Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

Where Credit is Due: The Relationship between Family Background and Credit Health

Sarena Goodman, Alice Henriques, and Alvaro Mezza

2017-032

Please cite this paper as:
Goodman, Sarena, Alice Henriques, and Alvaro Mezza (2017). "Where Credit is Due: The Relationship between Family Background and Credit Health," Finance and Economics Discussion Series 2017-032. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2017.032.

Where Credit Is Due: The Relationship between Family Background and Credit Health[1]

Sarena Goodman, Federal Reserve Board of Governors

Alice Henriques, Federal Reserve Board of Governors

Alvaro Mezza, Federal Reserve Board of Governors

March 2017

Abstract

Using a novel dataset that links an individual's background, education, and federal financial aid participation to her future credit records, we document that, even though it is not, and *cannot be*, used by credit agencies in assigning risk, family background is a strong predictor of early-career credit health (that is, an individual's credit score when she is around 30 years old). This relationship persists even after controlling for achievement, a range of postsecondary schooling variables (e.g., educational attainment, institutional quality, undergraduate borrowing), and key elements of early credit histories (e.g., default on educational loans). Interestingly, undergraduate borrowing, which is not underwritten, correlates with background and appears to explain some of the difference in scores. In light of the many important contexts in which credit scores are relied upon to evaluate consumers (e.g., lending, insurance, employment), our study offers a new dimension in understanding the transmission of socioeconomic status across generations.

[1] Email: sarena.f.goodman@frb.gov, alice.m.henriques@frb.gov, and alvaro.a.mezza@frb.gov. This paper does not necessarily reflect the views of the Federal Reserve Board. We thank Kyle Coombs and Peter Hansen for excellent research assistance, and Joanne Hsu, Karen Pence and Ronel Elul for helpful comments. We thank participants at the 2016 Association for Education Finance and Policy Annual Conference, the 2016 FRS Applied Micro Conference, and the fall 2016 FRB Applied Micro Lunch seminar. All errors are our own.

I. Introduction

While equal access to opportunity is the cornerstone of the American Dream, socioeconomic status (SES) is highly correlated between parents and their children (Solon, 1999, Chetty et al., 2014). This persistence raises questions of whether individuals from different backgrounds can access the same opportunities, and, if not, where policy may help level the playing field. For instance, the gaps in academic achievement that have been identified along several dimensions suggest that educational interventions could be effective.[2] Uncovering similar disparities elsewhere, especially early in the lifecycle, may expose new fruitful areas for policy.

Such a disparity in credit scores, for example, could yield new insight into these questions, given how they are both measured and used. The credit score is a dynamic statistic that reflects the likelihood an individual will default on debt within a set time frame, based on her historical interaction with credit markets at the point in time it is generated.[3] Despite this narrow definition, credit scores are relied upon within a broad variety of contexts to assess the risks of contracting with individual consumers, and thus can greatly influence whether they can consumption-smooth over the lifecycle or through periods of economic hardship (Herkenhoff, 2015; Herkenhoff, Phillips, and Cohen-Cole, 2016).[4] Lenders use credit scores to set prices and

---

[2] For example, students from disadvantaged backgrounds are far less likely to attend college, and those who do are less likely to attend a college commensurate with their abilities (e.g., Chetty et al., 2014; Bowen, Chingos, and McPherson, 2009; Hoxby and Avery, 2013; Smith, Pender, and Howell, 2013; Black, Cortes, and Lincove, 2015; Pallais and Turner, 2006; Spies, 2001).

[3] There are a number of types of credit scores, varying in purpose and definition, but they are all derived from observable dimensions of credit records and, *by law*, must exclude demographic characteristics. Examples of key inputs include: the credit markets in which she has participated, the amount of debt she has outstanding, her prior repayment behavior, and the length of time she has maintained healthy credit, all of which predict delinquency to some extent. One popular variant reflects the likelihood a consumer will become seriously delinquent within 24 months of scoring. (For more information, see: https://www.fdic.gov/regulations/examinations/credit_card/pdf_version/ch8.pdf.)

[4] While this discussion ignores endowments, the ability to consumption-smooth vis-à-vis credit markets is especially important for individuals with small or negligible endowments (e.g., those from economically disadvantaged backgrounds) relative to expected future income. This rationale is the policy basis for broad-based federal student lending programs, which, in theory, allow individuals with little or poor credit histories the opportunity to fund

terms of loans, whereby sufficiently low scores can even render certain lenders or loan types completely unavailable. Many businesses and organizations that do not provide credit also use credit scores to evaluate risk; for example, lower scores might restrict access to insurance, rental housing, utility contracts, and employment opportunities.

In this study, we establish a link between socioeconomic background and early-career credit health. Specifically, we examine the long-term credit outcomes of a random sample of college-bound individuals and find that, even though background is not and cannot be used by credit agencies in rating risk, a clear gap in credit scores has materialized by the time the members of our sample are about 30 years old.[5] Further, a gap remains even after accounting for achievement, postsecondary schooling, and key elements of early credit histories (e.g., defaulting on a federal undergraduate loan). The resilience of this relationship suggests that the credit market could be amplifying the transmission of economic well-being across generations.

The paucity of research in this area primarily reflects data constraints, as few, if any, datasets include observations of both family background and later credit outcomes. To overcome these constraints, we merge College Board (CB) records for a sample of SAT-takers who graduated high school between 1994 and 1999 (when the SAT was elective) to their future administrative credit bureau, college attendance, and federal student borrowing and Pell Grant records.[6] In general, the individuals who form our sample were, when they were in high school, planning to attend (a selective) college. Importantly, by 2008, the focal year of our analysis, they were about 30 years old and likely had completed college.

---

human capital investments with loans that are generally not underwritten at the student level and that, in expectation, will offer large payouts in earnings in the future.

[5] We extend the analysis to show that this gap remains 6 years later.

[6] Our analysis draws upon a large data effort specially prepared for the Federal Reserve Board that drew randomly among individuals with credit records in 2004 who were 23 to 31 years old at the time, as described in Mezza and Sommer (2016). Our sample is the subset of these individuals for whom we can match CB records.

Within this sample, background (i.e., Pell Grant receipt, parents' educational attainment) unambiguously predicts credit health, approximated with either raw credit scores or a dichotomous measure that we derive of access to prime lending. In our simplest specification, we estimate that credit scores are about 100 points lower for individuals from disadvantaged backgrounds, and that such individuals are about 20 percentage points more likely to be subprime. Conditioning on achievement erases as much as half the gap; even then, another 100 to 200 SAT points is required to fully eliminate it.

We extend the analysis in two ways. First, we allow the role of achievement to vary by background. The results indicate that although, all else equal, higher achievement reduces the gap in credit health, the gap persists even among students with very high achievement. Second, we investigate whether an array of factors that may influence credit health—either directly (e.g., the take-up of, the amount of, and defaulting on federal undergraduate loans; length of credit history) or indirectly (e.g., school quality; educational attainment)—correlate with background and potentially mediate the relationship between background and credit. We find that individuals from disadvantaged backgrounds attend lower-quality schools than their peers with similar SAT scores, consistent with evidence that disadvantaged students tend to "under-match" to postsecondary programs and, more broadly, have worse outcomes.[7] These factors may help explain why conditioning on achievement erases only part of the gap; nonetheless, when we include all of them as controls (even student loan defaults), there is still a discrepancy.

Altogether, because of how credit scores are measured and used, our findings point to a new mechanism underlying the persistence of socioeconomic circumstances across generations: the

[7] For example, low-SES individuals are less likely to complete programs and more likely to borrow for college and default on this debt. And although they have, on average, credit histories that are two to three months longer, this difference is small (about 2 percent of the sample mean) and may simply be an artifact of increased college borrowing rates among this group.

gap we uncover implies a material difference in how well individuals from different backgrounds can consumption-smooth and access key markets at relatively young ages, which is very likely to persist.[8] Indeed, estimates are very similar if we examine credit health in 2014 (i.e., when our sample is in their mid-30s) instead of 2008. In the paper's conclusion, we review phenomena that could generate this gap (e.g., social norms, financial literacy rates, or household circumstances; how credit scoring models assess risk), many of which may be addressed through policy.

Separately, we find that taking federal student loans—which, unlike other forms of debt, are not underwritten—is consistently negatively associated with credit health, even after accounting for all of our other controls.[9] This association points to an avenue through which student loans may deleteriously affect young adults' financial health (e.g. Mezza et al., 2016; Dettling and Hsu, 2014, Bleemer et al., 2014). Ironically, students who borrow through the federal student loan programs, which were created to equalize opportunity, may struggle with early debt obligations and foreclose on opportunities as a result.

The rest of the paper proceeds as follows. Section II provides background on credit scores and summarizes related literature. Section III describes the sample and construction of key variables. Section IV links family background and pre-collegiate achievement to credit outcomes. Section V extends the analysis by allowing for achievement to interact with background and by adding an array of controls that could mediate credit health. Section VI discusses the possible explanations for the gap in credit health and concludes.

---

[8] Negative credit events remain on credit records for fairly long periods of time and the presence of such an event is a major predictor of delinquency risk. For example, a personal bankruptcy can remain on a credit record for up to 10 years (Musto, 2004). More broadly, credit scores depend on one's historical experience managing and maintaining credit, and access to credit is reduced for those with lower scores.

[9] Although federal undergraduate loans are not underwritten and are generally widely available, some restrictions in eligibility still apply. For instance, students who are currently in default on a student loan may not take out another. In addition, students face maxima in the amount they can borrow both in a single year and over time. Other types of student loans that are available but that we do not study (e.g., Parent PLUS loans; private student loans) are less widely used and tend to have more stringent requirements.

II. Background and Related Literature

a. Determinants of Credit Scores

A credit score is a dynamic summary measure of an individual's credit risk, derived from elements of her existing credit record. Technically, it reflects her relative risk of default within a fixed time period, based on the risk profiles of other individuals with credit records and the experiences of those whose records are similar. According to the Fair Isaac Corporation (FICO)—the data analytics company that produces the "FICO score" (perhaps the most well-known variant of credit score)—the elements of credit records that predict credit risk fall into one of five categories, each assigned some weight within the methodology for a particular score. For the FICO score, payment history is given the most weight (0.35), then amount owed (0.3), length of credit history (0.15), new credit (0.1), and credit mix (0.1).[10] (Our study relies on a distinct credit score, the TransUnion TransRisk Account Management score—TU TransRisk AM 2.0.—which is computed similarly to the FICO score but may weight these categories differently.) Notably, in credit scoring models, a negative credit event, which can remain on a report for a long time, is often a strong predictor of delinquency.

Credit scores are used to evaluate applications for credit, identify prospective borrowers, and manage existing credit accounts. They also enter into eligibility determinations for rental housing, utility contracts, and employment opportunities. Individuals are frequently then further classified as either prime or subprime according to their credit scores. While the cutoff varies by credit score variant and institution, there is usually a distinct break in the types and costs of products and services available to borrowers of each type, particularly within the lending and

[10] For additional details, see: http://www.myfico.com/CreditEducation/WhatsInYourScore.aspx.

insurance industries. In general, prime individuals have markedly higher access to credit (and to opportunities in other markets that rely upon credit scores) than subprime individuals.

Because of their many uses, it would clearly be very worrisome if credit scoring models penalized particular demographic groups—such as those formed by race, ethnicity, or sex—and, indeed, by law, demographic information cannot be used to calculate scores.[11] Still, they could inadvertently penalize particular groups, if a model input only appears to predict credit risk because it proxies for a demographic characteristic that is correlated with risk. The existing evidence on this topic indicates that model inputs do not proxy for race, ethnicity, or sex (Avery, Brevoort, and Canner, 2012; Board of Governors, 2007).[12] However, systematic differences by socioeconomic background have not been ruled out.

b. Intergenerational Mobility

The correlation of income and wealth across generations in the United States is well documented. The most recent work, which relies on administrative income data, estimates that the current level of persistence is high relative to other countries but also generally unchanged from several decades ago (Lee and Solon, 2009; Chetty et al., 2014; Mitnik et al., 2015; and, for a review of prior work, Solon, 1999; Black and Devereux, 2011). Mitnik et al. (2015) find that the correlation appears to be *stronger* when children's outcomes are observed later in their lifecycle (their 40s instead of their 30s), suggesting that the role of family background does not diminish over time and may even grow. Studies that estimate intergenerational correlations within segments of the population offer mixed conclusions. Mazumder (2005) finds that

[11] For details, see the 1974 U.S. Equal Credit Opportunity Act (codified at 15 U.S.C. § 1691).
[12] According to this literature, different demographic groups have substantially different credit scores, on average. For example, individuals residing in low-income census tracts have lower credit scores than individuals residing in more affluent areas. However, these differences narrow—but are not always eliminated—when personal demographic characteristics, neighborhoods, or census-tract-based estimates of income are taken into account.

persistence is highest among families with low net worth, while Mitnik et al. (2015) find the highest persistence in the upper-middle class.

