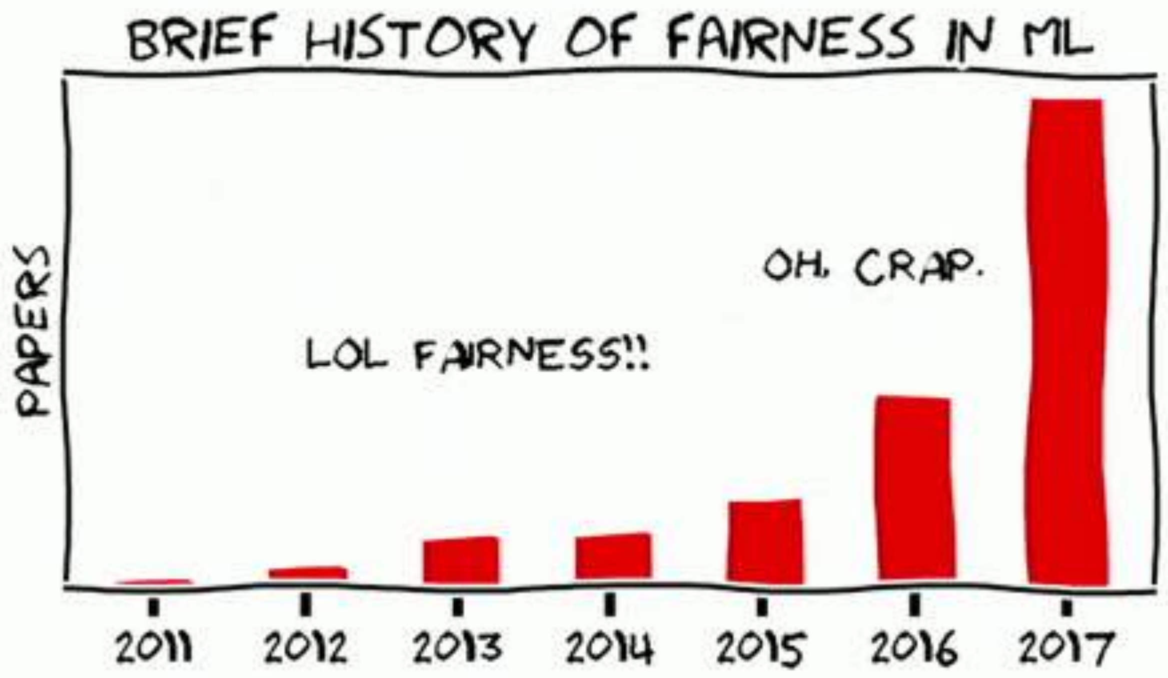
DELAYED IMPACT OF FAIR MACHINE LEARNING

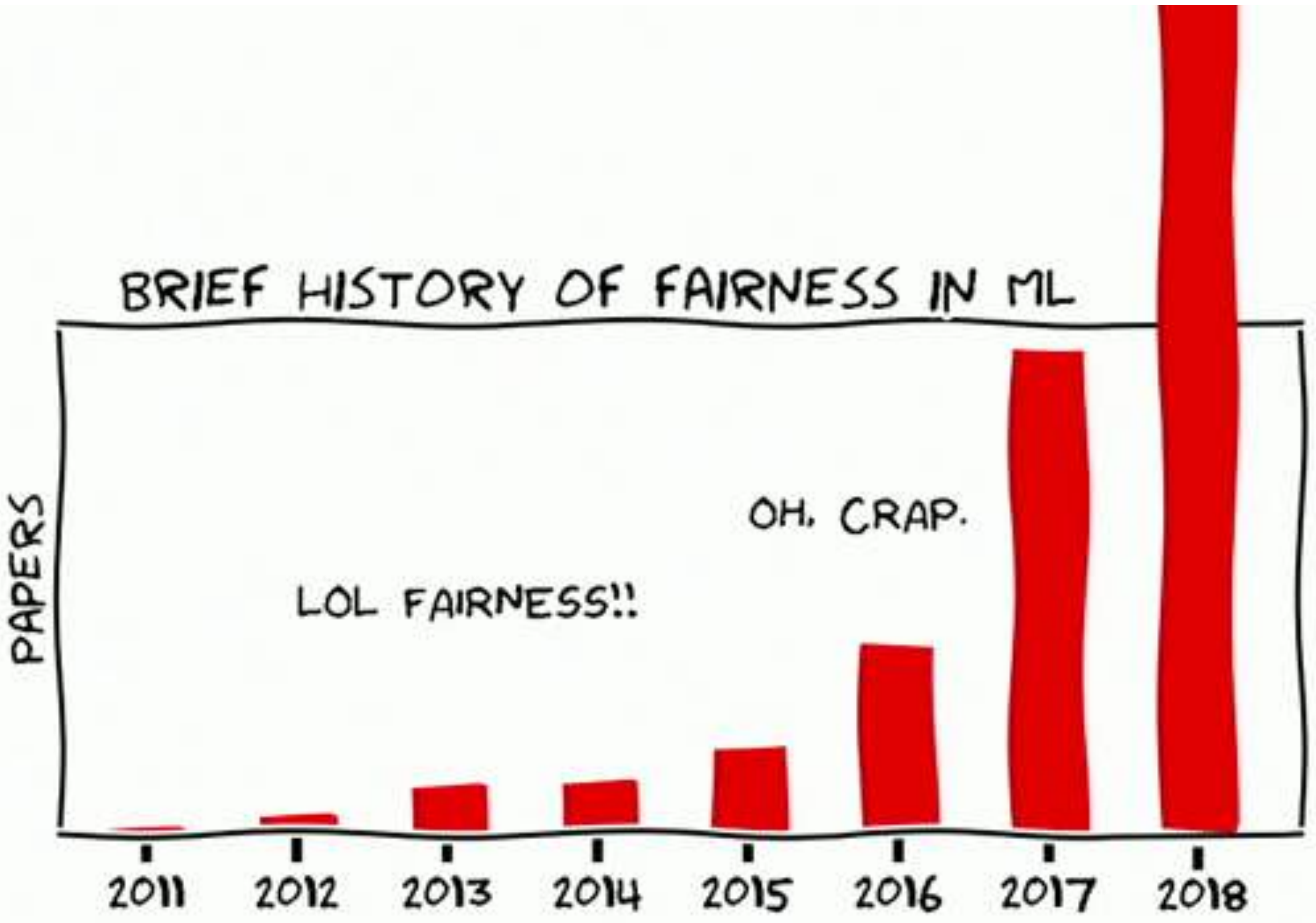
Lydia T. Liu (UC Berkeley)



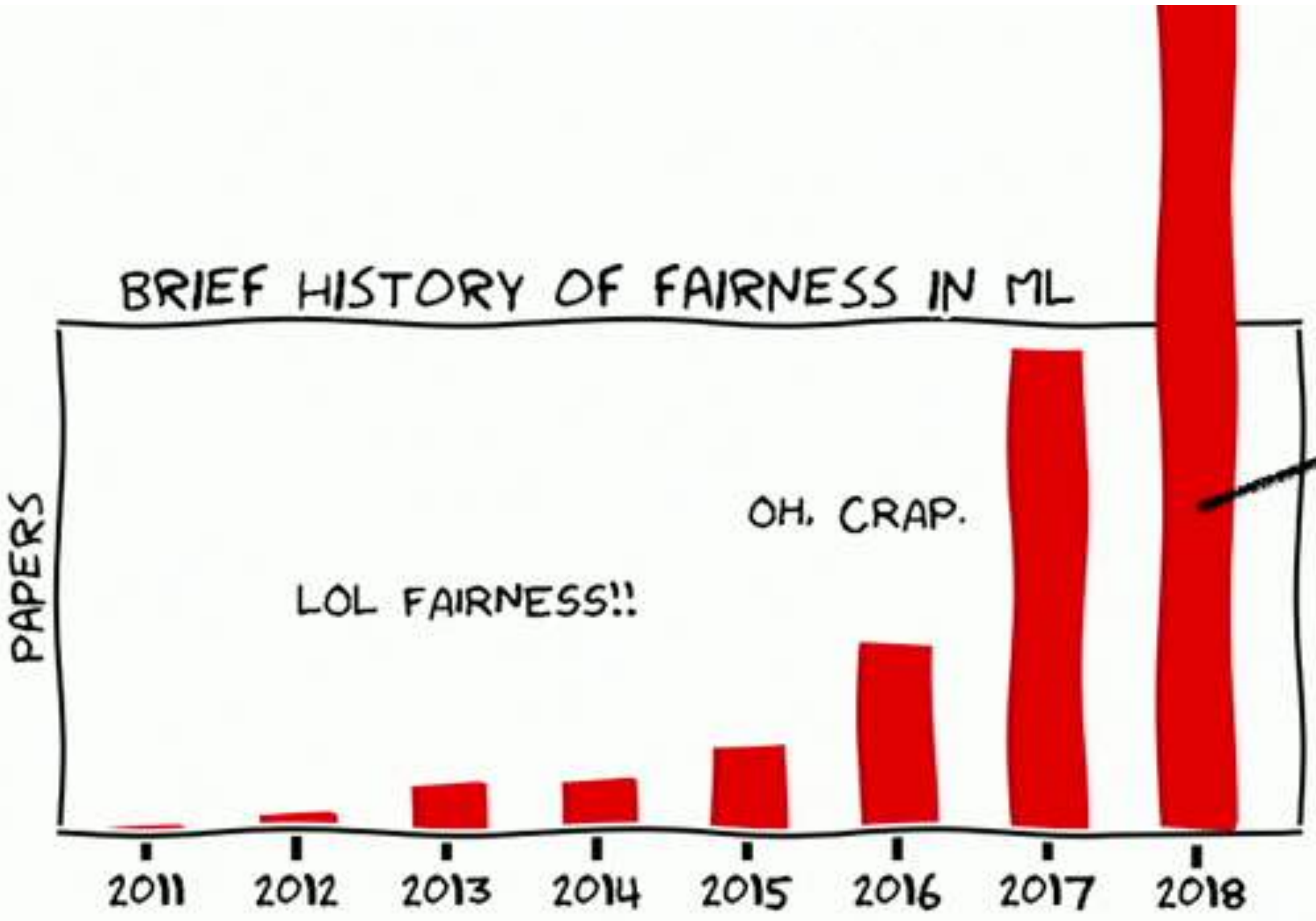

Joint work with **Sarah Dean, Esther Rolf, Max Simchowitz, Moritz Hardt**



source: mrtz.org



source: mrtz.org

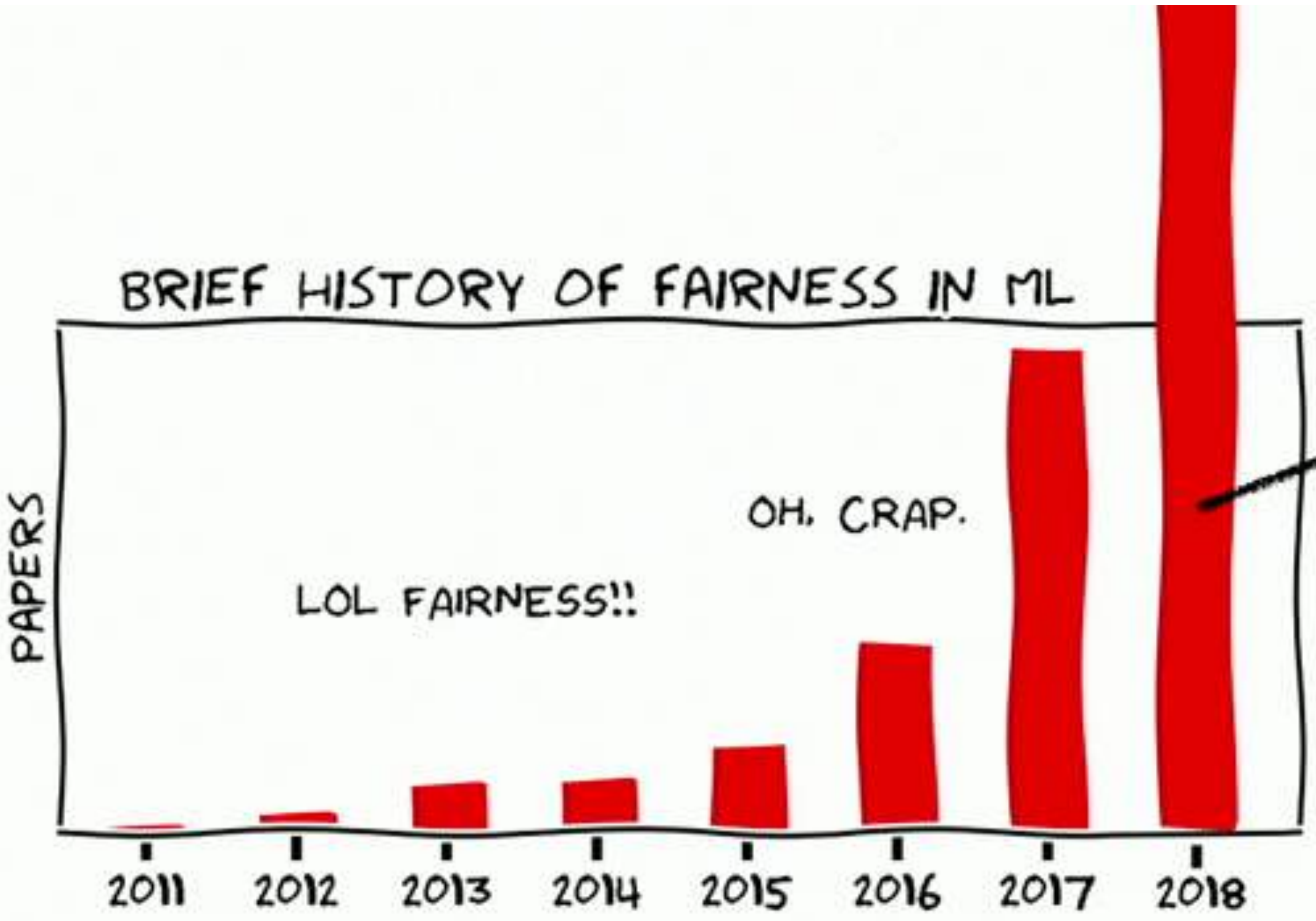


source: mrtz.org

“21 DEFINITIONS OF FAIRNESS” [Narayanan 2018]

1. DEMOGRAPHIC PARITY
2. EQUALITY OF OPPORTUNITY
3. PREDICTIVE VALUE PARITY
4. GROUP CALIBRATION

...



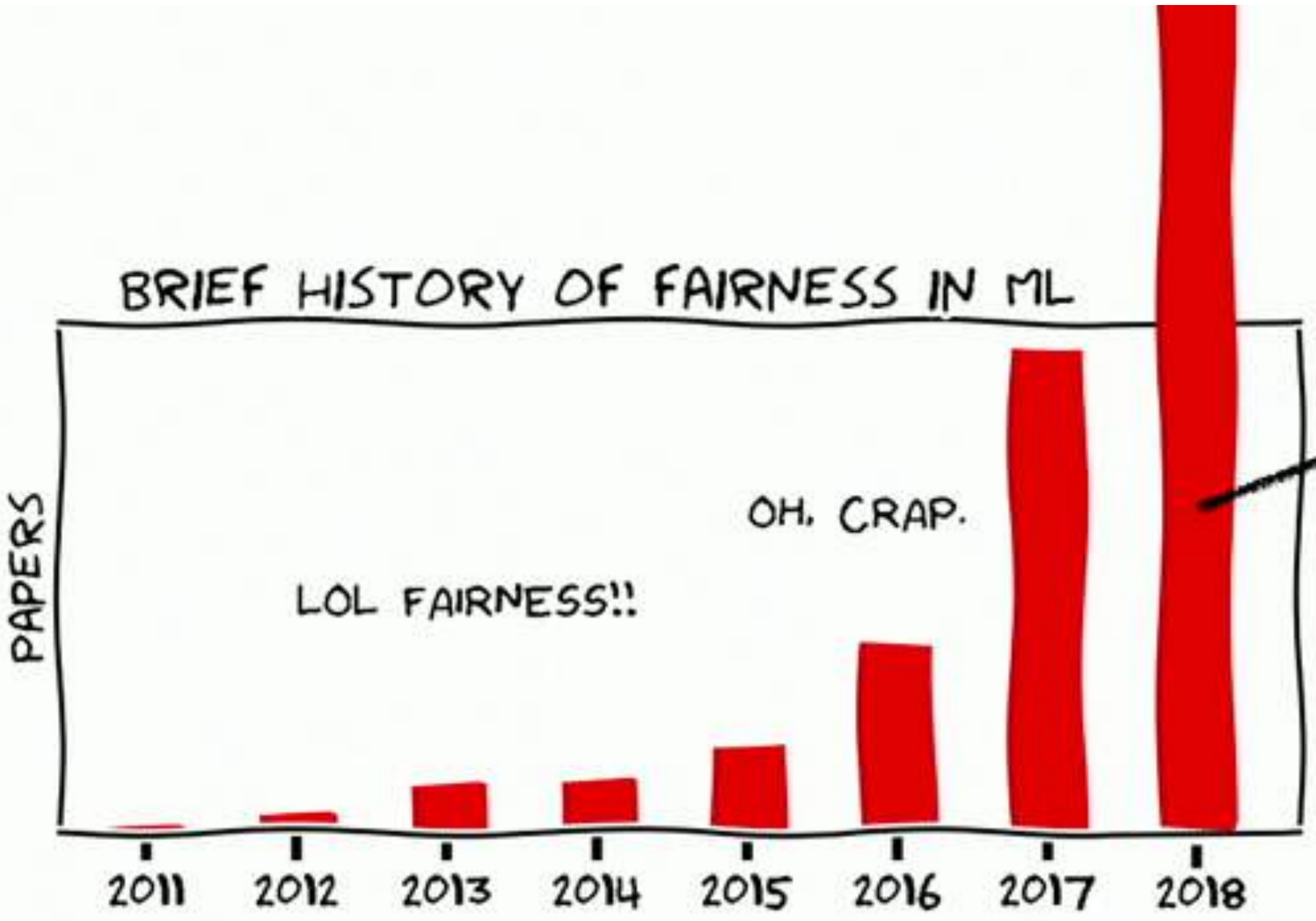
source: mrtz.org

"21 DEFINITIONS OF FAIRNESS" [Narayanan 2018]

1. DEMOGRAPHIC PARITY
2. EQUALITY OF OPPORTUNITY
3. PREDICTIVE VALUE PARITY
4. GROUP CALIBRATION

. . .

➤ **Many fairness criteria can be achieved individually using efficient algorithms**
post-processing [e.g. Hardt et al. 2016]; *reduction to black-box machine learning* [e.g. Dwork et al. 2018; Agarwal et al. 2018]; *agnostic learning* [e.g. Kearns et al. 2018; Herbert-Johnson et al. 2018]; *unconstrained machine learning* [Liu et al. 2018b]



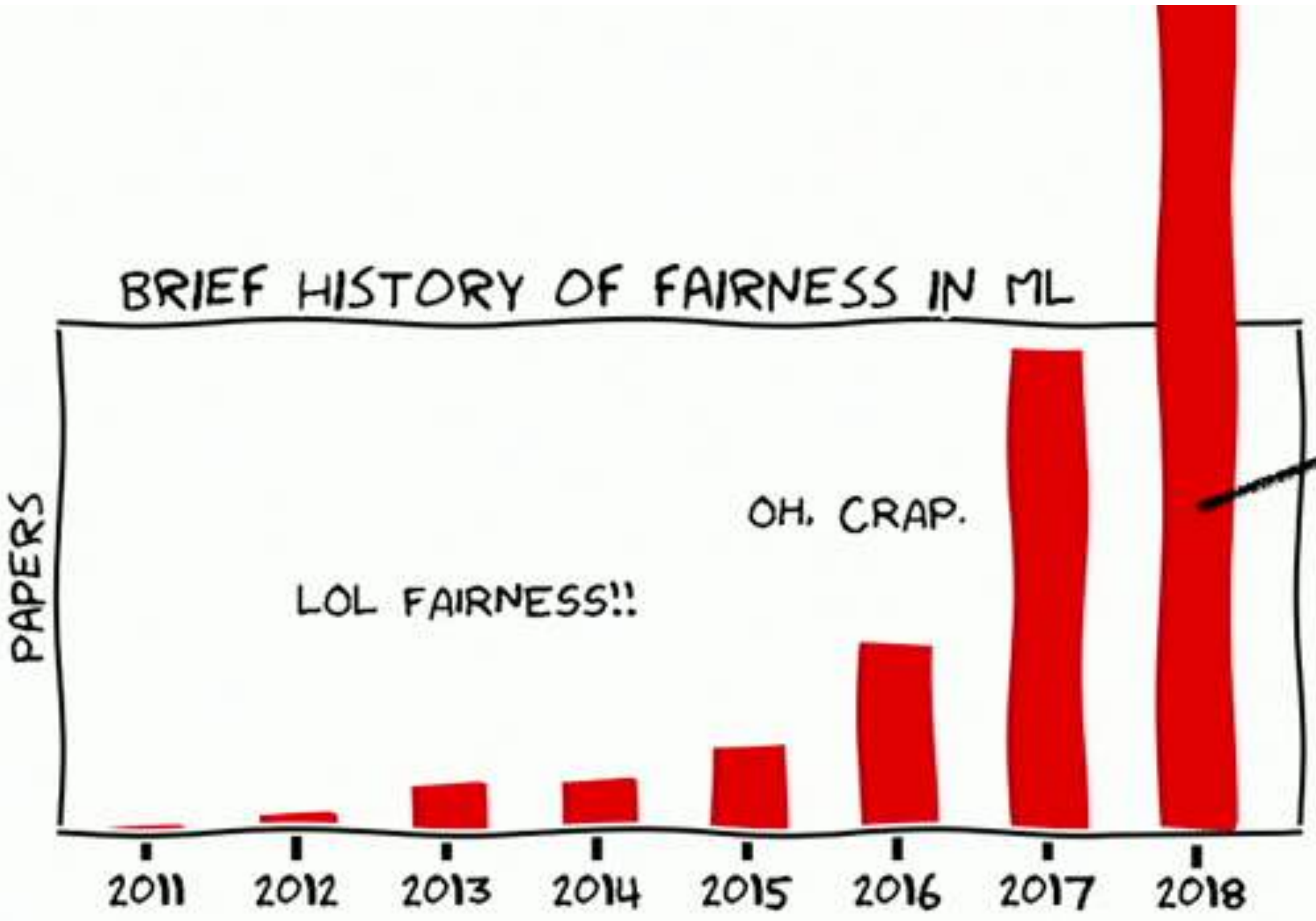
source: mrtz.org

"21 DEFINITIONS OF FAIRNESS" [Narayanan 2018]

1. DEMOGRAPHIC PARITY
2. EQUALITY OF OPPORTUNITY
3. PREDICTIVE VALUE PARITY
4. GROUP CALIBRATION

...

- **Many fairness criteria can be achieved individually using efficient algorithms**
  post-processing [e.g. Hardt et al. 2016]; *reduction to black-box machine learning* [e.g. Dwork et al. 2018; Agarwal et al. 2018]; *agnostic learning* [e.g. Kearns et al. 2018; Herbert-Johnson et al. 2018]; *unconstrained machine learning* [Liu et al. 2018b]
- **But typically impossible to satisfy simultaneously**
  [e.g. Kleinberg et al. 2016; Chouldechova, 2017]

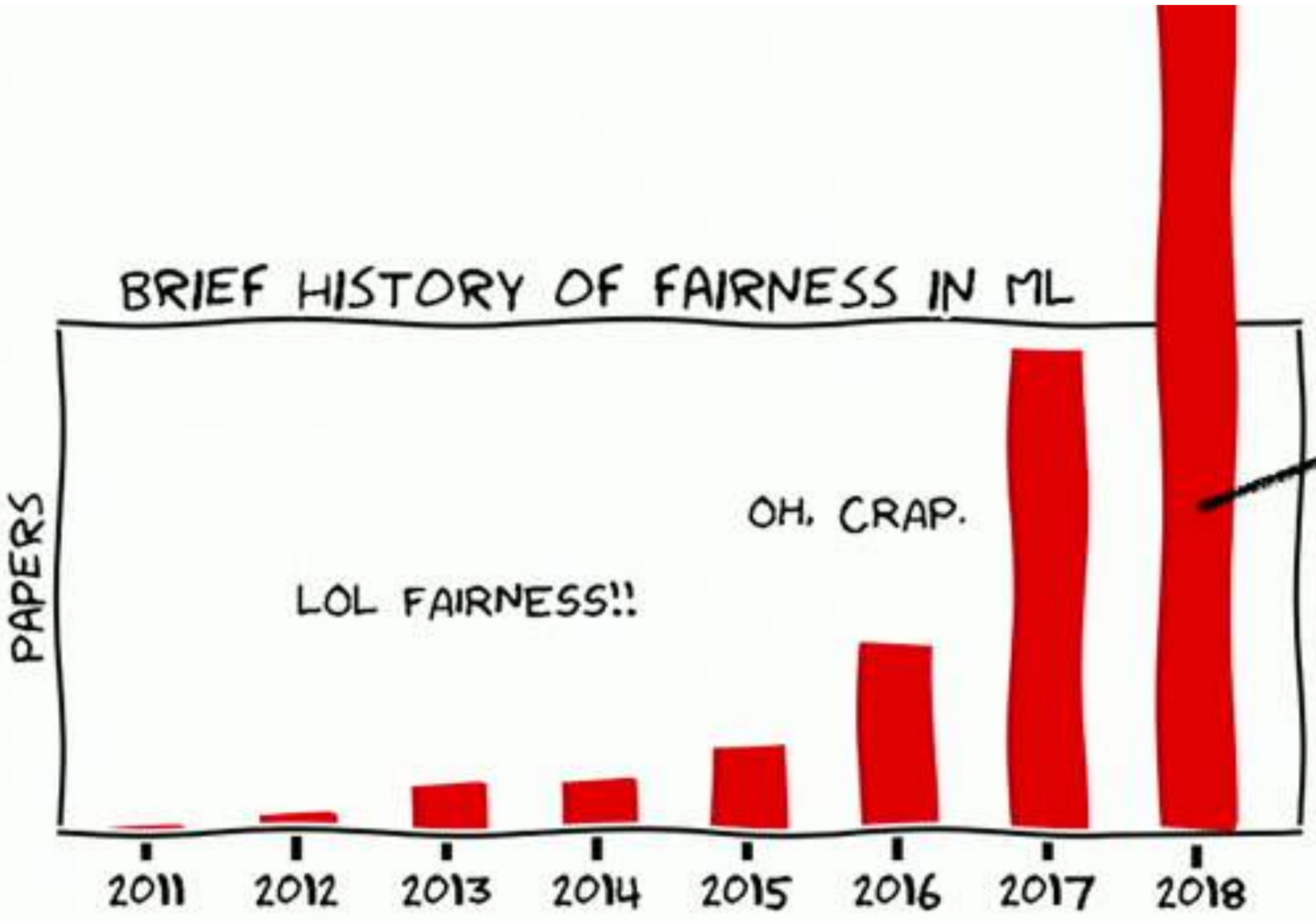


source: mrtz.org

"21 DEFINITIONS OF FAIRNESS" [Narayanan 2018]

