Immigration and Credit in America

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December 13, 2025

Abstract

We study the assimilation of immigrants into U.S. consumer credit markets. Although immigrants arrive without a U.S. credit history, we find that they are positively selected: immigrants' average credit scores at age thirty are 27 points higher than non-immigrants of the same age and 5-digit ZIP, and this gap widens with age. Despite greater creditworthiness, immigrants are less likely than non-immigrants to have ever had an auto loan or a mortgage by age 37, the end of our sample window. We compare credit access of same-age immigrants arriving one year apart, finding persistent differences in credit access lasting over a decade after immigration. Our results point to the importance of time in the U.S. for accessing credit.

Keywords: Immigration, Credit History, Household Credit, Debt Aversion
JEL Codes: D14, G51, J11, J15, J61, R23

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Thanks to Andrés Shahidinejad, Anthony DeFusco, Bianca Putz, Caitlin Gorback, Constantine Yannelis, Erica Jiang, Feng Zhang, Igor Livshits, James Vickery, John Gathergood, Jon Zinman, Luke Stein, Manju Puri, Marco Pagano, Matt Notowidigdo, Nathan Blascak, Neale Mahoney, Scott Nelson, Tom Akana, Yang Shi, Zack Liu, colleagues at CU Boulder, Rice, and UCSD, and seminar participants at Deakin, EDHEC, Federal Reserve Bank of Philadelphia, Federal Reserve Board, INSEAD, Lone Star Finance Conference, Monash, New Zealand Finance Meeting, NUS, UO Summer Finance Conference, RMIT, SAFE Household Finance Workshop, University of Edinburgh Credit Scoring and Credit Control Conference, and the University of Melbourne for their feedback. Cookson gratefully acknowledges financial support provided by the Michael A. Klump Professorship and the Leeds School of Business. Guttman-Kenney acknowledges support from the NBER Dissertation Fellowship on Consumer Financial Management. Thanks to the Kilts Center for Marketing and the Fama-Miller Center for Research in Finance at the University of Chicago Booth School of Business for supporting this research, and to Art Middlebrooks, Heather McGuire, Jennifer Williams, Marisa Milazzo, and Rich Cortez for their help. The results in this paper were calculated (or derived) based on credit data provided by TransUnion, a global information solutions company, through a relationship with the Kilts Center for Marketing at the University of Chicago Booth School of Business. TransUnion (the data provider) has the right to review the research before dissemination to ensure it accurately describes TransUnion data, does not disclose confidential information, and does not contain material it deems to be misleading or false regarding TransUnion, TransUnion's partners, affiliates or customer base, or the consumer lending industry.

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 (e.g., 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 and their immigration timing, in a 10% representative sample of U.S. consumer credit reporting data from TransUnion spanning 2000 to 2024. We study consumers born between 1975 and 1987 so that we can observe their entry into the credit system. Using this dataset, we track the progress of both non-immigrant and immigrant cohorts through the U.S. credit system, defining cohorts by their age at SSN assignment. This empirical strategy contrasts outcomes across immigration ages from 21 to 29 while including fixed effects for birth year and fine geography (ZIP5) to account for unobservables, enabling us to shed light on the connection between age at immigration and credit market trajectories.

Our core findings provide new empirical facts about immigration and credit in the United States. We show that immigrants appear in credit markets once they are assigned a SSN, supporting our empirical classification of immigrants in the credit reporting data. 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 27 points higher credit scores, on average, compared to non-immigrants of the same age in the same geographic area, and this gap widens with age. Figure 1 shows that the distribution of credit scores at age 30 for immigrants is systematically above that of non-immigrants, until the 90^{th} percentile, where they are effectively the same. Immigrants also have persistently lower delinquency rates and more conservative credit utilization patterns. This *positive selection* on credit quality is more pronounced among those who immigrate later.[1]

However, despite immigrants' higher credit quality upon entering U.S. credit markets, which is captured by their credit scores, we find they access less credit than non-immigrants. While the credit card access of immigrants converges relatively quickly to non-immigrant levels, significant gaps persist in whether immigrants ever access auto loans and mortgages by the end of our sample frame. By age 37, immigrants are 13 percentage points (17% of the mean) less likely to have ever had an auto loan and 7 percentage points (16%) less likely to have had a mortgage than non-immigrants of the same age in the same geographic area. The immigrant mortgage gap is explained by immigration timing, with 2 percentage points lower access by age 37 for immigrants arriving each year later 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, which also appears largely due to the timing of immigration.

A key mechanism behind these results is that the early timing of an immigrant's financial experiences sets a trajectory for their future—a phenomenon we term *history dependence*. To evaluate this idea, we use a paired cohort strategy that compares immigrant cohorts born in the same year, but who immigrated a single year apart. This strategy isolates the effect of a single additional year in the U.S. on long-term access to credit. We find that immigrants arriving to the U.S. a year later than same-age control immigrants have lower average access to auto loans and mortgages. Furthermore, this reduced credit access persists more than a decade post-immigration. The fact that immigrating a year later in your twenties matters for auto loans and mortgages, which are often accessed in a consumer's thirties, suggests that delayed entry into credit markets has long-term impacts on credit access.

We consider alternative mechanisms. Immigrants are more likely to leave the U.S. within our sample period, but we show that this emigration does not explain our results. Alternatively, immigrants may have a lower demand for credit, but we find that they have greater demand for credit in their twenties, both relative to non-immigrants and relative to same-age immigrants arriving a year before them. Further, using the Survey of Consumer Finances (SCF) we find that immigrants have a more negative attitude towards auto debt than non-immigrants, but no greater

[1] Legal immigrants to the United States have a broad range of immigration statuses, including employment-based, immediate relative, and family-sponsored. 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 Office of Homeland Security Statistics Immigration Statistics (2024) show that across 2004 to 2023, only 16% of legal immigrant temporary workers admitted were on H-1B visas, and only 9% of legal new arrivals awarded lawful permanent residence (green cards) for employment are professionals with advanced degrees or exceptional ability.

general aversion to debt (e.g., Martínez-Marquina and Shi, 2024), suggesting that this cannot explain our results for credit card and mortgage use.

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. As reviewed in Abramitzky and Boustan (2017), immigrants to the U.S. have swung between being positively selected and negatively selected, depending on the immigration wave, measure of selection, and the country of immigration. 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 and selection. 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 from the primarily labor market outcomes studied in the immigration literature.

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. By studying immigrants—an important consumer segment with shorter credit profiles due to their later credit market entry—our research provides a new perspective on credit access for consumers with "thin" credit reports that only contain a few accounts or a short credit history (e.g., Di Maggio et al., 2022, Blattner and Nelson, 2024) or no credit history (e.g., Chioda et al., 2025).[2] For example, it is striking that immigrants' delayed 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 those of 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). Related work has emphasized the importance of a good start in credit markets, either through good parental credit histories (e.g., Bach et al., 2023, Benetton et al., 2025, Bakker 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.[3]

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

2. Data and Empirical Design

In this section, we describe the data that we use and explain how we generate the two key data-points we need for each consumer: whether they are immigrants and, if so, when they immigrated. Subsection 2.3 provides context on lending to immigrants in the United States, while subsection 2.4 explains our empirical methodology.

[2] 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, Gorback and Schubert, 2025). 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.

[3] 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.

2.1 Data

2.1.1 Consumer Credit Reporting Data

We use 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 that contains monthly information from July 2000 to December 2024. To build this sample, TransUnion starts with a 10% representative sample of consumers who had a credit report in July 2000. For each month of data after July 2000, 10% of new consumers entering the main TransUnion data are added to the BTCCP to maintain its representativeness. We follow the best practices for using consumer credit reporting data described in Gibbs et al. (2025).

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, which contains information (i.e., outstanding balance and delinquency status) on each credit account held by a consumer. This tradeline dataset provides the date each account was opened, including those opened or closed prior to July 2000. 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 combining the consumer's birth date with the account opening date in tradeline data, we compute the consumer's age at account opening.[4] From the BTCCP's monthly consumer-level aggregated dataset we use a consumer's credit score, VantageScore, their ZIP code and state, and months since the last credit inquiry (search). From this last dataset, we use an annual panel of aggregated credit characteristics (observed each July) to construct outcomes, and use monthly data to calculate control variables for consumers' first credit score, first ZIP code, longest ZIP code, and the number of unique ZIP codes.

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 Microdataset Series, (Ruggles et al., 2025). These anonymous data contain birth years, years of immigration, and geographic location, providing us with benchmarks

[4] We follow standard practice in removing tradelines that have not been updated in the last twelve months (Gibbs et al., 2025). Some tradelines appear to be opened before the age of 18. We drop such cases to produce more plausible estimates of credit usage at age 18, as these cases are 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.

to evaluate our immigrant classification.

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 (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 the number of years since immigration, which is not available in earlier waves. The SCF does not contain geographic information or credit scores.

2.2 Immigrant Classification

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).[5] SSNs are nine-digit numbers created since 1936 that are unique to a consumer and are assigned by the Social Security Administration (SSA). Up until mid-2011, the SSA sequentially assigned SSNs using the same first five digits before moving onto another five-digit block, with the timing of these allocations being public. The first three digits denote an "area number," a geographic region within a state, the fourth and fifth digits are the "group number," assigned sequentially in blocks within that area, and the last four digits are the order of processing which are quasi-randomly assigned (see Puckett, 2009 for a comprehensive history of SSN assignment). As established in prior research, consumers assigned a SSN at age 21 or later in life are generally immigrants (Klopfer and Miller, 2024, Bernstein et al., 2025).

TransUnion observes SSNs, however, the BTCCP that we have access to is anonymized without SSNs, so we developed a process to enable us to classify immigrants in our data without directly accessing SSNs. To estimate the year of SSN assignment, $SSN\ Year$, we construct a lookup table using 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. We sent TransUnion a list of anonymous

[5] Advani et al. (2025) also uses a related method to study immigration in the United Kingdom. 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 included 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.

consumer identifiers in the BTCCP, 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. We follow the prior literature in classifying consumers as an immigrant if their age at SSN assignment, $SSN\ Age$, is greater than or equal to 21, where $SSN\ Age = SSN\ Year - Birth\ Year$.

For our analysis, we apply three sample restrictions. First, we restrict to consumers who have a SSN in TransUnion and whose birth years are between 1975 and 1987. Consumers with these birth years are mostly expected to enter the credit system after 2000 (and in our data we observe their accounts that were opened before 2000) and before the SSN assignment period ends in 2011. For example, from 2000 to 2024 (the BTCCP coverage window), consumers born in 1975 are observed from ages 25 to 49, while consumers born in 1987 are observed from ages 18 to 37. This part of the lifecycle – early adulthood to middle age – is when we expect credit access to be most economically important.[6] This follows similar approaches used in related papers (Ricks and Sandler, 2025, Bach et al., 2023, Bakker et al., 2025). Restricting to birth years 1975 to 1987 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 $SSN\ Age < 30$, which focuses our analysis on immigrants arriving in the United States at some point in their twenties. This ensures that, for all consumers, credit outcomes in a consumer's thirties occur *after* everyone in our sample has immigrated and we can examine longer-term credit outcomes observed by 2025. Third, we remove any consumers who have $SSNAge < 0$ and require consumers in our sample to have a credit report by 2011 (which can occur even if they only apply for credit and do not yet hold a credit product), because after 2011 the SSA randomly assigned all nine digits of consumers' SSNs, eliminating our ability to classify immigrants.

After applying these restrictions, we have a total of 6,122,932 consumers, 5.62% (344,261) of whom we classify as immigrants (i.e., SSN Ages 21 through 29). Appendix Figure A2 shows that this entrant sample is consistent with the ACS data, in which 6.57% immigrate between ages 21 to 29. Although some older consumers were assigned SSNs as adults, for the birth years that we study, non-immigrants were largely assigned a SSN at birth or before turning 18, as

[6] For some analyses that rely on outcomes constructed from the BTCCP's consumer-level datasets, we further restrict to birth years 1982 to 1987 to ensure that consumers enter the credit system after 1999.

demonstrated in administrative Social Security Administration data by Klopfer and Miller (2024).[7] The consumers we classify as immigrants are more geographically mobile than non-immigrants (Appendix Figure A4). Additional details on our data construction are in Appendix A.1.

Our classification of immigrants excludes certain groups. First, our immigrant classification does not include illegal immigrants (who lack SSNs), and who are less likely to use the formal credit system for demand and supply reasons. Second, we do not observe immigrants or non-immigrants who remain entirely outside the formal credit system, because we study formal credit only, not informal credit. Third, we do not study immigrants who arrive before adulthood or at older ages. Fourth, we do not include legal immigrants with Individual Taxpayer Identification Numbers (ITINs) or Enumeration at Entry numbers (EAE), as we do not know when these are assigned. However, these are typically only used before a consumer later receives a SSN.

2.3 Institutional Details on Lending to Immigrants

Lenders in the United States may consider an applicant's immigration status in their lending decisions – immigration status is *not* a protected characteristic under the Equal Credit Opportunity Act (ECOA). This contrasts with ECOA-protected characteristics such as gender, national origin, and race. However, as detailed in Consumer Financial Protection Bureau (2023), in practice, lenders have been constrained in how much they can rely on immigration status in their underwriting.[8]

Lenders in the United States use credit scores and other information in their lending decisions. Information frictions may affect lenders' decisions and impact immigrants' access to credit in several ways. First, immigrants initially lack a U.S. credit report and a credit score. Lenders may therefore have a prior that, given no information, immigrants are high credit risk. Second, after entering the U.S. credit system, immigrants have a shorter length of credit history than most non-immigrants of the same age, who often enter the credit system at age 18 or in their early twenties. The length of credit history positively affects credit scores (FICO, VantageScore) and may also be a direct input

[7] If we instead classify immigrants as those with SSN ages >18 the comparison is unaffected, as the non-immigrant baseline is almost unchanged and only 101,670 consumers have SSN Ages of 19 or 20 – see Appendix Table A1, Panel B. Appendix Figure A3 shows the distribution of SSN Ages by birth years in our data, which mirrors that in Klopfer and Miller (2024).

[8] A change in government policy towards immigrants may be altering this. In March 2025, the U.S. Department of Housing and Urban Development (2023) removed eligibility for "non-permanent residents" (legal immigrants) from Federal Housing Administration programs (illegal immigrants were always ineligible). This policy change is too recent to affect our results, but may reduce immigrants' access to mortgages. Similarly, financing auto lending to immigrants appears to be becoming harder in 2025. One auto lender, Tricolor, which specialized in selling and financing used cars to immigrants, filed for bankruptcy in 2025 (although this may reflect fraud). Another subprime auto lender, LendBuzz, warned of increased risks of lending to immigrants in its 2025 filing ahead of its Initial Public Offering.

in lenders' underwriting. Consumer credit markets vary in their reliance on credit scores and on information in the credit report (including the length of credit history), with credit card decisions typically more reliant on this information than auto loans or mortgages (Blattner et al., 2022). For example, Fannie Mae and Freddie Mac mortgage eligibility requirements depend not only on credit scores, but also on information obtained directly from the borrower, such as loan-to-value and debt-to-income ratios calculated using verified income information, and the liquid assets available to a consumer after closing.[9]

Cultural barriers may also prevent immigrants from accessing credit, such as differences in familiarity and willingness to use debt. Language barriers may play a role (Liu, 2025), and immigrants may not understand the U.S. credit system, particularly how one needs to take out credit to build a credit score.

2.4 Empirical Methodology

We use two main empirical specifications to analyze outcomes in our credit reporting data. For both of these specifications, we collapse the data to one observation per consumer, i, estimating OLS cross-sectional regressions, and clustering standard errors by birth year. Our first main specification is Equation (1):

$$\mathrm{Y}_i \quad = \quad \beta_1 \cdot \mathbb{I}\{Immigrant\}_i + \mu_{b(i)} + \eta_{g(i)} + \epsilon_i, \tag{1}$$

In this specification, β_1 is the coefficient of interest, estimating the average difference in outcomes between immigrants and non-immigrants. This is the coefficient on an indicator variable, $\mathbb{I}\{Immigrant\}_i$, which takes a value of one for *immigrants* – consumers with SSNs assigned at ages 21 through 29 – and takes a value of zero if their age of SSN assignment is less than 21 (we classify these as *non-immigrants*). This regression also includes birth year fixed effects ($\mu_{b(i)}$), as well as geographic fixed effects ($\eta_{g(i)}$) for the first five-digit ZIP code (First ZIP5) associated with a consumer in our data, to capture unobservable heterogeneity in local market conditions.

