Decomposing Gender Differences in Bankcard Credit Limits

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Introduction

- Card cards one of the common debt instruments in the U.S.
  - 76% own at least one credit card; 44% revolve a balance
- Prior literature has documented gender differences in other financial markets (auto loans, housing, mortgages)**;** no papers examining gender differences in credit card limits
- **Research questions:**
  - **Are there gender differences in total bankcard limits?**
  - **If so, how large are these differences?**
  - **What factors explain these differences?**

Data

- We use a unique merged data set that combines mortgage application, mortgage servicing, and credit bureau data:
  - **Home Mortgage Disclosure Act (HMDA)** – anonymized data on mortgage applications and outcomes; contains information on multiple types of mortgage products and includes a number of borrower, property, and loan characteristics.
  - **Equifax Credit Risk Insight Servicing data and Black Knight McDash (CRISM)** – anonymized monthly borrower-level credit bureau data from Equifax matched to the McDash loan-level mortgage data
  - **Black Knight McDash** – data set of anonymized information containing monthly mortgage servicing information for a majority of the largest residential mortgage servicers in the U.S
- We focus on *total bankcard limits* – the sum of all card limits an individual has in that time period

Sample Selection

- Focus on mortgages originated from 1992 to 2014
- Drop any mortgages containing a co-applicant or consumers with more than one mortgage
- Take one observation from each individual 24 months after mortgage origination
- Important: possible for sole mortgage applicants to be married or have others in the HH
- There is likely a selection issue on who does and does not include a spouse as a co-applicant
  - → marital status would explain some variation in limits, resulting in omitted variable bias
  - Since we do not observe martial status, **our analyses are subject to an unknown degree of bias**
- Final data set: 841,125 sole mortgage applicants from 2006 to 2016
  - 43% female, 74% white

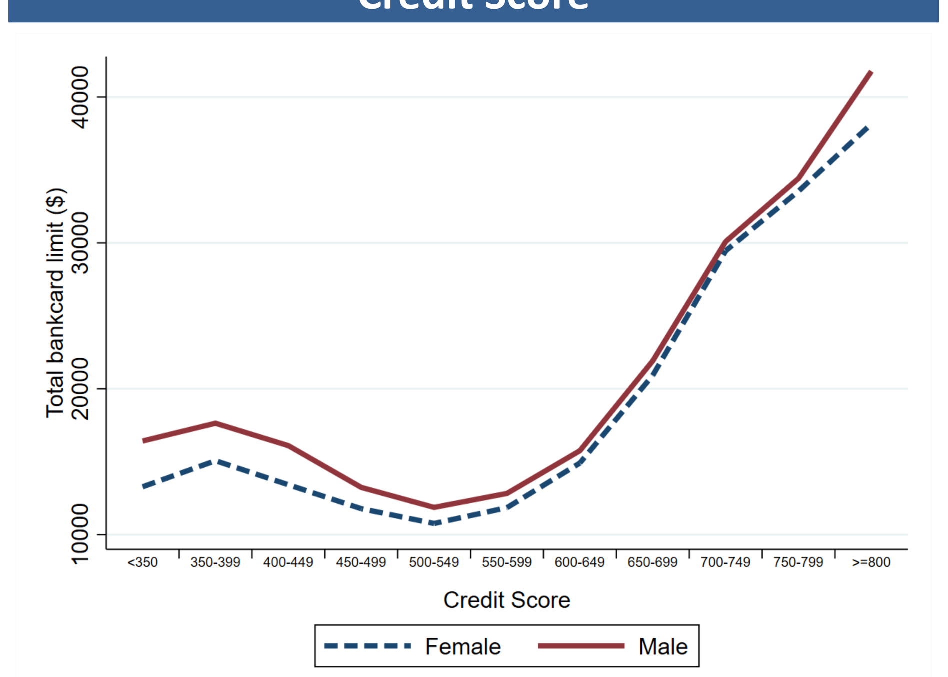
Summary Statistics

	Income	Credit Score	Number of Bankcard Accounts	Total Bankcard Balance ($)	Total Bankcard Limit ($)
Male					
Mean	99	723	3.22	8,340	30,079
Median	69	752	3	3,491	21,000
25^{th}	47	681	2	918	8,800
75^{th}	106	798	4	9,973	41,200
Female					
Mean	72	723	3.38	7,750	28,544
Median	56	752	3	3,394	20,700
25^{th}	39	679	2	933	8,800
75^{th}	83	799	4	9,673	39,800

