Immigration and Credit in America

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Abstract

We study the assimilation of immigrants into American consumer credit markets. Although immigrants enter America without an American credit history, we find that immigrants are positively selected: immigrants' average credit scores at age thirty are 20 points higher than non-immigrants, and this gap widens with age. Despite immigrants' greater creditworthiness, they—especially those who arrive later in life—have lower average credit card limits for a decade after entering America. Immigrants are less likely than non-immigrants to hold auto loans, a gap that persists by age forty and is explained by an immigrant aversion to purchasing autos with debt.

Keywords: Immigration, Credit History, Household Credit, Debt Aversion
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1. Introduction

When immigrants arrive in the United States, they bring their human capital and labor market credentials, which can help navigate U.S. labor markets. However, immigrants start American life with a blank U.S. consumer credit report: any foreign credit history is generally invisible to U.S. credit bureaus and lenders. This missing credit history may impede access to credit, potentially undermining immigrants' ability to realize their significant economic potential in areas such as innovation and entrepreneurship (Abramitzky and Boustan, 2017, Sequeira et al., 2019, Kerr and Kerr, 2020, Azoulay et al., 2022, Bernstein et al., 2025).

This paper provides the first large scale evaluation of how immigrants assimilate into the U.S. consumer credit system. We use variation in the lifecycle timing of Social Security Number (SSN) assignment: individuals assigned SSNs as adults (at age 21+) are predominantly immigrants (Klopfer and Miller, 2024, Bernstein et al., 2025). We combine this fact with the sequential assignment of SSN blocks within states to classify immigrants in a 10% representative sample of U.S. consumer credit reporting data from TransUnion spanning 2000 to 2024. Using this dataset, we track the progress of immigrant cohorts through the U.S. credit system, defining cohorts by their age at SSN assignment. This empirical strategy contrasts outcomes across different immigration ages while controlling for birth year effects, enabling us to shed light on the connection between immigration timing and credit market trajectories.

Our core findings provide new empirical facts about immigration and credit in the United States. We show that immigrants only appear in credit markets once they are assigned a SSN, supporting our empirical classification of immigrants in the credit reporting data. However, immigrants' likelihood of having a credit score catches up to that of non-immigrants within a few years of SSN assignment. More strikingly, once they enter the system, we find that immigrants have significantly higher credit scores compared to non-immigrants, as well as persistently lower delinquency rates and more conservative credit utilization patterns. This positive selection on credit quality is more pronounced among those who immigrate later in life.[1]

However, despite immigrants' stronger observable credit quality upon entering U.S. credit markets, we find they have lower credit use than non-immigrants. While credit card access of immigrants converges relatively quickly to non-immigrant levels, significant gaps persist in whether immigrants ever access auto loans by the end of our sample frame (i.e., by age 40 for cohorts that immigrate in their twenties). Even though *access* to credit cards exhibits fast and complete convergence to non-immigrant levels, credit card *limits* – an intensive margin of credit – lag behind, taking up to a decade to converge. These gaps are especially pronounced for those who immigrate later in life, suggesting that no or a limited credit history creates an information friction in credit access that are not reflected by immigrants' relatively high credit scores. The gaps in credit limits are particularly relevant given their role in shaping consumption (Aydin, 2022, Agarwal et al., 2024).

Next, to measure the magnitude and trajectory of the delays induced by limited credit history more precisely, we use a paired cohort strategy that compares cohorts of immigrants born in the same year, but who immigrated a single year apart. This allows us to measure the dynamics of how being in the U.S. one year longer affects access to credit.

Consistent with our comparisons between immigrants and non-immigrants, we observe significant heterogeneity in the dynamics associated with one year later in life immigration. We find access to credit cards converges quickly, but this is not true for other forms of credit: we find that immigrating only one year later in life results in a persistently lower use of auto loans and mortgages ten or more years post-immigration.

Our findings on immigrant creditworthiness and credit access are robust to controlling finely for geography (i.e., including fixed effects for the first, last, and longest-held ZIP5 by a consumer, and the number of ZIP5 addresses to proxy for mobility), ruling out geographic drivers of the results, such as urban versus rural differences in economic vibrancy (Dougal et al., 2015). Moreover, we

[1]Legal immigrants to the United States have a broad range of immigration statuses including on immediate relatives, family-sponsored, and employment-based. Most legal immigrants into the United States are *not* H-1B visa holders (a type of visas for workers in specialty occupations, often requiring higher education). Official statistics from of Homeland Security Statistics Immigration Statistics (2024) show that across 2004 to 2023, only 16% of the legal immigrant temporary workers admitted were on H-1B temporary work visas, and only 9% of the legal new arrivals awarded lawful permanent residence (green cards) for employment are professionals with advanced degrees / exceptional ability.

also find that later in life immigrants have greater demand for credit in their twenties, measured using recent credit inquiries. We examine emigration as an alternative mechanism and show that, while this is important, it does not explain our results. One plausible mechanism for our findings is that immigrants' lack of a credit history and shorter length of credit histories may hinder their credit access, even for immigrants with high credit scores.

We use the Survey of Consumer Finances to explain the persistent lower auto loan use by immigrants, compared to non-immigrants, found in our analysis of credit data. This shows that immigrants are significantly more averse to purchasing autos with debt than non-immigrants.

Our paper contributes to the understanding of immigrants, their entry into the U.S. credit system, and the importance of credit history for credit access in the U.S. First, our findings provide a new perspective on how immigrants are selected, a major theme in the immigration literature (Borjas, 1987, Abramitzky and Boustan, 2017). Historically, immigrants to the U.S. have swung between being positively selected and negatively selected, depending on the immigration wave, context, and the country of immigration. For example, in earlier immigration waves, immigrants were more likely to be relatively poor in their home countries (Mokyr and Gráda, 1982, Cohn, 1995, Abramitzky et al., 2012). However, most European immigrants were neither positively nor negatively selected. As the foreign-born share in the U.S. has increased with an influx of immigrants from Latin America, immigrants have become increasingly positively selected (Clemens and Mendola, 2024). We contribute to this literature in two ways. First, we provide a characterization of immigrants via detailed consumer credit reporting data. Relative to labor outcomes like education, literacy and income levels, credit reporting data offer a complementary perspective on immigrant characteristics. For example, we observe delinquency rates and uses of all major types of credit. Second, our analysis provides a representative picture of how immigrants compare to non-immigrant consumers in terms of their creditworthiness. Creditworthiness is a different and important characteristic than the, primarily labor market, outcomes studied in the immigration literature.[2]

In addition, our findings provide a fresh perspective on the assimilation of immigrants into the U.S. economy. There is a robust literature on the assimilation of immigrants, which has characterized the labor market and cultural assimilation and social integration of immigrants during different immigration waves (e.g., Borjas, 1985, Abramitzky et al., 2014, 2020, 2021, Lubotsky, 2007, Bleakley and Chin, 2010, Bailey et al., 2022, Doran et al., 2022, Bazzi and Fiszbein, 2025). Our evaluation of assimilation into U.S. consumer credit markets not only offers a distinct venue of assimilation into the U.S. economy — credit markets versus labor markets — but it also suggests that the reliance on credit history in credit markets, and the inability to port credit histories across national boundaries, can slow assimilation into the credit system, leaving a lasting impression on immigrant credit access.

Our paper also contributes to the household finance literature on frictions in credit scoring, credit access and real effects (e.g., Herkenhoff et al., 2021).[3] This growing research studies the credit access implications of different scoring models (e.g., Fuster et al., 2022) and "thin" credit reports that only contain a few accounts or a short credit history (e.g., Blattner and Nelson, 2024). It also emphasizes the challenges of being outside of the credit system (Brevoort et al., 2015, 2018, Kambara and Luce, 2025), and the barriers to entering U.S. credit markets (Brevoort et al., 2017, Brown et al., 2019). By studying immigrants—an important consumer segment with thin credit profiles due to their later credit market entry—our research provides a new perspective on credit access for consumers with thin credit files.[4] For example, it is striking that immigrants' delayed

[2]For example, theoretical work by Chatterjee et al. (2023) regards a credit score as the market's assessment of a person's unobservable type, which they interpret as patience. Meier and Sprenger (2010) and Arya et al. (2013) provide empirical support for this with time patience predicting credit scores. More generally, Gibbs et al. (2025) describe how credit scores are often interpreted by researchers as a summary statistic for financial well-being, with Beer et al. (2018) evaluating the correlation between credit scores and incomes.

[3]A segment of the literature examines the real impacts of *negative* credit history by removing information from one's credit file (Bos et al., 2018, Dobbie et al., 2020). Guttman-Kenney (2025) examines the impacts of disaster flags, which temporarily mask adverse credit outcomes after a natural disaster.

[4]Our perspective on immigrants differs in at least two ways from recent household finance research on immigrants and the dynamics of credit via movers. First, as reviewed in Gomes et al. (2021), the existing household finance literature on immigration has largely focused on cultural differences (e.g., Carroll et al., 1994, Osili and Paulson, 2004, Haliassos et al., 2017, Fuchs-Schündeln et al., 2020, Zillessen, 2022, Sodini et al., 2023). Second, we study the credit access of immigrants, which is a different focus to prior work by Keys et al. (2023) that has studied how consumer financial distress varies after moves within the United States. There is limited literature studying the role of immigrants in other fields of finance beyond household finance, (e.g., Aobdia et al., 2018, Chen et al., 2021, 2022, 2024, Zimmerschied, 2024).

entry into U.S. credit markets has delays in mortgage and auto loan access by age 40, even though immigrant credit scores are higher than non-immigrants.

Our findings on delayed entry into the U.S. credit system also relate to the work on the long-term impacts of delayed credit market entry (Brown et al., 2019, Nathe, 2021). Related work has emphasized the importance of a good start in credit markets, either through good parental credit histories (e.g., Ghent and Kudlyak, 2016, Bach et al., 2023, Hamdi et al., 2024, Benetton et al., 2025, Bakker et al., 2025, Blizard et al., 2025) or starting one's credit history in good economic times (Ricks and Sandler, 2025). Relative to this literature, our variation in credit market entry timing (and thus history) deploys a person-specific, near-mechanical reason for delay — immigrants cannot enter U.S. credit markets before immigration, nor get credit for their credit history in other countries. Although our results on credit access are similar to other factors that delay and restrict access to credit, our findings on immigrants' higher credit scores contrast with work on credit entry timing and later credit scores (Nathe, 2021), suggesting that later credit market entry has less of an impact on credit scores for immigrants.[5]

Our research on immigrant credit access relates to the FinTech literature (e.g., Buchak et al., 2018, Berg et al., 2022, Erel and Liebersohn, 2022), especially work on how FinTechs serve under-represented groups and younger borrowers (Dobbie et al., 2021, Cherry, 2025, Hair et al., 2025). More closely related is research focused on the lending decisions of FinTechs in the presence of little or no credit history. Di Maggio et al. (2022) shows that alternative credit scores identify "invisible primes" that are misclassified by traditional credit scoring. However, even in this setting, FinTech lending may still rely upon traditional credit scores (Chioda et al., 2025). Our results complement these perspectives in the literature by showing that immigrants' access to credit is delayed, and that this delay is not attributable to traditional credit scores.

Finally, our research also relates to the literature on cultural attitudes. Badarinza et al. (2016) document large and persistent differences in household finances across countries. Carroll et al. (1994) found no differences in cultural factors explaining saving patterns of immigrants to Canada

[5] Our paper complements Kovrijnykh et al. (2024), which shows that individuals can boost their overall access to credit not only via prompt repayment, but also via by opening new credit cards.

from different cultures. Bursztyn et al. (2019) and Paine et al. (2025) show the importance of moral values to explaining debt use. Our contribution to this literature is to document an immigrant "debt aversion" (Prelec and Loewenstein, 1998) specific to auto loan debt. Although there are other examples of debt aversion in the literature (e.g. Field, 2009, Berkouwer and Dean, 2022, Gopalan et al., 2024, Martínez-Marquina and Shi, 2024), we document a new and economically important case given that the U.S. auto loan market is $1.6 trillion in outstanding debt as of Q1 2025 (Federal Reserve Bank of New York, 2025).

The paper proceeds as follows. Section 2 explains our data, how we classify immigrants in our data, institutional details of lending to immigrants in America, and our empirical methodology. Section 3 shows our results. Section 4 contains the methodology and results for our paired cohorts analysis. Section 5 evaluates the mechanisms behind our results. Finally, Section 6 concludes.

2. Data, Institutional Details, and Empirical Specifications

In Section 2.1, we explain the data that we use, with subsections for each data source. Section 2.2 explains how we classify immigrants in our credit reporting data. Section 2.3 explains the Entrant sample that we use for analysis. Section 2.4 provides institutional details on lending to immigrants in America. Section 2.5 explains our empirical methodology.

2.1 Data

2.1.1 Consumer Credit Reporting Data

We obtain consumer credit reporting data from the University of Chicago Booth TransUnion Consumer Credit Panel, "BTCCP" (TransUnion, 2025). The BTCCP is an anonymous, representative sample of U.S. consumer credit reporting data provided by TransUnion. To build this sample, TransUnion starts with a 10% representative sample of consumers with a credit report in July 2000. For each month of data after July 2000, 10% of new consumers are added to the panel to maintain representativeness. The data have information on 10% of consumer credit records, monthly from July 2000 to December 2024. Gibbs et al. (2025) discusses best practice for using consumer credit reporting data, which we follow in this paper.

The BTCCP is a collection of datasets, linkable to one another via a consumer identifier. We primarily construct our outcomes from the BTCCP's monthly tradeline-level dataset for details on each consumer credit account held by a consumer (i.e., outstanding balance and delinquency status). Critically, this dataset provides the date that each account was opened, even those opened or closed prior to July 2000.[6] We also use the BTCCP's consumer-level header dataset, which contains each consumer's birth date and the date a consumer first has a credit report—even if this was before July 2000. By combing the consumer's birth date with the account open date in tradeline data we compute the consumer's age at account opening.[7] From the BTCCP's monthly consumer-level aggregated dataset we use a consumer's credit score, VantageScore, a consumer's ZIP code and state, and months since the last credit inquiry (search). From this last dataset, we primarily use an annual panel of aggregated credit characteristics (observed each July); we use monthly data to calculate consumers' first credit score, first ZIP code, longest ZIP code, and the number of unique ZIP codes.

We start with all consumers observed between July 2000 and September 2023 in the BTCCP.[8] We retain consumers with valid birth dates between 1951 and 2004 because we need birth dates to calculate the year of immigration.[9] These restrictions produce an anonymous sample of 31.87 million consumers, representative of 318.7 million consumers.

[6]Using tradeline dataset from July each year captures a consumers' history because each account is in the tradeline-level dataset while it is open, and remains there for seven to ten years after it first becomes delinquent or closed (Gibbs et al., 2025).

[7]Some tradelines appear to be opened at ages below 18 and we drop such cases because this is before a consumer can take out a credit agreement by themselves and are likely to either be a data error or a credit product taken out by their parent. This produces more plausible estimates of credit usage at age 18. Separately, for each month, we remove accounts not updated in the prior twelve months as these may contain less accurate information.

[8]We first queried the BTCCP for this project in September 2023. Because the data are regularly updated, we observe credit outcomes through December 2024. However, we had to set the sample frame at the outset to follow our immigrant classification procedure. In addition, we focus the sample on consumers who had at least one tradeline at any point between July 2000 and September 2023. This restriction drops fragmented credit reports, such as those with only credit inquiries.

[9]"Consumers" without birth dates are more likely to be credit reports in which debts are fragmented across multiple consumer identifiers; Gibbs et al. (2025) recommends dropping these observations. We start in 1951 for two reasons. First, prior to 1951, there are spikes around particular birth dates, suggesting that some older birth dates may be less accurate in this period. Second, the timing of deaths is not well measured in credit reporting data (Gibbs et al., 2025). Focusing the sample on relatively recent birth years limits this issue.

2.1.2 American Community Survey (ACS)

We use public Census data from the 5-year 2010 American Community Survey (ACS), accessed via the Integrated Public Use Microdatset Series (IPUMS), (Ruggles et al., 2025). These anonymous data contain birth years, years of immigration, and geographic location, enabling us to evaluate our immigrant classification by comparing summary statistics to those from nationally-representative official estimates.

2.1.3 Survey of Consumer Finances (SCF)

We use public data from the Survey of Consumer Finances (SCF) to help evaluate the mechanisms behind our results. The SCF is a triennial nationally-representative cross-sectional survey of consumers in America created by the Federal Reserve (Board of Governors of the Federal Reserve System, 2023). We use the 2022 wave of the SCF as this includes information on whether a consumer is an immigrant, and if they are an immigrant, the number of years since immigration. This information is not available in earlier waves of the SCF. We also use other information in the SCF: the consumer's age, their attitudes to taking on credit, whether they own a home or have a car, and how they acquired their home or car were purchased (e.g., whether a homeowner with or without a mortgage, leased an auto, financed with an auto loan, or purchased with cash), whether they have applied for credit in the last twelve months, and whether they were rejected, and they did not apply for credit, their reasons for not doing so. The SCF does not contain geographic information or credit scores.

2.2 Immigrant Classification

In our BTCCP data, we classify whether a consumer is an immigrant and their age at immigration following the "sequential SSN assignment" procedure used in recent research on U.S. immigration (Yonker, 2017, Doran et al., 2022, Bernstein et al., 2025, Klopfer and Miller, 2024, Engelberg et al., 2025).[10] SSNs are nine-digit numbers created since 1936 that are unique to a consumer and are assigned by the Social Security Administration. Through mid-2011, the Social Security Administration sequentially assigned SSNs, allocating all SSNs with the same first five digits before moving onto another block. The first three digits denoted an "area number", a geographic region within a state, the fourth and fifth digits are the "group number" that is assigned sequentially in blocks within that area, and the last four digits are in the order of processing which are quasi-randomly assigned. See Puckett (2009) for a comprehensive history of SSN assignment. Following the approach used in prior research, we classify a consumer as an immigrant if their age at SSN assignment, $SSN\ Age$, is greater than or equal to 21, where $SSN\ Age = SSN\ Year - Birth\ Year$. Bernstein et al. (2025) shows that their results are not sensitive to whether immigrants are classified based on SSN Ages 19+, 20+, or 21+. We therefore follow the prior work in using 21+, and also include results showing outcomes for SSN Ages 19 and 20.

To estimate the year of SSN assignment, $SSN\ Year$, we construct a lookup table, based on public information, that maps the first five digits of the SSN into the first year of SSN assignment, $SSN\ Year$, for all SSNs assigned before 2012.[11] We sent TransUnion the list of all 31.87 million consumers in the full sample, together with this lookup table. TransUnion then matched the consumer list and the lookup table to their underlying data, which includes consumers' SSNs, returning a dataset with the year of SSN assignment, an indicator for whether a consumer had any SSN in their data, and the BTCCP consumer identifier. This procedure guarantees that we never observe nor can we infer SSNs for any consumers in the BTCCP.[12]

Table 1 describes how we arrive at our sample. After removing the 21% of consumer identifiers

[10] The closest prior data to ours is Federal Reserve (2007) report to Congress, which evaluated traditional credit scoring models in a 2003 sample of 300,000 credit records that includes immigrants. Our dataset offers a substantial advancement over this early work because it is more recent, more comprehensive, more granular, and has information on immigration age. Because of these features and because our data cover 25 years, we are able to speak to the question of assimilation into U.S. credit markets by evaluating the dynamics of immigrant credit.

[11] Some 5-digit SSN sequences are assigned over a 2 or 3 year period, while others are assigned in a single year. In all cases, we take as the year of SSN assignment the *first* year the 5-digit sequence was assigned. This means that a subset of our consumers will, in reality, receive a SSN one or two years later than they appear to in our data.

[12] This classification depends on knowledge of the first five digits of a consumer's SSN (Advani et al., 2025 also uses a related method in the United Kingdom). Bernstein et al. (2025) use Infutor data, which was originally built from consumer credit reporting data. However, since the 1999 Gramm-Leach-Bliley Act, the bureaus cannot sell address lists to third parties, forcing Infutor and its competitors to rely on other data sources.

without SSN information, we have 25.2 million consumers. Requiring SSN information appears to drop what appear to be fragmented credit records with younger ages and credit reports that do not persist over time. It is common to focus research on credit reports with SSNs, most notably, the widely-used Federal Reserve Bank of New York's Consumer Credit Panel *only* contains information on consumers with SSNs (Gibbs et al., 2025). More fundamentally, our immigrant classification relies on SSN information in a consumer's TransUnion file. Without a SSN, we cannot establish a consumer's year of SSN assignment.[13]

Without further refinement, this procedure is noisy because all nine digits of SSNs were randomly assigned after mid-2011. Some of these later-assigned SSNs fall into blocks in our lookup table, erroneously assigning them to earlier SSN Years. To avoid such a misclassification, we require consumers in our sample to have a credit report by 2011. In addition, we remove any consumers who have $SSNAge < 0$, and any consumers with birth years values of 1988 or later, as they are too young to enter the data or to be classified as immigrants by 2011.

This sample has limitations. Our immigrant classification does not include illegal immigrants (who lack SSNs) nor does it allow us to identify people who immigrated before adulthood. It also does not include legal immigrants with Individual Taxpayer Identification Numbers (ITINs) or Enumeration at Entry (EAE), as we do not know when these are assigned. However, ITINs and EAEs are typically only used before a consumer receives a SSN. For the non-immigrant birth years relevant to our study, consumers were assigned a SSN at birth or before turning 18, as demonstrated in administrative Social Security Administration data by Klopfer and Miller (2024), although some older consumers were assigned SSNs as adults. The distribution of SSN Ages by birth years in our data, shown in Appendix Figure A5, corresponds to that in Klopfer and Miller (2024), and another independent validation of our classification is that the consumers that we classify as immigrants are more geographically mobile than non-immigrants (Appendix Figure A6). In addition, we do not observe people who remain outside the formal credit system.

Table 1 shows that the resulting "Clean Sample" has 18.57 million consumers, 2.09 million of

[13]Fragmentation will be less common in files with SSNs and birth dates because these identifiers are used to consolidate files. In our sample, each SSN is unique; thus, cases with fragmented files may slightly under-count the debt of those consumers.

whom we classify as immigrants, based on a SSN Age of 21+. The 11.27 percent of immigrants in this clean sample approximates the 10.20 percent of consumers in the ACS, applying the same birth year restrictions and also only classifying immigrants if their year of immigration was when they are aged 21 or older.

Further validation shows a close correspondence between our estimates and the ACS estimates of immigrants. In particular, panel A of Appendix Figure A1 shows how the distribution of immigrants by birth year compares in our classification, using SSN Age of 21+ in the BTCCP, to the ACS, using age of immigration of 21+. We see that from birth years 1970 onwards – we use cohorts born in 1975 and onwards in our analysis – our estimate for the percentage of immigrants within each birth year closely aligns with the ACS estimates.[14] In general, lower immigration rates would be expected for our data as we only capture legal immigrants with SSNs, whereas the ACS estimates also include illegal immigrants and legal immigrants without SSNs. In panel B of Appendix Figure A1, we see that using the Age at SSN Assignment in our data gives a similar distribution of adult age of immigration to the distribution found in the ACS. Both panels suggest that our immigrant classification matches the characteristics of the overall immigrant population *despite* focusing on consumers who have SSNs and whose credit files are not fragmented. Finally, in Appendix Figure A2 we show that the immigrant classification delivers a close match to the distribution of immigrants across states found in the ACS. These validation exercises, together with similar validations in the existing literature using the age of SSN assignment (Bernstein et al., 2025, Klopfer and Miller, 2024), suggest that our strategy to classify immigrants is accurate and reliable.

2.3 Entrant Sample

Starting from the "Clean Sample" of credit reporting data described above, we impose two additional restrictions to arrive at the "Entrant Sample" used for our analysis. First, we restrict to the set of consumers with birth years between 1975 and 1987. Consumers with these birth years

[14] Before birth year 1969 our classification appears to overestimate the share of immigrants. One reason for this is non-immigrants obtaining SSNs after age 21, but this practice was reduced by the Social Security Amendments of 1972 (P.L. 92-603), which authorized the provision of SSNs to children at the time they first entered school at around age 6 (https://www.ssa.gov/history/ssn/ssnchron.html) reducing mis-classification for cohorts born in 1967 onwards.

are expected to enter the credit system and begin accessing credit mostly after 2000 and before the SSN assignment period ends in 2011. Thus, we call this sample the “Entrant Sample.” For example, in the years 2000 to 2024 observed in the BTCCP, consumers born in 1975 are observed from age 25 to 49, while consumers born in 1987 is observed from ages 18 and 37. Given these sampling choices, Appendix Figure A4 displays how birth years, age at SSN assignment, and the time period we observe consumers in our data relate to one another. For some analysis that relies on consumer-level datasets, we further restrict to birth years 1982 to 1987 to ensure that consumers enter the credit system after 1999, following similar approaches used in related papers (Ricks and Sandler, 2025, Bach et al., 2023, Bakker et al., 2025). This sample restriction also corresponds to the subset of birth years in our data where the estimated immigration shares closely resemble those in the ACS, as shown in Panel A of Appendix Figure A1.

Second, we restrict our attention to consumers with $SSN\ Age < 30$. This sample restriction focuses our analysis on younger immigrants arriving in the United States at some point in their twenties. In turn, this ensures that, for all cohorts—groups of consumers with the same SSN Age—in our data, credit outcomes in a consumer’s thirties occur *after* everyone in our sample has immigrated. Thus, all cohorts in our entrant sample have at least 8 years of credit reporting data after the consumer’s immigration date, enabling us to examine longer-term credit outcomes.

This final sample has a total of 6,122,932 consumers, 5.62% (344,261) of who we classify as immigrants (i.e., SSN Ages 21 through 29). Appendix Figure A3 shows that this entrant sample closely matches the ACS data where 6.57% immigrate at ages 21 to 29. Within this sample, there are 102 immigration groups—i.e., birth year x SSN Age combinations. As shown by the counts of consumers by SSN Age in Appendix Table A1, each SSN Age group in this entrant sample has many consumers, ranging from 52,450 at SSN Age 21 to 19,202 at SSN Age 29.

In subsection 3.1, we show summary statistics based on collapsing our data into a cross-sectional dataset with one observation per consumer, constructing variables using information across the entire panel.

When using the SCF, we use similar birth year restrictions used in the entrant sample, and doing so reduces the sample size from 4,595 to 1,813 respondents. This focuses on respondents in their twenties, thirties, and forties in the 2022 survey year (corresponding to birth years 1972 to 2000). We use this restriction because those in their fifties and older would be expected to have limited credit demand irrespective of immigration status or credit supply. Given the small survey sample size, we keep respondents with ages of immigration older than 30. This means that we classify 213 of the 1,813 respondents as immigrants, having an age of immigration of 21+.

2.4 Institutional Details on Lending to Immigrants in America

Lenders in America are able to consider an applicant's immigration status as a relevant factor in their lending decisions. This is because immigration status is *not* a protected characteristic that lenders may not use, e.g., gender, national origin, and race, under the Equal Credit Opportunity Act (ECOA). However, as a joint statement between the Consumer Financial Protection Bureau and the Department of Justice set out in October 2023, lenders are constrained in how much they can rely on information on immigration status in their underwriting because lenders need to comply with ECOA to ensure that they are not discriminating against protected characteristics.[15] In March 2025, the Department of Housing and Urban Development (HUD) removed eligibility for "non-permanent residents" (i.e., legal immigrants) from Federal Housing Administration programs (illegal immigrants were always ineligible).[16] This HUD policy change is too recent to affect our results, however, we would expect it to reduce immigrants' access to mortgages in the future.