Our second main equation is Equation (2):

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

In this specification, we include a linear term for the age of SSN assignment ($SSN\ Age_i$) to

[9]Other factors could also lead lenders to restrict credit to immigrants. For example, in the United Kingdom, Dobbie et al. (2021) show how one subprime consumer lender's decisions are biased against immigrants due to loan examiner incentives focused on short-run outcomes, rather than long-run profits.

allow for heterogeneity in immigrant outcomes. To aid interpretation, we pool all non-immigrant SSN Ages (0 through 20) into one category. The β_2 coefficient reflects the marginal difference in average outcomes associated with being assigned a SSN one year later in life.

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 measure of their most permanent location, and the number of unique five-digit ZIP observed for a consumer (*Number ZIP5*) which is a measure of their geographic mobility.[10] All of these geographic controls are imperfect because consumers enter and exit our data at different times, partially based on their credit access. In the Appendix, we also show that our results are robust to restricting to consumers who have not emigrated, which we measure by conditioning on the subsample of consumers who are still observed in the data in 2024.

An important implementation detail is how to handle missing values of cross-sectional outcome variables, such as the age at which a consumer first takes out a mortgage. Because these consumers never accessed the credit product, excluding these from the estimation would understate any difference in credit access. We address this issue by assigning these observations a value which corresponds to accessing the product in 2025, one year after the end of our data.

3. Results

This section describes the main results on immigrant credit entry, creditworthiness and credit access. 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 1 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.

[10] Geographies 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 in areas with different incomes or other economic opportunities, and with consequently different credit access or economic vibrancy. This motivates our granular geographic controls.

Immigrants typically enter the U.S. credit system later than non-immigrants: The average age at first credit report for immigrants is 25.2 compared with 19.9 for non-immigrants. Their delay in accessing their first credit card is similar, with immigrants having an average age at first credit card of 28.0 versus 24.4 for non-immigrants. Though delayed, immigrants are just as likely to eventually have a credit card within our sample frame (94.0% versus 94.5% for non-immigrants).

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 percentage point difference in the probability of being scored by age 30), the difference between immigrants and non-immigrants in average credit scores is *larger* at age 40 (698.9 for immigrants versus 659.5 for non-immigrants, a 29.4 point difference), and by that point in the lifecycle effectively all consumers in the sample have been scored.

Turning to credit products typically accessed later in a consumer's lifecycle, we find that immigrants are significantly less likely to access auto loans (66.1% versus 80.0%) and mortgages (50.1% versus 46.4%) 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 31.6 (versus 27.6) and their average age at first mortgage is 33.8 (versus 30.6).

We also highlight differences in credit limits between immigrants and non-immigrants. At age 30, immigrants have similar, but slightly lower average credit limits than non-immigrants ($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). In the following subsections, we will examine each of these differences and dynamics more precisely, conditioning on the age of SSN assignment, and accounting for birth year and geography with fixed effects.

3.2 Credit Market Entry

We first present evidence that the age at which a consumer receives a SSN in our data (SSN Age) drives the timing of credit market entry, as we would expect. At the highest level, our evidence shows that later in life 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.

Table 2 presents the results from estimating our regression specifications (equations (1) and (2)). Columns 1 and 3 show that immigrants are around 5 years older than non-immigrants when they receive their first credit report, and 4.7 years older when they receive their first credit product, holding birth year and first ZIP5 equal via fixed effects. Delayed entry into the credit system is more pronounced for immigrants who arrive in the United States later in life. When we add SSN Age to the specification (in columns 2 and 4) the mean delay relative to non-immigrants falls to 1.8 and 1.6 years, for first credit report and product respectively. But for each additional year of later in life SSN assignment, the first credit report (product) is delayed by an additional 0.74 (0.72) years. We interpret this delay as primarily mechanical: immigrants who would have counter-factually received a credit report or product before their SSN age could not do so – they were outside the country.[11] These results are also robust to adding fixed effects for the consumer's *last* ZIP5 and *longest* ZIP5, and *number* of unique ZIP5s, as shown in Appendix Table A2. These delays are economically significant relative to the average age that non-immigrants receive their first credit report (aged 19.9) and their first credit product (aged 21.3).

To evaluate how SSN Age relates to the timing of credit market entry, Appendix Figure A5 plots the age at which each SSN age cohort receives credit products. As SSN Age increases, so does the average age at first credit report, and this increase is essentially linear. We observe similarly linear effects for age at first credit card, auto loan, and mortgage. Especially for later in life SSN Age cohorts, these findings reflect the reality that immigrants could not obtain credit products in America in the years before they immigrated.

3.3 Creditworthiness

A core aim of the immigration literature is to understand how immigrants assimilate into U.S. economy (e.g., Borjas, 1985). Our data enable us to measure how a consumer's creditworthiness evolves over their lifecycle via two comparisons: 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.

[11] 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, as shown in Appendix Figure A6 shows the lifecycle for the age of first credit report and first credit product by SSN Age. This pushes the mechanical effect below one.

3.3.1 First Credit Score

To complement the cross sectional regressions, in Figure 2 and later analyses that follow, we visually summarize our data for each combination of $SSN\ Age$ and Age observed in our panel data, grouping consumers assigned a SSN at age 18 or earlier into a single benchmark category of non-immigrants with black lines. Other SSN Ages contain immigrants and have shades of blue lines, with lighter shades for consumers assigned SSN Ages later in life. This figure, and subsequent analogous figures for other outcomes, show SSN Ages 19 and 20 separately, to illustrate how classifying these consumers as either immigrants or non-immigrants would not impact our conclusions (consistent with Bernstein et al. (2025), whose results are not sensitive to whether immigrants are classified based on SSN Ages 19+, 20+, or 21+).

We examine the timing of consumers' first credit scores. Panel A of Figure 2 displays the unconditional likelihood of having a credit score for each SSN Age cohort at different ages. At age 18, approximately 15% of SSN Age 18 consumers receive their first credit score; by age 22, over 80% of these consumers have a score. The consistent rightward shift in these lifecycle curves as SSN Age increases indicates that consumers with later in life SSN Ages receive a score later. In the years prior to the SSN Age (where $Age = SSNAge$ is indicated by a circle on each lifecycle curve), the likelihood of having a credit score is very low, and this is followed by a sharp jump in the percentage of scored consumers in the year following immigration. A small share of consumers have a credit score slightly before they receive a SSN, this is because it is possible to access credit without a SSN (e.g., some consumers will have an ITIN before receiving an SSN).

Shortly after their immigration year, immigrants (i.e., those with SSN Ages 21 to 29), quickly converge to their SSN Age 18 counterpart 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 later in life. 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. As SSN Ages 19 and 20 cohorts may contain a mixture of immigrants and non-immigrants, these 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 the SSN Age 18 cohort, which contains non-immigrants of the same age. Immigrant cohorts continue to have substantially higher average credit scores throughout their thirties, which is after immigrants are just as likely as the SSN Age 18 cohort 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), immigrant cohorts have higher credit scores than the SSN Age 18 cohort after a similar fraction of the immigrant cohorts and the SSN Age 18 cohort are scored. Thus, this result suggests that immigrants who are scored are more creditworthy than their scored non-immigrant counterparts of the same age, on average. Overall, these dynamics paint a somewhat unexpected picture: Even new immigrants with a credit score are *observably* more creditworthy.

To provide a more formal characterization of these lifecycle patterns, in Panel A of Table 3 we report estimates from equations (1) and (2) for how average credit scores at ages 30 and 40 depend on immigration status and SSN Age. Consistent with the descriptive lifecycle plots, column 1 shows that immigrants have average credit scores at age 30 that are 27 points higher than non-immigrants. In column 2, we allow for heterogeneity by SSN Age, and find that the mean difference in credit score at age 30 between immigrants and non-immigrants is 19 points, and increases by an additional 2 points per year of SSN Age.

The immigrant versus non-immigrant difference in credit scores widens as consumers age. Column 3 of Panel A of Table 3 shows how by age 40, the mean gap in credit scores widens to 33 points, and column 4 shows this mean gap is 26 points and increases by an additional 1.5 points per year for consumers who immigrate later in life. These higher average credit scores occur *despite* these consumers having a shorter credit history — the length of credit history is an important input into credit scores, accounting for approximately 15% of FICO and 20% of VantageScore models (VantageScore, 2019, FICO, 2025).

3.3.3 Distribution of Credit Scores

The mean credit score may mask important heterogeneity in credit scores. Figure 1 displays the quantiles of credit scores at age 30, calculated separately for immigrants and non-immigrants. Once scored, immigrants have a higher quality distribution of credit scores than non-immigrants of the same age. Panel B of Table 3 estimates the likelihood of having prime or higher credit scores, specifically, VantageScore > 660. Immigrants are 7 percentage points more likely to have prime or higher credit scores by age 30 than their non-immigrant counterparts, increasing to 9 percentage points at age 40. In addition, immigrants who arrive later in life are more likely to have prime or higher credit scores at age 40, an increase that is large in comparison to the baseline of 47% of non-immigrant consumers with prime or higher credit scores at age 40. Appendix Table A3 shows that results are similar when we use specifications that also include additional geographic fixed effects: *last* ZIP5, longest-held ZIP5, and the number of unique ZIP5s.

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—those without any credit score—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 SSN Age 18 consumer 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 SSN Age 18 cohort is nearly 15 percentage points by age 40.

Digging deeper into the credit score results, consistent with Figure 1, Appendix Figures A7 and A8 show that immigrants have a higher quality distribution of 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 a credit score.[12]

Panel B of Appendix Figure A8 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 reports. This result purely reflects differences in creditworthiness between immigrants and non-immigrants: Immigration status is not an input into credit scores. Overall, the results of this subsection indicate that immigrants' credit behavior mean that the credit scoring system classifies immigrants as lower credit risks on average than non-immigrants of the same age, and immigrants are classified as increasingly lower risks as they age, as 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 and are common inputs to credit scores.

The lifecycle of delinquency rates shown in Panel E of Figure 2 is consistent with our credit score results. SSN Age 18 consumers have higher delinquency rates than immigrants at all ages in our sample frame: from 21 to 40. Moreover, even among immigrants, those arriving later in life 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 3 shows the delinquency rates for immigrants and non-immigrants by age 37, conditional on credit scores at age 30 for the 94% of consumers who have a credit score by this age. Across all credit score bins, immigrants

[12] 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 A8. 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.

have lower average delinquency rates than non-immigrants. Appendix Table A4 shows estimates from our regression specifications, where the outcome is any delinquency by age 37. Alongside fixed effects for birth year, we also include fixed effects for both credit score at age 30 and for ZIP5 at age 30. Column 2 shows that immigrants' delinquency rates are 1.4 percentage points lower than for non-immigrants, or 5% of the non-immigrant mean (27.2%). These delinquency estimates do not differ by immigration age. Thus, even conditional on credit scores at age 30, immigrants are less likely to default, suggesting that credit scores for immigrants may under-estimate their creditworthiness relative to immigrants.

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 F of Figure 2. Credit card utilization is consistently lower for immigrants, especially for later in life SSN Age cohorts. Both delinquency rates and credit card utilization suggest that immigrants are more creditworthy relative to the SSN Age 18 non-immigrant benchmark.

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 to mortgages and auto loans. We observe whether consumers access these products, and later discuss whether these equilibrium outcomes are driven by demand or supply factors. The majority of houses and vehicles in the US are purchased on credit and are thus observed in credit reporting data (Gibbs et al., 2025). We show the lifecycle of credit access for each type of credit in Figure 4 by SSN Age cohort for each age. In contrast to credit risk, immigrant credit access lags that of non-immigrants. 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 C) disappears within 5 years of immigration. Unlike credit cards, we find that immigrants are *persistently* less likely to access auto loan credit (Panel A) and mortgages (Panel B), even up to the end of the panel: age 37. Moreover, for auto loans and mortgages, there is a larger gap, relative to the SSN Age 18 non-immigrant benchmark, for immigrants arriving later in their twenties than for immigrants arriving earlier — the lines do not converge. This marked 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. 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 even behind immigrants with an earlier immigration date.

We quantify this idea using our regression specifications, where the outcome is an indicator for age of first credit access, separately for each type of credit. Table 4, Panel A, presents the results. We find a significant immigrant versus non-immigrant delay in the average age of first accessing credit: 2 years for auto loans and 0.2 years years for mortgages, with this gap growing 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. Appendix Table A2 shows that these estimated delays in first accessing credit are robust to controlling for the consumer's last ZIP5, longest ZIP5, and number of ZIP5s.

To quantify the extensive margin – 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 SSN Age cohort arrives). Table 4, Panel B, presents the results. We find large and significant gaps in average long-run access to auto loans and mortgages: immigrants are 13 percentage points (17% of the outcome mean) less likely to have ever had an auto loan (column 1) and 7.2 percentage points (16%) less likely to have ever had a mortgage (column 3) by age 37. The lower use of auto loans and mortgages for immigrants, compared to non-immigrants, is substantially larger for the immigrants who arrive later in life (columns 2 and 4), and these results are robust to including the full suite of ZIP5 fixed effects. Importantly, the entire difference in mortgage access between immigrants and non-immigrants is explained by the timing of immigrants' arrival in America, with lower access emerging for the consumers with later in life SSN Ages (see Appendix Figure A5 which plots the average age of first credit product by SSN Age cohort, separately for credit cards, auto loans and mortgages). The gap remains in auto loan access, which we understand in the Section 5 by studying SCF data.

3.5 Access to Credit Cards

We now examine consumers' access to credit cards, a key source of unsecured borrowing in the United States. We use our regression specifications to study the extensive margin of credit card access, with outcomes being an indicator for age of first accessing a credit card, and whether a consumer has ever held a credit card by age 37 as outcomes. Estimates are reported in Table 4, Panel A, where we find a significant immigrant to non-immigrant gap in the average age of accessing credit cards: 4.3 years later for immigrants first taking out a credit card (column 5), and the gap is greater for later in life immigrants (column 6). In contrast to our auto loan and mortgage results, by age 37 these differences in credit card access disappear: Table 4, Panel B shows that immigrants are no less likely to have a credit card than non-immigrants (column 5) with no significant difference by SSN Age (column 6). As with our other results, all of these results are robust to controlling for the full suite of ZIP5 fixed effects (Appendix Table A2). The patterns in Figure 4, Panel C, also suggest that credit card access of immigrants catches up more quickly than access to auto loans and mortgages (Panels A and B).

We now look at the intensive margin of access to credit cards, examining how the number of credit cards and their limits evolve over the consumer lifecycle for different immigration cohorts. Figure 4, Panel D shows the number of credit cards, Panel E shows the total value of credit credit limits, and Panel F shows the credit card limit per card conditional on holding any card. Consistent with the evidence on access to auto loans and mortgages, credit card limits of immigrants with later in life SSN Ages take many years to catch up to immigrants with earlier in life SSN Ages and non-immigrants. For example, in Panel E of Figure 4, the SSN Age 29 cohort takes until age 33 to converge to the same total credit limit as SSN Age 18 consumers. This long delay in convergence reflects different dynamics for the average credit limit per card (Panel F) and the number of credit cards (Panel D). In Panel F, the average credit limit per card *never* catches up to earlier cohorts (i.e., by age 40, the SSN Age 29 cohort has the lowest mean credit limit per card of all immigrant cohorts). By contrast, the number of credit cards catches up and surpasses SSN Age 18 cohort within three years of immigration. Appendix Table A3, Panel B, provides results from cross-sectional regressions at age 30 (when some cohorts have not yet crossed the non-immigrant line) and at age 40 (when all immigrant cohorts have crossed).

4. Paired Cohorts

Immigrants and non-immigrants differ along 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 credit outcomes.

4.1 Methodology

While we have so far 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 with the same SSN Age are also the same age. 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 a 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 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. In our regressions we weight each observation by the size of its cohort.

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

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

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 a 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 focal cohort 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 SSN assignment. 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. This estimation approach is not a causal design, but it does allow us to provide evidence on how a single year difference in immigration timing is related to credit access for multiple products.

4.2 Results

We observe distinct dynamics for credit market entry versus later-in-lifecycle credit access using the paired cohort approach. Figure 5 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.

Unlike credit market entry and first credit card access in Panel A, access to mortgage and auto loans have not converged even over a decade after immigration in the paired cohort analysis. After thirteen years, immigrants, relative to same-age immigrants who were assigned a SSN one year earlier, 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 SSN Age gives rise to the long-run gaps that we saw in the earlier analysis.

