Stepping Stone or Quicksand? The Role of Consumer Debt in the U.S. Geography of Economic Mobility

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Introduction

Debt may enhance economic mobility, supporting otherwise impossible investments in human capital and small business, or it may trap low-income consumers in an inescapable cycle of obligation. Chetty et al. (2014) have provided the profession with a detailed description of the geography of intergenerational mobility in the United States and the economic and social factors correlated with upward mobility at the local level. This paper seeks to understand the role of consumer debt reliance in more and less mobile U.S. communities.

Using the Chetty et al. (2014) commuting zone (CZ)-level mobility measures in conjunction with the Equifax-sourced Federal Reserve Bank of New York (FRBNY) Consumer Credit Panel (CCP),[1] a large, proprietary data set on U.S. consumers' borrowing and creditworthiness over the past 15 years, we investigate the comparative mobility of more and less debt-reliant and more and less creditworthy metropolitan areas. Further, we look at the relationships between local consumers' use of different types of debt products and the region's level of intergenerational mobility. Credit risk scores here function as an additional measure of access to consumer loan products. Our estimates condition on local income variation and the major correlates of mobility identified by Chetty et al. (2014), which include factors such as average commute times and the fraction of single-parent households.

We compare maps of regional variation in credit scores and the ratio of consumer debt to income, both for all individuals and for residents of lower income ZIP codes, with the Chetty et al. (2014) mobility maps, and find that they foreshadow several of our main results. These maps demonstrate that absolute mobility, measured at the commuting zone level by Chetty et al. (2014) as the expected position in the national income distribution roughly 15 years later of a youth whose parents' household income places them at the 25th percentile in the national income distribution in 1996–2000, is highest in the Great Plains, Oklahoma, and Texas. Mobility is moderately high in New England and the West and substantially lower in the South and the Rust Belt.

1 Information on the Consumer Credit Panel can be found on the Federal Reserve Bank of New York's website at **www.newyorkfed.org/microeconomics/ccp.html**.

A map of the median credit risk score among lower-income households by commuting zone, using CCP data from the year 2000, is surprisingly similar. Credit risk scores overall, and among residents of lower-income communities in particular, are lowest in the Southeast and much of the Rust Belt, and highest in the Great Plains.[2] Both in general and in low-income communities, credit risk scores in New England and the Pacific Northwest are fairly high.

The remainder of the paper examines whether, and to what extent, the addition of debt characteristics enhances our understanding of mobility once one conditions on the leading mobility correlates identified by Chetty et al. (2014). The theoretical relationship between parents' debt and their children's realized household income is ambiguous. One conceptualization of the problem involves distinguishing credit access from the effect of the burden of debt. A family with more access to credit is more able to take advantage of investment opportunities, including investment in a child's human capital and entrepreneurial investment. In addition, the family may be more able to smooth transient income and health shocks, which may influence children's human capital attainment and overall productivity. At the same time, some have argued that bounded rationality among borrowers, in combination with exploitative lending contracts, can lead to borrowing that exceeds the optimum for the household and to debt burdens that narrow a family's opportunities.[3] Therefore, we seek measures of consumers' debt behavior that help us to separate the role of credit access from that of debt burden.

We estimate the dependence of children's mobility by 2011–12 on debt characteristics of the household in 2000, along with the correlates of mobility identified by Chetty et al. (2014) and measures of the local economic climate. To understand the role of credit access, we estimate the dependence of mobility on the mean credit risk score of residents of lower income ZIP codes in each CZ. It is worth noting that an individual's credit risk score in 2000 contains not only information on forward-looking credit access, but also evidence of the size and amount of unexpected shocks to employment, household structure, health, and investment returns that the individual has experienced over the past several years. Hence the estimated association between credit risk score and mobility is far from causal. However, it may be the cleanest description of the relationship between access to consumer credit and mobility available to us at this point.

We also estimate the relationship between realized mobility by 2011–12 and the prevalence in 2000 of overall debt, and of various categories of consumer debt, among residents of lower income ZIP codes in each CZ. Further, we

2 We define lower income communities as ZIP codes in which the mean household income, using IRS data described below, is below the median average ZIP code-level income among all (measured) U.S. ZIP codes.

3 See, for example, Sunstein (2006).

estimate its relationship to debt balances, both overall and by category. While the prevalence and size of existing debts among lower-income households each conflate initial debt access and ongoing debt burden, we estimate prevalence and balance coefficients separately based on the belief that the prevalence measures will be more informative regarding the share of the lower income population with no access to credit, though this group may be contaminated with those who prefer not to borrow. Similarly, debt balance coefficients may be comparatively informative regarding the relationship of the burden of debt repayment to mobility, despite the fact that balances reflect the supply-demand equilibrium in the consumer debt market, and lower balances may therefore constitute evidence not merely of lower repayment burdens but also of more limited credit access. Throughout the paper, we note instances in which coefficients are and are not sensitive to estimation using only debt balances, or only debt prevalence.

Controlling for the average balances of various types of consumer debt in each CZ, and for the Chetty et al. (2014) mobility correlates discussed below, we find economically large and statistically significant positive associations between a region's past student loan, credit card, and other debt prevalence, particularly among lower-income ZIP codes, and the realized income position by 2011–12 of a child of parents in the region with income at the 25th percentile of the national income distribution in 1996–2000.

Hence, the use of unsecured credit shows a meaningful positive association with both absolute and relative mobility. However, the estimated relationship between mobility and the prevalence of secured debts, such as auto, home equity, and mortgage debt, is either negative or mixed. Summing all consumer debts, we find that the total consumer debt burden of a region is weakly negatively associated with absolute intergenerational income mobility. Finally, conditioning on the above, as well as on income and the Chetty et al. (2014) measures, we find that the mean risk score among residents of lower income ZIP codes in the CZ is strongly (positively) correlated with realized absolute and relative mobility for their children. A standard deviation increase in mean risk score is associated with roughly a 0.2 standard deviation increase in realized absolute mobility. This substantial positive association between risk score and intergenerational income mobility is robust to a wide array of specifications and therefore does not appear to be mediated by either local income or by the Chetty et al. (2014) leading correlates of mobility.

Though not causal, these estimates suggest that more mobile areas are characterized by more prevalent student and credit card debt use, which certainly funds education and may fund small business expenses and parents' expenditures for children. On the other hand, less mobile metropolitan areas are characterized by greater mortgage, home equity, and auto balances, which are likely used to fund housing and auto purchases. On net, debt reliance has a somewhat ambiguous relationship to local economic mobility; rather, it appears that the types of consumer borrowing, and so perhaps the uses of borrowed funds, play a more meaningful role in intergenerational income mobility. Most importantly, the risk scores and debt prevalence of lower-income households are the debt measures we find to be most closely tied to economic mobility.

It is worth noting that the quality of these findings is entirely contingent on the quality of the Chetty et al. (2014) mobility measures. Based on PSID estimates, Mazumder (2015) argues that the Chetty et al. (2014) relative mobility measure is biased downward as a result of the comparatively short observation window they have available for their vast IRS sample of American families. To the extent that the downward bias that may result from a shorter window of observation is similar across commuting zones, our estimated coefficients should simply reflect somewhat weaker associations between debt or creditworthiness and economic mobility than is actually the case. To the extent that the importance of later-career achievement to realized economic mobility varies from community to community, however, the measurement over a shorter period of time may be pertinent not just to our quantitative but also to our qualitative findings.

The paper proceeds as follows. “Literature” provides an overview of the relevant literature, and notes crucial features of the Chetty et al. (2014) geography of mobility study on which we build, and of the mobility dataset that they have made public. In “Data,” we describe the Equifax-sourced FRBNY CCP, both in general and as employed in this study, and we detail additional data sources that describe features of U.S. commuting zones not measured by the CCP. “Geographic Patterns in Debt, Creditworthiness, and Mobility” uses a series of maps to illustrate geographic patterns in consumer debt-to-income (DTI) ratios and measured creditworthiness in 2000 and relates them to geographic patterns in mobility between 1996–2000 and 2011–12, as reported by Chetty et al. (2014). It also lays out a simple empirical model of the relationship between commuting zone debt and other characteristics and realized mobility. “Debt and Other Correlates of Economic Mobility” reports estimates generated by the model, and “Conclusion” offers concluding thoughts.