Lenders in America use credit scores and other information in their lending decisions. Information frictions may affect lenders' decisions and impact immigrants' access to credit in a couple of ways. First, immigrants to America do not have any U.S. credit report or credit score. Lenders may therefore have a prior that, given no information, they are high credit risk. Second, after entering the U.S. credit system, immigrants have a shorter length of credit history than many non-immigrants, who often enter the credit system at age 18 or in their early twenties. The length of credit history positively affects credit scores used by lenders (e.g., FICO). Immigrants' shorter

[15] https://files.consumerfinance.gov/f/documents/cfpb-joint-statement-on-fair-lending-and-credit-opportunities-for-noncitizen-b_jA2oRDf.pdf

[16] https://www.hud.gov/sites/default/files/OCHCO/documents/TI-490.pdf

credit history also means that lenders have less information on immigrants than they do on non-immigrants of the same age, this could matter if lenders rely on this information beyond credit scores.

Other cultural barriers may also prevent immigrants from accessing credit. Language barriers between credit applicants and lenders may prevent efficient transactions from occurring. An example of this is Liu (2025) who shows how a 2018 Federal Housing Finance Agency policy change to translate mortgage documents increased mortgage lending. Immigrants may also not understand the American credit system, and how you need to take out credit to build your credit score.

2.5 Empirical Specifications

In this subsection, we describe the two main empirical specifications that we apply to different outcomes in our entrant sample throughout the paper.

The first specification allows the average of a consumer-level variable to depend non-linearly on the consumer's $SSN\ Age(i)$. Specifically, we estimate the following via OLS:

$$\mathrm{Y}_i \quad = \quad \phi_{SSN\ Age(i)} + \mu_{b(i)} + \epsilon_i, \tag{1}$$

where i indexes consumers, b indexes birth years and $\mu_{b(i)}$ is a birth year fixed effect. Y_i is a consumer level outcome, such as age at first credit card (or mortgage, or auto loan) or a consumer's Vantage score at age 30. $\phi_{SSN\ Age(i)}$ is a vector of $SSN\ Age$ fixed effects. SSN Age ranges from 18 to 29 because we pool all consumers with a SSN Ages 0-18 into the SSN Age 18 category, to group non-immigrants. The SSN Age fixed effect estimates in this specification thus calculate the average outcome for each SSN Age cohort, conditional on birth year. In this specification, we do not group SSN Ages 19 and 20 with this SSN Age 18 category for illustrative purposes, because SSN Ages 19 and 20 may be a mix of immigrants and non-immigrants. However, consistent with prior work in Bernstein et al. (2025), using a classification of immigrants based on SSN Age 19+, 20+, or 21+ does not change our conclusions and is what we do in our later regression specifications. Also note that this threshold choice for classifying immigrants makes no meaningful difference to the non-immigrant baseline means that we compare our estimates to. This is because 5,677,001 consumers have an SSN Age of 18 or younger, and this would only increases to 5,778,671 if SSN Ages 19 and 20 are also included, as reported in Appendix Table A1, and therefore it has no meaningful impact on the means.

An important implementation detail is how to handle missing values of cross-sectional outcome variables, such as when a consumer does not take out a mortgage in our sample period. Because these consumers never accessed the credit product, leaving these consumers out of the sample would understate differences in credit access. We deal with missing outcome values (i.e., consumers who never take out a given credit product) by assuming they access the product in 2025, one year after the end of our data.

Our main specification is a linear version of Equation (1), which we also estimate via OLS:

$$\mathrm{Y}_i \quad = \quad \beta_1 \cdot \mathbb{I}\{SSN\ Age\ 21+\}_i + \beta_2 \cdot SSN\ Age_i + \mu_{b(i)} + \epsilon_i, \tag{2}$$

For many of our results, we find that outcomes have an approximately linear relation to SSN Age. Thus, this linear specification replaces the SSN Age fixed effects ($\phi_{SSN\ Age(i)}$) in Equation (1) with an indicator variable for whether SSN Assignment occurs at age 21 or later, $\mathbb{I}\{SSN\ Age\ 21+\}_i$, and a linear term for $SSN\ Age_i$. To aid interpretation, we pool all non-immigrant SSN Ages in one category, that is, those 0 through 20. The coefficient on $\mathbb{I}\{SSN\ Age\ 21+\}_i$ then reflects the average difference in immigrant outcomes compared to those of non-immigrants, and the coefficient on $SSN\ Age$ reflects the marginal difference in average outcomes associated with being assigned a SSN one year later. We show results with and without birth year fixed effects ($\mu_{b(i)}$). In all of our OLS regressions using credit data, standard errors are clustered by birth year.

We also estimate specifications (1) and (2) with geographic fixed effects to account for local market conditions. Specifically, we include *First ZIP5* fixed effects, which are indicators for the first five-digit ZIP code associated with a consumer in our data. In the Appendix, we show that our results are robust to adding fixed effects for additional geographic controls: the most recent five-digit ZIP observed for a consumer in our data (*Last ZIP5*), the five-digit ZIP observed for a consumer for the most months in our data (*Longest ZIP5*) which is a proxy for their most permanent location, and the number of unique five-digit ZIP observed for a consumer (*Number ZIP5*) which is as a proxy for their geographic mobility. All of these geographic controls are imperfect because consumers enter and exit our data at different times, partially based on their credit access.

We also show the *lifecycle* of means for how consumer credit use evolves over time across our panel. We summarize our data by each combination of $SSN\ Age$ and Age observed in our panel data. In this, we group consumers assigned a SSN at age 18 or younger into one category, to serve as a non-immigrant benchmark for our outcomes. This approach enables visual comparisons of the lifecycles of credit use for consumers assigned SSNs at different ages.

When analyzing the SCF, we use a regression of the same format as that in Equation (1). Except that, rather using SSN Age, we can directly observe age of immigration in the survey, and therefore we have an indicator for if a respondent immigrated at age 21 or older, and a variable for each year of immigrating beyond age 21. Given the small survey sample size we increase precision of our regression estimates by including demographic controls with fixed effects for birth year, male, race, hispanic, spouse, male spouse, marital status, household size, number of children, education levels, and quintiles of household wage income. We also use the SCF's recommended survey weights in our regressions to correct for the over-sampling of high-wealth consumers in the survey's design. With the SCF, we use heteroskedasticity-robust standard errors and follow the SCF's recommended multiply-imputed variance estimation technique to account for missing data.

3. Results

This section describes the main results on immigrant credit entry, creditworthiness and credit access of various products. We begin with summary statistics to examine cross-sectional differences in immigrant and non-immigrant credit, then move to our main analysis, with an alternative empirical design presented later in Section 4. In Section 5, we then discuss the mechanisms that could explain our results.

3.1 Summary Statistics

Table 2 presents sample means of variables for immigrants ($SSN\ Age$ 21+) versus non-immigrant consumers ($SSN\ Age < 20$). These statistics highlight first order differences in the nature and timing of immigrant versus non-immigrant consumer credit use.

As we would expect, immigrants enter the U.S. credit system later than non-immigrants. The average age at first credit report for immigrants is 25.21 compared with 19.86 for non-immigrants. Their delay in accessing their first credit card is similar, with immigrants having an average age at first credit card of 26.42 (versus 22.07 for non-immigrants). Though delayed, immigrants are just as likely to eventually have a credit card within our sample frame (97.85% versus 97.16% for non-immigrants), and by age 40, they are just as likely to have a credit report (99.08% versus 99.61% for non-immigrants). As of age 30, immigrants are less likely to have a credit report, suggesting that entry into the credit system takes time.

The average credit score (VantageScore) is *substantially* higher for immigrants than for non-immigrants. As of age 30, the average credit score of immigrants is 660.7 versus 626.1 for non-immigrants (34.6 point difference). Although some of this difference could be explained by immigrants of higher credit quality selecting into having credit scores at earlier ages (see the 9.4% difference in likelihood of being scored at age 30), the difference between immigrants and non-immigrants in average credit scores is *larger* at age 40, and at that point effectively all consumers in the sample have been scored (698.9 for immigrants versus 659.5 for non-immigrants, a 39.4 point difference).

Turning to credit products typically accessed later in a consumer's lifecycle, we find that immigrants are significantly less likely to access auto loans (69.07% versus 82.11%) and mortgages (47.62% versus 51.13%) than non-immigrants. Conditional on individuals who access these loans in the sample, immigrants access both auto loans and mortgages later than non-immigrants. Their average age at first auto loan is 30.30 (versus 26.03) and their average age at first mortgage is 32.73 (versus 29.49). Because immigrants have higher credit scores for any given age, this later access — insofar as it is related to more recent immigration — is consistent with lenders relying on credit history in addition to credit score to assign credit. The general differences in the access rates for auto loans and mortgages could also be consistent with different demand for autos and houses by immigrants versus non-immigrants.

We also see interesting differences in credit limits between immigrants and non-immigrants. At age 30, immigrants and non-immigrants have approximately the same average credit limits ($11,193 for immigrants versus $11,733 for non-immigrants), but by age 40, immigrants' total credit limits are $5,681 higher on average ($28,158 versus $22,477). This dynamic suggests that immigrant credit limits start low but surpass non-immigrants after some time, potentially owing to immigrants' higher credit scores. In the following subsections, we will examine each of these differences and dynamics more precisely, conditioning on the age of SSN assignment, accounting for birth year differences, and controlling finely for geography (ZIP5 fixed effects).

3.2 Credit Market Entry

We present evidence that the age at which a consumer receives a SSN in our data (SSN Age) drives the timing of credit market entry. At the highest level, our evidence shows that older SSN Age strongly predicts later credit market entry, both for first credit product and for the first date the consumer receives a credit score. These findings principally serve to support SSN Age as a proxy for immigration timing.

To evaluate how SSN Age relates to the timing of credit market entry, Figure 1 plots the estimated SSN Age fixed effects estimates ($\phi_{SSN\ Age(i)}$) from Equation (1). The coefficient for the non-immigrants (consumers with SSN Age of 18 or younger) is indicated by the gray horizontal dashed line — the average age at first credit product for this baseline group is 21.25 years. As SSN Age increases, so does the average age at first credit product, and this increase is essentially linear.[17] Especially for older SSN Age cohorts, these findings reflect the reality that immigrants could not have credit products before their immigration date.

Given this linear and positive relationship between SSN Age and credit entry, we move to results

[17] We also observe linear effects for age at first credit report, and the age of first credit card, auto loan, and mortgage in Appendix Figure A7.

from our main regression specification, Equation (1), for the rest of our results section. Table 3 presents the results from estimating this equation. In columns 1 to 3, we estimate the specification with increasingly demanding fixed effects. Broadly, we find that immigrants enter U.S. credit markets at later ages on average, and immigrants who immigrate later in life (older SSN Age) access credit at even later ages. Specifically, in columns 1 through 3, we estimate immigrants are nearly 2 years older than non-immigrants, on average, when they first have a credit report. Delayed entry into the credit system is more pronounced for immigrants who arrive to the United States later in life. For each additional year of older SSN assignment, we estimate that the age of first having a credit report is delayed by an additional 0.74 to 0.78 years. We interpret this delay as primarily mechanical in origin: immigrants who would have entered before their SSN age could not do so, due to their immigration timing.[18]

Our conclusions about delayed entry are not sensitive to how we measure entry into the U.S. credit system. We obtain similar estimates for the consumer's age upon receiving their first credit product — 1.68 years later and 0.74 years per year of SSN Age — as shown in Table 3 where we add fixed effects across columns 4 to 6.[19] These delays are economically significant relative to the average age that non-immigrants receive their first credit report (19.86 years) and the average age of first credit product (21.25).

One potential concern with interpreting these delayed entry results is that local markets vary in their economic opportunities or access to finance, and this may disproportionately affect immigrants. That is, immigrants may be more likely to arrive in cities rather than rural areas, or areas of different incomes or other economic opportunities, which have different credit access patterns or economic vibrancy (Dougal et al., 2015). Our results are robust to adding fixed effects for the first ZIP code, as displayed in columns 3 and 6 of Table 3.[20] These results are also robust to additionally including fixed effects for each consumer's last ZIP code, longest-held ZIP code, and

[18] Alternatively, one might expect that each additional year of SSN Age would mechanically delay the consumer's entry by one year. However, the estimates of around 0.7 are relative to non-immigrants, not all of whom have entered the credit system at each age, which drives the mechanical effect below one.

[19] Appendix Figure A8 shows the lifecycle for age of first credit report and first credit product by SSN Age.

[20] Appendix Figure A7, also shows that our linear results, as presented in Figure 1, are robust to including such fixed effects.

number of unique ZIP codes, as shown in Appendix Table A2.

3.3 Creditworthiness

A core feature of the immigration literature is to understand how immigrants assimilate into U.S. economy (Borjas, 1985). Our data enable us to measure a consumer's creditworthiness and the dynamics of how this evolves over a consumer's lifecycle, comparing non-immigrants to immigrants, and comparing the outcomes of immigrants assigned SSNs at different ages. In this section, we provide evidence on how immigrants assimilate into U.S. credit markets.

3.3.1 First Credit Score

First, we examine the timing of when a consumer first receives a credit score. This is an important outcome because it is risky to lend to unscored applicants. Panel A of Figure 2 displays the unconditional likelihood of having a credit score for each SSN Age cohort at different ages. The black line shows how the likelihood of having a credit score evolves for consumers with SSN Ages 18 or younger ("non-immigrants"). At age 18, approximately 15% of non-immigrants receive their first credit score; by age 22, more than 80% of these consumers have a score. Judging by the consistent rightward shift in these lifecycle curves as SSN Age increases, consumers with older SSN Ages access credit later. Much of this delayed access is due to consumers naturally having no access to the credit system before their immigration date. In the years prior to the SSN Age (where $Age = SSNAge$ is indicated by a circle on each lifecycle curve), there is *de minimus* access to credit, followed by a sharp jump in the percentage of scored consumers in the year following immigration.

Shortly after their immigration year, immigrants, those with SSN Ages 21 to 29, quickly converge to their non-immigrant counterparts in their likelihood of having a credit score. For example, while only 30% of SSN Age 22 consumers have a credit score at age 22, more than 80% have a credit score by age 26. The speed of convergence in the likelihood of having a credit score increases for immigrants assigned SSNs at older ages. Moreover, immigration cohorts arriving later in life have a higher likelihood of having a credit score in their year of immigration. For example, only around

10% of 21 year old immigrants (SSN Age of 21) have a credit score at age 21 whereas nearly 40% of 29-year-old immigrants have a credit score at age 29. This figure also separately includes SSN Ages 19 and 20 cohorts that may contain a mixture of immigrants and non-immigrants, and, as expected, those two cohorts fall between the SSN Age 18 and SSN Age 21 cohorts.

3.3.2 Mean Credit Scores

Panel B of Figure 2 plots the means of credit scores for each SSN Age cohort at different ages, *conditional* on having a credit score at that age. It is important to study credit scores at different ages because a consumer's borrowing needs and propensity to repay debt can change over the course of their lifecycle (see Chatterjee et al. (2023) for a theory of credit scoring). Strikingly, this plot shows that immigrant SSN Age cohorts (SSN Age > 21), start out with a higher mean credit score than non-immigrants (SSN Age $= 18$). Immigrant cohorts continue to have substantially higher average credit scores throughout their thirties, which is after immigrants are just as likely as non-immigrants to have a credit score. Although the high average credit score in the year of immigration might partly reflect selection (i.e., immigrants who are scored are higher credit quality), immigrants have higher credit scores than non-immigrants after a similar fraction of immigrants and non-immigrants are scored. Thus, this result suggests that immigrants who are scored are better credit risks than their scored non-immigrant counterparts of the same age, on average. Overall, this dynamic pattern paints a somewhat unexpected picture: Even new immigrants with a credit score are *observably* better credit risks.

To provide a more formal characterization of these lifecycle patterns, we estimate how average credit scores at ages 30 and 40 depend on immigration status and SSN Age. We estimate Equation (2) where the outcomes are the consumer's credit score at age 30 and 40. Panel A of Table 4 presents the results on average differences in immigrant credit scores by age 30 and by age 40. Consistent with the descriptive lifecycle plots, we estimate that immigrants have average credit scores that are 23.3 points higher than non-immigrants, and this difference in credit scores grows by an average of 2.7 points for each additional year of SSN Age. As we enrich the specification with birth year and first ZIP5 fixed effects, the difference between immigrants and non-immigrant consumers shrinks slightly to 18.8 points, and 2.0 points per year of SSN Age, but these differences remain large.

The immigrant versus non-immigrant difference in credit scores widens as consumers age. By age 40, the gap in credit scores increases to 31.5 points, with a similar $SSNAge$ gradient for consumers who immigrate later in life. Similarly to the results at Age 30, we find that the immigrant to non-immigrant difference is somewhat smaller upon including geographic fixed effects, though it remains large. These higher average credit scores occur *despite* these consumers having a shorter credit history, which is known to be a negative input to credit scores. The length of credit history is an important input in the credit scores that lenders use, accounting for approximately 15% of FICO and 20% of VantageScore models.[21]

3.3.3 Distribution of Credit Scores

The mean credit score may mask important heterogeneity in credit scores. Panel B of Table 4 estimates Equation (1) where the outcome is the likelihood of having prime or better credit scores, specifically, VantageScore > 660. Immigrants are nearly 10 percentage points more likely to have prime or higher credit scores by age 30 than their non-immigrant counterparts. Later in the lifecycle, at age 40, immigrants continue to be more likely than non-immigrants to have prime or higher credit scores (2 to 4 percentage points). In addition, immigrants who arrive later in life *are* more likely to have prime or higher credit scores at age 40. This increase in the likelihood of having prime or better credit is large in comparison to the baseline percentage of non-immigrant prime consumers (46.84% as of Age 40). In these specifications, ZIP5 fixed effects explain significant R^2 (going from around 1% without them to around 10% with them). Despite soaking up this much variation, our qualitative conclusions are similar using within ZIP5 variation. Appendix Table A3 shows that results are similar when we use specifications that also include additional geographic fixed effects: *last* ZIP5 as a proxy for a consumer's current geography, longest-held ZIP5 as a

[21] https://www.myfico.com/credit-education/whats-in-your-credit-score
https://vantagescore.com/resources/knowledge-center/the-complete-guide-to-your-vantagescore/

proxy for a consumer's most permanent residence, and the number of unique ZIP5 as a proxy for a consumer's geographic mobility.

Panel C of Figure 2 shows how the fraction of consumers with prime or higher credit scores evolves over the lifecycle for each SSN Age cohort. In panel C, unscored consumers are counted in the denominator, while panel D conditions the plot on having a score. In panel C, we observe two competing forces at play: On one hand, immigration cohorts arriving later in life are less likely to be scored, but on the other hand, they are more likely to have prime or higher credit once they are scored. In a cohort's twenties, the share of unscored consumers dominates the higher credit scores of the cohort's scored consumers, whereas by the cohort's thirties the higher credit scores of scored consumers dominate. Panel D shows that, conditional on having a credit score, immigrants are more likely to have prime or higher credit scores and the magnitude of these differences is relatively large. For example, at age 26, a consumer who immigrated at age 22 and is scored is over 10 percentage points more likely to have a prime credit score than a non-immigrant who is scored — over 50% versus under 40%. Moreover, because most SSN Age 22 consumers have a credit score by age 26, this difference is not explained by differential selection into the credit system. These credit risk differences are persistent over the lifecycle, and even grow slightly as people age. The gap between the SSN Age 22 cohort and the non-immigrant cohort is nearly 15 percentage points by age 40.

Digging deeper into the credit score results, Appendix Figures A9 and A10 shows that immigrants have more compressed credit scores than non-immigrants. The average immigrant is less likely to have a subprime credit score than the average non-immigrant at any stage in the life cycle that we observe. This applies irrespective of the age of immigration and irrespective of conditioning on having any credit score. The average immigrant is more likely to have a very high credit score, as measured by prime plus (VantageScore $>$ 720) or superprime (VantageScore $>$ 780), by their mid-to-late thirties, again irrespective of the age of immigration and irrespective of whether we condition on having any credit score.[22]

Panel B of Appendix Figure A10 shows the CDF of first credit scores by SSN Age cohort. The CDF for immigrants of all ages is to the right of that of non-immigrants, and shifts further right as SSN Age rises. This evidence shows that immigrants have higher credit scores immediately upon entry, despite these scores often being based on thin credit files.[23] Overall, the results of this subsection indicate that immigrants credit behaviors mean that they are lower credit risks on average, than non-immigrants of the same age, and immigrants are increasingly lower risk as they age and more information becomes available.

3.3.4 Credit Delinquency & Credit Utilization

To shed additional light onto immigrant credit risks, we now consider two alternative measures of credit quality: any delinquency 90 or more days past due, and the average credit card utilization rate (the ratio of the sum of credit card balances across cards to the sum of credit card limits across cards). Both measures are conditional on holding any credit card. These measures are common inputs to credit scores.

The lifecycle of delinquency rates shown in panel A of Figure 3 portrays results that are consistent with our credit score results. Non-immigrants have higher delinquency rates at all ages relative to immigrants, a difference that persists through their thirties. Moreover, even among immigrant cohorts, people arriving later in life (older SSN Ages) have lower delinquency rates. A complementary way to assess immigrants' creditworthiness is the "calibration bias" approach used in Bakker et al. (2025). Panel A of Figure 4 shows the delinquency rates for immigrants and non-immigrants seven years later, conditional on credit scores at age 30 for the 94% of consumers who have a credit score by this age (and Appendix Figure A12 shows for deciles of credit scores). Across all credit

[22]However, earlier in their life cycle immigrants are less likely to have very high credit scores. This makes sense, since when consumers can first be scored they typically have little information on their credit report — a "thin file" — and so the first credit score for an entrant to the credit system typically takes a relatively small number of values, as shown in Appendix Figure A10. The longer a consumer's credit history, the more time there is for more positive and negative events to occur that can shift a consumer's score up or down. More events allow for a more accurate measure of risk, leading to greater dispersion in credit scores.

[23]This result purely reflects differences in creditworthiness between immigrants and non-immigrants: Immigration status is not an input into credit scores.

score segments, immigrants have lower average delinquency rates than non-immigrants. Panel B of Appendix Figure A11 shows that consumers who immigrate later in life have lower average delinquency rates.[24] Appendix Table A4 shows the results of a regression of the form shown in our main specification, Equation 2, where the outcome is any delinquency by age 37, and alongside fixed effects for birth year, we also include fixed effects for both credit score at age 30 and for Zip5 at age 30. This shows that immigrants' delinquency rates are 1.4 percentage points lower than for non-immigrants. This is 5% lower than the non-immigrant mean of 27.2%, a small difference when benchmarked against the differences by race shown in Bakker et al. (2025). We find no statistically significant differences in any delinquency rates by age 37 by an additional year older SSN Age, conditional on credit score at age 30 and our other controls.

Beyond the lower delinquency rates, an important reason credit scores are higher in the first year for immigrants is because they have lower credit card utilization. We illustrate this pattern in panel B of Figure 3. Credit card utilization is consistently lower for immigration cohorts, especially for older SSN Age cohorts. These two measures point to immigrants being better credit risks once they are holding credit products in the U.S.

3.4 Access to Mortgages and Auto Loans

The previous subsections establish that immigrants have delayed entry into the credit system, but that once an immigrant has a credit report, they have higher average credit scores, lower delinquency rates, and lower credit card utilization than non-immigrants. These findings imply that, a few years after immigrating, the average immigrant has a higher credit score with a shorter credit history than a non-immigrant born in the same year.

We now consider the timing of first credit access across mortgages and auto loans.[25] Appendix Figure A7 plots the average age of first credit product by SSN Age cohort, separately for credit cards,

[24]Appendix Figure A10 panel D shows that an extremely small segment of SSN Age 28 and 29 consumers have superprime credit scores at age 30, and therefore while this small subset of these SSN Ages have slightly higher delinquency rates than other SSN Ages, we do not regard this as not economically important. Our overall pattern of results for immigrants compared to non-immigrants, and by SSN Age holds if assessed at different time horizons, with these additional results not presented to prevent repetition.

[25]The majority of vehicles in the US are purchased on credit (Benmelech et al., 2017) and are thus observed in credit reporting data (Gibbs et al., 2025).

auto loans and mortgages. Appendix Figure A7 presents similar results after further conditioning on ZIP5 fixed effects. These figures have two main messages. First, the average age of first credit access depends on the type of credit: for non-immigrants, the average age of first access is 22.5 years for credit cards, 29.7 years for auto loans and 36.3 years for mortgages.[26] Second, for all types of credit products, later in life immigration dates (older SSN Ages) correspond to later credit access. The fact that immigrating slightly later in your twenties matters for auto loans and mortgages, which are typically accessed in a consumer's thirties, suggests that delayed entry into credit markets has long-term impacts on credit access. This is plausibly related to later in life immigrants having shorter credit histories. However, another possible mechanism is that immigrants may purchase automobiles with cash, or they may be more likely to move within the U.S. or emigrate, potentially making them less likely to want to purchase a house. We discuss these alternative mechanisms in Section 5.

To evaluate this idea, we construct the lifecycle of credit access for each type of credit parallel to the earlier analysis. We find that immigrants have very limited access to credit in the year before their SSN Age, regardless of credit type. Figure 5 illustrates these patterns across the early adult lifecycle for cohorts of people with SSN Ages between 18 and 29.[27]

In contrast to credit risk, immigrant credit access lags that of non-immigrants. Non-immigrants are more likely than non-immigrants to access all types of credit at any point in the lifecycle. However, the difference in credit card access (panel A) disappears within 5 years of immigration. Unlike credit cards, we find that immigrants are *persistently* less likely to access auto loan credit (panel B) and mortgages (panel C), even up to the end of the panel: age 37. Moreover, for auto loans and mortgages, there is a larger gap to non-immigrants for immigrants arriving later in their twenties than for immigrants arriving earlier. This striking pattern suggests that delayed entry to the credit system leads to long-lived effects on credit access that go beyond observable measures of credit risk.

[26]For consumers who never access a credit product in our sample, we input their age at the end of the sample as the date of first access. Following this choice inflates the average age relative to people who access each product, but it also helps to make the average ages comparable across products.

[27]Note that $SSNAge$ of 18 in our analysis pools all of the SSN Ages 18 or younger into one category.

That is, even though later in life immigrants have significantly higher average credit scores, their access to mortgages and auto loans lags significantly behind non-immigrants and immigrants with an earlier immigration date.

We quantify this idea using our main regression specification (Equation (2)), replacing the dependent variable with an indicator for age of first credit access, separately for each type of credit. Table 5 presents the results. We find a significant immigrant versus non-immigrant delay in the average age of first accessing credit: 2 to 3 years for auto loans and 0.2 years to 0.8 years for mortgages. Moreover, this gap grows for later in life immigrants: an additional year of SSN Age predicts an additional delay of 0.6 years for a consumer's first auto loan, and 0.4 years for a consumer's first mortgage. These results on delays in first accessing credit are robust to controlling for the consumer's most recent ZIP5, to account for local market conditions, and longest held ZIP5 and number of unique ZIP5, as shown in Appendix Table A6.

