‘Phelpsian’ statistical discrimination: A brief history of thought

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drawing (toward the end) on work with

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⋆Economists on labour-market discrimination

Theory:

- first contribution, it seems: Edgeworth (1922)
- very influential: Becker (1957)
- surveys: many, recently Onuchic (2023)

Empirics: large lit.

Statistical discrimination

Two quite distinct strands of thought:

- equilibrium theories following Arrow (1973)
- pure inference theories following Phelps (1972a, 1972b)

Both called 'statistical discrimination'.

Today: the latter.

'CliffsNotes'

Plot:

1	Idea (vaguely)		Phelps, 1972a, 1972b
2	Clarification (uncharitably)		Aigner–Cain, 1977
3	Modernisation (mathematically)		Chambers–Echenique, 2021
4	Revision (Blackwellly)		Blackwell, 1951, 1953

Some themes:

noisy signals	$\rightsquigarrow$	random beliefs
parametric models	$\rightsquigarrow$	'flexible' models
economies & games	$\rightsquigarrow$	decision problems
worry about / maximise $\mathbb{E}$	$\rightsquigarrow$	worry about / maximise min
econ with formalisation	$\rightsquigarrow$	maths with applications

Plot

Introduction

Idea (vaguely) — Phelps (1972a, 1972b)

Clarification (uncharitably) — Aigner–Cain (1977)

Modernisation (mathematically) — Chambers–Echenique (2021)

Revision (Blackwellly) — Blackwell (1951, 1953)

Conclusion

Setup I: workers

Lotta workers. Each worker has

- a skill type $\in \Theta$
- a social identity $\in \{A, B\}$. Speak of 'group A' & 'group B'.

Use 'probability / $\mathbf{P}$' as shorthand for 'fraction of workers'.

Assumption: groups have same skill distribution:

$$\mathbf{P}(\text{skill} = \theta | \text{identity} = A) = \mathbf{P}(\text{skill} = \theta | \text{identity} = B) \quad \forall \theta \in \Theta.$$

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<u>Assumption:</u> firms care about skill, <u>not</u> identity.

$\implies$ if firms observe skill, then HR decisions $\perp$ identity.

'HR decisions': hiring, task assignment, pay, ...

No claim that assumptions are realistic. A thought experiment.

Setup II: information

Assumption: firms do not observe skill. Only observe

- identity
- a (possibly multi-dimensional) covariate $\in \mathcal{C}$
  (e.g. CV, test scores, ...)

Describe identity, skill & covariate as 'random variables' with some joint (cross-sectional) dist'n.

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  (e.g. CV, test scores, ...)

Describe identity, skill & covariate as 'random variables' with some joint (cross-sectional) dist'n.

To inform HR decisions, firms must guess skill
based on observables.

Assumption: firms are correctly-specified Bayesians. That is, for worker with observables $(\text{identity}, \text{covariate}) = (i, c)$, firm's (subjective) probability $p(\theta|c,i)$ that this worker has skill $= \theta$ is

$$p(\theta|c,i) = \mathbf{P}(\text{skill} = \theta | \text{identity} = i, \text{covariate} = c).$$

Setup III: firm homogeneity

In Phelps, firms homogenous: same pref's over skill types.

- all care about expectation of f(skill), where $f : \Theta \to \mathbf{R}$
- idea: single-task economy, skill = 'productivity',
  f = identity function.
- implication: workers <u>vertically</u> differentiated

Later (Chambers–Echenique): firms (extremely) <u>heterogeneous</u>

$\simeq$ workers <u>horizontally</u> different'd.

⋆Phelps's idea

Basic point: typically, for any given covariate value $c \in \mathcal{C}$,

$$\begin{aligned} &\mathbf{E}(f(\text{skill})|\text{identity} = A, \text{covariate} = c) \\ \neq\ &\mathbf{E}(f(\text{skill})|\text{identity} = B, \text{covariate} = c), \end{aligned}$$

so HR decisions depend on identity (not only covariate).

Why? identity $\perp$ skill, but identity helps interpret covariate.

Example 1: $f(\text{skill}) \equiv \text{skill} \sim U([0,1])$,

$$\text{covariate} = \begin{cases} \text{skill} & \text{if identity} = A \\ 1 - \text{skill} & \text{if identity} = B. \end{cases}$$

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Implies discrimination, says Phelps. Details left to imagination.

⋆Discrimination in Phelps's model

Phelps says his model predicts discrimination.

