Immigration and Credit in America

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Abstract

Immigrants enter the U.S. with a blank credit history, regardless of age or home country experience. Motivated by this, we study the assimilation of immigrants into American consumer credit markets. We find that immigrants are positively selected: immediately upon credit market entry, immigrant credit scores are, on average, 20 to 35 points higher than non-immigrants. Despite their greater creditworthiness, immigrants—especially those who arrive later in life—are delayed in their credit access and have lower average credit card limits for up to a decade. Immigrants are also less likely to access auto loans and mortgages, gaps that persist into their forties and are unexplained by geographic fixed effects.

Keywords: Immigration, Credit History, Household Credit, Thin Credit Files
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1. Introduction

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

This paper provides the first large scale evaluation of how immigrants assimilate into the U.S. consumer credit system. We use variation in the lifecycle timing of Social Security Number (SSN) assignment: individuals assigned SSNs as adults are very likely to be immigrants (Klopfer and Miller, 2024). We combine this fact with the sequential assignment of SSN blocks within states (also used in Yonker, 2017, Doran et al., 2022, Bernstein et al., 2025) to classify immigrants in a 10% representative sample of U.S. consumer credit reporting data from TransUnion spanning 2000 to 2024. Using this dataset, we track the progress of immigrant cohorts through the U.S. credit system, defining cohorts by their age at SSN assignment. This empirical strategy contrasts outcomes across different immigration ages while controlling for birth year effects, enabling us to shed light onto the connection between immigration timing and credit market trajectories.[1]

Our core findings provide new empirical facts about immigration and credit in the United States. First, we show that immigrants only appear in credit markets once they are assigned a SSN, supporting our empirical classification of immigrants in the credit reporting data. However, immigrants' likelihood of having a credit score catches up to that of non-immigrants within a few years of SSN assignment. More strikingly, once they enter the system, we find that immigrants have significantly higher credit scores compared to non-immigrants, as well as persistently lower

[1]The closest prior data to ours is Federal Reserve (2007) report to Congress, which evaluated traditional credit scoring models in a 2003 sample of 300,000 credit records that includes immigrants. Our dataset offers a substantial advancement because it is 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.

delinquency rates and more conservative credit utilization patterns. This positive selection on credit quality is more pronounced among those who immigrate later in life.

However, despite immigrants' stronger observable credit quality upon entering U.S. credit markets, we find they face persistent barriers to accessing certain types of credit. While credit card access 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 (i.e., by age 40 for cohorts that immigrate in their twenties). Even though *access* to credit cards exhibits fast and complete convergence to non-immigrant levels, credit card *limits* – an intensive margin of credit – lag behind, taking up to a decade to converge. These gaps are especially pronounced for those who immigrate later in life, suggesting that limited credit history creates frictions in credit access that are not reflected by immigrants' relatively high credit scores. The gaps in credit limits are particularly relevant given their role in shaping consumption (Aydin, 2022, Agarwal et al., 2024).

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

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

Our findings on immigrant creditworthiness and credit access are robust to controlling finely for geography (i.e., including fixed effects for the first, last, and longest-held ZIP5 by a consumer, and the number of ZIP5 addresses to proxy for mobility), ruling out geographic drivers of the results, such as urban versus rural differences in economic vibrancy (Dougal et al., 2015). Moreover, we also find that later in life immigrants have greater demand for credit in their twenties, measured using recent credit inquiries. These findings contrast with a demand-side view that immigrants have different preferences for and use of credit. We examine emigration as an alternative mechanism and show that, while this is important, it does not explain our results. One plausible mechanism for our findings is that immigrants' lack of a credit history and shorter length of credit histories may hinder their credit access, even for immigrants with high credit scores. We have work-in-progress to evaluate the potential mechanisms behind our results.

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

In addition, our findings provide a fresh perspective on the assimilation of immigrants into the U.S. economy. There is a robust literature on the assimilation of immigrants, which has

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

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

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

Our findings on delayed entry into the U.S. credit system also relate to the work on the long-term impacts of delayed credit market entry (Brown et al., 2019, Nathe, 2021). Related work has emphasized the importance of a good start in credit markets, either through good parental credit histories (e.g., Ghent and Kudlyak, 2016, Bach et al., 2023, Hamdi et al., 2024, Benetton et al., 2025,

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

[4]Our perspective on immigrants differs in at least two ways from recent household finance research on immigrants and the dynamics of credit via movers. First, as reviewed in Gomes et al. (2021), the existing household finance literature on immigration has largely focused on cultural differences. Zillessen (2022) study the savings choices of migrants in Germany. 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.

Blizard et al., 2025) or starting one's credit history in good economic times (Ricks and Sandler, 2025). Relative to this literature, our variation in credit market entry timing (and thus history) deploys a person-specific, near-mechanical reason for delay — immigrants cannot enter U.S. credit markets before immigration, nor get credit for their credit history in other countries. Although our results on credit access are similar to other factors that delay and restrict access to credit, our findings on immigrants' higher credit scores contrast with work on credit entry timing and later credit scores (Nathe, 2021), suggesting that later credit market entry has less of an impact on credit scores for immigrants.[5]

Finally, our research on immigrant credit access relates to the FinTech literature (e.g., Buchak et al., 2018, Berg et al., 2022, Erel and Liebersohn, 2022), especially work on how FinTechs serve underrepresented groups and younger borrowers (Dobbie et al., 2021, Cherry, 2024, Hair et al., 2025). More closely related is research focused on the lending decisions of FinTechs in the presence of little or no credit history. Di Maggio et al. (2022) shows that alternative credit scores identify "invisible primes" that are misclassified by traditional credit scoring. However, even in this setting, FinTech lending may still rely upon traditional credit scores (Chioda et al., 2025). Our results complement these perspectives in the literature by showing that immigrants' access to credit is delayed, and that this delay is not attributable to traditional credit scores.

2. Data, Immigrant Classification, and Empirical Specifications

2.1 Data

Consumer Credit Reporting Data

We obtain consumer credit reporting data from the University of Chicago Booth TransUnion Consumer Credit Panel, "BTCCP" (TransUnion, 2025). The BTCCP is an anonymous, representative sample of U.S. consumer credit reporting data provided by TransUnion. To build this sample, TransUnion starts with a 10% representative sample of consumers with a credit report in July 2000. For each month of data after July 2000, 10% of new consumers are added to the panel to maintain

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

representativeness. The data have information on 10% of consumer credit records, monthly from July 2000 to December 2024. Gibbs et al. (2025) discusses best practice for using consumer credit reporting data, which we follow in this paper.

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

American Community Survey (ACS)

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

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

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

2.2 Sample Construction and Immigrant Classification

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

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., Forthcoming). Through mid-2011, the Social Security Administration sequentially assigned SSNs, allocating all SSNs with the same first five digits before moving onto another block. See Puckett (2009) for a comprehensive history of SSN assignment. Following the approach used in prior research, we classify a consumer as an immigrant if their age at SSN assignment, $SSN\ Age$, is greater than or equal to 21, where $SSN\ Age = SSN\ Year - Birth\ Year$.

To estimate the year of SSN assignment, $SSN\ Year$, we construct a lookup table, based on public information, that maps the first five digits of the SSN into the first year of SSN assignment, $SSN\ Year$, for all SSNs assigned before 2012.[10] 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

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

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

[10] 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.

observe nor can we infer SSNs for any consumers in the BTCCP.[11]

Table 1 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 drop what appear to be fragmented credit records with younger ages and credit reports that do not persist over time. 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.[12]

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

This sample has limitations. Our immigrant classification does not include illegal immigrants (who lack SSNs) nor does it allow us to identify people who immigrated before adulthood. It also does not include legal immigrants with Individual Taxpayer Identification Numbers (ITINs) or Enumeration at Entry (EAE), as we do not know when these are assigned. However, ITINs and EAEs are typically only used before a consumer receives a SSN. For the non-immigrant birth years relevant to our study, consumers were assigned a SSN at birth or before turning 18, as demonstrated in administrative Social Security Administration data by Klopfer and Miller (2024), although some older consumers were assigned SSNs as adults. The distribution of SSN Ages by birth years in our data, shown in Appendix Figure A4, corresponds to that in Klopfer and Miller (2024), and another independent validation of our classification is that the consumers that we classify as immigrants are more geographically mobile than non-immigrants (Appendix Figure A5). In addition, we do

[11]This classification depends on knowledge of the first five digits of a consumer's SSN (Advani et al., 2024 also uses a related method in the United Kingdom). Bernstein et al. (2025) use Infutor data, which was originally built from consumer credit reporting data. However, since the 1999 Gramm-Leach-Bliley Act, the bureaus cannot sell address lists to third parties, forcing Infutor and its competitors to rely on other data sources.

[12]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.

not observe people who remain outside the formal credit system.

Table 1 shows that the resulting "Clean Sample" has 18.57 million consumers, 2.09 million of whom we classify as immigrants. The 11.27 percent of immigrants in this clean sample approximates the 10.20 percent of consumers in the ACS, applying the same birth year restrictions and also only classifying immigrants if their year of immigration was when they are aged 21 or older.

Further validation shows a close correspondence between our estimates and the ACS estimates of immigrants. In particular, panel A of Figure 1 shows how the distribution of immigrants by birth year compares in our classification to the ACS. The only departure we see from a near-identical percentage of immigrants by birth year is in the birth years 1985, 1986 and 1987, which we undercount because they only have a few years of adulthood before 2011 and our sample frame requires them to have a credit report by 2011. In panel B, 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. Finally, in Appendix Figure A2 we show that the immigrant classification delivers a close match to the distribution of immigrants across states found in the ACS. These validation exercises, together with similar validations in the literature (Bernstein et al., 2025, Klopfer and Miller, 2024), suggest that our strategy to classify immigrants is accurate and reliable.

2.3 Entrant Sample

Starting from the "Clean Sample" described above, we impose two further restrictions to arrive at the "Entrant Sample" used for our analysis. First, we restrict to the set of consumers with birth years between 1975 and 1987. Consumers with these birth years are expected to enter the credit system and begin accessing credit mostly after 2000 and before the SSN assignment period ends in 2011. Thus, we call this sample the "Entrant Sample." For example, in the years 2000 to 2024 observed in the BTCCP, consumers born in 1975 are observed from age 25 to 49, while consumers born in 1987 is observed from ages 18 and 37. Given these sampling choices, Appendix Figure A1 displays how birth years, age at SSN assignment, and the time period we observe consumers in our data relate to one another. For some analysis that relies on consumer-level datasets, we further restrict to birth years 1982 to 1987 to ensure that consumers enter the credit system after 1999, following the approach in Ricks and Sandler (2025) and Bach et al. (2023).

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

This final sample has a total of just over 6 million consumers, 344,261 who we classify as immigrants (i.e., SSN Ages 21 through 29). Appendix Figure A3 shows that this entrant sample closely matches the ACS data. This lower fraction of immigrants in the entrant sample (5.96%) is primarily due to dropping immigrants with $SSN\ Age \geq 30$. Within this sample, there are 102 immigration groups—i.e., birth year x SSN Age combinations. As shown by the counts of consumers by SSN Age in Appendix Table A1, each SSN Age group in this entrant sample has many consumers, ranging from 52,450 at SSN Age 21 to 19,202 at SSN Age 29.

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

2.4 Empirical Specifications

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

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

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

where i indexes consumers, b indexes birth years and $\mu_{b(i)}$ is a birth year fixed effect. Y_i is a consumer level outcome, such as age at first credit card (or mortgage, or auto loan) or a consumer's

Vantage score at age 30. $\phi_{SSN\ Age(i)}$ is a vector of $SSN\ Age$ fixed effects. SSN Age ranges from 18 to 29 because we pool all consumers with a SSN Ages 0-18 into the SSN Age 18 category, to group non-immigrants. The SSN Age fixed effect estimates in this specification thus calculate the average outcome for each SSN Age cohort, conditional on birth year.

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

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

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

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

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

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

3. Results

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

3.1 Summary Statistics

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

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

for non-immigrants). As of age 30, immigrants are less likely to have a credit report, suggesting that entry into the credit system takes time.

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

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

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

3.2 Credit Market Entry

We present evidence that SSN Age drives the timing of credit market entry. At the highest level, our evidence shows that older SSN Age strongly predicts later credit market entry, both for first credit product and for the first date the consumer receives a credit score. These findings also serve to further validate SSN Age as a proxy for immigration timing.

To evaluate how SSN Age relates to the timing of credit market entry, Figure 2 plots the estimated SSN Age fixed effects estimates ($\phi_{SSN\ Age(i)}$) from Equation (1). The coefficient for the non-immigrants (consumers with SSN Age of 18 or younger) is indicated by the gray horizontal dashed line — the average age at first credit product for this baseline group is 21.25 years. As SSN Age increases, so does the average age at first credit product, and this increase is essentially linear.[13] Especially for older SSN Age cohorts, these findings reflect the reality that immigrants could not have credit products before their immigration date.

Given this linear relationship between SSN Age and credit entry, we move to results from our main regression specification, Equation (1), for the rest of our results section. Table 3 presents the results from estimating this equation. In columns 1 to 3, we estimate the specification with increasingly demanding fixed effects. Broadly, we find that immigrants enter U.S. credit markets at later ages on average, and immigrants who immigrate later in life (older SSN Age) access credit at even later ages. Specifically, in columns 1 through 3, we estimate immigrants are nearly 2 years older than non-immigrants, on average, when they first have a credit report. Delayed entry into the credit system is more pronounced for immigrants who arrive to the United States later in life. For each additional year of older SSN assignment, we estimate that the age of first having a credit report is delayed by an additional 0.74 to 0.78 years.

Our conclusions about delayed entry are not sensitive to how we measure entry into the U.S. credit system. We obtain similar estimates for the consumer's age upon receiving their first credit

[13] We also observe linear effects for age at first credit report in Appendix Figure A6, and the age of first credit card, auto loan, and mortgage in Appendix Figure A8.

product — 1.68 years later and 0.74 years per year of SSN Age — as shown in Table 3 where we add fixed effects across columns 4 to 6.[14] These delays are economically significant relative to the average age that non-immigrants receive their first credit report (19.86 years) and the average age of first credit product (21.25).

One potential concern with interpreting these delayed entry results is that local markets vary in their economic opportunities or access to finance, and this may disproportionately affect immigrants. That is, immigrants may be more likely to arrive in cities rather than rural areas, or areas of different incomes or other economic opportunities, which have different credit access patterns or economic vibrancy (Dougal et al., 2015). Our results are robust to adding fixed effects for the first ZIP code, as displayed in columns 3 and 6 of Table 3.[15] These results are also robust to additionally including fixed effects for each consumer's last ZIP code, longest-held ZIP code, and number of unique ZIP codes, as shown in Appendix Table A2.

3.3 Creditworthiness

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

3.3.1 First Credit Score

First, we examine the timing of when a consumer first receives a credit score. This is an important outcome because it is risky to lend to unscored applicants. Panel A of Figure 3 displays the unconditional likelihood of having a credit score for each SSN Age cohort at different ages. The black line shows how the likelihood of having a credit score evolves for consumers with SSN Ages 18 or younger ("non-immigrants"). At age 18, approximately 15% of non-immigrants receive

[14] Appendix Figure A10 shows the lifecycle for age of first credit report and first credit product by SSN Age.

[15] Appendix Figures A6, A7 and A9, also show that our linear results as presented in Figure 2 are robust to including such fixed effects.

their first credit score; by age 22, more than 80% of these consumers have a score. Judging by the consistent rightward shift in these lifecycle curves as SSN Age increases, consumers with older SSN Ages access credit later. Much of this delayed access is due to consumers naturally having no access to the credit system before their immigration date. In the years prior to the SSN Age (where $Age = SSNAge$ is indicated by a circle on each lifecycle curve), there is *de minimus* access to credit, followed by a sharp jump in the percentage of scored consumers in the year following immigration.