To quantify whether consumers access credit at all within our sample frame, we now change the outcome to whether a consumer has accessed a specific credit product (credit card, auto loan, or mortgages) by the age of 37 (i.e., 8 years after the last immigration cohort arrives). Table 6 presents the results. In columns 4 through 9, we find significant gaps in long-run access to auto loans and mortgages: unconditionally, immigrants are 10.2 percentage points (13%) less likely to have ever had an auto loan and 2.2 percentage points (5%) less likely to have ever had a mortgage by age 37. This immigrant versus non-immigrant gap grows significantly for immigrants who arrive later in life. For example, for each year increase in SSN Age we estimate that immigrant consumers are 1.3 to 1.6 percentage points less likely to have a mortgage by age 37. The estimates shrink somewhat on controlling for first ZIP5 fixed effects (and, for mortgages, the immigrant indicator is non-significant but the SSN age coefficient remains significant), but we continue to find that immigrants with older SSN Ages are much less likely to access auto loans and mortgages, given the negative, large significant coefficients on $SSNAge$. Additionally, Appendix Table A7 show that these results are robust to including fixed effects for the consumer's *last* ZIP5 and longest ZIP5, which account for differences in local market conditions beyond formative local conditions via the consumer's first location in the credit file, and number of ZIP5 to also account for differential geographic mobility (and with these additional controls the mortgage result becomes significant again). These estimates point to large and significant differences in auto loan and mortgage credit access, which is correlated with the timing of immigration.

3.5 Access to Credit Cards

We now examine consumers' access to credit cards, a key source of unsecured borrowing in the U.S. We use our main regression specification (Equation (2)), instead using as dependent variables an indicator for age of first accessing a credit card, and then whether a consumer has ever held a credit card by age 37. Table 5 presents the results. We find a significant immigrant to non-immigrant gap in the average age of accessing credit: 1.17 years to 1.37 years for credit cards. Moreover, this gap grows for later in life immigrants: an additional year of SSN Age predicts about 0.7 years later first accessing a credit card. As with our results for auto loans and mortgages, these results are robust to controlling for other geographic fixed effects (last ZIP5, longest-held ZIP5, and number of unique ZIP5s), as shown in Appendix Table A6.

In columns 1 and 2 of Table 6, we observe that immigrants are slightly *more* likely to have a credit card by age 37 than non-immigrants. However, conditioning on first ZIP5 fixed effects leads this difference to be non-significant, and remains so with including last ZIP5 fixed effects, and also adding in longest ZIP5 fixed effects, but becomes significant again once including fixed effects for the number of unique ZIP5s. These are all shown in Appendix Table A7. Moreover, for credit card access by a consumers mid-thirties, the timing of immigration does not matter for whether the consumer has access to credit cards.

The results in Figure 5 suggest that credit card access of immigrants catches up more quickly than access to auto loans and mortgages. We now look at credit access *within* credit cards, examining how the number of credit cards and their limits evolve over the consumer lifecycle for different immigration cohorts. Figure 6 presents evidence on margins of adjustment for credit cards: Panel A shows the number of credit cards, panel B shows the total value of credit credit limits, and panel

C shows the credit card limit per card conditional on holding any card.

Consistent with the evidence on access to auto loans and mortgages, credit limits of immigrants with older SSN Ages take many years to catch up to immigrants with younger SSN Ages and non-immigrants. For example, in panel B of Figure 6, the SSN Age 29 cohort does not converge until age 36 to the same total credit limit as non-immigrants. This long delay in convergence reflects different dynamics for the average credit limit per card (panel C) and the number of credit cards (panel A). In panel C, the average credit limit per card *never* catches up to earlier cohorts (e.g., by age 40, the SSN Age 29 cohort has the lowest mean credit limit per card). By contrast, the number of credit cards catches up and surpasses SSN Age 18 cohort within three years of immigration. The fact that immigrant cohorts catch up to non-immigrants in their total credit card limits, but only through access to more credit cards provides unique evidence on this phenomenon. Appendix Figure A13 shows a consistent pattern of results when we condition on having any credit card. Appendix Tables A8 and A9 respectively, show the cross-sectional regression results for the number of credit cards and the total value of credit card limits and at ages 30 and 40 are consistent with these descriptive figures.

4. Paired Cohorts

Immigrants and non-immigrants are different on many dimensions. To account for this, we develop and apply a *paired cohort* strategy, which focuses comparisons on two immigrant cohorts, who are the same age but arrive in the United States a single year apart, and follow outcomes in the same year. This allows us to quantify the dynamics of how immigrating one year later in life correlates with their credit outcomes.

4.1 Methodology

While we have previously defined a cohort as all consumers with the same SSN age, in this section we define a cohort more narrowly, adding the requirement that all consumers in the cohort are also the same age and follow outcomes in the same year. Thus, we define a cohort c, as the set of consumers who have the same birth year *and* have the same year of SSN assignment—e.g., the set of people born in 1985 and who also immigrated in 2007 and were therefore assigned an SSN at age 22 is a cohort in this analysis (birth year 1985 × SSN Age 22). We aggregate the data such that there is one observation per cohort and year from 2000 to 2024. We then restrict to cohorts where $2003 \leq Birth\ Year + SSN\ Age \leq 2011$ to ensure that we observe pre-periods before a cohort enters the BTCCP.

A pair p, is a set of two cohorts $\{c', c''\}$, consisting of a focal cohort c', and a matched control cohort c''. Cohorts within a pair have the same birth year, but the SSN Age for the control cohort c'' is one year younger: $SSN\ Age_{c''} = SSN\ Age_{c'} - 1$. For example, our focal Birth Year 1985 × SSN Age 22 cohort is matched to a control of Birth Year 1985 × SSN Age 21 cohort. To implement this strategy, we restrict attention to focal cohorts of $SSN\ Age$ 22+ to ensure the availability of an immigrant cohort as a control. There are 68 pairs of cohorts ($<$ 102 cohorts in the entrant sample) that had their SSNs assigned between 2003 and 2011 and we trim the data to ensure that our panel is balanced within and across pairs. We define event time t based on the focal cohort, keeping 16 years of annual data from two years prior to the year when the focal cohort's Age = SSN Age, to thirteen years after. Therefore, our dataset consists of 2,176 cohort-by-year observations with a paired structure.

We estimate the following specification via OLS in leads and lags:

$$\mathrm{Y}_{k(p),t} = \sum_{\tau=-1}^{+13} \delta_\tau \left(\mathbb{I}\{focal\ cohort\}_{k(p)} \times \mathbb{I}\{t = \tau\}\right) + \pi_{k(p)} + \nu_{p,t} + \epsilon_{k(p),t} \tag{3}$$

where $\mathrm{Y}_{k(p),t}$ is the outcome variable in event time t for cohort k belonging to pair p. This specification is akin to difference-in-differences where the indicator $\mathbb{I}\{focal\ cohort\}_{k(p)}$ plays the role of the treatment variable, and the interacted event time indicators $\mathbb{I}\{t = \tau\}$ implement a dynamic difference-in-differences, relative to the omitted event time period $\tau = -2$. Given this, δ_τ shows how credit outcomes, observed in the same year within a pair, develop for each cohort relative to consumers with the same birth year who immigrated one year earlier.

To focus on variation within pair and to account for pair-specific trends, the specification includes fixed effects for each cohort in a pair $\pi_{k(p)}$ and pair-by-event time fixed effects $\nu_{p,t}$. Although event time t is the year of the focal cohort's year of SSN assignment, the pair is "treated" with one year less in the U.S. than the control cohort. To emphasize this non-standard timing in the plots, we label event time $t-1$ as "C" and event time t as "T" to respectively denote the control and focal cohorts' year of immigration.

We cluster standard errors by birth year to allow for dependence over the lifecycle and to allow for dependence within pairs. Such clustering is especially important in our context because one cohort can be a focal cohort in one pair but also act as a control group in another pair, although we only have 13 clusters. Finally, in our regressions we weight each observation by the size of its cohort.[28]

This estimation approach is not a causal design, but it does allow us to provide evidence on the timing of differences in credit access for different types of credit, and to empirically link these differences to a one year gap in immigration. Further, our focus is on immigration cohorts in their twenties, which allows us to analyze credit outcomes that are not mechanically delayed by the immigration date – specifically, auto loans and mortgages, which are commonly accessed later, and in the case of mortgages, often in a person's mid-to-late thirties.

4.2 Results

We observe distinct dynamics for credit market entry versus later-in-lifecycle credit access using the paired cohort design. Figure 7 presents the results on credit card access and entry into the credit system (panel A) and access to auto loans and mortgages (panel B). Reinforcing the descriptive results in the preceding sections, we observe a major but relatively fleeting difference in the likelihood of first having any credit product or first having a credit card: a nearly 25 percentage point difference in the year of the control cohort's immigration C, which returns to zero by two years after the focal cohort's immigration year.

In contrast to credit card access, the difference in access to mortgages and auto loans across

[28]Wing et al. (2024) shows how different weights in stacked difference-in-differences estimates can produce different parameters. Alternative weighting approaches, such as equal weighting cohorts and equal-weighting the control and treated cohorts, did not affect our conclusions.

paired cohorts shortly after immigration is relatively minor. And, unlike credit market entry and first credit card access in panel A, mortgage and auto loans have not converged even over a decade after immigration. After thirteen years, immigrants, relative to immigrants of the same birth year who were assigned a SSN one year younger, are 0.46 percentage points (s.e. 0.13) *less* likely to have had an auto loan and 0.92 percentage points (s.e. 0.28) *less* likely to have had a mortgage, in contrast to being 2.33 percentage points (s.e. 0.76) *more* likely to have had a credit card. Thus, even a one-year gap in immigration date gives rise to the long-run gaps that we saw in the earlier analysis.

One advantage of the paired cohort strategy for binary outcomes is that the coefficients in a given event year reflect the percentage difference in access for that year — the average amount of delay in accessing credit that we can attribute to that particular year. Viewed this way, we can accumulate coefficient estimates over the event window to quantify the cumulative delay in accessing credit by a given year.[29] Aside from providing an alternative way to compute the average delay in credit access, this cumulative statistic also helps quantify the long-run delay for each type of credit, which is especially useful if the different credit types have distinct dynamics.

Table 7 presents this exercise, displaying the cumulative delay as of year C, year T, year 5 and year 10, with Appendix Figure A14 showing the full estimates. We estimate that one year difference in immigration date is associated with cumulatively 0.69 years to 0.74 years less credit history, and most of this delay is realized by the focal cohort's immigration date T. This finding is consistent with the idea that later in life immigration cohorts eventually enter U.S. credit markets, but their credit access is initially delayed, resulting in persistently shorter credit histories. A shorter U.S. credit history is a natural, almost mechanical, consequence of immigrating later in life.

The results for auto loans and mortgages are different in terms of magnitude and dynamics. First, the cumulative delay is more modest. Ten years after the focal cohort's immigration, we estimate an average delay of 0.29 years for first mortgages, and a delay of 0.42 years for first auto loans. The shorter average delay for credit products typically accessed later in life suggests that

[29] For example, if we obtained an estimate of -0.2 in year T, -0.05 in year 1, and -0.03 in year 2 for credit card access, we could say that the focal cohort is delayed by an average of 0.2 years as of year T, an average of 0.25 years by year 1, and 0.28 years by year 2.

immigrants manage some degree of catch up over a ten year span. However, this catch up is not complete as of the end of the event window, and as the results in the previous section suggest, some immigrants might not access auto loans or home equity at any point in their lifecycle due to their later in life immigration dates.

Turning to the initial dynamics, only a small fraction of the delay in auto loan or mortgage access can be attributed to "mechanical delay" around the date of immigration. Instead, most of the delay emerges years after the immigration date, lining up with when in the lifecycle these products are typically accessed for the first time by non-immigrants. When taken together with the fact that immigrants in their thirties who immigrate at a later stage in their twenties have *higher* average credit scores throughout this period (Figure 2), the later-emergence and persistence of the delay in auto-loan and mortgage access constitute consequential longer-term effects of immigrating a single year later in life.

Finally, we see an interesting, non-monotonic difference in credit card limits for paired immigration cohorts, as displayed in panel C of Figure 7, and a similar pattern is observed in the number of credit cards in Appendix Figure A16 panel A. For the first eight years after the cohorts immigrate, we observe that the focal cohort has significantly lower credit card limits. This gap is at its widest two years after the focal cohort's year of SSN assignment, with average credit limits being $1,825 (s.e. $105) *lower* than those of the control cohort. However, the focal cohort's average credit limit overtakes the control cohort's average limit nine years after immigration. This gap grows over time, becoming significant from zero after eleven years. Thirteen years after the year of SSN assignment, the focal cohort's average credit limit is $707 (s.e. $162) *higher* than the control cohort's average limit.[30] This nonlinearity reflects the overarching tension inherent to immigration credit we find throughout this paper. On one hand, we find consistent evidence that immigrants and especially those who immigrate later in their twenties have substantially lower credit risk. Yet, their later entry into the U.S. credit system leaves them with less credit history. Thus, despite their better credit quality, their access to credit lags behind, in the case of auto loans and mortgages for at

[30] Two years after the year of SSN assignment, the focal cohort has 0.66 (s.e. 0.02) *fewer* credit cards, on average, than the control cohort's average. This negative effect has fully dissipated after eight years. After thirteen years, the focal cohort's average is 0.12 (s.e. 0.01) *higher* than the control cohort's average.

least thirteen years after immigrating.

5. Mechanisms

We now discuss the potential mechanisms that could explain our key results showing less access to credit for more creditworthy immigrants. Table 8 has a column summarizing each of our key credit access results, and a row for each of the potential mechanisms. Ticks denote where we find evidence in support of a mechanism explaining a key result, and crosses denote where we find evidence to rule a mechanism out. We evaluate each of these mechanisms in turn. Sections 5.1, 5.2, 5.3, and 5.4 respectively consider creditworthiness, emigration, tastes, and information frictions as potential mechanisms.

5.1 Creditworthiness

Our finding that immigrants (and later in life immigrants) typically have better credit scores and are less risky on other credit behaviors (e.g., lower delinquency rates and lower credit utilization) indicates that creditworthiness cannot explain our results. With higher credit scores, we would not expect lower long-term access to auto loans and mortgages, nor would we expect higher credit card limits to take a decade to materialize. Different consumer credit markets vary in their reliance on credit scores and credit histories, with credit card decisions typically more reliant on this information than auto loans or mortgages (Blattner et al., 2022).[31]

Further evidence ruling out creditworthiness is by taking our calibration bias approach, controlling for credit score at age 30 and studying credit outcomes at age 37. If creditworthiness explained subsequent credit access, then we would expect the coefficients on immigrants and age of immigration to become zero after controlling for credit score, however, Table A5 shows that our results remain. The exception is for credit cards, where the number of credit cards becomes significantly positive for immigrants compared to non-immigrants, and even more significantly positive for each additional year later in life of SSN Age. The result for credit card limits becomes insignificant from

[31] For example, Fannie Mae and Freddie Mac mortgage eligibility requirements depend not just credit scores, where credit histories are an input, but also loan-to-value and debt-to-income ratios calculated using verified income information, and the minimum liquid assets available to a consumer after closing.

zero, although the coefficient of an additional year later in life SSN Age remains significant and negative, consistent with our main results. The fact that the credit score groups where there are gaps in delinquency outcomes (panel A in both Figure 4 and Appendix Figure A12) are typically subprime, which do not correspond with the gaps in credit access that are typically superprime (panels B to F of these same Figures) also provides support that creditworthiness does not explain our results.

5.2 Emigration

One potential explanation for some of our results, especially lower long-term access to mortgages, could be emigration: consumers expecting to emigrate may be less likely to purchase property. Even if immigrants and non-immigrants were similarly likely to purchase property each year, emigration would mean that immigrants are present in our data for fewer years, making catch-up less likely. However, we find that the difference in mortgage access persists in the paired cohort analysis, which compares same-age immigrants assigned an SSN only one year apart. This suggests that emigration cannot fully explain these results, because we might naturally expect that, on average, a consumer who immigrates to the U.S. one year earlier to emigrate earlier. A similar logic applies to immigrants being more mobile than non-immigrants within the U.S. This may make immigrants less likely to want to purchase a house than non-immigrants. However, it is less clear why credit access would persistently differ between immigrants of the same age who immigrate one year later.

We consider the role of emigration by constructing proxies for emigration; measuring whether a consumer is no longer observed in our data. If a consumer no longer has a credit report or only has a non-missing credit score, then they may have died or have left the country (or their credit report was a fragment and merged with another report). Appendix Figure A17 shows that immigrants are more likely to exit our data than non-immigrants. It also shows that immigrants with younger SSN Ages exit before immigrants at older SSN Ages. These results are confirmed using our main regression specification presented in Appendix Table A10. Immigrants are significantly less likely to be observed in our data in 2024, but for each additional year of SSN Age beyond 21 they are marginally more likely to be observed. Appendix Figure A18 shows that emigration rates are higher for all SSN Ages above 18 than the SSN Age 18 baseline, and are broadly flat for SSN Ages 25 to 29, whereas emigration rates are decreasing in SSN Age 19 to 25.

After accounting for this differential attrition of immigrants and non-immigrants our key findings remain. We condition on consumers still present in the data in 2024 in Appendix Figures A19, separately for whether a consumer has any mortgage, any auto loan, or any credit card by age 37, and A20, for credit card outcomes (number of cards, limits, and limit per card), the results are consistent with our main Figures 5 and 6. The only slight difference is that with stricter sample restrictions, there is some convergence between SSN Age cohorts in their early twenties and the non-immigrant SSN Age 18 cohort. However, even then the same gaps in credit access emerge for the older SSN Age cohorts. Appendix Table A11 shows that the coefficients on SSN Age for whether a consumer has an auto loan, and especially a mortgage, by age 37 have larger negative sign (and the immigration indicators have a larger negative sign for auto loans and a larger positive sign for mortgages) than in the full sample results shown in Table 6 and Appendix Table A7. Therefore, while emigration is important, it does not appear to fully explain our results.

5.3 Tastes

We now turn to other potential mechanisms aside from the length of a consumer's U.S. credit history. One potential interpretation of these findings is that differences in consumers' credit demand drive differences in credit access. To shed light onto this potential mechanism, in Appendix Figure A15 we examine the outcome *months since last inquiry*, where a lower number of months since last inquiry indicates higher credit demand. On average, immigrants in their twenties have higher demand than non-immigrants. However, during their thirties, this pattern reverses and immigrants have lower demand. Appendix Figure A16 Panel B displays a pattern consistent with this result using the paired cohort design: the focal cohort has a significantly lower average time since last inquiry for up to five years (estimate after four years is -0.20 months, s.e. 0.04), indicating that they have *higher* demand for credit, and it is only after seven years that they have *lower* demand (estimate is 0.06 months, s.e. 0.02), stabilizing from years eleven onward (estimate after thirteen years is 0.35 months, s.e. 0.02). One caveat is that the lower credit demand later in the lifecycle may partly be a function of being deterred following earlier rejections. This suggests that delayed access to credit is not purely an artifact of delayed demand for credit for older SSN Age cohorts.

Although these demand differences are a plausible explanation for differences in credit card access, asset-linked credit (e.g., auto loans and mortgages) could also reflect differences in tastes for the underlying asset (i.e., immigrants may be less likely to purchase cars or more likely to rent), and to some degree, tastes for *financing* autos or homes (i.e., immigrants may be more likely to pay cash for these assets instead of financing them with debt or leasing, and, if using cash, would be unobserved in the credit reporting data). Immigrants are a heterogeneous group, with a variety of cultural backgrounds that vary in their familiarity and willingness to use debt. This would be expected to contribute some differences between immigrants and non-immigrants. However, we would not expect it to explain the differences in outcomes between immigrants who vary in SSN Age, in our paired cohorts analysis, or when controlling for birth year and geographic fixed effects.

We use the Survey of Consumer Finances (SCF) to explore this mechanism. As the survey is from 2022, the sample is conditional on *not* emigrating by this time. Given the smaller sample size, 1,813 respondents, these tests have lower statistical power than our main analysis, with our point estimates being less precisely estimated, and therefore we refer to the 95% confidence intervals.

We find that after controlling for birth year (and other demographic controls), immigrants are 6.2 percentage points (95% C.I.: -15.6 to 3.2) less likely to have an auto vehicle (irrespective of whether funded by an auto loan), relative to non-immigrants, relative to the non-immigrant mean of 89.2%. This is statistically insignificant from zero, however, the coefficient's size is broadly consistent with our main analysis. Conditional on having a car, immigrants are 12.5 percentage points (95% C.I.: -2.2 to 27.3) more likely to use cash to purchase any of their cars, a result that is statistically significant at the 10% threshold. These results are shown in Appendix Table A12.

Turning to credit attitudes for one explanation for the auto loan gap between immigrants and non-immigrants, we find significant differences in attitudes towards auto loan debt. The variable about auto debt attitudes is a binary variable that asks whether a respondent feels it is all right for someone like themselves to borrow money to finance the purchase of a car, which we code as a value of 1 if they respond yes and 0 if they respond no, with the mean for non-immigrants is 79.6%. Using this attitude towards auto debt variable, Appendix Table A13 shows that immigrants have an average of -22.7 percentage points (95% C.I.: -36.7 to -8.8) lower attitude towards purchasing an automobile with debt, a point estimate that is statistically significant at the 0.5% level. Reinforcing this difference in attitudes, Appendix Table A14 shows that immigrants are 12.0 percentage points less likely to demand auto loans than non-immigrants (95% C.I.: -22.2 to -1.8 percentage points) based on their likelihood of applying for an auto loan in the last twelve months. Both of these results, immigrant aversion to auto loans and lower auto loan demand, are slightly attenuated for each additional age of immigrating to America.

Therefore, this evidence from the SCF is consistent with immigrants having a greater aversion to purchasing autos with debt than non-immigrants, which could explain the persistent gaps in auto loan access by immigrants relative to non-immigrants in the credit data. We did not find a robust difference between immigrants and non-immigrants in their mortgage use in credit data. Similarly, though the evidence is much less strong, with no statistically significant results, there is suggestive evidence that any mortgage gap between immigrants and non-immigrants is also explained by similar demand differences.[32]

These patterns are consistent with suggestive evidence of a broader immigrant aversion to debt, with immigrants being more negative in their views of borrowing for different purposes than non-immigrants, except for financing education (Appendix Table A13) and also being less likely to apply for any type of credit (Appendix Tables A14) and report being more likely to not apply because they did not need credit (Appendix Table A15). All of these results are statistically insignificant

[32]Appendix Table A12 shows that, if anything, immigrants appear slightly less likely to own a home (point estimate of -2.4 percentage points, 95% C.I.: -10.8 to 15.6 percentage points), a result that is statistically insignificant from zero at the 10% level. Conditional on owning a home, immigrants are more likely to have no mortgage (point estimate of 7.0 percentage points, 95% C.I: -8.5 to 22.5), however, this is also statistically insignificant from zero at the 10% level. Appendix Table A14 shows that immigrants are more likely to apply for a mortgage than non-immigrants (point estimate of 6.3 percentage points with a 95% confidence interval of -7.5 to 20.0 percentage points), again this result is statistically insignificant from zero at the 10% level.

from zero because of a lack of power, so should be treated with caution.

We generally do not find any statistically significant effects on measures of supply restrictions, with one exception. The exception is that of the subset of consumers that are rejected in their application for credit, and also decide to reapply, immigrants are 48.6 percentage points (95% C.I.: 11.1 to 86.2) significantly more likely to have their reapplication rejected. Although, there are only 178 observations in this regression, and 17 immigrants so it is a highly selected, small subset of immigrants and non-immigrants.

Our results are organized around life cycles defined by consumers' birth years. However, it is possible that immigrants' life cycles are instead more closely linked to when they arrive in the United States — when their American labor market and immigrant experience begins. For example, being in the country for an additional year means that they always have one more year of potentially buying an auto or a house than an immigrant that arrives one year later, and therefore we may not expect complete catch-up. Arriving in America earlier in life may also mean that a consumer is better assimilated or integrated into the American economy, and better able to understand the American credit system. Such differences may be most pronounced in the initial years after arrival, but if they have longer-term persistence, they might contribute to the absence of full catch-up in some credit access outcomes. One way to think about this mechanism is to regard America as an area of opportunity to which consumers are moving to, given that even relatively impoverished neighborhoods in America are wealthy compared to much of the rest of the world. Our finding that small differences in arriving in America at slightly younger adult ages lead to a persistent effect on improved credit access is somewhat conceptually similar to how moving to a higher opportunity neighborhood within America at slightly younger ages has persistent effects on childhood outcomes (e.g. Chetty et al., 2016, Bakker et al., 2025), although Keys et al. (2023) do not find differential effects of intra-American movers on financial distress if they moved at younger ages of adulthood.

5.4 Information Frictions

Given the direct link between later in life immigration and shorter length of U.S. credit history, a plausible mechanism for our findings is that whether a consumer has any credit report, and the length of a consumer's credit history itself may be an important factor in lending decisions beyond credit scores.[33] Our strongest evidence on this point is that immigrants' first credit scores are higher and their average credit scores are higher than non-immigrants who are the *same age*, yet immigrant credit access is delayed for credit cards.

These findings suggest that the inability to port information on credit histories across national boundaries represents a significant market friction. This information friction appears to operate beyond the mechanics of credit scoring itself, as immigrants achieve high scores relatively quickly, despite a shorter credit history being a negative input into credit scores, but access certain credit products later. For financial institutions, our findings indicate untapped opportunities in the immigrant market segment. The combination of immigrants' relatively strong creditworthiness with restricted access points to potential opportunities in auto and mortgage financing, where delays are most pronounced.

Consistent with the existence of profitable opportunities, the market is now developing a variety of solutions. Some lenders, such as American Express, have linked data across countries to give immigrant consumers that hold a credit card with them elsewhere the opportunity to easily apply for an American Express credit card in the United States by considering their foreign repayment history.[34] FinTech firms, such as Nova Credit, and established credit bureaus are making progress on infrastructure to enable pulling foreign credit histories and translating foreign credit scores into consistent formats that lenders can use.[35] FinTech lenders, such as MPower Financing and Prodigy Finance, provide student finance to foreign students at leading universities, demonstrating

[33] If credit history length itself is the mechanism (separately from its effects on credit scores), then retaining positive credit information for shorter periods may be a more efficient credit market design, as indicated by the Kovbasyuk and Spagnolo (2024) model. Blattner et al. (2022) find that shorter credit histories have trade-offs, reducing credit for some existing borrowers but helping new consumers to enter the credit market.

[34] https://www.americanexpress.com/us/customer-service/global-card-relationship/

[35] https://fintechmagazine.com/articles/nova-credit-expands-fintech-reach-with-hsbc-sofi-deals, https://newsroom.transunion.ca/transunion-partners-with-nova-credit--to-improve-financial-access-for-new-canadians/, https://www.equifax.ca/about-equifax/press-releases/-/intlpress/equifax-canada-champions-financial-inclusion-for-newcomers-to-canada-with-the-launch-of-global-consumer-credit-file/

that lending to such groups can be profitable. To traditional lenders, such immigrants may appear high risk to lend to, given no U.S. credit history or income while studying, however, these FinTechs use foreign credit information and, by screening on which universities and degrees, can ensure that they only lend to immigrants that are expected to have a high and growing incomes after graduating and so are likely to repay their student debt.[36]

Aside from policy implications, this idea also has old theoretical roots. Pagano and Jappelli (1993) shows theoretically that credit bureaus fill an important role in reducing adverse selection by tracking consumers who move geographic locations. In addition, there is an emerging use of "cash-flow underwriting," using checking account information (e.g., Berg et al., 2020, Alok et al., 2025, Chioda et al., 2025), often via open banking (e.g., Babina et al., 2025), and using a variety of alternative data sources, including mobile phone behaviors (e.g., Björkegren and Grissen, 2020), grocery data (e.g., Lee et al., 2025a,b), and non-traditional credit reporting data (e.g., Blattner and Nelson, 2024, Jansen et al., 2025, Laudenbach et al., 2025), for lending decisions around the world. Such FinTech innovations may enable underwriting credit to immigrants and non-immigrants with no credit history, or a thin history such that no credit score can be calculated, who lenders may otherwise deem too risky to lend to (e.g., Blattner and Nelson, 2024, Chioda et al., 2025).