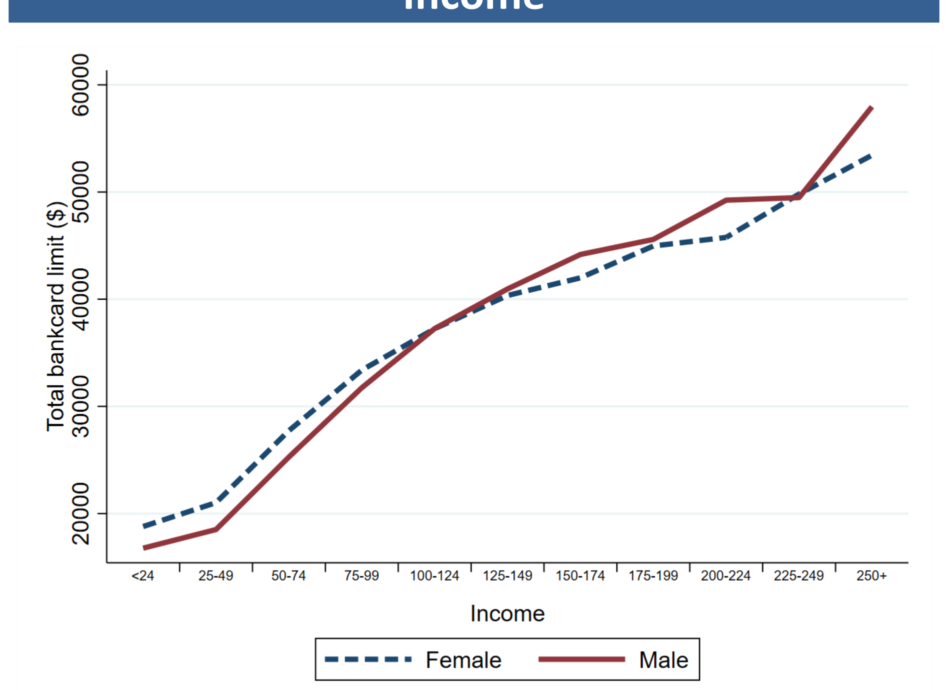
Notes: Authors' calculations using Home Mortgage Disclosure Act data, Black Knight McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Income is the HMDA income, reported at the time of mortgage application.

Relationship Between Bankcard Limits and Riskscore and Income

Credit Score



Income



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Linear Regression

- We estimate a linear regression to calculate average difference in total limits between genders
- Control for # of cards, income bin, Risk Score bin, race, age, state, year, and mortgage characteristics
  - Interact $Female$ dummy variable with # of cards, income bin, and Risk score bin
- Estimate an average marginal effect for the $Female$ dummy variable of **$-1,323**

Kitagawa-Oaxaca-Blinder (KOB) Methodology

- To understand the factors that drive this difference, we perform a Kitagawa-Oaxaca-Blinder (KOB) decomposition
- Estimate the following equation for each gender separately:
  - $\boldsymbol{y_g = \alpha_0 + X_g\beta_g + \varepsilon_g;\ g \in (M, F)}$
- Calculate mean predicted value for each gender: $\boldsymbol{E[y_g]}$
- Take the difference of the two means: $\hat{\Delta} = E[\boldsymbol{y_M}] - E[\boldsymbol{y_F}]$
- Re-arrange the components so:
  - $\hat{\Delta} = (E[\boldsymbol{y_M}] - E[\boldsymbol{y_W}])'\beta_W + E[\boldsymbol{y_W}]'(\beta_M - \beta_W) + (E[\boldsymbol{y_M}] - E[\boldsymbol{y_W}])'(\beta_M - \beta_W)$

KOB Results and Discussion

- Endowment effect (differences in *levels* of observed characteristics) explains ≈ 10% of $\hat{\Delta}$
- Coefficient effect (difference in *returns* to characteristics) explains ≈ 88% of $\hat{\Delta}$
- Next: Follow Firpo, Fortin, and Lemieux (2009) and use unconditional quantile regression methodology
  - Test if results change across time and across the limit distribution

	Coefficient	SE
Mean Male Outcome	$29,979	(55.94)
Mean Female Outcome	$28,480	(57.83)
Mean Gender Differential	$1,499	(80.46)
Endowment Effect	$156	(64.00)
Coefficient Effect	$1,315	(61.94)
Interaction Effect	$27	(25.30)