1. DEMOGRAPHIC PARITY
2. EQUALITY OF OPPORTUNITY
3. PREDICTIVE VALUE PARITY
4. GROUP CALIBRATION

. . .



source: mrtz.org

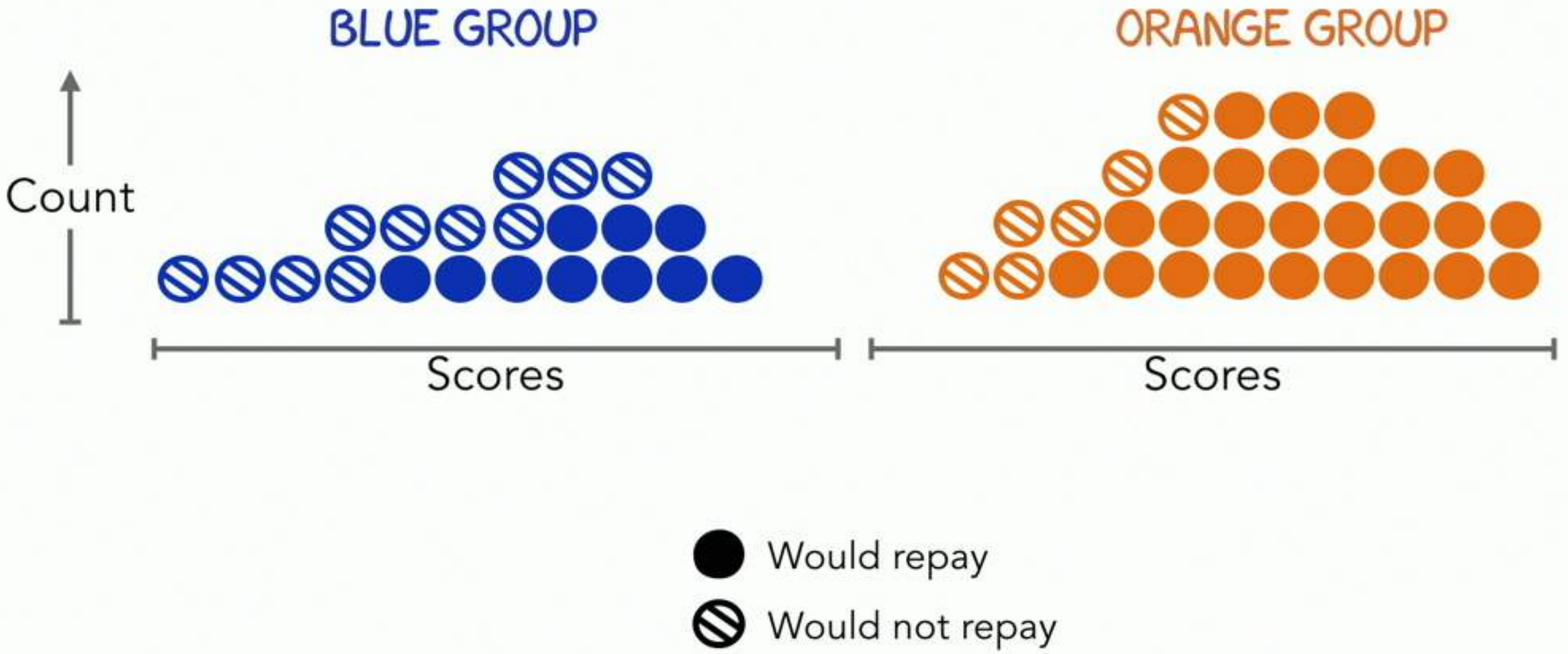
"21 DEFINITIONS OF FAIRNESS" [Narayanan 2018]

1. DEMOGRAPHIC PARITY
2. EQUALITY OF OPPORTUNITY
3. PREDICTIVE VALUE PARITY
4. GROUP CALIBRATION

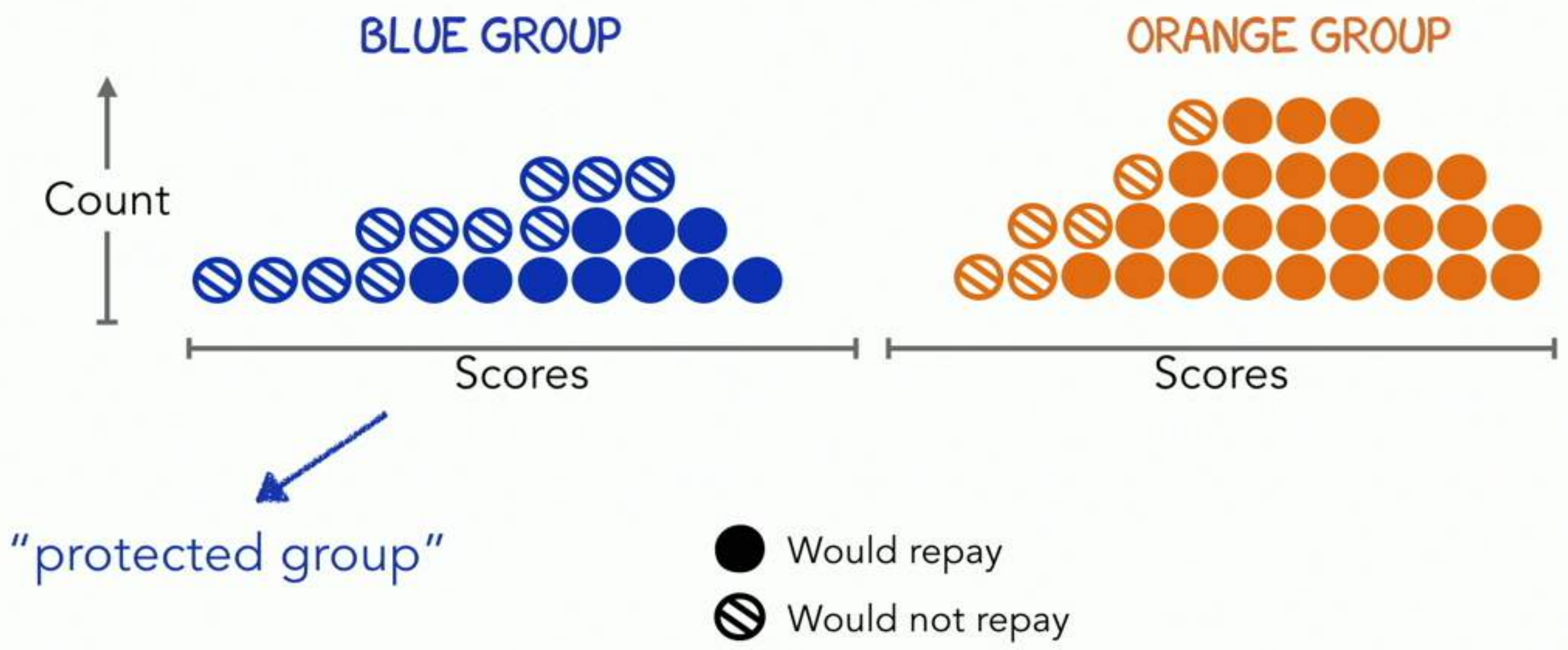
...

Machine learning systems are "fair" $\xrightarrow{?}$ Protected groups are "better off"

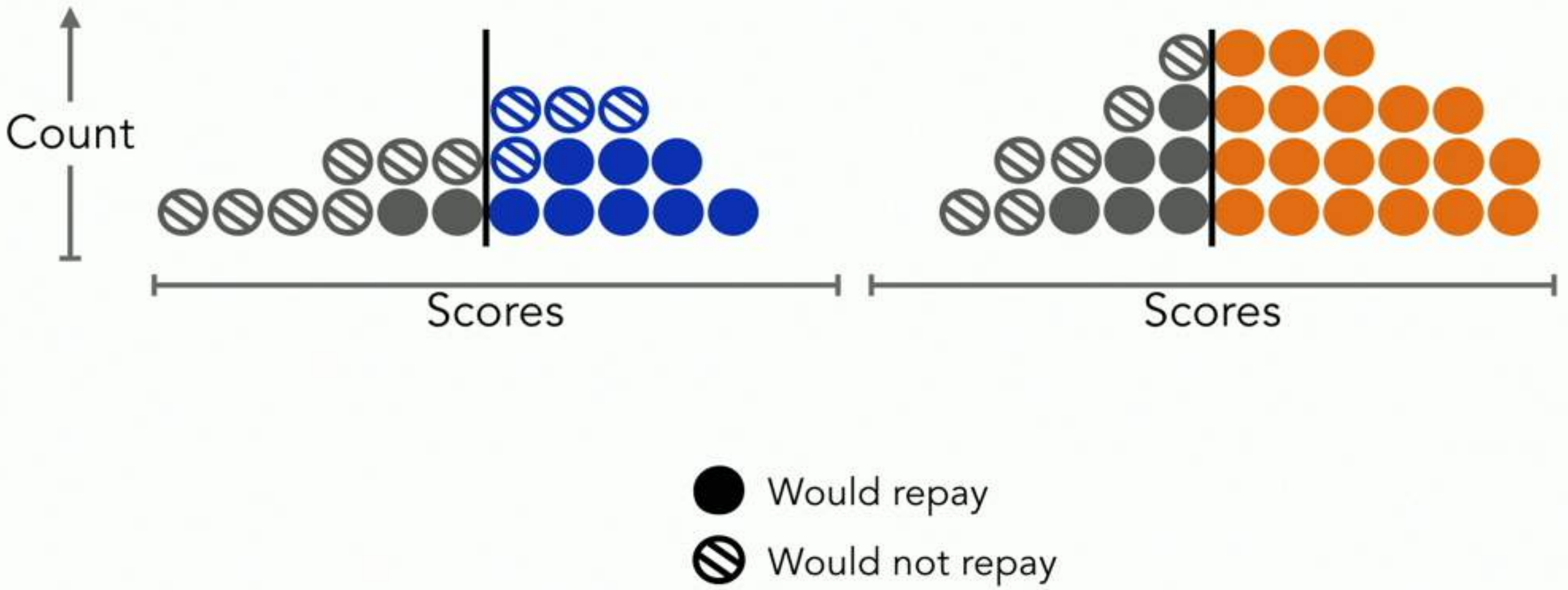
Two groups with different *score* distributions (e.g. credit scores)



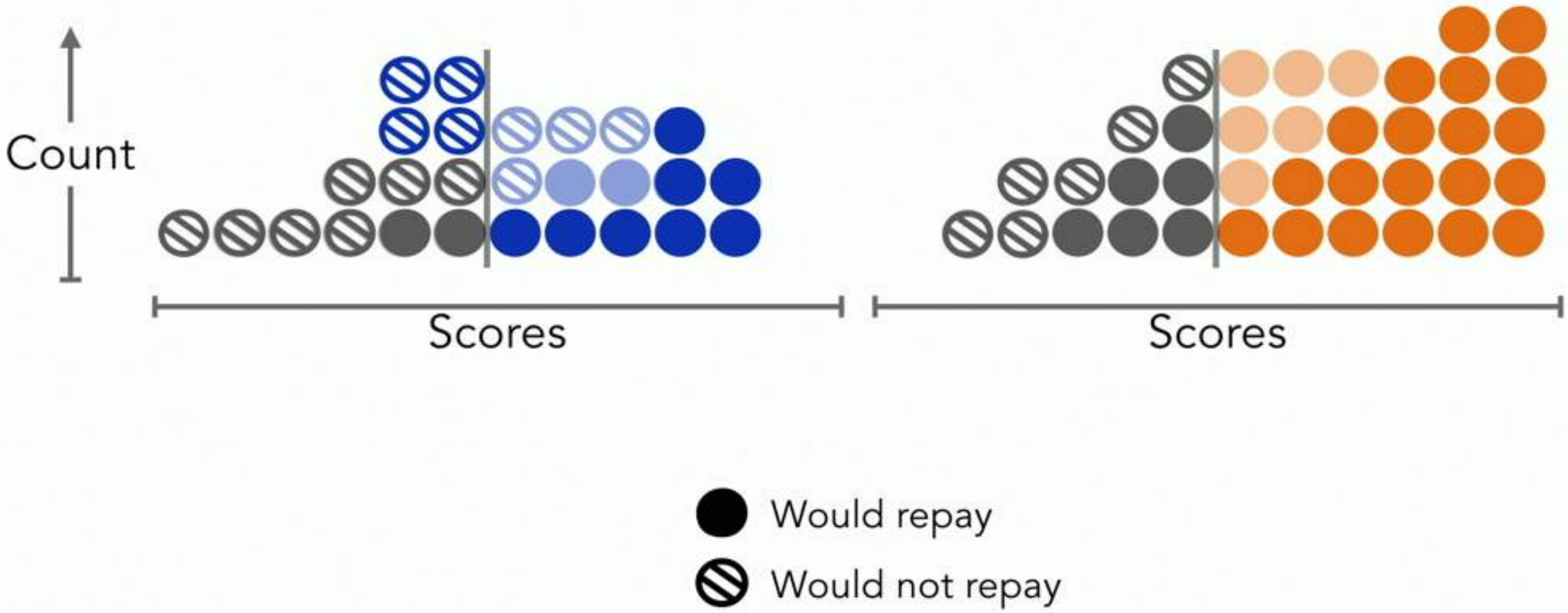
Two groups with different *score* distributions (e.g. credit scores)



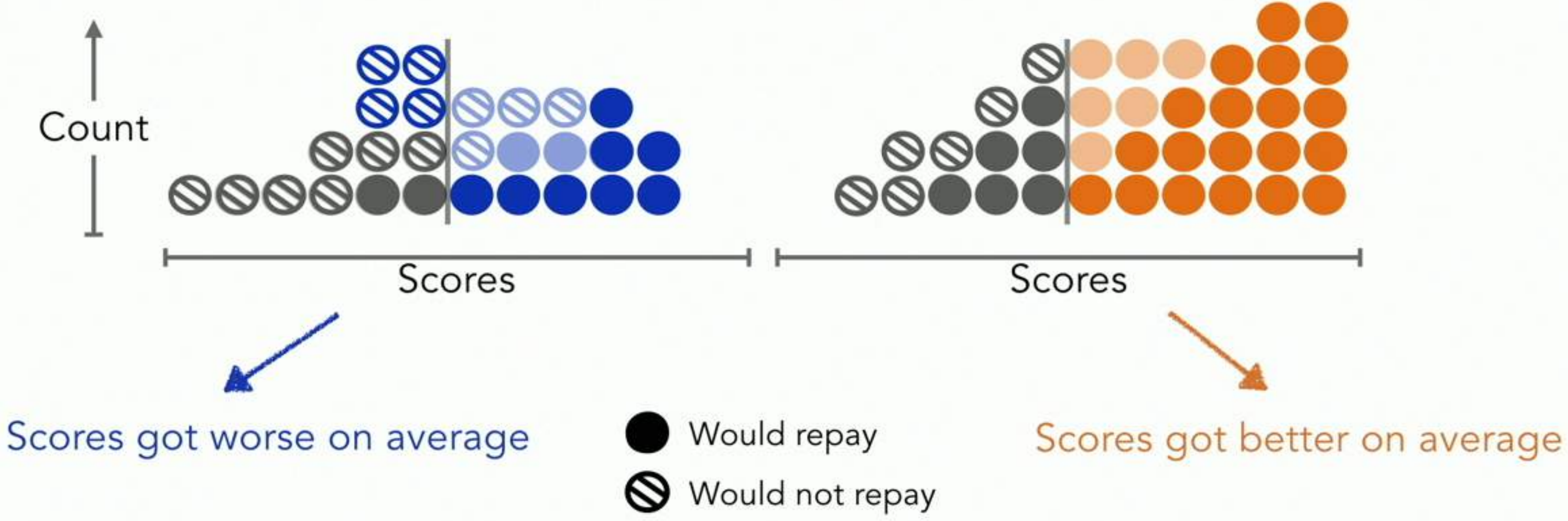
Approve loans according to **DEMOGRAPHIC PARITY**.



Credit scores change with repayment (+) or default (-).



Credit scores change with repayment (+) or default (-).



WHAT HAPPENED?

WHAT HAPPENED?

Fairness criteria didn’t seem to *help* the protected group, once we considered the *impact* of loans on scores.

OUR WORK

OUR WORK

1. Introduce the "**outcome curve**", a tool for comparing the delayed impact of fairness criteria

OUR WORK

1. Introduce the "**outcome curve**", a tool for comparing the delayed impact of fairness criteria
2. Provide a **complete characterization** of the delayed impact of 3 different fairness criteria

OUR WORK

1. Introduce the "**outcome curve**", a tool for comparing the delayed impact of fairness criteria
2. Provide a **complete characterization** of the delayed impact of 3 different fairness criteria
3. Show that fairness constraints **may cause harm** to groups they intended to protect

SCORE DISTRIBUTION WITHIN A GROUP

SCORE DISTRIBUTION WITHIN A GROUP

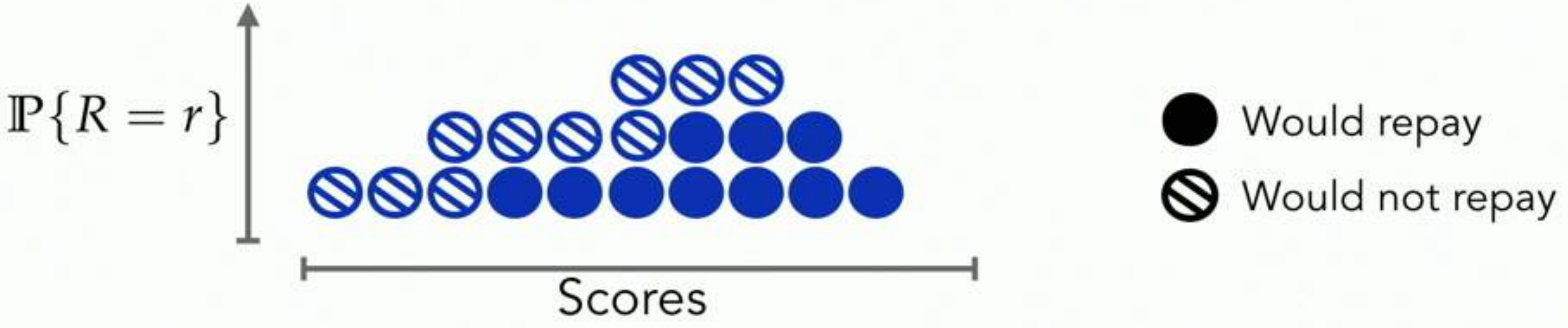
- A **score** $R(X)$ is a scalar random variable that is a function of an individual's features X
  - e.g. credit score is an integer from 300 to 850

SCORE DISTRIBUTION WITHIN A GROUP

- A **score** $R(X)$ is a scalar random variable that is a function of an individual's features X
  - e.g. credit score is an integer from 300 to 850
- Any group of individuals has a particular **distribution** over scores:

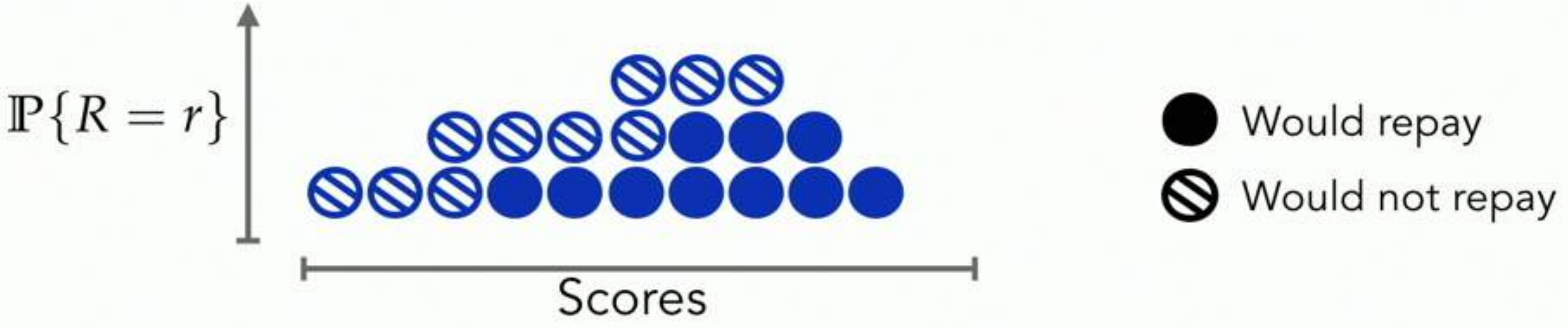
SCORE DISTRIBUTION WITHIN A GROUP

- A **score** $R(X)$ is a scalar random variable that is a function of an individual's features X
  - e.g. credit score is an integer from 300 to 850
- Any group of individuals has a particular **distribution** over scores:



SCORE DISTRIBUTION WITHIN A GROUP

- A **score** $R(X)$ is a scalar random variable that is a function of an individual's features X
  - e.g. credit score is an integer from 300 to 850
- Any group of individuals has a particular **distribution** over scores:



- Each score corresponds to an individual's success probability (e.g. probability of repaying a loan) once accepted

SCORE DISTRIBUTION WITHIN A GROUP

- A **score** $R(X)$ is a scalar random variable that is a function of an individual's features X
  - e.g. credit score is an integer from 300 to 850
- Any group of individuals has a particular **distribution** over scores:

- Each score corresponds to an individual's success probability (e.g. probability of repaying a loan) once accepted
- **<u>Monotonicity assumption</u>:** Higher scores implies **more likely** to repay

CLASSIFIERS ARE THRESHOLDS

CLASSIFIERS ARE THRESHOLDS

- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

CLASSIFIERS ARE THRESHOLDS

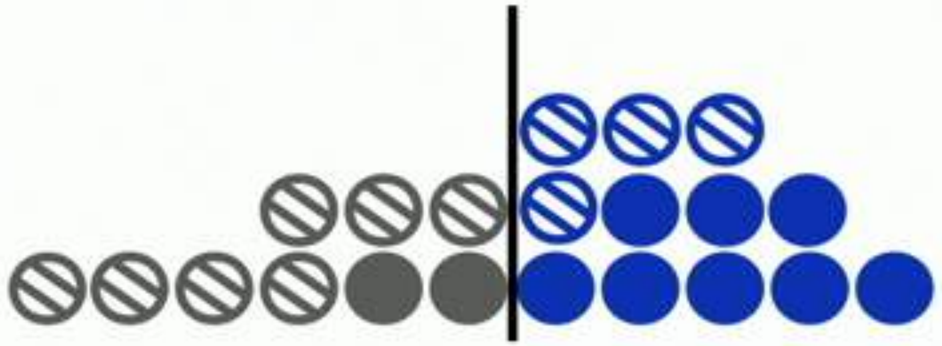
- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

$$\mathbb{E}[\text{utility}|T] = \mathbb{E}[\text{reward from repayments}|T] - \mathbb{E}[\text{loss from defaults}|T]$$

CLASSIFIERS ARE THRESHOLDS

- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

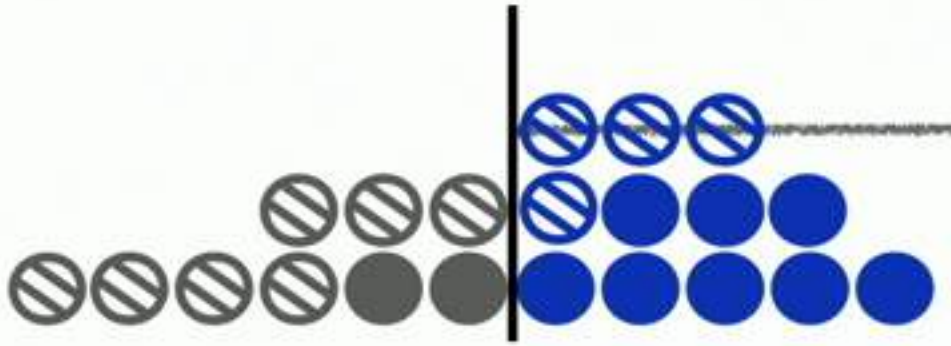
$$\mathbb{E}[\text{utility}|T] = \mathbb{E}[\text{reward from repayments}|T] - \mathbb{E}[\text{loss from defaults}|T]$$



CLASSIFIERS ARE THRESHOLDS

- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

$$\mathbb{E}[\text{utility}|T] = \mathbb{E}[\text{reward from repayments}|T] - \mathbb{E}[\text{loss from defaults}|T]$$

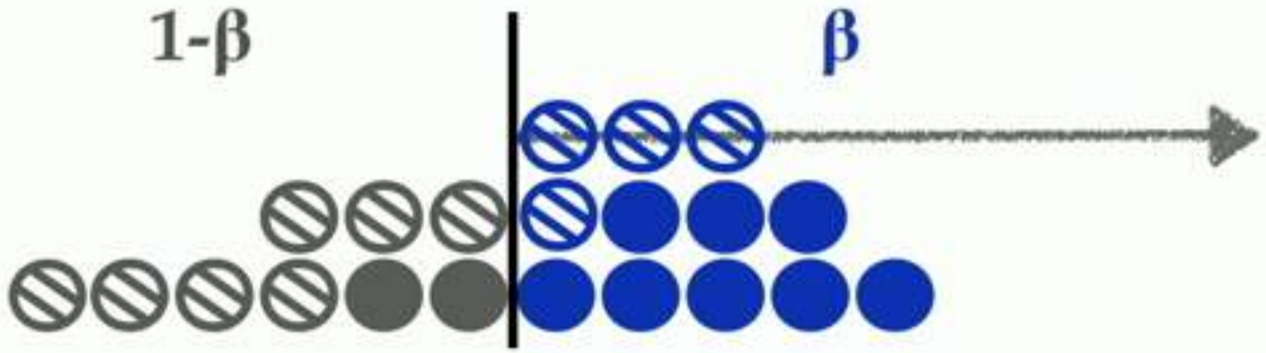


Threshold $\boldsymbol{T}$ corresponds to **acceptance rate β** for the group.

CLASSIFIERS ARE THRESHOLDS

- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

$$\mathbb{E}[\text{utility}|T] = \mathbb{E}[\text{reward from repayments}|T] - \mathbb{E}[\text{loss from defaults}|T]$$

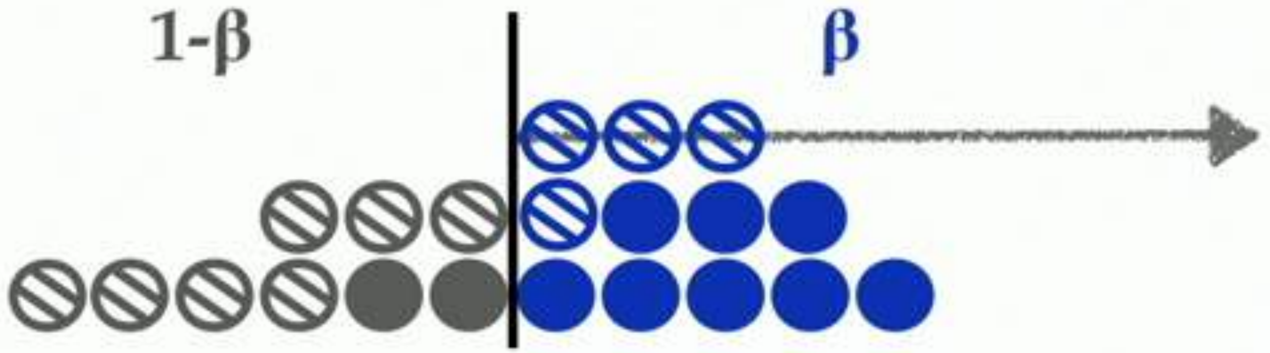


Threshold ***T*** corresponds to **acceptance rate β** for the group.

