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RESEARCH DEPARTMENT

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WP 22-21

PUBLISHED
August 2022

FRB CFI
PHILADELPHIA

ISSN: 1962-5361

DOI: https://doi.org/10.21799/frbp.wp.2022.21

Foreclosure Kids: Examining the Early Adult Credit Usage of Adolescents Affected by Foreclosure

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August 2022

Abstract

We investigate the long-term effects of foreclosure-induced relocations on adolescents and their subsequent use of credit. We ask whether individuals who experience a foreclosure-induced move between the ages of 10 and 17 are more likely to exhibit signs of credit scarring later in life. To establish a set of counterfactual outcomes, we implement propensity score matching with exact matching on certain characteristics and regression adjustment of the remaining covariate imbalances. We then compare the credit behavior of individuals who experienced a foreclosure-induced move in adolescence to similar individuals who neither experienced a foreclosure nor moved during adolescence. We find that young adults who experience a foreclosure-induced move tend to spend more time with one or more tradelines in a state of severe delinquency and tend to seek credit at a higher rate, which lowers their credit score trajectory relative to individuals who did not experience a foreclosure or a move in adolescence. This association is most evident within the group of children whose parents had nonprime credit scores one year prior to mortgage origination. Delinquency and low credit scores are also more pronounced in the group of adolescents who were between the ages of 10 and 14 at the time of foreclosure.

Keywords: foreclosure, credit scores, intergenerational credit, household finance

JEL Classification Numbers: D14, G21, R20

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Leigh-Ann Schultz participated in this research in her prior position at the Federal Reserve Bank of Philadelphia; she is now a Solutions Consultant at Experian. The views, information, and conclusions expressed in this paper do not represent Experian and any views, information, and conclusions expressed in this paper solely represent the views, information, and conclusions of the authors. The authors thank Nathan Blascak, Julia Cheney, Bob Hunt, and Slava Mikhed for their advice and suggestions. The authors thank Bryant Wright for his excellent research assistance while in his prior position at the Federal Reserve Bank of Philadelphia.

1. Introduction

The effects of foreclosure on families, in particular families with children, is an understudied area of economics. This is surprising, given that so many children appear to have been affected by the foreclosure crisis of the Great Recession. A 2012 report estimated that the families of as many as 2.3 million children had lost their (owner-occupied) homes as a result of the foreclosure crisis, and as many as 6 million more were at risk of losing their home (Isaacs, 2012). The report notes that foreclosure can affect children through at least four different pathways. First, families are more likely to move, which can affect child educational and social outcomes. Second, homeowners experience financial and psychological distress, which can affect parenting and other interpersonal relationships. Third, foreclosure and housing instability can affect physical and mental health through new medical conditions or the delayed treatment of existing conditions. Last, when foreclosures are geographically concentrated, neighborhoods may experience increased crime and lower levels of public goods and social services (Isaacs, 2012).

In many cases, foreclosure results in a change of residence. For the child, this can cause them to change schools, creating a disruption in their learning and social environments. For parents, the foreclosure process involves a great deal of time and effort on phone calls and in meetings with bankers and attorneys, and it is a significant cause of emotional and physical distress (Tsai, 2015; Currie and Tekin, 2015). Depending on state law and other factors, the foreclosure process may drag on for many months (Cordell and Lambie-Hanson, 2015). While parents can attempt to shield children from much of the anguish that accompanies losing one's home to foreclosure, adolescent children may be aware of their family's circumstances and come to associate their family's involuntary relocation with the acts of a financial service provider.[1]

In this paper, we investigate the long-term consequences of foreclosure-induced household relocations on adolescents and their subsequent use of credit. Our primary research question is whether individuals who experience a foreclosure-induced move in adolescence are more likely to exhibit signs of credit scarring or credit aversion — a reluctance to borrow or use credit products

[1] Although *adolescence* is often associated with the teenage years, the World Health Organization defines it as the phase of life between childhood and adulthood, from ages 10 to 19 (World Health Organization, 2021).

— later in life. We use panel credit bureau data and propensity score matching to compare the credit behavior of individuals who experienced foreclosure-induced moves in adolescence with similar individuals who did not experience a foreclosure and did not move during adolescence. We match on a set of observable characteristics including a child's year of birth, state of residence, year of mortgage origination, lagged parental credit variables, block-group level census variables, and county-level unemployment rates. We follow individuals from the age at which they enter the credit bureau — typically no earlier than age 18 — until age 27.

To establish a set of counterfactual outcomes, we implement a propensity score matching algorithm with exact matching on certain characteristics and regression adjustment of the remaining covariate imbalances. In our main results, we create a separate matched sample for each dependent variable and present results from three different propensity score matches, one kernel-based and two nearest-neighbor matches. We confirm graphically that each of our matching algorithms satisfy the common support assumption.

Relative to our matched comparison group, we find that young adults who experience a foreclosure-induced move (foreclosure movers) experience financial difficulty early in life that affects them for many years because of the influence of delinquency on credit scores.[2] These individuals tend to spend more time with one or more credit accounts (tradelines) in a state of severe delinquency, which in turn negatively affects their credit score trajectory. When we split the sample into prime and nonprime groups based on the parent's credit score one year prior to mortgage origination, we find that the signs of financial distress are more acute in the nonprime group. Thus, there is some evidence that children of nonprime borrowers may be more susceptible to credit scarring following a foreclosure move, perhaps a result of weaker resiliency among more financially vulnerable populations.

The life disruptions caused by foreclosure-induced moves in adolescence do not appear to be correlated with other aspects of credit usage. Relative to a comparison group selected via

[2] The credit score used in our analysis is the Equifax Risk Score (credit score) provided in the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data. Throughout our data analysis and results, the phrase credit score refers to the Equifax Risk Score.

propensity scoring with regression adjustment, we find no difference in a host of variables, including the age at which foreclosure movers first enter the bureau data, the number of open tradelines and credit score at first appearance in the bureau data, whether the individual has a credit score upon bureau entry, the number of quarters in which individuals are observed between the ages of 18 to 27, the average number of open accounts during the observation period, the number of open tradelines at last appearance, and the average percentage of tradelines that are delinquent each quarter.

To further examine the salience of the foreclosure-move experience on the adolescent mind, we split the sample into two additional groups based on the adolescent's age at the time the household entered foreclosure. We find that, relative to the comparable control group, individuals in the 10- to 14-year age group are more likely to become delinquent on one or more tradelines during the observation period and to have a higher percentage of delinquent tradelines. Individuals in both the 10- to 14-year- and 15- to 17-year-age groups tend to spend some time in delinquency during the observation period, have lower credit scores at the end of the observation period, have lower maximum credit scores during the observation period, and have more credit inquiries during the final 24 months of observation.

We assess the robustness of our main estimates to unobserved confounders using a sensitivity analysis proposed by Rosenbaum (2007). Such tests quantify the magnitude of bias from unobserved confounders that would need to exist to invalidate a statistically significant result. Our sensitivity analysis indicates that an unobserved confounder would have to increase the probability of an individual falling into the foreclosure-mover group by 26 percent to 71 percent before the coefficient estimates on the treatment variable were no longer statistically significant.

Our research contributes to the small but growing literature on intergenerational linkages in household credit (e.g., Ghent and Kudlyak, 2016) and has implications for housing policy, public health, and equity in financial and credit resiliency. We also contribute to the literature on the psychological effects of formative experiences on future behavior (e.g., Severen and van Benthem, 2019), as well as the growing literature at the intersection of health and the real economy (e.g., Blascak and Mikhed, 2018).