Shortly after their immigration year, immigrants quickly converge to their non-immigrant counterparts in their likelihood of having a credit score. For example, while only 30% of SSN Age 22 consumers have a credit score at age 22, more than 80% have a credit score by age 26. The speed of convergence in the likelihood of having a credit score increases for immigrants assigned SSNs at older ages. Moreover, immigration cohorts arriving later in life have a higher likelihood of having a credit score in their year of immigration. For example, only around 10% of 21 year old immigrants (SSN Age of 21) have a credit score at age 21 whereas nearly 40% of 29-year-old immigrants have a credit score at age 29.

3.3.2 Mean Credit Scores

Panel B of Figure 3 plots the means of credit scores for each SSN Age cohort at different ages, *conditional* on having a credit score at that age. It is important to study credit scores at different ages because a consumer's borrowing needs and propensity to repay debt can change over the course of their lifecycle (see Chatterjee et al. (2023) for a theory of credit scoring). Strikingly, this plot shows that immigrant SSN Age cohorts (SSN Age > 21), start out with a higher mean credit score than non-immigrants (SSN Age $= 18$). Immigrant cohorts continue to have substantially higher average credit scores throughout their thirties, which is after immigrants are just as likely as non-immigrants to have a credit score. Although the high average credit score in the year of immigration might partly reflect selection (i.e., immigrants who are scored are higher credit quality), immigrants have higher credit scores than non-immigrants after a similar fraction of immigrants and non-immigrants are scored. Thus, this result suggests that immigrants who are scored are better credit risks than their scored non-immigrant counterparts of the same age, on average. Overall, this dynamic pattern paints a somewhat unexpected picture: Even new immigrants with a credit score are *observably* better credit risks.

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

The immigrant versus non-immigrant difference in credit scores widens as consumers age. By age 40, the gap in credit scores increases to 31.5 points, with a similar $SSNAge$ gradient for consumers who immigrate later in life. Similarly to the results at Age 30, we find that the immigrant to non-immigrant difference is somewhat smaller upon including geographic fixed effects, though it remains large. These higher average credit scores occur *despite* these consumers having a shorter credit history, which is known to be a negative input to credit scores. The length of credit history is an important input in the credit scores that lenders use, accounting for approximately 15% of FICO and 20% of VantageScore models.[16]

3.3.3 Distribution of Credit Scores

The mean credit score may mask important heterogeneity in credit scores. Panel B of Table 4 estimates Equation (1) where the outcome is the likelihood of having prime or better credit scores,

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

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

Panel C of Figure 3 shows how the fraction of consumers with prime or higher credit scores evolves over the lifecycle for each SSN Age cohort. In panel C, unscored consumers are counted in the denominator, while panel D conditions the plot on having a score. In panel C, we observe two competing forces at play: On one hand, immigration cohorts arriving later in life are less likely to be scored, but on the other hand, they are more likely to have prime or higher credit once they are scored. In a cohort's twenties, the share of unscored consumers dominates the higher credit scores of the cohort's scored consumers, whereas by the cohort's thirties the higher credit scores of scored consumers dominate. Panel D shows that, conditional on having a credit score, immigrants are more likely to have prime or higher credit scores and the magnitude of these differences is relatively large. For example, at age 26, a consumer who immigrated at age 22 and is scored is over 10 percentage points more likely to have a prime credit score than a non-immigrant who is scored — over 50% versus under 40%. Moreover, because most SSN Age 22 consumers have a credit score by age 26, this difference is not explained by differential selection into the credit system. These credit risk differences are persistent over the lifecycle, and even grow slightly as people age. The gap between the SSN Age 22 cohort and the non-immigrant cohort is nearly 15 percentage points by age 40.

Digging deeper into the credit score results, Appendix Figure A11 shows that immigrants have more compressed credit scores than non-immigrants. The average immigrant is less likely to have a subprime credit score than the average non-immigrant at any stage in the life cycle that we observe. This applies irrespective of the age of immigration and irrespective of conditioning on having any credit score. The average immigrant is more likely to have a very high credit score, as measured by prime plus (VantageScore > 720) or superprime (VantageScore > 780), by their mid-to-late thirties, again irrespective of the age of immigration and irrespective of whether we condition on having any credit score.[17]

Panel B of Appendix Figure A12 shows the CDF of first credit scores by SSN Age cohort. The CDF for immigrants of all ages is to the right of that of non-immigrants, and shifts further right as SSN Age rises. This evidence shows that immigrants have higher credit scores immediately upon entry, despite these scores often being based on thin credit files.[18] Overall, the results of this subsection indicate that immigrants credit behaviors mean that they are lower credit risks on average, than non-immigrants of the same age, and immigrants are increasingly lower risk as they age and more information becomes available.

3.3.4 Credit Delinquency & Credit Utilization

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

[17]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 A12. 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.

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

inputs to credit scores.

The lifecycle of delinquency rates shown in panel A of Figure 4 portrays results that are consistent with our credit score results. Non-immigrants have higher delinquency rates at all ages relative to immigrants, a difference that persists through their thirties. Moreover, even among immigrant cohorts, people arriving later in life (older SSN Ages) have lower delinquency rates.

Beyond the lower delinquency rates, an important reason credit scores are higher in the first year for immigrants is because they have lower credit card utilization. We illustrate this pattern in panel B of Figure 4. Credit card utilization is consistently lower for immigration cohorts, especially for older SSN Age cohorts. These two measures point to immigrants being better credit risks once they are holding credit products in the U.S.

3.4 Access to Mortgages and Auto Loans

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

We now consider the timing of first credit access across mortgages and auto loans. Appendix Figure A8 plots the average age of first credit product by SSN Age cohort, separately for credit cards, auto loans and mortgages. Appendix Figure A9 presents similar results after further conditioning on ZIP5 fixed effects. These figures have two main messages. First, the average age of first credit access depends on the type of credit: for non-immigrants, the average age of first access is 22.5 years for credit cards, 29.7 years for auto loans and 36.3 years for mortgages.[19] Second, for all types of credit products, later in life immigration dates (older SSN Ages) correspond to later credit access. The fact that immigrating slightly later in your twenties matters for auto loans and mortgages, which are typically accessed in a consumer's thirties, suggests that delayed entry into credit markets

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

has long-term impacts on credit access. This is plausibly related to later in life immigrants having shorter credit histories. However, another possible mechanism is that immigrants may purchase automobiles with cash, or they may be more likely to move within the U.S. or emigrate, potentially making them less likely to want to purchase a house. We discuss these alternative mechanisms in Section 5.

To evaluate this idea, we construct the lifecycle of credit access for each type of credit parallel to the earlier analysis. We find that immigrants have very limited access to credit in the year before their SSN Age, regardless of credit type. Figure 5 illustrates these patterns across the early adult lifecycle for cohorts of people with SSN Ages between 18 and 29.[20]

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

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

We quantify this idea using our main regression specification (Equation (2)), replacing the dependent variable with an indicator for age of first credit access, separately for each type of credit. Table 5 presents the results. We find a significant immigrant versus non-immigrant delay in the average age of first accessing credit: 2 to 3 years for auto loans and 0.2 years to 0.8 years for mortgages. Moreover, this gap grows for later in life immigrants: an additional year of SSN Age predicts an additional delay of 0.6 years for a consumer's first auto loan, and 0.4 years for a

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

consumer's first mortgage. These results on delays in first accessing credit are robust to controlling for the consumer's most recent ZIP5, to account for local market conditions, and longest held ZIP5 and number of unique ZIP5, as shown in Appendix Table A4.

To quantify whether consumers access credit at all within our sample frame, we now change the outcome to whether a consumer has accessed a specific credit product (credit card, auto loan, or mortgages) by the age of 37 (i.e., 8 years after the last immigration cohort arrives). Table 6 presents the results. In columns 4 through 9, we find significant gaps in long-run access to auto loans and mortgages: unconditionally, immigrants are 10.2 percentage points (13%) less likely to have ever had an auto loan and 2.2 percentage points (5%) less likely to have ever had a mortgage by age 37. This immigrant versus non-immigrant gap grows significantly for immigrants who arrive later in life. For example, for each year increase in SSN Age we estimate that immigrant consumers are 1.3 to 1.6 percentage points less likely to have a mortgage by age 37. The estimates shrink somewhat on controlling for first ZIP5 fixed effects (and, for mortgages, the immigrant indicator is non-significant but the SSN age coefficient remains significant), but we continue to find that immigrants with older SSN Ages are much less likely to access auto loans and mortgages, given the negative, large significant coefficients on $SSNAge$. Additionally, Appendix Table A5 show that these results are robust to including fixed effects for the consumer's *last* ZIP5 and longest ZIP5, which account for differences in local market conditions beyond formative local conditions via the consumer's first location in the credit file, and number of ZIP5 to also account for differential geographic mobility (and with these additional controls the mortgage result becomes significant again). These estimates point to large and significant differences in auto loan and mortgage credit access, which is correlated with the timing of immigration.

3.5 Access to Credit Cards

We now examine consumers' access to credit cards, a key source of unsecured borrowing in the U.S. We use our main regression specification (Equation (2)), instead using as dependent variables an indicator for age of first accessing a credit card, and then whether a consumer has ever held a credit card by age 37. Table 5 presents the results. We find a significant immigrant to non-immigrant gap in the average age of accessing credit: 1.17 years to 1.37 years for credit cards. Moreover, this gap grows for later in life immigrants: an additional year of SSN Age predicts about 0.7 years later first accessing a credit card. As with our results for auto loans and mortgages, these results are robust to controlling for other geographic fixed effects (last ZIP5, longest-held ZIP5, and number of unique ZIP5s), as shown in Appendix Table A4.

In columns 1 and 2 of Table 6, we observe that immigrants are slightly *more* likely to have a credit card by age 37 than non-immigrants. However, conditioning on first ZIP5 fixed effects leads this difference to be non-significant, and remains so with including last ZIP5 fixed effects, and also adding in longest ZIP5 fixed effects, but becomes significant again once including fixed effects for the number of unique ZIP5s. These are all shown in Appendix Table A5. Moreover, for credit card access by a consumers mid-thirties, the timing of immigration does not matter for whether the consumer has access to credit cards.

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

Consistent with the evidence on access to auto loans and mortgages, credit limits of immigrants with older SSN Ages take many years to catch up to immigrants with younger SSN Ages and non-immigrants. These differences are mostly driven by credit limit per card, not the number of cards. For example, in panel B of Figure 6, the SSN Age 29 cohort does not converge until age 36 to the same total credit limit as non-immigrants. This long delay in convergence reflects different dynamics for the average credit limit per card (panel C) and the number of credit cards (panel A). In panel C, the average credit limit per card *never* catches up to earlier cohorts (e.g., by age 40, the SSN Age 29 cohort has the lowest mean credit limit per card). By contrast, the number of credit cards catches up and surpasses SSN Age 18 cohort within three years of immigration. The fact that immigrant cohorts catch up to non-immigrants in their total credit card limits, but only through access to more credit cards provides unique evidence on this phenomenon.

4. Paired Cohorts

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

4.1 Methodology

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

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

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

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

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 develop for each cohort relative to consumers with the same birth year who immigrated one year earlier.

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

We cluster standard errors by birth year to allow for dependence over the lifecycle and to allow for dependence within pairs. Such clustering is especially important in our context because one cohort can be a focal cohort in one pair but also act as a control group in another pair. Finally, in our regressions we weight each observation by the size of its cohort.[21]

This estimation approach is not a causal design, but it does allow us to provide evidence on the timing of differences in credit access for different types of credit, and to empirically link these

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

differences to a one year gap in immigration. Further, our focus is on immigration cohorts in their twenties, which allows us to analyze credit outcomes that are not mechanically delayed by the immigration date – specifically, auto loans and mortgages, which are commonly accessed later, and in the case of mortgages, often in a person's mid-to-late thirties.

4.2 Results

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

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

One advantage of the paired cohort strategy for binary outcomes is that the coefficients in a given event year reflect the percentage difference in access for that year — the average amount of delay in accessing credit that we can attribute to that particular year. Viewed this way, we can accumulate coefficient estimates over the event window to quantify the cumulative delay in accessing credit by a given year.[22] Aside from providing an alternative way to compute the average delay in credit access, this cumulative statistic also helps quantify the long-run delay for each type of credit, which is especially useful if the different credit types have distinct dynamics.

Table 7 presents this exercise, displaying the cumulative delay as of year C, year T, year 5 and year 10, with Appendix Figure A13 showing the full estimates. We estimate that one year difference in immigration date is associated with cumulatively 0.69 years to 0.74 years less credit history, and most of this delay is realized by the focal cohort's immigration date T. This finding is consistent with the idea that later in life immigration cohorts eventually enter U.S. credit markets, but their credit access is initially delayed, resulting in persistently shorter credit histories. A shorter credit history is a natural, almost mechanical, consequence of immigrating later in life.

The results for auto loans and mortgages are different in terms of magnitude and dynamics. First, the cumulative delay is more modest. Ten years after the focal cohort's immigration, we estimate an average delay of 0.29 years for first mortgages, and a delay of 0.42 years for first auto loans. The shorter average delay for credit products typically accessed later in life suggests that immigrants manage some degree of catch up over a ten year span. However, this catch up is not complete as of the end of the event window, and as the results in the previous section suggest, some immigrants might not access auto loans or home equity at any point in their lifecycle due to their later in life immigration dates.

Turning to the initial dynamics, only a small fraction of the delay in auto loan or mortgage access can be attributed to "mechanical delay" around the date of immigration. Instead, most of the delay emerges years after the immigration date, lining up with when in the lifecycle these products are typically accessed for the first time by non-immigrants. When taken together with the fact that immigrants in their thirties who immigrate at a later stage in their twenties have *higher* average credit scores throughout this period (Figure 3), the later-emergence and persistence of the delay in auto-loan and mortgage access constitute consequential longer-term effects of immigrating a single year later in life.

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

Finally, we see an interesting, non-monotonic difference in credit card limits for adjacent immigration cohorts, as displayed in panel C of Figure 7, and a similar pattern is observed in the number of credit cards in Appendix Figure A15 panel A. For the first eight years after the cohorts immigrate, we observe that the focal cohort has significantly lower credit card limits. This gap is at its widest two years after the focal cohort's year of SSN assignment, with average credit limits being \$1,825 (s.e. \$105) *lower* than those of the control cohort. However, the focal cohort's average credit limit overtakes the control cohort's average limit nine years after immigration. This gap grows over time, becoming significant from zero after eleven years. Thirteen years after the year of SSN assignment, the focal cohort's average credit limit is \$707 (s.e. \$162) *higher* than the control cohort's average limit.[23] This nonlinearity reflects the overarching tension inherent to immigration credit we find throughout this paper. On one hand, we find consistent evidence that immigrants and especially those who immigrate later in their twenties have substantially lower credit risk. Yet, their later entry into the U.S. credit system leaves them with less credit history. Thus, despite their better credit quality, their access to credit lags behind, in the case of auto loans and mortgages for at least thirteen years after immigrating.

5. Mechanisms

We now discuss the potential mechanisms that could explain our results, and we have work-in-progress to quantitatively evaluate these. Given the direct link between later in life immigration and shorter length of U.S. credit history, a plausible mechanism for our findings is that whether a consumer has a credit report, and the length of a consumer's **credit history** itself may be an important factor in lending decisions.[24] Our strongest evidence on this point is that immigrants' first credit scores are higher and their average credit scores are higher than non-immigrants who are the *same age*, yet immigrant credit access is delayed for credit cards.

