Intergenerational Mobility and Credit*

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Abstract

To what extent – and through what channels – does parental credit access affect the future earnings of children? To answer this question, we combine the Decennial Census, credit reports, and administrative earnings records to create the first panel dataset linking parental credit access to the labor market outcomes of children in the U.S. We find that a 10% increase in parental unused revolving credit during their children's adolescence (13 to 18 years old) is associated with 0.12% to 0.59% greater labor earnings of their children during early adulthood (25 to 30 years old), regardless of the educational attainment of the child or parent. We examine the mechanisms for this finding and show that increased parental credit access is associated with their children having higher rates of college graduation, fewer non-employment spells, and a greater likelihood of working at higher paying firms. We then use our empirical elasticities to estimate a theory of intergenerational mobility with defaultable debt. The rise in credit access between the 1970s and 2000s increased the the intergenerational earnings elasticity and income variance of young adults. The expansion of credit has reduced intergenerational mobility and increased inequality as the largest increase in credit has occurred among high income households.

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What are the long-run labor market implications of parental credit constraints? To what extent did the democratization of credit in the 1970s and 1980s (e.g., Livshits, Mac Gee, and Tertilt (2016), Braxton, Herkenhoff, and Phillips (2020), Herkenhoff and Raveendranathan (2020), and Aaronson, Faber, Hartley, Mazumder, and Sharkey (2021)) shape observed patterns of intergenerational mobility? A convincing answer to both of these questions requires micro-data on parental borrowing capacity during a child's adolescence as well as the child's future labor market outcomes. While there is a well-established literature estimating positive causal effects of parental credit access on college attendance (e.g., see reviews by Lochner and Monge-Naranjo (2012) for early U.S. studies and Mogstad and Torsvik (2021) for recent U.S. and international studies), there are no longitudinal surveys in the United States that allow researchers to measure the long-run effects of relaxing consumer credit constraints during a child's adolescence. The surveys suitable for measuring intergenerational mobility, e.g. the Panel Study of Income Dynamics (PSID) and National Longitudinal Surveys of Youth (NLSY), record debts of the parents but do not collect information on credit limits or borrowing capacity.[1] The fundamental measurement issue is that low-debt households may have significant potential to borrow or they may be severely constrained.

To address these questions, we create a new panel dataset of parental credit access and their children's labor market outcomes by combining the Decennial Census with TransUnion credit reports and administrative earnings records. We then combine several sets of instrumental variables to measure the causal effects of parental credit access during their children's adolescence (13 to 18 years old) on the children's future labor market outcomes (25 to 30 years old). We focus on three instruments, each of which have been used extensively in the consumer finance literature: (1) automatic limit increases (Gross and Souleles (2002), Herkenhoff, Phillips, and Cohen-Cole (2016)), (2) purchase cohort variation in house price growth (Gerardi, Herkenhoff, Ohanian, and Willen (2018), Bernstein and Struyven (2022)), and (3) bankruptcy flag removal (e.g., Musto (2004), Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2020), Herkenhoff, Phillips, and Cohen-Cole (2021)). Using these multiple instruments we demonstrate that our instruments pass overidentification tests.[2]

We find that a 10% increase in unused revolving credit during adolescence (13 to 18 years old) is associated with 0.12% to 0.59% greater labor earnings during early adulthood (25 to 30 years old). We explore several potential mechanisms for these findings. We find that a

[1] The only long-running U.S. survey to measure credit limits is the Survey of Consumer Finances (SCF) which is cross-sectional in nature.

[2] Each instrument has its own merits and drawbacks, but the presence of multiple instruments allows us to conduct overidentification tests. While no true test of exogeneity exists, the intuition behind overidentification tests is that if the recovered residuals from one instrument are correlated with one of the instruments, exogeneity is unlikely to hold. Our instruments pass overidentification tests at conventional significance levels.

10% increase in unused revolving credit during adolescence is associated with 0.1% greater likelihood of college graduation, 0.1% less likelihood of a quarter of unemployment, 0.14% greater average pay of their employers. We also find that the effects of credit are stronger among families with less educated parents. Likewise, higher earnings are observed regardless of the educational attainment of the child.

To interpret our results and measure how the democratization of credit affected income mobility in the United States, we develop a structural model that integrates defaultable debt with a theory of household dynasties. Our quantitative model features overlapping generations where parents make investment decisions in their child's human capital which impact the child's earnings as an adult (e.g. Daruich (2018), Abbott, Gallipoli, Meghir, and Violante (2019), Lee and Seshadri (2019), and Caucutt and Lochner (2020)).

To generate variation in parental credit access, we introduce defaultable debt that is individually priced as in Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007) and Livshits, MacGee, and Tertilt (2007). Our explicit modeling of the bankruptcy process allows us to simulate the flag removal instrument and identify parameters governing the importance of credit for human capital accumulation. By modeling the shocks that drive bankruptcy and estimating their persistence (including both income and expense shocks, such as health shocks), we are able to model selection into bankruptcy and discuss the difference between the way credit constraints affect the general population relative to bankrupt individuals. While we do not model mortgages nor automatic limit increases, we find that the elasticity of children's earnings with respect to credit constraints during adolescence is in line with our empirical estimates.

We then use the theory to estimate the effects of one the largest credit-related natural experiments in the United States: the democratization of credit in the 1970s and 1980s. A number of factors including deregulation of lending markets (and promotion of interstate competition via the *Marquette* decision in 1978), bankruptcy reform (White (1998)), the advent of credit scoring, and the end of regional lending policies led to the democratization of credit (e.g., Livshits, Mac Gee, and Tertilt (2016), Braxton, Herkenhoff, and Phillips (2020), Herkenhoff and Raveendranathan (2020), and Aaronson, Faber, Hartley, Mazumder, and Sharkey (2021)). We simulate the democratization of credit through two channels: (1) we model a reduction in the cost of bankruptcy (e.g. Livshits et al. (2010)), and (2) a rise in credit limits (Herkenhoff (2019)). By varying the bankruptcy and credit limit parameters, our model replicates the path of default rates and credit-to-income ratios observed in the data from the 1970s to 2000s.

We find that the democratization of credit led to an increase in the intergenerational elasticity of earnings of nearly 4%, and an increase in income inequality among the young of almost 1.5%. This increase in the intergenerational earnings elasticity implies that the expansion of credit markets has reduced intergenerational mobility. The reason that the expansion of credit markets has reduced mobility and increased income inequality is because the expansion of credit markets has occurred among high income families. For these high income families when parents lose their job or suffer unforeseen medical expenses, spousal job loss, or divorce, they are able to borrow and maintain high investment levels in their children. Lower income families have not seen this rise in insurance via credit markets and are faced with a trade-off of smoothing consumption or cutting investment in their children's human capital.

While early and influential work by Carneiro and Heckman (2002) argued against the importance of credit constraints for college attendance, our results contribute to a growing body of evidence that argues otherwise (e.g. Belley and Lochner (2007) and Caucutt and Lochner (2020)). We build the first panel dataset to link borrowing capacity to children's labor market outcomes, and both reduced form and quantitative evidence suggest that consumer credit plays a significant role in shaping mobility and inequality.

Related literature. This paper contributes to the literature which examines the factors that influence intergenerational mobility. Black and Devereux (2010) provide an excellent summary of early work on this topic. A number of recent studies including Chetty et al. (2014), Chetty and Hendren (2018), Derenoncourt (2019), and Chetty et al. (2020) provide discussion of recent innovations in the literature while also documenting the degree of intergenerational earnings mobility in the U.S.[3]

Within this literature, researchers have taken a number of approaches to measure the role of credit constraints on child outcomes. The first strand of the literature focuses on the relationship between family income (and the timing of earned income) and college attendance to infer credit constraints (e.g. Carneiro and Heckman (2002), Cameron and Taber (2004), Belley and Lochner (2007) and Caucutt and Lochner (2020)). Carneiro and Heckman (2002) argued that the family income-college attendance relationship weakens substantially once controls for ability are included in the regression, while more recent work by Belley and Lochner (2007) and Caucutt and Lochner (2020) argue that college attendance is increasing in family income in more recent data and that the timing of the receipt of income matters for college attendance.

The second strand of the literature uses regional natural experiments, such as state-level

[3]These papers argue that there is a causal effect of childhood environment (over an above selection effects) on subsequent earnings mobility. We refer the reader to these papers for discussion of recent papers that explore mobility-related mechanisms for intergenerational earnings elasticities. While these papers focus on intergenerational earnings mobility, there is also a literature on intergenerational wealth mobility. Black, Devereux, Lundborg, and Majlesi (2019) use the register of adopted children in Sweden and show that the adopting parents (nurture) play a large role than the biological parents (nature) in influencing the wealth of the children. A common theme of these papers is that the environment that a child is exposed to plays a significant role in their future outcomes and hence their mobility.

banking deregulation and the end of redlining, in combination with the Opportunity Atlas (e.g. Chetty et al. (2014)) to study the effects of credit institutions on income mobility (e.g., Sun and Yannelis (2016), Aaronson et al. (2021), and Mayer (2021)).[4] Long-run comparisons of cross-state or cross-region re-regulations may reflect greater firm credit access, private investment, or government investment (this is particularly so for redlining analyses) which presumably alter the labor market prospects of everyone in the state. While these regional analyses provide suggestive evidence that credit constraints matter for mobility, the first-stage of the regional regression is not observed (i.e., estimates take the form of a direct regression of outcomes on de-regulation dummies) making it difficult to map the estimates to models and quantify the importance of credit constraints.

The third stand of the literature uses natural experiments to analyze how variation in liquid and illiquid assets affects child test scores, college attendance and earnings (e.g. Dahl and Lochner (2012), Agostinelli and Sorrenti (2021), Bulman et al. (2021), and Cooper and Stewart (2021) in the United States and Løken, Mogstad, and Wiswall (2012) and Cesarini, Lindqvist, Östling, and Wallace (2016) for analysis in Europe, among others).[5] Several influential papers study how child outcomes – primarily college attendance – vary with housing wealth (e.g. Lovenheim and Reynolds (2013) and Cooper and Luengo-Prado (2015)) and credit constraints at the entry of college (e.g. Brown et al. (2012) for analysis in the United States and Solis (2017) for analysis in Chile, among others), while other have used hypothetical questions to elicit constraints during college directly from surveys (e.g. Stinebrickner and Stinebrickner (2008) in the United States and Attanasio and Kaufmann (2014) in Mexico).

The fourth strand of the literature uses structural models to study the effects of credit constraints on children's human capital accumulation, earnings, and welfare (e.g., Keane and Wolpin (2001), Lochner and Monge-Naranjo (2011), Hai and Heckman (2017), Daruich (2018), Abbott et al. (2019), and Caucutt and Lochner (2020)). Of particular note, Caucutt and Lochner (2020) finds that due to dynamic complementarity, relaxing borrowing constraints during childhood and adolescence interact non-linearly to produce large positive effects on human capital accumulation.

We make both empirical and theoretical contributions relative to the existing literature. Empirically, we build a new database that allows us to measure the long-run consequences of parental access to credit on the future labor market outcomes of their children. Using three sep-

[4]Recent work by Ringo (2019) uses contemporaneous credit scores in the rand ALP to study the covariance between credit scores and reported child education. Likewise, CCP address links have been used to measure the persistence of credit scores across generations Hartley et al. (2019).

[5]There is also a large literature in sociology on student debt, parental resources, and college attainment (e.g. Houle (2014) and Dwyer et al. (2012)).

arate instrumental variables, we show that greater parental credit access during their children's adolescence improves their children's earnings. We then provide evidence of the mechanisms that improve their children's subsequent earnings. We show that increased credit access is associated with greater rates of college graduation, fewer unemployment spells, and a greater likelihood of working at higher paying firms.

Theoretically, we contribute to the quantitative literature on intergenerational mobility in two ways: (1) we integrate defaultable debt into a model of family connectedness, and (2) we our instruments to inform our theory and measure the effects of the democratization of credit on observed intergenerational mobility patterns.

1 Impact of parental credit access on children's earnings

We begin by empirically estimating the effects of parental credit access on their children's future earnings using a newly linked sample combining the Decennial Census to administrative earnings records from the LEHD and individual credit reports from TransUnion.

1.1 Data

We start by creating a new data set that allows for tracking the evolution of earnings among parents and their children as well as the credit history of parents. We identify family structure using the 2000 Decennial Census. From the Decennial Census, we are able to observe all individuals living in a household in 2000. Our data on worker earnings comes from the Longitudinal-Employer Household Dynamics (LEHD) database. The LEHD is a matched employee-employer data set covering 95% of U.S. private sector jobs and includes quarterly data on earnings, worker demographic characteristics, firm size, firm age, as well as average wages. Our data on worker earnings spans from 2000 to 2014 for 24 states, covering approximately 44% of the U.S. population.[6] Finally, the TransUnion credit reports provide us with annual data from 2001-2014 on the balance, limit, and status (delinquent, current, etc.) of different classes of accounts held by individuals (including student debt, home equity lines of credit, etc.) for approximately 5 million individuals.[7]

[6] We have the LEHD for 24 states (covering roughly 44% of the U.S. population): AR, AZ, CA, CO, DC, DE, IA, ID, IL, IN, KS, MD, ME, MT, ND, NE, NM, NV, OH, OK, PA, TN, VA, WY. We have TransUnion data for 11 states (covering roughly 31% of the U.S. population): AZ, CA, CO, DE, IA, IL, IN, MD, NV, VA, WA. We isolate all parents who appear in our credit reports. We then follow their children into the 24 other states.