- Question 1 (next): discrimination in <u>which</u> HR decisions?
- Question 2 (later): definition of 'discrimination'?

Definition: random conditional mean

Useful: define random variable M^i by

$$M^i := \mathbf{E}(f(\text{skill})|\text{identity} = i, \underbrace{\text{covariate}}_{\text{random}}).$$

Describes within-group-i heterogeneity ('randomness')
of covariate-based estimate (= expectation) of $f(\text{skill})$.

Charitable reading of Phelps: hiring

Consider hiring. Simplest version:
worker hired iff expectation of her $f(\text{skill})$ exceeds a threshold.

$\implies$ fraction of group i hired $= \mathbf{P}\big(M^i \geq \text{threshold}\big)$

where $M^i = \mathbf{E}(f(\text{skill})|\text{identity} = i, \underbrace{\text{covariate}}_{\text{random}})$

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<u>Example 2:</u> $f(\Theta) = \{1, 2\}$, covariate $= \begin{cases} \text{skill} & \text{if identity} = A \\ \varnothing & \text{if identity} = B \end{cases}$
$1 < \text{threshold} < 2$.

- if $\mathbf{E}(f(\text{skill})) < \text{threshold}$:
  fraction A hired $= \mathbf{P}(f(\text{skill}) = 2) > 0 =$ fraction B hired

- if $\mathbf{E}(f(\text{skill})) \geq \text{threshold}$:
  fraction A hired $= \mathbf{P}(f(\text{skill}) = 2) < 1 =$ fraction B hired.

So Phelps's model predicts discrimination in hiring.

(jump to slide 17 / slide 32 / slide 35)

⋆Charitable reading of Phelps: minimum wage

Following variant is closest to what's actually in Phelps (1972a).

Pay in competitive market with minimum wage:

- worker paid expectation of her $f(\text{skill})$ if it's $\geq$ min_wage
- otherwise worker paid zero (not hired)

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Following variant is closest to what's actually in Phelps (1972a).

Pay in competitive market with minimum wage:

- worker paid expectation of her $f(\text{skill})$ if it's $\geq \text{min\_wage}$
- otherwise worker paid zero (not hired)

Example 2 again: assume $1 < \text{min\_wage} < 2$.

- if $\mathbf{E}(f(\text{skill})) < \text{min\_wage}$:
  As' avg. pay $= 2\mathbf{P}(f(\text{skill}) = 2) > 0 = B$s' avg. pay
- if $\mathbf{E}(f(\text{skill})) \geq \text{min\_wage}$:
  As' avg. pay $= 2\mathbf{P}(f(\text{skill}) = 2) < \mathbf{E}(f(\text{skill})) = B$s' avg. pay

So Phelps's model predicts discrimination in pay.

Plot

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Uncharitable reading of Phelps: pay

Consider pay in a frictionless competitive market:
worker paid expectation of her $f(\text{skill})$.

Average pay in group i: $\quad \mathbf{E}(M^i)$.

Law of iterated expectations:

$$\mathbf{E}\Big(M^A\Big) = \mathbf{E}\big(\mathbf{E}(f(\text{skill}) \mid \text{identity} = A, \text{covariate})\big)$$
$$= \quad \mathbf{E}(f(\text{skill}) \mid \text{identity} = A)$$

Uncharitable reading of Phelps: pay

Consider pay in a frictionless competitive market:
worker paid expectation of her $f(\text{skill})$.

Average pay in group i: $\mathbf{E}(M^i)$.

Law of iterated expectations + equal skill distributions:

$$\begin{aligned}
\mathbf{E}\Big(M^A\Big) &= \mathbf{E}\big(\mathbf{E}(f(\text{skill}) \mid \text{identity} = A, \text{covariate})\big) \\
&= \quad \mathbf{E}(f(\text{skill}) \mid \text{identity} = A) \\
&= \quad \mathbf{E}(f(\text{skill}) \mid \text{identity} = B) \\
&= \mathbf{E}\big(\mathbf{E}(f(\text{skill}) \mid \text{identity} = B, \text{covariate})\big) = \mathbf{E}\Big(M^B\Big).
\end{aligned}$$

So Phelps's model predicts <u>no</u> discrimination in pay.

Aigner and Cain (1977)...

– claim that Phelps claimed otherwise,
– 'prove him wrong' as above.

