Dissecting racial bias in an algorithm that guides health decisions for millions

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Joint work with Sendhil Mullainathan

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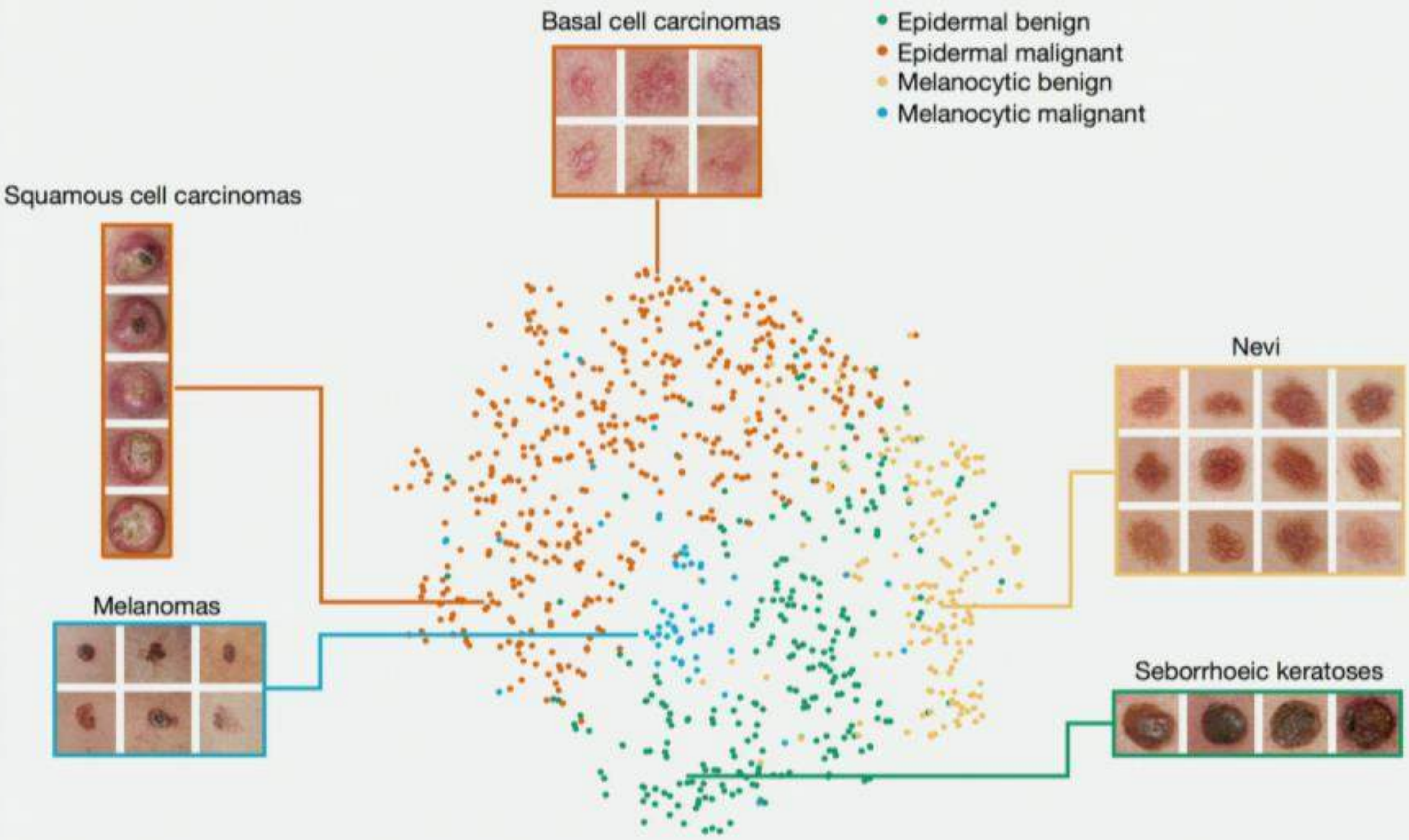
- But these tools can also do harm
  - May be harder to diagnose in health data
- We analyze a widely-used health algorithm
  - We find significant racial bias
  - This affects decisions for millions of patients
  - A unique dataset lets us trace the cause
  - And provide a solution

On the horizon: Melanoma detection



Esteva et al, Dermatologist-level classification of skin cancer with deep neural networks *Nature* 2017

Already at scale: Policy algorithms

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- **The kind already deployed in the health system**
  - Decisions for tens of millions affected every year
- Response to major policy changes
  - Incentives to manage populations of patients
  - Rather than fee-for-service model

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  - Multiple doctors: specialists, PCP, etc
  - Burdensome emergency visits, hospitalizations when health deteriorates
- Can we improve their interface with health care system?
- Widespread innovation: care coordination programs

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- Coordinate across doctors to reconcile medications, solve multi-specialty problems, …

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- Better quality, lower cost
  - Good for both patients and payers

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- Flag patients with "complex health needs" for "intervention before their health becomes catastrophic"
  - Predict next year's health care costs
  - Use claims data (and to a lesser degree EHR data)

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- We have unique access to
  - Algorithm <u>inputs</u> : predictors
  - Algorithm <u>outputs</u> : objective function, predictions
  - Rich contextual data on health

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- So we'll look at :
  - $E[Y \mid White, S]$ vs. $E[Y \mid Black, S]$
  - For a variety of (future) health outcomes Y

Chronic medical conditions

	All	White	Black
n (patient-years)	100,001	88,072	11,929
n (patients)	49,618	43,539	6,079
Prevalence of chronic illnesses			
Total number of illnesses	1.3	1.2	1.9
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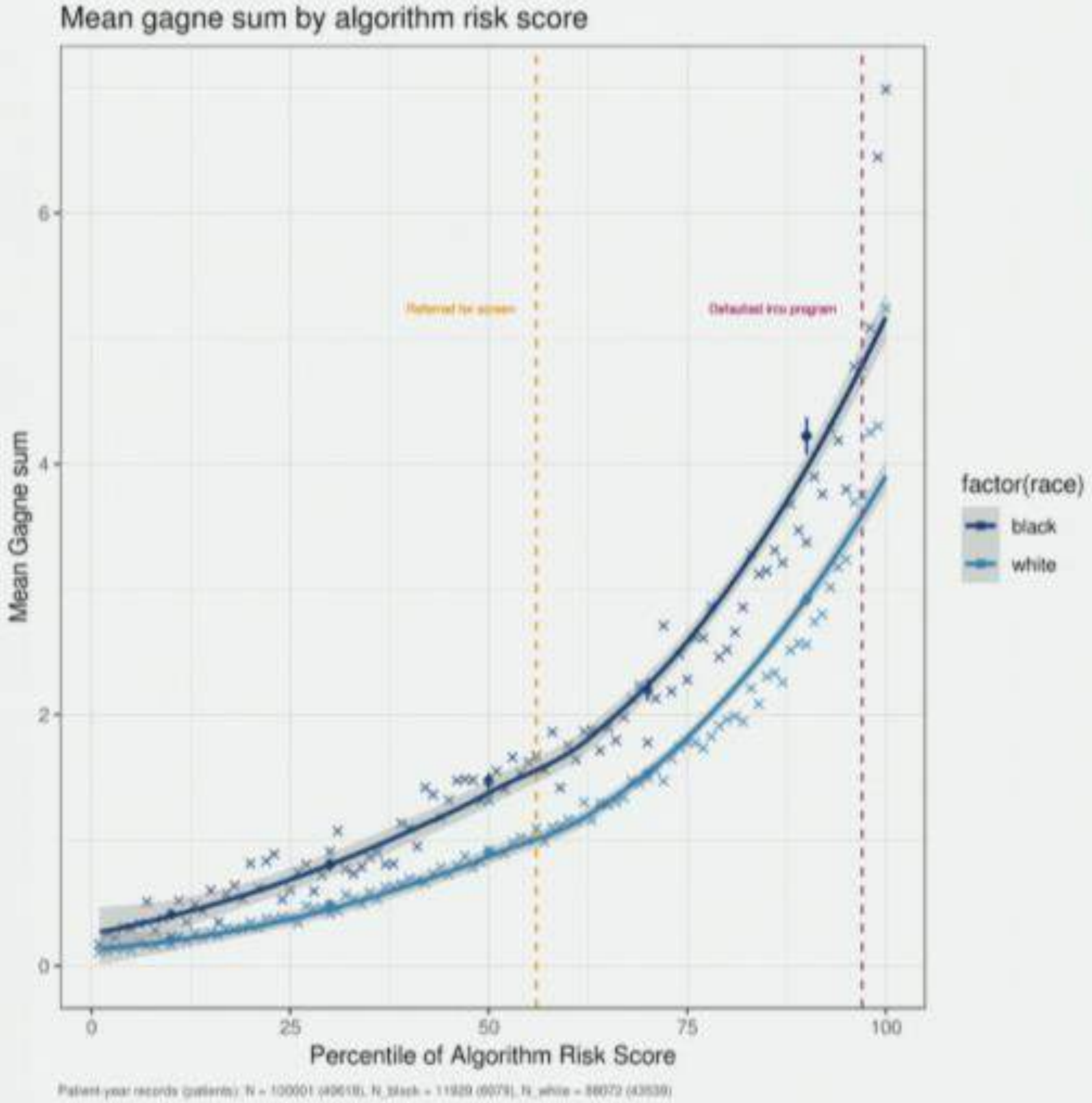
Black vs white, same risk score: More chronic illnesses

Chronic medical conditions vs risk score



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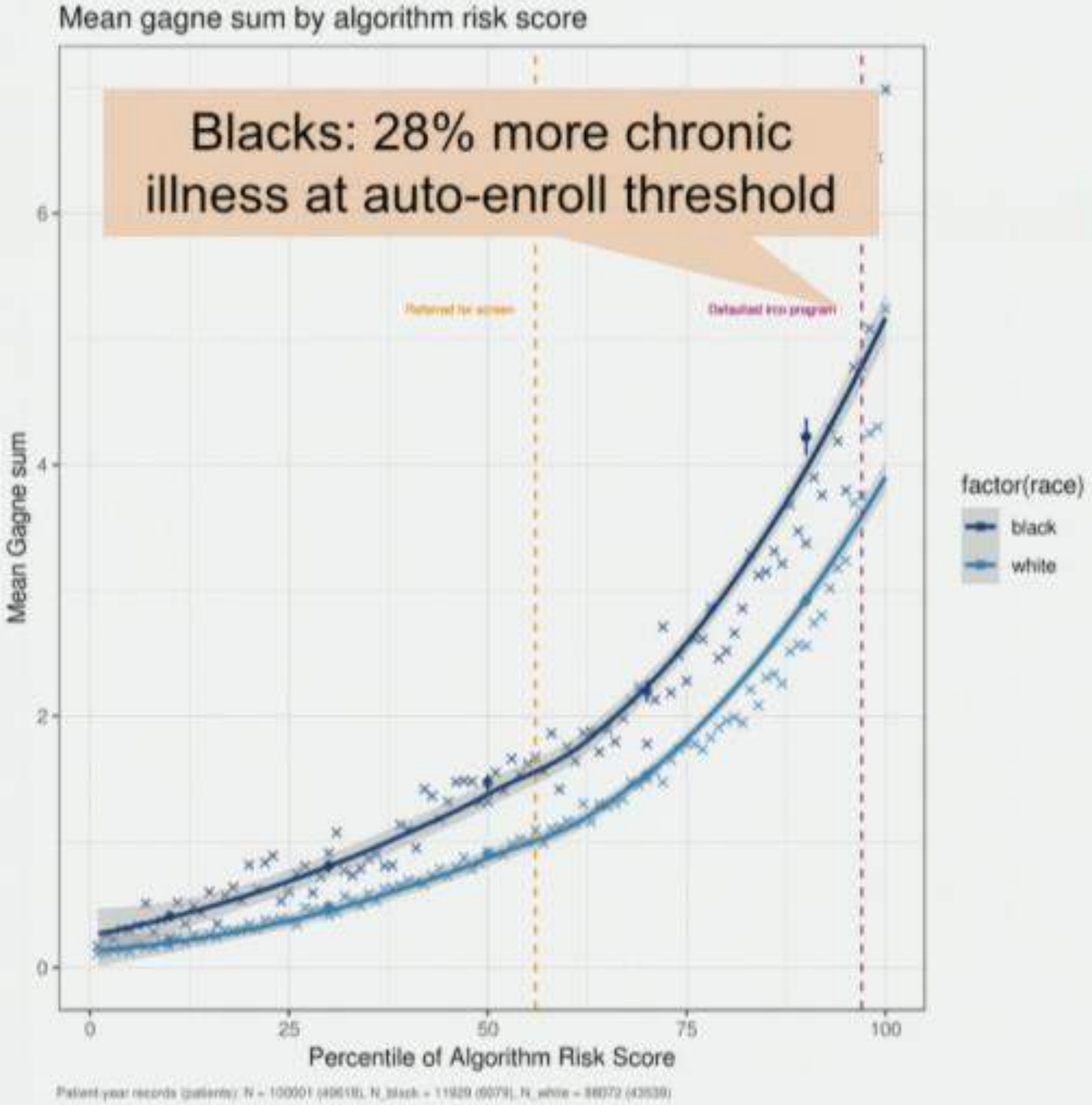