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

[24]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.

We now turn to other potential mechanisms aside from the length of a consumer's U.S. credit history. One potential interpretation of these findings is that differences in consumers' **credit demand** drive differences in credit access. To shed light onto this potential mechanism, in Appendix Figure A14 we examine the outcome *months since last inquiry*, where a lower number of months since last inquiry indicates higher credit demand. On average, immigrants in their twenties have higher demand than non-immigrants. However, during their thirties, this pattern reverses and immigrants have lower demand. Appendix Figure A15 Panel B displays a pattern consistent with this result using the paired cohort design: the focal cohort has a significantly lower average time since last inquiry for up to five years (estimate after four years is -0.20 months, s.e. 0.04), indicating that they have *higher* demand for credit, and it is only seven years that they have significantly *lower* demand (estimate is 0.06 months, s.e. 0.02), stabilizing from years eleven onward (estimate after thirteen years is 0.35 months, s.e. 0.02). We also caveat that the lower credit demand later on may partially be a function of being deterred following earlier rejections. This suggests that delayed access to credit is not purely an artifact of delayed demand for credit for older SSN Age cohorts.

Alternatively, the lower long-term auto loan credit access for immigrants versus non-immigrants, and for immigrants assigned SSNs at older versus younger ages, may be partially driven by these groups having different **tastes** and so *choosing* either not to purchase cars or to purchase cars without using credit. While the majority of vehicles in the US are purchased on credit (Benmelech et al., 2017) and are thus observed in our data, it is possible that immigrants (or immigrants with SSNs assigned at older ages) are more likely purchase autos without financing. If so, autos purchased without financing could explain some of the gap that we observe.[25] Although less common given the monetary commitment involved, this explanation may also apply to property if immigrants (or immigrants with SSNs assigned at older ages) disproportionately employ cash instead of mortgage debt. Immigrants are a heterogeneous group, with a variety of cultural backgrounds that vary in their familiarity and willingness to use debt. This would be expected to contribute some differ-

[25] It is also possible that immigrants disproportionately purchase low quality autos that have forms of subprime financing ("Buy Here Pay Here") that are not reported in credit reports, but have a relatively small market share (Clarkberg et al., 2021).

ences between immigrants and non-immigrants. However, we would not expect it to explain the differences in outcomes between immigrants who vary in SSN Age, in our paired cohorts analysis, or when controlling for birth year and geographic fixed effects.

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

We consider the role of emigration by constructing proxies for emigration; measuring whether a consumer is no longer observed in our data. If a consumer no longer has a credit report or only has a non-missing credit score, then they may have died or have left the country (or their credit report was a fragment and merged with another report). Appendix Figure A16 shows that immigrants are more likely to exit our data than non-immigrants. It also shows that immigrants with younger SSN Ages exit before immigrants at older SSN Ages. These results are confirmed using our main regression specification presented in Appendix Table A6. Immigrants are significantly less likely to be observed in our data in 2024, but for each additional year of SSN Age beyond 21 they are marginally more likely to be observed. Appendix Figure A17 shows that emigration rates are higher for all SSN Ages above 18 than the SSN Age 18 baseline, and are broadly flat for SSN Ages 25 to 29, whereas emigration rates are decreasing in SSN Age 19 to 25.

After accounting for this differential attrition of immigrants and non-immigrants our key findings remain. We condition on consumers still present in the data in 2024 in Appendix Figures A18, separately for whether a consumer has any mortgage, any auto loan, or any credit card by age 37, and A19, for credit card outcomes (number of cards, limits, and limit per card), the results are consistent with our main Figures 5 and 6. The only slight difference is that with stricter sample restrictions, there is some convergence between SSN Age cohorts in their early twenties and the non-immigrant SSN Age 18 cohort. However, even then the same gaps in credit access emerge for the older SSN Age cohorts. Appendix Table A7 shows that the coefficients on SSN Age for whether a consumer has an auto loan, and especially a mortgage, by age 37 have larger negative sign (and the immigration indicators have a larger negative sign for auto loans and a larger positive sign for mortgages) than in the full sample results shown in Table 6 and Appendix Table A5. Therefore, while emigration is important, it does not appear to fully explain our results.

Our results are organized around life cycles defined by consumers' birth years. However, it is possible that immigrants' life cycles are instead more closely linked to when they arrive in the United States — when their local labor market and immigrant experience begins. For example, being in the country for an additional year may mean that a consumer is better assimilated or integrated into the economy, and better able to understand the American credit system. Such differences may be most pronounced in the initial years after arrival, but if they have longer-term persistence, they might contribute to the absence of full catch-up in some credit access outcomes.

Our finding that immigrants (and later in life immigrants) typically have better credit scores and are less risky on other credit behaviors (e.g., lower delinquency rates and lower credit utilization) indicates that **creditworthiness** cannot explain our results. With higher credit scores, we would not expect lower long-term access to auto loans and mortgages, nor would we expect higher credit card limits to take a decade to materialize. Different consumer credit markets vary in their reliance on credit scores and credit histories, with credit card decisions typically more reliant on this information than auto loans or mortgages (Blattner et al., 2022).[26]

Another factor that may contribute to our results is lender **regulation**. Lenders are able to

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

consider an applicant's immigration status as a relevant factor in their lending decisions. This is because immigration status is *not* a protected characteristic—that lenders may not use e.g., gender, national origin, and race—under the Equal Credit Opportunity Act (ECOA). However, as a joint statement between the Consumer Financial Protection Bureau and the Department of Justice set out in October 2023, lenders are constrained in how much they can rely on information on immigration status in their underwriting because lenders need to comply with ECOA to ensure that they are not discriminating against protected characteristics.[27] We would therefore broadly expect–if anything–risk-averse lenders to be more willing to lend to immigrants, especially given their creditworthiness. In March 2025, the Department of Housing and Urban Development (HUD) removed eligibility for "non-permanent residents" (i.e., legal immigrants) from Federal Housing Administration programs (illegal immigrants were always ineligible).[28] This HUD policy change is too recent to affect our results, however, we would expect it to reduce immigrants' access to mortgages in the future. Finally, other barriers may prevent immigrants from accessing credit. Language barriers between credit applicants and lenders may prevent efficient transactions from occurring. An example of this is Liu (2025) that shows how a 2018 Federal Housing Finance Agency policy change to translate mortgage documents increased mortgage lending.

6. Conclusion

This study offers the first large-scale empirical examination of immigrants' assimilation into the U.S. consumer credit system. By tracking credit outcomes for immigrants across different arrival ages, we document several important facts about immigrant credit risk and their financial inclusion into American credit markets.

Our evidence paints a nuanced picture: upon credit market entry, immigrants have significantly higher credit scores than their non-immigrant counterparts, with credit scores 20 to 35 points higher on average, as well as lower delinquency rates. These differences remain just as significant after including ZIP code fixed effects. Yet, despite their superior measured creditworthiness, we

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

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

show that immigrants are persistently less likely to access auto loans and mortgages, with delays lasting through the end of our sample period into the end of their thirties. This disconnect between creditworthiness and credit access is striking: Even though immigrants have *observably* higher credit in their thirties, their access to major credit products, most notably mortgages, is delayed. Moreover, immigrants even have persistently delayed credit access relative to same-aged immigrants who arrive in the Unites States a year earlier.

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

Consistent with the existence of profitable opportunities, the market is now developing a variety of solutions. Some lenders, such as American Express, have linked data across countries to give immigrant consumers that hold a credit card with them elsewhere the opportunity to easily apply for an American Express credit card in the United States by considering their foreign repayment history.[29] FinTech firms, such as Nova Credit, and established credit bureaus are making progress on infrastructure to enable pulling foreign credit histories and translating foreign credit scores into consistent formats that lenders can use.[30] FinTech lenders, such as MPower Financing and Prodigy Finance, provide student finance to foreign students at leading universities, demonstrating that lending to such groups can be profitable. To traditional lenders, such immigrants may appear high risk to lend to, given no U.S. credit history or income while studying, however, these FinTechs use foreign credit information and, by screening on which universities and degrees, can ensure that they only lend to immigrants that are expected to have a high and growing incomes after graduating

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

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

and so are likely to repay their student debt.[31]

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

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

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

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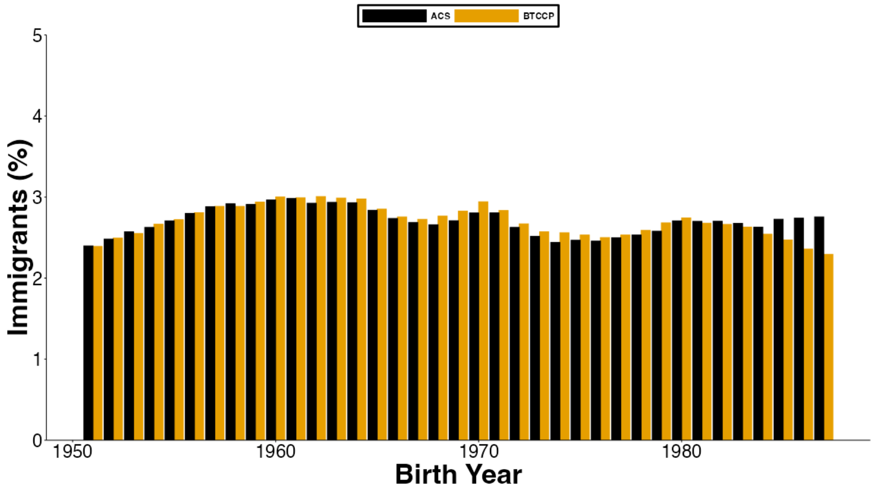
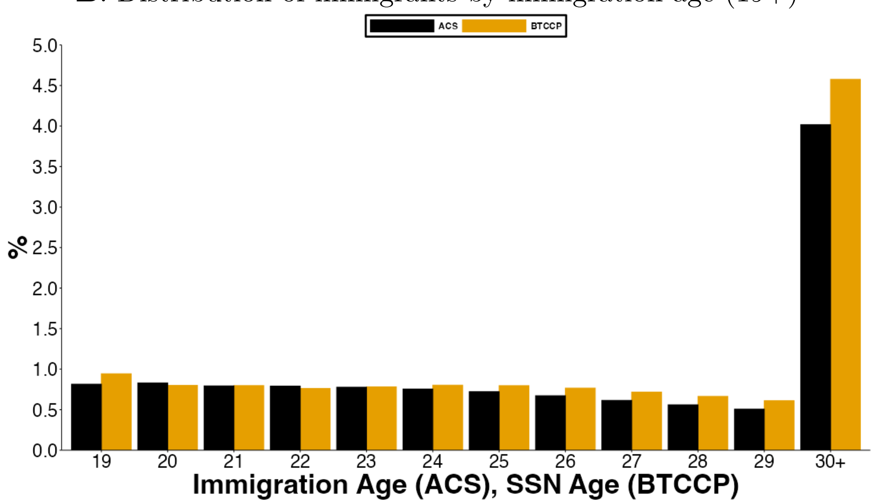
Figure 1: Immigrant classification in our data (BTCCP) versus the American Community Survey (ACS)

A: Distribution of immigrants by birth year

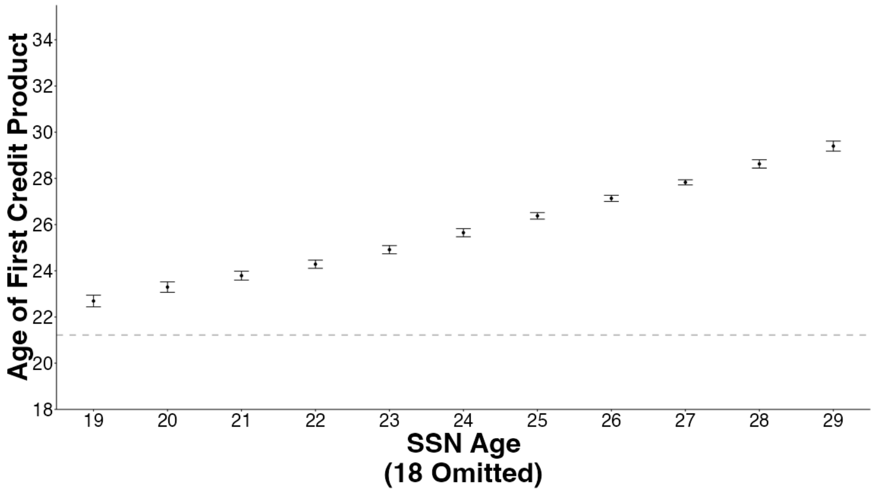


B: Distribution of immigrants by immigration age (19+)



This figure compares our classification of immigrants in the 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 TransUnion (yellow). Panel B presents the share of each sample by age at immigration.

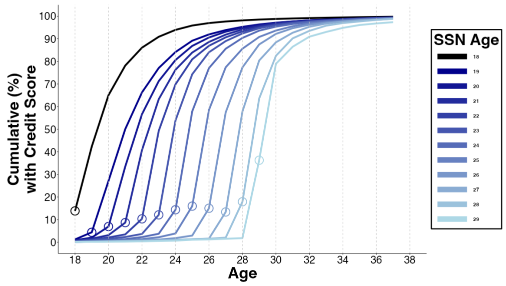
Figure 2: Mean age of first U.S. credit product by SSN Age



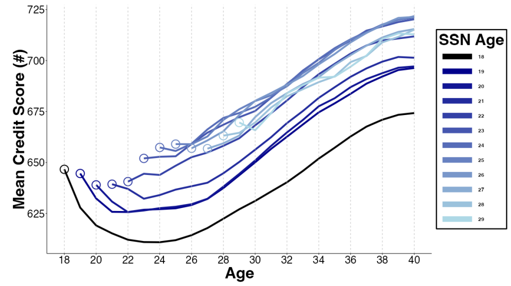
This figure presents graphical evidence on the timing of entry into U.S. consumer credit markets relative to a consumer's date of SSN assignment. The estimates (and 95% confidence intervals) are constructed from an individual-level regression of Age at first credit product on SSN Age fixed effects and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

Figure 3: Lifecycle of credit scores by SSN Age cohorts

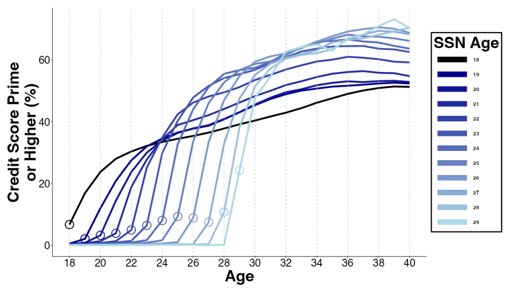
A: Any credit score (cumulative)