6. Conclusion

This study offers the first large-scale empirical examination of immigrants' assimilation into the U.S. consumer credit system. We document how immigrants compare to non-immigrants, and immigrants arriving later in life, in their creditworthiness and credit usage over the lifecycle.

Our evidence paints a nuanced picture: upon credit market entry, immigrants are positively selected in their creditworthiness. By age 30, immigrants' average credit scores are 20 points higher than non-immigrants. These differences remain just as significant after including ZIP code fixed effects. Yet, despite their superior measured creditworthiness, we show that immigrants are persistently less likely to access auto loans, with delays lasting through the end of our sample period

[36] https://www.bloomberg.com/news/articles/2025-06-25/foreign-grad-students-targeted-by-lenders-as-fast-growing-market

to age forty. This disconnect between creditworthiness and credit access is striking: Even though immigrants have *observably* higher credit in their thirties, their access to major credit products, most notably mortgages, is delayed. Moreover, immigrants even have persistently delayed credit access relative to same-aged immigrants who arrive in the United States a year earlier.

We find a persistent gap in auto loan use by immigrants compared to non-immigrants. This appears to be explained by immigrants being significantly more averse than non-immigrants to purchasing autos with debt.

There are persistent differences in credit access arising from one-year differences in the age of immigrating to America that may be partially due to credit market information frictions. As the foreign-born population in the United States approaches historic highs, addressing credit market information frictions is increasingly important. The delayed access to major credit products, especially mortgages, may impede immigrants' ability to build wealth through homeownership (Bernstein and Koudijs, 2024), and not experience the broader economic benefits of homeownership (e.g., Sodini et al., 2023, Disney et al., 2025, Fazio et al., 2025). Our findings suggest that the U.S. financial system, while efficient in many respects, leaves significant value on the table when it comes to immigrant access to credit. Resolving these inefficiencies represents not only an opportunity for financial innovation, but also a pathway to enhancing the already substantial economic contributions of America's immigrant population.

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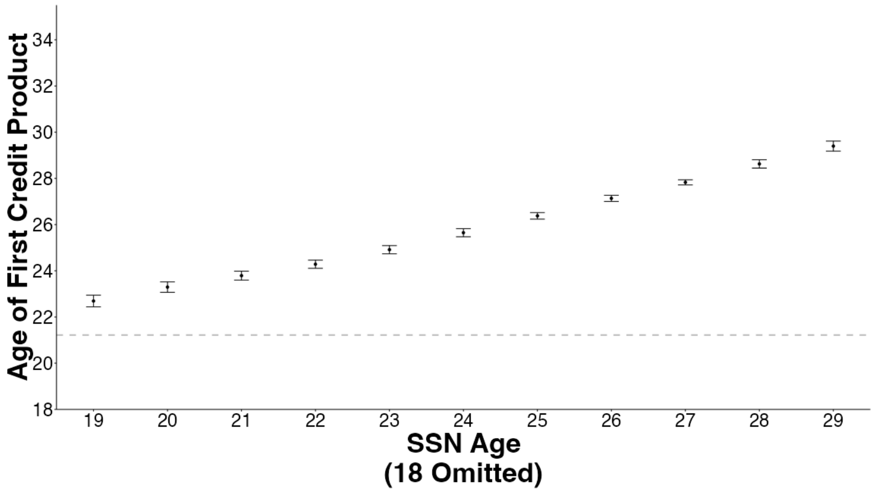
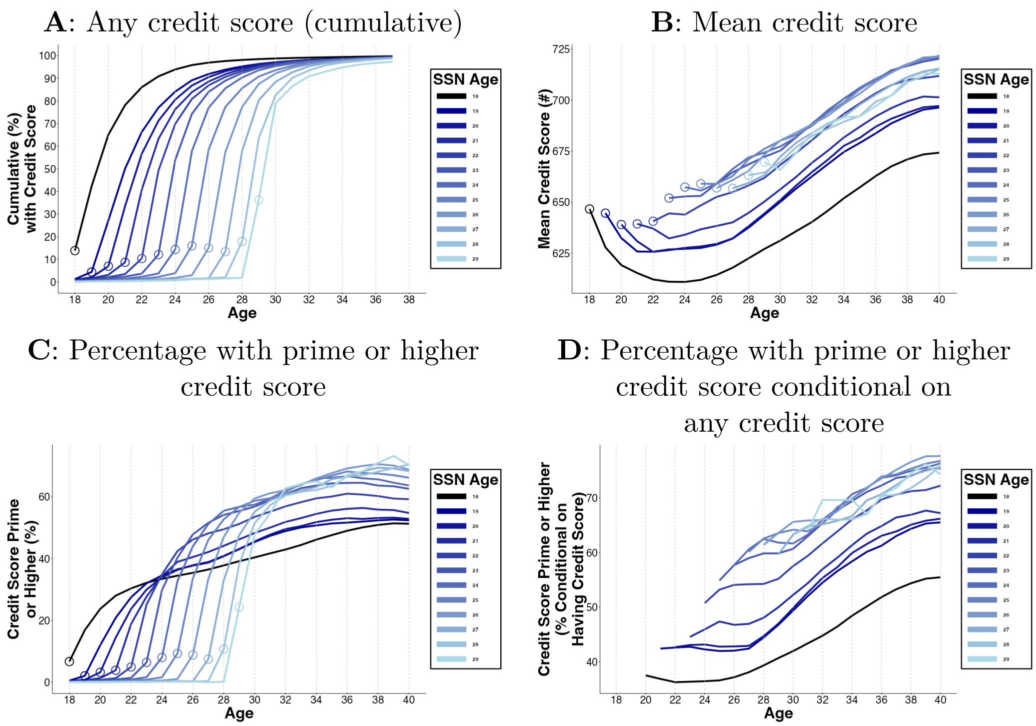
Figure 1: Mean age of first U.S. credit product by SSN Age



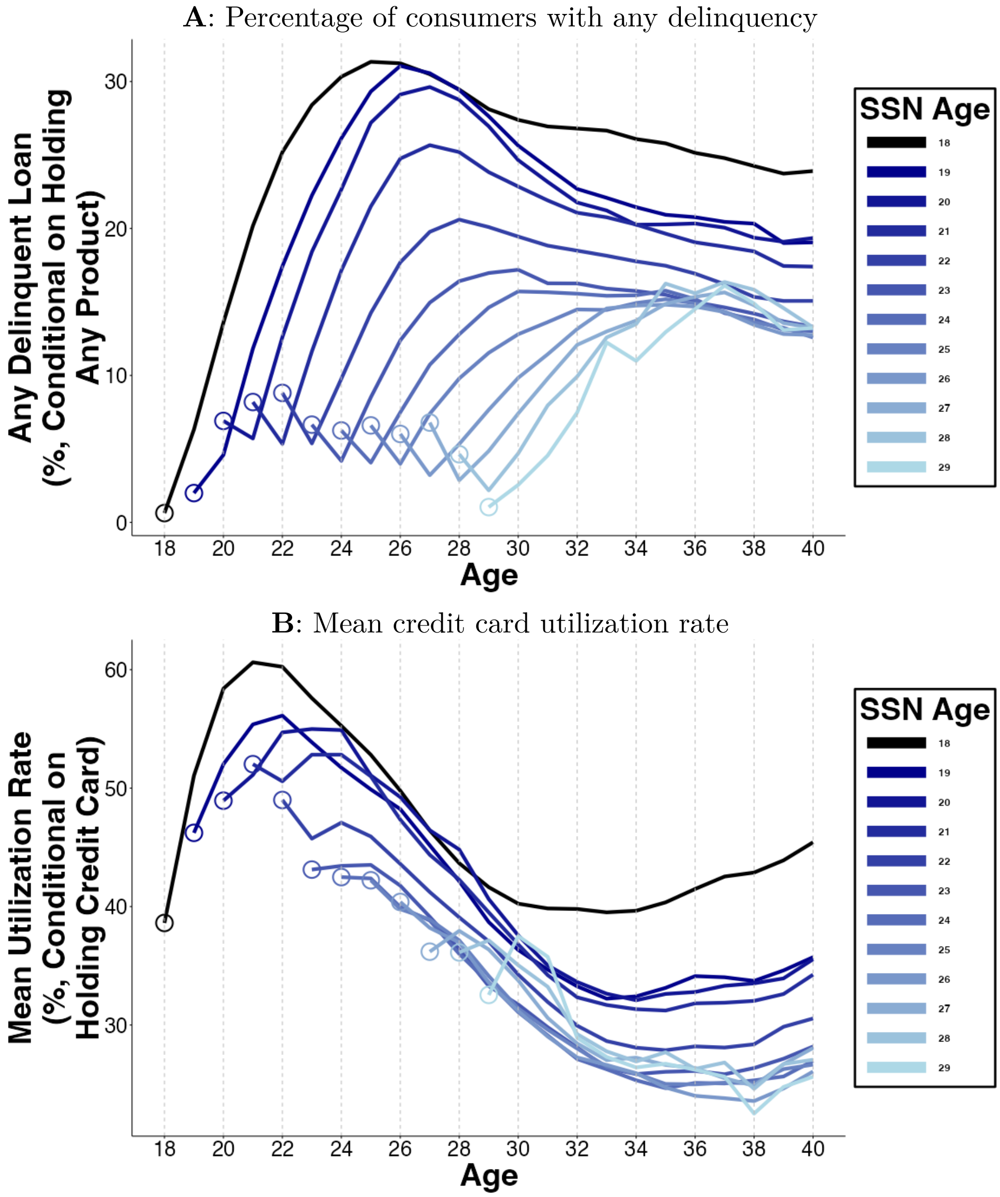
This figure presents graphical evidence on the timing of entry into U.S. consumer credit markets relative to a consumer's date of SSN assignment. The estimates (and 95% confidence intervals) are constructed from an individual-level regression of Age at first credit product on SSN Age fixed effects and Birth Year fixed effects. The baseline mean for the omitted category (SSN Age 18 or younger) is indicated by the dashed horizontal gray line and is 21.22 (this is effectively the same as the mean for SSN Age 21 or younger at 21.25). Standard errors are clustered by birth year.

Figure 2: Lifecycle of credit scores by SSN Age cohorts



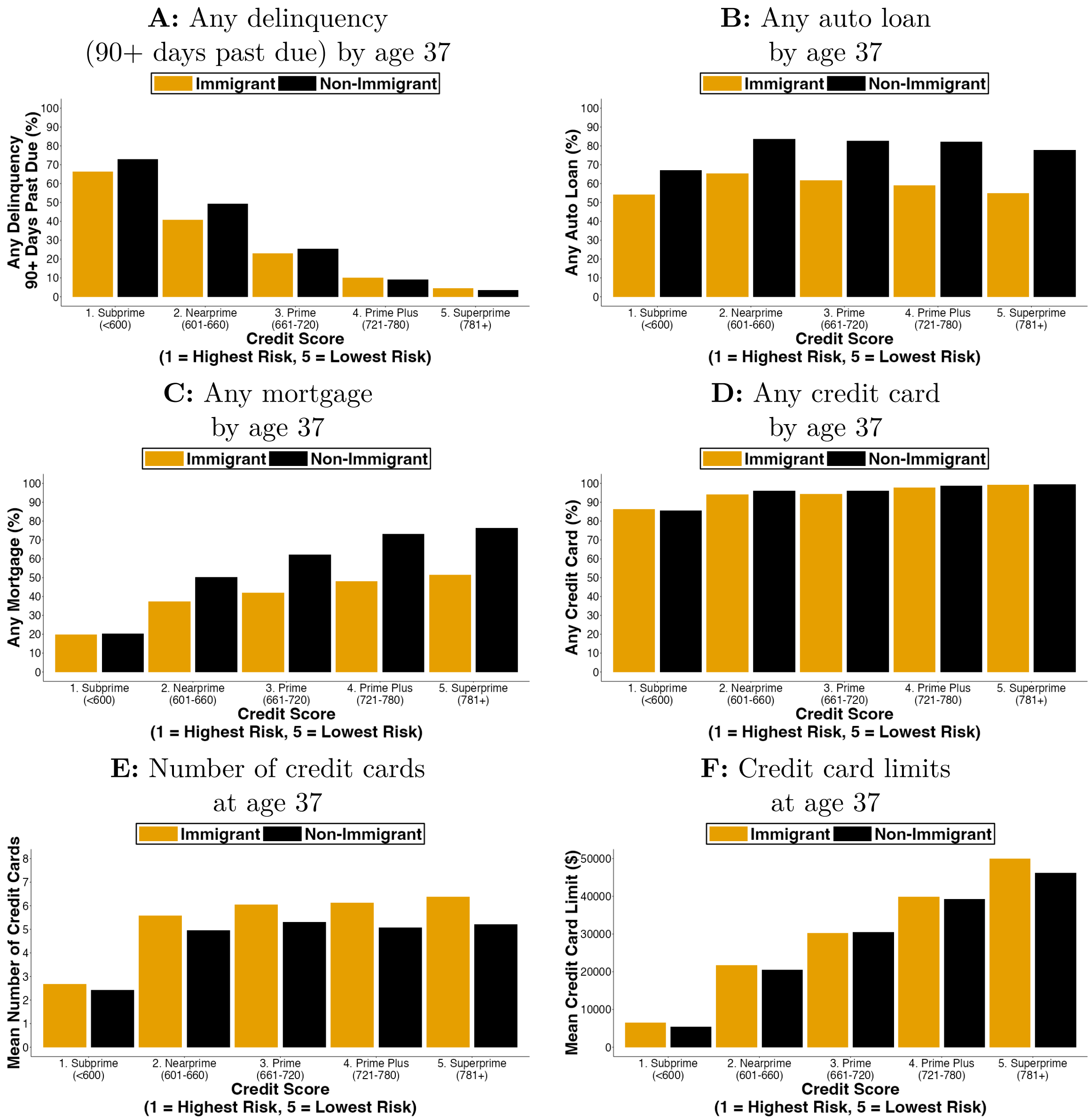
For each SSN Age cohort, this figure shows the share of consumers at each age with Any Credit Score (Panel A), Mean Credit Score conditional on having any credit score (Panel B), with Prime or Higher Credit Score (Panel C), and with Prime or Higher Credit conditional on having any credit score (Panel D). Panel A presents the cumulative fraction of consumers that have been credit scored by each age. In all panels, credit scores are measured by VantageScore. In Panels C and D, Prime or Higher Credit Score is a VantageScore of 660 or higher. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This figure uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024. Because Panel A is a cumulative chart we end it at age 37, whereas for the other panels the estimates for ages 38-40 account for this attrition.

Figure 3: Lifecycle of delinquencies and utilization by SSN Age cohorts



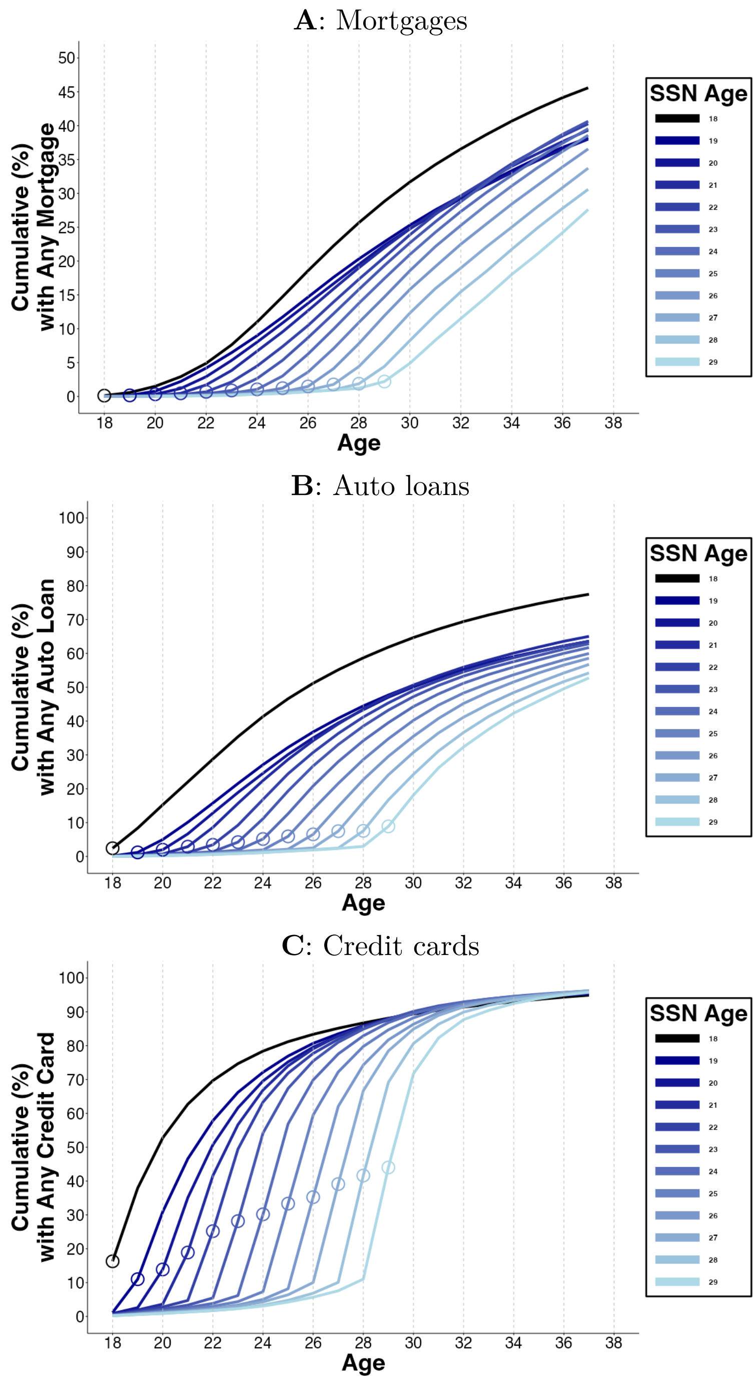
For each SSN Age cohort, this figure shows the share of consumers at each age with any delinquency (Panel A) the cohort's mean utilization rate (Panel B) by age. These averages are conditional on having a credit line. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024; the estimates for these ages account for this attrition.

Figure 4: Credit outcomes by age 37 conditional on credit score at age 30



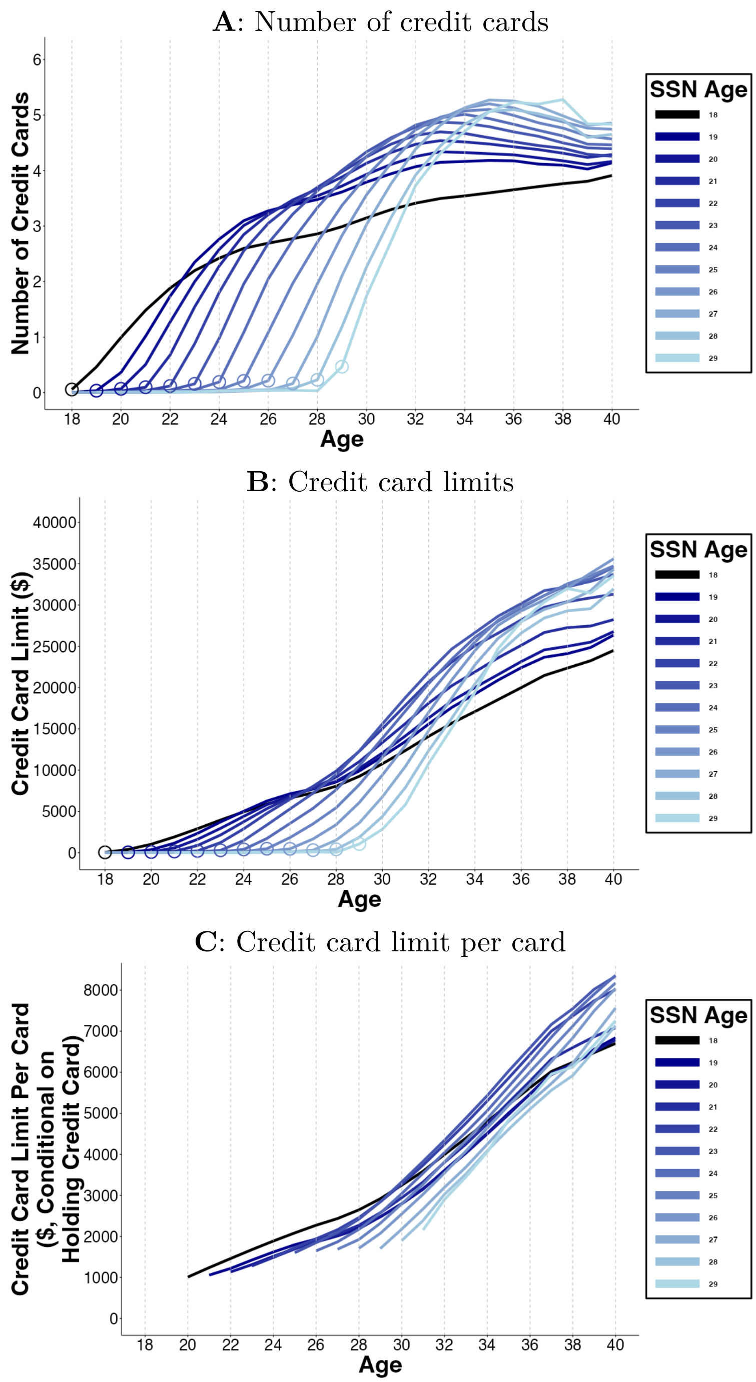
Each panel shows mean outcomes measured at age 37 conditional on a consumer's credit score measured at age 30. Each panel splits results by immigrants and non-immigrants, where immigrants are those with a SSN Age of 21+.

Figure 5: Lifecycle of credit access by type of credit and SSN Age cohorts



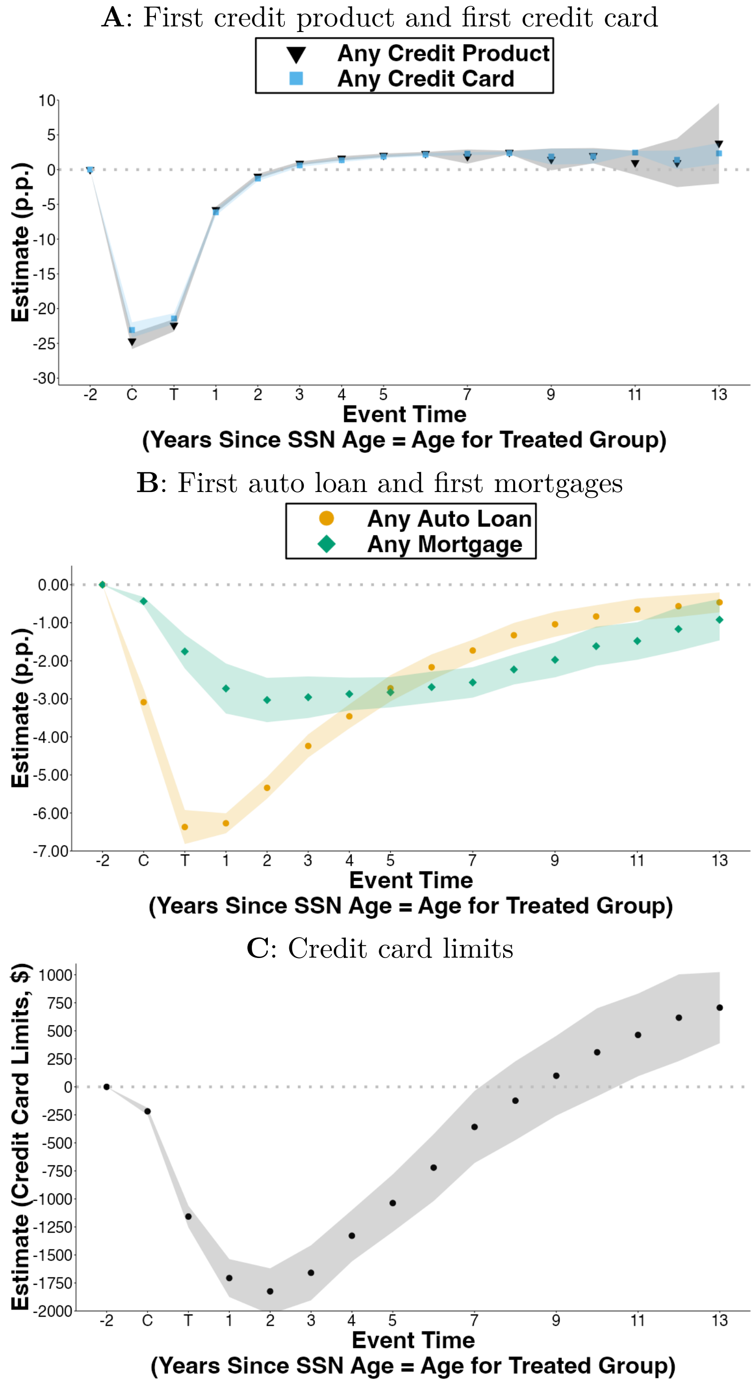
For each SSN Age cohort, this figure shows the cumulative share of consumers at each age who have ever had a mortgage (Panel A), an auto loan (Panel B), or a credit card (Panel C). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1975 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024, and so we end these charts at age 37.

Figure 6: Lifecycle of credit cards by SSN Age cohorts



For each SSN Age cohort, this figure shows the evolution of credit card limits over the lifecycle: number of credit cards (Panel A), total credit card limits (Panel B), and credit card limits per card (Panel C). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024; estimates for these ages account for this attrition.

Figure 7: Paired cohorts: Dynamics of credit access



This figure presents dynamic estimates for differences in credit access between a cohort with SSN Age = s and a cohort with SSN Age = $s-1$ matched at the same age. The differences are presented in event time where C is the year when age equals SSN Age for the $s-1$ cohort and T is the same for the s cohort. Credit access corresponds to first credit product and first credit card in Panel A, first auto loan and first home mortgage in Panel B, and credit card limits in Panel C. The shaded areas indicate 95% confidence intervals, clustering standard errors by birth year.

Table 1: Sample construction

This table presents an observation funnel that details how we obtain our final sample starting from the full BTCCP 10% sample. As each sample restriction is applied, the table details how the number of consumers changes, until we obtain the dataset used for our analysis: the *Entrant Sample*.

TransUnion Consumers	
... born 1951 to 2004	31,869,445
... with a SSN in TransUnion	25,237,917
Clean Sample	18,572,654
... SSN Age <21	16,478,940
... SSN Age 21+	2,093,714 (11.27%)
... Immigrant Cohorts (Birth Year x SSN Year)	775
Entrant Sample (SSN Age < 30)	6,122,932
... SSN Age < 21	5,778,671
... SSN Age 21-29	344,261 (5.62%)
... Immigrant Cohorts (Birth Year x SSN Year)	102

Table 2: Immigrant versus non-immigrant credit profiles

This table presents means and counts, separately for immigrants (*SSNAge* 21+) and non-immigrants (*SSNAge* < 21), for our main (entrant) sample. Instances of "Any" in this table, such as "Any Credit Card," indicate whether the consumer is ever observed to have a credit card in the sample.