Literature

The State of the Literature on Intergenerational Mobility and Its Relationship to Credit Access

The literature on intergenerational mobility is extensive. Reviews by Solon (2004) and Black and Devereux (2011) offer helpful summaries of important theoretical and empirical work in this area. In considering the relationship between student debt and mobility, our analysis contributes to a sizable body of work on the parental decision to invest in a child's human capital, formal modeling of which can be traced to Becker and Tomes (1979; 1986) and more recent studies of which include Han and Mulligan (2001), Grawe and Mulligan (2002), and Grawe (2004). Solon (2004) considers families who may face both life-cycle and intergenerational credit constraints, and hence underinvest in the human capital of their children. Though the model predicts that the intergenerational elasticity of earnings (IGE) should be greater for those who are credit-constrained, previous empirical attempts to estimate the IGE for this group have been thwarted by the difficulty of credibly identifying individuals who face credit constraints. In this context, our ability to observe the credit constraints of parents, and their relationship to the economic positions of their children around age 30, may help to shed light on Solon's predictions for the relationship of young families' access to credit to the life prospects of their children.

Another branch of the literature on intergenerational mobility relates early life experiences to adult income. Palloni (2006) estimates a substantial dependence of adult socioeconomic achievement on early childhood health. Case and Paxson (2010) also find that childhood health problems prevent poor children from realizing economic success, and Currie and Goodman (2010) conclude that there is evidence for links between both parental socioeconomic status and child health, and child health and future educational attainment. To the extent that the effects of childhood health problems on adult outcomes are mediated by access to credit, either to purchase better care or to replace temporary earnings losses so that parents can care for children, we may expect the parents' access to, and observed use of, credit to have meaningful positive effects on mobility for the subset of children who experience adverse health conditions.

Finally, the recent literature on economic mobility has addressed the relationship of several elements of parents' balance sheets to children's adult incomes. Mazumder (2011) argues that low levels of wealth among black parents, arising from a variety of persistent social and economic factors, limit the upward mobility of their children. Hanushek, Leung, and Yilmaz (2014) note that, relative to merit aid schemes, need-based aid for higher education has a greater (negative) impact on the intergenerational transmission of inequality. Bleemer, Brown, Lee, and van der Klaauw (2014) estimate a substantial decline in financial independence from parents in state-cohort groups that are more reliant on student debt. To the extent that student debt is concentrated among the children of lower-middle income families, this delayed independence may indicate a negative relationship between student debt and economic success for such children. Moreover, Chetty et al. (2015) find that areas with mortgage interest deductions that are larger as a share of local income see higher rates of economic mobility. This would seem to suggest that mortgage debt itself hampers economic mobility, though such inferences would require a more serious treatment of the influence of mortgage interest deductions on house prices than our speculation here offers.

In this context, the present study makes several unique contributions. First, we consider the relationship between intergenerational income mobility and the full set of standard consumer debt types, and not merely student debt, which has been the dominant focus of most previous work on debt and mobility. We are able to describe the relative strength of the conditional correlation between children's realized mobility and their parents' reliance on mortgage, credit card, auto, and student debt, for example. In addition, our credit score data allow us to proxy for access to credit among lower-income households in a commuting zone, which in turn allows us to consider the effect of credit access on mobility more directly than previous work. And lastly, by building on the work of Chetty et al. (2014), we can rule out a number of alternative explanations for a statistical relationship between debt and mobility by showing that the estimated conditional correlations between mobility and credit risk scores and use remain sound even after controlling for those covariates that Chetty and coauthors find to be most strongly associated with mobility.

Chetty, Hendren, Kline, and Saez (2014) Mobility Dataset and Central Findings

The primary contribution of Chetty et al. (2014) is the construction of a dataset of intergenerational economic mobility measures specific to several hundred U.S. communities, or "commuting zones," using IRS income tax records on more than 40 million children and their parents. Parents' characteristics, including location in the U.S. family income distribution, are measured between 1996 and 2000, when the children are aged 15 to 20. Children's adult incomes are measured in 2011 and 2012, when they are roughly 30 years old.

At the national level, they find that a 10 percentile increase in parent income in 1996–2000 is associated with a 3.4 percentile increase in a child's realized income by 2011–12. Further, Chetty et al. (2014) show that intergenerational mobility varies widely from community to community. While the probability of a child born to first income quintile parents reaching the fifth income quintile herself is 4.4 percent in Charlotte, for example, it is 12.9 percent in San Jose.

Most relevant to this study, they explore a number of commuting zone characteristics to determine which are most strongly correlated with measured economic mobility. Candidate characteristics include the degree of residential segregation, the level of income inequality in the 1996–2000 period, school quality, social capital, and family stability. Measures that they find to be most strongly associated with mobility include average commuting time (a measure relevant to economic segregation), the high school dropout rate, share of children being raised by single mothers, and prior measures of social capital.

Adopting the Chetty et al. (2014) measures of economic mobility at the commuting zone level, we first examine the relationship between geographic debt and credit access patterns and geographic income mobility patterns. The comparison is accomplished first using U.S. maps depicting mobility, credit access, and debt obligations by region, and second through estimates of the simple and conditional correlations of debt and mobility measures. Finally, we control for the five leading correlates of mobility from Chetty et al. (2014), and we investigate the robustness of our measured debt-mobility relationships to their inclusion in the empirical model.

Data

The FRBNY Consumer Credit Panel

The FRBNY CCP is a longitudinal dataset on consumer liabilities and repayment. It is built from quarterly consumer credit report data collected and provided by Equifax Inc. Data are collected quarterly from 1999:Q1, and the panel is ongoing. Sample members have Social Security numbers ending in one of five arbitrarily selected pairs of digits (for example, 10, 30, 50, 70, or 90), which are assigned randomly within the set of Social Security number holders. Therefore the sample comprises 5 percent of U.S. individuals with credit reports (and Social Security numbers). The CCP sample design automatically refreshes the panel by including all new reports with Social Security numbers ending in the above-mentioned digit pairs. Therefore the panel remains representative for any given quarter, and includes both representative attrition, as the deceased and emigrants leave the sample, as well as representative entry of new consumers, as young borrowers and immigrants enter the sample.[4] In addition to the debt, repayment, creditworthiness, and limited demographic characteristics available in a credit file, the dataset contains geographic information down to the census block, allowing us, for the purposes of this study, to tie credit bureau information to mobility, income, and other relevant factors at the commuting zone level and below.

In sum, the CCP permits unique insight into the question at hand as a result of the size, representativeness, frequency, and recentness of the dataset. Its sampling scheme allows extrapolation to national aggregates and spares us

4 See Lee and van der Klaauw (2010) for details on the sample design.

most concerns regarding attrition and representativeness over the course of a long panel.

While the sample is representative only of those individuals with Equifax credit reports, the coverage of credit reports (that is, the share of individuals with at least one type of loan or account) is fairly complete for American adults. Aggregates extrapolated from the data match those based on the American Community Survey, Flow of Funds Accounts of the United States, and the Survey of Consumer Finances (SCF).[5]

Since our analysis is purely cross-sectional, we consider only 2000:Q4 when constructing our commuting zone-level measures of mortgage, home-equity line of credit (HELOC), auto, credit card, and other debt. For measures of student loan debt, we use data from 2004:Q4 because of concerns about the reliability of the relevant CCP variables in earlier years.[6]

For each debt type, as well as for total debt, we consider two metrics: average balance per borrower with debt in each category, and share of CCP individuals with debt in each category.[7] The latter allows us to consider how prevalent the use of certain debt products is, which reflects, in some combination, the share of the population that has access to the type of debt and the share that demands the type of debt. More broadly construed, it reflects the degree of relevance of a given debt category to the broader population.