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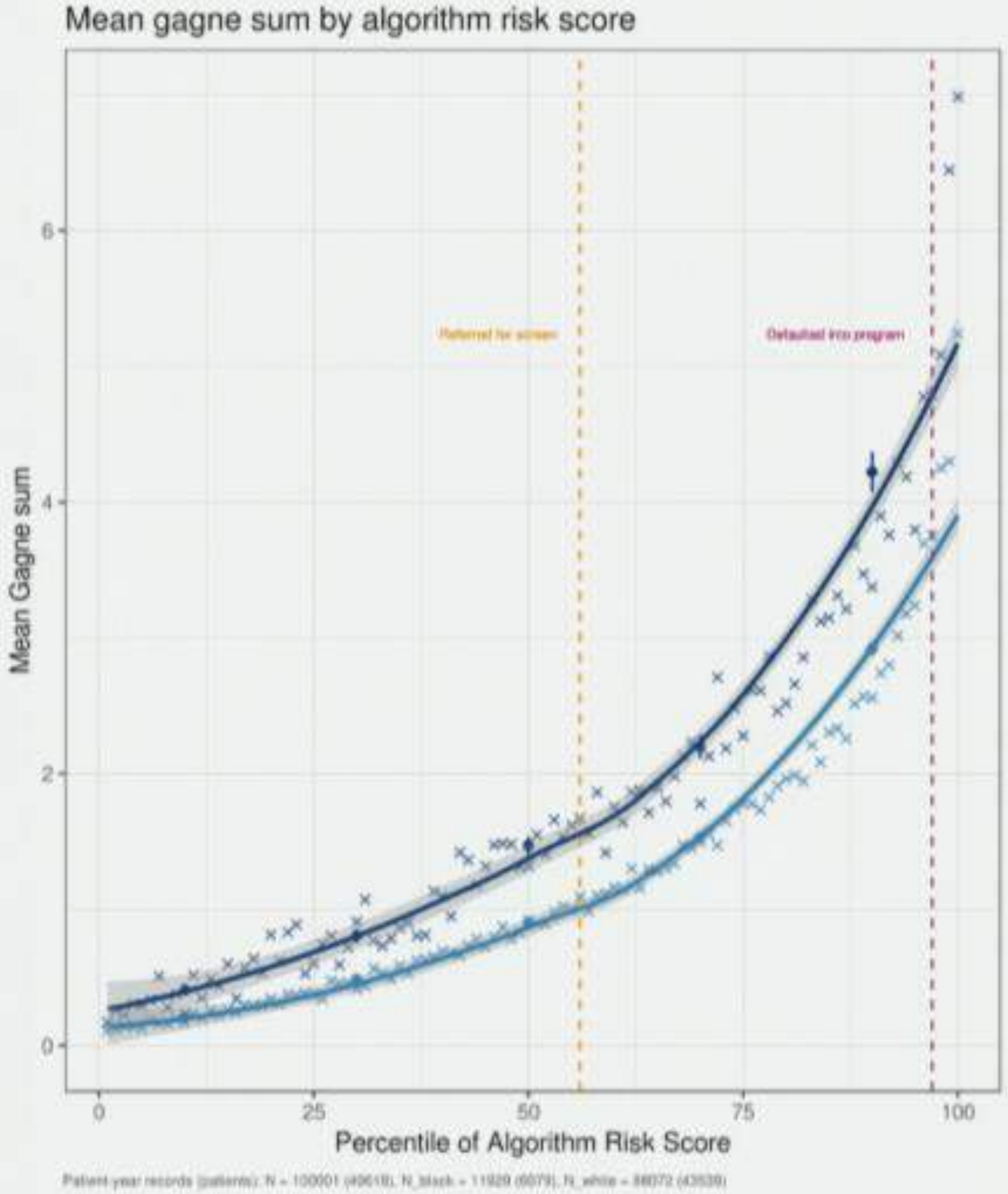

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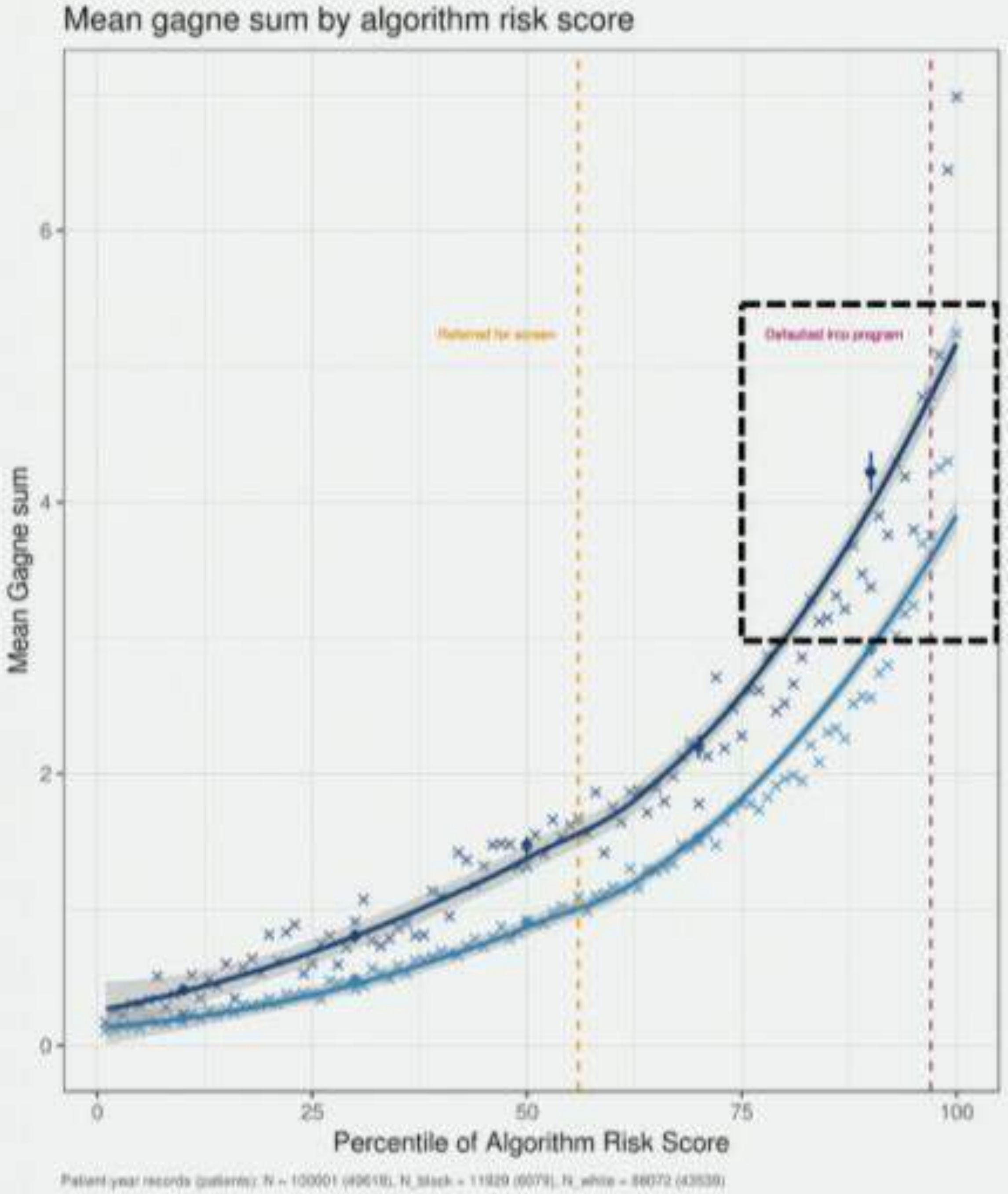

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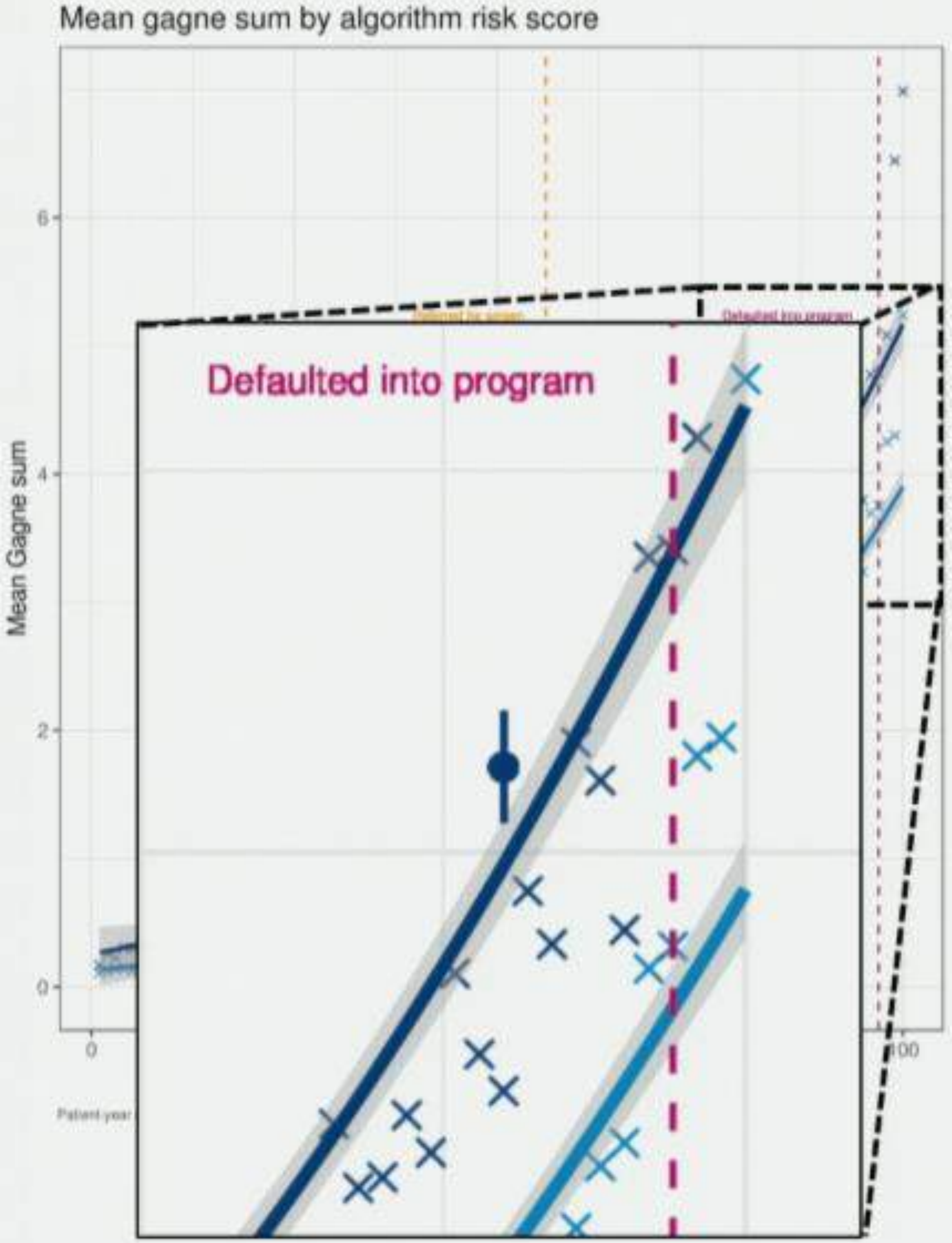