CLASSIFIERS ARE THRESHOLDS

- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

$$\mathbb{E}[\text{utility}|T] = \mathbb{E}[\text{reward from repayments}|T] - \mathbb{E}[\text{loss from defaults}|T]$$



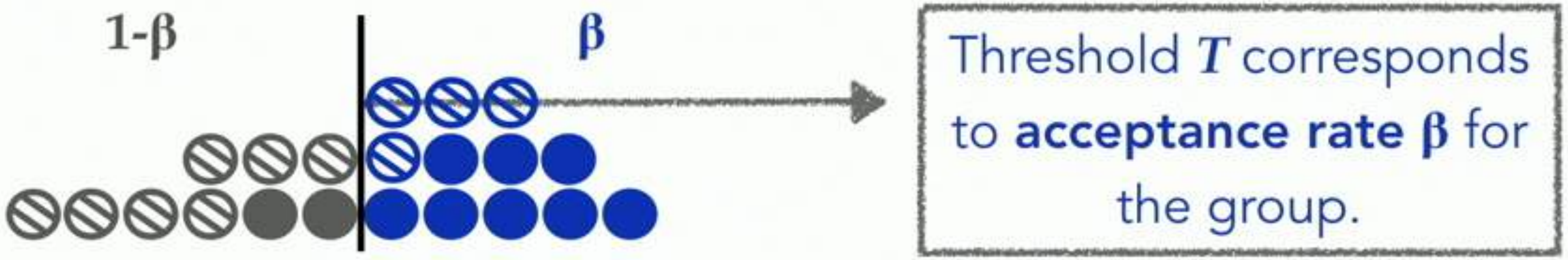
Threshold ***T*** corresponds to **acceptance rate β** for the group.

- When there are multiple groups, thresholds can be **group-dependent**.

CLASSIFIERS ARE THRESHOLDS

- Institution **classifies** individuals by choosing an **acceptance threshold** score T to maximize their expected **utility**:

$$\mathbb{E}[\text{utility}|T] = \mathbb{E}[\text{reward from repayments}|T] - \mathbb{E}[\text{loss from defaults}|T]$$



- When there are multiple groups, thresholds can be **group-dependent**.

MODEL DELAYED IMPACT ON GROUPS

MODEL DELAYED IMPACT ON GROUPS

- Scores of accepted individuals change depending on their success.

MODEL DELAYED IMPACT ON GROUPS

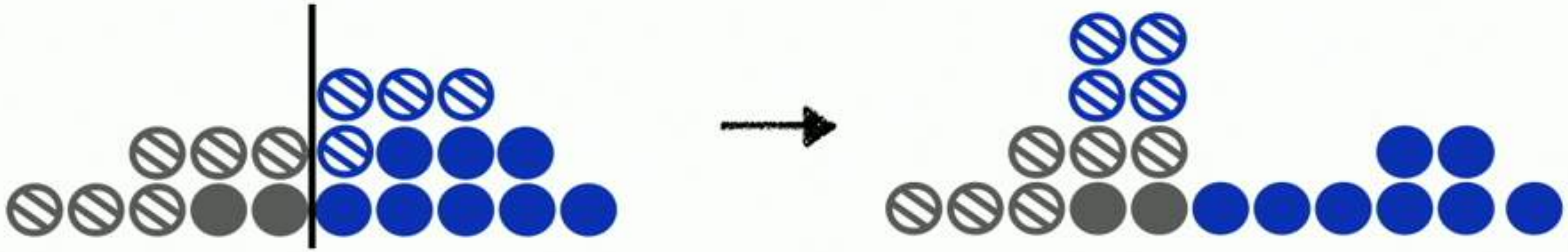
- Scores of accepted individuals change depending on their success.

$$R_{\text{new}} = \begin{cases} R_{\text{old}} + c_{+} & \text{if repaid} \\ R_{\text{old}} + c_{-} & \text{if defaulted} \end{cases}$$

MODEL DELAYED IMPACT ON GROUPS

- Scores of accepted individuals change depending on their success.

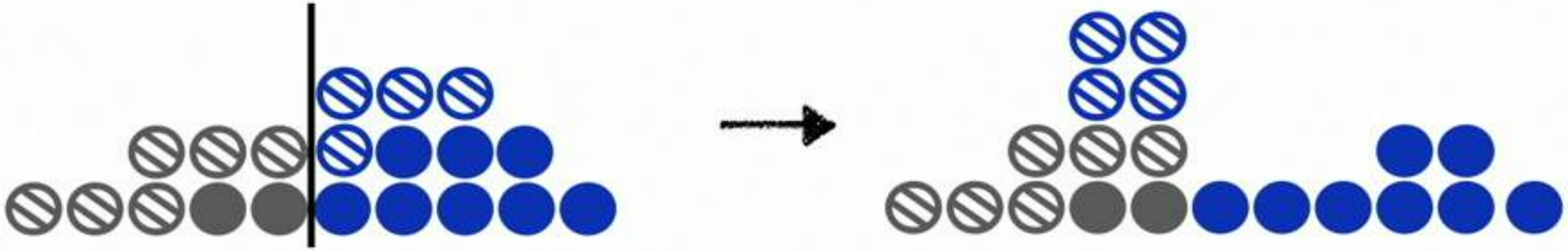
$$R_{\text{new}} = \begin{cases} R_{\text{old}} + c_+ & \text{if repaid} \\ R_{\text{old}} + c_- & \text{if defaulted} \end{cases}$$



MODEL DELAYED IMPACT ON GROUPS

- Scores of accepted individuals change depending on their success.

$$R_{\text{new}} = \begin{cases} R_{\text{old}} + c_{+} & \text{if repaid} \\ R_{\text{old}} + c_{-} & \text{if defaulted} \end{cases}$$

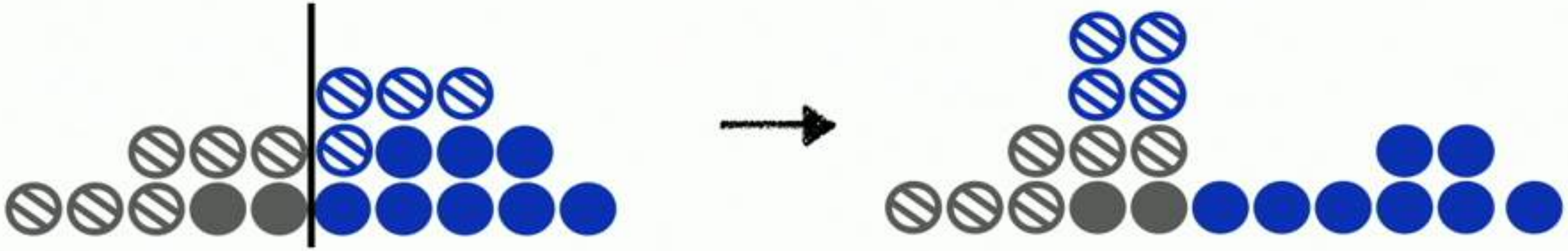


- The average change in score of each group is the **delayed impact**:

MODEL DELAYED IMPACT ON GROUPS

- Scores of accepted individuals change depending on their success.

$$R_{\text{new}} = \begin{cases} R_{\text{old}} + c_+ & \text{if repaid} \\ R_{\text{old}} + c_- & \text{if defaulted} \end{cases}$$



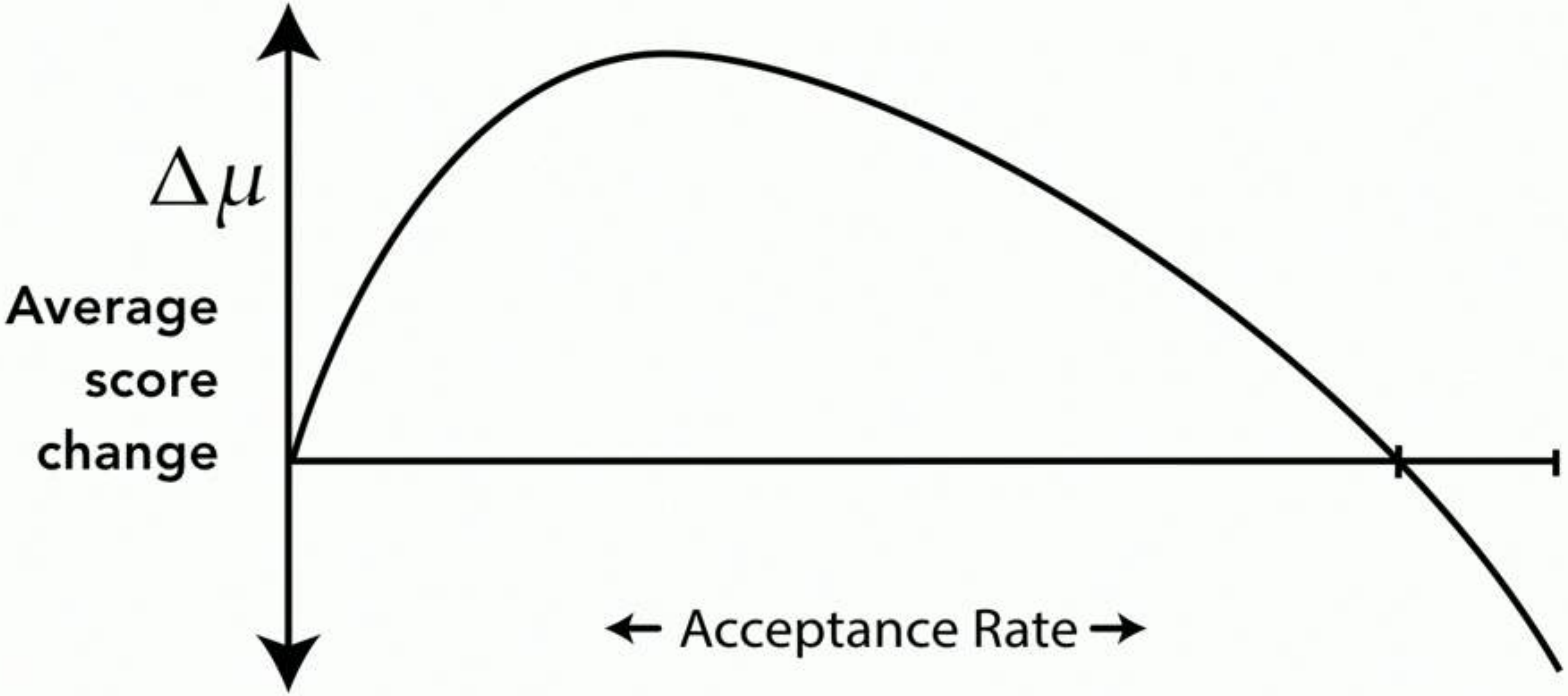
- The average change in score of each group is the **delayed impact**:

$$\Delta\mu = \mathbb{E}[R_{\text{new}} - R_{\text{old}}]$$

OUTCOME CURVE

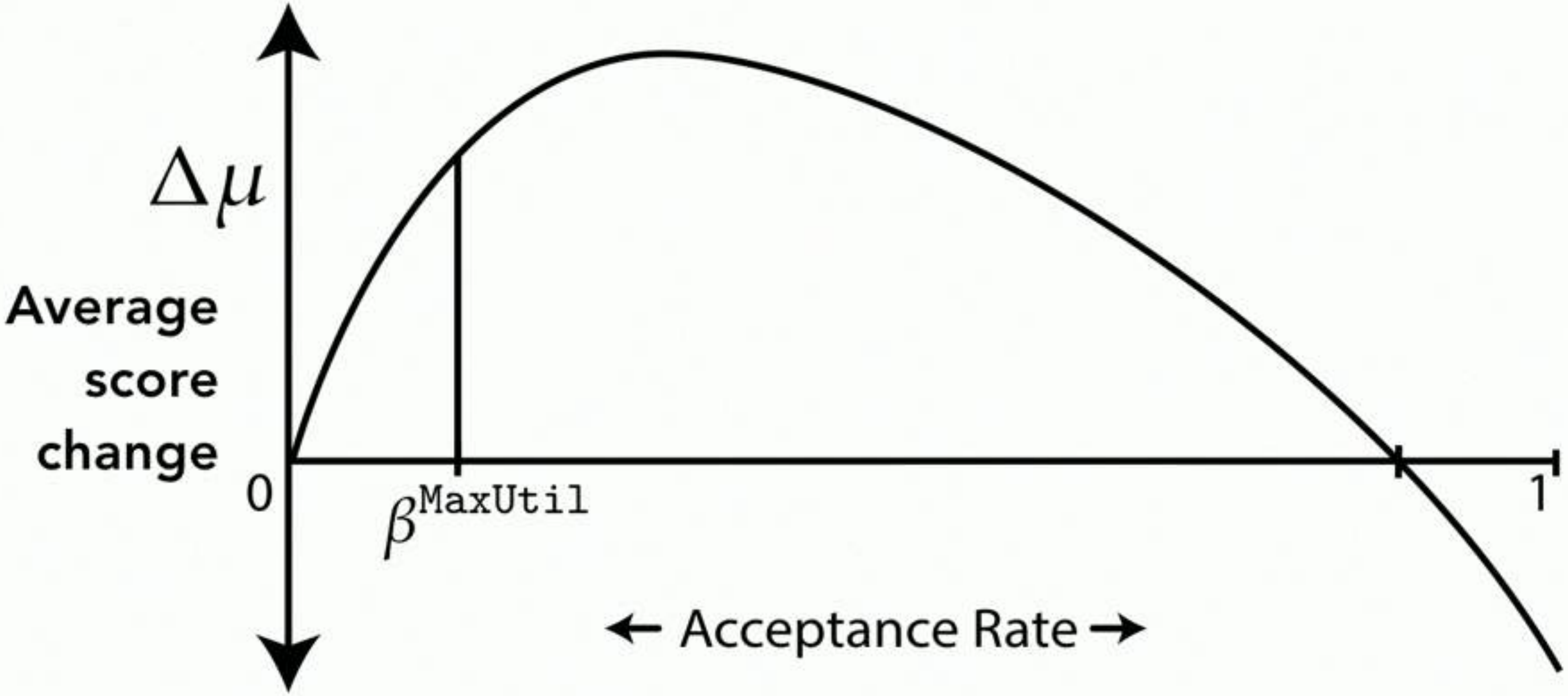
OUTCOME CURVE

<u>Lemma</u>: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



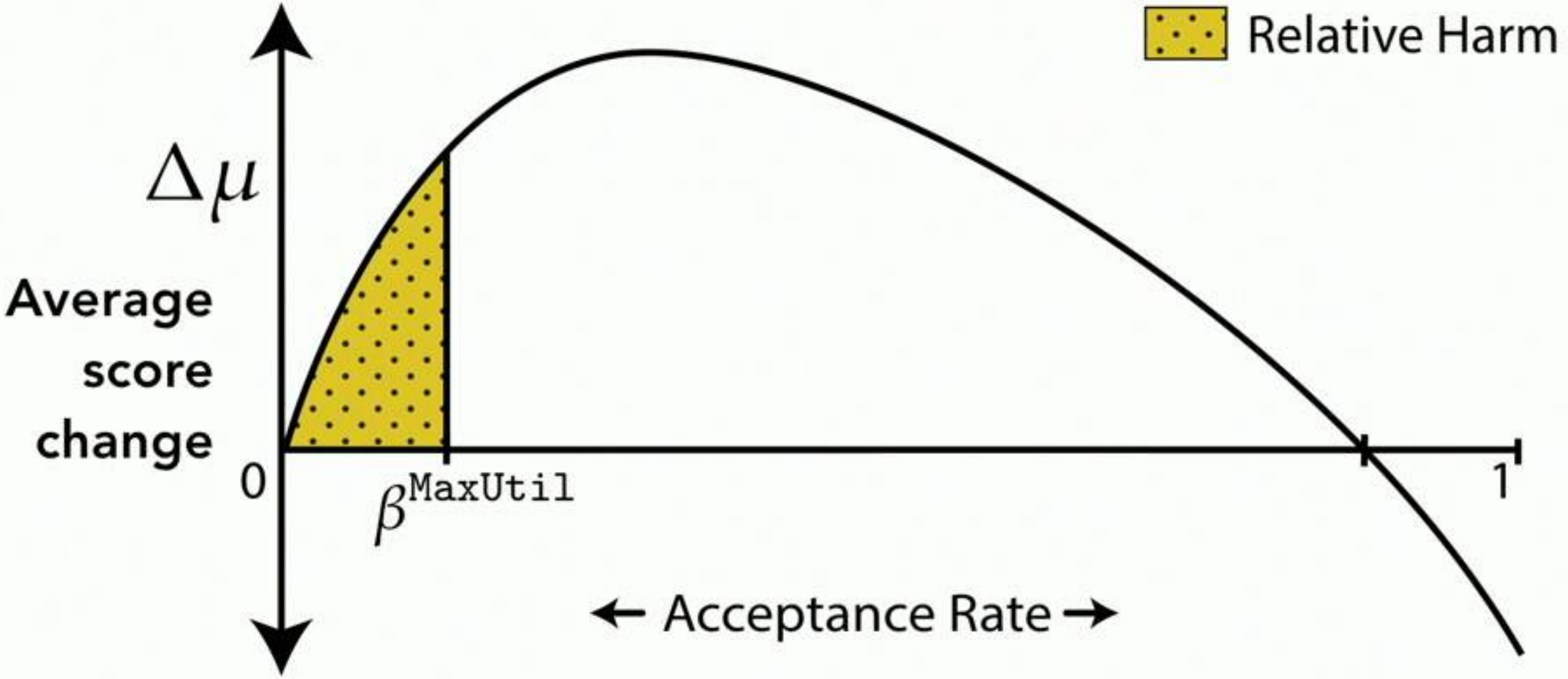
OUTCOME CURVE

<u>Lemma</u>: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



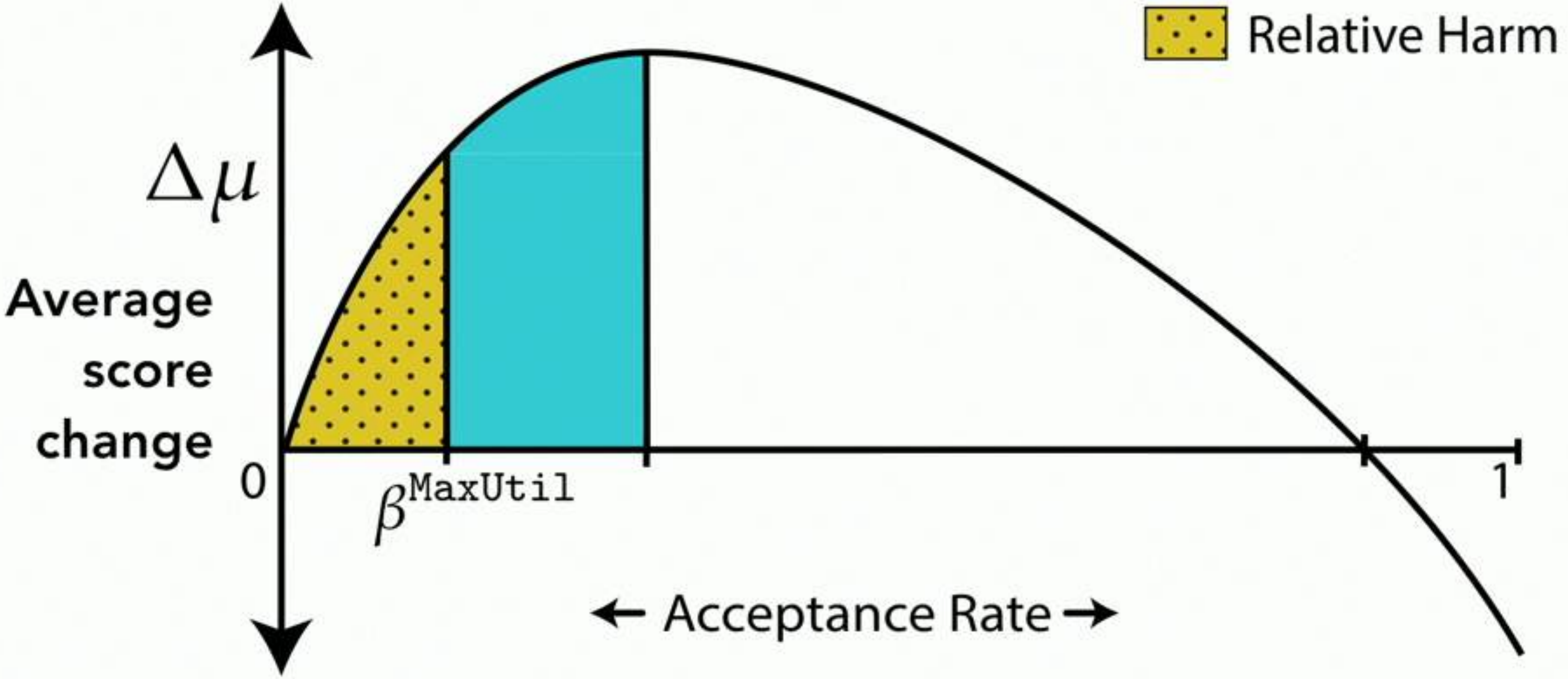
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



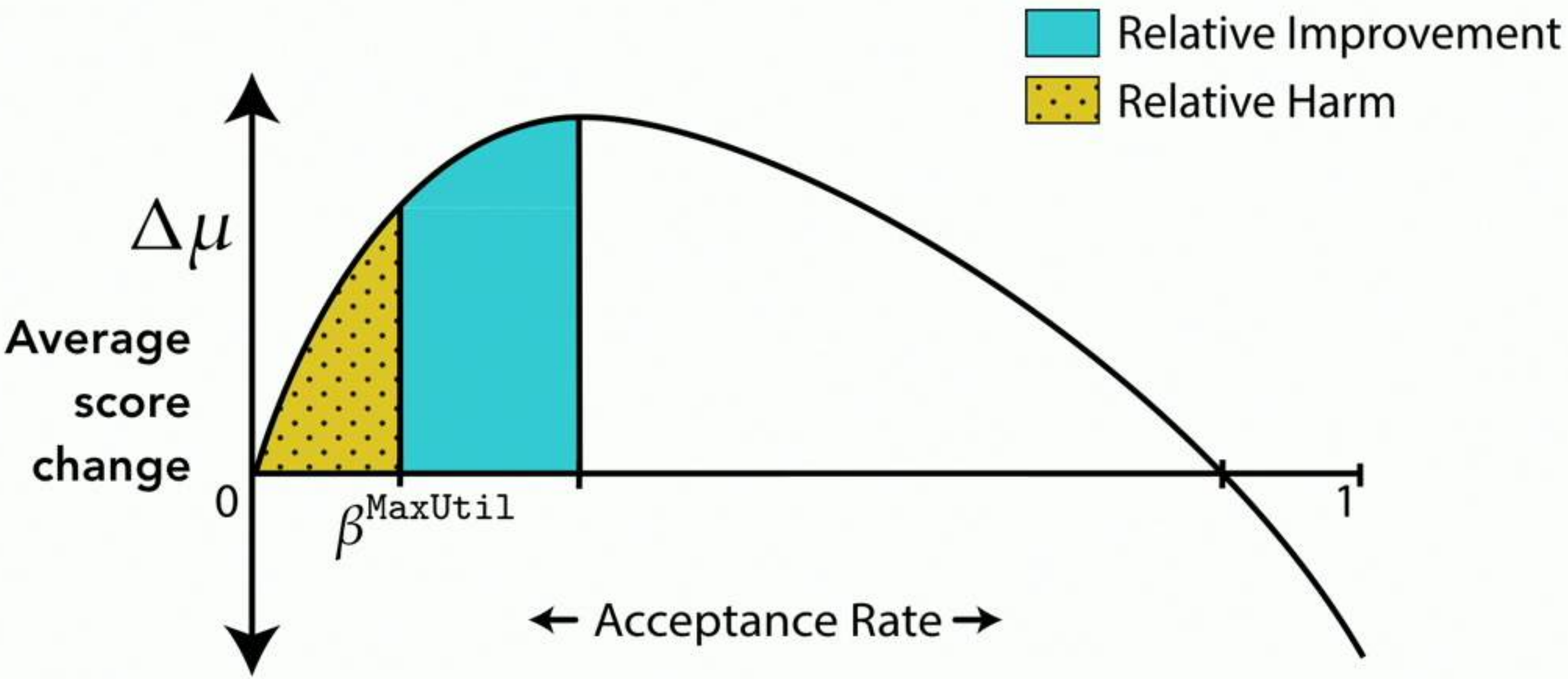
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



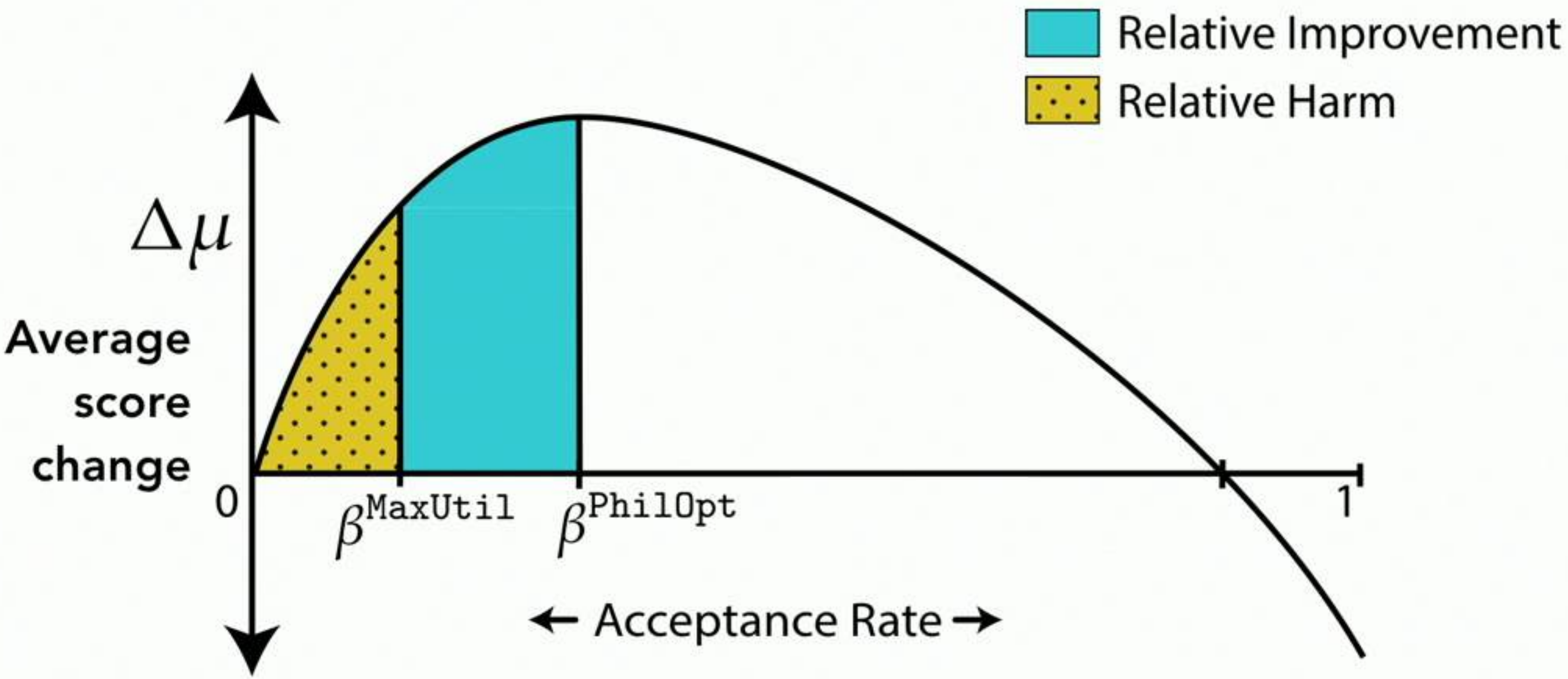
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