Other Data Sources

We are interested in determining whether the associations between debt and mobility that we identify include some independent relationship of debt to mobility once one accounts both for the role of the affluence of the

5 Lee and van der Klaauw (2010) extrapolate similar populations of U.S. residents aged 18 and over using the CCP and the American Community Survey, suggesting that the vast majority of U.S. individuals at younger ages have credit reports. Jacob and Schneider (2006) find that 10 percent of U.S. adults had no credit reports in 2006, and Brown et al. (2013) estimate that 8.33 percent of the (representative) SCF households in 2007 include no member with a credit report. See Lee and van der Klaauw and Brown et al. for further details.

6 Reporting incentives for student lenders and servicers before 2004 were consistent with partial coverage of the market by credit bureaus. For this reason, the principal investigators of the CCP have recommended relying on CCP student debt measures from 2004 forward. The later date of measurement may mean that the student debt we observe measures some combination of the youths' childhood circumstances and early realizations of economic mobility. To the extent that this concern clouds interpretation of our results, one can focus instead on the debts measured in 2000.

7 We measure prevalence as the fraction of borrowers in our dataset for 2000:Q4 that have a nonzero balance of a given debt product, and then multiply this number by 100 in order to interpret our later regression coefficients as the effect of a one percentage-point change in prevalence.

community and for the leading mobility correlates described by Chetty et al. (2014). They find the following five factors to be most strongly correlated with mobility: (1) availability of employment (as measured by the fraction of individuals who commute less than fifteen minutes to work); (2) income inequality (as measured by the Gini coefficient of the bottom 99 percent); (3) school quality (as measured by the high school dropout rate); (4) social capital (as measured by an index from Putnam 1995); and (5) family structure (as measured by the fraction of children with single parents); Chetty et al. (2014) have made their mobility data publicly available.[8] Throughout the paper, wherever we make mention of a mobility measure or of the five primary determinants of mobility identified by Chetty et al. (2014), we are relying on their data as posted at the noted site. After looking at simple regressions of mobility on our preferred debt measures, we consider whether the estimated debt effects are robust to inclusion of the covariates.

Following Chetty et al. (2014) further, we adopt the commuting zone as our level of geographic analysis. A CZ is the collection of counties that share a common labor market. It is somewhat analogous to the metropolitan statistical area (MSA) but can also be defined for more rural areas, widening the scope of our geographic analysis beyond urban centers.

Their preferred measure of mobility, which they term "absolute mobility" and which terminology we adopt as well, is the average percentile in the national income distribution in 2011–12 of children whose household income placed them at the 25th percentile of the 1996–2000 U.S. national income distribution. The children are aged 15–20 in 1996–2000, and are therefore around 30 by the time their income position is determined in 2011–12. Note that children's 2011–12 mobility realizations are included in the CZ in which their parents resided in 1996–2000, whether they stayed in that CZ in adulthood or moved across the country.

While the absolute mobility measure is informative regarding the prospects of a youth from a given CZ at a national level, it is less informative regarding movement within the income distribution of the CZ itself. For example, a city that realizes substantial productivity gains relative to the nation may have youth from lower-income households whose position in the national income distribution reflects extensive mobility, and yet that youth may experience no relative gains within her own community. To address mobility within the local income distribution, Chetty et al. (2014) also create a measure of "relative mobility," which relies on the "rank-rank slope" correlation coefficient first studied by Dahl and DeLeire (2008). Here suppose

8 As of the writing, their data and documentation are available at **http://www.equality-of-opportunity.org/**.

R_i is child i's percentile rank in the children's income distribution, and P_i is the parent's percentile rank in the parents' income distribution. Regressing the child's percentile rank on the parent's percentile rank yields a regression coefficient

$$\rho_{PR} = Corr(P_i, R_i),$$

which others have labeled the rank-rank slope. This correlation serves as a measure of the strength of the association between the child's and the parent's position in their respective income distributions. When calculated at the commuting zone level, it gives us a picture of how mobile members of the commuting zone are, accounting for the degree of progress of the children of both low- and high-income parents. As mentioned earlier, important questions about the reliability of these rank-rank estimates have recently been raised by Mazumder (2015), who argues using samples drawn from the PSID that the short time frames over which Chetty and coauthors are able to observe both parent and child income may be a source of considerable downward bias in both these estimates and estimates of the IGE. This work also suggests that the problem appears to be less severe for the rank-rank coefficient than for the IGE, which we do not make use of here. We also run several specifications that feature controls for mean adjusted gross income (AGI), which we compute from ZIP code-level Internal Revenue Service data on aggregate AGI and the number of tax returns filed.[9]

Table 1 summarizes the CZ-level mobility measures provided by Chetty et al. (2014). We see that, on average across commuting zones, the expected adult income percentile rank of a child whose parents' income stood at the 25th percentile is 43.94. Hence we observe substantial, but not perfect, regression to the mean. The average of the estimated within-CZ rank-rank slopes, denoting the degree of correlation in parent and child income percentiles, is 0.33. Perhaps more importantly, each mobility measure displays substantial heterogeneity across commuting zones. The standard deviation of the CZ-level expected percentile rank of a child of the 25th percentile is 5.68 percentile points, suggesting quite a high degree of variability across localities in the expected attainment of lower income children. The standard deviation of the CZ-level parent-child income percentile correlation is 0.07, which, on a base of 0.33, again indicates wide variation in mobility across U.S. communities.

Table 2 provides summary statistics for commuting zone-level debt measures. The debt prevalences and unconditional mean balances are reasonably

9 These data are available on the IRS Statistics of Income (SOI) website at **www.irs.gov/uac/SOI-Tax-Stats-Individual-Income-Tax-Statistics-ZIP-Code-Data-(SOI)**.

Table 1: Summary statistics of mobility measures

MOBILITY MEASURE	MEAN	STANDARD DEVIATION
Absolute upward mobility	43.94	5.68
Relative mobility	0.33	0.07
Probability of moving from the bottom to the top quintile	0.10	0.05

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax; Chetty, Hendren, Kline, and Saez (2014).

Table 2: Summary statistics of debt measures

DEBT TYPE	MEAN BALANCE		PREVALENCE	
	MEAN	STD. DEVIATION	MEAN	STD. DEVIATION
Total non-student	$22,967.65	$8,808.74	0.79	0.03
Mortgage	$41,439.93	$16,160.66	0.24	0.08
Home equity	$14,849.42	$8,469.85	0.02	0.02
Auto	$9,009.55	$1,488.81	0.24	0.05
Credit card	$4,004.37	$668.50	0.62	0.06
Student loan	$13,256.33	$4,938.42	0.08	0.04
Other	$5,728.45	$2,305.30	0.47	0.06

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax.

consistent with what we would expect for the year 2000, based on studies of the CCP, the Survey of Consumer Finances, and other sources.[10] Note that both home equity and student debt reliance was substantially lower in 2000 than it is today. Further, the equal weighting of commuting zones in these sample averages leads to an under-weighting, relative to population-weighted studies, in debts that are more prevalent in urban areas. This also lowers the measured prevalence and unconditional means we observe in the sample for student and home-equity-based debt.

As with the mobility measures, CZ-level debt reliance, overall and by debt type, is highly variable. The standard deviation of mean debt across commuting zones is $8,808.74, the prevalence of mortgages at the CZ level shows a standard deviation of 7.79 percentage points, and the prevalence of credit card borrowing across CZs has a standard deviation of 6.4 percentage points.

10 See, for example, Bricker et al. (2012) and Brown et al. (2013).

Geographic Patterns in Debt, Creditworthiness, and Mobility

As noted above, maps of geographic variation in the Chetty et al. (2014) mobility measures and in several of the indicators pertaining to consumer indebtedness are helpful in motivating our key findings. Figures 1–3 show how absolute upward mobility, relative mobility, and the probability of moving from the bottom to the top quintile of the national income distribution differ across regions of the United States.[11] Naturally, absolute mobility and the probability of moving to the top quintile exhibit similar patterns: Mobility according to these measures is highest in the Upper Midwest and Great Plains regions and lowest in the Southeast and the Rust Belt, while falling somewhere in between in most areas in the Northeast and along the West Coast.

