

# Born to be (sub)Prime: An Exploratory Analysis

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## Abstract

We study how inheriting parents' credit histories affects credit scores, access to credit, and subsequent experiences of young individuals entering the credit market. First, having an inherited credit history significantly positively affects credit scores at entry. Second, initial credit scores are very persistent. Third, inherited credit histories only affect outcomes through the initial credit score distribution. Finally, initial credit scores have significant persistent effects on credit use and access, such as having a mortgage or credit card penetration and utilization rate. Our results point to the importance of initial conditions in credit markets and are consistent with mechanisms based on multiplicity of equilibria and self-fulfilling liquidity traps in which lack of access to credit due to low credit scores re-affirms the low credit score ranking of an individual.

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Economic mobility is an important and long-studied topic in the economic literature (Solon (1992), Chetty et al. (2014), Jantti and Jenkins (2015)). However, mobility in the credit market has so far received far less attention, partially due to lack of available data, with the notable exception of Ghent and Kudlyak (2016). Credit score and consumer credit play a crucial role in consumption, investment and housing decisions (Guiso and Sodini (2013), Laufer and Paciorek (2022), Topel and Rosen (1988)), potentially affecting the ability to smooth out shocks (Keys, Tobacman and Wang (2017) and Hundtofte, Olafsson and Pagel (2019)) and finance investments in human capital (Wiederspan (2016), Solis (2017)). Additionally, credit scores are widely used in evaluating job applications (Bos, Breza and Liberman (2018), Ballance, Clifford and Shoag (2020)), or rental and utility contract applications.

In this paper, we use a large panel dataset of credit records that allows us to study how inheriting parents' credit histories affects credit scores and access to credit of young individuals entering the credit market, and their subsequent experiences in the credit market. First, having an inherited credit history significantly positively affects credit scores at entry. Second, initial credit scores are very persistent, with differences persisting for more than 10 years onwards. Third, inherited credit histories only affect outcomes through the initial credit score distribution, which then pins down the subsequent evolution of the credit scores. Finally, initial credit scores have significant persistent effects on credit use and access, such as having a mortgage or credit card penetration and utilization rate. Our results point to the importance of initial conditions in credit markets and are consistent with mechanisms based on multiplicity of equilibria and self-fulfilling liquidity traps in which lack of access to credit due to low credit scores re-affirms the low credit score

ranking of an individual.

## 1 Data

This paper is based on Experian proprietary data on credit reports for about a 1% of the US population with a valid credit score in 2010. For those individuals, the data spans the years 2004 to 2016 at yearly frequency. We pull the credit data around the 30th of June of each year. The data contain basic socio-demographic such as date of birth, zip code of residence, and a rich array of about 400 credit variables. These credit variables cover a range of outcomes, from the total number of accounts, to number of credit cards, their balances and limits, total number of mortgages, balances, plus delinquencies, default, and bankruptcy.

In what follows, we study the credit outcomes of individuals who are 18 years old in 2004 (born in 1986) across years 2004–2016. As **initial credit score** of these individuals, we take the first reported credit score for them, if observed before the age of 23. As **final credit score**, we take their credit score in 2016 (i.e. at age 30). We consider 4 bins of credit scores, with cutoffs taken from Experian’s risk categorization guidelines: a *Poor* credit score falls at or below 600; *Fair* credit score falls between 601 and 660; *Good* credit score is in the range 661–780; and a *Very good* credit score is above 780. Importantly, we are also able to capture the length of inherited credit histories by measuring the age of oldest account on the individual’s credit record at entry. On average, 56% of individuals have histories longer than 6 months at entry, which we interpret as coming from being added to parents’ account while being a minor.<sup>1</sup> These inherited histories are on average 28

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<sup>1</sup>The so called *piggybacking* on non-relatives’ credit accounts, the for-profit version of adding authorized users, started to gain popularity in later years, as per Martin (2022):

months long in our data and range from 0 to 32 years.

## 2 Life Cycle Profiles

We first study the evolution and persistence of individual credit scores as a function of initial credit score by bin. Initial credit scores exhibit slight growth over the lifecycle for individuals starting with a *Poor* initial credit score and essentially no growth for the *Fair* and *Good* initial credit scores (Figure I).