	Non-Immigrants *SSN Age < 21*		**Immigrants** *SSN Age 21+*	
	Mean	# Consumers	Mean	# Consumers
Credit Report				
Age at First Credit Report	19.86	5,778,671	25.21	344,261
Credit Score				
Any Score by Age 30 (%)	97.57	5,778,671	88.14	344,261
Credit Score at Age 30	626.1	5,461,785	660.7	293,349
Any Score by Age 40 (%)	99.61	4,487,804	99.08	312,391
Credit Score at Age 40	659.5	4,179,752	698.9	270,177
Auto Loan				
Any Auto Loan (%)	82.11	5,778,671	69.07	344,261
Age at First Auto Loan	26.03	4,745,108	30.30	237,797
Mortgage				
Any Mortgage (%)	51.13	5,778,671	47.62	344,261
Age at First Mortgage	29.49	2,954,699	32.73	163,937
Credit Card				
Any Credit Card (%)	97.16	5,778,671	97.85	344,261
Age at First Credit Card	22.07	5,614,625	26.42	336,869
Credit Card Limits				
Age 30	$11,733	5,778,671	$11,193	344,261
Age 40	$22,477	4,487,804	$28,158	312,391

Table 3: Timing of credit market entry

This table presents OLS estimates from the cross-sectional regression specified in Equation 2 that includes an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1 and 4 do not include any fixed effects. Columns 2, 3, 5, and 6 include fixed effects for the birth year of the consumer. Columns 3 and 6 also include fixed effects for consumers' first observed ZIP code. The outcome in columns 1 to 3 is age at first credit report, and in columns 4 to 6 it is age at first credit product. In these regressions, consumers who never have a credit report or never have a credit product are assigned their age as of 2025. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Dep Var: Age at First...	Credit Report			Credit Product		
	(1)	(2)	(3)	(4)	(5)	(6)
21+	1.989***	1.972***	1.809***	1.680***	1.665***	1.618***
	(0.119)	(0.101)	(0.088)	(0.129)	(0.112)	(0.106)
SSN Age	0.782***	0.740***	0.744***	0.744***	0.704***	0.720***
	(0.027)	(0.015)	(0.014)	(0.026)	(0.017)	(0.016)
Birth Year F.E.		X	X		X	X
First Zip5 F.E.			X			X
R^2	0.239	0.267	0.289	0.077	0.087	0.129
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	19.864	19.864	19.864	21.251	21.251	21.251

Table 4: Credit scores at ages 30 and 40

This table presents OLS estimates from the cross-sectional regression specified in Equation 2 that includes an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1 and 4 do not include any fixed effects. Columns 2, 3, 5, and 6 include fixed effects for the birth year of the consumer. Columns 3 and 6 also include fixed effects for consumers' first observed ZIP code (First ZIP5 FE). The outcomes in panel A are average credit score, measured by VantageScore, at ages 30 or 40. The outcomes in panel B are the likelihood of prime credit, measured by a VantageScore of 660 or higher, at ages 30 or 40. Standard errors are clustered by birth year. $^*p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Panel A: Average credit scores

Dep Var: Credit Score at ...		Age 30			Age 40	
	(1)	(2)	(3)	(4)	(5)	(6)
21+	23.3***	23.7***	18.8***	31.5***	32.3***	25.8***
	(2.3)	(2.1)	(1.6)	(0.6)	(0.7)	(0.7)
SSN Age	2.7***	3.2***	2.0***	1.7***	2.4***	1.5***
	(0.5)	(0.4)	(0.4)	(0.4)	(0.2)	(0.2)
Birth Year F.E.		X	X		X	X
First Zip5 F.E.			X			X
R^2	0.005	0.009	0.135	0.008	0.022	0.132
N	5,755,134	5,755,134	5,755,134	4,449,929	4,449,929	4,449,929
Mean, SSN Age <21	626.1	626.1	626.1	659.5	659.5	659.5

Panel B: Likelihood of prime or higher credit score

Dep Var: Prime or Higher at ...		Age 30			Age 40	
	(1)	(2)	(3)	(4)	(5)	(6)
21+	9.35***	9.50***	7.63***	3.86***	4.08***	2.01***
	(0.93)	(0.83)	(0.74)	(0.31)	(0.29)	(0.14)
SSN Age	0.01	0.29	-0.08	1.71***	1.92***	1.58***
	(0.28)	(0.23)	(0.20)	(0.14)	(0.10)	(0.09)
Birth Year F.E.		X	X		X	X
First Zip5 F.E.			X			X
R^2	0.002	0.006	0.104	0.004	0.010	0.092
N	6,122,932	6,122,932	6,122,932	4,800,195	4,800,195	4,800,195
Mean, SSN Age <21	37.71	37.71	37.71	46.84	46.84	46.84

Table 5: Credit market access by type of credit

This table presents OLS estimates from individual-level regressions for the age at first credit card, age at first auto loan, and age at first mortgage, on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1, 4, and 7 do not include any fixed effects. Columns 2, 3, 5, 6, 8, and 9 include fixed effects for the birth year of the consumer. Columns 3, 6, and 9 also include fixed effects for consumers' first observed ZIP code (First ZIP5 FE). Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Dep Var: Age at First...		Credit Card			Auto Loan			Mortgage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
21+	1.172***	1.160***	1.367***	2.954***	2.930***	1.967***	0.831***	0.781***	0.219*
	(0.182)	(0.169)	(0.158)	(0.239)	(0.217)	(0.217)	(0.124)	(0.097)	(0.083)
SSN Age	0.696***	0.663***	0.691***	0.673***	0.612***	0.619***	0.504***	0.403***	0.432***
	(0.030)	(0.022)	(0.020)	(0.045)	(0.023)	(0.024)	(0.048)	(0.018)	(0.018)
Birth Year F.E.		X	X		X	X		X	X
First Zip5 F.E.			X			X			X
R^2	0.029	0.033	0.085	0.025	0.030	0.082	0.008	0.024	0.081
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	22.677	22.677	22.677	29.151	29.151	29.151	36.356	36.356	36.356

Table 6: Credit access by type of credit by age 37

This table presents OLS estimates from individual-level regressions for whether the consumer has a credit card, an auto loan, or a mortgage at or before age 37 (i.e., 8 or more years after immigration for all immigration cohorts in our sample) on an indicator for immigration status ("21+," an indicator for whether the consumer's SSN was assigned at age 21 or older) and and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1, 4, and 7 do not include any fixed effects. Columns 2, 3, 5, 6, 8, and 9 include fixed effects for the birth year of the consumer. Columns 3, 6, and 9 also include fixed effects for consumers' first observed ZIP code (First ZIP5 FE). Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Dep. Var: By Age 37, has ...		Credit Card			Auto Loan			Mortgage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
21+	0.93***	0.97***	0.15	-10.24***	-10.22***	-6.87***	-2.19***	-2.28***	0.39
	(0.19)	(0.16)	(0.16)	(0.38)	(0.37)	(0.46)	(0.55)	(0.56)	(0.53)
SSN Age	0.03	0.10*	0.04	-1.48***	-1.42***	-1.44***	-1.34***	-1.58***	-1.77***
	(0.05)	(0.04)	(0.03)	(0.10)	(0.09)	(0.10)	(0.1)	(0.09)	(0.09)
Birth Year F.E.		X	X		X	X		X	X
First Zip5 F.E.			X			X			X
R^2	< 0.001	0.002	0.025	0.008	0.009	0.039	0.002	0.005	0.063
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	94.93	94.93	94.93	77.22	77.22	77.22	45.46	45.46	45.46

Table 7: Cumulative years of delayed access to credit from paired cohorts

This table presents estimates of cumulative years of delayed access to credit due to immigration occurring a single year later, obtained from the paired cohort strategy. The row "C" indicates the year in which the control group (which immigrated 1 year earlier tan the treatment group) is assigned an SSN while "T" is the year of the focal (or treatment) cohort's immigration. The specification includes all year lags from C through 13 years after the treatment cohort's immigration, and the omitted category is $t-2$. Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

	Any Credit Score	Credit Product	Credit Card	Auto Loan	Mortgage
	(1)	(2)	(3)	(4)	(5)
C	-0.085***	-0.272***	-0.254***	-0.033***	-0.005***
	(0.002)	(0.005)	(0.005)	(0.002)	(0.001)
T	-0.432***	-0.521***	-0.491***	-0.100***	-0.024***
	(0.009)	(0.009)	(0.009)	(0.004)	(0.003)
5	-0.712***	-0.667***	-0.640***	-0.332***	-0.173***
	(0.013)	(0.013)	(0.013)	(0.010)	(0.017)
10	-0.742***	-0.690***	-0.648***	-0.415***	-0.288***
	(0.016)	(0.018)	(0.016)	(0.017)	(0.028)
N Paired Cohorts	68	68	68	68	68
N Consumers	403,506	403,506	403,506	403,506	403,506
N	6,456,096	6,456,096	6,456,096	6,456,096	6,456,096

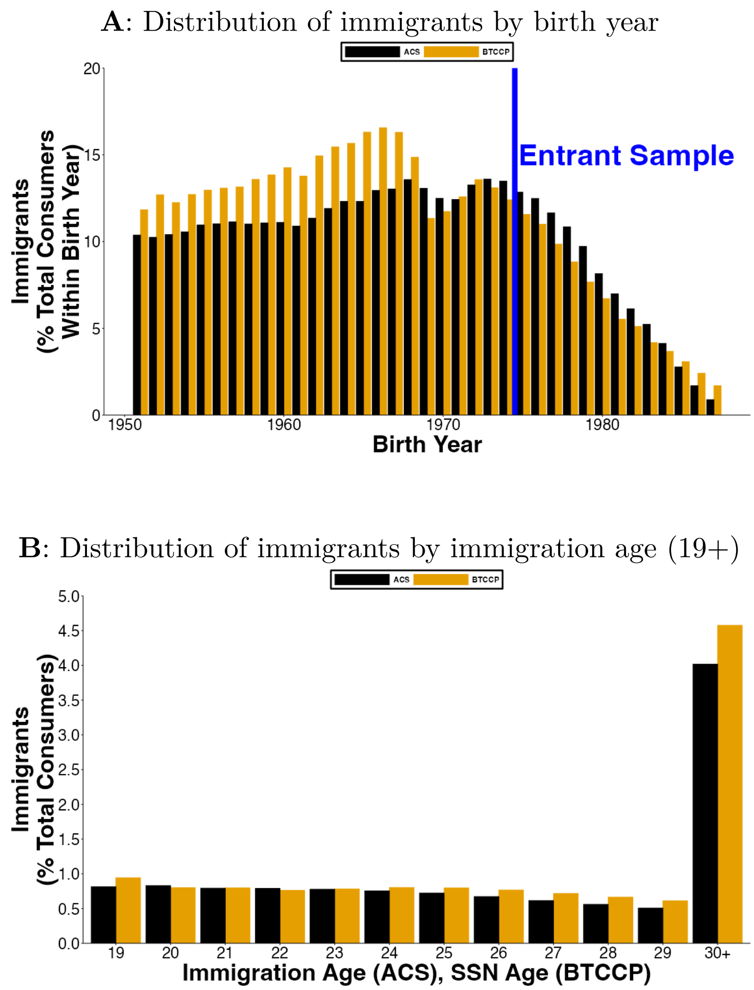
Table 8: Mechanisms explaining key credit access results of lower

	↓ Immigrant (Vs. Non-Immigrant) Use Of...	↓ Use By Immigrants Arriving at Older (Vs. Younger) Ages...		Immigrants Arriving At Older (Vs. Younger) Ages Have...	
				Lower Early	Higher Later
Potential Mechanisms	Auto Loans	Auto Loans	Mortgages	Credit Card Limits	
	(1)	(2)	(3)	(4)	(5)
A. Creditworthiness	✗	✗	✗	✗	✓
B. Emigration	✗	✗	✗	✗	✗
C. Tastes	✓	✓	✓	✓	✓
D. Information Frictions		✓	✓	✓	✓

A. Supplemental Appendix: Immigration and Credit in America

by J. Anthony Cookson, Benedict Guttman-Kenney and William Mullins[1]

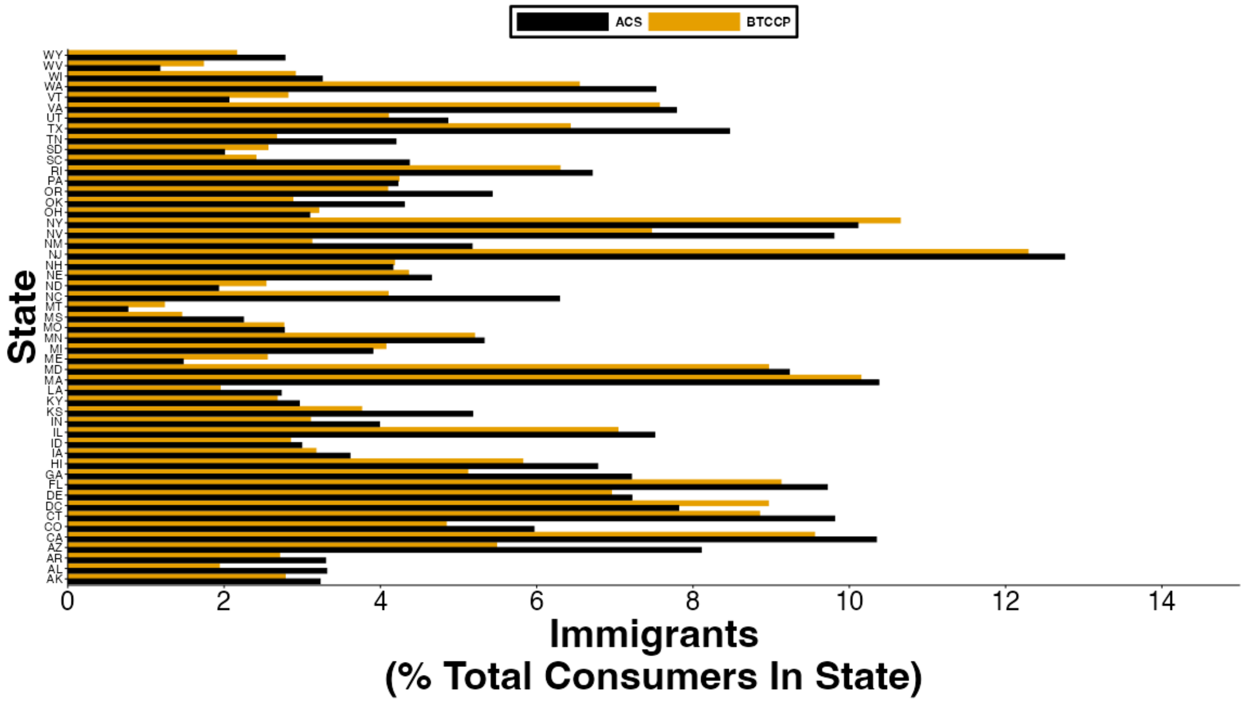
Figure A1: Immigrant classification in our data (BTCCP) versus the American Community Survey (ACS)



This figure compares our classification of immigrants in the Booth TransUnion Consumer Credit Panel (BTCCP) to comparable statistics computed from the American Community Survey (ACS). Panel A presents the share of immigrants in each birth year in the ACS (black) versus BTCCP (yellow). In Panel A, immigrants are defined as SSN at age 21+ in the BTCCP and if their age of immigration is 21+ in the ACS. The birth years to the right of the blue vertical line are the "Entrant Sample" of birth years 1975 to 1987 that are used for our analysis. Panel B presents the share of each sample by age at immigration, non-immigrants or those that immigrate at age 18 or younger are included in the denominator but the bar is excluded from this figure to ease presentation, it is 88.15% for the ACS and 86.98% for the BTCCP.

[1]Cookson: CU Boulder, tony.cookson@colorado.edu; Guttman-Kenney: Rice University, benedictgk@rice.edu; Mullins: UC San Diego, wmullins@ucsd.edu.

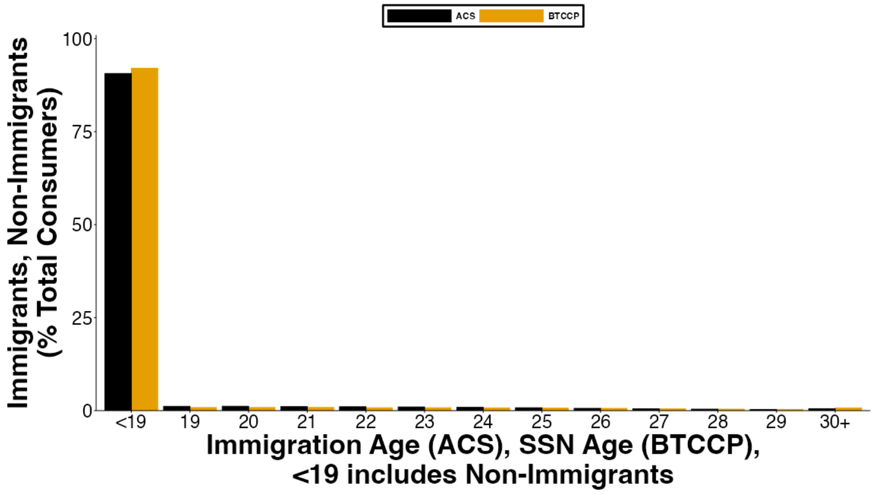
Figure A2: Geography of immigrant classification in our data (BTCCP) compared to the American Community Survey (ACS)



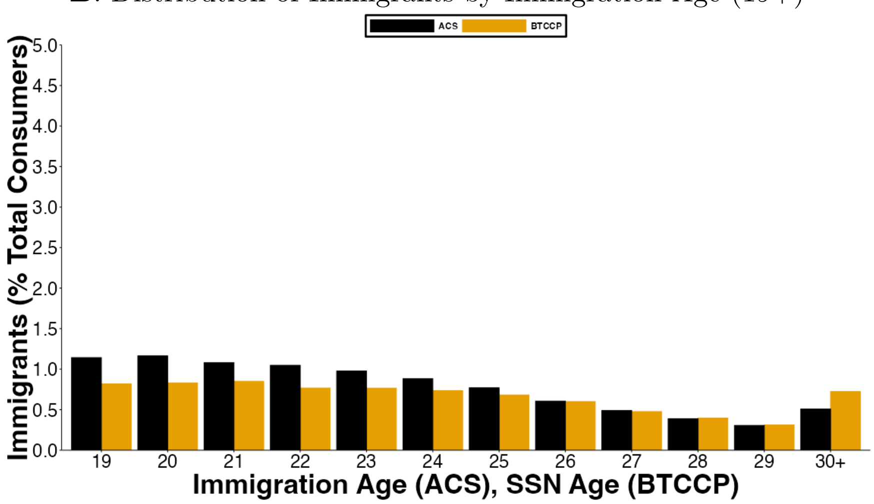
This figure presents a state-by-state comparison of the percentage of immigrants in the BTCCP data (yellow) versus the percentage of immigrants in the ACS sample. Geographic location is as of July 2012 in the BTCCP, with consumers not present at that time excluded. Immigrants are defined as SSN at age 21+ in the BTCCP and if their age of immigration is 21+ in the ACS.

Figure A3: Immigrant classification in our data (BTCCP) versus the American Community Survey (ACS) for entrant sample, with SSN Age 30+ added

A: Distribution of Non-Immigrants and Immigrants by Immigration Age



B: Distribution of Immigrants by Immigration Age (19+)



This figure compares our classification of immigrants in the BTCCP Entrant Sample to comparable statistics computed from the American Community Survey (ACS). The figure shows bars for immigrants with Age of Immigration (ACS) / SSN Age of 30+, these are consumes who are not included in the Entrant Sample used for analysis.Panel A presents the share of immigrants by immigration age, where < 19 includes non-immigrants or those that immigrate at age 18 or younger. Panel B presents a zoomed in version of Panel A that only shows the bars for the subset of immigration ages from 19 to 30+.

Figure A4: Sample frame and timing of SSN assignment

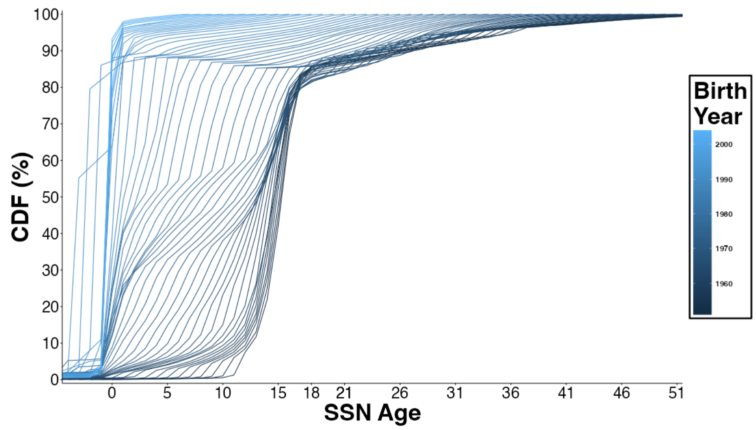
Birth year

Calendar year	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	
1993	≤18													
1994	19	≤18												
1995	20	19	≤18											
1996	21	20	19	≤18										
1997	22	21	20	19	≤18									
1998	23	22	21	20	19	≤18								
1999	24	23	22	21	20	19	≤18							
2000	25	24	23	22	21	20	19	≤18						
2001	26	25	24	23	22	21	20	19	≤18					
2002	27	26	25	24	23	22	21	20	19	≤18				
2003	28	27	26	25	24	23	22	21	20	19	≤18			
2004	29	28	27	26	25	24	23	22	21	20	19	≤18		
2005	30	29	28	27	26	25	24	23	22	21	20	19	≤18	
2006	31	30	29	28	27	26	25	24	23	22	21	20	19	
2007	32	31	30	29	28	27	26	25	24	23	22	21	20	
2008	33	32	31	30	29	28	27	26	25	24	23	22	21	*Age at SSN assignment*
2009	34	33	32	31	30	29	28	27	26	25	24	23	22	
2010	35	34	33	32	31	30	29	28	27	26	25	24	23	
2011	36	35	34	33	32	31	30	29	28	27	26	25	24	
2012	37	36	35	34	33	32	31	30	29	28	27	26	25	
2013	38	37	36	35	34	33	32	31	30	29	28	27	26	
2014	39	38	37	36	35	34	33	32	31	30	29	28	27	
2015	40	39	38	37	36	35	34	33	32	31	30	29	28	
2016	41	40	39	38	37	36	35	34	33	32	31	30	29	
2017	42	41	40	39	38	37	36	35	34	33	32	31	30	
2018	43	42	41	40	39	38	37	36	35	34	33	32	31	
2019	44	43	42	41	40	39	38	37	36	35	34	33	32	
2020	45	44	43	42	41	40	39	38	37	36	35	34	33	**Years of data in our sample**
2021	46	45	44	43	42	41	40	39	38	37	36	35	34	
2022	47	46	45	44	43	42	41	40	39	38	37	36	35	
2023	48	47	46	45	44	43	42	41	40	39	38	37	36	
2024	49	48	47	46	45	44	43	42	41	40	39	38	37	

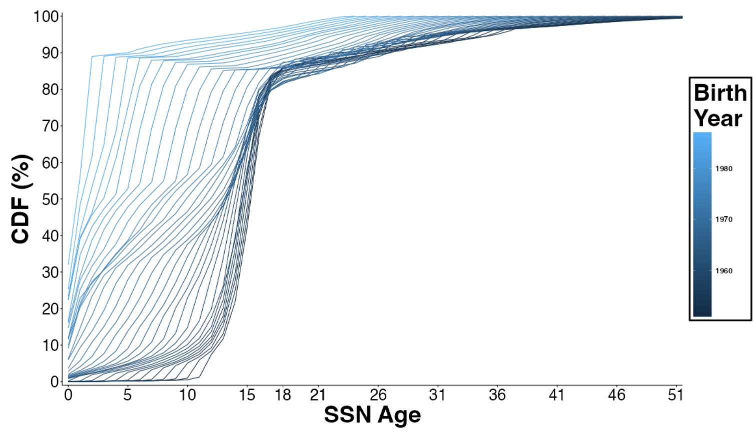
This figure presents a grid of Birth Years and Calendar Years, which describe our sample frame, classification of immigration cohorts, and their timing with respect to the TransUnion data. To illustrate the coverage of consumers by birth year in their 30s, we shade birth year x calendar year observations in dark graph between Ages 30-40. To illustrate the timing of SSN assignment classification by birth year, we color in red the SSN Ages available to our classification before 2012. Note that some specifications restrict to birth year cohorts between 1982-1987 because this is the set of consumers who are visible from age 18+ onward in the BTCCP data.

Figure A5: The distribution of SSN Age by birth year

A: Before cleaning sample

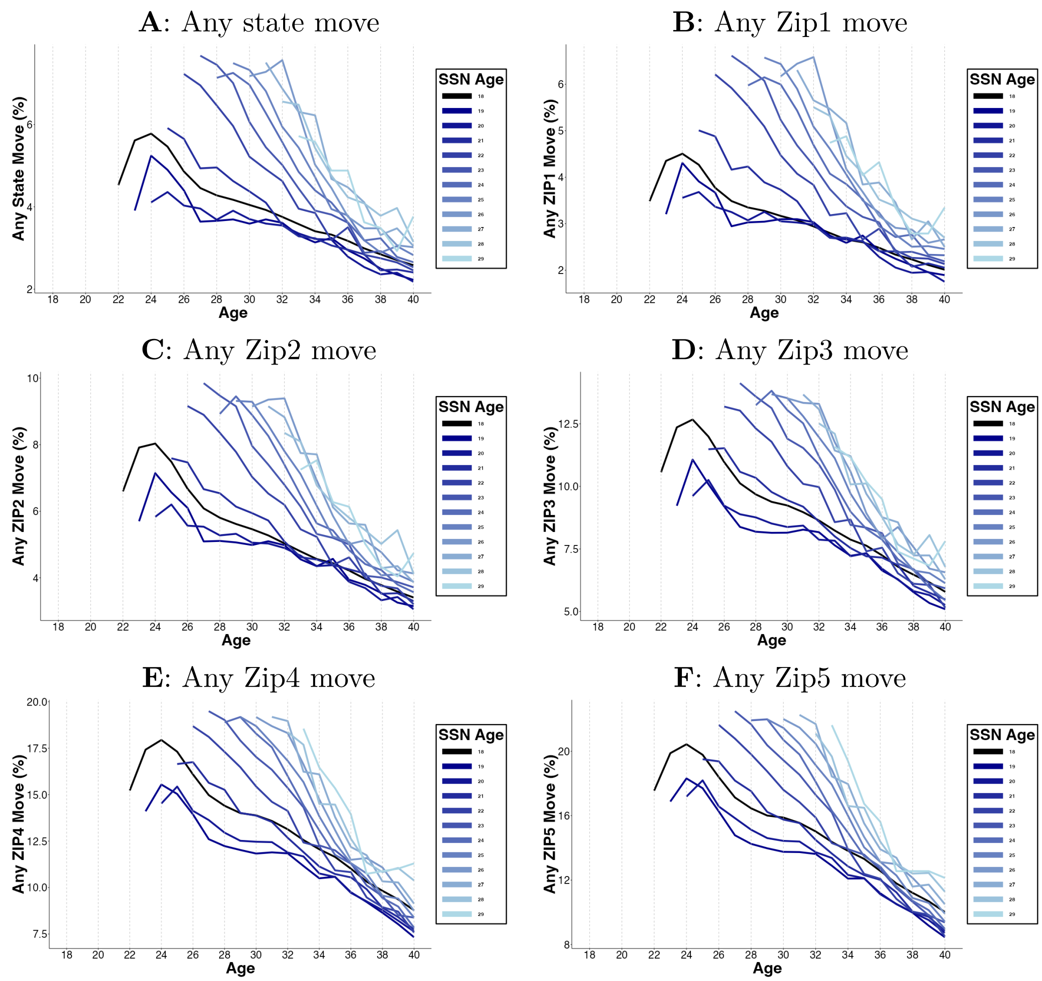


B: Clean sample



These panels show the CDFs of SSN Age for each birth year. Panel A shows data before cleaning (only removing consumers without SSNs). Panel B restricts to consumers after cleaning the data. These patterns of SSN Ages by birth years are consistent with Klopfer and Miller (2024) using administrative Social Security Administration data.