[7] Our underlying sample from TransUnion is comprised of a random sample of individuals (and all other credit reports at their address) as well as an oversample of individual credit reports with recorded bankruptcies, foreclosures, and delinquencies. We reweight our combined sample to match the aggregate bankruptcy, foreclosure, and delinquency rates in the relevant states.

From these datasets we create a new panel dataset which captures the credit access of parents along with the earnings history of parents and their children once they enter the labor market. Creating our linked sample of family records, credit reports, and earnings proceeds in 3 steps:

1. Using a scrambled social security number we link our sample of TransUnion credit reports to the Decennial Census.

2. Using the household identifier from the Decennial Census, we identify all individuals living in a household where we have credit information for an individual.

3. Using the sample of household members from step (2), we merge in earnings information from the LEHD using scrambled social security numbers.

This dataset, which includes millions of households, allows us to examine in finer detail the mechanisms through which earnings evolves across generations.

Definitions. From the Decennial Census we observe households in the year 2000 and identify family structure. For ease of exposition, individuals classified as children in the 2000 Decennial will be referred to as *children* throughout the remainder of the paper (even as they leave the home and enter the labor market). Similarly, individuals who are classified as parents in the 2000 Decennial will be referred to as *parents* throughout the remainder of the paper.

We measure the credit access of parents using their access to existing funds, e.g., unused credit limits on existing lines of credit. We measure the existing stock of parental credit using unused revolving credit limits (i.e., revolving limits minus balances).[8] We analyze revolving credit, including home equity lines of credit (HELOCs) and bankcards, since these forms of credit are associated with (in most cases) explicit credit limits.

We measure of the labor earnings of parents and their children using the LEHD. An important feature of the LEHD database is that it is based upon state UI records, meaning that we only observe an individual's quarterly earnings for each employer in LEHD-covered states. Given this structure, we cannot discern whether zero earnings are generated by non-employment or moves outside of the state. For this reason, we impose a series of minimum labor force attachment restrictions on parents and their children. In particular, we specify a minimum earnings criteria and then require parents and their children to satisfy this minimum earnings criteria in a given number of years.

[8]The main components of revolving credit include bank revolving (bank credit cards), retail revolving (retail credit cards), finance revolving credit (other personal finance loans with a revolving feature), and mortgage related revolving credit (HELOCs).

We impose a minimum annual earnings cutoff of \$10k.[9] For parents, we require that parents satisfy this minimum earnings criteria in each year between 2000 and 2002.[10] Our measure of parental earnings is average earnings over this 3-year period. For children, we require that they satisfy the minimum earnings criteria in both 2013 and 2014, and our measure of children's earnings is their average earnings over these two years. We additionally require that children are between the age of 25 and 30 in the year 2014. As in Chetty et al. (2014), we average earnings over several years to minimize the role of temporary earnings fluctuations.

1.2 Empirical approach

Let Y_i denote the real earnings of child i, and let Y_i^P denote the real earnings of their parent.[11] Let C_i denote the credit access (e.g., unused revolving limit) of their parent at the start of the sample. Let X_i denote a vector of controls, which includes child age fixed effects, age of parent, number of children and parents in the household in 2000, gender fixed effects, and tenure. We then examine how the credit access of the parents impacts the earnings of the child, using a regression of the form:

$$\log(Y_i) = \alpha + \beta \log(Y_i^P) + \eta \log(C_i) + \Gamma X_i + \epsilon_i \tag{1}$$

In equation (1), the coefficient β corresponds to the intergenerational earnings elasticity (IGE). The coefficient η summarizes how additional access to credit (e.g., a 1 percent increase in unused revolving limits) impacts the earnings of a child in the labor market. In particular, if $\eta > 0$ then we have evidence that greater credit access of parents increases the earnings of their children.

The main obstacle to estimating equation (1) is that credit access is not randomly assigned. To address this potential endogeneity issue, we use instrumental variables Z_i to estimate the following system of equations:

$$\log(Y_i) = \alpha + \beta \log(Y_i^P) + \eta \widehat{\log(C_i)} + \Gamma X_i + \epsilon_i, \tag{2}$$
$$\log(C_i) = \alpha_1 + \beta_1 \log(Y_i^P) + \eta_1 Z_i + \Gamma_1 X_i + u_i, \tag{3}$$

where $\widehat{\log(C_i)}$ in the second stage regression (equation (2)) is the predicted value from the

[9] All dollar amounts are in 2008 dollars and are deflated by the CPI.

[10] For households with multiple parents, we count the number of times each parent satisfies the minimum earnings cutoff and take the maximum. We then take the average of parental earnings over all years.

[11] As discussed in Section 1.1, children's earnings are their average earnings in 2013 and 2014, while parents earnings are their average earnings between 2000-2002.

first stage regression (equation (3)). For our instruments to be valid, we require *relevance* ($cov(Z_i, C_i) \neq 0$) and *strict exogeneity* ($cov(Z_i, \epsilon_i) = 0$) or *conditional exogeneity* ($cov(Z_i, \epsilon_i|X_i) = 0$) (e.g. Dawid (1979) and White and Chalak (2010)). We consider three instruments based on existing consumer finance studies.

Instrument 1: Age of oldest account. Our first instrumental variable relies on variation in the age of an individual's oldest credit account. Seminal work by Gross and Souleles (2002) exploited similar variation and showed that credit card limits increase automatically as a function of the length of time an account is open. As discussed in Gross and Souleles (2002), credit issuers revise account limits based on arbitrary timing thresholds, e.g., accounts aged 6 months or 12 months are more likely to receive automatic (issuer initiated) limit increases. These limit revisions are a function of credit scores, and credit scores, by construction, positively weight account ages.[12]

The impetus for such a large emphasis on account ages can be traced back to the Equal Credit Opportunity Act (ECOA) of 1974. ECOA banned the use of physical age as well as most other demographic characteristics in credit scoring algorithms. As a consequence, credit scoring companies began to use the age of the oldest account to proxy for physical age. Our identification strategy relies on conditional exogeneity: controlling for physical age (which is observed by us, but not the credit rating agencies), differences in credit access due to variation in account ages is random and simply an artifact of scoring and limit-increase algorithms.

We implement this approach by instrumenting a parent's unused revolving credit limit in the year 2002 (C_i) with the age of the oldest account among the parents in the year 2002 (Z_i). Our baseline set of controls X_i includes a linear control for parent age, and in Appendix A.3 we show that including parent age fixed effects instead yields similar results. A benefit of this instrumental variable approach is that it can be used for all households with a credit report and that it provides individual level variation in credit access. We next discuss our alternative instruments for credit access.

Instrument 2: Purchase cohort variation. Our second instrument exploits purchase cohort variation in home equity (e.g., Gerardi et al. (2018), Bernstein and Struyven (2022)). In this specification, we restrict our sample to children whose parents have a mortgage in 2002. We instrument the unused revolving credit limit of the parent in the year 2002 (C_i) with growth in housing prices in the individual's county between the year of mortgage issuance and the year

[12]See additional discussion of automatic credit limit increases here: https://wallethub.com/answers/cc/why-did-my-credit-limit-go-up-2140676730/

2002 (Z_i).[13]

Crucially, we include county fixed effects, mortgage age fixed effects as well as the log of home equity in X_i in addition to our baseline set of controls of child age fixed effects, age of parent, number of children and parents in the household in 2000, gender fixed effects, and tenure. The remaining variation in credit limits is driven by differences in housing price growth across mortgage issuance cohorts. The identifying assumption is that conditional on mortgage age, variation in house price growth due to the timing of the mortgage issuance is exogenous.

Instrument 3: Derogatory flag removal. Our final instrument exploits the fact that the Fair Credit Reporting Act of 1970 requires that negative information, including bankruptcy, foreclosure, and derogatory flags, are removed from an individual's credit report following an exogenously set period of time. For example, Chapter 7 bankruptcy flags must be removed from the credit report after 10 years, and foreclosure flags must be removed from the credit report after 7 years. To maximize estimation power, we examine derogatory public flags which aggregate all relevant delinquency information including bankruptcy, foreclosure, tax leins, civil court judgements, etc. Credit access abruptly increases when these derogatory flags are expunged from an individual's credit history (e.g. Musto (2004), Dobbie et al. (2020), Herkenhoff et al. (2021)). We exploit this natural experiment to isolate changes in parental credit access that are orthogonal to the parent's unobservable characteristics.

In this estimation approach, we restrict our sample to children whose parents have a derogatory flag removed between 2002 and 2008. We define C_i to be the unused revolving credit limit of child i's parent in the year 2004. We instrument the unused revolving limit by an indicator variable for the parent having a derogatory flag removed in 2004 or the preceding 2 years (Z_i).[14] In this specification, the first stage regression returns an estimate of the impact of flag removal on a parents credit access. By comparing parents who have already had their derogatory flag removed to those whose flag is still on their credit report we generate exogenous variation in credit access among families that have had derogatory events on their credit report. In these specifications, X_i includes our baseline set of controls.

1.3 Sample Descriptions and Summary Statistics

Our identification strategies require three samples.

[13] We use county housing prices provided by the Federal Housing Finance Agency (FHFA).

[14] Our data from TransUnion starts in 2001, meaning that we can only identify removals beginning in 2002. We pool the pre-2004 flag removals in order to obtain sufficient power.

1. **Main sample:** Our first sample includes all *children* who (1) are between the ages of 25 and 30 in 2014, (2) have earnings over the minimum earnings cutoff in 2013 and 2014, and (3) have parents with a TransUnion credit report and earnings over the minimum earnings cutoff in each year between 2000 and 2002. Under these criteria, we have a sample of 166,000 individuals (rounded to the nearest thousand given Census disclosure rules).

2. **Mortgagor Sample:** Our second sample is comprised of the 108,000 children in the main sample whose parents had a mortgage on their credit report in the year 2002. We will use this sample of children for our second instrumental variable strategy, which exploits variation in housing prices.

3. **Derogatory Sample:** Our third sample is comprised of the 23,000 children in the main sample whose parents had a derogatory public flag removed from their credit report between 2002 and 2008. We will use this sample of children for our third instrumental variable strategy, which leverages the removal of derogatory public flags.

In Table 1, we present summary statistics for the three samples used in this paper. In our main sample, children have average earnings of over \$35k and are on average 27.5 years old in the year 2014. Between 2000 and 2002, their parents have average earnings of over \$45k and their average age is 43 years old. Parents have revolving credit limits of almost \$35k, and on average, their unused revolving credit can replace just over 50% of annual earnings. As discussed in Braxton et al. (2020), the distribution of unused credit is highly skewed with many households having very little unused credit. In our main sample, almost 40% of household have unused revolving credit limits less than 10% of earnings, and over 50% of households have unused revolving credit limits less than 25% of earnings. Parents in the mortgage sample (column (2) of Table 1), have higher earnings, revolving credit limits and unused credit relative to the main sample. Conversely, parents in the derogatory sample (column (3) of Table 1) have lower earnings, and substantially lower revolving credit limits and unused limits. Using these samples of children we next examine how the credit access of parents impacts the earnings of their children using the empirical approaches outlined in Section 1.2.

1.4 OLS Results

In this section, we empirically examine the impact of parental credit access on their children's future earnings. Table 2 presents the results of estimating equation (1) via OLS, omitting con-

Table 1: Summary Statistics

Variable	(1) Main Sample	(2) Mortgage Sample	(3) Derogatory Sample
Child's earnings	\$35,240	\$36,250	\$33,460
Child's age	27.52	27.53	27.5
Parent's earnings	\$45,370	\$49,120	\$42,760
Parent's age	43.22	43.66	42.44
Revolving credit limit	\$34,660	\$42,330	\$13,680
Unused revolving credit over income	0.5316	0.6266	0.1705
Share with unused revolving credit $<$ 10% of earnings	0.3897	0.297	0.6946
Share with unused revolving credit $<$ 25% of earnings	0.5259	0.4413	0.8303
Observation (Rounded to 000s)	166000	108000	23000

Notes: See Section 1.3 for sample selection criteria. Children's earnings are measured in 2013-2014, while parents earnings are measured in 2000-2002. Revolving credit limits, and unused limits, are measured in 2001-2002. All dollar amounts are in 2008 dollars. Child age is measured in 2014, while parent age is measured in 2002.

trols X_i.[15] We first estimate equation (1) where we only include the log of parental earnings as an independent variable. The coefficient on the log of parental earnings is commonly referred to as the *intergenerational earnings elasticity* (IGE). In column (1) we present the results for our main sample of households. We estimate an IGE of 0.158, which indicates that on average, parents whose earnings are 10% greater have children whose earnings are 1.58% greater. This estimate of the IGE for the U.S. is lower than recent work by Chetty et al. (2014), who estimate an IGE of 0.344, but is within the range of estimates for the IGE (0.13-0.16) that have been found using the LEHD-Decennial sample (e.g., Staiger (2021)).[16] In columns (2) and (3) of Table 2 we find a similar estimate of the IGE using our mortgagor sample (column (2)) as well as our sample of households that have a derogatory flag on their credit report (column (3)).

We next consider the role of parent's credit access in shaping the future earnings of their children. In columns (4) to (6) of Table 2, we include the log of parent's unused revolving credit limit in equation (1), where we estimate equation (1) via OLS.[17] The positive and statistically

[15] In Appendix A.1 we present the results of estimating equation 1 with additional controls.