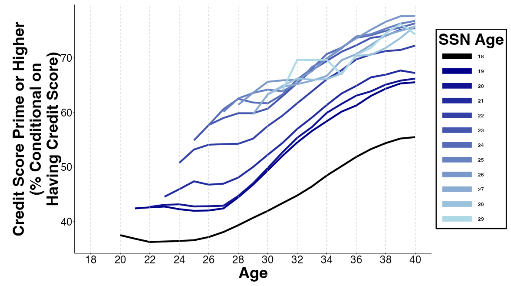
B: Mean credit score



C: Percentage with prime or higher credit score

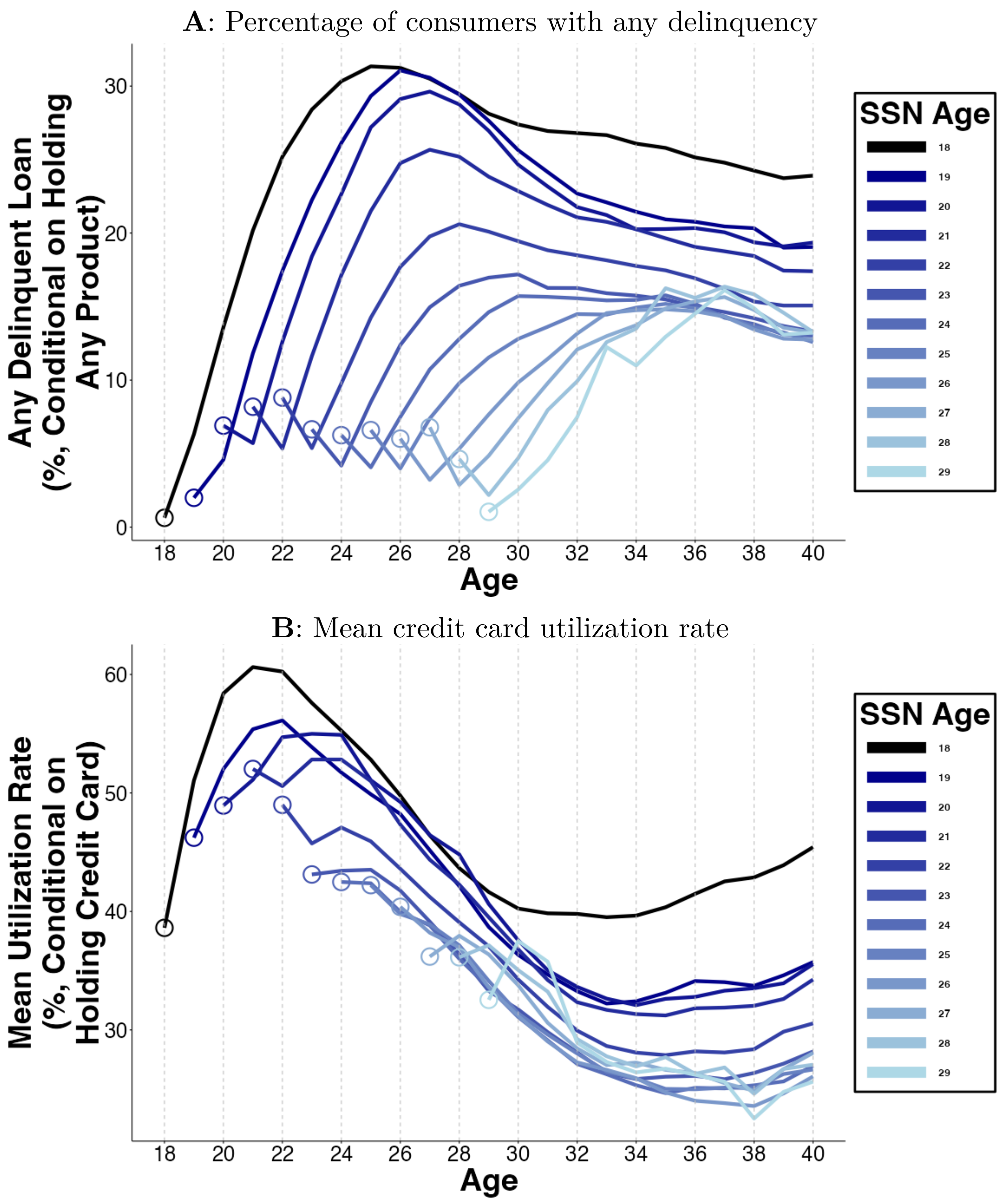


D: Percentage with prime or higher credit score conditional on any credit score



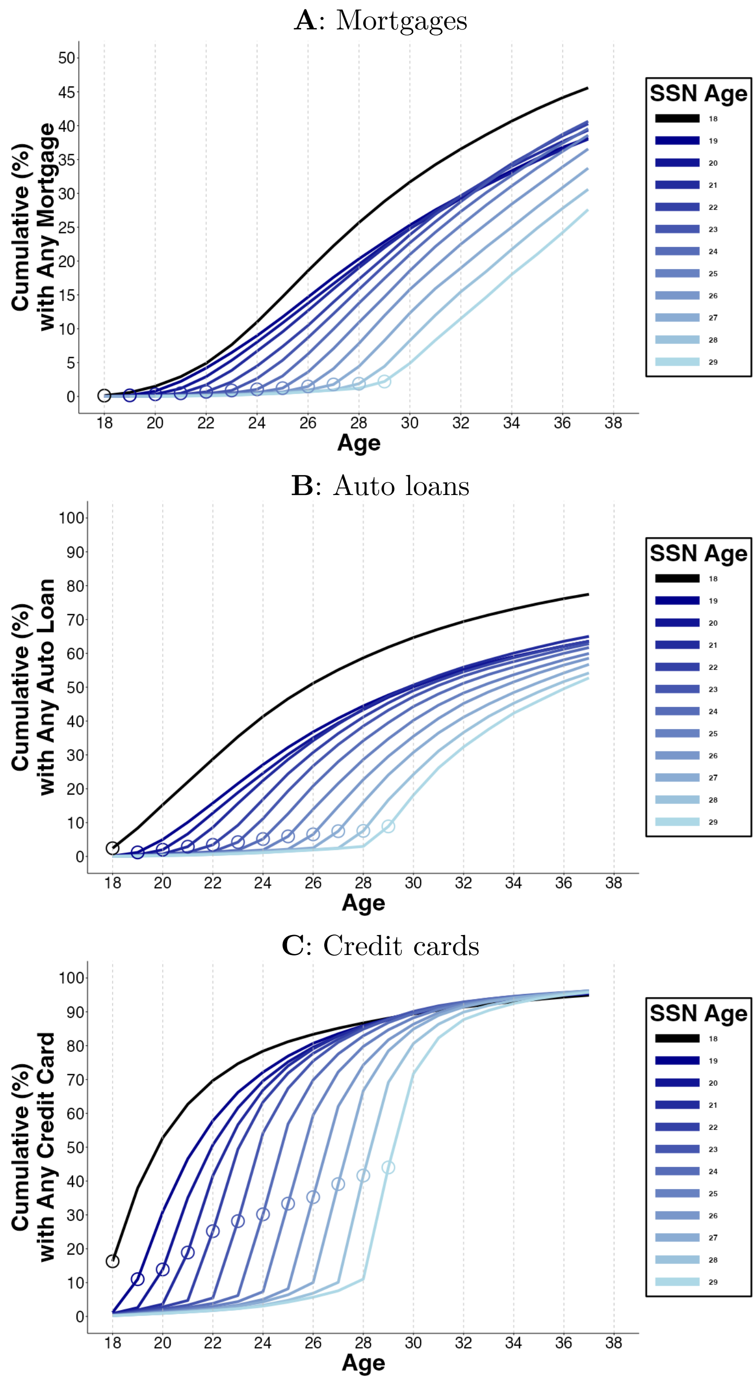
For each SSN Age cohort, this figure shows the share of consumers at each age with Any Credit Score (Panel A), Mean Credit Score conditional on having any credit score (Panel B), with Prime or Higher Credit Score (Panel C), and with Prime or Higher Credit conditional on having any credit score (Panel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

Figure 4: Lifecycle of delinquencies and utilization by SSN Age cohorts



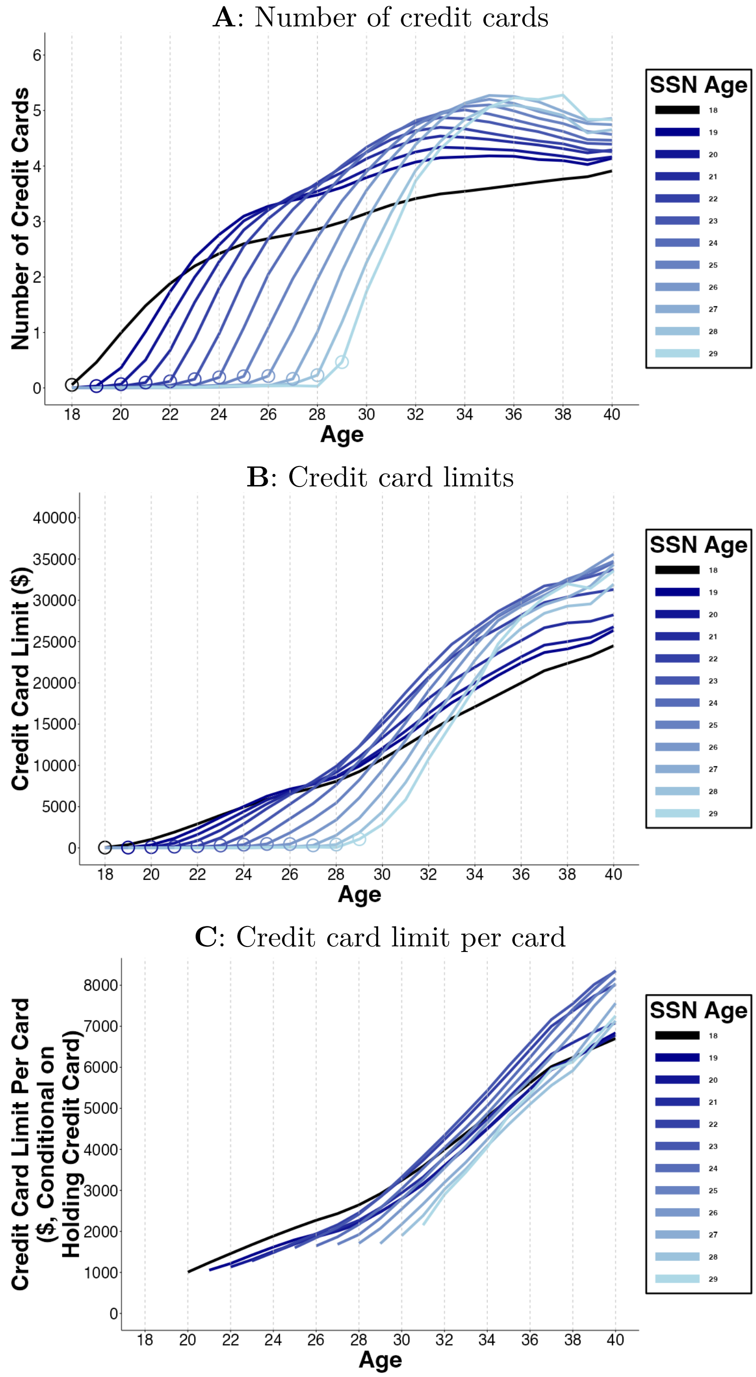
For each SSN Age cohort, this figure shows the share of consumers at each age with any delinquency (Panel A) the cohort's mean utilization rate (Panel B) by age. These averages are conditional on having a credit line. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter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

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



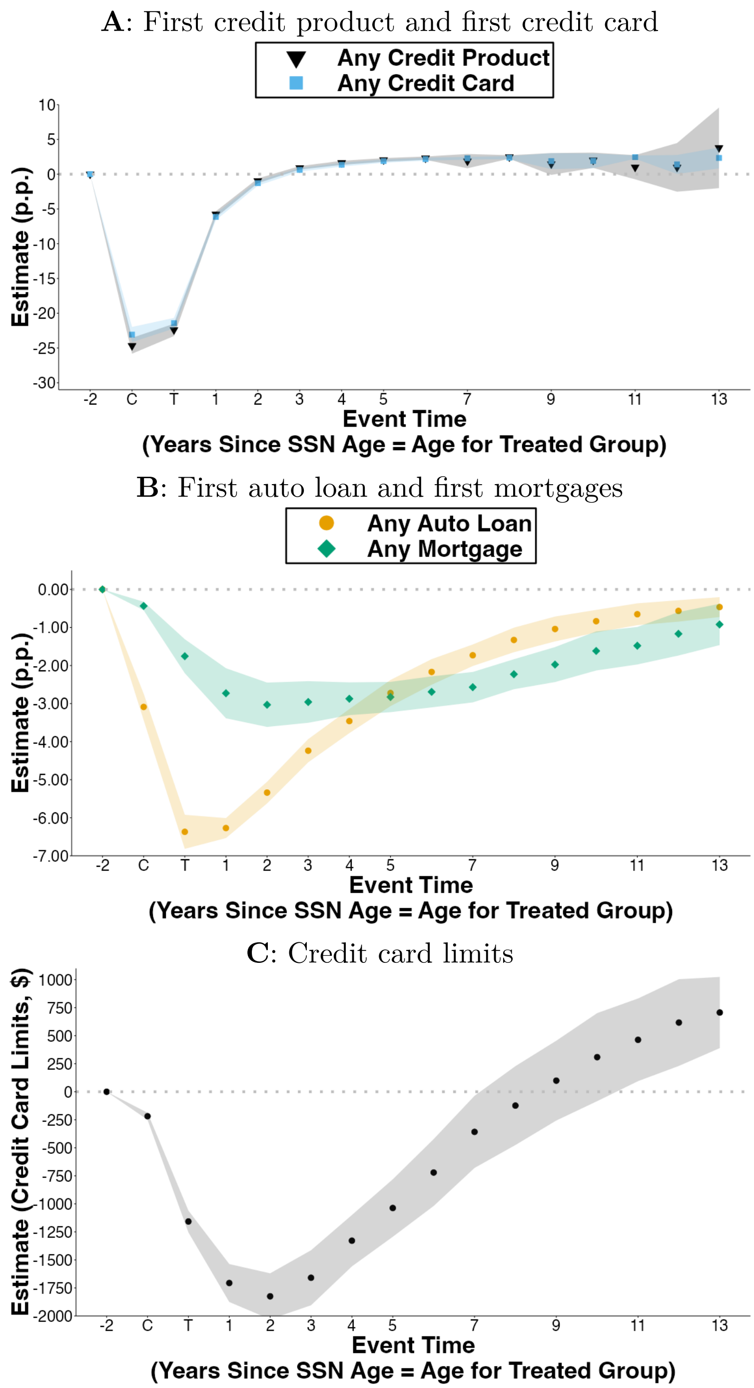
For each SSN Age cohort, this figure shows the cumulative share of consumers at each age who have ever had a mortgage (Panel A), an auto loan (Panel B), or a credit card (Panel C). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age cohorts.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

Figure 6: Lifecycle of credit cards by SSN Age cohorts



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

Figure 7: Paired cohorts: Dynamics of credit access



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

Table 1: Sample Construction

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

TransUnion Consumers	
... born 1951 to 2004	31,869,445
... with a SSN in TransUnion	25,237,917
Clean Sample	18,572,654
... SSN Age <21	16,478,940
... SSN Age 21+	2,093,714 (11.27%)
... Immigrant Cohorts (Birth Year x SSN Year)	775
Entrant Sample (SSN Age < 30)	6,122,932
... SSN Age < 21	5,778,671
... SSN Age 21-29	344,261 (5.96%)
... Immigrant Cohorts (Birth Year x SSN Year)	102

Table 2: Immigrant versus non-immigrant credit profiles

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

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

Table 3: Timing of credit market entry

This table presents OLS estimates from the cross-sectional regression specified in Equation 2 that includes an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned as an adult) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 2, 3, 5, and 6 include fixed effects for consumers' birth year. Columns 3 and 6 also include fixed effects for consumers' first observed ZIP code. The outcome in columns 1 to 3 is age at first credit report, and in columns 4 to 6 it is age at first credit product. In these regressions, consumers who never have a credit report or never have a credit product are assigned their age as of 2025. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

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

Table 4: Credit scores by age of SSN assignment

This table presents OLS estimates from the cross-sectional regression specified in Equation 2 that includes an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned as an adult) and *SSN Age*, the consumer's age at SSN assignment (pooling consumers with SSN Age 20 or younger into one group). Columns 2, 3, 5, and 6 include fixed effects for consumers' birth year. Columns 3 and 6 also include fixed effects for consumers' first observed ZIP code (First ZIP5 FE). The outcomes in Panel A are average credit score, measured by VantageScore, at ages 30 or 40. The outcomes in Panel B are the likelihood of prime credit, measured by a VantageScore of 660 or higher, at ages 30 or 40. Standard errors are clustered by birth year. $^*p < .05$; $^{**}p < .01$; $^{***}p < .005$.