⋆The critique in full

Fully, Aigner–Cain complain

(1) that Phelps's model predicts no pay discrimination
  – upshot (next slide): need non-linearity

(2) that 'identity helps interpret covariate' is a red herring
  – indeed (slide after next)

Pay discrimination requires non-linearity

Upshot: to have statistical discrimination in pay
in frictionless competitive model,
pay cannot be expectation of $f(\text{skill})$.

Expectation $\equiv$ linear function(al) of skill dist'n $\binom{\text{Riesz repres'n}}{\text{theorem}}$

$\Longrightarrow$ pay must be non-linear f'n of skill dist'n.

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Upshot: to have statistical discrimination in <u>pay</u>
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Expectation $\equiv$ linear function(al) of skill dist'n $\binom{\text{Riesz repres'n}}{\text{theorem}}$

$\implies$ pay must be non-linear f'n of skill dist'n.

One story: firms dislike variance of $f(\text{skill})$
$\implies$ if covariate more informative about skill for A than for B,
then A paid more than B on average.

Aigner–Cain seem quite wedded to this story.

It's special, though. In other natural stories,
more info not always better. Recall Example 2 on slide 12!

$\star$'Identity helps interpret covariate' is red herring

Example 2: $f(\Theta) = \{0, 1\}$, covariate $= \begin{cases} \text{skill} & \text{if identity} = A \\ \varnothing & \text{if identity} = B \end{cases}$

- recall discrimination occurs
- but identity doesn't help interpret covariate:
  covariate perfectly reveals identity.

⋆'Identity helps interpret covariate' is red herring

<u>Example 2:</u> $f(\Theta) = \{0, 1\}$, covariate $= \begin{cases} \text{skill} & \text{if identity} = A \\ \varnothing & \text{if identity} = B \end{cases}$

– recall discrimination occurs

– but identity <u>doesn't</u> help interpret covariate: covariate perfectly reveals identity.

This is very general:

– group i's average outcome (avg. pay, fraction hired, etc.) is a function of the dist'n of $f(\text{skill})$ conditional on '$\text{identity} = i, \underbrace{\text{covariate}}_{\text{random}}$'

– this dist'n obviously doesn't change if replace covariate by $\text{covariate}^\star := (\text{covariate}, \text{identity})$, & obviously identity doesn't help interpret $\text{covariate}^\star$.

What really matters: <u>what info</u> covariate conveys about skill.

⋆Some more uncharitable reading

To make point on previous slide, Aigner–Cain invent terms:

(i) 'individual-level discrimination': for some $c \in \mathcal{C}$,

$$\begin{aligned} &\mathbf{E}(f(\text{skill})|\text{identity} = A, \text{covariate} = c) \\ \neq\ &\mathbf{E}(f(\text{skill})|\text{identity} = B, \text{covariate} = c). \end{aligned}$$

(ii) 'group-level discrimination':
different average outcomes for groups A & B.

Phelps employs neither definition;
instead leaves meaning of 'discrimination' vague.

Aigner and Cain (1977)...

– claim that Phelps called (i) 'discrimination'
– note that (ii) is a better definition of 'discrimination'.

Plot

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FanFic origin story

maths Phelps:

Phelps, R. R. (2000). *Lectures on Choquet's theorem* (2nd). Springer. https://doi.org/10.1007/b76887

econ Phelps:

Phelps, E. S. (1972b). The statistical theory of racism and sexism. *American Economic Review*, *62*(4), 659–661

Chambers and Echenique (2021):
apply Phelps to Phelps!

Chambers–Echenique setup I: firm heterogeneity

Stick with Aigner–Cain story:

– discrimination in pay
– competitive market, no frictions (e.g. minimum wage)
– requisite non-linearity: convexity $\iff$ info good for avg. pay.

But formalise the story 'non-parametrically' / 'flexibly'
$\iff$ consider (extremely) heterogeneous firms

– a task is a vector $\in \mathbf{R}^{\Theta}$ (Θ finite)
= surplus as f'n of skill of worker performing the task

– a firm is a finite set of tasks

Chambers–Echenique setup I: firm heterogeneity

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– a task is a vector $\in \mathbf{R}^\Theta$ (Θ finite)
$=$ surplus as f'n of skill of worker performing the task

– a firm is a finite set of tasks

Assumption: consider all firms.

Firms (very) heterogeneous ('consider all firms')
$\iff$ workers horizontally differentiated
(different firms value different skills)

Chambers–Echenique setup II: production, pay

Production = task assignment.