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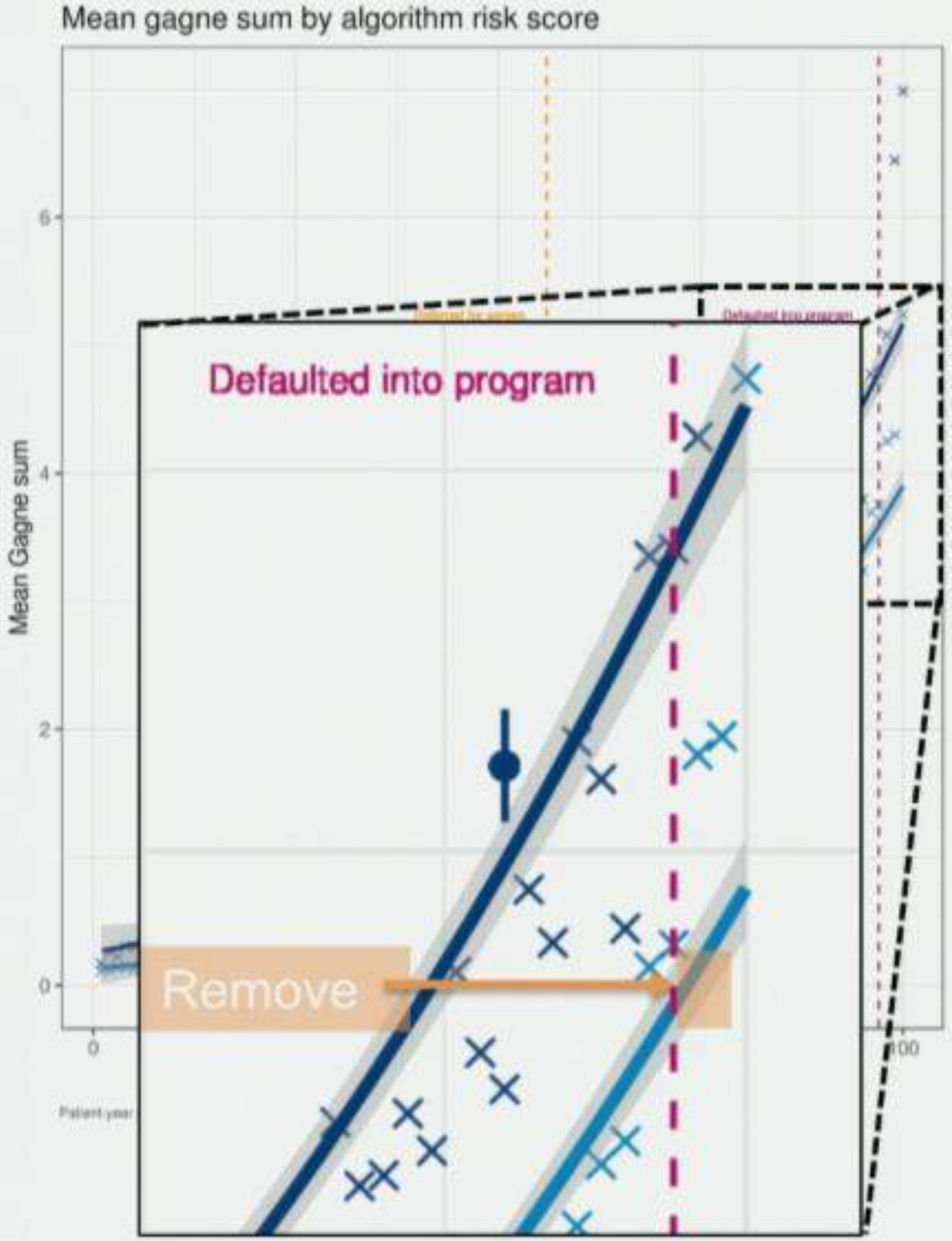

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- Simulate
  - Remove healthy whites

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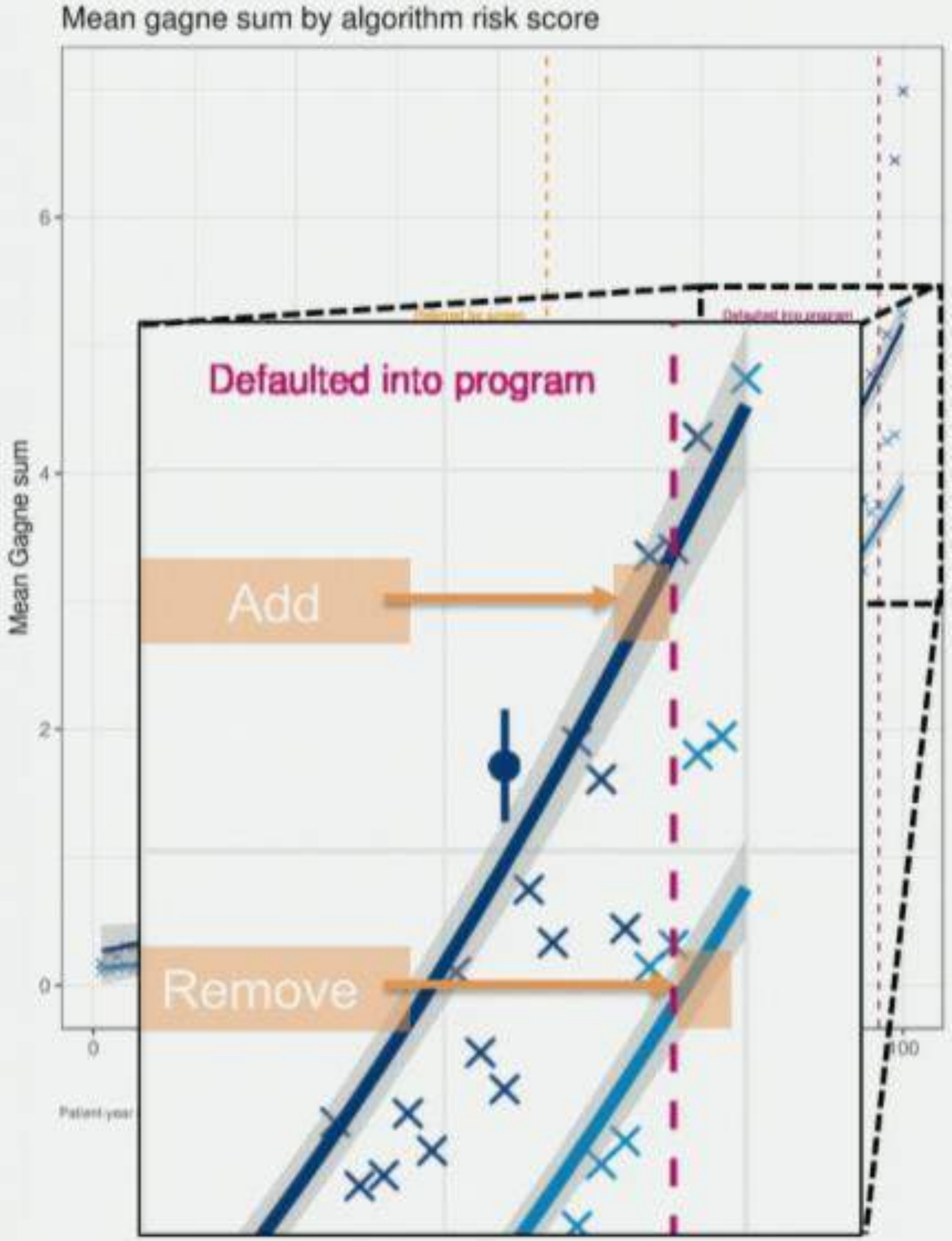

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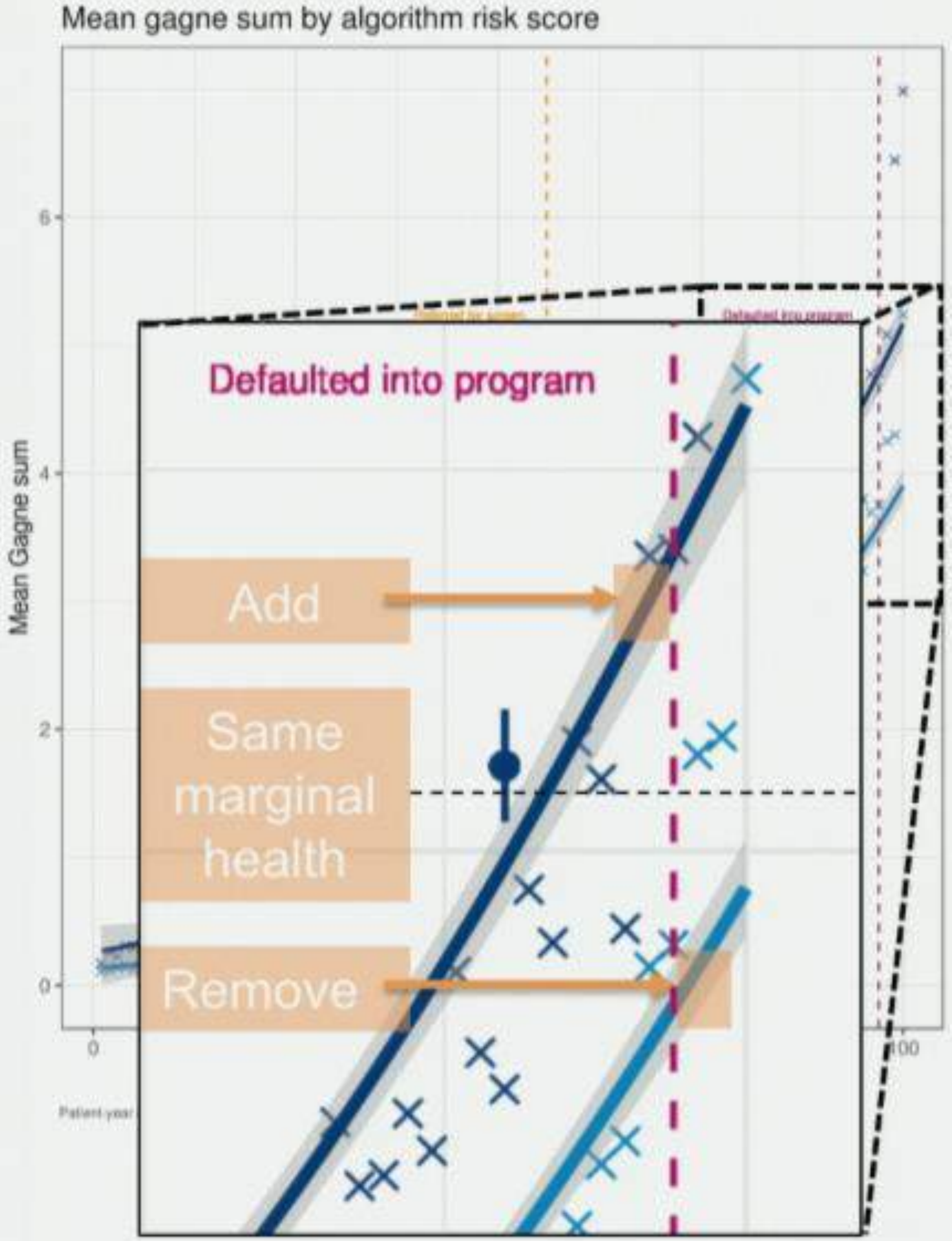

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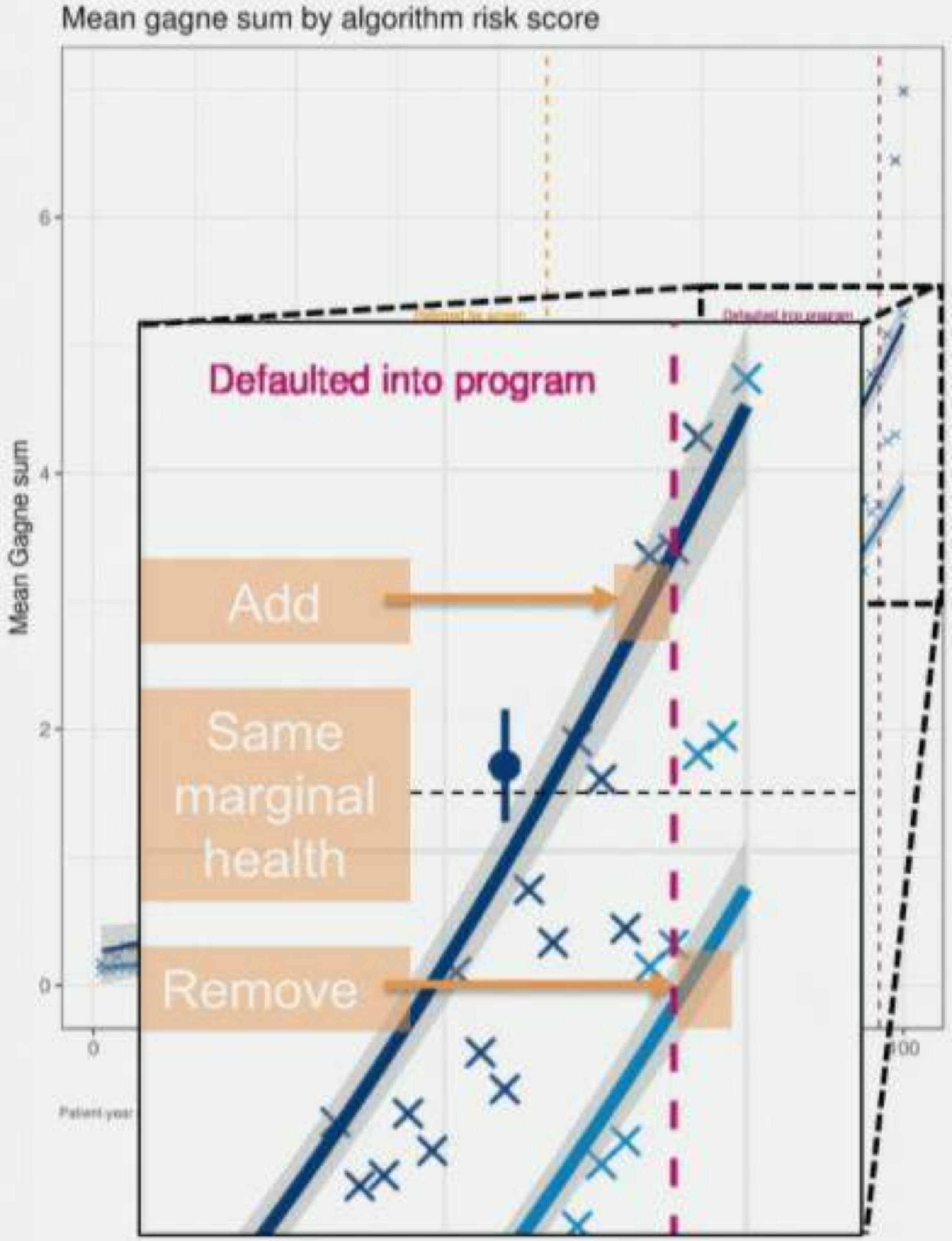