Table 5 displays the cumulative years of delay in accessing credit by year C, year T, year 5 and year 10, with Appendix Figure A9 showing the full estimates.[13] We estimate that one year difference in SSN Age 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 date T. This finding is consistent with the

[13]This is calculated by accumulating coefficient estimates over the event window. For example, if we obtained an estimate of -0.20 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 0.20 years as of year T, 0.25 years by year 1, and 0.28 years by year 2.

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 differ 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 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 mortgages at any point in their lifecycle due to their later in life immigration.

Turning to the initial dynamics, only a small fraction of the delay in auto loan or mortgage access can be attributed to "mechanical delay". Instead, most of the delay emerges several years after their year of SSN assignment, 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 outcomes correlating with 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 5, and a similar pattern is observed in the number of credit cards in Appendix Figure A9 Panel D. 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, with a similar pattern for the number of credit cards.[14] This nonlinearity reflects the overarching tension inherent to immigration credit we find throughout this paper. On

[14]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 estimate 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.

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 least thirteen years after immigrating.

5. Mechanisms

We now discuss potential mechanisms that could lead to reduced credit access for immigrants, despite their higher measured creditworthiness. The subsections that follow respectively consider creditworthiness, emigration, tastes, and history dependence as potential mechanisms.

5.1 Creditworthiness

We have shown that immigrants (and especially later-in-life immigrants) typically have better credit scores and exhibit lower risk profiles on other credit behaviors (lower delinquency rates and lower credit utilization), which indicates that **creditworthiness** cannot explain our results. Higher credit scores do not lead to lower long-term access to auto loans and mortgages, nor would they delay higher credit card limits by a decade. Further evidence against creditworthiness driving reduced credit access is provided by a calibration bias approach, in which we consider credit outcomes at age 37 while controlling for credit scores at age 30. If measured creditworthiness explained subsequent credit access, then the coefficients on immigrant status and age of immigration should fall to zero conditional on credit scores. However, Appendix Table A4, Panel B, shows that the reduced credit access for immigrants shown in Table 4 is still present after adding precisely this credit score control.

Moreover, immigrants are systematically less likely to be delinquent by 37 in all credit bins below Prime Plus, even after controlling for credit score at 30 (as shown in Panel A of Appendix Table A4). This suggests that the credit scores of most immigrants may be systematically *too low* relative to their creditworthiness. As a final piece of evidence against creditworthiness driving the reduced credit access of immigrants, Panels B and C of Figure 3 show lower access to auto and mortgage credit by age 37 for immigrants across every credit score bin (except for mortgage access by subprime borrowers, which is effectively the same for immigrants and non-immigrants).

5.2 Emigration

A different possible 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.

Our findings remain after accounting for this differential attrition of immigrants. In Appendix Figure A10 and Appendix Table A6 we condition on consumers still present in the data in 2024 and examine all of the main credit outcomes; the results are consistent with those in our main Figure 4. Therefore, while emigration may be a factor that drive some credit decisions, it cannot drive the gaps in credit access that we document.

A final related concern is that the *possibility* of future emigration leads consumers to avoid investing in assets that need financing. However, the relative likelihood of emigration across cohorts is inconsistent with this concern: later-in-life immigrants are *less* likely to emigrate than earlier-arriving immigrants (see Appendix Table A5), but have *lower* mortgage and auto credit access in the paired cohort analysis.

5.3 Credit Demand and Tastes

Another possible mechanism driving lower immigrant access to credit is that they have lower **credit demand** than non-immigrants. In Appendix Figure A6, Panel E, we examine the outcome *months since last inquiry*, where fewer months since last inquiry indicates higher credit demand. On average, immigrants in their twenties have substantially higher credit demand than non-immigrants. However, during their thirties, this pattern reverses and immigrants have slightly lower demand. Panel D of Appendix Figure A9 displays a similar pattern using the paired cohort design: the focal cohort initially has clearly higher credit demand, and it is only in year seven that they begin to have slightly lower demand. Moreover, the lower credit demand we observe later in the lifecycle may result from being deterred following earlier rejections. Thus, this evidence suggests that delayed access to credit is not purely an artifact of delayed demand for credit for later-in-life SSN Age cohorts.

Differences in asset-linked credit – auto loans and mortgages – could also reflect **different tastes** for the underlying asset, that is, immigrants could value autos less than non-immigrants or prefer renting over owning disproportionately. Additionally, immigrants could be more averse than non-immigrants to *financing* autos or homes, preferring instead to pay cash for these assets.

To explore the differences between immigrants and non-immigrants we use the 2022 Survey of Consumer Finances (SCF), which is the only vintage that identifies immigrants, making the sample conditional on *not* emigrating by 2022. The SCF allows us to control for income and education (and other demographics) and to measure asset ownership without inferring it from credit data – further details about the SCF are in Appendix A.2. Panel A of Table 6 shows that immigrants are around 7 percentage points less likely than non-immigrants to own cars (column 1) and 14 percentage points less likely to own houses (column 5).

Turning to asset-linked credit in Table 6 Panel A, immigrants are around 13 percentage points less likely to report having a mortgage (column 7). This is consistent with our results from the credit reporting data, but the limited statistical power of the SCF sample (1,813 respondents) means we do not detect any significant difference in the likelihood of having auto debt (column 3), although the estimates appear to be directionally consistent with our credit reporting data.

In columns 1 and 2 of Panel B of Table 6 we see that immigrants have a more negative attitude to auto debt. Immigrants are 15 percentage points less likely than non-immigrants to agree that it is "all right for someone like yourself to borrow money" to fund an auto purchase. Columns 3 to 6 of Panel B reveal that a positive auto loan debt attitude is strongly positively associated with higher car ownership and also with higher auto debt usage. Including this auto loan debt attitude control attenuates the estimates on the immigration indicator towards zero, however, noise in these estimates means that we cannot distinguish whether they are significantly different from the estimates without this control (columns 1 to 4 of Table 6 Panel A). There is no survey question regarding attitudes to credit card or mortgage debt that is directly analogous to the question regarding attitudes to auto loan debt. The SCF provides evidence that tastes may contribute to the lower auto loan use of immigrants via greater aversion to auto debt, but there is no conclusive evidence of a more general immigrant "debt aversion" (e.g., Martínez-Marquina and Shi, 2024), based on the evidence on general attitudes to debt (Panel B columns 7 and 8).[15]

[15]Panel B of Appendix Table A7 contains the other available measures of attitudes to debt in the survey, with no clear evidence of a more general aversion to debt by immigrants. Panel A of Appendix Table A7 examines SCF questions about whether respondents have applied for credit over the preceding twelve months, a measure of credit demand, however, we do not have the statistical power to detect differences between immigrants and non-immigrants.

5.4 History dependence

A plausible mechanism for our findings is that the length of a consumer's credit history itself may be an important factor in lending decisions, as immigrants arrive with no history and cannot be scored, while later-in-life immigration necessarily reduces credit history. This mechanism is consistent with our evidence of lower immigrant credit access together with higher creditworthiness than *same-age* non-immigrants. **History dependence** of credit is consistent with the gaps in credit access observed in the paired cohort analysis.[16]

However, we cannot be certain that the key mechanism for delayed immigrant credit access is only the number of years in the United States credit system, because there are also other sources of history dependence. This is because our results are organized around life cycles defined by consumers' birth years. 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 — which is a different type of history dependence. Being in the country for an additional year means that the control cohort has an additional year to potentially take out credit, an extra year of U.S. earnings, and is a year further along their personal and professional American life cycle, which in turn may mean they are a year further along in the credit demand life cycle. 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. History dependence is also consistent with the finding that the difference at age 37 in ever having had a mortgage, a product often not accessed by consumers until their thirties, is driven by differences in immigrant age of SSN assignment in their mid twenties — a delay in starting the U.S. lifecycle translates into a delay a decade later.

To the extent that immigrants' having no or a limited credit history is a financial friction that rations credit, market solutions using alternative data in lending decisions are emerging to expand credit access. American Express has linked their own credit history data internationally, allowing their foreign customers to easily apply for a U.S. American Express card. FinTech firms (e.g., Nova Credit) and credit reporting agencies are making progress on infrastructure to enable pulling foreign credit histories and translating foreign credit scores into consistent formats that lenders can use (FinTech Magazine, 2024, TransUnion, 2018, Equifax, 2024). FinTech lenders, such as MPower

[16] 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.

Financing and Prodigy Finance, provide student finance to foreign students at select universities (Bloomberg, 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 to immigrants arriving later in life, in terms of their creditworthiness and credit usage as they age. Upon credit market entry, immigrants are strongly positively selected in terms of their creditworthiness. By age 30, immigrants' average credit scores are 27 points higher than non-immigrants. Yet, despite immigrants' superior measured creditworthiness, we show that by age 37, immigrants are 13 percentage points less likely to have ever had an auto loan and 7 percentage points less likely to have had a mortgage, compared to non-immigrants of the same age in the same geographic area.

Our analyses also show persistent differences in credit access between same-age immigrant cohorts arriving at different times, even if they arrive a single year later. The pattern of our results is consistent with a role for history dependence in immigrant credit access. In light of the major contributions of immigrants in credit-dependent areas such as entrepreneurship, our results highlight an opportunity for market innovations to expand lending to immigrants in America.

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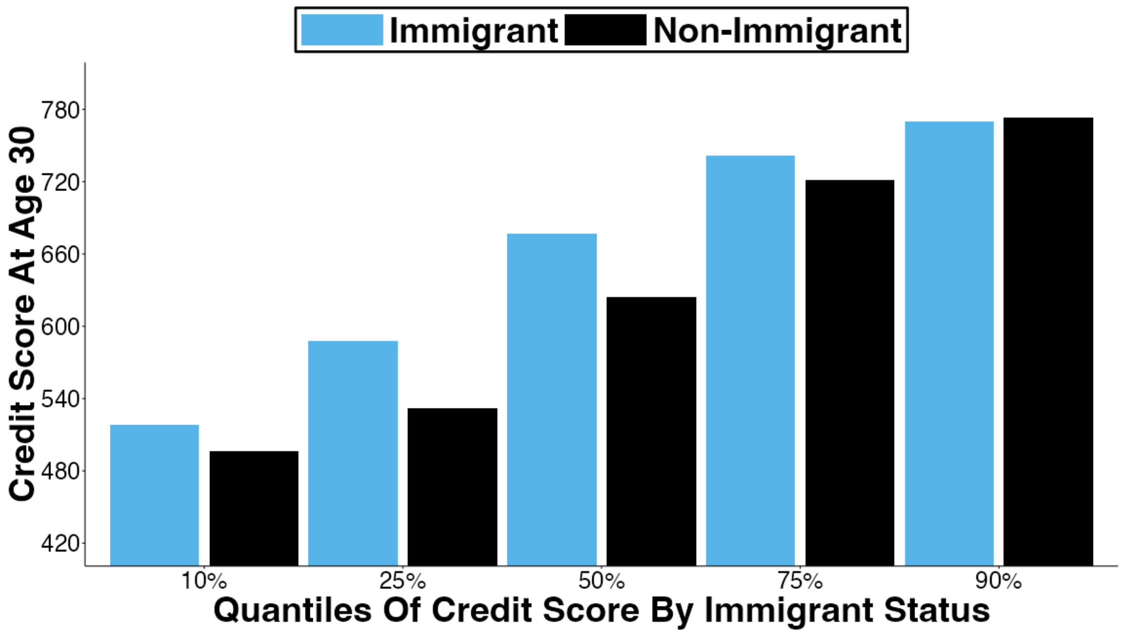
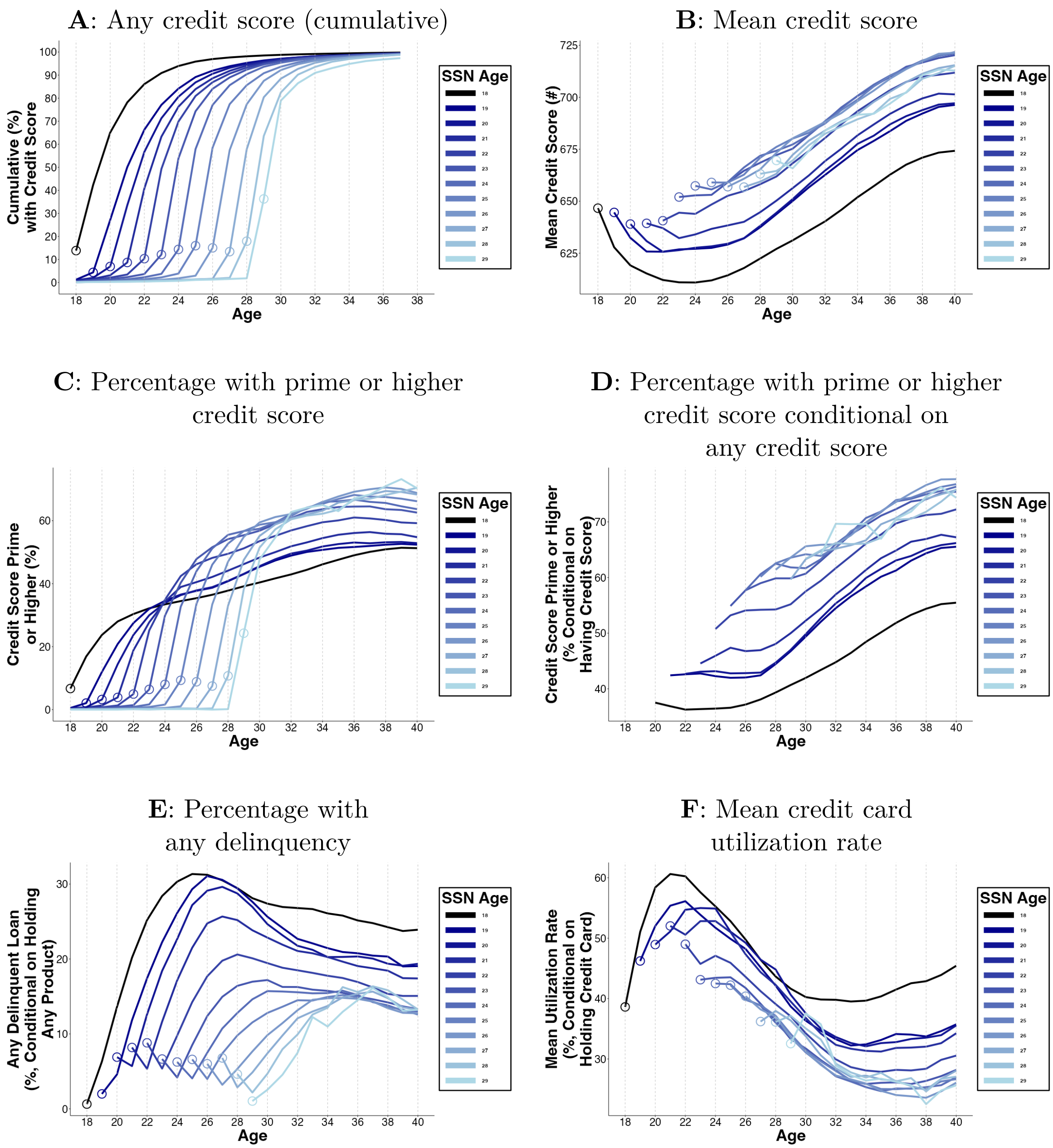
Figure 1: Quantiles of credit scores at age 30 by immigration status



