a dynamic model of statistical discrimination. Fryer’s (2007) main observation is that, if at the moment of hiring, an employer discriminates against members of group $A$, then, conditional on being hired, a member of group $A$ is relatively more talented than a member of group $B$. Consequently, if the employer then wishes to pick a member of the hired group to promote, they may favor members of group $A$, who were discriminated against in the initial stage, over members of group $B$.

The mechanisms of discrimination reversal in Bohren, Imas and Rosenberg (2019) and in Fryer (2007) are related, but distinct. In Fryer’s (2007) model, the employer does not have animus towards either group, and does not hold incorrect beliefs about the distribution of talent in groups $A$ or $B$. Note that, in Bohren, Imas and Rosenberg’s (2019) context, these assumptions would rule out the possibility of discrimination reversal.  

\[20\] As in equation (1) in Phelps’ (1972) model discussed in section 2.
The main extra ingredient in Fryer’s (2007) model is that, at each stage, workers can invest in their productivity – it is useful to think of Fryer’s (2007) model as a repeated version of Coate and Loury’s (1993) model, described in section 2.3. In the first stage, discrimination against group A is a self-fulfilling equilibrium, where group A members invest less in acquiring skills. But, conditional on a person A being hired, the employer expects that they are more likely to have a low cost of skill acquisition, and thus expects that they will acquire further skill in the second stage, before a promotion decision. As such, a group-A worker indeed has greater incentives to make a second-stage skill investment, and is thus relatively favored by the employer.

In both models, the discrimination reversal can be understood by an informal speech made by the evaluator/employer in the second stage: “stage 1 is really hard for group-A members, and so, conditional on having made through it, a group-A member must be exceptional.” But in Bohren, Imas and Rosenberg (2019) the motivation for this speech is that the impartial evaluator knows that there are partial evaluators out there. Rather, in Fryer (2007), the employer understands that being hired is a stronger sign of low investment costs for members of group A then for members of group B.

Another theme introduced by Bohren, Imas and Rosenberg (2019) is the question of how to identify discrimination, and its motivations, from observational data. This theme is further explored in Bohren, Haggag, Imas and Pope (2022). They argue that, with observational data from a single period, traditional tests for taste-based discrimination may not be able to distinguish between taste-based and statistical discrimination stemming from inaccurate beliefs.21

4.2. Stereotypes and Other Heuristics. Phelps’ (1972) model of discrimination clearly illustrates how misperceptions about the distribution of productivity types in a population may lead an observer to discriminate against members of a certain identity – think of equation (1). Further, Bohren, Imas and Rosenberg’s (2019) model clarifies dynamic implications of inaccurate beliefs.

Bordalo, Coffman, Gennaioli and Shleifer (2016) propose a model of stereotypes based on a representativeness heuristic,22 which describes an individual belief-formation process that

21The problem of measuring discriminatory behavior is tackled by an extensive theoretical and empirical literature. I comment briefly on that literature in section 7.
22Due to Kahneman and Tversky (1972), Tversky and Kahneman (1983).
may lead to inaccurate beliefs. This representativeness heuristic anchors itself on salient identity traits, such as gender or racial identity, and may thus be useful for understanding belief differences attributed to these different groups.

Take two groups $g \in \{A, B\}$, and evaluate the distribution of certain traits $t \in T$ in each group: let $\pi_g(t)$ be the probability that trait $t$ is present in group $g$. It is useful to think of the traits in set $T$ as mutually exclusive, such that each member of group $g$ has exactly one of the traits – for example, $t$ could be a number of schooling years, and $T$ the set of possible schooling years. Bordalo, Coffman, Gennaioli and Shleifer (2016) define the representativeness of trait $t$ in group $g$ to be

$$R(t, g) = \frac{\pi_g(t)}{\pi_{\neg g}(t)},$$

where $\neg g$ is the group that is not $g$. They posit that, while people understand the distributions $\pi_A$ and $\pi_B$, these are not the distributions that are salient to them when making assessments about groups $A$ and $B$. Rather, they use other, “stereotyped,” distributions $\pi_{st,A}$ and $\pi_{st,B}$, which overweight in the traits that are representative or groups $A$ and $B$, respectively – as measured by their representativeness given by equation (3).

Bordalo, Coffman, Gennaioli and Shleifer’s (2016) main results assess how small differences in trait distributions across groups can be exacerbated by the stereotyping heuristic. It is important to note that, while the behavioral economics literature has recently proposed models of a variety of belief-formation heuristics, this stereotyping behavior is particularly relevant to questions of discrimination, because it is based on the perceived distinction between groups $A$ and $B$ in the first place.

Recently, Esponda, Oprea and Yuksel (2023) propose a model where decision-makers employ the same representativeness heuristics not to the prior type distributions in populations $A$ and $B$, but rather to new information they learn about agents in these populations. They introduce a novel cognitive bias denoted “contrast-biased evaluation,” whereby agents misinterpret new information about an agent to be more representative of the agent’s group, in contrast to a reference group. The authors show in an experimental setting that this cognitive bias disappears when subjects either receive information before learning of the individual’s group or are prevented from contrasting different groups.

They also provide experimental and observational evidence that this heuristic is a good approximation for people’s belief formation processes. Bordalo, Coffman, Gennaioli and Shleifer’s (2019) specifically assesses the stereotyped belief formation process across genders – both by members of different gender groups, and across members of different gender groups.
Heidhues, Köszegi and Strack (2019) also propose a behavioral model of interpretation of individual outcomes, where group differences are sparked by the observer’s consideration that it is possible that individuals’ outcomes are affected by group-level discrimination. Again, discrimination is provoked by there being some perceived distinction between identity groups in the first place.

In their model, society is comprised of $K$ potentially overlapping groups, and each agent is either a member, a competitor, or a neutral outsider of a group. An agent observes the “recognition outcomes” of all members of society, including their own (for example, people’s achievements or social statuses). These outcomes are a result of each person’s underlying ability type, but also some noise. Moreover, the agent posits that there may be some discrimination in place, benefiting members of a group, and hurting the competitor groups.

The agent’s objective is to learn the true discrimination pattern in society based on his observations (the agent is a Bayesian learner). The one crucial behavioral assumption in the model is that the agent is “stubbornly overconfident:” they hold a point belief about their own ability, which is above the correct one. The authors show that adding this one behavioral element to an otherwise “standard” model generates a series of empirically verified patterns in social beliefs.

The first implication of the agent’s biased learning process is that, in the long-run (after gathering a lot of data on recognition outcomes), they overestimate societal discrimination against any group they are a member of, and underestimate it against any group they are in competition with. This conclusion is reached as an explanation for their own recognition outcomes, which fall short of their overconfident expectations – the stubbornness of the agent’s overconfidence implies that they update their beliefs about discrimination patterns, rather than review their beliefs about their own underlying ability.

An almost immediate implication of this first result is that the agent holds favorable views about the ability of people that belong to the same groups as their own, relative to their recognition outcomes. A converse to this “in-group bias” is that the agent holds overly unfavorable views about the ability of people in competing groups.

A more subtle result is that the agent’s pattern of biases derives not only from their overconfidence, but also from his thinking about society as divided into groups in the first place.24 To illustrate this point, Heidhues, Köszegi and Strack (2019) consider an example where there is no discrimination in society. First, they assume that the agent conceives of society as not being divided into groups, so that $K = 0$. In that case, in the long run, the agent develops unbiased

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24This statement is also true of Bordalo, Coffman, Gennaioli and Shleifer’s (2016) model.
beliefs about everyone. If conversely, they think of society as divided in \( K > 0 \) groups, then, despite there being no true discrimination, the agent concludes that groups are being treated differently, and develops in-group biases.

Like Heidhues, Köszegi and Strack (2019), Siniscalchi and Veronesi (2021) propose a model where discrimination is a consequence of agents having a self-image bias – more specifically, Siniscalchi and Veronesi (2021) propose a model that explains the dynamics of discrimination and representation within a profession, based on a self-image behavioral bias.