Figure A6: Lifecycle of geographic mobility by SSN Age cohorts

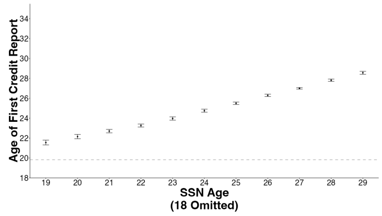


For each SSN Age cohort, this figure shows the share of consumers at each age who move state (Panel A), ZIP1 (Panel B), ZIP2 (Panel C), ZIP3 (Panel D), ZIP4 (Panel E), and ZIP5 (Panel F). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This figure uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024.

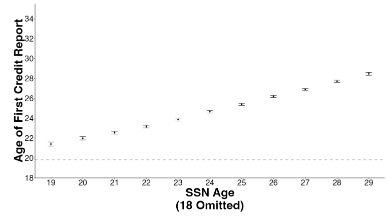
Figure A7: Age at first credit product by type of credit and SSN Age

I: Age at first credit report

A. Without Zip5 F.E.

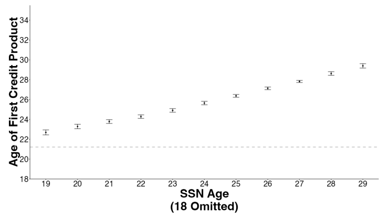


B. With Zip5 F.E.

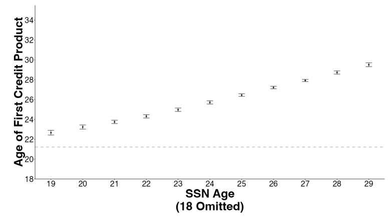


II: Age at first credit product

C. Without Zip5 F.E.

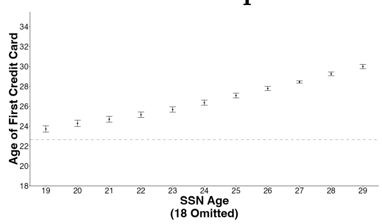


D. With Zip5 F.E.

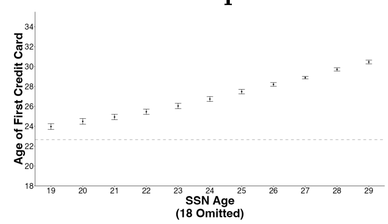


III: Age at first credit card

E. Without Zip5 F.E.

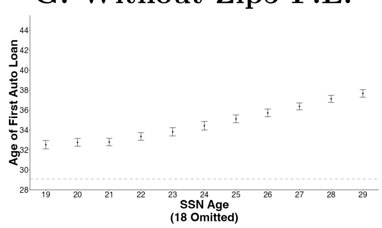


F. With Zip5 F.E.

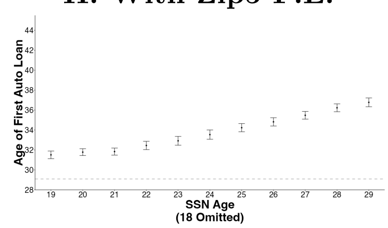


IV: Age at first auto loan

G. Without Zip5 F.E.

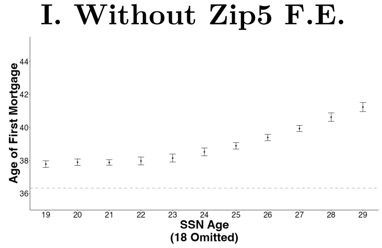


H. With Zip5 F.E.

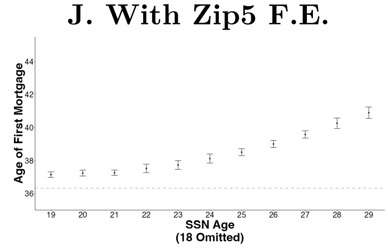


V: Age at first mortgage

I. Without Zip5 F.E.



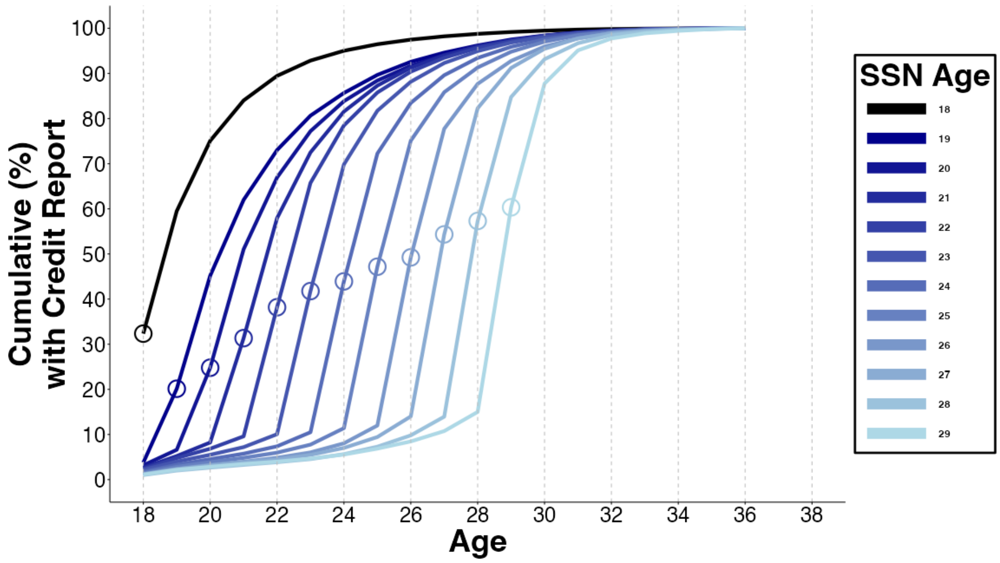
J. With Zip5 F.E.



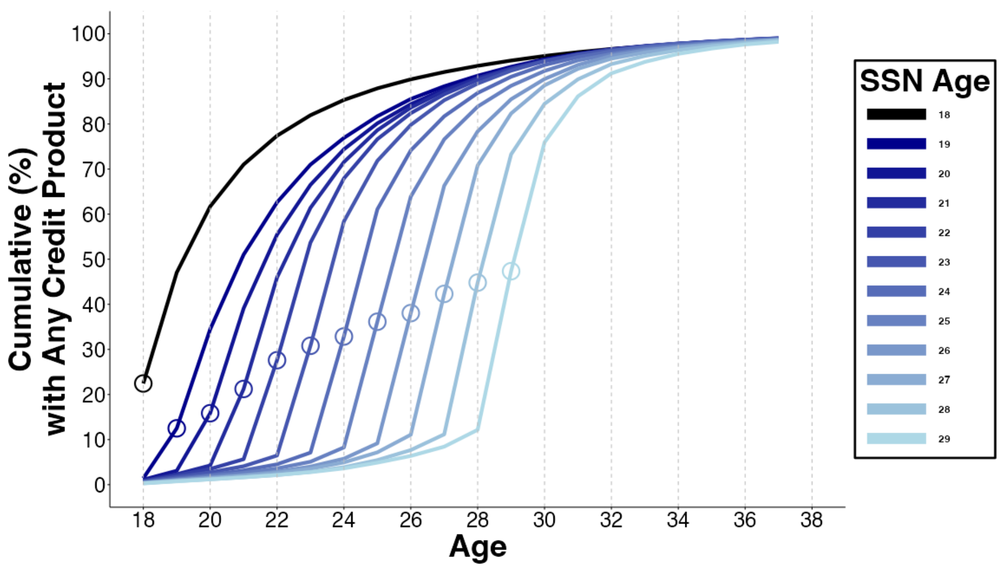
This figure presents estimates and 95% confidence intervals for the age at first credit report, receiving first credit product, and separately by credit type (credit card, auto loan and mortgage) and separately for SSN Age cohorts. The estimates are constructed from an individual-level regression of each outcome on SSN Age fixed effects and Birth Year fixed effects. Panels B, D, F, H, and J also include Zip5 fixed effects. The baseline mean for the omitted category (SSN Age 18 or lower) is indicated by the dashed gray line. Standard errors are clustered by birth year.

Figure A8: Age at first credit report and first credit product by SSN Age cohorts

A: Age at first credit report

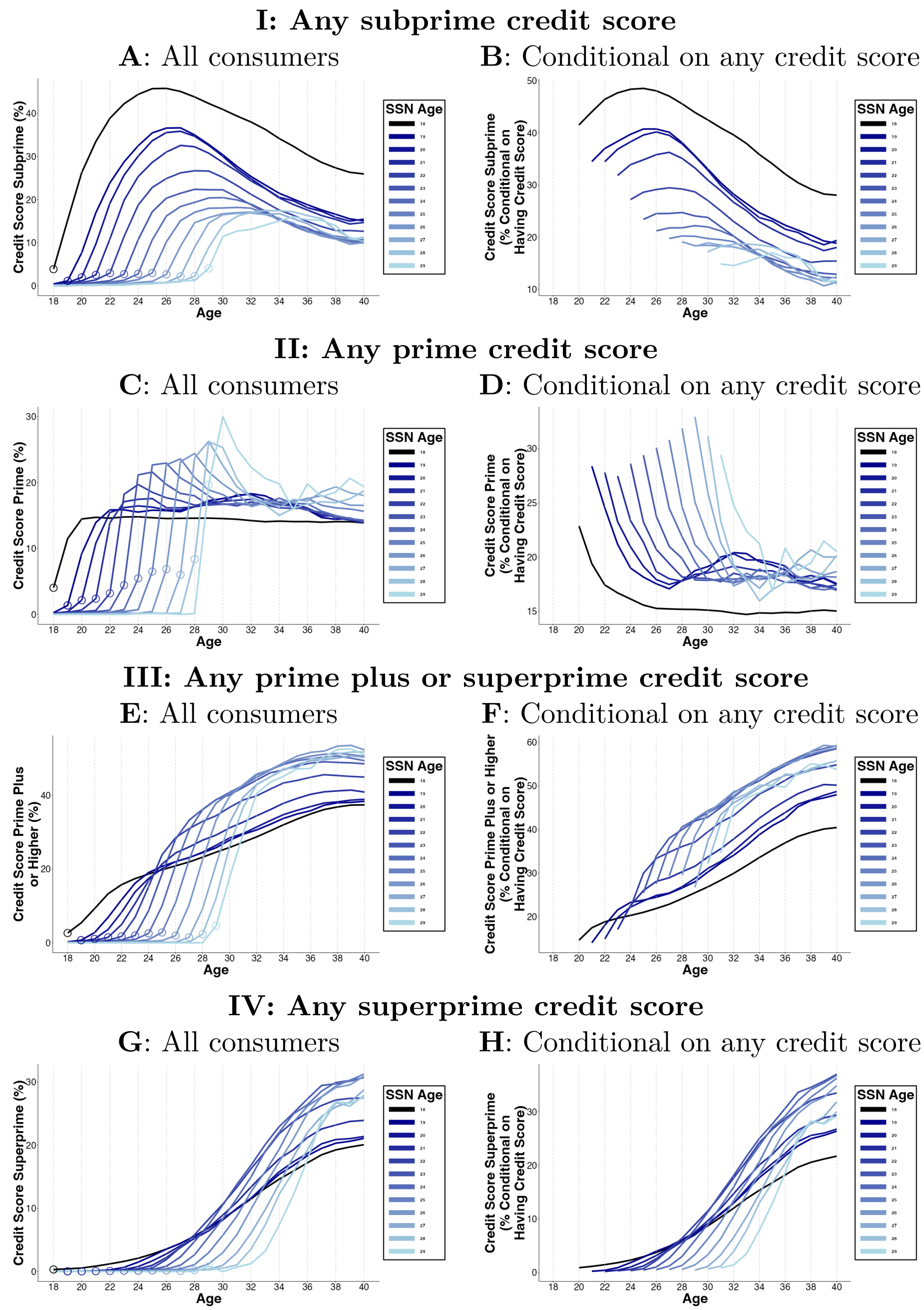


B: Age at first credit product



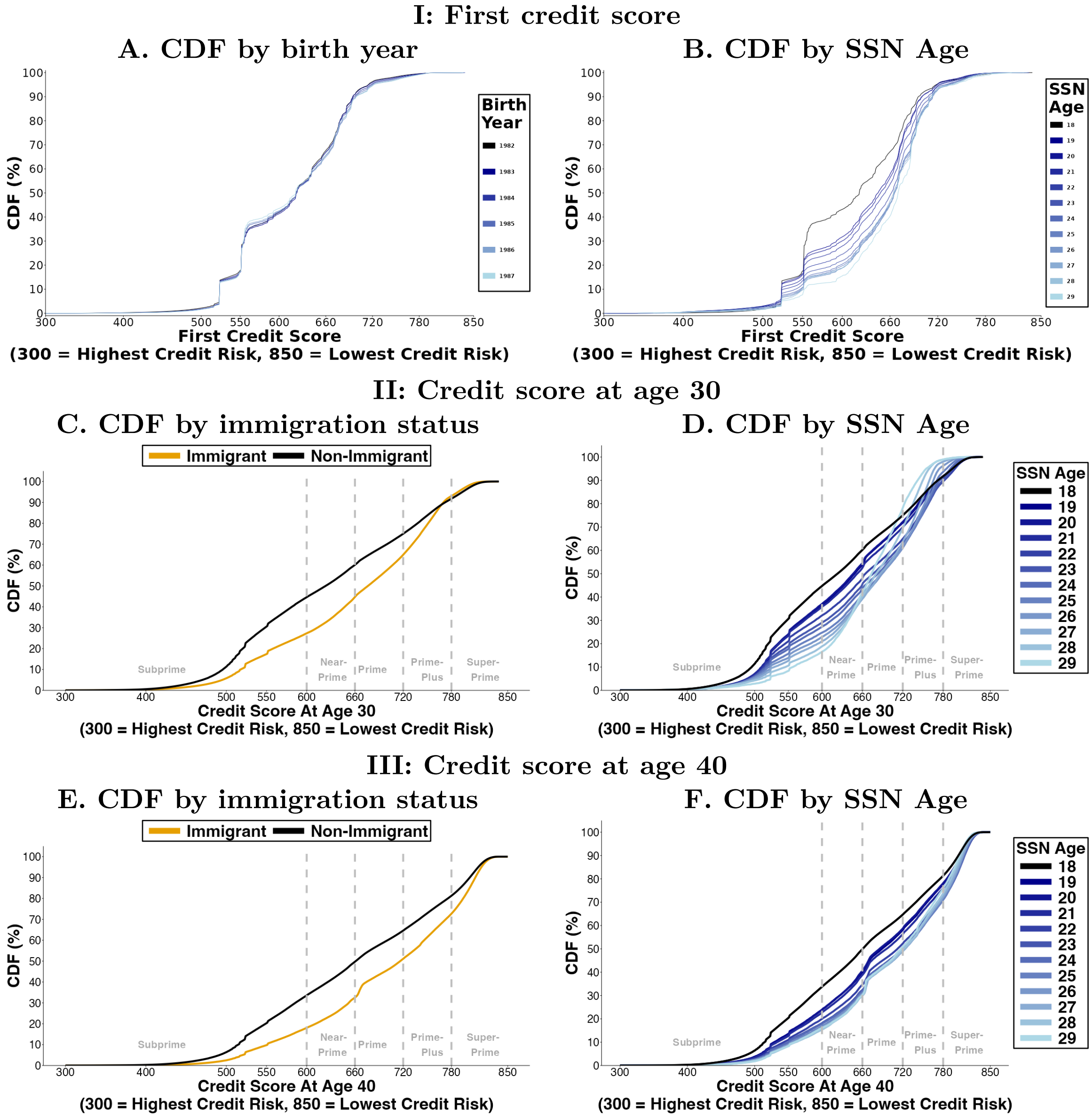
For each SSN Age cohort, this figure presents the evolution of age of first credit report (Panel A) and age of first credit product (Panel B) by age. These averages are conditional on having a credit score. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1975 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 38 to 40, 39 to 40, and 40 respectively by the end of our data in 2024 and therefore we stop these charts at age 37.

Figure A9: Lifecycle of the distribution of credit scores by SSN Age cohorts



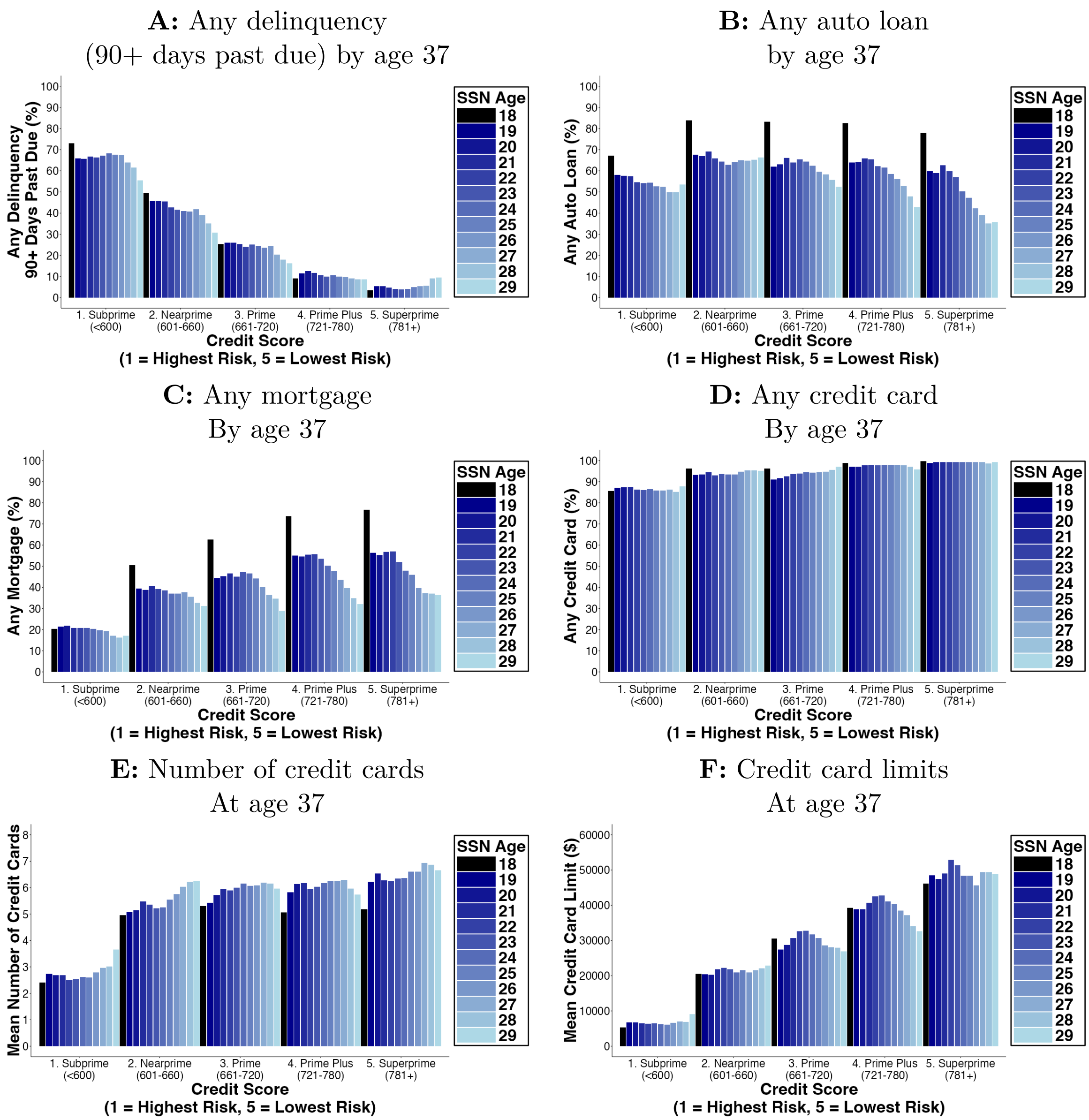
For each SSN Age cohort, this figure presents the evolution of credit scores by age. In all panels, credit scores are measured by VantageScore. In Panels A and B, Subprime Credit Score is VantageScore below 600. In Panels C and D, Prime Credit Score is VantageScore 661 to 719. In Panels E and F, Prime Plus or Superprime Credit Score is VantageScore 720 or higher. In Panels G and H, Superprime Credit Score is VantageScore of 780 or higher. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 38 to 40, 39 to 40, and 40 respectively by the end of our data in 2024 and the estimates for these ages account for this attrition.

Figure A10: The distribution of credit scores: first observed score, and scores at ages 30 and 40



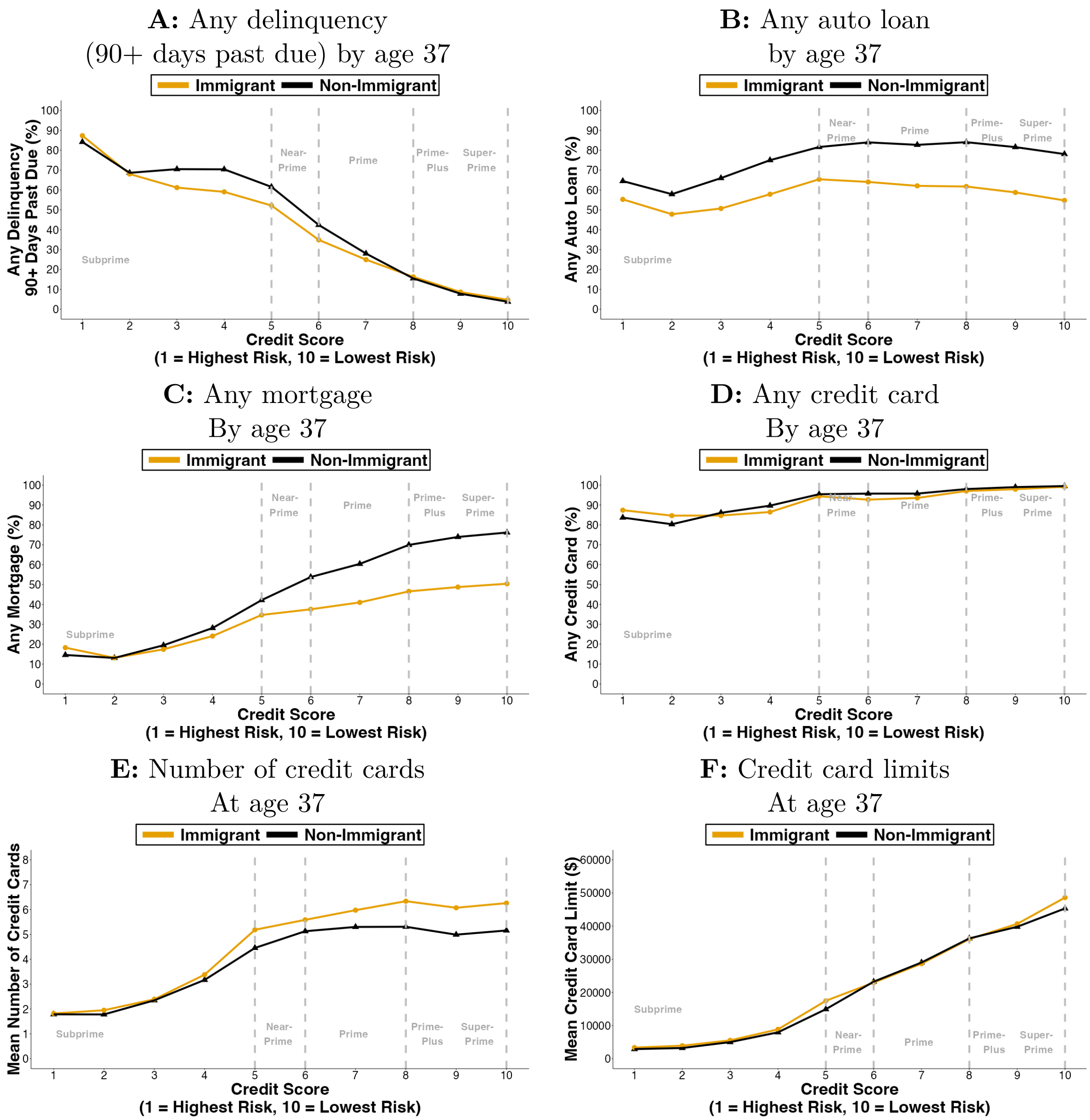
Panels A and B show the CDFs of the first credit score observed for a consumer at any point in our data. Panel A shows CDFs by birth years. Panel B shows CDFs by SSN Ages, where SSN Age 18 includes consumers that are assigned an SSN at Age 18 or younger. Panels C and D show CDFs of credit score at Age 30. Panels E and F show CDFs of credit score at Age 40. Panels C and E split by immigration, where immigrants are defined as SSN Age 21+, and Panels D and F split by SSN Age. All panels use data from our Entrant Sample, with Panels A and B use additional restrictions for birth years between 1982 and 1987 and also drop consumers with credit scores first observed in July 2000 where our data begins.

Figure A11: Credit outcomes by age 37 conditional on credit score at age 30, by SSN Age



Each panel shows mean outcomes measured at age 37 conditional on a consumer's credit score measured at age 30. Each panel splits results by SSN Age.

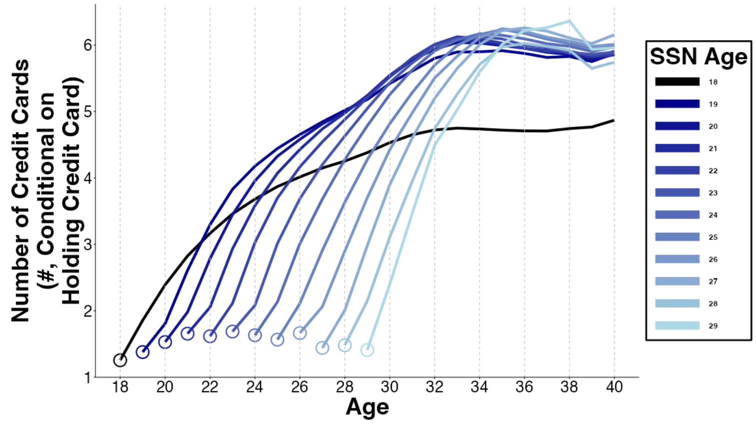
Figure A12: Credit outcomes by age 37 conditional on credit score deciles at age 30



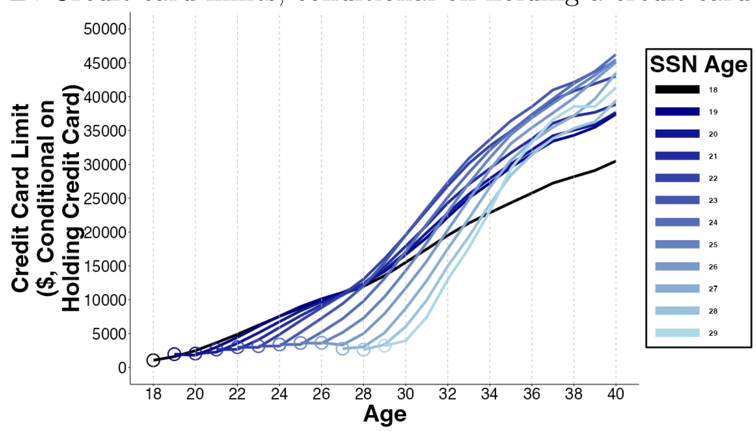
Each panel shows mean outcomes measured at age 37 conditional on deciles of a consumer's credit score measured at age 30.

