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Gender Differences in Credit Card Limits: Evidence from Sole Mortgage Applicants*

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Abstract

Using linked mortgage application and credit bureau data, we document the existence of unconditional and conditional gender gaps in the distribution of total credit card limits for sole mortgage applicants. We estimate that male borrowers have approximately $1,300 higher total credit card limits than female borrowers. This gap is primarily driven by a large gender gap in the right tail of the limit distribution. At the median and in the left tail of the total limit distribution, women's limits are approximately $100 to $300 higher than men's. Results from a Kitagawa-Oaxaca-Blinder decomposition show that 87 percent of the gap is explained by differences in the *effect* of observed characteristics, while 10 percent of the difference is explained by differences in the *levels* of observed characteristics. The gap is persistent across geographies but has varied over time. Overall, these gender gaps are small in economic magnitude and have changed over time favoring women.

Keywords: gender, credit, credit cards, decomposition
JEL Codes: J16, G51 G53

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1 Introduction

Access to credit is an important determinant of individual financial health. Credit cards, one of the most common debt instruments in the United States,[1] are one of the principal means through which individuals access credit. However, given the magnitude and persistence of the gender differences in wages and income in the U.S. (Blau and Kahn (2017)), access to credit may also not be equal across gender given that credit limits are determined, in part, by an individual's ability to pay. Given that credit cards are a household's primary source of liquidity, gender disparities in the credit card market may have implications for gender disparities in other dimensions of financial health.

We investigate if there are gender differences in the credit card market by examining differences in bankcard *limits*,[2] a commonly used measure of credit access in the academic literature (e.g., Gross and Souleles (2002), Agarwal et al. (2018), Aydin (2022), and Gross, Notowidigdo, and Wang (2020)). To assess if there are differences in bankcard limits by gender, we use a large, unique data set of successful mortgage applications (mortgage applications that are subsequently originated) from Home Mortgage Disclosure Act (HMDA) data that are merged with credit bureau data from Equifax. With these data, we observe both credit bureau characteristics, such as credit card limits and accounts, and demographic information that is not available on credit reports.[3] An important caveat to our analysis is that, in order to isolate the gender of the consumers in our data set, we restrict our analysis to sole mortgage applicants. While this restriction limits our sample in a specific way, we believe there are a number of advantages to examining sole mortgage applicants. In particular, this is a more homogeneous group of borrowers than the general population, which should limit the amount of bias due to unobservable factors. Despite this limitation, our data set consists of approximately 1 million individuals who originated a mortgage from 2004 to 2014.

Using these merged data, we first document the existence of an unconditional gender difference in total bankcard credit limits, with male borrowers having higher limits than female borrowers on average. This difference persists over time and has increased since the Great Recession. We find that at the start of our study period in January 2006, the average difference between genders for total bankcard credit limit among successful mortgage applicants was approximately $1,700, or 5.7 percent of the male average of $29,654. This difference declined during the recession, but it subsequently increased to over $2,300 (7.8 percent of the male average) by the end of 2017. When examining the gender gap at each decile of the bankcard limit distribution across time, we see that the majority of the gap is driven by large gender differences at the 80th and 90th deciles of the bankcard limit distribution. The gender gap at smaller deciles favors women, though by a much

[1] At the end of 2022, U.S. credit card debt totaled over $986 billion (Federal Reserve Bank of New York, 2022). Approximately 76 percent of Americans own at least one credit card (Green and Stavins, 2018), and 50 percent of consumers revolve a credit card debt balance (Fulford and Schuh, 2023).

[2] A bankcard is a credit card issued by a bank, bankcard company, national credit card company, or credit union.

[3] Because the Equal Credit Opportunity Act (ECOA) forbids creditors from discriminating on the basis of race, gender, marital status, national origin, or other demographic information in the underwriting, pricing, and scoring of credit, this long-standing regulation has disincentivized the joint collection of credit attributes and consumer demographics. For an extensive overview of ECOA, see https://files.consumerfinance.gov/f/201306_cfpb_laws-and-regulations_ecoa-combined-june-2013.pdf.

smaller magnitude. We also document that the gender gap is smallest for younger ages, with similar patterns in the gender gap across the limit distribution by age and year of birth.

Using a simple linear regression approach to control for demographic characteristics, geography, income, and credit score,[4] we find that the unexplained gender difference in bankcard limits is $1,312, with male borrowers having higher limits than female borrowers during our period of analysis. This is approximately 4.5 percent of the male sample mean. To put this number in context, this gap is smaller than the 17.5 percent (1.5pp) gender gap in unlevered housing returns estimated by Goldsmith-Pinkham and Shue (2023) but slightly larger than the 2 percent (0.13pp) gap in contract rate estimated in Fang and Munneke (2020). It is important to note that this estimated difference is for an *equilibrium* outcome (total bankcard limit), which is the result of the accumulation of both credit demand and supply decisions over time. Without clear exogenous variation from either the supply or demand side, we are only able to estimate a correlation between gender and total bankcard limits; we are unable to make any causal claims as to why these differences exist.

We conduct a number of robustness checks and this gap persist after accounting for a number of different factors. While we find that the average gender gap is fairly consistent across geographies, we find that the gender gap shrinks when examining individuals living in counties with high unemployment, and the gap closes almost entirely when restricting the analysis to individuals living in counties where a mass layoff has occurred. In these mass layoff counties, we estimate an average marginal effect of -$278 that is not statistically different from zero. This result suggests that gender differences in employment and income play a role in explaining the gender gap in credit card limits because (1) the decline in the magnitude of the gender gap is consistent with the results in Braxton, Herkenhoff, and Phillips (2024), who estimate that individuals who are laid off in a mass layoff event experience a $1,000 decline in total bankcard credit limit, and (2) that the majority of mass layoffs result in more men being laid off than women. Since more men than women are laid off, and subsequently have lower incomes, we would expect the gender gap in credit limits to close.

We then attempt to identify what factors explain this gender gap in total bankcard limits by decomposing the gender difference using the standard Kitagawa-Oaxaca-Blinder (KOB) decomposition method. This tool, frequently used in analyzing the gender wage gap, allows us to separately identify how observable and unobservable factors contribute to the male-female difference in total bankcard limits.

Our estimates show that the gender gap in total bankcard limits is primarily driven by the *coefficient* effect (the *effect*[5] of observable characteristics), which explains approximately 87 percent of the gender gap, while the *endowment* effect (the values of observable characteristics) explains only 10 percent of the difference between genders. This large magnitude for the coefficient effect implies that the effect of unobservable characteristics and the "returns" on observed characteristics (how

[4]Our credit score measure is the Equifax Risk Score, which is a proprietary credit score similar to other credit scores used in the industry.

[5]It is standard in the labor economics literature to interpret the coefficient effect as the difference in "returns" to different characteristics since individuals make intentional investments to earn higher wages. In our setting, it is not immediately clear that observed characteristics can be interpreted in this way. Thus, we will use "return" and "effect of" interchangeably through the rest of the paper.

the effect of observed characteristics affects the gap, not the difference in levels of the observable characteristics) are *lower* for female borrowers.[6]

That the majority of the gender difference is driven by unobservable characteristics is consistent with the results from our heterogeneity analyses, which implies that current income and employment (neither of which we observe in our data) play significant roles in explaining the gender gap. Although we are unable to make any causal claims as to why these differences exist, we are able to document that the majority of the gender differences in credit limits cannot be explained by observed differences in demographic, socioeconomic, and credit characteristics alone.

Given that the unconditional gender gap differs across time and across the credit limit distribution, we estimate and decompose the gender gap for each year at each decile of the total bankcard limit distribution from 2006 to 2016. Our results show that the magnitude of the male-female limit difference varies across the distribution of our credit limit variables and across time. At the lower deciles, conditional gender differences favor female borrowers at some deciles in the later years of the sample and are small in magnitude ($0 to $400 up to the 30th decile). At the higher deciles, gender differences are in favor of male borrowers and are larger ($2,000 and higher at the 80th percentile), with the gap growing over time. Our decompositions also reveal that factors driving these differences have changed over time and vary across the limit distribution.

Finally, to provide some insights into whether these effects are driven by credit supply or credit demand, we utilize data on direct mail credit card solicitations to examine if there are differences in credit card supply between men and women. Unlike the credit bureau data used in the regression and decomposition analyses, the credit card mail-offer data provide us with a more direct measure of credit supply. Using these data, we observe that women receive slightly fewer credit card mail offers than men, that women receive different kinds of offers than men, and that women receive higher *advertised* limits than men.

In the last section of the paper, we discuss three potential mechanisms that would explain the differences we find: (1) differential treatment in the credit market by gender, (2) differences in socioeconomic characteristics, especially at the time of card origination, or (3) differences in preferences for credit and credit cards, or some combination of the three. Given the established literature on gender differences in socioeconomic factors, such as the gender pay gap, and in preferences for credit and risk, a combination of differences in (2) and (3) are the likely reasons for the gap. Our results from both our regression and decomposition analyses are consistent with these mechanisms, and we note that our results also indicate that different combinations of these mechanisms are likely at play when examining the gender differences at different points in the credit limit distribution. While we cannot rule out differential treatment in the credit market on the basis of gender, this mechanism is unlikely to be a factor in explaining these differences, given that the underwriting of credit cards is now highly automated, thus limiting the scope for bias in the assignment of credit limits for bankcards (Bhutta et al., 2025).

[6] In other words, the large coefficient effect implies that total bankcard limits for women would be *higher* if they had male coefficients.

Although we cannot identify which specific mechanisms contribute to these gaps, our empirical results indicate that the difference in total bankcard limits between men and women is economically small. Relative to the overall sample mean of a total bankcard limit of $29,000, the conditional average gender difference of $1,300 translates to a 4 percent gap; the median difference of $300 is 2 percent. Despite the large gender gap in income in the U.S., and the important role that income plays in credit card underwriting, it does not appear that gender differences in income translates to materially lower total access to the credit card market for our subsample of borrowers. It is important to note, however, that this result for total bankcard limit does not necessarily rule out the possibility of gaps in limits at origination for individual credit card accounts.

This paper makes contributions to a number of important literatures on gender and economics. First, our research is related to the large body of research that has documented gender differences in a number of different economic settings. Much of the research in this area has focused on outcomes in the labor market, most prominently the gender wage gap (see Blau and Kahn, 2017; Goldin, 2014, for a survey of the literature), and the mortgage market (Fishbein and Woodall, 2006; Cheng, Lin, and Liu, 2011; Goodman, Zhu, and Bai, 2016; Fang and Munneke, 2020; Goldsmith-Pinkham and Shue, 2023). Although studies in this literature have also examined gender differences in financial markets (e.g., auto loans (Ayres and Siegelman, 1995; Morton, Zettelmeyer, and Silva-Risso, 2003), small business credit (Cavalluzzo and Cavalluzzo, 1998), and investing (Barber and Odean, 2001)) research on gender disparities in credit card markets has received significantly less attention. Mottola (2013) studies gender differences credit card interest rates and Li (2018) examines credit scores and credit use. We complement this previous research by supplying new empirical evidence of the gender gap in consumer credit markets and documenting how it has changed over time.

Our research also complements the literature on gender differences in financial literacy and confidence. Prior work by Lusardi and Mitchell (2008) and Lusardi, Mitchell, and Curto (2010) document the existence of a pronounced gender gap in financial literacy. Lusardi and Mitchell (2014) summarize the theory and evidence of the economic importance of financial literacy and document the growing body of literature that explains these differences between genders. Fonseca, Mullen, Zamarro, and Zissimopoulos (2012) find that differences in demographic characteristics do not explain the majority of the financial literacy gap between genders. Bucher-Koenen et al. (2017) find a significant financial literacy gap among young women, even though they have greater labor force participation and educational attainment on average than their male counterparts. Survey data have also shown gender differences with respect to confidence or comfort level when accessing the credit card market. Fernandez and Tranfaglia (2020) show that women are significantly less likely than men to be "very or somewhat" likely to think that a credit card application would be approved if they apply for an additional card, and Canilang et al. (2020) find that 60 percent of non-retired, college-educated men are confident managing self-directed retirement accounts compared with 32 percent of women with a bachelor's degree. While our analyses cannot identify if disparities in financial literacy levels between males and females contribute to differences in bankcard limits, we acknowledge that the connection between these differences warrants further attention.

2 Data

2.1 Data Description

To study the differences in credit card limits between males and females, we use a unique panel data set that combines information from three different data sources. The first data source is a merged data set of anonymized information from ICE McDash and data from the Home Mortgage Disclosure Act (HMDA) database. The ICE McDash data set contains monthly mortgage servicing information for the largest residential mortgage servicers in the U.S. from 1992 to present. These data cover approximately two-thirds of the installment-type loans in the residential market, or approximately 151 million loans. The data set contains multiple types of mortgage products and includes borrower, property, and loan characteristics.

The HMDA data contain records on mortgage applications, originations, and purchases by depository institutions and certain for-profit, non-depository institutions from 1990 to the present.[7] Importantly for our paper, this data set contains demographic information on mortgage applicants, including gender, and information on loan characteristics for those loans that are subsequently originated. Certain characteristics of the mortgage application are removed to maintain the anonymity of the applicant. The HMDA data are then matched to the ICE McDash data by the Risk Assessment, Data Analysis, and Research unit of the Federal Reserve Bank of Philadelphia.

This combined data set is then merged with the Equifax Credit Risk Insight Servicing and ICE McDash data (CRISM) database using another matching process by the Federal Reserve Bank of Philadelphia. The CRISM data contain anonymized monthly individual-level credit report information for the mortgage borrowers in the ICE McDash data. Since we do not observe account-level information, only information aggregated to the level of the consumer, we have information on the number of accounts and the aggregate account balances for credit cards, auto loans, and student loans. We also observe a consumer's Equifax Risk Score. The merger of the HMDA, ICE McDash, and CRISM (HIMC) databases produces a combined data set of over 56 million mortgage loans that were originated from 1992 to the present.

Our primary variable of interest is the total bankcard limit on all bankcard accounts. This variable is the sum of all individual bankcard credit limits that an individual has in a given month. Importantly, this variable represents the total accumulation of card limit decisions across the life of active cards and *not* the initial assignment of credit limits when the accounts were opened. From the credit bureau and mortgage servicing data, we utilize variables that contain information on the total number of bankcards that an individual has in a given month, the loan-to-value (LTV) ratio of the individual's mortgage, the individual's age,[8] an estimation of their income, and their credit score. From the HMDA data, we use information on the applicant's gender, race, ethnicity, state of residence, and reported income at the time of application.[9]

[7]See Avery, Brevoort, and Canner (2007) for a more detailed discussion of the HMDA data.

[8]We winsorize age at 25 and 80 to avoid outliers.

[9]HMDA income is the income that lenders report for a mortgage applicant, not necessarily an individual's "true" income. Therefore, HMDA income may understate true income. See Bhutta, Hizmo, and Ringo (2025) for details.

2.2 Sample Construction

We take a 5 percent random sample of loans in the HIMC database that were originated from 1992 to 2014, which produces a data set with approximately 277 million loan-month observations from June 2005 to December 2017. Since we have only six months of data in 2005, we restrict our sample to all full years of data, from January 2006 to December 2017. For each mortgage with a co-applicant, we have CRISM data for all applicants of that mortgage. However, the data do not identify which individual is the applicant and which individual is the co-applicant in the HMDA data. Consequently, we drop any co-signed mortgage in the data because, although we know the gender of the applicant and the co-applicant for each mortgage, we cannot accurately assign the applicant/co-applicant gender variables in the HIMC sample.[10] We also drop any individuals missing gender or year of birth. Furthermore, to avoid double counting individuals, we drop observations on mortgages beyond the first mortgage observed in the data for each consumer.

2.2.1 Panel Data Sample

We restrict the HIMC data set so that we take the 1st and 7th month of each year for each individual, which results in having an observation every six months for each sole mortgage applicant. We do this for two reasons: (1) total bankcard limits are quite stable month-to-month, so the monthly data have little variation and thus we do not lose very much information when making this restriction and (2) we greatly improve computational tractability by reducing the size of the entire data set. The resulting panel data set contains approximately 970,000 individuals and 10.5 million total observations from 2006 to 2017.

2.2.2 Cross-Sectional Sample

In addition to creating the panel data set sample, we also create a repeated cross-section data set of the sole mortgage applicants by taking one observation from each individual 24 months after they originate their mortgage. We focus on a period two years after individuals close on their mortgage since there is evidence some consumers adjust their credit product portfolios around the time of obtaining a mortgage (Fulford and Stavins, 2022). The final cross-sectional subsample consists of 530,122 individuals from 2006 to 2016.

2.3 Sample Selection

Because of the selected nature of our sample, we briefly discuss how individuals from our sample differ from individuals in the general U.S. adult populations in Appendix A. Appendix Table A1 includes demographic statistics for the entire U.S. population (not just those with a credit history, a limiting factor for inclusion in the HIMC data set). Unsurprisingly, sole mortgage applicants differ

[10]While we drop co-signed mortgages, it is important to note that couples can exist in the data in cases where only a single name is recorded on the mortgage. This can happen when the individuals in the household have different credit histories and choose to apply using only the strongest credit history, for example.

from the overall US population in a number of ways: Mortgage applicants have higher incomes and are more likely to be White individuals.

Along with comparing individuals in our sample with the overall U.S. population, in Appendix B.1 we discuss how our sample of individuals compare with individuals in the credit bureau population. Appendix Table A2 provides summary statistics for this comparison. Because sole mortgage applicants are a very specific segment of the entire credit bureau population, it is likely that these individuals are not representative of the credit bureau population. In particular, we expect that the average consumer in our sample would be more creditworthy and would have larger debt balances than an average individual in the overall credit bureau population. We compare summary statistics from our sample and a representative sample of U.S. consumers with a credit report from the FRBNY Consumer Credit Panel/Equifax (CCP) data in Appendix B.[11] Sole mortgage applicants differ from the overall credit bureau population along a number of dimensions: Sole applicants have higher credit scores, hold more bankcards, and have higher bankcard credit limits.[12] While the median birth year is the same in both data sets, the standard deviation in the CCP is larger than in the HIMC data; this is unsurprising as the total credit bureau population contains younger individuals who have not yet applied for a mortgage and older individuals who have no need for a mortgage or have already paid theirs off.

In Appendix B.2, we compare sole mortgage applicants to dual mortgage applicants (i.e., mortgages with co-applicants) and the overall mortgage application population. As we show in Appendix Table A3, dual mortgage applicants have higher credit scores on average and also have higher total bankcard credit limits. Finally, in Appendix B.3 we discuss the issue of selection into being a sole mortgage applicant.

3 Identifying the Gender Credit Gap in Aggregate Data

3.1 Summary Statistics for Sole Mortgage Applicants

To examine the raw differences between males and females in credit card limits, we focus on two different measures of credit limits: the total credit limit on all bankcard accounts and the average credit limit a consumer has on their bankcard accounts. To provide additional context, we produce summary statistics for total bankcard balances and the total number of bankcard accounts, though we do not focus on these variables in the main part of our analysis.[13]

Table 1 provides sample means and quartile values for our cross-sectional sample of successful sole mortgage applicants separately for female and male applicants. Females hold more bankcards on average than males (3.38 to 3.22). They also have lower total bankcard limits compared with

[11] For a detailed description of the CCP, see Lee and van der Klaauw (2010).

[12] The share of successful mortgage applicants who do have a co-applicant (sole applicants) remained stable throughout our period of study and was approximately 38 percent of our sample overall.

[13] It is important to note that one limitation of our data is that we cannot identify different types of credit cards that a consumer holds (general purpose, private label, small business, etc.). Therefore, we are unable to examine if females have more of one type of card in particular compared with males, or if the distribution of card types is similar among both genders.

male borrowers ($28,544 to $30,079) and lower average bankcard limits ($9,227 to $8,359). Also, as we show in Appendix Table A1, our sample consists mainly of White individuals (73 percent), although this percentage is representative of the mortgage-holding population in the U.S.

The results in Table 1 suggest that significant differences exist between male and female borrowers in both credit characteristics and in demographics, though median differences are relatively smaller in terms of economic significance. In absolute terms, mean gender differences tend to be larger than median differences because gender differences tend to be larger in the upper percentiles of their respective distributions. For example, the difference in HMDA incomes at the 75th percentile for men and women is $23,000, which is almost double the difference at the median, while gender differences in total bankcard limit at the 75th percentile is $1,400, which is over three times larger than the median difference. In percentage terms, the gender difference in income at the median is 18.8 percent and increases to 21.7 percent at the 75th percentile, while the difference in bankcard limits is 1.4 percent at the median and 3.4 percent at the 75th percentile.

Looking more closely at the entire income and credit score distributions in Table 1, we note that there are large differences in the income and total bankcard limit distributions by gender, while the credit score distribution for each gender is nearly identical. To better understand these relationships among income, credit score, and total bankcard limit for each gender, we create bins for both credit score and income and plot the average total bankcard limit for each bin for each gender. The relationship between total bankcard limit and credit score is displayed in Figure 1, while the relationship between total bankcard limit and HMDA income is displayed in Figure 2.

As can be seen in Figure 1, there is a non-linear relationship between credit score and total bankcard limit for individuals in our sample. Total limits are actually higher for individuals with very low credit scores ($\leq$500) than for individuals with scores from 500 to 600.[14] However, once scores move out of the deep subprime range, total bankcard limits increase consistently, with average total limits doubling for individuals with scores greater than 800, compared with individuals with scores in the 650-699 range.

We also document that for individuals in our sample, the non-linear relationship between credit score and total bankcard limits differs by gender across different parts of the credit score distribution. For scores less than 600, male borrowers have higher limits than female borrowers in every credit score bin, with a larger separation occurring among consumers with deep subprime scores. In the near-prime to prime score range (600-750), men and women have almost identical total bankcard limits for each credit score category. When scores approach the super prime range (800+), we again observe that men have higher limits relative to women even though they are in the same Risk Score category.

When we look at the relationship between income and total bankcard limits, women have higher total limits than men in the left tail of the income distribution (Figure 2). We observe that, on average, female borrowers have higher total bank limits than male borrowers for incomes of less

[14]The presence of individuals with such low credit scores in our sample is due to bankruptcy and/or foreclosure; 75 percent of individuals with credit scores lower than 500 in our sample have either form of financial distress on their credit report.

than $100,000; for incomes higher than $100,000, male borrowers have higher total limits. This result is consistent with two facts: (1) gender differences in income are greater in the right tail of the wage distribution (i.e., "the glass ceiling" effect (Albrecht, Bjorklund, and Vroman, 2003; Fortin, Bell, and Boehm, 2017)) and (2) income is an important factor in determining credit limits at account origination. These relationships among credit scores, income, and total bankcard limits suggest that any analysis examining the gender gap in bankcard limits would be biased if it did not control for these differences.