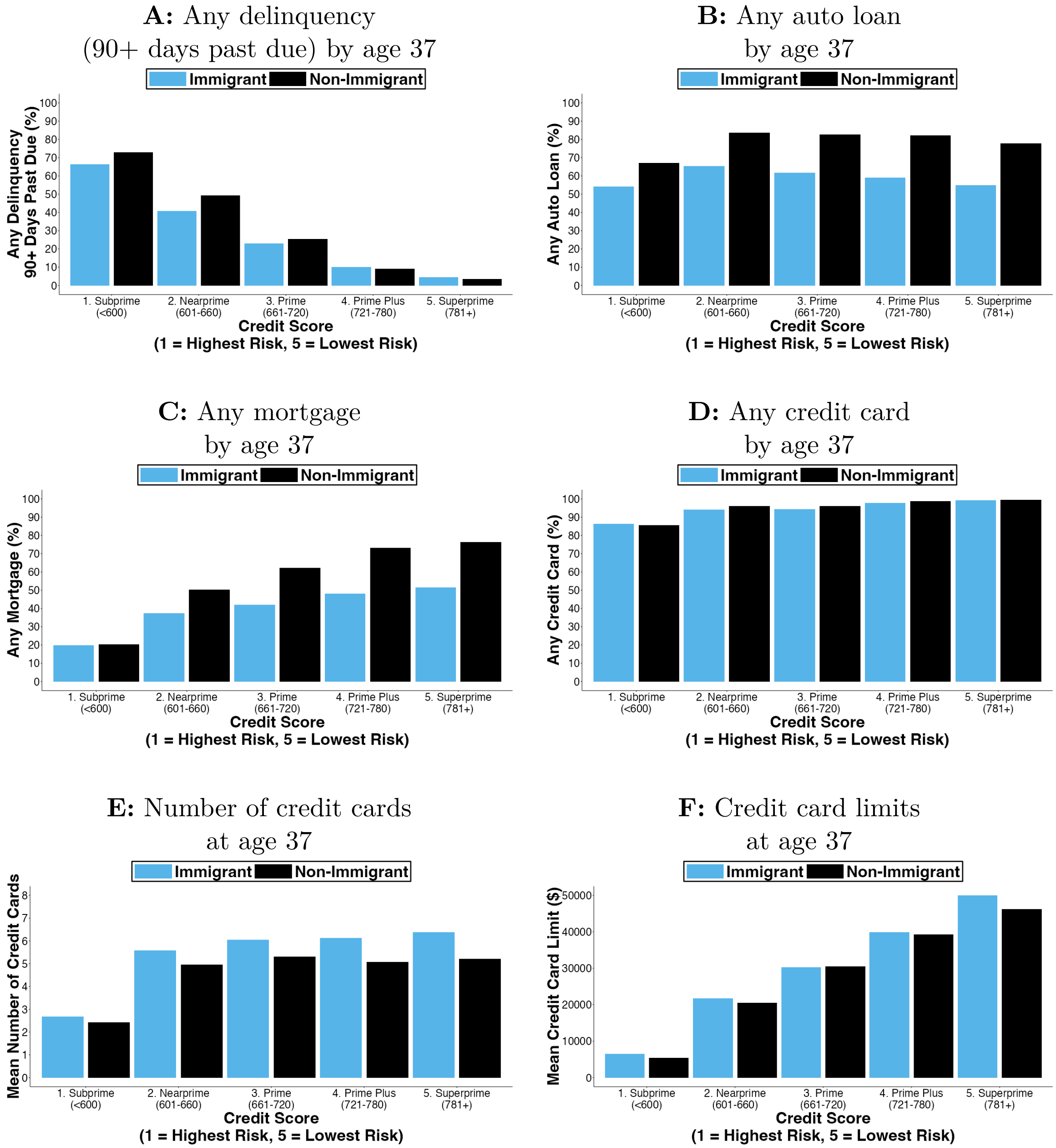
This figure shows the values of credit scores at age 30 taken at the 10%, 25%, 50%, 75%, and 90% quantiles of the distribution. These quantiles are calculated separately for immigrants and non-immigrants. We classify immigrants as those assigned SSNs at ages 21 to 29, and non-immigrants as those assigned SSNs at age 20 or younger. The data consists of 5,755,134 consumers with non-missing credit scores at age 30, of which 293,349 are immigrants and 5,461,785 are non-immigrants.

Figure 2: Lifecycle of creditworthiness by SSN Age cohorts



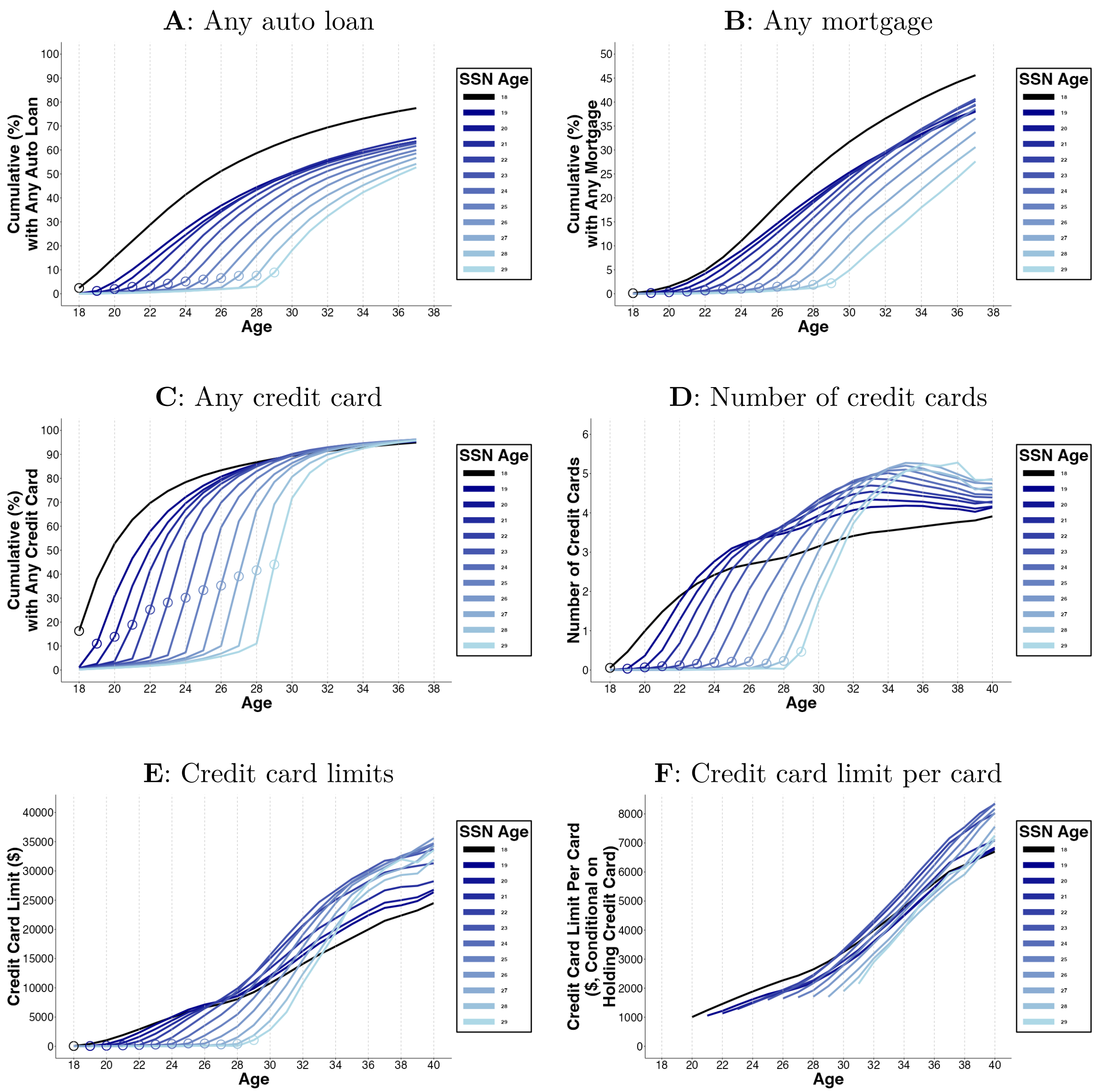
This figure plots outcomes at different calendar ages for each SSN Age cohort. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later in life SSN Age cohorts from 19 to 29. We classify immigrants as the SSN Age cohorts 21 to 29. $Age = SSNAge$ is indicated 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. Panel A presents the cumulative fraction of consumers that have been credit scored by each age. In panels A to D, credit scores are measured by VantageScore. In Panels C and D, Prime or Higher Credit Score is a VantageScore of 660 or higher. Panel E is conditional on holding any credit product; Panel F is conditional on holding a credit card.

Figure 3: Credit outcomes by age 37 conditional on credit score at age 30



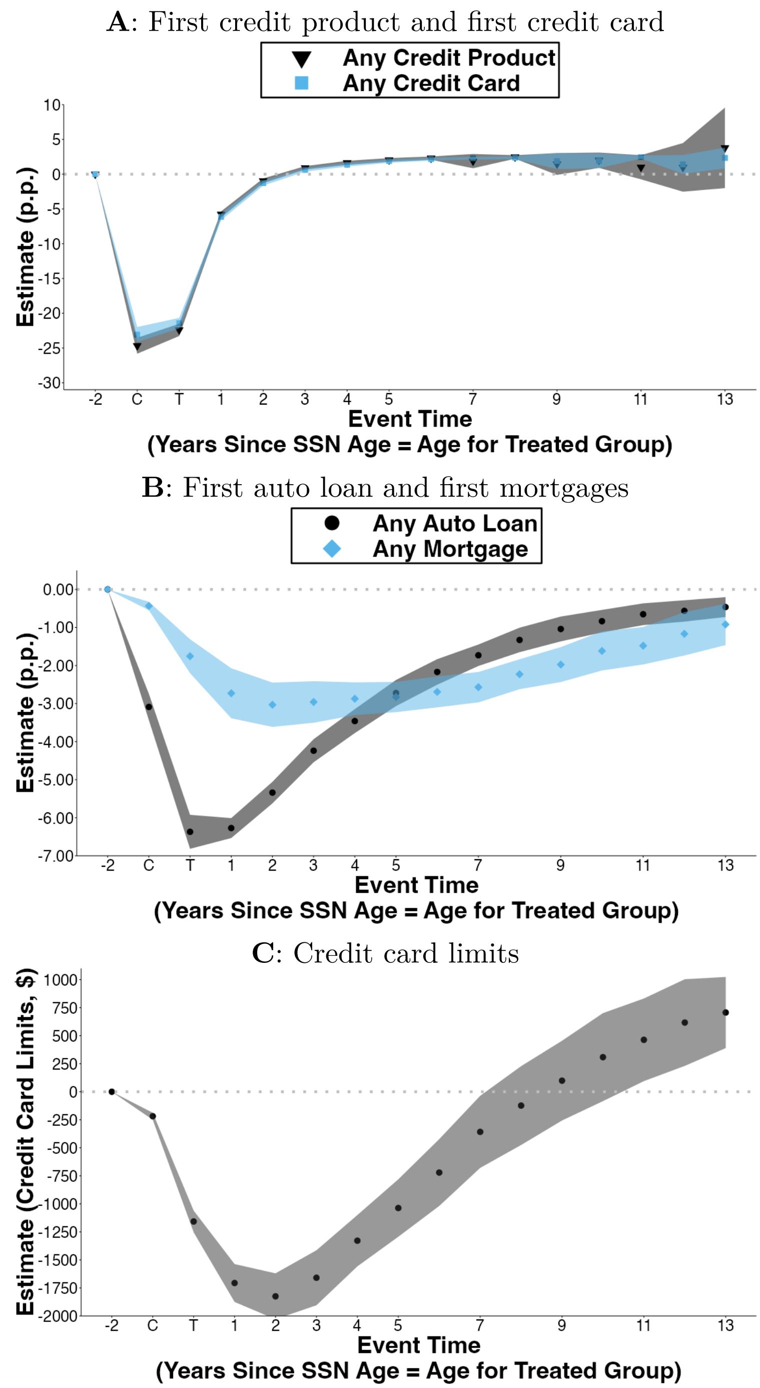
Each panel shows mean outcomes measured at age 37 conditional on a consumer's credit score measured at age 30. Each panel splits results by immigrants and non-immigrants, where immigrants are those with a SSN Age of 21+.

Figure 4: Lifecycle of credit access by SSN Age cohorts



This figure plots credit outcomes at different calendar ages for each SSN Age cohort. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later in life SSN Age cohorts from 19 to 29. We classify immigrants as the SSN Age cohorts 21 to 29. $Age = SSNAge$ is indicated by the circles on each line. Panels A, B, and C use data for birth years from 1975 to 1987. Panels D, E, and F use data for birth years from 1982 to 1987 and plot means of the outcomes. 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 5: 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 matched same-age control cohort with SSN Age = $s - 1$. The differences are presented in event time, where C is the year when age equals SSN Age for the $s - 1$ (control) cohort and event time T is the year when age equals SSN Age for the s (treatment) 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: Summary statistics on immigrants and non-immigrants

This table presents means and counts for the number of consumers (N) these are calculated from. Means are calculated separately for non-immigrants ($SSNAge < 21$) and immigrants ($SSNAge$ 21 to 29) in our data. *SSN Age* is the age that a consumer is assigned an SSN. The variables *Credit Score at Age 30* and *Credit Score at Age 40* and are conditional on having a non-missing credit score at ages 30 and 40 respectively. The variables *Any Auto Loan*, *Any Mortgage*, and *Any Credit Card*, indicate whether, up to the end of our data in 2024, the consumer is ever observed to have any auto loan, mortgage, or credit card respectively. The variables *Age at First Auto Loan*, *Age at First Mortgage*, and *Age at First Credit Card* are each conditional on the consumer ever having auto loans, mortgages, credit cards respectively at any point up to the end of our data in 2024. The variables *Credit Score at Age 40* and *Credit Card Limits at Age 40* have smaller sample sizes because birth years 1985, 1986, and 1987 are not observed at age 40.

	Non-Immigrants *(SSN Age < 21)*		Immigrants *(SSN Age 21 to 29)*	
	Mean	N	Mean	N
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 (%)	99.68	4,487,804	99.14	312,391
Credit Score at Age 40	659.5	4,179,752	698.9	270,177
Auto Loan				
Any Auto Loan (%)	79.97	5,778,671	66.07	344,261
Age at First Auto Loan	27.62	4,621,146	31.61	227,439
Mortgage				
Any Mortgage (%)	50.06	5,778,671	46.41	344,261
Age at First Mortgage	30.59	2,892,536	33.79	159,758
Credit Card				
Any Credit Card (%)	94.51	5,778,671	94.00	344,261
Age at First Credit Card	24.42	5,461,356	27.97	323,607
Credit Card Limits at Age 30	\$11,733	5,778,671	\$11,193	344,261
Credit Card Limits at Age 40	\$22,477	4,487,804	\$28,158	312,391

Table 2: Timing of credit market entry

Columns 1 and 3 in this table are estimates from the cross-sectional OLS regression specified in Equation 1 that includes an indicator for immigration status (*Immigrant* equals 1 if the consumer's SSN was assigned at age 21 or older). Columns 2 and 4 in this table are estimates from the OLS regression specified in Equation 2 that contains both the indicator for immigration status, and also *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). All regressions include fixed effects for the birth year of the consumer and fixed effects for consumers' first observed ZIP code (First Zip5). The outcome in columns 1 and 2 is age at first credit report, and the outcome in columns 3 and 4 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. The units in this table are years of age. 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)
Immigrant	4.979***	1.808***	4.686***	1.618***
	(0.143)	(0.088)	(0.149)	(0.106)
SSN Age		0.744***		0.720***
		(0.014)		(0.016)
F.E. Birth Year	X	X	X	X
F.E. First Zip5	X	X	X	X
R^2	0.264	0.289	0.120	0.129
N	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	19.864	19.864	21.251	21.251

Table 3: Credit scores at ages 30 and 40

As in Table 2, this table reports estimates of equations 1 and 2. *Immigrant* is an indicator for whether the consumer's SSN was assigned at age 21 or older; *SSN Age* is the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). The outcomes in Panel A are average credit score, measured by VantageScore, at ages 30 (columns 1 and 2) and 40 (columns 3 and 4). The outcomes in Panel B are the probability of prime or higher credit score, measured by a VantageScore of 660 or higher, at age 30 (columns 1 and 2) and at age 40 (columns 3 and 4). The units in Panel A are credit score points, and the units in Panel B are percentage points. 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)
Immigrant	27.1***	18.8***	32.7***	25.8***
	(1.1)	(1.6)	(1.0)	(0.7)
SSN Age		2.0***		1.5***
		(0.4)		(0.2)
F.E. Birth Year	X	X	X	X
F.E. First Zip5	X	X	X	X
R^2	0.135	0.135	0.132	0.132
N	5,755,134	5,755,134	4,449,929	4,449,929
Mean, SSN Age <21	626.1	626.1	659.5	659.5

Panel B: Probability of prime or higher credit score

Dep Var: Prime or Higher at ...	Age 30		Age 40	
	(1)	(2)	(3)	(4)
Immigrant	7.30***	7.63***	9.00***	2.01***
	(1.02)	(0.74)	(0.20)	(0.14)
SSN Age		-0.08		1.58***
		(0.20)		(0.09)
F.E. Birth Year	X	X	X	X
F.E. First Zip5	X	X	X	X
R^2	0.104	0.104	0.092	0.092
N	6,122,932	6,122,932	4,800,195	4,800,195
Mean, SSN Age <21	37.71	37.71	46.84	46.84

