DISCUSSION PAPER
PAYMENT CARDS CENTER

Residential Migration, Entry, and Exit as Seen Through the Lens of Credit Bureau Data

Keith Wardrip*
Federal Reserve Bank of Philadelphia

Robert M. Hunt*
Federal Reserve Bank of Philadelphia

December 2013

FEDERAL RESERVE BANK OF PHILADELPHIA

Residential Migration, Entry, and Exit as Seen Through the Lens of Credit Bureau Data

Keith Wardrip and Robert M. Hunt
Federal Reserve Bank of Philadelphia

Summary: We analyze a large, nationally representative anonymized data set of consumers with a credit report from 2002 to 2010. This is a period that encompasses a boom and bust in consumer credit. Using census data, we classify consumers into four categories of relative neighborhood income and find that, over time, the number and proportion of consumers with a credit report fell in low- and moderate-income neighborhoods and rose in higher-income neighborhoods. Population trends evident from census data explain only a portion of these changes in the location of the credit bureau population. In most instances, the primary driver reflects residential migration from relatively poorer neighborhoods to ones with relatively higher incomes. Patterns of entry into or exit from the credit bureau population were correlated with the credit cycle, as well as with relative neighborhood income, resulting in slower sample growth in low- and moderate-income neighborhoods during periods of credit contraction. These results are interesting in themselves, but they are also important for interpreting empirical results estimated from credit bureau data.

I. Introduction

In this paper, we explore the distribution of a nationally representative sample of individuals with credit histories across different categories of relative income in the neighborhoods where they live. Our study spans the years from 2002 through 2010 — a period that includes both a credit boom and bust. We focus primarily on changes in the composition of the credit bureau populations living in these different categories of neighborhood income.[1] We find systematic changes that are not fully explained by broader population trends. By the end of the sample period, both the number and proportion of consumers with a credit report living in middle- or upper-income neighborhoods increased, while the opposite was true for low- and moderate-income neighborhoods. In most cases, the primary driver reflects residential migration to neighborhoods with higher relative incomes. However, we also find systematic differences across neighborhood income categories in the entry and exit rates among the credit bureau population. In general, entry and exit rates are influenced by the credit cycle: There is more entry and less exit when credit supply is expanding, while the opposite is true when credit supply is contracting. The effects of the credit cycle on entry and exit rates appear to be accentuated among consumers living in low- and moderate-income neighborhoods.

Our motivations for undertaking this research are twofold. First, from a community development perspective, it is important to know whether households in low- and moderate-income communities have experienced disproportionate reductions in access to, or participation in, the credit market since the onset of the Great Recession. Credit plays a critical role in a variety of asset-building and community revitalization efforts, and changes in its availability are of interest to researchers and practitioners alike. Second, although the consumer credit data by construction are representative of the credit-using population in the United States, it does not follow that the data will be representative of specific segments of the U.S. population, as illustrated by the variations we find across categories of neighborhood income.

---

[1] As discussed below, credit bureau files generally do not contain information on the income of a borrower. Our analysis relies on neighborhood-level estimates of median incomes using data from the U.S. Census Bureau.

This is an important distinction to keep in mind when interpreting empirical estimates from credit bureau data.

At the risk of stating the obvious, we begin by noting that access to, usage of, and performance in the mainstream credit market are not evenly distributed across the American residential landscape. Some U.S. neighborhoods are populated by households with higher incomes, higher credit scores, and 30-year mortgages, while others are home to low-income renters who, by choice or by necessity, have little or no experience with mainstream credit and are more likely to conduct their transactions in cash or rely on alternative sources of financing. For example, in a 2007 report to Congress, the Board of Governors of the Federal Reserve System found that individuals living in low-income areas or areas with a predominantly minority population generally have lower credit scores, higher rates of delinquency, and appear more likely to be denied credit than those living in other types of neighborhoods. These are statements about correlation, not causation.

Just as credit availability varies spatially, it also varies over time. The study period used in this paper encompasses years of strong economic growth with expanding credit followed by a severe recession and contraction in credit supply. According to the Federal Reserve's Senior Loan Officers' Opinion Survey, underwriting standards for mortgages were consistently relaxed between 2004 and 2006, and then they were consistently tightened from the end of 2006 to at least the middle of 2010 (Board of Governors of the Federal Reserve System, 2013). A similar pattern is evident for lending standards on credit cards and other consumer loans, although the inflexion point varies. The two most recent editions of the Survey of Consumer Finances provide additional evidence of the contraction in credit supply and suggest a rising share of consumers who refrained from even applying for credit because they expected to be denied (Bricker, et al., 2012).

We use consumer credit data from one of the three largest credit bureaus to compare both the residential location of individuals with a credit history at two points in time – June 2002 and June 2010 – and the quarterly flows into and out of the credit sample during the study period. Others have used

2

consumer credit data to explore the influence of neighborhood characteristics on the level of available credit (Cohen-Cole, 2011; Brevoort, 2011), the impact of labor markets and negative home equity on intermetropolitan residential mobility (Demyanyk, Hryshko, Luengo-Prado, & Sorensen, 2013), and housing consumption and neighborhood choice following foreclosure (Molloy and Shan, 2013). A recent study by Munoz (2013), based on the same data set we utilize, reveals a decline in active credit users in low- and moderate-income neighborhoods in Massachusetts relative to the trend among credit users living in higher-income neighborhoods in the same state. However, we believe that ours is the first study to examine this phenomenon for the nation as a whole and that explores the contributing effects of migration and the rate of credit history formation by relative neighborhood income. We attempt to answer the following four research questions:

1. Is the sample growth independent of, or contingent upon, neighborhood income?

2. Are changes in the sample size consistent with rates of growth and decline in the underlying population?

3. Are changes in the sample size a function of residential migration between and among neighborhood income categories or of disparate rates of entry to and exit from the sample?

4. Is the rate of growth resulting from entry and exit constant over the study period, or does it vary over time?

These research questions are very clearly defined and narrow in scope. We do not attempt to address causality in answering them. Rather, we employ only descriptive techniques to compare trends across neighborhood income categories and through time, and our methodology, described in the next section, allows us to shed light on some of the processes underlying changes in the sample uncovered in this analysis.

It is important to emphasize the following points. First, nothing in our analysis should be interpreted to suggest the underlying credit bureau data set is not representative of the population of

3

consumers who use mainstream credit products (e.g., credit cards, auto loans and leases, mortgages, installment loans, or student loans). Producing such information is critical to the business model of credit reporting agencies, which invest considerable resources to this end. Second, the results reported in this paper have little probative value for an analysis of fair lending issues. Such an analysis requires more fine-grained data and different estimation techniques than the ones employed in this paper.[2]

The remainder of this paper is organized as follows: In the Data and Methods section, we describe our treatment of the consumer credit data, the classification of consumers by relative neighborhood income, and the distinctions between our "stock" and "flow" analyses. The subsequent section summarizes the results from these two analyses. In the conclusion, we explore the implications of our findings for the community development field, emphasize the importance of these findings for the interpretation of research using consumer credit data, and highlight avenues for future research.

II. Data and Methods

A. Consumer Credit Data

The vast majority of the nation's lenders report account-level data for their borrowers to a subset of the roughly 1,000 consumer credit bureaus in the United States. Credit bureaus operate as clearinghouses for consumer credit data, collecting information from participating lenders, aggregating it, and redistributing it in the form of credit reports that creditors can use to assess the creditworthiness of prospective (and existing) borrowers and the terms under which any new credit should be extended. The three largest bureaus – Equifax, Experian, and TransUnion – have had national coverage of borrowers in the United States since the 1980s (Hunt, 2005). Access to anonymous data from any of these three credit bureaus allows researchers to develop a very thorough and nuanced understanding of trends in the U.S. credit market related to credit availability, debt levels, credit utilization, and delinquency rates.

---

[2] For a recent review of fair lending issues and analyses, see Ritter (2012).