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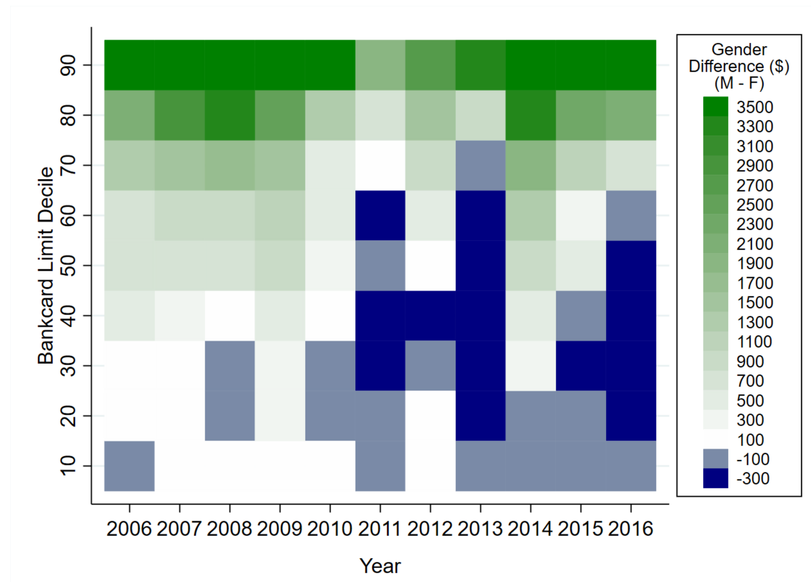
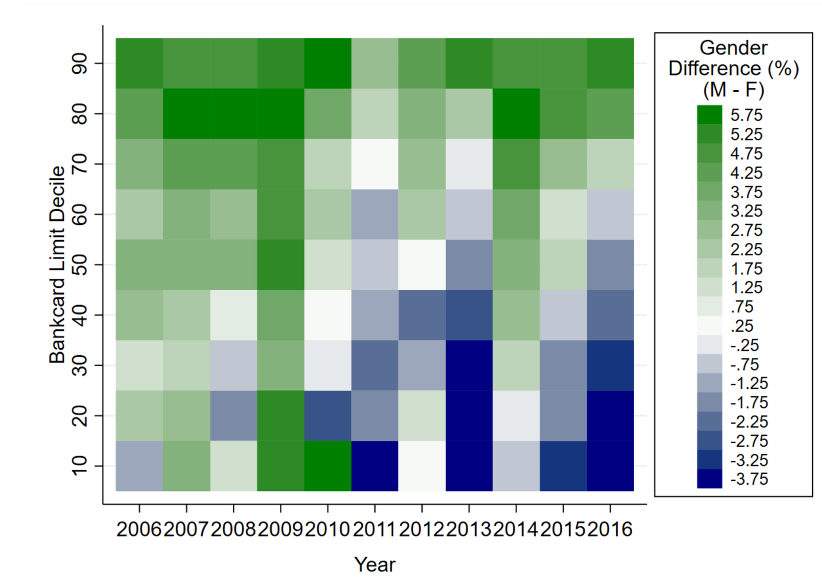
Heterogeneity in the Decomposition