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- **Double fraction of auto-enrolled blacks**
  - **17.7% → 46.5%**

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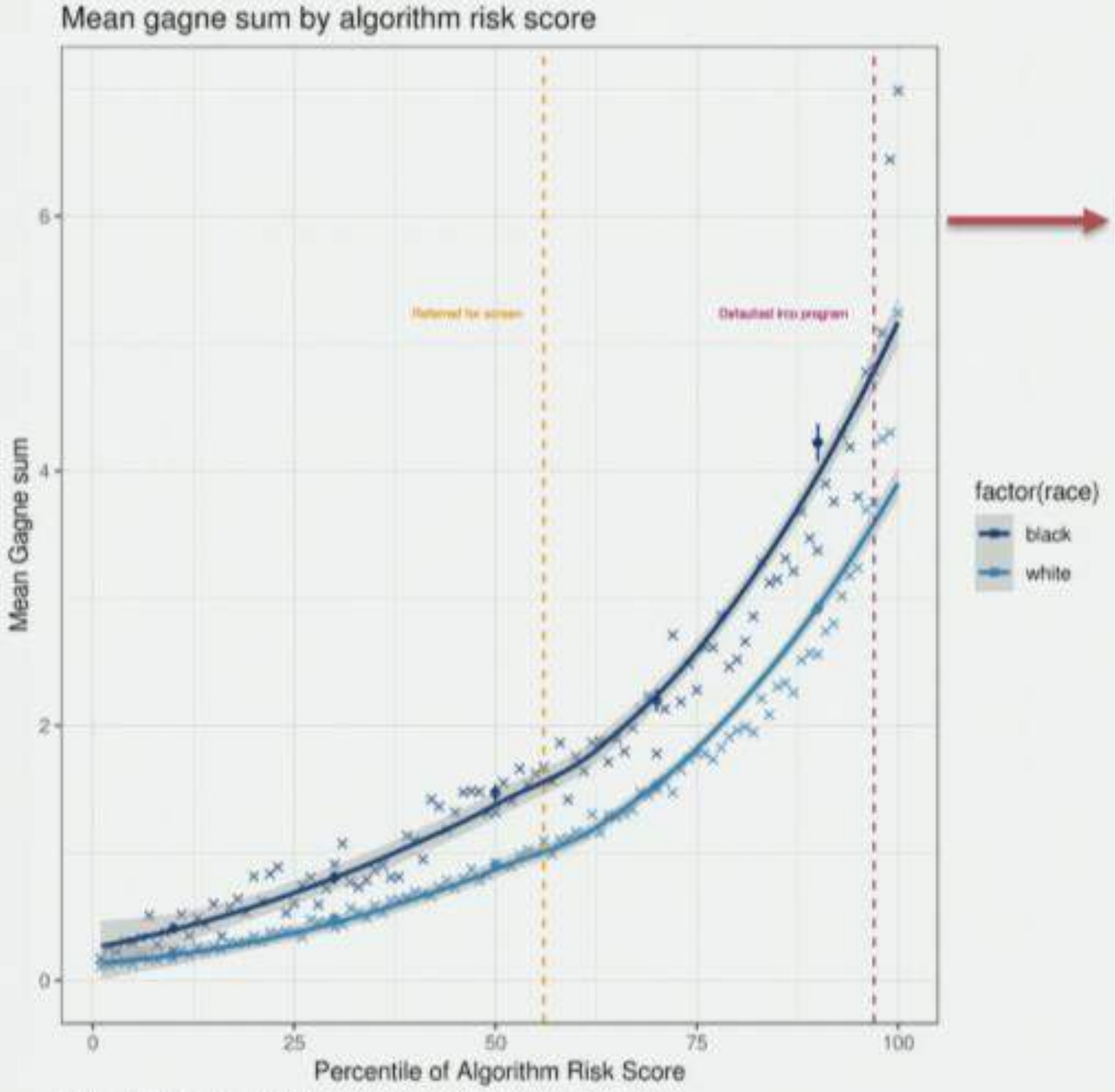

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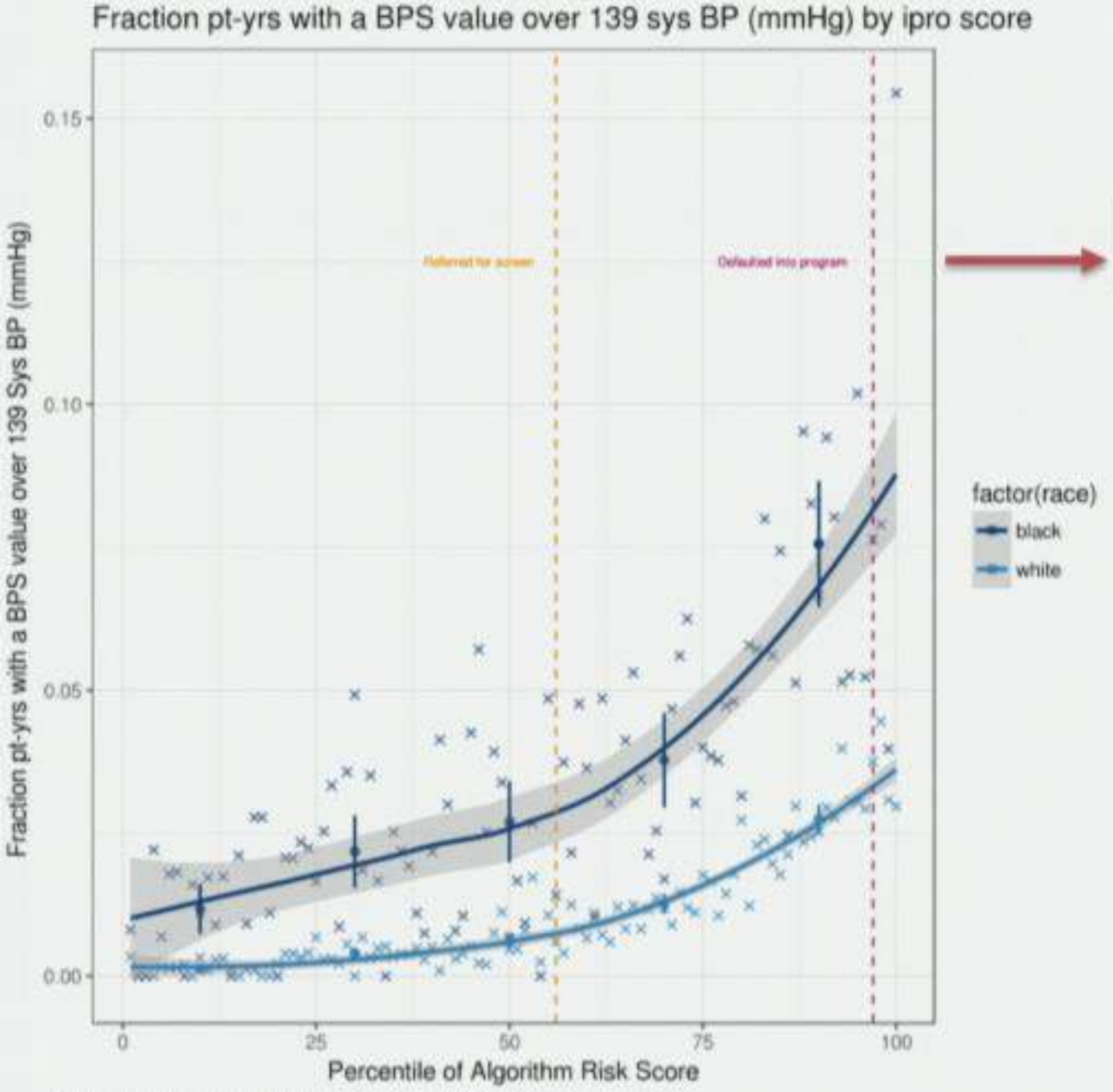
Black vs white, same risk score: Higher blood pressure

Uncontrolled SBP vs risk score



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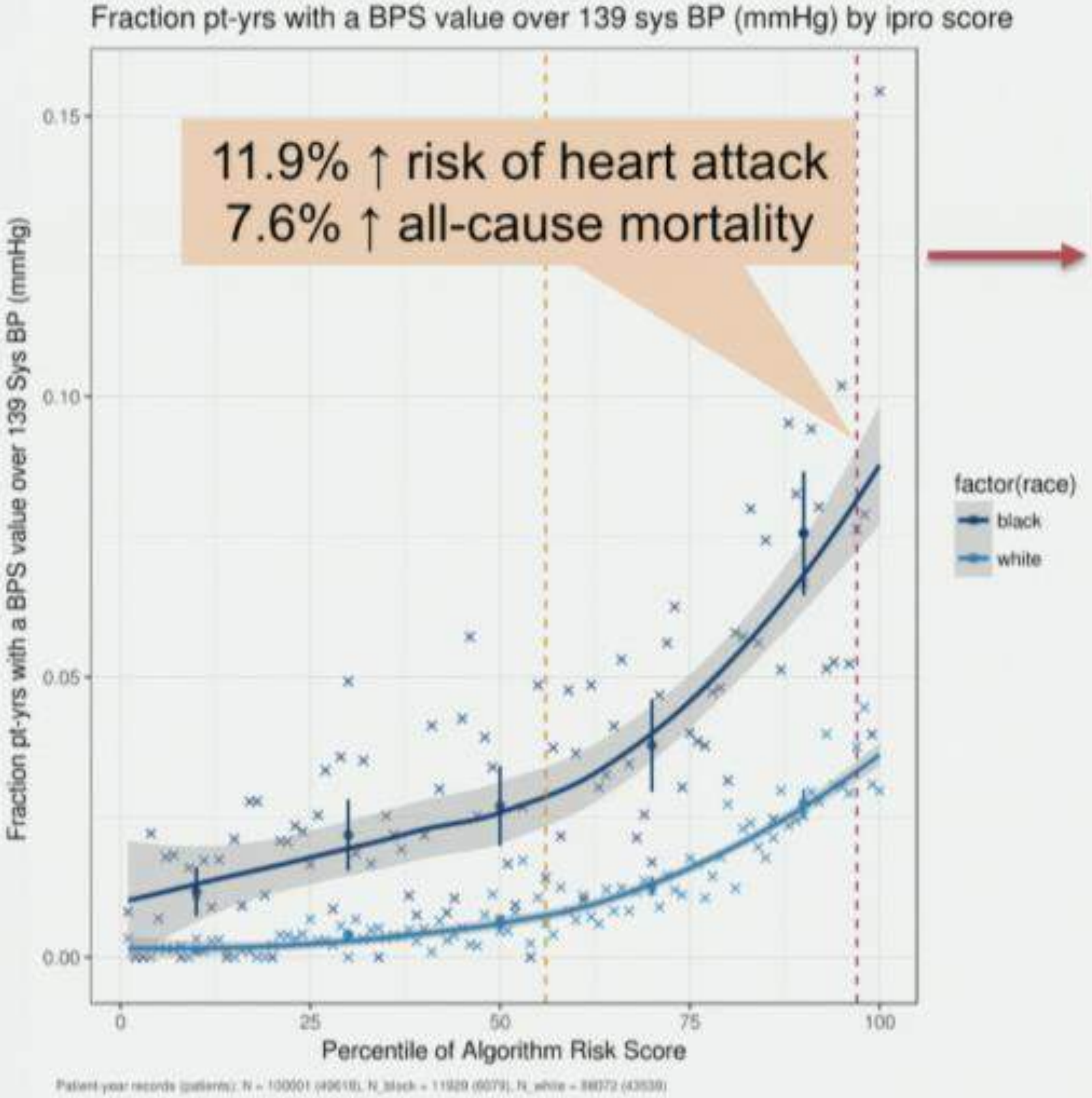

