TRICKLE-DOWN CONSUMPTION

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Abstract

Using state-level variation over time in the top deciles of the income distribution, we observe that non-rich households consume a larger share of their current income when exposed to higher top income and consumption levels. We argue that permanent income, wealth effects, and upward local price pressures cannot provide the sole explanation for this finding. Instead, we show that the budget shares which non-rich households allocate to more visible goods and services rise with top income levels, consistent with status-maintaining explanations for our primary finding. Non-rich households exposed to higher top income levels self-report more financial duress; moreover, higher top income levels in a state are correlated with more personal bankruptcy filings. Non-rich households might have saved up to 3 percent more annually by the mid-2000s had incomes at the top grown at the same rate as median income since the early 1980s.

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I. Introduction

Since the early 1980s, real incomes in the lower and middle parts of the U.S. income distribution have risen much more slowly than those in the upper part of the distribution (see Goldin and Katz (2007), Autor et al. (2008) and Piketty and Saez (2003), among others). While this growing income inequality has coincided with increased sorting of households by income level across cities and states (Moretti (2012), Diamond (2013)), inequality has also risen within geographic markets. This implies that non-rich households within a market, whose real income has been essentially stagnant since the mid-1980s, has been increasingly exposed to increasingly rich or very rich co-residents.

In this paper, we start by documenting that this growing local inequality has been associated with a change in consumption for non-rich households. Specifically, using the Consumer Expenditure Survey (CEX), we construct a micro, cross-sectional dataset of households' consumption for the period 1980 to 2008. We merge this dataset to a state-year panel of household income distribution data from the March Current Population Surveys (CPS). Exploiting state-level variation over time in the income of households in the upper part (top quintile or top decile) of the income distribution, we show that non-rich households consume a larger share of their current income when exposed to higher income (and consumption) at the top. This association is robust and economically meaningful. A 10 percent increase in the 80th percentile of the income distribution is correlated with an increase in the consumption of households below the 80th percentile of about 3 percent, holding these households' own current income (and other characteristics) constant.

In a second step, we investigate whether the correlation might be causal. In the absence of an obvious instrument for the variation in top income levels across markets over time, our approach to address causality is indirect. Specifically, we first test for a set of explanations that might imply a non-causal positive relationship between non-rich consumption and top income levels. After finding little support for these non-causal explanations in the data, we then argue that the systematic changes we observe in the consumption portfolio of the non-rich as top income levels increase are consistent with more causal mechanisms.

The first non-causal explanation we consider is Friedman (1957)'s permanent income hypothesis. Specifically, we consider the possibility that rising top incomes in a given state-year are predictive of faster future income growth lower down in the income distribution in the same state. Maybe the non-rich are consuming more out of current income today in those state-years where the rich are getting richer because they expect their own future income to rise. Using the Panel Study of Income Dynamics (PSID), we fail to find support for this explanation. Holding own current household income constant, rising top income levels in a state are not systematically associated with higher future income for non-rich households. Moreover, using micro data from the University of Michigan's Surveys of Consumers, we fail to find any evidence that non-rich households' self-reported expectations about their own future income growth, or overall expectations about future economic conditions, are positively correlated with top income levels in their state. In the PSID, we also fail to find support for the view that rising top income levels in a state are predictive of more stable future income for non-rich households in that state, contrary to what one would have expected under a precautionary saving motive explanation for our primary finding (Carroll, 1992).

We next consider the possibility that wealth effects are driving our primary finding. The housing boom that characterized the second half of the period under study may have led households with growing net wealth to save less out of current income (Mian and Sufi, 2011). If house prices grew more quickly in markets with rapidly-rising top incomes, our primary finding might simply be capturing such wealth effects. Yet, contrary to this being the key explanation, we find that rising top income levels are associated with higher consumption out of current income not only for home owners but also for renters; moreover, our primary finding holds in sub-periods of the data that were less exposed to the housing boom.

If non-rich households have strong consumption habits, or if there are important rigidities inherent in their consumption portfolio of goods and services (Chetty and Szeidl, 2007), they may end up spending more out of their current income just because the local prices of the goods and services they are "committed to" go up. Thus, if rising top income levels in a state cause a rise in local prices, such stickiness in non-rich households' consumption portfolio may lead to higher spending out of current income without any actual behavioral changes in consumption. Indeed, we find a positive and significant relationship between top income levels in a state and the local Consumer Price Index (CPI). However, controlling for the local CPI does not eliminate the primary relationship we had uncovered between non-rich households' consumption and top income levels.

We then consider two other channels through which rising income and consumption at the top of the income distribution might cause the non-rich to make changes to their real consumption portfolio, and actively increase their spending. First is the possibility that higher top income levels in a market increase the supply of "rich" goods within this market. Such positive local shocks to the supply of "rich" goods might induce the non-rich to demand and consume more of these goods. The non-rich might then end up spending more out of current income if this increased consumption of "rich" goods happens without fully scaling back on the consumption of other goods. A second possibility relies on social comparisons (Veblen (1899), Duesenberry (1949)). While a relative income hypothesis has been mainly formulated and tested in the context of social comparisons to the "Jones" (see for example, Luttmer (2005)), Frank et al. (2014) propose a variant of this relative income model where a given household's consumption is directly positively affected by the consumption of the households whose income is above theirs, generating what they label as "expenditure cascades." Expenditure cascades result in a negative relationship between income at the top and the savings rate of non-rich households.

We test for these two explanations by studying whether the sensitivity of budget shares to top income levels varies in a systematic way with the income elasticity or visibility of different expenditure categories. We find evidence consistent with a social comparison explanation, in that the budget shares non-rich households allocate to more visible goods and services increase with top income levels.

We also look for corroborating evidence of a causal story by studying the process by which many non-rich households with stagnant incomes might have increased their consumption. There is now ample evidence that the period under study, from the early 1980s to the onset of the financial crisis and the Great Recession, was a period of rapid expansion of credit supply, not just because of the housing boom in the later part of the period, but also because of financial innovation and financial liberalization (White (2007); Dynan and Kohn (2007); Mian and Sufi (2009)). We provide indirect evidence in support of the hypothesis that non-rich households may have relied on easier credit to stretch their personal finances to "keep up" with their richer co-residents. In the Consumer Sentiment Survey data, we show that more non-rich households report being financially worse off the current year compared to last year when exposed to higher top income levels in their state. Also, in the same spirit as Frank et al. (2014), we show, in a state-year panel, that there is positive relationship between the number of personal bankruptcy filings and lagged top income levels.

Finally, we conjecture, with admittedly preliminary but nevertheless suggestive evidence, that the political process may have internalized these trickle-down pressures and responded to them by further easing access to credit, as argued by Rajan (2010). We study voting patterns on the Federal Housing Enterprise Safety and Soundness Act (H.R. 5334) which Congress passed in 1992. Among other things, this Act mandated that HUD set specific affordable housing goals for Fannie Mae and Freddie Mac, opening up the credit supply. While essentially all Democrats voted in favor of this bill, voting was more divided among Republicans. We find that Republican Congressmen that represented districts with a larger income gap between the 80^{th} percentile-household and the median household were more likely to vote in favor of H.R. 5334.

To get a better sense of economic magnitude, we perform a simple counterfactual exercise. Assuming a causal interpretation, we ask by how much would non-rich households' consumption-out-of-current-income have gone down, and hence their savings rate gone up, had incomes at the top grown at the same rate as median income since the beginning of our sample period (1980). We estimate that, by

2005, non-rich households would have spent up to 3 percent less annually under this counterfactual. We argue that this might explain a non-trivial part of the decline in the aggregate personal savings rate.

The rest of the paper is structured as follows. Our CEX dataset is presented is Section II. Section III reports our primary finding of a positive relationship between non-rich consumption and top income levels. Section IV investigates the various possible explanations for this primary finding. Section V discusses the relationship between top income levels and the use and supply of credit. Section VI provides the counterfactual analysis and a discussion of economic magnitude. We conclude in Section VII.

II. Data: Consumer Expenditure Survey (CEX) Sample

Our primary data source is the Interview Survey of the Consumer Expenditure Survey (CEX) of the U.S. Bureau of Labor Statistics (BLS). We measure consumption in the 1980-2008 expenditure data of the CEX as the summation over four quarters of expenditure surveys for a given household. We exclude households who fail to complete all four surveys, except at the beginning and end of our sample, where we annualize answers for respondents truncated to two quarters. Following Aguiar and Bils (2012), we drop households whose consumption in any of these categories (other than food and shelter) is greater than one-half of total consumption for the year and, following Dynan et al. (2009), we drop households with zero income or with zero food consumption.

We exclude the purchasing and selling of homes and vehicles. Instead, following Cutler and Katz (1991), Chetty and Szeidl (2007) and Meyer and Sullivan (2010), our annual consumption measures for shelter and vehicles try to capture how much service flow of these items a given household decides to consume.[1] In particular, for vehicles, we closely follow the method of Meyer and Sullivan (2010) by using the CEX asset data to infer rental equivalence consumption in vehicles. The CEX asset data records the year, make, and model of each household's car(s). From this, we calculate rental service flows of car consumption using an accelerated depreciation method. For households with no vehicles, we assign a value of zero.[2]

We construct two alternative consumption measures for shelter. Our first measure is based on the annual payments households make for shelter. Thus, for renters, we use rent paid; for homeowners, we

[1] We also exclude savings deposit outflows and gifts.
[2] The CEX records purchase prices of cars only if a household buys a car in that year. Like Meyer and Sullivan (2010), we collect original purchases prices of specific makes and models using all purchases in the CEX for the same car. We then apply these values to individuals who own that car but were not surveyed in the purchase years. We fill in missing price information using blue books and dealer guides. We then compute the service flow using the guidelines from Kelley Blue Book that a depreciation rate is applied each year at the then-valued value of the car, more along the lines of double-declining balance accounting rather than straight line accounting. In particular, we apply the estimate that 15% of a car's value is lost in each year of ownership. For example, consumption from $20,000 new car would be $3,000 the first year (=20,000*0.15) and $2,550 the second year (=(20,000-3,000)*0.15).

use the sum of mortgage payments, property taxes and home repair. Our second measure relies on rental equivalence, which can be constructed using the rental equivalence questions included in the CEX (see for example Charles et al. (2009)). However, due to missing data on the rental equivalence questions (especially in the earlier years), we choose to use the first measure as our default measure. We however establish the robustness of our key findings to the second measure.

While the first part of our analysis below will focus on total consumption, we later present results where we break down total consumption into more and less visible, and more and less income elastic, categories. We start with the 14 broad consumption categories used by Charles et al. (2009) and reported in Appendix Table A1 (column 3). We then rely on Heffetz (2011) to assign a visibility measure to these categories.[3] Because Heffetz's (2011) visibility score was constructed for 31 distinct categories (see columns 4-6 in Appendix Table A1), we map Heffetz's (2011) finer categories into the broader categories of Charles et al. (2009). We then compute a weighted average of the visibility score for each of the broader category, using average budget shares among the non-rich for each of the finer category as weights. In two instances, aggregating to the consumption categories in Charles et al. (2009) would result in collapsing together goods and services that have rather different visibility scores. To preserve some of this valuable variation, we break down "food" into "food at home" and "food away from home", and we keep "communication & media" (mainly phones) separate from "utilities." Also, given the sporadic education expenses in our data (the median budget share on education is zero), we regroup the two categories in Charles et al. (2009) related private human capital expenditures (education and health) into a single category. This process results in the 15 consumption categories listed in columns 1 and 2 of Appendix Table A1.

In addition to quarterly surveys of consumption, the CEX conducts surveys of households' demographic characteristics and income, for the first and last quarters in which a household participates in the consumption survey. The income variable in the CEX (FINCBTAX) includes wage income, income from businesses, transfers, dividends, interest, alimony, child care, veteran's benefits, benefits from social security and other retirement plans, and workers' compensation. We use income in the last survey in which it is reported to capture the income over the measured consumption period. We drop households with zero or negative total income.

Our empirical design calls for measuring income distribution in each geographic unit-year cell, and in particular top income levels in each of those cells. The smallest geographic unit identifiable in the

[3] Heffetz (2011) employs the CEX category aggregation of Harris and Sabelhaus (2000), who assign 100 classifications to the UCC codes in the CEX. Heffetz (2011) collapses these to 31 categories.

CEX is the state.[4] While income distribution by state and year can be constructed within the CEX, we instead use the much larger March Current Population Survey (CPS). Specifically, we start from the full March CPS samples, which include all households including those without labor force participants. We place no restrictions on age of household head, armed force membership or group living but exclude households with any allocated income variables. We define a given household's income as the sum of total money income for all adult household members. Total money income in the CPS includes income from business, farm rent and government transfers, in addition to wage income. We then compute percentiles of the household income distribution in each state-year cell using the household weights provided in the CPS. We assign each CEX household to a CPS state-year income decile cell.

Since our study concerns the consumption of the non-rich, we drop from the main CEX sample all households whose total income is above the 80th percentile in their state-year cell. We use the CPS measures of income at the 80th (or 90th percentile) as our key independent variables. In what follows, we will refer to all households below the 80th percentile in their state-year cell as "non-rich," and households above the 80th (90th) percentile as "rich" ("very rich").

Panel A of Appendix Table A2 reports consumption, income and demographic characteristics for our final CEX sample of non-rich households. Consumption and income data are deflated to 1999 using the CPI deflator from the Bureau of Labor Statistics. All statistics are weighted using the CEX-provided weights. The average head of household in our sample is 49.6 years old. About 83 percent of the households' heads are white; 54 percent are male; and 20 percent have a bachelor or graduate degree. The average household consists of 1.82 adults and 0.67 children and has an income of $31,707.

Panel B of Appendix Table A2 reports half-decade log income thresholds for the 20th, 50th, 80th, 90th, and 95th percentiles of the state income distribution in our CEX sample, as well as half-decade averages of the logarithm of CEX consumption for the median, rich, and very rich. We define rich and very rich consumption as the average annual total consumption in the CEX among households above the 80th (90th) percentile in their state-year cell. As established in the prior literature, median household income levels have been stagnating over the period under study, growing by –.01 log points between the second half of the 1980s and the second half of the 2000s. Incomes at the top of the distribution have been growing steadily, except for an apparent slowdown at the onset of the financial crisis. Household income at the 80th percentile grew by .16 log points between the first half of the 1980s and the first half of the 2000s; household income at the 90th percentile grew by .21 log points over the same period. The top rows

[4] Our CEX sample only covers 44 states plus the District of Columbia. The CEX does not sample from all states, and state identifiers from sparsely-sampled states are not included. We are missing Mississippi, Montana, New Mexico, North Dakota, South Dakota, and Wyoming.

of Panel B show similar growth in both rich and non-rich consumption, although the rate is somewhat slower for the very rich group compared to its income. Aguiar and Bils (2012) show some systematic, and growing overtime, under-reporting of consumption in the CEX among top income households. So, it is likely that the level and growth of Log(ConsumptionofRich) and Log(ConsumptionofVeryRich) reported in Appendix Table A2 are biased downwards.