However, not all adults have a file with one of the three national credit reporting agencies. According to an analysis of the Survey of Consumer Finances, slightly more than 8 percent of households do not include a member with a credit report (Brown, Haughwout, Lee, & van der Klaauw, 2011).[3] Typically, these are consumers who have either never obtained a mainstream loan product (e.g., credit card, mortgage, auto loan) or have not obtained such a product for a very long time. It may also include some consumers who defaulted on debts seven or more years ago and have not subsequently obtained new credit. Consumers who have *exclusively* used alternative forms of credit, such as payday loans, are unlikely to appear in the files of the national credit reporting agencies, but they may appear in one of the specialized credit bureaus that serve payday lenders.

In this analysis, we use the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data set (hereafter noted as CCP), a 5-percent, anonymized, nationally representative random sample of individuals in the United States with a Social Security number and a credit report. The data set includes roughly 12 million "primary" consumers, randomly selected into the data set based on the last two digits of their Social Security number.[4] In addition, to be included as a "primary" observation in the CCP, an individual must also have at least one of the following in his or her credit bureau file: An item of public record (e.g., a judgment) within the last seven years, a bankruptcy filing within the last 10 years, an open credit account that is regularly updated by the lender or servicer, or a closed account that continues to be reported, which can occur for up to seven years if the account was not in good standing (Lee & van der Klaauw, 2010).

In the analysis that follows, we relax the inclusion conditions on the number of accounts and public records just described. While it's not important for many studies of consumer credit, we feel it is

---

[3] For additional information about "thin" or "no" file consumers and efforts to incorporate alternative data sources into underwriting, see Cheney (2008).

[4] To be clear, the data set does not include actual Social Security numbers (SSNs). Equifax uses SSNs to assemble the data set, but the actual SSNs are not shared with researchers. In addition, the data set does not include any names, actual addresses, demographics (other than age), or other codes that could identify specific consumers or creditors.

important for this one to include consumers who shop for credit but who don't necessarily obtain or maintain it (we call these inquiry-only files). In other words, subject to some additional exclusions described next, we are counting all consumers in the data set whose Social Security numbers would fall into the set defining the 5-percent sample of all files.[5]

The CCP is an unbalanced panel in which new individuals are included over time as they develop a credit history or immigrate to the United States. Similarly, consumers can be dropped from the sample when they die, emigrate from the U.S., or "age off," following a prolonged period of inactivity and no new items of public record. The sample was designed in this way to generate "the same entry and exit behavior as present in the population" so that "nationally representative estimates of household-level debt and credit" could be calculated (Lee & van der Klaauw, 2010, p. 1).

The data in the CCP are reported quarterly, reflecting the credit characteristics of sample members annually in March, June, September, and December beginning in 1999. Ideally, our study period would have begun in April 2000 and would have ended in April 2010 — the months of data collection for the last two decennial censuses — to allow for a direct comparison of sample size and population growth and decline over an identical 10-year period. However, the geographic information in the data prior to 2002 is less precise. Relying on this geographic data for consumers in earlier years may introduce selection issues that would compromise the analysis. As such, our study begins in June 2002 and ends in June 2010, which is as close as we can approximate to the census dates.

We exclude from this analysis consumers in the data set who are coded as deceased. We also attempt to exclude what we describe as credit file "fragments." Such fragments can occur when a new record is created and subsequently merged with an existing record when the two records are found to correspond to the same individual. Some portion of fragments may also represent fictitious identities that

---

[5] Still, 88 percent of the observations in the sample we study have at least one open account or public record. As a robustness check, we verified that the aggregate patterns of entry and exit are extremely similar when we restrict observations to only those consumers with at least one account or public record on file at the time they first appear in the data set.

were created to obtain credit fraudulently. Since there is no formal definition of a fragment, we operationalize our own. We define a file fragment as a record that persists in the data set for no more than one year as determined by the difference between two derived fields indicating the quarter that the consumer first and last appeared in the CCP. Controlling for fragments is important for the analysis of entry and exit, especially because there is a time trend in their numbers: According to our definition, file fragments represent 2.7 percent of the June 2002 sample but only 0.2 percent of the June 2010 sample.[6]

In this analysis, we focus primarily on changes throughout the study period in the sample size and neighborhood category of consumers with a credit report. The CCP includes the state, county, and census tract codes associated with each consumer's credit file, which, together, can be combined into an 11-digit code that allows each to be linked to one of more than 66,000 census tracts in the United States and Puerto Rico (hereafter listed as U.S.). Following a long history of social science research, we use the census tract, with a typical population of about 4,000 people, as a proxy for the neighborhood.

B. Categories of Relative Neighborhood Income

Using data collected by the U.S. Census Bureau through the American Community Survey (ACS) from 2005 to 2009, we assign each census tract in the United States to an income category based on the ratio of its median family income (MFI) to the MFI of its metropolitan statistical area, its metropolitan division, or, for nonmetropolitan tracts, the MFI of the nonmetro portions of its state. Using this categorization of census tracts described in Table 1, in concert with the geographic information in the CCP, we can discern the distribution of consumers in the data set across the four neighborhood income categories. As indicated in Table 1, approximately 1 percent of all census tracts cannot be classified by income, primarily because their MFI is not reported in the ACS.

---

[6] In the June 2002 sample, roughly 35 percent of records defined as file fragments are missing a credit score, compared with only 10 percent for the remainder of the sample. A similar disparity exists in the June 2010 sample (25 percent versus 8 percent).

In classifying consumers into income categories based on their neighborhood of residence, we assign those consumers with a nonresidential address (e.g., an address indicated to be a post office box, business, military installation) to an "other" category but include them in the estimates of the full sample. We assign consumers with geographic information that cannot be matched to a standard census tract in the United States and those who live in a tract that cannot be classified by income to the same "other" category. Roughly 7 percent to 8 percent of consumers in the sample in 2002 and 2010 are classified as "other," primarily because the address associated with their credit file is not residential.

C. U.S. Population Trends

In order to compare changes in the sample size with changes in the U.S. population for the various income categories, we rely on decennial census data collected in 2000 and 2010. Because the U.S. Census Bureau redefines a significant number of census tracts every 10 years, we use the bureau's 2010 Census Tract Relationship File to aggregate the 2010 population to tract definitions used in 2000. Doing so permits us to compare the census 2000 and 2010 populations for nearly the same set of census tracts categorized by income using ACS data previously described.[7]

Unfortunately, approximately 16 percent of the consumers with a residential address in the June 2000 consumer credit data sample have incomplete or inaccurate geographic information. In order to make comparisons with the census data, we need to adjust the size of our neighborhood income categories in 2000. To do that, we hold constant the number of consumers reported as nonresidential in the original June 2000 data. Next, we note that in June 2002, only 0.9 percent of consumers in the credit bureau sample had incomplete or inaccurate geographic information. From this, we assume that about 15 percentage points represent consumers with incomplete or inaccurate geographic information in 2000 that could have been assigned to a neighborhood income category if the better geographic information of later years existed. We inflate the size of our neighborhood income categories in 2000 by allocating this 15

---

[7] Due to inconsistencies between the tract definitions used in the 2000 census and in reporting the ACS data, nine of the more than 66,000 census tracts cannot be classified by income.

percentage points of consumers based on the proportions of those consumers who were successfully assigned to an income category in that same quarter (about 7 percent to low-income tracts, 23 percent to moderate-income tracts, 44 percent to middle-income tracts, 27 percent to upper-income tracts, and a 0.1 percent to tracts with no income reported).

This methodology for estimating the income category sizes in June 2000 is defensible only if the credit characteristics of consumers with accurate geographic information are comparable with consumers who lack it. We find that compared with residential consumers with valid geographic data, those with missing or inaccurate information have a slightly lower mean risk score (677 versus 686) and slightly fewer open accounts (6.2 versus 6.4). Not surprisingly, given our sample size, both of those differences are statistically significant. However, the direction of these differences suggests, if anything, that consumers with invalid geographic information may be more likely to reside in low- or moderate-income census tracts, where risk scores and credit usage are generally lower, than the distribution of consumers with good geographic data would indicate. The implication is that our June 2000 estimates may slightly underestimate the size of the low- and moderate-income categories and overestimate the size of the higher-income categories by a corresponding amount.[8]

D. Stock versus Flow Analysis

In what we call our "stock" analysis, we develop a data set that includes nearly 14 million consumers in one or both of June 2002 and June 2010 samples. Consumers in the sample in both quarters constitute the vast majority of the combined sample (Table 2). Roughly 46 percent of them reside in the same neighborhood income category during both quarters, 16 percent reside in a different neighborhood type during the two quarters, and 8 percent are in the sample for both quarters but are classified as "other" in at least one quarter.[9] Remaining sample members are classified as either sample entrants (17 percent)

---

[8] This means that our assumptions here, if anything, will provide a downward bias of our estimates for the decline in the number of consumers with credit reports observed in the low- and moderate-income categories over this period.