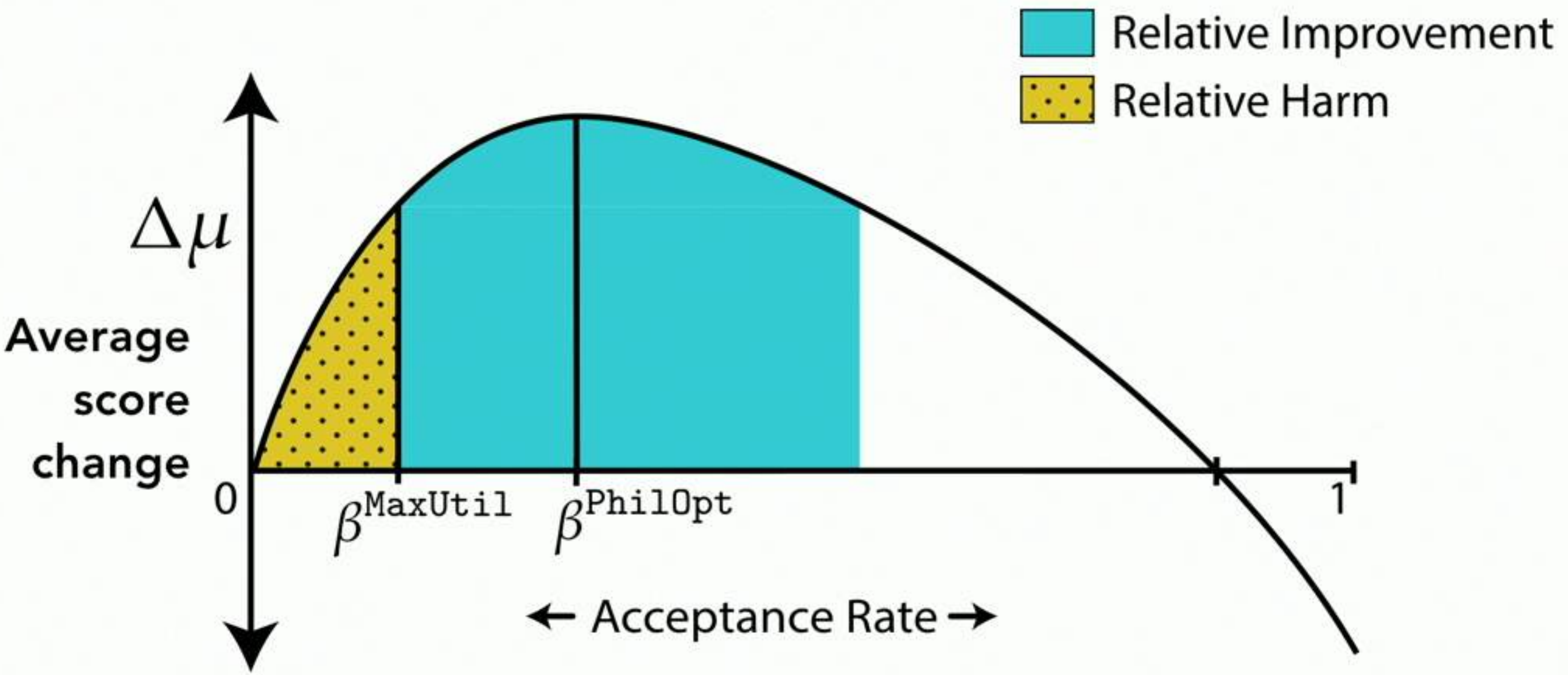
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



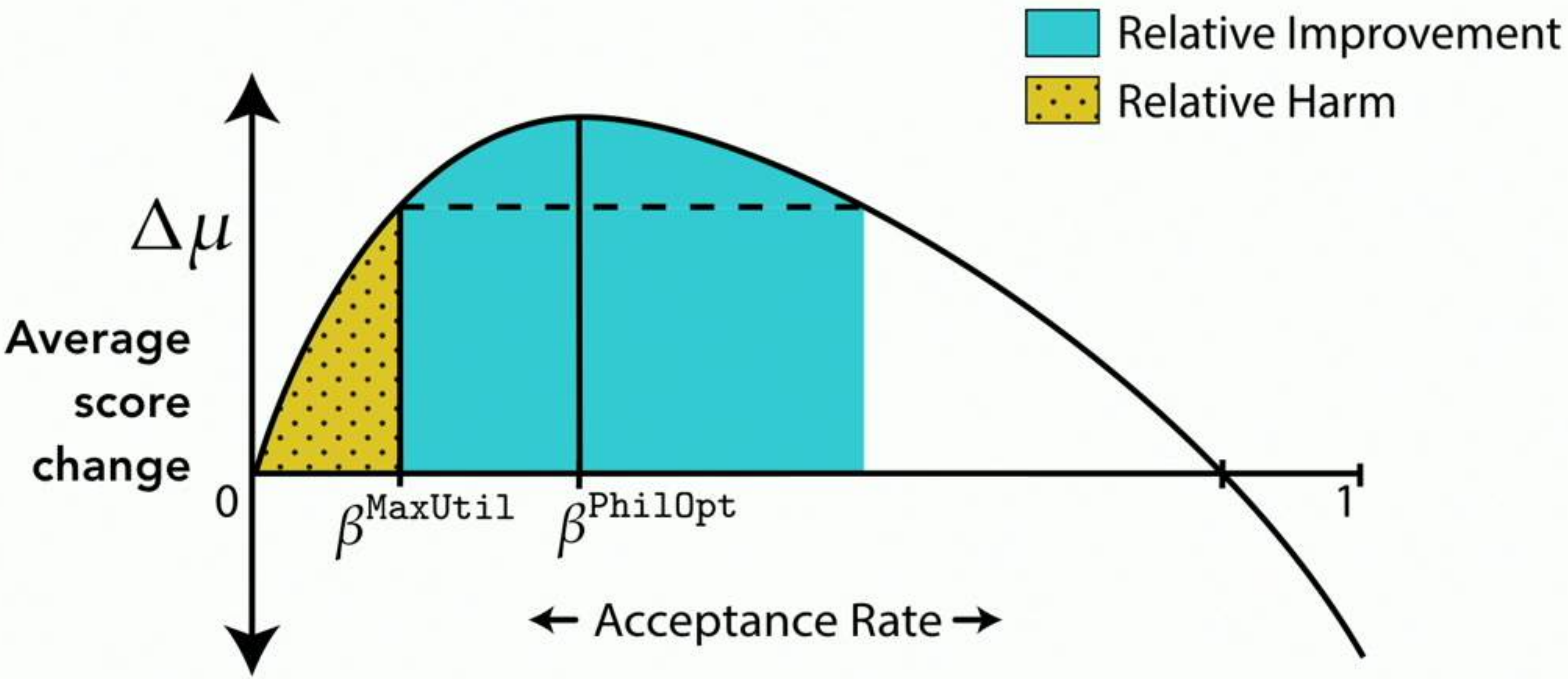
OUTCOME CURVE

<u>Lemma</u>: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



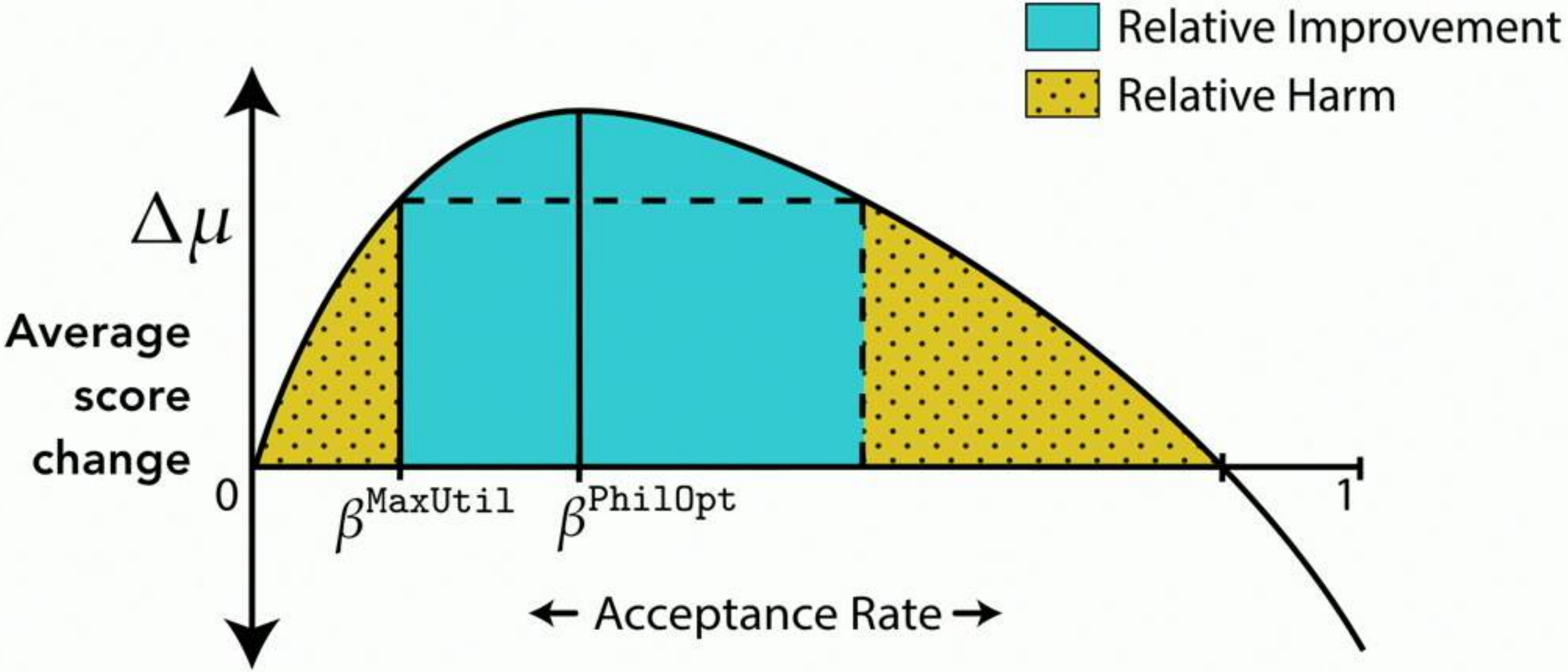
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



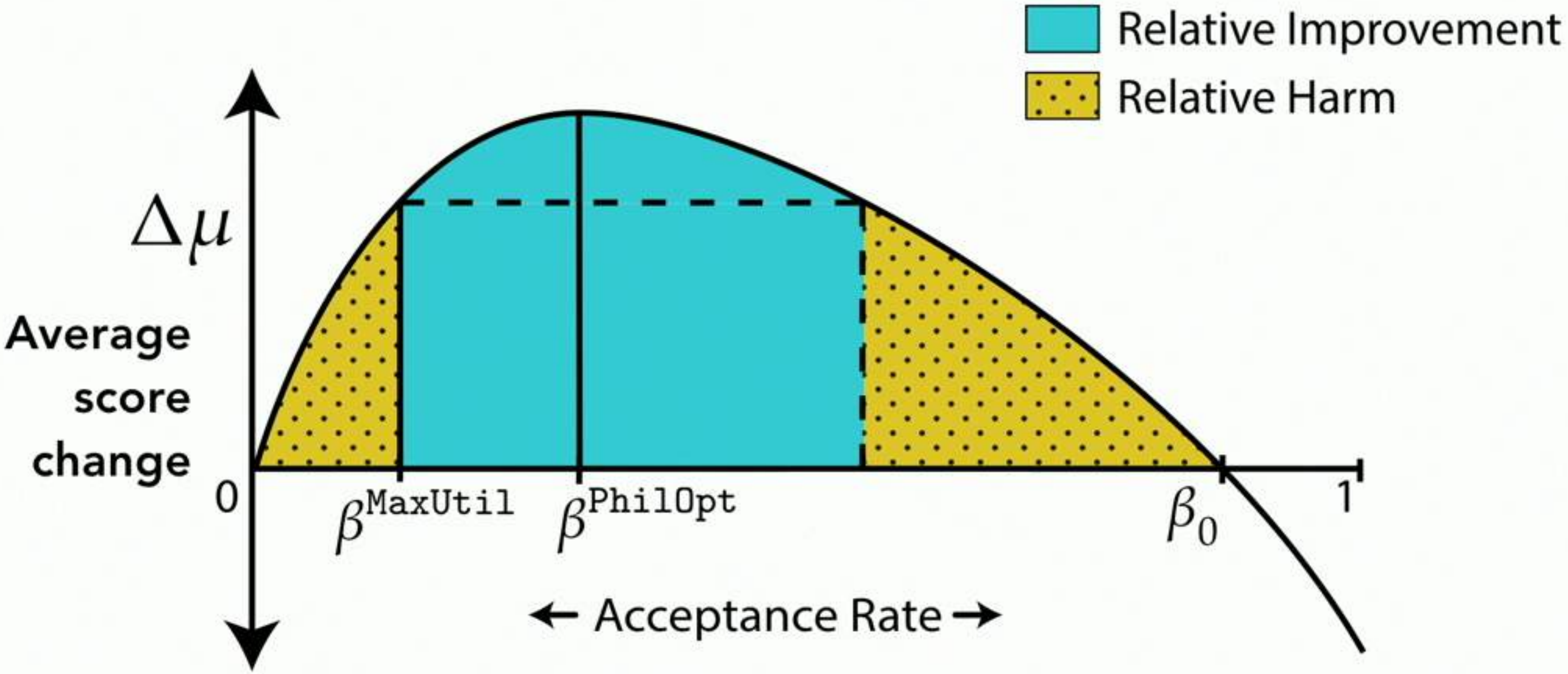
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



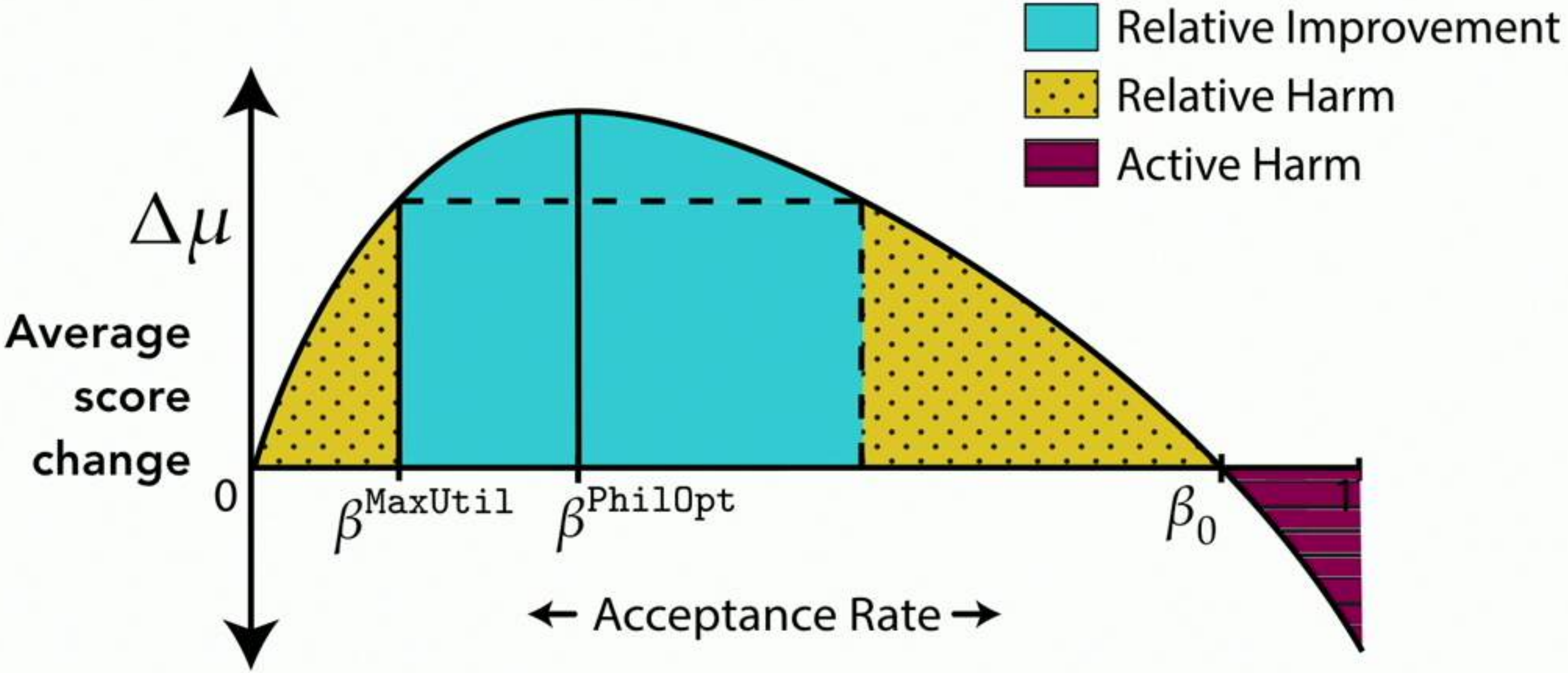
OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



OUTCOME CURVE

Lemma: $\Delta\mu$ is a **concave** function of acceptance rate $\boldsymbol{\beta}$ under mild assumptions.



FAIRNESS CONSTRAINTS

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate

FAIRNESS CONSTRAINTS

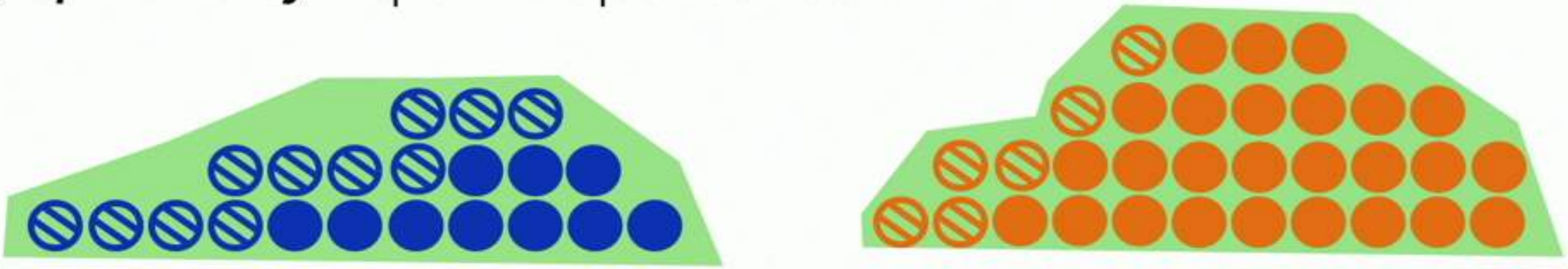
- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate

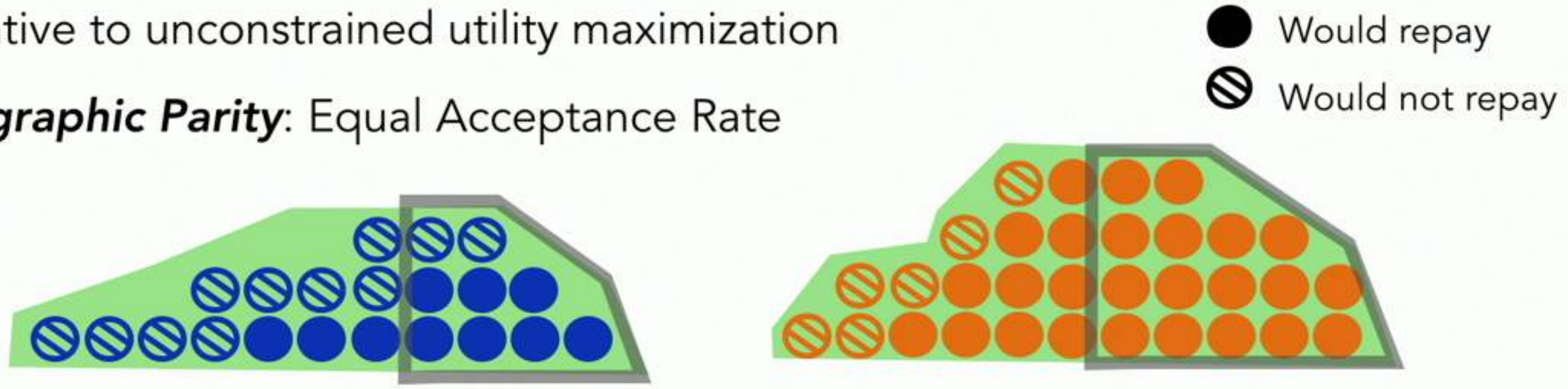
Would repay

Would not repay



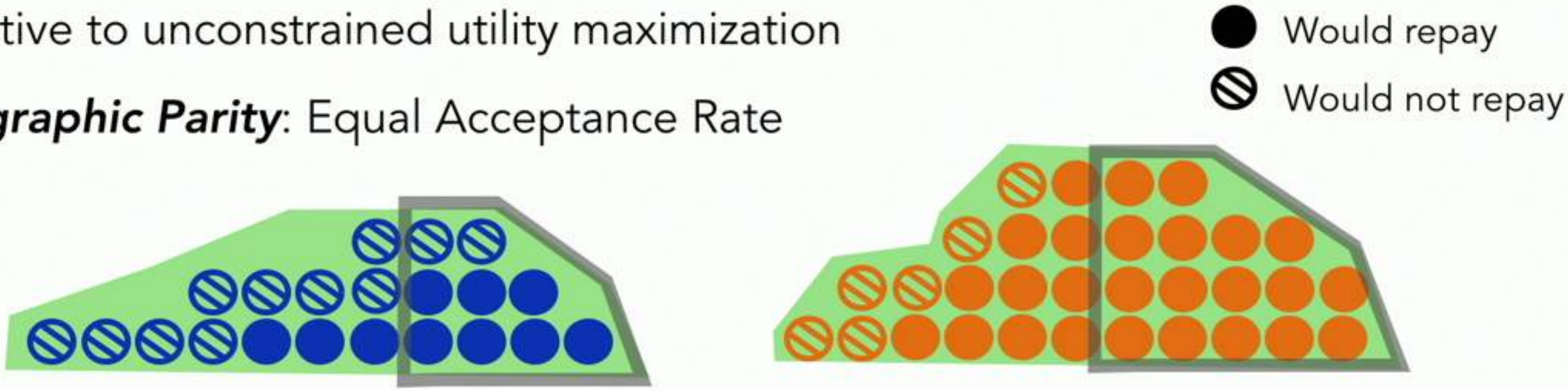
FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate



FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate



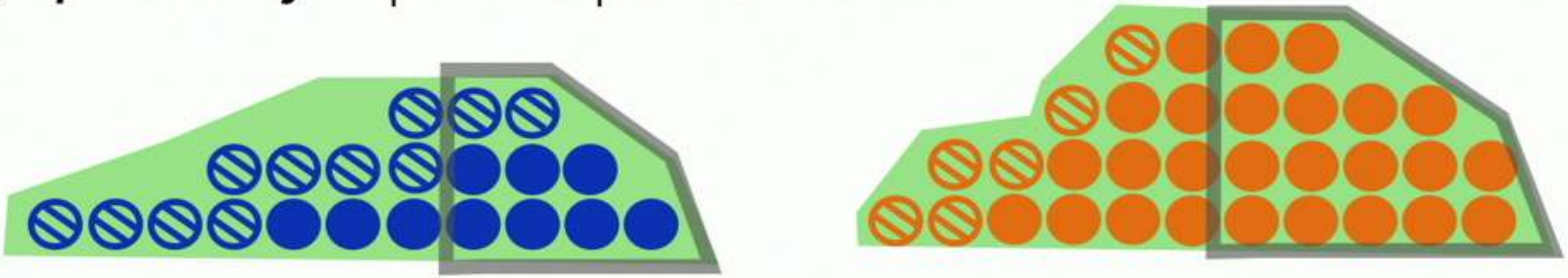
- ***Equal Opportunity***: Equal True Positive Rates

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate

Would repay

Would not repay



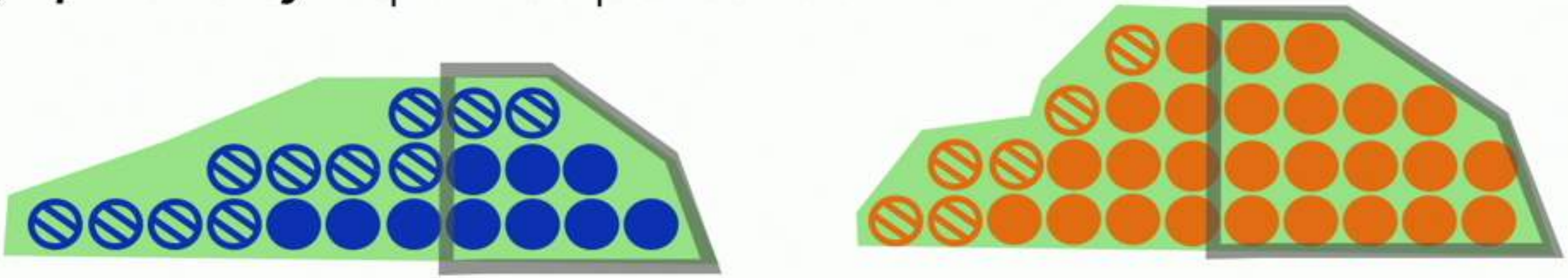
- ***Equal Opportunity***: Equal True Positive Rates

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate

Would repay

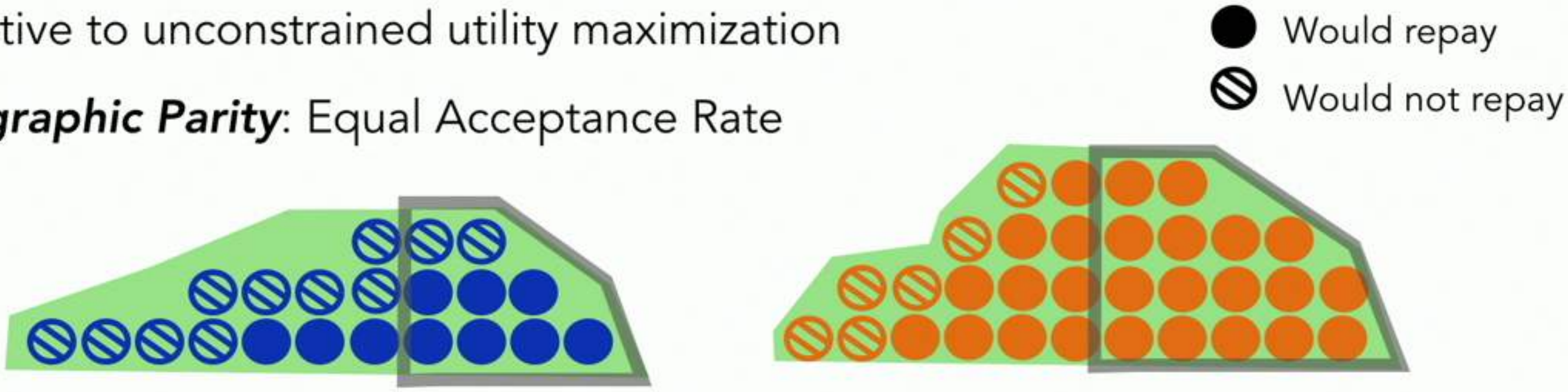
Would not repay



- ***Equal Opportunity***: Equal True Positive Rates

FAIRNESS CONSTRAINTS

- Alternative to unconstrained utility maximization
- ***Demographic Parity***: Equal Acceptance Rate



- ***Equal Opportunity***: Equal True Positive Rates

MAIN THEOREMS

MAIN THEOREMS

Theorem 1 [All outcome regimes are possible]

Equal opportunity and demographic parity may cause relative improvement, relative harm, or active harm.