Siniscalchi and Veronesi’s (2021) model is applied to the academic profession: there is an overlapping-generations environment where established researchers evaluate new researchers. Each researcher – new or established – belongs to one of two groups, say \( A \) and \( B \), and their group membership is not payoff relevant in itself. Beyond their group membership, researchers are also heterogeneous with respect to the set of characteristics they are endowed with – for example, whether they are theoretical or empirical researchers, or whether they are interested in macro- or micro-economic questions. The distribution of characteristics differs across groups, but importantly all characteristics have the same positive effect on the likelihood of high-quality research, so that both groups are “equally qualified.”

In each period, each new researcher produces research of some quality that depends stochastically on their own underlying characteristics. The research quality is then perfectly observed by one member of the established generation (the referee), who decides whether or not to accept the young researcher as a member of the established population. This is where the self-image bias comes in: each referee, in deciding whether to accept the young researcher, cares not only about their research quality, but also about whether the young researcher’s characteristics match their own (but beyond the quality-relevant characteristics, the evaluation does not depend on group membership). Accepted researchers become established in the next period, and thus referees of future cohorts, and researchers who are rejected leave the model.

In that environment, Siniscalchi and Veronesi’s (2021) study the dynamics of the population of academics. Their main observation is that, in the presence of self-image bias, even mild between-group heterogeneity generates a persistent bias in favor of young researchers who belong to the initially larger group (say, group \( A \)). Beyond that, even though there are successful group-\( B \) researchers, they are more likely to be those whose characteristics are close to the ones more prevalent in group \( A \). An interesting implication is that the pro-group-\( A \) bias is in fact perpetrated even by established group \( B \) researchers, because these successful \( B \) researchers were endogenously selected to be “closer” to common group-\( A \) characteristics.
Finally, Hübert and Little (2023) propose a theory of “discrimination in policing,” stemming from a learning heuristic they denote non-conditioning bias – akin to correlation neglect, as in Ortoleva and Snowberg (2015) and Levy and Razin (2015). In Hübert and Little (2023), a police department must decide how to allocate policing resources between different communities. To do so efficiently, they must form beliefs about the amount of crime to be expected in these different locations. When forming these beliefs, the officers “misinterpret” crime statistics: they do not properly account for the fact that they will detect more crime in more heavily policed communities. This creates a feedback loop, whereby communities that are over-policed generate crime statistics that are then “misinterpreted,” justifying the initial decision to over-police them.

5. Discriminatory Social Norms

Small and Pager (2020) recognize that research in economics – both empirical and theoretical – has traditionally adopted either the taste-based or the statistical discrimination perspectives, focusing substantially on assessing which approach is a more appropriate description of discrimination as a sociological phenomenon. They go on to criticize this economic research agenda, arguing that it misses “what sociologists and others have called ‘institutional discrimination,’ ‘structural discrimination,’ and ‘institutional racism,’ which are all terms used to refer to the idea that something other than individuals may discriminate by race.” In their essay, they define “institutional discrimination” as “differential treatment that may be caused by organizational rules or by people following the law,” and say that it need not result from personal prejudice or from rational guesses on the basis of group characteristics.

The contributions reviewed in sections 2, 3, and 4 are all either rooted on personal prejudices or based on rationally (or irrationally) biased beliefs. In contrast, sections 5 and 6 review theories that do not rely on either of those two traditional pillars. I refer to these theories as broadly relying on “discriminatory institutions,” alluding to institutional discrimination, as defined in Small and Pager (2020). Specifically, in the current section, I review models of informal discriminatory institutions, enforced by societal norms.

5.1. Social Norms as Institutions. According to Young (2015),

25 Despite the allusion to “institutional discrimination” and to Small and Pager’s (2020) critique, I by no means believe the economic theories in sections 5 and 6 to fully describe the sociological perspective. Rather, they are some notable examples of economic theories of discrimination that come closer to that approach.
Social norms are patterns of behavior that are self-enforcing within a group: Everyone conforms, everyone is expected to conform, and everyone wants to conform when they expect everyone else to conform. Social norms are often sustained by multiple mechanisms, including a desire to coordinate, fear of being sanctioned, signaling membership in a group, or simply following the lead of others.

The first class of models I consider (section 5.2) are roughly embedded in Kandori’s (1992) environment, and view discrimination as a social norm enforced in communities. Section 5.3 describes an evolutionary game theory approach to social norms, and comments on the stability of discriminatory norms. Both approaches conform with Young’s (2015) view that a discriminatory social norm is sustained by a society’s desire to coordinate, and by society members’ fear of being sanctioned.

It is worth noting that models of equilibrium statistical discrimination, following Arrow (1973), also rely on a coordination mechanism – think of Coate and Loury’s (1993) theory, where populations of different identities coordinate on different, Pareto-ranked, equilibria. In contrast to models of equilibrium statistical discrimination, the models of discriminatory social norms rely only on coordination, that is, discrimination is not supported by beliefs about agents’ underlying ability types.

In section 5.4, I briefly comment on a literature stemming from Akerlof and Kranton (2000), which proposes that group-dependent behavior stems from people’s desire to conform with socially-determined identity-norms.

5.2. Community Enforcement of Discrimination. Pęski and Szentes (2013) study a dynamic economy where a continuum of agents repeatedly and randomly match in pairs, and each pair has the opportunity to form a (short-term) profitable partnership. In every bilateral interaction, one agent is randomly picked to be the employer, and the other is the worker. The employer decides whether or not to employ the worker (form a partnership). If a partnership is formed, it is profitable to both parties, and both parties receive zero payoff otherwise.

Each agent has an unchanging characteristic, their physical color, which can be black or white. Before an agent decides whether to partner up or not, they observe the physical color of their potential partner, and also an additional piece of information, which conveys information about the past partners of this potential match. This additional information is a binary signal,

\[26\text{Kandori’s (1992) model of community-enforced social norms is not the only economic approach to modeling social norms. For other seminal contributions, see for example Young (1993) and Bernheim (1994).}\]
referred to as the agent’s *social* color, and it can also be either black or white. Importantly, unlike their physical color, an agent’s social color is not fixed, and can change on the path of play (or, more importantly, off the path of play). Specifically, if an agent enters a partnership, then their social color may switch to either the physical or the social color of his partner.

In this setup, if forming a partnership were a one-time decision, then all agents would always choose to enter these relationships. However, in the dynamic context, their desire to form partnerships may be affected by how the agents expect their partnership history to influence their future partnership opportunities. Because an agents’ social color is an (imperfect) signal of their partnership history, this information may be conveyed to future matches, who may react (positively or negatively) to it.

The main result of Pęski and Szentes (2013) is that, under some conditions, there exist equilibria that involve discrimination. In discriminatory equilibria, agents refuse to form relations with potential partners of social or physical color that does not match their own. For instance, a white employer may not propose a (profitable) partnership to a black worker because he fears that, if he did so, they might be refused employment by other white workers in the future. Indeed, these fears may be well-founded in equilibrium.

To see this, suppose that the *equilibrium social norm* is such that white employers are expected to discriminate against black workers, by not proposing partnerships to any agent of either black physical color or black social color, and vice-versa (black employers are expected to discriminate against white workers). This social norm can be sustained in equilibrium. Remember that the social color of a white worker can turn to black even if he employs a white agent with black social color. Consequently, if the white employer understands the social norm, they expect to be punished after employing the black worker. The technology of the changing social color makes it possible to punish not only those who discriminate, but also those who fail to punish non-discriminators.

It is worth noting once more that, in this context, discriminatory equilibria are *not* supported by differences (or perceived differences) in the underlying ability of members of different

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27There are three possible types of discriminatory equilibria. The first involves full segregation, and members of both colors symmetrically discriminate against each other. The other two types are asymmetric discriminatory equilibria, where one color strongly discriminates against the other, while members of this disfavored color at most weakly discriminate.

