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 marital 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

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>99</td>
<td>72</td>
</tr>
<tr>
<td>Credit Score</td>
<td>723</td>
<td>723</td>
</tr>
<tr>
<td>Number of Bankcard Accounts</td>
<td>3.22</td>
<td>3.38</td>
</tr>
<tr>
<td>Total Bankcard Balance ($)</td>
<td>8,340</td>
<td>7,750</td>
</tr>
<tr>
<td>Total Bankcard Limit ($)</td>
<td>30,079</td>
<td>28,544</td>
</tr>
</tbody>
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Mean
- Mean Male Outcome $29,979 (55.94)
- Mean Female Outcome $28,480 (57.83)
- Mean Gender Differential $1,499 (55.94)

Regression Results and Discussion
- To understand the factors that drive this difference, we perform a Kitagawa-Oaxaca-Blinder (KOB) decomposition
- Estimate the following equation for each gender separately:
  \[ y = \alpha_F + X \beta_F + \epsilon_F \Rightarrow g = (M, F) \]
- Calculate mean predicted value for each gender: \( E[y_F] \)
- Take the difference of the two means: \( \Delta = E[y_M] - E[y_F] \)
- Re-arrange the components so:
  \[ \Delta = (E[y_M] - E[y_F]) + \beta_F (\beta_M - \beta_F) + (E[y_F] - E[y_M]) (\beta_M - \beta_F) \]

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

Notes: Authors' calculations using Home Mortgage Disclosure Act data, Black Knight McDash loan servicing data, and Equifax Credit Risk Insight Servicing data.

Endowment Effect
- Endowment effect (differences in levels of observed characteristics) explains ≈ 10% of \( \Delta \)

Coefficient effect (difference in returns to characteristics) explains ≈ 10% of \( \Delta \)

Notes: Authors' calculations using Home Mortgage Disclosure Act data, Black Knight McDash loan servicing data, and Equifax Credit Risk Insight Servicing data.

Relationship Between Bankcard Limits and Riskscore and Income

Notes: Authors' calculations using Home Mortgage Disclosure Act data, Black Knight McDash loan servicing data, and Equifax Credit Risk Insight Servicing data.

Credit Score
- Take one observation from each individual 24 months after mortgage origination
- Estimate an average marginal effect for the \( \delta \) female dummy variable of -1,323

Notes: Authors' calculations using Home Mortgage Disclosure Act data, Black Knight McDash loan servicing data, and Equifax Credit Risk Insight Servicing data.