Panel A: Average credit scores

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

Panel B: Likelihood of prime or higher credit score

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

Table 5: Credit market access by type of credit

This table presents OLS estimates from the individual-level regression of age at first credit card (or auto loan or home mortgage) on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned as an adult) and *SSN Age*, the consumer's age at SSN assignment. Some specifications include fixed effects for consumers' birth year and first ZIP code. Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

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

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

This table presents OLS estimates from the individual-level regression for whether the consumer has a credit card, auto loan or home mortgage at or before age 37 (i.e., 8 or more years after immigration for all immigration cohorts in our sample) on an indicator for immigration status ("21+," an indicator for whether the consumer's SSN was assigned as an adult) and *SSN Age*, the consumer's age at SSN assignment. Some specifications include fixed effects for consumers' birth year and first ZIP code. Standard errors are clustered by birth year. *$p < .05$; **$p < .01$; ***$p < .005$.

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

Table 7: When does delayed access to credit emerge?

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

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

A. Supplemental Appendix: Immigration and Credit in America

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

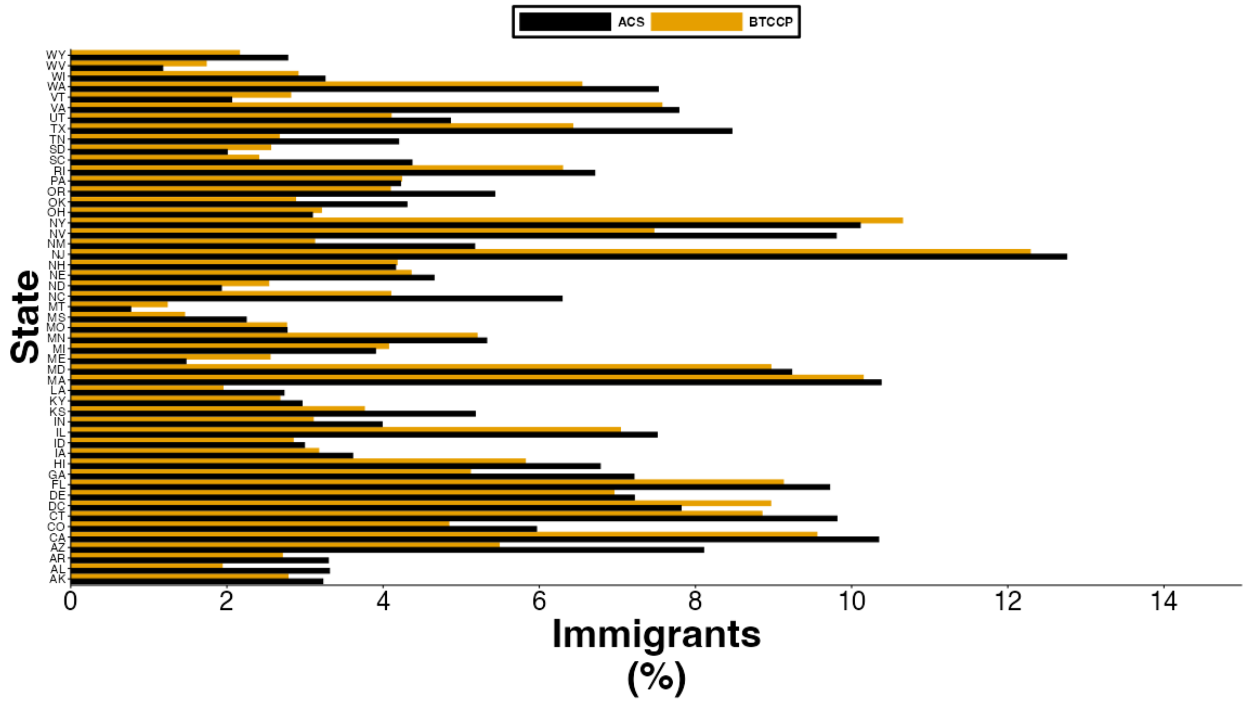
Figure A1: Sample Frame and Timing of SSN Assignment

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

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

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

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

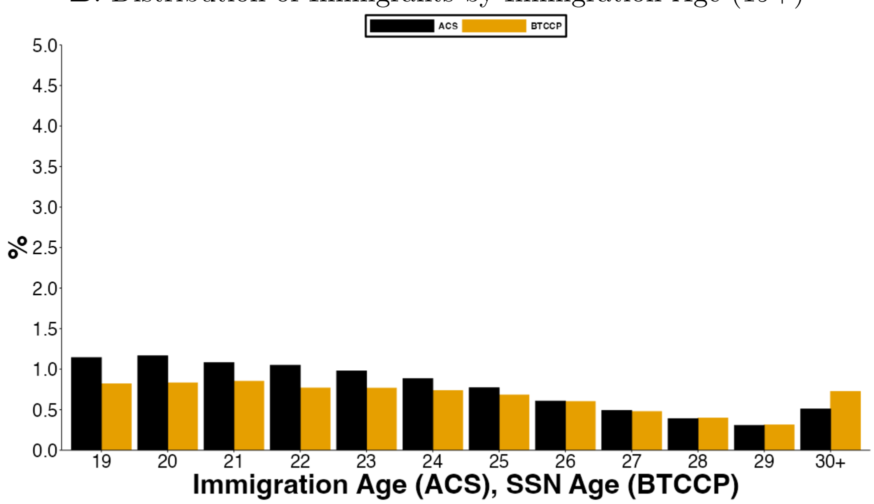


This figure presents a state-by-state comparison of the percentage of immigrants in the BTCCP data (yellow) versus the percentage of immigrants in the ACS sample. Geographic location is as of July 2012 in the BTCCP, with consumers not present at that time excluded.

Figure A3: Immigrant classification in our data (BTCCP) versus the American Community Survey (ACS) for entrant sample

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

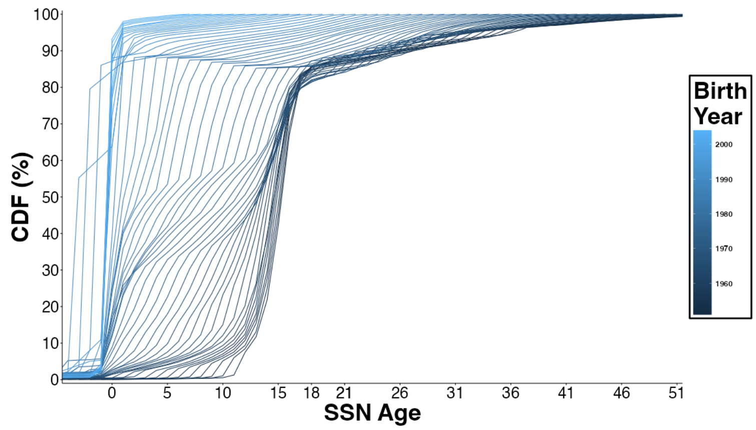
B: Distribution of Immigrants by Immigration Age (19+)



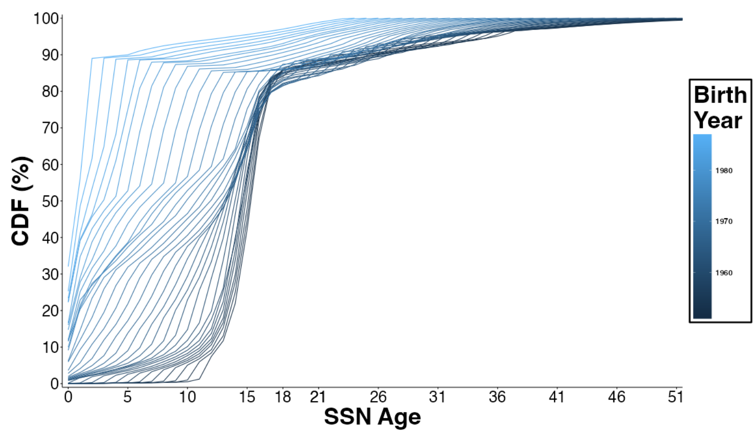
This figure compares our classification of immigrants in the BTCCP Entrant Sample to comparable statistics computed from the American Community Survey (ACS). Panel A presents the share of immigrants by immigration age. Panel B presents the subset excluding non-immigrants.

Figure A4: The distribution of SSN Ages by birth year

A: Before cleaning sample

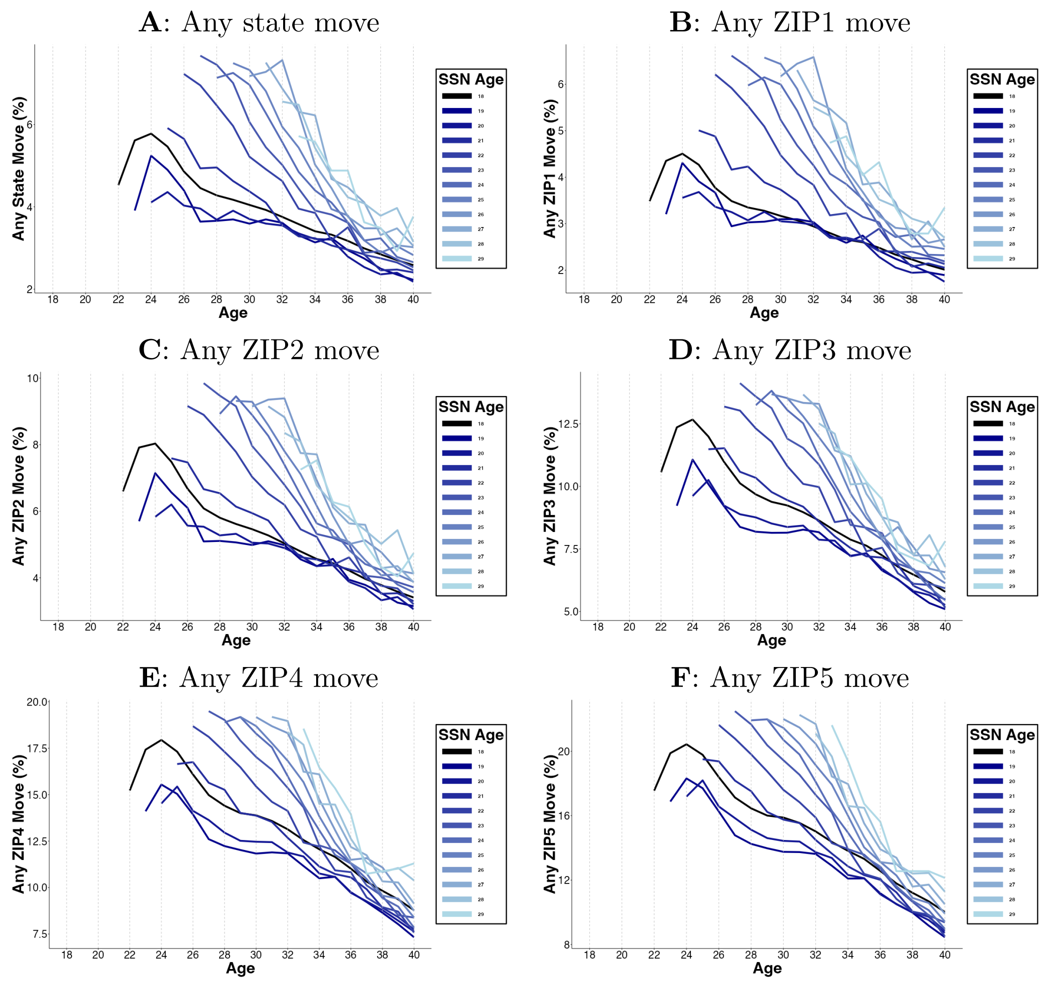


B: Clean sample



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.

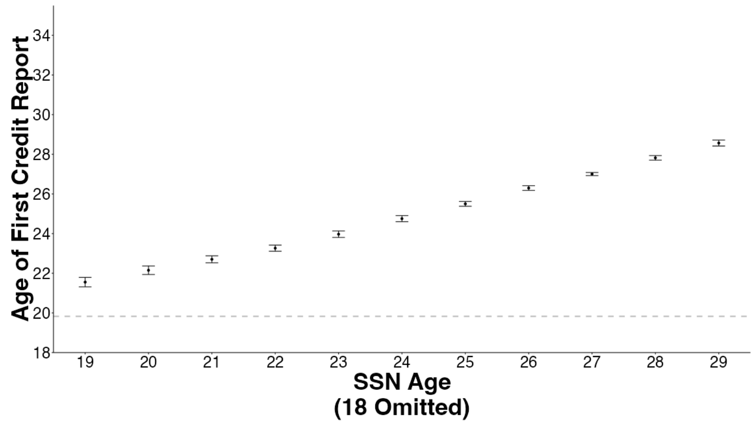
Figure A5: Lifecycle of geographic mobility by SSN Age cohorts



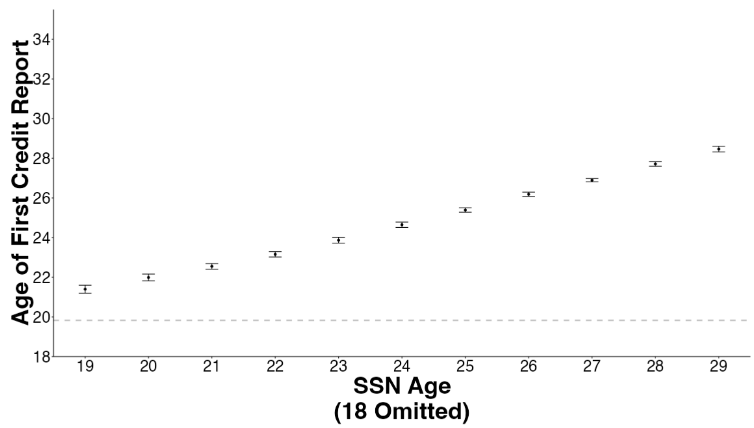
For each SSN Age cohort, this figure shows the share of consumers at each age who move state (Panel A), ZIP1 (Panel B), ZIP2 (Panel C), ZIP3 (Panel D), ZIP4 (Panel E), and ZIP5 (Panel F). The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later SSN Age 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 A6: Entry to the U.S. credit reporting system by SSN Age

A: Age at first credit report

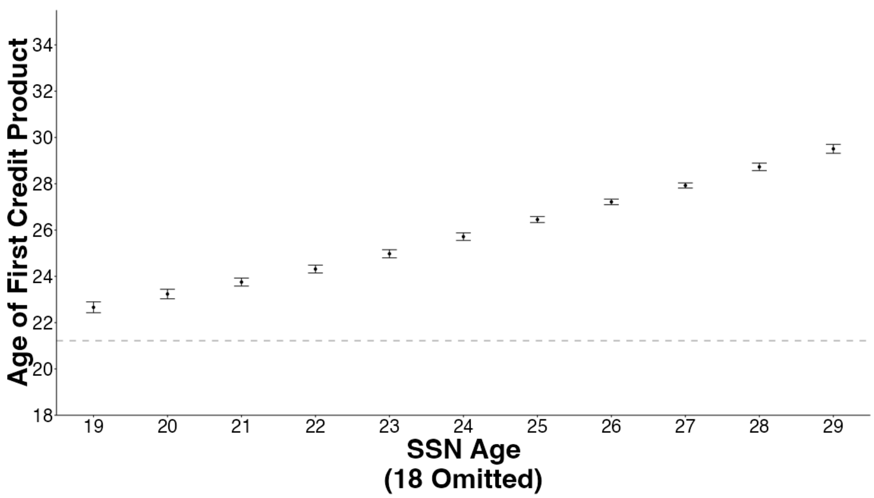


B: Age at first credit report (Zip5 F.E. included)



The baseline mean for the omitted category (SSN Age 18 or lower) is indicated by the dashed gray line. 95% confidence intervals; standard errors are clustered by birth year.