28Pęski and Szentes (2013) argue that this discriminatory mechanism is more than a theoretical possibility in the following quote: “Are there social institutions with similar features? The Indian caste system, for example, prescribes several rules which prohibit certain kinds of relationships between members of different castes (see Pruthi 2004). These rules are often enforced using the idea of pollution. Some castes are considered inherently polluted. A person who accepts a favour or food from a polluted person becomes polluted himself. That is, pollution is treated as something contagious which can only be cured by performing costly rituals.”
color-groups. In fact, from a payoff perspective, all workers are identical, both ex-ante and ex-post. Instead, agents act discriminatorily because it is the social norm to discriminate; and the social norm is upheld by agents’ fears of being punished for not conforming.

Eeckhout (2006) also proposes a model in which discrimination and segregation are social norms that arise, despite agents being homogeneous in their payoff-relevant characteristics. He studies a dynamic market where agents bilaterally and randomly match and have the opportunity to form “marriages,” which are potentially long term partnerships. Upon meeting, two agents play a partnership game modeled as a potentially repeated Prisoner’s Dilemma. After any transaction, each partner can choose either to remain matched or to terminate the partnership and randomly match with a new agent.

In each period within a partnership, agents weigh a trade-off between defecting, which is myopically valuable, and their cooperative continuation payoff. An agent can always defect and then go back to the matching market in search for a new partnership. This mechanism makes full cooperation, which is efficient, impossible to attain in equilibrium. Eeckhout (2006) shows that equilibria often involve incubation strategies, where the norm is for partnerships to be started “cautiously,” with an initial phase of defection, followed by cooperation. This initial trial period makes equilibrium deviation costly, because if an agent returns to the matching market, then they will need to start a new relationship and go through the “caution” period once more. This initial costly phase is the deviation punishment that allows cooperation to be sustained in later phases of a long-term partnership.29

Beyond the “trial phase,” Eeckhout (2006) shows that discriminatory norms can also help support cooperation and, as such, may be welfare enhancing.30 If agents coordinate on not forming partnerships with members of a different color-group, then mixed matches lead to no cooperative value. But, due to random matching, these mixed matches still occur in equilibrium, and so segregation decreases the deviation value of cheating on a current partner and returning to the matching market. As such, the within-color matches can become more cooperative. Eeckhout (2006) shows that such segregating equilibria can attain higher welfare than corresponding color-blind equilibria.

29Eeckhout (2006) is not the first paper to observe that “trial phases” in long-term relationships help sustain later cooperative phases. The idea that gradual trust-building has a beneficial effect on discipling long-term cooperation was already present in Datta (1996), Ghosh and Ray (1996), Kranton (1996), Watson (1999) and Lindsay, Polak and Zeckhauser (2000). Eeckhout’s (2006) main contribution lays in showing that, beyond the trust-building phase, discriminatory norms can also help support cooperation.
30In another context, Onuchic (2022) also considers welfare properties of asymmetric equilibria with social norms based on agents’ “labels.”
Choy (2018) is a more recent paper that also proposes a socially enforced reputation model of group-segregation. As in Eeckhout (2006), segregation acts in equilibrium as a coordinating device that is welfare enhancing. However, Choy’s (2018) proposed equilibrium structure features a series of hierarchically ranked groups, with higher ranking groups refusing to interact with lower ranking groups but not vice versa.

Bramoullé and Goyal (2016) also study a repeated partnership-formation game in which agents belong to different identity groups. In their model, a principal always wishes to form partnerships with high-quality agents (experts), and have no inherent preferences for forming partnerships with members of their own identity. Bramoullé and Goyal (2016) study the circumstances under which it may be beneficial for an identity-group as a whole to only form within-group partnerships, even if that means passing on experts belonging to another group. They call this in-group favoritism, and argue that favoritism is a mechanism for surplus diversion away from the society at large and toward the group. They show that, depending on economic frictions in the game, it may be beneficial for groups to favor their own members, even if that is detrimental for the economy as a whole.

Note that in both Peški and Szentes (2013) and in Eeckhout (2006), discrimination and segregation is supported by equilibrium punishment strategies according which individuals perceive that the cost of “cheating” or “not collaborate” with others depends on their identities. Similarly, Harbaugh and To (2014) propose that opportunistic discrimination arises when firms perceive that they are less harshly punished for opportunistic behavior against individuals belonging to a minority identity, compared to individuals belonging to a majority identity. In their model, a firm repeatedly interacts with individuals belonging to a population of (majority identified and minority identified) agents. In each stage interaction, the firm may choose to cheat or not cheat on the individual with whom they are interacting. Harbaugh and To (2014) characterize parameter regions under which discriminatory equilibria exist in which the firm’s opportunistic behavior against minority (majority) agents is only punished in future interactions with other minority (majority) agents. Consequently, the firm is willing to cheat on minority agents precisely because there are less of them, and therefore as a group they impose punishment only on occasional interactions. Conversely, the firm is not willing to cheat on majority agents, as the company foresees frequent future interactions with other members of that group (and therefore frequent punishment). The prediction that smaller groups —

31 Both Eeckhout (2006) and Choy (2018) note that the coordination based on individual identities could be mimicked by other public randomization devices that are not related to social identity. As a retort, Eeckhout (2006) remarks: “...while exogenous public randomization devices may be common, for example, in the case of traffic lights, they are far less common in other environments with decentralized social interaction. Here, the point is precisely that a randomization device is being used and that the one used is readily available from the composition of the population.”
precisely by virtue of being smaller — are more susceptible to discrimination distinguishes Harbaugh and To’s (2014) model from other work in this section.

All models mentioned in this section show that agents’ identity-labels can be used as coordination devices in discriminatory equilibria. As such, they show that otherwise payoff-irrelevant labels endogenously acquire payoff value, in the context of equilibria with discriminatory social norms. With similar mechanisms in mind, Mailath and Postlewaite (2006) introduce the notion of a *social asset*, an attribute that has value *only* because of the social institutions governing society.

Mailath and Postlewaite (2006) study a matching model, where men and women pair up, consume, and have children. Each person cares about their own consumption, as well as their future kid’s consumption. People differ in terms of their wealth – which is inherently valuable because couples consume jointly – as well as in terms of a heritable attribute that is independent of income and does not directly enter people’s utility functions (say, blue eyes).

There are equilibria where this payoff-irrelevant attribute is ignored, and people match only based on their wealth. However, suppose that in this society people with blue eyes are considered more desirable mates – that is, people are willing to trade a high-wealth mate for a slightly less wealthy one, but with blue eyes. In that case, people would prefer to have kids with blue eyes, because they will be more successful in the matching market, when their time comes. But if people prefer to have kids with blue eyes, and blue eyes are a heritable attribute, then they necessarily prefer to find a partner with blue eyes. Consequently, people’s preferences for blue eyes may be self-fulfilling. In that case, Mailath and Postlewaite (2006) say that blue eyes are a *socially valuable asset*, despite them not being *intrinsically* desirable.

5.3. *Evolutionarily Stable Social Norms*. There is a literature on *evolutionary game theory* — Foster and Young (1990) and Young (1993) are early contributions — which sees social norms as self-reinforcing patterns of behavior which emerge spontaneously from the decentralized interactions of many individuals that cumulate over time into a set of social expectations. Models in this literature normally pose that agents in a population match with each other over time to repeatedly play some game. When called to play, an agent forms expectations about how their opponent will play based on their own previous interactions (about which they have limited memory). With high probability, each agent then chooses their optimal action based on this prior knowledge; and with some small probability, agents randomize their actions —

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32In a recent related contribution, Dewan and Wolton (2022) analyze the distributional effects of labor market segregation. In particular, they establish conditions under which a plurality of the citizenry demands the implementation of segregating policies, anticipating their labor market consequences.
this random component is likened to natural variation in other evolutionary processes. Typical analyses then use stochastic dynamical systems theory to compute the distribution of long run “equilibria,” so as to characterize evolutionarily stable behavior.