Figure A13: Lifecycle of number of credit cards and credit card limits, conditional on holding any credit card, by SSN Age cohorts

A: Number of credit cards, conditional on holding a credit card



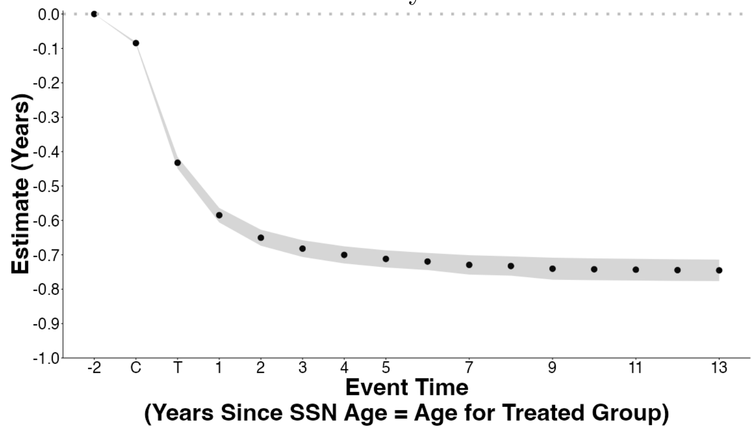
B: Credit card limits, conditional on holding a credit card



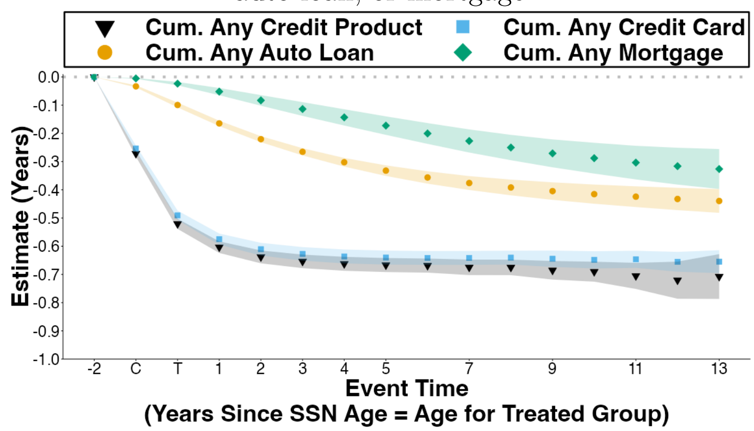
For each SSN Age cohort, this figure shows the evolution of credit card limits over the lifecycle: number of credit cards (Panel A), total credit card limits (Panel B). These are both conditional on holding any credit card. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024; estimates for these ages account for this attrition.

Figure A14: Paired cohorts: dynamics of credit access

A: Cumulative any credit score

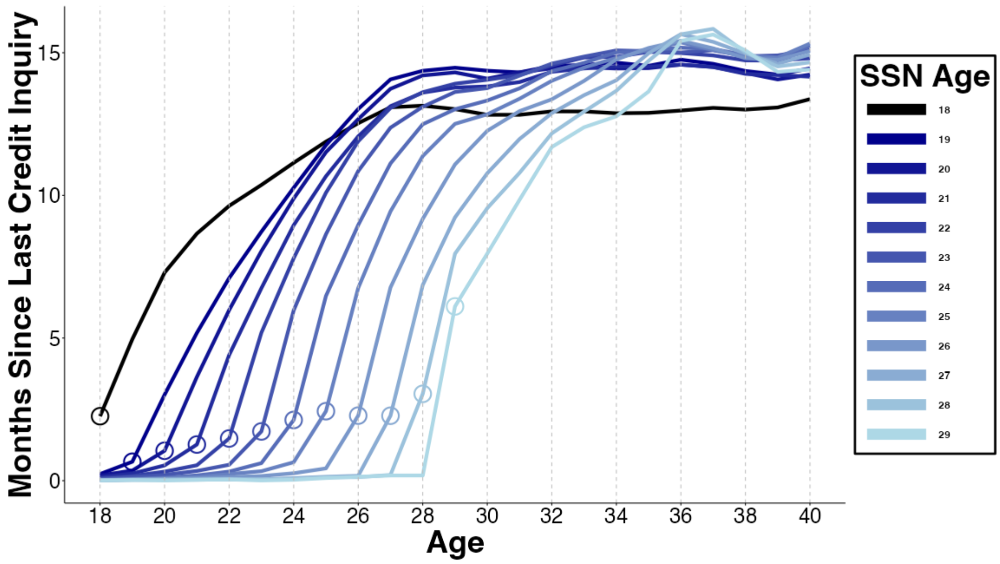


B: Cumulative any credit product, credit card, auto loan, or mortgage



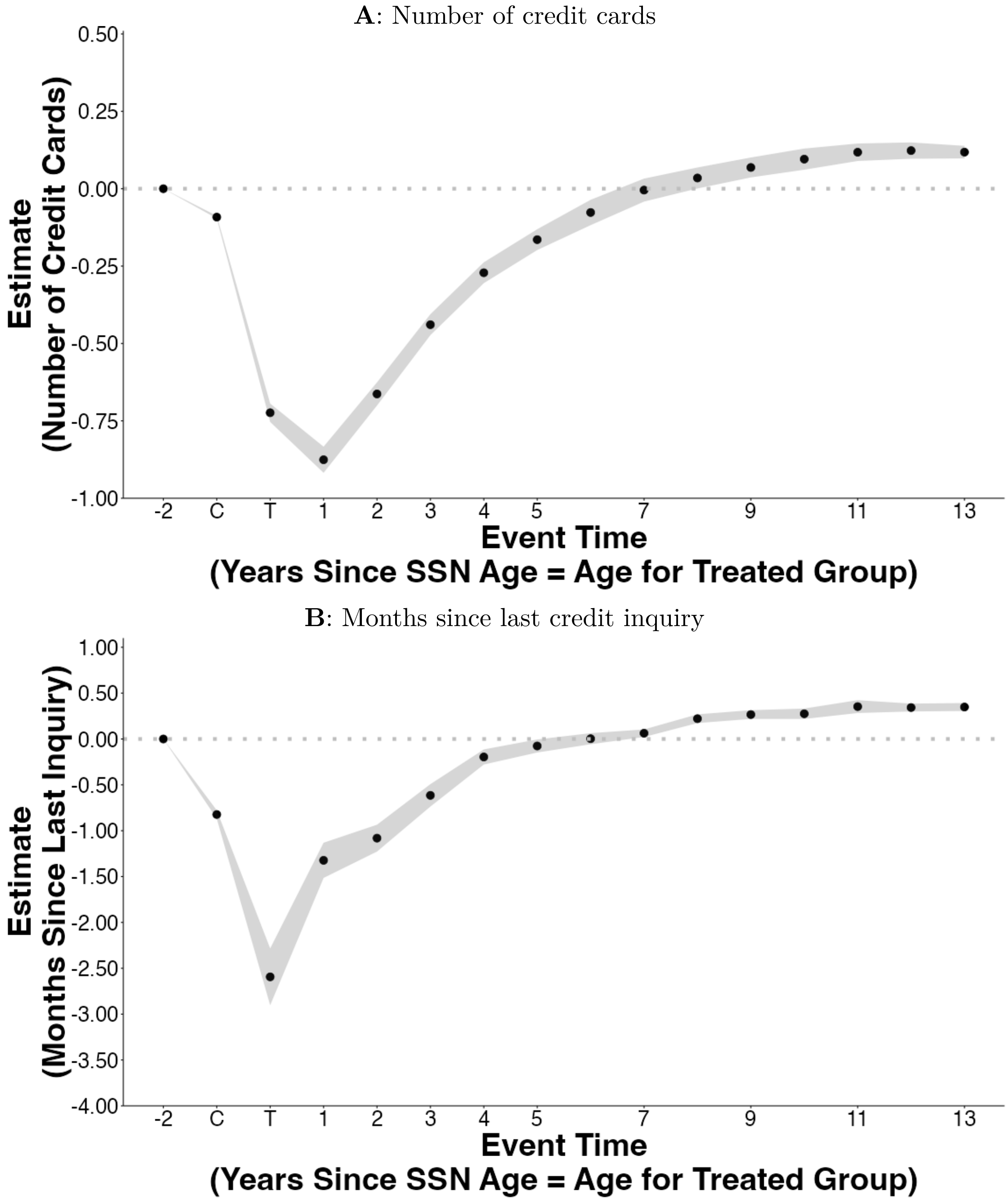
This figure presents dynamic estimates for differences in credit access (of different types) between a cohort with SSN Age = s and a cohort with SSN Age = $s-1$ matched at the same age. The differences are presented in event time where C is the year when age equals SSN Age for the $s-1$ cohort and T is the same for the s cohort: first credit product or credit card (Panel A), auto loans and home mortgages (Panel B), and credit card limits (Panel C). The shaded areas indicate 95% confidence intervals, clustering standard errors by birth year.

Figure A15: Months since last credit inquiry by SSN Age cohorts



For each SSN Age cohort, this figure presents the evolution of months since last credit inquiry by age. Months since last credit inquiry takes a value between 0 and 24, and is assigned 25 if missing. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 38 to 40, 39 to 40, and 40 respectively by the end of our data in 2024 and therefore we stop these charts at age 37.

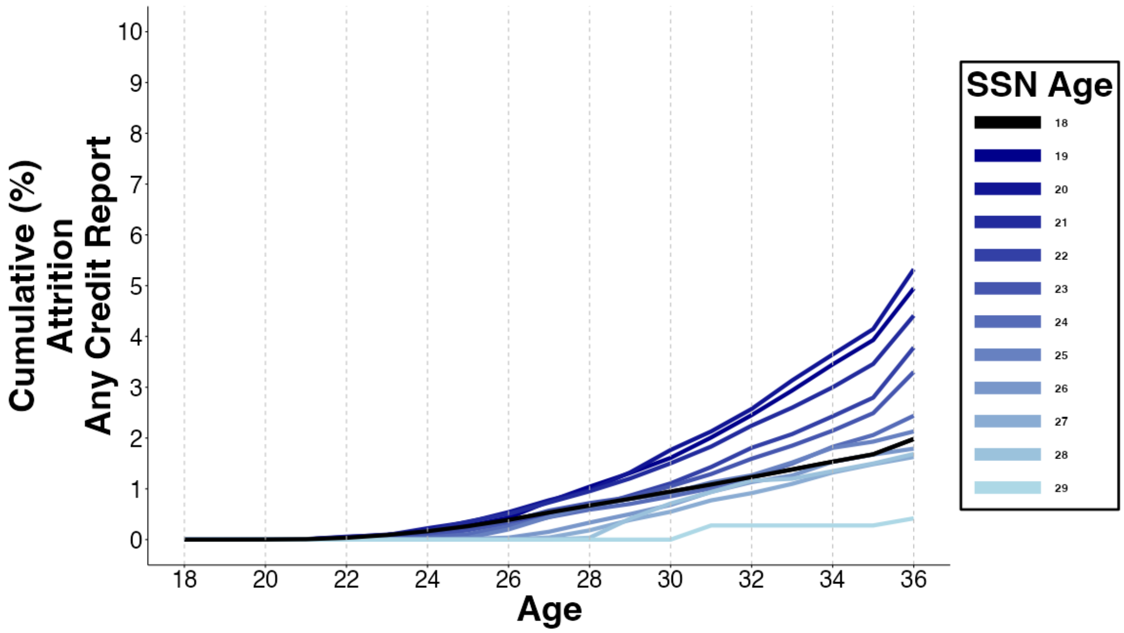
Figure A16: Paired cohorts: Number of credit cards and months since last credit inquiry



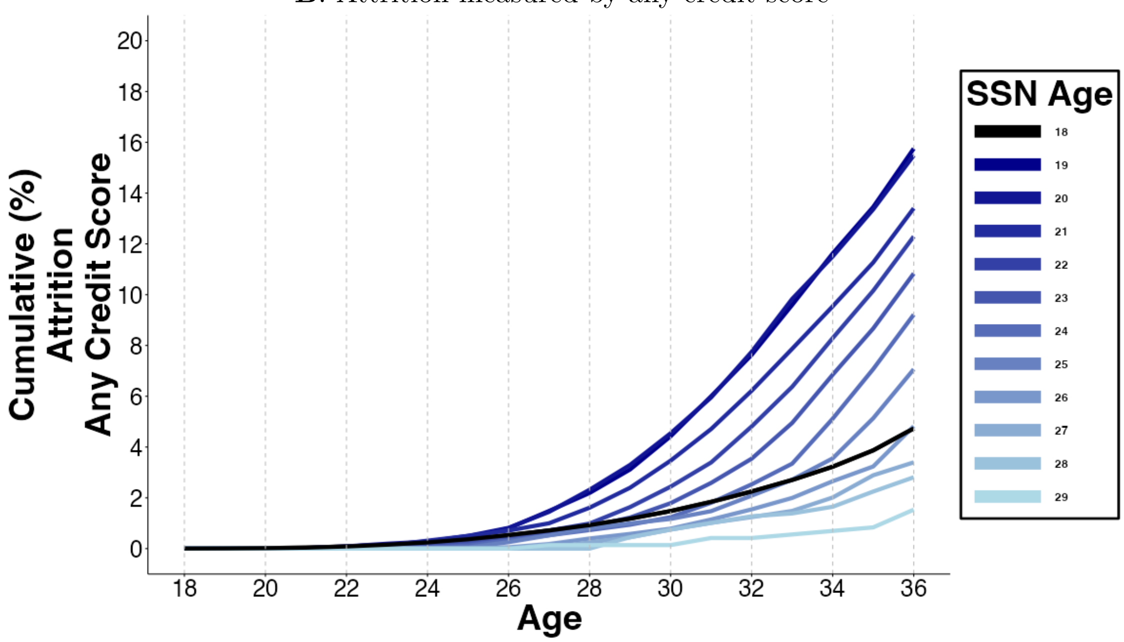
This figure presents dynamic estimates for differences for number of credit cards and the number of months since last inquiry (a proxy for credit demand) between a cohort with SSN Age = s and a cohort with SSN Age = $s-1$ matched at the same age. The differences are presented in event time where C is the year when age equals SSN Age for the $s-1$ cohort and T is the same for the s cohort. The shaded areas indicate 95% confidence intervals, clustering standard errors by birth year.

Figure A17: Attrition from the data, by SSN Age cohorts

A: Attrition Measured by Any Credit Report



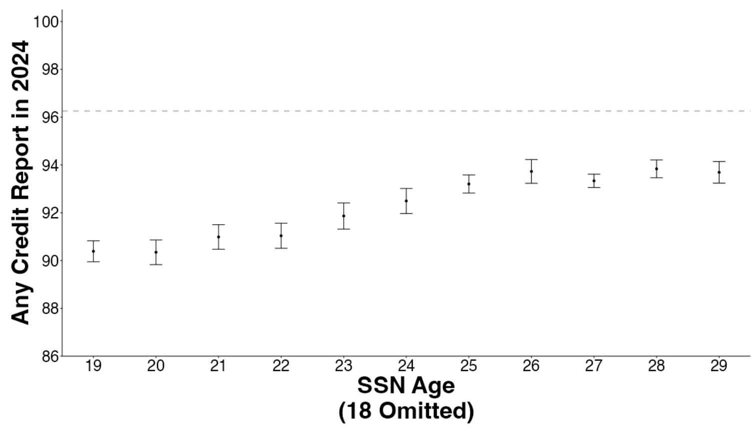
B: Attrition measured by any credit score



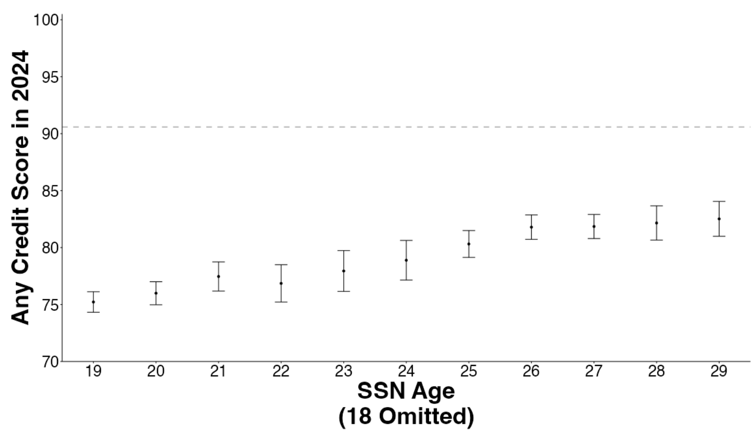
For each SSN Age cohort, this figure presents the cumulative percent who are no longer observed in the data. Panel A measures attrition by the year at which a consumer has a non-missing credit report. Panel B measures attrition by the last year at which a consumer has a non-missing credit score. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 38 to 40, 39 to 40, and 40 respectively by the end of our data in 2024 and therefore we stop these charts at age 36.

Figure A18: Consumers observed in the data in 2024, by SSN Age

A: Any credit report in 2024

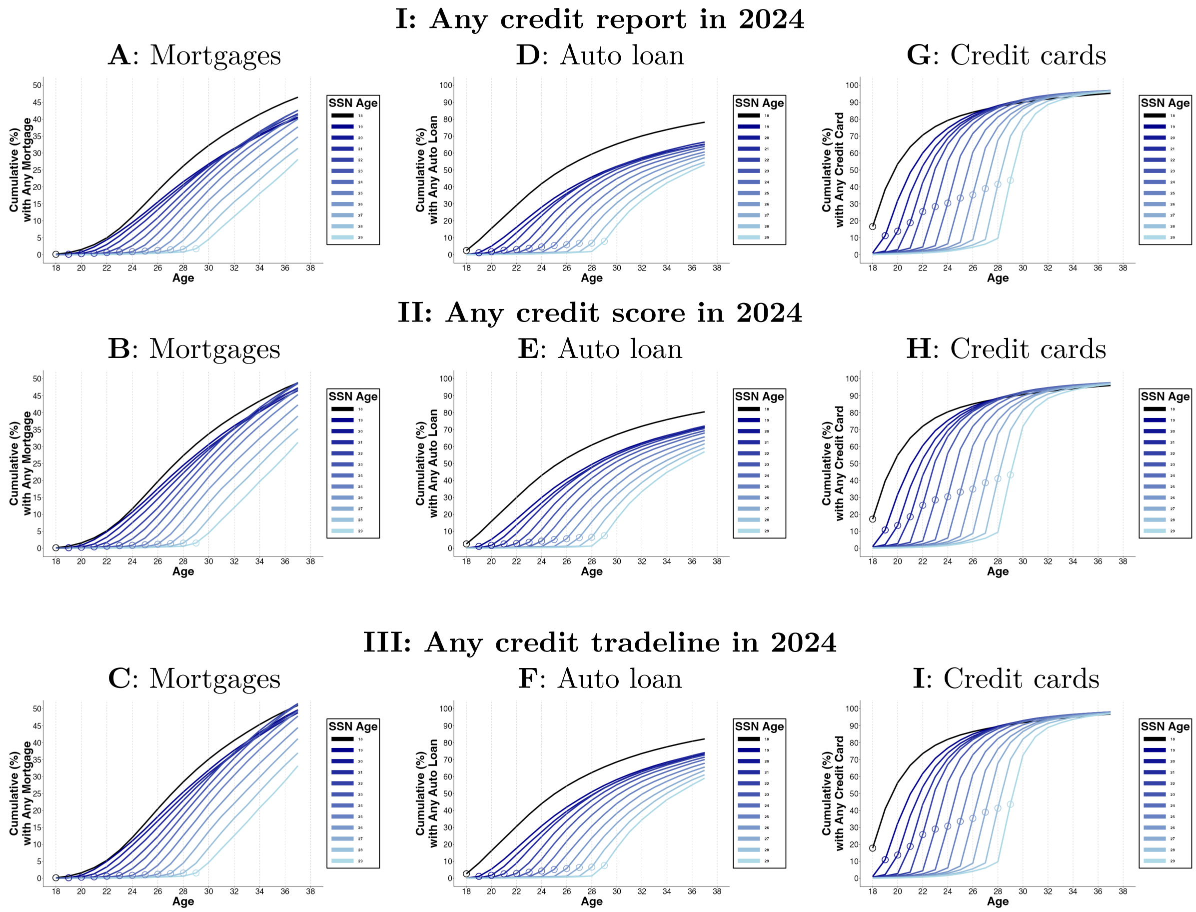


B: Any credit score in 2024



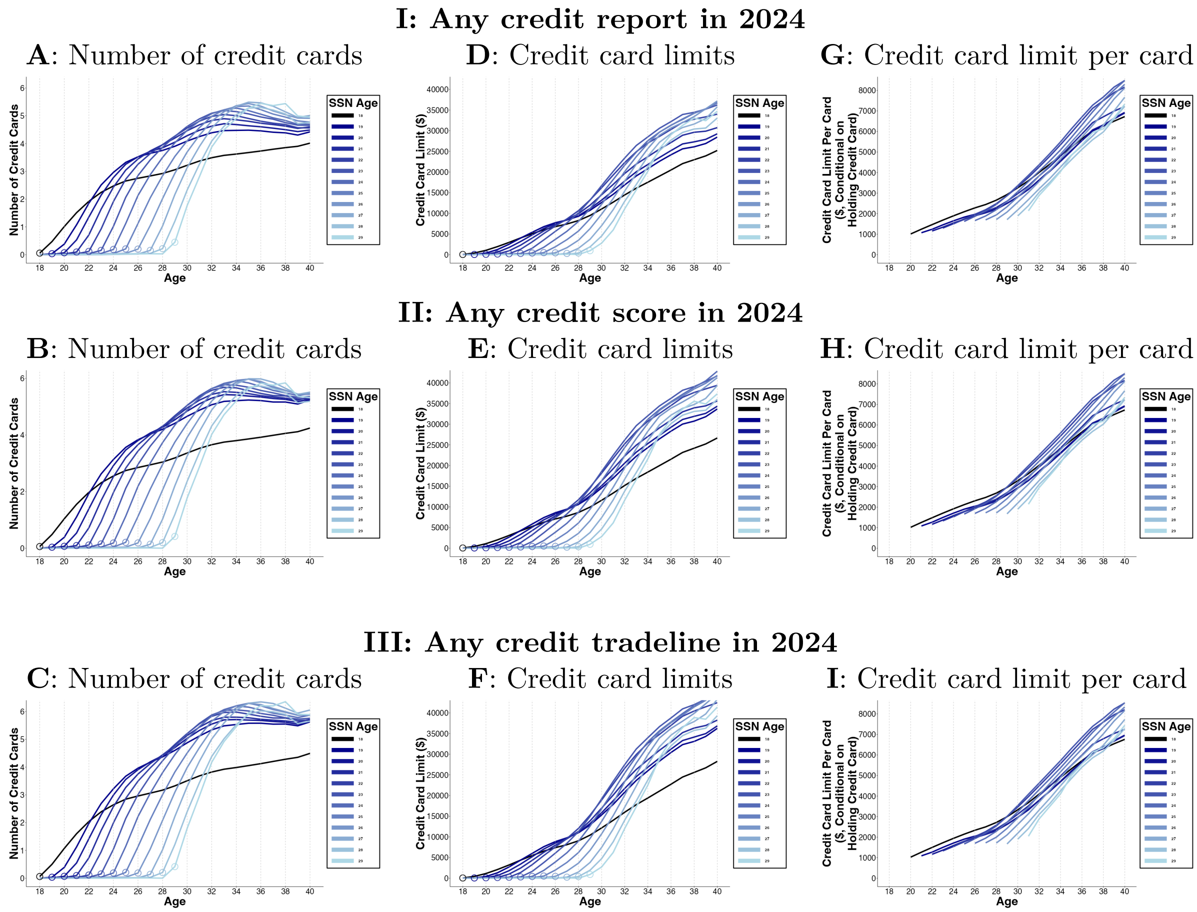
This figure presents 95% confidence intervals for a consumer is no longer observed in the data. This is done separately for SSN Age cohorts using two measures of attrition. Panel A shows whether a consumer has any non-missing credit report in 2024. Panel B shows whether a consumer has any non-missing credit score in 2024. The confidence intervals are constructed from an individual-level regression of Age at first credit product (for each type) on SSN Age fixed effects, Birth Year fixed effects, and Zip5 fixed effects. The baseline mean for the omitted category (SSN Age 18 or lower) is indicated by the dashed gray line. Standard errors are clustered by birth year.

Figure A19: Lifecycle of credit access by type of credit and SSN Age cohorts, restricting sample to consumers observed in 2024



Each row shows a different sample restriction to account for attrition from the data. Row I. restricts the sample to consumers with a non-missing credit report in 2024. Row II. restricts the sample to consumers with a non-missing credit score in 2024. Row III. restricts the sample to consumers with a non-missing credit report tradeline in 2024. For each SSN Age cohort, this figure shows the cumulative share of consumers at each age who have ever had a mortgage (Panels A, B, C), an auto loan (Panels D, E, F), or a mortgage (Panels, G, H, I). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1975 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024, and so we end these charts at age 37.

Figure A20: Lifecycle of credit cards by SSN Age cohorts, restricting sample to consumers observed in 2024



Each row shows a different sample restriction to account for attrition from the data. Row I. restricts the sample to consumers with a non-missing credit report in 2024. Row II. restricts the sample to consumers with a non-missing credit score in 2024. Row III. restricts the sample to consumers with a non-missing credit report tradeline in 2024. For each SSN Age cohort, this figure shows the evolution of credit card limits over the lifecycle: number of credit cards (Panels A, B, C), total credit card limits (Panels D, E, F), and credit card limits per card (Panels G, H, I). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts. $Age = SSNAge$ is indicated by the circles on each line. This uses data for birth years from 1982 to 1987. Consumers with the birth years 1985, 1986, and 1987, are not observed for ages 40, 39 to 40, and 38 to 40, respectively, by the end of our data in 2024; estimates for these ages account for this attrition.

Table A1: Counts of consumers by SSN Age: "clean sample" and "entrant sample"

This table presents observation counts for the "Clean Sample" (indicated in Table 1) by SSN Age in column 1. Column 2 presents similar counts for consumers whose SSN Assignment year falls between 2000 and 2012, and thus, fall in our credit market entrant sample. Our main analysis sample additionally drops the 44,642 consumers who have SSN Age 30+ from this sample.