The paper proceeds as follows. In Section 2, we discuss the related literature. The data are described in Section 3. In Section 4, we discuss our empirical strategy. Results are presented in Section 5. We conclude in Section 6 with a discussion of the results and areas for future research.

2. Literature Review

Our work is related to the literature on the relationship between financial distress and long-run financial behaviors. This association has been studied through several lenses that intersect with our research question, including intergenerational economic trends, the financial and physical consequences of economic stress on credit risk, especially during formative years, and the impacts of foreclosure.

Though we believe ours to be the first to link parent foreclosure to child credit habits, several papers have studied the links between parent-and-child credit and economic health. Most relevant is the Ghent and Kudlyak (2016) study, which introduces a correlative link in intergenerational credit behaviors in the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP).[3] The authors find that children of parents with higher credit scores, lower levels of credit utilization, and no serious defaults are less likely to file for bankruptcy or enter serious default. They are also more likely to have credit cards, higher credit scores, and to become homeowners. They also present a comprehensive literature review on intergenerational wealth, income and economic mobility, and preferences.

Of the intergenerational studies mentioned, most notable are those that study the Panel Survey of Income Dynamics (PSID). The PSID has been used to link intergenerational habits in terms of both wealth (Charles and Hurst, 2003) and consumption (Waldkirch, Ng, and Cox, 2004, and Charles et al., 2014), while controlling for relevant correlators such as income. Likewise, there is a related literature on credit and household formation, part of a broader intrahousehold credit literature. Dokko, Li, and Hayes (2015) present evidence of assortative matching of couples on credit scores even after controlling for relevant potential confounders.

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[3] The CCP is described in greater detail in Section 4.

Several studies of economic stress and credit risk are relevant to our work. Banerjee and Canals-Cerdá (2012) use a credit risk analysis framework to show the relationship between stressful events (unemployment or economic downturn) and credit risk. They find unemployment shifts significantly affect changes in delinquency, though the effect is close to zero on changes in account balance linked to delinquency changes. They also show that macroeconomic conditions are a good predictor of loss given default and recovery rate. Malmendier and Shen (2020) identify a psychological channel through which the effects of macroeconomic shocks can persist long after a recession has ended, finding that "scarring" from economic downturns leads to lower spending and more accumulated wealth. Malmendier and Nagel (2011) also find that negative macroeconomic experiences can diminish risk preferences, stock market participation rates, and expectations of future stock returns, particularly for young people.

The impact of foreclosure tends to be even more direct than negative macroeconomic experiences. Brevoort and Cooper (2013) show that foreclosures tend to cause credit score decline and slow recovery in credit health, especially for Great Recession foreclosures. Molloy and Shan (2013) study the experience of households post-foreclosure, finding that foreclosure raises the probability of a move, though movers are not more likely to substantially downgrade in living conditions or consumption habits. Demographic and economic relationships seem to exist on both sides of a foreclosure — before and after. Mykyta (2015) finds that families with lower incomes, more food insecurity, and more dependence on social support are more likely to experience foreclosure and, after foreclosure, are more likely to be worse off economically. Other research shows that foreclosure populations tend to have overrepresentations of Black and renter households, households with children and foreign-born homeowners, and households in poorer and higher-crime neighborhoods (Allen, 2011, and Comey and Grosz, 2011).

For children in these households, the effects could be wide ranging, including move effects such as changing schools and social life to negative impacts on financial, psychological, and physical health (Isaacs, 2012). Been et al. (2011) link foreclosure-induced moves to an increased likelihood of children switching schools and more often going to schools with weaker academic standing than their counterparts. Moves in general are linked to numerous instability-driven outcomes, including the loss of parent and child social networks and worse child behavior. Many of these outcomes are interdependent: Pribesh and Downey (1999) find that, while most moveinduced academic decline among children can be explained by family characteristics, part of the decline can be attributed to a loss of social relationships after moving.

Our work is also related to the growing literature at the intersection of health and the real economy, which includes Blascak and Mikhed (2018). Financial distress is intimately linked to physical and mental health. Tsai (2015) finds that 32 of 35 studies about foreclosure, health, and mental health concluded that foreclosure had adverse effects on physical or mental health. Currie and Tekin (2015) suggest that financial distress has both direct effects on health as well as indirect effects through changes in health behaviors. They find that people living in a neighborhood with a high foreclosure rate are more likely to have urgent unscheduled doctor visits, including visits for preventable conditions.

Experiencing economic stress during formative years has the potential to cause more long-term harm than any other life stage. Giuliano and Spilimbergo (2014) find support that experiencing a recession in youth impacts long-term beliefs and preferences. Severen and Benthem (2019) find a similar relationship between gas prices during formative years and long-run driving habits and perceived costs. Shigeoka (2019) studies the impact on growing up in a recession on economic risk preferences, finding that men who experienced extreme economic shocks in youth were more risk averse in the long run in adulthood, were less likely to be self-employed, and were more likely to have longer tenure. The impressionable experiences during youth are not limited to shocks. Brown, Cookson, and Heimer (2019) show that a lack of early exposure to banks and financial markets can have large and persistent effects on how consumers use credit over their lifetime.

3. Data

Our primary data source is the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP), an anonymous and nationally representative 5 percent random sample of U.S. consumers with credit files, as well as all their household members.[4] The CCP is a long and nationally representative panel; updates arrive quarterly, and the data begin in 1999. The

[4] For additional information about the CCP, see Lee and van der Klaauw (2010).

CCP includes each individual's year of birth as well as several geographic designations, including current census block, tract, zip code, and state. It contains no additional demographic information, such as race or gender, nor does it contain any information about the individual's income or asset holdings. It also includes the Equifax Risk Score (credit score), a proprietary credit score based on the odds that a consumer will become severely delinquent on one or more of their credit tradelines in the next 24 months.

For the purpose of our research, the CCP has several important shortcomings. The first shortcoming, surprisingly, is sample size. By construction, the CCP captures the full credit life cycle of just 5 percent of adults with a credit file, and 5 percent of their children, such that the probability of observing both a parent and a child with credit files is 0.25 percent. Fortunately, the data also contain credit files for individuals residing in the same household as those in the primary sample for as long as those individuals reside in a household with someone in the primary sample. Thus, we are able to observe the children of parents in the primary sample while they reside at the same address, even if the child is not a member of the primary sample. This group of children appears to vary meaningfully in terms of credit outcomes when compared with children in the primary sample. One reason for this is if censoring creates a selection issue. In other words, the longer we observe these children living with their parents, the more likely they are to be different from children in the 5 percent sample.

Second, the concept of a household is fluid in the CCP by construction. In the cross section, individuals are considered to be members of the same household if they share the same mailing address and are all assigned a household identification number that — like household composition itself — is not constant over time. The household identification number will be different next period regardless of whether the household composition remains the same. As a result, household members who enter the bureau at a future point in time cannot always be matched to the household they were once a part of in their adolescence, since they may now be part of another household. An individual who enters the CCP at age 18 may no longer reside with her parents, guardians, or whomever was responsible for paying the mortgage on the individual's childhood home. For example, this may occur when a young adult resides elsewhere and has a loan that is being reported to the credit bureau with the borrower's new address. In such cases, we are unable to retain the individual in the sample. The majority of new entrants do appear to retain their relationship with the childhood household at bureau entry, which allows us to identify "parent-child" relationships using an age cutoff rule that requires parents to be at least 18 years older than the oldest child in the household.