MAIN THEOREMS

Theorem 1 [All outcome regimes are possible]

Equal opportunity and demographic parity may cause relative improvement, relative harm, or active harm.

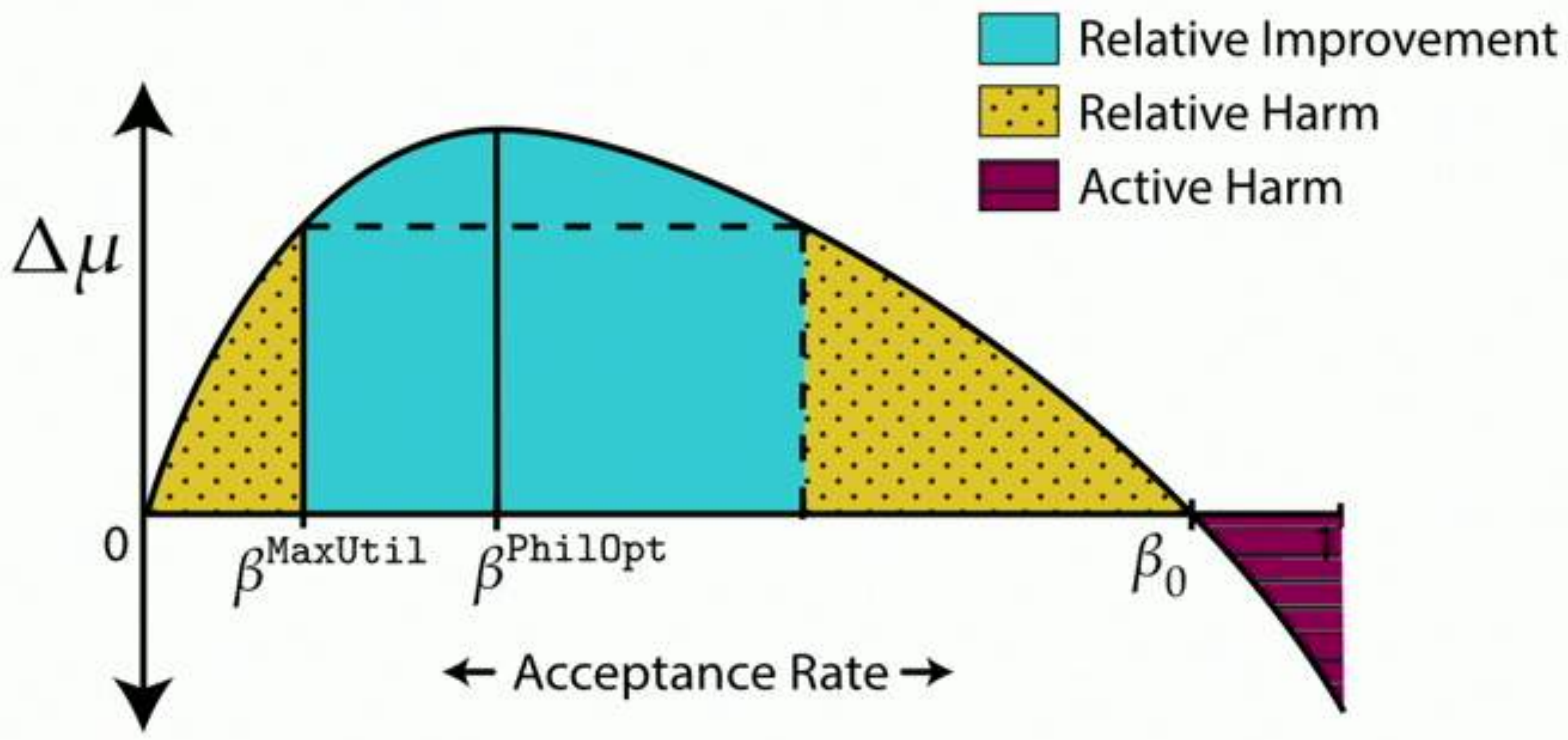
- unconstrained utility maximization never causes active harm.

MAIN THEOREMS

Theorem 1 [All outcome regimes are possible]

Equal opportunity and demographic parity may cause relative improvement, relative harm, or active harm.

- unconstrained utility maximization never causes active harm.



CHOICE OF FAIRNESS CRITERIA MATTERS

CHOICE OF FAIRNESS CRITERIA MATTERS

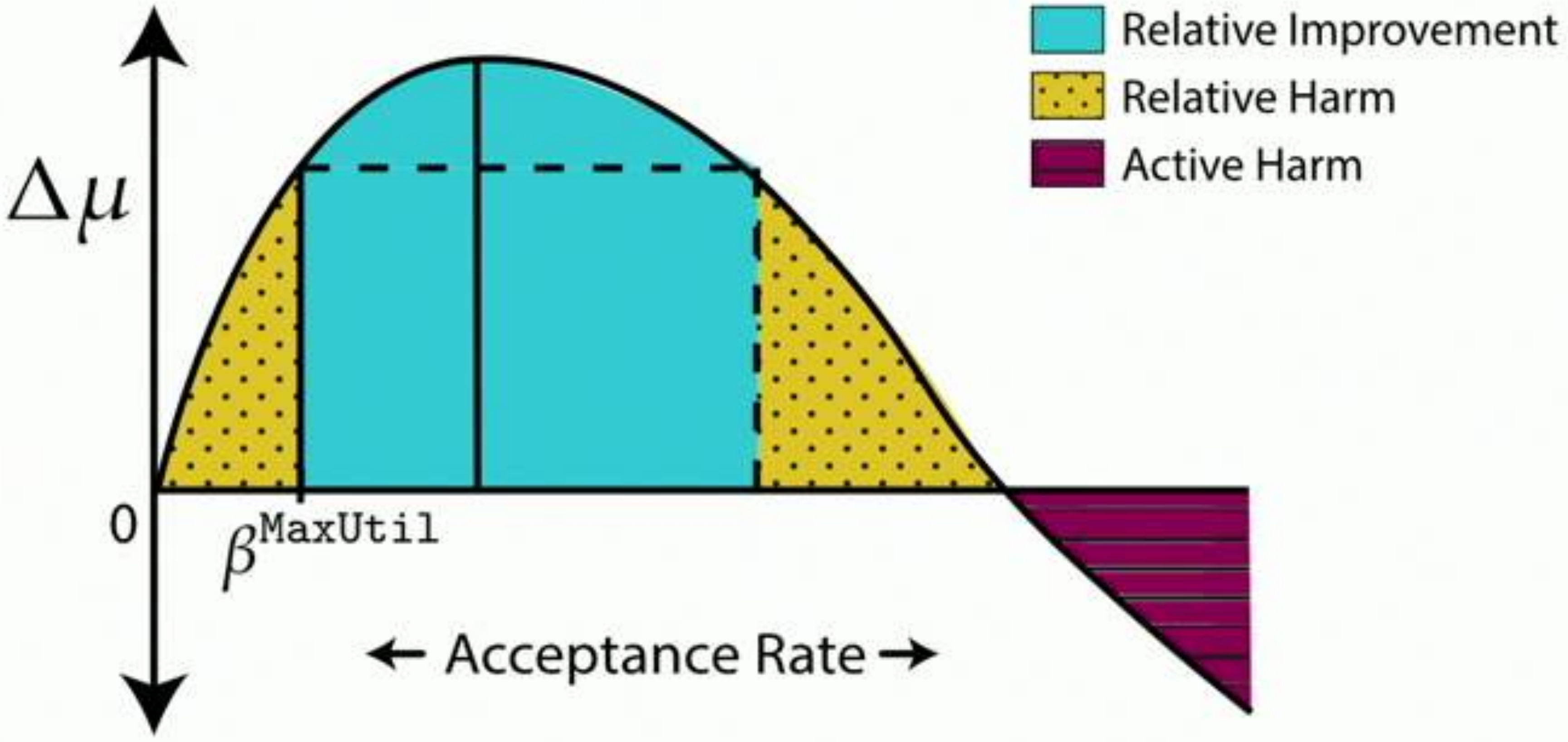
Theorem 2

Demographic parity (DP) may cause active or relative harm by **over-acceptance**; equal opportunity (EO) doesn't.

CHOICE OF FAIRNESS CRITERIA MATTERS

Theorem 2

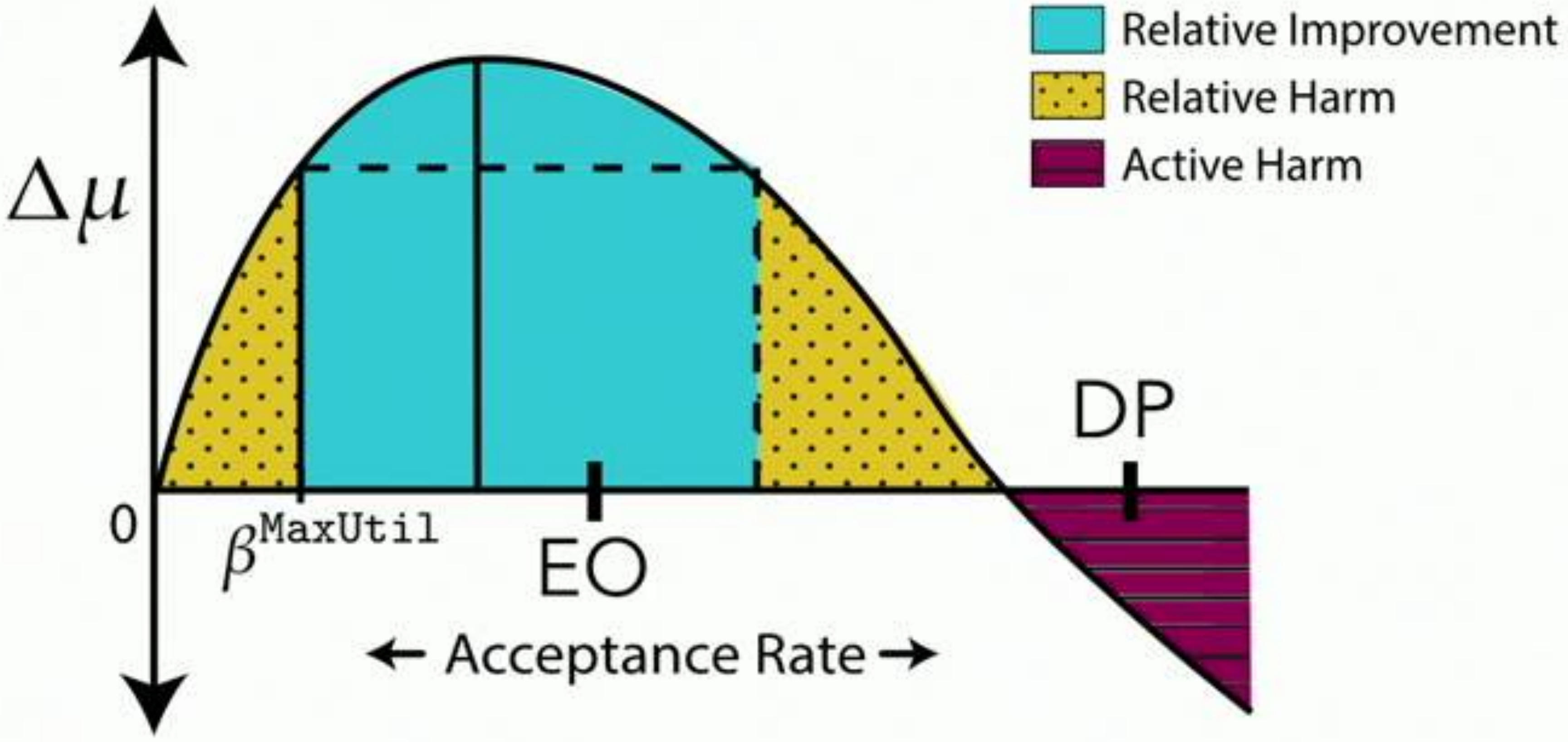
Demographic parity (DP) may cause active or relative harm by **over-acceptance**; equal opportunity (EO) doesn't.



CHOICE OF FAIRNESS CRITERIA MATTERS

Theorem 2

Demographic parity (DP) may cause active or relative harm by **over-acceptance**; equal opportunity (EO) doesn't.



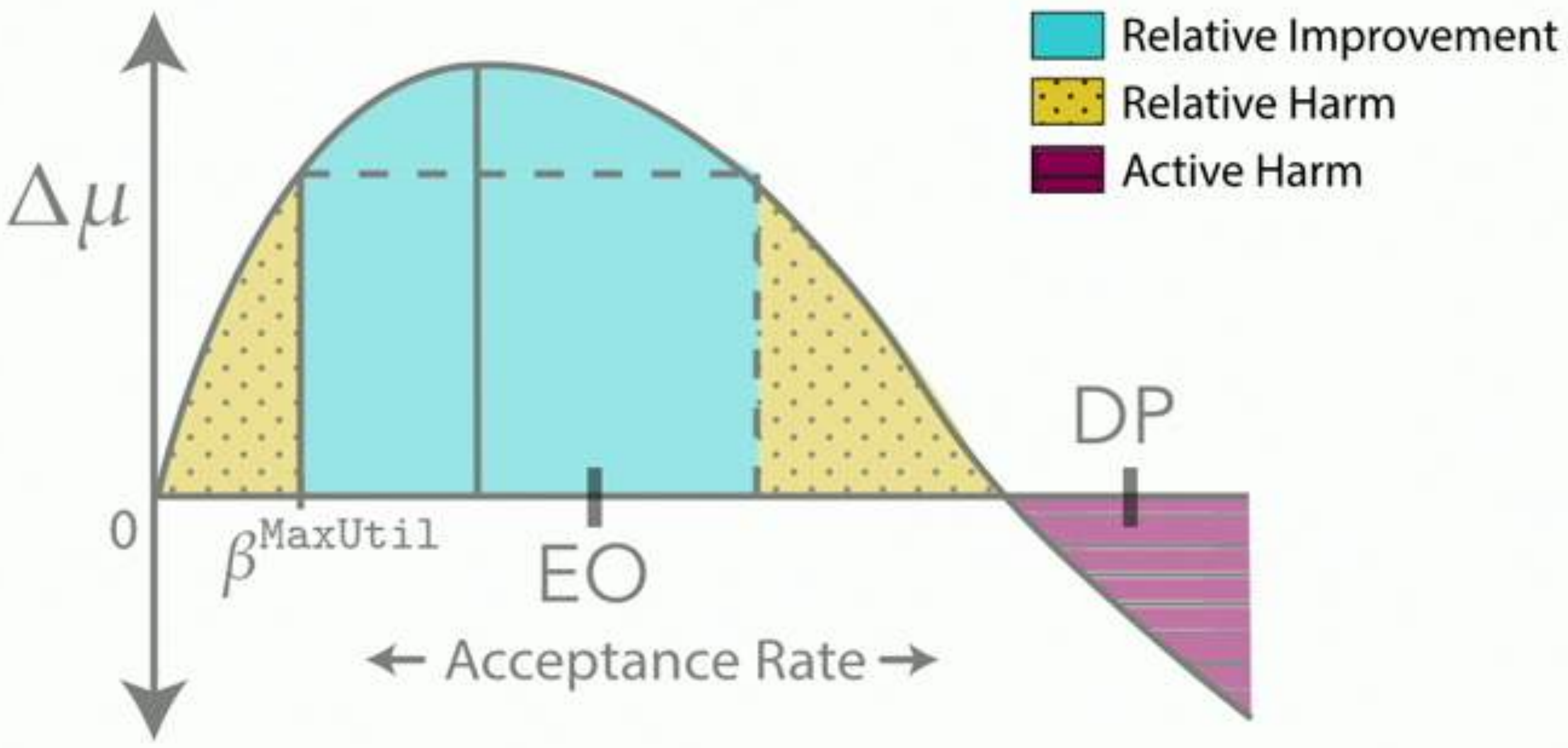
CHOICE OF FAIRNESS CRITERIA MATTERS

Theorem 2

Demographic parity (DP) may cause active or relative harm by **over-acceptance**; equal opportunity (EO) doesn't.

Theorem 3

Equal opportunity may cause relative harm by **under-acceptance**; demographic parity never under-accepts.



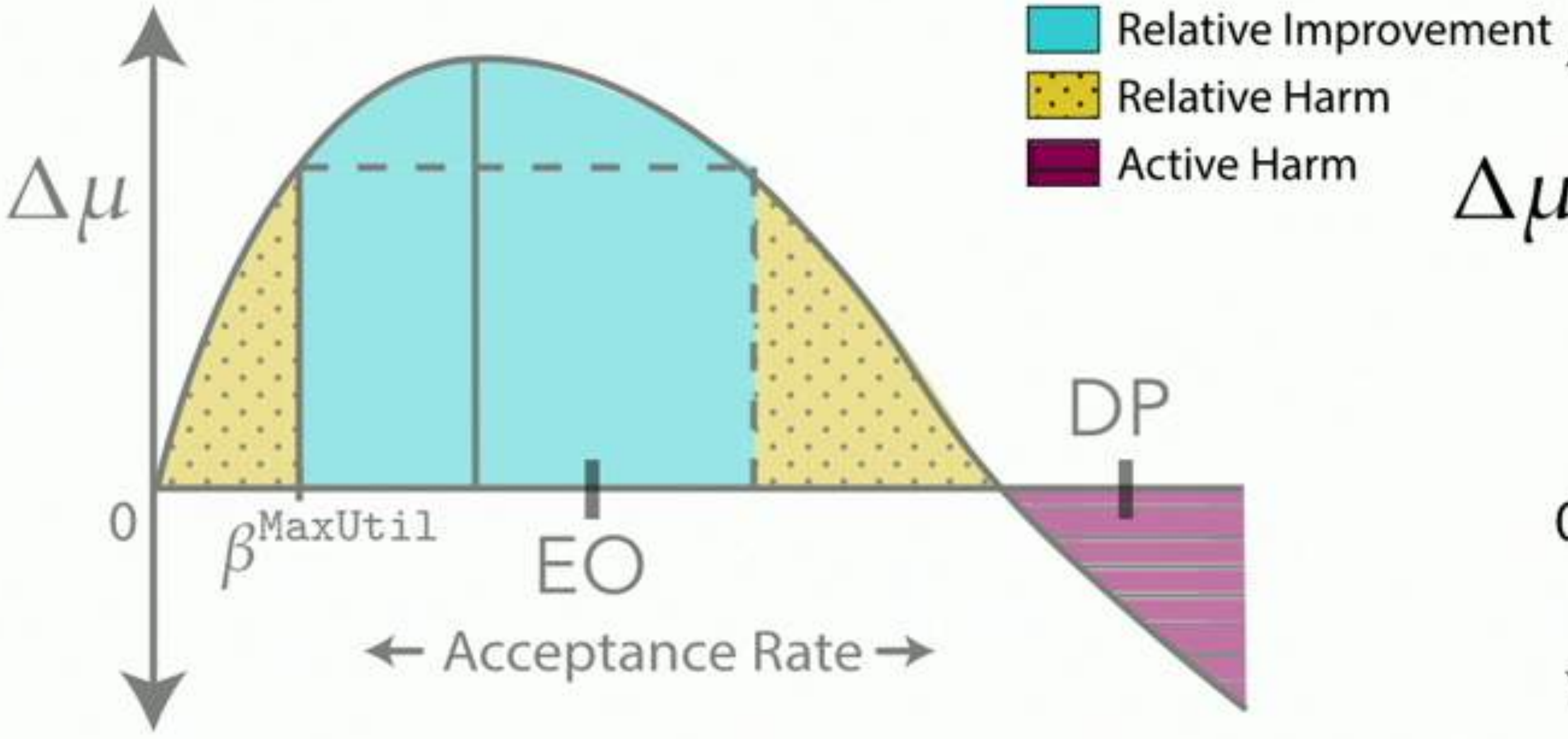
CHOICE OF FAIRNESS CRITERIA MATTERS

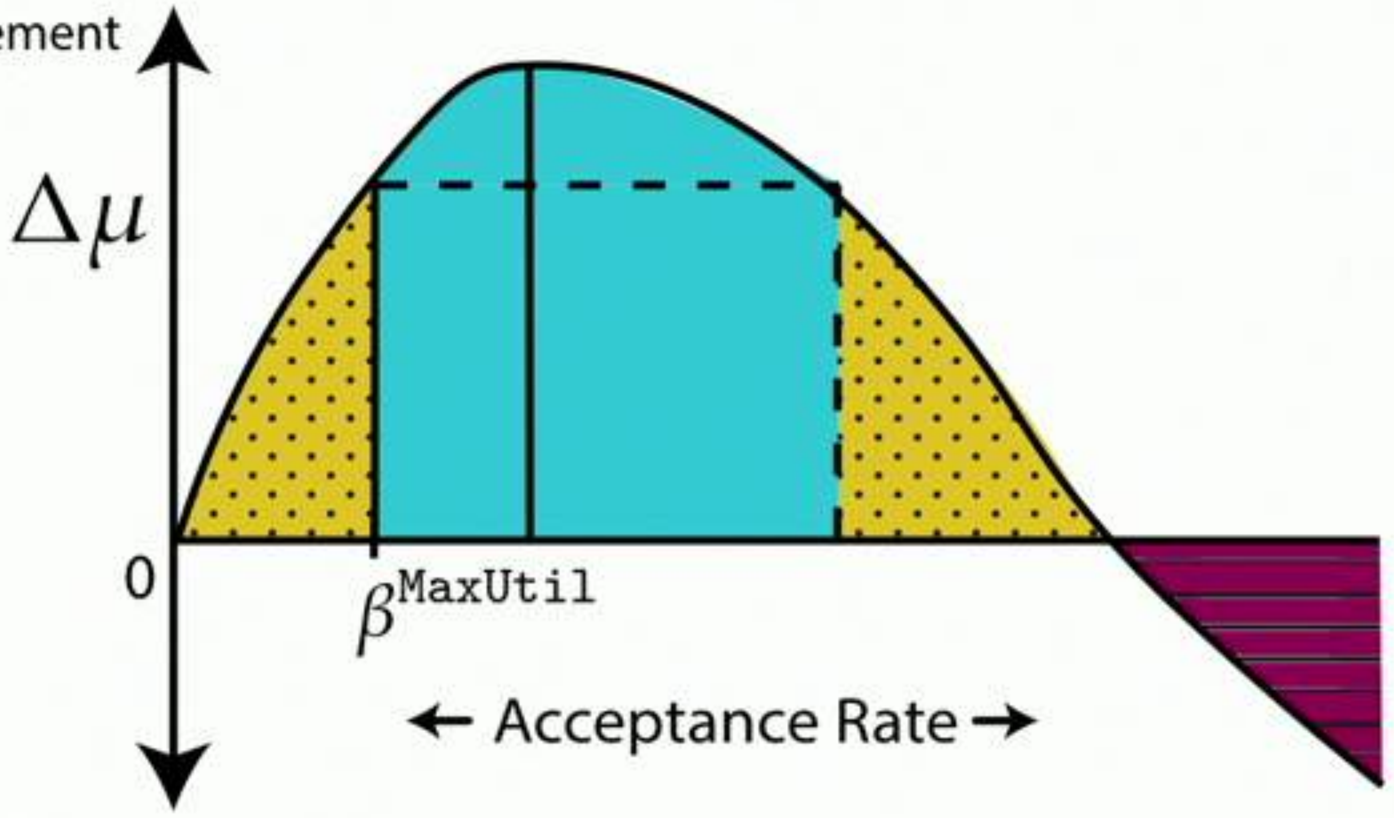
Theorem 2

Demographic parity (DP) may cause active or relative harm by **over-acceptance**; equal opportunity (EO) doesn't.

Theorem 3

Equal opportunity may cause relative harm by **under-acceptance**; demographic parity never under-accepts.





“MEASUREMENT ERROR”

"MEASUREMENT ERROR"

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

“MEASUREMENT ERROR”

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

"MEASUREMENT ERROR"

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

- orange group

"MEASUREMENT ERROR"

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

- orange group
- **0.8** probability of repaying loan

"MEASUREMENT ERROR"

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

- orange group
- **0.8** probability of repaying loan
- assigned credit score of **700**

"MEASUREMENT ERROR"

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

- orange group
- **0.8** probability of repaying loan
- assigned credit score of **700**

“MEASUREMENT ERROR”

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

- orange group
- **0.8** probability of repaying loan
- assigned credit score of **700**

- blue group
- **0.8** probability of repaying loan

"MEASUREMENT ERROR"

- The bank systematically **underestimates** the repayment ability of the disadvantaged group
  - e.g. Bank thinks credit score = **700** corresponds to **0.8** probability of repaying loan

- orange group
- **0.8** probability of repaying loan
- assigned credit score of **700**

- blue group
- **0.8** probability of repaying loan
- but assigned credit score of **600** (*underestimated*)

“MEASUREMENT ERROR”

“MEASUREMENT ERROR”

- *Theorem*: **Acceptance rate for blue group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.