3.2 Summary Statistics over Time

Along with documenting the existence of differences in bankcard credit limits between male and female sole mortgage applicants using our cross-section sample, we can use the panel data sample to track these differences over time. Given that our data cover the Great Recession and its recovery period, along with numerous regulatory changes in the form of the Credit Card Accountability Responsibility and Disclosure (CARD) Act and the Dodd-Frank Act, it is possible that these gender differences may have changed over time. To examine if the gender credit gap changed during our study period, we use the panel data sample and plot the mean of our bankcard limit variable for each gender over time in Figure 3. We also plot the time trends by gender over time for number of bankcards and average bankcard limit in Appendix Figure A1, and plot the time trends in the gender difference over time by credit score bin to see if the across-time variation in the gender gap varies by credit score in Appendix Figure A2.

In panel A of Figure 3, we can see that, at the start of our sample in 2006, the difference in total bankcard limits was $1,800, or 6.5 percent of the average male total bankcard limit. However, by the end of 2017, this difference had grown to over $2,300, approximately 7 percent of the male total limit. In all years of our sample, total bankcard limit was higher on average for men than for women. Panel B of Figure 3 shows the gender difference across the bankcard limit distribution for each year in our sample. In the right tail of the limit distribution, male borrowers have significantly higher total limits than female borrowers for all years, with the gap fluctuating between $1,000 and $6,000. However, for the middle and left tail of the limit distribution, we can see that the difference between genders has changed over time, with limits slightly favoring female borrowers. Overall, Figure 3 illustrates two important stylized facts regarding credit card borrowing in our sample: (1) men have higher total bankcard credit limits, on average, over our sample period, with the gap only marginally widening in favor of male borrowers, and (2) the difference in average total bankcard limit masks heterogeneity in how the distribution of limits have changed for men and women over time.[15] It is also important to note that women hold more bankcard accounts on average than men throughout our sample frame, with the difference widening over time in favor of female borrowers.

[15] Given that we may also expect to see differences in these gaps by credit score, we also examine how the gap differs across time by credit score category. We discuss the summary statistics for these gaps in Appendix C.

3.3 Summary Statistics by Age and Year of Birth

Beyond the overall gender wage gap, women and men's earnings also diverge following the birth of their first child. This finding holds among those who were on similar career trajectories before having children (Goldin, Kerr, and Olivetti, 2024). Given this finding, we can use the panel data to explore differences in total credit limits by age and year of birth. While we cannot observe parental status in our data, age ranges can serve as a proxy. In panel A of Figure 4, we can see that the gender gap is largest for the oldest birth years and the gap shrinks as we move to the most recent birth years. In panel B of Figure 4, we show the total bankcard limit distribution by year of birth. This figure shows that the gender difference favors male borrowers for larger limits consistently across all years of birth, while the gap shrinks for smaller limits. Interestingly, the gender gap narrowly favors male borrowers, and sometimes favors female borrowers for the more recent birth years in the smaller deciles. In Figure 5, instead of graphing male and female limits by year of birth, we do so by age. Unsurprisingly, the trends we document for age in Figure 5 are very similar to those in Figure 4: gender differences are largest for older ages, favoring male borrowers, and narrow for younger individuals and at lower total bankcard limits. That we don't see gender differences for the youngest adults may reflect that individuals in this group are less likely to be parents than adults age 30 or older. Finally, we also note that the gender gap favors women at much older ages for the lowest credit limits.

As mentioned previously, ECOA was passed in 1974, which prohibited discrimination on the basis of a number of demographic characteristics, including gender. Given the size of the HIMC sample, in Appendix D, we examine if the gender gap for men and women who were relatively younger or older during ECOA's passage differs. However, because the HIMC sample spans only 12 years, we are severely limited in our ability to analyze the law's effect and to draw any definitive conclusions.

4 Estimating Gender Differences in Bankcard Credit Limits

4.1 Empirical Specification

To better understand the differences between men and women for total bankcard limits, we use our repeated cross-section data set to estimate a series of simple linear regressions of the following form to calculate average differences between genders after controlling for a number of demographic and geographic factors:

$$y_i = \beta_0 + \beta_1 Female_i + \gamma score_i + \theta income_i + \mathbf{\Pi_i X_i} + \epsilon_i. \tag{1}$$

We define the dummy variable $Female_i$ to be equal to one if individual i's gender is female. To account for the nonlinear effect of credit score and income on bankcard limits, we follow Han, Keys, and Li (2018) and include the vector $score_i$, which contains dummy variables for 50-point credit score bins, and the vector $income_i$, which contains dummy variables for income bins.[16] $\mathbf{X_i}$ is a vector of control variables that include age fixed effects, race fixed effects, quarter-of-the-year fixed effects, calendar year fixed effects, state fixed effects, state-by-year fixed effects, the loan-to-value (LTV) ratio of the mortgage at origination for individual i, and the number of bankcard accounts.

Although the relationship between the number of bankcards and total bankcard limit is endogenous, the process through which limits change and future limits are assigned is dependent upon the number of cards an individual has. Therefore, when modeling the differences in total bankcard limit between men and women, it is necessary to control for the number of cards held.[17] To properly account for how limits change with the number of bankcards, we instead include the number of cards as a control variable on the right-hand side of Equation (1).[18]

As we previously documented in Figures 1 and 2, the non-linear relationship between total bankcard limits, credit score, and income differ by gender. In our preferred specification, we account for these non-linear differential effects between male and female borrowers by estimating Equation (1) with two sets of gender interaction terms:

$$y_i = \beta_0 + \beta_1 Female_i + \gamma score_i + \theta income_i + \mathbf{\Gamma} Female_i \times score_i + \mathbf{\Theta} Female_i \times income_i + \mathbf{\Pi_i X_i} + \epsilon_i. \tag{2}$$

The first set of interaction terms are $Female_i \times income_i$, which capture any non-linear differential effects between males and females in how income affects credit limits. The second set of interaction terms are $Female_i \times score_i$, which capture any nonlinear differential effects between males and female in how credit score affects credit limits. We also include the number of bankcard accounts interacted with the female dummy variable to account for any gender differences in how limits change with the number of cards.

4.2 Results

We report results from estimating Equations (1) and (2) for total bankcard limit in Figure 6. Because our preferred specification in Equation (2) includes interaction terms between the gender dummy variable and other covariates, we summarize our regression results by reporting the average marginal effect (AME) for the female dummy variable.[19] AMEs calculated using our cross-sectional data sample are in panel A of Figure 6 and the AMEs using the panel data sample are presented in panel B. In addition to showing AMEs for our baseline and preferred specifications (rows 1 and 2 for each figure), we also show how much of the gender gap is explained by various consumer attributes

[16] We use the reported HMDA income variable to measure an individual's income.

[17] Another potential way to address this concern would be to use the average bankcard limit (total bankcard limit divided by the total number of bankcards) as our left-hand side variable of interest. This is problematic, however, because the increase in the credit limit on each marginal bankcard is decreasing in the number of cards, and using the average limit would not reflect this concave relationship between total limit and total number of bankcards. For example, an individual with four bankcards applying for a fifth card will be offered a different amount of credit than an individual applying for their first card, assuming all other characteristics of the two individuals are equal.

[18] We also examine a specification where we include dummy variables for bins of cards instead of a continuous measure of cards. Results are very similar across specifications.

[19] To be precise, average marginal effects are the difference in predicted outcomes for each gender.

by reporting the AMEs when dropping different covariates from our estimating equation. We also report the full tables of regression output for the results in Appendix E.

The first row of panel A of Figure 6 shows our baseline specification results from Equation (1). We can see that after controlling for race, age, credit score, number of existing bankcard accounts, income, year, and state of residence, female borrowers have, on average, $1,272 less in total limit relative to male borrowers. However, given that the relationship among income, credit score, and total limit differ by gender, this simple difference from our baseline specification may not fully capture the gap. In the second row of panel A, results from our preferred specification show that including the full set of interaction terms does change our estimate of the gender gap. Including interaction terms for the number of bankcards, credit score bins, income bins, and the female dummy variable generates an AME of $1,312.

For rows three to eight of panel A, we adjust the controls in Equation (2) to explore how much of the gap is affected by each attribute. We can clearly see that two variables play a major role in explaining the gender gap: the number bankcard accounts and income. The AME on the gender dummy when we do not control for number of cards is $317. This implies that if we don't control for the number of cards, we would mistakenly conclude that female borrowers have *larger* limits than male borrowers. This result is not surprising, given that female borrowers have more cards than male borrowers on average but have *lower* limits per card than male borrowers. Therefore, within the same number of bankcards, male borrowers have higher limits than female borrowers.

The AME on the gender dummy in the regression specification where we do not control for income is -$3,218, significantly larger than the AME from the full specification. Therefore, when not controlling for income, the gender gap is much larger, over doubling the magnitude from the full specification in row 2 of Figure A4. As was the case with omitting the number of bankcards, this result is unsurprising: men have higher incomes than women in our sample (1) and the gender gap in limits is particularly large in the right tail of the income distribution. Therefore, by controlling for income, we see that within income categories (holding income fixed), the gender gap is smaller.

In panel B of Figure 6, we report the same estimates but using our panel data sample. While the magnitudes of the AMEs differ with all estimates showing larger gender gaps than the results from the cross-sectional sample (e.g., the full model estimate using the panel data sample is $1,838, approximately $500 greater than the cross-sectional sample estimate), the results are very consistent across the two data sets: results are consistent across specifications, except for those omitting income or the number of bankcards.

In Appendix Figure A4, we plot the average marginal effects for the female dummy variable at each income and credit score level while holding the values of the other covariates at their mean values among those with similar credit and income characteristics. In panel A of Figure A4, we see that female borrowers have a lower total bankcard limit than male borrowers at each credit score bin except for the bottom two categories. This result tells us that for an average male and an average female borrower from our sample, the female borrower would have a higher total limit than a male borrower if they were in the lowest two Risk Score categories, and the female borrower would have a lower total limit than the male borrower in all of the subsequent Risk Score bins. For income, we see in panel B that female borrowers have lower total bankcard limits at every income category. Similar to the credit score marginal effects, these income results tell us that, if you had a male and a female borrower with the same average characteristics, the female borrower would have lower total bankcard limits at every income level.

4.3 Robustness Checks

As mentioned in Section 3.1, approximately 19 percent of the individuals in our sample have ever had either a bankruptcy or a foreclosure on their credit report. It is plausible that these individuals are sufficiently different than the borrowers who have never had either form of financial distress. To test if our results are sensitive to the inclusion of these individuals in our cross-sectional sample, we (1) include a dummy variable that is equal to one if an individual ever had a bankruptcy or a foreclosure in our estimating equation, (2) interact the financial distress indicator with the female dummy variable, and (3) omit the individuals with financial distress entirely from the sample.[20] Results are reported in Appendix Figure A5 and in Appendix Table A5. Overall, the AMEs on the female dummy variable after controlling for financial distress are very similar to the AME for our preferred specification.

We also test the robustness of our main results by dropping different sets of fixed effects from our main estimating equation. Specifically, we check if our results change when we (1) exclude the state-by-year fixed effects and (2) exclude all time effects: both the year and state-by-year fixed effects. The estimated AMEs are reported in the final two rows of Appendix Figure A5 and in both cases, the results are very similar to our main result. Interestingly, that our results are robust to leaving out the year fixed effects implies that time is not a driving aspect of the average gender difference. Additionally, we test the robustness of results by excluding the year 2006 from our sample, as it has been shown that the HMDA income variable may be misreported in this year (Avery et al., 2012; Blackburn and Vermilyea, 2012). The AME on the female dummy variable in this specification is very similar to our main estimate. Finally, in tests not reported in the tables, we find that our results are robust to the inclusion of gender-specific time trends, gender by year fixed effects, county fixed effects, and county-by-year fixed effects.

4.4 Heterogeneity Analyses

If credit market conditions or preferences for credit vary by geography, it is possible we could see differences in the gender gap in different areas of the U.S. To address this, we split our sample into the four primary census regions and re-estimate Equation (2) for each region separately. The average marginal effects are presented in Appendix Figure A6. We find that average marginal effects are generally similar in each region, though the gender gap is smallest in the Midwest and

[20] By restricting our sample in this way, we drop approximately 99,000 observations; 57 percent of those individuals dropped are male.

is largest in the Northeast. We also split our sample by the presence of "common law" marital property laws (see Appendix F).

To further examine if geographical factors play a role in explaining the gender gap, we divide our sample using county-level variation in labor market conditions. Labor market conditions could play an important role in the bankcard limit gender gap if gender differences in employment lead to differences in income (i.e., ability to pay). To examine if this is the case, we split our sample using two different employment measures. First, we split our sample by the presence of a mass layoff in a county using the mass layoff definition used in Foote et al. (2019). We do this by using Bureau of Labor Statistics (BLS) data on mass layoffs, which was a monthly data set that identified mass layoff events when more than 50 workers filed an unemployment insurance claim against a single establishment. Unfortunately, the BLS discontinued this data series in 2011, so we are able to examine gender differences only between 2006 and 2011 in these counties. Given that this sample period coincides with the Great Recession and the initial year of the CARD Act, we interpret these results with some caution. We also split our sample by county-level unemployment rate, examining individuals living in counties with very high or very low unemployment rates (counties in either the top or bottom decile of unemployment rate).

Estimates of the AME of the female dummy variable are presented in panel A of Figure 7, along with the average marginal effect we estimated from our preferred specification in the previous section to serve as a baseline. When we examine individuals who do not live in a mass layoff county, we can see that our estimate of the average gender difference is similar to our baseline estimate. However, when looking at individuals living in a mass layoff county, we see that the gender gap shrinks: The average marginal effect is approximately -$280 and is not statistically different than zero. We can also see that the gender gap is smaller in *high* unemployment counties relative to low unemployment counties by about $400, though both estimates indicate that men have higher limits on average compared with women. This evidence together seems to suggest that labor market conditions explain some of the gender gap in total limits.

Our results showing that the gender gap closes in mass layoff counties are consistent with the results from Braxton, Herkenhoff, and Phillips (2024), who show that individuals who lose their jobs in a mass layoff event experience a decline of approximately $1,000 in total bankcard credit limit. However, the authors do not look at this result separately by gender. For the gender gap in limits to close following a mass layoff, we would expect that men should become unemployed at a higher rate than women. To test this, we divide mass layoff counties into two groups: those counties where the percent of men involved in a mass layoff is greater than the percent of women involved and those counties where the percent of women involved in a mass layoff is greater than the percent of men involved. We note that 90 percent of mass layoffs resulted in more men being laid off than women. Estimates of the average marginal effects from these two subsamples are presented in panel B of Figure 7. The results show that in the counties where a higher percent of men are involved in mass layoffs, the gender gap shrinks relative to the baseline difference, while in counties where a higher percent of women are involved in a mass layoff, the gender gap widens.

This is the result we should expect if employment status plays a role in the gender gap.

Overall, these results suggest that income and employment are important determinants of the gender gap bankcard limits. While these results are not causal, they do provide additional contextual evidence on the potential drivers of the gender gap.

5 Decomposing the Gender Difference

While the previous results document the gender differences in total bankcard limit and some sources of heterogeneity, we are also interested if observable factors drive this difference. If the gender credit gap is driven completely by differences in observable borrower characteristics, then the gap might be attributable to gender differences in socioeconomic and/or demographic factors. However, if the gap is not due to level differences in borrowers' characteristics, but due to differences in how the characteristics are weighted or due to differences in unobservable factors, this could be suggestive of a number of explanations, including differential treatment in the market. To assess if differences in either observable or unobservable factors explain the gender gap in limits, we employ the three-fold version of the Kitagawa-Oaxaca-Blinder (KOB) decomposition (Kitagawa, 1955; Blinder 1973; Oaxaca 1973).[21] Using this technique, we divide the gender gap into three parts: the part of the gap that can be explained by gender differences in observable characteristics (the endowment effect), the part of the gap that can be attributed to gender differences in the *effect* of the observable characteristics (the coefficient effect), and an interaction term that accounts for the fact that differences in endowments and coefficients can happen simultaneously (the interaction effect).[22]

5.1 Empirical Decomposition Specification

To analyze and decompose the average difference between genders, we estimate the following reduced form specification for each gender.

$$y_{i\theta} = \beta_{0\theta} + \gamma_\theta score_{i\theta} + \delta_\theta income_{i\theta} + \mathbf{\Pi}_\theta \mathbf{X_{i\theta}} + \epsilon_{i\theta}; \theta \in (A, B), \tag{3}$$

where groups A and B represent male and female borrowers, respectively. Similar to Equations (1) and (2) in Section 4, we include the vectors $score_i$ and $income_i$, which contain dummy variables for 50 point credit score bins and $25,000 income bins, respectively, and the total number of bankcard accounts.[23] The control variable vector $\mathbf{X_{i\theta}}$ contains year fixed effects, race fixed effects, month-of-the-year fixed effects, state-fixed-effects, and year-of-birth fixed effects.[24] Because we estimate Equation (3) separately for gender, we are unable to include the interaction terms that were previously included in Equation (2). After estimating Equation (3) for each gender, we then

[21] See Jann (2008) and Fortin et al. (2011) for details on three-fold variation.

[22] We summarize the method in Appendix Section G.

[23] As before, credit score is the Equifax Risk Score.

[24] We include year-of-birth fixed effects and exclude state-year fixed effects from the main aggregate decomposition for computational efficiency. Our decomposition results are robust to alternate specification where we use age fixed effects instead of year-of-birth fixed effects and including state-by-year fixed effects.

obtain the estimated mean decomposition of the difference between genders by taking the difference of the predicted values from each regression in Equation (3) and then algebraically rearranging the difference as expressed in Equation (5) in Appendix E.

There are two caveats to our decomposition analysis. First, because of data limitations, there are a number of unobserved factors that we cannot account for in Equation (3), such as education and marital status, which could also affect the gender gap in credit. However, our results will be consistently estimated if the dependence between the unobservable and observable elements is the same for both males and females (Fortin et al., 2011). Since our sample includes a relatively narrow group of individuals (i.e., successful mortgage borrowers who are sole applicants), it is plausible that this assumption is met. Second, since Equation (3) also suffers from an endogeneity problem, due to omitted variable bias, our decomposition analysis is constructed from correlation measures, not strictly causal ones. Thus, we do not offer a causal interpretation of our results.

5.2 Decomposition Results

The KOB decomposition results from our cross-section sample of sole mortgage applicants for total bankcard limit are displayed in Table 2. We estimate that men's limits are higher than women's limits by $1,499.09, which is 5 percent of the mean male total bankcard limit.[25] When decomposing this gap, we find a positive endowment effect of $162.83, a positive coefficient effect of $1,312.65, and a positive interaction effect of $23.61.

The endowment effect of $162.83 implies that 10.9 percent of the gender difference in total bankcard limit is due to differences in the values of observed characteristics between male and female borrowers. If female borrowers had the same characteristics as men (i.e., the same covariate values), female total bankcard limits would be $162.83 higher. Results from the detailed decomposition, presented in Appendix Table A9, show that this effect is primarily driven by differences in the level of income between genders, with male borrowers having higher incomes than female borrowers, and differences in the number of bankcards, where women have more bankcards than men.

The estimate of the coefficient effect implies that 87.6 percent of the estimated gap of $1,499.09 is due to the difference in the values of the coefficients on the observed characteristics. This large, positive coefficient effect indicates that male borrowers receive a larger effect, or return, from the same values of observed characteristics than female borrowers.[26] In the KOB framework, this suggests that women's limits would increase by $1,312.65 if we applied the men's coefficients to the women's characteristics. The detailed decomposition results in Appendix Table A9 show that the coefficient effect is driven primarily by differences in returns to (1) the number of bankcards and credit score, with male borrowers having larger effects (higher return) than female borrowers, and (2) income, with women having larger effects. Larger effects for these covariates in the detailed decomposition indicate that these factors play a larger role in explaining the differences in the

[25]This estimate differs from our estimates reported in Table A4 because Equation (3) includes different regressors than Equation (2).

[26]Using the term "return" to explain the coefficient effect is commonplace in labor economics, where workers receive returns on their investments, such as human capital, on their wages.

effects (i.e., returns) between men and women sole applicants.

5.3 Heterogeneity in the Decomposition

While performing this decomposition at the mean of the sample provides us with a meaningful analysis of what drives the gender gap for the average male and female sole mortgage applicants, these decomposition results may not hold at different points in the credit limit distribution. For example, the summary statistics on both total and average bankcard limits in Table 1 indicate that the gender gap increases in magnitude as limits get larger.[27] Also, based on the time trends we observe for total bankcard limits in Figure 3, we know that there are differences in the gender gap over time. Given the differences in the gender gap across these dimensions, it is reasonable to assume that performing the decomposition at different points in the distribution at different points in time would yield substantially different results than those reported in Table 2. To test this, we conduct decomposition analyses across the credit limit distribution for each year in our data using the unconditional quantile regression methodology from Fortin et al. (2011). We discuss the method in more detail in Appendix H.

Figure 8 shows the estimated gender differences for our total bankcard limit variable across time for each decile of the limit variable. At the lower end of the total bankcard credit limit distribution, the differences between genders is relatively small, with the gender gap generally favoring female borrowers with magnitudes varying from \$0 to \$300 up to the 30th percentile. This gender difference in the left tail of the distribution has increased over time, with the gap growing more in favor of female borrowers. For the middle of the distribution, the gender gap at the beginning of our sample in 2006 favors male borrowers and is \$300 to \$900. The gap shrinks starting in 2010, actually favoring female borrowers, with the gap as high as -\$300 at the median of the distribution. The gap favors male borrowers in 2014 and 2015 before becoming negative again in 2016.

Differences between male and female borrowers at the higher deciles favor male borrowers and is larger in magnitude: At the 80th percentile, the gender gap ranges from \$700 to \$3,300, while at the 90th percentile the difference is over \$3,400 for the majority of years in our sample. Unlike the gender differences in the center and left tail of the distribution, the difference at the 90th percentile has remained relatively constant from 2006 to 2016.[28] The results for the coefficient and endowment effects from these distributional decomposition analyses are reported in Appendix H. For the upper 70 percent of the limit distribution, women have increasingly *benefited* from having more favorable characteristics over time (the *endowment* effect has become negative). However, the returns to these characteristics are lower, resulting in the credit gap. Additionally, over the same time period, the gap in the returns to those characteristics (the coefficient effect) for the top half of the distribution has increased, which partially explains why the gender gap in limits has grown

[27] This kind of heterogeneity is also observed in the gender wage gap, where the largest disparity between groups occurs at the right hand tail of the distribution (Blau and Kahn, 2017).