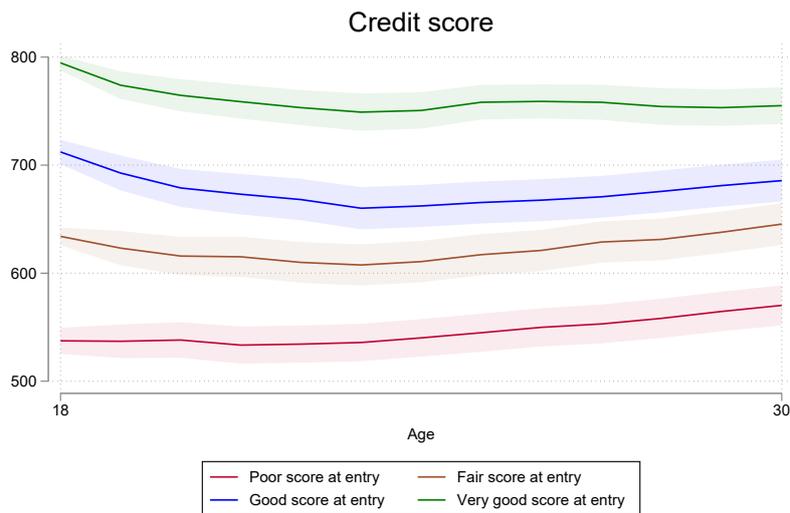


Figure I: Credit score by age and initial bin

This results in very high persistence of the initial credit score bins, especially for *Poor* and *Very good* initial credit scores. As Figure II documents, 68% of individuals entering with a *Poor* credit score remain in that bin by age 30, while only 18% end up in the *Good* or better bins. This points to the importance of initial credit scores, and begs the question of what determines “...These piggybacking companies, which started to emerge in 2007...”.

the credit score of individuals with extremely short personal credit histories. Below, in Section 3, we document the role of inherited histories in pinning down the initial credit score distribution.

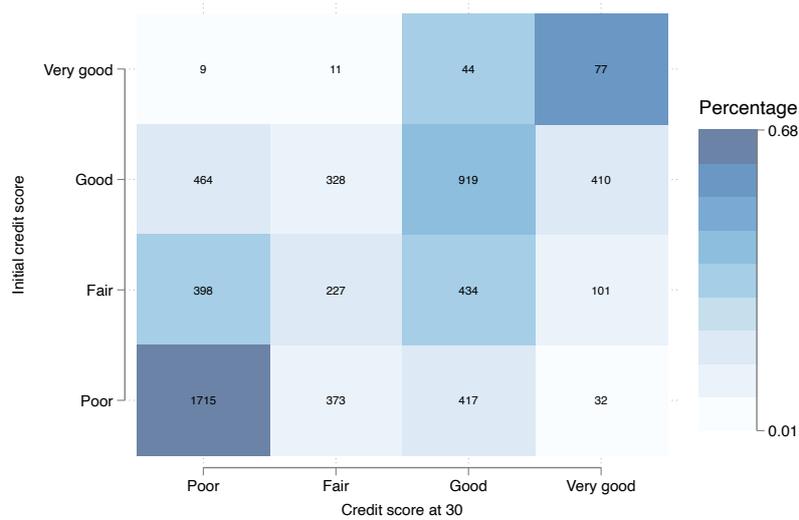


Figure II: Persistence of initial credit score bins.

### 3 Inter-generational Linkages

We measure the importance of inherited histories by regressing the initial credit score on the length of the inherited credit history (intensive margin) or on a dummy variable that takes the value of one if an individual has an inherited credit history and zero otherwise. We report the estimates in Table I. Inherited histories, at the intensive margin (extensive margin), are able to explain about 20% (10%) of the variation of the initial credit scores. On the intensive margin, an individual with an average inherited history (28 months) has an initial credit score at entry that is 36 points higher than an individual

with no inherited history (column (1)). Overall, having any inherited history increases credit score at entry by 58 points (column (2)). Both of these imply an economically sizeable impact of inherited histories on initial credit scores, large enough to be able to shift individuals across the credit score bins.