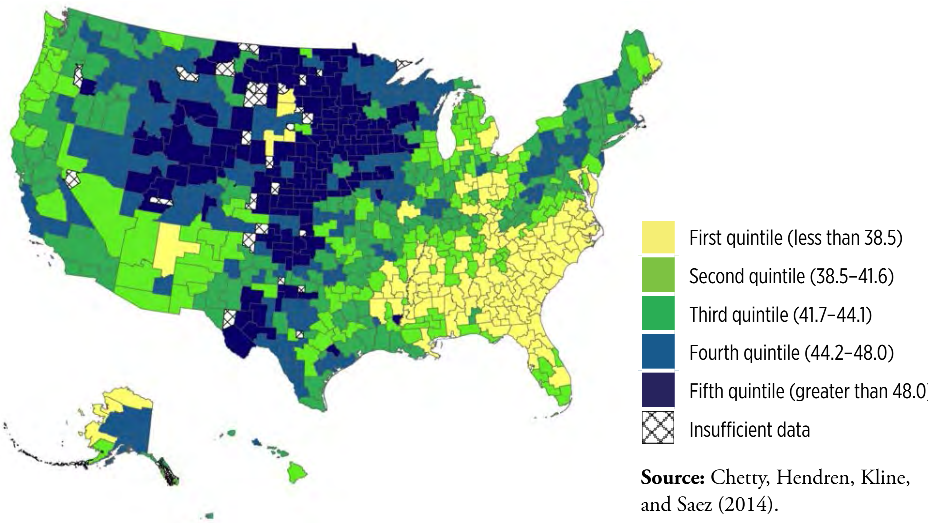
With regard to relative mobility, lower values of the Chetty et al. (2014) index reflect higher levels of relative income mobility for children of the commuting zone. While relative mobility, like absolute mobility, is weakest in the Southeast and the Rust Belt, the West Coast and Upper Midwest seem to dominate even much of the Northeast and New England. And perhaps somewhat surprisingly, relative mobility actually seems quite strong in pockets of Appalachia, which lags behind in terms of absolute mobility. The modest differences in these patterns are a further reminder that there is no *a priori* reason why a particular variable should be related to different measures of mobility in the same way or with the same sign.

Figures 4 and 5 show variation at the commuting zone level in the mean Equifax risk score and the mean risk score for ZIP codes with an average AGI in the bottom half of the national distribution. (For figure 5, we retain the quintile cutoffs used in figure 4 to facilitate comparison of the two.) The results are striking: While average risk scores are consistently high across the Upper Midwest for both all borrowers and borrowers in low-income ZIP codes, they tend to fall into the bottom quintile in low-income ZIP codes across the entire southern half of the country. Also of note is the fact that the lowest risk scores are found in states such as Louisiana, Alabama, Mississippi, Georgia, and South Carolina, which also exhibited the lowest levels of absolute and relative mobility.

Finally, figures 6 and 7 present debt-to-income ratios for both all ZIP codes and those in the bottom half of the national distribution by mean AGI, respectively. The numerator is aggregate debt as measured from the CCP and the denominator is aggregate AGI, which is taken from the Internal Revenue

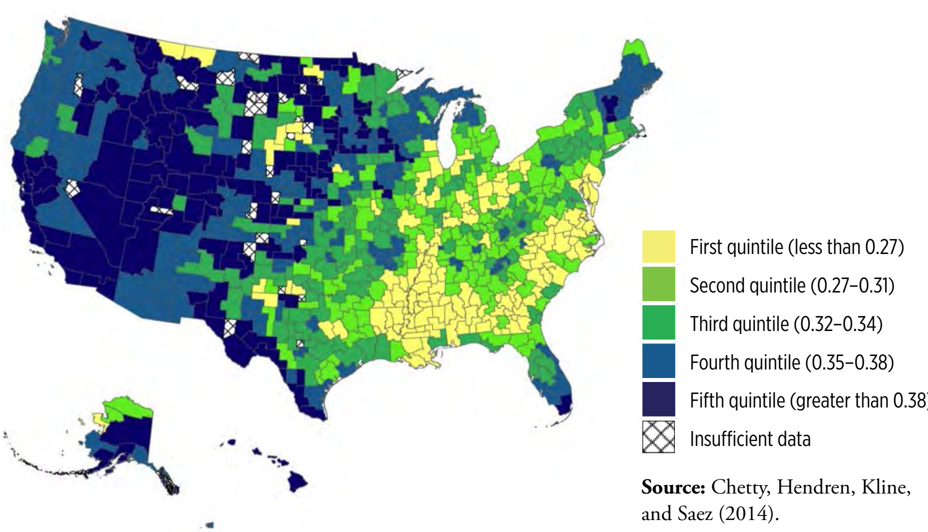
11 Figures 1 and 2 are based on figures VI(A) and VI(B) from Chetty et al. (2014).

Figure 1. Absolute upward mobility



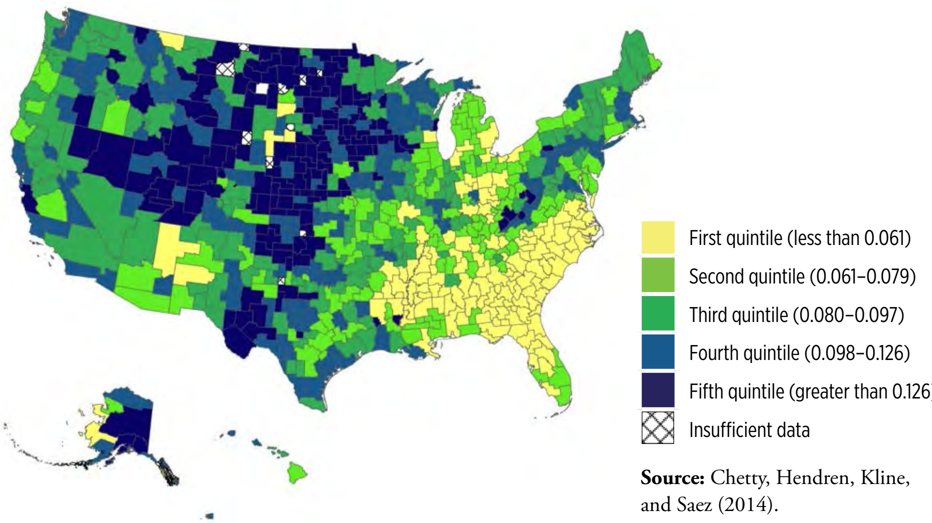
Source: Chetty, Hendren, Kline, and Saez (2014).

Figure 2. Relative mobility



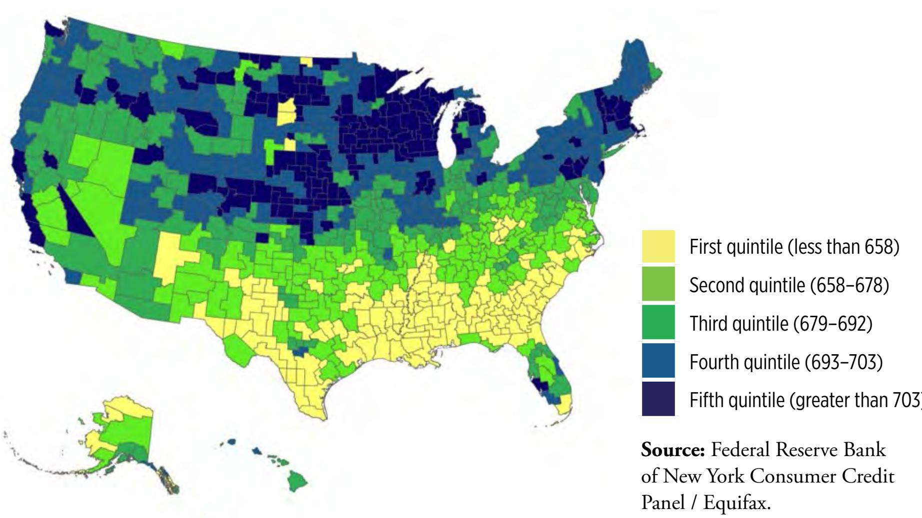
Source: Chetty, Hendren, Kline, and Saez (2014).