[9] Lee and van der Klaauw (2010) note that the process by which a consumer's address is changed at the credit bureau became more restrictive in 2003. Molloy and Shan (2013) find that although the methodology used prior to

or sample exits (14 percent). Entrants are consumers who are in the sample in 2010 but who are not included in 2002. Following the same logic, exits appear in the June 2002 sample but are not in the CCP in June 2010. We use this base data set and the methodology described in the preceding subsection to compare sample and population trends between 2000 and 2010.

In addition to investigating the magnitude and components of sample size changes from June 2002 to June 2010, we also analyze entrants and exits to the sample in each of the 33 quarters during this study period. In this "flow" analysis, the definitions of sample entrants and exits, although conceptually similar, are a departure from those used in the stock analysis. Here, we utilize two derived fields indicating the quarter that the consumer is first and last available in the CCP. Each consumer is considered an entrant in the quarter in which the record is first available and an exit in the quarter in which the record is last available. After identifying entrants and exits, we use the geographic information provided in the data set to assign each to a neighborhood income category. As in the stock analysis, file fragments and consumers coded as deceased are excluded from the flow analysis. Using these definitions, we analyze the quarterly rates of entry to and exit from the sample for each neighborhood income category.

The different methodologies used to define entrants and exits in the stock and flow analyses can be compounded by data irregularities to produce differences in implied sample growth that are worth noting. The two primary issues are that (1) consumers do not always appear in every quarter between their first and last available dates, and (2) the variable indicating living or deceased is not always internally consistent. As a result, in the stock analysis, roughly 1.2 percent of the 2.3 million consumers classified as sample entrants actually appear in the sample prior to June 2002, but they were excluded from the stock analysis data set in that quarter because they were either missing or were coded as deceased in that

2003 resulted in more frequent address changes, the implied migration rate in the credit bureau data was only "somewhat higher" than that observed in the Current Population Survey during this period. It is impossible to know whether this procedural change, which occurred during our study period, could have affected the findings presented here with regard to residential migration.

quarter. Likewise, about 2.7 percent of the nearly 2.0 million consumers classified as sample exits in the

stock analysis actually appear in the CCP after June 2010, but they were excluded from the stock analysis

data set in that quarter because they were either missing in that quarter or were coded as deceased. These

consumers are considered entrants and exits in the stock analysis, but they would not be captured in the

flow analysis because the latter depends on first and last available dates that fall outside the study period.

Similarly, the absence of a consumer from the data set or the miscoding of the deceased variable in June

2002 or June 2010 could result in a consumer entering or exiting the sample during the study period but

going uncounted in the stock analysis because the data indicated that they were not present at the start or

end of the study period. A miscoding of the deceased variable would also affect quarterly counts of

entrants and exits, but the effect in any given quarter would be negligible.

III. Results

A. Stock Analysis

Based on the findings of our stock analysis, the CCP grew by approximately 3 percent between

June 2002 and June 2010. As Table 3 illustrates, the growth rates were highest in middle- (7 percent) and

upper- (13 percent) income neighborhoods, while moderate- and low-income census tracts experienced

declines of 5 percent and 13 percent, respectively, over this eight-year period.[10] By themselves, these

stark differences tell us little, because we do not know whether these disparate rates of growth and decline

in the income categories simply reflect changes in the underlying population or whether they are specific

to the CCP.

Table 4 compares the estimated June 2000 sample size for the various income categories with the

actual category sample sizes in June 2010, and Table 5 provides the population totals from the last two

decennial censuses. As Figure 1 illustrates, both the U.S. population and the CCP sample grew at roughly

---

[10] Because file fragments are more numerous at the start rather than at the end of the study period, their inclusion
would lower the sample growth rate to 0.4 percent over the eight-year period. However, the pattern of declining
sample size in low- and moderate-income neighborhoods and increasing sample size in middle- and upper-income
communities would persist.

the same rate during this 10-year period – 10 percent for the former and 11 percent for the latter.[11]

Further, both report absolute declines in low-income neighborhoods, little change in moderate-income neighborhoods, and more robust growth in middle- and upper-income census tracts. However, changes in the CCP, while generally consistent in direction with population trends, are of a greater magnitude, showing a steeper decline in low-income neighborhoods and greater rates of growth in middle- and upper-income communities.[12]

Figure 2 demonstrates the effects of these disparate growth rates on the estimated percentage of the total population in each neighborhood income category with a credit history in 2000 and 2010. Because the population decline reported in the census was not as steep as the decline found in the credit bureau sample in low-income neighborhoods, the share of the population with a credit history for this category fell from 70 percent to 61 percent during the decade. Conversely, because population growth reported in the census was not as robust as the growth found in the credit bureau sample in middle- and upper-income neighborhoods, the share of the population with a credit history grew modestly in these income categories.[13]

Observed changes in the CCP among the neighborhood income categories appear to be partly — but not entirely — consistent with shifting residential patterns in the United States, suggesting that other processes may also be at work. For the purposes of the stock analysis, the sample size for an income category can increase or decrease in three ways over the course of the study period. For consumers in the

---

[11] The considerable difference in the growth of consumers in the CCP between the census years (11 percent) versus the eight-year period beginning in June 20002 (3 percent) is due to very rapid growth in the sample between 2000 and 2002, followed by much slower growth in the later years.

[12] A search for existing research investigating population growth by neighborhood income between 2000 and 2010 proved fruitless, but similar findings spanning different time periods are worth mentioning. In a study of Washington, D.C., neighborhoods, Lazere and Rodgers (2005) find that population loss between 1990 and 2000 was greatest in the city's low-income neighborhoods. More recent research also demonstrates a positive correlation between median home price at the census tract-level in 1970 or 1980 and the rate of population change through the 2005–09 period in select cities (Guerrieri, Hartley, and Hurst, 2012; Hartley, 2013).

[13] Note that the total sample includes a significant number of consumers with nonresidential addresses that are not classified by income. Including those consumers in the calculation makes the total percentage of the population with a credit history larger than the percentages for any of the individual income categories reported in Figure 2.

sample at both the start and the end of the study period, this shift can occur through residential migration or through the reclassification of a consumer into or out of the "other" category.[14] The sample size for an income category can also grow or decline through the process of sample entry and exit during the study period.

Table 6 provides detailed information on the determinants of sample size changes between June 2002 and June 2010. It is clear from Table 6 that low- and moderate-income census tracts lost a considerable number of long-time sample members to middle- and upper-income communities during the study period through residential migration — nearly 260,000 in total. These changes represent a 13-percent decline in the low-income sample, an 8-percent decline in moderate-income tracts, and a 7-percent increase in the sample in upper-income neighborhoods. Net migration had a minimal impact on the sample size in middle-income tracts.

Table 6 also shows that only low-income neighborhoods experienced a net loss of consumers as a result of entry to and exit from the sample over the study period. Although minimal (-1 percent) and exerting much less influence than migration on the sample size in low-income neighborhoods, it is noteworthy that the other three neighborhood income categories experienced sample size gains through this process, ranging from 2 percent to 5 percent. For middle-income neighborhoods, the process of sample entry and exit was the primary driver of the sample size increase during the study period. The reclassification of consumers into and out of the "other" category had little net impact on any of the income categories.