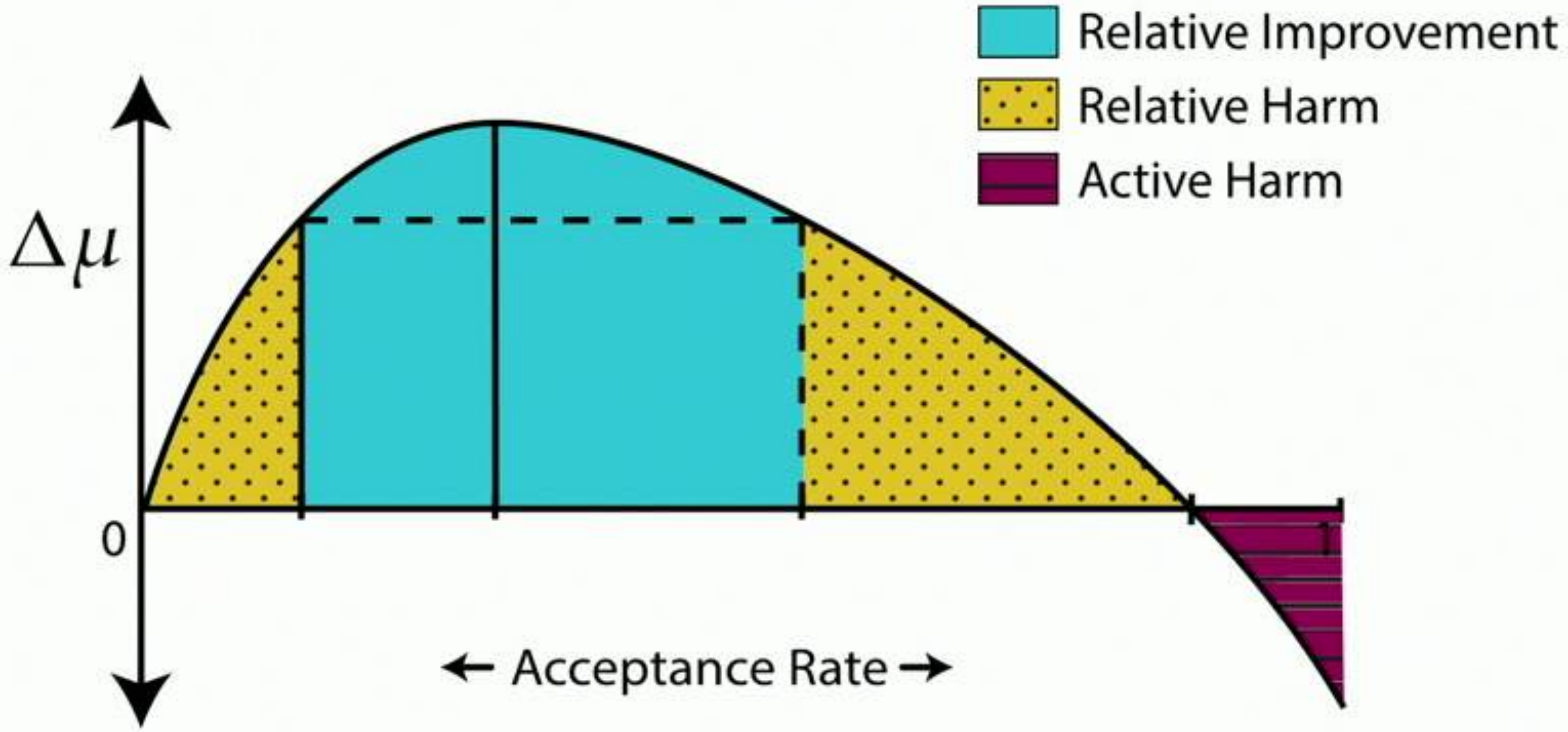
"MEASUREMENT ERROR"

- *Theorem*: **Acceptance rate for** blue **group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**

*under an additional condition.

"MEASUREMENT ERROR"

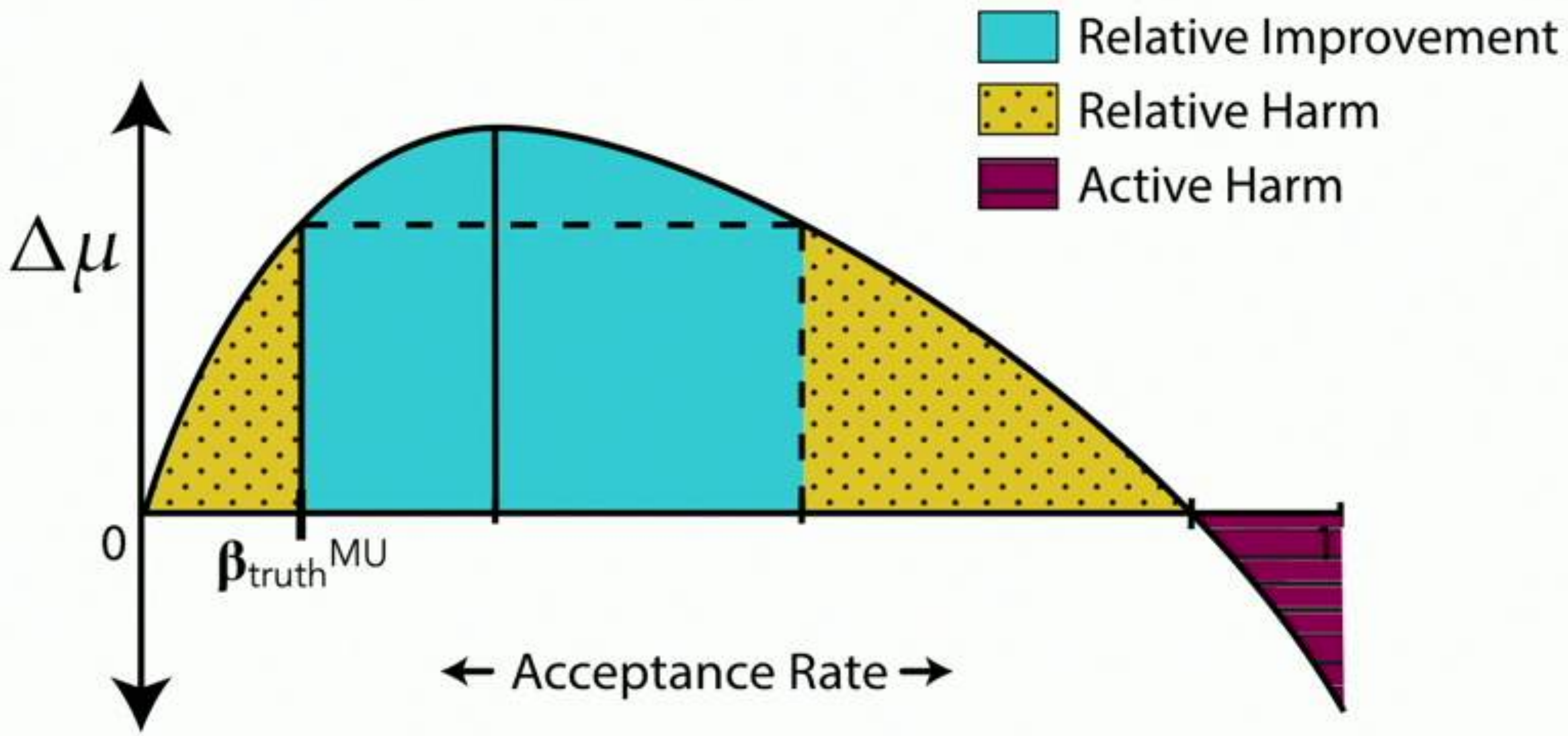
- *Theorem*: **Acceptance rate for blue group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**



*under an additional condition.

"MEASUREMENT ERROR"

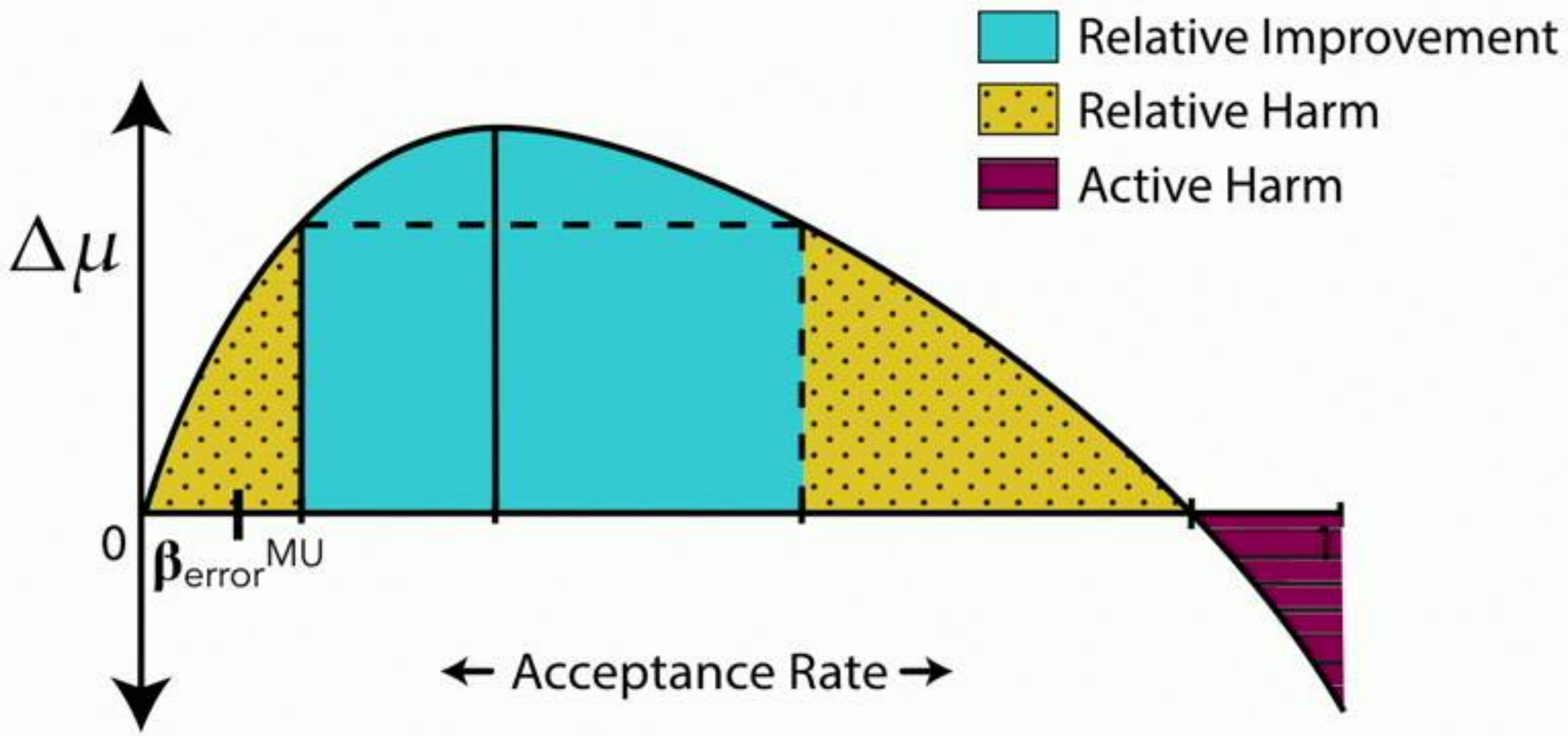
- *Theorem*: **Acceptance rate for blue group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**



*under an additional condition.

"MEASUREMENT ERROR"

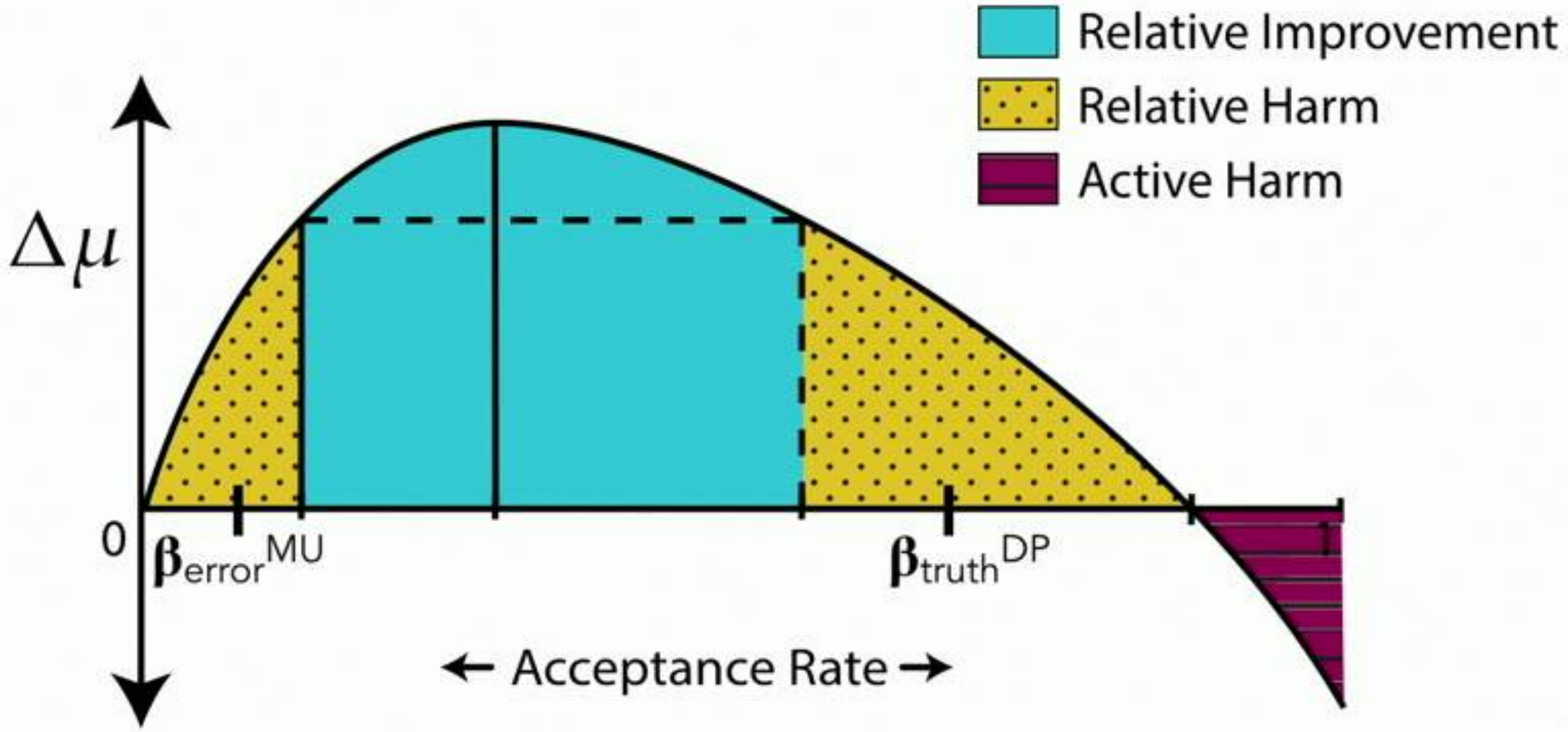
- *Theorem*: **Acceptance rate for** blue **group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**



*under an additional condition.

“MEASUREMENT ERROR”

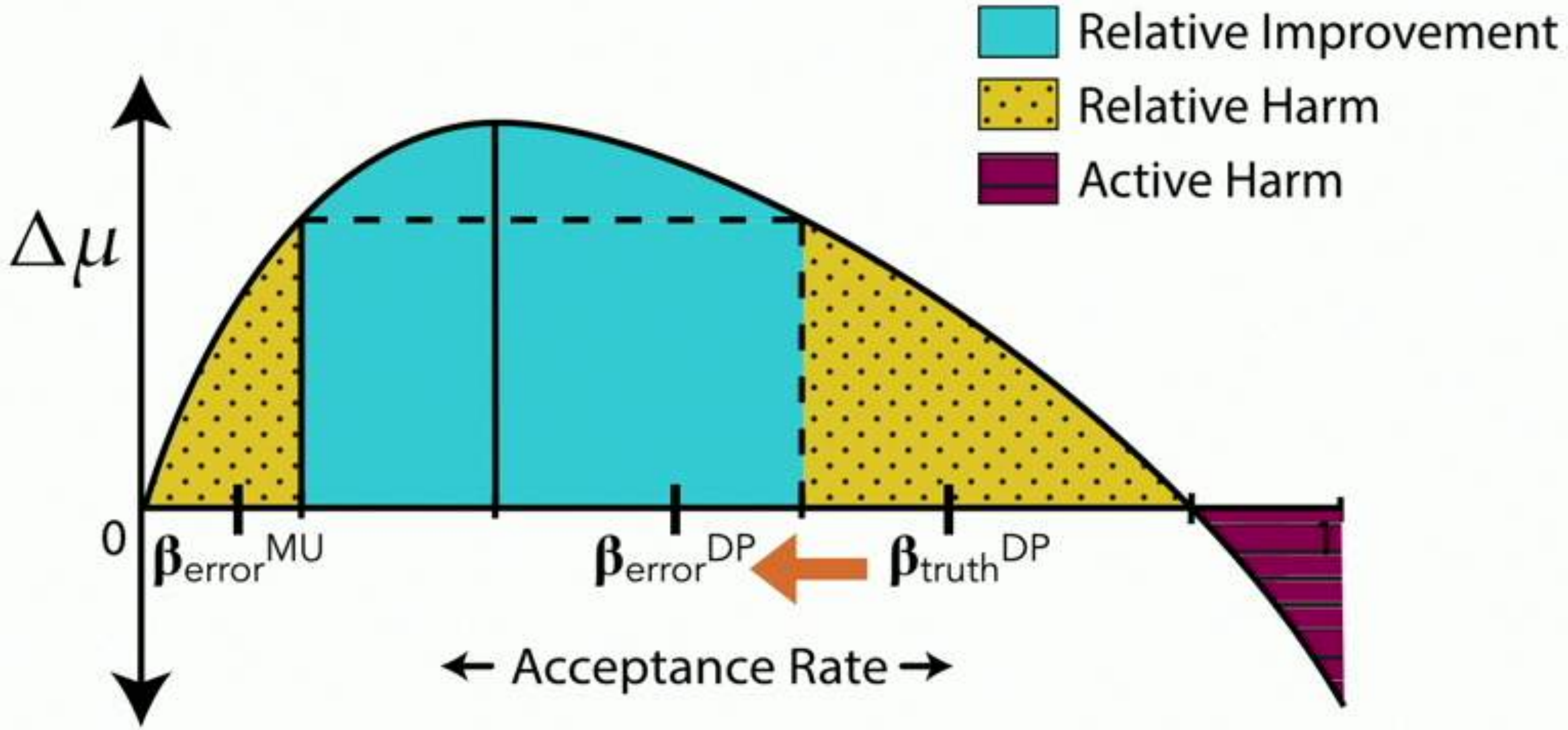
- *Theorem*: **Acceptance rate for blue group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**



*under an additional condition.

“MEASUREMENT ERROR”

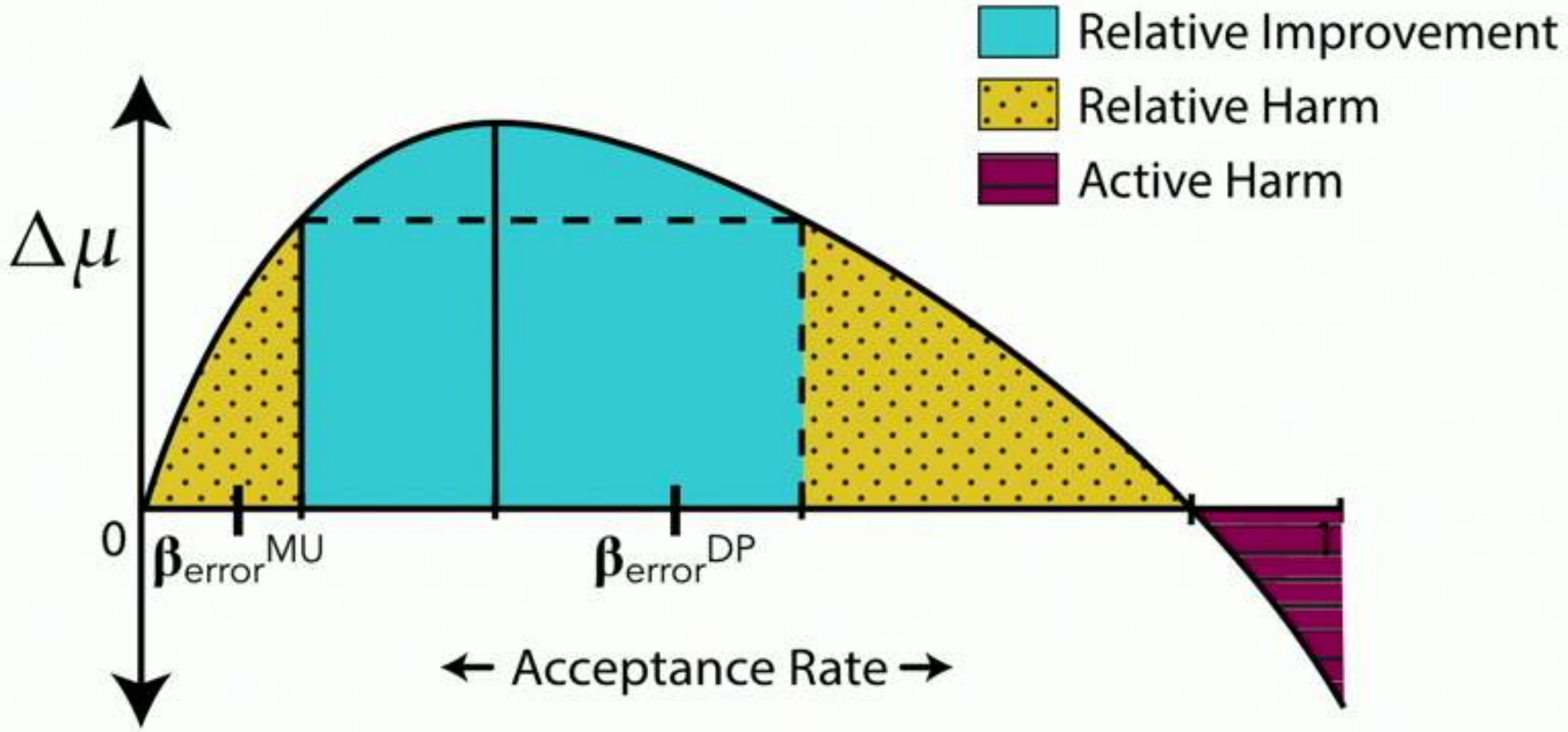
- *Theorem*: **Acceptance rate for** **blue** **group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**



*under an additional condition.

"MEASUREMENT ERROR"

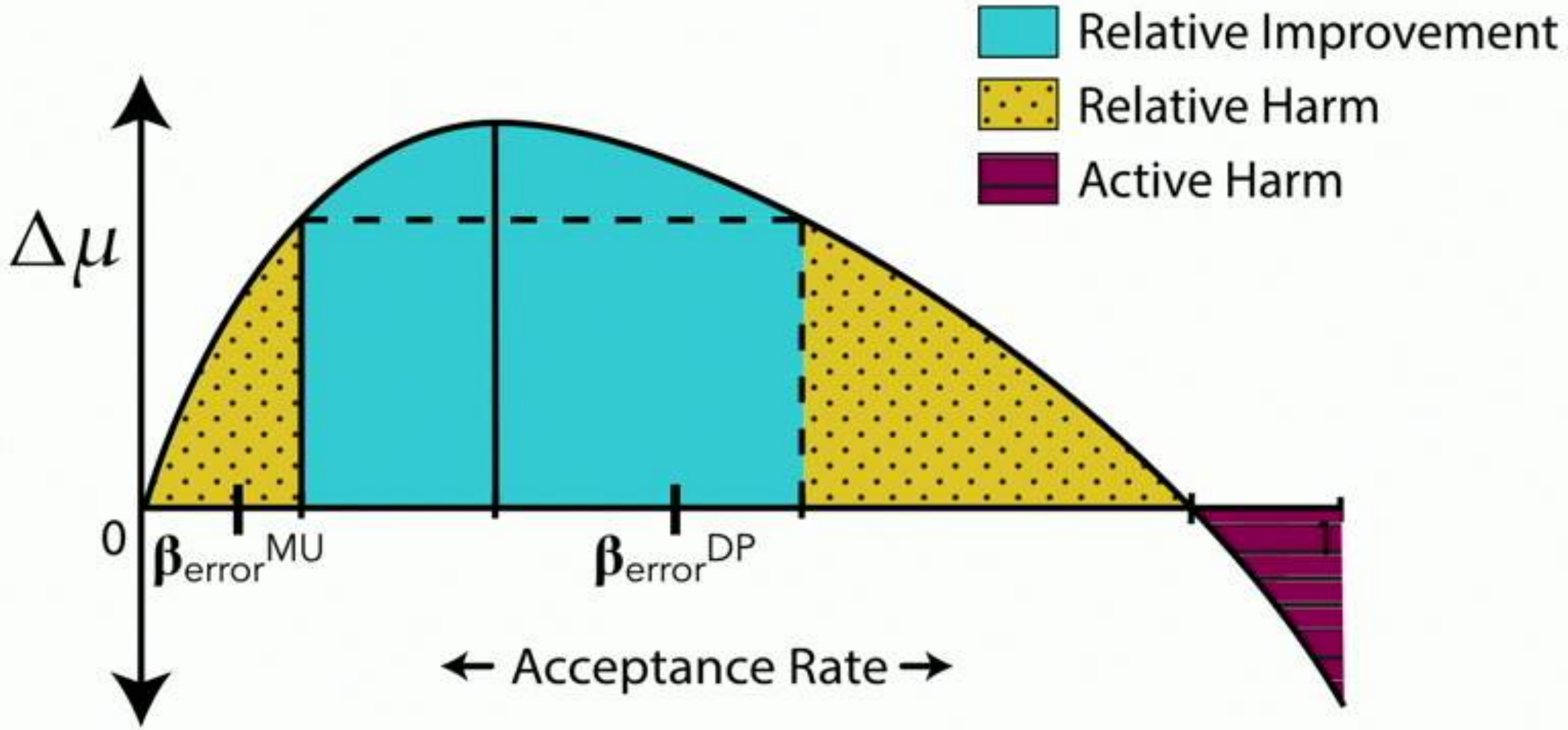
- *Theorem*: **Acceptance rate for blue group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**



*under an additional condition.

"MEASUREMENT ERROR"

- *Theorem*: **Acceptance rate for blue group is lower** if their scores are systematically underestimated than when their scores reflect true probability of repayment.
- This holds for **unconstrained utility maximization, demographic parity,** as well as **equal opportunity*.**
- Example:
  If there's measurement error, **demographic parity** yields more favorable delayed impact by promoting higher acceptance rate.



*under an additional condition.

