NBER Panel Discussion: Innovative Uses of Credit Bureau Data

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[1] These slides are inevitably citation-incomplete; comments and additions are very welcome.

Traditional Credit Report Data

What we see:

- Loan balances
- Delinquency history
- Credit limits
- Applications/inquiries
- Debt in collection
- Bankruptcies
- Civil judgments

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Loan balances

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What we don't:

Income

Expenditure / consumption

Credit card spending

Interest rates / prices

Demographics and education

Lender (vs. servicer)

"Alternative" financial products

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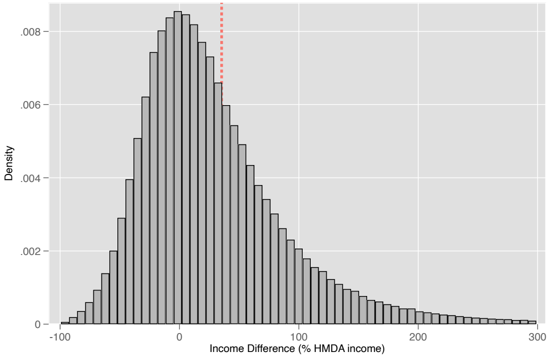
"Enhanced" Credit Report Data

- Predicted income and/or linked payroll processor data (Blattner and Nelson, 2021; Mello, 2021; Di Maggio, Kalda, and Yao, 2019)
- Race and ethnicity via BISG (CFPB, 2014; Blattner and Nelson, 2021)
- Education (Di Maggio, Ratnadiwakara, and Carmichael, 2021)
- Mortgage servicing data (Ganong and Noel, 2021; Berger, Milbradt, Tourre, and Vavra, 2021; Bartlett, Morse, Stanton, and Wallace, 2019)
- Payday loan data (Fonseca, 2021; Blattner and Nelson, 2021; Bhutta, Skiba, and Tobacman, 2015)
- Household structure (Lee and van der Klaauw, 2010; Dokko, Li, and Hayes, 2015)
- Medical shocks and health insurance (Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018; Gupta, Morrison, Fedorenko, and Ramsey, 2018; Kluender, Mahoney, Wong, and Yin, 2021; Hu, Kaestner, Mazumder, Miller, and Wong, 2018)
- "Shadow debt" (Argyle, Iverson, Nadauld, and Palmer, 2021)
- Credit card spending / revolving (Fulford and Schuh, 2020; Nelson, 2020)

Predicted Income

HMDA vs. Bureau-predicted Income differences (Blattner and Nelson, 2021):

- Match CoreLogic deeds, credit records, and HMDA mortgages: 38m matched observations in years '06-'17.
- Bureau's income estimator: trained on 1.2 m sample of IRS form 1040 joint income data from tax years '08-'12.



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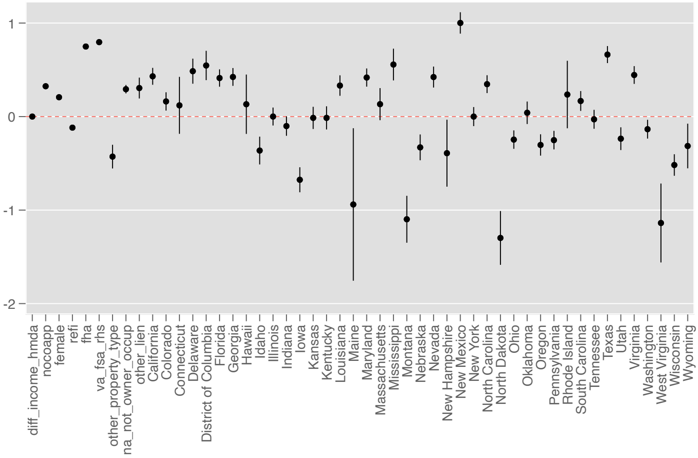
Predicted Race and Ethnicity

BISG minority false-negative rates by state (Blattner and Nelson, 2021):

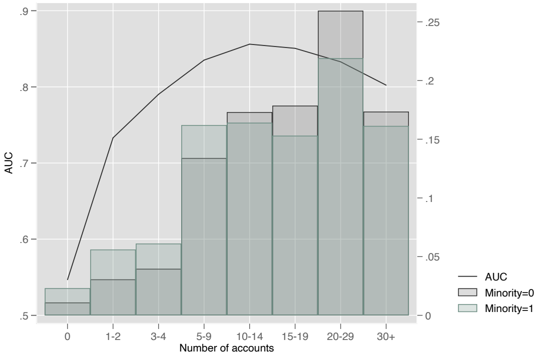
- See Maine, Montana, North Dakota, West Virginia...



Minority and non-Minority Credit Bureau Data

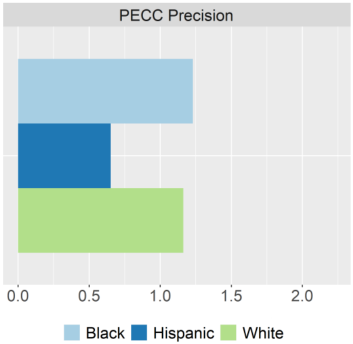
In Blattner and Nelson (2021), we find minority and low-income consumers' credit report data have **characteristics with low predictive power** for *all* groups (see also Avery, Brevoort, and Canner, 2012).

- Sparse, non-diverse, and/or "dirty" data
- For example, file thickness by minority status:



What We Predict with Credit Report Data

- Loan default (90 DPD, 2 year horizon) (Fed Board, 2007; Thomas, 2009)
- Property/liability insurance claim risk (Kiviat, 2019)
- Apartment rental default (Humphries, Nelson, van Dijk, and Waldinger, 2022)
- Employability / worker productivity (pre-employment credit checks or "PECCs" (Bartik and Nelson, 2021; Dobbie, Goldsmith-Pinkham, Mahoney, and Song, 2020; Corbae and Glover, 2018)



Why We (Can) Predict with Credit Report Data

- Persistent human capital (Corbae and Glover, 2018)
- Persistent time preference (Chatterjee, Corbae, Dempsey, and Rios-Rull, 2020)
- Persistence in multidimensional (demand/risk) types (Nelson, 2020; Blattner, Nelson, and Hartwig, 2022)
- Credit score hysteresis (Brown, Cookson, and Heimer, 2019; Blattner and Nelson, 2021)