[28] We report the results in Figure 8 as a percentage of the male total bankcard limit in Appendix Figure A7.

over time. In summary, we find that gender differences in total bankcard limits vary across both the bankcard limit distribution and time, and that the factors that explain these differences also vary across time and across the limit distribution.

5.3.1 Decomposition Across the Lifecycle

Based on our summary statistics in Section 3, it is clear that the gender gap differs by age, with the unconditional gap being smallest at younger ages (youngest birth years) and is largest at older ages (oldest birth years). Given the different environments in which these individuals initially acquired, and subsequently obtained, credit, as well as the gender pay gap among parents, it is likely that the factors that explain the gender gap differ across the lifecycle. To explore this source of heterogeneity, we divide our sample into five age groups ($\leq$35, 35-44, 44-54, 55-64, and $\geq$65) and perform the KOB decomposition for each group. Results are summarized in Appendix Figure A11.

The first bar for each age group shows the raw difference between male and female borrowers, while the second through fourth bars represent the endowment, coefficient, and interaction effects from the decomposition respectively. Similar to the statistics we report in panel A of Figure 5, the raw gender gap is increasing in age: for individuals under 35, the gender gap is approximately $1,100 while the gender gap for individuals over 65 is over $4,000. Turning to the decomposition results, there are no clear patterns across the different age groups. For the youngest group, the coefficient effect drives the majority of the difference between male and female borrowers, explaining about 80% of the gap. However, for all the other ages, the endowment effect plays a larger role ranging from 35% to 60% of the gap. This suggests that for the younger ages, that male borrowers receive a larger return from the same values of observed characteristics than female borrowers, while for older ages, the gap can be explained by differences in observed characteristics.

Overall, these results provide evidence that the coefficient effect is the primary factor in explaining the gender gap in total bankcard limits. Although we cannot draw any causal conclusions regarding the nature of this differential return, as we do not identify if these disparities are derived from demand or supply (nor the relative share between the two), our findings do suggest that the differences in bankcard limits are primarily due to the difference in the *returns* to observed characteristics rather than the levels of these characteristics.

6 Credit Card Supply

Thus far, our analysis has focused on total bankcard credit limits, which is an equilibrium outcome of the amount of credit card debt available to an individual. Because of the limitations we faced in our earlier analyses, it is not possible to identify which portions of the gender differences we estimate for total bankcard limit are due to demand side factors and which are due to supply side factors. To better understand how credit card supply may differ by gender, we follow Firestone (2014) and Han, Keys, and Li (2018) and utilize an anonymized data set of direct mail credit card solicitations from Mintel Comperemedia, Inc. Direct Mail Monitor to test if there are differences in this measure of credit supply. Mintel Comperemedia is a consumer and marketing research firm that collects direct mail credit card offers, among other items, from a set of households every month. Along with information on each piece of mail from the household participants, the data set includes demographic and other household information from a separate survey and is then merged with credit bureau data from TransUnion. The resulting Mintel Comperemedia, Inc. Direct Mail Monitor and TransUnion LLC Match data set (Mintel/TransUnion data) gives us a snapshot of lenders' offers of credit, as opposed to our main HIMC data set, which captures the accumulation of supply and demand decisions of consumer credit over time.

We restrict the Mintel/TransUnion data to mailers that have been sent to consumers from 2009 to 2017 and where we can identify the gender of the survey respondent, which is approximately 79 percent of the entire data set.[29] We provide demographic summary statistics for male and female respondents in the Mintel/TransUnion data in Table 3 and credit card mailer summary statistics in Table 4.

Approximately 44 percent of the individuals in our Mintel/TransUnion data are female and the sample overall heavily is skewed toward White individuals, relative to mortgage holders (see Appendix Table A1). Individuals in our sample have an average VantageScore credit score of 737.[30] As can been seen in Table 4, female survey respondents received 2.09 mailers on average, compared with 2.36 mailers for male respondents during our sample period. We also observe a difference in advertised credit limits[31] by gender: Male respondents receive slightly higher average advertised limit offers than female respondents ($4,969 compared with $4,447), though this difference is not statistically significant; males and females also have the same median offer of $1,500. When we restrict to individuals with a mortgage, however, women receive larger advertised limits. Using the TransUnion credit bureau variables, we also examine some recent measures of credit seeking activity: hard inquiries and the success rate[32] of the inquiries prior to the credit card solicitations. While they occur within 6 months of receiving the credit card mailers, they are not a response to receiving solicitations.[33] Interestingly, we find that although men receive more credit mailers on average than females in our sample, they have slightly fewer inquiries for credit than females do (0.413 versus 0.428). We also observe that females have fewer newly opened bankcard accounts within the previous 12 months, compared with males (0.34 for men compared with 0.31 for women).

Similar to total bankcard limit, it is likely that the relationship between the number of credit card offers and credit score is nonlinear. To see how the number of credit card mailers individuals receive varies by credit score, we calculate the average number of mailers received by consumers in each VantageScore 2.0 score bin for both genders. The results are plotted in Figure 9. We can see

[29] Specifically, we can accurately identify gender in 535,431 out of 679,242 observations in the full data.

[30] Credit score in the Mintel/TransUnion data is the VantageScore 2.0. The VantageScore 2.0 credit risk score model is a credit scoring model used to assess a borrower's financial responsibility. It ranges from 501 to 990. We re-scale the VantageScore 2.0 credit risk score so that its range of possible scores is similar to other commercial credit scores.

[31] Credit limit is defined as the maximum amount of credit available on the card.

[32] We define success rate as the number of bankcard trades opened in previous 6 months divided by the number of inquiries in the past 6 months, excluding auto and mortgage inquiries.

[33] In addition, we are unable to identify if specific inquiries lead to the opening of specific accounts.

that men and women with credit scores below 600 receive similar numbers of offers and receive fewer credit card offers than individuals with higher credit scores. Individuals with credit scores from 650 to 749 receive the most credit offers by mail, with men receiving more mailers than women. Interestingly, individuals in the highest credit score bin receive fewer offers than individuals with credit scores in the 650-799 range.[34]

To better examine these differences between men and women for the number of credit card offers received, we follow Firestone (2014) and estimate a standard Poisson regression model where the dependent variable is the number of mailers received in a month.[35] Our estimating equation takes the following form:

$$Pr(Y_i) = F(\beta_1 Female_i + \mathbf{X_i \Pi})). \tag{4}$$

The vector X_i contains a number of control variables, including race, education, marital status, state of residence, credit score bin, income bin, credit limit utilization, number of inquiries in the past 6 months, a dummy variable equal to one if the individual has ever filed for bankruptcy, and the age of the individual's oldest credit account. Similar to Equation (2), we also include interaction terms between the female dummy and credit score and income bins.

Results from the Poisson regression are reported in Table 5. The coefficient estimate on the $Female$ dummy variable shows that female respondents receive fewer offers than male respondents, and the coefficients on interaction terms for $Female$ and income categories indicate that female borrowers receive fewer offers in every income category. Translating these interaction coefficients into incidence rate ratios, females receive offers at a rate of 0.8-0.9 times the rate of male borrowers at each income bin. That women receive fewer offers than men at higher income levels is consistent with our HIMC results that show that women had lower total bankcard limits than men at higher income categories. Interestingly, we do not observe statistically significant differences between men and women in the offers received within different credit score bins, except for the lowest bin, where women receive more offers than men. This would seem to imply that while female borrowers receive fewer offers than male borrowers overall, these differences do not change as credit score changes. Although these results indicate that women receive fewer offers than men, our results are only correlations and do not suggest what mechanisms may be driving this result.

7 Discussion

The results presented so far in this analysis illustrate that there are gender differences in both total bankcard limits and in the credit supplied to consumers as measured by credit card mail offers. As mentioned previously, the nature of our data and analyses do not allow us to causally identify the specific mechanisms that drive these differences. Despite this limitation, we believe that there are three broad potential explanations for our results and that it is highly likely that some combination

[34]These results are very similar if we restrict our sample to consist of only mortgage holders in the Mintel data.

[35]To better match our main sample, we restrict this analysis to those respondents who also have a mortgage. Using the full sample of all consumers in the Mintel/TransUnion data produces very similar results.

of these mechanisms are at play.

The first possible explanation for our results is that banks and lenders are consciously assigning limits differently based on gender. We view this as both infeasible and highly unlikely, given the intense scrutiny given to banks' lending strategies. For example, satisfying ECOA regulations effectively removes gender from directly entering the underwriting decision and banks generally do not collect information on gender and other protected demographic characteristics to avoid even the appearance of treating individuals of specific characteristics differently. We also note that the current system for applying and underwriting bankcards is highly automated, which further reduces lenders' ability to introduce bias into the process. This is in stark contrast with the experience 50 years ago when loan officers would actually know the person they were lending to. This automation is likely responsible for the narrowing of the gender gap in total limits over time.

That we find gender differences in total limits even after controlling for a wide variety of factors may indicate instead that automation in the credit card market has its own limitations. Recent research has suggested that use of algorithms, machine learning, and artificial intelligence in credit markets can still lead to biased outcomes (Morse and Pence, 2021; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022).[36] This possibility is further strengthened by the fact that we do not observe significant differences in the likelihood of delinquency between men and women in Appendix Table A8. We can see that there are no significant differences in the probability of delinquency between male and female borrowers across the income distribution and the credit score distribution. The possibility of the limitations of technology would also be consistent with the broader interdisciplinary research that has found that the use of these kinds of technologies may lead to biased outcomes in a number of other settings.

A second possible explanation is that there are substantial differences in the socioeconomic factors of average male and average female bankcard applicants at the time of credit card origination and these differences in initial credit limits subsequently do not converge during the account's lifetime. We view this rationale as significantly more probable as women face disparities along a number of dimensions that can potentially affect credit line assignment.[37] For example, it is well documented that, on average, women experience worse labor market outcomes than men do, which in turn leads to a gap in wages.[38] With regard to wealth, it has been shown that single women own 32 cents on the dollar compared with single men (Baker, Martin-West, and Famakinwa, 2018). Since ability to pay is an important determinant of how much limit a credit card lender will offer, disparities in employment and income will likely impact gender differences in total bankcard limits. Even if men and women receive similar *subsequent* bankcard limit increases over time, this may not be enough to make up for the initial disparity in credit line assignment.

[36] As these technologies, and alternate data, are used more in lending decisions, it is possible that variables used in lending decisions may inadvertently serve as a *proxy* for membership in a protected class such as gender. See Morse and Pence (2021) for an overview of these developments.

[37] As shown in Bohren, Hull, and Imas (2025), disparities can arise in an outcome of interest due to cumulative disparities in inputs into the outcome of interest and not necessarily just at the outcome of interest itself.

[38] In 2019, full-time, year-round female workers made 82 cents for every dollar men earned (Hegewisch and Barsi, 2020).

Although we do not have data on employment and income at the time of bankcard origination (which would allow us to more definitively test this mechanism), our regression and decomposition results are consistent with employment and current income likely playing an important role in explaining the gender differences in total bankcard limits. As we show in Figure 7, we observe that the gender gap shrinks in geographic areas experiencing economic distress (as measured by employment). For individuals living in counties with high unemployment rates, we estimate the gender gap is -$750, and for individuals living in counties experiencing mass layoffs (as defined in Foote et al., 2019), the estimate is -$280 and is not statistically different than zero. That the gender gap shrinks in these counties experiencing distress indicates that employment status, along with income, is an important factor in explaining the gender gap in bankcard limits. It is also likely that employment and income have important interaction effects, with employment status mediating the effect of income on limits while also affecting limits directly.

Additionally, our detailed decomposition results in Appendix Table A9 show that differences in the *level* of income (the endowment effect) favor male borrowers and play a large role in explaining the part of the gender difference that is due to levels of observed characteristics. Though we document that the endowment effects contribute less to the gender gap than the coefficient effect, these results suggest that the majority of the endowment effect is almost entirely driven by differences in income. For our regression results, we see that even within the same income bins, female borrowers have lower total limits than male borrowers. This may indicate that income information, along with information on employment status and/or occupation and job tenure, may be processed differently by the same algorithm if this information is a proxy for the future ability to pay. This may be the case since there are documented gender differences in occupational choice and career trajectories, and these differences may lead to income information being treated differently by gender.

The third possible explanation is that there is a fundamental difference in credit card seeking, shopping, and management behavior by gender, and this in turn leads to different accumulation patterns of credit card limits over time. This mechanism is also very plausible as prior research has shown that women and men manage housing credit differently (Goodman, Zhu, and Bai, 2016), which may extend to behavior with credit cards. There is also evidence that women have lower levels of financial literacy and are less confident about their math skills, which makes women more likely to engage in more costly credit card behavior (Mottola, 2013). Additionally, there is evidence that shopping behavior can partially explain the different prices individuals pay for credit (Morse and Pence, 2021). While it is technically possible that men and women have *identical* credit card management behaviors, we view this as also unlikely.

Unfortunately, the HIMC data do not contain information that would allow us to assess credit card preferences or risk preferences. As mentioned previously, total bankcard limit is a measure of accumulated supply and demand decisions over time, which prevents us from being able to disentangle which portion of total limit is due to risk preferences and which portion is due to other factors. We could use information from the mortgage application data to infer some information regarding risk preferences over loan products, but that would implicitly assume that risk preferences for housing are a good proxy for risk preferences for credit cards. While we view this as unlikely given the substantial differences between a mortgage and a credit card, this is a potential area for further study.

8 Conclusion

We present new evidence on the presence of gender differences in bankcard limits in the United States using a unique data set that combines mortgage application information with credit bureau data. After accounting for differences in income, credit score, and other demographic characteristics, we estimate an average marginal effect of -$1,323 for female borrowers, indicating that female sole mortgage applicants, on average, have lower total bankcard limits relative to male sole applicants. Our results show that this gap is primarily driven by a large gender gap in the right tail of the total bankcard limit distribution. At the median and in the left tail of the limit distribution, the gap in limits favors female borrowers, though at smaller magnitudes. Overall, while statistically significant, the gender gap in total bankcard limits is economically small, with the average marginal effect result representing a 4 percent difference relative to the overall sample mean.

Results from a Kitagawa-Oaxaca-Blinder decomposition show that approximately 87 percent of this difference can be explained by differences in the returns to observable characteristics rather than the characteristics themselves. This implies that differences in the *coefficients* of our observed characteristics, not the levels, explain the majority of this gender difference. Our heterogeneity analyses show that, in addition to varying across the limit distribution, the gender differences are not consistent over time. Our analyses show that (1) gender differences have decreased over time for the bottom 6 deciles of the total bankcard limit distribution, favoring female borrowers, and (2) the factors that drive these gender differences have varied over time for a large portion of the credit limit distribution, with the *coefficient* effect typically favoring male borrowers.

Our analysis of the credit card mail offers indicates that women receive fewer offers than men and receive different kinds of offers, though these differences are not large in economic magnitude. Results from a standard Poisson regression show that this gender gap in offers persists after controlling for a number of demographic and credit variables.

Given that the gender gap in bankcard limits varies across the credit limit distribution and favors women at smaller- and medium-sized limits, it is likely that there are multiple mechanisms at play that explain these gaps. That the median gap is economically small suggests that the automation of credit card underwriting, in conjunction with fair lending supervision, has likely played a large role in reducing the potential for deliberate discrimination on the basis of gender. Nevertheless, disparities remain, in part because applicant income is an input to the determination of unsecured credit lines, and disparities in the distribution of income between women and men continue to persist. This makes it likely that socioeconomic characteristics at the time of credit line assignment play an important role in explaining these disparities. To what extent this is the case is an important question to be addressed by future research.

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Table 1: Summary Statistics for Male and Female Borrowers

	Income (1,000s) ($)	Credit Score	Num. of Bankcard Accounts	Total Bankcard Balance ($)	Average Bankcard Limit ($)	Total Bankcard Limit ($)
Cross-Sectional Data Sample						
Total						
Mean	87	723	3.29	8,086	8,854	29,419
Median	63	752	3	3,449	7,650	20,900
25th Percentile	43	680	2	925	4,000	8,800
75th Percentile	96	798	4	9,842	12,100	40,550
Male						
Mean	99	723	3.22	8,340	9,227	30,079
Median	69	752	3	3,491	7,945	21,000
25th Percentile	47	681	2	918	4,100	8,800
75th Percentile	106	798	4	9,973	12,625	41,200
Female						
Mean	72	723	3.38	7,750	8,359	28,544
Median	56	752	3	3,394	7,372	20,700
25th Percentile	39	679	2	933	3,900	8,800
75th Percentile	83	799	4	9,673	11,500	39,800
Panel Data Sample						
Total						
Mean	57	721	3.22	8,819	8,094	28,815
Median	51	747	3	7,567	3,456	20,205
25th Percentile	40	672	2	3,900	929	8,200
75th Percentile	67	796	4	12,114	9,850	39,900
Male						
Mean	58.6	721	3.15	9,226	8,385	29,553
Median	53	748	3	7,900	3,520	20,500
25th Percentile	41	674	2	4,000	924	8,250
75th Percentile	70	795	4	12,667	10,038	40,600
Female						
Mean	54.2	719	3.31	8289	7,715	27,853
Median	50	747	3	7,250	3,374	20,000
25th Percentile	39	670	2	3,750	934	8,124
75th Percentile	64	796	4	11,460	9,607	38,900
Percent Female: 42.97%						
Percent White: 73.81%						

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing (CRISM) data. Credit Score is the Equifax Risk Score. Income in the cross-sectional data sample is the HMDA income, reported at the time of mortgage application. Income in the panel data sample is an income estimate from the CRISM data. Demographic information comes from the HMDA data.

Table 2: Aggregate Kitagawa-Oaxaca-Blinder Decomposition Results

	Total Bankcard Limit
Mean Male Outcome	\$29,979.91
	(55.94)
Mean Female Outcome	\$28,480.82
	(57.83)
Mean Gender Differential	\$1,499.09
	(80.46)
Endowment Effect	\$162.83
	(64.02)
Coefficient Effect	\$1,312.65
	(52.04)
Interaction Effect	\$23.61
	(25.61)
N	530,125

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data. Specification includes year fixed effects, race fixed effects, month-of-the-year fixed effects, state-fixed effects, and age-fixed effects. Standard errors are calculated using the standard Huber/White estimator and reported in parentheses.

Table 3: Demographic and Credit Characteristics of the Mintel/TransUnion Sample

	Full sample			Mortgage holders		
Variable	**Mean**	**Median**	**Std. Dev**	**Mean**	**Median**	**Std. Dev**
Birth Year	1960	1959	16	1961	1961	12
Credit Score	737	763	94.6	767	792	81.4
Num. of Cards	7.48	6	6.01	8.76	7	6.11
Num. of Cards, Bal> \$0	1.93	2	1.84	2.27	2	1.94
Total Card Limit (\$)	36,716	20,500	53,308	49,305	34,000	55,914
	Full sample			**Mortgage holders**		
	Overall	**Males**	**Females**	**Overall**	**Males**	**Females**
Income						
<\$30,000	18.1%	15.4%	20.2%	8.4%	6.5%	10.3%
\$30,000 - \$74,499	37.8%	39.4%	36.5%	36.5%	35.0%	38.2%
\$75,000 - \$149,999	37.4%	38.2%	36.9%	46.9%	49.4%	44.0%
≥\$150,000	6.7%	7.1%	6.4%	8.4%	9.1%	7.5%
Education						
High School or Less	39.8%	39.2%	40.3%	32.7%	33.0%	32.4%
Some College	20.4%	20.5%	20.4%	21.7%	21.6%	21.8%
Bachelor's Degree+	39.8%	40.4%	39.3%	45.6%	45.4%	45.8%
Race						
White	88.2%	88.9%	87.6%	88.4%	89.4%	88.3%
Black	5.1%	4.4%	5.6%	4.5%	3.9%	5.3%
Asian/Pacific Islander	2.9%	2.9%	2.9%	3.0%	3.1%	3.0%
$N = 46,428$						

Notes: Authors' calculations using data from Mintel/TransUnion. Demographic information comes from the Mintel data. The mortgage holders sample includes individuals who had an active mortgage from 2009 to 2017 and received at least one credit card promotional mailer. We drop any observations where we are unable to determine gender for all cases (e.g., members of a multi-person household where we are unable to determine the gender of the individual who received the mailer). Resulting data set includes individuals who are single, married, or living by themselves within multi-person households. All calculations are made with sample weights provided by the vendor. Credit score is a scaled version of VantageScore 2.0.

Table 4: Card Offer Characteristics of the Mintel/TransUnion Sample

	Full sample		**Mortgage holders**	
	Males	**Females**	**Males**	**Females**
Avg. # of Mailers (per consumer)	2.36	2.09	2.52	2.23
Breakdown of Card Type				
Affinity	0.042	0.032	0.039	0.034
Co-Brand	0.191	0.172	0.205	0.197
Credit	0.678	0.671	0.691	0.690
Lifestyle	0.090	0.124	0.065	0.079
Average Credit Limit Advertised ($)	4,969	4,447	5,997	6,217
Limit by Application Type ($)				
Affinity	15,470	12,201	14,883	12,520
Co-Brand	7,669	7,225	9,343	8,339
Credit	8,846	8,598	12,118	12,866
Lifestyle	1,657	1,759	1,818	1,779
Avg. # of Inquiries	0.413	0.428	0.495	0.503
Avg. # of Bankcards Opened†	0.34	0.31	0.37	0.33
Success Rate‡	0.273	0.234	0.246	0.227

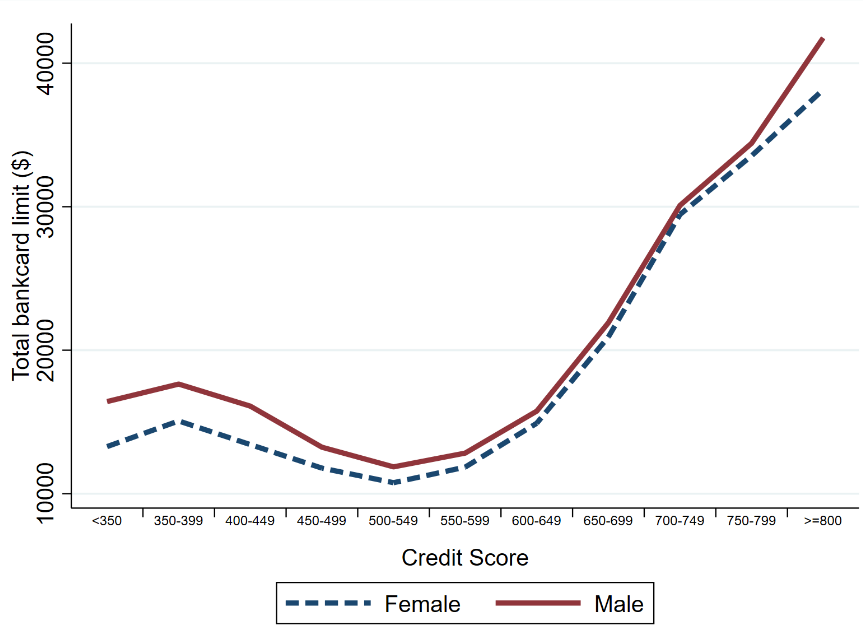
Notes: Authors' calculations using data from Mintel/TransUnion. Demographic information comes from the Mintel data. The mortgage holders sample includes individuals who had an active mortgage from 2009 to 2017 and received at least one credit card promotional mailer. We drop any observations where we are unable to determine gender. Data set includes individuals who are single, married, or living by themselves within multi-person households. All calculations are made with sample weights provided by the vendor. Advertised credit limit is the maximum amount of credit available on the card.
† In the past 12 months.
‡ Calculated as the number of bankcard trades opened in the past 6 months divided number of inquiries in the past 6 months, excluding auto and mortgage inquiries.