Table 4: Credit access by type of credit

As in Table 2, this table reports estimates of equations 1 and 2. *Immigrant* is an indicator for whether the consumer's SSN was assigned at age 21 or older; *SSN Age* is the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). The outcomes in Panel A are age at first auto loan, age at first mortgage, and age at first credit card. The outcomes in Panel B are the probability of having ever held an auto loan by age 37, held a mortgage by age 37, or held a credit card by age 37. The units in Panel A are years of age and the units in Panel B are percentage points. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Age of credit products first taken out

Dep Var: Age at First...	Auto Loan		Mortgage		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	4.604***	1.967***	2.058***	0.219*	4.309***	1.367***
	(0.274)	(0.217)	(0.151)	(0.083)	(0.184)	(0.158)
SSN Age		0.619***		0.432***		0.690***
		(0.024)		(0.018)		(0.020)
F.E. Birth Year	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X
R^2	0.080	0.082	0.080	0.081	0.080	0.085
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	29.151	29.151	36.356	36.356	22.677	22.677

Panel B: Probability of having held a credit product by age 37

Dep. Var: By Age 37, has ...	Auto Loan		Mortgage		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-12.99***	-6.87***	-7.18***	0.39	0.31	0.15
	(0.80)	(0.46)	(0.74)	(0.53)	(0.22)	(0.16)
SSN Age		-1.44***		-1.77***		0.04
		(0.10)		(0.09)		(0.03)
F.E. Birth Year	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X
R^2	0.039	0.039	0.062	0.063	0.025	0.025
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	77.22	77.22	45.46	45.46	94.93	94.93

Table 5: Cumulative years of delayed access to credit from paired cohorts

This table presents estimates of the cumulative years of delayed access to credit due to immigration occurring a single year later, obtained from the paired cohort OLS regression strategy. The row "C" indicates the year in which the control group (which immigrated 1 year before the treatment group, i.e., $C \equiv T - 1$) 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	Auto Loan	Mortgage	Credit Card
Event Time	(1)	(2)	(3)	(4)	(5)
C	-0.085***	-0.272***	-0.033***	-0.005***	-0.253***
	(0.002)	(0.005)	(0.002)	(0.001)	(0.005)
T	-0.432***	-0.521***	-0.099***	-0.024***	-0.491***
	(0.009)	(0.009)	(0.004)	(0.003)	(0.008)
T+5	-0.712***	-0.667***	-0.332***	-0.173***	-0.640***
	(0.013)	(0.013)	(0.01)	(0.017)	(0.013)
T+10	-0.742***	-0.690***	-0.415***	-0.288***	-0.648***
	(0.016)	(0.018)	(0.017)	(0.028)	(0.016)
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 6: Survey of Consumer Finances (2022): asset ownership, credit use, and debt attitudes

This table uses public data from the 2022 Survey of Consumer Finances (SCF), keeping birth years 1972 to 2000 such that respondents are aged between 22 and 49. Odd-numbered columns in both Panels are estimates from the cross-sectional OLS regression that includes an indicator for immigration status (*Immigrant* is an indicator for whether the consumer's age of immigration was at age 21 or older). Even-numbered columns add *Immigration Age*, the consumer's age at immigration (pooling consumers with an age of immigration of 20 or younger into one group) to the specification. See Appendix A.2 for details of the survey variables used. The units are percentage points, except for Panel A columns 9 and 10 which are in dollars of credit card limits, and Panel B columns 7 and 8 where the estimates are multiplied by 100 to be on a similar scale to percentage points (this outcome takes values -1, 0, and +1). All regressions include a control for normal income (winsorized at the 99th percentile), and fixed effects for the birth year of the consumer and fixed effects for other demographic control variables: male, race, Hispanic, spouse, marital status, household size, number of children, and education levels. Panel B columns 3 to 6 also include a control for the binary auto loan debt attitude variable, where a value of 1 is considering borrowing for auto is all right. 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. $^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Panel A: Asset ownership and credit use

Dep Var:	Has Car		Any Auto Debt		Homeowner		Any Mortgage		Credit Card Limits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	-7.13*	-6.14	-4.27	-11.14	-13.55***	0.35	-13.09***	-5.27	-3,078.8	6,373.8
	(3.15)	(4.96)	(5.08)	(8.27)	(4.64)	(6.85)	(4.64)	(7.22)	(3,460.2)	(6,316.0)
Immigration Age		-0.13		0.88		-1.78***		-1.00		-1,213.9*
		(0.47)		(0.76)		(0.59)		(0.64)		(582.4)
Demographic Controls	X	X	X	X	X	X	X	X	X	X
R^2	0.110	0.110	0.063	0.063	0.258	0.261	0.258	0.259	0.254	0.256
N	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813
Mean, Immigration Age <21	89.23	89.23	47.14	47.14	53.98	53.98	45.25	45.25	$20,275.9	$20,275.9

Panel B: Debt attitudes, and also asset ownership and credit use controlling for debt attitudes

Dep Var:	Auto Debt Attitude		Has Car		Any Auto Debt		General Debt Attitude	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	-15.41***	-23.02***	-5.79^{+}	-4.13	-0.21	-5.10	-8.96	-15.94
	(4.58)	(7.25)	(3.26)	(5.06)	(5.01)	(7.87)	(7.92)	(13.71)
Immigration Age		0.98		-0.21		0.63		0.89
		(0.62)		(0.45)		(0.69)		(1.19)
Auto Debt Attitude			8.70***	8.73***	26.34***	26.24***		
			(2.48)	(2.49)	(3.23)	(3.24)		
Demographic Controls	X	X	X	X	X	X	X	X
R^2	0.049	0.050	0.121	0.121	0.106	0.106	0.026	0.026
N	1,813	1,813	1,813	1,813	1,813	1,813	1813	1,813
Mean, Immigration Age <21	79.58	79.58	89.23	89.23	47.14	47.14	3.80	3.80

Supplemental Appendix: Immigration and Credit in America

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

A. Supplemental Details On Data

A.1 Additional Details On Credit Reporting Data Construction

We start constructing our data by taking all consumers observed between July 2000 and September 2023 in the the University of Chicago Booth TransUnion Consumer Credit Panel, "BTCCP" (TransUnion, 2025). We first queried the BTCCP for this project in September 2023, however, because the data are regularly updated, we observe credit outcomes through to December 2024. We focused 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. We retain consumers with valid birth dates between 1951 and 2004 because we need birth dates to calculate the year of immigration. "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. These restrictions produce an anonymous sample of 31.87 million consumers, representative of 318.7 million consumers.

To estimate the year of SSN assignment, $SSN\ Year$, we construct a lookup table that maps the first five digits of the SSN into the first year of SSN assignment, $SSN\ Year$, for all SSNs assigned before 2012. 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. 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.[1]

Panel A of Table A1 describes how we arrive at our sample. After removing the 21% of consumer identifiers without SSN information, we have 25.2 million consumers. Requiring SSN information appears to remove 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. 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.

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 of 1988 or later, as they are too young to enter the data or to be classified as immigrants by 2011.

Panel A of Table A1 shows that the resulting *"Clean Sample"* has 18.57 million consumers, 2.09 million of 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. We then apply additional restrictions to arrive at the *"Entrant Sample"* used for our paper's analysis. These restrictions are that consumers have a SSN Age of < 30 and birth years from 1975 to 1987 for the reasons described in the main paper. Within this sample, there are 102 immigration combinations of birth years and SSN Ages. As shown by the counts of consumers by SSN Age in panel B of 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. Panel B of Appendix Table A1 also shows that, of the consumers with birth years 1975 to 1987,

[1]This classification depends on knowledge of the first five digits of a consumer's SSN. 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.

there are 44,642 consumers assigned a SSN Age of 30+, who we do not include in the Entrant Sample. This means that our SSN Ages 21 to 29 cover 89% of legal immigrants who arrive during adulthood in our data for those birth years.

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.[2] 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 reports are not fragmented. Finally, in panel C of Appendix Figure A1 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 reliable.

A.2 Additional Details On The Survey of Consumer Finances (2022)

When using the SCF, we apply similar restrictions to our credit reporting data, and doing so reduces the SCF sample size from 4,595 to 1,813 respondents, of whom we classify 213 as immigrants based on an age of immigration of 21+. We study respondents in their twenties, thirties, and forties in the 2022 survey year (corresponding to birth years 1972 to 2000). We use this restriction because consumers in their fifties and older are expected to have limited credit demand irrespective of immigration status or credit supply. Given the small survey sample size, we retain respondents with ages of immigration older than 30.

When analyzing the SCF, we use cross-sectional regressions of the same overall form as Equa-

[2] 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.

tions 1 and 2, with a few minor changes. Rather than using $SSN\ Age$, we directly observe the age of immigration in the survey, and therefore $\mathbb{I}\{Immigrant\}_i$ measures whether an a respondent immigrated at age 21 or later in life, and instead of $SSN\ Age_i$ we have $Immigrant\ Age_i$, a variable for each year of immigrating at age 21 or later in life. Given the small survey sample size, we increase the precision of our regression estimates by including demographic controls for normal income (winsorized at the 99$^{\text{th}}$ percentile) and fixed effects for birth year ($\mu_{b(i)}$), male, race, hispanic, spouse, marital status, household size, number of children, and education levels, but cannot include geographic fixed effects ($\eta_{g(i)}$) as these are not in the data. The SCF is conditional on a consumer being in the United States when surveyed in 2022 and, therefore our results are conditional on not emigrating. We 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, and we use heteroskedasticity-robust standard errors and follow the SCF's recommended multiply-imputed variance estimation technique to account for missing data.

In all of the regression in Table 6 and Appendix Table A7, the age of immigration is constructed from the survey variable x6906 (years lived in the United States) and from variable x8022 (age). The indicator for immigration status (*Immigrant*) takes a value of one if the consumer's age of immigration was at 21 or older, and zero otherwise. The variable *Immigration Age*, the consumer's age at immigration, pools all consumers with ages of immigration at 20 or younger at a value of 20.

In Table 6 columns 1 and 2 of Panel A and also columns 5 and 6 of Panel B, the outcome in is whether a consumer has any auto vehicle (constructed from variable x2201). The outcome in columns 3 and 4 of Panel A and also columns 7 and 8 of Panel B is whether a consumer has any outstanding auto loan debt or lease on any of their vehicles (constructed from the auto financing and leasing variables x2102, x2208, x2308, x2408, x7157). The mean of this variable may appear to be lower than one might expect, given that most car purchases in the United States are financed with debt (see cites in Gibbs et al., 2025). This is because some consumers will have taken out auto loans but have paid this debt off by the time of being surveyed. The outcome in columns 5 and 6 of Panel A is whether a consumer is a homeowner (i.e., not a renter, constructed from variables x701 and x601). The outcome in columns 7 and 8 of Panel A is whether a consumer has any outstanding mortgage debt (constructed from x723). The outcome in columns 9 and 10 of Panel A is the total credit card limits across all cards (constructed from variable x414, and winsorized at the 99th percentile).

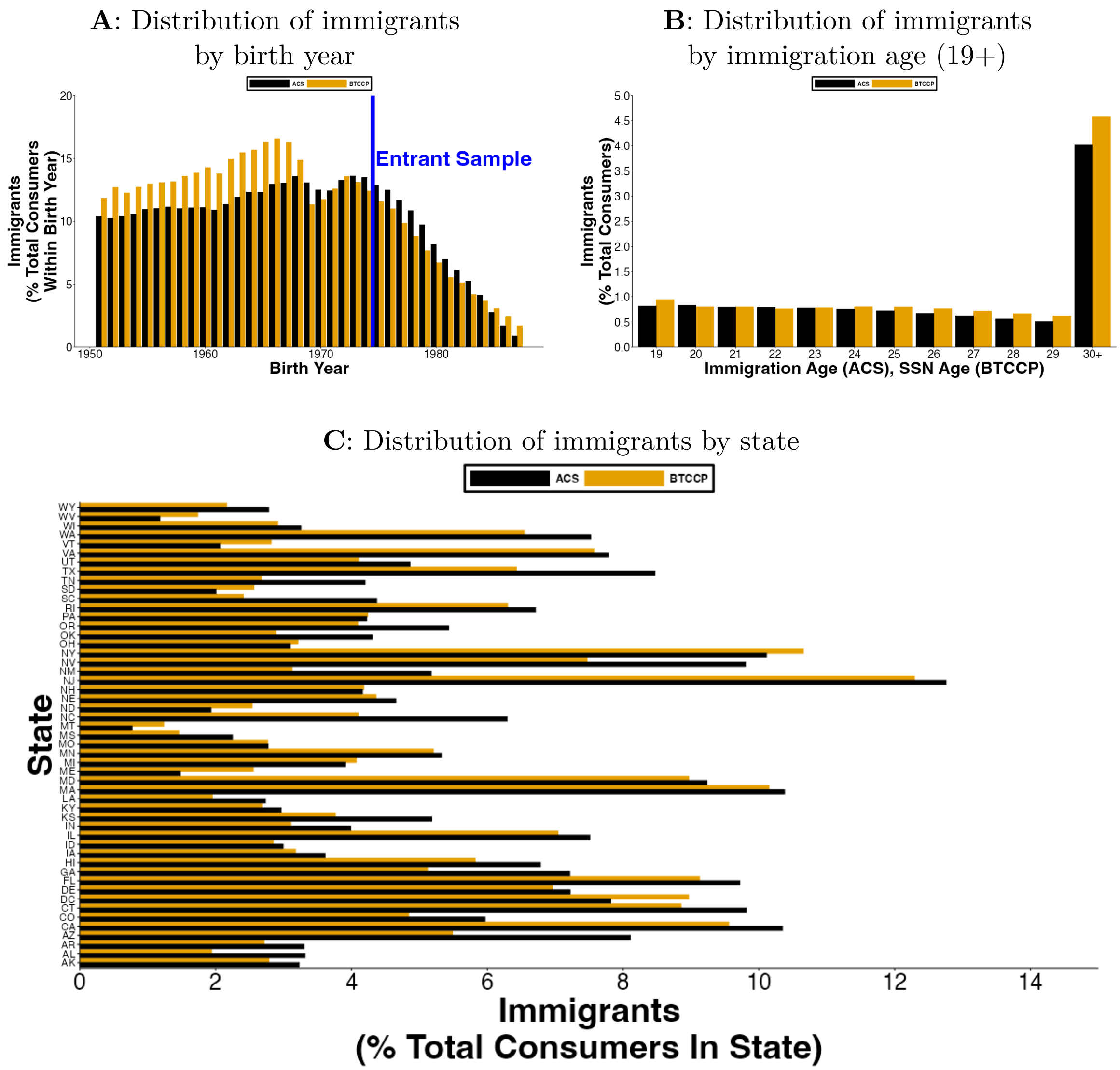
In Panel B of Table 6, the outcome in columns 7 and 8 is "Now I would like to ask you some questions about how you feel about credit. In general, do you think it is a good idea or a bad idea for people to buy things by borrowing or on credit?" (constructed from variable x401), with the variable having three potential values: 1 if they regard it as a good idea, 0 if good in some ways, bad in others, and -1 if they regard it as a bad idea. In this table we multiply estimates by 100 to be on a similar scale to other estimates. In Panel B of Appendix Table A7, we decompose this variable into binary measures. In columns 1 and 2 of Appendix Table A7, this outcome takes a value of 1 if they regard it as a good idea, and zero otherwise. In columns 3 and 4 of Appendix Table A7, this outcome takes a value of 1 if they regard it as a bad idea, and zero otherwise.

The outcome (constructed from variable x405) in columns 1-2 of Panel B of Table 6, and also used as a control variable *Auto Debt Attitude* in columns 3 to 6 of this same panel, is a binary variable for whether they feel it is all right to borrow money to finance the purchase of a car. Specifically, this is following the prompt "people have many different reasons for borrowing money which they pay back over a period of time, 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.

The outcomes in columns 5 to 10 of Appendix Table A7 Panel B are all 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.The outcome in columns 5-6 (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. The outcome in columns 7-8 (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. The outcome in columns 9-10 (constructed from variable x406) is whether they feel it is all right for someone like yourself to borrow money to finance educational expenses.