Axtell, Epstein, and Young (2001) study an evolutionary model of bargaining in which the interacting agents may be labelled with different identity tags. These identities do not affect their payoffs in the stage game, but are remembered by agents when they choose their actions to best responses to interactions they’ve had in the past. In this bargaining environment, the authors show that long-run evolutionarily stable behavior involves an equity norm, in which property is shared equally among claimants, and there are no “class” distinctions based on individuals’ identities. However, they argue that “metastable” norms may comprise discriminatory and inequitable regimes. Under such discriminatory norms, claimants get different amounts based on observable characteristics that have become socially salient (but are fundamentally irrelevant). Computationally, the authors estimate the time it takes to exit from these discriminatory regimes as a function of the number of agents, the length of agents’ memory, and the level of background noise. And indeed, they show that the waiting time increases exponentially in memory length and the number of agents, and can be immense even for relatively modest values of these parameters.

5.4. Identity as a Social Norm. In “Economics and Identity” (QJE, 2000), Akerlof and Kranton consider how identity, a person’s sense of self, affects economic outcomes. They consider an economic environment where each person starts out with a “social identity” – for example, their gender. They posit that each social identity is associated with a class of prescribed behaviors, which specify how members of each social identity group are expected to act. Finally, in their model, they propose that in choosing how to behave, each member of a society cares not only about some direct payoff they get from a behavior, but also about whether that behavior “conforms” with the prescription for their own identities. Specifically, every agent dislikes (at least to some extent) acting in ways that do not conform with behaviors prescribed to their own underlying identity.34

Naturally, in a model where agents have an underlying preference for conforming with their (gender) identity, two agents who differ only in their identity-memberships may choose to behave differently. Akerlof and Kranton (2010) observe, amongst other applications, that

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33See also Weisbuch (2018) which revisits Axtell, Epstein, and Young’s (2001) model with a more elaborate model of agent cognition.

34Relatedly, Akerlof and Rayo (2020) and Akerlof, Matouschek and Rayo (2020) propose models in which economic agents care about the narrative that is conveyed by their actions. In wishing to convey proper “family stories,” Akerlof and Rayo (2020) show that women and men may conform with traditional gender narratives.
gender discrimination in the workplace, may be attributed to people’s desire to conform with their gender identities. They observe that many jobs are socially gendered; they entail tasks that seen as either “appropriate for men” or “appropriate for women.” In their model, women will dominate jobs whose requirements match construed female attributes, while men eschew them; and vice-versa.

In a later paper, Kranton (2016) refers to some criticism her work (with Akerlof) received when it came out:

> When this work was first presented, critics, friendly and otherwise, posed a challenging question, which went something like this: ‘You argue that social difference and norms should be in utility, but where do these divisions and norms come from? And how can they ever be empirically identified?’

She argues that, in the elapsed time, some new work in economics started to tackle those precise questions by proposing models of the evolution of identities as social norms. These are evolutionary models, where, in the short run, agents take norms and social categories as given and choose their behavior in order to maximize their utility (including their identity-related utility). But in the long term these (myopically) chosen actions themselves determine the evolution of the identity norms and social categories.

For example, Carvalho and Pradelski (2022) model the evolution of identity-specific norms based on groups’ representation in different activities. Similarly, Akerlof and Rayo (2020) assume that activities are more identity-appropriate when more members of the identity group engage in them. Using a different approach, Akerlof (2017) proposes a model of “identity-formation” where agents choose how much effort to dedicate to two different activities, as well as their values over the two activities. In social interactions, agents derive value from self-esteem – how much they excel at activities they value – and peer-esteem – how much they excel at activities valued by their chosen peers. Akerlof (2017) applies this model to study people’s choices to conform or differentiate from their peer groups.

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35 The fact that people’s labor supply choices are affected by their desire to conform to their social identities is empirically well documented. For example, Oh (2021) documents in a field experiment in India that “workers are less willing to accept offers that are linked to castes other than their own, especially when those castes rank lower in the social hierarchy.”

36 For other approaches to modeling the evolution of identity-specific norms, see references in Kranton (2016).
6. Discriminatory Institutional Design

The papers in section 5 illustrate one way of thinking about “institutional discrimination,” where the institutions are social norms that people follow simply because they are the norm, and breaking a social norm may be associated to some future punishment. These discriminatory norms at times reduce overall social welfare, inducing people to coordinate on “bad” equilibria. But disparate treatment across “equal” agents can also be welfare-enhancing (though not necessarily fair), for example in Eeckhout’s (2006) model of long-term partnerships.

In this section, we take the perspective of a mechanism designer (a manager, or a regulator, for example), who wishes to set rules that guide people’s behavior in an institution with the goal of maximizing some objective, be it some notion of welfare, or profit. The papers reviewed here show that, in different contexts, asymmetric mechanisms can be optimal because they improve the overall incentives when agents have hidden actions – for example, choose to engage in criminal activity or exert effort at their job. Further, they also demonstrate that asymmetric mechanisms can also be used to coordinate the actions of multiple agents within an organization.

Before starting, I want to make a strong cautionary remark about how these papers should be read. All of them find that, for one reason or another, it may be gainful for a mechanism designer to use mechanisms that treat “effectively-equal” agents differently. In other words, these papers delineate situations and motives such that one should (or would like to) discriminate. But what these papers do not say is which groups should be discriminated against, or how each agent should be allocated across the “better”- or “worse”-treated groups.

Indeed, in all of the delineated models, the designer would be equally happy assigning differential treatment based on observable, but payoff-irrelevant, characteristics of the agents (such as their race or gender, for example) or simply randomly assigning treatment across the agents (keeping the same distribution of treatments). So, while this literature does teach us that unequal treatment may be effective at providing agents with incentives, or at coordinating their actions, it absolutely does not justify unequal treatment based on specific identity traits.37

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37This discussion relates to a broader open question in the literature: even if we have models that “explain” discriminatory behavior, most (or all) of them have little to say about which particular identity groups “should” or would end up being discriminated against. A related point was made earlier in this survey, when I mentioned in Bordalo, Coffman, Gennaioli and Shleifer’s (2016) and in Heidhues, Köszegi and Strack (2019) that discrimination sprouts from there being some initial perceived distinction between identity groups in the first place. Neither of those models (nor other models mentioned in this survey) provide an explanation as to what makes these particular identity groups salient from the get-go.
These papers are part of a more extensive literature on mechanism design that discusses the optimality of asymmetric mechanisms. I remain agnostic as to whether these discriminatory mechanisms speak to the “sociological” question of discrimination, and choose to discuss only a few, more immediately relevant, contributions.

6.1. Discrimination in Crime Deterrence. Eeckhout, Persico and Todd (2010) study a problem of crime deterrence, and argue that treating observably equal agents asymmetrically, with different police-monitoring intensities, can increase the police’s effectiveness at deterring crime. To explain the mechanics of this result, they introduce an example:

Consider a population of 100 citizens, half of whom would never commit a crime, and half of whom would commit a crime unless they are certain that they will be caught. A citizen’s propensity to commit a crime is unobservable to the police. The police resources are such that they can check only 50 citizens. Suppose that the police check citizens at random (note that all citizens look the same to police), so that each citizen has a probability $\frac{1}{2}$ of being checked. Then, only the high propensity citizens will commit a crime, giving rise to a crime rate of $\frac{1}{2}$. Suppose now that half of the citizens have blue eyes, half have brown eyes and that eye color is known to be independent of the propensity to commit a crime. Nevertheless, suppose that police crack down on brown eyed citizens and check them all and completely ignore the blue eyed citizens. Then no brown eyed ever commits a crime because they are sure that they would be caught, and only those blue eyed citizens commit a crime who have high criminal propensity. Thus, the crime rate with a crackdown on brown eyed persons is $\frac{1}{4}$, which is lower than the crime rate of $\frac{1}{2}$ obtained without crackdowns.