[16] There are several reasons why our estimates of the IGE are lower than Chetty et al. (2014). First, we use a sample of children between the ages of 25 and 30. Chetty et al. (2014) estimates an IGE of 0.344 for children who are 30 years old and shows that IGEs increase in the age of the child. Second, our measure of income for the child is individual income, while the estimate from Chetty et al. (2014) is household earnings, which produces a higher IGE relative to individual income (see their Appendix Table 1). Finally, and as noted by Staiger (2021), to account for individuals moving across states that are not in our LEHD sample we impose a series of labor force attachment restrictions. These restrictions remove low earnings (i.e., below \$10k), which can lead to a higher IGE.

[17] Note that we must take a stance on negative values of unused credit (which is quite rare), in order to take the

Table 2: Parental credit access and children's earnings: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log of child's earnings					
Log Parent's Earnings	0.158***	0.153***	0.145***	0.130***	0.131***	0.122***
	(0.00264)	(0.00335)	(0.00740)	(0.00272)	(0.00657)	(0.00756)
Log Unused Revolving Limit				0.0165***	0.0169***	0.0123***
				(0.000404)	(0.000758)	(0.000967)
R-squared	0.031	0.027	0.025	0.043	0.036	0.034
Observations	166000	108000	23000	166000	108000	23000
Controls	N	N	N	N	N	N
Fixed Effects	N	N	N	N	N	N
Sample	Main	Mortgage	Derogatory	Main	Mortgage	Derogatory

*Notes: The table shows regression results from the estimation of equation (1) via OLS, where the dependent variable is the log of children's real earnings. No controls or fixed effects are included in these regressions. Earnings are measured in 2008 dollars. Children's earnings are measured in the years 2013-2014 when children are between the ages of 25 and 30 (in 2014). Parents earnings are measured in 2000-2002, and unused revolving credit limits are measured in 2001 and 2002. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

significant coefficient on the log of parent's unused revolving credit limit indicates that greater access to credit among parents is associated with higher earnings for their children. In particular, the coefficient indicates that a 10% increase in unused revolving credit limits is associated with a 0.16% increase in earnings. Additionally, the results in column (4) also show that including parent's credit access in equation (1) lowers the estimate of the IGE from 0.158 (column (1)) to 0.130. In columns (5) and (6) of Table 19 we show that we find similar results for our mortgagor and derogatory flag samples respectively.

1.5 IV Results

The results presented in Table 2 show that greater parental credit access is associated with higher earnings of their children. However, credit access is not randomly allocated and households with greater access to credit may systematically differ in some unobserved manner which leads to higher earnings for their children. To obtain exogenous variation in credit access we apply the three instrumental variables described in Section 1.2. We provide first stage regressions in Appendix A.2.

logarithm of unused credit variables. We winsorize negative values of unused credit to zero. We then work with the logarithm of unused credit plus one.

Our first instrument exploits individual level variation based upon when an individual first opened a line of credit. Table 3 presents the results of estimating equation (2) on our main sample where the log of unused revolving credit limits is instrumented with the age of oldest account (AOA). The positive and statistically significant coefficient on the log of unused revolving credit limits indicates that children in households with greater credit access have greater earnings as adults. In particular, we find that an additional 10% of unused revolving credit for parents is associated with their children having earnings that are 0.3% greater.

To provide a benchmark for the role of credit, we compare the coefficient on unused revolving credit to the impact of parental earnings. The coefficient on the log of parental earnings in column (1) of Table 3 indicates that a 10% increase in parental earnings is associated with a 1% increase in the child's earnings. Therefore, a one log point increase in a parent's earnings is roughly three times more impactful on future earnings as a one log point increase in unused credit.

Our second instrument exploits a different source of variation based on geography and mortgage purchase cohort. In column (2) of Table 3, we instrument the log of unused revolving credit with cumulative house price growth (HPG) in an individual's county between the year of mortgage origination and 2002, while including county and mortgage age fixed effects. We find that greater access to credit among parents corresponds to higher earnings for their children. In particular, we find that a 10% increase in unused revolving credit among parents is associated with 0.59% increase in the child's earnings.

Our third instrument exploits the time-dependent removal of derogatory flags (DF) from an individual's credit report. In column (3) of Table 3 we instrument unused revolving credit limits with an indicator for having a derogatory flag removed between 2002 and 2004.[18] The coefficient on the log of unused revolving limits indicates that a 10% increase in revolving credit among parents is associated with a 0.32% increase in their children's future earnings.

We conclude this section by using combinations of our instruments to further examine the robustness of our results and conduct over-identification tests (i.e., J-tests). In column (4) of Table 3, we use the age of oldest account and housing price growth as an instrument for unused revolving credit. Using this combination of instruments, we find that a 10% increase in unused revolving credit among parents is associated with a 0.43% increase in the child's earnings. Incorporating multiple instruments allows us to conduct a J-test for over-identification. We fail to reject the null that the instruments are valid at any significance level below 55%. Finally, in column (5) we instrument the log of unused revolving credit with the age of oldest account and an indicator for having a derogatory flag removed. We find that in response to a 10% increase

[18] In Appendix A.4, we show that flag removal is not associated with higher earnings among parents, consistent with recent work by Dobbie et al. (2020) and Herkenhoff et al. (2021).

Table 3: Parental Credit Access and Children's Earnings: IV Regressions

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log of children's earnings				
Log Parent's Earnings	0.103***	0.0723***	0.0865***	0.0846***	0.0775***
	(0.00362)	(0.0220)	(0.0252)	(0.00540)	(0.0105)
Log Unused Revolving Limits	0.0308***	0.0592**	0.0323**	0.0434***	0.0371***
	(0.00156)	(0.0271)	(0.0128)	(0.00363)	(0.00402)
R-squared	0.110	0.041	0.083	0.078	0.070
J-test	–	–	–	0.554	0.698
Observations	166000	108000	23000	108000	23000
Controls	Y	Y	Y	Y	Y
Fixed Effects	N	Y	N	Y	N
Instrument	AOA	HPG	DF	AOA & HPG	AOA & DF
Sample	Main	Mortgage	Derogatory	Mortgage	Derogatory

*Notes: The first stage includes the age of oldest account (AOA) in columns (1), (4), and (5), house price growth (HPG) in columns (2) and (4), and derogatory flag (DF) removal in columns (3) and (5). Controls include child age fixed effects, age of parent, number of children and parents in the household in 2000, gender fixed effects, and tenure. Fixed Effects (FE) include county and mortgage age. The table shows regression results from the IV estimation of equation (2), where the dependent variable is the log of children's real earnings. Earnings are measured in 2008 dollars. Children's earnings are measured in the years 2013-2014 when children are between the ages of 25 and 30 (in 2014). Parents earnings are measured in 2000-2002. Unused revolving credit limits are measured in 2001-2002 in columns (1), (2), and (4) and in 2004 in columns (3) and (5). See Section 1.3 for sample selection details. The null of the J-test is that the instruments are valid (i.e., a p-value of 0.1 indicates a failure to reject the null at the 10% level). Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

in revolving credit among parents, the earnings of their children increase by 0.37%. We again fail to reject the null that the instruments are valid at any significance level below 69%.

Despite the use of very different sources of variation, all three instruments and samples point to a significant positive effect of parental credit access on children's future earnings. Moreover, our reliance on multiple instruments allows us to conduct – and show that our instruments pass – over-identification tests. Our next sections explore heterogeneity across subgroups and potential mechanisms underlying our results.

1.6 Heterogeneity

We measure the heterogeneous response of child earnings to parental credit access by interacting all variables in equations (2) and (3) with a set of categorical dummy variables. The categorical dummies $D_{i \in k}$ equal one when individual i is in group k, partitioning our sample into $K > 1$ groups. We estimate specifications of the form,

$$\log(Y_i) = \sum_{k \in K} D_{i \in k} \Big\{ \alpha_k + \beta_k \log(Y_i^P) + \eta_k \log(C_i) + \Gamma_k X_i \Big\} + \epsilon_i \tag{4}$$

where the coefficients $\{\eta_k\}_{k=1}^K$ denote the impact of parental credit access for children in group $k \in K$. This specification is equivalent to estimating K separate regressions with K specific slopes and intercepts. We estimate equation (4) among our main sample and instrument the unused revolving credit limit with the age of oldest credit account. We examine heterogeneity by the age of children in 2014, their parent's education status (college/non-college) and the children's education status (college/non-college). Figure 1 summarizes the results by presenting the coefficients η_k from estimating equation (4) across the different partitions of the data.[19]

We first partition our sample by the child's age and split our sample into (1) children between the ages of 25 and 27 in 2014, and (2) children between the ages of 28 and 30 in 2014. The blue bars in Figure 1 present the coefficient estimates for the impact of unused revolving credit on children's earnings. The figure shows that for children between the ages of 25 and 27, an increase in their parent's unused revolving credit limit of 10% is associated with 0.27% greater earnings. Conversely, for children between the age of 28 and 30, this increase in parental credit access is associated with 0.32% greater earnings.[20] Thus, we find that greater access to credit among parents leads to *persistently* higher earnings among their children in the labor market. This result, that greater credit access among parents leads to persistently higher earnings among their children, will help to inform our discussion on the mechanisms that drive this result and be used to discipline our quantitative model.

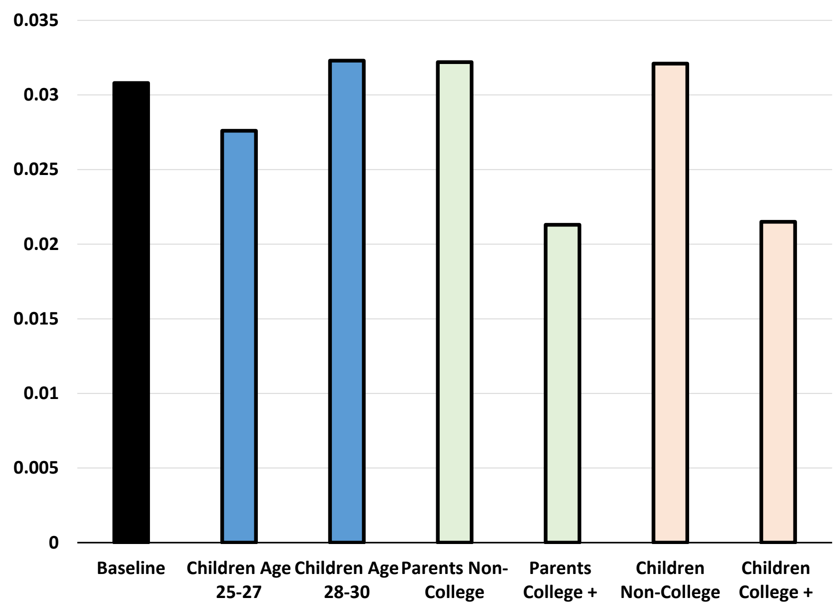
We next partition our sample by the education level of parents and split our sample into (1) the children of non-college educated parents, and (2) the children of college educated parents. The green bars in Figure 1 present the coefficient estimates on the log of unused revolving credit for these two groups. The figure shows that the impact of additional credit access of parents on their children's earnings is greater for the children of non-college educated parents. In particular, we find an additional 10% of unused revolving credit limits among non-college educated parents increases their children's earnings by 0.32% while for the children of college educated parents the increase is 0.21%.

Finally, we partition our sample by the education level of children and split our sample into (1) children who attend college, and (2) children who do not attend college. The tan bars in Figure 1 present the coefficient estimates on the log of unused revolving credit for these

[19] The tables containing the regression results presented in Figure 1 are in Appendix A.5.

[20] In Appendix A.5 we show that these two coefficients are not statistically different from one another (p-value = 0.127).

Figure 1: Heterogeneity in Impact of Parental Credit Access on Earnings



Note: This figure shows the coefficient estimate on the impact of parental credit access from estimating equation (2) (black bar) and equation (4) (blue, green, and tan bars). Across all cases, the instrumental variable is the age of the oldest account. The blue bar report the results where the sample is split by the child's age, the green bars when the sample is split by the parents level of education and the tan bars when the sample is split by the child's education.

two groups. Similar to the results by parent's level of education, the figure shows that greater access to credit has a larger impact on the earnings of children who do not go to college. Our estimates show that an additional 10% of unused revolving credit limits among parents increases the earnings of non-college children by 0.32% while the increase is 0.22% for college-educated children.

The results of this section show that greater credit access among parents increases the earnings of their children regardless of the parent's education level and the child's education level, and we find that the effects are persistent. We next examine the mechanisms through which greater access to credit among parents increases the earnings of their children.

1.7 Mechanisms

In this section, we examine a series of mechanisms through which credit access impacts the earnings of children. To examine the mechanisms through which greater access to credit among parents increases the earnings of their children, we estimate equation (2) for a series of dependent variables including an indicator of college graduation, quarters spent non-employed (which we refer to as unemployment), and average firm wages. In all specifications, we instrument the log of unused revolving credit limits with the age of oldest credit account.

We first examine how the credit access of parents impacts the likelihood that a child graduates from college. In column (1) of Table 4, we present the results of estimating equation (2) when the dependent variable is a dummy variable for the child having graduated college.[21] The positive and statistically significant coefficient on the log of unused revolving credit indicates that the children of parents with greater access to credit are more likely to graduate from college. A 10% increase in unused revolving credit increases the likelihood of college graduation by 0.1 percentage points. Compared to the coefficient on parental earnings, revolving credit is 3 times less impactful on the college graduation rate. To the extent that there is a college wage premium, increasing the likelihood of college graduation will contribute to higher earnings among the children with greater credit access. However, as we showed in Section 1.6, parental credit access increases earnings within education groups (i.e., for both non-college graduates and college graduates). For this reason, we next explore a series of labor market mechanisms.