Table 7 explores the topic of residential migration by providing information on the destination neighborhoods for consumers who moved from one neighborhood income category to another during the study period. As shown in the first section of the table, a substantial share of movers from low- (41

---

[14] The reclassification of a consumer into or out of the "other" category occurs, for example, when a consumer's credit file address changes from a residential one (e.g., street address) to a nonresidential one (e.g., post office box), or vice versa, between 2002 and 2010. It also occurs when a consumer appears in the sample in both June 2002 and June 2010 but has valid geographic information in only one of the two quarters.

percent), moderate- (61 percent), and upper- (75 percent) income neighborhoods moved to middle-income neighborhoods by the end of the study period — a relatively unsurprising finding considering that 44 percent of census tracts are classified as middle income.

In order to put these migration patterns into context, the second section of Table 7 shows the distribution of residential consumers in the 2002 sample (excluding the origin neighborhood), and the third section normalizes migration flows using the distribution of the 2002 sample. A ratio of 1.00 would suggest that consumers from an origin neighborhood moved into a destination income category in a way that mirrored the sample distribution in 2002. The actual ratios indicate that movers from low-income neighborhoods disproportionately settled in moderate-income census tracts (1.65), while consumers that left moderate-income neighborhoods were fairly proportionately settled across the three other income categories in 2010 (ratios that range from 0.88 to 1.15). Very few middle- and upper-income residents moved to low-income neighborhoods during the study period (ratios of 0.48 and 0.45, respectively).

B. Flow Analysis

Turning to the flow analysis, it is instructive first to examine the entry and exit rates for the four neighborhood income categories between June 2002 and June 2010.[15] This is calculated as the number of consumers either first or last available in a given quarter as a percentage of the sample size for the income category in the same quarter (based on a straight-line interpolation of the June 2002 and June 2010 sample sizes reported in the stock analysis).[16] As Figures 3 through 6 illustrate, the entry and exit rates in low-income neighborhoods, in some cases above 2 percent, were much higher than in the other three neighborhood types. Also noteworthy were the sharp spikes in the exit rate for low-income

---

[15] To reiterate a point made above, entrants and exits are defined slightly differently in this flow analysis. A consumer is considered an entrant in the quarter in which he or she enters the sample, even if not present at the end of the study period (true of 25 percent of all entrants). Similarly, an exit in this flow analysis is an exit in the quarter in which it is last available, even if it was not in the sample at the beginning of the study period (true of roughly 28 percent of all exits). Consumers in the sample for no more than one year are excluded from this analysis.

[16] None of the following results is materially affected when we take into account the year-to-year changes in the overall growth rate of the sample.

neighborhoods in March 2004 and in the second half of 2007. Exits rates increased in the other three neighborhood types during these quarters but to a lesser degree.[17] In general, entry and exit rates were much more stable in middle- and upper-income neighborhoods, rarely exceeding 1 percent during the study period. Of note, the entry rate exceeded the exit rate in low-income neighborhoods in only 20 of the 33 study period quarters, notably fewer than in middle- (24), and upper- (28) income neighborhoods.

Reflecting the differences between the entry and exit rates, Figure 7 illustrates the quarterly net rate of growth (entrants minus exits, as a percentage of the interpolated sample size) during the study period and includes the estimated quarterly growth rates for the U.S. population age 18 and older as a basis for comparison. It is interesting to note that when the net rate of growth was consistently positive — at the beginning of the period and from roughly mid-2004 through mid-2007 — the net rate in low-income neighborhoods typically exceeded those observed for the other neighborhood types. During this period, the overall net rate of growth approximated or exceeded growth in the 18 and older population.[18]

However, when the net rate of growth in the credit bureau sample stalled in 2003 and turned negative in 2004, the net rate was the lowest in low-income neighborhoods. Another period of negative net rates for the overall sample in 2007 was followed by relative stagnation for the remainder of the study period. In the low-income neighborhood category, the net rate was consistently negative after mid-2007. In fact, in all 13 quarters for which data are available between June 2007 and June 2010, a period characterized by tighter lending standards and lagging growth in the entire sample, the net rate of growth in low-income neighborhoods was the lowest of the four income categories. This was true in only five of the preceding 20 quarters.

The net rate for each of the income categories is affected slightly by the proportion of residential entrants and exits that cannot be classified into an income category because of imprecise geographic

---

[17] The underlying cause of these sharp increases is unclear, but the spikes are consistent with what would occur if one or more firms had stopped reporting data on their accounts to the credit bureau during these quarters.

[18] As noted earlier, this also corresponds to the period in which underwriting standards for most categories of consumer loans were being relaxed.

information. In 30 of the 33 quarters in the study period, a greater share of residential exits than entrants is not successfully categorized into a neighborhood income category. The implication is that in most quarters, the net rate calculated for the income categories is slightly inflated, but because imprecise geographic data are at the root of this issue, it is impossible to know whether one category is affected more than any other.[19]

It is worth noting the irregularities that occurred in September 2004. In that quarter, the percentage of consumers with residential addresses that cannot be classified into an income category is far above average, primarily because their census tract information is missing. This affects a slightly greater share of residential sample exits (13.8 percent) than entrants (12.2 percent) and suppresses both the entry and exits rates for neighborhood income categories in this quarter.

Figure 8 illustrates the impact of these quarterly growth rates by showing the cumulative difference in entrants and exits for each neighborhood income category.[20] Based on the flow analysis, the number of net new consumers in the sample in low-, moderate-, and middle-income neighborhoods peaked in June 2007. Following this quarter through the end of the study period, exits exceeded entrants in all but the upper-income neighborhood category, where quarterly growth remained relatively consistent. Declines after June 2007 for the low- and moderate-income neighborhood categories were substantial.

Using the interpolated quarterly sample size for each income category, Figure 9 normalizes the cumulative increase resulting from sample entry and exit reported in Figure 8.[21] In June 2007, the cumulative difference between sample entrants and exits represented nearly 8 percent of the estimated

---

[19] Overall, only 1.28 percent of residential entrants and 1.49 percent of residential exits are not categorized by income, so the difference, and thus the effect, is small.

[20] The aforementioned higher level of missing census tract data in September 2004 also slightly suppresses the estimates of cumulative growth by income category depicted in Figures 8 and 9, since a greater number of consumers cannot be classified by income in that quarter.

[21] The cumulative impact of entrants and exits on the full sample includes consumers in the "other" category, which is not depicted in Figure 9 and which declines over the study period. As a result, the total cumulative increase shown in Figure 9 lags the growth for the income categories in the middle of the study period.

sample size in low-income neighborhoods, the greatest increase among the four income categories over the period. Subsequent net losses lowered the cumulative increase to roughly 3 percent of the estimated sample size in low-income neighborhoods, a level well below the rates for the other neighborhood income categories and the total sample (3.8 percent). The pattern was similar for moderate-income census tracts but not for upper-income neighborhoods, where the process of sample entry and exit alone led to a cumulative increase that represented more than 5 percent of the estimated sample size in June 2010.[22]

As a robustness check, we reran the analyses presented in this paper after adding an additional quarter of data. Adding to the time series will change some of the derived variables used to classify consumers in our analyses; for example, the "last available" date can change if a consumer reappears after an absence. As result, there can be some reclassification of apparent file fragments into entrants, and some apparent exits will turn out to be consumers who remain in the panel. Both of these effects could increase the rates of entry, quarterly net growth, and cumulative growth rates, but we estimate these changes are minimal. For example, the addition of a quarter of data to the sample adds what were 500 apparent fragments to the 3.2 million sample entrants in the flow analysis. Conversely, the flow of 2.7 million sample exits is reduced by 1,100.

IV. Conclusion

In this analysis, we find that a nationally representative sample of adults in the United States with a credit report grew by roughly 3 percent between June 2002 and June 2010. During this period, the sample declined by 13 percent and 5 percent in low- and moderate-income neighborhoods, respectively, and grew by 7 percent and 13 percent in middle- and upper-income neighborhoods. We find that these trends are generally consistent with the underlying population change between the censuses in direction but not in magnitude: Changes in the sample appear to magnify population decline in low- and moderate-income communities and the growth observed in more affluent communities. The residential migration of

---

[22] Total and neighborhood category growth rates suggested in Figure 9 are not comparable to those attributed to sample entrants and exits in Table 6 because income category assignment, sample entry, and sample exit are calculated differently in the stock and flow analyses, as noted above.

consumers included in the sample for the duration of the study period exerted more influence on growth and decline than did differential rates of entry and exit for all except the middle-income category, where the latter was more important.