	(1)	(2)
History (months)	1.309*** (0.0510)	
History (months) squared	-0.00284*** (0.000195)	
<b>1 {History}</b>		58.19*** (2.270)
Constant	594.0*** (1.319)	586.8*** (1.699)
Observations	6064	6064
Adjusted $R^2$	0.175	0.098

Standard errors in parentheses

Dependent variable: initial credit score.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table I: Initial Credit Score and History

The next set of results, presented in Figure III, show the life-cycle profiles of credit score conditional on initial credit score bin *and* having some or zero inherited histories. For the *Poor* and *Fair* categories, once we condition on initial credit score bin, having inherited history does not bring in new information, as the profiles with and without histories are not statisti-

cally different from each other. For the *Good* credit score category, initial conditions pin down the difference between the two life-cycle profiles, which then evolve in parallel, exhibiting no convergence. In this case, again, initial conditions contain all information needed to pin down the difference. Summarizing, inherited histories affect life-cycle profile of credit scores through initial credit scores as a sufficient statistic for the three categories (there are no individuals with no history entering the *Very good* bin).

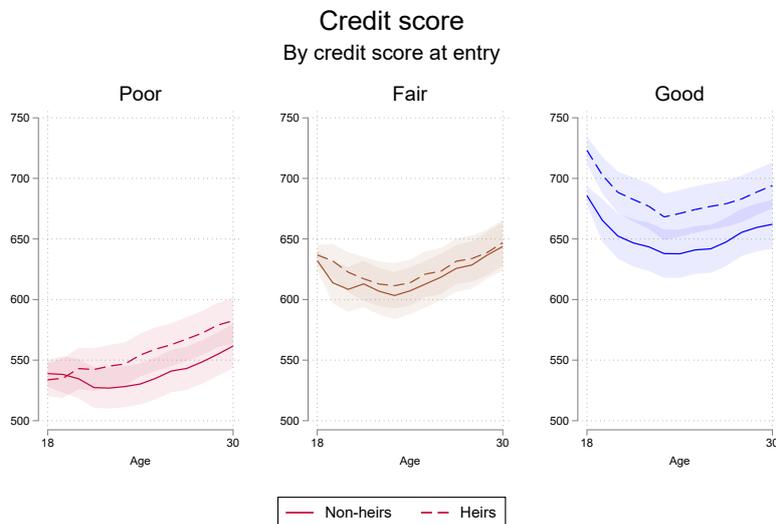
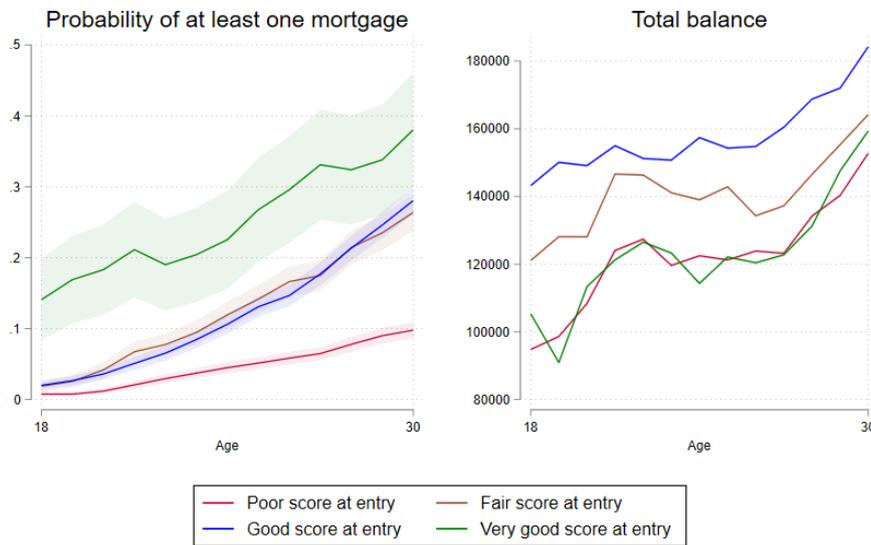