Another noteworthy limitation of the data is that, since the CCP is an individual-level data set and individuals may have more than one mortgage, the data do not include an owner-occupancy indicator. We exclude foreclosures on nonprimary residences, including second homes and investment properties. Following Haughwout et al. (2011), we identify foreclosures on primary residences through the narrative codes on mortgage tradelines. Haughwout et al. (2011) separate mortgage borrowers based on the number of distinct first-lien mortgage accounts appearing on their credit report. They note that, since each property can secure at most one first-lien mortgage, the number of such mortgages on a borrower's credit report is a reliable indicator of the minimum number of properties a given individual has borrowed against. We implement this logic using a data set on the individual mortgage accounts of consumers in the CCP. The tradeline-level data include two narrative code variables for each mortgage tradeline that indicate whether the account was in some stage of the foreclosure process at the time the lender reported to the credit bureau. We refer to the quarter in which either of the narrative codes indicate foreclosure as the foreclosure-start quarter, which should correspond to the quarter in which the lender sent a Notice of Default to the severely delinquent mortgagor. This is similar to Brevoort and Cooper (2013), who identify foreclosures by the foreclosure-start quarter found in the individual-level CCP data.

A fourth limitation is that, given a foreclosure has been initiated, we are unable to distinguish between households that move as a result of losing their home through foreclosure and households that exit foreclosure but end up moving for other reasons. As noted in Molloy and Shan (2013) a homeowner might not move after a foreclosure start if a deal can be arranged through refinancing or loan modification. We look for changes in the mortgagor's census block to identify households that moved. While the CCP has proven to be a valuable resource for researchers studying internal migration patterns (e.g., DeWaard, Johnson, and Whitaker, 2019), there appears to be a great deal of variability in the geographic data that amounts to measurement error rather than true household relocation. One potential source of error arises from the probabilistic algorithm the credit bureaus use to determine each consumer's true address, particularly for consumers with multiple residences, post office boxes, and those who have recently moved. DeWaard, Johnson, and Whitaker (2019) explain that to determine a consumer's address, Equifax feeds a list of recently reported addresses through a proprietary algorithm that determines whether the address currently on file should be replaced with a different address. They note that different types of creditors are given different weights based on the perceived reliability of their data, so that a mortgage lender would have a high reliability weight because of the importance of the address in identifying the location of the loan collateral.

To reduce the number of false positives identified by our move algorithm, we created a longitudinal data set with geographic information at the state, county, census tract, and census block levels from mortgage origination to the year the child turns 18. Using this data set, we then eliminated records with changes that occurred in the first quarter after mortgage origination, since it often reflects a change from the old address to the new address. We excluded areal changes that persisted for only one quarter or changes that persisted for more than one quarter but later reverted to the address at mortgage origination. Last, we excluded any areal changes at the state, county, tract, or block level that were not accompanied by a change of at least one lower areal unit (e.g., change in census tract without change in census block). This process resulted in the elimination of approximately 59 percent of all changes in the areal unit in the data set. While this approach may be overly restrictive, given the importance of moving to our analysis, it was critical to have a high degree of certainty around the identification of movers.

We implement several other data cleaning procedures. Most notably, we restrict our analysis to households with two or fewer parent-age individuals and two or fewer grandparent-age individuals. This helps exclude group living quarters such as military housing, dormitories, and prisons, but it may also cause us to exclude persons residing in multifamily dwellings if such dwellings are incorrectly coded as a single residence, as might be the case if the credit bureau could not identify an apartment number. We also remove deceased individuals as well as fragment files. Wardrip and Hunt (2013) define fragment files as "a record that persists in the data set for no more than one year." Removing fragments is particularly important in an analysis of credit behavior when a person first enters the credit bureau data; it is often the case that what at first appears to be two or more individuals with separate tradelines is later found to be a single person. When this occurs, the consumer records are consolidated to a single person, but the earlier fragments will remain in the data set.

Last, we note that, as stated previously, the CCP is an anonymous sample of adults with credit files. One important implication of the anonymity is that children in our foreclosure-mover group may reside with aunts, uncles, grandparents, or other guardians. While this aspect of the child's living arrangement does not affect our analysis, our work would benefit from additional details on the precise relationship between adults and children in the household. Knowing more about the guardian–child relationship would help us determine the relative contributions of nature and nurture to children's credit behavior.

4. Empirical Strategy

In this paper, we ask whether individuals who experience a foreclosure-induced move in adolescence are more likely to exhibit signs of credit scarring or credit avoidance later in life. We follow individuals from the age at which they enter the credit bureau — typically no younger than age 18 — until age 27. We measure a set of credit characteristics that we expect to vary with exposure. To establish a set of counterfactual outcomes, we use a propensity score matching criterion, augmented with exact matching on certain characteristics and regression adjustment of remaining imbalances. We compare the credit behavior of foreclosure movers with similar individuals who did not experience a foreclosure and did not move during adolescence.

We discuss the matching algorithm in further detail in the following section. We then discuss our attempt to identify and estimate a causal effect using an instrumental variable that is commonly used in the foreclosure literature.

4.1. *Propensity Score Matching*

Because we have gathered observational data, individuals are not randomly assigned to treatment and control groups. Household selection into foreclosure-move treatment could be related to observed and unobserved covariates that also affect adolescent children's future credit behaviors. The conditional independence assumption requires that we control for all variables that influence both selection into treatment and future credit outcomes. Only then may we conclude that the counterfactual outcomes are independent of treatment assignment. The assumption may be violated if there are other variables that we do not observe that are correlated both with treatment status and credit outcomes and are independent of observed variables.

While foreclosure and household relocation are clearly exogenous to the adolescent, household selection into foreclosure is not exogenous. To the extent that an adolescent's future credit usage is influenced by the same factors influencing parental selection into foreclosure, *the exogeneity of foreclosure on the adolescent should be set aside in favor of a household-level view of selection.* At a minimum, the likelihood of experiencing foreclosure is correlated with household credit characteristics and demographics (Elul et al., 2010; Mykyta, 2015). Foreclosure likelihood is also affected by macroeconomic conditions and local economic conditions. Recent research by Ganong and Noel (2020) finds that adverse life events such as unemployment account for almost all mortgage defaults. We attempt to control for these potential confounders using a combination of demographic and credit characteristics contained within our credit bureau data, census data matched at the block-group level, and county-level unemployment.[5] We match exactly on: (1) a child's year of birth, (2) state of residence at the time of mortgage, (3) year of mortgage origination, and (4) a dummy variable indicating whether the parent was also in the primary sample. Matching on a child's year of birth is equivalent to matching on the year the child turns 18 and is eligible to have a credit file; thus, this serves as a control for differences observed across time. The work of Ganong and Noel (2020) make it clear that household-level unemployment shocks are a major contributor to foreclosure. While we cannot identify which households in our sample experienced an unemployment shock, matching exactly on the state of residence and year of mortgage origination allows us to control for some degree of variation in local economic conditions as well as features of the mortgage and housing markets that vary with time, such as underwriting standards and average home prices. We also control for county-level unemployment at the time of mortgage origination, as described next.

After creating groups of exactly matched individuals, we construct a propensity score using lagged parental credit variables, census variables measured at the block-group level, and county-level unemployment rates, and use the score to match individuals in the foreclosure-mover group to control units within the same exactly matched group.[6] The parental credit variables include: (1)

[5] Block groups are statistical divisions of census tracts that typically contain between 600 and 3,000 people (United States Census Bureau glossary).