III. Relationship between Top Income Levels and Non-Rich Consumption

Our objective in this section is to investigate whether a relationship exists between non-rich households' consumption and top income levels in their state-year cell. Among observationally similar non-rich households, are those exposed to higher top income levels spending more? To do so, we start by estimating the following OLS regression in the CEX sample of non-rich households:

$$\begin{aligned} Log(Consumption)_{ist} &= Log(80^{th}\ PercentileIncome)_{st} + Household\ controls_{ist} \\ &+ Household\ Income\ dummies_{ist} + State_s + Year_t + \varepsilon_{ist}, \end{aligned} \tag{1}$$

where *i* indexes households, *s* indexes states and *t* indexes years. The dependent variable is the logarithm of total consumption for a given household in a given state and year. They key independent variable in equation (1) is Log(80^{th}PercentileIncome), which is the logarithm of the average of the 80^{th} percentile of household income distribution in a given state in the current year (t) and the prior two years (t-1 and t-2), as computed in the CPS. The 3-year averaging is motivated by the fact that, were there to be any causal relationship between non-rich consumption and top income levels, such a relationship would realistically come with a delay.

To account for systematic differences in consumption level across different types of households, we control for a battery of household socio-demographic characteristics. These include: household head's gender, seven household head's education categories, five household head's race categories, a quadratic in household head's age, indicator variables for the number of adults in the household, and indicator variables for the number of children in the household. Moreover, we control in a flexible way for household income: we include indicator variables for every \$2,000 buckets of current income. We also include state dummies to capture any fixed differences across states in the consumption of the non-rich, and year dummies to capture aggregate changes over time. When we estimate equation (1), we weight observations with the CEX population weights and cluster standard errors at the state-level.

Panel A of Table 1 presents the results from this analysis. For brevity, we only report coefficients on the variables of interest. Columns 1 and 2 show that the elasticity of consumption of the non-rich to income levels at the top of the distribution is positive and statistically significant. This positive association holds whether we use Log(80^{th}PercentileIncome) (column 1) or Log(90^{th}PercentileIncome) (column 2). A 1 percent increase in Log(80^{th}PercentileIncome) associates with an increase in non-rich consumption of .270 percent, holding non-rich households characteristics and own income constant. Likewise, a 1 percent increase in Log(90thPercentileIncome) associates with an increase in non-rich consumption of .214 percent, all else equal. Columns 3 and 4 show that the estimated coefficient on Log(80thPercentileIncome) is not statistically affected (in fact, the point estimate goes up) when we allow for differential time trends by state (column 3) and further control for the current state unemployment rate (computed from the March CPS; column 4). [5]

Further indication of the robustness of the positive association between non-rich consumption and top income levels is provided in Appendix Tables A3 and A4. In Appendix Table A3, we show that the association exists across all three decades covered in our sample, even though it appears somewhat weaker in the 2000s. Furthermore, the association is robust to controlling for state-year employment share in finance and other one-digit industries (computed the CPS), as well as controlling for annual population inflows and outflows into a state. Finally, the association is robust to controlling for annual measures of household income inequality (also computed from the CPS). In Appendix Table A4, we show that the association is robust to limiting the analysis to various subsets of states, even though it appears somewhat stronger excluding East Coast states.

Mis-measurement of current household income, and in particular, the misclassification of some rich households as non-rich, might be mechanically driving the observed association between non-rich consumption and top income levels. We address this possibility in column 5 of Table 1 where we replicate column 4 on the subsample of non-rich households that are below the 60th percentile in their state-year cell, thereby dropping from the sample those households that would be most subject to such a misclassification. The estimated coefficient on Log(80thPercentileIncome) remains the same in this subsample of the data.

While we focus our attention on documenting (and later on, trying to explain) a positive association between non-rich consumption and income of the rich, it seems worthwhile to also ask whether non-rich consumption is uniquely correlated with top income levels, or could it be that non-rich consumption is also correlated with median or low income levels in a state? In addition, does a "symmetric" relationship exist between rich consumption and income of the non-rich? These questions are addressed in the remaining columns of Table 1. Column 6 adds Log(50thPercentileIncome) and Log(20thPercentileIncome) (both constructed based on the 3-year averaging method described above) as additional explanatory variables to the specification in column 4. There is no significant association

[5] In results not reported here but available upon request, we have re-estimated column 4 on the following subsamples of the data: households with or without children, and households where the primary member is below or above 40. The estimated coefficient on Log(80thPercentileIncome) is very similar across these various subsamples of the data.

between non-rich consumption and either median household income or income at the 20th percentile; moreover, the estimated coefficient on Log(80^{th}PercentileIncome) remains unchanged.

Column 7 allows for the associations between non-rich consumption and income at the top (80^{th} percentile), median, and bottom (20^{th} percentile) explored in column 6 to vary across different groups of non-rich households. Specifically, we break down the non-rich into 2 groups: those whose income is between the 40^{th} and 80^{th} percentile of the state-year income distribution, and those whose income is below the 40^{th} percentile. The correlation between Log(80^{th}PercentileIncome) and consumption seems to hold both for middle- and low-income households, even though it appears somewhat stronger (economically and statistically) for middle-income households. Log(50^{th}Percentile Income) and Log(20^{th}PercentileIncome) are not statistically related to the consumption of either group of households.

Finally, in column 8, we study the sample of rich households (e.g. those whose income is above the 80th percentile in their state-year cell) and ask whether their consumption is correlated to either Log(50^{th}PercentileIncome) or Log(20^{th}PercentileIncome). No statistically or economically significant relationship emerges.

Panel B of Table 1 reproduces the same regressions as Panel A but uses the ratio of consumption to current income as an alternative dependent variable. We continue to control for every $2,000 income buckets, hence allowing the ratio of consumption to income among non-rich households to vary flexibly by income levels. The results are qualitatively similar to those in Panel A. Non-rich households exposed to higher top income levels spend a higher share of their income.

The causal explanations we investigate later on in the paper to explain the pattern in Table 1 tend to rely on increases in the consumption, and not just the income, of the rich inducing the non-rich to spend more.[6] In Table 2, we show that such a relationship between rich and non-rich consumption also exists in the data. Our preferred econometric model to show this relationship is an IV specification, where we instrument Log(ConsumptionofRich) and Log(ConsumptionofVeryRich) with top percentiles of the income distribution in a state-year cell. We prefer an IV specification over OLS for two reasons. First, concerns about unobserved state-shocks are particularly acute when relating consumption of the rich to consumption of the non-rich. For example, if households at all income levels in a given state have correlated tastes for high-end technology goods, then both rich and non-rich may be more likely to buy the latest generation products when they are released to the market. Likewise, both rich and non-rich consumption might be exposed to changes in local sales taxes or utility price increases. Second, an IV

[6] These causal explanations below however do not rule out the possibility though that non-rich consumption is also *directly* affected by the income of the rich. For example, while social comparisons and status-related explanations may fit more naturally into the non-rich responding to rich consumption, any signal or proxy for the earnings of one's neighbors may also trigger higher non-rich spending on more visible goods.

specification helps address the measurement error in the consumption of the rich in the CEX.[7] For completeness, we also however also report OLS estimates in the bottom two rows of Table 2.

We use Log(80thPercentileIncome) and Log(95thPercentileIncome) as instruments for Log(ConsumptionofRich); we use Log(95thPercentileIncome) as an instrument for Log(Consumption ofVeryRich). We present the two first-stage regressions and report second-stage results for the two dependent variables considered in Table 1: Log(Consumption) and the ratio of consumption to income. The controls included in each regression are the same as in column 4 of Table 1. Across all these IV specifications, we find a positive and statistically significant relationship between consumption of the non-rich and consumption of the rich. For example, column 1 of Table 2 suggests that a 10 percent increase in the consumption of the rich is associated with a 4.39 percent increase in the consumption of the non-rich.

IV. Possible Explanations

The relationships we identify in Tables 1 and 2 do not imply a causal interpretation. While we hold household characteristics constant (including current income), it remains possible that the variation in the income or consumption of the rich picks up on some un-modeled or unobserved state-year variables. Our goal in this section is to: 1) empirically address some of the most likely non-causal explanations (Sections IV.A. to IV.D) and 2) provide some evidence that might corroborate more causal pathways (Section IV.E).

IV.A. Permanent Income

The permanent income hypothesis could explain our results in Section III if non-rich households rationally expect their own income to go up in the future in markets where top income levels are higher. In other words, a higher income level at the 80th or 90th percentile in a state today may be systematically related to higher future income for households below the 80th percentile.

Since we cannot directly address this possibility in the cross-sectional CEX, we turn to another dataset that is structured as a panel: the Panel Study of Income Dynamics (PSID). Specifically, we study the determinants of future family income among PSID households over the period 1980 to 2007. The income variable we consider in the PSID is “total family income,” dropping observations with negative or zero family income. For each household in the PSID with non-missing total family income in a given year, we consider total family income in year t+1, t+2 and t+4.[8] We merge the CPS income variables measuring the 80th, 90th, 50th and 20th percentiles of household income in each state-year cell (3-year averages, as in Section III) into state-years cells of PSID micro data. We focus our analysis on the subset of households with incomes below the 80th percentile in their state-year cell. Summary statistics for the PSID data are presented in Appendix Table A5. The PSID sample is somewhat lower income than the CEX sample, and has a higher share of minority households.

We regress the logarithm of future family income on the logarithm of current family income, state and year fixed effects, household controls, and the logarithm of household income at the 80th (or 90th) percentile in the state-year cell (averaged over the years t, t-1 and t-2). Specifically, we estimate the following regression:

$$\begin{aligned} & Log(FutureIncome)_{is,t+j} = Log(80^{th}\ PercentileIncome)_{st} + Log(CurrentIncome)_{ist} \\ & + HouseholdControls_{it} + State_s + Year_t + \varepsilon_{ist} \end{aligned} \qquad (2)$$

where *i* is a household, *s* a state, and *t* a year. The household controls include age (quadratic), race, gender and marital status of the head of household, as well as dummies for the number of children and adults in the household. Standard errors are clustered at the state level.

The results of this analysis are reported in Table 3. In Panel A, we use Log(80thPercentileIncome); in Panel B, we use Log(90thPercentileIncome). In no specification do we find evidence that higher top income levels in a state in a given year are significantly predictive of higher future income levels for non-rich households in that state (where future is defined as t+1 in columns 1 to 3, t+2 in columns 3 to 6, and t+4 for columns 7 and 8), controlling for current family income. The same holds if we use as dependent variables the average of future income between t+1 and t+2 (columns 9 and 10) or the average of future income between t+1 and t+4 (columns 11 and 12).[9] In fact, most of the point estimates we estimate are negative (but most are statistically insignificant). Note that these findings are robust to controlling for the logarithm of household income lower down in the state-year distribution (50th and 20th percentiles). These findings are also robust to the inclusion of household fixed effects (columns 3 and 6).

While our PSID analysis does not support a "permanent income" explanation for our earlier findings, it is true that many of the estimates in Table 3 are quite noisy. To further address the possibility that higher top income levels might be related to higher future income growth among the non-rich, we provide a complementary analysis of non-rich households' self-reported expectations about their future

[8] Note that because the PSID becomes bi-annual after 1997 and because total family income was not asked in 1994 to 1996, total family income in t+1 can only be observed for years prior to 1993. In contrast, total family income in t+2 and t+4 can be defined for later sample years.
[9] Future income measures in columns 9 to 12 are averages of all non-missing values over the relevant time horizon.

income growth. In particular, we ask whether these expectations positively correlate with top income levels in their state.

We use micro data from the University of Michigan's Survey of Consumers. These surveys, which have been conducted by the Survey Research Center at the University of Michigan since 1946, are used to construct indices of consumer confidence. Each month, 500 individuals are randomly selected from the contiguous United States (48 states plus the District of Columbia) to participate in the Surveys of Consumers. We append all of these monthly surveys into a single dataset that covers the time period 1980 to 2008. For each state-year cell, we merge the CPS information on key percentiles of the income distribution into the Michigan data cell. Again, we restrict our analysis to those individuals whose family income is below the 80th percentile in their state-year cell. Summary statistics for this dataset are presented in Appendix Table A6. In terms of demographics and income, this sample is very comparable to the CEX sample.

The following questions in the Surveys of Consumers are used to assess a given individual's expectations about their future income. First, individuals are asked: "During the next year or two, do you expect that your (family) income will go up more than prices will go up, about the same, or less than prices will go up?" Based on this question, we create a dummy variable that equals 1 if the individual report expecting his or her family income to go up more than prices, 0 otherwise. On average across all individuals and years, about 17 percent expect their real income to go up in the next year or two. Survey participants are also asked to report their expected percentage change in family income: "By about what percent do you expect your (family) income to (increase/decrease) during the next 12 months?" On average across all individuals and years, the expected percent change in family income in the next year is 5.6 percent.

We regress answers to these income expectation questions on top income levels in the state-year cell. In particular, we estimate the following baseline regression:

$$\begin{aligned} &IncomeChangeExpectation_{ist} = Log(80^{th}\, PercentileIncome)_{st} + Individual\ Controls_{ist} \\ &+ Household\ \ Income\, dummies_{ist} + State_s + Year_t + \varepsilon_{ist}, \end{aligned} \tag{3}$$

where i is an individual, s, a state, and t a year. Individual controls include a quadratic in age, dummies for the respondent's gender, race and marital status, and dummies for the number of adults and children in the household; household income fixed effects are dummies for \$2000 buckets of total household income. Each observation is weighted by household head weight provided in the Surveys. Finally, standard errors are clustered at the state level.

The results of this analysis are presented in Table 4. The dependent variable in Panel A is a dummy variable that equals 1 if the individual expects his or her real family income to go up in the next year or two, 0 otherwise. The dependent variable in Panel B is the individual's expected percent change in family income in the next year. We also present results where we further control for the logarithm of income in lower parts of the income distribution (50^{th} and 20^{th} percentile).

In none of the regressions in Table 4 do we find a positive and statistically significant relationship between expectations about future income growth and top income levels. In fact, all the estimated coefficients on Log(80^{th}PercentileIncome) and Log(90^{th}PercentileIncome) are negative. In other words, we fail to find any evidence that non-rich households expect higher future income growth when exposed to higher top income levels in their market. Under the view that consumers' expectations are rational, this evidence corroborates the PSID analysis in Table 3. This evidence also appears inconsistent with the view that consumers that are exposed to richer co-residents might have upwardly-biased expectations about their future income growth.

The University of Michigan's Survey of Consumers also constructs indices of overall consumer confidence. In Panel C, we use one of these indices, the Index of Consumer Expectations, as an alternative dependent variable. This index more broadly summarizes consumers' optimism about future economic conditions.[10] Consistent with the evidence in Panels A and B, we do not find that non-rich households are more optimistic about the future when exposed to higher top income levels. In fact, all the estimate coefficients on Log(80^{th}PercentileIncome) and Log(90^{th}PercentileIncome) in Panel C are negative and statistically significant.