Most closely related to our study are two recent studies that include credit scores in their analysis. First, Ghent and Kudlyak (2015) examine persistence across generations within the FRBNY Consumer Credit Panel, an individual-level panel dataset of credit records which is augmented with the credit records of any person sharing an address with these individuals for the duration of their co-residence. They identify parent-child pairs from the set of 19-year olds ("child") that live with an older individual ("parent") and detect a positive association between "parents'" credit scores when their "children" were 19 years old and the credit scores of these "children" 5 to 10 years later. Second, Ringo (2015), using the Survey of Consumer Payment Choice (SCPC), estimates a positive relationship between parents' reported credit scores and both the likelihood their children attend college and the likelihood they complete a four-year degree. Tight correlations between parents' credit health and children's outcomes, particularly their educational outcomes, are not surprising. While the most recent evidence on whether this relationship is causal is mixed (Lovenheim and Reynolds, 2013; Hilger, 2016; Bulman et al., 2016), parents' credit scores may reflect other household conditions, like income, and there is considerable evidence that college attendance rates vary by family income (described below).

c. Disparities in College Attendance by Background

College attendance reflects the cost of education, the return to education, and, in a credit constrained environment, family income. A large and growing literature has estimated substantial returns to college and, more specifically, college quality, particularly among disadvantaged students (e.g., Card, 1995; Black and Smith, 2006; Hoekstra, 2009; Dale and Krueger, 2002, 2011; and, more recently, Zimmerman, 2014).

However, despite the potential for large returns, the disparity in college attendance between children from low- and high-income families has been increasing over time. Over the 20 years between 1980 and 2000, although average college entry rates rose nearly 20 percentage points, the gap between the bottom- and top-income quartiles increased 12 percentage points (Bailey and Dynarski, 2011).[13] Moreover, many students, especially those from disadvantaged backgrounds, do not apply to or attend a college commensurate with their abilities (e.g., Bowen, Chingos, and McPherson, 2009; Pallais and Turner, 2006; Spies, 2001; Hoxby and Avery, 2013). For instance, Pallais and Turner (2006) find strong evidence of systematic under-match—high-scoring, low-income test-takers are as much as 20 percent less likely to apply to selective schools than equally high-scoring but higher-income peers—which they attribute to a combination of information constraints, credit constraints, and pre-collegiate underachievement. Further, many of these studies rely on application and score data from elective admissions tests; thus, while the shortage of these students attending and applying to top schools is likely larger than conventional estimates suggest, one takeaway from these studies is that relatively ambitious students (i.e., those who plan to attend competitive schools) are under-matching.

III. Data

Our sample consists of person-level records that link socioeconomic background and achievement to postsecondary credit outcomes. The sample is formed retrospectively by first randomly selecting a nationally representative cohort of about 35,000 individuals with credit records from TransUnion (TU) who were 23 to 31 years old in 2004. Within this "base cohort," we are able to observe an array of credit outcomes in snapshots taken periodically between 1997 and 2014. We merge a subset of these records to administrative records from other institutions,

[13] Meanwhile, earnings have been essentially steady among the college-educated and have dropped substantially for everyone else (The College Board, 2007; Deming and Dynarski, 2010).

allowing us to observe additional characteristics, including demographics and postsecondary schooling. (A double-blind process between TU and the other data sources was used to maintain the integrity and privacy of each party's records. The records in our dataset are anonymous.)

Specifically, we acquired CB data for SAT-takers spanning the 1994 to 1999 high school graduation cohorts, and, for about 15 percent of the base cohort, we are able to identify a matching SAT score record. The SAT is an elective competitive exam administered during students' junior and senior years of high school that is used in admissions determinations at selective colleges (and course placement at non-selective colleges). During the period we study, the SAT was fully elective and only considered to be a requirement among college admissions and placement committees, so the subsample of individuals for whom we can identify SAT records very likely plan to attend college.[14] Hence, in general, the subset of students for whom we can successfully identify an SAT record are "college bound." In addition to SAT scores, the CB records also contain student demographic characteristics (e.g., parental education; student gender; state of residence) from a survey that the CB administers to students who take the SAT.

[14] Because, in general, students must register for the SAT exam with their Social Security Numbers, the matched set likely approximates the full set of SAT-takers among individuals in our base sample. Still, not all students who attend postsecondary institutions necessarily appear in the CB data. Indeed, about 75 percent of the individuals in our base credit sample for which we can identify either a National Student Clearinghouse (NSC) or National Student Loan Data System (NSLDS) record cannot be matched to a CB record. There are at least three explanations for this seemingly low match rate. First, although our base credit bureau sample is formed from nine birth cohorts, our CB data span only six graduation years. Thus, to begin with, we would expect, at most, a 67 percent match rate. Second, students may elect a competing exam, the ACT, for their college applications. Because a student's proclivity to elect a particular exam is not necessarily randomly assigned, the omission of ACT-takers is a potential threat to the external validity of our analysis. However, our descriptive statistics are broadly in line with national statistics among all college students and are little changed when we restrict the sample to students from states where the SAT prevails. (Appendix Table 2 indicates our main estimates are not sensitive to this restriction.) Thus, for our purposes, the election of the ACT over the SAT in our sample is approximately random. Third, many postsecondary students attend schools that do not require an admissions exam. In 2000, less than 10 percent of four-year postsecondary institutions, but 80 percent of two-year institutions, fell into this category (Breland et al., 2002). Therefore, our analysis is most precisely an examination of *four-year college-bound* individuals, which, if anything, should be a positively selected group among the full set of postsecondary attendees who appear in the NSC or NSLDS. We will further discuss implications of such selection when we turn to our analysis.

These characteristics are part of an endowment bundle that individuals inherit from their parents' genetics, household conditions, and other circumstances beyond their control.

For these same individuals, we identify any records that exist within (1) the Department of Education (DoEd) NSLDS pertaining to their federal Title IV grant and borrowing behavior (e.g., whether an individual received Pell Grants, borrowed for education, the total amount she borrowed, and whether she defaulted over our period of study), and (2) the NSC pertaining to their enrollment and educational attainment.[15] These records each pertain to a particular postsecondary institution, which can then be linked to two DoEd external data sources to identify important characteristics of that school. The first is the Integrated Postsecondary Education Data System (IPEDS) database, which compiles responses from an annual survey of all Title IV institutions over our full period of study and contains snapshots of school characteristics (e.g., sector; level; selectivity; price) over time. The second is the "college scorecard," which includes borrowing and later-life earnings outcomes for every cohort beginning in 1996.[16]

The final sample comprises the SAT survey and testing, post-secondary, and credit outcomes of 5,421 college-bound individuals. Within this sample, we generate several key variables. As a first measure of family socioeconomic circumstances, we use parents' educational attainment, as reported by SAT-takers in the CB survey. We code the following two measures: (1) a binary measure of the mother's B.A. status ("mom"), where a value of 0 reflects completing at least a B.A. and 1 reflects not completing a B.A.; and (2) a binary measure of the father's B.A. status ("dad"), coded similarly to measure 1.[17] Note that higher values of the parents' education

[15] These data sources contain the universe of their respective administrative records in a given academic year and contain records through 2008.
[16] https://collegescorecard.ed.gov/data/
[17] The analysis excludes students for whom the corresponding parent's education is either missing or reported as a zero.

variables are associated with *less* education (i.e., “disadvantage”) in order to permit a consistent interpretation of the signs across all of our family background variables.

As a complement to these variables, we derive a second set of measures from the NSLDS records. Specifically, Pell Grants, which are awarded to qualifying low-income financial aid applicants with the amount of the grant fully determined by financial need, enrollment status, and school’s tuition level, offer a second snapshot of a student’s socioeconomic background, particularly financial well-being, around the time of the schooling decision. We code the following two measures: (1) whether the individual was ever awarded a Pell Grant (“any pell”), and (2) because the award amount is subject to a statutory limit set in each year, whether the individual was awarded the maximum Pell Grant (“max pell”).[18] Note that any student who receives the maximum Pell Grant, by definition, is coded as 1 for “any pell”; thus, relative to “any pell,” “max pell” captures a more extreme measure of need (and cost).

The two sets of measures together offer a fairly comprehensive snapshot of an individual’s background. Compared with parental education, the Pell measures offer the relative benefit of directly quantifying financial need; however, unlike the parental education measures, they in part reflect a student’s schooling decision (and decision to apply for financial aid) and, thus, are not fully predetermined. Because of the differences in what each measure captures, the correspondence is not exact; for instance, the correlation between “dad” and “any pell” is 0.25. Still, those with less educated fathers are about twice as likely to receive a Pell Grant as those with more educated fathers, which mirrors the association between parental education and Pell Grant receipt within the 2003–04 DoEd National Postsecondary Student Aid Study (NPSAS).

[18] Technically, the Pell Grant measures are derived from observations of whether individuals were *scheduled* to receive a Pell Grant and the amount that they were *scheduled* to receive (rather than the actual amounts).

The other key variables are achievement and credit health. Achievement is measured prior to college, using SAT scores ("maxsat100"), measured in hundreds and ranging from 4 to 16 in increments of 0.1.[19] The SAT score delivers a rough sense of an individual's cognitive ability and, because of its direct use in the college admissions process, the opportunities available to an individual test-taker at the time she graduates high school. We measure credit health in two ways, both using the TU credit score observed in 2008 ("tuscore2008"), at which point the youngest individual is 27 or 28 years old. First, we use the raw score, which ranges from 270 to 900. Second, to provide a mapping between credit health and credit *access*, we derive a binary variable ("prime") that approximates whether an individual would qualify for most types of credit in 2008. By this metric, members of our sample are considered prime borrowers if their credit score is above the base cohort's median score in 2008.[20] Our results are not very sensitive to the choice of this cutoff.[21]

We augment our analysis with an array of postsecondary variables that may influence credit health, either directly or indirectly. We use the NSLDS borrowing records to create the following: a binary measure ("borrowed ug") that takes a value of 1 if the individual took federal

[19] For ease of interpretation of the coefficients and the constant, we transform this variable to range between 0 and 12 in the regression analysis.

[20] This threshold corresponds to a TU credit score of 580.5. Key distributional characteristics of the TU score differ from those of the FICO score, with which people are most familiar. Laufer and Paciorek (2016) show that there is a close relationship between the FICO score and the Equifax Risk score within the FRBNY Consumer Credit Panel (CCP), a dataset that is available to us as well. We mimic our sample restrictions within the CCP and calculate a median Equifax Risk score in December 2008 of 645. (According to the "Quarterly Report on Household Debt and Credit," less than one-quarter of mortgages and slightly more than one-quarter of auto loans during the last quarter of 2008 were originated to individuals with scores below 645.)

[21] Appendix Table 3 presents estimates using alternative thresholds, two of which relate to mortgage lending standards and a third that roughly accords with a current industry consensus definition of a prime borrower: (1) a TU score of 526, which corresponds to an Equifax Risk score of 620—a cutoff commonly used by mortgage lenders in applications for credit, especially after 2009 (Laufer and Paciorek, 2016); (2) a TU score of 351, which corresponds to an Equifax Risk score of 550—a score at which very few mortgage originations occur, even in 2008; and (3) a TU score of 620, which approximates the probability of default associated with a FICO score between 680 and 700. (We thank Ezra Becker and Transunion for helpful guidance in developing our third threshold.) Estimates are qualitatively similar under all three measures, even under the most stringent threshold.

student loans to fund her undergraduate studies; the cumulative undergraduate student loan borrowing through federal loans, measured in thousands of dollars (“amount borrowed”); and a binary measure that takes a value of 1 if the individual ever defaulted on a federal undergraduate-level student loan (“defaulted”). Moreover, we make use of two school quality measures based on the first college an individual attends—i.e., the first enrollment spell we observe in either the NSC or the NSLDS. The first is the average income in 2007 among employed individuals who had been enrolled in that school in 1997 (“school’s mean income,” measured in thousands of dollars). The second is the average SAT score of students admitted in 2003 (“SAT school”).[22]

We construct four mutually exclusive measures of degree status. We primarily rely on NSC graduation records but complement this information with NSLDS records when possible. We group degrees into the following categories: (1) dropouts (i.e., those with at least some college but no degree), (2) certificate or associate degree, (3) bachelor’s degree, and (4) master’s degree or more.[23] We also construct a persistence variable that counts days enrolled and expresses them in years (“years in school”), combining information from NSC and NSLDS enrollment records. Finally, we make use of a variable in the credit records (“length of credit history”), counting the number of months an individual has had an established credit record.