Figure 3. Probability of moving from the bottom to top quintile



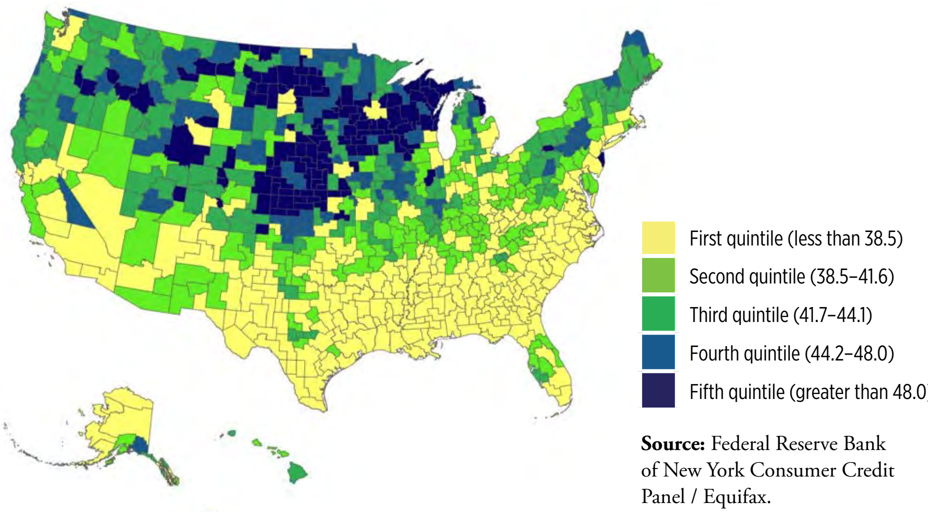
Source: Chetty, Hendren, Kline, and Saez (2014).

Figure 4. Mean risk score (all ZIP codes)



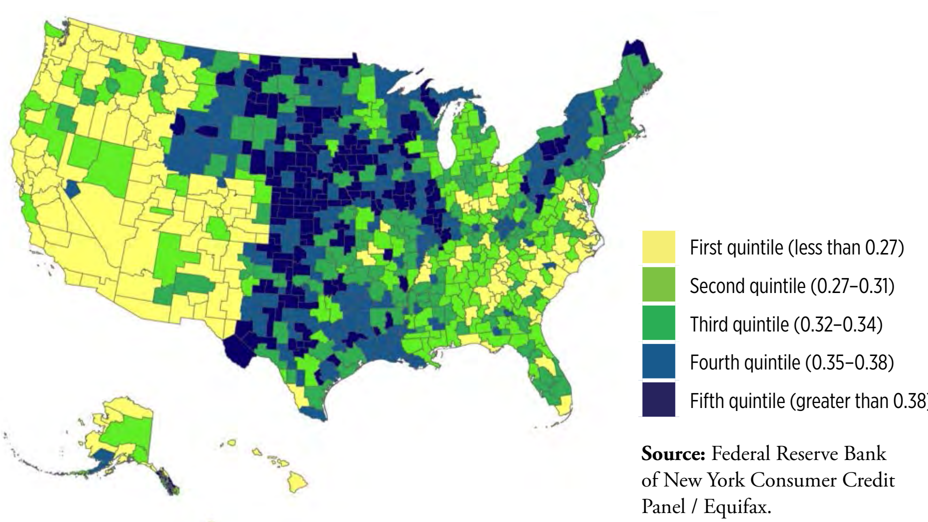
Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax.

Figure 5. Mean risk score (ZIP codes with mean AGI below national median only)



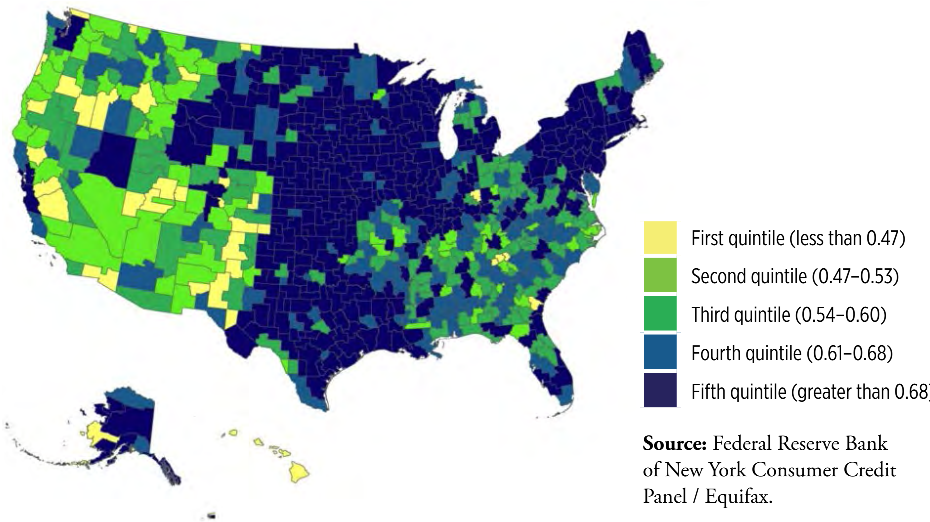
Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax.

Figure 6. Debt-to-income ratio (all ZIP codes)



Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax.

Figure 7. Debt-to-income ratio (ZIP codes with mean AGI in the bottom half of the national distribution only)



Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax.

Service Statistics of Income (SOI).[12] (We again use the same cutoffs in both maps for ease of comparison.) Here we see that debt-to-income ratios are highest in the West and parts of the Southeast, with the same pattern holding in a less pronounced form for the subsets of each commuting zone consisting of the low-income ZIP codes. The major difference between the risk score and mobility maps is in the Southwest, where scores are low but mobility moderately high. While low debt-to-income areas, such as the Plains, Oklahoma, and New England, are largely high mobility and high credit risk score areas, the Southwest is unusual. It is characterized by very high DTI, low risk scores, and yet high income mobility. Texas is peculiar for its low DTI and high mobility, and yet low credit risk scores. In sum, more mobile areas often are also areas characterized by better debt conditions for the poor, in terms of both low DTI and high risk scores, but notable exceptions exist.

Although the mobility measures and consumer debt variables do not perfectly covary, a brief inspection of these maps can provide a rough sense of the relationship between them. Both absolute mobility and mean risk scores are highest in the Upper Midwest, while mobility and risk scores are lowest

12 This numerator includes all standard debt types except student debt, as sufficiently reliable student debt measures are not available in our data for 2000.

in the Southeast. Consumer debt as a share of income also seems to be lowest in those parts of the country with the greatest degree of both absolute and relative mobility.

Our simple empirical approach involves estimating

$$M_z = X_z\beta^C + D_z\beta^D + \varepsilon_z,$$

using ordinary least squares. Here z indexes the commuting zone, vector X contains the Chetty et al. (2014) determinants of mobility and any income measures for z that may be included in the specification, and D is the vector of debt measures drawn from the CCP that are included in the estimation. We impose no geographic correlation structure on the error.

Debt and Other Correlates of Economic Mobility

Correlation of Mobility with the Chetty et al. Mobility Determinants

We begin by reviewing the relationship between economic mobility and the five local factors identified by Chetty et al. (2014) to be most closely correlated with mobility. This serves to illustrate the nature of the geographic variation in economic mobility evident in their data. Given these relationships, we will be able to examine not only the additional variation in mobility that is explained by the commuting zone's debt characteristics, but we will also be able to report the degree of robustness of these mobility correlates to the inclusion of a range of debt measures.