IV.B. Precautionary Savings

In columns 13 and 14 of Table 3, we consider the possibility that rising top income levels in a state are correlated with more stable future income for non-rich households in that state. Indeed, if this were the case, our primary finding could be reconciled with a precautionary savings motive (Carroll, 1992). If non-rich households expect less uncertain income in the future, their precautionary motive for savings diminish, which would translate into higher consumption out of current income.

In the PSID, we measure the uncertainty of future income with the standard deviation of log(household income) between t+1 and t+4. We then estimate equation (3) above using this alternative dependent variable. We fail to find support for the view that either Log(80^{th}PercentileIncome) (Panel A of Table 3) or Log(90^{th}PercentileIncome) (Panel B of Table 3) are systematically negatively correlated with

[10] The Index of Consumer Expectations comprises the 3 following component questions: 1) "Now looking ahead--do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"; 2) "Now turning to business conditions in the country as a whole--do you think that during the next twelve months we'll have good times financially, or bad times, or what?" and 3) "Looking ahead, which would you say is more likely--that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

the standard deviation of future income for non-rich households. In fact, in all specifications, the point estimates indicate a positive relationship between top income levels and the standard deviation of future income. This positive relationship is however only statistically significant in column 13 (Panels A and B), where we do not control for Log(50^{th}PercentileIncome) and Log(20^{th}PercentileIncome).

IV.C. Wealth Effects

A large literature documents that individuals consume from 3 to 9 cents out of every $1 shock to housing wealth (Case et al. (2005), Campbell and Cocco (2007), Attanasio et al. (2009), and Carroll et al. (2011)), and that home equity generally is a very active source of consumption funds for constrained households (Hurst and Stafford (2004)). Mian and Sufi (2011) find that borrowing against the increase in home equity by existing homeowners is responsible for a significant fraction of the rise in U.S. household leverage from 2002 to 2006. Is it possible that our primary finding is driven by such wealth effects? To the extent that rising top income levels in a state are associated with rising home prices (as suggested by Matlack and Vigdor (2008)), a key missing variable in our analysis so far might be home equity. More specifically, our finding might be driven by the subset of homeowners who are seeing the value of their home equity rise as the share of the very rich in their geographic market increases. We test for this possibility in Table 5.

For this analysis, we return to the CEX sample of non-rich households. Table 5 columns 1 and 2 replicate the specification in column 4 of Table 1 separately for homeowners and renters. In contrast with the prediction of a home equity explanation, the point estimates indicate if anything moderately larger sensitivities for renters, even though the difference is not statistically significant. Given the much stronger appreciation in house value in the US in the second half of our sample period, we also assess in column 3 whether the sensitivity of non-rich consumption to top income levels among the subset of homeowners is concentrated in the post-1995 period. Again, in contrast with the prediction of a home equity explanation, we find that the sensitivity is if anything greater in the pre-1995 period. Finally, in the last two columns of Table 5, we follow the approach in Dettling and Kearney (2014) and instrument for the state level house price with the national house price index in the same year interacted with the (state-level) housing supply elasticity (Saiz (2010)).[11] The estimated coefficients on Log(80thPercentileIncome)

[11] We construct state house prices for a given year following the method described in Dettling and Kearney (2014)'s appendix. Specifically, we start with the 2000 Census median state house prices. We then take this value and scale it by the percent change in the state housing price index from 2000 to the year of interest using the house price index from the Federal Housing Finance Agency (FHFA) which is available at the state level. State house prices in a given year are then expressed into 1999 dollars.

and Log(90thPercentileIncome) are qualitatively unaffected compared to a baseline specification that does not include state house prices as a control. [12]

In summary, based on the evidence in Table 5, we do not believe that a home equity-based wealth channel is the core explanation for our primary finding.

IV.D. Local Price Pressures

If non-rich households have strong consumption habits, or if there are important rigidities inherent in the consumption of many goods and services in their consumption portfolio (Chetty and Szeidl, 2007), households may end up spending more out of their current income when the local prices rise for the goods and services to which they are "committed." Moreover, if rising top income levels in a state are associated with higher local prices, such stickiness in non-rich households' consumption portfolio may lead to higher spending out of current income, without non-rich households making active changes to their real consumption.

To analyze the effect of local prices, we use MSA-level local CPI indices from the BLS that we turn into a state-year panel.[13] In columns 1 and 2 of Table 6, we first show that there is indeed a strong positive correlation between the state CPI index and top income levels in that state. Specifically, in a state-year panel regression that covers all state-years included in our CEX sample, we find a positive correlation between Log(LocalCPI) and both Log(80thPercentileIncome) (column 1) and Log(90thPercentileIncome) (column 2). In contrast, neither Log(50thPercentileIncome) nor Log(20thPercentileIncome) are positively related to Log(LocalCPI).

In the remaining columns of Table 6, we replicate the regressions in column 4 of Table 1 and columns 1 and 3 of Table 2, but now also directly control for local prices in these regressions. Log(Local CPI) enters positively in each regression, but the estimates are quite noisy. Controlling for Log(LocalCPI) does not qualitatively affect the estimated coefficients on top income levels (OLS regressions in columns 3 and 4) or consumption of the rich (IV regressions in columns 7 and 8). These results are qualitatively

[12] While the CEX allows us to separate renters from homeowners, there is no variable capturing when a household bought their current house. This limits our ability to push this analysis further. Optimally, we would have preferred to follow the research design in Chetty and Szeidl (2010) where the home equity effect is being proxied for by the change in house prices in a given geographic market from the time of purchase to the current time (and instrumented for by the change in the national house price index over the same period interacted with the housing supply elasticity). This is unfortunately impossible given this data constraint in the CEX. Our inability to follow this preferred design to proxy for home equity may explain the statistically insignificant effects of house price for homeowners in the last column of Table 5.

[13] We force the indices to all be equal to 100 for 1980 to make them comparable over time. For states with only one MSA, we apply the local MSA index to the state. For MSAs crossing state lines and for states with multiple MSAs we gather county-level populations and constructed weighted averages of the indices. Fourteen states in our sample have no MSA covered by the BLS CPI indices. We drop these states for this analysis, thus resulting in a slight decrease in observation count.

unchanged when we control for the entire available vector of local prices (food, shelter, apparel, transportation and medical), even though statistical significance drops below conventional levels in columns 5 and 6.

One consumption category that might be particularly sensitive to local prices in the period under study is shelter. Thus, it seems appropriate to assess further how sensitive our results are to the measurement, and inclusion of shelter expenses. Appendix Table A7 columns 1 and 2 report that our results are if anything a bit stronger if we use the surveyed rental equivalence measure of shelter for homeowners, rather than our default payment flows measure. In columns 3 and 4, we exclude shelter altogether from our measure of non-rich consumption. We show that the elasticity of non-rich households' total consumption *excluding shelter* to top income levels is about 3/4 the size of the elasticity of their total consumption to top income levels. (P-values on Log(80thPercentileIncome) are below 0.10 in both columns for both panels.)

In summary, while we find that higher top income levels in a state appear correlated with upward price pressures in that state, our analysis in Table 6 suggests that such local price effects are not the sole explanation for the positive association we observe between non-rich consumption and top income levels. Nevertheless, the patterns in the first two columns of Table 6 do suggest that non-rich households exposed to higher top income levels may face higher local prices.[14] Those higher local prices might be particularly relevant for sticky consumption categories, such as shelter. In the sub-section below, we do show that non-rich households' budget share for shelter increases substantially when top income levels rise. While we propose in that sub-section other possible explanations for this finding (e.g. the possibility that non-rich households' *demand* for housing might be increasing with top income levels), we however do not rule out that at least part of the increase in the shelter budget share might be a reflection of such higher local prices.

IV.E. Social Comparisons and Supply-Driven Demand

In this section, we propose and look for evidence supporting two channels through which rising income and consumption at the top of the income distribution might cause the non-rich to make changes to their real consumption portfolio, and actively increase their spending. One hypothesis is that a non-rich consumption response might be driven by social comparisons and relative income considerations. The

[14] We take the additional step of exploring biases in the price index. In particular, we replicated the analysis in Handbury and Weinstein (2014) for the 49 U.S. cities for which they calculated and "exact price index," which corrects for the availability of different goods and across locations as well a variety bias. The relationship between the exact price index and Log(80thPercentileIncome) (as computed across households in the 2000 Census) was positive, but not statistically significant, leaving it unlikely that it is the bias in local prices that accounts for our results.

idea that social comparisons might play a role in household consumption behavior goes back to the early work of Veblen (1899) and Duesenberry (1949). While the relative income hypothesis has been mainly formulated and tested in the context of social comparisons to the "Jones" (see for example, Luttmer (2005)), Frank et al. (2014) propose a variant where a given household's consumption is directly positively affected by the consumption of the households whose permanent income is above theirs, generating what they label as "expenditure cascades." Expenditure cascades generate a negative relationship between income and consumption at the top and the savings rate of middle-income households.

To test for the possibility that such relative comparison considerations might be a driver of our primary finding, we go back to Veblen's (1899) original intuition that consumption induced by social comparisons should be more "conspicuous" in nature: a way to signal or advertise income and wealth through spending on more "visible" items. Hence, we ask whether the sensitivity of consumption goods budget share to top income levels varies in a systematic way with the visibility of consumption categories. In the data section, we described the 15 consumption categories we use for this analysis, starting from Heffetz (2011)'s assignment of a visibility score to 31 consumption categories, and collapsing to the categories of Charles et al. (2009). Heffetz (2011)'s index is based on answers to a household telephone survey, in which he asks survey respondents:

> "*Imagine that you meet a new person who lives in a household similar to yours. Imagine that their household is not different from other similar households, except that they like to, and do, spend more than average on [goods or services category]. Would you notice this about them, and if so, for how long would you have to have known them, to notice it? Would you notice it almost immediately upon meeting them for the first time, a short while after, a while after, only a long while after, or never?*"

For each consumption category, answers were coded as 0 (never); .25 (a long while after); .5 (a while after); .75 (a short while after) and 1 (almost immediately). Heffetz's main visibility index averages answers to these questions across survey respondents. Appendix Table A1 reports these visibility scores at the 31-category level and Panel B of Table 7 at the 15-category level.

A second hypothesis is that higher top income levels in a market increases the supply of "rich goods" within this market. For example, higher top income levels within a market may induce the replacement of some low-end grocery stores with higher-end ones, or the entry of more beauty salons, fashion stores or bars. Handbury (2012) and Handbury and Weinstein (2012) find that the variety of goods changes in proximity to demand from richer households. Positive local shocks to the supply of "rich goods" might induce the non-rich to demand and consume more of these goods. The non-rich might then end up spending more out of current income if this increased consumption on "rich goods" happens without fully scaling back on the consumption of other goods, either because of self-control problems or because much of this other consumption is already "committed to."

To look for evidence supporting this hypothesis, we ask whether the sensitivity of non-rich budget shares to the income or consumption of the rich varies in a systematic way with the income elasticity of the consumption categories. Panel B of Table 7 reports income elasticity estimates for each of the 15 consumption categories. These elasticity estimates are the coefficients on after-tax income in the CEX from a population-weighted regression of log consumption in that category on log(income), a quadratic of age, and dummies for race, education, number of children and number of people in the household.

The correlation between visibility and income elasticity is positive, but only 0.215. While some goods like clothing and jewelry which score high on both visibility and income elasticity, other goods like health and education are quite income elastic, and one might expect their local availability to increase when top incomes go up (e.g., more private schools, more health centers and specialists). Their consumption, however, is not very visible.

To proceed with this analysis, we estimate the following demand system in the CEX sample:

$$\begin{aligned}\omega_{ist}^{k} &= \beta^{k} IV[Log(ConsumptionofRich)] + \alpha_0^k \log\left(\frac{p_{st}}{P_t}\right) + \sum_{l=1}^{5} \alpha_l^k \log\left(\frac{p_t^l}{P_t}\right) \\ &+ HouseholdControls_{ist} + HouseholdIncomeDummies_{ist} \\ &+ State_s + Year_t + State_s * Trend_t + \varepsilon_{ist}\end{aligned} \tag{4}$$

where ω_{ist}^{k} is the budget share (consumption as a ratio of total consumption) on good *k* (with *k*=1 to 15) by household *i* in state *s* and year *t*; P_t is the US CPI; p_t^l are the US CPI for *l* = food, shelter, transportation, clothing and other goods; and p_{st} is the local CPI. We instrument Log(ConsumptionofRich) with Log(80thPercentileIncome) and Log(95thPercentileIncome). As in all of our specifications, we include the full array of household control variables (demographics), \$2,000-income-bucket fixed effects, state fixed effects, year fixed effects, and a state-year trend, and we cluster errors at the state level. We then plot how the vector of estimated coefficients β^k lines up with the income elasticity and visibility measures presented above.

For completeness, we estimate 3 additional demand systems, replacing Log(ConsumptionofRich) (IV) in equation (4) with Log(ConsumptionofVeryRich) (IV), Log(80thPercentileIncome) (OLS) and Log(90thPercentileIncome) (OLS). Moreover, we estimate variants of these demand systems where we use Log(Consumption) in each of the 15 categories as the dependent variable instead of the category's budget share. In this case, the estimated coefficients of interest are elasticities, making it easier to assess whether spending on a category is going up or down with income (or consumption) at the top. Indeed, the budget share of a given category may go down with top income even if spending on that category goes up if spending on other categories goes up by more. Hence, in total, we estimate 8 different demand systems.

Appendix Table A8 reports the estimated α^k and the estimated β^k for each consumption category k for the demand system specification under equation (4). Panel A of Table 7 summarizes the estimated β^k for each of the 8 demand systems we estimate. Panel B of Table 7 reports visibility index and estimated income elasticity for each of the 15 consumption categories. To provide a meaningful indication of relative economic magnitude of the estimates of budget share responses (from systems 1 and 2) from Panel A, we need to scale each estimate by the mean budget share in the category in our CEX sample. These scaled estimates are reported as the last rows of Panel B, and are the magnitudes which we further explore in Figures 1 and 2.

A consistent picture emerges across the various models we estimate. Food away from home, shelter, personal care, and clothing and jewelry are the four consumption categories that are appear most positively responsive to top income and consumption. Spending on these categories goes up for households exposed to higher top income (or consumption) levels, and they comprise a larger share of total spending for these households. Food at home and entertainment services also go up with top income (or consumption) levels, but the magnitudes are smaller and not statistically significant. The only categories for which we seem to find a rather systematic decline in spending (and hence also in budget share) when top incomes rise are utilities, other non-durables (house care, landscaping, child care, tax accountants, etc.), other transportation, and health and education.