Given firm $\subseteq \mathbf{R}^{\Theta}$ & belief $\in \Delta(\Theta)$ about worker,

$$\text{pay} = \text{expected surplus} = \max_{\text{task} \in \text{firm}} (\text{belief} \cdot \text{task}).$$

Chambers–Echenique setup II: production, pay

Production = task assignment.

Given firm $\subseteq \mathbf{R}^{\Theta}$ & belief $\in \Delta(\Theta)$ about worker,

$$\text{pay} = \text{expected surplus} = \max_{\text{task} \,\in\, \text{firm}} (\text{belief} \cdot \text{task}).$$

A firm's exp. surplus f'n $\text{belief} \mapsto \max_{\text{task} \,\in\, \text{firm}} (\text{belief} \cdot \text{task})$
is a convex f'n $\Delta(\Theta) \to \mathbf{R}$.

- all firms $\simeq$ all convex f'ns $\Delta(\Theta) \to \mathbf{R}$ (formally: up to uniform closure)
- 'special case': f'n = mean $- \, k \times$ variance

Summary

	Aigner–Cain	Chambers–Echenique
workers	vertically differentiated	horizontally diff'ed
firms	homogeneous	(very) heterogeneous
surplus	'parametric'	'non-parametric' / 'flexible'
	(mean $-\ k \times$ variance)	(arbitrary convex f'n)

Definition: random conditional distribution

Let P^i be random vector $\in \Delta(\Theta)$ defined by

$$P^i_\theta \coloneqq \mathbf{P}\big(\text{skill} = \theta \;\big|\; \text{identity} = i,\ \underbrace{\text{covariate}}_{\text{random}}\big) \quad \forall \theta \in \Theta.$$

Describes within-group-i heterogeneity (‘randomness’)
of covariate-based estimate of (= belief about) skill dist’n.

Random belief. ‘Belief-based approach’ $\begin{cases} \text{Blackwell,} \\ \text{Aumann–Maschler,} \\ \text{Kamenica–Gentzkow} \end{cases}$

CE go as far as to identify covariate with P^i! Very modern.

CE's definition of '(statistical) discrimination'

CE's def'n: (statistical) discrimination against group B iff some firm pays Bs strictly less on avg.: $\exists$ firm $\subseteq \mathbf{R}^{\Theta}$ s.t.

$$\mathbf{E}\left(\max_{\text{task} \in \text{firm}} P^{A} \cdot \text{task} \right) > \mathbf{E}\left(\max_{\text{task} \in \text{firm}} P^{B} \cdot \text{task} \right)$$

Results & interpretation

Note can view skill = 'state',
covariate = 'signal' = 'Blackwell experiment' = 'info structure'.

Question: when is there (CE-def'n) discrimination?

Answer: iff skill dist'n not identified off covariate iff XYZ.

Proved via Choquet theory from 'maths Phelps' book.

Big upshot from CE's introduction:

> *We show that the focus on informativeness in Phelps (1972b) and Aigner and Cain (1977) is misleading. There may be statistical discrimination even when the information structure of one [group] is not more informative than the other. [...] Aigner and Cain trace statistical discrimination to pure informativeness. We argue that the situation is more general.*

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Comments on CE

CE model very natural. Comments on results / interpretation:

(1) CE's definition of 'discrimination' is weak.
Propose a better definition.

(2) Contrary to CE's claim, in CE's model,
discrimination is precisely about informativeness
(of covariate about skill).

(3) Relabelling Blackwell's theorem yields nice
characterisation of discrimination in CE's model.

Better definition of '(statistical) discrimination'

New def'n: (statistical) discrimination against group B iff both

(1) every firm pays Bs weakly less on avg.: $\forall$ firm $\subseteq \mathbf{R}^{\Theta}$,

$$\mathbf{E}\Big(\max_{\text{task}\,\in\,\text{firm}} P^A \cdot \text{task}\Big) \geq \mathbf{E}\Big(\max_{\text{task}\,\in\,\text{firm}} P^B \cdot \text{task}\Big)$$

(2) some firm pays Bs strictly less on avg.: $\exists$ firm $\subseteq \mathbf{R}^{\Theta}$ s.t.

$$\mathbf{E}\Big(\max_{\text{task}\,\in\,\text{firm}} P^A \cdot \text{task}\Big) > \mathbf{E}\Big(\max_{\text{task}\,\in\,\text{firm}} P^B \cdot \text{task}\Big)$$

Recall $P^i_\theta = \mathbf{P}\big(\text{skill} = \theta \,\big|\, \text{identity} = i,\ \underbrace{\text{covariate}}_{\text{random}}\big) \quad \forall \theta \in \Theta$

CE's def'n: (2) only. Can interpret as 'robustness concern': worry about 'worst-case' firm. ('maxmin')

Opinion: that's too weak to deserve name 'discrimination'.