Table 1 describes the final dataset. About 20 percent of the sample received the maximum Pell Grant in at least one year during our period of study, and nearly 40 percent received a Pell Grant at least once. The latter figure is higher than statistics on Pell Grant receipt among college students in 2003–04, which indicate take-up of 27.2 percent.[24] Our period of study covers at least

---

[22] We also code a binary measure (“no SAT school”) that takes a value of 1 if an individual’s first school does not require standardized tests for admissions.
[23] For some individuals, we observe a graduation date, but no degree reported. This group is labeled as “graduated but degree unknown” in Table 1, but, for practical purposes, it has been included in the group of certificate or associate degree holders in the regression analysis.
[24] Statistics generated using NCES Quickstats tool for 2003–04 NPSAS.

one economic downturn, so a discrepancy between our average and need during a healthier year for the economy is unsurprising. Turning to our other, more static measure of background, we see that about 40 percent of fathers and just over 30 percent of mothers have completed a B.A.. These statistics are roughly in line with what national estimates imply; for instance, according to the DoEd, about 40 percent of undergraduates in 2003–04 had at least one parent who earned a B.A. In addition, within our sample, the average SAT score is 1014—ranging from 430 to a perfect 1600—almost exactly corresponding to published statistics for the full population of SAT-takers around our timing.[25] The average SAT score for the 1996–97 graduating cohort was 1016. The similarities between the statistics we can produce from our data and published statistics on parental education among college students and SAT-scoring among test-takers lend credence to the national representativeness of our sample in describing college students.

Parental education among college students is higher than parental education among all children.[26] (For instance, in 2005, 25.5 percent of mothers and 29.7 percent of fathers of children aged 6 to 18 had earned at least a B.A.[27]) Similarly, the average credit score in our final sample is 639, which is well above the threshold we use for credit scores in the prime range. Indeed, about 68 percent of our sample meets our definition of prime borrowers. These statistics suggest that our sample is positively selected from the population, but also imply an association between background and credit health.[28] The remainder of our analysis explores this relationship.

---

[25] U.S. Department of Education, National Center for Education Statistics (2015). Digest of Education Statistics, 2013 (NCES 2015-011), Table 226.10.

[26] SAT-taking is very highly correlated with a student's family background because, as noted earlier, admissions test-taking generally reflects an aspiration to attend college. Such aspirations are typically higher among students from high-SES families. According to a study by the DoEd of a sample of 1992 high school graduates, the admissions test-taking rate was more than two times higher when at least one of a graduate's parents completed a B.A.. Even among graduates who indicated in 10th grade that they planned to pursue a B.A. (at least twice as common among graduates with more educated parents), the fraction of students who went on to take an exam was about 25 percent higher when they had more educated parents. See http://files.eric.ed.gov/fulltext/ED546120.pdf.

[27] See http://nces.ed.gov/pubs2007/minoritytrends/tables/table_5.asp#sthash.yxGEbobp.dpuf.

[28] See Appendix Figure 1 for full distribution.

IV. Family Background and Credit Health

a. Basic Relationship

We begin by examining the simple reduced-form relationship between family background and early-career credit health. Figures 1a and 1b plot the distribution of credit scores in 2008 according to our binary measures of SES. Each indicate that children from higher-SES backgrounds have higher credit scores.

Next, we generate a regression-adjusted correspondence. Specifically, we estimate:

$$c_{iy} = \beta_0 + \beta_1 * disadvantage_{iy} + \delta_y + \varepsilon_{iy}, \text{ (1)}$$

where c_{iy} is one of our two measures of 2008 credit access, $disadvantage_{iy}$ is one of four family background indicators, i denotes a college-bound individual, and y denotes a graduation year, whereby $\delta_y$is a high school graduation year effect that absorbs fixed differences between cohorts. β_1 represents the association between family background and credit health.

Across the board, children from higher-SES backgrounds tend to have higher credit scores, though the extent varies by measure (Table 2). For example, if an individual's father did not earn a B.A., her credit score, on average, is about 80 points lower (nearly one-half a standard deviation) (column 2), while receiving the maximum Pell Grant is associated with a 120 point lower score (two-thirds of a standard deviation) (column 4). Turning to our binary credit measure, children from better backgrounds appear to have greater access to credit: they are about 14 to 26 percentage points more likely to be prime borrowers than their peers (columns 5–8). Finally, if we examine credit outcomes in 2014 instead of 2008 (i.e., credit scores when the individuals in our sample are in their mid-30s), results are qualitatively similar on both dimensions (Appendix Table 4).

Before proceeding, we make two notes regarding the interpretation of β_1. First, there are many factors that potentially correlate with both family background and credit health. Because the omission of such factors from equation (1) could introduce bias into our estimates, β_1 may not represent the causal effect of background on credit outcomes. Some of these factors cannot be directly observed but can be approximated in our data; for instance, the SAT score is arguably an ample proxy for student achievement. (SAT scores are particularly well-suited for our analysis because performance on the SAT explicitly affects college admissions determinations, and thus opportunity set.) Some, however, are harder-to-quantify characteristics for which there are no good proxies in our data (e.g., grit; conscientiousness; motivation). Generally, most factors that positively correlate with background would also positively correlate with credit, implying that our estimates probably overstate the true relationship.[29]

Second, the association between family background and credit scores over the full population may be stronger than the one we recover in our analysis. Higher-income students, as a group, take the SAT more frequently than low-income students; thus, low-income students who take the SAT may be positively selected in unobservable ways that could influence their credit scores. For example, low-income SAT-takers may exhibit more grit than high-income SAT-takers. If increased grit is associated with better credit outcomes, the association between background and credit scores that we estimate may be muted relative to the population estimate. Indeed, Appendix Table 1 indicates that the estimates of β_1 produced from the full credit sample, using only the Pell indicators, are larger than those from our main analysis.

b. Role of Pre-Collegiate Achievement

[29] In the next section, we will include intermediate educational and borrowing outcomes to attempt to reduce bias in β_1; however, technically, intermediate outcomes are choice variables (that is, they likely reflect qualities of individuals we cannot measure) and may, thus, themselves introduce new biases that cannot easily be signed.

As noted above, achievement potentially correlates with both background and credit scores. Figures 2a and 2b plot SAT score distributions according to family background, and indicate that the distributions are consistently bell-shaped but also are clearly left-shifted for low-SES students.[30] The mean SAT score for low-SES students is about 100 points lower. (This difference suggests that, all else equal, applicants from disadvantaged backgrounds to need-blind colleges are less admissible than their peers.) Per the latter, Figure 3 displays SAT scores for prime and subprime borrowers. The distribution of scores among subprime borrowers is left-shifted relative to prime borrowers but also left-skewed. These patterns underscore the inclusion of SAT scores to reduce bias in β_1.[31]

Thus, Equation (1) becomes:

$$c_{iy} = \beta_0 + \beta_1 * disadvantage_{iy} + \beta_2 * SAT_{iy} + \delta_y + \varepsilon_{iy} \text{ (2).}$$

The inclusion of SAT_{iy} enables a rough estimate of the interplay between background and achievement—that is, all else equal, the amount of additional SAT points that would be needed to offset the credit effects of coming from a disadvantaged background.

In each specification of equation (2), β_2 is positive and significant such that, all else equal, individuals with higher SAT scores tend to have higher credit scores (Table 3). Additionally, once achievement is controlled for, the association between family background and credit decreases but remains highly significant. In particular, having less educated parents is associated with a 25 to 41 point credit score reduction, and receiving a Pell Grant is associated with a credit score reduction of as much as 82 points. Combining the information in $\beta_1$and β_2, if a college

[30] Because, after holding background constant, test-takers appear to be drawn from similar distributions of test scores, comparisons in distributional outcomes are likely valid (since the shapes of the distributions are comparable once the level effect is removed). While for brevity, we present figures only for "dad" and the "any_pell" measures of SES throughout this section, the graphs look very similar for the measures that we exclude.

[31] Also, we might expect this inclusion to absorb some other potentially important unobservables, to the extent that high-scoring students from low-SES backgrounds have more grit than those from high-SES backgrounds.

student receives a Pell Grant, she would need an additional 200 to 300 SAT points to ultimately have a credit score in line with her counterpart without a Pell Grant. The estimate of $\beta_2$is quite stable across the specifications with different SES measures.

Estimates are qualitatively similar using the binary measure of whether an individual could qualify for most types of credit. Similar-achieving college students with less educated parents are about 5 to 10 percentage points more likely to be subprime. Using the Pell measures, this figure is closer to 15 to 20 percentage points. An individual generally needs at least 100 additional SAT points to compensate for her background to end up on even footing with her higher-SES peers. Potentially, this relationship could reflect that lower-SES individuals may have more debt to manage, leading to more opportunity to miss payments which would lower their credit score.

V. Extensions

This section extends our analysis in two ways. First, we allow the role of achievement to vary by background. Then, we examine the extent to which other factors observable in our data (e.g., attainment; borrowing; length of credit history) explain the credit gap.

a. Differential "Returns to Achievement"

The primary goal of this exercise is to examine how meaningful achievement differences are for students from different backgrounds.[32] For instance, to what extent does the credit gap narrow (or widen) when students move along the achievement distribution and/or surpass key

[32] Whether SAT score differences are more or less meaningful for low-SES students is theoretically ambiguous. On one hand, high-SES students likely already have a safety net and support network and are more financially literate, so that achievement alone may have little influence on their financial health. Further, high SAT scores may be more useful in expanding opportunity sets for disadvantaged students. Finally, if high SAT scores are harder earned for low-SES students (who may have less access to SAT prep classes or increased obligations at home), we might expect SAT scores to be a better early signal of later-life successes for that group. On the other hand, the literature on under-matching finds that low-SES students are less likely to pursue the educational opportunities that higher SAT scores offer (so their actions and choices that could influence their credit health may be less likely to reflect achievement differences), which could imply that SAT score differences are *less* meaningful for low-SES students.

thresholds (e.g., 1200, which is high enough to gain entry to many selective colleges and is just one standard deviation above the mean)?

We augment equation (2) to include an interaction between SES and SAT score:

$$c_{iy} = \beta_0 + \beta_1 * disadvantage_{iy} + \beta_2 * SAT_{iy} + \beta_3 * disadvantage_{iy} * SAT_{iy} + \delta_y + \varepsilon_{iy}, \quad (3)$$

whereby the estimate of β_3 reflects the differential change in credit scores for low-SES students associated with every 100 point increase in SAT scores. If β_3 is large, relatively small differences in SAT scores would imply large changes in the credit gap.

Regression results reveal that β_3 is not particularly large but always positive (Table 4). The coefficients are largest (and statistically significant) under the "any pell" and "dad" specifications, and the same patterns hold whether prime status or credit scores are on the left-hand side.[33] Altogether, the estimates imply that credit scores among low-SES students are a bit more sensitive to achievement—e.g., in column 3, 100 additional SAT points are associated with nearly a 35-point credit score gain among Pell Grant recipients (compared to about 25 points among those who do not receive a Pell Grant)—but also that a gap exists even in very high SAT ranges—the coefficient on background remains significant across all specifications and is generally at least an order of magnitude larger than β_3.

To aid in interpretation, Figures 4a and 4b offer an alternative depiction of these results. The graphs make clear that, relative to a very low SAT score (i.e., two standard deviations below the mean), a very high SAT score (i.e., two standard deviations above the mean) substantially reduces the gap in credit scores—by as much as 60 points (more than 60 percent) using "any

[33] Behrman and Rosenzweig (2002) compare the schooling outcomes of children of twin mothers and twin fathers (with different levels of education) and find that a child's outcomes are more strongly associated with his father's attainment than his mother's. Black, Devereux, and Salvanes (2005) find a similar relationship, analyzing compulsory schooling law changes in Norway, but surmise that these associations (at least in their setting) are driven by selection rather than causation.

pell," and by as much as 30 points (more than 40 percent) using "dad." Nonetheless, even within very high SAT score ranges, a gap remains.

b. Intermediate Outcomes

Students from different backgrounds may differ along other potentially important dimensions that could correlate with credit outcomes. Table 5 presents regression results of alternative specifications of the dependent variable—c_{iy}—in equation (2), most of which relate to educational outcomes (e.g., borrowing; school characteristics). Panels (a) to (d) present results for each background measure in succession.

