Measuring Fairness in the US mortgage market[a]

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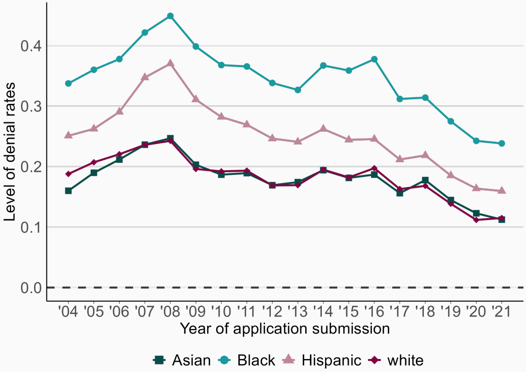
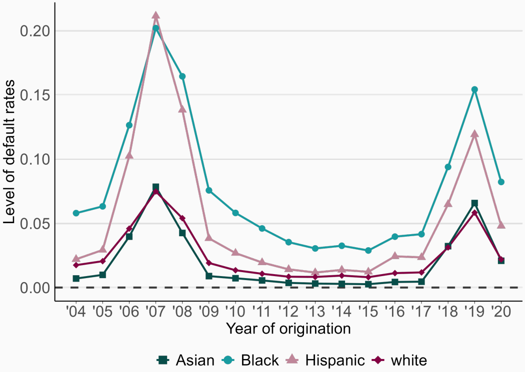
[a]The views expressed in this presentation are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

Denial and Default rates over time





Fairness in the US mortgage market

Does the outcome of this market look fair?

- Need a definition of fairness.
- Different definitions proposed in the academic literature; e.g. *Translation tutorial: 21 fairness definitions and their politics* [Narayanan, 2018]
- Different definitions used in public debate/news media News headlines
- Different definitions alluded to in the law/regulatory guidance.

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Does it matter what definition of Fairness we use?

Why the US Mortgage market?

1. Mortgage balances are the largest source of debt for most Americans.
2. Mortgage market plays a prominent role in the persistence of wealth gaps across generations (Charles and Hurst [2003], Kuhn et al. [2020]).
3. Mortgage underwriting has seen a shift towards algorithmic underwriting over the past two decades.
4. Protected attributes of the applicant (e.g. race or gender) are directly observable.

Measuring Fairness in consumer finance and the US mortgage market

We're in good company at the Philadelphia Fed!

- Giacoletti, Heimer, and Yu [2022]
- Bhutta and Hizmo [2021]; Bhutta, Hizmo, and Ringo [2022]
- Fuster, Plosser, Schnabl, and Vickery [2019]
- Conklin, Gerardi, and Lambie-Hanson [2022]
- An, Cordell, Geng, and Lee [2022]
- Meursault, Moulton, Santucci, and Schor [2022]
- Carlin and Divringi [2018]

Also of note: Federal Reserve Bulletin (now CFPB). Most papers focus on one particular measure.

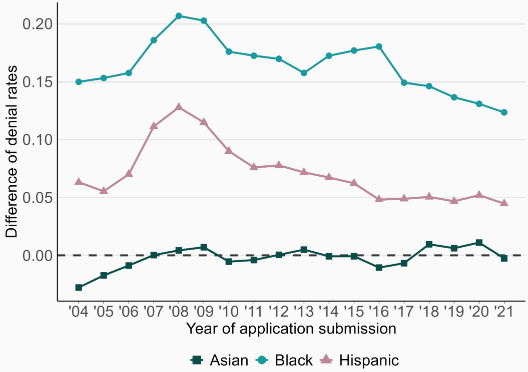
Defining Fairness

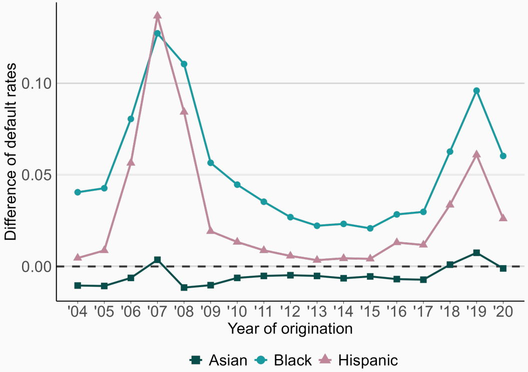
We consider 5 classes of Fairness definitions:

1. Statistical Parity
2. Predictive Parity
3. Marginal Outcome test
4. Equalized Odds
5. Conditional Statistical Parity

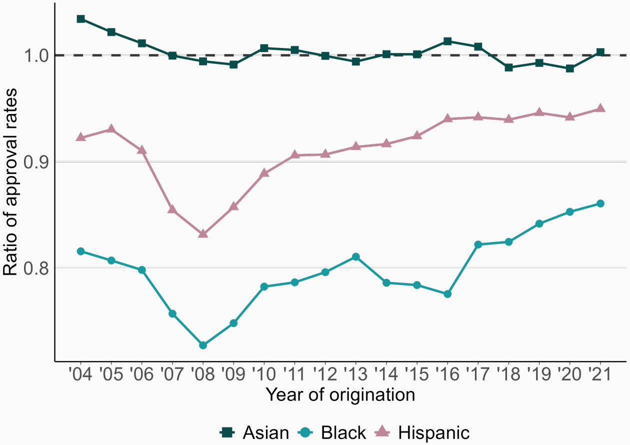
Adverse impact (29 CFR § 1607.4):
“A selection rate for any race [...] which is less than four-fifths [..] will generally be regarded [..] as evidence of adverse impact.”

Statistical Parity and Predictive Parity





The four-fifths rule



Defining Fairness

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Equal Credit Opportunity Act (Regulation B), 12 CFR § 1002.4(a):
“Equal credit standards”

Marginal outcome test

- Economics has traditionally used the outcomes of "marginal candidates" to assess whether credit standards are equal
- Idea: If the same risk threshold is used for Black and white applicants, people at the threshold should default at the same rate

Interagency Fair Lending Examination Procedures

"The examiner-in-charge should, during the following steps, judgmentally select from the initial sample only those denied and approved applications which constitute marginal transactions."

Marginal outcome test

- Issue: Obtaining “marginal applicants” is often difficult.

Interagency Fair Lending Examination Procedures

“The examiner-in-charge should, during the following steps, judgmentally select from the initial sample only those denied and approved applications which constitute marginal transactions.”

- We develop a novel way to construct marginal applicants by identifying candidates who apply for multiple mortgages.
- An applicant is marginal if she has one approval and one denial.

Identifying Crossapplicants

We use Machine Learning to transform cHMDA into an applicant level dataset.

1. Split the data into partitions, characterized by the distinct outcomes of 9 categorical variables.
   Example: census tract of the property

2. Apply a state-of-the-art agglomerative hierarchical clustering algorithm to further break down these partitions into clusters based on 5 additional continuous attributes.
   Example: application date

Identifying Crossapplicants

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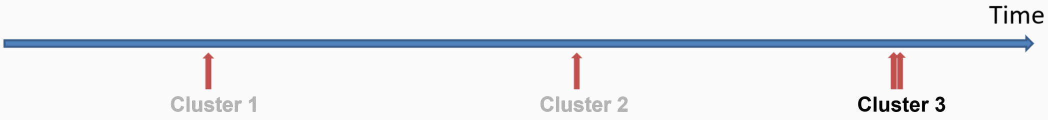


Identifying Crossapplicants

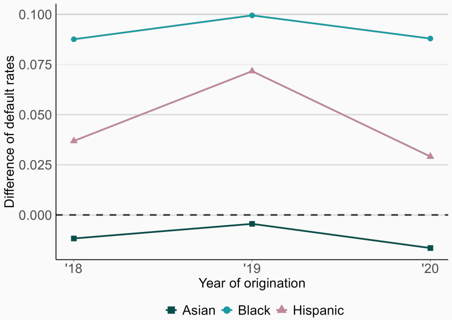
- All applications in a given cluster are “near-identical”.
- Rate at which clusters contain multiple origination informative about whether clusters correspond to single individuals.
  - Bad algorithm - all clusters are pairs of applications from two applicants: Most clusters with two approvals have two originations
  - Perfect algorithm - all clusters are pairs of applications from one applicant: No clusters with two approvals have two originations
- We estimate that 92% of clusters represent single individuals.

Marginal Candidates

- Can subset to those clusters that contain both one approval, and one denial.
- Individuals that submitted two near-identical applications:
  - One loan officer approved the application
  - Another loan officer denied the application
- We consider such an applicant marginal by "revealed preference".

Marginal Candidates

- If same risk threshold is used across lenders, default rate should be the same across groups
- Marginal Black applicants default more frequently
- Not consistent with higher lending standards for Black applicants
- Fairness violation is “negative” for this definition



Defining Fairness - feasibly

We consider 6 broad classes of Fairness definitions:

1. Statistical Parity
2. Predictive Parity
3. Marginal Outcome test
4. Equalized Odds
5. Conditional Statistical Parity

Equal Credit Opportunity Act (Regulation B), 12 CFR § 1002.1(b): “availability of credit to all creditworthy applicants without regard to race [...]”