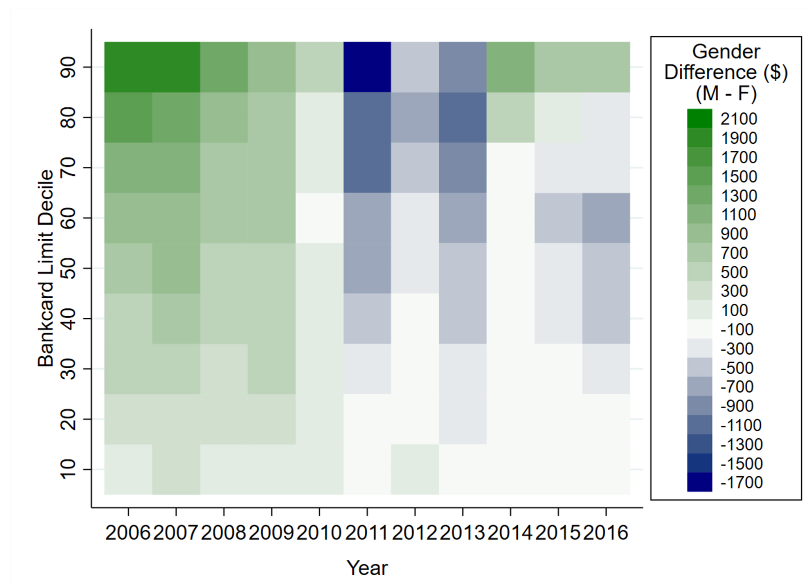
Difference



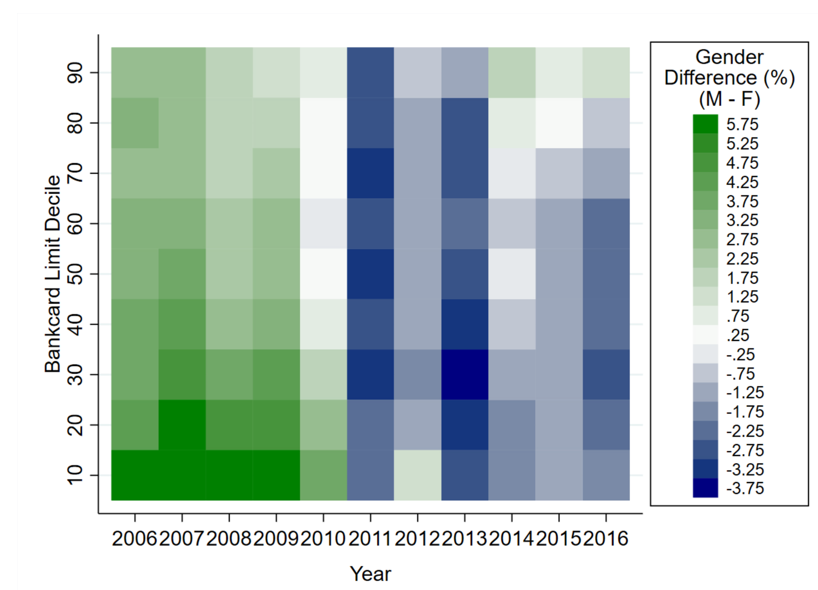
As a % of Male Limit



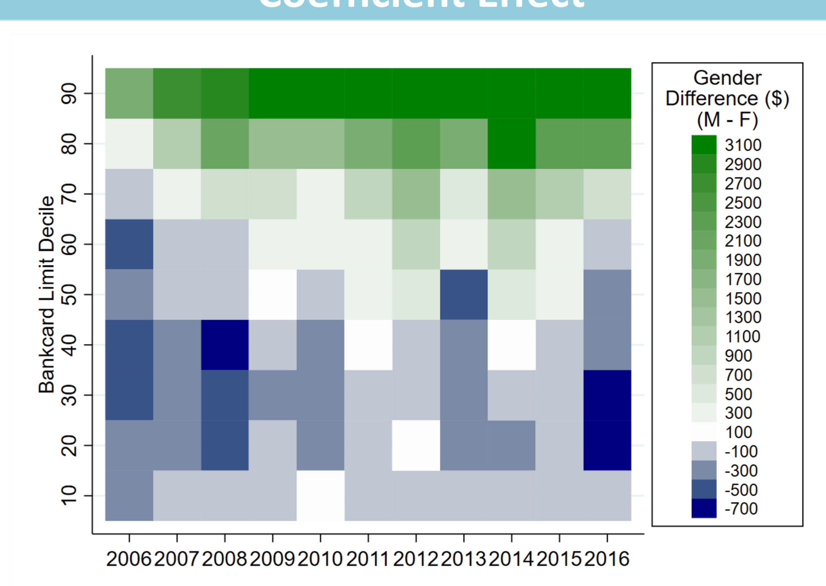
Endowment Effect



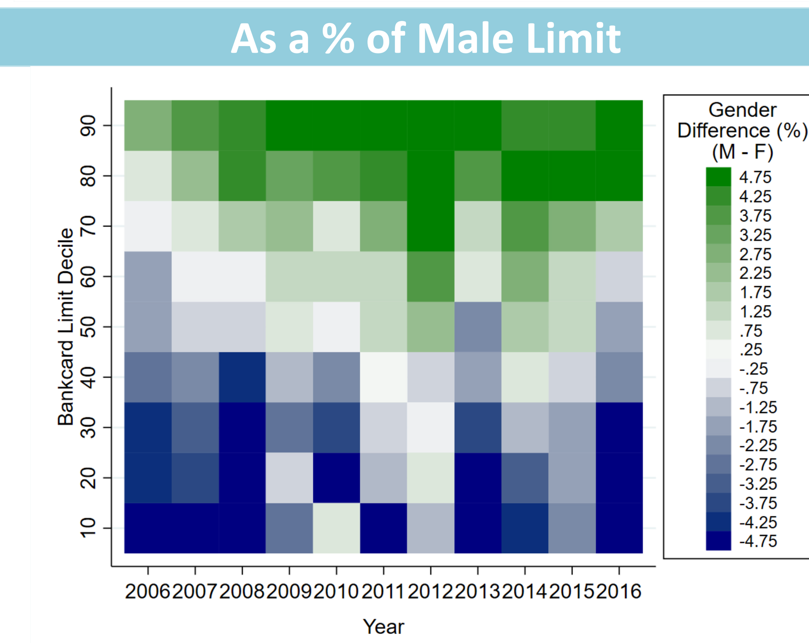
As a % of Male Limit



Coefficient Effect



As a % of Male Limit



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