Figure III: Evolution of credit score by initial credit score bin and inherited history status. – 95% Confidence intervals shaded

## 4 Other Credit Outcomes

In this section, we expand our analysis to other credit market outcomes, focusing on mortgages and credit cards. For mortgage outcomes, presented in Figure IV, the differences by initial credit scores are mostly on the extensive margin. Only 10% of *Poor* initial credit score individuals have a mortgage by age 30, while the same fraction is 30% for *Good* and *Fair* initial scores and 40% for *Very good* initial scores. At the intensive margin, what we notice

in the right panel of Figure IV is that the amounts borrowed by *Very good* and *Poor* initial credit score individuals are very similar, while the other two categories borrow more. This result is driven by geographical variation, as when we control for zip code effects, the differences between bins disappear. That means that credit scores mostly affect access and use of mortgage credit, with the conditional amounts pinned down by location.



Entry age: 18-22. Intensive margin conditioning on having a mortgage.

Figure IV: Evolution of mortgage balances by initial credit score bin. – 95% Confidence intervals shaded

For credit cards, the pattern continues. By age 30, 60% of *Poor* initial credit scores have at least one credit card versus 100% for *Good* and *Very good* initial credit scores and above 90% for *Fair* (Figure V). The dynamics are also interesting, as in essence nothing happens at the extensive margin after age 22, with all the profiles being flat. At the intensive margin, presented in Figure VI, higher initial credit score individuals have higher credit limits, which, combined with similar balances, results in higher utilization rates for

low initial credit scores: 60% utilization for *Poor* versus 20% for *Very good* initial credit scores. Of course, these large utilization rates negatively affect future scores and therefore lower the chances of additional access to credit.

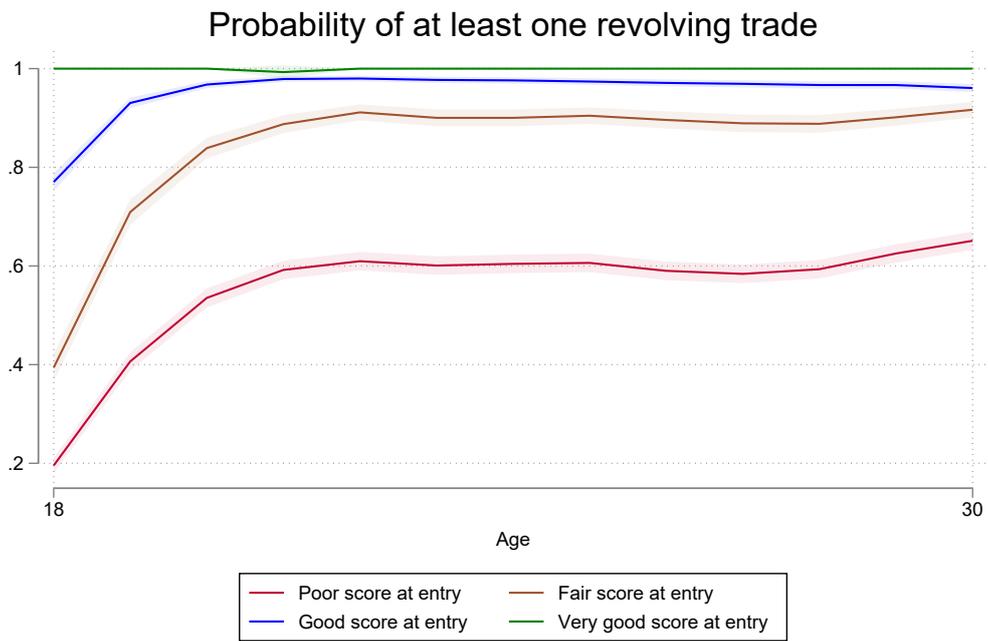


Figure V: Evolution of credit card penetration. – 95% Confidence intervals shaded