B. Supplemental Figures and Tables

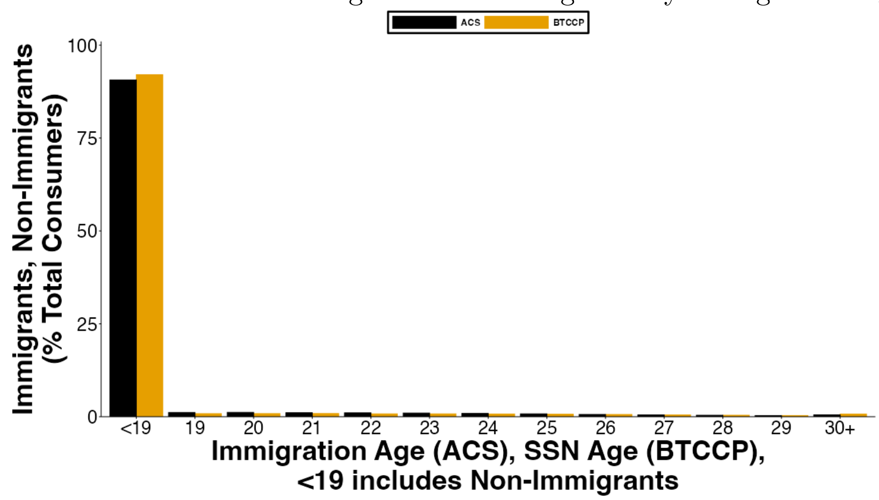
Figure A1: Immigrant classification in our data (BTCCP) versus the American Community Survey (ACS)



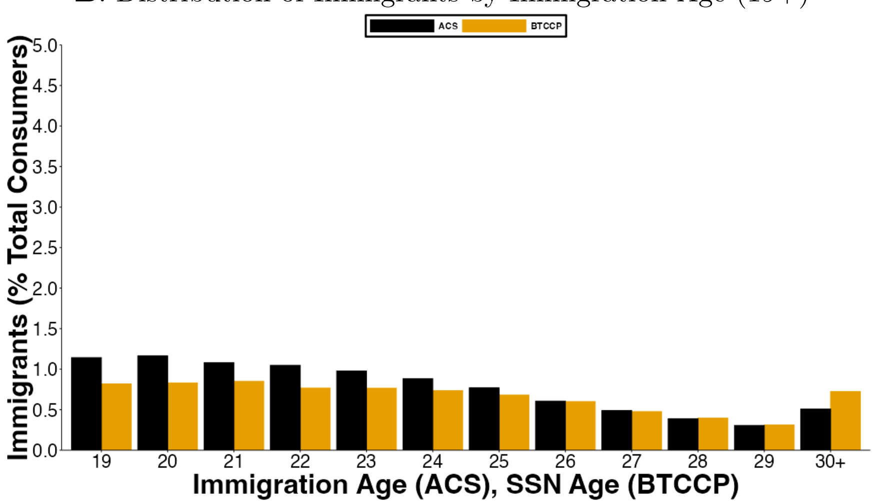
This figure compares our classification of immigrants in the Booth TransUnion Consumer Credit Panel (BTCCP) to comparable statistics computed from the American Community Survey (ACS). Panel A presents the share of immigrants in each birth year in the ACS (black) versus BTCCP (yellow). In Panel A, immigrants 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.

Figure A2: 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



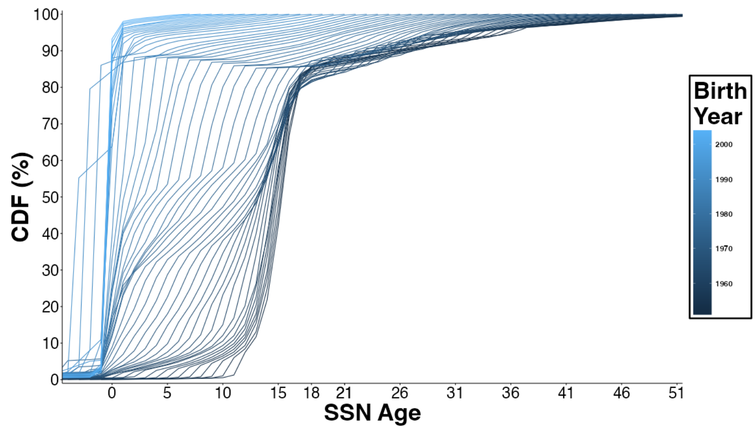
B: Distribution of Immigrants by Immigration Age (19+)



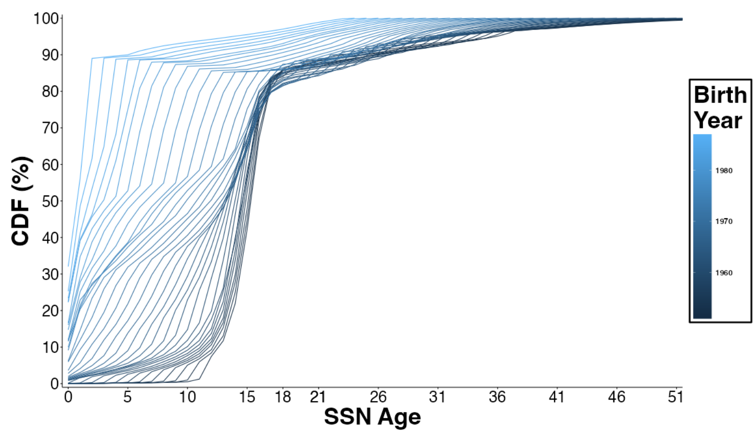
This figure compares our classification of immigrants in the BTCCP Entrant Sample to comparable statistics computed from the American Community Survey (ACS). The figure shows bars for immigrants with Age of Immigration (ACS) / SSN Age of 30+, these are consumes who are not included in the Entrant Sample 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 A3: Distributions of SSN Age by birth year

A: Before cleaning sample

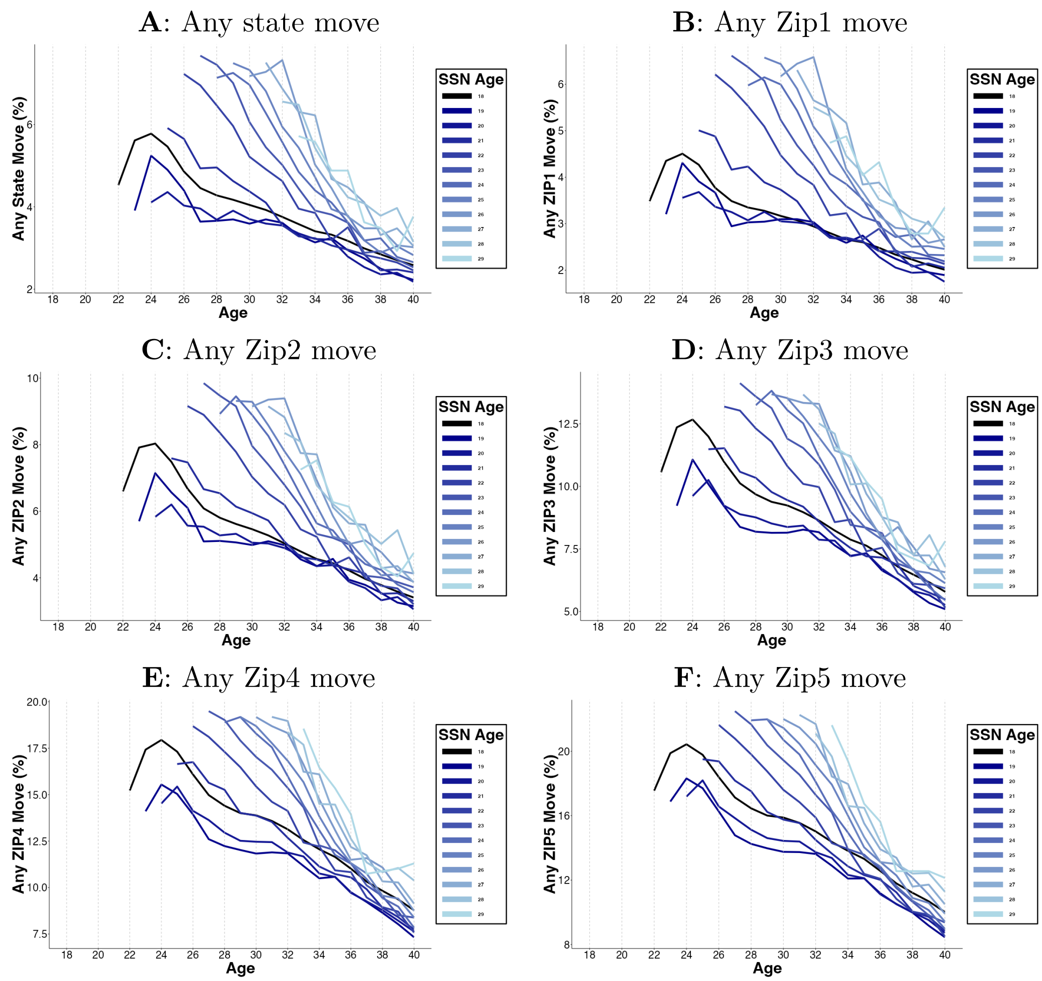


B: Clean sample



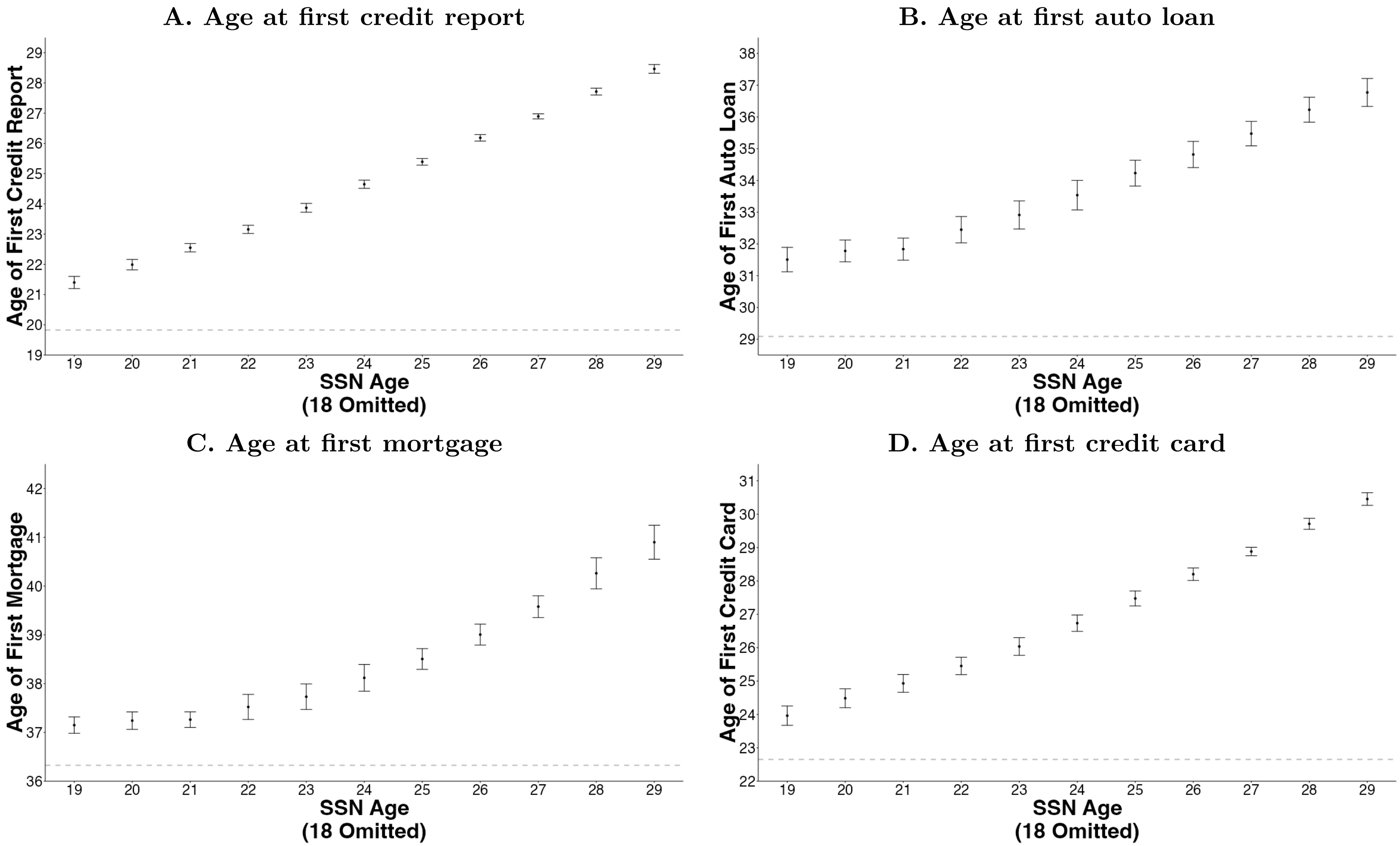
These panels show the CDFs of SSN Age for each birth year. Panel A shows data before cleaning (only removing consumers without SSNs). Panel B restricts to consumers after cleaning the data. These patterns of SSN Ages by birth years are consistent with Klopfer and Miller (2024) using administrative Social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

Figure A4: 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.

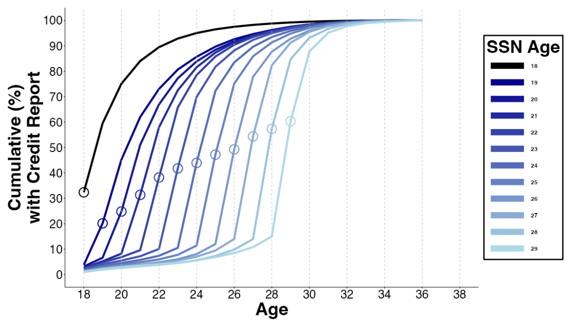
Figure A5: Age at first credit product by SSN Age



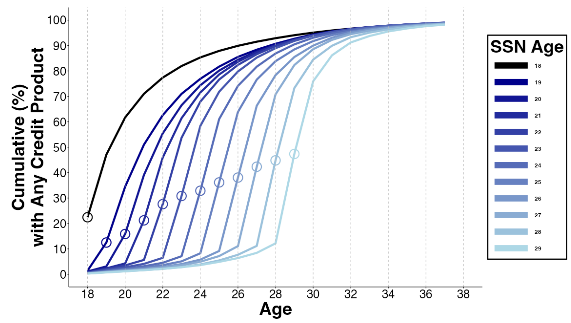
This figure presents estimates and 95% confidence intervals for age at first credit report (Panel A), age at first auto loan (Panel B), age at first mortgage (Panel C), and age at first credit card) separately by SSN Age cohorts. The estimates are constructed from an individual-level regression of each outcome on SSN Age indicators, Birth Year fixed effects, and fixed effects for consumers' first observed ZIP code. 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 A6: Additional credit outcomes by SSN Age cohorts

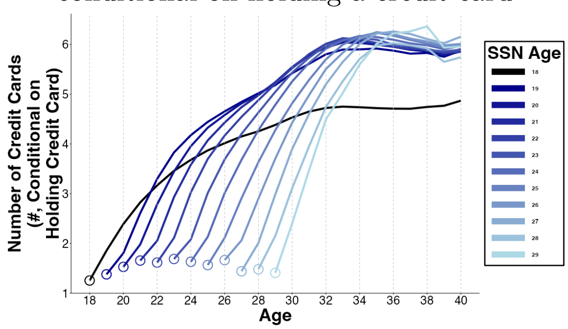
A: Age at first credit report



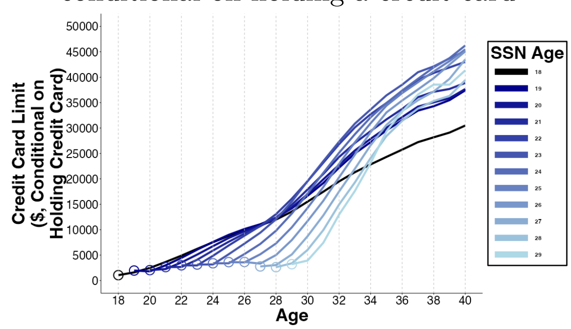
B: Age at first credit product



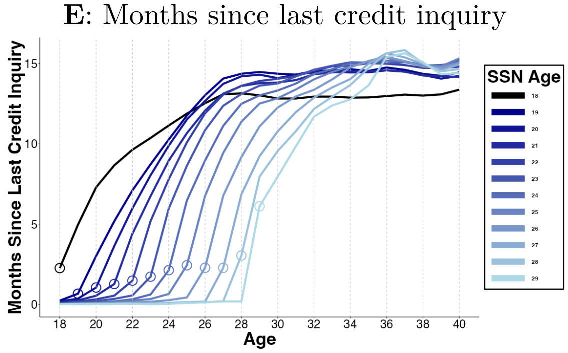
C: Number of credit cards, conditional on holding a credit card