Our quarterly analysis of the sample shows that from 2002 through the middle of 2007, the process of sample regeneration generally produced greater relative growth in low- and moderate-income census tracts than in those characterized as middle and upper income. Relative net growth resulting from sample entry and exit in low- and moderate-income neighborhoods lagged middle- and upper-income neighborhoods during the period of sample contraction and stagnation that began in mid-2007. Although we cannot determine their cause definitively, these trends appear to correspond to changes in lenders' credit standards, with below-average net rates of growth in low- and moderate-income census tracts roughly corresponding to stricter standards and above-average net rates of growth in the same set of tracts occurring during a period of looser credit.

None of the findings reported in this paper casts any doubt on the consumer credit data set's representativeness of active users of mainstream credit products in the United States or its utility for producing "nationally representative estimates of household-level debt and credit" (Lee & van der Klaauw, 2010, p. 1). In fact, we should not be surprised that in a random sample of individuals with a credit history, the geographic distribution of consumers in the sample would change over time both as a function of residential migration and as a by-product of lenders' credit standards. Regarding the former, earlier research has suggested a positive association between neighborhood income and home prices, on the one hand, and the rate of population change, on the other (Lazere and Rodgers, 2005; Guerrieri, Hartley, and Hurst, 2012; Hartley, 2013) — a process that would be expected to influence active borrowers as well as those outside the mainstream credit system. Moreover, as for lending standards, in relatively restrictive credit environments, credit would likely be extended primarily to the least-risky applicants, and research has shown that credit quality, as measured by credit score, is correlated with neighborhood income (Federal Reserve Bank of Philadelphia, 2012; Board of Governors of the Federal

Reserve System, 2007). In addition to tighter lending standards or a conscious decision by potential borrowers to avoid debt, any number of factors could contribute to lower levels of participation in the mainstream credit market. These include lower levels of application for credit for fear of refusal (Bricker, Kennickell, Moore, & Sabelhaus, 2012), heightened information asymmetries across lenders (Bhutta, 2011), and changes in the accessibility of bank branches (Ergungor, 2010).

Setting aside issues of causation, which this paper cannot address, and focusing instead on implications, this paper suggests that low- and moderate-income neighborhoods in the United States lost active credit users at a greater rate than they lost population between 2000 and 2010. This trend could have significant ramifications on both household wealth-building strategies and community-revitalization efforts. Credit availability is particularly important in low- and moderate-income communities, as Belsky and Calder (2004) note, because in the absence of savings, credit is necessary to acquire productive but costly assets that provide economic security (e.g., a home or a small business). The presence or absence of these kinds of private-sector investments can influence whether a disadvantaged neighborhood rebounds or remains distressed, and the research presented in this paper suggests that in recent years, access to credit in such neighborhoods diminished. During periods of credit contraction, targeted lender outreach to low- and moderate-income neighborhoods might help maintain the flow of credit to creditworthy individuals and support the momentum of any nascent revitalization efforts.[23]

For researchers accustomed to using longitudinal consumer credit data sets, this paper makes important contributions to understanding the ways in which residential mobility and the macro-level credit environment can have disparate micro-level geographic impacts. Our findings serve as an important reminder to users of unbalanced panel data that, through the process of mobility and sample entry and exit, the geographic distribution and, quite possibly, the socioeconomic characteristics, of the sample can change over time.

---

[23] See Campbell and Blizzard (2008) for examples of targeted investment strategies pursued by Community Development Financial Institutions (CDFIs) after the onset of tighter lending standards in 2007.

The findings presented in this paper suggest a number of opportunities for researchers interested in this topic. For example, future research could attempt to control for individual characteristics related to credit history, usage, and performance in order to determine if neighborhood characteristics have an independent effect on sample growth or whether entry and exit simply reflect the geographic distribution of creditworthiness. It would also be worthwhile to compare the characteristics of consumers who make vertical moves between neighborhood income categories with the characteristics of those who do not undertake such moves. Finally, a closer analysis of the characteristics of those exiting the consumer credit sample is also warranted. Preliminary analysis suggests that consumers exiting the sample are more likely than other sample members to have "thin" files and less likely to have recent credit activity than their counterparts and that this is particularly true in low- and moderate-income neighborhoods.

Table 1. Neighborhood Income Categories

	Percent of Median Family Income	Distribution of Census Tracts
Low Income	0–50%	8%
Moderate Income	51–80%	23%
Middle Income	81–120%	44%
Upper Income	>120%	24%
Not Classified	---	1%

Notes: N=66,304 census tracts in the United States and Puerto Rico using the Census 2000 tract definitions

Table 2. Classification of Consumers in the CCP, June 2002 and June 2010 (thousands)

	N	Percent
Lived in the same neighborhood type	6,297.5	46%
Lived in a different neighborhood type	2,181.0	16%
In sample both quarters but classified as "other" in at least one quarter	1,062.8	8%
Entered the sample during the study period	2,310.7	17%
Exited the sample during the study period	1,971.9	14%
Total	13,824.0	100%

Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: Categories may not sum to total due to rounding. Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased. Consumers classified as "other" have a nonresidential address in their credit file, have geographic information that cannot be matched to a standard census tract in the United States, or live in a tract that cannot be classified by income.

Table 3. CCP Sample Size by Neighborhood Income Category, June 2002–June 2010 (thousands)

	Low Income	Moderate Income	Middle Income	Upper Income	Other	Total
6/1/2002	637.0	2,285.7	4,763.1	2,876.1	951.4	11,513.3
6/1/2010	552.4	2,164.4	5,073.9	3,263.9	797.5	11,852.0
% change	-13%	-5%	7%	13%	-16%	3%

Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased. Consumers classified as "other" have a nonresidential address in their credit files, have geographic information that cannot be matched to a standard census tract in the United States, or live in a tract that cannot be classified by income. The decline in "other" consumers, in part, reflects a marked drop in the number of consumers with a nonresidential address in their credit files.

Table 4. CCP Sample Size by Neighborhood Income Category, June 2000–June 2010 (thousands)

	Low Income	Moderate Income	Middle Income	Upper Income	Census Tract with No Income Data	Invalid Census Tract Data	Nonresidential	Total
					Other			
6/1/2000 (original)	552.3	1,884.0	3,682.2	2,244.4	5.3	1,628.3	701.1	10,697.5
6/1/2000 (estimate)	653.6	2,229.7	4,357.8	2,656.2	6.3	92.8	701.1	10,697.5
6/1/2010 (actual)	552.4	2,164.4	5,073.9	3,263.9	3.6	81.6	712.4	11,852.0
% change from 2000 estimate to 2010 actual	-15%	-3%	16%	23%	-43%	-12%	2%	11%

Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased. To create income category estimates for June 2000, we hold constant the number of consumers reported as nonresidential in the original June 2000 data. Then, using the percentage of residential consumers with imprecise geographic information in June 2002 (0.9 percent), we calculate the number of consumers that we would "expect" to have invalid geographic data in June 2000 if the geographic variables had been as precise as they are in later years (92,800). We then distribute the remaining consumers with invalid geographic data in June 2000 to the four neighborhood income categories based on the proportions of those consumers successfully assigned to an income category in that same quarter. Consumers classified as "other" have a nonresidential address in their credit file, have geographic information that cannot be matched to a standard census tract in the United States, or live in a tract that cannot be classified by income.

Table 5. Decennial Census Population, April 2000–April 2010 (thousands)

	Low Income	Moderate Income	Middle Income	Upper Income	Other	Total
2000	18,673.6	63,408.7	130,055.9	72,535.1	557.2	285,230.5
2010	18,006.7	64,808.2	142,458.7	86,485.8	712.0	312,471.3
% change	-4%	2%	10%	19%	28%	10%

Source: Authors' calculations using data from the U.S. Census Bureau

Notes: Population totals are based on a merge of census tract-level population data from the 2010 Census Tract Relationship File and Census 2000 Summary File 1 data obtained from American FactFinder; Puerto Rico is included. The 2010 population totals predate minor revisions conducted under the 2010 Census Count Question Resolution Program Population totals reported in the "other" category represent the aggregate population of census tracts that could not be classified by income, primarily because their median family income was not reported in the American Community Survey.