The results presented in Section 1.5 were for annual earnings which includes both an intensive margin (earnings conditional on employment) and an extensive margin (quarters employed). We parse these two components of earnings in columns (2) and (3) of Table 4, respectively. We compute earnings conditional on employment by taking the average of earnings in all quarters in which an individual earns more than \$2.5k (corresponding to one-quarter of our annual minimum cutoff). Column (2) shows that a 10% increase in unused credit among parents implies 0.29% greater earnings conditional on employment. With some abuse of terminology, one can interpret this result as credit access positively influencing the "wage" of children. We next compute an indicator for whether an individual earns less than \$2.5k in at least one quarter between 2013 and 2014. Column (3) shows that a 10% increase in unused credit among parents implies a 0.1% lower probability of experiencing one or more quarters of unemployment. Our results suggest that greater parental credit access is not primarily used to finance longer job searches.

Finally, we examine the characteristics of the children's firms. A number of studies have documented the growing importance of firms in Mincer regressions (e.g., Card et al. (2018) and Song et al. (2019) among others). In column (4) of Table 4 we present the results of estimating equation (2) when the dependent variable is the average quarterly earnings of the child's pri-

[21]Our education metric is based on the Individual Characteristic File (ICF) in the LEHD. The ICF imputes a majority of education outcomes but obtains high quality education data from the Decennial long form and the American Community Survey.

Table 4: Parental Credit Access and Children's Earnings: Mechanisms

	(1) $\mathbb{1}$(College)	(2) Earnings (Cond'l on Employment)	(3) $\mathbb{1}$(Unemployed)	(4) Log Firm. Avg. Earn
Log Unused Revolving Credit	0.0105***	0.0285***	-0.00987***	0.0135***
	(0.00126)	(0.00148)	(0.00144)	(0.00194)
Log Parents Earnings	0.0335***	0.108***	0.00482	0.120***
	(0.00294)	(0.00344)	(0.00330)	(0.00449)
R-squared	0.008	0.112	0.061	0.053
Observations	166000	166000	166000	166000
Controls	Y	Y	Y	Y
Fixed Effects	N	N	N	N
Sample	Main	Main	Main	Main

*Notes: The table shows regression results from the IV estimation of equation (2). In all specifications the log of unused revolving credit is instrumented with the age of oldest account. Earnings are measured in 2008 dollars. Children's earnings are measured in the years 2013-2014 when children are between the ages of 25 and 30 (in 2014). Parents earnings are measured in 2000-2002, and unused revolving credit limits are measured in 2001 and 2002. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

mary firm.[22] The positive and statistically significant coefficient on the log of unused revolving credit indicates that greater parental credit access is associated with children working at higher paying firms. We find that a 10% increase in unused revolving credit is associated a 0.14% increase in firm pay.

Summary of empirical findings. Our empirical results yield significant effects of credit access on earnings for both parents and children, with and without college degrees. Greater credit access is associated with workers finding higher paying jobs at higher paying firms while spending less time unemployed. In the next section, we show that many of our empirical results are rationalized by parents investing more in their children's human capital when financial constraints slacken. We use the model to interpret our findings and better understand the selection and composition effects of our empirical estimators, and then we use the theory to isolate the effects of the democratization of credit on intergenerational mobility in the United States.

[22]We define the primary firm as the firm at which a child earns the greatest share of their earnings in a given year.

2 Quantitative Model

To interpret our empirical results and measure the effects of the democratization of credit on income mobility, we develop an overlapping generations model in which parents rely on defaultable debt to finance investments in their children's human capital. Our model incorporates individual specific borrowing costs (e.g. Chatterjee et al. (2007) and Livshits et al. (2007)) into a model of dynastic households (e.g., Becker and Tomes (1986)). Both parents and children face uncertainty over future income and the efficacy of human capital investments. Since markets are incomplete with respect to income risk, indebted households default in equilibrium to smooth consumption. Parent-specific interest rates reflect default risk, and the punishment for default involves persistently more expensive costs of accessing credit.

We additionally impose income-specific credit limits, which can be tighter than those implied by the one-period defaultable debt contracts, in order to capture observed borrowing capacity. Therefore, parents face a tradeoff between investing early in childhood when human capital investments are more productive (dynamic complimentary, e.g., Cunha and Heckman (2007)) and maintaining borrowing capacity to smooth subsequent income risk. In what follows, we provide more details on our model economy and define an equilibrium.

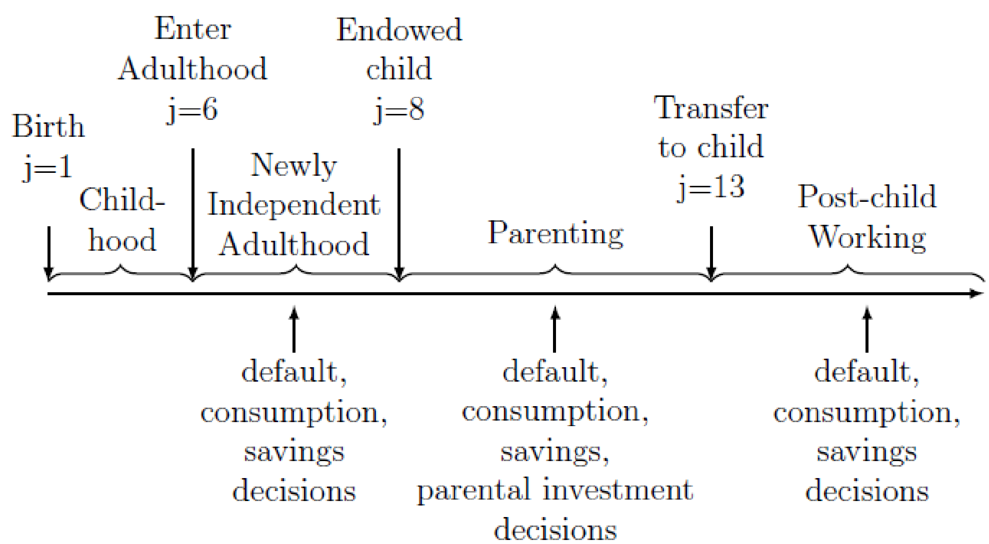
2.1 Model Overview

Demographics. Households are dynastic and each generation's lifecycle last $T = 16$ periods, divided among four stages: childhood, newly independent adulthood, parenting, and post-child working stage. Let $j \in \{1, 2, .., T\}$ denote model age. Each period in the model corresponds to four years (i.e. $j = 1$ corresponds to age $0 - 3$, $j = 2$ corresponds to age $4 - 7$, etc.). Individuals are heterogeneous in their age j, human capital h, and asset position b. Figure 2 illustrates the life cycle of an individual. From $j = 1$ to $j = 5$, the child lives with her parents and does not make any choices. In period $j = 6$ individuals enter adulthood where they make their own decisions, given a level of skills and assets determined by her parent's decisions during the parenting stage. Newly independent adults ($j = 6, 7$) work in the labor market, make a default decision, and a consumption/savings decision in the Bewley-Huggett-Aiyagari tradition.

At $j = 8$, individuals become parents and have one child of their own.[23] In the parenting stage, parents decide how much to invest, i, in their child's human capital, h^c, in addition to their default and consumption/savings decisions. Parents are responsible for the child for five periods ($j = 8, 9, 10, 11, 12$) and then make a monetary transfer to the child immediately

[23] Note that Daruich (2018) and Caucutt and Lochner (2020) rely on the same fertility process, among others.

Figure 2: Life-cycle stages



before the child becomes a newly independent adult. Finally, parents work for an additional four periods ($j = 13, 14, 15, 16$) in the post-child working stage before retirement. During these periods parents simply makes a default decision and a consumption/savings decision. Figure 2 presents a timeline of the model stages that individuals experience during the model.

Credit Market. Individuals have the ability to default on outstanding debt obligations. When an individual defaults: (1) their assets are set to zero, (2) they incur a utility penalty of default $\psi(b) \geq 0$, where the utility penalty of defaulting is an increasing function of assets defaulted upon as in Braxton et al. (2020), and (3) a flag is placed upon their credit report, which subjects them to tighter borrowing limits. We refer to individuals without a flag on their credit report to be in “good credit standing" and individuals with a flag on their report to be in “bad credit standing." We let $k \in \{C, N\}$ denote an individual’s credit standing, where $k = C$ ($k = N$) denotes being in good (bad) credit standing. Flags are removed from an individual’s credit report stochastically such that the probability of flag removal corresponds to the ten year duration of bankruptcy flags in the U.S.

The ability to default on outstanding debt causes debt to be priced individually as in Eaton and Gersovitz (1981). In particular, individuals can save in a one period risk-free bond. The interest rate on positive savings is the risk-free rate (r_f) however the interest rate on borrowing depends on the probability of default, which differs by individual. The bond price on debt follows Eaton and Gersovitz (1981) according to

$$q(\cdot) = \frac{\mathbb{E}\left[1 - D(\cdot)\right]}{1 + r_f + \tau_b} \tag{5}$$

where D is the probability of default, r_f is the risk-free rate, and τ_b is the transaction cost on making a loan. $q(\cdot)$ is a function of the amount borrowed, b', and the individual's states. Likewise, the default decision next period $D(\cdot)$ depends on the evolution of those states. The states of an individual – and thus the states that enter their bond pricing function – change over their lifecycle, which we detail in Section 2.2.

The bond pricing function $q(\cdot)$ defines an implicit borrowing limit (e.g., the point where $q(\cdot)$ is zero). As we discuss in the calibration section, the implicit borrowing limits are often counterfactual relative to the observed levels and ranking (across income) of borrowing limits observed in the data. Therefore, we impose an additional income-specific borrowing limit, $b' \geq \underline{b}_K(w(h))$, where $\underline{b}_K(\cdot)$ is a flexible function of income. As we discuss in more detail in the calibration section, $\underline{b}_K(w(h))$ is a function of an individuals credit standing $k \in \{C, N\}$. This allows for for individuals with a flag on their credit report to still borrow, albeit with a tighter borrowing limit.

Finally, as in Livshits et al. (2007) and Chatterjee et al. (2007) we assume that households are subjected to expense shocks, which decrease the assets of households exogenously. These shocks are a reduced from way of modeling other life-events that are known to be associated with bankruptcy, e.g., medical bills (see Sullivan et al. (1999)). Expense shocks occur with probability p_x and lower the asset position of the household by x.

Wages and human capital. The labor market is simple here so that we can focus on the role of credit markets in intergenerational mobility. We assume wages are a deterministic function of human capital,

$$w(h) = \exp(h), \tag{6}$$

Human capital during adulthood, h, is governed by the following law of motion:

$$h^{'} = \rho_h h + \eta, \tag{7}$$

where η is a normally distributed shock to human capital, $\eta \sim N(\mu_\eta, \sigma_\eta^2)$.

Children's human capital, h_c, evolves based on parental investment, i, as well as public investment d,

$$h^{c'} = (1-\omega_c)h^c + \omega_c \log\left(\frac{i+d}{\zeta_c}\right), \tag{8}$$

where ζ_c is the human capital anchor (e.g., Lee and Seshadri (2019)).[24] The child skill technology features dynamic complementarities where prior investments in children's human capital make current investments more productive (e.g., Cunha and Heckman (2007)).

Preferences Individuals are risk averse, altruistic, and discount the future by $\beta \in [0,1]$. Parents value consumption, c, according to the utility function $u(c)$, and they value the utility of their children in adulthood according to parameter θ.[25]

2.2 Value functions

In this section, we present value functions over the life-cycle of an individual. We begin the exposition at the stage when children leave their parents.

2.2.1 Newly Independent Adulthood Stage ($j = 6, 7$)

New adults in good credit standing. Let $V_j^C(b,h)$ denote the value function for an age j newly independent adult in good credit standing, who has assets b and human capital h. In the current period, the newly independent adult makes a consumption/savings decision. At the start of the next period (when the individual is age $j+1$), shocks to human capital are revealed, and then expense shocks are realized and the individual makes their default decision. If the individual chooses to repay, then they remain in good credit standing. If the individual defaults, they incur a utility penalty $\psi(b) \geq 0$, their assets are set to zero, and a flag is placed upon their credit report. Additionally, when the individual is age $j = 7$, the individual takes into account that in the next stage they will become a parent and take expectations over the value of becoming a parent.

The decision problem for an age $j \in \{6, 7\}$ newly independent adult in good credit standing

[24]Note the human capital process in 8 follows from Lee and Seshadri (2019), who find that the production function is a Cobb-Douglas in investment and current human capital. To align with the wage equation (equation 6) we have taken logs of their Cobb-Douglas production function.

[25]Note that parent's normalize the value of consumption to take into account changes in household size using the OECD consumption equivalents.

with assets b, and human capital h is given by,

$$V_6^C(b,h) = \max_{b'} u(c) + \beta \mathbb{E}\left[\widehat{V}_7^C(b',h')\right]$$
$$V_7^C(b,h) = \max_{b'} u(c) + \beta \mathbb{E}\left[\widehat{V}_8^C(b',h',h^{c'})\right],$$

where default decisions are made after the realization of the expense shock,

$$\widehat{V}_7^C(b,h) = p_x \max\{V_7^C(b-x,h); V_7^N(0,h) - \psi(b)\} + (1-p_x)\max\{V_7^C(b,h); V_7^N(0,h) - \psi(b)\}$$
$$\widehat{V}_8^C(b,h,h^c) = p_x \max\{V_8^C(b-x,h,h^c); V_8^N(0,h,h^c) - \psi(b)\} + (1-p_x)\max\{V_8^C(b,h,h^c); V_8^N(0,h,h^c) - \psi(b)\},$$

subject to a budget constraint,

$$c + q_{j,C}(b',h)b' \leq w(h) + b,$$

and borrowing limit,

$$b' \geq \underline{b}_C(w(h)),$$

where $q_{j,C}(b',h)$ is the bond price on debt, which is determined by equation (5).