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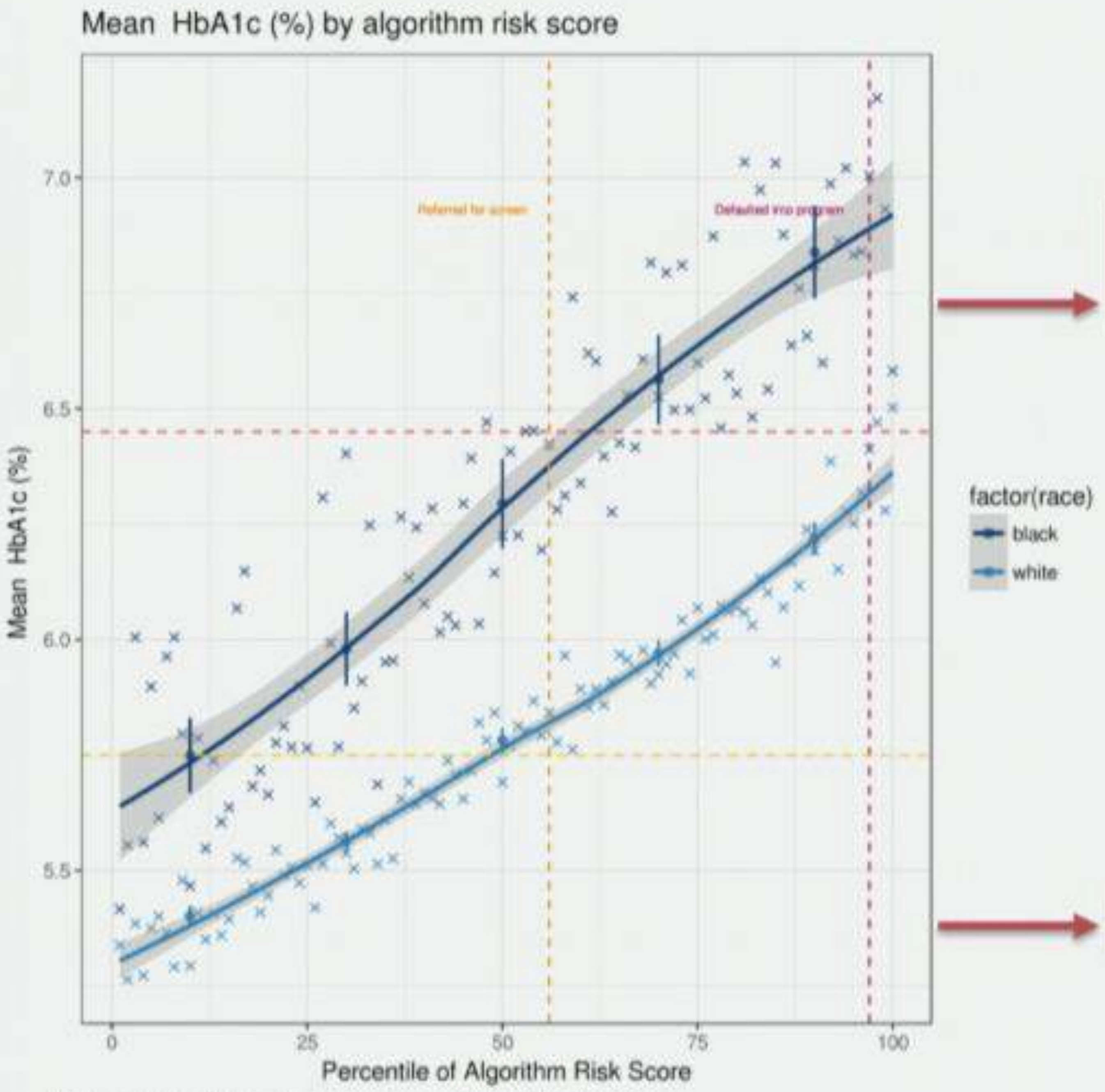
Blood glucose (HbA1c) vs risk score



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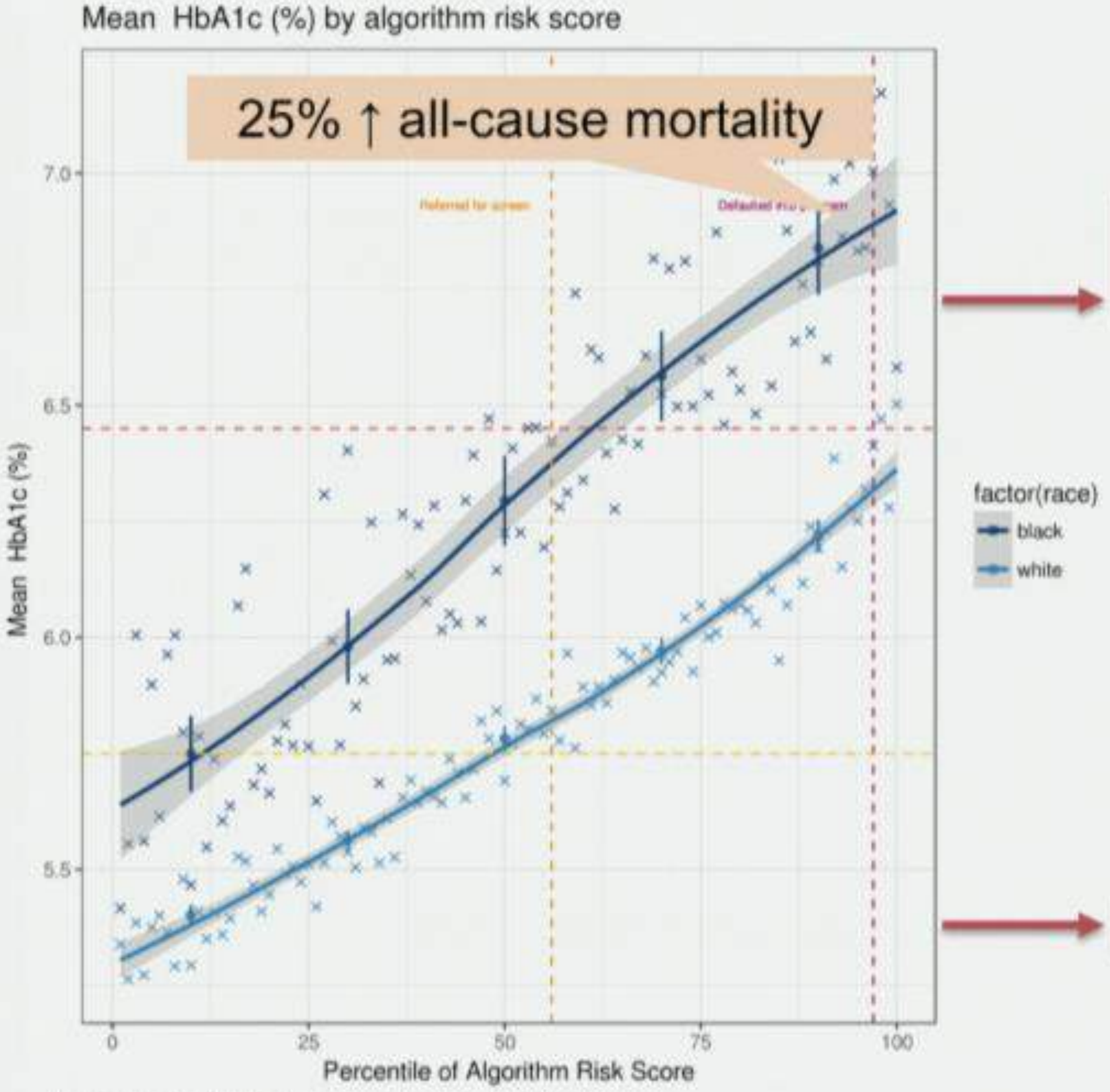

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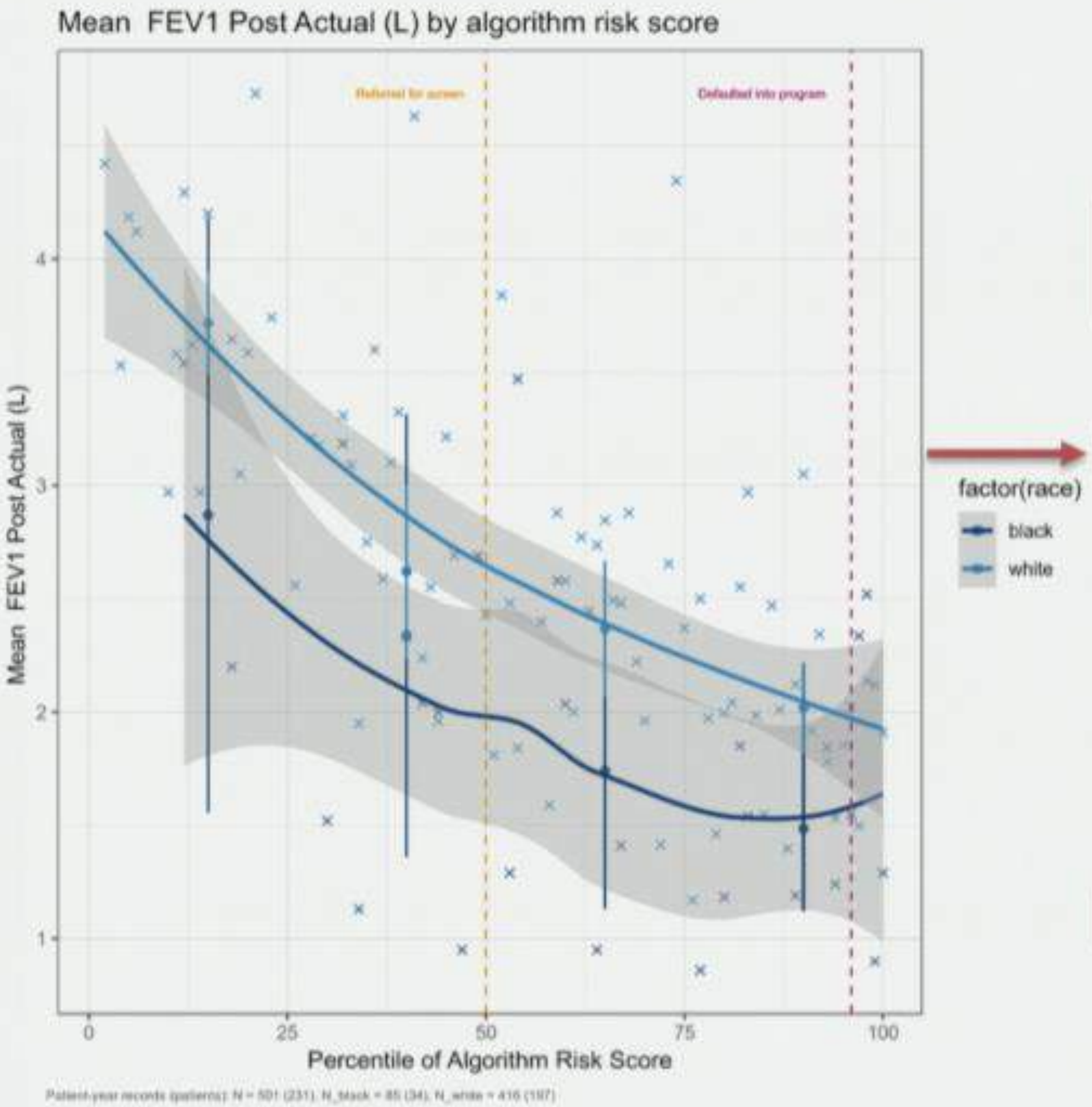
Black vs white, same risk score: Worse lung function