Columns (1) to (3) indicate that, holding achievement constant, students from low-SES backgrounds are more likely to borrow from the federal government to fund their undergraduate studies, borrow more federal money, and are more likely to default on this debt.[34] Students with less educated parents are about 10 percentage points more likely to borrow and borrow almost $3,000 more. (Using the Pell measures, these figures are closer to 15 percentage points and $5,000.[35]) Students with less educated parents are about 1.5 to 5 percentage points more likely to default, while those receiving Pell Grants are nearly 10 percentage points more likely to.[36]

Columns (4) to (6) present evidence consistent with under-matching. Column (4) indicates that students from low-SES backgrounds are more likely to attend colleges associated with lower earnings. For example, children with mothers with less than a B.A. attend schools where students

[34] The exception is students with less educated mothers, for whom the estimate on amount borrowed is not statistically significant.
[35] The tighter link between background and borrowing when we measure background with the Pell Grant measures (compared with our parental education measures) is almost tautological, as students who qualify for Pell Grants are eligible for more subsidized loans. If borrowing is correlated with lower credit scores, this relationship could help explain why the effects we detect throughout the paper are stronger for the Pell Grant measure than the parental education measure.
[36] Results in columns (1) through (3) hold if we replace the borrowing and default measures of federal student loans for undergraduate studies by total student loan borrowing and higher order delinquency measures for all post-secondary education.

make, on average, $1,770 less, compared to equally able children with more educated mothers. Additionally, children from low-SES backgrounds are more likely to attend less selective schools (columns (5) and (6)).[37]

Columns (7) and (8) investigate differences in attainment. Column (7) shows that students from less affluent backgrounds are also significantly more likely to leave school without a degree. In particular, students with less educated parents are about 9 percentage points more likely to drop out, while students receiving Pell Grants are 6 percentage points more likely to drop out. Column (8) presents mixed evidence of years spent in school by background. Although children with less educated mothers are in school about one-quarter of a year less than those with more educated mothers, there is no difference by fathers' education. Additionally, children who receive Pell Grants spend more than half a year more in school, which could be an artifact of the subsidy they are receiving to attend.

Finally, column (9) examines whether an individual's background correlates with how early her credit record began. Theoretically, the relationship is ambiguous. On the one hand, more affluent parents might be more likely to be able to help their children build their credit files earlier in life (by opening credit accounts for them). On the other hand, students from less affluent backgrounds are more likely to fund their undergraduate education with student loans, which can help them build credit files at young ages. Across all specifications, estimates are highly significant and reveal that low-SES individuals have longer credit histories, but the difference is very small—on average, two more months.

We next extend our baseline specification to incorporate these findings. Our goal is to examine the extent to which background itself maintains predictive power for credit scores, after

[37] Only students who attend schools that report (and thus tend to require) SAT scores are included in this model. Thus, this subsample is a subset of college students who attended above-average quality schools.

accounting for other potentially important factors. We begin with undergraduate borrowing, which is of particular interest because such loans—unlike other forms of debt—are widely available to students at fixed prices. We then additively include the variables that remain. In our most comprehensive specification, we control for undergraduate borrowing, school quality (e.g., mean earnings of graduates), educational attainment, whether individuals default on their undergraduate debt, and when the credit record was first established.

The credit score gap shrinks substantially after we account for undergraduate borrowing, by about 40 points, as does the gap in the probability of being a prime borrower, by about 10 percentage points (Table 6). However, both remain statistically significant and large. For example, holding ability and borrowing constant, individuals from low-SES backgrounds have credit scores that are 21 to 74 points lower and are 4 to 16 percentage points less likely to be prime borrowers than their high-SES peers. Interestingly, the table implies that there may be a separate, inverse relationship between borrowing and credit scores.[38]

We next include measures of college quality (Tables 7a and 7b, columns (1), (4), (7), and (10)).[39] Unsurprisingly, attending a higher-quality college is positively associated with credit scores, and, because low-SES students tend to go to lower-quality schools, accounting for quality decreases the credit gap slightly. Then, we add attainment measures—dummy variables for various degree categories (with leaving school without a degree serving as the omitted category) and years spent in school—in columns (2), (5), (8), and (11). Although credit health is positively and significantly correlated with the degree-based measures, the coefficient on years spent in

[38] The coefficients on borrowing might be partly driven—as shown in Table 5—by students from low-SES backgrounds borrowing greater sums of money or being more likely to default on such debt, though Tables 7a and 7b show that undergraduate borrowing remains significant in specifications that also include these measures. Mezza et al. (2016) find that increased student loan debt raises the probability of having poor credit.

[39] In addition, we introduce an indicator variable that takes a value of 1 if the individual never pursued post-secondary education.

school is not significant (though positive). Again, as low-SES students are more likely to leave school without a degree, the credit gap shrinks further, though remains statistically significant (with the exception of Table 7b, column (2)).

Finally, we add an indicator for defaulting on undergraduate loans as well as a continuous measure of length of credit history—both items that could appear on credit reports (columns (3), (6), (9), and (12)). Unsurprisingly, defaulting is highly significantly and inversely related to both credit scores and the probability of being prime, reducing them by about 170 points and 40 percentage points, respectively; however, "length of credit history" offers little additional information. Despite the strong link between default and credit, the credit gap is little changed by the inclusion of these variables, with the largest changes observed among the Pell-based measures; even then, the gap continues to be large and highly significant.

In sum, when we include all of the choice variables from Table 5, the credit gap shrinks substantially—by as much as 80 percent in one specification. Still, in our most inclusive specification, the coefficient on disadvantage remains same-signed and highly significant, implying that borrowing costs for adults from disadvantaged backgrounds are relatively high, even holding these choices constant, and, potentially, that family background itself has predictive power for credit health.

VI. Conclusion

Prior work has documented that children's socioeconomic opportunities depend critically upon their parents' socioeconomic status. Some of this persistence invariably owes to immutable aspects of the household environment. Still, to the extent that a central policy goal is to reduce inequality of opportunity, identifying early differences in important outcomes could expose new areas for corrective policy. Our analysis estimates a gap in credit health that emerges early in the earnings cycle and remains even after accounting for achievement and an array of postsecondary variables. The gap exists whether we measure credit health using raw credit scores or a summary measure derived from these scores that approximates credit access. Because of the many settings in which an individual's credit health is a key ingredient in assessing her risk type, these early differences could be contributing to overarching socioeconomic divides; thus, our findings reveal one potentially fruitful area for intervention that may help level the playing field.

Recall that an individual's credit score is derived using the default outcomes of similar consumers, which credit scoring models estimate based on elements of credit records. These characteristics include: payment history, amount owed, length of history, new credit, and types of credit used. Importantly, they exclude demographic information. So, how could such a gap emerge? There are a few non-exclusive possibilities, each with different policy implications.

First, individuals from disadvantaged backgrounds may face larger financial headwinds (e.g., fewer avenues through which to build healthy credit, larger shocks to their finances, fewer resources to weather financial shocks). Second, individuals from disadvantaged backgrounds may be less versed in the importance of healthy credit records and may even, as a result, take unadvisable credit risks (e.g., cumulating debt they will be unable to repay).[40] Third, individuals from disadvantaged backgrounds may have different consumption preferences or attitudes toward risk. Fourth, and relatedly, elements of the formulas for credit scores may proxy for socioeconomic background as opposed to independently predicting credit performance in a demographically neutral environment (i.e., where demographics are controlled for or where the

[40] The CFPB (2014) found that, with respect to the information credit scoring agencies rely upon, minorities and individuals from low-income households are more likely to be credit invisible or to have unscored credit records than other groups.

estimation sample is limited to a single demographic group).[41] For example, one type of credit might highly correlate with default in credit scoring models, but the utilization of such credit may reflect a cultural norm within disadvantaged communities. Finally, if discriminatory lending practices restrict certain groups' ability to access credit, these groups may have a more difficult time accumulating a strong credit history, which could then affect their scores.[42]

Future research should explore which of the above mechanisms underlie the early gaps in credit health we detect and the effectiveness of policies in ameliorating them. In particular, a key question is whether the differences in credit scores that we document by socioeconomic group stem solely from the underlying default risk of different household types or are partially an unintended artifact of how credit scores are constructed.

---

[41] Relatedly, CFPB (2015) found that the identical treatment of medical and non-medical collections that was being employed by credit scoring agencies was not justified by subsequent debt payment patterns.

[42] Recent studies that have examined the extent to which there is evidence of race-based redlining—an illegal practice whereby residents of certain geographic areas are not given the same access to credit as similarly-qualified residents of other areas and a central concern among regulators of the mortgage industry—yield mixed results (Ethan Cohen-Cole, Brevoort, 2011). Some banks—e.g., Hudson City Savings Bank, BancorpSouth Bank—have been fined millions of dollars in relation to discriminatory mortgage lending practices. See, for example, http://www.consumerfinance.gov/about-us/newsroom/cfpb-and-doj-order-hudson-city-savings-bank-to-pay-27-million-to-increase-mortgage-credit-access-in-communities-illegally-redlined/ or http://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-and-department-justice-action-requires-bancorpsouth-pay-106-million-address-discriminatory-mortgage-lending-practices/.

Work Cited

Avery, R., K. Brevoort, and G. Canner (2012). Does Credit Scoring Produce a Disparate Impact? *Real Estate Economics*: 40(1), 65-114.

Bayle, M. and S. Dynarski (2011). Gains and Gaps: Changing Inequality in U.S. College Entry and Completion. NBER Working Papers 17633.

Behrman, J., and M. Rosenzweig (2002). Does increasing women's schooling raise the schooling of the next generation? *American Economic Review*: 92, 323-334.

Black, S., K. Cortes, and J. Lincove (2015). Academic Undermatching of High-Achieving Minority Students: Evidence from Race-Neutral and Holistic Admissions Policies. *American Economic Review papers and proceedings*: 105(5), 604-610.

Black, S., P. Devereux, and K. Salvanes (2005). Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital. *American Economic Review*: 96(1), 437-449.

Black, S., and P. Devereux (2011). Recent Developments in Intergenerational Mobility, in *Handbook of Labor Economics*, Orley Ashenfelter and David Card, editors, North Holland Press, Elsevier.

Black, D., and J. Smith (2006). Estimating the Returns to College Quality with Multiple Proxies for Quality. *Journal of Labor Economics*: 24(3), 701–728.

Bleemer, Z., M. Brown, D. Lee, and W. van der Klaauw (2014). Debt, Jobs, or Housing: What's Keeping Millennials at Home? Federal Reserve Bank of New York Staff Reports, no. 700.

Board of Governors (2007). Report to the Congress on Credit Scoring and Its Effect on Availability and Affordability of Credit. Federal Reserve Board: Washington, DC.

Bowen, W., M. Chingos, and M. McPherson (2009). Crossing the Finish Line: Completing College at America's Public Universities. Princeton, NJ: Princeton University Press.

Bowles, S., and H. Gintis (2002). The inheritance of inequality. *Journal of Economic Perspectives*: 16, 3-30.

Breland, H., Maxey, J., Gernand, R., Cumming, T., and Trapani, C. (2002). Trends in use college admission 2000: A report of a survey of undergraduate admissions policies, practices, and procedures. Sponsored by ACT, Inc., Association for Institutional Research, The College Board, Educational Testing Service, and the National Association for College Admission Counseling.

Brevoort, K. (2011). Credit card redlining revisited. *The Review of Economic and Statistics*, 93(2), 714-724.

Bulman, G., R. Fairlie, S. Goodman, and A. Isen (2016). Parental Resources and College Attendance: Evidence from Lottery Wins. NBER Working Papers 22679.

Card, D. (1995). Using Geographic Variation in College Proximity to Estimate the Return to Schooling. *Aspects of Labour Economics: Essays in Honour of John Vanderkamp*, edited by L. Christofides, E. K. Grant, and R. Swindinsky. University of Toronto Press, 1995.

CFPB (2014). Data point: Medical Debt and Credit Scores. http://files.consumerfinance.gov/f/201405_cfpb_report_data-point_medical-debt-credit-scores.pdf

CFPB (2015). Data Point: Credit Invisibles. http://files.consumerfinance.gov/f/201405_cfpb_report_data-point_medical-debt-credit-scores.pdf

Chetty, R., N. Hendren, P. Kline, E. Saez, and N. Turner (2014). Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility, *American Economic Review*: 104(5), 141-47.

Clark, M., J. Rothstein, and D. Schanzenbach (2009). Selection Bias in College Admissions Test Scores. *Economics of Education Review*: 28(3), 295-307.

Cohen-Cole, E. (2011). Credit Card Redlining. *The Review of Economics and Statistics*, 93(2), 700-713.

Cohodes S. and J. Goodman (2012, August). First Degree Earns: The Impact of College Quality on College Completion Rates. Working Paper RWP12-033. Harvard Kennedy School Faculty Research Working Paper Series.

Dale, S. and A. Krueger (2002). Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables. *Quarterly Journal of Economics*: 117(4), 1491–1527.

Dale, S. and A. Krueger (2011, June). Estimating the Return to College Selectivity over the Career Using Administrative Earnings Data. Working Paper 17159, NBER.