Finally, note that parents form expectations about the initial draw of their children's human capital. We assume that a child's initial human capital at birth is correlated to their parent's human capital according to,

$$h^c = \rho_c h + \eta_c, \tag{9}$$

where ρ_c governs the persistence of human capital across generations and $\eta_c \sim N(0, \sigma^2_{\eta,c})$ governs the dispersion.

New adults in bad credit standing. Let $V_j^N(b,h)$ denote the value function for an age j adult in bad credit standing (i.e., with a flag on their credit report), who has assets b and human capital h. In the current period, the new adult makes a consumption/savings decision subject to the borrowing limit for individuals with a flag on their credit report. At the start of the next period (when the individual is age $j+1$), shocks to human capital are revealed, and the individual then learns whether or not the flag on their credit report will be removed. With probability p the flag on their credit report is removed, and with probability $1-p$ the flag on their credit report remains. The value function for a newly independent adult in bad credit standing is given by,

$$V_6^N(b,h) = \max_{b'} u(c) + \beta \mathbb{E}\left[p\widehat{V}_7^C(b',h') + (1-p)\widehat{V}_7^N(b',h')\}\right]$$
$$V_7^N(b,h) = \max_{b'} u(c) + \beta \mathbb{E}\left[p\widehat{V}_8^C(b',h',h^{c'}) + (1-p)\widehat{V}_8^N(b',h',h^{c'})\}\right]$$

where default decisions are made after the realization of the expense shock,

$$\widehat{V}_7^N(b,h) = p_x \max\{V_7^N(b-x,h); V_7^N(0,h) - \psi(b)\} + (1-p_x)\max\{V_7^N(b,h); V_7^N(0,h) - \psi(b)\}$$
$$\widehat{V}_8^N(b,h,h^c) = p_x \max\{V_8^N(b-x,h,h^c); V_8^N(0,h,h^c) - \psi(b)\} + (1-p_x)\max\{V_8^N(b,h,h^c); V_8^N(0,h,h^c) - \psi(b)\},$$

subject to a budget constraint:

$$c + q_{j,N}(b',h)b' \leq w(h) + b$$

and borrowing limit,

$$b' \geq \underline{b}_N(w(h)),$$

where wages evolve as in equation (6), human capital evolves as in (7), and the child's draw of initial human capital is governed by (9). We next present the continuation values for parents with children at home.

2.2.2 Parenting Stage ($j = 8, 9, 10, 11, 12$)

Let $V_j^C(b,h,h^c)$ denote the value function for an age j parent in good credit standing, with assets b, human capital h, and whose child has human capital h^c.[26] In the current period, each parent makes a consumption/savings decision, as well as a decision for how much to invest in their child's human capital. Investing in the child's human capital (i) increases the child's human capital and subsequently affects their earnings.[27]

At the start of the next period (when the parent is age $j+1$), shocks to human capital, as well as expense shocks, are revealed to the parent, and the parent makes their default decision. If the parent chooses to repay, then the parent continues on as an individual in good credit

[26] Note that because of the life-cycle structure of the model, we only need to keep track of the age of the parent.

[27] Parental investments are modeled as a goods investment in children's human capital. Extending this to a framework in which parents invest both goods and time does not change the main tradeoff of this model where parents tradeoff between investing more early in childhood and maintaining access to credit markets. Note that when the child reaches adulthood, human capital is subject to shocks and thus parental investments reflects this uncertainty.

standing and the period repeats. If the parent defaults, they incur a utility penalty $\psi(b) \geq 0$, their assets are set to zero, and a flag is placed upon their credit report. The decision problem for an age $j \in \{8, 9, 10, 11, 12\}$ parent in good credit standing with assets b, human capital h, and a child with human capital h^c is given by,

$$V_j^C(b, h, h^c) = \max_{b', i \geq 0} u(c) + \beta \mathbb{E}\left[\widehat{V}_{j+1}^C(b', h', h^{c'})\right] \tag{10}$$

where the default decision is given by,

$$\begin{aligned}\widehat{V}_j^C(b, h, h^c) = p_x \max\{V_j^C(b - x, h, h^c); V_j^N(0, h, h^c) - \psi(b)\} \\ + (1 - p_x) \max\{V_j^C(b, h, h^c); V_j^N(0, h, h^c) - \psi(b)\}\end{aligned}$$

subject to a budget constraint,

$$c + q_{j,C}(b', i, h, h^c)b' + i \leq w(h) + b,$$

and borrowing limit,

$$b' \geq \underline{b}_C(w(h)),$$

where $q_{j,C}(b', i, h, h^c)$ is the bond price on debt, which takes into account the investment decision of parents and the child's human capital since these are inputs into the parents default decision. The wage process for adults is governed by equation (6), the parent's human capital is governed by the law of motion in (7), and the child's human capital is governed by the law of motion in equation (8). Parents in bad credit standing face a similar problem except they are subjected to the borrowing limit for individuals with a flag on their credit report and in future periods have the credit flag removed with probability p. We present the value function for parents in bad credit standing in Appendix B.1. We next discuss the value functions for agents after their children leave the home.

2.2.3 Post Child Working Stage ($j = 13, 14, 15, 16$)

Individuals begin their post child working stage ($j = 13$) by making a one-time transfer $\tau \geq 0$ to their child when making their consumption savings decision. The transfer to the child (τ) governs the amount of assets with which the child begins their newly independent adult stage. The parent receives utility from this transfer to the child, which is governed by an altruism parameter θ. At the start of the next period, shocks to human capital as well as expense shocks are realized and the parent decides whether or not to default:

$$
\begin{aligned}
V_{13}^{C}(b,h,h^{c}) &= \max_{b',\tau\geq 0} u(c)+\theta V_{6}^{C}(\tau,h^{c})+\beta\mathbb{E}[\widehat{V}_{14}^{C}(b',h')],\\
V_{j}^{C}(b,h) &= \max_{b'} u(c)+\beta\mathbb{E}[\widehat{V}_{j+1}^{C}(b',h')] \ \text{ for } j=14,15,16,\\
V_{j}^{C}(b,h) &= 0 \ \ \forall j>16,
\end{aligned}
$$

where the default decision is given by,

$$
\begin{aligned}
\widehat{V}_{j}^{C}(b,h) = {} & p_x \max\{V_{j}^{C}(b-x,h); V_{j}^{N}(0,h)-\psi(b)\}\\
& +(1-p_x)\max\{V_{j}^{C}(b,h); V_{j}^{N}(0,h)-\psi(b)\} \quad j=14,15,16
\end{aligned}
$$

subject to the budget constraint,

$$
\begin{aligned}
c+\tau+q_{j,C}(b',h)b' &= w(h)+b \ \text{ for } j=13,\\
c+q_{j,C}(b',h)b' &= w(h)+b \ \text{ for } j=14,15,16,
\end{aligned}
$$

the borrowing limit,

$$
b' \geq \underline{b}_{C}(w(h)),
$$

the wage equation (equation (6)), and the law of motion for the parent's human capital (equation (7)). Individuals in bad credit standing face a similar problem except they are subjected to the borrowing limit for individuals with a flag on their credit report and in future periods have the credit flag removed with probability p. We present the value function for post-child working parents B.1. We next define equilibrium for the model economy.

2.3 Equilibrium

A recursive competitive equilibrium consists of (1) a sequence of prices $\{(q_{j,k}(b',h)\}_{j\in\{6,7,13,\ldots,16\},k\in\{C,N\}}$, $\{q_{j,k}(b^{'},i,h,h^{c})\}_{j\in\{8,\ldots,12\},k\in\{C,N\}}$, and $\{w(h)\}$, (2) policy functions for consumption c, savings/borrowing (b), default (D) and investments in children's human capital (i), and (3) a stationary distribution of individuals over states $\Omega : \{C,N\}\times j\times b\times h\times h^{c}\to[0,1]$ such that

1. Given prices $\{(q_{j}(b',h)\}_{j\in\{6,7,13,\ldots,16\}}$, $\{q_{j}(b^{'},i,h,h^{c})\}_{j\in\{8,\ldots,12\}}$,and$\{w(h)\}_{\forall j\geq 6}$, household policy functions are optimal;

2. Lenders earn zero profits (i.e., debt is priced as in (5));

3. Ω is consistent with household policy functions.

3 Calibration

In this section we discuss the calibration of the model. We calibrate the model using a series of aggregate credit and labor market statistics.

Where possible we calibrate our model using data from the 2001-2004 waves of the Survey of Consumer Finances (SCF). These waves of the SCF align with the measurement of credit variables among parents in Section 1.1.

Demographics and Preferences. Each model periods corresponds to 4-years. Preferences over non-durable consumption are given by

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}$$

We set the risk aversion parameter to a standard value, $\sigma = 2$. When agents are parents we normalize consumption by the size of the household using the OECD consumption equivalent scale of 1.5. We calibrate the discount factor β to match the ratio of aggregate credit to earnings, which in the SCF we measure to be 2.6%.[28]

Credit markets. Given the 4-year timing of the model, we set the probability of credit market re-entry to be 2/3 to correspond with the 10 year nature of bankruptcy flags. Similarly, given the 4-year timing of the model, we set the risk-free rate to 17%.[29] The utility penalty of default is assumed to be linear in the amount of assets defaulted upon:

$$\psi(b) = -b \cdot \psi_D.$$

We set the default penalty ψ_D to match the aggregate bankruptcy rate. Using data from the American Bankruptcy Institute (ABI) on all non-business bankruptcies we measure that 0.83% of individuals between the ages of 16 and 65 filed for bankruptcy each year between 2001 and 2004. Given the four-year timing of the model, we target a 3.3% bankruptcy rate.

We assume that borrowing limits are a linear function of earnings, i.e., $\underline{b}_k = \alpha_k + \delta_k \times w(h)$. We refer to δ_k as the slope of the borrowing constraint. We estimate the slope of the borrowing

[28] To measure the aggregate credit to earnings ratio we take the (weighted) sum of all credit card balances and divide the (weighted) sum of earnings.

[29] This corresponds to an annual risk-free rate of 4%.

constraint for agents in good credit standing (δ_C) using data from the SCF. Let $\underline{b}_i$ the borrowing limit for an individual i, and let $y_{i,}$ be their earnings. We estimate the parameter δ_C by running the following cross-sectional regression,[30]

$$\underline{b}_i = \alpha + \delta_C y_i + \epsilon_i$$

We estimate a slope parameter $\hat{\delta}_C = 0.204$, which suggest that for each additional dollar of income an individual's limit increases by approximately 20 cents. To calibrate α_C, we target the average ratio of limits to income, which we measure to be 25.5% in the SCF. Finally, we discuss how we discipline the parameters for agent's in bad credit standing. In the SCF, we measure that the ratio of average limits for individuals with a bankruptcy in the past 12 months relative to limits for individuals without a bankruptcy in the past 12 months is equal to 0.199. We thus set $\alpha_N = 0.199 \times \alpha_C$ and $\delta_N = 0.199 \times \delta_C$.

As in Livshits et al. (2007) and Chatterjee et al. (2007) we assume that households are subjected to expense shocks, which decrease the assets of households exogenously. We calibrate the frequency of expense shocks to match the share of individuals who switch from positive to negative net worth as measured in the 2007-2009 SCF Panel.[31] We estimate that 7.7% of individuals switch from being a saver to borrower between this window. We calibrate the size of the expense shock x to match the chargeoff rate. The Federal Reserve Board reports that the chargeoff rate for credit cards was 5.65% between 2001 and 2004.

Income process. We discipline the income process using data from the 2001 and 2004 waves of the SCF. As in Storesletten, Telmer, and Yaron (2004) we set the income process to be a unit root, i.e., $\rho_h = 1$. Following Storesletten et al. (2004), we estimate the standard deviation of shocks to human capital (σ_η) using the variance of log earnings over the life-cycle. In the SCF, we measure the variance of log earnings among individuals aged 52-55 (model age $t = 14$) to be 0.972. To calibrate the mean of the shock to human capital (μ_η), we calibrate the model to match the change in average log earnings between ages 24-27 (model age $t = 7$) and age 52-54 (model age $= 14$), which we measure to be 1.086 log points in the SCF.

[30]We estimate this regression using individuals in the SCF between the ages of 20 and 63 to align with the age structure of the model. Additionally to remove the impact of extreme earnings observations we winsorize the limits and earnings for the top 5% of individuals. Note we include individuals with zero limits to incorporate the extensive margin.

[31]This moment requires multiple net worth observations, which precludes us from using the other SCF waves.

Children's human capital. Children draw their initial human capital following the process in equation (9). We calibrate the persistence parameter ρ_c to match estimates of the intergenerational earnings elasticity (IGE). In Section 1.1, we estimated an IGE of 0.158. We calibrate the dispersion parameter ($\sigma_{\eta,c}$) to match the variance of log earnings among young workers, which we measure using data from the SCF. We measure the variance of log earnings among individuals between the age of 24 and 27 (model age $t = 7$) to be 0.475 log points.

We calibrate the human capital investment parameter ω_c to match our estimate of the credit coefficient in the OLS regression in equation 1. In Section 1.1, we estimated this coefficients to be 0.018. We calibrate the investment anchor (ζ_c) on the relationship between parental income and monetary investment in their children's human capital. Let I_i denote the investment in the human capital of child i and let y_i denote the income of their parents. We estimate an investment elasticity using a regression of the form,

$$\log I_i = \alpha + \beta_I \log(y_i) + \epsilon_i$$

As in Daruich (2018), we calibrate our model to match an estimate of the investment elasticity (β_I) equal to 0.39. Finally, we calibrate the value of public investments in children's human capital d to match the ratio of public investment to mean earnings in the economy. Based upon the estimates Lee and Seshadri (2019) we calibrate d to match a target of public investments being equal to 7% of mean earnings.