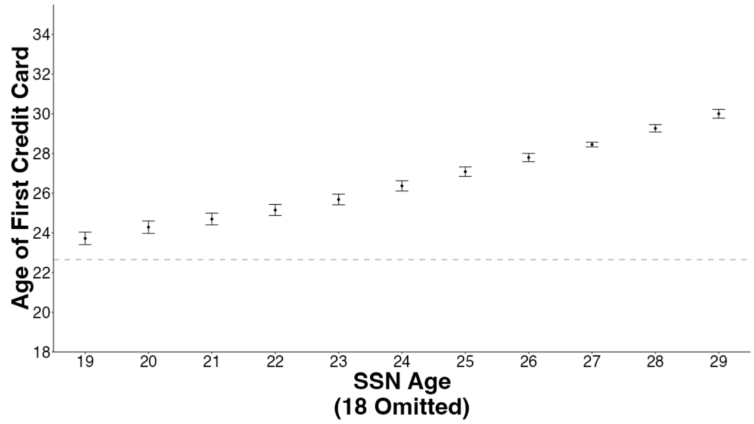
Figure A7: Age of first U.S. credit product by SSN Age (Zip5 F.E. included)



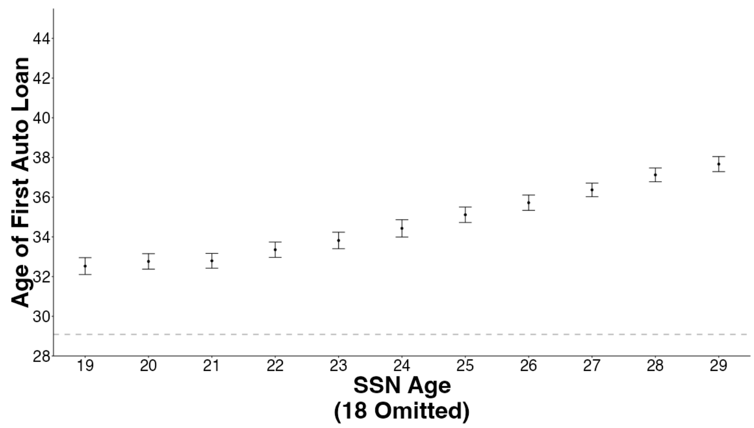
This figure plots coefficients after adding ZIP5 fixed effects to the specification in Figure 2. The baseline mean for the omitted category (SSN Age 18 or lower) is indicated by the dashed gray line. 95% confidence intervals; standard errors are clustered by birth year.

Figure A8: Age at first credit product by type of credit and SSN Age

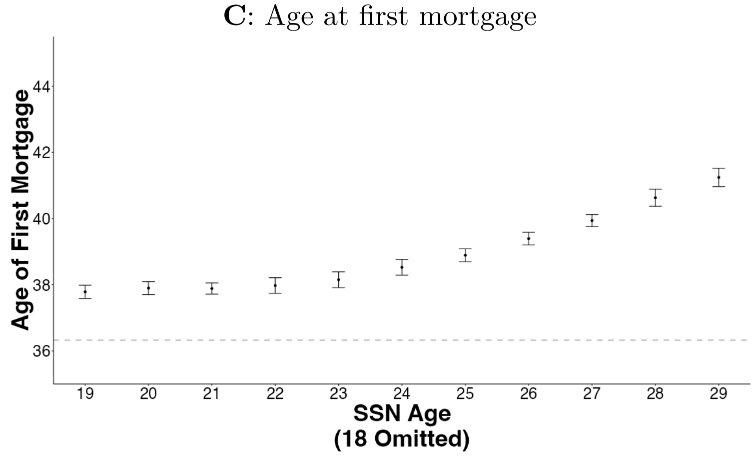
A: Age at first credit card



B: Age at first auto loan



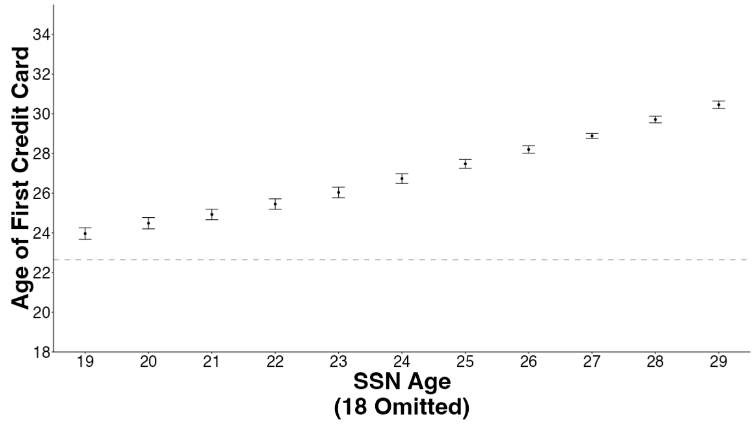
C: Age at first mortgage



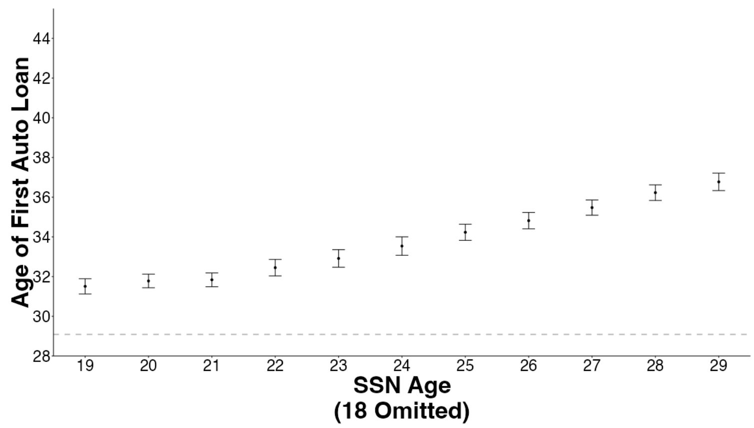
This figure presents 95% confidence intervals for the age at receiving first credit product, separately by credit type (credit card, auto loan and mortgage) and separately for SSN Age cohorts. The confidence intervals are constructed from an individual-level regression of Age at first credit product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

Figure A9: Age at first credit product by type of credit and SSN Age (Zip5 F.E. included)

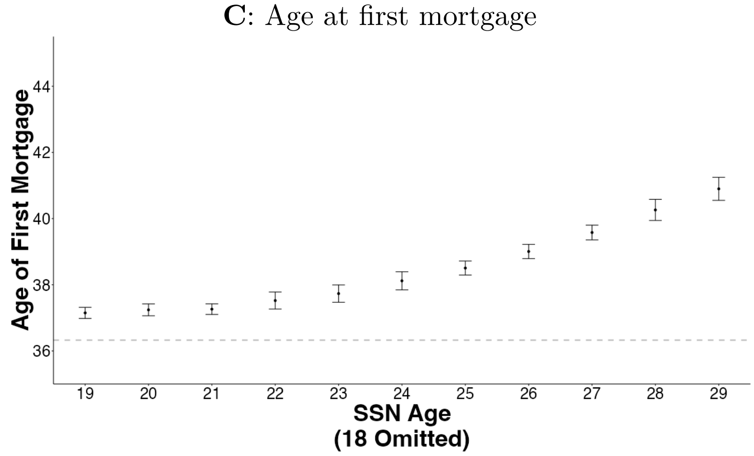
A: Age at first credit card



B: Age at first auto loan



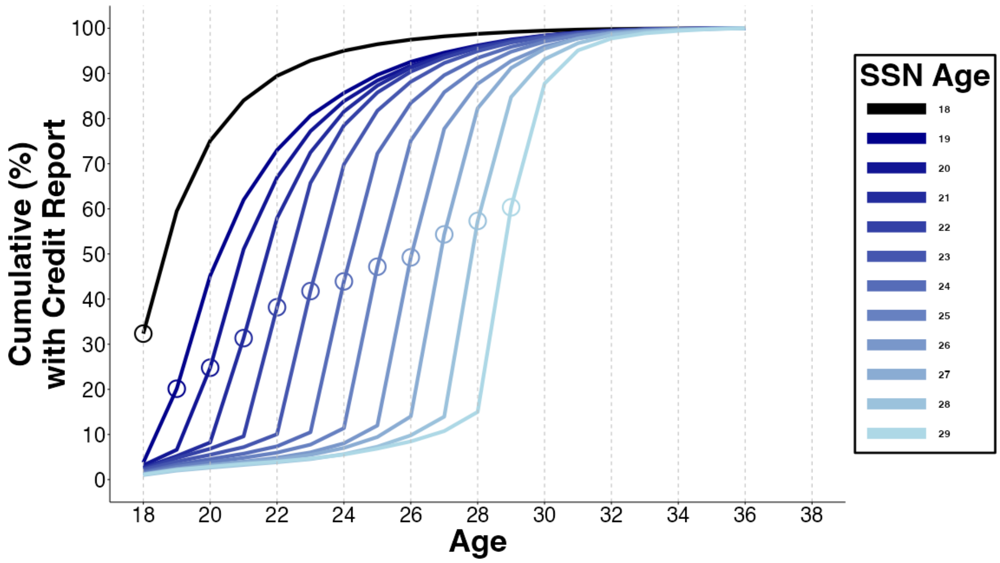
C: Age at first mortgage



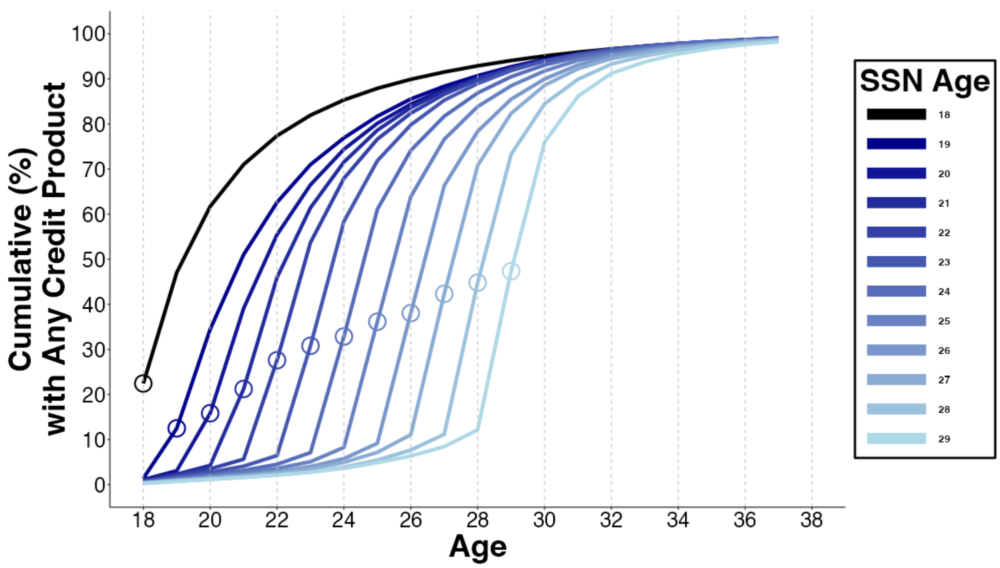
This figure presents 95% confidence intervals for the age at receiving first credit product, separately by credit type (credit card, auto loan and mortgage) and separately for SSN Age cohorts. The confidence intervals are constructed from an individual-level regression of Age at first credit product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

Figure A10: Age at first credit report and first credit product by SSN Age cohorts