Dettling, L. and J. Hsu (2014). Returning to the Nest: Debt and Parental Co-Residence Among Young Adults. Finance and Economics Discussions Series 2014-80. Washington: Board of Governors of the Federal Reserve System.

Ghent, A. and M. Kudlyak (2015). Intergenerational Linkages in Household Credit. *Federal Reserve Bank of Richmond Working Paper Series.*

Herkenhoff, K. (2015). "The Impact of Consumer Credit Access on Unemployment." Unpublished manuscript.

Herkenhoff, K., G. Phillips, and E. Cohen-Cole (2016). How Credit Constraints Impact Job Finding Rates, Sorting & Aggregate Output. NBER Working Paper 22274.

Hilger, N. (2016). Parental Job Loss and Children's Long-Term Outcomes: Evidence from 7 Million Fathers' Layoffs. *American Economic Journal: Applied Economics* 8(3): 247-283.

Hoekstra, M. (2009). The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach. *The Review of Economics and Statistics*: 91(4), 717-724.

Hoxby, C. (2009). The Changing Selectivity of American Colleges. *Journal of Economic Perspectives*: 23(4), 95-118.

Hoxby, C. and C. Avery (2013). The Missing "One-Offs": The Hidden Supply of High-Achieving, Low-Income Students. *Brookings Papers on Economic Activity* 46(1), 1-65.

Kane, T. (1995, July). Rising Public College Tuition and College Entry: How Well Do Public Subsidies Promote Access to College? Working Paper 5164, NBER.

Laufer, S., and A. Paciorek (2016). The Effects of Mortgage Credit Availability: Evidence from Minimum Credit Score Lending Rules. Finance and Economics Discussion Series 2016-098. Washington: Board of Governors of the Federal Reserve System.

Lee, C., and G. Solon (2009). Trends in Intergenerational Income Mobility. *Review of Economics and Statistics*: 91(4), 766-772.

Lovenheim, M. and C. Reynolds (2013). The Effect of Housing Wealth on College Choice: Evidence from the Housing Boom. *Journal of Human Resources*: 48(1), 1-35.

Mazumder, B. (2005). Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data. *The Review of Economics and Statistics*: 87(2), 235-255.

Mezza, A., and K. Sommer (2016). A Trillion Dollar Question: What Predicts Student Loan Delinquencies? *Journal of Student Financial Aid*: 46(3), 16-54.

Mezza, A., D. Ringo, S. Sherlund, and K. Sommer (2016). On the Effect of Student Loans on Access to Homeownership. Finance and Economics Discussions Series 2016-010. Washington: Board of Governors of the Federal Reserve System.

Mitnik, P., V. Bryant, M. Weber, and D. Grusky (2015). New Estimates of Intergenerational Mobility Using Administrative Data. SOI working paper.

Musto, D. (2004). What Happens When Information Leaves a Market? Evidence From Post-Bankruptcy Consumers. *The Journal of Business*: 77(4): 725-748.

Pallais, A., and S. Turner (2006). Opportunities for Low Income Students at Top Colleges and Universities: Policy Initiatives and the Distribution of Students. *National Tax Journal*: 59(2), 357-386.

Ringo, D. (2015). Parental Credit Constraints and Child College Attendance. Unpublished manuscript.

Smith, J., M. Pender, and J. Howell (2013). The Full Extent of Academic Undermatch. *Economics of Education Review*: 32, 247-261.

Solon, G. (1999). "Intergenerational Mobility in the Labor Market," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*: 3A, 1761-800.

Spies, R. (2001). The Effect of Rising Costs on College Choice: The Fourth and Final in a Series of Studies on This Subject. Princeton University Research Report Series, No. 117.

Zimmerman, S. (2014). The Returns to College Admission for Academically Marginal Students. *Journal of Labor Economics*: 32(4), 711-754.