[6] County-level unemployment rates are from the U.S. Bureau of Labor Statistics. We use Stata package called *kmatch* (Jann, 2017) to construct propensity scores and estimate coefficients. The kmatch ps option applies

credit score, (2) presence of severe derogatory record on credit file, (3) number of credit inquiries over the prior 12 months, and (4) count of distinct tradeline types. The census demographic variables include: (1) percent of residents who are non-White, (2) percent of residents who are female, (3) percent of residents who have a bachelor's degree or higher, and (4) the log of median income.[7]

Although our matching and scoring algorithm accounts for a comprehensive set of potentially confounding covariates, we cannot rule out the existence of other unobserved household-level characteristics that might be uncorrelated with the observed covariates and affect both household selection into treatment as well as future child credit performance. Ghent and Kudlyak (2016) suggest that risk preferences, financial literacy, or financial awareness may be at play in the transmission of credit behaviors across generations. We also suggest that the degree of social connectedness may influence both the household's selection into a foreclosure-induced move and future credit behavior. While it seems reasonable to assume that such unobserved household-level characteristics influence our observed variables, it seems less plausible that they operate directly upon selection into treatment and outcomes via channels independent of credit, income, and demographic channels. Our analysis makes a convincing case that our estimates are causal; however, we cannot claim definitive proof. We conduct a sensitivity analysis on our main results using the Rosenbaum bounds method (Rosenbaum, 2007), the results of which indicate that invalidation of our primary results would require a good deal of unobserved confoundedness. Depending on the dependent variable, an unobserved confounder would have to increase the probability of an individual falling into the foreclosure-mover group by 26 percent to 71 percent before the coefficient estimates on the treatment variable were no longer statistically significant at 5 percent.

We measure a variety of credit characteristics that we anticipate would vary with exposure, including age at bureau entry, the number of quarters individuals are observed in the data between ages 18 and 27, the average number of open tradelines each quarter, the number of open tradelines

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propensity score matching, using kernel matching or nearest-neighbor matching and including regression adjustment.

[7] The parent is identified as the mortgage holder. If there are two parent-aged people holding a joint mortgage, the maximum credit score among them is used.

during their first and last quarters, the first and highest credit scores, the average credit score of the last two quarters, the number of inquiries within the last two years observed, the total number of instances of delinquency, the percent of quarters with any delinquency, the percent of account observations in delinquency, and the average percent of trades in delinquency by quarter.

For each of the dependent variables, the parameter of interest is the average difference in outcomes between the treated and counterfactual groups, or average treatment effect on the treated, θ, which can be decomposed into two components:

$$\theta = E[Y^1 - Y^0 | D = 1]$$
$$= E[Y^1 | D = 1] - E[Y^0 | D = 1],$$

where θ is the effect of a foreclosure-induced move, $D = 1$ indicates treatment, and Y^1 and Y^0 denote outcomes with and without treatment, respectively. We observe the sample analog of the first component of the above equation, $E[Y^1 | D = 1]$, and estimate the unobserved counterfactual $E[Y^0 | D = 1]$ as described previously.

In our main results, we create a separate matched sample for each dependent variable and explore the bias/variance tradeoff by presenting results from three different propensity score matches, one kernel-based and two nearest-neighbor matches. For our kernel-based matching estimators, we assume a quartic kernel, given by $K(s) = \frac{15}{16}(s^2 - 1)^2$ for $|s| < 1$ and 0 otherwise (Todd, 2008).

We confirm graphically that each of our matching algorithms satisfy the common support assumption.[8] This condition requires there to be a positive probability of finding a comparable control unit at or nearby each treated unit. If some units in the treatment group have combinations of characteristics that cannot be matched by those units in the comparison group, it is not possible to construct a counterfactual, and therefore, the impact for this subgroup cannot be accurately estimated.

[8] Common support charts are available upon request.

4.2. Instrumental Variables

There are several papers that have used an instrumental variable (IV) to identify the causal effect of foreclosure in various contexts. Common instruments include random assignment of judges, legal differences in state foreclosure requirements, and exogenous shocks to interest rates on adjustable-rate mortgages (ARM). Munroe and Wilse-Samson (2013) and Diamond, Guren, and Tan (2020) use random assignment of chancery-court judges in Cook County, IL. Mian, Sufi, and Trebbi (2015) exploit the judicial foreclosure requirement in certain states that requires a foreclosure to take place through the court system. Gupta (2019) exploits the within-month variation in interest rates paid by borrowers with a resetting ARM.

Of the three approaches described previously, only legal differences in state foreclosure requirements was a feasible candidate for instrument based on our data. As described in the following section, our data provide no indication of which judge may have been assigned to the foreclosure in a judicial foreclosure state, nor allow us to determine whether a household had a fixed- or adjustable-rate mortgage. Following Mian, Sufi, and Trebbi (2015), we created a state classification variable using information from RealtyTrac.com (2013). Within the context of our analysis, the judicial foreclosure instrument did not meet the requirement for relevance. The F-statistics from our first-stage regressions fell within the range of 4.91 to 8.17, well below weak-IV thresholds of 10 to 13; thus, the judicial foreclosure instrument was too weak to rely on for our analysis.

5. Results

In this section, we present several sets of results. We begin with descriptive statistics from our unmatched and unbalanced sample, a comparison of foreclosure-mover neighborhoods before and after moving, and coefficient estimates from multivariate ordinary least squares (OLS). We then present results of our matched estimation analysis, in which individuals in the foreclosure-mover group are matched to individuals in the control pool. In the final two sections, we split the sample by parent credit score and child age at the time of the move and compare coefficient estimates across subgroups.

5.1. Descriptive Statistics

A foreclosure move occurs when a foreclosure status appears on a mortgagor's credit file and his census block subsequently changes. We only flag foreclosure moves (denoted fcl_move = 1) that occur while the adolescent child is between the ages of 10 and 17, and both the foreclosure start and the move must occur while the child is within the age window. We construct a control group (denoted fcl_move = 0) of children whose mortgage-holding parents did not experience a foreclosure or a move while the child was between the ages of 10 and 17. For both the foreclosure mover and control group, we include children only with at least five quarters of credit records between the ages of 18 and 27.

In **Table 1**, we present descriptive statistics for the unmatched and unbalanced sample of foreclosure movers and individuals eligible for selection into the control population via the matching algorithm discussed in Section 3.1. The unmatched sample contains 1,185 foreclosure movers and 37,859 individuals who experienced neither a foreclosure nor a relocation during adolescence. Relative to the pool of control candidates and measured one year prior to mortgage origination, the parents of individuals in the foreclosure-mover group are more than three times as likely to have a severe derogatory in their credit file. On average, they have 2.6 additional credit inquiries during the 12-month period preceding measurement and, at the time of measurement, have slightly fewer distinct types of tradelines on their credit file (2.3 compared with 2.5).

The census block groups of individuals in the foreclosure-mover group tend to have a higher proportion of non-White residents and lower levels of education and income. The average percentage of persons of color (i.e., non-White) in blocks associated with the foreclosure-mover group is 27.3 percent, compared with 20.6 percent in the control pool. The average percentage of those with at least a bachelor's degree in blocks associated with the foreclosure-mover group is 13.3 percent, compared with 17.6 percent in the control pool. Median income is about $3,545 lower on average in the foreclosure-mover group compared with the control candidate pool. Average county-level unemployment in the foreclosure-mover group is 5.23 percent, slightly lower than in the control candidate pool (5.35 percent).