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

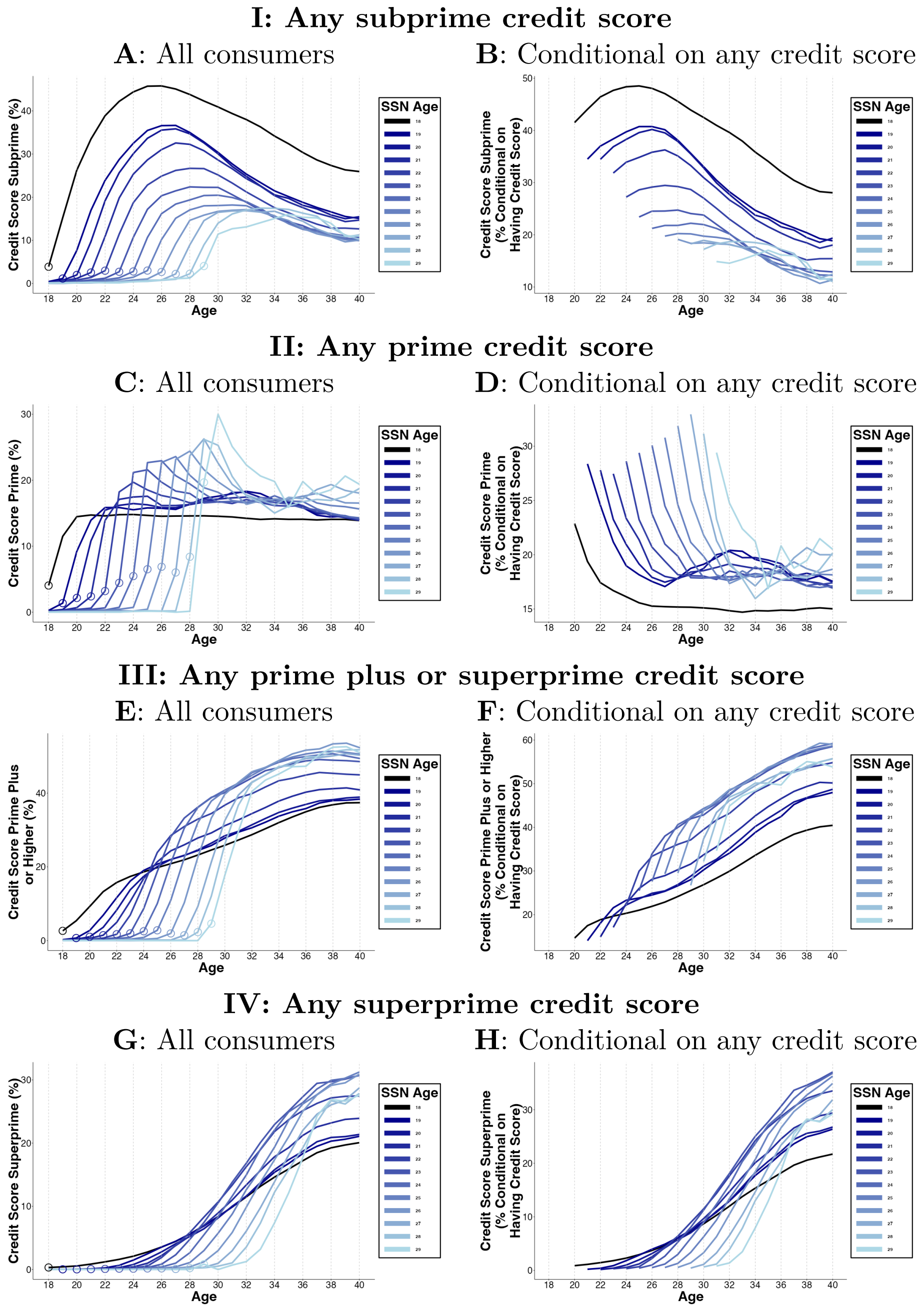


E: Months since last credit inquiry



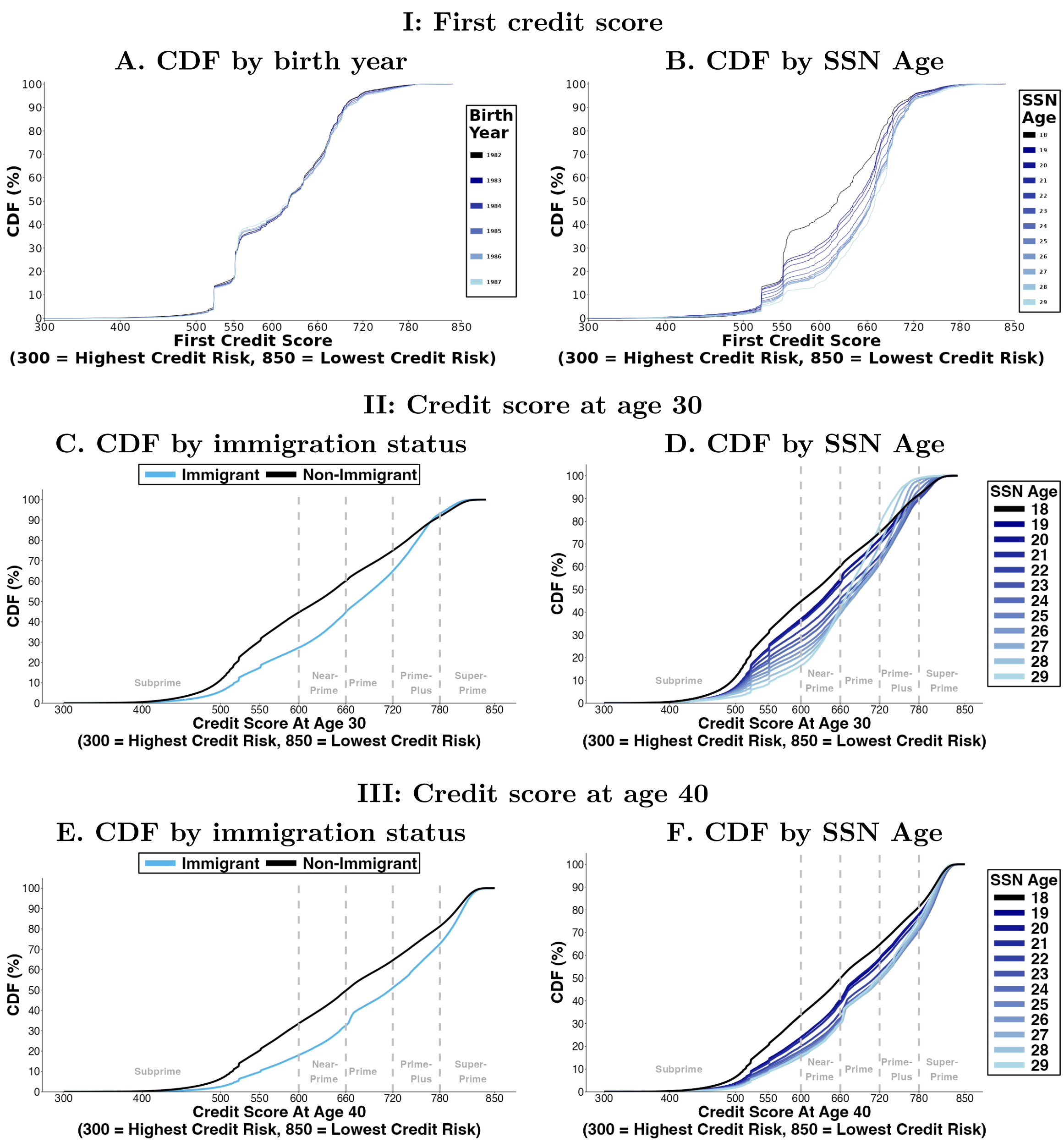
For each SSN Age cohort, this figure presents the evolution of age of first credit report (Panel A) and age of first credit product (Panel B) by age. These averages are conditional on having a credit score. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate 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 A7: Lifecycle of credit scores by SSN Age cohorts



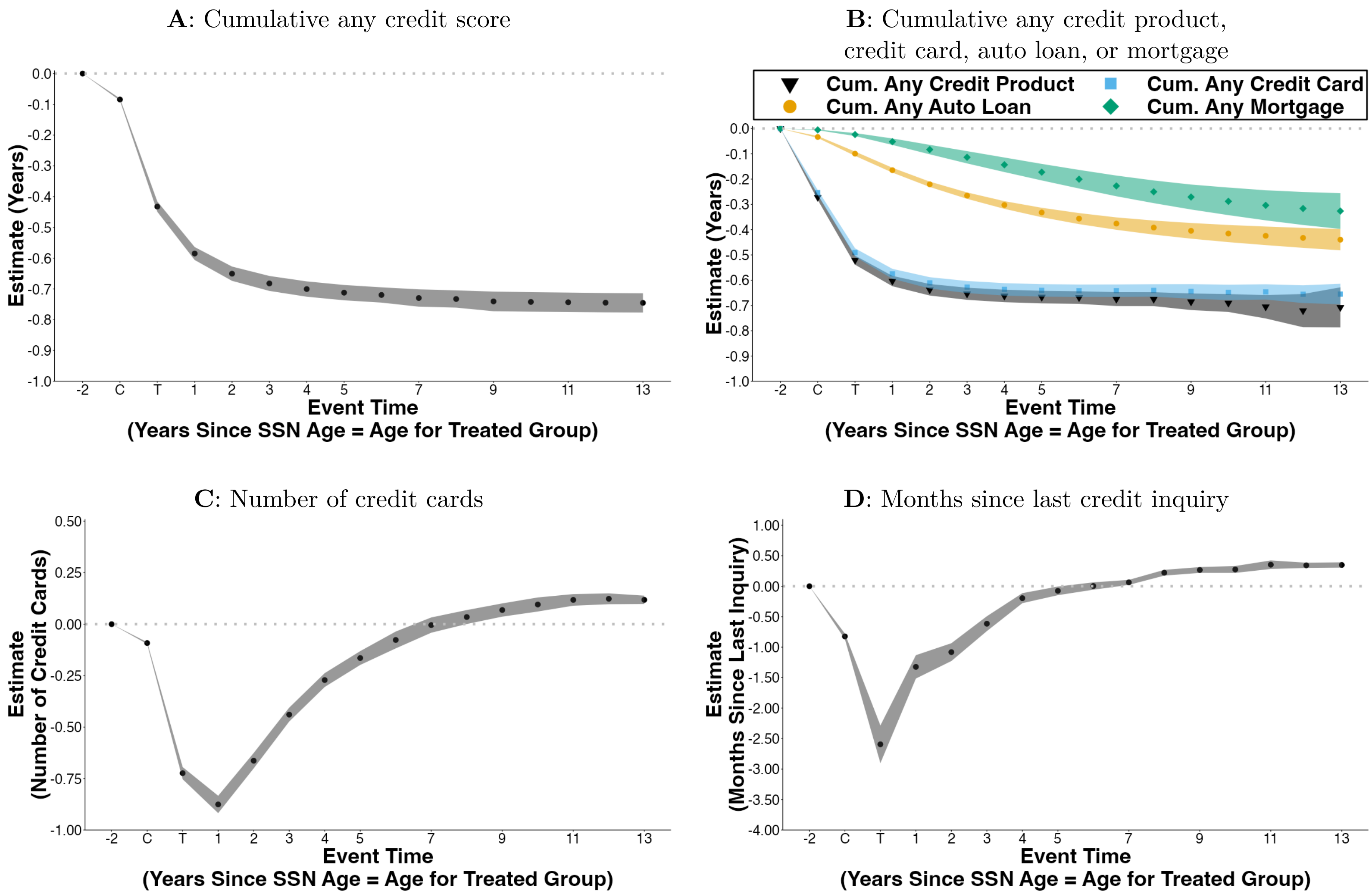
For each SSN Age cohort, this figure presents the evolution of credit scores by age. In all panels, credit scores are measured by VantageScore. In Panels A and B, Subprime Credit Score is VantageScore below 600. In Panels C and D, Prime Credit Score is VantageScore 661 to 719. In Panels E and F, Prime 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 A8: Distribution of credit scores



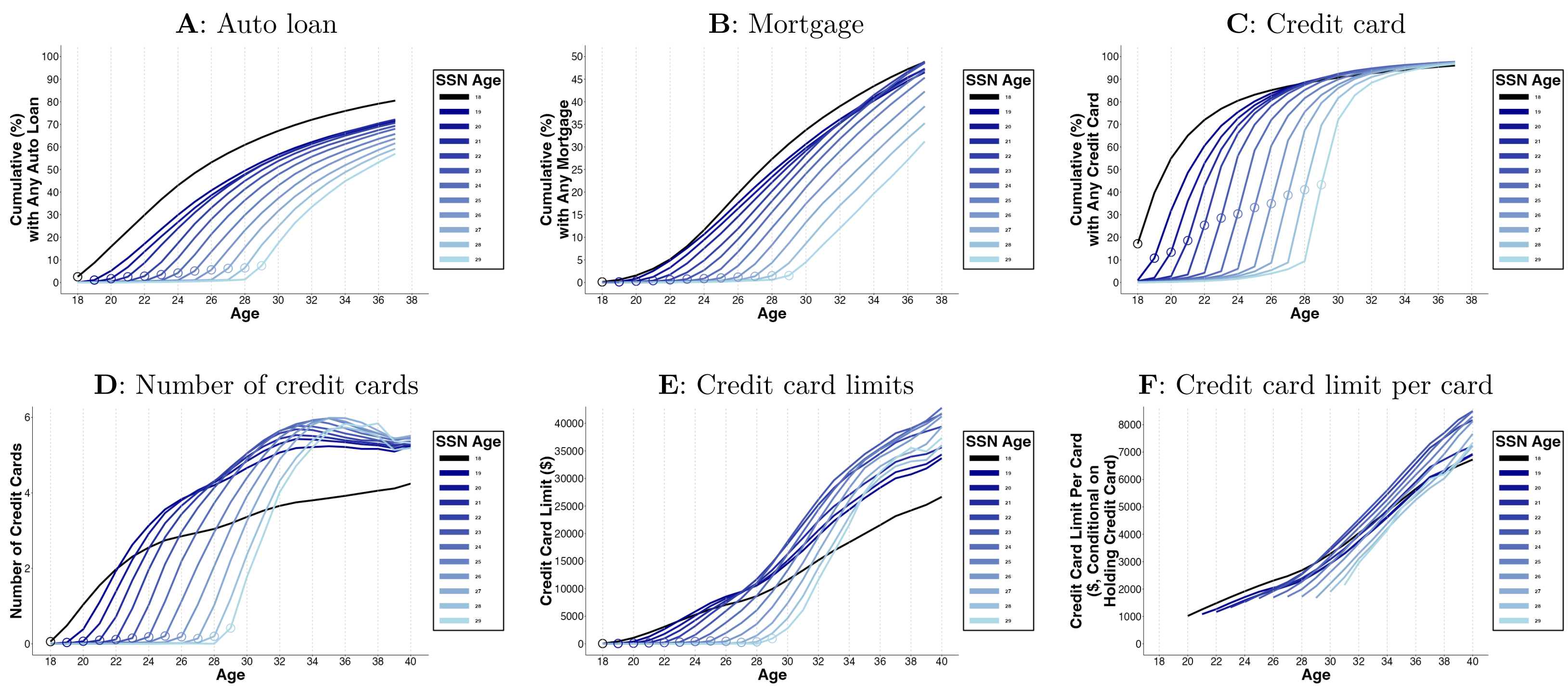
Panels A and B show the CDFs of the first credit score observed for a consumer at any point in our data. Panel A shows CDFs by birth years. Panel B shows CDFs by SSN Ages, where SSN Age 18 includes consumers that are assigned an SSN at Age 18 or younger. Panels C and D show CDFs of credit score at Age 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 A9: Paired cohorts: dynamics of credit access



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 A10: Lifecycle of credit access by SSN Age cohorts, restricting sample to consumers still 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.

Table A1: Data Sample

Panel A 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*. Panel B presents observation counts for the "Clean Sample" (indicated in Table A1) 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 entrant sample. Our entrant sample additionally drops the 44,642 consumers who have SSN Age 30+, who are shown in this table for completeness.