Chetty et al. (2014) report coefficients on the five correlates in terms of standard deviations in the regressors. Because of the widely varying units of measure across the various leading correlates of mobility, this allows some degree of comparability across the estimated mobility associations with, for example, rates of high school graduation or single parenting, and the level of social trust. In reporting our debt estimates, we follow suit wherever reasonable. This yields some ease of comparison of debt dollars, risk score points, and, for example, levels of social trust.

Table 3 reports our replication of table 6 in Chetty et al. (2014), which contains OLS estimates of the conditional correlation between mobility and the five leading correlates. Here we see that a one standard deviation increase in the fraction of commuting zone residents with a short commute is associated with a 0.3 standard deviation in absolute upward mobility. This estimate is highly significant, and is robust to estimation including state fixed effects or using only

Table 3: Correlates of intergenerational mobility

DEPENDENT VARIABLE	ABS. UPWARD MOBILITY			REL. MOBILITY		PR. Q1-Q5
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction short commute	0.302***	0.227***	0.314***	-0.290***	-0.277***	0.017***
	(0.07)	(0.08)	(0.05)	(0.06)	(0.06)	(0.00)
Gini bottom 99%	-0.009	-0.017	0.06	0.006	-0.142	-0.002
	(0.05)	(0.04)	(0.10)	(0.07)	(0.09)	(0.00)
High school dropout rate	-0.147**	-0.120***	-0.109	0.01	-0.006	-0.005
	(0.06)	(0.04)	(0.09)	(0.06)	(0.08)	(0.00)
Social capital index	0.169***	0.065	0.173***	0.154**	0.232***	0.002
	(0.05)	(0.05)	(0.06)	(0.06)	(0.09)	(0.00)
Fraction single mothers	-0.487***	-0.477***	-0.555***	0.591***	0.687***	-0.022***
	(0.06)	(0.07)	(0.09)	(0.05)	(0.09)	(0.00)
State FEs		X				
MSAs only			X		X	
Observations	709	709	325	709	325	709
R-squared	0.76	0.86	0.67	0.48	0.47	0.60

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Standard errors, shown in parentheses, are clustered at the state level.
Source: Chetty, Hendren, Kline, and Saez (2014).

urban commuting zones.[13] A one standard deviation decline in the high school dropout rate increases absolute mobility by 0.15 standard deviations, and this is significant and robust to estimating with state fixed effects, but precision is lost when estimating among only commuting zones that intersect with MSAs.[14] A one standard deviation increase in social capital is associated with a 0.17 standard deviation increase in mobility, and much of this estimated effect arises from cross-state variation. The measure that shows the highest degree of correlation with mobility is the fraction of single mothers. A one standard deviation increase in the fraction of children being raised by single mothers is associated with roughly a 0.5 standard deviation decline in absolute mobility, and this estimate is highly significant and robust to all of the specification changes described above.

Estimated effects of the Chetty et al. (2014) five on absolute and relative mobility uncover revealing relationships. Shorter commuting distances

13 By "urban commuting zones," we mean commuting zones that intersect with metropolitan statistical areas.

14 The magnitude of the point estimate remains comparable.

and lower rates of single parenting are associated with large and significant improvements in both the absolute gains of poor children of the commuting zone relative to the rest of the country and, within the commuting zone, the relative progress of children of the poor when compared with children of the rich in the same locale. The latter is demonstrated by the large and significant coefficients on the commute and single parenting measures in the relative mobility models in columns (4) and (5). Note that a negative coefficient in the relative mobility model indicates a weaker dependence of child income on parent income, and hence more relative mobility among the children of poorer 1996–2000 parents. At the same time, a decrease in the high school dropout rate in the commuting zone is associated with a substantial improvement in absolute mobility for children of poorer parents in the commuting zone, but it not associated with any gains in relative mobility. Perhaps most surprisingly, a one standard deviation increase in the social capital index not only increases absolute upward mobility relative to the United States of children of poorer parents in the commuting zone, but it also weakens their relative mobility. Poorer children in commuting zones characterized by high social capital do an impressive job of catching up with the rest of the country, and yet a much worse job of catching up with their less disadvantaged local peers.

From here, we begin by adding mean risk score among low-income households to the list of regressors. Given the absolute mobility measure, expected income percentile of a child of 25th percentile parents, the debt characteristics of low-income families seem most pertinent. We calculate the mean risk score in each commuting zone *among parents who lived in ZIP codes whose mean income was below the national median in 1998.* In table 4, we estimate the correlation of this low-income risk score with mobility in the pooled sample of commuting zones, conditioning on the Chetty et al. (2014) regressors and IRS CZ income means. We find that a one standard deviation increase in the commuting zone's mean risk score among low-income households is associated with a 0.116 to 0.259 standard deviation increase in absolute mobility. These point estimates are substantial, and their significance and magnitude grow when we include a state fixed effect, or estimate among MSAs only. Further, a one standard deviation increase in risk score among low-income residents is associated with a 0.358 to 0.492 standard deviation decrease in the dependence of child income percentile on parent income percentile, and hence with a noteworthy jump in relative mobility. This is our first evidence of a strong positive correlation between measured creditworthiness and mobility.

Note, of course, that this substantial estimated conditional correlation between risk score and both absolute and relative mobility appears despite controls for local income levels, social capital, inequality, family stability, commuting distances, dropout rates, and state fixed effects (though the relationship

Table 4: Correlates of mobility including creditworthiness

(ZIP codes with below-median average AGI only)

DEPENDENT VARIABLE	ABSOLUTE UPWARD MOBILITY			REL. MOBILITY		PR. Q1-Q5
	(1)	(2)	(3)	(4)	(5)	(6)
Mean risk score	0.116	0.161**	0.259**	-0.358***	-0.492***	0.000
	(0.07)	(0.08)	(0.11)	(0.07)	(0.09)	(0.00)
Controls	X	X	X	X	X	X
State FEs		X				
MSAs only			X		X	
Observations	706	706	324	706	324	706
R-squared	0.76	0.86	0.71	0.52	0.57	0.60

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Standard errors, shown in parentheses, are clustered at the state level.
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax; Chetty, Hendren, Kline, and Saez (2014).

with absolute mobility becomes insignificant for urban areas). The measured relationship between creditworthiness among lower earners and their children's realized mobility evidently has a substantial independent component, which is not mediated by these leading correlates of geographic variation in intergenerational income mobility. To put a finer point on the argument, we observe that the (adjusted) R-squared generated by the Chetty et al. (2014) model is improved, in some cases meaningfully, by the inclusion of risk scores for lower-income residents. The greatest gains in the fit of this simple model appear where the outcome is relative mobility; in the MSA-only relative mobility model, the addition of low-income risk scores increases the adjusted R-squared from the 0.46 generated by the Chetty et al. (2014) top five correlates to 0.56.

But how do debt prevalence and accumulated (and unrepaid) debt balances relate to local mobility? Further, which categories of consumer debt are most closely tied to mobility? We expand vector *D* of CCP debt measures to include the prevalence and mean balance among residents of lower income ZIP codes of mortgage, home-equity-based (HELOC), auto, and credit card debt in 2000, and student debt in 2004, along with their mean risk scores. Table 5 reports the results.[15] We see that the risk score coefficient estimates are robust to the expansion of the debt vector in this way. In fact, inclusion of debt

15 Note that the mean debt balances among residents of lower-income ZIP codes are defined by summing the total debt in the category over all residents in the lower-income ZIP code and dividing by the 18-and-over census population in the ZIP code.