Individuals (children of the mortgage holder) in the foreclosure-mover group tend to be younger, with an average birth year of 1994, compared with 1990 in the control pool. The two groups appear similar in terms of age at bureau entry and number of open accounts at bureau entry, but they are quite different along other dimensions of credit. Individuals in the foreclosure-mover group are 11.6 percentage points less likely to have a credit score at the time of bureau entry (57.7 percent versus 69.3 percent). Conditional on having a credit score at bureau entry, scores in the foreclosure-mover group tend to be lower. The difference in the average score between individuals in the foreclosure-mover group and the control pool is -13 score points.

After bureau entry, individuals in the foreclosure-mover group tend to appear in the bureau data five quarters less often than individuals in the control pool. We suspect this is either a result of foreclosure movers having more frequent spells of credit inactivity or of the credit bureau having a more difficult time linking credit records provided by data furnishers to individual credit files, which could occur because of identifier discrepancies, such as in name or address. During the observation period, individuals in the foreclosure-mover group tend to have fewer open accounts both on average each quarter (3.1 compared with 3.5), as well as at final observation (4.6 compared with 5.0).

Stark differences between foreclosure movers and control candidates emerge when we examine delinquency. About 44.6 percent of foreclosure movers are delinquent on one or more tradelines during the observation period, compared with 31.4 percent in the control pool. Foreclosure movers are in a state of delinquency on average about 16.7 percent of the time, compared with 9.9 percent of the time for control candidates. In the foreclosure-mover group, about 14.6 percent of trades are delinquent at any point in time, compared with 8.9 percent in the control pool. Foreclosure movers also tend to seek credit at higher rates than individuals in the control pool. The average number of credit inquiries over the last 24 months that each foreclosure mover is observed in the bureau data is 2.38, slightly higher than the 2.25 inquiries for individuals in the control pool.

The additional time spent in a delinquent status compounds the difference in initial credit scores, since delinquency has the effect of lowering credit scores. Accounts in the control pool have a 39-point higher credit score by the end of the observation period. Likewise, the highest score obtained during the observation period is about 31 points lower in the foreclosure-mover group.

5.2. Mover Analysis

Our data set allows us to compare the neighborhoods where foreclosure movers reside prior to moving to the neighborhood they live in after the move. In this section, we present several findings from our analysis of foreclosure movers.

Using tract-level census data and year 2000 census tract boundaries, we compare unweighted means for the foreclosure-movers' origination tract and the tract of the first address flagged as a move (move tract) in **Table 2**. Our results are consistent with Molloy and Shan (2013), who find that most households that relocate after a foreclosure move to neighborhoods that share a variety of demographic similarities with their preforeclosure neighborhood. Relative to the preforeclosure tract, move tracts have slightly higher income and education levels. Though not statistically significant, the log of median household income is .03 higher (about $1,285) for the average move tract, compared with the average preforeclosure tract. The average percent of move-tract residents with at least a bachelor's degree is 1 percentage point higher than in the preforeclosure tracts (22 compared with 21 percent). Move tracts also have slightly higher shares of White residents. The average percent of persons of color is 4 percentage points lower among movers' new tracts compared with preforeclosure tracts.

In **Table 3**, we compare preforeclosure-to-move changes in racial composition, gender, education, and income, as well as move distance overall and within parent credit score groups. For brevity, the data are presented in differences from the preforeclosure tract. Move distances are calculated as the distance between census tract centroids. Across all foreclosure movers, the mean move distance was 109 miles, though the median was only 6.6 miles. This suggests that, although some households move very far, most end up close to their preforeclosure residence. Comparing average relocation distances by credit score group, we find that credit score group rank orders distance moved, with households with parents in the prime score group moving an average of 159 miles, households in the near-prime group moving 127 miles, and households in the subprime group moving 90 miles. Comparing median relocation distances removes some of the long-distance mover skew and results in move distances that are quite similar across score groups and that are not rank ordered by score. At the median, households with parents in the prime score group moved 7 miles, households in the near-prime group moved 7.3 miles, and households in the subprime group moved 6.6 miles.

In addition to being more likely to move farther, parents with higher credit scores are also more likely to move into neighborhoods with lower incomes, compared with parents with lower credit scores. The log of median household income between origination tract and move tract decreases by an average of 0.02 for prime parents; whereas for subprime parents, tract log median income *increases* on average by 0.04.[9] Further, although both prime and subprime parents are likely to move to more predominantly White and higher-educated tracts, these differences are much larger for subprime parents. On average, the percent of persons of color in move tracts was 4 percentage points less than that of origination tracts. For children of prime parents, this change was much smaller at -2 percentage points, while subprime parents show the largest change of -5 percentage points. The percent with a bachelor's degree or more increases an average of 2 percentage points between origination and move tract. For children of prime parents, this difference is smaller at 1 percentage point; for near-prime parents, it's greater at 3 percentage points.

Our move analysis reveals interesting trends for foreclosure movers, who tend to move to neighborhoods with higher income and education but lower shares of minority residents. A median move distance of 6.6 miles also reveals that, while most foreclosure movers are likely to stay within the same county, children are likely to leave their neighborhood upon the move.

5.3. Ordinary Least Squares

In this section, we present multivariate OLS estimates on the unmatched sample, which can be found in **Table 4**. Each regression is run with a full set of control variables, including lagged parental credit variables, census variables measured at the block-group level, and county-level unemployment rates. We identify a statistically significant association between the foreclosure-mover flag and eight of the 14 dependent variables. In each instance, the sign of the coefficient indicates that the foreclosure-move experience is associated with poorer credit outcomes. Individuals in the foreclosure-mover group tend to be slightly older at bureau entry, are observed

[9] We emphasize the sign over the magnitude of the means since the difference in log transformed income will imply different dollar amounts at different income levels.

for fewer quarters, are more likely to ever be delinquent, and are more likely to have at least one delinquent tradeline at any quarter observed. In addition, they are less likely to have a credit score at entry and have lower scores when a score exists. Foreclosure movers also tend to have lower final credit scores and lower highest credit scores during the observation period. OLS estimates on the number of open accounts on average and at first and last observation are not statistically significant, nor are the coefficients on score change, average percent of trades delinquent, or number of credit inquiries during the final 24 months of observation.

In terms of coefficient magnitude, with the exception of age at bureau entry, the OLS coefficient estimates tend to be 74 percent to 83 percent smaller than the differences in unmatched means. For example, OLS estimates suggest that individuals in the foreclosure-mover group are about 3.1 percentage points more likely to be delinquent on one or more tradelines during the observation period, compared with 13.2 percentage points in the unmatched sample. In contrast, the OLS estimate on age at bureau entry is 0.101, compared with 0.051 in the unmatched sample. Given the lack of precision in measuring date of birth (only the year of birth is known), a loose interpretation of the OLS coefficient is that individuals in the foreclosure-mover group tend to enter the bureau about 37 days later than those not in the group, compared with about 19 days in the unmatched sample.

5.4. Main Results — Matched Estimates

In this section, we present the results of our matched estimation process using a difference-in-differences approach in which individuals in the foreclosure-mover group are matched to individuals in the control pool along a number of dimensions and their subsequent credit outcomes are compared. As a reminder, the matching process is described in detail in Section 4.