Figure 1a
Distribution of Credit Scores by Parents' Educational Attainment

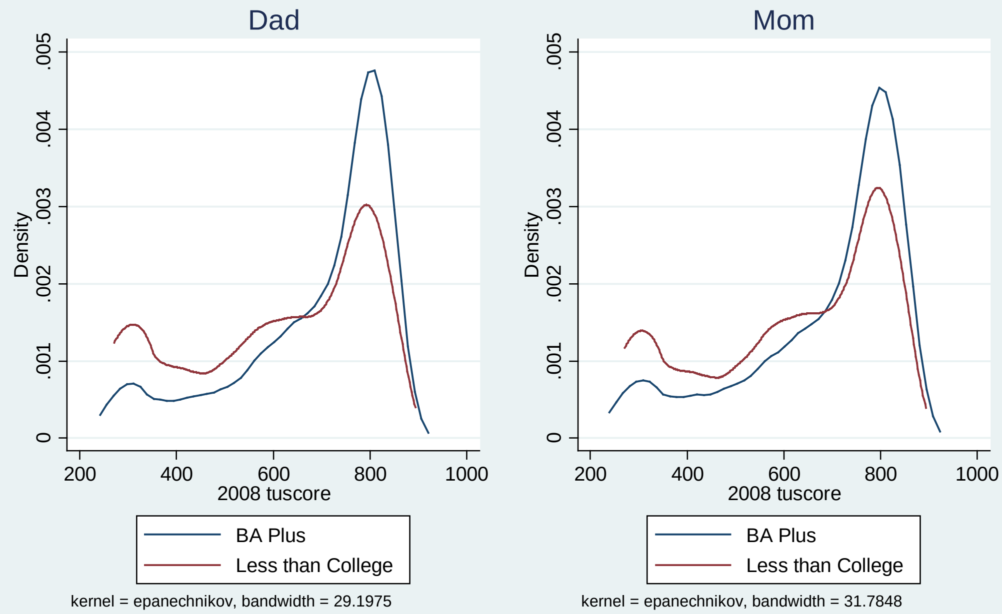


Figure 1b
Distribution of Credit Scores by Pell Grant Receipt

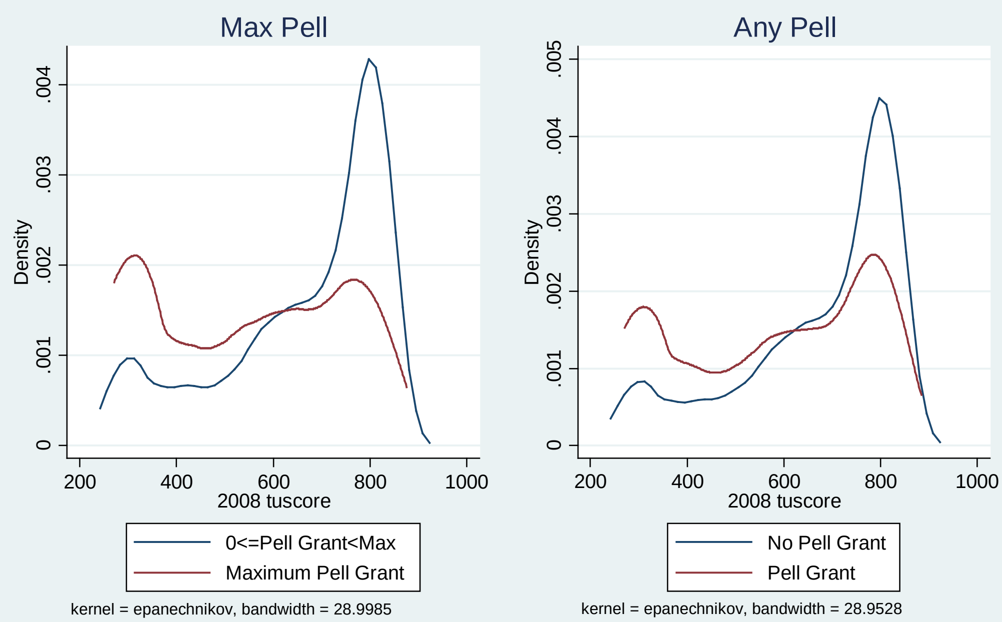


Figure 2a
Distribution of SAT Scores by Dad's Education

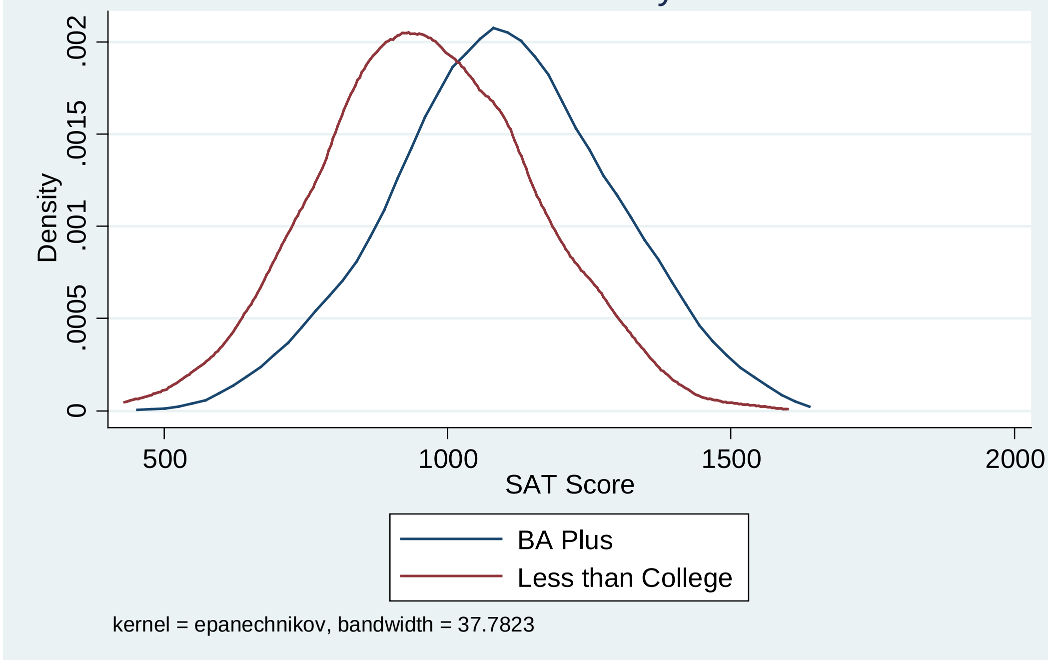


Figure 2b
Distribution of SAT Scores by Pell Grant Receipt

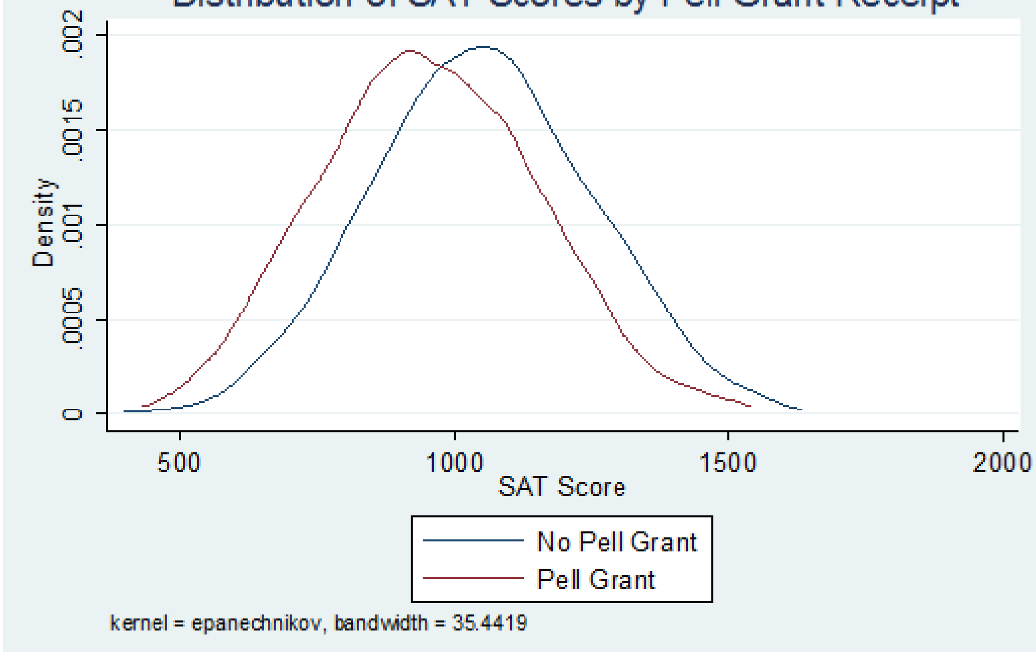


Figure 3
Distribution of SAT Scores by Creditworthiness

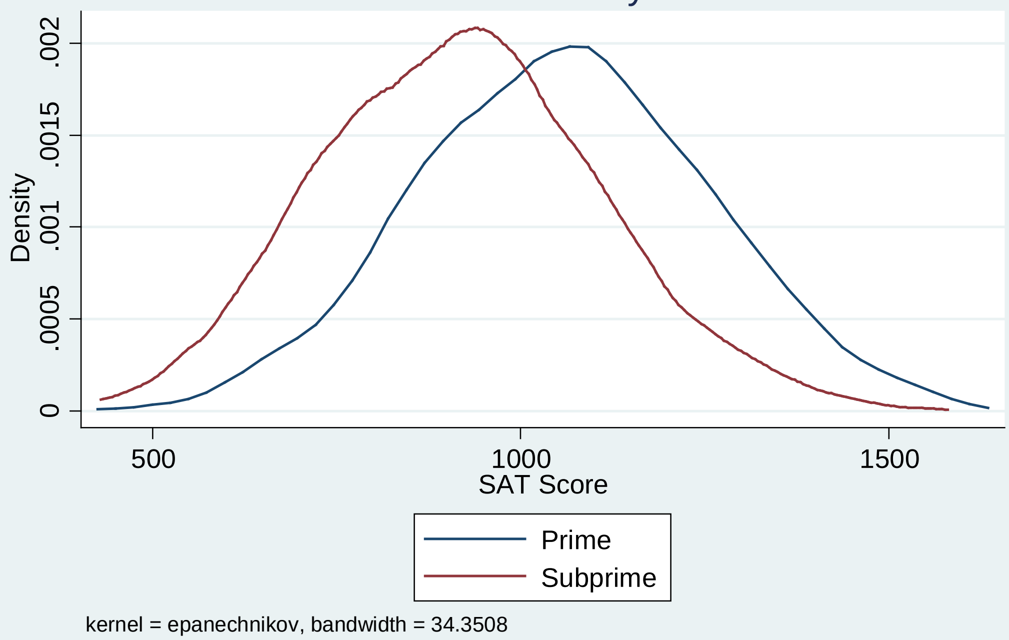
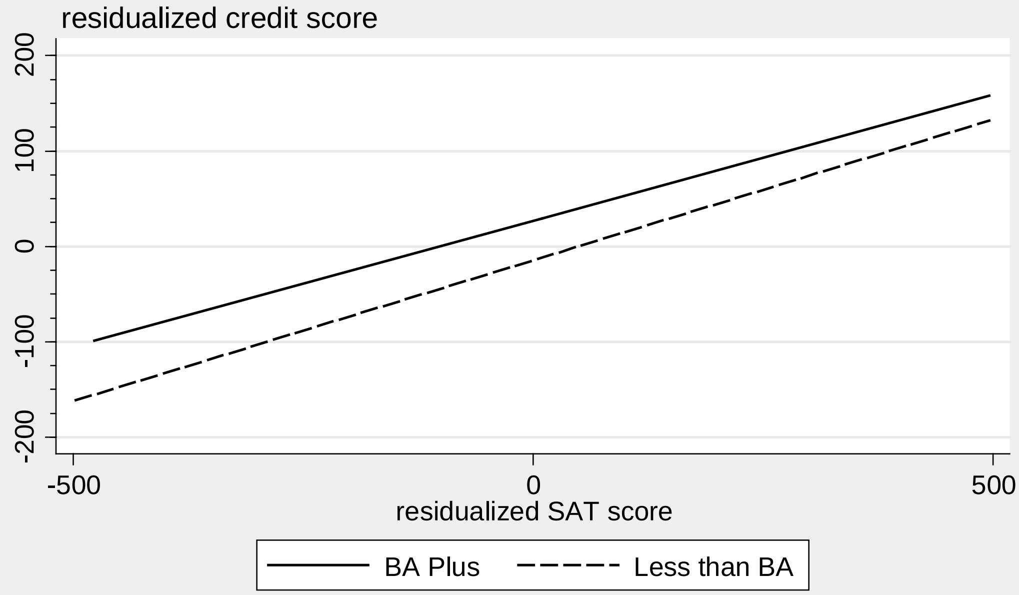
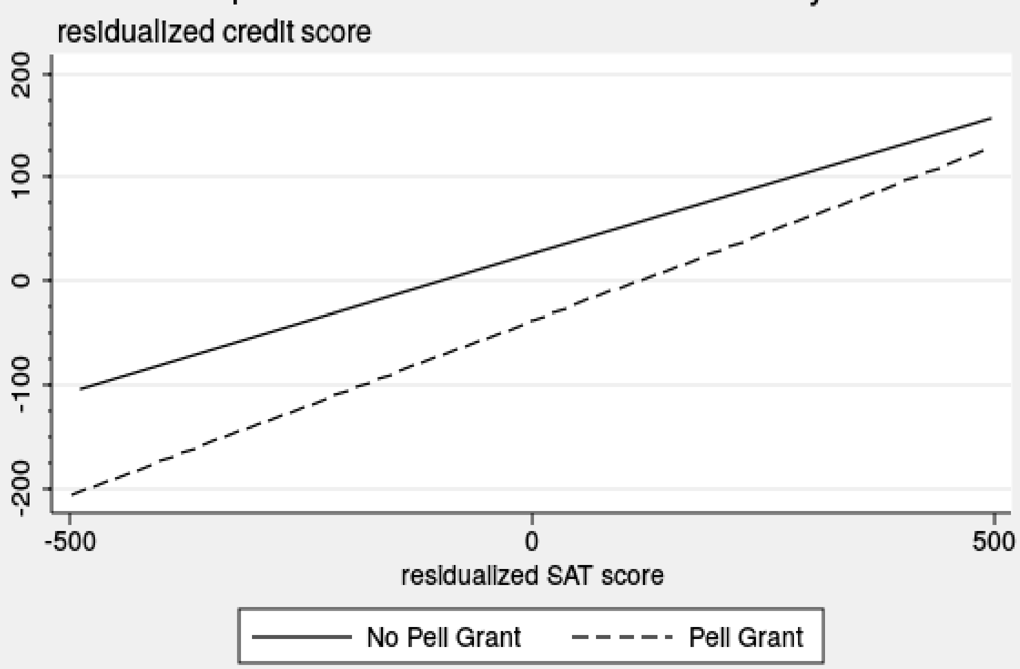


Figure 4a:
Relationship between SAT and Credit Scores by Dad's Ed.



Note: Graph plots residuals after netting out cohort effects and a constant.

Figure 4b:
Relationship between SAT and Credit Scores by Pell Status



Note: Graph plots residuals after netting out cohort effects and a constant.

Table 1: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
dad	4,790	0.563	0.496	0	1
mom	4,867	0.650	0.477	0	1
any_pell	5,421	0.368	0.482	0	1
max_pell	5,421	0.193	0.395	0	1
maxsat100	5,421	10.1	2.1	4.3	16
tuscore2008	5,421	639.3	183.0	271	894
prime	5,421	0.679	0.467	0	1
no school	5,421	0.056	0.230	0	1
borrowed ug	5,421	0.578	0.494	0	1
amount borrowed for ug	5,421	12.602	17.147	0	154.064
defaulted	5,421	0.086	0.280	0	1
school's mean income	4,945	36.94	14.45	7.6	134
sat school	5,421	7.2	5.4	0	14.88
no sat school	5,421	0.352	0.478	0	1
dropout	5,421	0.478	0.500	0	1
graduated but degree unknown	5,421	0.218	0.413	0	1
certificate/associate's	5,421	0.031	0.173	0	1
bachelor's	5,421	0.235	0.424	0	1
master's or more	5,421	0.037	0.189	0	1
years in school	4,736	4.282	2.136	0.01	13.35
length of credit history	5,421	132.9	25.9	16	421
graduation year: 1995	5,421	0.14	0.35	0	1
graduation year: 1996	5,421	0.17	0.38	0	1
graduation year: 1997	5,421	0.17	0.38	0	1
graduation year: 1998	5,421	0.18	0.39	0	1
graduation year: 1999	5,421	0.18	0.38	0	1

Table 2. Family Background and Credit Health

	Credit Score				Prime Borrower?			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-63.92***	-78.59***	-93.60***	-119.1***	-0.138***	-0.177***	-0.210***	-0.259***
	(5.390)	(5.150)	(4.991)	(6.085)	(0.0138)	(0.0133)	(0.0128)	(0.0157)
Constant	692.5***	697.8***	682.0***	671.8***	0.791***	0.810***	0.771***	0.747***
	(7.505)	(7.151)	(6.442)	(6.274)	(0.0193)	(0.0184)	(0.0166)	(0.0162)
Observations	4,867	4,790	5,421	5,421	4,867	4,790	5,421	5,421
R-squared	0.031	0.050	0.064	0.069	0.022	0.038	0.049	0.050

Note: Displayed are coefficients from a simple regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header). Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5).Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. *** denotes significance at 1%.

Table 3: Family Background, Achievement, and Credit Health

	Credit Score				Prime Borrower?			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-25.25***	-41.15***	-65.72***	-82.05***	-0.0497***	-0.0927***	-0.147***	-0.176***
	(5.350)	(5.189)	(4.846)	(5.956)	(0.0139)	(0.0135)	(0.0126)	(0.0156)
maxsat100	29.90***	28.09***	28.82***	28.38***	0.0682***	0.0636***	0.0643***	0.0637***
	(1.252)	(1.270)	(1.138)	(1.144)	(0.00326)	(0.00331)	(0.00297)	(0.00299)
Constant	480.2***	500.8***	494.3***	489.5***	0.307***	0.364***	0.352***	0.337***
	(11.37)	(11.21)	(9.596)	(9.455)	(0.0296)	(0.0292)	(0.0250)	(0.0247)
Observations	4,867	4,790	5,421	5,421	4,867	4,790	5,421	5,421
R-squared	0.133	0.138	0.163	0.164	0.103	0.107	0.125	0.124

Note: Displayed are coefficients from a regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header) and a student's SAT score. Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5). Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. *** denotes significance at 1%.

Table 4: Family Background, Achievement, and Credit Health (Interacting Background with Achievement)

	Credit Score				Prime Borrower?			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-33.50*	-68.35***	-108.6***	-90.00***	-0.119**	-0.174***	-0.254***	-0.191***
	(17.78)	(17.04)	(14.71)	(16.80)	(0.0462)	(0.0444)	(0.0384)	(0.0439)
maxsat100	29.11***	25.72***	26.16***	28.10***	0.0615***	0.0565***	0.0577***	0.0632***
	(2.059)	(1.899)	(1.427)	(1.267)	(0.00535)	(0.00495)	(0.00372)	(0.00331)
Disadvantage ×	1.262	4.277*	7.300***	1.493	0.0105	0.0127*	0.0181***	0.00285
maxsat100	(2.593)	(2.553)	(2.363)	(2.950)	(0.00674)	(0.00666)	(0.00616)	(0.00770)
Constant	485.9***	517.5***	511.5***	491.2***	0.354***	0.414***	0.395***	0.341***
	(16.23)	(14.98)	(11.10)	(10.09)	(0.0422)	(0.0391)	(0.0290)	(0.0264)
Observations	4,867	4,790	5,421	5,421	4,867	4,790	5,421	5,421
R-squared	0.133	0.139	0.165	0.164	0.104	0.108	0.126	0.124

Note: Displayed are coefficients from a regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header), a student's SAT score, and the interaction of the two. Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5). Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. ***, **, * denote significance at 1%, 5%, and 10%.

Table 5a: Association between Family Background and Other Outcomes, Using Mom's Educational Attainment to Measure Family Background

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Borrowed for Ug	Cumul Ug Bor--incl. non-bor	Defaulted on Ug loan?	Mean School Income	Avg SAT for schools reporting SAT	Attending a school that doesn't report SAT	No Degree	Years in School	Length of Credit History
Mom	0.0829***	0.919	0.0153*	-1.770***	-0.204***	0.0375***	0.0887***	-0.255***	1.851***
	(0.0157)	(0.563)	(0.00921)	(0.408)	(0.0388)	(0.0140)	(0.0153)	(0.0689)	(0.617)
maxsat100	0.000310	0.243*	-0.0174***	3.303***	0.344***	-0.0728***	-0.0668***	0.214***	0.0458
	(0.00370)	(0.133)	(0.00217)	(0.0969)	(0.0101)	(0.00329)	(0.00360)	(0.0165)	(0.145)
Constant	0.573***	1215***	0.208***	19.29***	8.958***	0.706***	0.771***	3.023***	159.3***
	(0.0339)	(1.213)	(0.0198)	(0.884)	(0.0909)	(0.0301)	(0.0330)	(0.151)	(1.329)
Observations	4,562	4,562	4,562	4,456	3,185	4,562	4,562	4,259	4,562
R-squared	0.007	0.004	0.019	0.245	0.310	0.121	0.099	0.055	0.465

Note: Displayed are coefficients from regressions of various credit-related outcomes (denoted by the column headers) on mom's education and a student's SAT score. Mom is a binary measure of the mother's educational attainment (where a value of 0 reflects having a BA); therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Debt measured in thousands and real adjusted to 2008 dollars. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text, restricted to those who attended post-secondary school. Regressions include graduation year effects. ***, **, * denote significance at 1%, 5%, and 10%.