Lung function (FEV1) vs risk score



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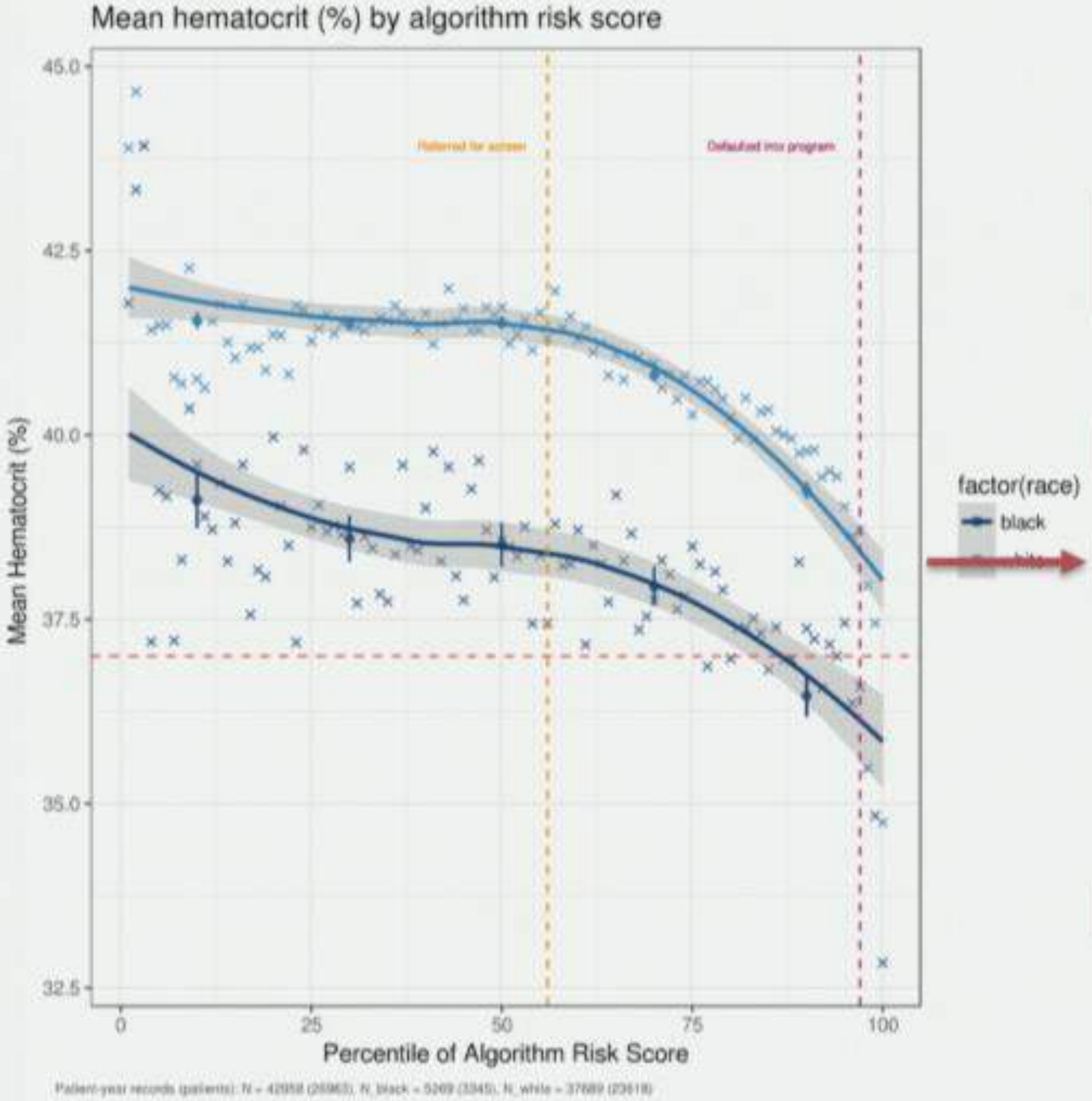
Red blood cells (hematocrit) vs risk score



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n (patients)	49,618	43,539	6,079
Prevalence of chronic illnesses			
Total number of illnesses	1.3	1.2	1.9
Hypertension	0.30	0.29	0.44
Diabetes, uncomplicated	0.14	0.08	0.22
Arrythmia	0.09	0.09	0.08
Hypothyroid	0.08	0.09	0.05
Obesity	0.08	0.07	0.18
Pulmonary disease	0.08	0.07	0.11
Cancer	0.07	0.07	0.06
Depression	0.06	0.06	0.07
Anemia	0.06	0.05	0.10
Arthritis	0.04	0.04	0.04
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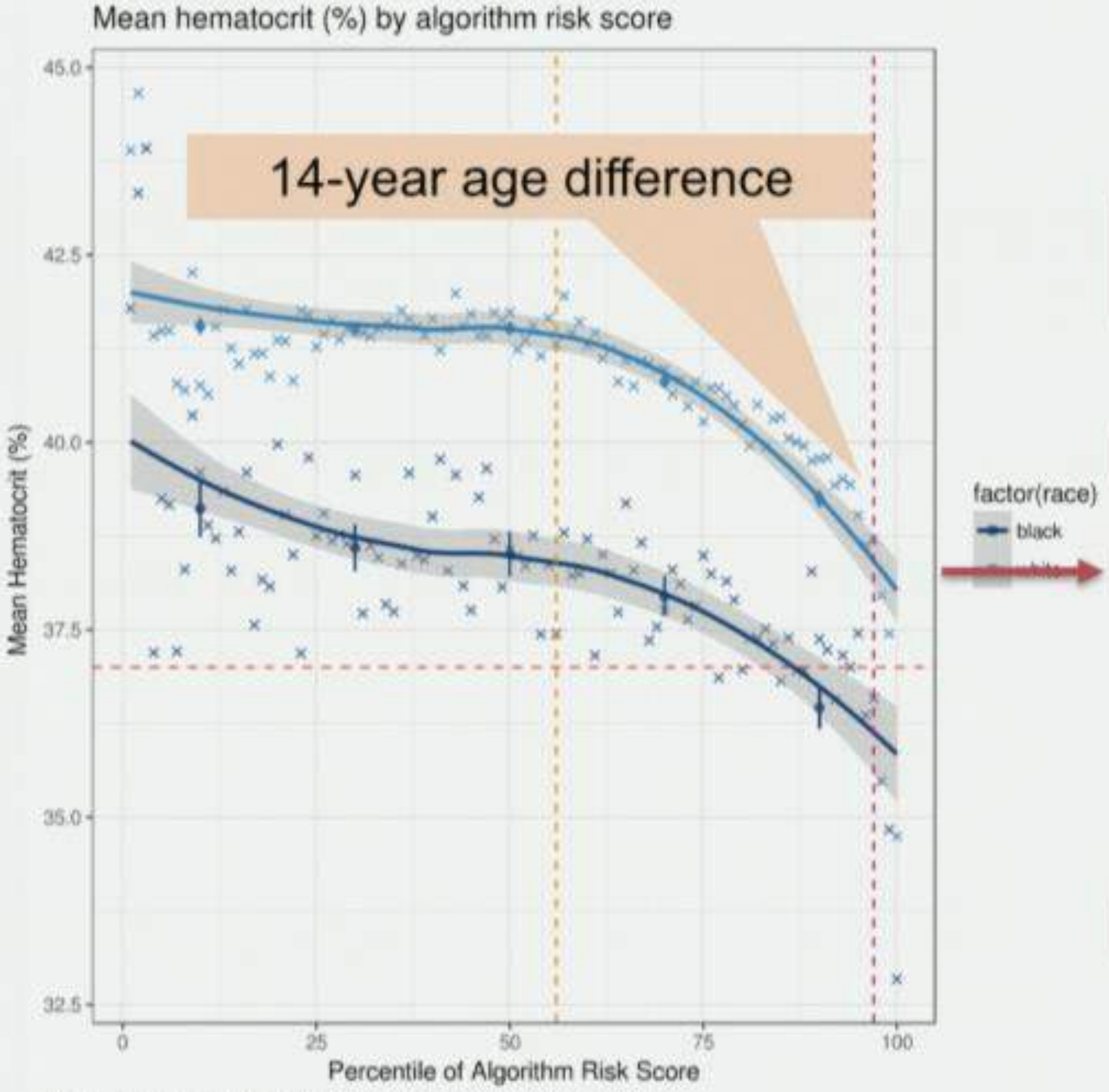
Black vs white, same risk score: Worse anemia

Red blood cells (hematocrit) vs risk score



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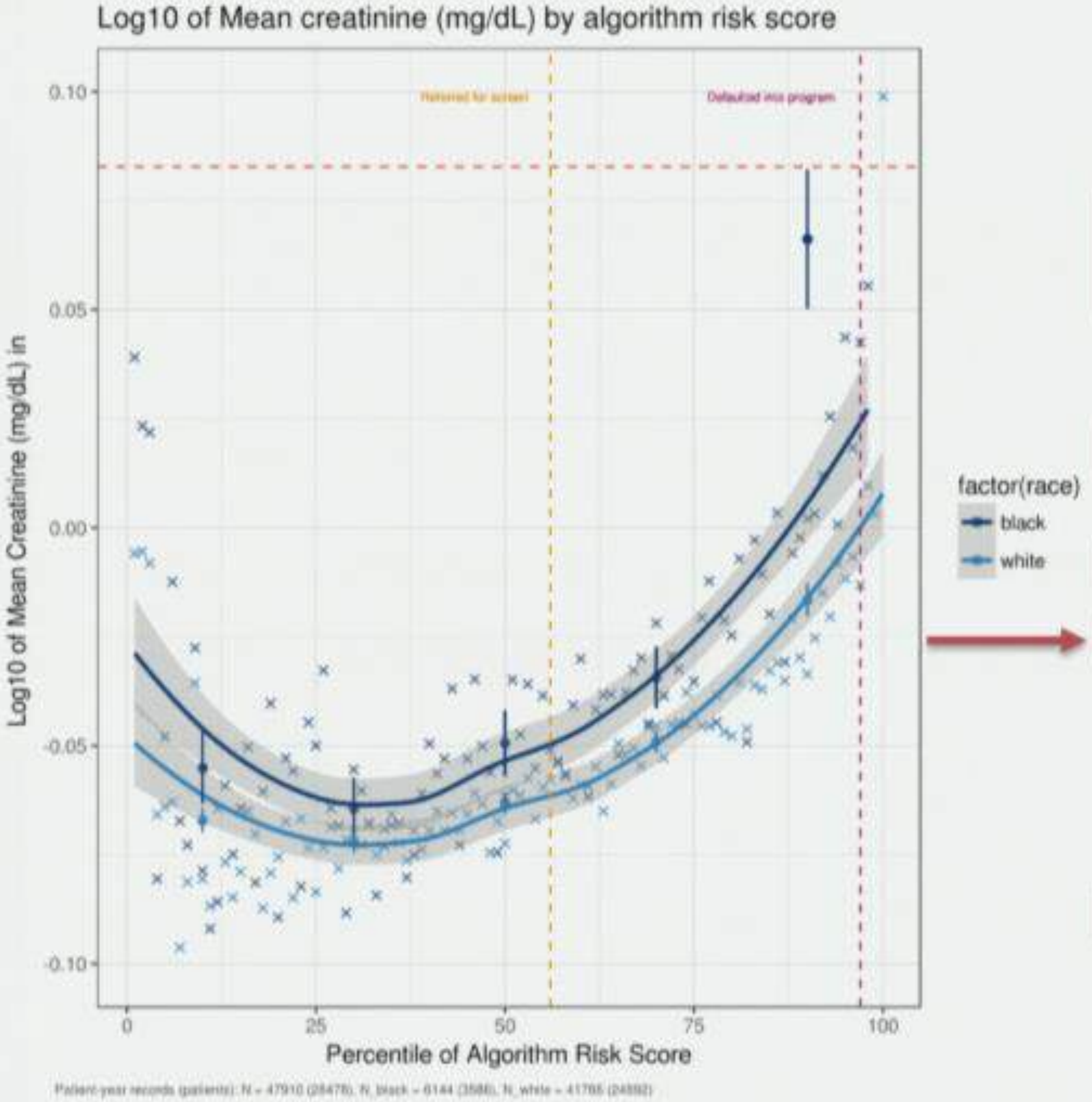