Transfers. Finally, we discuss the calibration of the altruism parameter θ. Higher values of the altruism parameter are associated with larger transfers to children, which increases their net worth. We calibrate the altruism parameter θ to match the ratio of net worth to earnings among young individuals (age 24-27). In the SCF we measure this ratio to be 2.33.

Table 5 contains a summary of the model parameters, and Table 6 displays the calibrated parameters and their calibration targets. The estimated model matches the targeted moments well. We discuss non-targeted moments in the next section.

3.1 Non-Targeted Moments

In this section, we provide a model validation by examining moments from the distribution of unused credit using model simulated data. Our empirical results showed greater unused credit of parents was associated with higher earnings for their children. Thus, for our model

Table 5: Model Parameters

Variable	Value	Description
		Non-calibrated
Variable	Value	Description
r_f	4%	Annual risk free rate
ρ_H	1	Persistence of human capital (adult)
σ	2	Risk-aversion
δ_C	-0.204	Slope of borrowing constraint, good credit standing
δ_N	-0.041	Slope of borrowing constraint, bad credit standing
δ_N	-0.024	Intercept of borrowing constraint, bad credit standing
		Jointly-calibrated
Variable	Value	Description
ψ_D	5.821	Default penalty
β	0.722	Discount factor
d	0.080	Public investment
ζ_c	0.663	Human capital anchor
ω_c	0.096	Childhood investment elasticity
ρ_c	0.267	Persistence of parental human capital
$\sigma_{\eta,c}$	0.154	Std. dev., initial draw of human capital
θ	0.481	Parental altruism
p_x	0.011	Probability of expense shock
x	1.039	Size of expense shock
σ_η	0.354	Std. dev., shocks to human capital
μ_η	0.093	Mean, shocks to human capital
α_C	-0.120	Intercept of borrowing constraint, good credit standing

Table 6: Model calibration

Variable	Value	Target	Model	Data	Source
ψ_D	5.821	Bankruptcy Rate	2.758	3.319	ABI 2001-2004
β	0.722	Agg. credit to earnings	0.054	0.026	SCF 2001-2004
d	0.080	Public inv. to earnings	0.050	0.070	Lee & Seshadri (2019)
ζ_c	0.663	Investment elasticity	0.274	0.390	Dariuch (2018)
ω_c	0.096	Credit IGE	0.009	0.018	TU-LEHD-Dec
ρ_c	0.267	IGE	0.235	0.158	TU-LEHD-Dec
$\sigma_{\eta,c}$	0.154	Variance log earn, age 24-27	0.212	0.475	SCF 2001-2004
θ	0.481	Agg. assets to earnings, age 24-27	1.478	2.328	SCF 2001-2004
p_x	0.011	Share switching pos. to neg. net worth	0.100	0.078	SCF 2007-2009
x	1.039	Chargeoff rate	6.566	5.651	FRB 2001-2004
σ_η	0.354	Variance log earn, age 52-55	1.108	0.973	SCF 2001-2004
μ_η	0.093	Chg. mean log earn, age 24-27 to 52-55	0.658	1.086	SCF 2001-2004
α	-0.120	Avg. credit limits to earnings	0.268	0.255	SCF 2001-2004

Notes: Individuals aged 24-27 in the data correspond to age $t = 7$ in the model. Individuals aged 52-55 in the data correspond to age $t = 14$ in the model.

to accurately measure the impact of credit markets on mobility and inequality is critical that we have a reasonable distribution of unused credit. Table 7 compares moments of the unused credit to income distribution for the model (column (1)) and the data (column (2)). In Section 1.2, we showed that nearly 40% of parents have unused credit less than 10% of earnings, and over 50% have unused credit less than 25% of earnings. In our calibrated model, households have similar amounts of unused credit. In particular, in our model 26.2% of households have unused credit less than 10% of income, while nearly 46% of households have unused credit less than 25% of income. We view these estimates as suggesting that the distribution of unused credit in our calibrated model closely resembles the data. Using our calibrated model we next examine how changes in the credit market shape intergenerational mobility and inequality.

Table 7: Model validation

	(1) Model	(2) Data
Unused credit to income $< 10\%$	0.262	0.390
Unused credit to income $< 25\%$	0.459	0.526

4 Credit Expansion, Mobility, and Inequality

Using the calibrated model, we quantitatively examine the implications on earnings mobility and inequality of the spread of consumer credit. We first discuss the changes in the consumer credit market in the U.S. since 1970 and then quantitatively examine the implications for inequality and mobility.

In our counterfactual experiment we model two changes in the expansion of credit access that have been documented in the previous literature. In this counterfactual experiment, we go “back in time" and adjust the credit market to be consistent with the early 1970s. First, we model that bankruptcy costs were higher in the 1970s (e.g., Livshits et al. (2010) and references therein). In particular, in the 1970s economy we increase the bankruptcy cost parameter (ψ_D) so that we match the difference in bankruptcies between the 1970s and early 2000s. In the historical data from ABI, bankruptcies increase by a factor of 6 between the early 1970s and the early 2000s. In our calibrated model this corresponds to increasing the bankruptcy cost by a factor of 8.75 in our 1970s economy.

Second, in our 1970s economy we tighten borrowing limits. We use the historical SCF files to measure how credit limits have evolved over time.[32] First, we examine how the relationship between credit limits and income have evolved over time and estimate that $\delta_C = -0.044$ in our 1970s economy. Next, we calibrate the intercept of the borrowing limit function to match the change in the size of aggregate credit limits to earnings between the 1970s and the early 2000s. We measure that from 1970 to the early 2000s aggregate credit limits to income increased by a factor of 8. To match this change, we set $\alpha_C = -0.012$ in our 1970s economy. As in the baseline model we scale the coefficients for individuals in bad credit standing (α_N, δ_N) by 0.199. Table 8 summarizes the parameters for the credit experiment and the data moments used to discipline the credit market experiment.

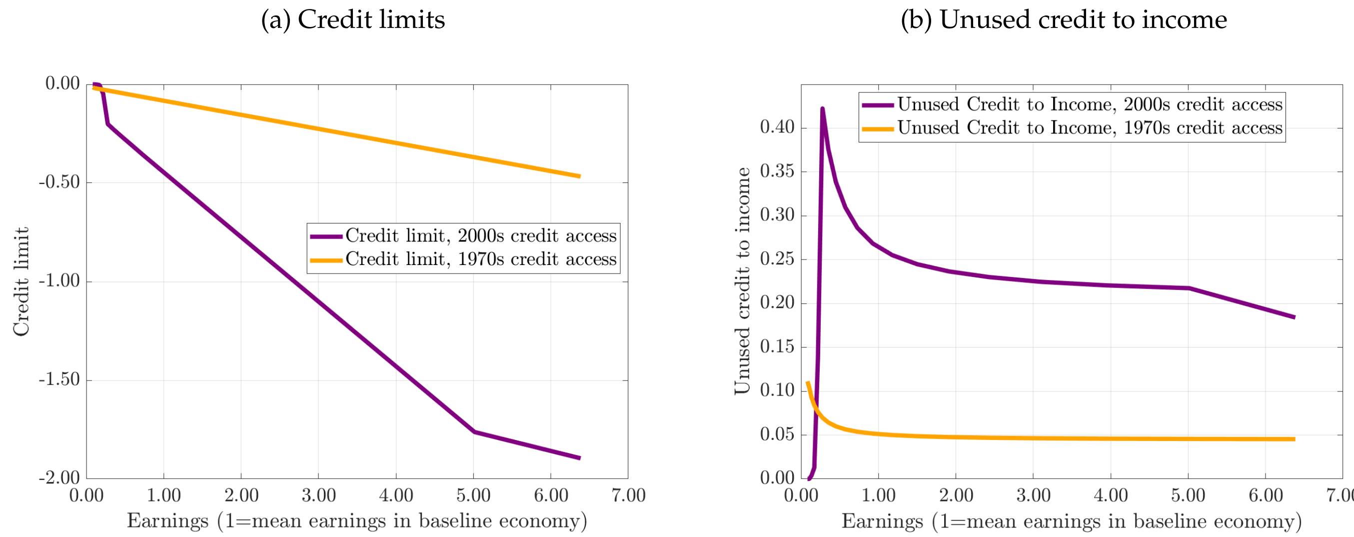
Table 8: Modeling credit markets over time

Panel (a): Parameters		
	(1) 2000s	(2) 1970s
ψ_D	5.821	50.93375
δ_C	-0.204	-0.044
α_C	-0.120	-0.012
Panel (b): Credit market predictions		
	(1) Bankruptcy rate (annual)	(2) Credit limits to agg. earnings
Data, 2001-2004	0.830	0.271
Data, 1970-1973	0.139	0.034
Ratio Data, 2000s/1970s	5.971	8.029
Ratio Model, 2000s/1970s	5.215	4.461

In Figure 3 we compare the credit limits and the unused credit limits to income in the two economies. In Panel (a) of Figure 3, we plot the average credit limits across the income distribution for the economy with the 2000s level of credit access (purple line) and the economy with the 1970s level of credit access (orange line). The figure shows that across the income distribution that limits increase substantially when we move from the 1970s economy to the 2000s economy. In Panel (b) of Figure 3, we show the ratio of unused credit to income across the two economies. In the 1970s economy, unused credit is between 5 and 10 percent of income for all households. Conversely, in the 2000s economy the average amount of unused credit is over 20% of income for nearly all households. These figures show that moving from the 1970s economy to the 2000s economy is associated with a substantial increase in credit access.

[32] See Appendix C for details.

Figure 3: Credit Access 1970s and 2000s Economy



Notes: Figure presents credit limits (Panel (a)) and unused credit limits to income (Panel (b)) for the 1970s economy (orange line) and 2000s economy (purple line). Credit limits and unused credit to income are plotted as a function of parental earnings (x-axis), where the x-axis is scaled so that the value of 1 corresponds to mean earnings in the baseline economy.

Comparing the two economies we can examine the impact of credit access on the evolution of mobility and inequality. We measure mobility using the intergenerational earnings elasticity (IGE). The first column of Table 9 shows that in our economy with the 2000s level of credit access the IGE is 0.235. When credit access is cut to its 1970s level, the IGE decreases by nearly 4 percent to 0.226. Going from the 1970s to the 2000s, an increase in the IGE indicates that the degree of economic mobility has decreased, i.e., parents earnings play a larger role in shaping the earnings of their children. Thus, these results indicate that the increase in credit access since the 1970s has decreased economic mobility.

Table 9: Credit and Inequality

	(1) 2000s	(2) 1970s
Intergenerational earnings elasticity (IGE)	0.235	0.226
Variance log earnings, 24-27 yr olds	0.212	0.209
Variance consumption	0.776	0.758

We next examine the impact of credit access on inequality. We first examine dispersion in earnings among young workers (those aged 24-27). We focus on young workers as recent research has shown that much of lifetime inequality is determined by initial conditions at labor market entry (e.g., Huggett et al. (2011), and Lee and Seshadri (2019)). The first column of Table

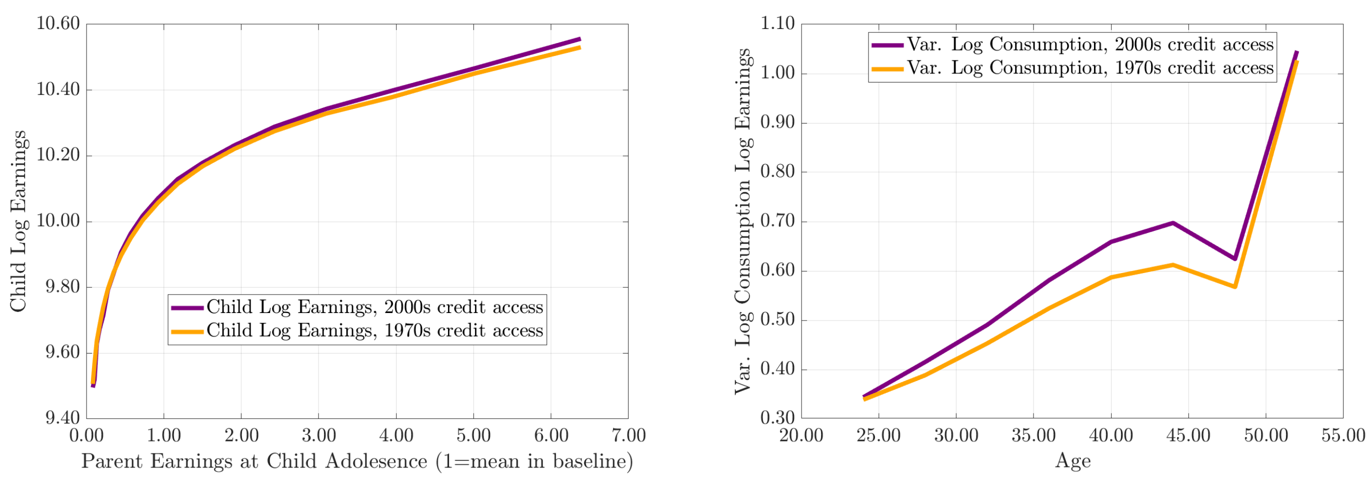
9 shows that that the variance of log earnings among young workers is 0.212 log points in our 2000s economy. When credit access is at its 1970s level, the variance of log earnings among the young is 0.209 log points, nearly 1.5% lower. Thus, the expansion of credit access between the 1970s and 2000s has increased earnings inequality among the young.