Table 5: Poisson Results for Number of Credit Card Offers

	Coefficient	**(Std. Error)**
$Female$	-0.042	(0.059)
(Household) Income Category		
$Female \times I(30-74)$	-0.108***	(0.030)
$Female \times I(75-150)$	-0.185***	(0.030)
$Female \times I(>150)$	-0.186***	(0.038)
Credit Score Category		
$Female \times I(550-599)$	0.168**	(0.066)
$Female \times I(600-649)$	0.081	(0.061)
$Female \times I(650-699)$	0.058	(0.059)
$Female \times I(700-749)$	0.011	(0.057)
$Female \times I(750-799)$	0.022	(0.056)
$Female \times I(800-850)$	0.048	(0.054)
N	46,428	

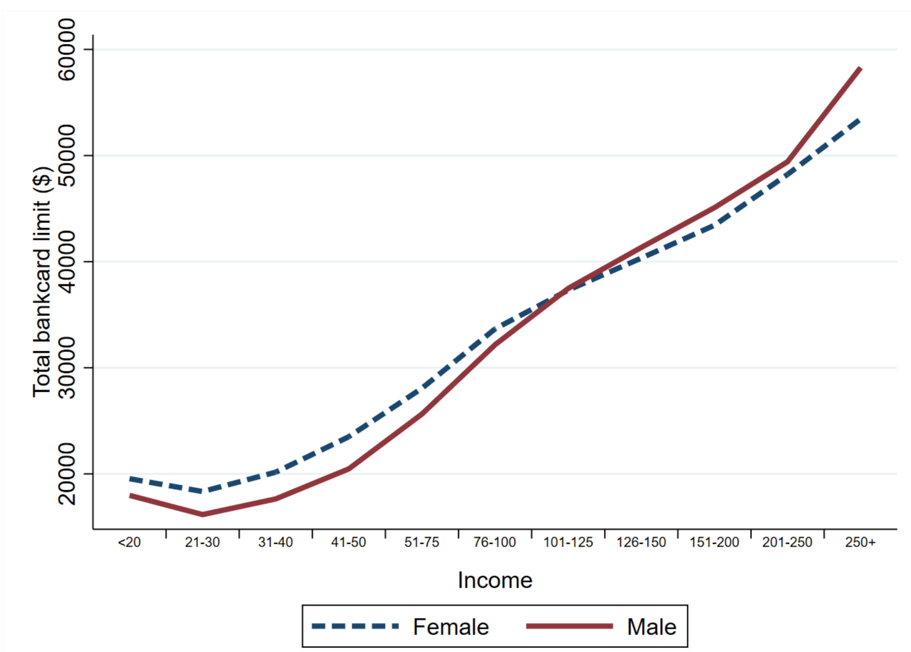
Notes: Authors' calculations using data from Mintel/TransUnion. Demographic information from the Mintel data. Sample includes individuals who had an active mortgage from 2009 to 2017 and received at least one credit card promotional mailer. We drop any observations where we are unable to determine gender. Data set includes individuals who are single, married, or living by themselves within multi-person households. Regression includes state and year fixed effects. All calculations are made with sample weights provided by the vendor. Credit score is a scaled version of VantageScore 2.0. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 1: Relationship Between Credit Score and Total Bankcard Limit by Gender



Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit score is the Equifax Risk Score. Demographic information comes from the HMDA data.

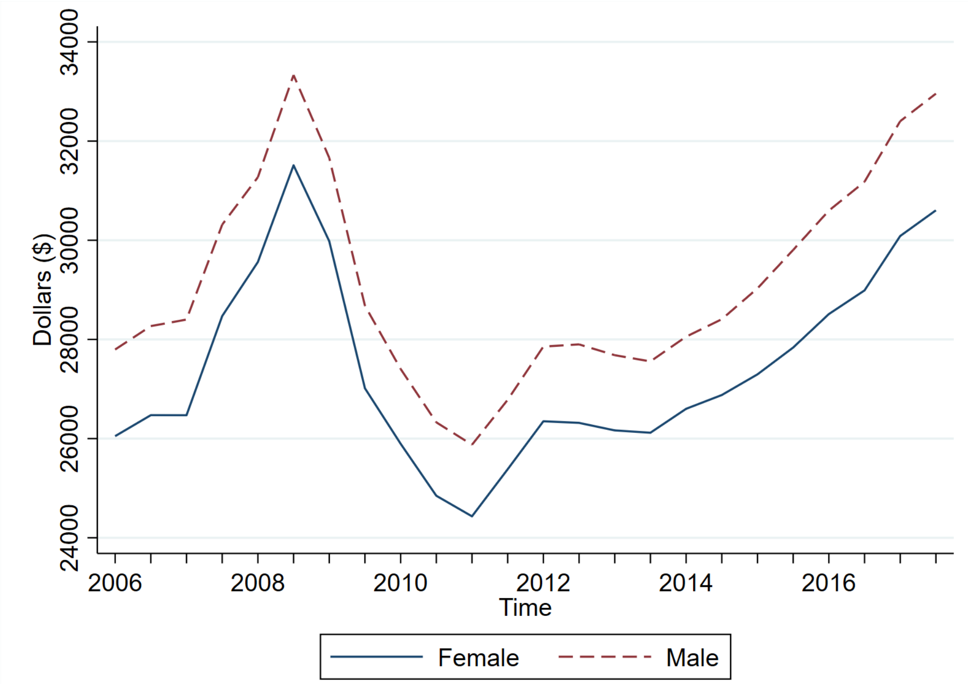
Figure 2: Relationship Between Income and Total Bankcard Limit by Gender



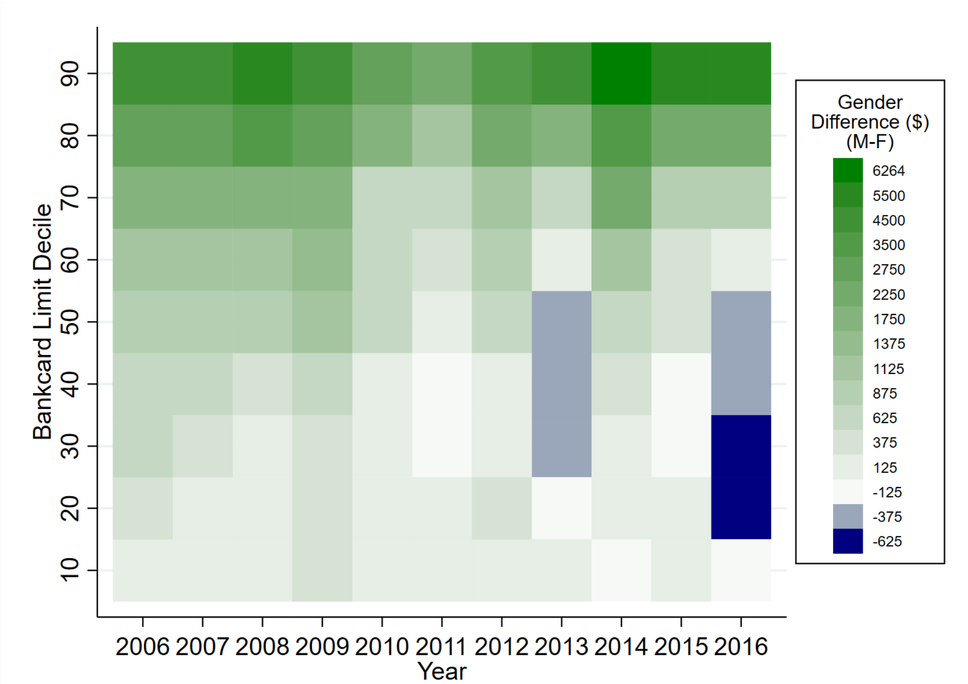
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Income is the HMDA income, reported at the time of mortgage application. Demographic information comes from the HMDA data.

Figure 3: Bankcard Differences over Time by Gender

Panel A. Total Bankcard Credit Limit



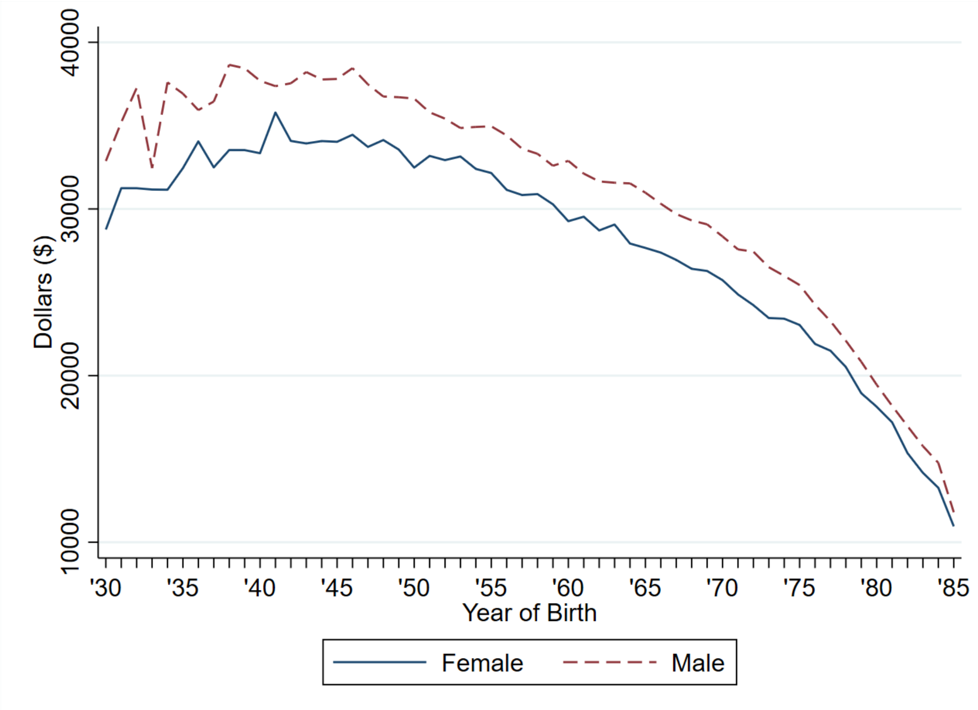
Panel B. Unconditional Differences in Total Bankcard Limit by Year and Limit Decile



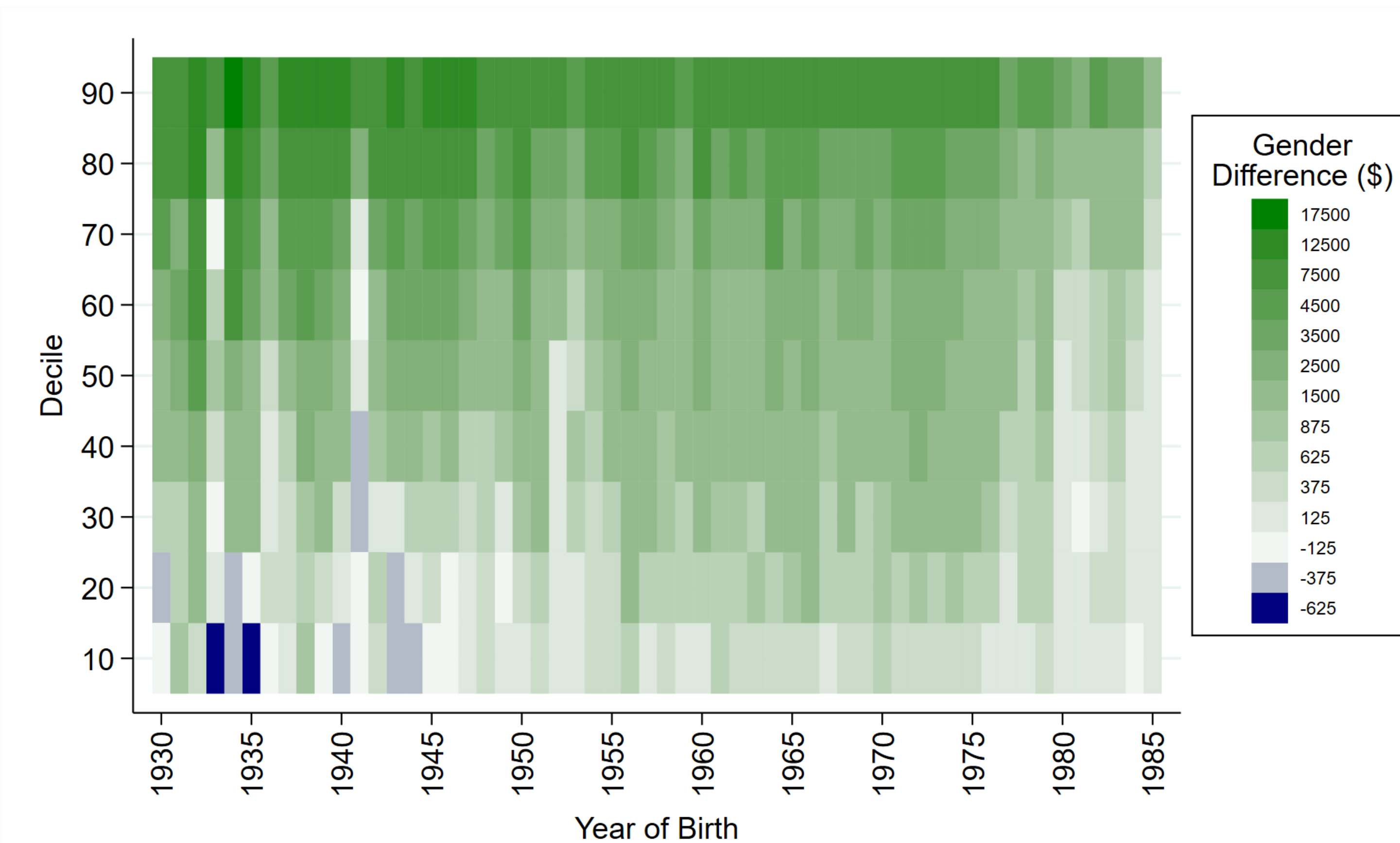
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data.

Figure 4: Total Bankcard Credit Limit by Year of Birth

Panel A. Difference by Birth Year



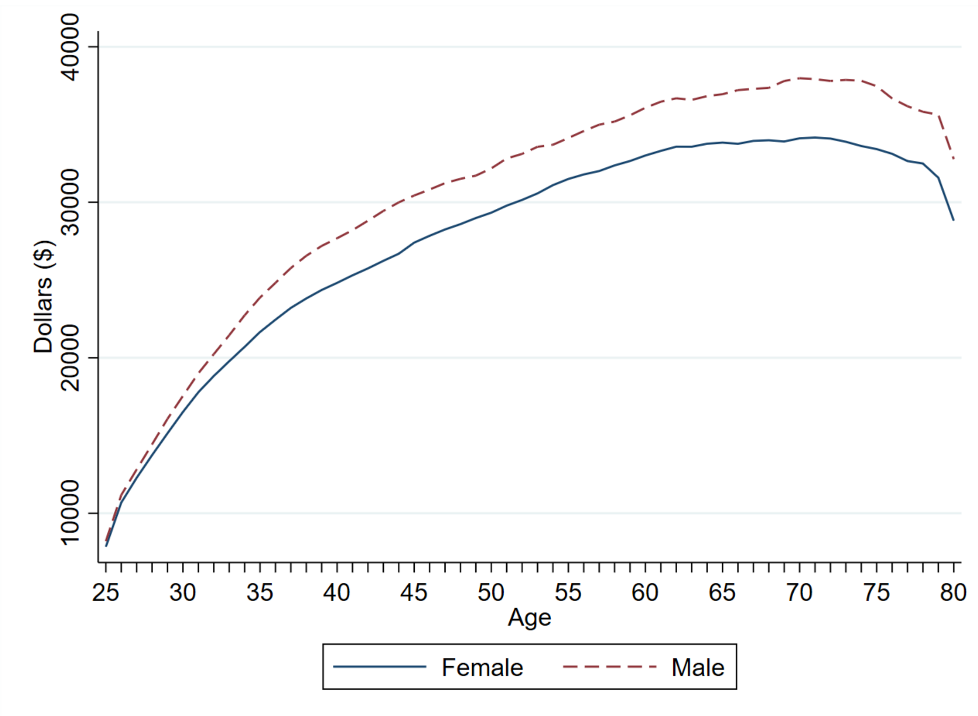
Panel B. Difference by Birth Year, by Limit Decile



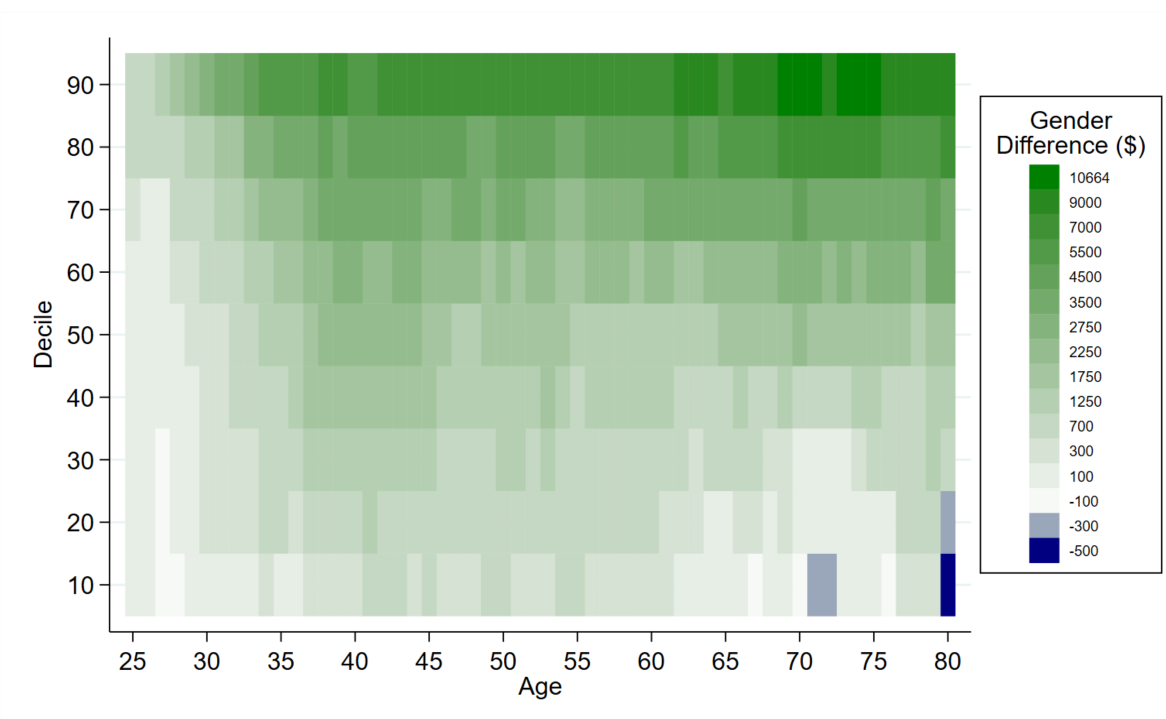
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Birth year is winsorized at 1985 and 1930 to avoid outliers.

Figure 5: Total Bankcard Credit Limit by Age

Panel A. Difference by Age



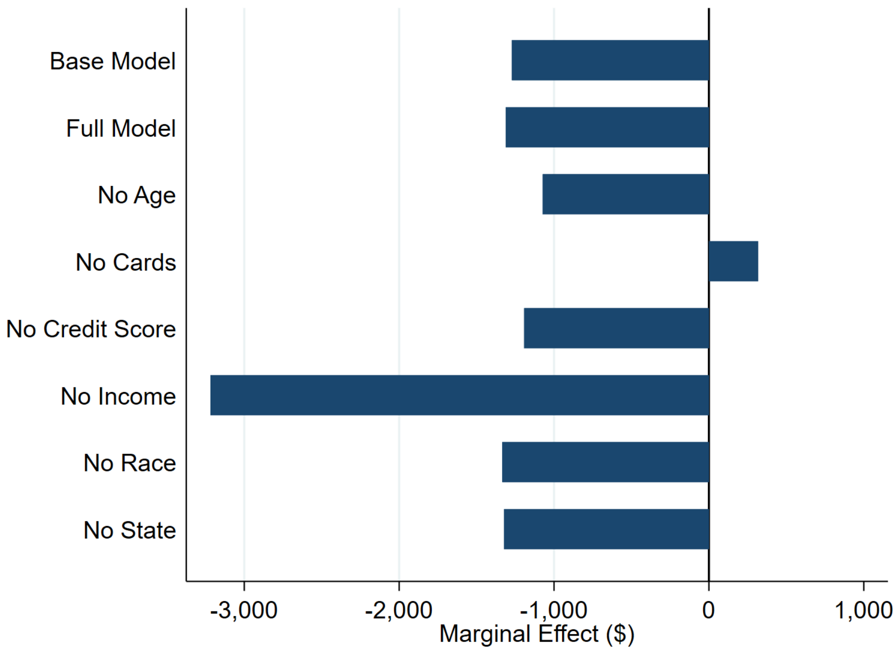
Panel B. Difference by Age, by Limit Decile



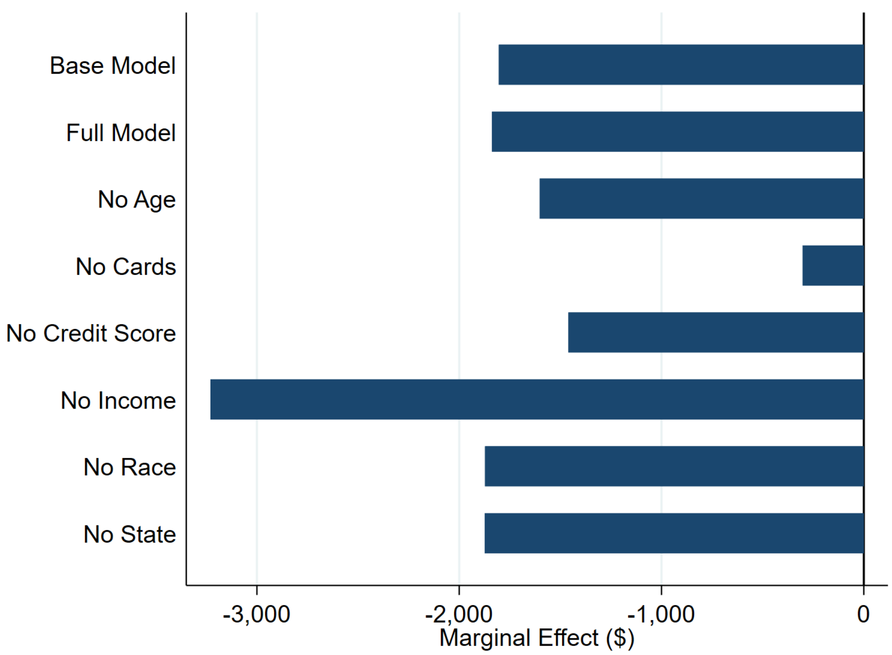
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Age is winsorized at 25 and 80 to avoid outliers.