Discrimination = informativeness I

CE model		Blackwell decision model
skill	$\rightsquigarrow$	state
covariate	$\rightsquigarrow$	signal / experiment / info struc.
task	$\rightsquigarrow$	action
firm	$\rightsquigarrow$	decision problem
(avg.) pay / surplus	$\rightsquigarrow$	(exp.) value

Recall def'n of Blackwell (strictly) less informative:

'weakly lower exp. value in every decision problem
(& strictly lower exp. value in some decision problem')

Discrimination = informativeness I

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Recall def'n of Blackwell (strictly) less informative:

'weakly lower exp. value in every decision problem
(& strictly lower exp. value in some decision problem')

Obs'n: (new-definition) statistical discrimination against Bs

$$\iff \begin{cases} \quad B\text{s weakly lower avg. pay in every firm} \\ \&\ \ B\text{s strictly lower avg. pay in some firm} \end{cases}$$

$\iff$ covariate str. less info'tive about skill for Bs than for As

Discrimination = informativeness I

CE model	$\rightsquigarrow$	Blackwell decision model
skill	$\rightsquigarrow$	state
covariate	$\rightsquigarrow$	signal / experiment / info struc.
task	$\rightsquigarrow$	action
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(avg.) pay / surplus	$\rightsquigarrow$	(exp.) value

Recall def'n of <u>Blackwell (strictly) less informative</u>:

'weakly lower exp. value in every decision problem

(& strictly lower exp. value in some decision problem')

<u>Obs'n:</u> <u>CE-definition</u> statistical discrimination against Bs

$\Longleftrightarrow$ Bs strictly lower avg. pay in some firm

$\Longleftrightarrow$ not: Bs weakly higher avg. pay in every firm

$\Longleftrightarrow$ covariate <u>not more</u> info'tive about skill for Bs than for As.

Discrimination = informativeness II

Upshot: contrary to CE's claim, in their model,
discrimination is precisely about informativeness
(of covariate about skill).

However: $\exists$ other natural models
in which CE's claim is true
(recall Example 2 on slide 12).

⋆Identification and inevitability

Recall Obs'n: CE-definition statistical discrimination

$\iff$ covariate not more info'tive for Bs than for As.

Corollary: 'CE-discrimination' against neither As nor Bs

$\iff$ covariate both more and less info'tive for Bs than for As

$\iff$ groups informationally identical. Extremely stringent.

Upshot: on CE's def'n, 'discrimination' is inevitable!

(Not shocking. Again, CE's def'n too weak.)

Modulo details, this is CE's 'identification' result,
re-stated in non-econometric language.

Characterising discrimination in CE's model

Informativeness well-understood, so can borrow insights. E.g.

Blackwell's theorem. The following are equivalent:

(i) (new-definition) statistical discrimination against Bs: covariate str. less info'tive about skill for Bs than for As

(ii) P^B strictly less variable than P^A in convex-order sense (a.k.a. 'mean-preserving spread')

(iii) B's covariate is a non-trivial garbling of A's

Recall $P^i_\theta = \mathbf{P}\big(\text{skill} = \theta \,\big|\, \text{identity} = i,\ \underbrace{\text{covariate}}_{\text{random}}\big) \quad \forall \theta \in \Theta$

⋆Characterising discrimination in CE's model

Informativeness well-understood, so can borrow insights. E.g.

Blackwell's theorem v2. The following are equivalent:

(i) CE-definition statistical discrimination against Bs:
covariate not more info'tive about skill for Bs than for As

(ii) P^B not more variable than P^A
in convex-order sense (a.k.a. 'mean-preserving spread')

(iii) A's covariate is not a garbling of B's

Recall $P^i_\theta = \mathbf{P}\left(\text{skill} = \theta \,\middle|\, \text{identity} = i,\ \underbrace{\text{covariate}}_{\text{random}}\right) \quad \forall \theta \in \Theta$

Suggestion for future work

One observation:

- Lit since Aigner–Cain very focussed on models
  in which more info $\Longleftrightarrow$ higher avg. pay.
- But this is quite special. Recall Example 2 on slide 12.

Needed: analysis of statistical discrimination
in labour-market models beyond this special class.

Thanks!

$$b^2 - 4ac$$

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