What do these patterns imply for the possible causal pathways we have proposed? We address this question visually in Figures 1 and 2. We plot the scaled estimated budget share responses (last two rows of Panel B of Table 7) against the visibility index (Figure 1) and income elasticity estimate (Figure 2) for the 15 consumption categories. While Figure 2 does not show much of a relationship between income elasticity and the estimated budget share responses, Figure 1 presents a much more striking pattern, with consumption categories that are indexed as more visible having larger budget share responses to higher income and consumption at the top.

One surprising category in Figure 1 we want to highlight is vehicles. We see essentially no change in the amount spent on vehicles as top incomes rise. This is surprising given how high the vehicle category scores on the visibility (and income elasticity) scale. It is also surprising given that given that prior work has reported strong evidence of a "keeping up with the Jones" effect when it comes to car purchases.[15] While we know from prior literature that the adjustment process for buying a new vehicle is slow (Bertola and Caballero (1990), Eberly (1994), Caballero (1990)), such a slow adjustment rationalization seems inconsistent with the substantial response we observe for shelter. While raising the caveat of this important outlier, we do conclude the overall patterns in Table 7 and Figure 1 appear broadly consistent with status-seeking (or status-maintaining) as a causal pathway for the non-rich consumption behaviors documented in Tables 1 and 2.

An additional piece of suggestive evidence for this pathway is presented in Appendix Table A9. For the consumption of the rich to induce status-seeking (or status-maintaining) consumption among the non-rich, it is important that the non-rich be exposed to that consumption. In other words, we would predict that the patterns in Table 1 might be more pronounced in geographic markets where income segregation is lower. For the analysis in Appendix Table A9, we computed state averages for the 3 measures of income segregation available in the Chetty et al. (2014)'s social mobility dataset: income segregation, segregation of affluence and segregation of poverty. [16] We then replicated column 4 of Table 1 separately for households in our CEX sample that are above or below the median in terms of their income segregation exposure. While we cannot reject that the estimated coefficients on Log(80thPercentileIncome) are the same for both groups of households based on the income segregation of the place in which they live, only the estimated coefficients on Log(80thPercentileIncome) for the households that live in less income segregated states are statistically significant. Most interestingly, the difference in the point estimates on Log(80thPercentileIncome) is particularly striking for the income segregation measure that we would ex ante have expected to be most relevant for us: segregation of affluence. The estimated coefficient on Log(80thPercentileIncome) is .472 (s.e.=.150) for households that are below the median in terms of segregation of affluence in the place they live in; the estimated coefficient on Log(80thPercentileIncome) is .213 (s.e.=.150) for households that are above the median in terms of segregation of affluence in the place they live in.[17]

VI. Use and Supply of Credit

[15] For example, the Kuhn et al (2011) find that neighbors of lottery winners are significantly more likely to buy a car. See also Grinblatt et al (2008) and Shemesh and Zapatero (2012).

[16] This dataset is available at http://www.equality-of-opportunity.org/. The formulas used for these three measures of income segregation are taken directly from Reardon (2011). While the data is at the commuting zone level, we cannot exploit this variation given that the constraint imposed by the CEX. When computing state averages, we weigh each commuting zone by its population. Also, the measures are based on data from the 2000 Census and hence might be quite noisy especially for the first half of our sample period.

[17] Alternative specifications which exploit the continuous variation in the segregation measures (e.g. interact the segregation measures with the top income level) do not yield statistically significant results.

The period under study, covering the early 1980s to the onset of the financial crisis and the Great Recession, was a period of rapid expansion of credit supply, not just because of the housing boom in the later part of the period, but also because of financial innovation and financial liberalization (White (2007); Dynan and Kohn (2007); Mian and Sufi (2009)). Hence, greater access to, and greater use of, credit might have enabled non-rich households to stretch their personal finances, possibly facilitating their ability to consume more in response to rising income and consumption at the top of the income distribution. In this section, we provide two indirect sources of evidence consistent with this hypothesis.

In a state-year panel, we document a positive relationship between the number of personal bankruptcy filings in a state and top income levels in that state. Complementing this aggregate evidence, we also show in the Michigan Survey of Consumers systematic evidence of greater financial duress self-reports for middle income households exposed to higher top income levels. Finally, in the last part of this section, we suggest the possibility that lawmakers may have internalized these consumption pressures and responded to them by further easing credit supply.

VI.B. Personal Bankruptcy Filings

It is well-known that personal bankruptcy filings have increased dramatically over the last few decades. A natural implication of our analysis is that the rise in top income levels, to the extent that it triggered higher consumption-out-of-income among the non-rich, may have pushed a greater share of the non-rich into financial distress. While the various micro datasets we have exploited so far in our analysis do not allow us to directly study whether exposure to higher top income levels predict a higher likelihood of filing for personal bankruptcy among otherwise similar non-rich households, we can study the relationship between top income levels and the rate of personal bankruptcies (e.g. number of personal bankruptcy filings/population) in a state-year aggregates panel. This analysis is related to earlier work by Frank et al. (2014) who explored this relationship in the 100 most populous U.S. counties between 1990 and 2000. We expand on their analysis by studying a longer time period and investigating additional checks to the robustness of this relationship.

Specifically, we obtain information on annual number of personal bankruptcy filings by state for the period 1980 to 2009.[18] We then merge this data by state-year to the CPS measures of income percentiles discussed above, and to Census information on the number of households by state and decade.[19] We are interested in whether higher top income levels in a state are predictive of a higher rate of

[18] This data can be found at www.abiworld.org, by clicking on the link "online resources" and then "bankruptcy statistics."
[19] We assign Census information from Census year T to years covering the first 5 years of a decade starting in year T and Census information from Census year T+1 to the last five years of a decade starting in year T.

personal bankruptcy filings in that state going forward. We do not expect a rise in top income levels in a given year in a state to immediately translate into a higher number of bankruptcies. Unlike the consumption responses documented above, which could theoretically take place quite rapidly, the bankruptcy response, if it exists, would likely be based on an accumulation of past consumption responses. Therefore, we propose to use two-year lagged Log(80thPercentileIncome) (or Log(90thPercentileIncome)) as our independent variable of interest.[20] The results of this analysis are presented in Table 8. We weight each observation by population size (number of households in the state) and cluster standard errors at the state level.

Perhaps not surprisingly given the already-well established trend up in top income levels and trend up in the number of personal bankruptcies (e.g., Fay, Hurst and White (2002)), we find a positive univariate correlation between top income levels and the number of personal bankruptcy filings (columns 1 and 2 of Table 8). In columns 3 and 4, we add state and year fixed effects to the specifications of columns 1 and 2, respectively. While the estimated R^2 jumps from 0.04 (or .08 in column 2) to 0.87 in both columns 3 and 4, the estimated coefficients on the top income variables remain of the same order of magnitude as in columns 1 and 2. Specifically we find that a 10 percent increase in average income level at the 80th percentile between t-2 and t-4 raises the rate of personal bankruptcy filings in that state in year t by 10 percent (column 3).

In columns 5 and 6, we add a vector of controls to proxy for current economic conditions in a given state in a given year. This includes the unemployment rate (from the March CPS) and current income level at the 50th, 20th and 80th percentile. Not surprisingly, the current local unemployment rate is a strong positive predictor of the bankruptcy rate. Also, a higher median income negatively correlates with bankruptcy filings. Adding these contemporaneous controls however does not change our estimates of interest.[21]

Because of the concern related to pinning down the right lag structure for this analysis, we re-estimate the specifications in columns 5 and 6 in lower frequency data, e.g. focusing on longer differences. In columns 7 and 8, we restrict the sample to the years 1980, 1985, 1990, 1995, 2000, 2005 and 2009. Again, our estimates of interest remain qualitatively unchanged.

Columns 9 and 11 of Table 8 present additional robustness analysis. For this, we focus on the relationship between personal bankruptcy filings and income at the 80th percentile. In column 9, we allow for differential year trend in the personal bankruptcy filing rate by state. The estimated coefficient on

[20] Since Log(80/90thPercentileIncome) is based on averaging between year t and t-2, two-year lagged Log(80/90thPercentileIncome) is based on averaging between year t-2 and t-4.

[21] We also experimented with controlling for other time-varying state-level controls, such as the self-employment rate, age, educational and racial composition. These variables do not predict the personal bankruptcy rate in a specification that includes state and year effects.

Log(80[th]PercentileIncome) goes from 1 (column 5) to .9 (column 9). In column 10, we allow for differential time trend in the bankruptcy filing rate based on an *initial value* (1976-1978) of Log(80[th]PercentileIncome) in a state. The estimated coefficient on Log(80[th]PercentileIncome) is the same as in column 5. Finally, in column 11, we further control for two-year lagged Log(50[th]PercentileIncome) and Log(20[th]PercentileIncome). While statistical significance drops below the 5 percent level (p=.07), the point estimate on our main variable of interest remains unchanged.

VI.B. Self-Reported Financial Duress

A key limitation of the analysis in Table 8 is that, given its aggregate nature, it does not allow us to "zoom in" on non-rich households in micro-data. In Table 9, we thus complement the analysis from Table 8 with a study of household-level self-reports of financial well-being from the University of Michigan Survey of Consumers. Included in that survey is the following subjective financial well-being question: "*We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?*" We create a dummy variable that equals 1 for individuals who report getting along financially worse today than a year ago. Thirty-two percent indicate being financially worse off today than a year ago (Appendix Table A6). We then ask whether exposure to higher top income levels is associated with greater self-reported financial duress, holding household income and household characteristics constant. Specifically, we estimate the following regression, which directly mirrors equation (3):

$$\begin{aligned} &Financial\ Worse\ Off\ \ Today_{ist} = Log(80thPercentileIncome)_{st} + IndividualControls_{ist} \\ &+Household\ \ Income\ Dummies + State_s + Year_t + \varepsilon_{ist} \end{aligned} \quad (5)$$

In addition to this general financial well-being question, survey respondents are also asked to report up to two reasons for why they currently feel better off or worse off than a year ago. From this list of possible reasons, we create a dummy variable that equals 1 if an individual mentions increased expenses or higher debt, increased interest or debt payments as the reason for being worse off today than a year ago.[22] About 7 percent of respondents indicate higher expenses and debt payments today than a year ago (Appendix Table A6).

Table 9 follows the same structure as Table 4. All regressions in Panel A of Table 9, where the dependent variable is "Financially Worse Off Today," point towards more financial duress among non-

[22] Specifically, we single out the two following reasons for the self-reported current financial well-being (based on variables PAGOR1 and PAGOR2): 1. Increased expenses; more people to be supported by FU; spending more, not applicable if the individual also mentioned higher prices or higher taxes; 2. Debt: interest, debt, or debt payments high or higher.

rich households that are exposed to higher top income levels. Consider column 1 for example. A 10 percent increase in the income level at the 80th percentile increases the likelihood that a given individual reports being worse off financially today than a year ago by a statistically significant 2.3 percentage points. All the estimates in Panel B, where the dependent variable is "More Expenses/More Debt, Interest and Debt Payments than a Year Ago," are also positive, but not statistically significant at standard levels.

In summary, the evidence in Tables 8 and 9 is consistent with the view that higher income levels among the rich in a state are positively associated with both subjective and objective measures of financial duress in that state. These results are consistent with greater reliance on credit, up to the point of financial distress, among non-rich households exposed to higher top income levels.

VI.C. Political Economy of Credit Supply: Voting Patterns on the H.R. 5334

While the prior two subsections show evidence consistent with greater use of credit among the non-rich exposed to higher top income levels, the supply of credit, and in particular political constraints to that supply, might also be endogenous to pressures to consume more among non-rich households exposed to richer co-residents. In particular, political representatives in areas where the median voter is exposed to higher top incomes may be particularly favorable toward policies aiming to increase access to credit for this median voter. In this section, we provide some suggestive evidence of such political economy implications in the context of the Federal Housing Enterprise Safety and Soundness Act (H.R. 5334), which Congress passed in 1992.

The Federal Housing Enterprise Safety and Soundness Act established the Office of Federal Housing Enterprise Oversight (OFHEO) within the United States Department of Housing and Urban Development (HUD) and put the government-sponsored enterprises Fannie Mae and Freddie Mac under its oversight. This Act also mandated that HUD set specific affordable housing goals for Fannie Mae and Freddie Mac. Some observers (see for example Rajan (2010)) have argued that this Act was a key factor in the deterioration of credit quality in the U.S. and ultimately contributed to the recent financial crisis.[23]

With home ownership rates in the US being between 60 to 70 percent at the time this Act was passed, it is reasonable to argue that the population that was targeted by this expanded housing lending

[23] Rajan (2010) refers to this 2004 HUD announcement: "Over the past ten years, there has been a 'revolution in affordable lending' that has extended homeownership opportunities to historically underserved households. Fannie Mae and Freddie Mac have been a substantial part of this 'revolution in affordable lending'. During the mid-to-late 1990s, they added flexibility to their underwriting guidelines, introduced new low-down-payment products, and worked to expand the use of automated underwriting in evaluating the creditworthiness of loan applicants. HMDA data suggest that the industry and GSE initiatives are increasing the flow of credit to underserved borrowers. Between 1993 and 2003, conventional loans to low income and minority families increased at much faster rates than loans to upper-income and nonminority families."

policy was not those with the lowest income but rather the politically more influential set of middle income households. Based on our analysis so far, we predict that the median voter's demand for more credit would have been particularly strong when this median voter is exposed to higher top incomes. Hence, if Congressmen are responsive to their constituents, we would expect a higher likelihood of voting in favor of this new legislation among Congressmen representing districts with more income inequality, and in particular districts with a large gap between the middle and the top of the income distribution.

To perform this analysis, we obtained individual voting records on H.R. 5334. We then mapped each congressional district from the 102^{nd} Congress (which was in session when this bill was passed in 1992) into the 1990 census tracts that cover this district. We use the 1990 Census tract data to construct measures of family income at 80^{th}, 50^{th} and 10^{th} percentile of the distribution for each congressional district. We define income inequality within a congressional district as the difference between log(family income) at the 80^{th} (or 90^{th}) percentile and log(family income) at the median.

Ideology was a clear determinant of voting on H.R. 5334. Among Democrat Congressmen that expressed a vote, 257 voted in favor while only 2 voted against. There is therefore essentially no variation to exploit among Democrats. However, voting was more divided among Republican Congressmen. While 111 Republicans voted in favor of this new legislation, 52 voted against. In Table 10, we therefore focus on Republican Congressmen and asked whether their likelihood of supporting H.R. 5334 was systematically correlated to income inequality in their congressional district.

In column 1 of Table 10, we regress the likelihood of voting in favor of H.R. 5334 on income inequality in the district. We absorb ambient differences in economic conditions across states with state fixed effects. The estimated relationship between a yes vote and income inequality is positive and statistically significant (p=0.04). A one standard deviation increase in income inequality (0.08) increases the likelihood of a Republican voting in favor of H.R. 5334 by about 8 percentage points. When we measure inequality based on the gap between the 90^{th} and 50^{th} percentile (column 2), we continue to find a positive relationship between district inequality and a yes vote, but the relationship is no longer statistically significant.