Figure 6: Average Marginal Effects

Panel A. AMEs Using Cross-Sectional Data



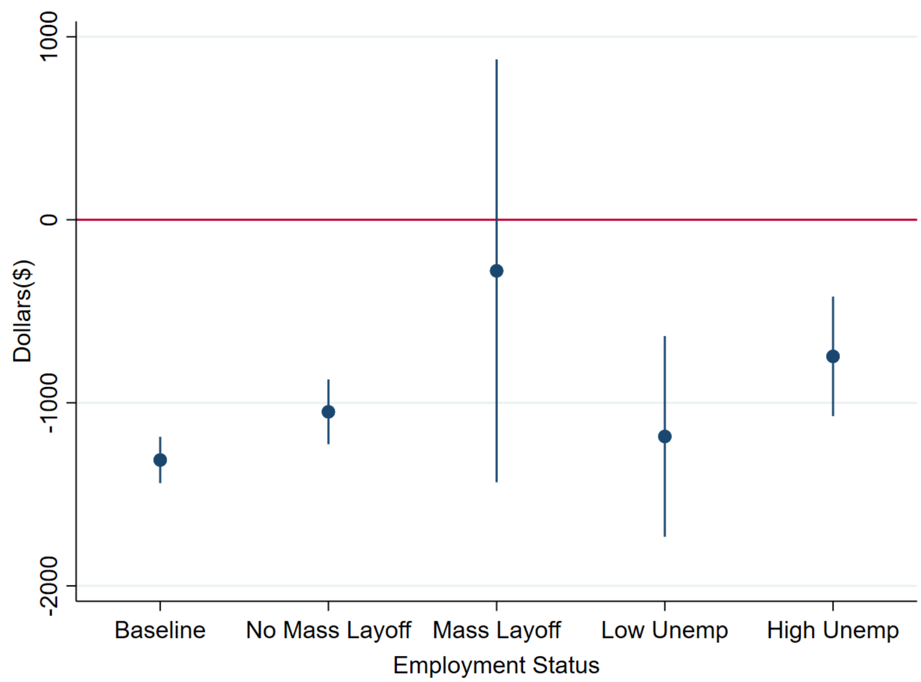
Panel B. AMEs Using Panel Data



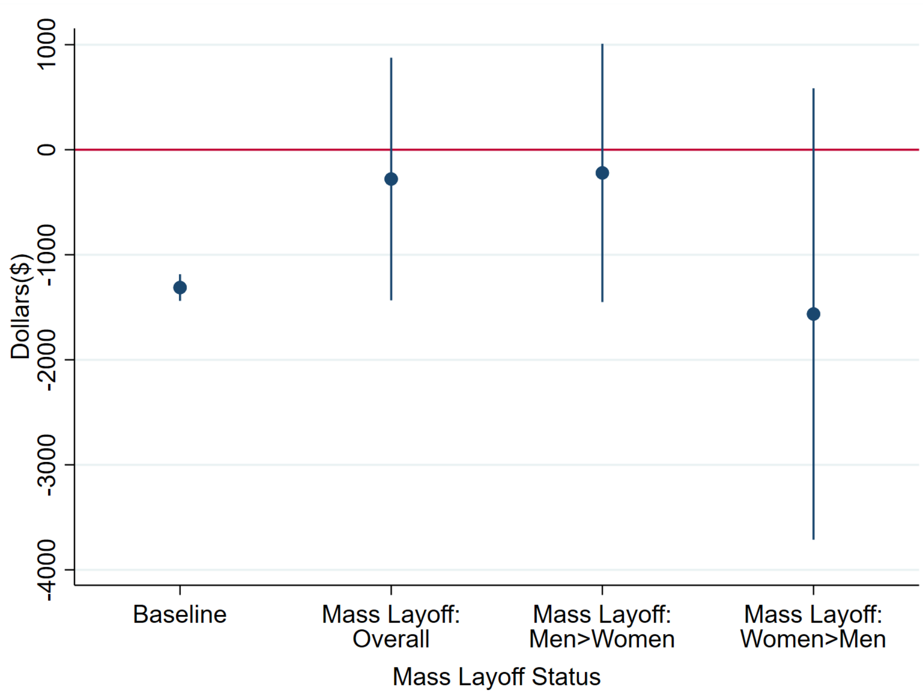
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. All Credit Score is the Equifax Risk Score. Income in the cross-sectional data sample is the HMDA income, reported at the time of mortgage application. Income in the panel data sample is an income estimate from the CRISM data. Demographic information comes from the HMDA data.

Figure 7: Average Marginal Effects by County Employment Status

Panel A: Employment Status

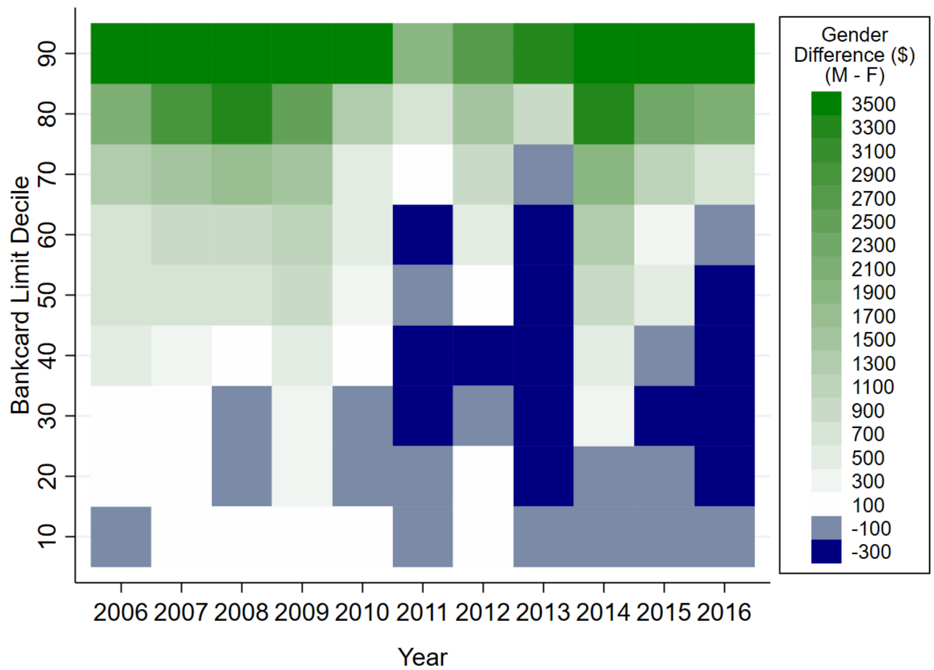


Panel B: Mass Layoff Status



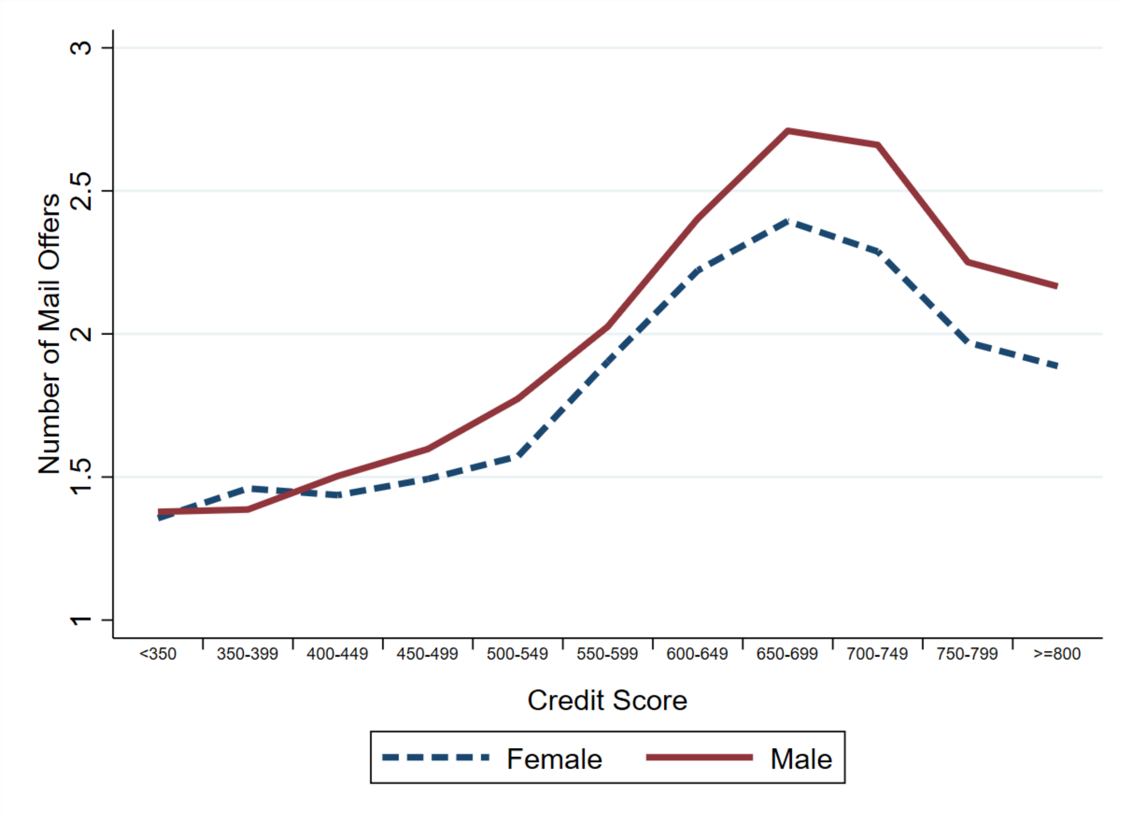
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data. Results for mass layoff analyses use data from 2006 to 2011, while results for the baseline and unemployment rate analyses use data from 2006 to 2016.

Figure 8: Unconditional Quantile Regression Results: Gender Differences ($) Across Time by Limit Decile



Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data. Reported Z-axis values are the midpoint of each bin.

Figure 9: Relationship Between Credit Score and Bankcard Mail Offers Received by Gender



Notes: Authors' calculations using Mintel/TransUnion data with sample weights provided by the vendor. Demographic information comes from the Mintel data. Sample consists of all borrowers and includes years 2009-2017. Credit score is a scaled version of VantageScore 2.0.

ONLINE APPENDIX

A Selected Features of U.S. Adult Population, 2006-2017

We present summary statistics of the U.S. adult population and adults with a mortgage in Table A1. During our study period, adults ages 18 years or older in the U.S. were majority females (51.38 percent) and more than half of U.S. adults were married (55.11). With respect to race and ethnicity, 63 percent of U.S. adults were White, non-Hispanic, 12 percent were Black, non-Hispanic, and 5 percent were Asian; 15 percent were Hispanic. Median income for all adults for this period was \$35,418; median income for female adults was \$17,100, while male median income was \$30,000. The median age among adults was 46, and nearly 40 percent owned their home and had a mortgage (39.4 percent).

However, the race distribution changes when considering the subset of adults with a mortgage. In this group, the vast majority were White, non-Hispanic adults (72.37). Black, non-Hispanic adults and Hispanic adults each represent less than 10 percent of the set of adults with a mortgage (8.5 percent and 9.4 percent, respectively) and during our study time frame, 5 percent of U.S. adults with a mortgage were Asian adults.

B Details on Sample Selection

B.1 Differences Between Mortgage Borrowers and the Credit Bureau Population (Equifax Data)

In Appendix Table A2, we present summary statistics from our HIMC data and from the CCP. We see that individuals with mortgages have greater Risk Scores than the average credit bureau individual (725.86 to 696.89, respectively) and that mortgage holders have more bankcard accounts than the average individual (2.77 to 1.87, respectively). We also observe that more credit has been extended to mortgage holders than non-mortgage consumers: Mortgage owners have larger bankcard credit limits, on average, than the average consumer ($31,069 to $22,404, respectively). Interestingly, mortgage owners apply for credit more than the average credit consumer, averaging 2.25 credit inquiries in the past 12 months, compared with the credit bureau average of 1.88. Overall, the summary statistics in Appendix Table A2 suggest that mortgage owners have lower credit risk and borrow more than the general population. Broadly speaking, this implies that any results we derive from the HIMC sample would have an upward bias relative to the U.S. credit bureau population. While this prevents us from generalizing our result to the entire borrowing population, we argue that the mortgage-holding population is an important subgroup of interest, as approximately 83 million Americans held mortgage debt of $11.9 trillion by the end of 2022.[1]

B.2 Differences Between Sole Mortgage Applicants and Dual Applicants

As mentioned in the previous subsection, in addition to owning a mortgage, individuals in our sample are sole applicant mortgage owners. Sole applicants make up approximately 39 percent of the set of mortgage holders. While sole mortgage applicants are similar to dual applicant mortgage owners on many dimensions, there are also important differences between the two groups. Appendix Table A3 provides a comparison between these two types of applicants.

Individuals in our sole applicant sample are younger, on average, than dual applicant mortgage holders, as the mean birth year of sole applicants is 1964, as compared with 1960 for dual applicants. In terms of credit market traits, sole applicants have greater credit seeking behavior, as illustrated by a greater volume of inquiries compared with dual applicant mortgage individuals (2.50 to 2.07, respectively). Additionally, sole mortgage applicants have lower credit Risk Scores, on average, than dual applicant mortgage holders (707.04 to 738.51, respectively). Not surprisingly, dual applicant mortgage holders also have greater credit limits than individuals who have mortgages without a co-applicant ($33,031 to $28,029, respectively). Overall, we observe differences between sole and dual mortgage applicants, with the summary statistics indicating that our sample of sole applicant mortgage borrowers is less creditworthy and has less total bankcard debt than individual mortgage holders who have a co-applicant.

B.3 Selection in Being a Sole Applicant

Even though we focus on sole applicants, we cannot make any assumptions about marital status for the consumers in our sample because we do not observe marital status in our data.[2] Currently, there is no regulation or law that requires partners to serve as co-applicants, and there are many potential cases where it would be rational for individuals to not include their partner on a mortgage

[1] See Federal Reserve Bank of New York, "Quarterly Report on Household Debt and Credit (Q4:2022)".

[2] While it is very plausible that the majority of dual applicant mortgage holders are not single, the fact that married applicants can apply for mortgages as sole applicants prevents us from determining the marital status of sole applicants.

application. For example, if one partner has a significantly lower credit score than another, a household may decide to omit that person from the mortgage application.

If there is selection on who does and does not include a spouse as a co-applicant on a mortgage application by gender, then our analysis may suffer from an endogeneity problem. For example, if married men are more likely to omit their partner on a mortgage application than women, then marital status would explain some of the variation in bankcard limits, resulting in omitted variable bias. In addition, it is likely that the correlation between sole applicant status and marriage is correlated with other variables such as income, in addition to gender.[3] As we discuss in the next section, differences in bankcard limits vary along a number of other characteristics besides gender. To understand the magnitude and sign of this bias, we would need a data set with information on marital status, gender, and mortgage application status (sole vs. co-applicant), along with demographic and socioeconomic characteristics. Thus, an important caveat to our analysis is that there is an unknown degree of bias relating to this specific type of selection.

[3] For example, it could be the case that male borrowers in high-income households are more likely to omit their partner than low-income households.

C Additional Summary Statistics over Time

In this section, we plot two additional bankcard variables over time in Figure A1. In panel A of Appendix Figure A1, we see that, despite a large reduction in the number of total bankcard accounts for both genders during the Great Recession, female borrowers had more bankcard accounts than male borrowers throughout our period of study, and that this gap has grown over time. There was almost no gap between male and female borrowers at the start of 2006, but this difference increases over our sample period, with females having 0.27 more bankcard accounts than males by the end of 2017.

Panel B shows the gender difference in the average bankcard limit. Throughout the entire sample period, male mortgage holders experienced greater average bankcard credit limits than female mortgage owners.[4] We also note that male borrowers have seen greater growth in average limits than females: Differences in the average bankcard limit were approximately $400 in 2006 and had grown to $1,400 by the end of 2017.

C.1 Summary Statistics over Time by Risk Score Category

It is possible that the aggregated results in Figure 3 and Appendix Figure A1 mask significant heterogeneity in gender differences along a number of dimensions. One of the dimensions where we could expect to see differences is by credit score. Although males and females have similar credit score distributions, as shown in Table 1, it is not clear if this would translate to men and women having similar bankcard limits across time across credit score categories.

To examine if gender differences in bankcard limits differ by credit score, we calculate each gender's average in each credit score bin in each month of our data, and then take the difference between the two. Appendix Figure A2 tracks these gender differences by credit score bin over time. After splitting our sample by credit score bin, new patterns emerge as consumers at opposite ends of the Risk Score distribution display substantial differences. In panel A of Appendix Figure A2, we observe that individuals in the lowest Risk Score bucket have the smallest average difference in the number of bankcard accounts, while individuals in the second-highest Risk Score bucket have the greatest difference. For all Risk Score buckets, the difference grows more negative throughout the study period, indicating that not only do women hold more bankcards than men at each Risk Score level, but that this difference has increased in favor of female borrowers over time.

Panels B and C of Appendix Figure A2 show the gender differences in total and average bankcard credit limits by credit score category. In both of these figures, the largest gender difference between males and females occurs at the highest credit score group (super prime scores of 800 and above), and this difference grows over time. For total bankcard limits, the gender difference among super prime consumers increases from $2,600 in January 2006 to over $4,000 by December 2017. For this group, the difference in average bankcard limits almost doubles over the same period. In terms of economic significance, male borrowers went from having 6.7 percent higher limits than females in 2006 to having 10 percent higher limits in 2017.

By the end of the sample, this gender difference for the highest credit score bin is also significantly larger than the next largest difference. In December 2017, the difference between genders for total bankcard limits at the highest credit score category is over two times larger than the next largest difference ($4,200 to $1,500); for the average bankcard limit, the difference is approximately 1.5 times as large ($2,200 to $1,300). The heterogeneity in trends is evident when looking at gender

[4]Throughout the analysis, we calculate the average bankcard limit as the consumer's total bankcard limit divided by the number of bankcard accounts.

differences for the lower credit score categories, where differences in total bankcard limits have fallen since the Great Recession and differences in average bankcard limit have increased only modestly.

It is also worth noting that the magnitudes of the gender differences do not monotonically increase with the credit score category. In panel B of Appendix Figure A2, the group of individuals with the lowest credit scores exhibit the second-highest gender difference in total bankcard credit limits for a majority of the sample period. For average limits, the second highest gender difference consists of consumers in the second-highest Risk Score bucket. This difference is likely driven by the difference in the average number of bankcard accounts shown in panel A of Figure 3.

D Analyzing the Gender Gap by Age and Year of Birth

We pick two groups of three birth year cohorts, 1938-1940 and 1945-1947, that were adults during the time of ECOA's passage, but one group is relatively older and one group is relatively younger. The relatively younger cohort (ages 27-29 in 1974) would likely see more benefits from ECOA relative to the older cohort of individuals (ages 34-36 in 1974). The restrictions to these years of birth and ages ensures that each birth year cohort has data for each age in our data (68, 69, and 70). It is also important to note that the calendar years in which these two groups turn 68-70 are quite different, with the older cohort turning 68-70 at the beginning of the sample (during the Great Recession), while the younger cohort turns 68-70 at the end of the sample, during the recovery period.

In panel A of Appendix Figure A3, we plot the gender gap in average total bankcard limit for each age for each birth year group using the raw data. It is clear that the gender gap is larger for the older cohort (pre-ECOA) than for the younger group: the magnitude of the gap is approximately \$3,000 less for each age for the younger group (post-ECOA) than for the older cohort. However, as we noted in the paragraph above, the two groups turn ages 68-70 during dramatically different periods of our sample, so the differences in the raw data could be driven by calendar time differences when each group turns ages 68-70. We attempt to control for this by estimating the gender gap separately for each group using a simple linear regression framework, where we regress total bankcard limit on the interaction of the female dummy variable with age dummy variables. The estimating equation takes the following form for each birth year group:

$$y_{ig} = \beta_{0g} + \beta_{1g}Female_{ig} + \phi_{\mathbf{g}}Age_{ig} + \mathbf{\Phi_g}Female_{ig} \times \mathbf{Age_{ig}} + \mathbf{\Pi_{ig}X_{ig}} + \epsilon_{ig}; g \in (Pre, Post), \quad (5)$$

where group *Pre* consists of individuals born 1938-1940 and group *Post* consists of individuals born 1945-1947. We also include calendar time, state, and state by calendar time fixed effects. To calculate the gender gap between male and female borrowers at each age, we estimate the average marginal effect of the female dummy variable. These results are reported in panel B of Appendix Figure A3.

Similar to summary statistics from the raw data, the estimated gender gap in limits for individuals in the *Pre* group is larger than for individuals in the *Post* group, with the gap shrinking from age 68 to 70. Estimated magnitudes of the average marginal effects are also similar to the gaps we calculate in panel A of Appendix Figure A3. Taken together, these results suggest that gender gap is smaller for the younger individuals who were more likely to benefit from ECOA. However, given the limitations of our data and the sample period we study, we are unable to draw any definitive conclusions on how ECOA affected the gender gap in total bankcard limits.

E Detailed OLS Regression Results

In Section 4.2, we summarized our regression estimates by reporting the average marginal effects (AMEs) for the female dummy variable. In this Appendix section, we report the regression estimates in tabular format for a number of covariates of interest and provide some discussion on interpreting these estimates and the overall gender gap.