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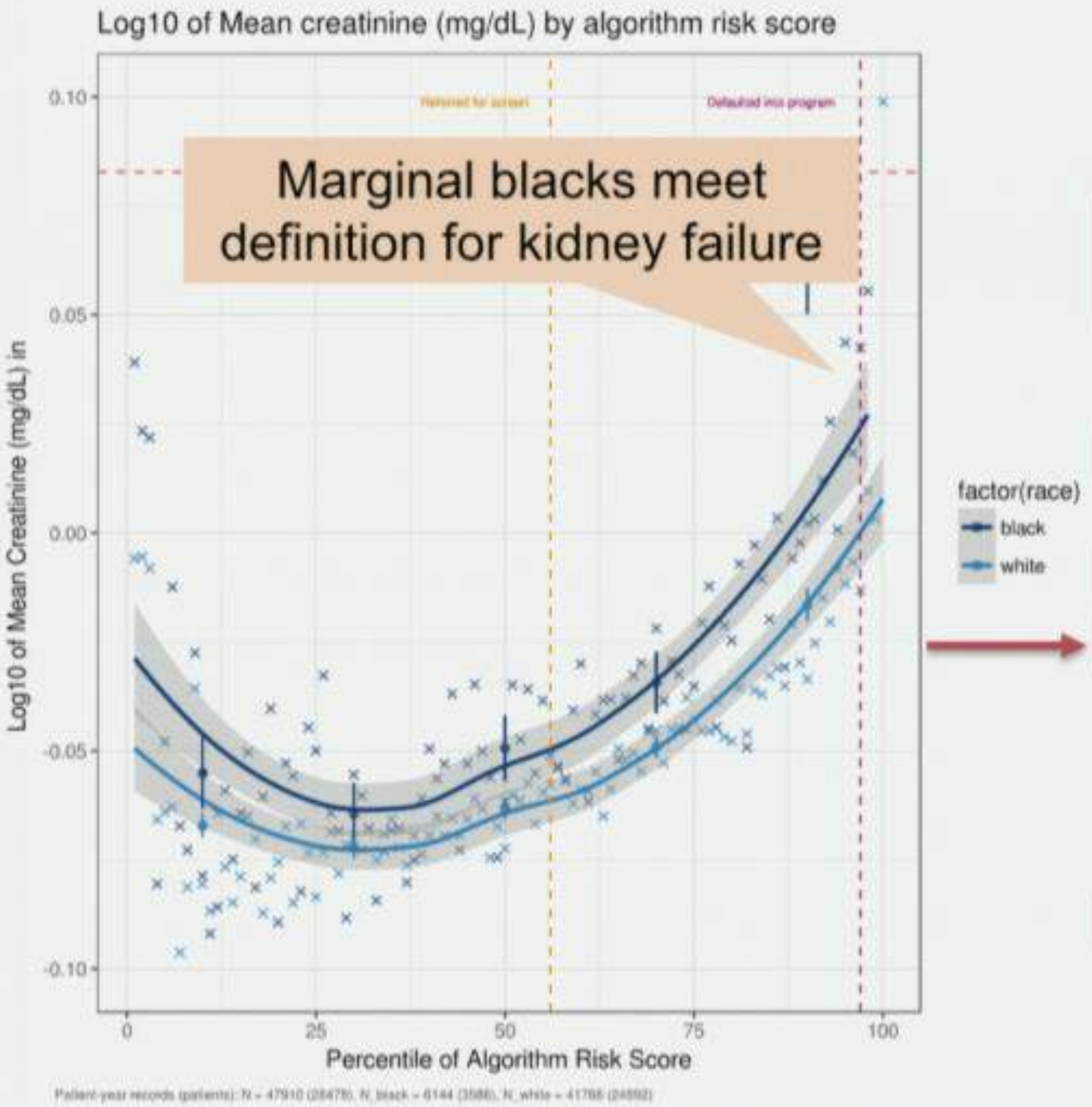

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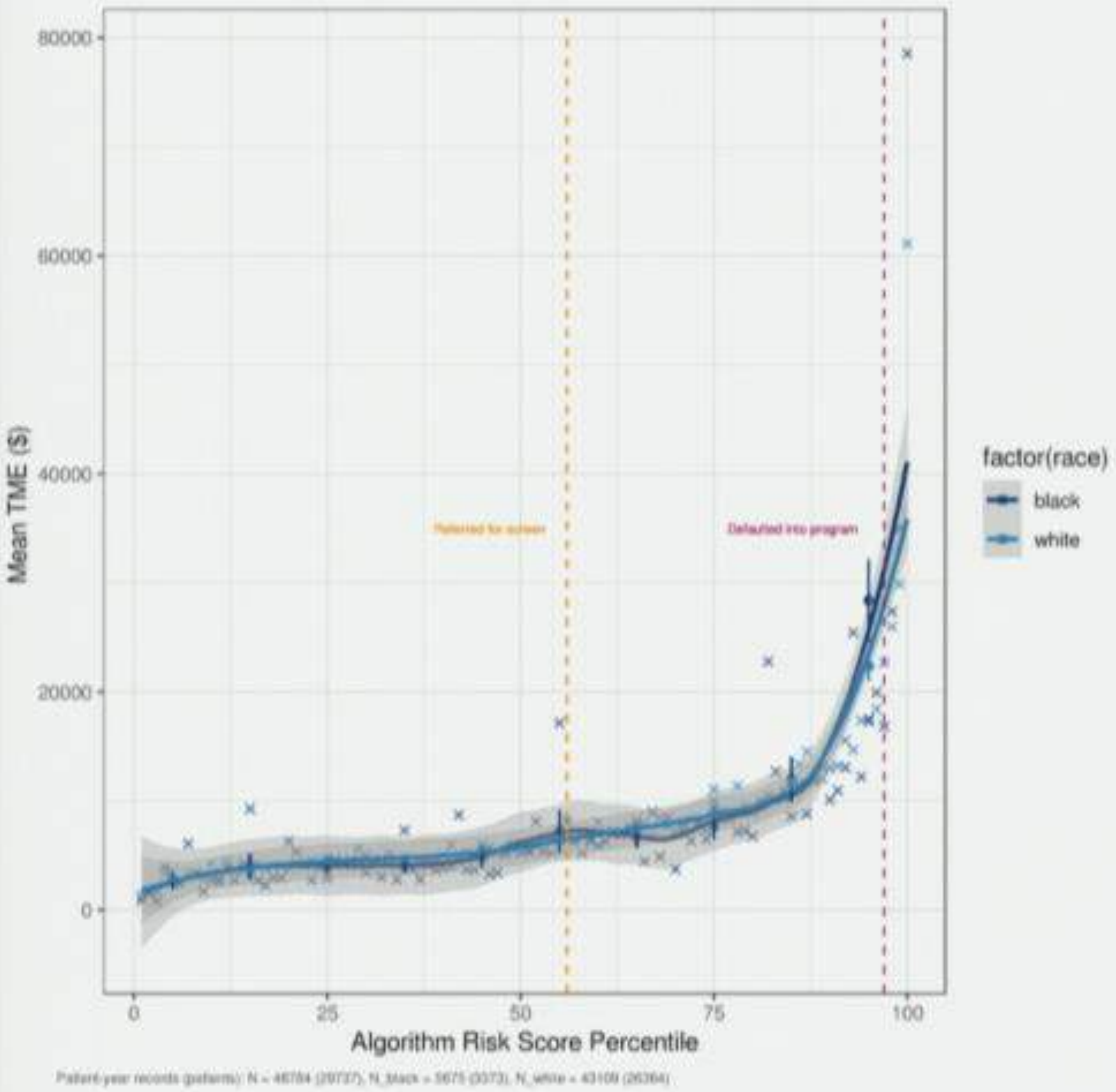
Where is the algorithm going wrong?

A clue is where it's going right:
*unbiased **cost** prediction*



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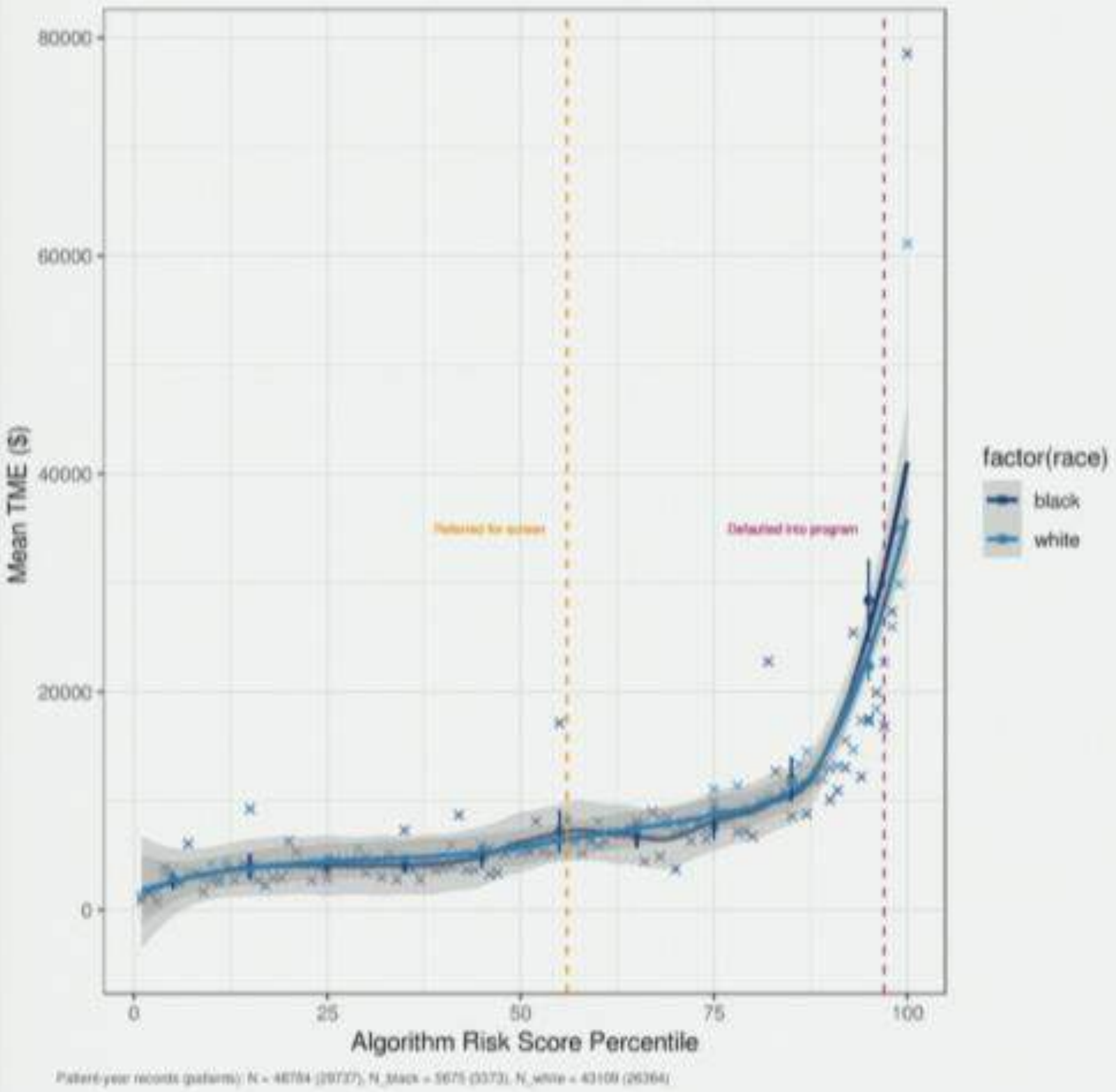
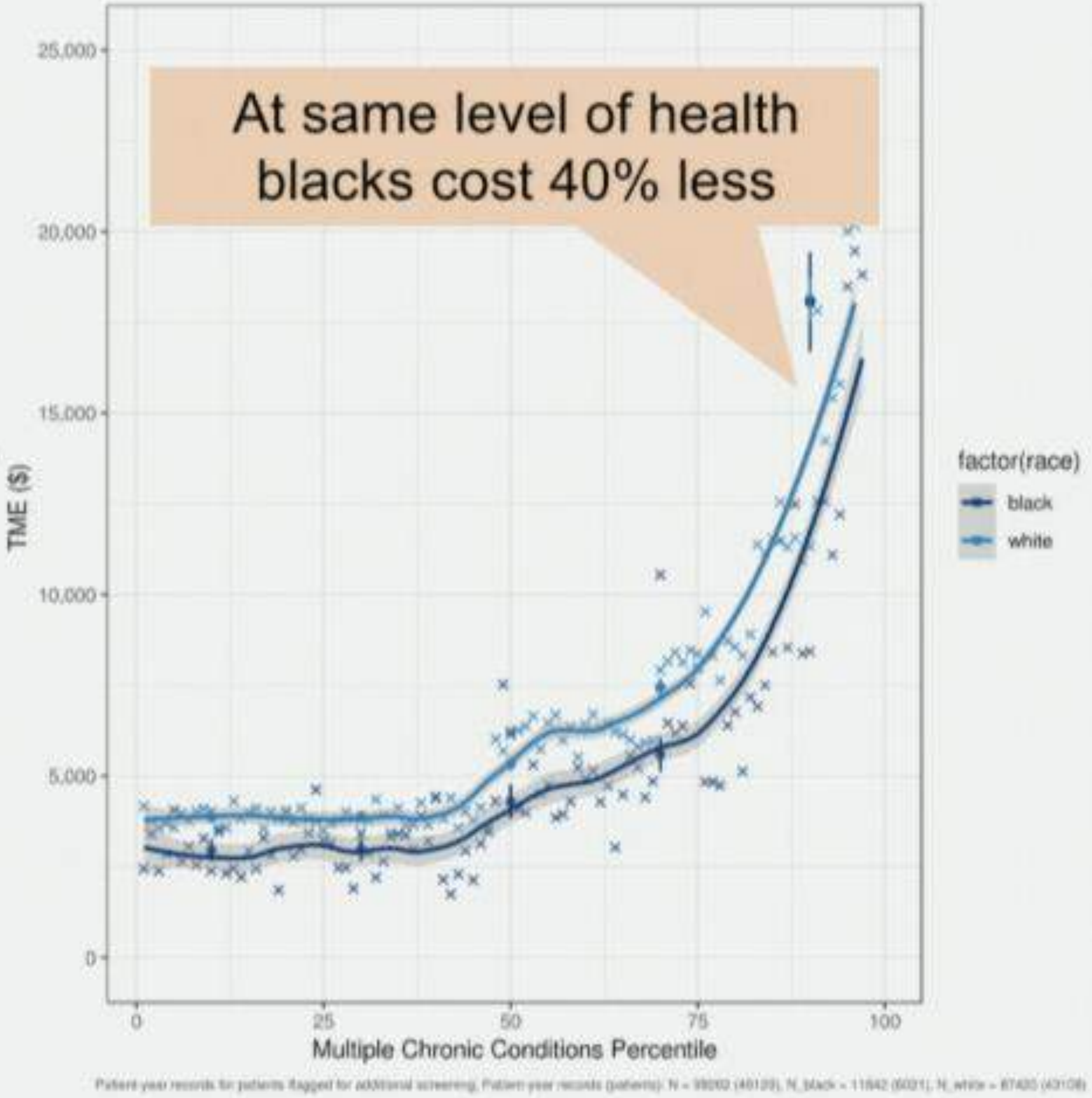


*Race differences in cost–health relationship: biased **health** prediction*



Composition of costs also very different

Category	$[B–W]	
Overall cost	*-1808*	***
IP Surgical	-640	***
OP Specialists	-423	***
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  - 20-30% ↓ medical care

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Dissecting the problem

- Summary so far: Predicting <u>cost</u> accurately means
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  - Why was cost chosen?