Table 6. Components of CCP Sample Size Change, June 2002–June 2010 (thousands)

	Low Income	Moderate Income	Middle Income	Upper Income	Other	Total
Consumers in sample in June 2002	637.0	2,285.7	4,763.1	2,876.1	951.4	11,513.3
Consumers in sample in June 2010	552.4	2,164.4	5,073.9	3,263.9	797.5	11,852.0
Aggregate net change	-84.7	-121.3	310.8	387.8	-153.9	338.8
Percent change	-13%	-5%	7%	13%	-16%	3%
Net change attributable to residential migration	-80.2	-179.1	55.0	204.2	0.0	0.0
Percent change	-13%	-8%	1%	7%	0%	0%
Net change attributable to sample entrants and exits	-5.0	48.8	208.7	156.8	-70.6	338.8
Percent change	-1%	2%	4%	5%	-7%	3%
Net exchange of consumers between income and Other categories	0.5	8.9	47.1	26.8	-83.3	0.0
Percent change	0%	0%	1%	1%	-9%	0%

Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased. Consumers classified as "other" have a nonresidential address in their credit file, have geographic information that cannot be matched to a standard census tract in the United States, or live in a tract that cannot be classified by income.

Table 7. Patterns of Residential Migration, June 2002–June 2010

Destination Neighborhood (June 2010)	Origin Neighborhood (June 2002)			
	Low Income	Moderate Income	Middle Income	Upper Income
Percent of out-migrants moving into each neighborhood income category				
Low Income	---	9%	5%	4%
Moderate Income	38%	---	33%	21%
Middle Income	41%	61%	---	75%
Upper Income	21%	31%	62%	---
Total	100%	100%	100%	100%
Distribution of 2002 sample (excluding origin neighborhood income category)				
Low Income	---	8%	11%	8%
Moderate Income	23%	---	39%	30%
Middle Income	48%	58%	---	62%
Upper Income	29%	35%	50%	---
Total	100%	100%	100%	100%
Ratio				
Low Income	---	1.15	0.48	0.45
Moderate Income	1.65	---	0.84	0.71
Middle Income	0.86	1.05	---	1.21
Upper Income	0.71	0.88	1.24	---

Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: The percent of out-migrants moving into each neighborhood income category includes all consumers who were living in neighborhoods classified into different income categories in June 2002 and June 2010. Excluded from this table are sample entrants and exits, consumers who lived in neighborhoods classified into the same income category at the beginning and end of the study period, consumers living in a census tract classified as "other" in one or both periods, file fragments (i.e., in the sample for no more than one year), and consumers coded as deceased. The distribution of the 2002 sample shows the share of all residential consumers living in each of the three income categories excluding the origin neighborhood type. Categories may not sum to total due to rounding.

Figure 1. Rates of Growth and Decline for the CCP and the U.S. Population, 2000-2010
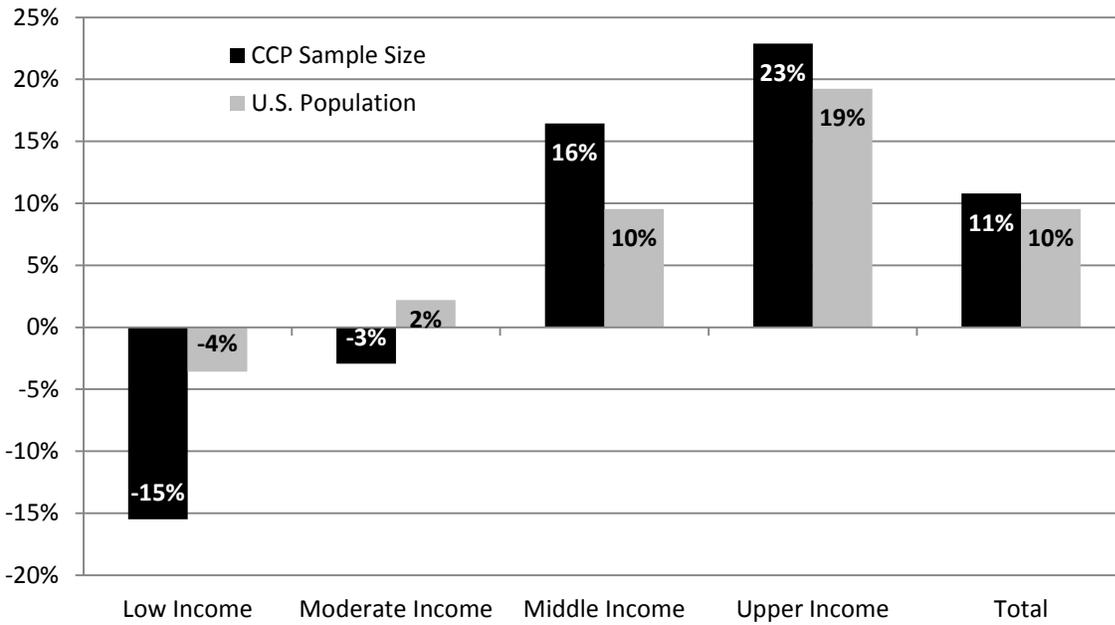
Sources: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set and U.S. Census data

Notes: Sample growth and decline rates are based on neighborhood income category estimates for June 2000 described in the text and exclude file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased. Consumers and populations classified into the "other" category for reasons explained in the text are included in the total growth rates.

Figure 2. Percentage of the Population with a Credit History, 2000–2010
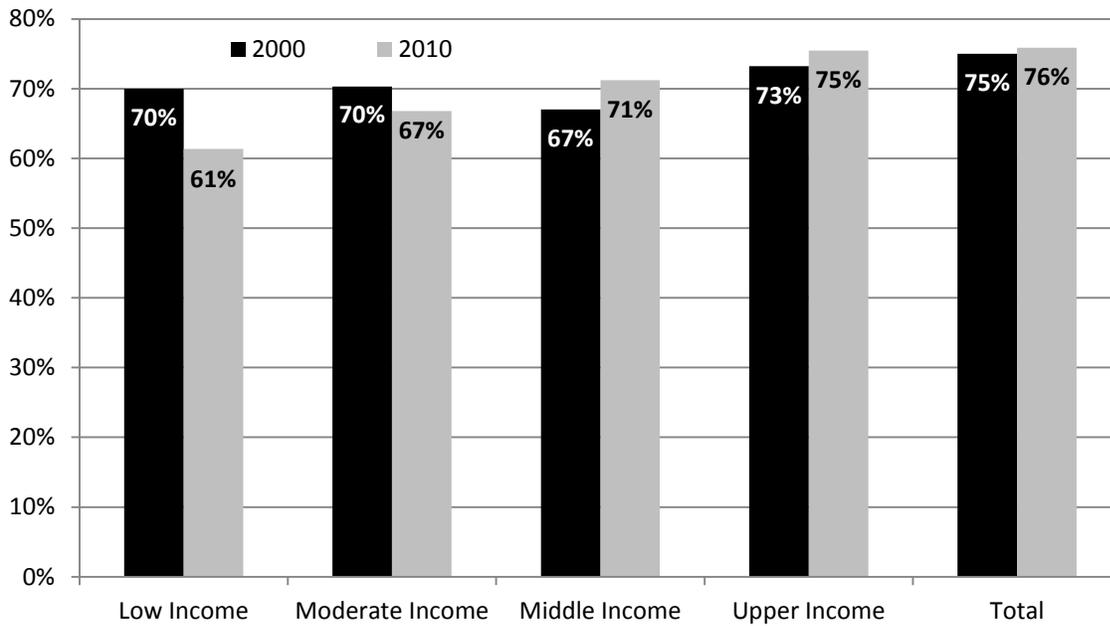
Sources: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set and U.S. Census Data

Notes: Because the CCP is a 5-percent random sample, the percentage of the population with a credit history can be calculated as simply the sample size in a given year multiplied by 20 and divided by the population reported in the 2000 and 2010 censuses. It would have been preferable to use the population 18 and older as the divisor in order to be more consistent with the age range at which most consumers acquire a credit history, but this information was not readily available in 2010 for tract definitions used in the 2000 census. The sample size in 2000 is estimated for the neighborhood income categories as described in the text. Estimates for both years exclude file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased. Consumers and populations classified into the "other" category for reasons explained in the text are included in the total calculations.