In columns 3, 4 and 5, we cumulatively augment the model in column 1 with controls for log median income, lower tail inequality (gap between the 50^{th} and 20^{th} percentile), and log (population) in the congressional district. The point estimate on the gap between the 80^{th} and 50^{th} percentile remains virtually unchanged and statistically significant at the 10 percent level (p=0.09 in column 5).

While the evidence in Table 10 should be viewed as merely suggestive, the associations found in this table suggest an additional mechanism by which non-rich income households with stagnating real income may have been made to raise their consumption in response to increasing income at the top of the income distribution: politically-mandated credit expansion. The preliminary evidence in this table should encourage further work on the political responses to rising inequality, especially with regard to the regulation and deregulation of access to credit.

V. Economic Magnitude

Assuming that the findings in Tables 1 and 2 are indeed markers of a change in consumption behavior by the non-rich as the income of their richer co-residents rise, it is worthwhile to try to give a better sense of the economic magnitude of these effects. To do so, we perform a simple counterfactual exercise. We ask how much lower non-rich households' consumption-out-of-current-income would have been, and hence how much larger their saving rate would have been, had income levels at the top grown at the same rate as income levels at the median since the beginning of our sample period.

Specifically, we compute the decrease in Log(Consumption) under the assumption that Log(80thPercentileIncome) or Log(90thPercentileIncome) had grown at the same rate as Log(50thPercentileIncome). We perform the calculation of these counterfactual growth rates using the change in average Log(50thPercentileIncome) by year in our CEX sample. We use the estimates from Table 1 of the sensitivity of Log(Consumption) for non-rich households to either Log(80thPercentile Income) (column 1) or Log(90thPercentileIncome) (column 2) to compute counterfactual Log(Consumption).

The results of this analysis are presented in Table 11. We report results for 4 different years: 1990, 2000, 2005 and 2008. Panel A presents the counterfactual for column 1 of Table 1 (Log(80thPercentileIncome), while Panel B presents the counterfactual for column 2 of Table 1 (Log(90thPercentileIncome). We report gaps between actual and counterfactual consumption both in log points (column 1) and dollar figures (column 2).[24] For 1990, we estimate that Log(Consumption) by non-rich households would have been between .9 (Panel A) and 1.1 (Panel B) percent lower under the counterfactuals. By 2000, the gap between actual and counterfactual consumption grows to between 2.2 (Panel A) and 2.8 percent (Panel B). For 2005, we estimate that non-rich income households would have consumed between 2.7 and 3.2 percent less in that year had top income levels grown at the same rate as the median since the beginning of the sample period. This corresponds to between \$1763 and \$2116 less in consumption in 2005 for non-rich households (column 2). Because the rise in income inequality is modest in the second half of the 2000s, the counterfactual calculations are very similar for 2005 and 2008.

As is well known, macroeconomic data reveals a steady decline in the personal saving rate from the early 1980s to until about the beginning of the Great Recession. Series from the National Income and

[24] The dollar figures are obtained by multiplying column 1 by average consumption (in 1999\$) across all non-rich households in the CEX in a given year.

Product Accounts (NIPAs) show that the personal savings rate dropped from about 10 percent of disposable income in the early 1980s to about 1 percent in the mid-2000s. One could therefore ask what fraction of this aggregate decline in the personal savings rate could be accounted for under our counterfactual exercise. To answer this, we multiply the dollar figure reduction in consumption by an estimate of the number of non-rich households in the US in each year.[25] This defines the additional savings that would have occurred in each of the years listed in Table 11 under the counterfactuals. We report this number in column 4 of Table 11, with the actual personal savings figures from the NIPA data in column 3. Both are reported in billions of dollars; also, for comparability, both are reported in nominal terms. Finally, in columns 5 and 6, respectively, we report the actual personal savings rate from the NIPA data and the counterfactual rate. To compute the counterfactual rate, we take the actual aggregate personal savings from NIPA (column 3) and add the additional savings under the counterfactual (column 4); we then divide by aggregate disposable income from the NIPA data.

We estimate that the personal savings rate in 2000, which was 2.9 percent, would have been between 4.5 (Panel A) to 5.0 (Panel B) percent if top income levels had grown at the same rate as the median income between 1982 and 2000. In 2005, the actual personal savings rate was 1.5 percent; we estimate counterfactual personal savings rates for that year between 3.5 and 3.9 percent. Hence, a non-trivial fraction of the decline in the personal savings rate could be attributed to non-rich households' consumption response to rising top income levels.

Another worthwhile back-of-the-envelope exercise is to relate our estimates to most recent evidence on the relative rise in income and consumption inequality. The view that there was no rise in consumption inequality over the last 3 decades (Krueger and Perry, 2006) appears to have been somewhat undermined in light of the demonstration of non-classical measurement error problems in the underlying data, and in particular, as we already discussed, the difficulty in measuring consumption among rich and very rich households in the CEX (Aguiar and Bils, 2012). More recent attempts at quantifying the change in consumption inequality suggest that consumption inequality may have increased by between 50 to 100 percent as much as income inequality (Attanasio et. al., 2013). A simple back-of-the-envelope calculation suggests that our estimates are not inconsistent with this latest evidence.

In column 2 of Table 1, we estimate a .21 percent increase in consumption among non-rich households for every 1 percent increase in income at the 90th percentile. Given that median income household is essentially stagnant over the period under study (see Appendix Table A2), this is roughly equivalent to a .21 percent increase in consumption for median-income household for every 1 percent

[25] We use 1990, 2000 and 2010 Census data on total number of households in the US and assume that the number of non-rich households is 4/5 of the total number. For 2005, we average the 2000 and 2010 numbers (equal weights); for 2008, we also average the 2000 and 2010 numbers, with a weight of .2 on 2000 and .8 on 2010.

increase in the income gap between the 90th and 50th percentile households. If the elasticity of consumption to income for upper decile households was 1, this would mean that a 1 percent increase in the income gap between the 50th and 90th percentile would translate in a .79 percent increase in the consumption gap between the 50th and 90th percentile. If the elasticity of consumption to income for upper decile households was .75, this would mean that a 1 percent increase in the income gap between the 50th and 90th percentile would translate in a .54 percent increase in the consumption gap between the 50th and 90th percentile. In the CEX, we estimate an elasticity of consumption to income for households above the 90th percentile of .7. However, this is an underestimate because of under-reporting of consumption by the rich in the CEX. In fact, Maki and Palumbo (2001) suggest strong consumption to income elasticities among the rich during the 1990s because of wealth effects (such as those induced by the rise in the stock market over that period). For both reasons, it is reasonable to expect an elasticity of consumption to income above the 90th percentile greater than .75. Hence, the magnitude of our estimates does not appear inconsistent, under reasonable assumptions, with the current evidence on the relative rise of income and consumption inequality.

VII. Conclusion

The question that originally motivated this research was whether the rise in income inequality and the decline in the personal savings rate over the last 3 decades were related phenomena. We exploit state-year variation in income and consumption in the upper decile and quintile of the distribution to inform our thinking about this question. The evidence we have put together suggests that there might indeed be an economically relevant link. Holding their own current income constant, non-rich households that are exposed to higher top income levels in their market spend a higher share of their incomes.

In the absence of an instrument for the variation in the rise in top incomes we exploit in our analysis, we cannot formally rule out that the presence of a third omitted time-varying factor that causes top incomes to rise and also causes non-rich households to consume more. A battery of robustness checks suggests that no simple combination of states or years is driving this finding. We also tested for a series of specific non-causal explanations for this finding and found little support for them in the data, with the exception of possible upward pressures on local prices as top incomes rise in a state.

Instead, we showed evidence consistent with one possible causal pathway: status-seeking (or status-maintaining) consumption. In particular, we found that non-rich households particularly increase their spending on more visible goods and services when exposed to higher to higher top income and consumption. The limitations of the CEX, and in particular the lack of finer geographic indicators than the state, prevent us from digging deeper into the rich dynamics that such status-seeking consumption behavior, and subsequent expenditure cascades, might induce. While it is difficult to envision a field experiment that might help uncover those dynamics, future research might help in isolating some relevant naturally occurring experiments. Finally, the laboratory setting, which has recently be used to study how relative position in the income distribution may impact decision-making (see for example Kuziemko et al. (2014)), could be an attractive place to take future work on this topic.

Our analysis of personal bankruptcies and self-reported financial duress suggest that the use of credit might have been particularly large for households living in proximity to richer co-residents. We also suggest the possibility, in some very preliminary analysis, that lawmakers may have responded to trickle-down pressures in their constituency by voting in favor of further expansion of access to credit at the national level. If some of this credit translated in bad credit, rising income inequality might have been a contributing factor in the recent financial crisis. More systematic research on the political economy of credit expansion over this period, and how it relates to the rise in income inequality should be encouraged. This research should also explore whether state or more local policies towards credit expansion over the period under study are related to the rise in incomes at the top. Finally, it seems worthwhile to explore in future work whether and how financial institutions reacted to the growing inequality in the markets they serve when deciding who to lend to, and how much.

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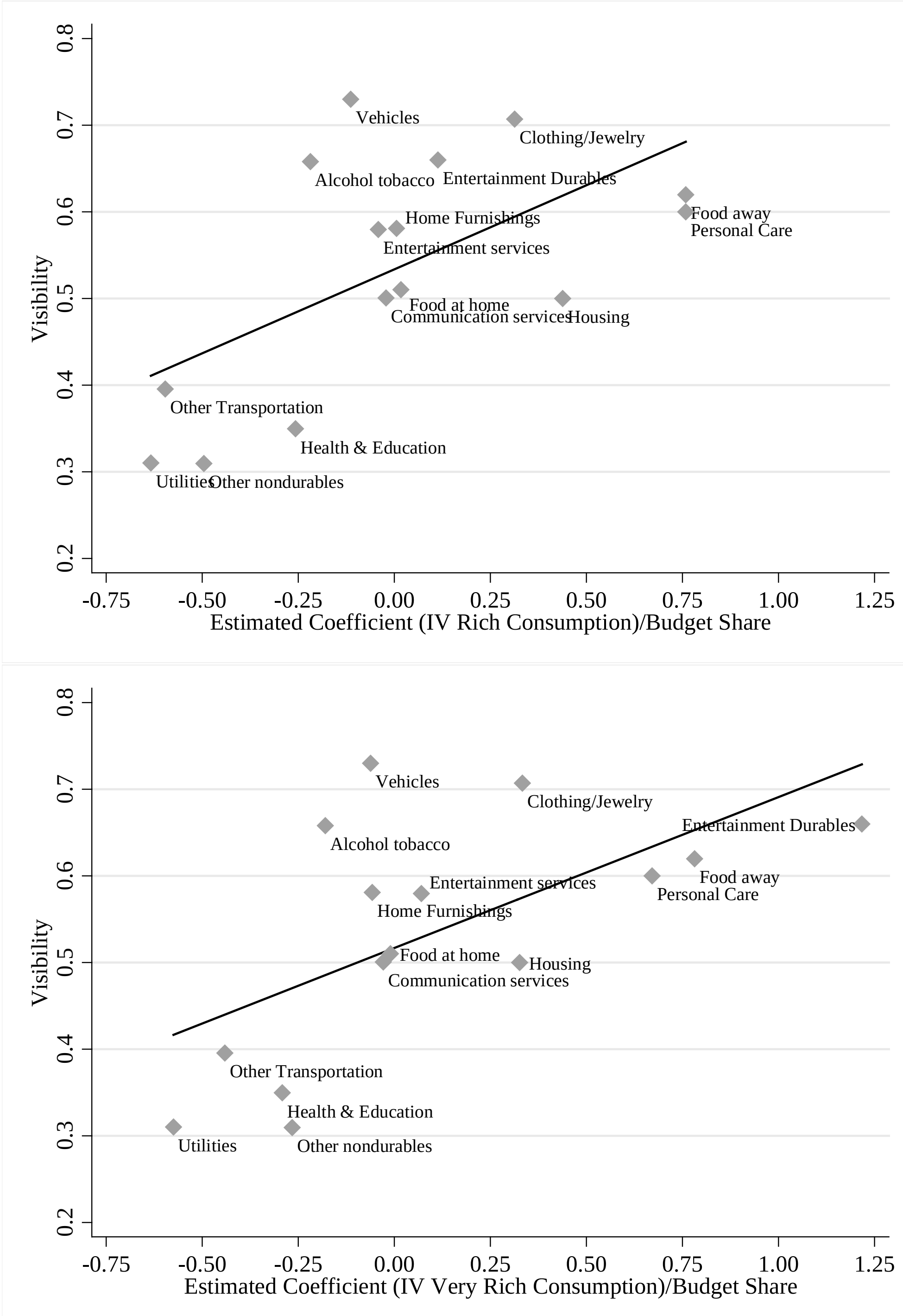

Figure 1: Plot of Elasticity and Budget Share Trickle Effect by Consumption Category

On the Y-axis is Heffetz (2011)'s scoring of "Visibility" from a survey of how noticeable expenditure items of one's contemporaries are. On the X-axis are the IV coefficients on consumption of the rich [very rich] (instrumented with income) from an estimation of the household budget share of the consumption good on the demand system equation from Table 7. The coefficients plotted, which measure the trickle effect on the budget share, are scaled by the budget share mean level of that consumption good, for comparability. Plotted regression lines are fitted as follows (with standard errors in brackets): Visibility = 0.534 [0.030] + 0.194 [0.072] *(Coefficient on Rich Consumption / Budget Share) and Visibility = 0.517 [0.030] + 0.174 [0.063] *(Coefficient on Very Rich Consumption / Budget Share).