In **Table 5**, we present results from three different propensity score-based matches. In column 1, we show the results of control units matched using a quartic kernel as described in Section 3.[10] Columns 2 and 3 contain estimates from propensity score-based nearest neighbor ("nn") matches of one (nn=1) and five (nn=5), respectively. In our discussion, we focus only on

[10] We also ran the matching algorithm with an Epanechnikov kernel and found the results were almost identical to the quartic kernel. Those results are not provided here but are available upon request.

consensus results, those results that are significant to all three models. The remaining results are deemed too sensitive to the matching method to be reliable. In column 4, the coefficient estimates are averaged across the three matching methods. We take these means as our true estimates and refer to them in the discussion that follows.

Across matching methods, we observe statistically significant associations between individuals who experienced a foreclosure move and four of the 14 dependent variables. In each instance, the magnitude of the matched coefficient estimate is larger than the OLS estimate. Five of the eight statistically significant unmatched OLS coefficients are not significant in the matched regression. As we discuss in more detail next, the four variables with statistically significant associations with a foreclosure move all measure some aspect of consumer credit risk. This is in contrast with variables measuring aspects of bureau entry and tradeline quantities.

Being in the foreclosure-mover group is associated with a higher percentage of quarters in delinquency, more credit inquiries during the last 24 months of observation, a lower maximum score during the observation period, and a lower final credit score. During the observation period, foreclosure movers are in a state of delinquency about 3.3 percentage points more often than individuals in the control group, higher than the 1.8 percentage point coefficient estimated using OLS on the unmatched sample. Foreclosure movers are associated with higher rates of credit seeking, with 0.43 more credit inquiries over the last 24 months of observation, compared with a statistically insignificant 0.09 OLS estimate.

The highest credit score obtained by individuals in the foreclosure-mover group is 8.4 score points lower than the matched control group, compared with 5.9 score points estimated using OLS. Final credit scores, measured as the average of the last two quarters observed, tend to be 13.7 points lower for individuals in the foreclosure-mover group, compared with 9.7 points estimated using OLS.

5.4.1. Sensitivity Analysis

In this section, we use a type of sensitivity analysis proposed by Rosenbaum (2007) to assess how sensitive our main results are to the presence of unobserved confounders. While such tests cannot tell us anything about either the existence — or type — of any unobserved variables, the tests can help us understand how much interference from unobserved confounders our results could absorb and still be statistically significant.

We conduct the sensitivity analysis on matched pairs from our previous nn=1 results using an R package called *sensitivitymw* (Rosenbaum, 2015). The intuition behind the analysis is straightforward. If we have correctly matched on all the covariates that cause differences in the distribution of the foreclosure mover and control groups, pairs of matched individuals should have equal chances of being selected for treatment, as would be the case under random assignment. In that scenario, the ratio of the selection odds of each individual in a matched pair, Γ, is 1. The sensitivity analysis assumes that one individual in each matched pair may be $\Gamma \geq 1$ times more likely than another to receive treatment because they differ in terms of unobserved covariates. In this situation, the p-value on the t-test of the null hypothesis of a zero coefficient is replaced with a range of p-values. Should this range include 0.05, then the coefficient estimate is said to no longer be statistically significant for the degree of unobserved variation implied by the value of gamma.

To implement the test, we provide the software with a range of gamma values from 1.01 to 2 in 100th increments. The package reports the p-value in the relevant tail (positive for positive coefficient estimates, negative for negative coefficient estimates), and the user selects the gamma value just below 0.05. Our results are reported in **Table 6** for the four dependent variables with statistically significant coefficient estimates in the matched analysis. Gamma values corresponding to a p-value just shy of 0.05 fall within a range of 1.25 to 1.69.[11] To put that range into perspective, consider that our data set creation and cleaning procedure identified 1,185 foreclosure movers and 37,859 individuals in the control pool, corresponding to the odds of approximately 32:1, or about a 3 percent chance of experiencing a foreclosure-move event. The sensitivity analysis indicates that an unobserved confounder would have to increase the probability of being in the foreclosure-mover group from 3 percent to about 3.79 to 5.12 percent — a misclassification of 26 percent to 71 percent — before the coefficient estimates were no longer statistically significant at 5 percent.

[11] Gamma values corresponding to a p-value just shy of 0.1 fall within a range of 1.29 to 1.75.

The coefficient estimate that is the most sensitive (least robust) to potential unobserved confounders is the number of credit inquiries during the last 24 months of observation; whereas, the estimates on both the highest and final credit score are least sensitive (most robust) to unobserved confounders. For the credit inquiries variable, $\Gamma = 1.25$ implies that to attribute a higher rate of credit inquiries to an unobserved covariate rather than to the foreclosure move, the unobserved covariate would need to generate a 25 percent increase in the odds of foreclosure.

It is important to note that this sensitivity analysis is not a pass/fail type of test; there are only degrees of failure, any of which must be considered in light of the size of the potential risk posed by unobserved confounders. For example, researchers who judge selection into treatment to be highly influenced by a number of unobserved confounders will find little comfort in values of gamma (described next) that suggest a high tolerance for unobserved confoundedness. Likewise, researchers who judge selection into treatment to be well represented by observed variables will tend to discount gamma values suggesting a low tolerance for unobserved confounders, as there should be none. In this paper, we have attempted to control for as many observable variables as possible, including credit, geographic, demographic, socioeconomic, and macroeconomic variables and suggest that any remaining unobserved variables should be highly correlated with the observables and thus add little independent variation. However, we accept the possibility that some degree of unobserved confoundedness does exist and perform this exercise to determine how much confoundedness our results can support.

5.5. Subsample Results — Prime and Nonprime

In this section, we present two sets of results estimated on subsamples of the primary data set. We first split the sample into prime and nonprime groups based on the parent's credit score one year prior to mortgage origination. Individuals were split into prime and nonprime groups depending on whether their parent's credit score fell above or below 660. The coefficient estimates for the prime and nonprime groups can be found in columns 1 and 2 of **Table 7**. We present results from a kernel-based propensity score-matching method that is identical to the one used to generate the main results in column 1 of Table 5.[12]

Our results indicate that the foreclosure-induced move is associated with more adverse future credit experiences for adolescents in the nonprime group than those in the prime group. In the nonprime group, foreclosure movers spend 4.6 percentage points more time in delinquency on at least one tradeline. Nonprime foreclosure movers have an 18.7 point lower final credit score. From last to first observation, their credit score decreases by 13.8 points, and their maximum credit score is 8.8 points lower than individuals in the control group. In contrast, each of these coefficient estimates are not statistically significant in the prime group. However, individuals in the prime foreclosure-mover group are almost twice as likely to be delinquent at any time during the observation period, compared with the nonprime group (11.4 percent compared with 6.2 percent).[13] Individuals in the prime foreclosure-mover group also tend to have many more credit inquiries than the nonprime group. Foreclosure movers in the prime group tend to have 0.65 additional credit inquiries during the last 24 months of observation, compared with 0.46 for foreclosure movers in the nonprime group.

5.6. Subsample Results — Ages 10–14 and Ages 15–17

Next, we split the sample into two groups based on the adolescent's age at the time of foreclosure. Rather than splitting the sample at age 14 to create two equal groups by age (i.e., 10–13 and 14–17), we split the sample at age 15. We chose this split because there are only 58 10-year-old foreclosure movers in the data set, and, as shown in **Table 8**, setting the age cutoff to 15 creates a 50/50 split of foreclosure movers between the two age groups. The coefficient estimates for the group of individuals aged 10–14 at the time of foreclosure can be found in column 3 of Table 7, alongside the estimates for the 15–17 age group in column 4.