SSN Age	Total	Entrants
<19	16,155,157	5,677,001
19	175,194	50,475
20	148,589	51,195
21	148,019	52,450
22	141,492	47,302
23	145,218	47,214
24	149,000	45,314
25	147,899	42,005
26	142,319	36,976
27	133,147	29,383
28	123,338	24,415
29	113,435	19,202
30+	849,847	44,642

Table A2: Credit market entry timing by immigration status and age of immigration, with additional geographic fixed effects

This table presents OLS estimates from individual-level regressions for Age at First Credit Report (or First Credit Product) on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1 and 4 include include fixed effects for the birth year of the consumer, first Zip5, and last Zip5. Columns 2 and 5 also include additional fixed effects for a consumers' longest Zip5 (a proxy for their most permanent location). Columns 3 and 6 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Dep Var: Age at First...		Credit Report			Credit Product	
	(1)	(2)	(3)	(4)	(5)	(6)
21+	1.7757***	1.7721***	1.6915***	1.6322***	1.6353***	1.477***
	(0.0787)	(0.0779)	(0.0733)	(0.0907)	(0.0884)	(0.0878)
SSN Age	0.7466***	0.7463***	0.7273***	0.7271***	0.7264***	0.6886***
	(0.0133)	(0.0133)	(0.0144)	(0.0155)	(0.0154)	(0.0157)
Birth Year F.E.	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X
Number Zip5 F.E.			X			X
R^2	0.299	0.299	0.323	0.152	0.156	0.192
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	19.864	19.864	19.864	21.2508	21.2508	21.2508

Table A3: Credit scores by age of SSN assignment, with additional geographic fixed effects

This table presents OLS estimates from an individual-level regression of Vantage Score (panel A) or Prime Credit Indicator (panel B) at Ages 30 and 40 on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1 and 4 include include fixed effects for the birth year of the consumer, first Zip5, and last Zip5. Columns 2 and 5 also include additional fixed effects for a consumers' longest Zip5 (a proxy for their most permanent location). Columns 3 and 6 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Average credit scores

Dep Var: Credit Score at...		Age 30			Age 40	
	(1)	(2)	(3)	(4)	(5)	(6)
21+	15.7***	15.4***	15.7***	21.6***	21.1***	21.6***
	(1.3)	(1.2)	(1.2)	(0.6)	(0.6)	(0.6)
SSN Age	1.5***	1.5***	1.6***	1.3***	1.3***	1.5***
	(0.3)	(0.3)	(0.3)	(0.1)	(0.1)	(0.2)
Birth Year F.E.	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X
Number Zip5 F.E.			X			X
R^2	0.193	0.201	0.202	0.192	0.199	0.200
N	5,755,134	5,755,134	5,755,134	4,449,929	4,449,929	4,449,929
Mean, SSN Age <21	626.1	626.1	626.1	659.5	659.5	659.5

Panel B: Likelihood of prime or higher credit score

Dep Var: Prime or Higher Score at...		Age 30			Age 40	
	(1)	(2)	(3)	(4)	(5)	(6)
21+	6.45***	6.32***	6.60***	1.32***	1.19***	1.99***
	(0.60)	(0.55)	(0.57)	(0.23)	(0.27)	(0.21)
SSN Age	-0.22	-0.22	-0.14	1.43***	1.43***	1.58***
	(0.18)	(0.18)	(0.19)	(0.07)	(0.07)	(0.09)
Birth Year F.E.	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X
Number Zip5 F.E.			X			X
R^2	0.149	0.155	0.156	0.141	0.146	0.152
N	6,122,932	6,122,932	6,122,932	4,800,195	4,800,195	4,800,195
Mean, SSN Age <21	37.71	37.71	37.71	46.84	46.84	46.84

Table A4: Any delinquency (90+ days past due) by age 37 conditional on credit score at age 30, Zip5 at age 30, and birth year, split by credit score group at age 30

This table presents OLS estimates from individual-level regressions for credit outcomes on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Each column is a separate regression for a different outcome. All regressions include fixed effects for the birth year of the consumer, Zip5 observed at age 30, and credit score at age 30. The outcome in all columns is whether a consumer has any delinquency, measured by 90 or more days past due, by age 37. Each column shows results for a different credit score group at age 30. Column 1 shows results for all credit scores at age 30. Columns 2, 3, 4, 5, and 6 respectively show results for the subsets of consumers with subprime (<600, the highest credit risk segment), nearprime (601-660), prime (661-720), prime plus (721-780), and superprime (781+, the lowest credit risk segment) credit scores at age 30. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Dep Var: Any Delinquency by age 37	All Credit Scores (1)	Subprime (2)	Nearprime (3)	Prime (4)	Prime Plus (5)	Superprime (6)
21+	-0.0140***	-0.0369***	-0.0272***	0.0006	0.0099***	0.0037
	(0.0041)	(0.0074)	(0.0058)	(0.0049)	(0.0019)	(0.0028)
SSN Age	-0.0004	0.0023	-0.0019	-0.0034***	-0.0021***	-0.0003
	(0.0005)	(0.0012)	(0.0009)	(0.0007)	(0.0003)	(0.0007)
F.E. Birth Year	X	X	X	X	X	X
F.E. Age 30 Zip5	X	X	X	X	X	X
F.E. Age 30 Credit Score	X	X	X	X	X	X
R^2	0.185	0.032	0.028	0.027	0.025	0.022
N	5,755,134	2,515,933	898,118	871,578	999,130	470,375
Mean, SSN Age <21	0.2722	0.4553	0.2620	0.1314	0.0451	0.0163

Table A5: Credit outcomes by age 37 conditional on credit score at age 30, Zip5 at age 30, and birth year

This table presents OLS estimates from individual-level regressions for credit outcomes on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Each column is a separate regression for a different outcome. All regressions include fixed effects for the birth year of the consumer, Zip5 observed at age 30, and credit score at age 30. The outcomes in columns 1, 2, and 3 are whether, by age 37, a consumer has had any auto loan, any mortgage, and any credit card, respectively. The outcomes columns 4 and 5 are, at age 37, the number of credit cards held and the total credit card limits, respectively. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Dep Var: Outcomes at Age 37...	Any Auto Loan	Any Mortgage	Any Credit Card	Number of Credit Cards	Credit Card Limits
	(1)	(2)	(3)	(4)	(5)
21+	-0.0889***	-0.0233***	-0.0161***	0.2174***	981.1
	(0.0039)	(0.0050)	(0.0013)	(0.0324)	(561.8)
SSN Age	-0.0142***	-0.0235***	0.0005	0.0435***	-434.6**
	(0.0006)	(0.0012)	(0.0003)	(0.0110)	(131.7)
F.E. Birth Year	X	X	X	X	X
F.E. Age 30 Zip5	X	X	X	X	X
F.E. Age 30 Credit Score	X	X	X	X	X
R^2	0.108	0.268	0.110	0.142	0.306
N	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134
Mean, SSN Age <21	0.7534	0.4473	0.9221	3.9179	20515.6

Table A6: Credit market access by type of credit, with additional geographic fixed effects

This table presents OLS estimates from individual-level regressions for age at first credit card, age at first auto loan, and age at first mortgage, on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1, 4, and 7 include include fixed effects for the birth year of the consumer, first Zip5, and last Zip5. Columns 2, 5, and 8 also include additional fixed effects for a consumers' longest Zip5 (a proxy for their most permanent location). Columns 3, 6, and 9 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Dep Var: Age at First...		Credit Card			Auto Loan			Mortgage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
21+	1.4213***	1.4318***	1.1952***	1.7944***	1.7860***	1.4242***	0.0911	0.0735	-0.0822
	(0.1344)	(0.1308)	(0.1250)	(0.1736)	(0.1729)	(0.1356)	(0.0653)	(0.0671)	(0.0518)
SSN Age	0.7010***	0.7000***	0.6435***	0.6271***	0.6255***	0.5401***	0.4454***	0.4434***	0.4057***
	(0.0191)	(0.0190)	(0.0194)	(0.0208)	(0.0215)	(0.0230)	(0.0162)	(0.0163)	(0.0173)
Birth Year F.E.	X	X	X	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X		X	X
Number Zip5 F.E.			X			X			X
R^2	0.114	0.118	0.159	0.120	0.125	0.169	0.131	0.143	0.154
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	22.6771	22.6771	22.6771	29.1511	29.1511	29.1511	36.3559	36.3559	36.3559

Table A7: Credit access by type of credit by age 37, with additional geographic fixed effects

This table presents OLS estimates from individual-level regressions for whether the consumer has a credit card, an auto loan, or or a mortgage on or before Age 37 (i.e., 8+ years after immigration for all immigration cohorts in our sample) on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1, 4, and 7 include include fixed effects for the birth year of the consumer, first Zip5, and last Zip5. Columns 2, 5, and 8 also include additional fixed effects for a consumers' longest Zip5 (a proxy for their most permanent location). Columns 3, 6, and 9 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Dep Var: By Age 37, has...		Credit Card			Auto Loan			Mortgage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
21+	-0.02	-0.05	0.50***	-6.18***	-6.16***	-4.43***	1.09*	1.13*	2.33***
	(0.12)	(0.12)	(0.14)	(0.34)	(0.35)	(0.20)	(0.49)	(0.46)	(0.35)
SSN Age	0.02	0.02	0.15***	-1.48***	-1.47***	-1.06***	-1.86***	-1.85***	-1.56***
	(0.03)	(0.03)	(0.04)	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.09)
Birth Year F.E.	X	X	X	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X		X	X
Number Zip5 F.E.			X			X			X
R^2	0.040	0.042	0.060	0.076	0.079	0.124	0.117	0.127	0.146
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	94.93	94.93	94.93	77.22	77.22	77.22	45.46	45.46	45.46

Table A8: Number of credit cards at ages 30 and 40

This table presents OLS estimates from the cross-sectional regression specified in Equation 2 that includes an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1 do not include any fixed effects. Columns 2, 3, 4, 5, and 6 include fixed effects for the birth year of the consumer. Columns 3, 4, 5, and 6 also include fixed effects for consumers' first observed ZIP code (First ZIP5 FE). Columns 4, 5, and 6 also include additional fixed effects for a consumers' last Zip5. Columns 5 and 6 also include additional fixed effects for a consumer's longest Zip5 (a proxy for their most permanent location), column 6 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). The outcome in panel A are the number of credit cards of a consumer at age 30, and at age 40 in panel B. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Number of credit cards at age 30

	(1)	(2)	(3)	(4)	(5)	(6)
21+	1.52***	1.51***	1.25***	1.18***	1.17***	1.29***
	(0.07)	(0.07)	(0.08)	(0.06)	(0.06)	(0.05)
SSN Age	-0.29***	-0.31***	-0.32***	-0.33***	-0.33***	-0.30***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
F.E. Birth Year		X	X	X	X	X
F.E. First Zip5			X	X	X	X
F.E. Last Zip5				X	X	X
F.E. Longest Zip5					X	X
F.E. Number Zip5						X
R^2	0.002	0.007	0.058	0.091	0.097	0.123
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	3.42	3.42	3.42	3.42	3.42	3.42

Panel B: Number of credit cards at age 40

	(1)	(2)	(3)	(4)	(5)	(6)
21+	0.33***	0.33***	0.01	-0.01	-0.02	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
SSN Age	0.10***	0.10***	0.09***	0.08***	0.08***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
F.E. Birth Year		X	X	X	X	X
F.E. First Zip5			X	X	X	X
F.E. Last Zip5				X	X	X
F.E. Longest Zip5					X	X
F.E. Number Zip5						X
R^2	0.002	0.003	0.028	0.058	0.060	0.092
N	4,800,195	4,800,195	4,800,195	4,800,195	4,800,195	4,800,195
Mean, SSN Age <21	3.97	3.97	3.97	3.97	3.97	3.97

Table A9: Credit card limits at ages 30 and 40

This table presents OLS estimates from the cross-sectional regression specified in Equation 2 that includes an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1 do not include any fixed effects. Columns 2, 3, 4, 5, and 6 include fixed effects for the birth year of the consumer. Columns 3, 4, 5, and 6 also include fixed effects for consumers' first observed ZIP code (First ZIP5 FE). Columns 4, 5, and 6 also include additional fixed effects for a consumers' last Zip5. Columns 5 and 6 also include additional fixed effects for a consumer's longest Zip5 (a proxy for their most permanent location), column 6 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). The outcome in panel A are total credit card limit of a consumer at age 30, and at age 40 in panel B. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Credit card limits at age 30

	(1)	(2)	(3)	(4)	(5)	(6)
21+	4982.1***	4948.6***	3788.2***	3307.3***	3248.8***	3656.3***
	(528.6)	(571.3)	(489.8)	(406.9)	(386.8)	(373.2)
SSN Age	-1288.4***	-1360.7***	-1490.8***	-1545.1***	-1542.4***	-1446.1***
	(79.9)	(77.2)	(74.2)	(68.5)	(68.7)	(67.2)
F.E. Birth Year		X	X	X	X	X
F.E. First Zip5			X	X	X	X
F.E. Last Zip5				X	X	X
F.E. Longest Zip5					X	X
F.E. Number Zip5						X
R^2	0.002	0.009	0.080	0.124	0.130	0.142
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	11,733.1	11,733.1	11,733.1	11,733.1	11,733.1	11,733.1

Panel B: Credit card limits at age 40

	(1)	(2)	(3)	(4)	(5)	(6)
21+	4262.0***	4327.3***	1633.6*	639.6	526.8	1696.6***
	(744.4)	(712.9)	(536.3)	(353.4)	(327.8)	(385.8)
SSN Age	318.3	456.9*	192.4	59.7	61.5	273.0
	(188.7)	(149.1)	(135.4)	(110.3)	(111.7)	(137.9)
F.E. Birth Year		X	X	X	X	X
F.E. First Zip5			X	X	X	X
F.E. Last Zip5				X	X	X
F.E. Longest Zip5					X	X
F.E. Number Zip5						X
R^2	0.002	0.008	0.082	0.151	0.157	0.181
N	4,800,195	4,800,195	4,800,195	4,800,195	4,800,195	4,800,195
Mean, SSN Age <21	22,477.2	22,477.2	22,477.2	22,477.2	22,477.2	22,477.2

Table A10: Consumers observed in the data in 2024

This table presents OLS estimates from individual-level regressions for whether the consumer remains observed in the data on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Attrition is measured by any non-missing credit report in 2024 (columns 1 and 2), any non-missing credit score (columns 3 and 4), and any non-missing credit tradeline (columns 5 and 6). Columns 1, 3, and 5 include include fixed effects for the birth year of the consumer and their first Zip5. Columns 2, 4, and 6 also include additional fixed effects for a consumers' last Zip5, longest Zip5 (a proxy for their most permanent location), and the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Dep Var: In 2024, has...	Any Credit Report		Any Credit Score		Any Credit Tradeline	
	(1)	(2)	(3)	(4)	(5)	(6)
21+	-0.0543***	-0.0485***	-0.1404***	-0.1216***	-0.1442***	-0.1207***
	(0.0020)	(0.0022)	(0.0070)	(0.0048)	(0.0063)	(0.0042)
SSN Age	0.0043***	0.0052***	0.0080***	0.0109***	0.0068***	0.0108***
	(0.0005)	(0.0004)	(0.0009)	(0.0007)	(0.0007)	(0.0006)
Birth Year F.E.	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X
Last Zip5 F.E.		X		X		X
Longest Zip5 F.E.		X		X		X
Number Zip5 F.E.		X		X		X
R^2	0.007	0.034	0.020	0.111	0.023	0.138
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	0.9615	0.9615	0.9031	0.9031	0.8503	0.8503

Table A11: Credit access by type of credit by age 37, for consumers where credit score observed in 2024

Data in this sample is restricted to only consumers with a non-missing credit score in 2024. This table presents OLS estimates from individual-level regressions for whether the consumer has a credit card, auto loan, or mortgage at or before age 37 (i.e., 8 or more years after immigration for all immigration cohorts in our sample) on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned at age 21 or older) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 1, 4, and 7 include include fixed effects for the birth year of the consumer, first Zip5, and last Zip5. Columns 2, 5, and 8 also include additional fixed effects for a consumers' longest Zip5 (a proxy for their most permanent location). Columns 3, 6, and 9 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Dep Var: By Age 37, has...		Credit Card			Auto Loan			Mortgage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
21+	0.56***	0.51***	0.67***	-2.56***	-2.56***	-2.01***	6.33***	6.31***	6.57***
	(0.11)	(0.11)	(0.13)	(0.34)	(0.35)	(0.22)	(0.49)	(0.48)	(0.41)
SSN Age	-0.04	-0.03	0.08	-1.83***	-1.83***	-1.46***	-2.45***	-2.44***	-2.20***
	(0.03)	(0.03)	(0.04)	(0.10)	(0.10)	(0.12)	(0.08)	(0.08)	(0.11)
Birth Year F.E.	X	X	X	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X		X	X
Number Zip5 F.E.			X			X			X
R^2	0.038	0.042	0.054	0.067	0.071	0.099	0.114	0.125	0.134
N	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726
Mean, SSN Age <21	96.05	96.05	96.05	80.37	80.37	80.37	48.76	48.76	48.76

Table A12: Survey of Consumer Finances (2022): auto vehicle holding and homeownership, and how these assets are funded

This table uses public data from the Survey of Consumer Finances (2022), keeping birth years 1972 to 2000 such that respondents are aged between 22 and 49. This table presents OLS estimates from individual-level regressions for outcomes on an indicator for immigration status ("21+," which is an indicator for whether the consumer's age of immigration was at age 21 or older) and *Immigration Age*, the consumer's age at immigration (pooling consumers with an age of immigration of Age 20 or younger into one group). Age of immigration is constructed from the survey variable x6906 (years lived in the United States) and x8022 (age). The outcome in column 1 is whether a consumer has any auto vehicle (constructed from variable x2201). The outcomes in column 2 is conditional on holding any auto vehicle. Column 2 is whether any vehicle is purchased with cash without financing or leasing (constructed from variables x2201 and the auto financing and leasing variables listed next), The outcome in column 3 is whether a consumer is a homeowner (i.e., not a renter). The outcome in column 4 is conditional on owning a home, whether they do so without any mortgage. All regressions include fixed effects for the birth year of the consumer and fixed effects for other demographic control variables: male, race, hispanic, spouse, male spouse, marital status, household size, number of children, education levels, and quintiles of household wage income. Heteroskedasticity-robust standard errors. Missing data in the SCF are imputed five times using a multiple imputation technique, storing data in five "implicates". We run a separate regression on each of the five implicates and follow the SCF's recommended multiply-imputed variance estimation technique for combining standard errors. *$p < .10$; **$p < .05$; ***$p < .01$.

Dep Var:		Conditional On Having A Car		Conditional On Homeowner
	Has Car	Auto Cash	Homeowner	No Mortgage
	(1)	(2)	(3)	(4)
21+	-0.0620	0.1254*	0.0241	0.0704
	(0.0477)	(0.0753)	(0.0675)	(0.0791)
Immigration Age	-0.0003	-0.0164**	-0.0155***	-0.0100*
	(0.0044)	(0.0077)	(0.0055)	(0.0058)
F.E. Birth Year	X	X	X	X
F.E. Demographic Controls	X	X	X	X
R^2	0.156	0.038	0.298	0.175
N	1,813	1,568	1,813	883
Mean, Immigration Age <21	0.8923	0.7396	0.5398	0.1619

Table A13: Survey of Consumer Finances (2022): credit attitudes

This table uses public data from the Survey of Consumer Finances (2022), keeping birth years 1972 to 2000 such that respondents are aged between 22 and 49. This table presents OLS estimates from individual-level regressions for outcomes on an indicator for immigration status ("21+," which is an indicator for whether the consumer's age of immigration was at age 21 or older) and *Immigration Age*, the consumer's age at immigration (pooling consumers with an age of immigration of Age 20 or younger into one group). Age of immigration is constructed from the survey variable x6906 (years lived in the United States) and x8022 (age). The outcome in column 1 is "Now I would like to ask you some questions about how you feel about credit. In general, do you think it is a good idea or a bad idea for people to buy things by borrowing or on credit?" (constructed from variable x401), with the variable having three potential values: 1 if they regard it as a good idea, 0 if good in some ways, bad in others, and -1 if bad idea. The outcomes in columns 2, 3, 4, and 5 all are binary variables responding to different scenarios following the prompt "people have many different reasons for borrowing money which they pay back over a period of time. For each of the reasons I read, please tell me whether you feel it is all right for someone like yourself to borrow money...", taking a value of 1 if they respond yes and a value of 0 if they respond no. Column 2 (constructed from variable x402) is whether they feel it is all right for someone like yourself to borrow money to cover the expenses of a vacation trip. Column 3 (constructed from variable x403) is whether they feel it is all right for someone like yourself to borrow money to cover living expenses when income is cut. Column 4 (constructed from variable x405) is whether they feel it is all right for someone like yourself to borrow money to finance the purchase of a car. Column 5 (constructed from variable x406) is whether they feel it is all right for someone like yourself to borrow money to finance educational expenses. All regressions include fixed effects for the birth year of the consumer and fixed effects for other demographic control variables: male, race, hispanic, spouse, male spouse, marital status, household size, number of children, education levels, and quintiles of household wage income. Heteroskedasticity-robust standard errors. Missing data in the SCF are imputed five times using a multiple imputation technique, storing data in five "implicates". We run a separate regression on each of the five implicates and follow the SCF's recommended multiply-imputed variance estimation technique for combining standard errors. R^2 is the adjusted r-squared averaged across the regressions for the five implicates. *$p < .10$; **$p < .05$; ***$p < .01$.

Dep Var: All Right To Borrow...	In General	For Vacation	For Living Expenses	For Auto Purchase	For Education
	(1)	(2)	(3)	(4)	(5)
21+	-0.1499	-0.0774	-0.0804	-0.2273***	0.0905
	(0.1375)	(0.0518)	(0.0781)	(0.0712)	(0.0559)
Immigration Age	0.0100	0.0041	-0.0011	0.0113*	-0.0149**
	(0.0122)	(0.0056)	(0.0075)	(0.0060)	(0.0068)
F.E. Birth Year	X	X	X	X	X
F.E. Demographic Controls	X	X	X	X	X
R^2	0.030	0.018	0.029	0.072	0.052
N	1,813	1,813	1,813	1,813	1,813
Mean, Immigration Age <21	0.0380	0.1530	0.7338	0.7958	0.8424

Table A14: Survey of Consumer Finances (2022): credit demand

This table uses public data from the Survey of Consumer Finances (2022), keeping birth years 1972 to 2000 such that respondents are aged between 22 and 49. This table presents OLS estimates from individual-level regressions for outcomes on an indicator for immigration status ("21+," which is an indicator for whether the consumer's age of immigration was at age 21 or older) and *Immigration Age*, the consumer's age at immigration (pooling consumers with an age of immigration of Age 20 or younger into one group). Age of immigration is constructed from the survey variable x6906 (years lived in the United States) and x8022 (age). The outcome in column 1 is a binary variable for whether a consumer has applied for any credit in the past twelve months (constructed from variables listed below, and also variable x438 whether applied for student loan). Column 2 (constructed from variable x437) is whether applied for auto loan. Column 3 (constructed from variable x435) is whether applied for mortgage. Column 4 (constructed from variable x436) is whether applied to refinance mortgage. Column 5 (constructed from variable x433) is whether applied for credit card or respond to a pre-approved credit card. Column 6 (constructed from variable x434) is whether applied for a credit card limit increase. Column 7 (constructed from variable x439) is whether applied for other consumer credit. All outcomes refer to applications in the last twelve months. All regressions include fixed effects for the birth year of the consumer and fixed effects for other demographic control variables: male, race, hispanic, spouse, male spouse, marital status, household size, number of children, education levels, and quintiles of household wage income. Heteroskedasticity-robust standard errors. Missing data in the SCF are imputed five times using a multiple imputation technique, storing data in five "implicates". We run a separate regression on each of the five implicates and follow the SCF's recommended multiply-imputed variance estimation technique for combining standard errors. R^2 is the adjusted r-squared averaged across the regressions for the five implicates. *$p < .10$; **$p < .05$; ***$p < .01$.

Dep Var: Apply For...	Any Credit	Auto	Mortgage	Refinance Mortgage	Credit Card	Limit Increase	Other Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
21+	-0.0071	-0.0690	0.0625	0.0437	0.0519	-0.0279	-0.0729
	(0.0695)	(0.0739)	(0.0700)	(0.0401)	(0.0843)	(0.0609)	(0.0458)
Immigration Age	0.0050	0.0112	-0.0036	-0.0048	-0.0102	0.0073	0.0128**
	(0.0060)	(0.0072)	(0.0067)	(0.0039)	(0.0086)	(0.0062)	(0.0055)
F.E. Birth Year	X	X	X	X	X	X	X
F.E. Demographic Controls	X	X	X	X	X	X	X
R^2	0.059	0.059	0.056	0.033	0.039	0.043	0.040
N	1,813	1,813	1,813	1,813	1,813	1,813	1,813
Mean, Immigration Age <21	0.6481	0.1995	0.1128	0.0670	0.4043	0.1533	0.1208

Table A15: Survey of Consumer Finances (2022): credit supply

This table uses public data from the Survey of Consumer Finances (2022), keeping birth years 1972 to 2000 such that respondents are aged between 22 and 49. This table presents OLS estimates from individual-level regressions for outcomes on an indicator for immigration status ("21+," which is an indicator for whether the consumer's age of immigration was at age 21 or older) and *Immigration Age*, the consumer's age at immigration (pooling consumers with an age of immigration of Age 20 or younger into one group). Age of immigration is constructed from the survey variable x6906 (years lived in the United States) and x8022 (age). Columns 1 and 2 are conditional on a consumer reporting that they did not apply for credit in the last twelve months. The outcome in column 1 is a binary variable for whether a consumer has reported that they did not apply for credit in the last twelve months because they had no need or want additional credit (constructed from variable x441). Column 2 (constructed from variable x441) is a consumer's reason for not applying for credit is interest rates being too high. Column 3 (constructed from variable x407) is conditional on a consumer reporting that they did apply for credit in the last twelve months, whether they have been turned down for credit or did not get as much credit as they applied for in the last twelve months. Column 4 (constructed from variable x408) is conditional on applying for credit and being rejected, whether they reapplied. Column 5 (constructed from variable x408) is conditional on applying for credit and being rejected, and also conditional on reapplying for credit, whether they were then unable to get the full amount requested. All outcomes refer to applications in the last twelve months. All regressions include fixed effects for the birth year of the consumer and fixed effects for other demographic control variables: male, race, hispanic, spouse, male spouse, marital status, household size, number of children, education levels, and quintiles of household wage income. Heteroskedasticity-robust standard errors. Missing data in the SCF are imputed five times using a multiple imputation technique, storing data in five "implicates". We run a separate regression on each of the five implicates and follow the SCF's recommended multiply-imputed variance estimation technique for combining standard errors. R^2 is the adjusted r-squared averaged across the regressions for the five implicates. *$p < .10$; **$p < .05$; ***$p < .01$.

	Why Did Not Apply For Credit?		Outcome After Applying For Credit?		
(Conditional On...	...Not Applying)		...Applying)	...Reject)	...Reject & Reapply)
Dep Var:	No Demand	Rate Too High	Reject/Less	Reapply	Reapply Reject
	(1)	(2)	(3)	(4)	(5)
21+	0.0862	-0.0015	-0.0156	-0.1510	0.4863**
	(0.1261)	(0.0827)	(0.0734)	(0.2250)	(0.1917)
Immigration Age	-0.0077	0.0121	-0.0060	0.0270	-0.0089
	(0.0111)	(0.0088)	(0.0061)	(0.0188)	(0.0204)
F.E. Birth Year	X	X	X	X	X
F.E. Demographic Controls	X	X	X	X	X
R^2	0.177	0.095	0.085	0.092	0.340
N	666	666	1,147	292	178
Mean, Immigration Age <21	0.7952	0.0753	0.2707	0.603	0.6022