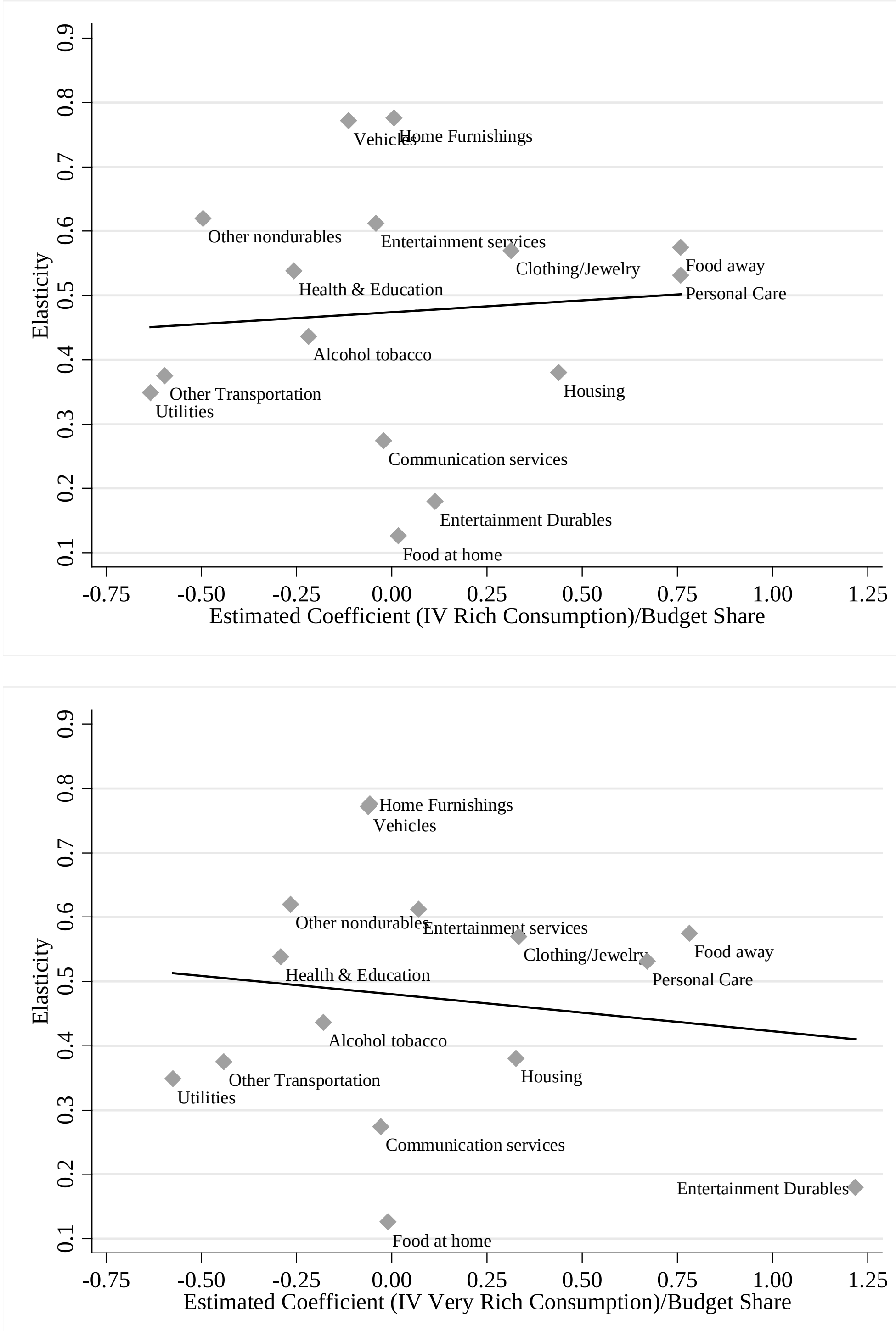

Figure 2: Plot of Elasticity and Budget Share Trickle Effect by Consumption Category

On the Y-axis is the category income elasticity, the coefficient on after-tax income in the CEX from a population-weighted regression of log consumption in that category on log(income), a quadratic of age, and dummies for race, education, number of children and number of people in the household. On the X-axis are the IV coefficients on consumption of the rich [very rich] (instrumented with income) from an estimation of the household budget share of the consumption good on the demand system equation from Table 7. The coefficients, which measure the trickle effect on the budget share, are scaled by the budget share mean level of that consumption good, for comparability. Plotted regression lines are fitted as follows (with standard errors in brackets): Elasticity = 0.474 [0.052] + 0.037 [0.125]*(Coefficient on Rich Consumption / Budget Share) and Elasticity = 0.484 [.053] - 0.057 [0.109] * (Coefficient on Very Rich Consumption / Budget Share).

Table 1: Top Income Levels and Non-Rich Consumption

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:				*Log(Consumption)*				
Sample:	x < 80th %ile	x < 80th %ile	x < 80th %ile	x < 80th %ile	x < 60th %ile	x < 80th %ile	x < 80th %ile	x > 80th %ile
Log(80thPercentileIncome)	0.270		0.345	0.344	0.358	0.338		
	[0.112]*		[0.133]*	[0.134]*	[0.146]*	[0.145]*		
Log(90thPercentileIncome)		0.214						
		[0.091]*						
Unemployment Rate				-0.069	-0.114	-0.057	-0.055	-0.602
				[0.262]	[0.261]	[0.238]	[0.237]	[0.372]
Log(80thPercentileIncome)*							0.365	
40th%ile < Household < 80th%ile							[0.147]*	
Log(80thPercentileIncome)*							0.309	
0th%ile < Household < 40th%ile							[0.159]	
Log(50thPercentileIncome)						-0.007		0.136
						[0.131]		[0.151]
Log(50thPercentileIncome)*							-0.128	
40th%ile < Household < 80th%ile							[0.175]	
Log(50thPercentileIncome)*							0.103	
0th%ile < Household < 40th%ile							[0.126]	
Log(20thPercentileIncome)						0.014		-0.062
						[0.093]		[0.108]
Log(20thPercentileIncome)*							0.11	
40th%ile < Household < 80th%ile							[0.111]	
Log(20thPercentileIncome)*							-0.078	
0th%ile < Household < 40th%ile							[0.089]	
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77523	77523	77523	77523	58393	77523	77523	20775
R-squared	0.59	0.59	0.59	0.59	0.53	0.59	0.59	0.38

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample for all columns except columns 5 and 8 includes all CEX households whose income is below the 80th percentile in the state-year cell measured in the CPS. The sample for columns 5 is all CEX households whose income is below the 60th percentile in the state-year cell, and the sample for column 8 is all households above the 80th percentile in the state-year. Income and consumption measures are in real terms (1999=100). The dependent variable is the logarithm of total consumption for a given CEX household in a given state and year. Log(80th [or 90th, 50th, or 20th] PercentileIncome) is the logarithm of the 80th [or 90th, 50th, or 20th] percentile income in a given state, averaged over the current year and the prior two years from CPS data. Dummy variables [40th%ile < Household < 80th%ile] and [0th%ile < Household < 40th%ile] indicate if the observation is in the higher or lower half of the non-rich sample, divided at the 40th percentile in state-year income, with income percentile data from the CPS. Household income F.E.s are dummies for $2000 buckets of total household income from the CEX. CEX household controls include a quadratic in age of head, dummies for the head's gender, race and education, and dummies for the number of adults and children in the household. Unemployment rate is the state unemployment rate in the current year (computed from the March CPS). Each observation is weighted by the household head weight provided in the CEX Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 1 (cont)

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	*Ratio of Consumption to Income*							
Sample:	x < 80th %ile	x < 80th %ile	x < 80th %ile	x < 80th %ile	x < 60th %ile	x < 80th %ile	x < 80th %ile	x > 80th %ile
Log(80thPercentileIncome)	0.381		0.469	0.469	0.548	0.513		
	[0.163]*		[0.207]*	[0.208]*	[0.245]*	[0.213]*		
Log(90thPercentileIncome)		0.309						
		[0.126]*						
Unemployment Rate				0.004	0.01	0.033	0.038	-0.380
				[0.330]	[0.373]	[0.284]	[0.283]	[0.217]
Log(80thPercentileIncome)* 40th%ile < Household < 80th%ile							0.620	
							[0.220]**	
Log(80thPercentileIncome)* 0th%ile < Household < 40th%ile							0.405	
							[0.221]	
Log(50thPercentileIncome)						-0.112		0.105
						[0.177]		[0.083]
Log(50thPercentileIncome)* 40th%ile < Household < 80th%ile							-0.384	
							[0.183]*	
Log(50thPercentileIncome)* 0th%ile < Household < 40th%ile							0.140	
							[0.227]	
Log(20thPercentileIncome)						0.065		-0.040
						[0.131]		[0.066]
Log(20thPercentileIncome)* 40th%ile < Household < 80th%ile							0.230	
							[0.127]	
Log(20thPercentileIncome)* 0th%ile < Household < 40th%ile							-0.092	
							[0.161]	
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77523	77523	77523	77523	58393	77523	77523	20775
R-squared	0.55	0.55	0.56	0.56	0.53	0.56	0.56	0.19

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample for all columns except columns 5 and 8 includes all CEX households whose income is below the 80th percentile in the state-year cell measured in the CPS. The sample for columns 5 is all CEX households whose income is below the 60th percentile in the state-year cell, and the sample for column 8 is all households above the 80th percentile in the state-year. Income and consumption measures are in real terms (1999=100).The dependent variable is the ratio of a CEX household's total consumption-to-income in a given state and year. Log(80th [or 90th, 50th, or 20th] PercentileIncome) is the logarithm of the 80th [or 90th, 50th, or 20th] percentile income in a given state, averaged over the current year and the prior two years from CPS data. Dummy variables [40th%ile < Household < 80th%ile] and [0th%ile < Household < 40th%ile] indicate if the observation is in the higher or lower half of the non-rich sample, divided at the 40th percentile in state-year income, with income percentile data from the CPS. Household income F.E.s are dummies for $2000 buckets of total household income from the CEX. CEX household controls include a quadratic in age of head, dummies for the head’s gender, race and education, and dummies for the number of adults and children in the household. Unemployment rate is the state unemployment rate in the current year (computed from the March CPS). Each observation is weighted by the household head weight provided in the CEX Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 2: Rich Consumption and Non-Rich Consumption: IV Regressions

	First Stage Regression for Columns (1) and (2)	(1)	(2)	First Stage Regression for Columns (3) and (4)	(3)	(4)
		Second Stage IV			Second Stage IV	
Dependent Variable:	*Log (Consumption of Rich)*	*Log (Consumption)*	*Ratio of Consumption to Income*	*Log (Consumption of Very Rich)*	*Log (Consumption)*	*Ratio of Consumption to Income*
Sample:	All Non-Rich	All Non-Rich	All Non-Rich	All Non-Rich	All Non-Rich	All Non-Rich
Log(80thPercentileIncome)	0.764					
	[0.176]**					
Log(95thPercentileIncome)	0.201			0.674		
	[0.111]			[0.183]**		
IV Log(ConsumptionofRich)		0.439	0.605			
		[0.132]**	[0.210]**			
IV Log(ConsumptionofVeryRich)					0.299	0.434
					[0.134]*	[0.204]*
Unemployment Rate	-0.298	0.008	0.104	0.076	-0.028	0.061
	[0.297]	[0.173]	[0.236]	[0.309]	[0.213]	[0.276]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77523	77523	77523	77416	77416	77416
R-squared	0.86	0.594	0.555	0.840	0.593	0.555
First Stage F-Statistic	37.34			13.59		
OLS Coefficient		0.192	0.258		0.071	0.09
		[0.053]**	[0.086]**		[0.029]*	[0.046]

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample includes all CEX households whose income is below the 80th percentile in the state-year cell measured in the CPS. Income and consumption measures are in real terms (1999=100). The dependent variable in columns 1 and 3 is Log(Consumption), the logarithm of total consumption for a given CEX household in a given state and year. The dependent variable in columns 2 and 4 is the ratio of a CEX household's total consumption-to-income in a given state and year. IV Log(ConsumptionofRich) is the instrumented logarithm of average consumption among rich (e.g. above 80th percentile) households in a given state in the current year and prior two years in the CEX. IV Log(ConsumptionofVeryRich) is the instrumented logarithm of average consumption among very rich (e.g. above 90th percentile) households in a given state in the current year and prior two years in the CEX. The column before columns 1-2 and the column before columns 3-4 report the first stage regression for the subsequent two columns. The instruments are Log(80th PercentileIncome) and Log(95th PercentileIncome), the logarithms of the 80th and 95th percentile income in a given state, averaged over the current year and the prior two years from CPS data. All numbered columns report second-stage results. Household income F.E.s are dummies for $2000 buckets of total household income. Household controls include a quadratic in age of head, dummies for the head's gender, race and education, and dummies for the number of adults and children in the household. Also included is the state unemployment rate in the current year form the CPS. Each observation is weighted by the household weight provided in the CEX Surveys. The last two rows report OLS estimates [standard errors] on Log(ConsumptionofRich) (columns 1 and 2) and Log(ConsumptionofVeryRich) (columns 3 and 4) from separate estimates of the form in the column, but not instrumented. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 3: Do Higher Top Income Levels Today Correlate with Higher or More Stable Future Income for the Non-Rich?

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent Variable:	*Log(HH income) in t+1*			*Log(HH income) in t+2*			*Log(HH income) in t+4*		*Log (average HH income) between t+1 and t+2*		*Log (average HH income) between t+1 and t+4*		*S.D. of Log(HH income) between t+1 and t+4*	
Log(HH income)	0.689	0.689	0.17	0.625	0.625	0.073	0.547	0.547	0.636	0.636	0.585	0.585	-0.102	-0.102
	[0.007]**	[0.007]**	[0.015]**	[0.008]**	[0.008]**	[0.015]**	[0.009]**	[0.009]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.006]**	[0.006]**
Log(80thPercentileIncome)	0.019	0.121	0.012	-0.116	0.021	0.016	-0.210	-0.095	-0.017	0.041	-0.056	0.027	0.161	0.112
	[0.096]	[0.159]	[0.213]	[0.083]	[0.147]	[0.176]	[0.122]	[0.126]	[0.080]	[0.139]	[0.084]	[0.114]	[0.042]**	[0.086]
Log(50thPercentileIncome)		-0.047	0.223		-0.066	0.126		-0.095		-0.009		-0.048		0.051
		[0.250]	[0.293]		[0.186]	[0.246]		[0.181]		[0.185]		[0.154]		[0.106]
Log(20thPercentileIncome)		-0.068	-0.023		-0.089	-0.082		-0.03		-0.06		-0.042		-0.003
		[0.094]	[0.114]		[0.087]	[0.109]		[0.098]		[0.073]		[0.069]		[0.043]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household F.E.s	No	No	Yes	No	No	Yes	No	No	No	No	No	No	No	No
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55870	55870	55870	55377	55377	55377	42293	42293	64993	64993	71596	71596	50468	50468
R-squared	0.65	0.65	0.79	0.57	0.57	0.78	0.51	0.51	0.64	0.64	0.62	0.62	0.1	0.1
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent Variable:	*Log(HH income) in t+1*			*Log(HH income) in t+2*			*Log(HH income) in t+4*		*Log (average HH income) between t+1 and t+2*		*Log (average HH income) between t+1 and t+4*		*S.D. of Log(HH income) between t+1 and t+4*	
Log (HH income)	0.689	0.689	0.17	0.625	0.625	0.073	0.546	0.547	0.636	0.636	0.585	0.585	-0.102	-0.102
	[0.007]**	[0.007]**	[0.015]**	[0.008]**	[0.008]**	[0.015]**	[0.009]**	[0.009]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.006]**	[0.006]**
Log(90thPercentileIncome)	0.014	0.053	0.022	-0.116	-0.042	-0.027	-0.25	-0.217	-0.029	-0.024	-0.069	-0.045	0.139	0.065
	[0.095]	[0.126]	[0.167]	[0.084]	[0.126]	[0.178]	[0.132]	[0.147]	[0.082]	[0.107]	[0.086]	[0.094]	[0.046]**	[0.074]
Log(50thPercentileIncome)		0.008	0.214		-0.01	0.163		0.006		0.049		0.014		0.093
		[0.214]	[0.269]		[0.173]	[0.258]		[0.176]		[0.153]		[0.129]		[0.090]
Log(20thPercentileIncome)		-0.071	-0.021		-0.102	-0.089		-0.061		-0.072		-0.055		-0.005
		[0.096]	[0.119]		[0.091]	[0.116]		[0.098]		[0.073]		[0.068]		[0.042]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household F.E.s	No	No	Yes	No	No	Yes	No	No	No	No	No	No	No	No
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55870	55870	55870	55377	55377	55377	42293	42293	64993	64993	71596	71596	50468	50468
R-squared	0.65	0.65	0.79	0.57	0.57	0.78	0.51	0.51	0.64	0.64	0.62	0.62	0.1	0.1