Given our empirical results that greater access to credit among parents increases earnings of their children, one might have expected that the expansion of credit would increase mobility and reduce inequality. However, Panel (a) of Figure 3 shows that the largest gains in credit access have occurred among high income families. Thus, it is among high income families that parents are able to smooth shocks via credit and still make investments in their children's human capital, while low income families face a tradeoff between smoothing consumption and investing in their children's human capital. Panel (a) of Figure 4 graphically illustrates that the expansion of credit between the 1970s and 2000s has increased mean (log) earnings for the children of high income families. For low income families there is very little change in mean (log) earnings across economies. Thus, the increase in inequality (and reduction in mobility) due to the expansion of credit markets has occurred due to the children of high income families pulling further away from the rest of the distribution.

Figure 4: Earnings and consumption inequality

(a) Child log earnings

(b) Consumption variance



Notes: Figure presents the variance of child earnings during young adulthood (24 to 27 years old) stratified by the human capital of their parents during the child's adolescence (12 to 15 years old).

We also measure inequality by looking at consumption inequality. In Table 9, we find that the expansion of credit markets between 1970 and 200 increased consumption inequality by nearly 2.5%. Further, the increase in consumption inequality occurs across the life-cycle. In Panel (b) of Figure 4 we plot the variance of log consumption between the ages of 24-27 and

54-57 (model ages 7 through 14). The figure shows that consumption inequality has increased for individuals of all ages.

The results presented in this section show that the democratization of credit between the 1970s and 2000s has increased mobility and decreased inequality. In particular, parent's earnings play a smaller role in shaping the earnings of their children. Further, we see observe that there is less dispersion among labor market entry and that for nearly the first twenty years of adulthood consumption inequality is lower.

5 Conclusion

In this paper, we examine the long-run labor market implications of parental credit constraints on their children's earnings and their children's intergenerational mobility. We then ask what the consequences of the democratization of credit on the patterns of intergenerational mobility.

To answer these questions, we use micro-data on parental borrowing capacity during their children's adolescence linked to their children's future labor market outcomes. We then develop a quantitative overlapping generations model where parents can invest in their children's human capital and finance this investment with credit.

Empirically, we use three different instrumental variables to show that greater parental credit access during their children's adolescence improves their children's earnings. We then provide evidence on the mechanisms that improve children's subsequent earnings. We show that increased credit access of the parents is associated with their children's greater college attendance, fewer unemployment spells, and a greater likelihood of working at higher-paying firms.

Theoretically, our model shows how parents can invest in their children's human capital and finance this investment using defaultable debt. We show that the calibrated model is consistent with our empirical evidence. In a counterfactual exercise, we find that the democratization of credit led to an increase in the intergenerational elasticity of earnings. Thus, we find that the expansion of credit markets have reduced intergenerational mobility. Further, we find that the expansion of credit markets have increased income and consumption inequality. Key to this result is that we find that credit markets have expanded the most for high income families, which allows them to smooth consumption and invest in their children's human capital, while lower income households continue to face a trade-off between those two options.

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A Additional Results

In this appendix we present a series of additional results.

A.1 OLS results with controls

In this appendix we present the results of estimating equation (1) via OLS and including a series of controls and fixed effects. Table 10 presents the results.

Table 10: Parental credit access and children's earnings: OLS with controls

	(1)	(2)	(3)
	––Dependent variable: log of children's earnings––		
Log Parents Earnings	0.130***	0.117***	0.128***
	(0.00266)	(0.00438)	(0.00736)
Log Unused Revolving Limit	0.0139***	0.0142***	0.0104***
	(0.000396)	(0.000734)	(0.000944)
R-squared	0.122	0.133	0.111
Observations	166000	108000	23000
Controls	Y	Y	Y
Fixed Effects	N	Y	N
Sample	Main	Mortgage	Derogatory

Notes: The table shows regression results from the estimation of equation (1) via OLS, where the dependent variable is the log of children's real earnings. No controls or fixed effects are included in these regressions. Earnings are measured in 2008 dollars. Children's earnings are measured in the years 2013-2014 when children are between the ages of 25 and 30 (in 2014). Parents earnings are measured in 2000-2002, and unused revolving credit limits are measured in 2001 and 2002. Controls include child age fixed effects, age of parent, number of children and parents in the household in 2000, gender fixed effects, and tenure. Fixed Effects (FE) include county and mortgage age. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

A.2 IV: First stage results

We first present the results from our first stage regressions (equation (3)) in Table 11. In column (1), we instrument the parent's log unused revolving credit with the age of the parent's oldest credit account (e.g., Gross and Souleles (2001)). The age of oldest credit account is positively associated with the log of unused revolving credit. A one month increase in the age of the oldest credit account is associated with approximately a 1.28% increase in unused revolving credit limits. The F-statistic reveals that the age of the oldest account is a strong instrument.

In column (2), we instrument the parent's log unused revolving credit with county-level cumulative house price growth since origination, controlling for county and mortgage age fixed effects (e.g., Gerardi et al. (2018) and Bernstein and Struyven (2022)). The positive and statistically significant coefficient on housing price growth shows that households in purchase cohorts that experienced greater house price growth also have greater unused revolving credit.

In column (3), we estimate that the removal of a derogatory flag from a parent's credit report is associated with over a 50% increase in their amount of unused revolving credit. In Appendix A.4, we show that the removal of a derogatory flag is not associated with a change in earnings among the parents, consistent with recent work by Dobbie et al. (2020) and Herkenhoff et al. (2021).

A benefit of having multiple instruments is that it will allow us to include combinations of instruments in the first stage regression and conduct over-identification tests (i.e., J-tests). In column (4), we show the first stage regression results where we include both the age of the oldest credit account and the housing price growth in an individual's county since mortgage origination. The positive and statistically significant coefficient on both the age of the oldest account as well as housing price growth indicate that these instrument provide independent variation in unused revolving credit in the mortgagor sample. Finally, in column (5) we show that the age of oldest account as well as the removal of derogatory flags provide independent variation in unused revolving credit among parents in our derogatory sample.

The first stage regression results show that our instruments are highly correlated with unused revolving credit, and generate variation in unused credit access. We next use these first stage regressions in estimating equation (1) via an IV regression, which we discuss next.

A.3 Age of oldest account

In this appendix, we show that our results are robust to using parent age fixed effects instead of linear controls for age in our specifications that utilize the age of oldest account instrument. In Table 12 we present the results of estimating equation 2 including parent age fixed effects. Using parent age fixed effects rather than a linear control for the parents age, we find nearly identical results to those presented in Section 1.5.

A.4 Derogatory Flag Removal

In this appendix, we present additional results relating to derogatory flag removal.

In particular, we examine if the removal of a derogatory public flag is associated with a change in earnings. Let $Y^P_{i,2004}$ denote the earnings of a parent i in the year 2004. Let $D_{i,2004}$

Table 11: Parental credit access and children's earnings: first stage regressions

	(1)	(2)	(3)	(4)	(5)
	———Dependent variable: log of unused revolving credit———				
Log Parent's Earnings	1.025***	0.777***	1.864***	0.456***	1.401***
	(0.0174)	(0.0321)	(0.0546)	(0.0330)	(0.0553)
Age of Oldest Account	0.0128***			0.00909***	0.0131***
	(0.000139)			(0.000359)	(0.000426)
Housing Price Growth		2.014***		2.037***	
		(0.371)		(0.367)	
Derogatory Flag Removed			0.565***		0.661***
			(0.0570)		(0.0554)
R-squared	0.183	0.171	0.097	0.208	0.146
F-statistic	1905	254.5	127.9	227.2	197.7
Observations	166000	108000	23000	108000	23000
Controls	Y	Y	Y	Y	Y
Fixed Effects	N	Y	N	Y	N
Sample	Main	Mortgage	Derogatory	Mortgage	Derogatory

Notes: The table shows regression results from the estimation of first stage regression in the IV regression of equation (1), where the dependent variable is the log of unused revolving credit limits in 2002 in columns (1), (2), and (4), and in 2004 in columns (3) and (5) Parents earnings are measured in 2000-2002 and are in 2008 dollars. Unused revolving credit limits and the age of oldest credit account are measured in 2001 and 2002. Housing price growth is measured at the county level with FHFA housing prices and is between the time of mortgage origination and 2002. Derogatory flag removed is an indicator variable for having a derogatory flag removed between 2002 and 2004. Controls include child age fixed effects, age of parent, number of children and parents in the household in 2000, gender fixed effects, and tenure. Fixed Effects (FE) include county and mortgage age. See Section 1.3 for sample selection details. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

be an indicator variable that is equal to one if the parent i has had a derogatory public flag removed from their credit report between 2002 and 2004. The specification, we use is of the form,

$$Y^P_{i,2004} = \alpha + \beta D_{i,2004} + \Gamma X_{i,t} + \epsilon_{i,t} \tag{11}$$

We estimate equation (11) on our derogatory sample, which includes household who have a derogatory public flag on their credit report between 2002 and 2008. The coefficient β reports if having a flag removed from the credit report is associated with a change in earnings.

Table 13 presents the results of estimating equation (11). The coefficient on derogatory flag removed in the first column of Table 13 indicates that the removal of a derogatory public flag is associated with a decrease in earnings of $219. However, this coefficient is not statistically significant (t-stat = -0.805). In column (2) of Table 13 we find a similar result that having a

Table 12: Parental Credit Access and Children's Earnings: IV Regressions

	(1)	(2)	(3)
	——Dependent variable: log of children's earnings——		
Log Parents Earnings	0.102***	0.0841***	0.0770***
	(0.00361)	(0.00534)	(0.0105)
Log of Unused Revolving Limits	0.0308***	0.0431***	0.0375***
	(0.00158)	(0.00363)	(0.00404)
R-squared	0.110	0.068	0.057
J-test		0.575	0.733
Observations	166000	108000	23000
Controls	Y	Y	Y
FE	N	Y	N
Parent Age FE	Y	Y	Y
Instrument	AOA	AOA & HPG	AOA & DF
Sample	Main	Mortgage	Derogatory

Notes: The first stage includes the age of oldest account (AOA) in columns (1), (2), and (3), house price growth (HPG) in column (2), and derogatory flag (DF) removal in column (5). Controls include child age fixed effects, parent age FE, number of children and parents in the household in 2000, gender fixed effects, and tenure. Fixed Effects (FE) include county and mortgage age. The table shows regression results from the IV estimation of equation (2), where the dependent variable is the log of children's real earnings. Earnings are measured in 2008 dollars. Children's earnings are measured in the years 2013-2014 when children are between the ages of 25 and 30 (in 2014). Parents earnings are measured in 2000-2002. Unused revolving credit limits are measured in 2001-2002 in columns (1) and (2) and in 2004 in columns (3). See Section 1.3 for sample selection details. The null of the J-test is that the instruments are valid (i.e., a p-value of 0.1 indicates a failure to reject the null at the 10% level). Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

derogatory flag removed is not associated with a change in the log of parental earnings (t-stat = 0.174). The results presented in Table 13 provide evidence that the removal of a derogatory public flag is not associated with changes in earnings, which is consistent with recent work by Dobbie et al. (2020) and Herkenhoff et al. (2021). More broadly, this results suggest that the removal of a derogatory flag is shock which increases credit access but does not increase resources available to a household via other channels (i.e., earnings).

A.5 Additional Results: Heterogeneity

A.6 Additional results: Revolving limits

In this appendix, we provide additional results where our measure of credit access is revolving credit limits. In Table 17 we present OLS results where we use revolving credit limits as our

Table 13: Derogatory flag removal and earnings

	(1) Real Earnings	(2) Log Real Earnings
Derogatory Flag Removed	-219.4 (272.7)	0.00446 (0.0239)
R-squared	0.571	0.116
No. Obs	23000	23000
Sample	Derogatory Sample	Derogatory Sample

*Notes: The table shows regression results from the estimation of equation (11). Controls include the age of the parents and number of parents in the household. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

Table 14: Parental Credit Access and Children's Earnings: Heterogeneity by Child's Age

	(1)	(2)	(3)
Dependent variable: log of children's earnings			
Log Unused Revolving Credit	0.0308*** (0.00156)	0.0276*** (0.00216)	0.0323*** (0.00223)
R-Squared	0.110	0.113	
Observations	166000	166000	
P-value Difference		0.127	
Age Range	25-30	25-27	28-30
Sample	Main Sample	Main Sample	Main Sample

*Notes: The table shows regression results from the IV estimation of equation (1) (column (1)) and (4) (columns (2) and (3)), where the dependent variable is the log of children's real earnings and the sample is split by the child's age in columns (2) and (3). In all specifications the log of unused revolving credit is instrumented with the age of oldest account. Earnings are measured in 2008 dollars. Children's earnings are measured in the year 2014 when children are between the ages of 25 and 30. Parents earnings and unused revolving credit limits are measured in 2001 and 2002. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

measure of credit access. In Table 18 we present the first-stage regression results for our instrumental variables where the dependent variable is log revolving credit limits. Finally, in Table 19 we present the second stage results for revolving credit.