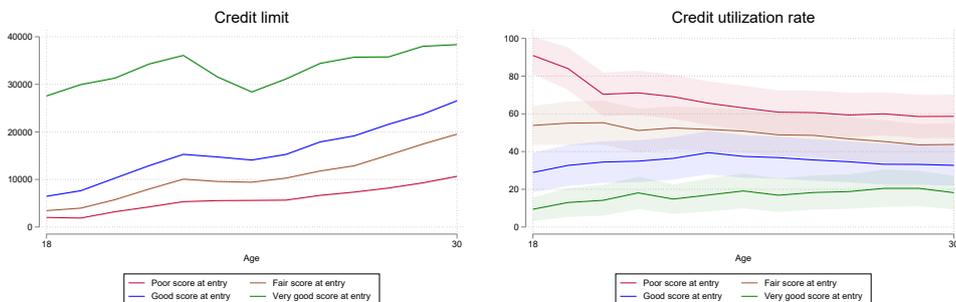


Figure VI: Evolution of credit card limits and utilization. – 95% Confidence intervals shaded

## 5 How Predictive are History and Initial Scores?

To further assess the relevance of the initial conditions in the credit market, we perform a simple exercise of classification through a machine learning procedure. Specifically, we compare how much predictive power there is in only two variables: i. number of months of the oldest open account; ii. initial credit score, versus an extended model, where we use these two variables plus another 156 variables which record individual behavior for all the years 2004 to 2016.<sup>2</sup>

For this exercise, we define as subprime those individuals with a score below 620 at age 30, and use a random forest model (Breiman (2001)) to classify whether individuals are subprime borrowers at age 30. In the two-variables model, the use of a random forest is perhaps extreme, but will allow for a meaningful comparison. We train the model on a random subsample of 75% of the individuals in the original sample. We then evaluate the model's performance by means of a confusion matrix; i.e., a matrix whose rows represent the instances in the actual class (how many subprime-at-30

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<sup>2</sup>The full list of variable used is: i. number of months of the oldest open account; ii. initial credit score; plus for all the available years 2004 to 2016, iii. total number number of trades ; iv. total number of mortgages trades; v. total number of open trades; vi. total number of open mortgage trades; vii. total balance on open trades reported in the last 6 months; viii. total balance on open revolving trades reported in the last 6 months; ix. total number of revolving trades; x. total balance on open trades reported in the last 6 months; xi. total number of trades with max delinquencies of 30 days; xii. total number of trades with max delinquencies of 60 days; xiii. total number of trades with max delinquencies of 90 days; xiv. total number of trades with max delinquencies of 90-180 days. That is 156 variables.

and prime-at-30 people there are in the data) and columns represent the instances in the predicted class (how many subprime-at-30 and prime-at-30 people the model predicts). We find that the two-variable model is able to correctly classify subprime borrowers with a 69% probability and prime borrowers with a 67% probability, for an accuracy rate of .68 (95% Confidence Interval, .66 - .7). The enhanced model correctly classifies subprime and prime borrowers with an 85% and 86% probability respectively, for an accuracy rate of .85 (95% Confidence Interval, .83 - .87). This means that the two-variable model, which uses only the initial conditions, is 80% as accurate as the model where we use a 13-year-long history of credit market behavior, including information that is contemporaneous (2016) to the classification.

## 6 Conclusions

Our empirical results point to the importance of initial conditions (credit scores) for the subsequent evolution of credit scores and other credit outcomes such as use of mortgage and revolving credit. A natural question arises: since initial credit scores are not based on past behavior of the specific individual, why do we see persistent effects of initial conditions over the life-cycle? One hypothesis is that initial credit scores already contain a lot of information about an individual's creditworthiness. Alternatively, our findings are also consistent with the hypothesis that since one needs a high credit score in order to obtain credit and credit to have a higher credit score, initial condition serve as a self-fulfilling prophecy by keeping individuals locked into their initial low credit bins by cutting them off from credit. In addition to the constraints imposed on individuals due to low credit scores outside of the credit market,

reduced access to mortgage credit can have long term consequences for wealth accumulation via housing equity. Shedding more light on this issue is an important avenue for future research.

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