Equalized Odds - Equality of Opportunity

- Consider crossapplicants with an originated loan that did not default.
- How likely were they denied at least once?
- Intuitively captures notion of “unfairly denied”

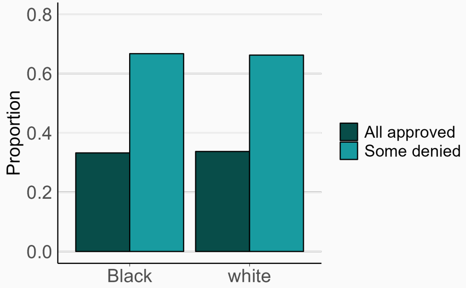
Does the rate of “unfair denials” vary by race?

Equalized Odds - Equality of Goodwill

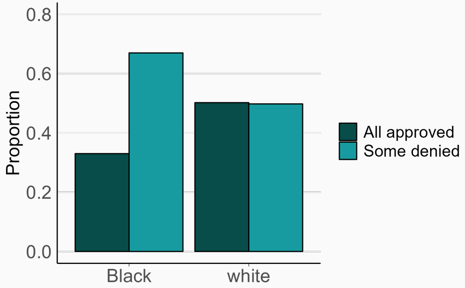
- Consider crossapplicants with an originated loan that did default.
- How likely were they approved on all their applications?
- Intuitively captures notion of “unfairly approved”

Does the rate of “unfair approvals” vary by race?

Equalized Odds (based on crossapplicants)



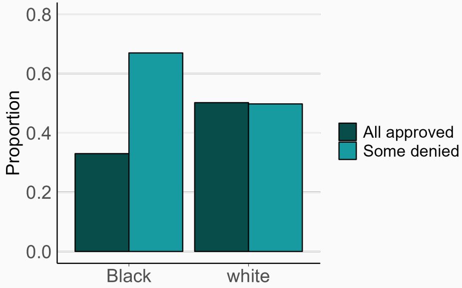
Defaulters



Non-defaulters

Equality of Opportunity (based on crossapplicants)

- Black applicants:
  67% chance at least one denial for non-defaulters
- white applicants:
  50% chance at least one denial for non-defaulters
- Intuitively, captures the rate of being “unfairly denied”



Non-defaulters

Defining Fairness - feasibly

We consider 5 classes of fairness definitions:

1. Statistical Parity
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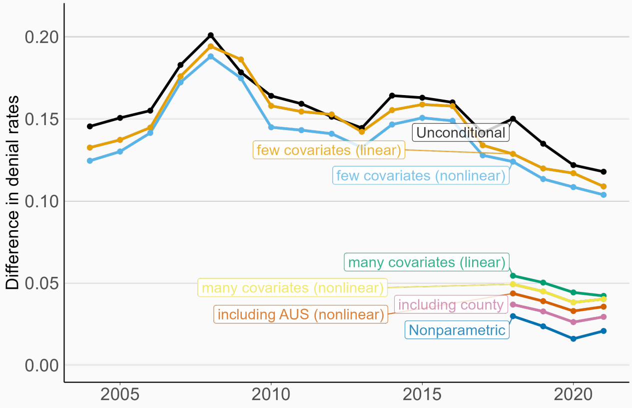
Disparate treatment/impact: “disparate impact tests should only include controls for attributes that are plausibly business justified.”[Ayres, 2010]

Conditional Statistical Parity

Conditional Statistical Parity measures the difference in denial rates across groups, conditional on varying information sets (e.g. a set of covariates X).

- Choice of X is extremely important
- Potential for
  1. missing covariates
  2. included variable bias

Conditional Statistical Parity



Specifications differ in

1. set of covariates
2. functional form

Interactive dashboard

- All results are based on two works-in-progress (joint works with Minchul and Hadi Elzayn)
- Interactive Appendix available, allows the user to explore the different measures we discussed today (and more!) across time and space
- Hoping to expand this to other protected attributes, and make this available through the Philadelphia Fed to Researchers and the general public.

Taking stock

Does it matter what definition of Fairness we use?

- Yes, different definitions lead to different results.
- No “right" definition, but will be context-dependent
- Even then, perhaps a more comprehensive view considers multiple definitions.

Defining Fairness - Theory

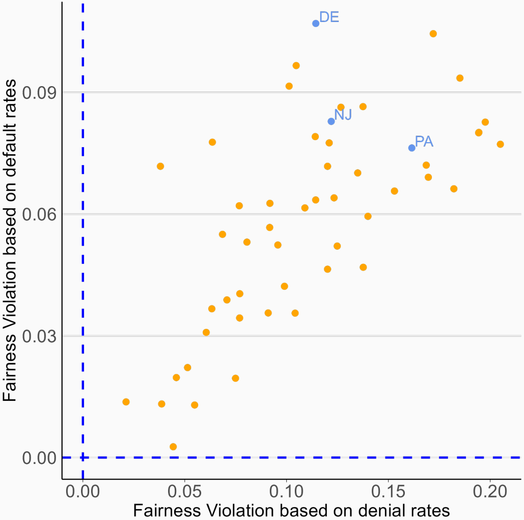
- Theoretical results exist that prove how seemingly reasonable definition are at odds with each other.
- *Inherent Trade-Offs in the Fair Determination of Risk Scores* [Kleinberg, Mullainathan, and Raghavan, 2017] considers three widely used definitions of fairness.
  (related to: Marginal Outcome test, Equality of Opportunity, Equality of Goodwill)