A: Age at first credit report

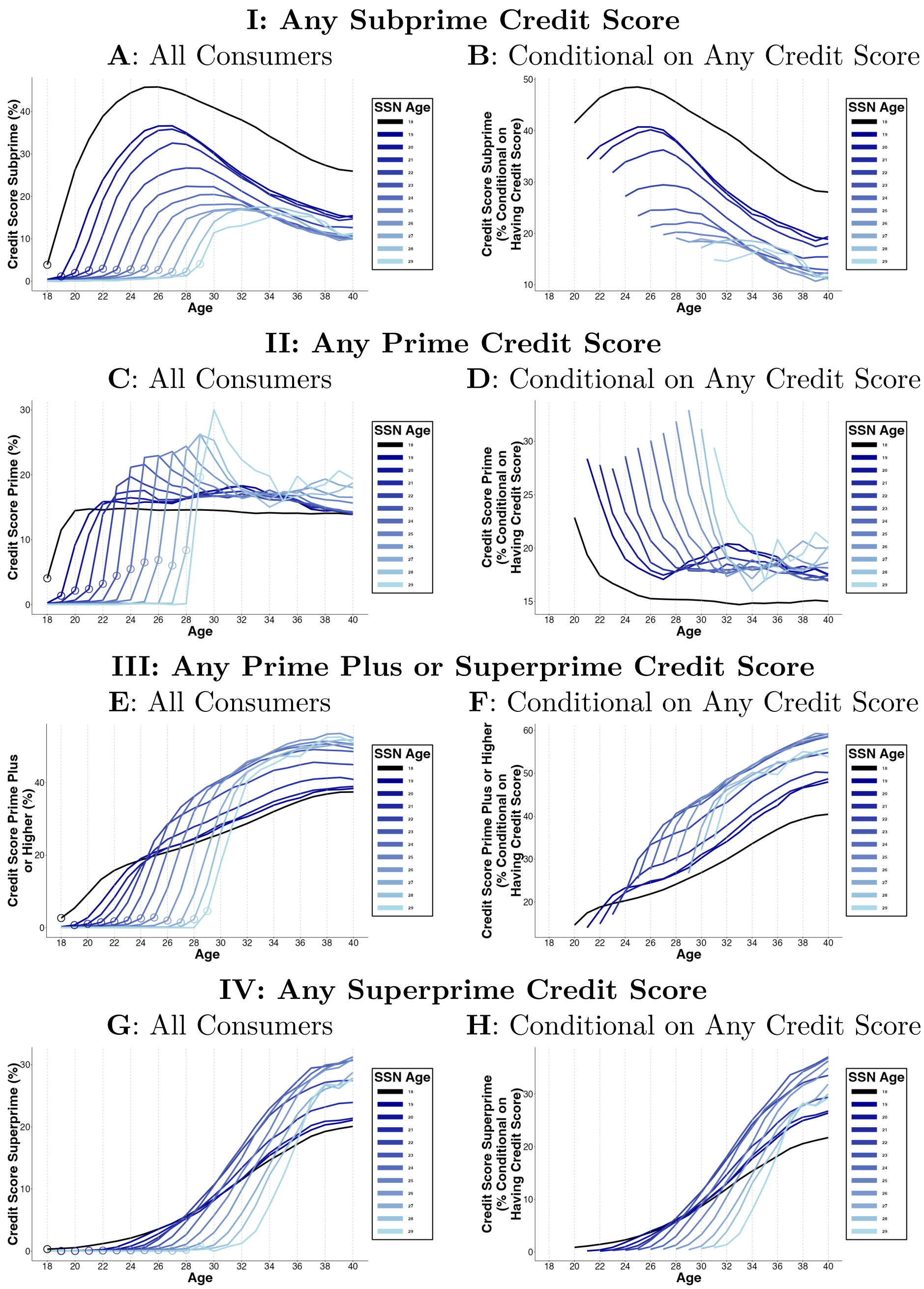


B: Age at first credit product



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

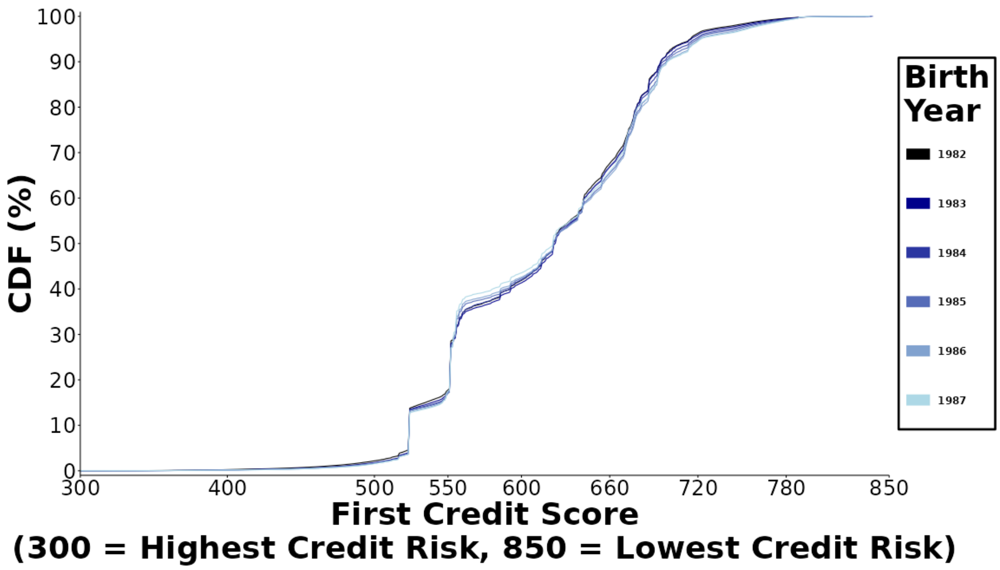
Figure A11: Lifecycle of the distribution of credit scores by SSN Age cohorts



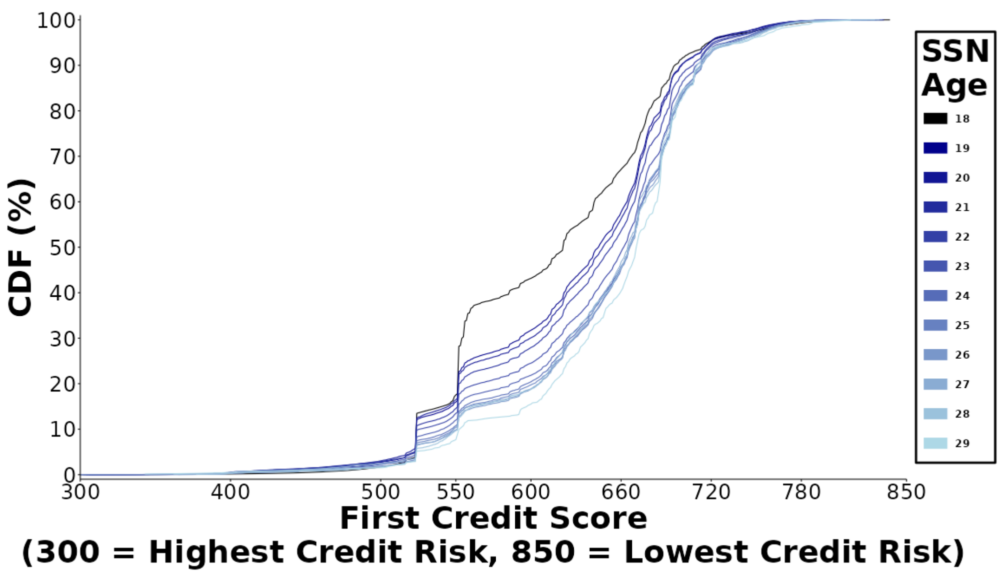
For each SSN Age cohort, this figure presents the evolution of credit scores by age. In all panels, credit scores are measured by VantageScore. In Panels A and B, Subprime Credit Score is VantageScore below 600. In Panels C and D, Prime Credit Score is VantageScore 661 to 719. In Panels E and F, Prime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

Figure A12: The distribution of first credit scores

A: CDF by birth year



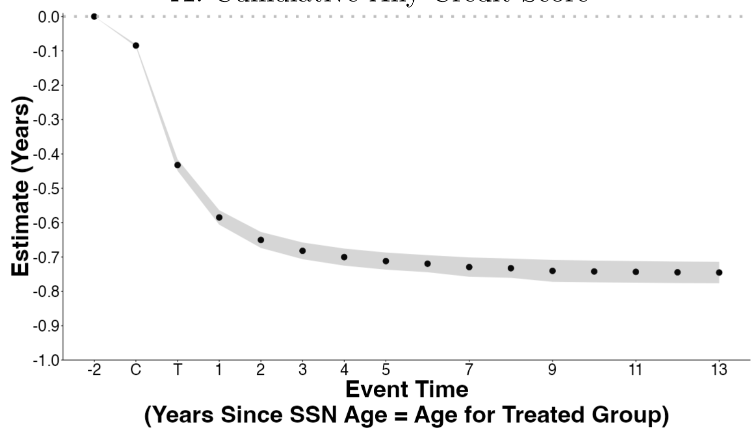
B: CDF by SSN Age



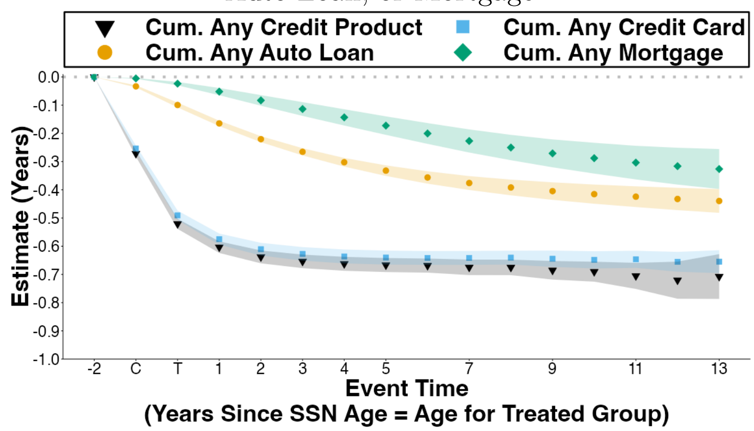
This Figure shows the CDFs of the first credit score observed for a consumer at any point in our data. Panel A shows CDFs by birth years. Panel B shows CDFs by SSN Ages, where SSN Age 18 includes consumers that are assigned an SSN at Age 18 or younger. Both panels use data from our Entrant Sample, with additional restrictions for birth years between 1982 and 1987, and also dropping credit scores first observed in July 2000 where our data begins.

Figure A13: Paired cohorts: Dynamics of credit access

A: Cumulative Any Credit Score

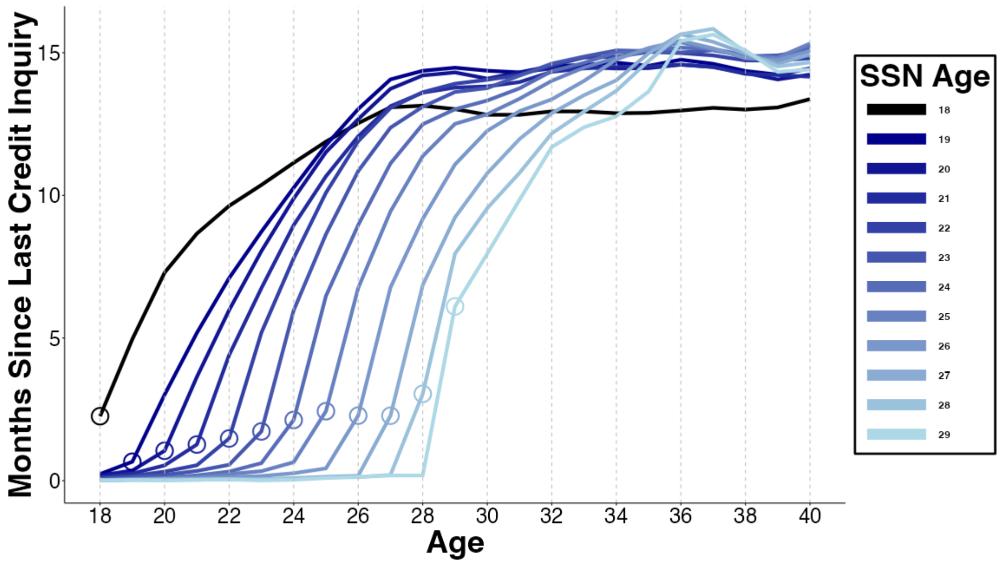


B: Cumulative Any Credit Product, Credit Card, Auto Loan, or Mortgage



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

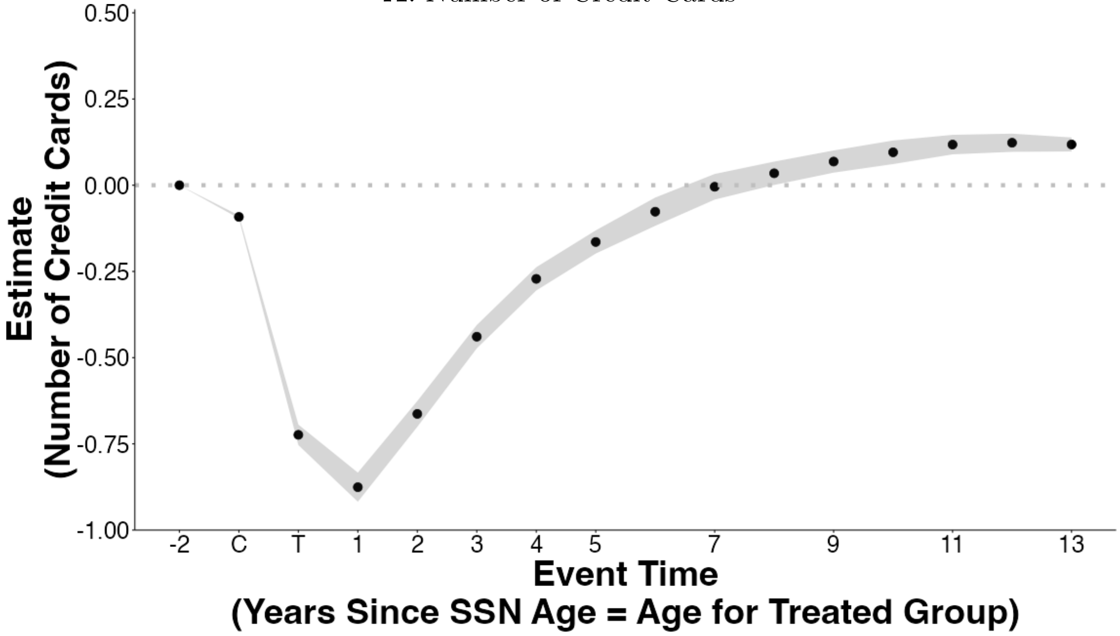
Figure A14: Months since last credit inquiry by SSN Age cohorts



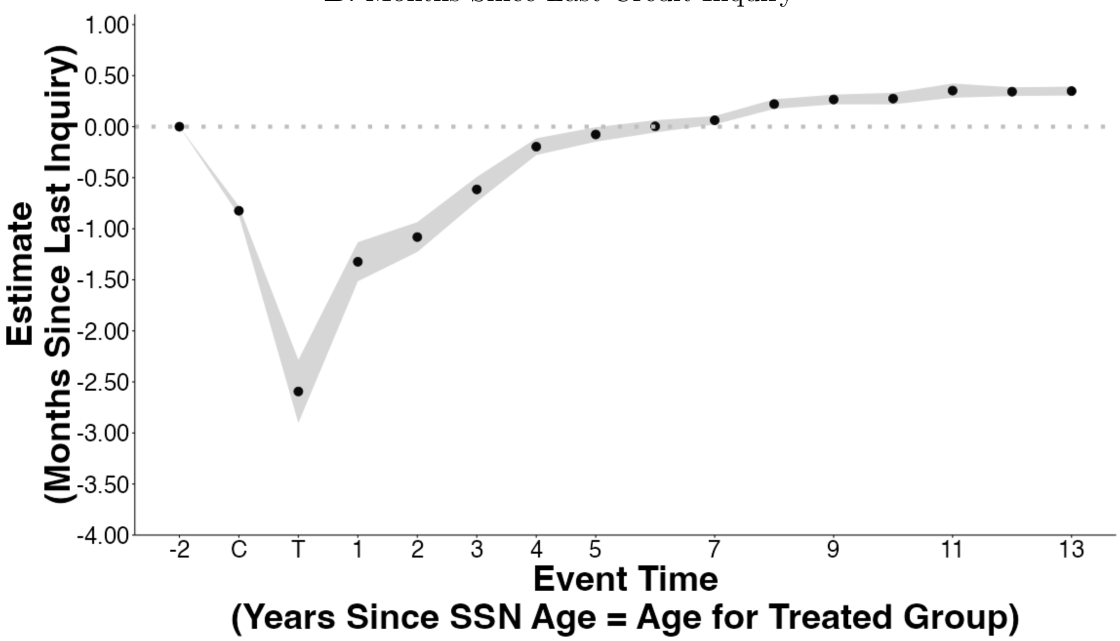
For each SSN Age cohort, this figure presents the evolution of months since last credit inquiry by age. Months since last credit inquiry takes a value between 0 and 24, and is assigned 25 if missing. The black line (SSN Age 18) pools all consumers with SSN Age 18 or younger. Lighter colors indicate later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

Figure A15: Paired cohorts: Number of credit cards and months since last credit inquiry