Note: Data source is the PSID, 1980 to 2006. The sample is restricted to those household-year observations where household income is below the 80th percentile in the state-year cell. The dependent variables in columns 1 to 8 are future incomes for the PSID household, measured at intervals as noted. The dependent variables in columns 9 to 12 are changes in income in the future, also at different intervals. The dependent variable in columns 13 and 14 is the standard deviation of log income income from (t+1) to (t+4). Household controls include a quadratic in head's age, dummies for the head of household's gender, race, education, and marital status, and dummies for the number of adults and children in the household. Log(80/90/50/20th PercentileIncome) is the logarithm of the average of the 80/90/50/20th percentile of household income distribution in a given state in the current year and the prior two years. Samples in columns 1 to 8 is restricted to observations for which the relevant future income variable is observed. Samples in columns 9 to 14 include all observations for which at least one of the future income variable is observed; average is taken based on the number of observed values. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 4: Top Income Levels and Expectations about Future Income Growth

Panel A	(1)	(2)	(3)	(4)
Dependent Variable:	*Expect Real Income to Go Up in the Next Year (Y=1)*			
Sample:	All Non-Rich			
Log(80thPercentileIncome)	-0.054	-0.091		
	[0.029]	[0.056]		
Log(90thPercentileIncome)			-0.055	-0.071
			[0.030]	[0.045]
Log(50thPercentileIncome)		0.025		0.008
		[0.071]		[0.065]
Log(20thPercentileIncome)		0.017		0.017
		[0.038]		[0.039]
Household income F.E.s	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	126177	126177	126177	126177
R-squared	0.1	0.1	0.1	0.1
Panel B	(1)	(2)	(3)	(4)
Dependent Variable:	*Expected Percent Change in Household Income in the Next Year*			
Sample:	All Non-Rich			
Log(80thPercentileIncome)	-3.015	-2.821		
	[1.637]	[2.670]		
Log(90thPercentileIncome)			-1.913	-0.589
			[1.609]	[2.003]
Log(50thPercentileIncome)		-0.713		-2.44
		[2.714]		[2.389]
Log(20thPercentileIncome)		0.547		0.797
		[1.241]		[1.289]
Household income F.E.s	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	117534	117534	117534	117534
R-squared	0.07	0.07	0.07	0.07
Panel C	(1)	(2)	(3)	(4)
Dependent Variable:	*Index of Consumer Expectations*			
Sample:	All Non-Rich			
Log(80thPercentileIncome)	-15.926	-20.933		
	[6.891]*	[9.158]*		
Log(90thPercentileIncome)			-20.33	-25.39
			[6.432]**	[8.154]**
Log(50thPercentileIncome)		2.043		4.977
		[11.004]		[10.720]
Log(20thPercentileIncome)		3.665		2.076
		[5.372]		[5.539]
Household income F.E.s	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	126701	126701	126701	126701
R-squared	0.13	0.13	0.13	0.13

Note: Data source is the University of Michigan Surveys of Consumers, 1980 to 2008. The sample is restricted to those household-year observations where household income is below the 80th percentile in the state-year cell. The dependent variables in Panels A and B are respectively responses to the survey questions "During the next year or two, do you expect that your (family) income will go up more than prices will go up, about the same, or less than prices will go up?" (a dummy) and "By about what percent do you expect your (family) income to (increase/decrease) during the next 12 months?". The dependent variable in Panel C is the household Index of Consumer Expectations, a scoring from questions in the survey. Log(80/90/50/20th PercentileIncome) is the logarithm of the average of the 80/90/50/20th percentile of household income distribution in a given state in the current year and the prior two years. Individual controls include a quadratic in age, dummies for the respondent's gender, race, education and marital status, and dummies for the number of adults and children in the household. Household income fixed effects are dummies for $2000 buckets of total household income. Each observation is weighted by the household head weight provided in the Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 5: Home Equity Channel

Panel A	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			*Log(Consumption)*		
Sample:			All Non-Rich		
Subsample:	Homeowners	Renters	Homeowners	All	Homeowners
Estimation	*OLS*	*OLS*	*OLS*	*IV*	*IV*
Log(80thPercentileIncome)	0.331	0.402	0.183	0.354	0.326
	[0.122]**	[0.181]*	[0.11]	[0.146]*	[0.133]*
Log(80thPercentileIncome)*(Year<=1995)			0.214		
			[0.087]*		
House Price (100Ks)				-0.004	0.003
				[0.019]	[0.023]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes
Observations	46476	30317	46476	75404	45360
R-squared	0.54	0.61	0.54	0.34	0.345

Panel B	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			*Log(Consumption)*		
Sample:			All Non-Rich		
Subsample:	Homeowners	Renters	Homeowners	All	Homeowners
Estimation	*OLS*	*OLS*	*OLS*	*IV*	*IV*
Log(90thPercentileIncome)	0.272	0.349	0.109	0.287	0.257
	[0.121]*	[0.158]*	[0.118]	[0.132]*	[0.12]*
Log(90thPercentileIncome)*(Year<=1995)			0.238		
			[0.101]*		
House Price (100Ks)				0.000	0.007
				[0.018]	[0.022]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes
Observations	46476	30317	46476	75404	45360
R-squared	0.54	0.61	0.54	0.34	0.35

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample is restricted to households whose real income is below the 80th percentile in the state-year cell. In columns 1, 3 and 5, the sample is further restricted to only homeowners; in column 2, the sample is restricted to renters. Income and consumption measures are in real terms (1999=100). Log(Consumption) is the logarithm of total consumption for a given household in a given state and year. Log(80/90th PercentileIncome) is the logarithm of the average of the 80/90th percentile of household income distribution in a given state in the current year and the prior two years. Household income F.E.s are dummies for $2000 buckets of total household income. (Year <=1995) is a dummy variable for the year restriction. Household controls include a quadratic in age of head, dummies for the head's gender, race and education, and dummies for the number of adults and children in the household. Also included as a control is the state unemployment rate in the current year. Each observation is weighted by the household head weight provided in the CEX Surveys. Regressions in columns 1-3 are estimated using OLS. Regressions in columns 5 and 6 are estimated using IV. We instrument state-level house prices in a given year with the national house price index in that year interacted with Saiz (2011)'s housing supply elasticity measure. State and national house price indices are from the Federal Housing Financial Agency; baseline median state house prices are from the 2000 Census. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 6: Local Price Channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	*Log(Local CPI)*		*Log(Consumption)*							
Sample:	State-year panel		All Non-Rich							
Estimation	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*	*IV*
Log(80thPercentileIncome)	0.539		0.335		0.314					
	[0.108]**		[0.157]*		[0.161]					
Log(90thPercentileIncome)		0.312		0.285		0.256				
		[0.089]**		[0.135]*		[0.145]				
Log(50thPercentileIncome)	-0.252	-0.097								
	[0.117]*	[0.110]								
Log(20thPercentileIncome)	0.093	0.081								
	[0.062]	[0.063]								
IV Log(ConsumptionofRich)							0.545		0.487	
							[0.075]**		[0.069]**	
IV Log(ConsumptionofVeryRich)								0.499		0.430
								[0.123]**		[0.110]**
Log(Local CPI)			0.271	0.293			-0.027	-0.018		
			[0.168]	[0.153]			[0.055]	[0.089]		
Log(Local CPI-Food)					0.154	0.163			0.194	0.225
					[0.273]	[0.272]			[0.143]	[0.180]
Log(Local CPI-Apparel)					0.002	0.01			0.061	0.096
					[0.102]	[0.102]			[0.066]	[0.076]
Log(Local CPI-Shelter)					0.207	0.208			0.007	0.034
					[0.136]	[0.141]			[0.082]	[0.110]
Log(Local CPI-Transportation)					-0.234	-0.205			0.12	0.173
					[0.191]	[0.196]			[0.104]	[0.131]
Log(Local CPI-Medical)					0.06	0.054			-0.176	-0.233
					[0.102]	[0.105]			[0.061]**	[0.089]**
Unemployment Rate	0.077	0.118	-0.068	-0.083	0.016	-0.006	0.17	0.274	0.08	0.141
	[0.211]	[0.213]	[0.287]	[0.293]	[0.236]	[0.245]	[0.265]	[0.352]	[0.248]	[0.331]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	553	553	68145	68145	67787	67787	68145	68101	67787	67743
R-squared	0.95	0.95	0.59	0.59	0.59	0.59	0.590	0.588	0.592	0.590

Note: Data Source: CEX, March CPS, and BLS (Local CPIs), 1980 to 2008. In columns 1 and 2, the sample is a state-year panel covering all the states and years included in the CEX sample. Observations are equally weighted in columns 1 and 2. In columns 3 to 10, the CEX sample is restricted to households whose real income is below the 80th percentile in the state-year cell. Income and consumption measures are in real terms (1999=100). The dependent variable is Log(Consumption), the logarithm of total consumption for a given household in a given state and year. IV Log(ConsumptionofRich) is the instrumented logarithm of average consumption among rich (e.g. above 80th percentile) households in a given state in the current year and prior two years. IV Log(ConsumptionofVeryRich) is the instrumented logarithm of average consumption among very rich (e.g. above 90th percentile) households in a given state in the current year and prior two years. Log(80/90/50/20th PercentileIncome) is the logarithm of the average of the 80/90/50/20th percentile of household income distribution in a given state in the current year and the prior two years. All CPI measures are from the BLS and are scaled to be 100 in 1980 before taking logarithms. Columns 3-6 are OLS estimates; columns 7-10 are IV estimates (of the same form as Table 2). Household income F.E.s are dummies for $2000 buckets of total household income. Household controls include a quadratic in age of head, dummies for the head's gender, race and education, and dummies for the number of adults and children in the household. Also included in each regression is the state unemployment rate. Each observation in columns 3 to 6 is weighted by the household head weight provided in the CEX Surveys. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 7: Visibility, Demand Elasticity and Non-Rich Consumption's Responses to Top Income Levels, by Expenditure Category

Panel A: Demand System Estimations

		Clothing / Jewelry	Housing	Food at home	Food away	Alcohol/ Tobacco	Personal Care	Commu-nication & Media	Entertain-ment Services	Utilities	Other Trans-portation	Health & Education	Other Non-durable	Home Furnish-ings	Entertain-ment Durables	Vehicles
	Dependent Variable is Expressed as: Household Category Consumption / Total Household Consumption															
System 1	IV Log(ConsumptionRich)	0.010	0.084	0.004	0.035	-0.005	0.007	-0.001	-0.001	-0.039	-0.058	-0.019	-0.014	0.000	0.000	-0.005
		[0.007]	[0.036]**	[0.052]	[0.012]***	[0.008]	[0.003]*	[0.005]	[0.008]	[0.016]**	[0.013]***	[0.017]	[0.007]**	[0.021]	[0.005]	[0.014]
System 2	IV Log(ComsumptionVeryRich)	0.011	0.062	-0.003	0.036	-0.004	0.006	-0.001	0.002	-0.035	-0.043	-0.021	-0.008	-0.004	0.004	-0.002
		[0.007]*	[0.036]*	[0.051]	[0.014]**	[0.008]	[0.004]	[0.005]	[0.009]	[0.016]**	[0.017]***	[0.018]	[0.007]	[0.020]	[0.005]	[0.012]
	Dependent Variable is Expressed as: Log Household Category Consumption															
System 3	IV Log(ConsumptionRich)	0.724	0.967	0.548	1.676	0.464	0.825	0.241	0.326	-0.277	-0.253	-0.307	-0.186	0.044	-0.043	0.047
		[0.254]***	[0.321]***	[0.287]*	[0.508]***	[0.386]	[0.348]**	[0.206]	[0.459]	[0.199]	[0.184]	[0.288]	[0.275]	[0.448]	[0.118]	[0.504]
System 4	IV Log(ComsumptionVeryRich)	0.435	0.651	0.407	1.353	0.403	0.596	0.201	0.304	-0.252	-0.049	-0.403	-0.239	-0.074	0.005	-0.036
		[0.265]	[0.288]**	[0.267]	[0.454]***	[0.285]	[0.315]*	[0.164]	[0.429]	[0.183]	[0.195]	[0.283]	[0.260]	[0.396]	[0.124]	[0.429]
	Dependent Variable is Expressed as: Household Category Consumption / Total Household Consumption															
System 5	Log(80thPercentileIncome)	0.007	0.086	0.011	0.024	-0.004	0.006	0.000	-0.004	-0.032	-0.059	-0.012	-0.017	0.005	-0.005	-0.006
		[0.006]	[0.034]**	[0.044]	[0.007]***	[0.007]	[0.003]**	[0.005]	[0.006]	[0.015]**	[0.010]***	[0.016]	[0.008]**	[0.018]	[0.004]	[0.013]
System 6	Log(90thPercentileIncome)	0.008	0.076	0.011	0.027	-0.002	0.005	0.000	0.001	-0.026	-0.053	-0.025	-0.013	-0.005	-0.005	-0.001
		[0.005]	[0.031]**	[0.040]	[0.007]***	[0.006]	[0.003]*	[0.005]	[0.007]	[0.013]*	[0.011]***	[0.012]*	[0.006]**	[0.015]	[0.004]	[0.012]
	Dependent Variable is Expressed as: Log Household Category Consumption															
System 7	Log(80thPercentileIncome)	0.441	0.863	0.455	1.318	0.190	0.557	0.193	-0.014	-0.385	-0.329	-0.140	-0.449	-0.142	-0.193	-0.012
		[0.198]**	[0.350]**	[0.255]*	[0.367]***	[0.386]	[0.329]*	[0.218]	[0.302]	[0.163]**	[0.172]*	[0.238]	[0.269]	[0.416]	[0.111]*	[0.416]
System 8	Log(90thPercentileIncome)	0.498	0.742	0.380	1.251	0.275	0.508	0.180	0.283	-0.170	-0.367	-0.354	-0.227	-0.189	-0.165	-0.032
		[0.184]**	[0.311]**	[0.238]	[0.362]***	[0.305]	[0.287]*	[0.187]	[0.355]	[0.151]	[0.168]**	[0.196]*	[0.204]	[0.363]	[0.108]	[0.397]

Panel B: Visibility, Demand Elasticity and Non-Rich Consumption's Responses, as Plotted in Figures 1 and 2

	Clothing / Jewelry	Housing	Food at home	Food away	Alcohol/ Tobacco	Personal Care	Commu-nication & Media	Entertain ment Services	Utilities	Other Trans-portation	Health & Education	Other Non-durable	Home Furnish-ings	Entertain-ment Durables	Vehicles
Visibility	0.707	0.500	0.510	0.620	0.658	0.600	0.501	0.580	0.310	0.395	0.349	0.309	0.581	0.660	0.730
Demand Elasticity	0.570	0.380	0.126	0.575	0.436	0.532	0.274	0.613	0.349	0.375	0.538	0.620	0.776	0.180	0.772
Budget Share	0.033	0.191	0.268	0.046	0.021	0.009	0.040	0.026	0.061	0.097	0.073	0.028	0.062	0.004	0.041
System 1 Estimates/Budget Share	0.314	0.438	0.017	0.759	-0.219	0.759	-0.022	-0.041	-0.633	-0.596	-0.257	-0.495	0.006	0.114	-0.113
System 2 Estimates/BudgetShare	0.334	0.326	-0.011	0.782	-0.180	0.671	-0.028	0.070	-0.575	-0.441	-0.291	-0.266	-0.057	1.218	-0.061

Notes: See next page.