This example shows that, given a resource constraint that requires the police to monitor only half the citizens, then a higher deterrence rate can be achieved by (committing to) concentrating all the police resources on only half of the citizens, and letting the other half be free of any monitoring. This result would be more trivial if the police were able to concentrate their efforts only on citizens they know to be more likely to commit crime, but Eeckhout, Persico and Todd’s (2010) example shows that, even if people’s propensity to commit crime is unobservable to the police, “crackdown” deterrence can be more effective.
To study the problem of designing crackdowns more generally, Eeckhout, Persico and Todd (2010) introduce a model where a continuum of agents have heterogeneous criminal propensities, described by a distribution $F$ of agents’ benefits from committing crime. An agent’s benefit from crime is unobservable to the police. The police has some limited capacity to monitor the population, and chooses how to distribute monitoring intensities across all these observably homogeneous (but effectively heterogeneous) agents.

Their main result states that the optimal policy falls in one of two categories: either (i) all the monitoring capacity is spread evenly across the population; or (ii) the population is divided into at most two groups, which are monitored with different intensities. Further propositions relate the underlying distribution of criminal propensity, $F$, to optimal police monitoring strategies, showing that case (ii) often holds, so that asymmetric monitoring is effective.

Notice that the effectiveness of asymmetric monitoring relies on the assumption that the police commits to their monitoring strategy. Take the example introduced above, and note that when the police commits to monitoring only the brown-eyed population, then it is affecting both brown- and blue-eyed people’s incentives to commit a crime. In fact, it is transferring some cost of committing crime from the blue-eyed group to the brown-eyed group. In the example, the increase in crime cost for the latter was enough to compensate the reduction in crime cost for the former. More generally, the shape of the criminal propensity distribution $F$ determines which way this trade-off is resolved.

Note further that, in order to maximize the probability of catching any crime that is committed, the police would ex-post like to deviate from the optimal crackdown policy. Even in the example, the police knows that the brown-eyed people expect to be monitored and thus do not commit crime. Consequently, in the absence of commitment, they would deviate and instead monitor only the blue-eyed population.

While Eeckhout, Persico and Todd (2010) provides a sharp characterization of the optimal monitoring strategy, it does not prescribe which individual characteristics the police should use when defining the crackdown and the non-crackdown groups. In the model, it is important that both the police, as well as the agents, are able to tell the crackdown agents apart – in the example, the eye color is the coordinating device. However, any means of dividing the population into two equal subgroups would have led to the same crime deterrence outcome.

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38Persico (2002) studies a version of the monitoring problem without the commitment assumption. In that case, almost a reverse result to the one in Eeckhout, Persico and Todd (2010) holds. Persico (2002) finds that, even if two subgroups of the population have different propensities to commit crime, it can be efficient to force the police to monitor both groups with the same intensity.

39Lee, Pai and Vohra (2021) study the how this commitment assumption should be incorporated into the measurement of discrimination.
6.2. Biased Contests and Other Asymmetric Mechanisms. In the deterrence context, differential monitoring can help reduce total crime by reallocating incentives to commit crimes between groups. Similarly, there are other contexts in which incentives can be reallocated between groups in a manner that improves the principal’s outcome of interest. For example, many economic prizes, such as promotions or bonuses, are allocated via contests. In a seminal contribution, Meyer (1991) considers the problem of a contest designer who wishes to allocate a promotion to one of two workers. The designer observes the workers’ relative outcomes in multiple rounds of a contest, where their outcomes are positively related to their underlying abilities – the designer is boundedly rational, in that they can only observe the workers’ ranks.

The main question Meyer (1991) asks is whether the designer would benefit, in terms of improving the probability of promoting the better worker, from biasing the contest (say, by giving a “head start” to one of the two workers). She first shows that the designer always benefits from biasing later rounds of the contest in favor of the winner of earlier rounds, reinforcing the likely ability advantage of the “leader.” At that point, the beneficial “discrimination” is simply an exacerbation of already existing differences between the two workers, rather than an unequal treatment of two equal workers. However, Meyer (1991) also shows some conditions under which the designer would like to bias the contest even at the initial round, where the two workers are still symmetric from the designer’s perspective.

Kawamura and Moreno de Barreda (2014) show that in contests with strategic agents – workers are non-strategic in Meyer (1991) – it is also in the contest-designer’s interest to create bias, improving one agent’s success probabilities at the expense of others’. Drugov and Ryvkin (2017) show that the designer often benefits from biasing contests even if their objective is not to improve the probability of promoting the better worker, but rather to maximize aggregate effort, or the winner’s effort. Deng, Fang, Fu, Wu (2023) highlight information disclosure as a separately valuable tool in biasing optimal contests. They show that, if the principal wishes to maximize the contest winner’s effort, then the optimal contest is biased in two separate, and opposing, ways: it preferentially informs one of the competitors about the value of the contest’s prize, and favors the other competitor in terms of the contest’s scoring rule. Mealem and Nitzan (2016) survey the literature on biased contests, and relate the optimality of asymmetric contests to the optimality of asymmetric mechanisms in auction contexts.

Winter (2004) also argues that discriminating across “equal” workers, by offering them different contracts, can be an effective way to incentivize effort within an organization. The mechanism in play in Winter’s (2004) model differs from all those in the papers mentioned above. He proposes a model of an organization where the success of a project success relies on the contribution of multiple workers whose tasks are complementary. Workers are rewarded
based on overall project outcomes, and may be reluctant to do their share unless they expect that others will as well. Winter (2004) shows that discriminatory incentive design can be an effective tool to manage workers’ expectations and facilitate coordination.

Athey, Avery and Zemsky (2000) study a model where a firm designs career paths for its employees. The firm is an overlapping generations environment, where the “diversity” among older-generation workers affects the career prospects of younger-generation workers through mentoring. In each period, there is a new population of entry-level workers, characterized by their ability and their group membership. There are two groups, $A$ and $B$, and half of the entry-level workers belongs to each group.\footnote{In a recent paper, Muller-Itten and Öry (2022) extend Athey, Avery and Zemsky (2000) to account for differential group sizes, examining steady-state outcomes and policy under majority bias.} Additionally, the agents’ abilities are equally distributed in the two groups. There are also agents in upper-level positions, whose group-memberships are not necessarily evenly split. We say that the majority group is the one that has most of the upper-level positions; the other group constitutes the minority.

Entry-level employees augment their initial ability by acquiring specific human capital in mentoring interactions with upper-level employees. Importantly, an entry-level employee acquires more human capital from mentoring when the firm has more upper-level employees who match her type.

Athey, Avery and Zemsky (2000) consider the problem of the firm who decides a rule to promote employees from entry-level positions to upper-level positions. Any entry-level employee who is not promoted exits the model, and the entry-level positions are replenished with a new cohort. Similarly, all upper-level employees leave the model at the end of each period, and are substituted by promoted entry-level workers. The firm’s promotion decisions may depend on employees’ abilities and acquired human capital, as well as their group memberships.

The firm’s optimal promotion rule balances two forces. On the one hand, the firm’s myopic optimal decision is to promote the most productive agents, accounting for both their inherent abilities and human capital acquired through mentoring. In this respect, the firm is more likely to promote majority workers, who receive more mentoring. On the other hand, the firm has a forward-looking goal to promote agents so as to achieve a desired level of upper-level diversity in the long run. At least some level of diversity is desirable, because the firm wishes to have minority workers with high inherent ability receive good mentoring.

The paper has two types of results. First, they study what is the optimal bias the firm should implement in their promotion rule in order to balance their myopic and forward-looking goals.
In general, they find that the optimal bias need not favor the minority, even if there are decreasing returns to having more mentors of a given type. They explain: “Because majority employees are better mentored, their promotion rates can be higher than those of minorities, leading the firm to care more about the effective mentoring of majority than minority employees. As a result, a profit-maximizing firm will bias its promotions to favor increased diversity only if there are sufficiently decreasing returns to mentors of a given type.”