Table 5b: Association between Family Background and Other Outcomes, Using Dad's Educational Attainment to Measure Family Background

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Borrowed for Ug	Cumul Ug Bor--incl. non-bor	Defaulted on Ug loan?	Mean School Income	Avg SAT for schools reporting SAT	Attending a school that doesn't report SAT	No Degree	Years in School	Length of Credit History
Dad	0.130***	2.774***	0.0487***	-2.529***	-0.256***	0.0518***	0.0973***	-0.0985	1.849***
	(0.0153)	(0.547)	(0.00888)	(0.399)	(0.0382)	(0.0136)	(0.0149)	(0.0677)	(0.604)
maxsat100	0.00509	0.373***	-0.0139***	3.258***	0.339***	-0.0719***	-0.0654***	0.224***	0.0602
	(0.00377)	(0.135)	(0.00218)	(0.0989)	(0.0102)	(0.00335)	(0.00367)	(0.0169)	(0.149)
Constant	0.523***	10.23***	0.166***	19.85***	8.991***	0.693***	0.762***	2.837***	159.5***
	(0.0335)	(1.199)	(0.0194)	(0.879)	(0.0898)	(0.0298)	(0.0327)	(0.151)	(1.322)
Observations	4,487	4,487	4,487	4,383	3,144	4,487	4,487	4,190	4,487
R-squared	0.017	0.009	0.024	0.248	0.311	0.123	0.099	0.052	0.465

Note: Displayed are coefficients from regressions of various credit-related outcomes (denoted by the column headers) on dad's education and a student's SAT score. Dad is a binary measure of father's educational attainment (where a value of 0 reflects having a BA); therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Debt measured in thousands and real adjusted to 2008 dollars. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text, restricted to those who attended post-secondary school. Regressions include graduation year effects. *** denotes significance at 1%.

Table 5c: Association between Family Background and Other Outcomes, Using any_pell to Measure Family Background

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Borrowed for Ug	Cumul Ug Bor--incl. non-bor	Defaulted on Ug loan?	Mean School Income	Avg SAT for schools reporting SAT	Attending a school that doesn't report SAT	No Degree	Years in School	Length of Credit History
any_pell	0.307***	6.567***	0.0919***	-0.991***	-0.0966***	-0.00122	0.0551***	0.584***	2.502***
	(0.0138)	(0.509)	(0.00841)	(0.378)	(0.0374)	(0.0129)	(0.0141)	(0.0640)	(0.559)
							-		
maxsat100	0.00946***	0.559***	-0.0143***	3.415***	0.356***	-0.0774***	0.0683***	0.253***	0.110
	(0.00330)	(0.121)	(0.00200)	(0.0908)	(0.00950)	(0.00307)	(0.00336)	(0.0153)	(0.133)
Constant	0.442***	7.842***	0.161***	18.04***	8.817***	0.764***	0.805***	2.435***	159.1***
	(0.0283)	(1.042)	(0.0172)	(0.779)	(0.0814)	(0.0264)	(0.0289)	(0.132)	(1.144)
Observations	5,072	5,072	5,072	4,945	3,511	5,072	5,072	4,736	5,072
R-squared	0.090	0.035	0.044	0.246	0.309	0.123	0.093	0.063	0.475

Note: Displayed are coefficients from regressions of various credit-related outcomes (denoted by the column headers) on any_pell and a student's SAT score. any_pell denotes whether the individual was ever awarded a Pell Grant; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Debt measured in thousands and real adjusted to 2008 dollars. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text, restricted to those who attended post-secondary school. Regressions include graduation year effects. *** denotes significance at 1%.

Table 5d: Association between Family Background and Other Outcomes, Using max_pell to Measure Family Background

VARIABLES	(1) Borrowed for Ug	(2) Cumul Ug Bor--incl. non-bor	(3) Defaulted on UG loan?	(4) Mean School Income	(5) Avg SAT for schools reporting SAT	(6) Attending a school that doesn't report SAT	(7) No Degree	(8) Years in School	(9) Length of Credit History
max_pell	0.202***	4.685***	0.0897***	-0.429	-0.0988**	0.0167	0.0598***	0.642***	2.577***
	(0.0173)	(0.624)	(0.0102)	(0.461)	(0.0471)	(0.0156)	(0.0171)	(0.0785)	(0.678)
maxsat100	0.00152	0.409***	-0.0151***	3.452***	0.357***	-0.0764***	-0.0685***	0.252***	0.0953
	(0.00342)	(0.123)	(0.00202)	(0.0913)	(0.00950)	(0.00308)	(0.00338)	(0.0154)	(0.134)
Constant	0.572***	10.43***	0.183***	17.50***	8.792***	0.754***	0.815***	2.536***	159.6***
	(0.0287)	(1.033)	(0.0169)	(0.764)	(0.0797)	(0.0258)	(0.0283)	(0.130)	(1.122)
Observations	5,072	5,072	5,072	4,945	3,511	5,072	5,072	4,736	5,072
R-squared	0.028	0.014	0.036	0.245	0.308	0.124	0.092	0.060	0.474

Note: Displayed are coefficients from regressions of various credit-related outcomes (denoted by the column headers) on max_pell and a student's SAT score. max_pell denotes whether the individual was ever awarded the maximum Pell Grant for a given year; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Debt measured in thousands and real adjusted to 2008 dollars. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text, restricted to those who attended post-secondary school. Regressions include graduation year effects. ***, ** denote significance at 1% and 5%.

Table 6: Family Background, Achievement, and Credit Health (Controlling for Whether Individual Borrowed for Undergraduate Studies)

	Credit Score				Prime Borrower?			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-20.63***	-34.19***	-55.77***	-73.90***	-0.0397***	-0.0778***	-0.128***	-0.159***
	(5.290)	(5.165)	(5.154)	(6.038)	(0.0138)	(0.0135)	(0.0135)	(0.0158)
maxsat100	29.88***	28.34***	28.74***	28.16***	0.0680***	0.0640***	0.0640***	0.0632***
	(1.237)	(1.257)	(1.138)	(1.139)	(0.00323)	(0.00329)	(0.00298)	(0.00299)
Borrowed for undergraduate?	-60.12***	-56.19***	-43.97***	-50.48***	-0.130***	-0.120***	-0.0916***	-0.108***
	(5.082)	(5.112)	(5.000)	(4.822)	(0.0133)	(0.0134)	(0.0131)	(0.0126)
Constant	515.6***	531.0***	521.0***	522.6***	0.385***	0.430***	0.410***	0.409***
	(11.67)	(11.47)	(9.996)	(9.910)	(0.0305)	(0.0300)	(0.0262)	(0.0260)
Observations	4,867	4,790	5,421	5,421	4,867	4,790	5,421	5,421
R-squared	0.158	0.159	0.177	0.182	0.121	0.122	0.134	0.136

Note: Displayed are coefficients from a regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header), a student's SAT score, and whether the individual borrowed from the Federal government for undergraduate studies. Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5). Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects and a dummy variable taking a value of 1 if an individual did not attend postsecondary school. *** denotes significance at 1%.

Table 7a: Family Background, Achievement, and Credit Scores (Sequentially Adding Controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		mom			dad			any_pell			max_pell	
Disadvantage	-16.39***	-10.09*	-11.49**	-29.81***	-20.64***	-18.21***	-52.47***	-42.14***	-34.41***	-71.50***	-62.22***	-52.12***
	(5.316)	(5.200)	(5.008)	(5.214)	(5.126)	(4.939)	(5.204)	(5.242)	(5.061)	(6.105)	(6.174)	(5.971)
maxsat100	24.80***	20.00***	18.36***	23.76***	19.25***	17.98***	23.65***	19.42***	18.09***	22.89***	18.58***	17.37***
	(1.414)	(1.411)	(1.361)	(1.429)	(1.430)	(1.378)	(1.318)	(1.324)	(1.277)	(1.320)	(1.327)	(1.279)
Borrowed for Undergraduate?	-68.13***	-58.17***	-34.24***	-63.88***	-54.60***	-32.05***	-54.12***	-45.33***	-23.38***	-60.69***	-50.10***	-27.45***
	(6.541)	(6.507)	(6.413)	(6.589)	(6.563)	(6.457)	(6.344)	(6.353)	(6.235)	(6.180)	(6.181)	(6.087)
Cumulative Undergraduate Borrowing	0.0329	-0.453**	-0.471***	0.0269	-0.464**	-0.452**	0.140	-0.404**	-0.419**	0.162	-0.394**	-0.413**
	(0.182)	(0.187)	(0.180)	(0.184)	(0.189)	(0.182)	(0.173)	(0.178)	(0.171)	(0.172)	(0.177)	(0.171)
Mean School Income	0.601**	0.430*	0.237	0.514**	0.351	0.197	0.604***	0.394*	0.258	0.657***	0.443**	0.299
	(0.239)	(0.237)	(0.229)	(0.239)	(0.238)	(0.229)	(0.224)	(0.223)	(0.215)	(0.223)	(0.222)	(0.214)
Avg SAT for Schools reporting SAT	3.278***	1.234*	2.307***	3.086***	1.194*	2.173***	3.050***	1.225**	2.197***	3.016***	1.172*	2.138***
	(0.655)	(0.652)	(0.630)	(0.658)	(0.655)	(0.633)	(0.617)	(0.616)	(0.595)	(0.614)	(0.614)	(0.593)
Certificate or Associate's		93.09***	78.45***		92.36***	77.65***		85.66***	71.46***		83.82***	70.01***
		(6.943)	(6.727)		(6.978)	(6.765)		(6.614)	(6.407)		(6.597)	(6.393)
Bachelor's		107.9***	88.17***		105.7***	86.63***		102.2***	83.47***		101.5***	83.02***
		(6.578)	(6.417)		(6.609)	(6.445)		(6.265)	(6.104)		(6.241)	(6.085)
Master's or Above		126.0***	107.7***		123.5***	105.8***		116.9***	100.2***		116.4***	99.82***
		(13.30)	(12.84)		(13.28)	(12.82)		(12.59)	(12.15)		(12.53)	(12.10)
Years in School		0.782	-0.406		0.618	-0.533		2.124	0.655		2.547*	1.048
		(1.402)	(1.350)		(1.406)	(1.355)		(1.332)	(1.284)		(1.328)	(1.282)
Defaulted on UG Loan?			-173.7***			-173.7***			-173.2***			-171.3***
			(9.255)			(9.381)			(8.767)			(8.747)
Length of Credit History			-0.106			-0.102			-0.111			-0.0979
			(0.120)			(0.121)			(0.115)			(0.115)
Constant	501.4***	482.9***	527.0***	518.9***	497.6***	535.4***	510.4***	486.6***	525.6***	511.7***	488.8***	525.5***
	(12.50)	(12.78)	(22.25)	(12.36)	(12.63)	(22.22)	(10.85)	(11.09)	(20.82)	(10.73)	(10.97)	(20.71)
Observations	4,723	4,439	4,439	4,649	4,371	4,371	5,249	4,939	4,939	5,249	4,939	4,939

R-squared	0.168	0.228	0.286	0.168	0.226	0.283	0.185	0.237	0.293	0.191	0.243	0.298