The results do not indicate a concentration of adverse associations in a particular age group, although the younger group does appear to be more likely to experience delinquency both

[12] As was the case in the full matched sample, the results from the nn=1 and nn=5 matches are very similar to the kernel-density matched estimates, including statistical significance levels.

[13] This result is to some degree a function of opportunity since prime consumers tend to have more tradelines than do nonprime consumers.

at any time as well as across multiple tradelines during the observation period. In all, six of the coefficient estimates are statistically significant in the 10–14 age group, and each of these estimates are larger in magnitude than the same coefficient estimates in the 15–17 age group, three of which are not statistically significant. For example, individuals in the 10–14 age group who experience a foreclosure move tend to have a final credit score that is 14.8 points lower than those without a foreclosure move; whereas those in the 15–17 age group who experience a foreclosure move have a final credit score that is 11.5 points lower than those without a foreclosure move. Likewise, the foreclosure movers in both age groups tend to have lower maximum credit scores (-8.8 in the 10–14 age group, compared with -8.1 points in the 15–17 group), and more credit inquiries (0.45 in the 10–14 age group, compared with 0.42 in the 15–17 group).

6. Conclusion

This paper contributes a set of novel findings to a small but growing literature on intergenerational linkages in household credit. To our knowledge, it is the first paper to examine the long-term consequences of foreclosure on adolescents and their subsequent credit usage patterns. We compare the credit behavior of individuals who experienced foreclosure-induced moves in adolescence to similar individuals who did not experience a foreclosure or move during their adolescent years. We implement a matching algorithm that relies upon the careful use of propensity scores with exact matching on several characteristics and regression adjustment to absorb covariate imbalances remaining after matching. We match on a set of observable characteristics including a child's year of birth, state of residence, year of mortgage origination, lagged parental credit variables, block-group level census variables, and county-level unemployment rates. In our main results, we create a separate matched sample for each dependent variable and present results from three different propensity score matches.

Our results suggest that young adults who experience a foreclosure-induced move tend to experience problems with credit repayment that may follow them for many years through their effect on credit scores. So-called foreclosure movers tend to spend more time with one or more tradelines in a state of severe delinquency and tend to seek credit at a higher rate, which in turn negatively impacts their credit score trajectory.

The highest credit score obtained by individuals in the foreclosure-mover group is 8.4 score points lower than the matched control group, and final credit scores (measured as the average of the last two quarters observed) tend to be 13.7 points lower for individuals in the foreclosure-mover group. Score differences tend to be most important on the margin, in situations in which lenders employ score cutoffs to approve or reject credit applicants or to assign credit limits and interest rates. Researchers have noted that credit scores are mean reverting (Chatterjee et al., 2020). That highest and final credit scores are lower for foreclosure movers suggests that foreclosure-induced moves in adolescence have some long-term effect on the consumer's lifetime score trajectory. Thus, although a 13.7 point score difference matters most relative to one's starting position, persistent 10+ point differences in credit scores could result in consumers receiving less — and more expensive — credit over their lifetime.

The signs of financial distress are most evident in the group of individuals whose parents had nonprime credit scores prior to their mortgage origination and children who were between the ages of 10 and 14 at the time of foreclosure. This finding is consistent with Ghent and Kudlyak (2016) and other research findings that children whose parents have generally nonprime credit scores have a harder time building credit and suggests that children of nonprime borrowers may be more susceptible to credit scarring following a foreclosure move, perhaps a result of weaker resiliency among more financially vulnerable populations.

Our research has some important limitations that, if addressed in future research, would enhance the conclusiveness of our results. First, the CCP contains some degree of imprecision in the measurement of households that actually experience a home loss because of foreclosure, as well as whether the foreclosure is on an owner-occupied residence as opposed to an investment property. Our methods for addressing these challenges are described in Section 3. Second, our data set contains just 1,185 foreclosure movers, which both weakens our statistical power and prevents us from examining within-household variation in credit outcomes (our analysis identified fewer than 30 possible sets of siblings) as in Ghent and Kudlyak (2016). It also prevents us from exploiting the exogenous implementation of a federal mortgage modification program called the Home Affordable Modification Program (HAMP), described in Agarwal et al. (2017). With a larger bureau sample, we could test a regression discontinuity design within a window of mortgage balances, taking advantage of a program eligibility requirement that the borrower's mortgage has an outstanding balance of less than $729,750. We estimate that our data-cleaning process would identify approximately 1,185/0.05= 23,700 foreclosure movers in the full consumer credit bureau. Third, we are unable to measure household risk preferences or financial literacy, and we cannot identify households that entered foreclosure because of an income shock because of job loss. Despite these limitations, our results shed new light on an understudied area of consumer finance and highlight the need for additional research into the intergenerational effects of parental credit behavior and foreclosure on children's future credit usage and financial health.

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Table 1. Descriptive Statistics for Unbalanced Sample

Parent Credit Characteristics, Measured 1 Year Prior to Mortgage Origination

	Fcl_move = 1			Fcl_move = 0				
	Obs	**Mean**	**Std Dev**	**Obs**	**Mean**	**Std Dev**	**Mean Diff**	**Std Dev Diff**
Not in CCP primary sample	1185	0.226	0.419	37859	0.492	0.500	-0.266	-0.081
Presence of severe derogatory	1185	0.302	0.459	37859	0.098	0.298	0.204	0.162
Credit inquiries, past 12 months	1185	4.472	3.931	37859	1.889	2.460	2.583	1.471
Trade mix (# distinct trade types)	1185	2.316	1.262	37859	2.508	1.159	-0.191	0.103

Block-group Level Demographic Characteristics

	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Mean Diff	Std Dev Diff
Percentage persons of color	1136	0.273	0.273	37078	0.206	0.234	0.067	0.039
Percentage female	1136	0.511	0.030	37078	0.510	0.031	0.001	-0.001
Percentage with bachelor’s degree	1136	0.133	0.102	37078	0.176	0.128	-0.043	-0.026
Log of median household income	1134	10.17	0.489	37045	10.29	0.532	-0.128	-0.043
Unemployment rate	1185	5.23	1.792	37840	5.35	1.815	-0.120	-0.023

Child Characteristics

	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Mean Diff	Std Dev Diff
Year of birth	1185	1994.6	3.082	37859	1990.4	4.249	4.168	-1.167
Age at bureau entry	1185	19.59	1.779	37859	19.54	1.832	0.051	-0.053
Quarters observed	1185	23.59	9.675	37859	28.78	9.510	-5.186	0.164
Avg num of open accounts	1161	3.112	3.072	37526	3.483	2.956	-0.371	0.116
Num open accounts, first qtr	1038	0.935	1.008	35730	0.959	0.874	-0.023	0.133
Num open accounts, last qtr	1122	4.572	4.847	36887	5.015	4.775	-0.443	0.072
Delinquent ever	1050	0.446	0.497	36197	0.314	0.464	0.132	0.033
Percent of qtrs delinquent	1050	0.167	0.253	36197	0.099	0.201	0.069	0.053
Avg percent of trades delinquent	1006	0.146	0.297	35415	0.089	0.254	0.057	0.043
Has credit score at bureau entry	1185	0.577	0.494	37859	0.693	0.461	-0.116	0.033
Score at bureau entry	684	640.3	41.57	26241	653.7	42.05	-13.37	-0.479
Avg credit score, last 2 qtrs obs	998	632.3	90.50	35202	671.7	92.37	-39.43	-1.867
Score change, last to first qtr	661	-0.917	86.31	25783	21.23	88.18	-22.15	-1.871
Highest score obs	1028	692.0	54.81	35794	723.1	56.99	-31.07	-2.183
Num cred inq, last 24m obs	1122	2.381	3.099	36897	2.253	3.063	0.128	0.036

Notes: Authors’ calculations using CCP data. Please refer to Section 3 for a description of the CCP.