Second, they characterize long-run diversity in the firm, under the optimal promotion rule, as well as features of employees’ careers. They show that diversity of the upper level can converge to multiple steady states, which can range from full diversity to complete homogeneity. Moreover, equilibria can exhibit a “glass ceiling” phenomenon, where the minority in the upper-level starts increasing, but the progress is stalled by the group-based mentoring dynamics, before full diversity is achieved.

6.3. Affirmative Action. The discriminatory mechanisms mentioned in sections 6.1 and 6.2 prescribe unequal treatment to members of different groups, based solely on their group identities, rather than ex-ante differences. Those papers found that this discriminatory treatment was beneficial to a designer who wishes to maximize some objective such as aggregate effort, or crime deterrence.

A converse approach is to ask what type of mechanisms are optimally chosen by a principal who understands underlying treatment differences between societal groups, but wishes to offer “equal opportunities” to agents with different group memberships – hopefully compensating for unduly differential treatment they would receive in the were it not for affirmative action. That is the essential question of the extensive literature on affirmative action. Affirmative action is normally used because the designer believes there to be some ex-ante differences across groups, possibly due to a discriminating world. He then wishes to “re-balance” the playing field, by favoring the group that would be worse-off in the absence of intervention.4142

The literature on affirmative action is extensive, and surveying it is beyond the scope of this current paper. Fang and Moro’s (2011) survey includes a thorough treatment of affirmative action.
action, and its relation to different models of discrimination. An exciting recent contribution is Carvalho, Pradelski and Williams (2022). They observe that people’s identities and group memberships are multidimensional objects; but existing affirmative action policies predominantly treat people’s different identity dimensions (e.g., race, gender, caste) independently. In the paper, they study the effectiveness of such non-intersectional affirmative action policies, and find that they generically cannot eliminate under-representation, and often worsen the representativeness of at least one intersectional group.

6.4. Algorithmic Fairness. Beyond affirmative action, there is a growing literature at the intersection of economics and computer science studying algorithmic fairness. Algorithms are increasingly used in various contexts to classify people based on some observable characteristics and guide decisions such as whether they should receive loans, should receive bail, or be hired by firms. Classification algorithms can be evaluated in terms of their accuracy – the degree to which they correctly assign individuals to decisions – as well as fairness – the degree to which mistakes are correlated with individual’s group identities. Most of this literature studies the design of algorithms to maximize a combination of these two objectives. See, for example, Kasy and Abebe (2021) and Liang, Lu and Mu (2023), and references therein, for an economic approach to the question.

7. The Measurement of Discrimination

In tandem with the development of theories to explain the causes of discrimination, a large literature emerged on how to measure discrimination. As a starting point, that literature notes that discrimination happens when “otherwise equal agents” are “treated differently” based solely on their group-identities; but the characteristics that make two agents “equal” are almost never observed by the econometrician, and very often not observed by the decision-maker whose bias they are trying to measure.

To make the observation more tangible, take a generic “model” of discrimination. There are two populations of agents who characterized by their productivity types and their productivity-irrelevant identity types. An agent’s productivity type is not observed by the decision-maker, who instead observes some imperfect productivity signal before making a decision that is relevant for that agent’s outcome. In this setup, an econometrician might be interested in

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43 Similarly, a small developing literature in mechanism design studies optimal mechanisms when principals have redistributive concerns. For example, Dworczak Kominers Akbarpour (2021) characterize the optimal use of price regulations by policymakers who wish to address inequality in the markets they control; and Akbarpour Dworczak Kominers (2022) study “reistributive allocation mechanisms,” and show that market makers may prefer to allocate public resources through non-markets, sacrificing some surplus in order to improve equity.
measuring discrimination according to two different perspectives: (i) an *ex-post* perspective: for a given signal realization observed by the decision-maker, does their decision vary with the agent’s identity?; (ii) an *ex-ante* perspective: for a given productivity type, averaging across their possible signal realizations, how does an agent’s expected outcome vary with their identity?

To measure (i), the econometrician would need to observe the productivity-signals that are seen by the decision-maker before choosing the agent’s outcome. And to measure (ii), the econometrician would need to know agents’ true productivity types – which are not observed by the decision maker. The main issue addressed by the literature briefly reviewed below is that often one or both of these objects are often not observable to the econometrician. In section 7.1, I discuss audit and correspondence studies which measure discrimination from the ex-post perspective in experiments, where the signal observed by the decision-maker is controlled by the experimenter.

A criticism of audit and correspondence studies is that it is impossible to distinguish whether their provided measures of ex-post discrimination reflect true biases of the decision maker or the fact that accurate productivity assessments based on observed signals may indeed vary with agent’s identities (statistical discrimination). In section 7.2 I briefly review the literature on outcome-based measures of discrimination, focusing mainly on a few recent developments. Unlike measurements provided by audit and correspondence studies, these outcome-based measurements can be attributed to underlying biases of the decision maker, or at times decomposed into bias and “statistical discrimination” components.

Finally, in sections 7.3 and 7.4 I discuss two other recently proposed decompositions of discrimination measures. Bohren, Haggag, Imas, and Pope (2022) propose an identification procedure to distinguish discrimination due to biases in the decision-maker’s preferences and biases in their (inaccurate) beliefs. Bohren, Hull and Imas (2023) propose a decomposition of a total measure of discrimination into a *direct* component, attributable to the decision maker, and a *systemic* component, resulting from cumulative biases in the agent’s previous interactions with the “economic system.”

7.1. Audit and Correspondence Studies. Audit and correspondence studies are two experimental methods used to measure discrimination. Their methods and produced empirical evidence are thoroughly surveyed in Bertrand and Duflo (2017); see also Baert (2018), and Lippens, Vermeiren, and Baert (2022).
In an audit study in the labor market context, two job candidates (the auditors) belonging to two distinct identity groups (say, one white and one black auditor) are chosen so as to be as equal as possible in terms of all characteristics potentially relevant their sought jobs, such as their age and education. The two individuals are then sent to to apply for the same job (perform the audit), and they are trained to behave equally during the job application process. Their performance at the application process is measured; for example, the experimenters will register whether the candidates were called for interviews, whether they made it to further stages of the search process, and whether they were offered the job. These performances are then compared across the individuals, and the difference in their outcomes is then attributed to discrimination by the potential employer, because all other possible explanations for the differential treatment were controlled for by the matching and training of the auditors.

This type of study has been conducted in many contexts beyond the labor market, such as vehicle purchases, the housing market, and mortgage applications. In each context, the idea is that the experimenter is able to observe (and control) the signal observed by the decision maker; and ensure that this signal is the same across a matched pair of auditors, who differ from each other only in terms of their identities.

Such studies have been criticized by, for example, Heckman and Siegelman (1993) and Heckman (1998), who question the experimenter’s ability to create such matched pairs of auditors. They are skeptical that an experimenter would be able to know what would be “all the relevant characteristics” for auditors to be matched on; and remark on how unlikely an experimenter would be to find pairs of people who would exactly match on all these characteristics. Further, Heckman and Siegelman (1993) question whether any bias is introduced into the study through the process by which the auditors are trained to perform the audit.

Correspondence studies were designed so as to address some of the mentioned weaknesses of audit studies. In a correspondence study, there are no real job seekers, and therefore no matching of pairs of auditors. Rather, fictional job seekers are created, whose resumés are designed to be equal in every way except for the name of the applicant, which is chosen to have strong identity associations that vary across the fictional job seekers. Once the fictional resumés are sent to existing job vacancies, the experimenter observes the rates at which jobs contact the applicants to schedule interviews. Any differences in such callback rates across applicants’ identities are then measured and attributed to discrimination by the potential employers.