A: Number of Credit Cards



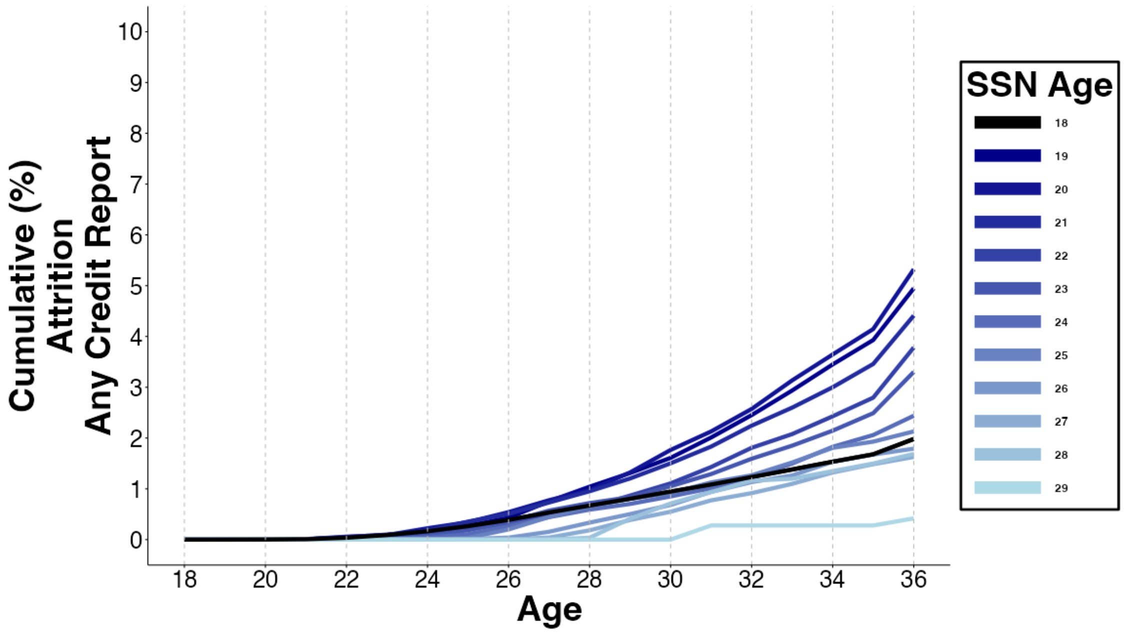
B: Months Since Last Credit Inquiry



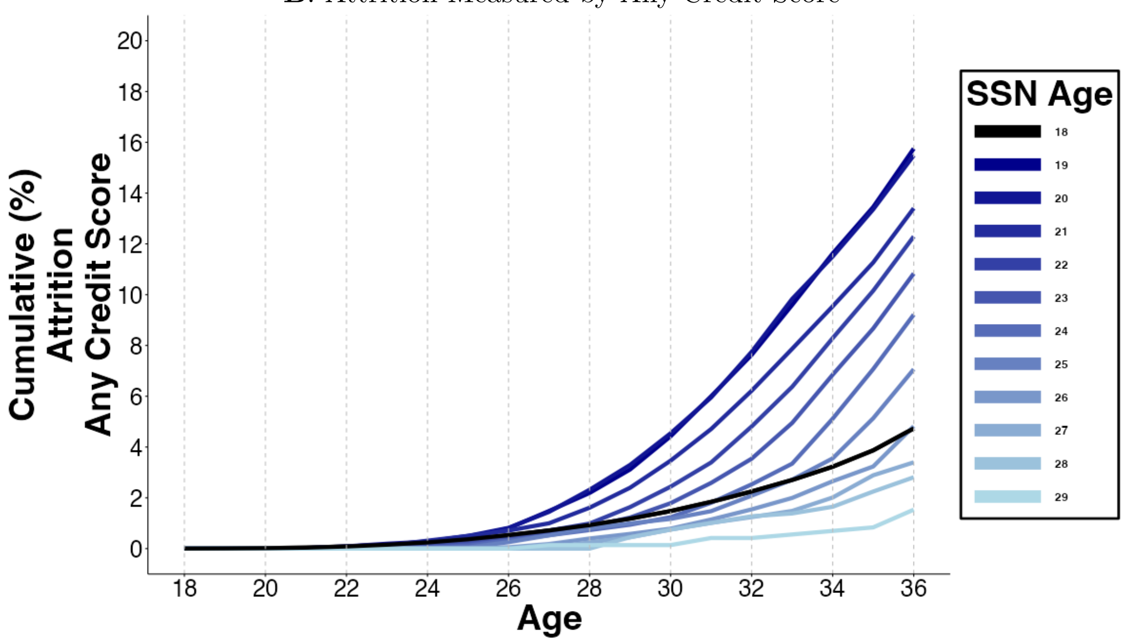
This figure presents dynamic estimates for differences for number of credit cards and the number of months since last inquiry (a proxy for credit demand) between a cohort with SSN Age = s and a cohort with SSN Age = $s-1$ matched at the same age. The differences are presented in event time where C is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

Figure A16: Attrition from the data, by SSN Age cohorts

A: Attrition Measured by Any Credit Report



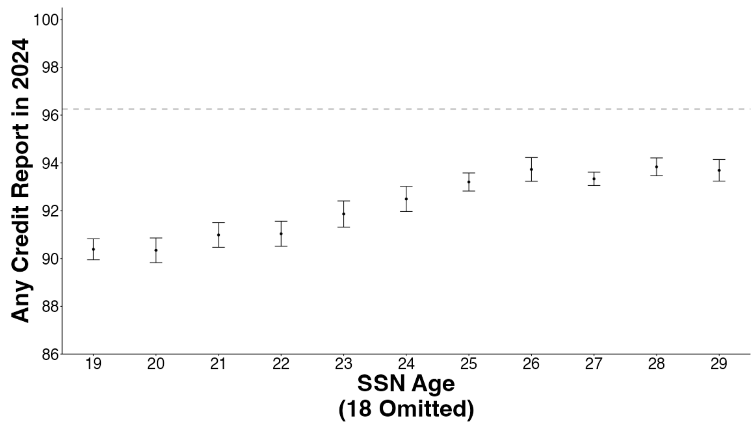
B: Attrition Measured by Any Credit Score



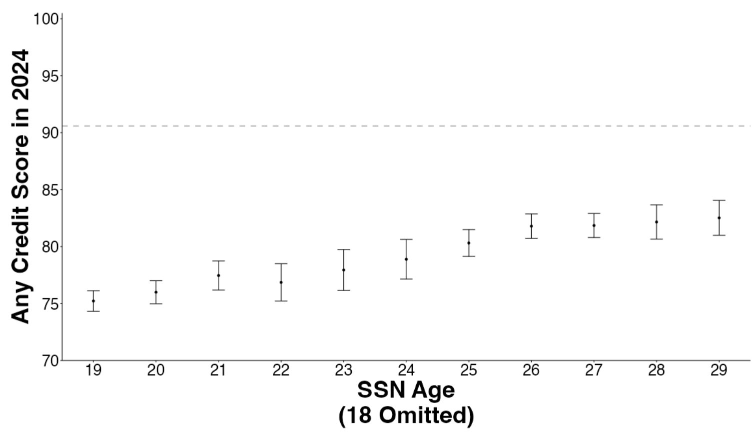
For each SSN Age cohort, this figure presents the cumulative percent who are no longer observed in the data. Panel A measures attrition by the year at which a consumer has a non-missing credit report. Panel B measures attrition by the last year at which a consumer has a non-missing credit score. The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

Figure A17: Consumers observed in the data in 2024, by SSN Age

A: Any credit report in 2024

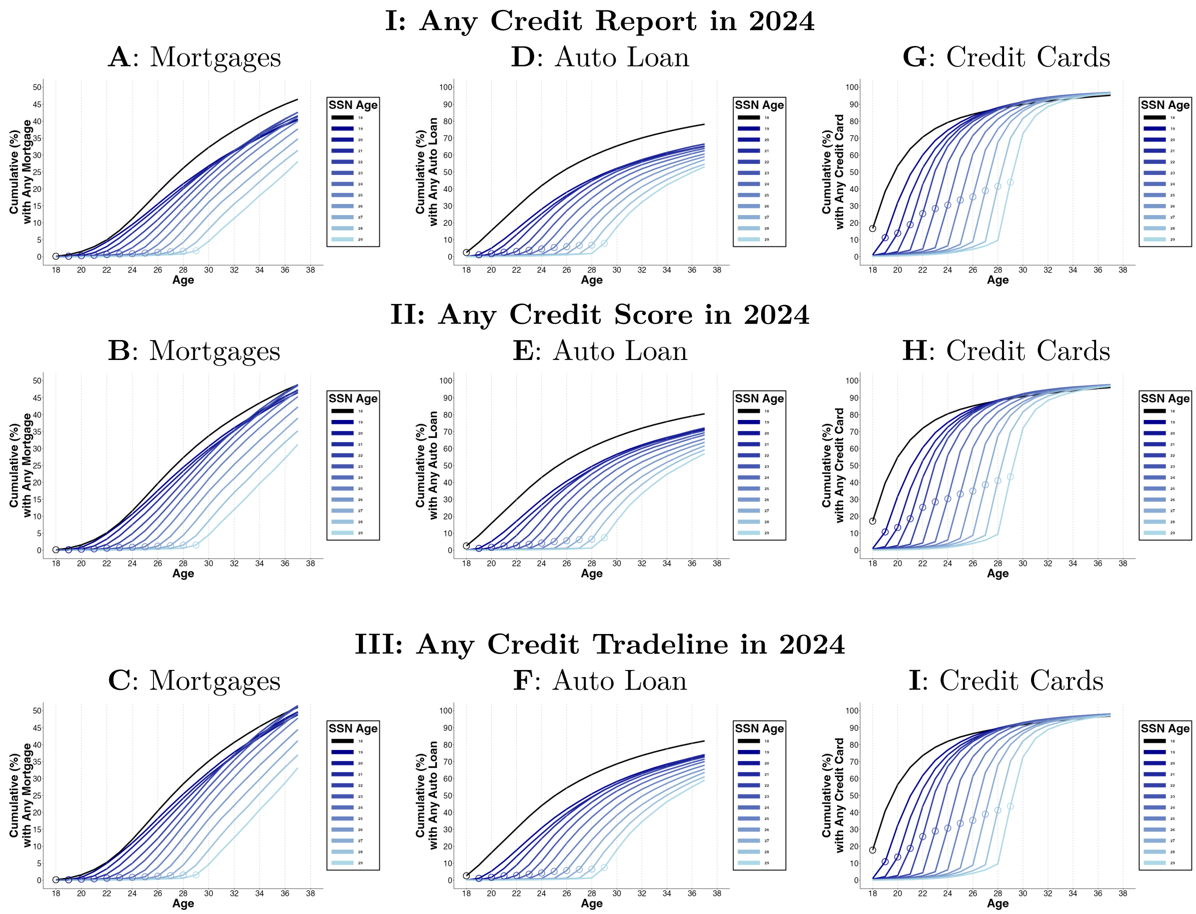


B: Any credit score in 2024



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

Figure A18: Lifecycle of credit access by type of credit and SSN Age cohorts, restricting sample to consumers observed in 2024

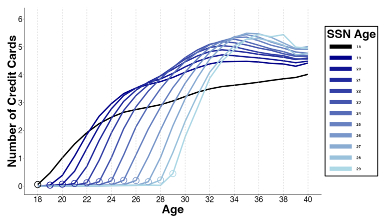


Each row shows a different sample restriction to account for attrition from the data. Row I. restricts the sample to consumers with a non-missing credit report in 2024. Row II. restricts the sample to consumers with a non-missing credit score in 2024. Row III. restricts the sample to consumers with a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

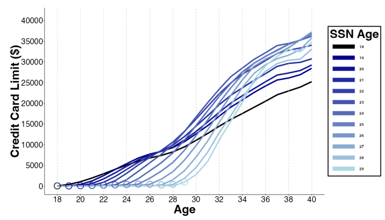
Figure A19: Lifecycle of credit cards by SSN Age cohorts, restricting sample to consumers observed in 2024

I: Any Credit Report in 2024

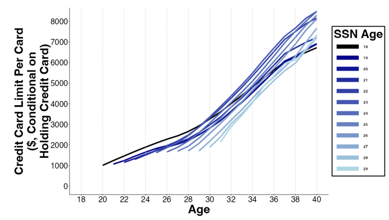
A: Number of Credit Cards



D: Credit Card Limits

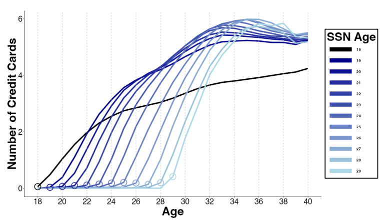


G: Credit Card Limit Per Card

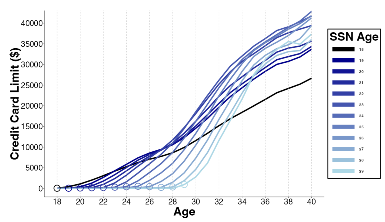


II: Any Credit Score in 2024

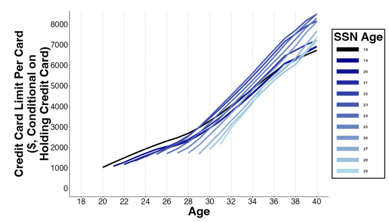
B: Number of Credit Cards



E: Credit Card Limits

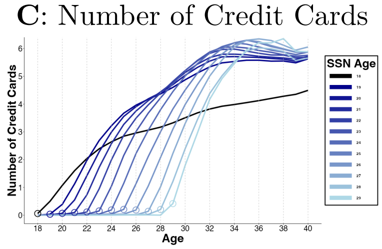


H: Credit Card Limit Per Card

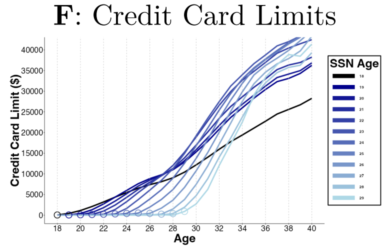


III: Any Credit Tradeline in 2024

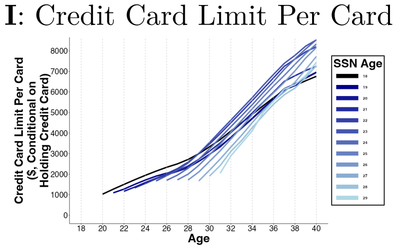
C: Number of Credit Cards



F: Credit Card Limits



I: Credit Card Limit Per Card



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

Table A1: Counts of Consumers by SSN Age: "Clean Sample" and "Entrant Sample"

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

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

Table A2: Credit Market Entry Timing by Immigration Status and Age of Immigration, with Additional Geographic Fixed Effects

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

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

Table A3: Credit Scores by Age of SSN Assignment, with Additional Geographic Fixed Effects

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

Panel A: Average Credit Scores

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

Panel B: Likelihood of Prime or Higher Credit Score

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

Table A4: Credit Market Access by Type of Credit, with Additional Geographic Fixed Effects

This table presents OLS estimates from the individual-level regression of Age at First Credit Card (or Auto Loan or Home Mortgage) on an indicator for immigration status ("21+," which is an indicator for whether the consumer's SSN was assigned as an adult) and *SSN Age*, which tells the age at SSN assignment. Columns 1, 4, and 7 include include fixed effects for consumers' birth year, first Zip5, and last Zip5. Columns 2, 5, and 8 also include additional fixed effects for a consumers' longest Zip5 (a proxy for their most permanent location). Columns 3, 6, and 9 also include additional fixed effects for the number of unique Zip5s that we observe (a proxy for their mobility). Standard errors are clustered by birth year. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .005$.

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

Table A5: Credit Access by Type of Credit by Age 37, with Additional Geographic Fixed Effects

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

Dep Var: By Age 37, has...		Credit Card			Auto Loan			Mortgage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
21+	-0.02	-0.05	0.5***	-6.18***	-6.16***	-4.43***	1.09*	1.13*	2.33***
	(0.12)	(0.12)	(0.14)	(0.34)	(0.35)	(0.2)	(0.49)	(0.46)	(0.35)
SSN Age	0.02	0.02	0.15***	-1.48***	-1.47***	-1.06***	-1.86***	-1.85***	-1.56***
	(0.03)	(0.03)	(0.04)	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.09)
Birth Year F.E.	X	X	X	X	X	X	X	X	X
First Zip5 F.E.	X	X	X	X	X	X	X	X	X
Last Zip5 F.E.	X	X	X	X	X	X	X	X	X
Longest Zip5 F.E.		X	X		X	X		X	X
Number Zip5 F.E.			X			X			X
R^2	0.040	0.042	0.060	0.076	0.079	0.124	0.117	0.127	0.146
N	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932	6,122,932
Mean, SSN Age <21	94.93	94.93	94.93	77.22	77.22	77.22	45.46	45.46	45.46

Table A6: Consumers observed in the data in 2024

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

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

Table A7: Credit access by type of credit by age 37, for consumers where credit score observed in 2024

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

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