EXPERIMENTS ON FICO CREDIT SCORES

EXPERIMENTS ON FICO CREDIT SCORES

- 300,000+ TransUnion TransRisk scores from 2003
- Scores range from 300 to 850 and are meant to predict default risk

EXPERIMENTS ON FICO CREDIT SCORES

- 300,000+ TransUnion TransRisk scores from 2003
- Scores range from 300 to 850 and are meant to predict default risk

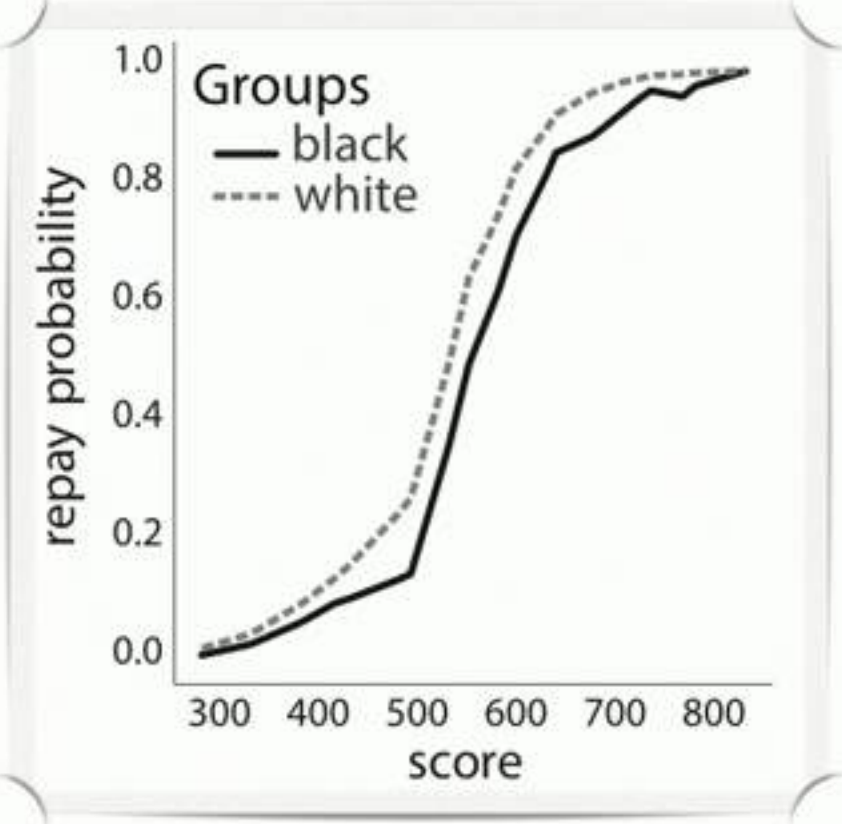
What we did

EXPERIMENTS ON FICO CREDIT SCORES

- 300,000+ TransUnion TransRisk scores from 2003
- Scores range from 300 to 850 and are meant to predict default risk

What we did

- Use empirical data labeled by race ("white" and "black") to estimate group score distributions, repayment probabilities, and relative sizes

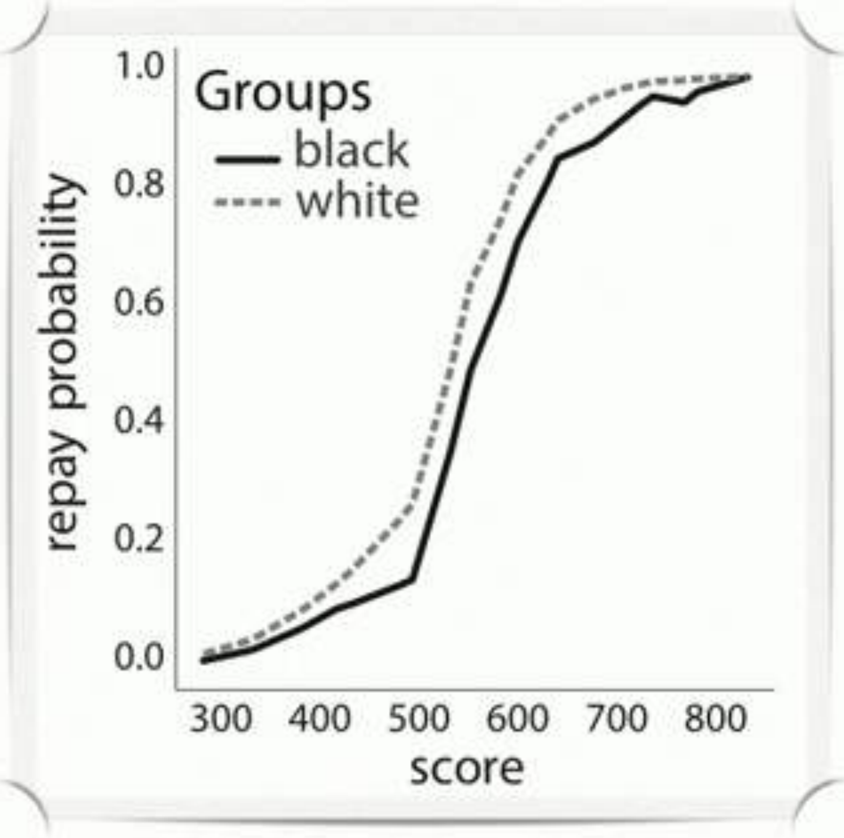


EXPERIMENTS ON FICO CREDIT SCORES

- 300,000+ TransUnion TransRisk scores from 2003
- Scores range from 300 to 850 and are meant to predict default risk

What we did

- Use empirical data labeled by race ("white" and "black") to estimate group score distributions, repayment probabilities, and relative sizes
- Model the bank's profit/loss ratio, e.g. +1:-4

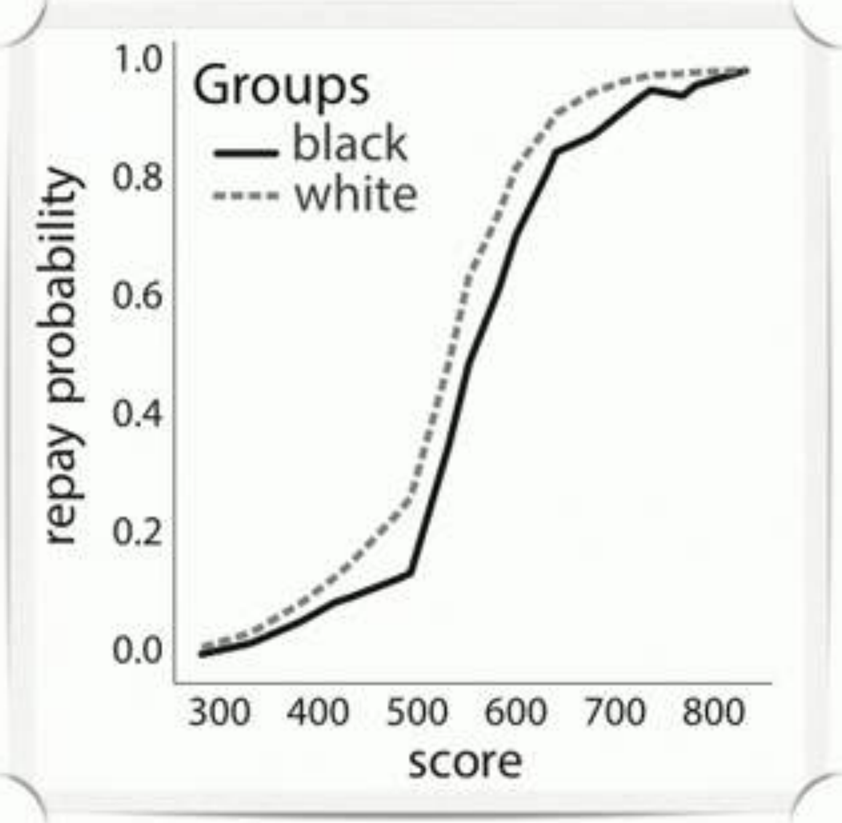


EXPERIMENTS ON FICO CREDIT SCORES

- 300,000+ TransUnion TransRisk scores from 2003
- Scores range from 300 to 850 and are meant to predict default risk

What we did

- Use empirical data labeled by race ("white" and "black") to estimate group score distributions, repayment probabilities, and relative sizes
- Model the bank's profit/loss ratio, e.g. +1:-4
- Model the delayed impact of repayment/default on credit score, e.g. +75/-150

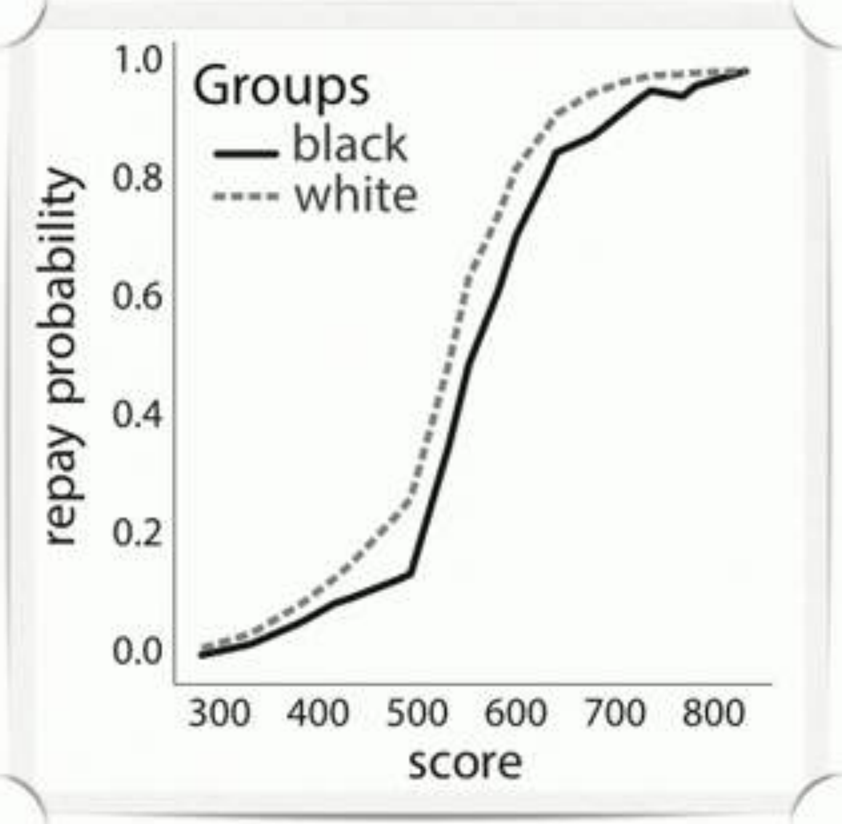


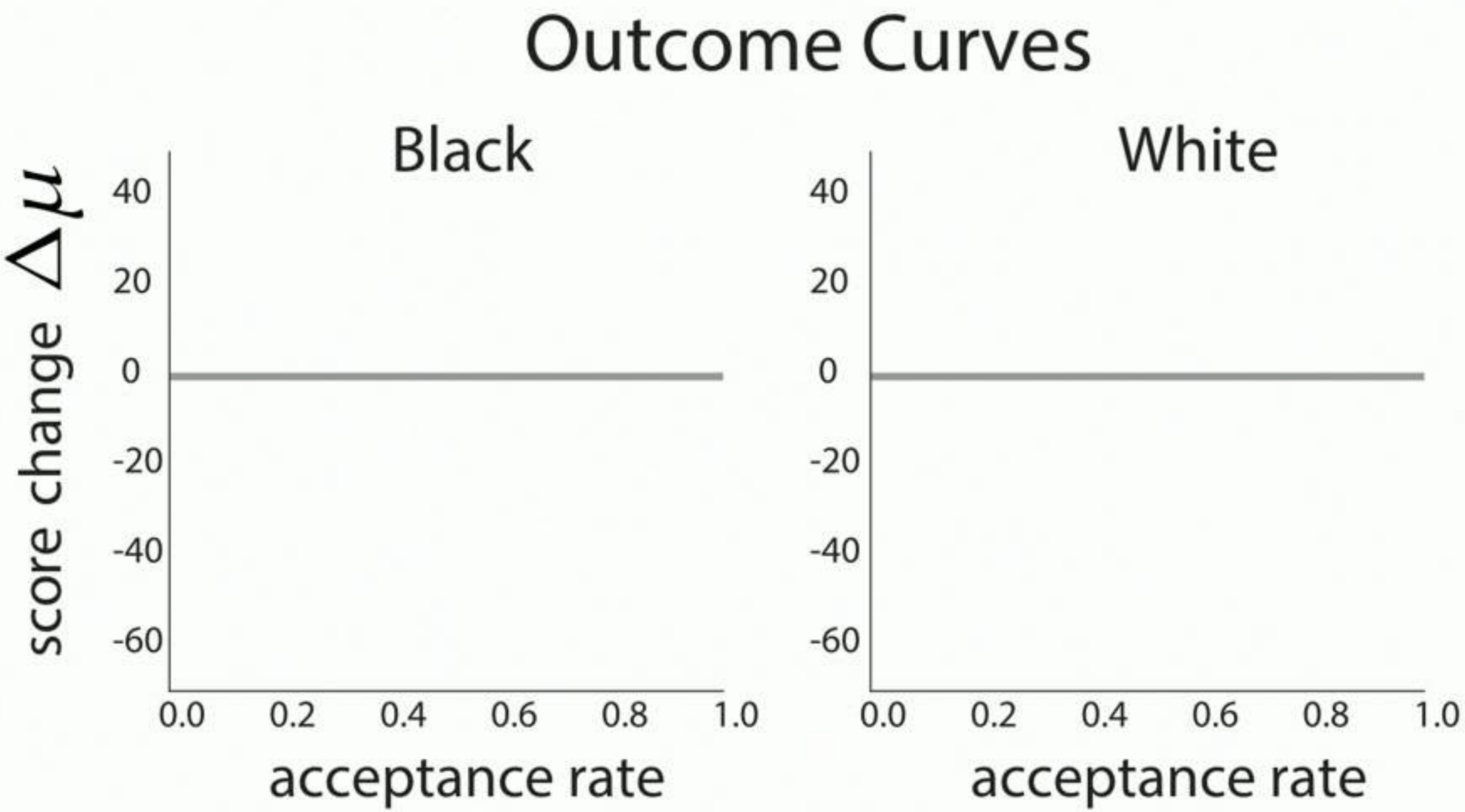
EXPERIMENTS ON FICO CREDIT SCORES

- 300,000+ TransUnion TransRisk scores from 2003
- Scores range from 300 to 850 and are meant to predict default risk

What we did

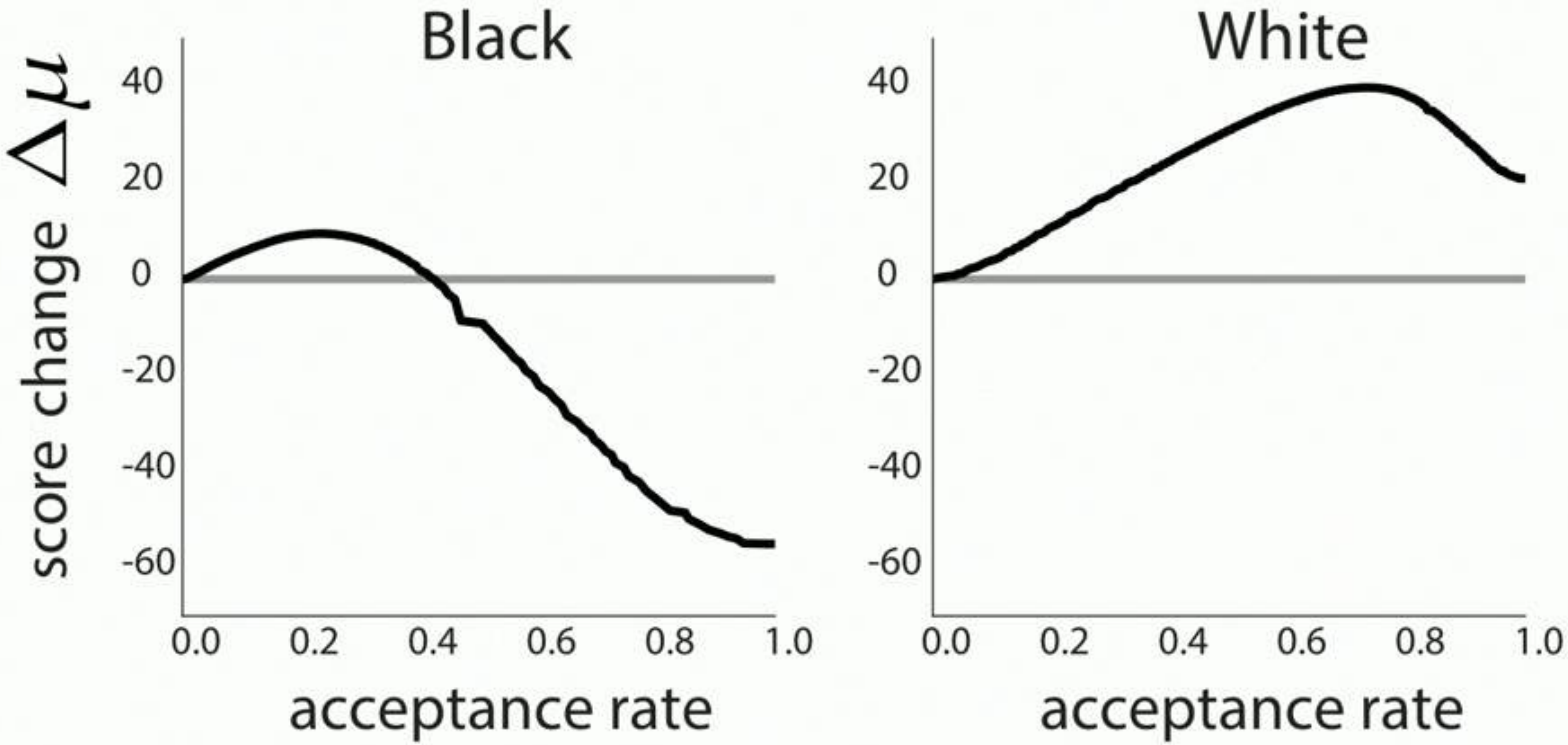
- Use empirical data labeled by race ("white" and "black") to estimate group score distributions, repayment probabilities, and relative sizes
- Model the bank's profit/loss ratio, e.g. +1:-4
- Model the delayed impact of repayment/default on credit score, e.g. +75/-150
- Compute "outcome curves" and delayed impact under different fairness criteria

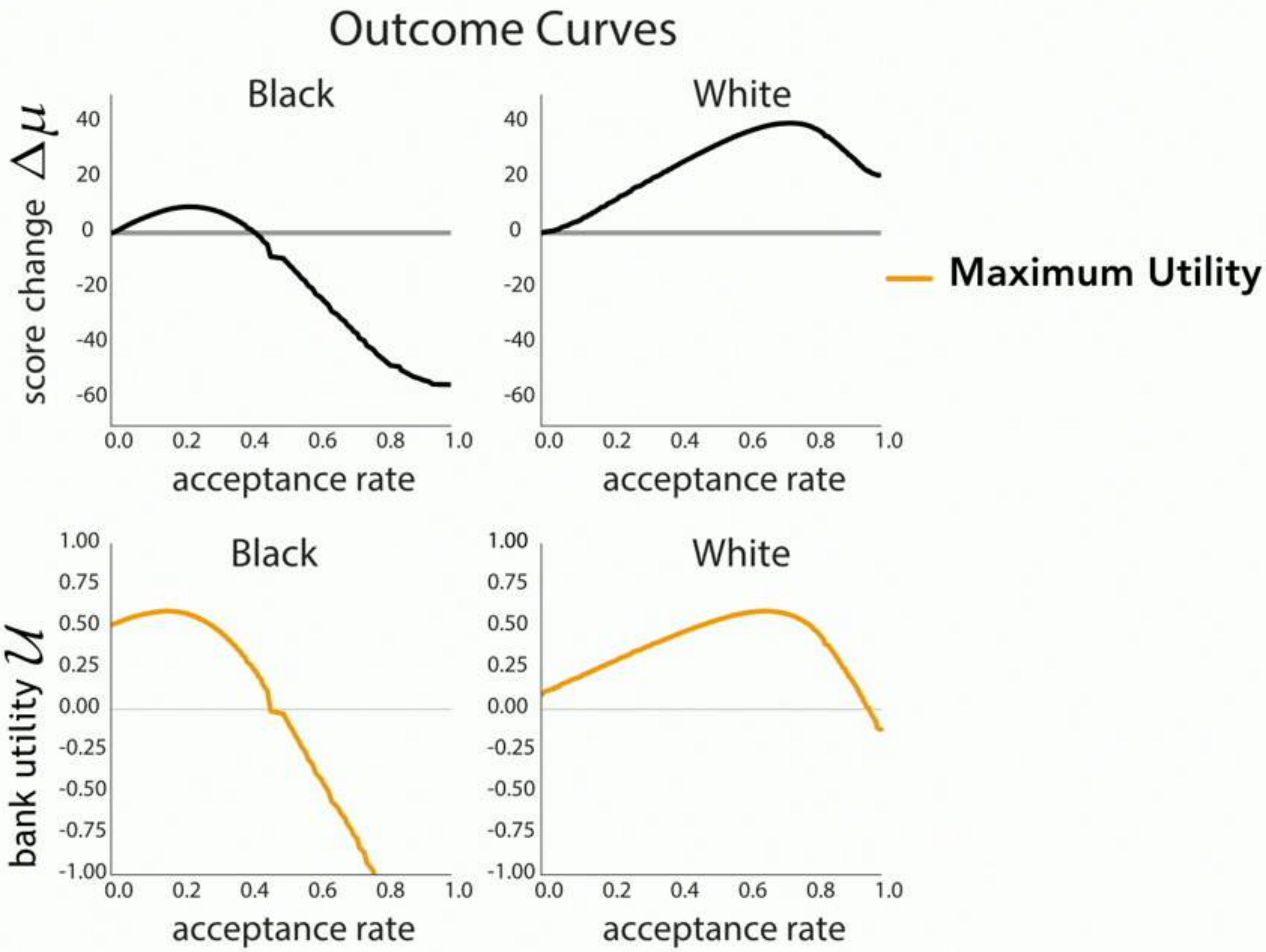


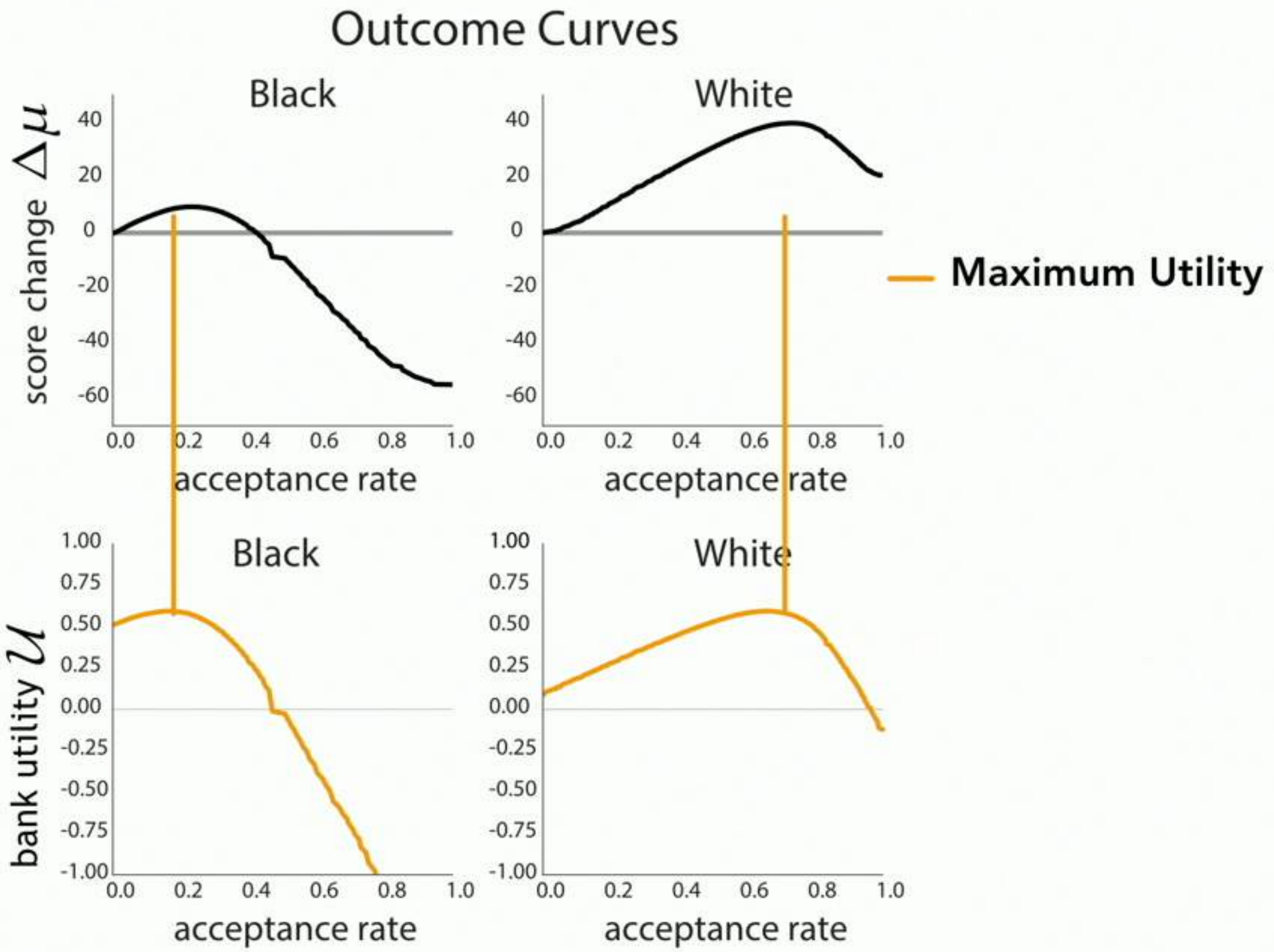


Outcome Curves
Black
White
score change Δμ
40
20
0
-20
-40
-60
0.0
0.2
0.4
0.6
0.8
1.0
acceptance rate
acceptance rate

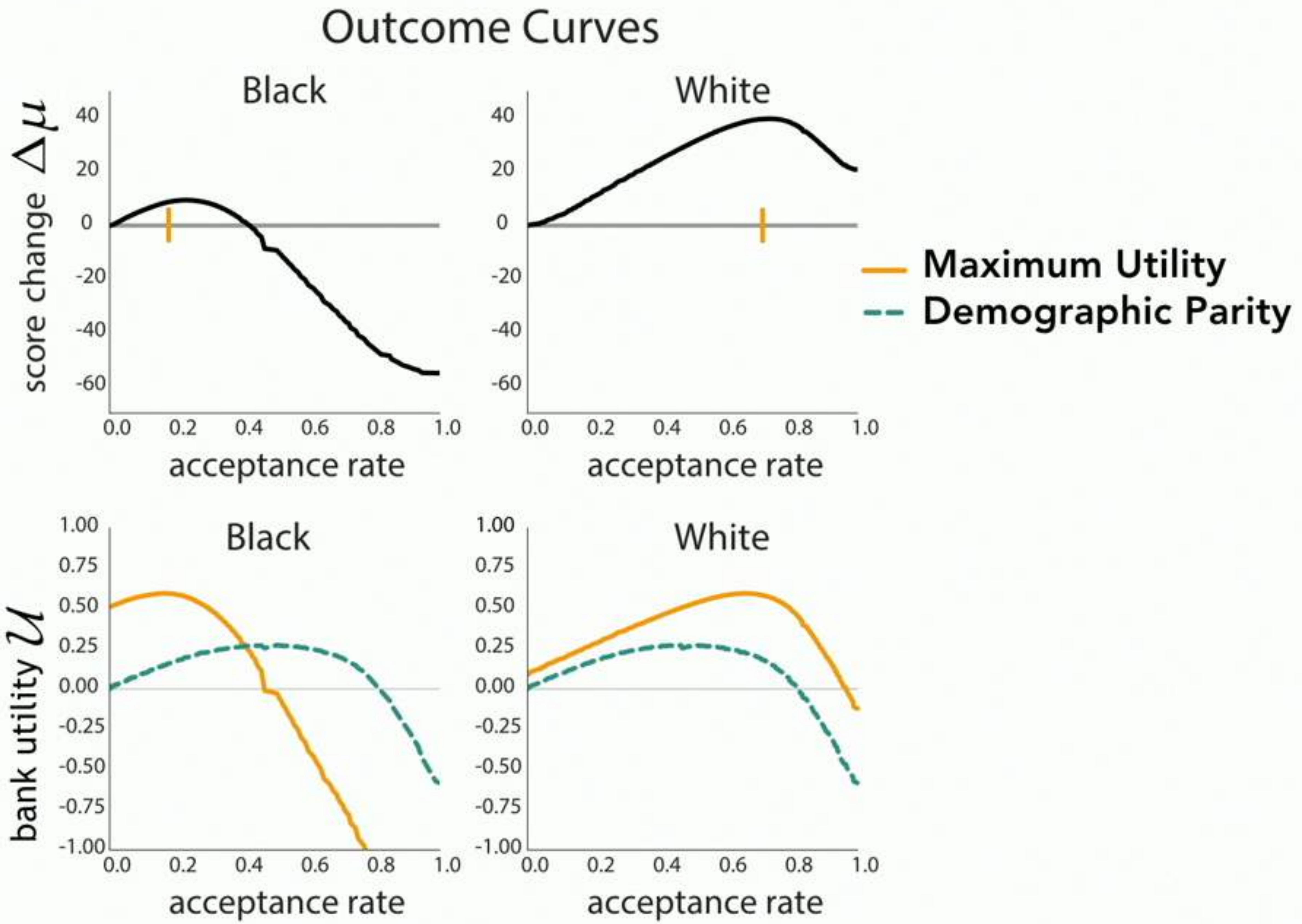
Outcome Curves




Outcome Curves
Black
White
score change $\Delta\mu$
40
20
0
-20
-40
-60
0.0
0.2
0.4
0.6
0.8
1.0
acceptance rate
Maximum Utility
bank utility $\mathcal{U}$
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00