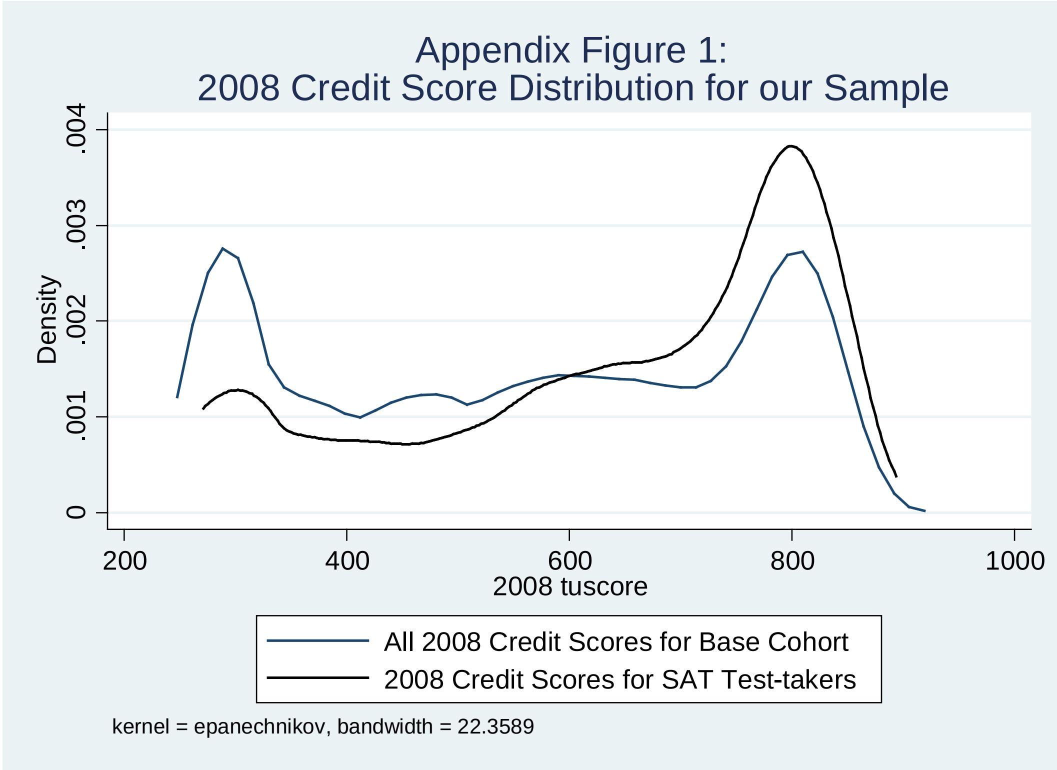
Note: Displayed are coefficients from a regression of 2008 credit score on a measure of disadvantage (denoted by the column header), a student's SAT score, the credit-related outcomes examined in Tables 5a-5d, and a dummy variable taking a value of 1 if an individual did not attend postsecondary school. Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Debt measured in thousands and real adjusted to 2008 dollars. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. ***, **, and * denote significance at 1%, 5%, and 10%.

Table 7b. Family Background, Achievement, and Prime Borrower Status (Sequentially Adding Controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		mom			dad			any_pell			max_pell	
Disadvantage	-0.0294**	-0.0127	-0.0161	-0.0670***	-0.0433***	-0.0380***	-0.119***	-0.0905***	-0.0731***	-0.153***	-0.127***	-0.104***
	(0.0139)	(0.0138)	(0.0134)	(0.0137)	(0.0136)	(0.0133)	(0.0136)	(0.0139)	(0.0136)	(0.0160)	(0.0164)	(0.0160)
maxsat100	0.0564***	0.0458***	0.0421***	0.0536***	0.0438***	0.0409***	0.0519***	0.0429***	0.0399***	0.0506***	0.0413***	0.0386***
	(0.00370)	(0.00374)	(0.00364)	(0.00374)	(0.00380)	(0.00370)	(0.00345)	(0.00351)	(0.00342)	(0.00346)	(0.00352)	(0.00343)
Borrowed for Undergraduate?	-0.150***	-0.128***	-0.0736***	-0.140***	-0.120***	-0.0692***	-0.116***	-0.0985***	-0.0493***	-0.132***	-0.110***	-0.0586***
	(0.0171)	(0.0172)	(0.0172)	(0.0173)	(0.0174)	(0.0173)	(0.0166)	(0.0168)	(0.0167)	(0.0162)	(0.0164)	(0.0163)
Cumulative Undergraduate Borrowing	0.000229	-0.000979**	-0.00103**	0.000255	-0.000946*	-0.000929*	0.000405	-0.000939**	-0.000984**	0.000450	-0.000917*	-0.000968**
	(0.000476)	(0.000496)	(0.000482)	(0.000482)	(0.000503)	(0.000489)	(0.000452)	(0.000472)	(0.000459)	(0.000451)	(0.000471)	(0.000458)
Mean School Income	0.00135**	0.000995	0.000541	0.00118*	0.000833	0.000465	0.00139**	0.000913	0.000591	0.00151***	0.00102*	0.000677
	(0.000625)	(0.000629)	(0.000612)	(0.000627)	(0.000632)	(0.000615)	(0.000586)	(0.000591)	(0.000576)	(0.000585)	(0.000590)	(0.000575)
Avg SAT for Schools reporting SAT	0.00744***	0.00264	0.00509***	0.00682***	0.00238	0.00463***	0.00734***	0.00307*	0.00527***	0.00729***	0.00298*	0.00517***
	(0.00171)	(0.00173)	(0.00169)	(0.00173)	(0.00174)	(0.00170)	(0.00161)	(0.00163)	(0.00159)	(0.00161)	(0.00163)	(0.00159)
Certificate or Associate's		0.212***	0.179***		0.207***	0.174***		0.190***	0.157***		0.186***	0.155***
		(0.0184)	(0.0180)		(0.0185)	(0.0182)		(0.0175)	(0.0172)		(0.0175)	(0.0171)
Bachelor's		0.245***	0.200***		0.240***	0.196***		0.226***	0.183***		0.225***	0.183***
		(0.0174)	(0.0172)		(0.0176)	(0.0173)		(0.0166)	(0.0163)		(0.0166)	(0.0163)
Master's or Above		0.276***	0.234***		0.270***	0.230***		0.254***	0.215***		0.253***	0.216***
		(0.0352)	(0.0343)		(0.0353)	(0.0344)		(0.0334)	(0.0325)		(0.0333)	(0.0325)
Years in School		0.00227	-0.000442		0.00180	-0.000841		0.00642*	0.00309		0.00717**	0.00376
		(0.00371)	(0.00361)		(0.00374)	(0.00364)		(0.00353)	(0.00344)		(0.00353)	(0.00344)
Defaulted on UG Loan?			-0.398***			-0.400***			-0.395***			-0.391***
			(0.0248)			(0.0252)			(0.0235)			(0.0235)
Length of Credit History			-7.21e-05			-4.80e-05			-8.01e-05			-5.52e-05
			(0.000322)			(0.000323)			(0.000309)			(0.000308)
Constant	0.353***	0.308***	0.383***	0.403***	0.352***	0.410***	0.385***	0.328***	0.390***	0.383***	0.330***	0.388***
	(0.0327)	(0.0339)	(0.0595)	(0.0324)	(0.0336)	(0.0596)	(0.0284)	(0.0294)	(0.0557)	(0.0281)	(0.0291)	(0.0555)
Observations	4,723	4,439	4,439	4,649	4,371	4,371	5,249	4,939	4,939	5,249	4,939	4,939

R-squared	0.128	0.175	0.221	0.128	0.172	0.218	0.141	0.179	0.224	0.143	0.182	0.226

Note: Displayed are coefficients from a regression of 2008 prime status on a measure of disadvantage (denoted by the column header), a student's SAT score, the credit-related outcomes examined in Tables 5a-5d, and a dummy variable taking a value of 1 if an individual did not attend postsecondary school. Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5). Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. maxSAT100 is SAT score, measured in hundreds and ranging from 0 to 12. Debt measured in thousands and real adjusted to 2008 dollars. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. ***, **, and * denote significance at 1%, 5%, and 10%.


Appendix Figure 1:
2008 Credit Score Distribution for our Sample
Density
0
.001
.002
.003
.004
200
400
600
800
1000
2008 tuscore
All 2008 Credit Scores for Base Cohort
2008 Credit Scores for SAT Test-takers
kernel = epanechnikov, bandwidth = 22.3589

Appendix Table 1: Estimated Relationship between Family Background and 2008 Credit Health, All College-Goers

	Credit Access	
	Score	Prime
any_pell	-113.2***	-0.255***
	(2.551)	(0.00645)
Constant	621.1***	0.642***
	(4.012)	(0.0102)
Observations	22,162	22,162
R-squared	0.085	0.067

Note: Displayed are coefficients from a simple regression of a measure of 2008 credit health (denoted by super column header) on Pell Grant receipt. Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5). Sample is all individuals with 2004 credit records in our sample that can be matched to college-going activity (i.e., any individual with a record in the National Student Loan Data System, the National Student Clearinghouse, or information on student loan originations to fund post-secondary education available in TU) as described in the main text. Regressions include year of birth effects. *** denotes significance at the 1%.

Appendix Table 2. Family Background and Credit Health, SAT States

	Credit Score				Prime Borrower?			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-66.45***	-79.72***	-91.11***	-117.5***	-0.141***	-0.174***	-0.206***	-0.260***
	(6.237)	(5.923)	(5.669)	(6.874)	(0.0161)	(0.0153)	(0.0146)	(0.0177)
Constant	686.2***	691.4***	672.8***	662.8***	0.776***	0.792***	0.752***	0.729***
	(8.613)	(8.211)	(7.316)	(7.110)	(0.0222)	(0.0212)	(0.0188)	(0.0183)
Observations	3,815	3,752	4,274	4,274	3,815	3,752	4,274	4,274
R-squared	0.032	0.050	0.060	0.067	0.023	0.036	0.046	0.050

Note: Displayed are coefficients from a simple regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header). Threshold for prime borrower is median TU credit score in 2008 (i.e., 580.5). Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text, restricted further to test-takers from states where the SAT was the dominant exam (Clark, Rothstein, and Schanzenbach, 2009). Regressions include graduation year effects. *** denotes significance at 1%.

Appendix Table 3. Family Background and Prime Borrower Status, Alternative Prime Thresholds

A. Mortgage Market Definitions

	Prime Cutoff from Laufer and Paciorek (2016) TU credit score > 526				Bottom of Mortgage Market TU credit score > 351			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-0.111***	-0.149***	-0.194***	-0.253***	-0.0701***	-0.0887***	-0.121***	-0.156***
	(0.0130)	(0.0124)	(0.0120)	(0.0147)	(0.00975)	(0.00932)	(0.00915)	(0.0112)
Constant	0.840***	0.857***	0.830***	0.811***	0.936***	0.942***	0.933***	0.920***
	(0.0180)	(0.0172)	(0.0155)	(0.0151)	(0.0136)	(0.0129)	(0.0118)	(0.0115)
Observations	4,867	4,790	5,421	5,421	4,867	4,790	5,421	5,421
R-squared	0.018	0.032	0.048	0.055	0.014	0.022	0.034	0.038

B. Current Industry Consensus Definition

	TU credit score > 620			
	mom	dad	any_pell	max_pell
Disadvantage	-0.146***	-0.185***	-0.215***	-0.266***
	(0.0144)	(0.0138)	(0.0134)	(0.0163)
Constant	0.735***	0.751***	0.709***	0.684***
	(0.0201)	(0.0192)	(0.0172)	(0.0168)
Observations	4,867	4,790	5,421	5,421
R-squared	0.022	0.038	0.047	0.048

Note: Displayed are coefficients from a simple regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header). A TU score of 526 corresponds to an Equifax Risk score of 620—a cutoff commonly used by mortgage lenders in applications for credit, especially after 2009 (Laufer and Paciorek, 2016). A TU score of 351 corresponds to an Equifax Risk score of 550—a score at which very few mortgage originations occur, even in 2008. A TU score of 620 approximates the probability of default associated with a FICO score between 680 and 700, a current industry consensus definition of a prime borrower. Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. *** denotes significance at 1%.

Appendix Table 4. Family Background and 2014 Credit Health

	Credit Score				Prime Borrower?			
	mom	dad	any_pell	max_pell	mom	dad	any_pell	max_pell
Disadvantage	-62.36***	-76.53***	-85.04***	-108.7***	-0.144***	-0.171***	-0.198***	-0.259***
	(5.232)	(5.010)	(4.880)	(5.952)	(0.0138)	(0.0132)	(0.0129)	(0.0157)
Constant	706.7***	710.2***	693.2***	684.2***	0.800***	0.804***	0.763***	0.744***
	(7.273)	(6.943)	(6.282)	(6.121)	(0.0191)	(0.0183)	(0.0166)	(0.0161)
Observations	4,806	4,729	5,351	5,351	4,806	4,729	5,351	5,351
R-squared	0.031	0.049	0.055	0.060	0.024	0.036	0.043	0.050

Note: Displayed are coefficients from a simple regression of a measure of 2008 credit health (denoted by the super column header) on a measure of disadvantage (denoted by the subcolumn header). Threshold for prime borrower is median TU credit score in 2014 (i.e., 597). Mom and dad are binary measures of the corresponding parent's educational attainment (where a value of 0 reflects having a BA), any_pell denotes whether the individual was ever awarded a Pell Grant, and max_pell denotes whether the individual was ever awarded the maximum Pell Grant available in a given year; therefore, higher values are associated with higher SES. Sample is SAT test-takers matched to the nationally-representative cohort of 23- to 31-year-old individuals with credit records in 2004 as described in the main text. Regressions include graduation year effects. *** denotes significance at 1%.