Table 5: Correlates of mobility including creditworthiness, debt balances, and prevalence

(ZIP codes with below-median average AGI only, over-18 census population)

DEPENDENT VARIABLE	ABS. UPWARD MOBILITY			REL. MOBILITY		PR. Q1-Q5
	(1)	(2)	(3)	(4)	(5)	(6)
Mean risk score	0.273***	0.183***	0.371***	-0.325***	-0.442***	0.007**
	(0.063)	(0.048)	(0.097)	(0.063)	(0.075)	(0.003)
Mean mortgage balance	0.118**	-0.076	0.166**	-0.479***	-0.564***	0.010***
	(0.058)	(0.075)	(0.072)	(0.069)	(0.098)	(0.003)
Mortgage prevalence	-0.232***	-0.069	-0.238***	0.228***	0.185*	-0.015***
	(0.065)	(0.048)	(0.071)	(0.075)	(0.097)	(0.004)
Mean HELOC balance	0.036	0.005	-0.074	-0.027	-0.011	-0.001
	(0.051)	(0.034)	(0.077)	(0.051)	(0.073)	(0.003)
HELOC prevalence	-0.142**	-0.073	-0.078	0.119*	0.166**	-0.005
	(0.058)	(0.048)	(0.099)	(0.063)	(0.081)	(0.003)
Mean auto balance	0.095*	0.036	0.149	-0.013	-0.015	0.002
	(0.054)	(0.059)	(0.090)	(0.072)	(0.091)	(0.004)
Auto prevalence	-0.128**	-0.100*	-0.235**	0.018	0.055	-0.002
	(0.057)	(0.050)	(0.088)	(0.077)	(0.109)	(0.005)
Mean credit card balance	-0.080**	-0.024	-0.066	0.031	-0.056	-0.004**
	(0.038)	(0.030)	(0.112)	(0.041)	(0.097)	(0.002)
Credit card prevalence	0.117*	0.103	0.142	-0.103*	0.038	0.007**
	(0.067)	(0.077)	(0.123)	(0.057)	(0.127)	(0.003)
Mean student loan balance	-0.008	-0.013	0.066	0.022	0.006	-0.001
	(0.022)	(0.016)	(0.064)	(0.035)	(0.054)	(0.001)
Student loan prevalence	0.087**	0.032	0.039	-0.105**	-0.047	0.003
	(0.040)	(0.029)	(0.074)	(0.042)	(0.057)	(0.003)
Mean other debt balance	-0.090**	-0.073***	-0.205***	0.071**	0.174**	-0.004*
	(0.036)	(0.019)	(0.056)	(0.033)	(0.073)	(0.002)
Other debt prevalence	0.180***	0.111*	0.269***	0.000	-0.078	0.009***
	(0.058)	(0.061)	(0.082)	(0.056)	(0.112)	(0.003)

TABLE 5 CONTINUED ON NEXT PAGE

TABLE 5 CONTINUED

DEPENDENT VARIABLE	ABS. UPWARD MOBILITY			REL. MOBILITY		PR. Q1-Q5
	(1)	(2)	(3)	(4)	(5)	(6)
Controls	X	X	X	X	X	X
State FEs		X				
MSAs only			X		X	
Observations	705	705	324	705	324	705
R-squared	0.81	0.88	0.79	0.63	0.74	0.65

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Standard errors, shown in parentheses, are clustered at the state level.
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax; Chetty, Hendren, Kline, and Saez (2014).

category means and prevalences actually increases the magnitude and precision of the risk score coefficient in column (1), the specification without state fixed effects and estimating using the full sample.

Next we discuss the debt prevalence and balance estimates that appear in table 5. While our baseline estimates represent the results of estimating expression (1) with an extended vector of debt measures, the reader might note the possibility of a high degree of correlation among some subset of our county-level debt use and credit risk measures, and this might lead to questions regarding the interpretation of coefficient estimates in table 5. In order to give some sense of the interdependence of the coefficient estimates, and the robustness of these particular observed associations to alternative specifications, we add footnotes reporting estimates in which each debt measure is the sole entry in debt vector D in expression (1), though the Chetty et al. (2014) measures are included as before, and comparing these to the table 5 results.

Turning to debt prevalence and balance, we find, surprisingly, that both housing and auto debt prevalence among lower-income families appear to weaken mobility.[16] Note that mortgage, home equity, and auto debt represent the three major types of secured consumer credit. Hence what we observe is a modest negative and significant correlation between debt secured by durable goods or assets held by lower income residents and the level of mobility in a commuting zone. A one standard deviation increase in mortgage prevalence

16 These relationships appear whether we measure auto, mortgage, and home-equity debt as mean debt among all CZ residents or as mean debt among residents of lower-income ZIP codes within the CZ. This result holds whether the housing and auto debts are included in the extended debt vector or are used as the sole county-level debt measure, though in the case of auto debt prevalence the coefficient on the measure when included alone becomes small and insignificant.

among lower income households is associated with a 0.23 standard deviation decrease in absolute mobility. Much of the variation driving this result appears to be at the state level, as adding state fixed effects decreases the magnitude of the coefficient and leads to insignificance. It is, however, just as apparent when estimating only among MSAs. The dollar amount of mortgage balances among low-income residents has a positive but weaker association with absolute mobility. HELOC prevalence is also associated with decreased absolute mobility, if somewhat less strongly.

Turning to relative mobility, again the picture is somewhat mixed. Both mortgage debt and HELOC debt prevalence are modestly but significantly associated with reduced relative mobility.[17] At the same time, we estimate a large and highly significant positive association between mortgage balance among low-income residents of the commuting zone and relative mobility.[18] A one standard deviation climb in low-income mortgage balances is associated with a 0.479 to 0.564 standard deviation drop in the rank-rank slope coefficient, and hence a marked decline in the extent to which a child's realized income depends on her parents' income in that commuting zone. On net, it appears that more prevalent housing debt among lower-income residents of a commuting zone is associated with somewhat less success for a child of the commuting zone in catching up with the rest of the United States, but that higher mortgage balances among lower-income residents of the commuting zone are associated with substantially more success for that child in catching up with her own regional peers.

In the case of auto debt, our third major category of secured consumer debt, we again see a negative, substantial, and significant association between debt prevalence and absolute mobility. A one standard deviation increase in auto debt is associated with a 0.100 to 0.235 standard deviation decline in absolute mobility. However, the coefficients on mean auto balance in the absolute mobility model are small, positive, and insignificant, and the coefficients on all auto debt measures in both relative mobility models are quite small and insignificant.[19] Hence it appears that, on net, auto debt has a weak negative relationship to absolute mobility and no clear relationship to relative mobility. In sum, secured debts, taken together, show a weak negative association with absolute mobility.

17 Unlike the secured debt prevalence results for absolute mobility, these relative mobility results are sensitive to the exclusion of other debt regressors. When included separately, HELOC prevalence has no significant relationship to relative mobility, and mortgage prevalence is actually strongly positively associated with relative mobility.

18 This results holds up whether or not one includes the other debt regressors. Hence we find a strong positive association between all measures of lower-income ZIP codes' mortgage reliance and relative mobility.

19 These results are similar whether auto debt is included alone or with the extended vector of debt measures.

On the other hand, the prevalence of each category of unsecured debt—student debt, credit card debt, and other debt (including consumer finance loans and retail debt)—is associated with greater absolute mobility.[20] A one standard deviation increase in the prevalence of credit card, student, and other debt among low-income residents is associated with, respectively, a 0.117, 0.087, and 0.180 standard deviation increase in absolute mobility.[21] Hence the estimates indicate that, while secured debt among lower-income families such as mortgage, home equity, and auto loans is negatively associated with absolute and, in many cases, relative mobility, participation in unsecured debt markets is associated with significant and substantial increases in mobility. The estimates for the unsecured debt cases are somewhat smaller and less robust, but they are, nevertheless, of economically important magnitude.