Figures 3–6. CCP Sample Entry and Exit Rates as a Percentage of the Interpolated Sample Size, June 2002–June 2010

Figure 3. Low-Income Neighborhoods
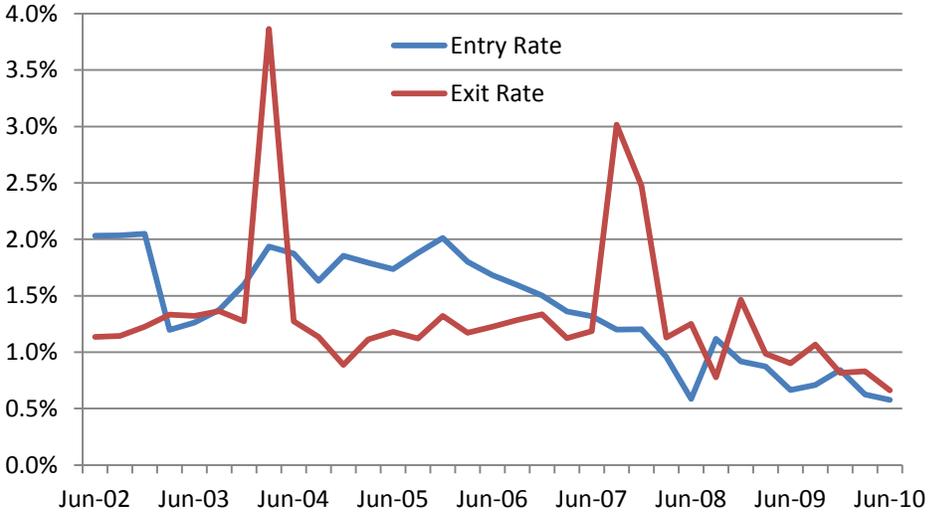
Figure 4. Moderate-Income Neighborhoods
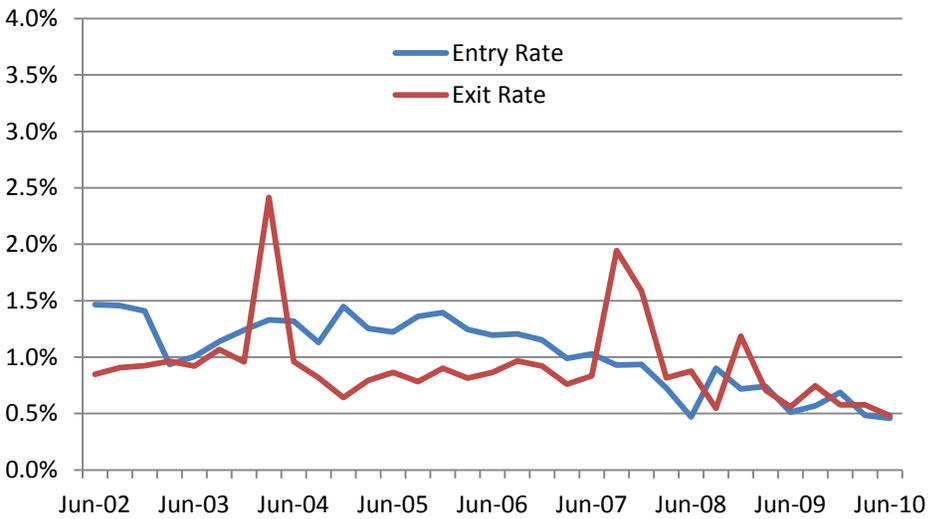
Figure 5. Middle-Income Neighborhoods
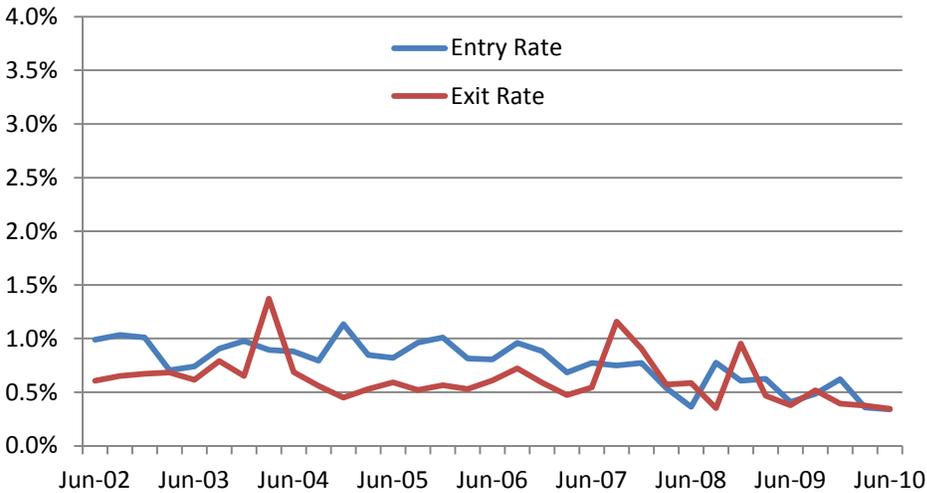
Figure 6. Upper-Income Neighborhoods
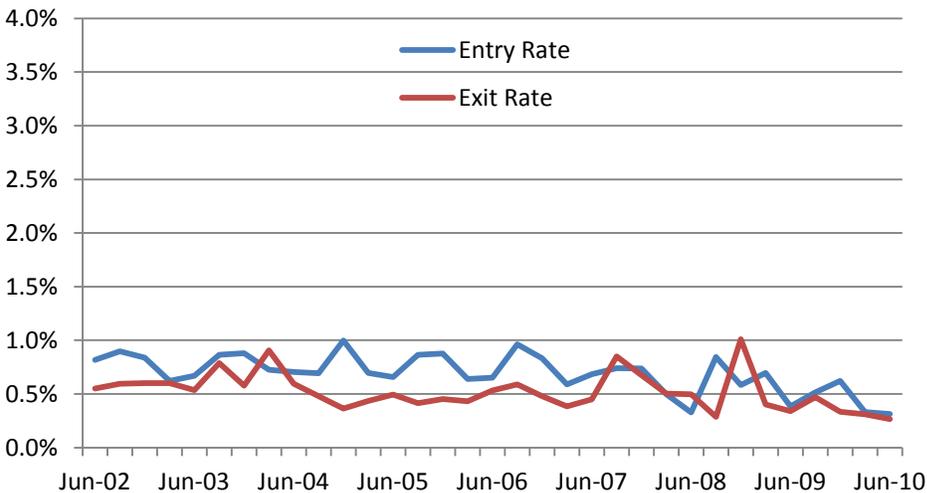
Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: Figures 3–6 exclude file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased and do not reflect changes attributable to residential migration or the reclassification of consumers between the income and "other" categories. A consumer is considered an entrant in the quarter in which it first appears in the data set and an exit in the quarter in which it last appears, based on two derived variables in the CCP. The sample size for each income category is calculated for each quarter as a straight-line interpolation between the June 2002 and June 2010 sample sizes reported in the stock analysis. Entry and exit rates are calculated as the number of entrants and exits in a given quarter divided by the estimated sample size in the same quarter. See text for additional discussion.