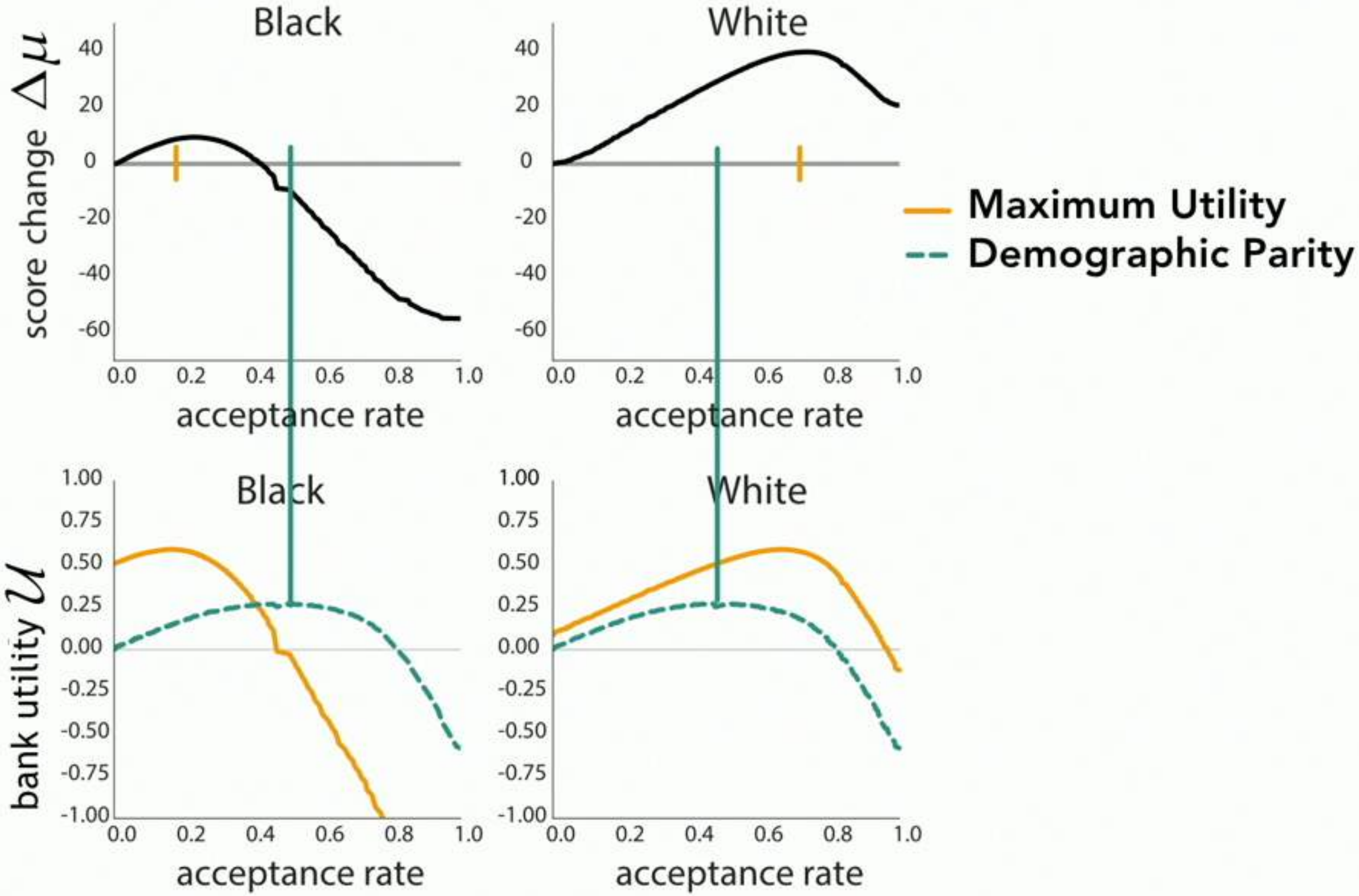


Outcome Curves
Black
White
score change $\Delta\mu$
40
20
0
-20
-40
-60
0.0
0.2
0.4
0.6
0.8
1.0
acceptance rate
Maximum Utility
bank utility $\mathcal{U}$
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00

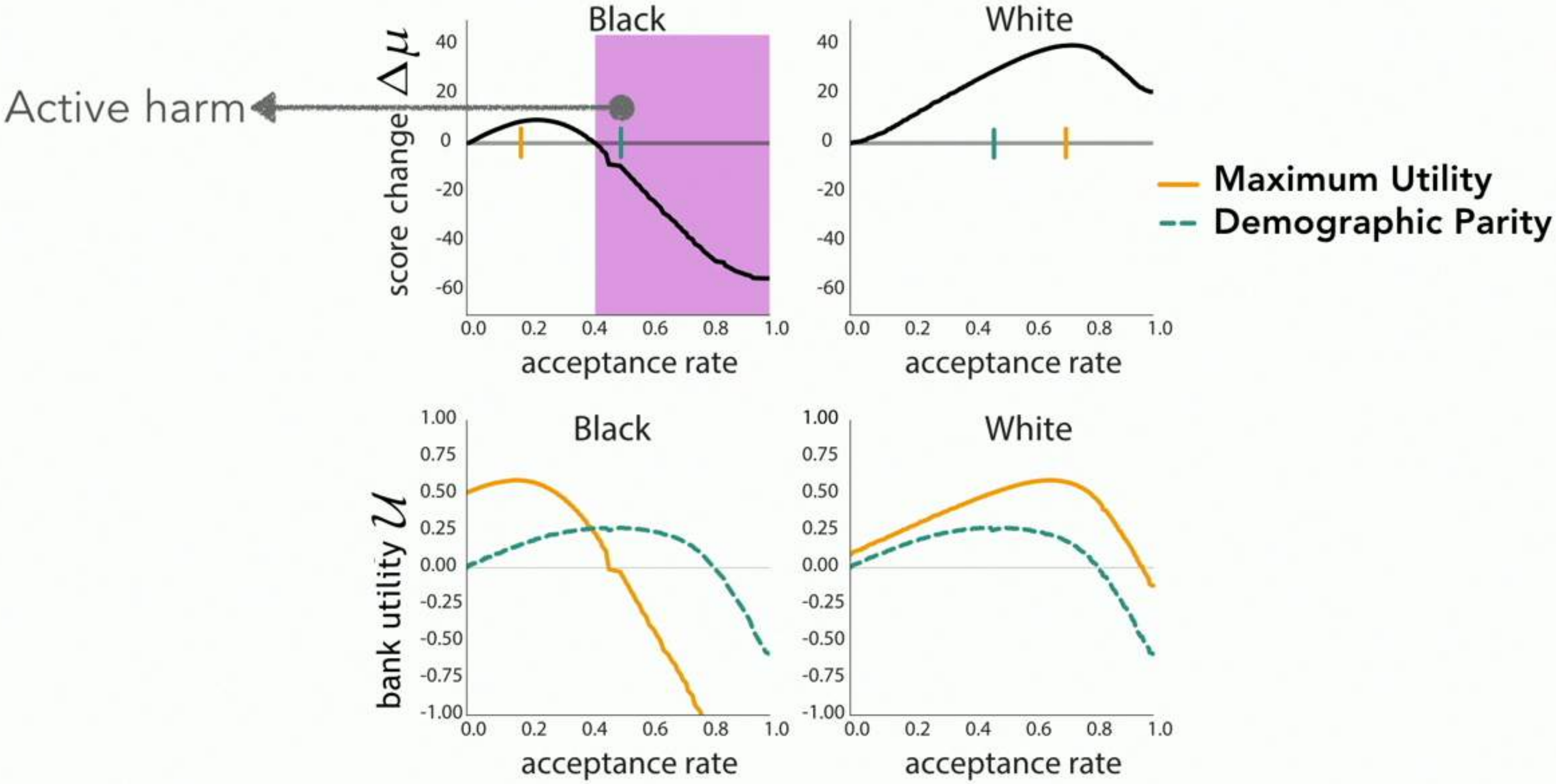


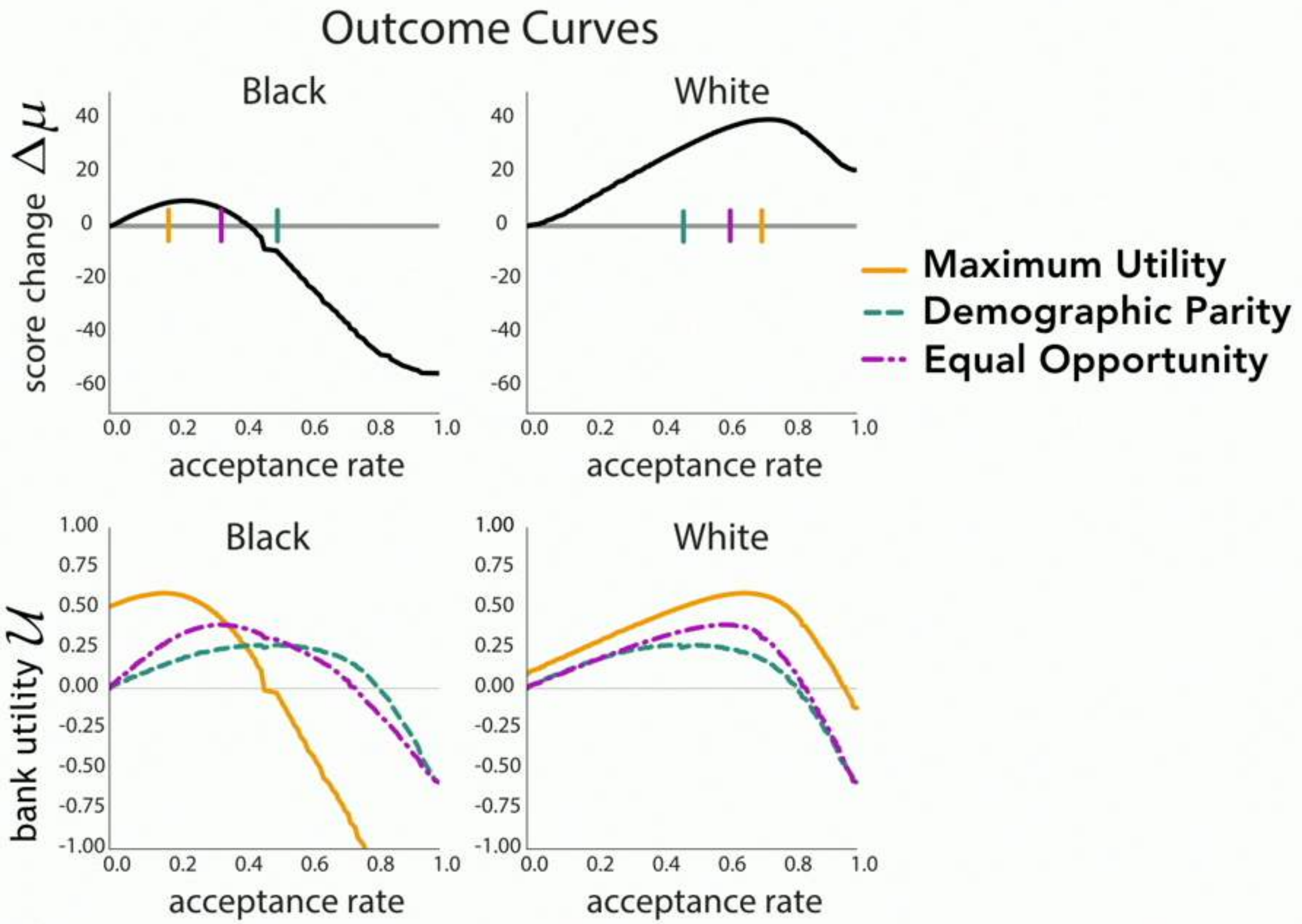
Outcome Curves
Black
White
score change $\Delta\mu$
40
20
0
-20
-40
-60
0.0
0.2
0.4
0.6
0.8
1.0
acceptance rate
Maximum Utility
Demographic Parity
bank utility $\mathcal{U}$
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00

Outcome Curves

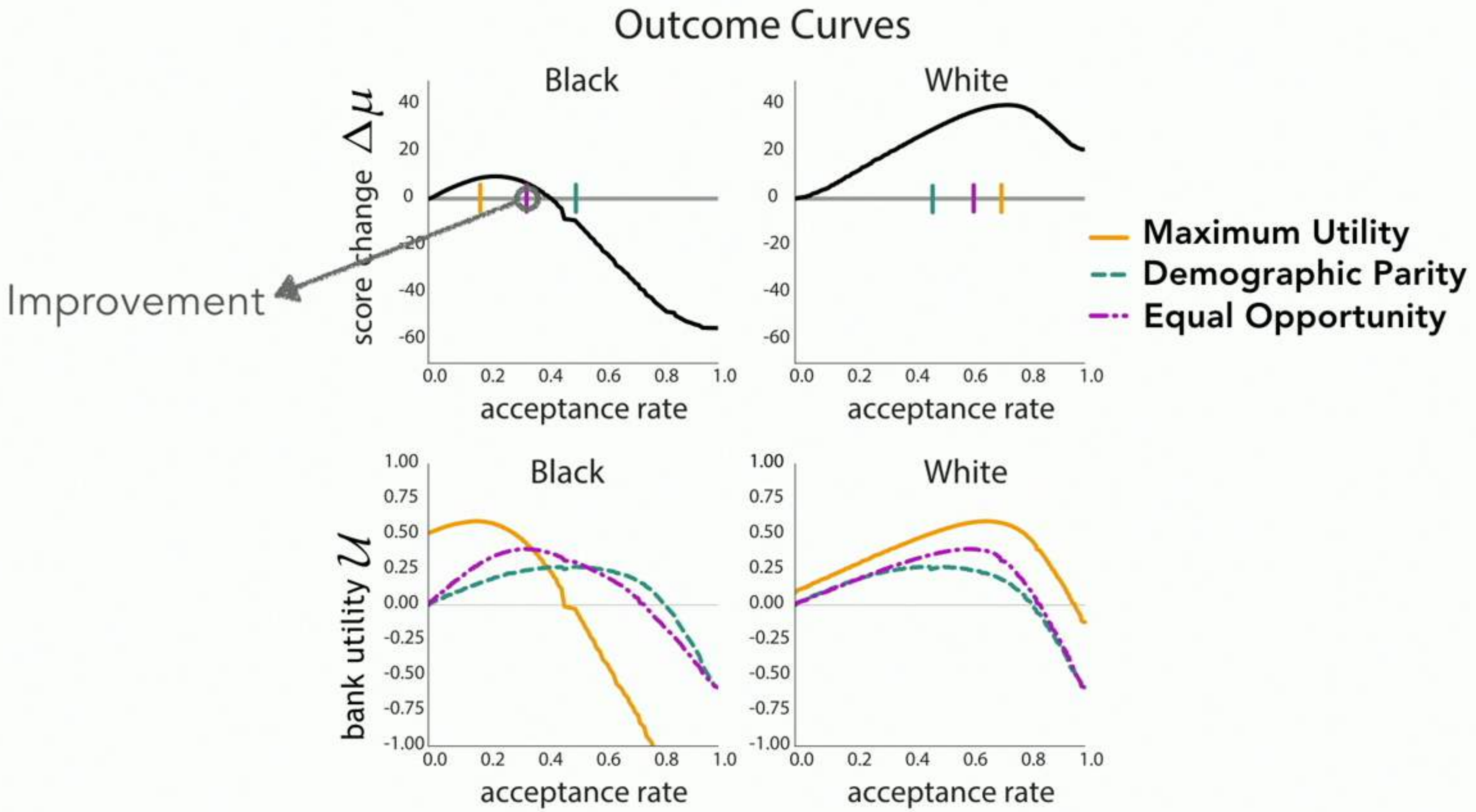


Outcome Curves

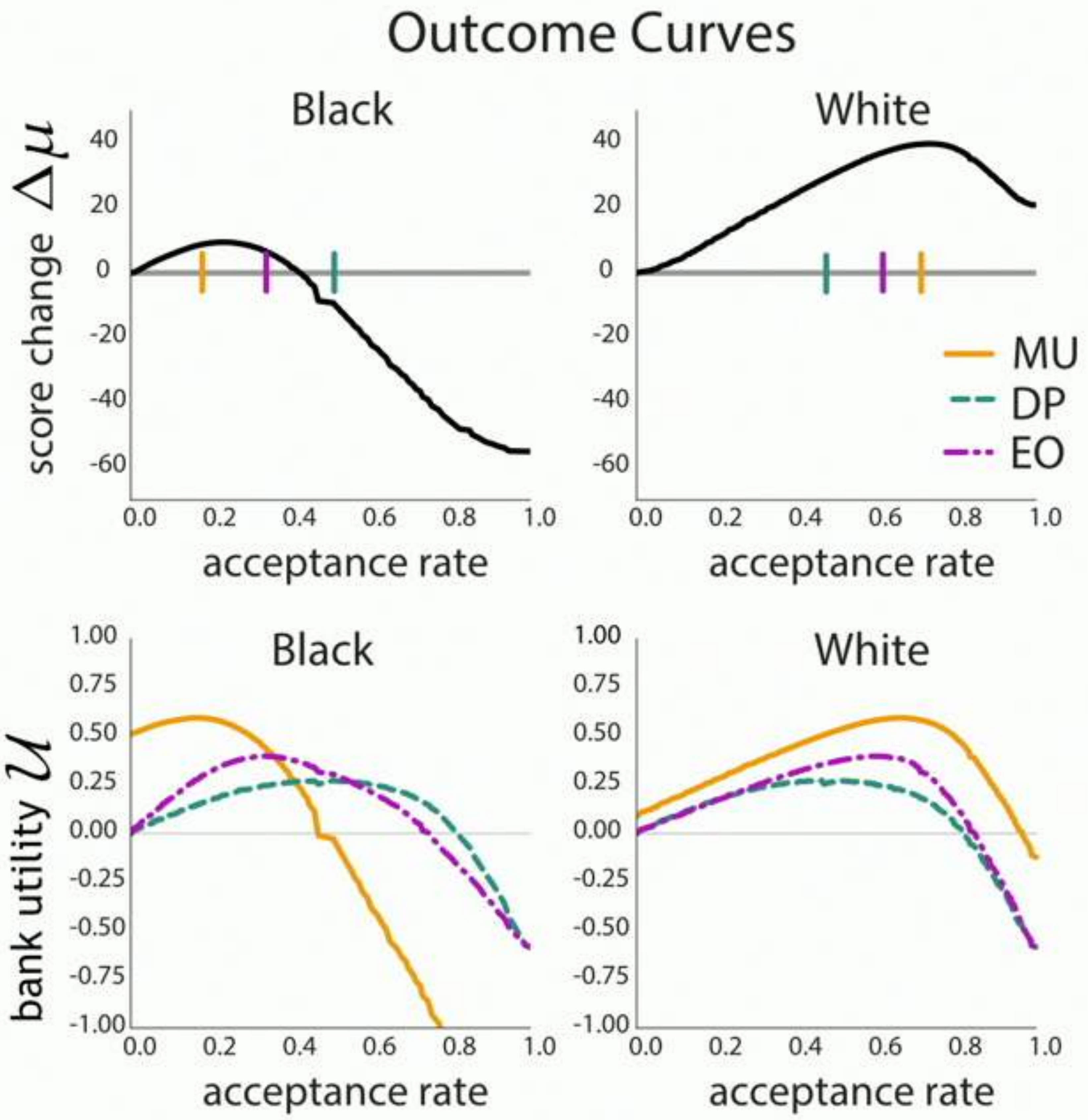




Outcome Curves
Black
White
score change $\Delta\mu$
acceptance rate
bank utility $\mathcal{U}$
Maximum Utility
Demographic Parity
Equal Opportunity

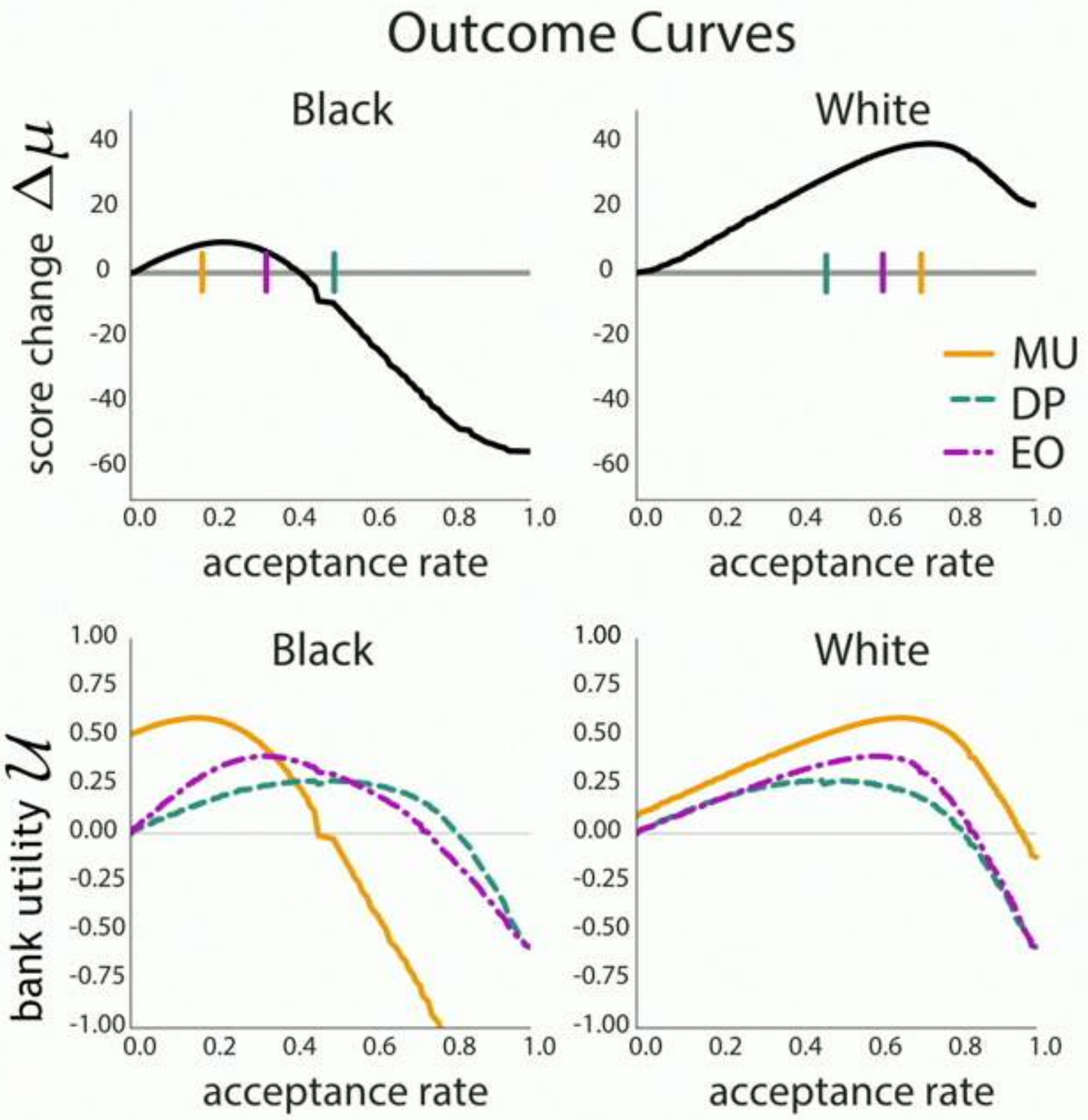

Outcome Curves
Black
White
score change $\Delta\mu$
40
20
0
-20
-40
-60
0.0
0.2
0.4
0.6
0.8
1.0
acceptance rate
Improvement
Maximum Utility
Demographic Parity
Equal Opportunity
bank utility $\mathcal{U}$
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00

Why the large difference in delayed impact?



Why the large difference in delayed impact?

Maxima of *outcome* and *utility curves under fairness criteria* are **more misaligned** in the minority "black" group



DISCUSSION

DISCUSSION

- **Outcome curves** provide a way to deviate from maximum utility while improving outcomes.

DISCUSSION

- **Outcome curves** provide a way to deviate from maximum utility while improving outcomes.
- Need for **domain-specific** models of delayed impact
  - Context-sensitive nature of fairness in machine learning

DISCUSSION

- **Outcome curves** provide a way to deviate from maximum utility while improving outcomes.
- Need for **domain-specific** models of delayed impact
  - Context-sensitive nature of fairness in machine learning

FUTURE WORK

DISCUSSION

- **Outcome curves** provide a way to deviate from maximum utility while improving outcomes.
- Need for **domain-specific** models of delayed impact
  - Context-sensitive nature of fairness in machine learning

FUTURE WORK

- Moving beyond **binary** decisions

DISCUSSION

- **Outcome curves** provide a way to deviate from maximum utility while improving outcomes.
- Need for **domain-specific** models of delayed impact
  - Context-sensitive nature of fairness in machine learning

FUTURE WORK

- Moving beyond **binary** decisions
- Moving beyond the **mean** score as measure of impact

DISCUSSION

- **Outcome curves** provide a way to deviate from maximum utility while improving outcomes.
- Need for **domain-specific** models of delayed impact
  - Context-sensitive nature of fairness in machine learning

FUTURE WORK

- Moving beyond **binary** decisions
- Moving beyond the **mean** score as measure of impact
- **Dynamics** of the **distributional impact** of machine learning algorithms
  [Ensign et al. 2017; Hu and Chen 2017]

THANK YOU

Details in full version:
https://arxiv.org/abs/1803.04383