Two recent papers on the experimental detection of discrimination, Kline and Walters (2021) and Kline, Rose, and Walters (2022), further develop the experimental design and develop
econometric tools to measure the discriminatory behavior not of “the labor market” as a whole, but rather of particular employers.

In all mentioned experimental designs, the experimenter measures how the decision-maker’s behavior varies with the agent’s identity, fixing the relevant signal observed by the decision maker. This concept corresponds to the ex-post discrimination notion introduced above. Ex-post discrimination is in itself an object of interest, however the econometrician cannot with certainty attribute observed ex-post discrimination to employers’ biases against minority identities. Rather, fixing a particular observed signal, discriminatory behavior across identities may be (partly or fully) explained by statistical discrimination, as in the Phelpsian model introduced in section 2.2.

7.2. Distinguishing Bias and Statistical Discrimination. An alternative approach to measuring discrimination is the use of marginal outcome tests. For concreteness, I introduce these tests in the language of vehicle searches by police officers looking for contraband — this context is studied in Knowles, Persico and Todd (2001), among others. In this scenario, an agent’s underlying type is the probability that they are carrying contraband in their vehicle. The police officer sees relevant characteristics of the vehicle (a signal about whether it carries contraband), as well as the identity of the driver, and decides whether to search the vehicle. If the vehicle is searched, the presence or absence of contraband is revealed; otherwise, the agent’s true type remains unobserved.

The signal observed by the police officer gives them some idea of how likely the vehicle is to be carrying contraband. A rational police officer decides to search a vehicle if the likelihood of contraband is large enough (above some threshold). We say that the police officer is biased if they use different threshold rules to decide whether to search a vehicle, depending on the identity of the driver. The econometrician, who wants to assess the police officer’s bias, cannot observe the true underlying types of all agents, or the signals seen by the police officer at the time of the search decision. However, Becker (1957) notes that it suffices for the econometrician to compare the incidence of contraband in “the marginal vehicle” stopped by the police officer for drivers with different identities.

Intuitively, suppose we knew that a set of drivers of identity $A$ produced signals that made the officer just about indifferent between stopping and not stopping the car, and suppose they were stopped. And suppose there is a similar such population of drivers with identity $B$. Now say the econometrician observes that the average incidence of contraband in the population $A$ of such marginally stopped vehicles is larger than that in population $B$. The test then indicates that the officer uses a lower threshold to stop vehicles with drivers with identity $B$,
thereby revealing that the officer is biased against population $B$. Specifically, the officer is “more willing” to stop vehicles with identity-$B$ drivers, revealing the officer’s preference for stopping such vehicles.

While the intuition above is clear, there are many hurdles with actually implementing marginal outcome tests, the main one being how to identify who the “marginal stopped driver” is in each population. Some contributions such as Knowles, Persico and Todd (2001) and Persico and Todd (2006) specify complete behavioral models for both the drivers and the police officers, in which the marginal outcome can be identified by the average outcome amongst stopped drivers (the *infra-marginality problem* is circumvented). More recently, Arnold, Dobbie, and Yang (2018) — see also Canay, Mogstad, and Mountjoy (2022) and Hull (2021) — propose new econometric tools to identify bias “at the margin.”

Unlike audit and correspondence studies, marginal outcome tests capture the bias component of discrimination, but not statistical discrimination. This is the case because marginal outcome tests are leveraging the econometrician’s (imperfect) observation of the agents’ true types (whether the vehicle carried contraband or not), which are revealed after the vehicle’s search is conducts. Contrastingly, remember that in audit and correspondence studies, the econometrician observes the agent’s signal, but never their true underlying type.

A recent contribution to this literature, in Arnold, Dobbie, and Hull (2022), shows that in the context of bail decisions (a context often explored for marginal outcome tests), the quasi-random assignment of judges to cases can be used to measure a broader notion of discrimination – including not only biases in judges preferences and beliefs, but also statistical discrimination. The authors use the quasi-random assignment of judges to purge the omitted variable bias which is introduced by the fact that “true types” are not observed for all the agents (in the vehicle search example, “true types” are only observed for vehicles that are stopped). By doing so, Arnold, Dobbie, and Hull (2022) are able to measure differences in treatment of agents with different identities, but the same underlying “true type” — this notion corresponds to ex-ante discrimination, as introduced in the beginning of this section. Arnold, Dobbie, and Hull (2022) are then able to decompose which portion of the ex-ante discrimination is due to judges’ biases and which portion is due to statistical discrimination. See also a recent contribution by Benson, Board, and Meyer-ter-Vehn (2023), which in the context of a major US retailer attempts to distinguish bias, statistical discrimination, and complementarity in productivity among members of the same identity group.

A related exercise is pursued by Deb and Renou (2022). In their setup, the econometrician is assumed to observe *not* the agents’ true types or their signals, but rather the average true type
in each population. In their model, there are two populations \( A \) and \( B \) of workers with the same average productivity type. There is an employer who sees some signal about an agent’s productivity and forms a posterior mean \( p \in \mathbb{R} \) about their type. The employer then offers the agent some wage \( w_A(p) \) if they belong to population \( A \) and wage \( w_B(p) \) if they belong to population \( B \), where \( w_A \) and \( w_B \) are two strictly increasing functions. We say the employer is biased if the function \( w_A \) is different from the function \( w_B \), and unbiased otherwise.

The econometrician in their paper observes realized wage distributions \( G_A \) and \( G_B \) for the respective populations, and wishes to identify whether differences in these distributions are due to populations \( A \) and \( B \) having different signaling technologies (statistical discrimination) or to the employer being biased. Deb and Renou (2022) find that if neither wage distribution \( G_A \) or \( G_B \) dominates the other in the first order stochastic, then differences between the distributions can be “justified” by statistical discrimination. That is, there exist two signaling technologies, for populations \( A \) and \( B \) respectively, such that the wage distributions can be generated by those signals and identical wage functions \( w_A = w_B \). If instead one of the wage distributions first-order dominates the other, then it must be that \( w_A \neq w_B \), and therefore the employer is biased.

Martin and Marx (2022) also propose a “robust” test for bias, in that they characterize situations where differential outcomes across two populations cannot be explained by differences in signals. Martin and Marx (2022) consider the decision-maker makes a binary decision (to hire or not to hire the agent, say), and the agents’ true type is revealed to the econometrician after either decision is made. Martin and Marx (2022) show that if the average productivity amongst un-hired agents in population \( A \) is larger than the average productivity amid hired agents in population \( B \), then this is a robust indicator of the decision-maker’s bias.

7.3. Measuring Biased Beliefs. Much of the literature reviewed above aims to not only measure discrimination, but also to decompose it into “statistical” discrimination and discrimination due to the decision-maker’s bias. A recent literature – Bohren, Imas, Rosenberg (2019), Bohren, Haggag, Imas, Pope (2022), Hull (2021) — notes that it is sometimes possible to further distinguish whether the bias component of discrimination is due to biases in the decision-maker’s preferences or to inaccuracies in the decision-maker’s beliefs.\(^{44}\)

\(^{44}\)A related decomposition is pursued by Cunningham and de Quidt (2022), who note that a decision maker’s discriminatory behavior may reflect an explicit or an implicit bias in their preferences. In their leading example, they consider a hiring manager who always chooses to hire a woman over a man with the same qualifications, but always chooses to hire a man over a woman if their qualifications differ. They interpret such observation as evidencing an explicit bias of the manager for women — whom they hire when the woman and the men are directly comparable — but an implicit bias for men, who are hired when the two candidates’ qualifications are not directly comparable.
Bohren, Haggag, Imas, Pope (2022) propose an experiment in a labor market setting where they are able to disentangle preference biases and belief biases. Agents (“workers”) with different identities perform some task in a lab, and their performances in that task are observed – these are their “true productivity types.” Other individuals, denoted “employers,” are shown profiles of workers including their identities, but excluding their performances, and report the maximum “wages” they would offer these workers (employers are incentivized in the lab so as to truthfully report these maximum wages). One of their observations is that American workers are systematically offered lower wages than Indian workers; even though performances do not systematically differ between American and Indian workers.