Kleinberg et al. [2017]:

"We prove that except in highly constrained special cases, there is no method that can satisfy these three conditions simultaneously."

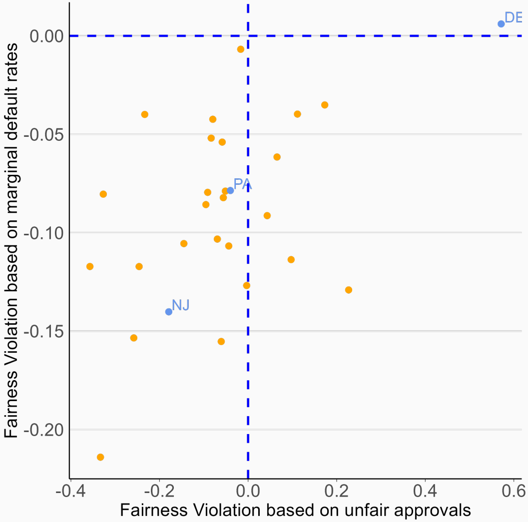
Stylized Facts

- Broad measures point to systemic inequality between demographic groups
- Not necessarily reflective of discrimination in the mortgage sector



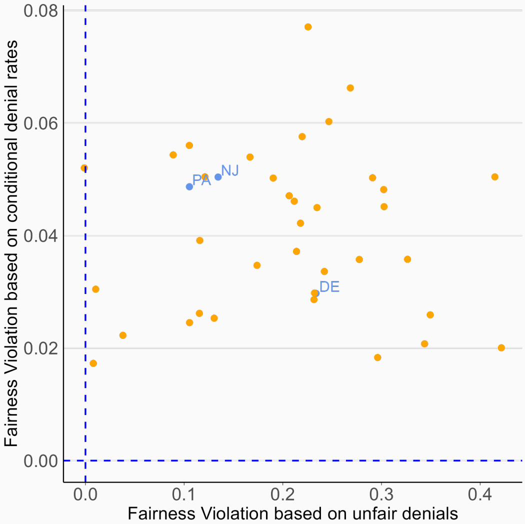
Stylized Facts

- Isolating the mortgage decision yields a more nuanced picture
- On the one hand:
  1. Marginal candidates more likely to default in minority group
  2. “Defaulters” denied at same rate across demographic groups

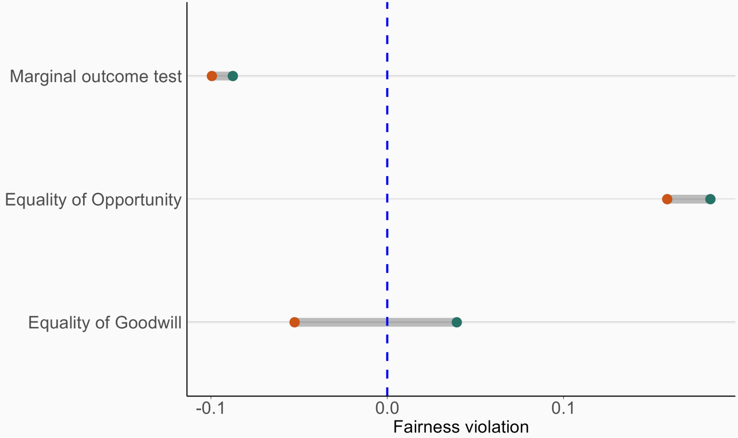


Stylized Facts

- Isolating the mortgage decision yields a more nuanced picture
- On the other hand:
    1. Minority applicants more likely to be denied conditional on rich set of covariates
    2. Minority “Non-defaulters” denied at substantially higher rates



Fairness definition matters



Range for each definition based on yearly measures for 2018-2020

Conclusion

- Definition of fairness matters, both theoretically and empirically.
- Any one measure (or study) may not paint the full picture

Conclusion

- Definition of fairness matters, both theoretically and empirically.
- Any one measure (or study) may not paint the full picture

Does the outcome of the US mortgage market look fair?

- Broad measures of fairness point to systematic inequality
- More narrow measures are more ambiguous

Thank you

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Fairness in the US mortgage market

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