Dissecting the problem

- Story 1: Follow the money

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Dissecting the problem

- **Story 1: Follow the money**
  - Society cares about health H
  - Hospitals, insurers care about dollars C
  - Many health care problems arise from $(C - H)$
    - Choice of cost is privately optimal
    - But socially suboptimal
  - Another instance of profit distorting health care

A thought experiment

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- A self-interested algorithm developer could just be making a trade-off
  - Willing to tolerate racial bias
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A thought experiment

- A self-interested algorithm developer could just be making a trade-off
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  - To get better cost prediction, cost savings
- But what if we could construct an algorithm that
  - Achieves these goals just as well
  - Is less biased

Performance of a modified algorithm

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- Procedure
  - Rank by health
  - Then rank by cost
  - Results from holdout

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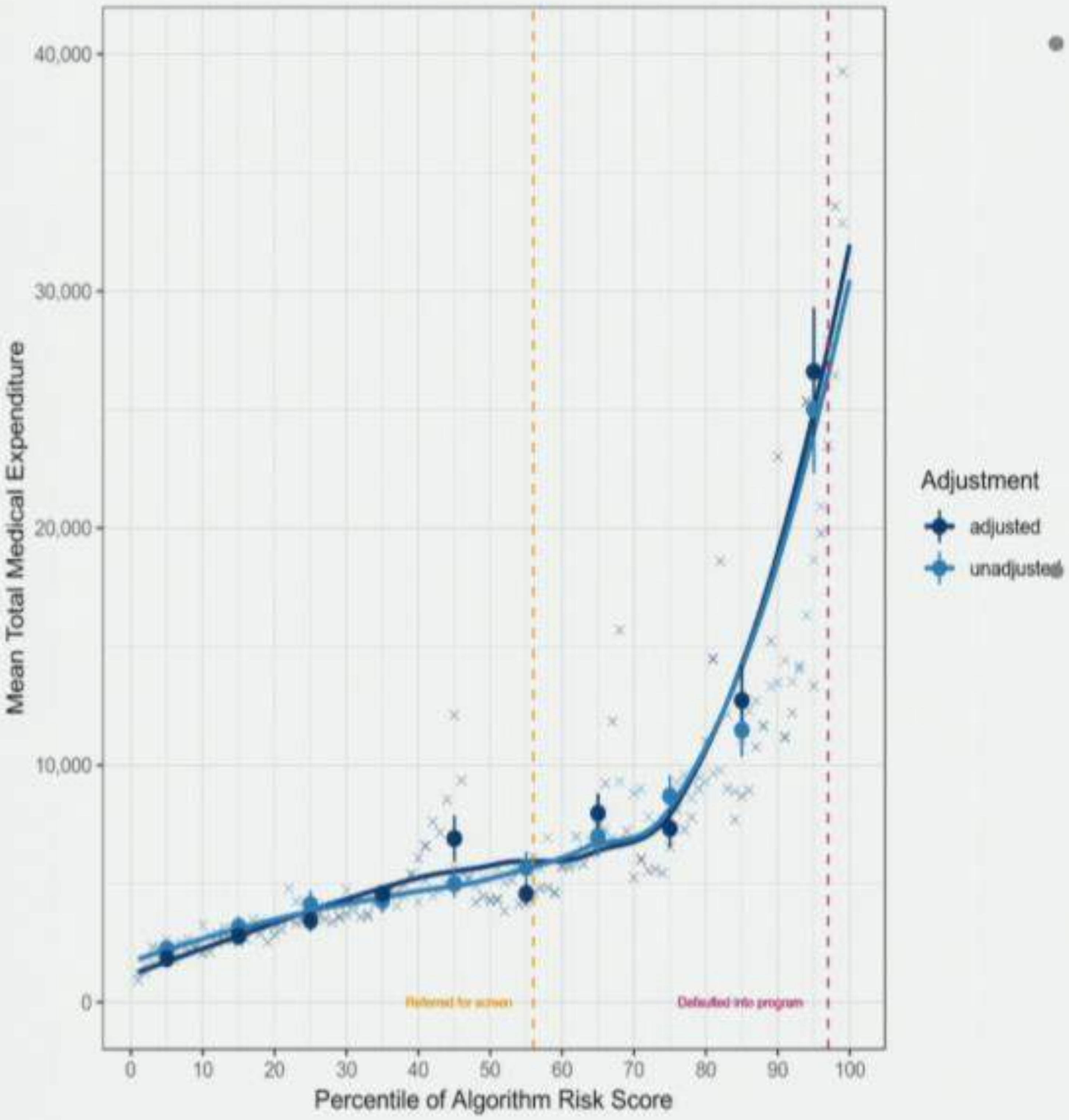

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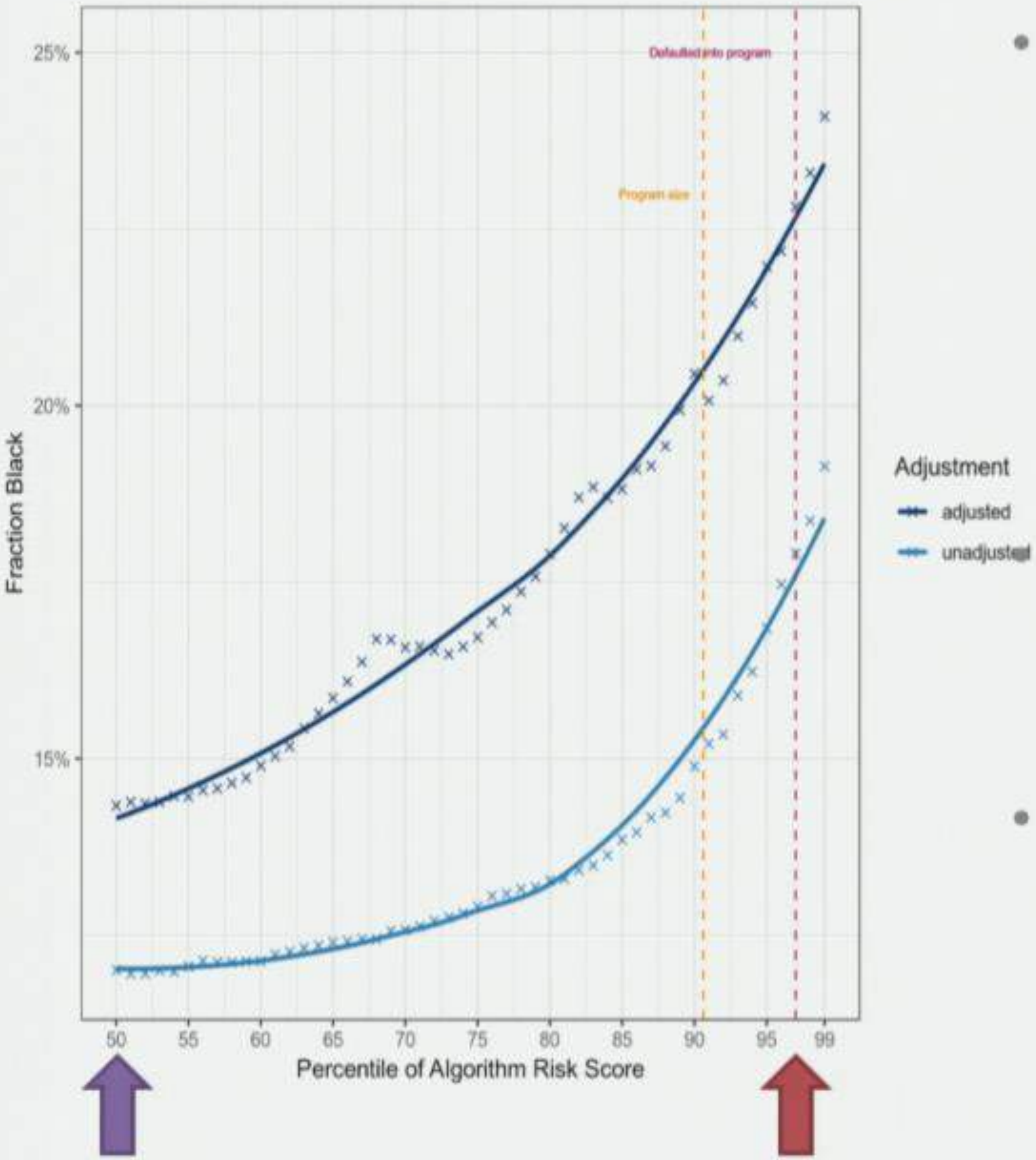

- Procedure
  - Rank by health
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  - Results from holdout
- Still predicts cost
  - R^2: 0.088 vs 0.077
- **Far less biased**
  - At **≥50th** percentile
  - At **97th** percentile: **61.3% ↑ blacks**

What could be going on here?

- Changing the objective function to incorporate health
  - Reductions in bias
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- Is cost in $t+1$ the most accurate prediction target?
  - Capitalized cost over likely coverage period?
  - Avoidable cost savings from health problems that could be averted by the program?
  - …

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  – Cost was chosen because of
    1. Convenience
    2. Not appreciating consequences in terms of bias

This is a generic problem in health and social policy

Passi and Barocas 2019

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- Health algorithms: complex data x in, label y out
  - X-ray → radiologist's interpretation
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- But 'problem formulation' choices mean that y is often a convenient proxy

- Can mean automation of errors, biases, inequalities
  - Physicians have incentives and biases
  - Structural inequalities affect diagnosis and utilization

Passi and Barocas 2019

Mis-measurement framework for prediction problems

Mullainathan and Obermeyer, *AER P&P* 2017

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- Predictions depends on balance of $E[Y^*|x]$ and $E[\Delta|x]$

Mullainathan and Obermeyer, *AER P&P* 2017

Why we might worry about this in general

Mullainathan and Obermeyer, *AER P&P* 2017

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- We often might suspect $Cov[\Delta,x] > Cov[y^*,x]$
- In general, y^* is complex
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  - …
- Δ can be very simple
  - Biases, errors
  - Often correlated with age, insurance, race, …

Mullainathan and Obermeyer, *AER P&P* 2017

General insight #1: Predicting better may be worse

Mullainathan and Obermeyer, *AER P&P* 2017

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- Evaluating quality of predictions

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- We may actually prefer 'bad' predictions!
  - Predictors that fit to errors could look good
  - Predictors that get Δ out of $\hat{y}$ could look bad

Mullainathan and Obermeyer, *AER P&P* 2017

General insight #2: This reinforces inequalities

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- **This leads us to allocate more to those who have more to begin with**

Mullainathan and Obermeyer, *AER P&P* 2017

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  - Original algorithm: 48,772 excess chronic conditions in blacks vs. white, conditional on risk score
  - Adjusted algorithm: 7758 excess chronic conditions – **84% reduction in bias**

Epilogue

- In collaboration with manufacturer, we are developing methods to adjust predictions
  - Predict basket of outcomes H rather than C
- Early results: substantial reductions in bias
  - Original algorithm: 48,772 excess chronic conditions in blacks vs. white, conditional on risk score
  - Adjusted algorithm: 7758 excess chronic conditions – **84% reduction in bias**
- Recognition that C is a proxy for H means we can work to find better proxies (i.e., learning view)

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  - Did not need to ‘enrich’ with more non-white populations
- The predictors are the same
  - Did not need to remove race (directly or indirectly)
  - In fact, we would rather have more info on race
- **Only the prediction target (label) changed**

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  - Root cause: cost prediction vs. health prediction
- Original algorithm reinforced structural inequalities
  - Patients who already use care get more care
- Modified algorithm does not solve these problems
  - But it is built on understanding them
  - And works to reverse them