Table 15: Parental Credit Access and Children's Earnings: Heterogeneity by Parent's Education

	(1)	(2)	(3)
Dependent variable: log of children's earnings			
Log Unused Revolving Credit	0.0308***	0.0322***	0.0213***
	(0.00156)	(0.00182)	(0.00303)
R-Squared	0.110	0.114	
Observations	166000	166000	
P-value Difference		0.00208	
Parents Edu.		Non-College	College +
Sample	Main Sample	Main Sample	Main Sample

Notes: The table shows regression results from the IV estimation of equation (1) (column (1)) and (4) (columns (2) and (3)), where the dependent variable is the log of children's real earnings and the sample is split by the parent's education in columns (2) and (3). In all specifications the log of unused revolving credit is instrumented with the age of oldest account. Earnings are measured in 2008 dollars. Children's earnings are measured in the year 2014 when children are between the ages of 25 and 30. Parents earnings and unused revolving credit limits are measured in 2001 and 2002. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

B Additional Model Elements

B.1 Value functions for agents in bad credit standing

In this appendix, we present value functions that govern the behavior of agents in bad credit standing. In Appendix B.1.1 we present the value function for agents in the parenting stage who are in bad credit standing. Then in Appendix B.1.2 we present the value function for parents in the post child working stage who have bad credit standing.

B.1.1 Parent stage, bad credit standing

Let $V_j^N(b, h, h^c)$ denote the value function for an age j parent in bad credit standing with assets b, human capital h, and whose child has human capital h^c. In the current period, the parent makes a consumption/savings decision, as well as a decision about how much to invest in their child's human capital. Because the parent does not have credit access, their consumption savings decision is constrained by the borrowing limit for individuals with a flag on their credit report. At the start of the next period, shocks to human capital, and expense shocks, are revealed, and the parent learns if the flag has been removed from their credit report. With

Table 16: Parental Credit Access and Children's Earnings: Heterogeneity by Child's Education

	(1)	(2)	(3)
	Dependent variable: log of children's earnings		
Log Unused Revolving Credit	0.0308***	0.0321***	0.0215***
	(0.00156)	(0.00167)	(0.00431)
R-Squared	0.110	0.110	
Observations	166000	166000	
P-value Difference		0.0210	
Child's Edu.		Non-College	College +
Sample	Main Sample	Main Sample	Main Sample

Notes: The table shows regression results from the IV estimation of equation (1) (column (1)) and (4) (columns (2) and (3)), where the dependent variable is the log of children's real earnings and the sample is split by the child's education in columns (2) and (3). In all specifications the log of unused revolving credit is instrumented with the age of oldest account. Earnings are measured in 2008 dollars. Children's earnings are measured in the year 2014 when children are between the ages of 25 and 30. Parents earnings and unused revolving credit limits are measured in 2001 and 2002. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 17: Parental Credit Access and Children's Earnings: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log of child's earnings					
Log Parents Earnings	0.158***	0.153***	0.145***	0.130***	0.130***	0.122***
	(0.00264)	(0.00335)	(0.00740)	(0.00274)	(0.00691)	(0.00762)
Log Revolving Limit				0.0181***	0.0200***	0.0118***
				(0.000469)	(0.000855)	(0.000991)
R-squared	0.031	0.027	0.025	0.042	0.035	0.032
Observations	166000	108000	23000	166000	108000	23000
Controls	N	N	N	N	N	N
FE	N	N	N	N	N	N
Sample	Main	Mortgage	Derogatory	Main	Mortgage	Derogatory

Notes: The table shows regression results from the estimation of equation (1) via OLS, where the dependent variable is the log of children's real earnings and our measure of credit is revolving credit limits. No controls or fixed effects are included in these regressions. Earnings are measured in 2008 dollars. Children's earnings are measured in the years 2013-2014 when children are between the ages of 25 and 30 (in 2014). Parents earnings are measured in 2000-2002, and revolving credit limits are measured in 2001 and 2002. See Section 1.3 for sample selection details. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

probability $p \geq 0$, the flag is removed from the parent's credit report. When in the bad credit

Table 18: Parental Credit Access and Children's Earnings: First Stage Regressions

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log of revolving credit limits				
Log Parents Earnings	0.958***	0.810***	1.962***	0.513***	1.491***
	(0.0150)	(0.0251)	(0.0533)	(0.0207)	(0.0536)
Age of Oldest Account	0.0117***			0.00841***	0.0130***
	(0.000123)			(0.000250)	(0.000422)
Housing Price Growth		1.804***		1.825***	
		(0.321)		(0.313)	
Derogatory Flag Removed			0.531***		0.620***
			(0.0550)		(0.0535)
R-squared	0.197	0.165	0.105	0.213	0.159
F-statistic	1827	201.5	138.2	222	167.8
Observations	166000	108000	23000	108000	23000
Controls	Yes	Yes	Yes	Yes	Yes
Sample	Main Sample	Mortgage Sample	Derogatory Sample	Mortgage Sample	Derogatory Sample

*Notes: The table shows regression results from the estimation of equation (1), where the dependent variable is the log of revolving credit limits. Columns (1) ... . ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

Table 19: Parental Credit Access and Children's Earnings: IV Regressions

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log of child's earnings				
Log Parents Earnings	0.102***	0.0647***	0.0792***	0.0803***	0.0731***
	(0.00365)	(0.0243)	(0.0281)	(0.00579)	(0.0109)
Log of Revolving Limits	0.0337***	0.0661**	0.0344**	0.0469***	0.0375***
	(0.00171)	(0.0288)	(0.0137)	(0.00411)	(0.00407)
R-squared	0.110	0.054	0.105	0.086	0.069
J-test				0.506	0.814
Observations	166000	108000	23000	108000	23000
Controls	Yes	Yes	Yes	Yes	Yes
Instrument(s)	AOA	HPG	Derog. Flag	AOA & HPG	AOA & Derog. Flag
Sample	Main Sample	Mortgage Sample	Derogatory Sample	Mortgage Sample	Derogatory Sample

*Notes: The table shows regression results from the estimation of equation (1), where the dependent variable is the log of revolving credit limits. Columns (1) ... . ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

state, the value function for an age $j \in \{8, 9, 10, 11, 12\}$ parent with assets a, human capital h, and a child with human capital h^c is given by,

$$V_j^N(b, h, h^c) = \max_{b', i \geq 0} u(c) + \beta \mathbb{E}\left[p \widehat{V}_{j+1}^C(b', h', h^{c'}) + (1-p)\widehat{V}_{j+1}^N(b', h', h^{c'})\right],$$

where the default decision is given by,

$$\widehat{V}_j^C(b, h, h^c) = p_x \max\{V_j^C(b-x, h, h^c); V_j^N(0, h, h^c) - \psi(b)\} + (1-p_x)\max\{V_j^C(b, h, h^c); V_j^N(0, h, h^c) - \psi(b)\}$$
$$\widehat{V}_j^N(b, h, h^c) = p_x \max\{V_j^N(b-x, h, h^c); V_j^N(0, h, h^c) - \psi(b)\} + (1-p_x)\max\{V_j^N(b, h, h^c); V_j^N(0, h, h^c) - \psi(b)\},$$

subject to the budget constraint,

$$c + q_{j,N}(b', i, h, h^c)b' + i \leq w(h) + b,$$

and borrowing limit for agents in bad credit standing,

$$b' \geq \underline{b}_N(w(h)),$$

the wage equation (equation (6)), and the laws of motion for the parent's human capital (equation (7)) as well as the child's human capital (equation (8)).

B.1.2 Post child working parents with bad credit standing

Post child working parents without credit face a similar problem, but are constrained in that they are not allowed to borrow (i.e. $b' \geq 0$). The value function for these individuals is given by,

$$V_{13}^N(b, h, h^c) = \max_{b', \tau \geq 0} u(c) + \theta V_6^C(\tau, h^c) + \beta \mathbb{E}\left[p \widehat{V}_{14}^C(b', h') + (1-p)\widehat{V}_{14}^N(b', h')\}\right],$$
$$V_j^N(b, h) = \max_{b'} u(c) + \beta \mathbb{E}\left[p \widehat{V}_{j+1}^C(b', h') + (1-p)\widehat{V}_{j+1}^N(b', h')\right] \quad \text{for } j = 14, 15, 16,$$
$$V_j^N(b, h) = 0 \ \ \forall j > 16,$$

where the default decision is given by,

$$\widehat{V}_j^C(b, h) = p_x \max\{V_j^C(b-x, h); V_j^N(0, h) - \psi(b)\} + (1-p_x)\max\{V_j^C(b, h); V_j^N(0, h) - \psi(b)\}$$
$$\widehat{V}_j^N(b, h) = p_x \max\{V_j^N(b-x, h); V_j^N(0, h) - \psi(b)\} + (1-p_x)\max\{V_j^N(b, h); V_j^N(0, h) - \psi(b)\} \quad j = 14, 15, 16$$

subject to the budget constraint,

$$c + \tau + q_{j,N}(b', h)b' = w(h) + b \quad \text{for } j = 13,$$
$$c + q_{j,N}(b', h)b' = w(h) + b \quad \text{for } j = 14, 15, 16,$$

and borrowing limit,

$$b' \geq \underline{b}_N(w(h)),$$

the wage equation (equation (6)), and the law of motion for the parent's human capital (equation (7)).

C Credit experiment: additional details

In this appendix, we present additional details on the credit experiment. In appendix C.1, we discuss how measure credit limits over time for the credit market experiment.

C.1 Credit limits over time

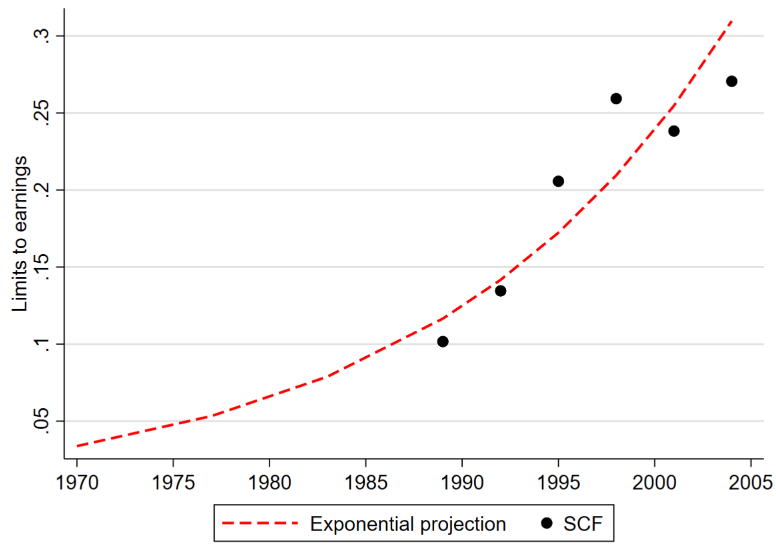
In this appendix, we discuss how we measure credit limits over time using the SCF. We first discuss our measurement of credit limits to income over time, and then discuss how we measure the relationship between credit limits and income over time.

Credit limits to income over time Using the SCF we can measure the ratio of credit limits to income starting with the 1989 wave of the SCF.[33] To arrive at an estimate of credit limits to income for the early 1970s we "back cast" the time series for credit limits to income using an exponential regression. Figure 5 presents a visual representation of this projection back in time. In Figure 5, the black dots correspond to the point estimates that we obtain from the SCF. The red dashed line is the predicted value from an exponential regression using these point estimates. From this projection, we obtain an estimate that credit limits to income in 1970 were equal to 0.034.

Relationship between income and credit limit As in Section 3, let $\underline{b}_i$ denote the borrowing limit for an individual i, and let $y_{i,}$ be their earnings. We estimate the relationship between

[33] To our knowledge, credit limits are not recorded in the 1970, 1977, or 1983 SCF

Figure 5: Credit limits to income over time



income and borrowing limits by estimating the following regression for each SCF wave since 1989,

$$\underline{b}_i = \alpha + \delta y_i + \epsilon_i \tag{12}$$

In equation 12, comparing the the constant term (α) over SCF waves measures how borrowing limits have expanded among all individuals over time, while examining δ over SCF waves measures how borrowing limits have expanded for individuals of different income levels. Table 20 presents the results of estimating equation 12 for each SCF wave since 1989. The first column of Table 20 shows that in 1989 for each extra dollar of income an individual's credit card limit increases by 10.9 cents. By 2004 (column (6)) for each extra dollar of income, limits increase by over 22 cents. Additionally, comparing the constant across columns (1) and (6) shows that there have been expansions in credit access that are common to all individuals.

As discussed above, credit limits are first reported in the SCF in 1989. To arrive at a slope parameter for the borrowing limit in 1970 we use the parameters from on income in Table 20 and use an exponetial regression to "backcast" the evolution of the slope parameter. Figure 6 presents a visual representation of this projection back in time. In Figure 6, the black dots correspond to the point estimates from Table 20. The red dashed line is the predicted value

Table 20: Credit limits and income over time

	(1)	(2)	(3)	(4)	(5)	(6)
	——— Dependent variable: credit card limits ———					
Income	0.109***	0.116***	0.164***	0.182***	0.183***	0.223***
	(0.00562)	(0.00456)	(0.00643)	(0.00837)	(0.00674)	(0.00806)
Constant	-70.01	788.1***	1,940***	3,005***	2,348***	2,142***
	(293.5)	(260.6)	(380.7)	(541.7)	(447.7)	(538.4)
Observations	2,351	2,916	3,279	3,305	3,452	3,566
R-squared	0.264	0.268	0.238	0.186	0.262	0.260
SCF Wave	1989	1992	1995	1998	2001	2004

Notes: Table presents the results of estimating equation 12 across SCF waves. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

from an exponential regression using these point estimates. From this projection, we obtain an estimate that the slope coefficient on the borrowing limits in 1970 is equal to 0.044.

Figure 6: Relationship between credit limits and income over time