Student debt and credit card debt are also modestly and significantly associated with improved relative mobility for children of lower-income residents. On the other hand, other debt shows no meaningful association with relative mobility, and the dollar amounts of other debt are associated with lower absolute and relative mobility for children of low-income parents across the board.[22] The estimates for our three leading categories of unsecured debt suggest that use of unsecured borrowing (and hence some combination of demand for and access to unsecured loans) has a meaningful positive association with mobility, but that higher amounts of such borrowing is associated with more limited mobility, perhaps through the effects of unmanageable debt burden on parents' investments.[23]

20 This is true for credit card and student debt whether one includes the prevalence measure alone or with the extended vector of debt measures. Including other debt prevalence alone, however, leads to small and insignificant absolute mobility coefficients.

21 These point estimates are significant at the 10, 5, and 1 percent levels, respectively.

22 These results, by and large, are the same whether one estimates including each debt measure alone or with the extended vector of debt measures. One exception is the prevalence of student debt, whose estimated association with relative mobility is both significant and very large when estimated in the absence of the other debt measures; a 1 percentage point increase in student debt prevalence is associated with a decrease of 0.122 in the rank-rank slope coefficient.

23 Estimating a model analogous to that represented in table 5 that instead measures risk scores and debt using all CZ residents, instead of residents of low-income ZIP codes, produces surprisingly similar results. Coefficients on risk score and on debt prevalence and balance for auto, mortgage, and other debt are similar in both magnitude and significance. The primary differences that emerge are for the cases of student and credit card debt. There the estimated impact on mobility is similar in direction but stronger in magnitude, significance, or both when we measure debt using all CZ residents. A table of these estimates is available from the authors.

One last insight based on the estimates is that the addition of debt measures improves the fit of the Chetty et al. (2014) mobility models, and does so most effectively for the case of relative mobility. The addition of risk score, income, and debt prevalence and mean among lower-income residents by leading consumer debt categories improves the fit of the Chetty et al. (2014) absolute mobility model based on CZs that intersect MSAs from an adjusted R-squared of 0.66 to one of 0.78; it improves the fit of the MSA-level relative mobility model from 0.46 to 0.72.[24]

Conclusions

This paper extends the rich depiction of the U.S. geography of economic mobility provided by Chetty et al. (2014) to include commuting zone-level relationships between parents' debt profiles in 2000 and their children's realized economic progress by 2011–12. In a series of maps, we render the geography of debt use and creditworthiness as it pertains to the parents in the Chetty et al. (2014) mobility measures. Separate maps describe debt and creditworthiness in lower-income regions, which is, arguably, of particular relevance to economic mobility. Though the debt and mobility measures vary widely, and reflect substantial independent variation, we observe that areas characterized by weak absolute and relative mobility for children of lower-income parents are also, more often than not, characterized by poor risk scores among lower-income ZIP code residents, high debt to income ratios, or some combination of the two.

Estimates of the dependence of absolute and relative mobility on debt prevalence, levels, and low-income risk scores provide several novel insights. Higher risk scores are strongly positively associated with the mobility realized by children of lower-income parents in the commuting zone; commuting zone risk scores offer extensive explanatory power in models of mobility, even when accounting for both income and correlates of local mobility such as average commuting time, social capital, and share of single-parent households. Unsecured debt prevalence within lower income ZIP codes in a region is positively and, in many cases, substantially associated with both absolute and relative mobility. While one must recognize the conflation of evidence regarding credit access and demand for credit represented by the prevalence of unsecured debt in a county, these estimates at least suggest that access to unsecured borrowing, which can be used to smooth consumption and provide support around income, health, and household shocks, may be advantageous in producing labor market productivity in the rising generation. At the same

24 We include a mean income regressor in each of our new specifications. However, its coefficients are generally small and far from significant. Addition of only the income regressor does very little to improve fit.

time, secured debts show either a negative or a mixed association with absolute and relative mobility for children of the commuting zone, suggesting that credit used to finance large purchases may have more mixed consequences for children's attainment.

These estimated relationships are merely correlational, and should therefore be interpreted with caution. Estimating a causal relationship between local debt reliance and creditworthiness and intergenerational mobility occurring over the span of many years would be challenging for a number of reasons. This study exploits the availability of two elaborate panels, each representing millions of U.S. families over the years from 1996 (or 1999) to 2011–12, and each offering fine geographic detail, to reveal debt and economic mobility relationships that reach far beyond what was available in the past. The resulting evidence, while not causal, reveals strong relationships between unsecured debt, secured debt, creditworthiness, and intergenerational mobility that may be used to inform a wide variety of models of parental investment under credit constraints and the economic outcomes realized by their children many years later.

The strength of the relationship estimated in this paper between credit risk scores and intergenerational economic mobility gives rise to an array of questions. For example, what are the relative contributions of the household's prior economic experiences and its forward-looking credit access to this stark observed relationship between parents' measured creditworthiness and their children's outcomes? Policy-induced or other similar variation in access to credit may eventually shed light on the close correlation between current credit conditions and the opportunities available to American children. ■

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Appendix table 1: Correlates of mobility including creditworthiness, debt balances, and prevalence

(ZIP codes with above-median average AGI only, over-18 census population)

DEPENDENT VARIABLE	ABS. UPWARD MOBILITY			REL. MOBILITY		PR. Q1-Q5
	(1)	(2)	(3)	(4)	(5)	(6)
Mean risk score	0.086**	0.070*	0.386***	-0.154**	-0.331***	0.002
	(0.04)	(0.04)	(0.08)	(0.06)	(0.10)	(0.00)
Mean mortgage balance	0.061	-0.098	0.179**	-0.350***	-0.514***	0.008**
	(0.07)	(0.10)	(0.09)	(0.09)	(0.12)	(0.00)
Mortgage prevalence	-0.080*	-0.024	-0.278***	0.106	0.08	-0.005**
	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)	(0.00)
Mean HELOC balance	-0.026	-0.006	0.028	-0.183*	-0.212	0.000
	(0.098)	(0.067)	(0.119)	(0.094)	(0.152)	(0.004)
HELOC prevalence	-0.059	0.033	-0.179	0.303***	0.335**	-0.004
	(0.077)	(0.044)	(0.125)	(0.076)	(0.129)	(0.003)
Mean auto balance	0.211**	0.206**	0.119	-0.066	-0.040	0.013**
	(0.098)	(0.083)	(0.115)	(0.154)	(0.106)	(0.005)
Auto prevalence	-0.151**	-0.158***	-0.141	0.086	0.087	-0.008**
	(0.061)	(0.049)	(0.094)	(0.074)	(0.093)	(0.004)
Mean credit card balance	-0.063**	-0.012	-0.033	0.044	0.002	-0.005***
	(0.028)	(0.022)	(0.092)	(0.081)	(0.112)	(0.001)
Credit card prevalence	0.072	0.044	0.025	-0.142**	-0.055	0.004
	(0.044)	(0.037)	(0.086)	(0.056)	(0.148)	(0.003)
Mean student loan balance	0.027	0.016	-0.097	-0.076*	0.110	-0.001
	(0.028)	(0.020)	(0.061)	(0.044)	(0.069)	(0.002)
Student loan prevalence	0.017	-0.014	0.271***	0.039	-0.171*	0.001
	(0.023)	(0.019)	(0.073)	(0.027)	(0.086)	(0.001)
Mean other debt balance	-0.039	0.016	-0.294***	0.091*	0.211	-0.002
	(0.042)	(0.038)	(0.108)	(0.052)	(0.138)	(0.003)
Other debt prevalence	0.058	0.012	0.276***	0.073	-0.029	0.004
	(0.039)	(0.052)	(0.090)	(0.046)	(0.112)	(0.003)

APPENDIX TABLE 1 CONTINUED ON NEXT PAGE

DEPENDENT VARIABLE	ABS. UPWARD MOBILITY			REL. MOBILITY		PR. Q1-Q5
	(1)	(2)	(3)	(4)	(5)	(6)
Controls	X	X	X	X	X	X
State FEs		X				
MSAs only			X		X	
Observations	617	617	320	617	320	617
R-squared	0.78	0.87	0.78	0.61	0.7	0.67

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Standard errors, shown in parentheses, are clustered at the state level.
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax; Chetty, Hendren, Kline, and Saez (2014).