Figure 7. Net Rate of Growth Attributable to Entrants and Exits in the Flow Analysis as a Percentage of the Interpolated Sample Size, June 2002–June 2010 (Quarterly)
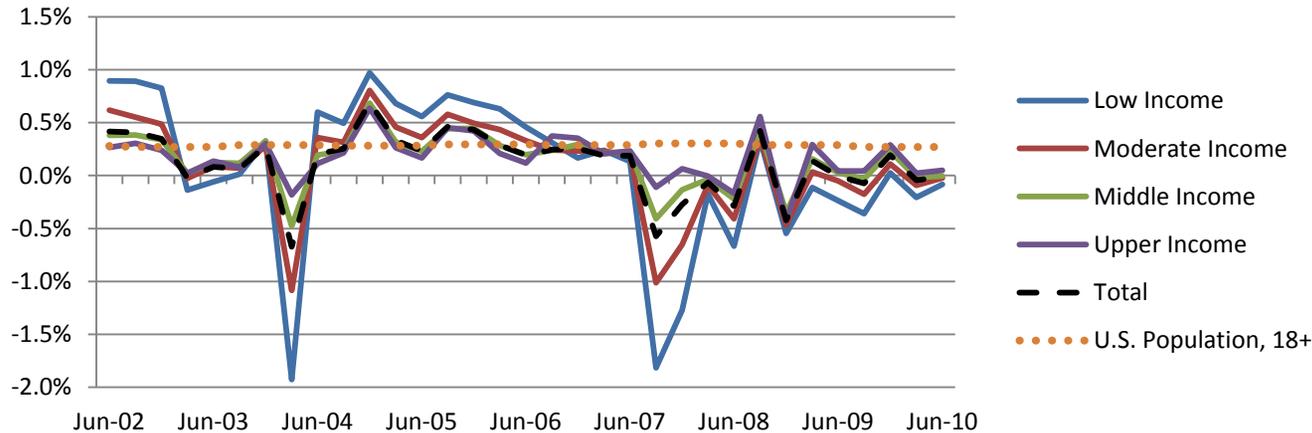
Sources: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set and U.S. Census data

Notes: Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased and does not reflect changes attributable to residential migration or the reclassification of consumers between the neighborhood income categories and the "other" category. A consumer is considered an entrant in the quarter in which it first appears in the data set and an exit in the quarter in which it last appears, based on two derived variables in the CCP. The sample size for each income category is calculated for each quarter as a straight-line interpolation between the June 2002 and June 2010 sample sizes reported in the stock analysis. The net rate of growth is calculated as the difference between the number of entrants and exits in a given quarter divided by the estimated sample size in the same quarter. Quarterly U.S. population growth rates for the population age 18 and older are derived from Table 1. Intercensal Estimates of the Resident Population by Sex and Age for the United States: April 1, 2000 to July 1, 2010 (US-EST00INT-01) produced by the U.S. Census Bureau, Population Division (September 2011).

Figure 8. Cumulative Increase Attributable to Entrants and Exits in the Flow Analysis, June 2002–June 2010 (thousands)

Source: Authors' calculations using the FRBNY Consumer Credit Panel/Equifax data set

Notes: Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased and does not reflect changes attributable to residential migration or the reclassification of consumers between the neighborhood income categories and the "other" category. A consumer is considered an entrant in the quarter in which it first appears in the data set and an exit in the quarter in which it last appears, based on two derived variables in the CCP. The cumulative increase is calculated as the difference between the total number of entrants and the total number of exits between June 2002 and each subsequent quarter.

Figure 9. Cumulative Increase Attributable to Entrants and Exits in the Flow Analysis as a Percentage of the Interpolated Sample Size, June 2002–June 2010

Source: Authors' calculations using the FRBNY Consumer Credit Panel/ Equifax data set

Notes: Excludes file fragments (i.e., in the sample for no more than one year) and consumers coded as deceased and does not reflect changes attributable to residential migration or the reclassification of consumers between the neighborhood income categories and the "other" category. A consumer is considered an entrant in the quarter in which it first appears in the data set and an exit in the quarter in which it last appears, based on two derived variables in the CCP. The cumulative increase is calculated as the difference between the total number of entrants and the total number of exits between June 2002 and each subsequent quarter. The sample size for each income category is calculated for each quarter as a straight-line interpolation between the June 2002 and June 2010 sample sizes reported in the stock analysis and is used to normalize the cumulative increase.

References

Belsky, E., & Calder, A. (2004). "Credit Matters: Low-Income Asset Building Challenges in a Dual Financial Service System," Harvard University, Joint Center for Housing Studies BABC Working Paper No. 04–01.

Bhutta, N. (2011). "The Community Reinvestment Act and Mortgage Lending to Lower Income Borrowers and Neighborhoods," *Journal of Law and Economics,* 54(4), 953–983.

Board of Governors of the Federal Reserve System. (2007). *Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit.* Washington: Board of Governors of the Federal Reserve System.

Board of Governors of the Federal Reserve System. (2013). *Senior Loan Officer Opinion Survey on Bank Lending Practices Chart Data* (January). Retrieved March 18, 2013, from http://www.federalreserve.gov/boarddocs/snloansurvey/201302/chartdata.htm.

Brevoort, K. P. (2011). "Credit Card Redlining Revisited," *The Review of Economics and Statistics*, 93(2), 714–24.

Bricker, J., Kennickell, A. B., Moore, K. B., & Sabelhaus, J. (2012). "Changes in U.S. Family Finances from 2007 to 2010: Evidence from the Survey of Consumer Finances," *Federal Reserve Bulletin*, 98(2).

Brown, M., Haughwout, A., Lee, D., & van der Klaauw, W. (2011). "Do We Know What We Owe? A Comparison of Borrower- and Lender-Reported Consumer Debt," Federal Reserve Bank of New York Staff Report No. 523.

Campbell, A., & Blizzard, J. (2008). Community Development Finance: Innovative Paths to Capital During the Credit Squeeze," Federal Reserve Bank of Richmond *MARKETWISE* (Fall/Winter)

Cheney, J. S. (2008). "Alternative Data and Its Use in Credit Scoring Thin- and No-File Consumers," Federal Reserve Bank of Philadelphia Payment Cards Center Discussion Paper No. 08–01.

Cohen-Cole, E. (2011). "Credit Card Redlining," *The Review of Economics and Statistics*, 93(2), 700–13.

Demyanyk, Y., Hryshko, D., Luengo-Prado, M. J., & Sorensen, B. E. (2013). "Moving to a Job: The Role of Home Equity, Debt, and Access to Credit," Federal Reserve Bank of Cleveland Working Paper No. 13–05.

Ergungor, O. E. (2010). "Bank Branch Presence and Access to Credit in Low- to Moderate-Income Neighborhoods," *Journal of Money, Credit and Banking*, 42(7), 1321–1349.

Federal Reserve Bank of Philadelphia. (2012). *Community Development Data Dashboard, Consumer Credit Data.* Retrieved February 27, 2013, from http://www.philadelphiafed.org/community-development/data-dashboard/consumer-credit-data.cfm.

Guerrieri, V., Hartley, D., & Hurst, E. (2012). "Within-City Variation in Urban Decline: The Case of Detroit," *American Economic Review: Papers & Proceedings*, 102(3), 120–126.

Hartley, D. (2013, May 20). *"Urban Decline in Rust-Belt Cities,"* Federal Reserve Bank of Cleveland *Economic Commentary* No. 2013–06.

Horan, J. (2005, December 15). *FICO Scores and the Credit Underserved Market.* Retrieved February 24, 2013, from Brookings Institution: http://www.brookings.edu/metro/umi/20051215_Jhoran_FairIssac.pdf.

Hunt, R. M. (2005). "A Century of Consumer Credit Reporting in America," Federal Reserve Bank of Philadelphia Working Paper No. 05–13.

Lazere, E., & Rodgers, A. (2005). *Losing Ground: The District's Lowest-Income Neighborhoods Suffered Large Population and Income Losses in the 1990s.* Washington, DC: Fiscal Policy Institute.

Lee, D., & van der Klaauw, W. (2010). "An Introduction to the FRBNY Consumer Credit Panel," Federal Reserve Bank of New York Staff Report No. 479.

Molloy, R. Shan, H. (2013). "The Postforeclosure Experience of U.S. Households," *Real Estate Economics*, 41(2), 225–254.

Munoz, A. P. (2013). "Credit Conditions by Neighborhood Income: The Picture in Massachusetts," Federal Reserve Bank of Boston Community Development Discussion Paper No. 2013–03.

Ritter, D. (2012). "Do We Still Need the Equal Credit Opportunity Act?" Federal Reserve Bank of Philadelphia Payment Cards Center Discussion Paper No. 12–03.