Table 2. Comparison of Mortgage Origination Tract with Move Tract

	Preforeclosure Tract			Move Tract		
	Mean	SD	Median	Mean	SD	Median
Percent POC	0.34***	0.30	0.23	0.30***	0.28	0.20
Percent w/BA or more	0.21***	0.14	0.17	0.22***	0.14	0.18
Log Med HH Inc	10.65	0.37	10.64	10.68	0.36	10.68

Notes: T-test for statistically significant difference in means - *p<0.1 ** p<0.05 *** p<0.01. Means are unweighted using 2000 tract-level calculations from data.census.gov. N = 1,127. The abbreviation for persons of color is POC, bachelor's degree is BA, and household is HH.

Table 3. Tract Comparison in Differences and by Parent Credit Score

	Full Sample (N = 1,127)			Prime (N = 215)			Near-Prime (N = 182)			Subprime (N = 730)		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Distance Moved (Miles)	109.0	322.3	6.6	159.23*	397.8	7.0	127.1	327.8	7.3	89.67*	293.5	6.6
Change in…												
Percent POC	-0.041	0.23	-	-0.021*	0.2	-	-0.037	0.25	-	-0.049*	0.24	-
Percent w/BA or more	0.018	0.15	-	0.007	0.14	-	0.026	0.15	-	0.019	0.15	-
Log Med HH Inc	0.024#	0.39	-	-0.015*#	0.36	-	0.025	0.4	-	0.035*	0.39	-

Notes: T-test for statistically significant difference in means legend below. Parent credit score categories are prime (660 or more), near-prime (620-659), and subprime (less than 620). Distances are calculated between tract centroids. Means are unweighted using 2000 tract-level calculations from data.census.gov. The abbreviation for persons of color is POC, bachelor's degree is BA, and household is HH Significance key:

* Statistically significantly different means between prime and subprime, p<0.1

Statistically significantly different means between all observations and prime, p<0.1

Table 4. OLS Estimates

Child Outcome	Coefficient		Std. Error	N	Adj. R-squared
Age at bureau entry	0.101	*	1.84	38160	0.082
Quarters observed	-0.889	***	-3.22	38160	0.244
Avg num of open accounts	0.052		0.53	37808	0.042
Num open accounts, first qtr	0.008		0.25	35936	0.059
Num open accounts, last qtr	0.078		0.49	37149	0.028
Delinquent ever	0.031	*	1.94	36384	0.131
Percent of qtrs delinquent	0.018	**	2.24	36384	0.108
Avg percent of trades delinquent	0.007		0.69	35577	0.063
Has credit score at bureau entry	-0.026	*	-1.70	38160	0.055
Score at bureau entry	-3.116	*	-1.91	26258	0.097
Avg credit score, last 2 qtrs obs	-9.66	***	-3.36	35367	0.182
Score change, last to first qtr	-3.806		-1.11	25793	0.102
Highest score obs	-5.930	***	-3.40	35968	0.214
Num cred inq, last 24m obs	0.093		0.98	37159	0.096

Notes: All ordinary least squares (OLS) regressions were estimated with a full set of control variables as described in the text and with robust standard errors. *$p<0.1$ ** $p<0.05$ *** $p<0.01$.

Table 5. Main Results

Child Outcome	(1)		(2)		(3)		(4)
Age at bureau entry	0.109		0.114		0.064		0.096
Quarters observed	-0.504		-0.734		-0.202		-0.480
Avg num of open accounts	0.029		-0.095		-0.062		-0.043
Num open accounts, first qtr	0.014		-0.027		0.011		-0.001
Num open accounts, last qtr	0.019		-0.152		-0.176		-0.103
Delinquent ever	0.050	*	0.037		0.040		0.042
Percent of qtrs delinquent	0.037	***	0.031	**	0.032	*	0.033
Avg percent of trades delinquent	0.023		-0.012		0.036	*	0.015
Has credit score at bureau entry	0.004		-0.007		-0.032		-0.011
Score at bureau entry	-3.341		-3.21		-0.76		-2.44
Avg credit score, last 2 qtrs obs	-13.08	***	-12.11	**	-16.00	***	-13.73
Score change, last to first qtr	-11.52	**	-8.457		-12.53		-10.836
Highest score obs	-8.192	***	-8.682	**	-8.239	**	-8.371
Num cred inq, last 24m obs	0.467	***	0.443	***	0.367	**	0.426
Match type	PS		PS		PS		
Kernel	Y		N		N		
Num. of nearest neighbors	--		1		5		
Regression balancing	Y		Y		Y		
Exact matched variables	Y		Y		Y		

Notes: *p<0.1   ** p<0.05   *** p<0.01. Mean estimates are provided in column 4. Individuals included in the control groups are restricted to the region of common support.

Table 6. Sensitivity Analysis

Child Outcome	Coefficient Estimate (nn=1)		Gamma (α = .05)	Gamma (α = .1)
Percent of qtrs dlq	0.031	**	1.52	1.58
Num cred inq, last 24m obs	0.443	***	1.25	1.29
Avg credit score, last 2 qtrs	-12.11	**	1.47	1.52
Highest score obs	-8.682	**	1.69	1.75

Notes: Bounds are computed using 1:1 matched pairs from the k-nearest neighbor estimates provided in Table 5.

Table 7. Subgroup Analysis

Child Outcome	(1) Prime	(2) Nonprime	(3) Ages 10–14	(4) Ages 15–17
Age at bureau entry	0.099	0.062	0.022	0.176
Quarters observed	-0.433	-0.126	-0.259	-0.641
Avg num of open accounts	0.332	-0.153	0.112	-0.010
Num open accounts, first qtr	0.030	0.044	0.117	-0.048
Num open accounts, last qtr	0.478	-0.292	0.021	0.028
Delinquent ever	0.114 **	0.062 *	0.085 **	0.021
Percent of qtrs dlq	0.025	0.046 ***	0.045 ***	0.031 *
Avg percent of trades dlq	0.027	-0.01	0.040 **	0.014
Has credit score at entry	-0.039	0.017	0.001	0.015
Score at entry	-4.723	-5.34	-1.793	-3.98
Avg credit score, last 2 qtrs	-10.44	-18.71 ***	-14.80 **	-11.46 *
Score change, last to first qtr	1.331	-13.77 *	-11.25	-9.42
Highest score obsv'd	-5.61	-8.832 **	-8.76 **	-8.143 *
Num cred inq, last 24m	0.647 **	0.457 ***	0.445 **	0.416 **
Match type	PS	PS	PS	PS
Kernel	Y	Y	Y	Y
Num. of nearest neighbors	--	--	--	--
Regression balancing	Y	Y	Y	Y
Exact matched variables	Y	Y	Y	Y

Notes: *p<0.1 ** p<0.05 *** p<0.01. Restricted to region of common support.

Table 8. Age Distribution of Foreclosure Movers

Age	Frequency	Percent	Cumulative Percent
10	58	4.89	4.89
11	80	6.75	11.65
12	142	11.98	23.63
13	147	12.41	36.03
14	170	14.35	50.38
15	173	14.6	64.98
16	186	15.7	80.68
17	229	19.32	100
Total	**1185**	**100**	

Notes: Authors' calculations using CCP data.