The tabular results from Equations (1) and (2) for total bankcard limits are presented in Appendix Table A4, with the first two columns reporting results for our baseline regression with no interaction effects and the last two columns reporting results from our preferred specification that contains a full set of interaction terms. From our baseline specification, we see that after controlling for race, age, credit score, income, year, and state of residence, female borrowers on average have \$1,272.13 less in total limit relative to male borrowers.[5] However, as discussed in Section 4.2, this simple difference from our baseline specification does not fully explain the reasons for the gap.

Results from our preferred specification, reported in the last two columns of Appendix Table A4, show that this is indeed the case. When including the full set of interaction terms among the number of bankcards, credit score bins, income bins, and the female dummy variable, we can see that the average gender difference in total limit will vary at different income and credit score levels. To properly calculate the gender difference, we first note that the inclusion of the interaction terms means that the coefficient on the female dummy variable of \$4,471.98 is not the average gender difference in total bankcard limits. Second, the coefficient on the number of bankcard accounts is positively correlated with total bankcard limit: One additional bankcard is associated with an increase of \$9,042 in total bankcard limit. However, the coefficient on the interaction term of the female dummy and the number of bankcards indicates that females have \$817 less in total limit than male borrowers per additional bankcard. For the low-income and low-credit score group, which owns four bankcards on average, this implies that our reference group (low credit score, low income, White, male borrowers) has an average total bankcard limit of \$5,967.18.[6] Compared with the reference group, women in the *lowest income and credit score bins* who hold four bankcards have *higher* average total bankcard limits than men by $\$4,471.98 - (4 \times \$817.50) = \$1,202$.[7]

Using the regression coefficients for the interaction between the gender dummy variable and each credit score and income bin variable in Appendix Table A4, we can see that the difference reverses in the higher income and credit score categories, with male borrowers having higher limits than female borrowers. For example, the gender difference for women with three bankcards at the 600 to 649 credit score bin and the \$101,00–\$125,000 income bin is \$666.01 (relative to men with the same income and credit score), and it increases to \$1,700.48 when moving up to the highest credit score bin. Similarly, women with three bankcards and a credit score in the 600-649 bin in the highest income bin would see a gender difference of $\$4,471.98 - (3 \times \$817.51) - \$2,979.60 - \$4,173.15 = -\$5,133.30$.

We report our tabular regression estimates controlling for financial distress in Appendix Table A5. The first two columns of Appendix Table A5 report results when just including a dummy variable for past financial distress, and the last two columns report results when interacting this financial distress dummy variable with the female dummy variable. The estimated coefficient on the gender dummy is very similar to the results from our preferred specification in Appendix Table A4.

[5] This is equivalent to the marginal effect estimate reported in Figure A4.

[6] Since our estimated constant is -\$30,203.14 and the coefficient on the total number of bankcards is \$9,042.58, this implies that the average limit for the reference group is $-\$30,203.14 + 4 \times \$9,042.58 = \$5,967.18$.

[7] More specifically, the average bankcard limit for females in the lowest income and Risk Score bins with four bankcards is $-\$30,203.14 + (4 \times \$9,042.58) + \$4,471.98 + (4 \times -\$817.50) = \$7,169.16$, which yields $\$7,169.16 - \$5,967.18 = \$1,202$.

The coefficient on the financial distress dummy variable indicates that having a prior bankruptcy or foreclosure on a credit report is associated with having $1,740 less in total bankcard limit.

In the last two columns of Appendix Table A5, we interact the financial distress dummy with the female dummy to see if the effects of prior bankruptcy and foreclosure differ by gender. Our results differ slightly from those in the last columns of Appendix Table A4, but they are generally in-line with our main result. When we include the interaction between the financial distress dummy variable with the female dummy variable, we see that females are impacted less by the presence of prior financial distress by $423. Overall, our main results are robust to controlling for prior financial distress in our estimating equation.

In Appendix Table A6, we report tabular results for regressions where we restrict our sample to individuals who had no previous financial distress. Compared with our main results, many of our estimated coefficients from using this subsample of individuals are larger in magnitude, especially those on the $Female \times Score$ interactions. This is unsurprising, given that the approximately 20 percent of our sample that we drop primarily consists of individuals with low credit scores and lower limits. However, when we calculate gender differences at certain values of our covariates, the differences are similar to those we had previously calculated. For example, in the previous section, the difference between a man and a woman with three bankcards, in the 600-649 credit score bin, and the highest income bin is $5,133.3 (in favor of the male borrower); in the non-financial distress sample, the gender gap for the same group is $\$8,179.7 - (3 \times \$914.21) - \$6,376.70 - \$4,049.29 = \$4,988.92$. While our estimates differ when restricting our sample, the implied gender differences that this empirical setup yields are quantitatively similar to our main results.

In the first two columns of Appendix Table A7, we exclude the state-by-year fixed effects, and in the last two columns, we exclude both the year and state-by-year fixed effects. In both cases, our results are very similar to our main results in Appendix Table A4.

F U.S. Marital Property Laws

There are two systems of marital property law in the United States: common law and community property law. Property and debts under common law regimes can be owned by one partner or both; ownership of property (and debts) can be separated. Community property law in the U.S. is derived from the Spanish legal system. Therefore, the traditional community property law states are: Arizona, California, Idaho, Louisiana, Nevada, New Mexico, Texas, Washington, and Wisconsin.[8] In community property states, spouses are considered to be one economic unit; that is, they have joint ownership over assets and liabilities.

With respect to mortgages in community property law states, if a couple buys a home after they are married, each spouse automatically owns half of it, regardless if there are one or two buyers on the mortgage application. Married home buyers in community property law states will have their spouse's debt added to their debt-to-income ratio calculation, regardless if they are a co-buyer on the mortgage application or not. Likewise, tax liens, judgments, and collections will be taken into account, but generally not the spouse's credit score. To summarize, even though both spouses own the property in community property law states, both individuals do not need to have their names on the mortgage application.

Due to multiple legal systems across our study area, we might expect slightly different rates of sole applicant mortgage takeup by married couples. However, the addition of the state fixed effect alleviates this concern.

[8] Alaska and Tennessee have optional community property law that individuals can opt in to.

G Kitagawa-Oaxaca-Blinder Decomposition Methodology

To assess if observed characteristics are the main driver of the observed disparities in total bankcard limits, we implement a variant of the standard Kitagawa-Oaxaca-Blinder (KOB) decomposition method.[9] This methodology, introduced by Kitagawa (1955) and popularized in economics by Blinder (1973) and Oaxaca (1973), is based on estimating separate equations for each of the two groups of interest to obtain mean predicted values $E(Y_A)$ and $E(Y_B)$. The gap in the variable of interest, $\hat{\Delta}$, is then calculated as difference in the mean of outcome Y between two groups: $\hat{\Delta} = E(Y_A) - E(Y_B)$. This difference is then algebraically decomposed into "explained" and "unexplained" components, which then can be used to demonstrate how much of a difference can or cannot be explained by observable characteristics. Our analysis uses a variation of the method, first introduced in the sociology literature, that decomposes the group difference into three components, commonly referred to as a "threefold decomposition" (Winsborough and Dickinson, 1971; Jones and Kelley, 1984; Jann, 2008; Fortin et al., 2011).

In the threefold decomposition case, if we assume that estimating equations for each group are $Y_A = X_A\beta_A + \epsilon_A$ and $Y_B = X_B\beta_B + \epsilon_B$, the outcome gap $\hat{\Delta}$ can be represented as:

$$\hat{\Delta} = [E(X_A) - E(X_B)]'\beta_B + E(X_B)'(\beta_A - \beta_B) + [E(X_A) - E(X_B)]'(\beta_A - \beta_B). \tag{6}$$

Following Jann (2008), we take each term from Equation (3) and specify the following equation:

$$\hat{\Delta} = E + C + I. \tag{7}$$

The first component of Equation (5), E, corresponds to

$$E = [E(X_A) - E(X_B)]'\beta_B.$$

This is often called the "endowment effect," and it represents the portion of the gap that is generated by group (gender) differences in the explanatory variables. E measures the expected change in group B's mean outcome if group B had group A's levels of explanatory variables.

The next segment of Equation (5) is

$$C = E(X_B)'(\beta_A - \beta_B),$$

which corresponds to the "coefficient effect." This part of the gap is generated by differences in the two sets of coefficients for both the explanatory variables and the intercepts. C measures how much group B's mean outcome would change if group B experienced the returns to endowments (coefficients) that group A did. By allowing group B to take on group A's endowments and coefficients, this part of the decomposition effectively creates a counterfactual to compare with the original two groups.

Finally, the last component,

$$I = [E(X_A) - E(X_B)]'(\beta_A - \beta_B),$$

represents the "interaction effect." This effect exists because a portion of the differences in explanatory variables and beta coefficients occurs simultaneously. In other words, the interaction effect measures how much the mean outcome for group B would change if group B had the same

[9] Frequently used in labor applications, the Kitagawa-Oaxaca-Blinder decomposition is a multivariate regression analysis technique that estimates counterfactual outcomes of variables of interest.

endowments as group A and if the additional amount of the endowments for group B had the same coefficients as group A.[10]

In our setting, female and male mortgage holders make up the two mutually exclusive groups, A and B, our estimating equations $Y_A = X_A\beta_A + \epsilon_A$ and $Y_B = X_B\beta_B + \epsilon_B$ are credit limit equations for each gender, and $\hat{\Delta}$ is the gender credit gap for total bankcard limits.

[10] For example, in the gender wage gap literature, the interaction effect would be interpreted as the additional wage that women would earn if they worked the same hours as men *and* if those additional hours were paid at the male wage (Jones and Kelley, 1984).

H Heterogeneity in the Decomposition

H.1 Unconditional Quantile Regression Methodology

To perform the decomposition analyses at other points in the credit limit distribution for each year in our data, we follow Fortin et al. (2011) and use the unconditional quantile regression methodology developed by Firpo, Fortin, and Lemieux (2009). We do this by running a series of regressions of the recentered influence function (RIF) on our observed characteristics for each decile in each year for each gender.[11] To decompose the gender differences at different quantiles, we use the same approach as the one outlined in Section 5.1 but now replace the outcome variable with the RIF of the outcome variable and define separate estimating equations for each gender: $RIF(Y_i; Q_\tau)_{tA} = X_A\beta_A + \epsilon_A$ and $RIF(Y_i; Q_\tau)_{tB} = X_B\beta_B + \epsilon_B$. Taking the difference of the fitted values for each gender to create the gender gap $\widehat{\Delta}_{\tau_t}$, we can then write an equivalent KOB decomposition for any unconditional quantile τ in time t. To analyze the magnitudes of gender differences across time for different deciles, we present our results in the form of heat maps for more compact presentation.

H.2 Additional Decomposition Heterogeneity Results

As a complement to Figure 8 in the main text, Appendix Figure A7 shows the gender gap as a percentage of the male average total bankcard limit. This figure shows the economic significance of the gender gap across deciles and across time. In the middle and right tail of the distribution, the size of the gap is frequently 2 percent to 3 percent of the male total bankcard limit and never exceeds 6 percent, indicating that while the gender gap is statistically significant, its magnitude does not reach the levels of the gender wage gap, which are approximately 18 percent for full-time workers (Hegewisch and Barsi, 2020). We discuss results for the endowment effect and the coefficient effect in both dollars and in percentage in terms in the next section.

Appendix Figure A8 displays the endowment effects of our decompositions, which identifies the part of the gender gap due to differences in observable characteristics. In panel A, which shows the magnitude of the endowment effect, we observe significant heterogeneity both across deciles and across time. We first note that for the first five years of our sample, the endowment effect is positive across the entirety of the credit limit distribution, implying that portions of the gender gap were driven by male borrowers having an advantage in the values of their observed characteristics. For smaller limits (at or below the 20th percentile, or approximately $5,500 to $8,000), the endowment effect was between $0 and $400, while at higher limits, it ranged from $1,000 to over $2,000.

Starting in 2010, we see that the endowment effect decreases and by 2011 becomes *negative* for all deciles. A negative endowment effect implies that women have an advantage in the levels of their endowments relative to men.[12] In other words, we would expect the gender gap to be smaller (e.g., less in favor of men or more in favor of women) if female borrowers had the same observed characteristics as male borrowers. This effect is largest in the right tail of the distribution, where the endowment effect ranges from -$1,300 to -$1,700 starting at the 70th percentile. Although the negative endowment effects shrink in magnitude in 2014, they remain negative for most of the distribution. The exception is for the top two deciles, where the endowment effects have favored male borrowers in the final years of our sample.

[11] We refer readers to the Firpo et al. (2009) and Fortin et al. (2011) studies for the technical details of this methodology.

[12] While uncommon, negative values for the parts of the KOB decomposition are possible. We provide a stylized example of a situation graphically in Appendix Figure A10.

Panel B of Appendix Figure A8 shows the endowment effect as a percentage of the average male total bankcard limit. We can see that from 2006 to 2010, the magnitude of the endowment effect in panel A ranges from 0 percent to 6 percent of the average male total bankcard limit, with the endowment effect being relatively larger in economic terms in the left tail of the distribution. When the endowment effect becomes negative in 2011, the size of the endowment effect ranges from -1.5 percent to -4 percent of the male average total limit and is consistently in that range until the end of the sample in 2016.

Appendix Figure A9 documents how the coefficient effect, which explains the part of the gender gap that is due to differences in the returns on observable characteristics of borrowers, differs across deciles and over time. In panel A of Appendix Figure A9, we can see that for almost all years in our sample, the coefficient effect is negative for the deciles below the median of the total limit distribution. This implies that female borrowers would have lower bankcard limits than male borrowers if they had male coefficients. In other words, in this part of the distribution, female borrowers receive higher returns on their observed characteristics than male borrowers. For the deciles above the median of the limit distribution, we can see that the coefficient effect is growing positive over time, going from negative values from the 50th to 70th percentiles in 2006, to positive values by 2009. For the 70th to 90th deciles, the coefficient effect is consistently positive for almost all years in our sample, with large values at the highest decile. This indicates that total bankcard limits for women would be higher if they had male coefficients.

We also see that the coefficient effect for deciles below the median have been relatively stable over time. However, the effect has become less negative starting in 2011. For the deciles above the median, the coefficient effect has become more positive over time; at the 70th percentile of the total bankcard limit distribution, the coefficient effect was between -\$200 and \$0 in 2006 and increases to \$600-\$800 by 2016. At the highest bankcard limits in the 90th decile, the coefficient effect has consistently been over \$3,000 since 2010, indicating that male borrowers receive very high returns on their observed characteristics relative to female borrowers. In panel B of Appendix Figure A9, we present the coefficient effect as a percentage of the male total bankcard limit. When compared with the endowment effect, the size of the coefficient effect is larger. For example, in the latter years of our sample, the coefficient effect at the 80th percentile ranges from \$1,800 to \$3,200, which translates to 3 percent to 6 percent of the male total bankcard limit.

Overall, in Figure 8, we observe that gender differences in total bankcard limit vary across the bankcard limit distribution and across time. In the left tail of the total limit distribution, the gender gap favors female sole applicants, where differences range from \$0 to \$300. In the right tail of the total limit distribution, the gender gap favors male sole applicants, with differences over \$3,400 at the 90th decile, which represent up to 7.5 percent of the male total bankcard limit at each decile and year. The decomposition analyses in Appendix Figures A9 and A8 reveal that the factors driving the gender gap in total bankcard limits vary over time and by decile of the limit variable. In particular, we note that the large coefficient effect we documented in Table 5 is driven completely by the upper tail of the credit limit distribution. Our results also show that the relatively large changes in both the gender gap and in the endowment effect occur in 2010 and 2011, which was the period immediately after the implementation of the CARD Act, which was a comprehensive reform of the credit card industry.[13]

[13] For a more detailed discussion of the CARD Act, see Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015).

Appendix References

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Table A1: Census Summary Statistics: Overall U.S. Adult Population

Characteristic	Percent
Sex	
Male	48.62
Female	51.38
Race	
White, non-Hispanic	63.22
Black, non-Hispanic	12.23
Asian, non-Hispanic	5.22
Hispanic or Latino	14.54
Marital Status	
Married	51.11
Education	
High school or less	38.89
Some college/associate degree	28.67
Bachelor's degree	18.25
Graduate or professional degree	10.95
Owns Home and Has Mortgage	39.36
Race and Ethnicity Among Adults 18+ with a Mortgage	
Race/Ethnicity	**Percent**
White, non-Hispanic	72.37
Black, non-Hispanic	8.52
Asian, non-Hispanic	4.34
Hispanic or Latino	9.41
Other	5.36
Median Age (in years)	46
Income, Adults 18+	
Mean	$36,418
Median	$23,000
25th Percentile	$8,500
75th Percentile	$46,100

Notes: Authors' calculations using IPUMS USA data (Ruggles et al., 2021) from 2006 to 2017. Statistics are for adults 18 years and older, except education estimates (25 years and older).

Table A2: Summary Statistics: HIMC Sample vs. CCP Sample

Variable	Mean	Median	Std. Dev	Obs.
Birth year: HIMC	1962	1963	13	168,885,478
Birth year: CCP	1961	1963	19	2,434,769
Credit score: HIMC	725.86	754	94.90	167,279,935
Credit score: CCP	696.89	718	106.21	2,176,960
Number of credit cards: HIMC	2.77	2	2.31	167,549,933
Number of credit cards: CCP	1.87	1	2.11	2,194,070
Total credit card limit: HIMC	31,069.39	22,547	30,537.59	147,082,985
Total credit card limit: CCP	22,404.07	13,700	30,822.11	1,509,530
Number of inquiries, past 12 months: HIMC	2.25	2	2.45	138,061,352
Number of inquiries, past 12 months: CCP	1.884	1	2.291	1,492,699

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, Equifax Credit Risk Insight Servicing data, and FRBNY Consumer Credit Panel/Equifax data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data.

Table A3: HIMC Summary Statistics: Sole Applicants vs. Dual Applicants

Variable	**Mean**	**Median**	**Std. Dev**	**Obs.**
Birth year: total	1962	1963	13	168,885,478
Birth year: sole applicants	1964	1965	13	65,915,540
Birth year: co-applicants	1960	1961	13	99,382,295
Credit score: total	725.86	754	94.90	167,279,935
Credit score: sole applicants	707.04	731	100.34	65,301,769
Credit score: co-applicants	738.51	767	88.86	98,421,911
Number of credit cards: total	2.77	2	2.31	167,549,933
Number of credit cards: sole applicants	2.80	2	2.35	65,462,821
Number of credit cards: co-applicants	2.74	2	2.28	98,523,985
Total card limit: total	31,069	22,547	30,537	147,082,985
Total card limit: sole applicants	28,029	19,500	29,298	57,184,245
Total card limit: co-applicants	33,021	24,800	31,054	86,704,287
Inquiries, past 12 months: total	2.25	2	2.45	138,061,352
Inquiries, past 12 months: sole applicants	2.50	2	2.70	56,146,290
Inquiries, past 12 months: co-applicants	2.07	1	2.23	78,872,446

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data.

Table A4: OLS Results for Total Bankcard Limit

	Baseline		**Preferred**	
	Coefficient	**(Std. Error)**	**Coefficient**	**(Std. Error)**
Constant	-27,610.25***	(1,018.88)	-30,203.14***	(1,049.07)
Female	-1,272.14***	(74.40)	4,471.98***	(928.43)
Number of cards	8,684.44***	(136.32)	9,042.58***	(131.56)
Female × *Number of cards*			-817.51***	(37.78)
Credit Score Category				
$Female \times I(350-399)$			-1,205.12	(1,050.35)
$Female \times I(400-449)$			-2,719.95***	(907.81)
$Female \times I(450-499)$			-2,727.47***	(900.08)
$Female \times I(500-549)$			-2,665.04***	(834.10)
$Female \times I(550-599)$			-2,993.77***	(923.74)
$Female \times I(600-649)$			-2,979.60***	(914.80)
$Female \times I(650-699)$			-2,874.40***	(905.34)
$Female \times I(700-749)$			-2,934.04***	(914.77)
$Female \times I(750-799)$			-3,005.27***	(878.09)
$Female \times I(800-850)$			-4,014.08***	(877.88)
Income Categories				
$Female \times I(21-30)$			-354.24	(326.32)
$Female \times I(31-40)$			-34.29	(285.18)
$Female \times I(41-50)$			354.27	(266.26)
$Female \times I(51-75)$			404.32	(286.29)
$Female \times I(76-100)$			777.59**	(347.95)
$Female \times I(101-125)$			294.14	(393.67)
$Female \times I(126-150)$			-542.81	(360.66)
$Female \times I(151-200)$			-466.08	(449.06)
$Female \times I(201-250)$			-839.18	(574.03)
$Female \times I(> 250)$			-4,173.15***	(614.63)
Year FE	Yes		Yes	
State FE	Yes		Yes	
State × Year FE	Yes		Yes	
R^2	0.6299		0.6305	
N	530,122		530,122	

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Standard errors are clustered at the state level. Reference group consists of White males with the lowest credit score (280-349), and the lowest income (less than $20,000). Items omitted from table include uninteracted income and credit score groups. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A5: Robustness Check: Controlling for Prior Financial Distress

	Fin. Dist. Dummy		Fin. Dist. Interaction	
	Point Estimate	(Std. Error)	Point Estimate	(Std. Error)
Constant	-28,972.15***	(1,145.05)	-28,818.27***	(1,126.59)
Female	4,485.47***	(934.87)	4,135.67***	(975.79)
Number of cards	9,036.33***	(132.03)	9,036.22***	(132.00)
Financial distress	-1,740.44***	(124.42)	-1,923.97***	(137.55)
Female × *Number of cards*	-820.90***	(37.37)	-820.09***	(37.72)
Female × *Financial distress*			422.94***	(157.04)
Credit Score Category				
$Female \times I(350-399)$	-1,243.25	(1,052.37)	-1,224.59	(1,053.30)
$Female \times I(400-449)$	-2,748.15***	(913.02)	-2,718.13***	(915.17)
$Female \times I(450-499)$	-2,768.96***	(906.78)	-2,708.67***	(912.26)
$Female \times I(500-549)$	-2,690.23***	(835.34)	-2,592.26***	(844.46)
$Female \times I(550-599)$	-3,012.82***	(930.06)	-2,870.02***	(944.75)
$Female \times I(600-649)$	-2,968.25***	(924.26)	-2,774.22***	(939.98)
$Female \times I(650-699)$	-2,845.06***	(912.89)	-2,603.14***	(935.33)
$Female \times I(700-749)$	-2,912.29***	(922.40)	-2,618.27***	(946.20)
$Female \times I(750-799)$	-2,986.25***	(886.18)	-2,650.92***	(916.90)
$Female \times I(800-850)$	-3,989.88***	(884.09)	-3,634.20***	(925.27)
Income Categories				
$Female \times I(21-30)$	-352.32	(330.63)	-353.87	(330.61)
$Female \times I(31-40)$	-44.09	(288.15)	-48.27	(287.13)
$Female \times I(41-50)$	335.93	(269.90)	329.25	(268.08)
$Female \times I(51-75)$	374.11	(291.24)	362.10	(288.36)
$Female \times I(76-100)$	749.62**	(350.52)	730.15**	(345.50)
$Female \times I(101-125)$	273.00	(398.58)	245.25	(390.93)
$Female \times I(126-150)$	-563.25	(363.53)	-595.23	(357.66)
$Female \times I(151-200)$	-462.80	(454.47)	-501.09	(446.73)
$Female \times I(201-250)$	-848.90	(571.71)	-888.89	(567.50)
$Female \times I(>250)$	-4,168.69***	(613.86)	-4,212.5***	(625.01)
Year FE	Yes		Yes	
State FE	Yes		Yes	
State × Year FE	Yes		Yes	
R^2	0.6314		0.6314	
N	530,122		530,122	