Next, the authors elicit the beliefs of the employers in the experiment, and find that employers mistakenly predicted that American workers perform much worse than their Indian counterparts. Therefore, the employers’ bias can be mostly attributed to their inaccurate beliefs, rather than to biases in their preferences. Bohren, Haggag, Imas, Pope (2022) perform one final treatment, where they reveal the true performance distributions of both populations to the employers, and note that after this observation employers significantly change their wage offers in the direction consistent with correcting their beliefs. This result highlights that employers’ inaccurate beliefs are due to lack of information, as opposed to “motivated biased beliefs” fueled by employers’ underlying preference biases.

7.4. Systemic vs. Direct Discrimination. A recent paper by Bohren, Hull and Imas (2023) comments on the various measures of discrimination in the economic literature, and compare them to the distinction between direct and systemic discrimination in the broader social sciences literature. Specifically, they refer to a large body of work in other social sciences that views discrimination as a systemic phenomenon, viewing disparate group-based treatment as a “cumulative outcome of both direct and indirect interactions between outcomes and evaluations across different stages and domains.”

Bohren, Hull and Imas (2023) propose a simple motivating example to disentangle the definitions of direct and systemic discrimination. Imagine a hiring process consisting of two stages. In a first stage, a recruiter meets a potential hire and issues an evaluation. This recruiter is biased and consistently evaluates female candidates less favorably than equally able male candidates. At a second stage, a hiring manager at the firm observes the recruiter’s evaluation and makes a hiring decision.

Suppose an econometrician is only able to observe the second stage of the hiring process: they see the evaluations of all potential hires and the hiring decisions. Analyzing that data, the econometrician may find no statistically significant differences between hiring probabilities
for female candidates and male candidates, conditional on the recruiter’s evaluation. At that point, the econometrician may conclude that the hiring process is not discriminatory, as male and female candidates with equal observable outcomes are equally likely to be hired. Bohren, Hull and Imas (2023) instead suggest that the econometrician should conclude that “there is no direct discrimination by the hiring manager.”

However, this statistical finding does not rule out systemic discrimination in the hiring process as a whole. Indeed, we know that the recruiter consistently under-evaluates women and so, if the econometrician could observe the hiring process as a whole, they would find that women are less likely to be hired, when compared with equally able men. Systemic discrimination takes place in this example because women and men are treated equally in the second period, when instead the “overall” non-discriminatory outcome should have men being discriminated against at that stage.

To connect this to the language developed in this survey, note that the measurement of direct discrimination corresponds to the measurement of ex-post discrimination introduced in the beginning of this section. That is, direct discrimination occurs when the decision-maker treats two individuals “with the same signals” differently, based on their identities. Contrastingly, Bohren, Hull and Imas’ (2022) notion of total discrimination corresponds to my introduced notion of ex-ante discrimination, that is, the differential treatment of individuals who have “the same underlying types,” based on their identities. Finally, systemic discrimination corresponds to the difference between total and expected direct discrimination, or equivalently, the difference between ex-ante and expected ex-post discrimination.

Beyond noting that it is possible to decompose discrimination into such direct and systematic components, an important contribution by Bohren, Hull and Imas (2023) is highlighting that the systemic component can be regarded as discrimination in previous stages of agents’ lives, or in other spheres. This interpretation establishes an important connection between the economic literature and the broader view in social sciences that discrimination is a cumulative process.

The significance of this systemic discrimination notion indicates a need for developing dynamic theories of discrimination, that studies discrimination as a cumulative process throughout people’s careers and in different spheres of their economic lives. Most of the dynamic theories presented in this survey already hint at the importance of that systemic component. For example, take the case of spiralling discrimination in Bardhi, Guo and Strulovici (2023). If an econometrician were to see data about the interaction between the firm and workers with different identities at any point in time (except the very first instant), they would conclude
that no discrimination is taking place. Indeed, any two workers with the same “track record” would be treated equally by the firm. However, as the authors show, discrimination is a cumulative process, which spirals out of any very small differences between workers at an early career stage. In their model, discrimination is a “systemic” process, in the sense proposed by Bohren, Hull and Imas (2023).

Other models of discrimination arising from learning traps in social learning dynamics – Che, Kim and Zhong (2019), Komiyama and Noda (2021) and Li, Raymond and Bergman (2021) – also highlight the systemic nature of discrimination. The models in Bohren, Imas and Rosenberg (2019) and Fryer (2007), described in section 4.1, are especially close to the Bohren, Hull and Imas’ (2022) motivating example, and also view discrimination as arising from a “systemic” failure of social learning. While the idea that discrimination is not only direct, but also possibly systemic, is not entirely new in the literature, Bohren, Hull and Imas (2023) contribute by proposing this useful classification (and relating it to research in other social sciences), and more importantly by proposing methods to measure discrimination and decompose it into its direct and systemic components.

Finally, the observation that the measurement of discrimination may differ depending on the econometrician’s vantage point hints at the importance of theories that highlight and contrast their predictions in terms of these different notions of discrimination. In one recent example, Onuchic Ray (2023) make such predictions in the context of discrimination in credit assignment for teamwork. In their model, conjecture an equilibrium where women systematically receive less credit for joint work than their male counterparts and suppose we want to know what is the relative likelihood that a woman would attain a certain career outcome (a “target posterior”), relative to a man. They find that, if this career outcome is sufficiently ambitious (say, receiving a prestigious award), then women would be relatively more likely to reach that outcome – the same is true if the target posterior is sufficiently low, while men are relatively more likely to attain moderate career outcomes. In that context, if an econometrician were to evaluate the relative likelihood that members of either group win an award and were to find that women are statistically more likely to win it, then it would be wrong to view this result as a “proof” that no discrimination takes place, or that men are the ones subject to discrimination. According to their model, this outcome is possibly consistent with a discriminatory equilibrium where women are the dis-favored group.
8. Conclusion

This article surveys recent contributions to theories of discrimination. It attempts to contribute to the understanding of the literature by making the following points:

1. The expansion of the literature on information design provides some new language and baseline results with which to regard traditional models of (statistical) discrimination. For example, Chambers and Echenique (2021) use this new framework to more fully characterize market conditions that foster Phelpsian statistical discrimination.

2. Within the broad framework of statistical discrimination, the analysis of specific features of learning and signaling environments – for example, dynamic social learning, learning by myopic algorithms, learning with rational inattention, or signaling in teams – generates novel empirical predictions and policy implications.

3. Recent contributions have expanded traditional models to consider “behavioral agents,” with behavioral learning heuristics or misspecified beliefs about their environments. These theories differ crucially from frameworks with fully rational agents.

4. Thus far, most of the literature on economic theories of discrimination has been classified as either taste-based or statistical discrimination. In contrast, work in sociology often treats the discrimination phenomenon as arising from neither personal prejudice nor rational guesses based on group characteristics, but rather from discriminatory institutions (Small and Pager, 2020). While economic theories do not fully describe the sociological perspective on institutional discrimination, sections 5 and 6 surveys theories that come closer to that approach – including theories of discriminatory social norms and the design of discriminatory institutions.

5. Some new work on the measurement of discrimination has also helped contextualize the economic perspective on “theories of discrimination” within the broader scope of social science research on discrimination. In section 7, amongst other comments about the measurement of discrimination, this survey highlights Bohren, Hull and Imas’ (2022) categorization of discrimination as direct and systemic discrimination, and connects it to other definitions of discrimination in the economic literature.

This paper is still very much a work in progress. I am sure there is a lot of recent literature I do not know, or failed to fit in the framework of this survey. Please, email me with any leads and tips on how to make it better and more complete.
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