Panel A: Sample construction

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

Panel B: Counts of consumers by SSN Age: "clean sample" and "entrant sample"

SSN Age	Clean Sample	Entrant Sample
<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 access, with additional geographic fixed effects

Columns 1, 3, 5, 7, and 9 in Panel A and columns 1, 3, and 5 in Panel B of this table are estimates from the cross-sectional OLS regression specified in Equation 1 that includes an indicator for immigration status (*Immigrant* is an indicator for whether the consumer's SSN was assigned at age 21 or older). Columns 2, 4, 6, 8, and 10 in Panel A and columns 2, 4, and 6 in Panel B of this table are estimates from the OLS regression specified in Equation 2 that contains both the indicator for immigration status, and also *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). All sixteen regressions include fixed effects for the birth year of the consumer, fixed effects for consumers' first observed ZIP code (First Zip5), last observed ZIP code (Last Zip5), longest ZIP code (Longest Zip5) as a proxy for their most permanent location, and the number of unique ZIP codes (Number Zip5) as a proxy for their mobility. The outcome in Panel A columns 1 and 2 is the age at first credit report. The outcome in Panel A columns 3 and 4 is the age at first credit product. The outcome in Panel A columns 5 and 6 is the age at first auto loan. The outcome in Panel A columns 7 and 8 is the age at first mortgage. The outcome in Panel A columns 9 and 10 is the age at first credit card. The outcome in Panel B columns 1 and 2 is the probability of having ever held an auto loan by age 37. The outcome in Panel B columns 3 and 4 is the probability of having ever held a mortgage by age 37. The outcome in Panel B columns 5 and 6 is the probability of having ever held a credit card by age 37. The units in Panel A are years of age and the units in Panel B are percentage points. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Age of credit products first taken out

Dep Var: Age at First...	Credit Report		Credit Product		Auto Loan		Mortgage		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	4.782***	1.691***	4.403***	1.477***	3.719***	1.424***	1.642***	-0.082	3.929***	1.195***
	(0.117)	(0.073)	(0.116)	(0.088)	(0.206)	(0.136)	(0.101)	(0.052)	(0.146)	(0.125)
SSN Age		0.727***		0.689***		0.540***		0.406***		0.644***
		(0.014)		(0.016)		(0.023)		(0.017)		(0.019)
F.E. Birth Year	X	X	X	X	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X	X	X	X	X
F.E. Last Zip5	X	X	X	X	X	X	X	X	X	X
F.E. Longest Zip5	X	X	X	X	X	X	X	X	X	X
F.E. Number Zip5	X	X	X	X	X	X	X	X	X	X
R^2	0.299	0.323	0.184	0.192	0.168	0.169	0.153	0.154	0.155	0.159
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	6,122,932
Mean, SSN Age <21	19.864	19.864	21.251	21.251	29.151	29.151	36.356	36.356	22.677	22.677

Panel B: Probability of having held a credit product by age 37

Dep Var: By Age 37, has...	Auto Loan		Mortgage		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-8.94***	-4.43***	-4.30***	2.33***	1.14***	0.50***
	(0.67)	(0.20)	(0.67)	(0.35)	(0.22)	(0.14)
SSN Age		-1.06***		-1.56***		0.15***
		(0.11)		(0.09)		(0.04)
F.E. Birth Year	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X
F.E. Last Zip5	X	X	X	X	X	X
F.E. Longest Zip5	X	X	X	X	X	X
F.E. Number Zip5	X	X	X	X	X	X
R^2	0.124	0.124	0.146	0.146	0.060	0.060
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	77.22	77.22	45.46	45.46	94.93	94.93

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

Columns 1, 3, 5, and 7 in both Panels A and B of this table are estimates from the cross-sectional OLS regression specified in Equation 1 that includes an indicator for immigration status (*Immigrant* is an indicator for whether the consumer's SSN was assigned at age 21 or older). Columns 2, 4, 6, and 8 in both Panels A and B of this table are estimates from the OLS regression specified in Equation 2 that contains both the indicator for immigration status, and also *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). All sixteen regressions include fixed effects for the birth year of the consumer, fixed effects for consumers' first observed ZIP code (First Zip5), last observed ZIP code (Last Zip5), longest ZIP code (Longest Zip5) as a proxy for their most permanent location, and the number of unique ZIP codes (Number Zip5) as a proxy for their mobility. The outcome in Panel A columns 1 to 4 is average credit score, measured by VantageScore, at age 30, in columns 1 and 2, and at age 40, in columns 3 and 4. The outcome in Panel A columns 5 to 8 is the probability of prime or higher credit score, measured by a VantageScore of 660 or higher, at age 30, in columns 5 and 6, and at age 40, in columns 7 and 8. The units in Panel A columns 1 to 4 are credit score points, and the units in Panel A columns 5 to 8 are percentage points. The outcome in Panel B columns 1 to 4 is the number of credit cards at age 30, in columns 1 and 2, and at age 40, in columns 3 and 4. The outcome in Panel B columns 5 to 8 is the value of credit card limits at age 30, in columns 5 and 6, and at age 40, in columns 7 and 8. The units in Panel B columns 1 to 4 are number of credit cards, and the units in Panel B columns 5 to 8 are dollars of credit card limits. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Credit score outcomes

	Credit Score At...				Probability of Prime or Higher Score At...			
	Age 30		Age 40		Age 30		Age 40	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	22.27***	15.69***	28.14***	21.56***	5.99***	6.60***	8.97***	1.99***
	(1.03)	(1.24)	(0.94)	(0.64)	(0.92)	(0.57)	(0.27)	(0.21)
SSN Age		1.61***		1.46***		-0.14		1.58***
		(0.31)		(0.16)		(0.19)		(0.09)
F.E. Birth Year	X	X	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X	X	X
F.E. Last Zip5	X	X	X	X	X	X	X	X
F.E. Longest Zip5	X	X	X	X	X	X	X	X
F.E. Number Zip5	X	X	X	X	X	X	X	X
R^2	0.202	0.202	0.200	0.200	0.156	0.156	0.151	0.152
N	5,755,134	5,755,134	4,449,929	4,449,929	6,122,932	6,122,932	4,800,195	4,800,195
Mean, SSN Age <21	626.10	626.10	659.52	659.52	37.71	37.71	46.84	46.84

Panel B: Credit card outcomes

	Number of Credit Cards At...				Credit Card Limits At...			
	Age 30		Age 40		Age 30		Age 40	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	0.018	1.293***	0.672***	0.167***	-2488.1***	3656.3***	2903.6***	1696.6***
	(0.134)	(0.055)	(0.028)	(0.036)	(601.4)	(373.2)	(699.9)	(385.8)
SSN Age		-0.300***		0.114***		-1446.1***		273.0
		(0.014)		(0.009)		(67.2)		(137.9)
F.E. Birth Year	X	X	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X	X	X
F.E. Last Zip5	X	X	X	X	X	X	X	X
F.E. Longest Zip5	X	X	X	X	X	X	X	X
F.E. Number Zip5	X	X	X	X	X	X	X	X
R^2	0.121	0.123	0.092	0.092	0.14	0.142	0.181	0.181
N	6,122,932	6,122,932	4,800,195	4,800,195	6,122,932	6,122,932	4,800,195	4,800,195
Mean, SSN Age <21	3.416	3.416	3.973	3.973	$11,733.1	$11,733.1	$22,477.2	$22,477.2

Table A4: Credit outcomes by age 37

Odd-numbered columns in both Panels are estimates from Equation 1; even-numbered columns are estimates from Equation 2. The outcome in Panel A is whether a consumer has any delinquency, measured by 90 or more days past due, by age 37, in percentage points. Each column of Panel A shows results for a different credit score group at age 30. Panel A, columns 1 and 2 show results for all credit scores. Panel A, columns 3 through 11 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 risk segment) credit scores. The outcome in Panel B columns 1 and 2 is the probability of having ever held an auto loan by age 37. In columns 3 and 4 it is the probability of having ever held a mortgage by age 37; in columns 5 and 6 it is the probability of having ever held a credit card by age 37. The units in columns 1 to 6 are percentage points. The outcome in columns 7 and 8 is the number of credit cards held. The units in columns 5 to 8 are dollars (credit card limits). Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Panel A: Any delinquency (90+ days past due) by age 37, split by credit score at age 30

Dep Var: Any	All		Subprime		Nearprime		Prime		Prime Plus		Superprime	
delinquency by age 37	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Immigrant	-1.58***	-1.40***	-2.85***	-3.69***	-3.53***	-2.72***	-1.49***	0.06	0.08	0.99***	0.28	0.37
	(0.24)	(0.41)	(0.40)	(0.74)	(0.36)	(0.58)	(0.24)	(0.49)	(0.10)	(0.19)	(0.14)	(0.28)
SSN Age		-0.04		0.23		-0.19		-0.34***		-0.21***		-0.03
		(0.05)		(0.12)		(0.09)		(0.07)		(0.03)		(0.07)
F.E. Birth Year	X	X	X	X	X	X	X	X	X	X	X	X
F.E. Age 30 Zip5	X	X	X	X	X	X	X	X	X	X	X	X
F.E. Age 30 Credit Score	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.185	0.185	0.032	0.032	0.028	0.028	0.027	0.027	0.025	0.025	0.022	0.022
N	5,755,134	5,755,134	2,515,933	2,515,933	898,118	898,118	871,578	871,578	999,130	999,130	999,130	470,375
Mean, SSN Age <21	27.22	27.22	45.53	45.53	26.20	26.20	13.14	13.14	4.51	4.51	1.63	1.63

Panel B: Credit outcomes by age 37

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)	(6)	(7)	(8)	(9)	(10)
Immigrant	-14.68***	-8.89***	-1.42***	-1.61***	-11.93***	-2.33***	0.40***	0.22***	-795.8	981.1
	(0.49)	(0.39)	(0.06)	(0.13)	(0.49)	(0.50)	(0.04)	(0.03)	(565.0)	(561.8)
SSN Age		-1.42***		0.05		-2.35***		0.04***		-434.6**
		(0.06)		(0.03)		(0.12)		(0.01)		(131.7)
F.E. Birth Year	X	X	X	X	X	X	X	X	X	X
F.E. Age 30 Zip5	X	X	X	X	X	X	X	X	X	X
F.E. Age 30 Credit Score	X	X	X	X	X	X	X	X	X	X
R^2	0.107	0.108	0.268	0.268	0.110	0.110	0.142	0.142	0.306	0.306
N	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134	5,755,134
Mean, SSN Age <21	75.34	75.34	44.73	44.73	92.21	92.21	3.92	3.92	$20,515.6	$20,515.6

Table A5: Consumers still observed in 2024

Odd-numbered columns in this table are estimates from the cross-sectional OLS regression specified in Equation 1 that includes an indicator for immigration status (*Immigrant* is 1 if a consumer's SSN was assigned at age 21 or older). Even-numbered columns are estimates from the OLS regression specified in Equation 2 that contains both the indicator for immigration status, and also *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). All six regressions include fixed effects for the birth year of the consumer, fixed effects for consumers' first observed ZIP code (First Zip5), last observed ZIP code (Last Zip5), longest ZIP code (Longest Zip5) as a proxy for their most permanent location, and the number of unique ZIP codes (Number Zip5) as a proxy for their mobility. The outcome in columns 1 and 2 is the probability of a consumer having a non-missing credit report in 2024. The outcome in columns 3 and 4 is is the probability of a consumer having a non-missing credit score in 2024. The outcome in columns 5 and 6 is is the probability of a consumer having anon-missing credit tradeline in 2024. The units are percentage points. 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)
Immigrant	-2.64***	-4.85***	-7.52***	-12.16***	-7.50***	-12.07***
	(0.13)	(0.22)	(0.29)	(0.48)	(0.32)	(0.42)
SSN Age		0.52***		1.09***		1.08***
		(0.04)		(0.07)		(0.06)
F.E. Birth Year	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X
F.E. Last Zip5	X	X	X	X	X	X
F.E. Longest Zip5	X	X	X	X	X	X
F.E. Number Zip5	X	X	X	X	X	X
R^2	0.034	0.034	0.110	0.111	0.138	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	96.15	96.15	90.31	90.31	85.03	85.03

Table A6: Credit access by age 37, for consumers still observed in 2024

Data in this sample is restricted to only the consumers with a non-missing credit score in 2024. Columns 1, 3, and 5 of this table are estimates from the cross-sectional OLS regression specified in Equation 1 that includes an indicator for immigration status (*Immigrant* is an indicator for whether the consumer's SSN was assigned at age 21 or older). Columns 2, 4, and 6 of this table are estimates from the OLS regression specified in Equation 2 that contains both the indicator for immigration status, and also *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). All six regressions include fixed effects for the birth year of the consumer, fixed effects for consumers' first observed ZIP code (First Zip5), last observed ZIP code (Last Zip5), longest ZIP code (Longest Zip5) as a proxy for their most permanent location, and the number of unique ZIP codes (Number Zip5) as a proxy for their mobility. The outcome in columns 1 and 2 is the probability of having ever held an auto loan by age 37. The outcome in columns 3 and 4 is the probability of having ever held a mortgage by age 37. The outcome in columns 5 and 6 is the probability of having ever held a credit card by age 37. The units are percentage points. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

Dep Var: By Age 37, has...	Auto Loan		Mortgage		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-8.30***	-2.01***	-2.89***	6.57***	1.03***	0.67***
	(0.81)	(0.22)	(0.71)	(0.41)	(0.20)	(0.13)
SSN Age		-1.46***		-2.20***		0.08
		(0.12)		(0.11)		(0.04)
F.E. Birth Year	X	X	X	X	X	X
F.E. First Zip5	X	X	X	X	X	X
F.E. Last Zip5	X	X	X	X	X	X
F.E. Longest Zip5	X	X	X	X	X	X
F.E. Number Zip5	X	X	X	X	X	X
R^2	0.099	0.099	0.134	0.134	0.054	0.054
N	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726	5,489,726
Mean, SSN Age <21	80.37	80.37	48.76	48.76	96.05	96.05

Table A7: Survey of Consumer Finances (2022): credit demand and debt attitudes

This table uses public data from the 2022 Survey of Consumer Finances (SCF), keeping birth years 1972 to 2000 such that respondents are aged between 22 and 49. Odd-numbered columns in both Panels are estimates from the cross-sectional OLS regression that includes an indicator for immigration status (*Immigrant* is an indicator for whether the consumer's age of immigration was at age 21 or older). Even-numbered columns add *Immigration Age*, the consumer's age at immigration (pooling consumers with an age of immigration of 20 or younger into one group) to the specification. See Appendix A.2 for details of the survey variables used. 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 in Panel A refer to applications in the last twelve months. The outcomes in Panel B are a variety of measures of attitudes to debt, as described more in Appendix A.2. The units in both Panels are percentage points. All regressions include a control for normal income (winsorized at the 99th percentile), and fixed effects for the birth year of the consumer and fixed effects for other demographic control variables: male, race, Hispanic, spouse, marital status, household size, number of children, and education levels. 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. $^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Panel A: Credit demand

Dep Var: Apply For...	Any Credit		Auto		Mortgage		Credit Card		Other Credit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	2.32	-1.08	2.03	-6.55	2.11	5.65	1.63	2.02	1.84	-7.66^{+}
	(4.56)	(7.17)	(4.37)	(7.53)	(3.8)	(6.85)	(3.22)	(5.32)	(3.62)	(4.61)
Immigration Age		0.44		1.10		-0.45		-0.05		1.22*
		(0.62)		(0.72)		(0.65)		(0.48)		(0.55)
Demographic Controls	X	X	X	X	X	X	X	X	X	X
R^2	0.051	0.051	0.051	0.053	0.045	0.045	0.045	0.045	0.026	0.029
N	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813
Mean, Immigration Age <21	64.81	64.81	19.95	19.95	11.28	11.28	9.28	9.28	12.08	12.08

Panel B: Debt attitudes

Dep Var: All Right To Borrow...	In General (Positive)		In General (Negative)		For Living Expenses		For Vacation		For Education	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	-4.27	-4.29	4.69	11.65	-8.76^{+}	-8.35	-5.01	-8.37	-2.80	9.07
	(4.83)	(8.95)	(4.65)	(7.09)	(4.89)	(7.66)	(3.40)	(5.21)	(4.18)	(5.59)
Immigration Age		0.00		-0.89		-0.05		0.43		-1.52*
		(0.80)		(0.62)		(0.74)		(0.56)		(0.67)
Demographic Controls	X	X	X	X	X	X	X	X	X	X
R^2	0.016	0.016	0.043	0.044	0.032	0.032	0.020	0.020	0.040	0.045
N	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1,813	1813
Mean, Immigration Age <21	29.51	29.51	25.71	25.71	73.38	73.38	15.30	15.30	84.24	84.24