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Specification includes state, year, and state-by-year fixed effects. Standard errors are clustered at the state level. Reference group consists of White males, with the lowest credit score (280-349), and the lowest income (less than $20,000). *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A6: Robustness Check: Restrict Sample to Individuals Without Prior Financial Distress

	Point Estimate	(Std. Error)
Constant	-36,482.03***	(2,477.83)
Female	8,179.7***	(2,753.69)
Number of cards	9,449.06***	(135.70)
Female $\times$ *Number of cards*	-914.21***	(34.74)
Credit Score Category		
$Female \times I(350-399)$	-2,614.25	(2,846.92)
$Female \times I(400-449)$	-5,217.79*	(2,780.23)
$Female \times I(450-499)$	-6,260.57**	(2,598.56)
$Female \times I(500-549)$	-5,956.93**	(2,669.81)
$Female \times I(550-599)$	-6,616.15**	(2,906.46)
$Female \times I(600-649)$	-6,376.70**	(2,7031.67)
$Female \times I(650-699)$	-6,582.52**	(2,804.19)
$Female \times I(700-749)$	-6,514.57**	(2,769.85)
$Female \times I(750-799)$	-6,565.81**	(2,760.35)
$Female \times I(800-850)$	-7,490.78***	(2,723.42)
Income Categories		
$Female \times I(21-30)$	-341.78	(329.09)
$Female \times I(31-40)$	67.41	(316.68)
$Female \times I(41-50)$	525.41	(342.50)
$Female \times I(51-75)$	479.21	(337.57)
$Female \times I(76-100)$	777.41*	(411.66)
$Female \times I(101-125)$	205.61	(427.32)
$Female \times I(126-150)$	-499.69	(497.03)
$Female \times I(151-200)$	-370.91	(538.33)
$Female \times I(201-250)$	-508.17	(758.02)
$Female \times I(> 250)$	-4,049.29***	(666.04)
Year FE	Yes	
State FE	Yes	
State $\times$ Year FE	Yes	
R^2	0.6424	
N	431,413	

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Specification includes state, year, and state-by-year fixed effects. Standard errors are clustered at the state level. Reference group consists of White males, with the lowest credit score (280-349), and the lowest income (less than $20,000). *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A7: Robustness Checks: Exclude Fixed Effects

	(No State × Year FEs)		(No Time FEs)	
	Coefficient	**(Std. Error)**	**Coefficient**	**(Std. Error)**
Constant	-30,256.78***	(1,028.25)	-29,489.44***	(1,149.50)
Female	4,518.63***	(938.31)	4547.90***	(935.80)
Number of cards	9,044.73***	(132.05)	9,072.55***	(129.18)
Female x Number of cards	-818.46***	(38.02)	-830.93***	(39.25)
Credit Score Category				
$Female \times I(350-399)$	-1,229.04	(1,048.59)	-1,227.04	(1,055.14)
$Female \times I(400-449)$	-2,744.54***	(909.99)	-2,730.23***	(906.50)
$Female \times I(450-499)$	-2,766.75***	(905.67)	-2,756.94***	(900.90)
$Female \times I(500-549)$	-2,701.67***	(844.80)	-2,692.56***	(842.07)
$Female \times I(550-599)$	-3,022.59***	(929.40)	-2,986.67***	(924.17)
$Female \times I(600-649)$	-3,026.46***	(921.31)	-3,009.95***	(921.87)
$Female \times I(650-699)$	-2,919.57***	(910.77)	-2,887.81***	(905.86)
$Female \times I(700-749)$	-2,974.21***	(918.41)	-2,932.04***	(917.83)
$Female \times I(750-799)$	-3,056.18***	(882.38)	-3,006.41***	(875.25)
$Female \times I(800-850)$	-4,058.17***	(882.42)	-4,030.36***	(876.31)
Income Categories				
$Female \times I(25-49)$	-370.37	(323.30)	-383.85	(323.39)
$Female \times I(50-74)$	-40.37	(282.62)	-63.58	(285.21)
$Female \times I(75-99)$	358.19	(263.77)	326.57	(262.31)
$Female \times I(100-124)$	398.45	(284.69)	353.6	(287.76)
$Female \times I(125-149)$	783.25**	(344.75)	754.79**	(349.11)
$Female \times I(150-174)$	290.44	(391.44)	289.27	(398.24)
$Female \times I(175-199)$	-567.98	(353.49)	-560.71	(361.66)
$Female \times I(200-224)$	-506.73	(436.58)	-481.37	(437.48)
$Female \times I(225-249)$	-853.98	(567.62)	-806.80	(565.28)
$Female \times I(\geq 250)$	-4,216.94***	(619.46)	-4,162.39***	(627.21)
Year FE	Yes		No	
State FE	Yes		Yes	
State × Year FE	No		No	
R^2	0.6305		0.6298	
N	530,122		530,122	

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Standard errors are clustered at the state level. Reference group consists of White males, with the lowest credit score (280-349), and the lowest income (less than $25,000). *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A8: Probability of Having a Delinquent Bankcard Account

	Point Estimate	**(Std. Error)**
Constant	-0.946***	(0.007)
Female	-0.009	(0.01)
Number of cards	0.006	(0.0002)
Female × *Number of cards*	-0.0004*	(0.0002)
Credit Score Category		
$Female \times I(350-399)$	-0.0011	(0.0107)
$Female \times I(400-449)$	-0.0115	(0.0127)
$Female \times I(450-499)$	-0.008	(0.0136)
$Female \times I(500-549)$	-0.0121	(0.0093)
$Female \times I(550-599)$	-0.0054	(0.0105)
$Female \times I(600-649)$	-0.0164*	(0.0094)
$Female \times I(650-699)$	-0.0152	(0.0096)
$Female \times I(700-749)$	-0.0111	(0.0091)
$Female \times I(750-799)$	-0.01	(0.0092)
$Female \times I(800-850)$	-0.01	(0.0092)
Income Categories		
$Female \times I(21-30)$	-0.0011	(0.0041)
$Female \times I(31-40)$	-0.0014	(0.0038)
$Female \times I(41-50)$	-0.0029	(0.0034)
$Female \times I(51-75)$	-0.0034	(0.0036)
$Female \times I(76-100)$	-0.0039	(0.0033)
$Female \times I(101-125)$	-0.0015	(0.0039)
$Female \times I(126-150)$	0.0004	(0.0041)
$Female \times I(151-200)$	0.0002	(0.004)
$Female \times I(201-250)$	0.0005	(0.0051)
$Female \times I(> 250)$	0.0015	(0.0052)
Year FE	Yes	
State FE	Yes	
State × Year FE	Yes	
R^2	0.4251	
N	582,023	

Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Specification includes state, year, and state-by-year fixed effects. Standard errors are clustered at the state level. Reference group consists of White males, with the lowest credit score (280-349), and the lowest income (less than $20,000). *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

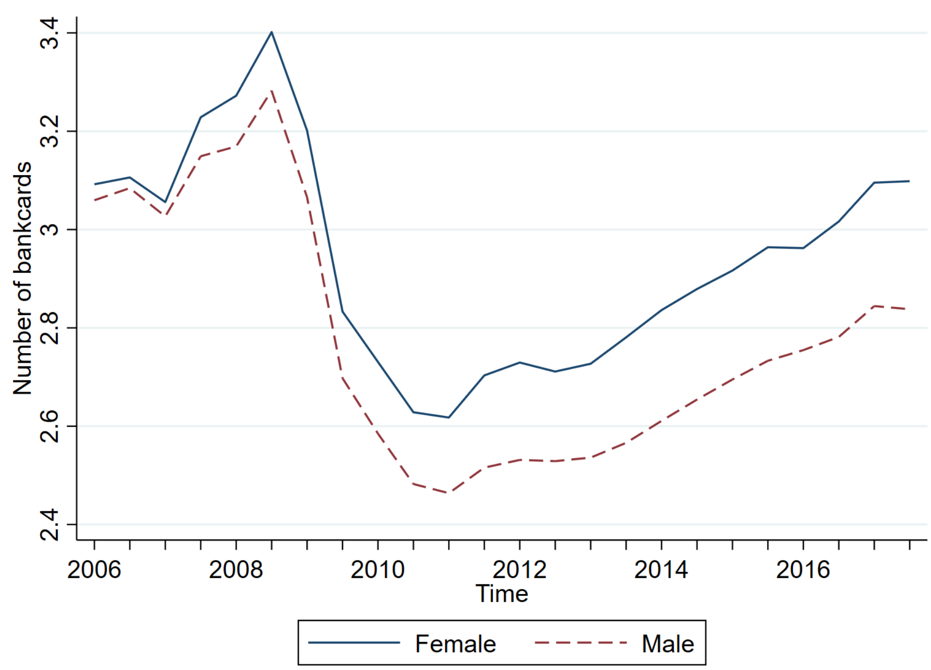
Table A9: Detailed Aggregate KOB Decomposition

	Detailed Decomposition		
	Endowment Effects	**Coefficient Effects**	**Interaction Effects**
Number of cards	-1,334.44***	2,774.38***	-133.44***
	(51.55)	(75.74)	(6.31)
Income	1,788.19***	-598.69***	168.79***
	(20.46)	(54.64)	(20.22)
Risk Score	26.19	425.01***	-6.835***
	(21.90)	(107.07)	(1.86)
Race	13.52**	-55.69	14.77
	(6.57)	(185.25)	(9.06)
Age	-266.15***	-104.271	-33.57***
	(9.14)	(40.71)	(11.24)
Calendar year	5.112***	-40.37***	-0.494
	(3.08)	(11.09)	(2.02)
State	-7.902**	-104.45	10.03**
	(3.61)	(73.17)	(4.45)
N	530,125		

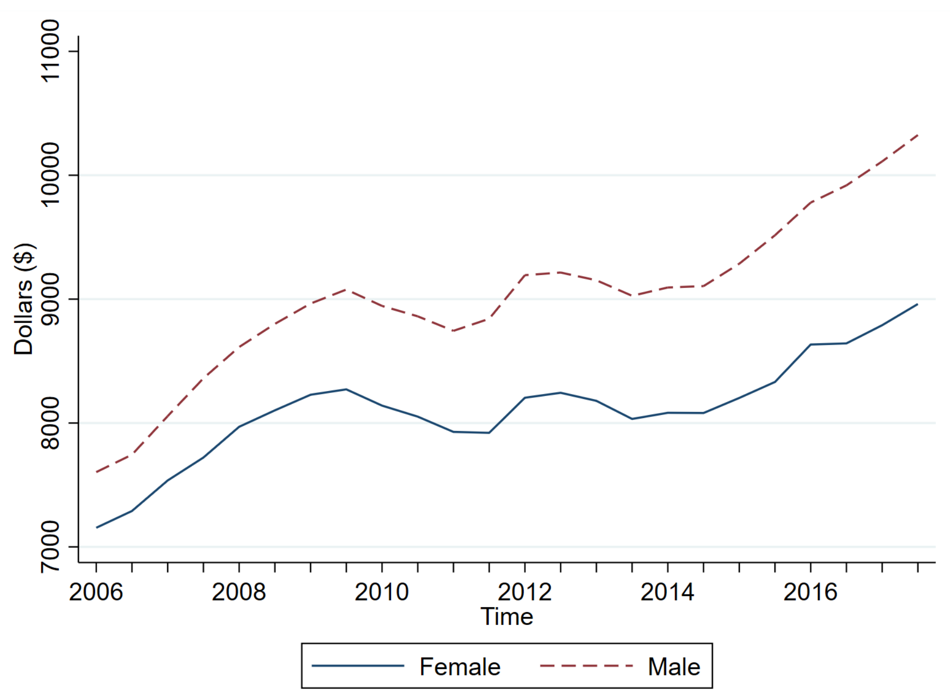
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Risk Score is the Equifax Risk Score. Demographic information comes from the HMDA data. Results for the detailed decomposition results for categorical variables are based on "normalized" effects so our results do not rely upon our choice for the omitted category. For more information, see Jann (2008). We report the sum of coefficients for each variable category for tractability. For example, *Income* is the sum of all coefficients for each income bin in the regression. Specification includes year fixed effects, race fixed effects, month-of-the-year fixed effects, state-fixed effects, and age. Standard errors are calculated using the standard Huber/White estimator and reported in parentheses. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A1: Bankcard Differences over Time by Gender

Panel A. Number of Bankcard Accounts



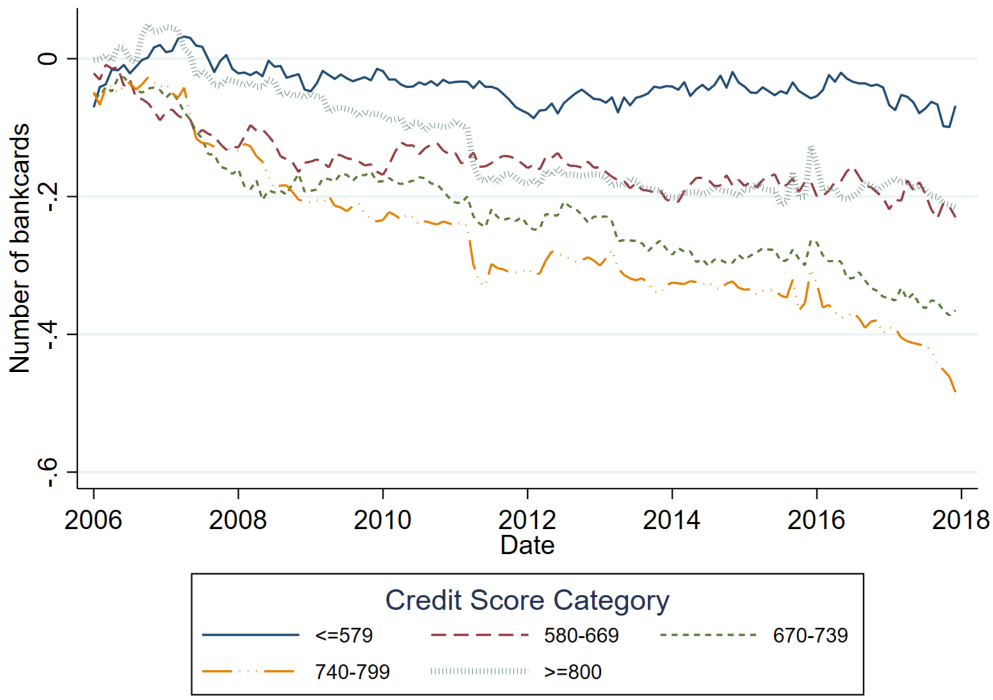
Panel B. Average Bankcard Credit Limit



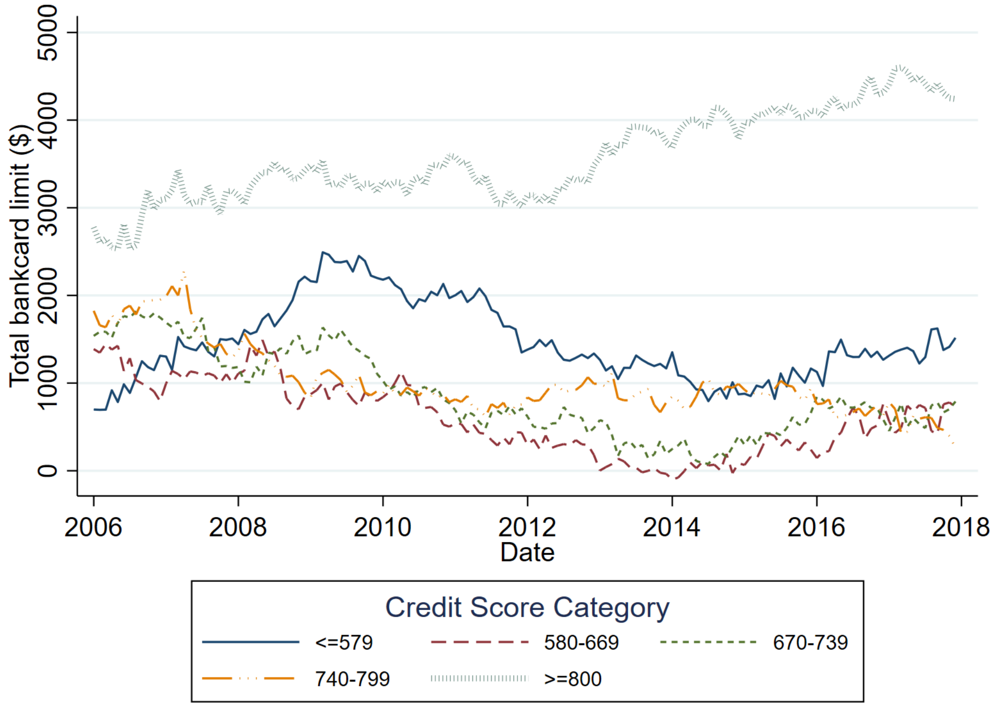
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data.

Figure A2: Bankcard Differences by Credit Score Category

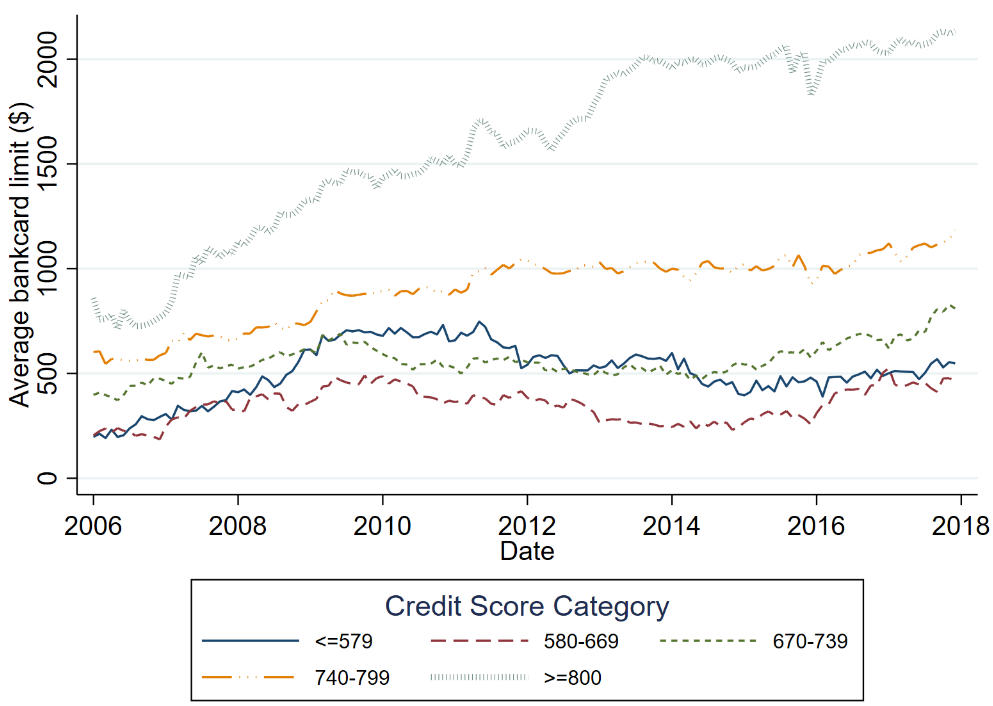
Panel A. (Male-Female) Difference in the Number of Bankcard Accounts



Panel B. (Male-Female) Difference in Total Bankcard Credit Limit



Panel C. (Male-Female) Difference in Average Bankcard Credit Limit

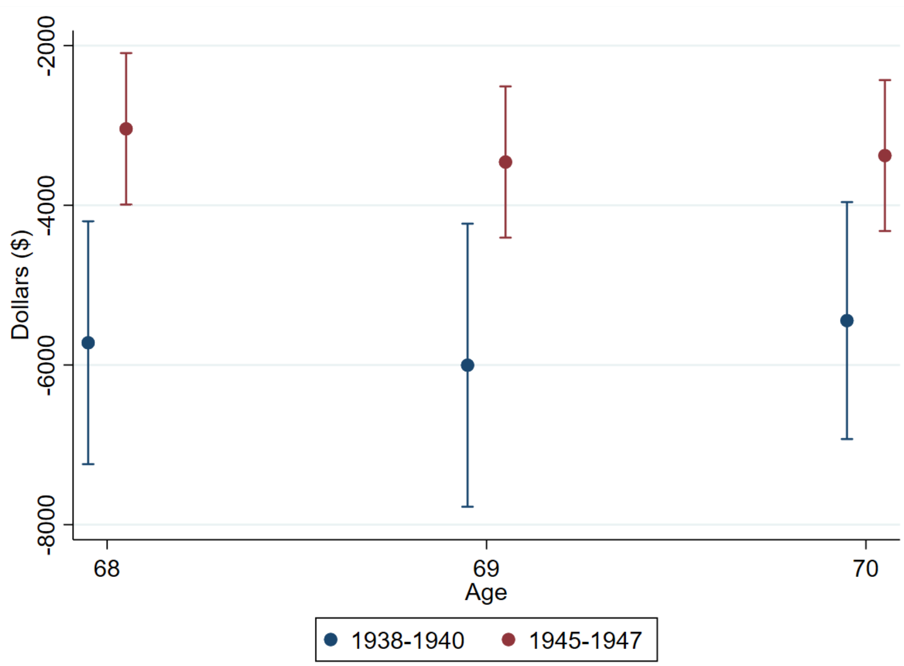


Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data.

Figure A3: Age by Birth Year Cohort Analysis

Panel A. Summary Stats

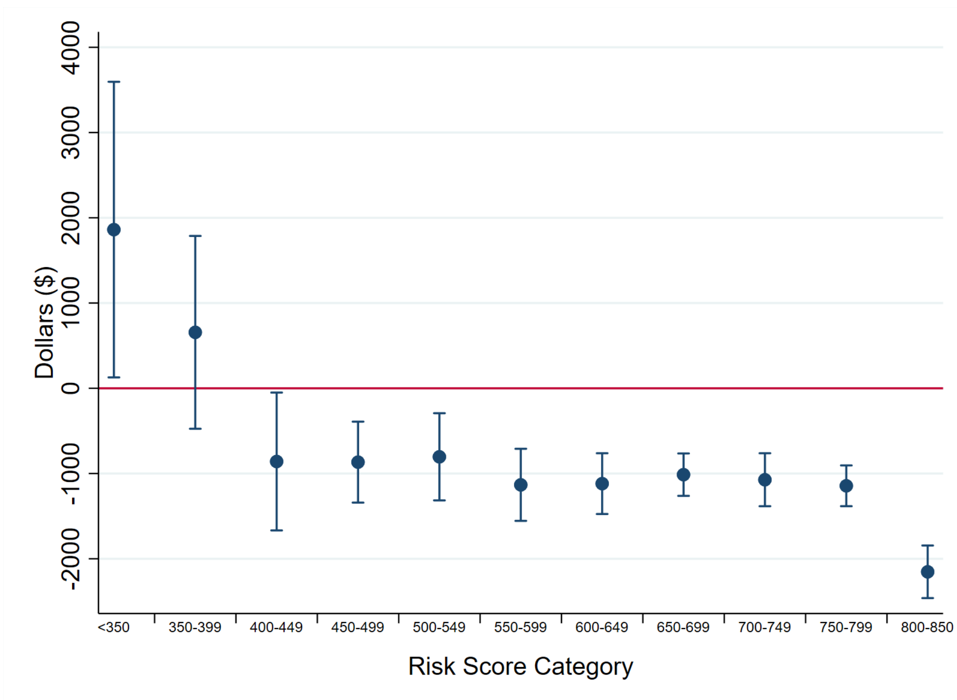
Panel B. Regression Analysis



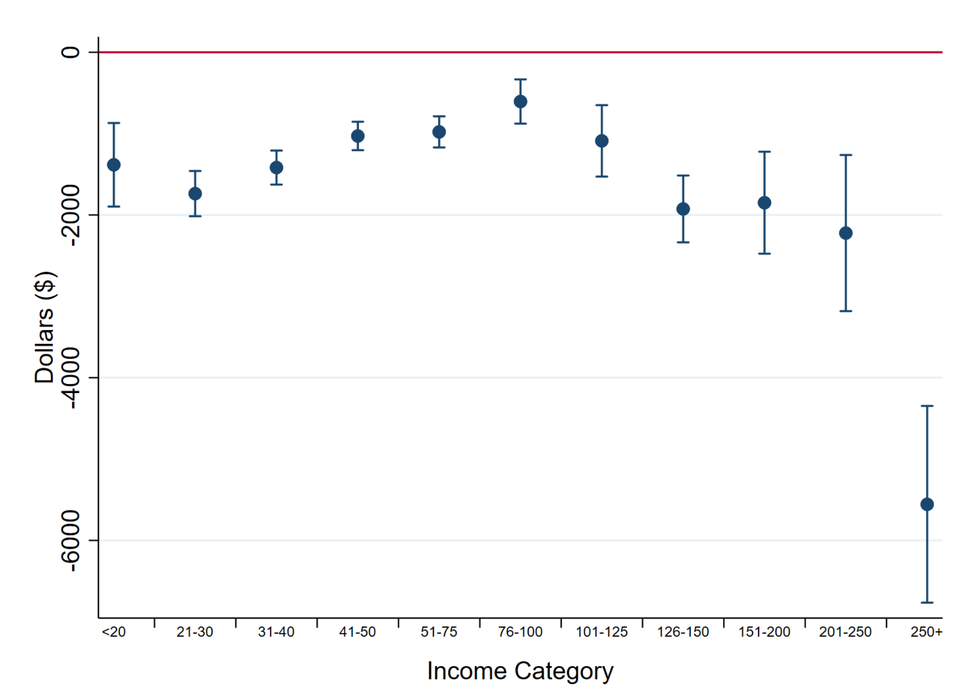
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data.

Figure A4: Average Marginal Effects for Credit Score and Income, by Category

Panel A: Credit Score Category

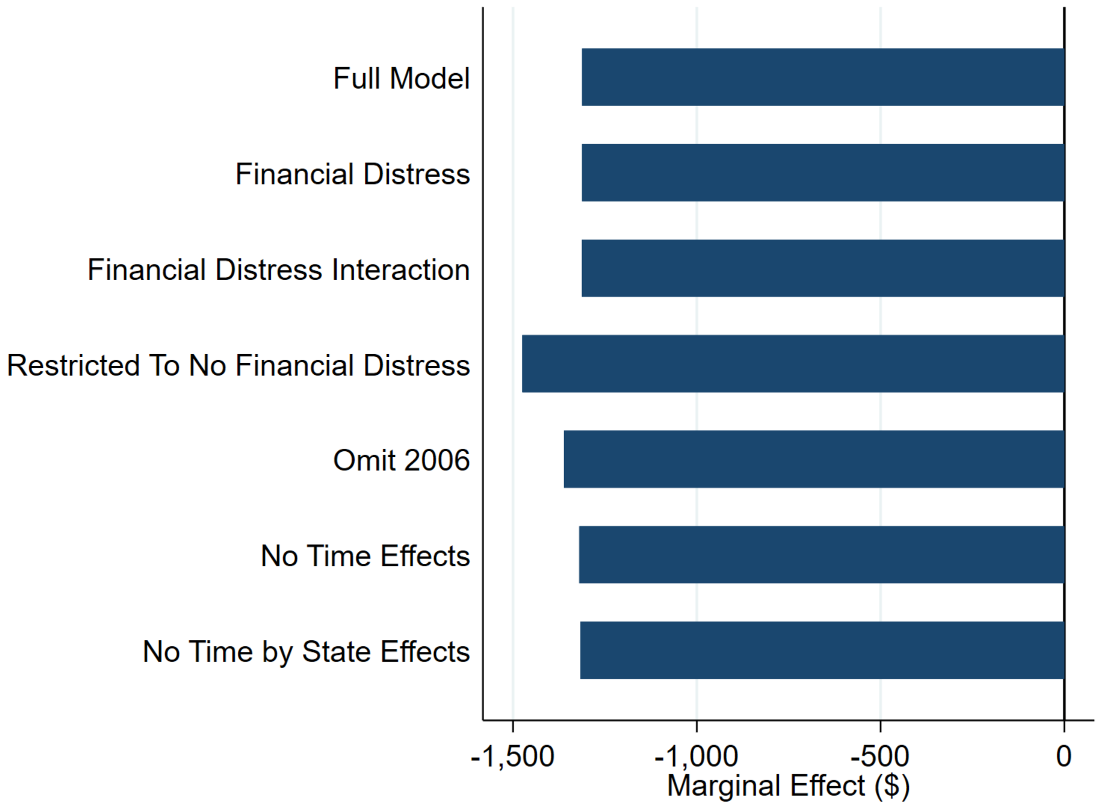


Panel B: Income Category



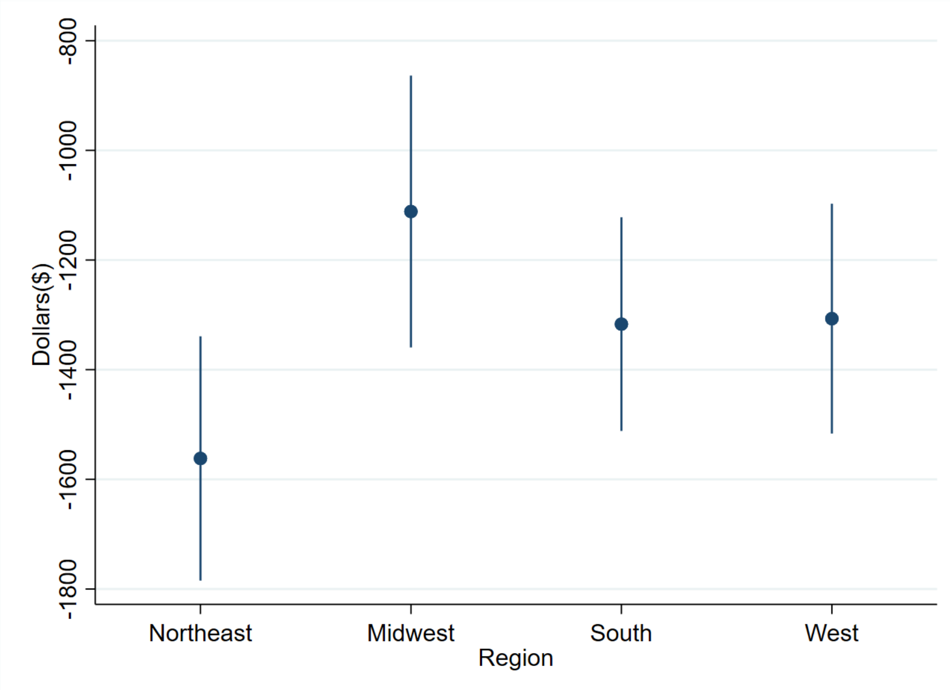
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Income is the HMDA income, reported at the time of mortgage application. Demographic information comes from the HMDA data. Bars represent 95% confidence intervals.

Figure A5: Robustness Checks: Average Marginal Effects



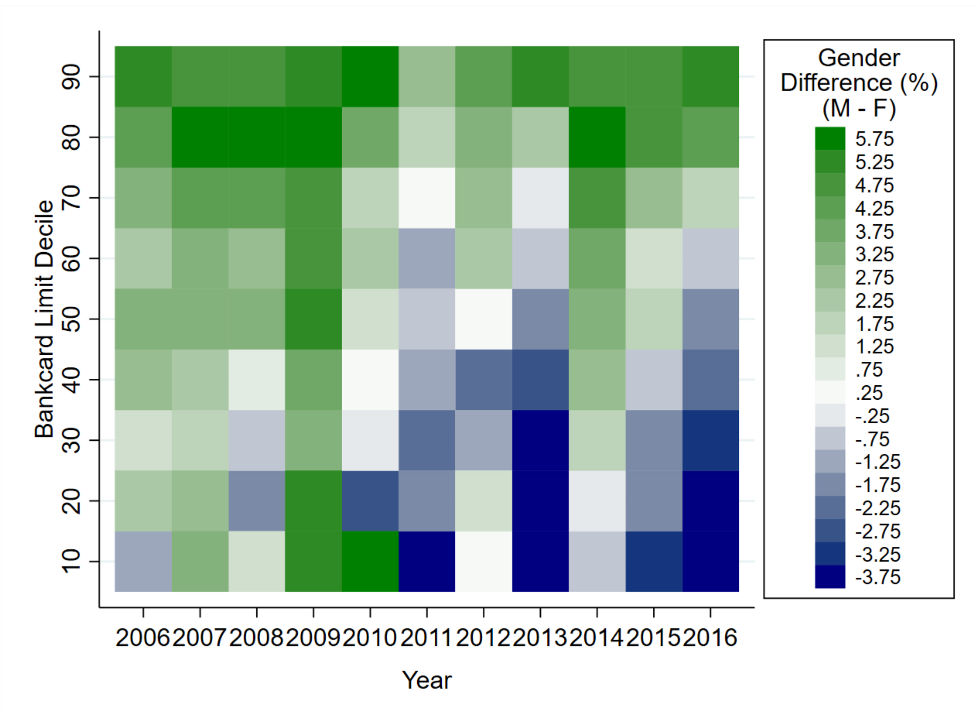
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit score is the Equifax Risk Score. Demographic information comes from the HMDA data.

Figure A6: Average Marginal Effects by Census Region



Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit score is the Equifax Risk Score. Demographic information comes from the HMDA data.

Figure A7: Gender Differences Across Time by Decile, as a Percentage of the Male Total Bankcard Limit

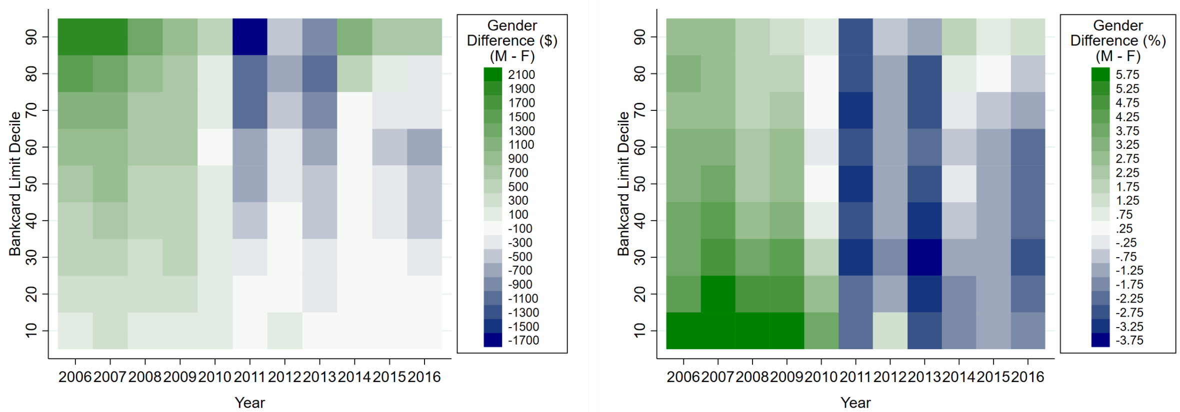


Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data. Reported Z-axis values are the midpoint of each bin.

Figure A8: Heat Maps of the Endowment Effect Across Time by Decile

Panel A. Difference due to the Endowment Effect, Measured in Dollars ($)

Panel B. Difference, As a Percentage of the Male Total Bankcard Limit

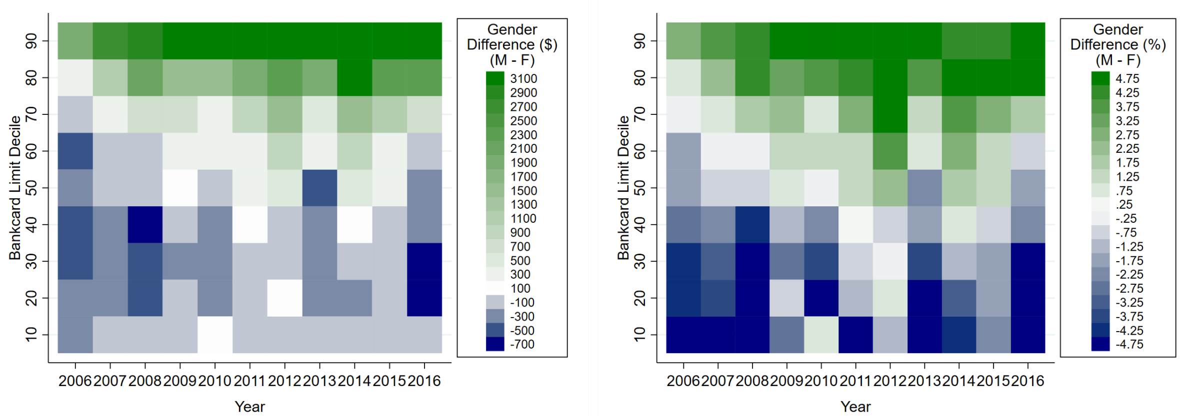


Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data. Reported Z-axis values are the midpoint of each bin.

Figure A9: Heat Maps of the Coefficient Effect Across Time by Decile

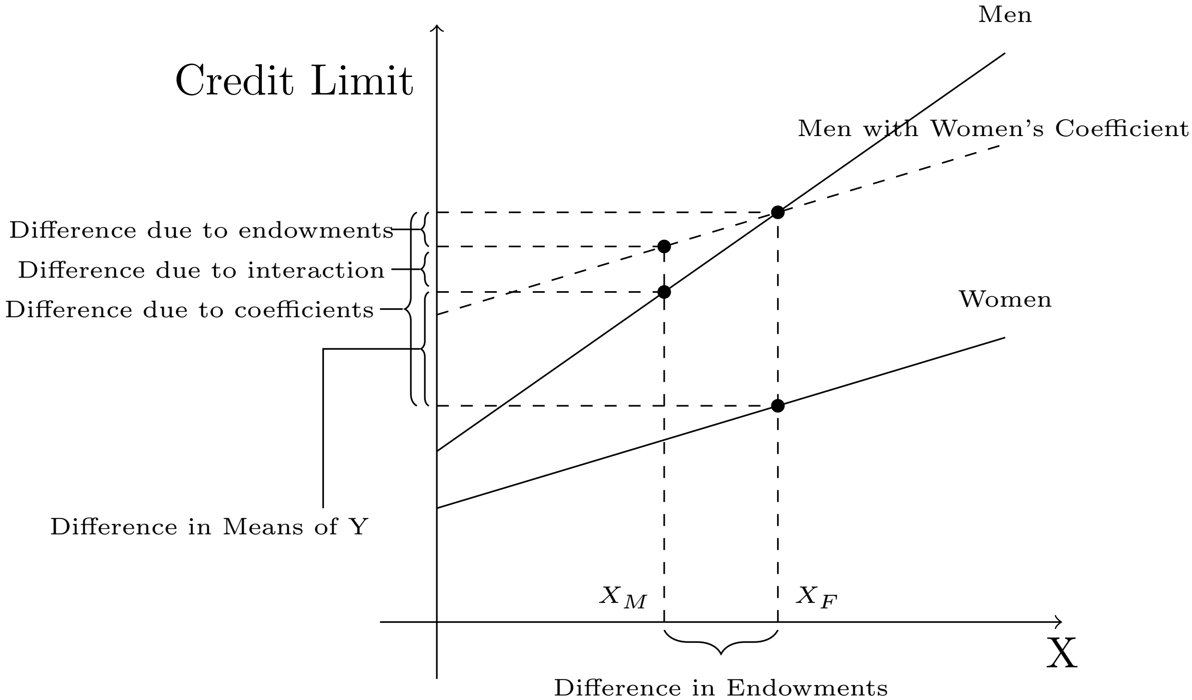
Panel A. Difference due to the Coefficient Effect, Measured in Dollars ($)

Panel B. Difference, As a Percentage of the Male Total Bankcard Limit



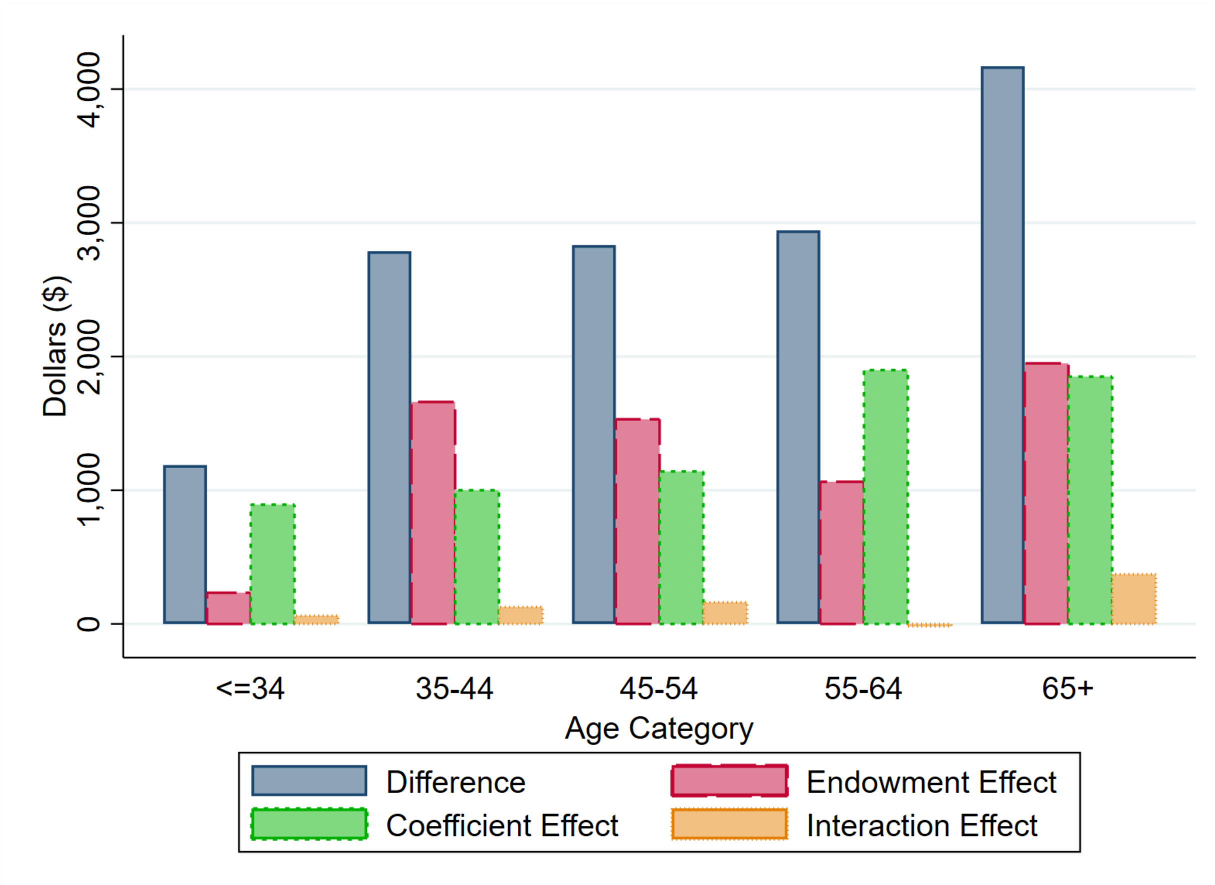
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Demographic information comes from the HMDA data. Reported Z-axis values are the midpoint of each bin.

Figure A10: Example KOB Decomposition



Notes: This example produces a KOB decomposition where the interaction and endowment effects are negative, but the coefficient effect is positive. To generate this result, female endowments are greater than male endowments, while men have greater average values for the Y variable than women. If the relationship for men is given by $Y_M = a_M + \beta_M X_M$ and the relationship for women is given by $Y_W = a_W + \beta_W X_W$, then the coefficient effect is $(\beta_M - \beta_W)X_M$, the endowment effect is given by $\beta_W(X_M - X_W)$, and the interaction effect is given by $(\beta_M - \beta_W)(X_M - X_W)$. For a canonical example in this format, see Jones and Kelley (1984).

Figure A11: KOB Decomposition by Life Cycle Period



Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data, ICE McDash loan servicing data, and Equifax Credit Risk Insight Servicing data. Credit Score is the Equifax Risk Score. Demographic information comes from the HMDA data.