Notes for Table 7:

1) Each cell of Panel A summarizes a single result from the estimation of one of 8 demand system estimations, following equation (4) in the text. Each cell is an estimation. The coefficeint presented is that relating a category consumption of the non-rich to either the income or consumption of the rich or very rich. To illustrate the full specification, System 1 reproduces the coefficient on IV Log(ConsumptionofRich) from the demand system presented in Appendix Table A7 (and equation (4)), where Log(ConsumptionofRich) is instrumented with Log(80thPercentileIncome) and Log(95thPercentileIncome). System 2 is similar to System 1, except that the main variable of interest is Log(ConsumptionofVeryRich), instrumented with Log(95thPercentileIncome). Systems 3 and 4 are the same as systems 1 and 2, respectively, except that the dependent variable is expressed in logs of category consumption rather than budget shares of consumption. Systems 5, 6, 7 and 8 are parallel to systems 1, 2, 3 and 4 respectively, except that the main independent variable is the log of top income (80th percentile or 90th percentile) rather than (rich or very rich) consumption.

2) Panel B provides the inputs used to plot Figures 1 and 2. The visibility scores are from Heffetz (2011), collapsed to the fifteen consumption catogries (see Appendix Table A1 for the mapping of goods and services). Demand elasticities are the coefficients on after-tax income in the CEX from a population-weighted regression of log consumption in that category on log(income), a quadratic of age, and dummies for race, education, number of children and number of people in the household. The budget shares are the weighted average budget shares of the consumption category in CEX households below the 80th percentile in the state-year, with the threshold defined by CPS data and weights applied from the CEX. The final two rows are the estimates from Systems 1 and 2 of panel A, scaled to the budget share on that category in our CEX sample.

Table 8: Personal Bankruptcy Filings and Top Income Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent Variable:						*Log (Number of Personal Bankruptcy Filings/Population)*					
Sample:			All years				1980, 1985, 1990, 1995, 2000, 2005 and 2009			All years	
Log(80thPercentileIncome)	1.06		0.994		1.018		1.289		0.896	1.024	1.167
(t-2)	[0.406]*		[0.365]**		[0.343]**		[0.474]**		[0.261]**	[0.347]**	[0.639]
Log(90thPercentileIncome)		1.321		0.917		0.839		1.144			
(t-2)		[0.355]**		[0.379]*		[0.395]*		[0.485]*			
Log unemployment rate					0.176	0.183	0.164	0.168	0.217	0.171	0.171
(t)					[0.048]**	[0.050]**	[0.088]	[0.090]	[0.047]**	[0.049]**	[0.049]**
Log(80thPercentileIncome)					-0.209	-0.181	0.051	0.054	-0.414	-0.109	-0.045
(t)					[0.286]	[0.300]	[0.535]	[0.535]	[0.258]	[0.320]	[0.298]
Log(50thPercentileIncome)					-0.426	-0.398	-0.82	-0.735	-0.14	-0.573	-0.605
(t)					[0.381]	[0.380]	[0.621]	[0.613]	[0.265]	[0.415]	[0.415]
Log(20thPercentileIncome)					-0.145	-0.126	0.052	0.047	-0.361	-0.169	-0.218
(t)					[0.238]	[0.235]	[0.337]	[0.333]	[0.131]**	[0.228]	[0.204]
Log(50thPercentileIncome)											-0.621
(t-2)											[0.858]
Log(20thPercentileIncome)											0.514
(t-2)											[0.489]
State F.E.s	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s*year	No	No	No	No	No	No	No	Yes	Yes	No	No
Log(1976-1978 average 80thPercentileIncome)*year	No	No	No	No	No	No	No	No	No	Yes	Yes
Observations	1530	1530	1530	1530	1530	1530	357	357	1530	1530	1530
R-squared	0.04	0.08	0.87	0.87	0.88	0.88	0.91	0.91	0.92	0.88	0.88

Note: Dataset is a state-year panel of number of personal bankruptcy filings (1980 to 2009). Datasource: www.abiworld.org<http://www.abiworld.org. The dependent variable is the logarithm of the number of bankruptcy filings per capita for a given state-year. Population estimates by state and year are from the Census (1980-1984 : 1980 Census; 1985-1994: 1990 Census; 1995-2004: 2000 Census; 2005-2009: 2010 Census). The mean of the number of bankruptcy filings per capita is .34 percent. Log(80/90/50/20th PercentileIncome) (t) is the logarithm of the 80/90/50/20th percentile of household income distribution in a given state in the current year. Log(80/90/50/20th PercentileIncome) (t-2 to t-4) is the logarithm of the average of the 80/90/50/20th percentile of household income distribution in a given state two to four years prior to the current year. Unemployment rate by state and year is from the March CPS. Log(1976-1978 average 80th Percentile Income)*year is a trend variable from the pre-period average rich income threshold. Each observation is weighted by population in the state-year cell. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 9: Current Financial Well-Being and Top Income Levels

Panel A	(1)	(2)	(3)	(4)
Dependent Variable:	*Worse Off Financial than a Year Ago (Y=1)*			
Sample:	All Non-Rich			
Log(80thPercentileIncome)	0.228	0.226		
	[0.065]**	[0.090]*		
Log(90thPercentileIncome)			0.25	0.244
			[0.059]**	[0.076]**
Log(50thPercentileIncome)		0.058		0.049
		[0.103]		[0.100]
Log(20thPercentileIncome)		-0.061		-0.049
		[0.056]		[0.057]
Household income F.E.s	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	126551	126551	126551	126551
R-squared	0.07	0.07	0.07	0.07

Panel B	(1)	(2)	(3)	(4)
Dependent Variable:	*More Expenses/More Debt, Int. and Debt Payments than a Year Ago (Y=1)*			
Sample:	All Non-Rich			
Log(80thPercentileIncome)	0.031	0.026		
	[0.026]	[0.035]		
Log(90thPercentileIncome)			0.043	0.048
			[0.022]	[0.027]
Log(50thPercentileIncome)		0.006		-0.01
		[0.038]		[0.035]
Log(20thPercentileIncome)		-0.001		0.004
		[0.023]		[0.023]
Household income F.E.s	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	126701	126701	126701	126701
R-squared	0.01	0.01	0.01	0.01

Note: Data source is the University of Michigan Surveys of Consumers, 1980 to 2008. The sample is restricted to those household-year observations where household income is below the 80th percentile in the state-year cell. The dependent variable in panel A is the survey response to the question "Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?" (a dummy). The dependent variable in panel B is a dummy variable that equals 1 if an individual mentions increased expenses, higher debt, or increased interest or debt payments as the reason for being worse off today than a year ago. Log(80/90/50/20th PercentileIncome) is the logarithm of the average of the 80/90/50/20th percentile of household income distribution in a given state in the current year and the prior two years. Individual controls include a quadratic in age, dummies for the respondent's gender, race, education and marital status, and dummies for the number of adults and children in the household. Household income fixed effects are dummies for $2000 buckets of total household income. Each observation is weighted by the household head weight provided in the Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 10: Republican Congressmen's Voting on H.R. 5334

	Dependent Variable: Yes Vote				
	(1)	(2)	(3)	(4)	(5)
Log(80thPercentileIncome)-Log(50thPercentileIncome)	1.077		1.053	1.000	0.961
	[0.536]*		[0.564]	[0.564]	[0.565]
Log(90thPercentileIncome)-Log(50thPercentileIncome)		0.52			
		[0.342]			
Log(50thPercentileIncome)			-0.03	0.028	0.121
			[0.206]	[0.211]	[0.228]
Log(50thPercentileIncome)-Log(20thPercentileIncome)				-0.524	-0.431
				[0.420]	[0.428]
Log(population)					0.471
					[0.439]
State F.E.s	Yes	Yes	Yes	Yes	Yes
Observations	163	163	163	163	163
R-squared	0.33	0.32	0.33	0.34	0.34

Note: Included in the table are all Republican Congressmen that expressed a vote on H.R. 5334. The dependent variable is a dummy for a Yes vote. Log(80/90/50/20thPercentileIncome) refer to the 80/90/50/20th percentile of household income in each of these Congressmen's Congressional District in the 1990 Census. These measures are obtained by mapping 102nd Congress' Congressional District lines into 1990 Census data at the census tract level. Log(population) is also constructed at the Congressional District level using the same mapping. Standard errors are in brackets. * significant at 5%; ** significant at 1%.

Table 11: Counterfactual Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	**Counterfactual Analysis for Column 1 of Table 1, Panel A**					
Variable:	Change in Log(Consumption) under counterfactual	Change in Consumption under counterfactual	Actual Personal Savings (NIPA)	Additional Savings under counterfactual	Actual Personal Savings Rate (NIPA)	Personal Savings Rate under counterfactual
1990	-0.009	-526.1	276.7	30.3	0.065	0.072
2000	-0.022	-1,360.1	213.1	118.6	0.029	0.045
2005	-0.027	-1,762.9	143.2	183.7	0.015	0.035
2008	-0.027	-1,902.1	592.3	225.1	0.054	0.074
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B:	**Counterfactual Analysis for Column 2 of Table 1, Panel A**					
Variable:	Change in Log(Consumption) under counterfactual	Change in Consumption under counterfactual	Actual Personal Savings (NIPA)	Additional Savings under counterfactual	Actual Personal Savings Rate (NIPA)	Personal Savings Rate under counterfactual
1990	-0.011	-681.6	276.7	39.2	0.065	0.074
2000	-0.028	-1,728.1	213.1	150.7	0.029	0.050
2005	-0.032	-2,116.1	143.2	220.5	0.015	0.039
2008	-0.032	-2,241.0	592.3	265.2	0.054	0.078

Notes: Source: Author's calculation, CEX, NIPA, and Census (for number of households). Reported in the Table are estimated changes in non-rich households' consumption and the aggregate personal savings rate using the estimates of columns 1 and 2 of Table 1 under the counterfactual assumption that income at the 80th Percentile (Panel A) or 90th Percentile (Panel B) grew at the same rate as income at the 50th Percentile. Column 1 reports the implied change in log consumption of the non-rich from replacing rich income with the counterfactual per the estimation. Column 2 reports the dollar implication from column 1, in real dollars. The national income statistics in columns 3 are NIPA data in billions of nominal dollars. Column 4 parallels column 3, reporting the additional aggregate savings in billions of nominal dollars, aggregated to the economy from column 2 calculations via the number of non-rich households in the United States. Columns 5 and 6 are the savings rate equivalents of columns 3 and 4 for NIPA and our counterfactual respectively.

Appendix Table A1: CEX Consumption Categories

This table shows the mapping we use to construct the 15 consumption categories. The visibility score is Heffetz's survey result as to how visibile consumption goods are. Heffetz (2011) chooses 31 categories from the Consumer Expenditure Survey, a collapsed aggregation from Harris and Sabelhaus (2000). We start from Heffetz's codings (columns 4-6), and collapse to the categories used by Charles, Hurst, and Roussanov (CHR) (2009), column (3). Our final categories, columns (1) and (2) are very similar to those in CHR, except that, where the collapsing would average large differences in visibility score, we preserve some of the original Heffetz categories. In particular, Food at Home and Food Away are kept separate, and we separate Commincation (mainly phones) from Utilities. We aggregate human capital expenditures (education and health) into a single category.

(1)	(2)	(3)	(4)	(5)	(6)
Category	Bertrand Morse Category	CHR Category	Heffetz Category	Visibility	Heffetz Description
1	Clothing/Jewelry	Clothing/Jewelry	Clothing	0.71	clothing and shoes, not including underwear, undergarments, and nightwear.
	Clothing/Jewelry	Clothing/Jewelry	Jewelry	0.67	jewelry and watches.
	Clothing/Jewelry	Clothing/Jewelry	Underwear	0.13	underwear, undergarments, nightwear and sleeping garments.
2	Housing	Housing	Rent/home	0.50	rent, or mortgage, or purchase, of their housing.
3	Food at Home	Food	Food home	0.51	food and nonalcoholic beverages at grocery, specialty and convenience stores.
4	Food Away	Food	Food out	0.62	dining out at restaurants, drive-thrus, etc, excl. alcohol; incl. food at school.
5	Alcohol and Tobacco	Alcohol and Tobacco	Alcohol home	0.61	alcoholic beverages for home use.
	Alcohol and Tobacco	Alcohol and Tobacco	Alcohol out	0.60	alcoholic beverages at restaurants, bars, cafeterias, cafes, etc.
	Alcohol and Tobacco	Alcohol and Tobacco	Cigarettes	0.76	tobacco products like cigarettes, cigars, and pipe tobacco.
6	Personal Care	Personal Care	Barbers etc	0.60	barbershops, beauty parlors, hair dressers, health clubs, etc.
7	Communication & Media	Utilities	Cell phone	0.47	mobile phone services.
	Communication & Media	Utilities	Home phone	0.30	home telephone services, not including mobile phones.
	Communication & Media	Entertainment Services	books etc	0.57	books incl. school books, newspapers and magazines, toys, games, and hobbies.
8	Entertainment Services	Entertainment Services	Recreation 2	0.58	cable TV, pets and veterinarians, sports, country clubs, movies, and concerts.
9	Utilities	Utilities	Home utilities	0.31	home utilities such as electricity, gas, and water; garbage collection.
10	Other Transportation	Other Transportation	Air travel	0.46	airline fares for out-of-town trips.
	Other Transportation	Other Transportation	Public trans.	0.45	public transportation, both local and long distance, like busses and trains.
	Other Transportation	Other Transportation	Car insur.	0.23	vehicle insurance, like insurance for cars, trucks, and vans.
	Other Transportation	Other Transportation	Car repair	0.42	vehicle maintenance, mechanical and electrical repair and replacement.
	Other Transportation	Other Transportation	Gasoline	0.39	gasoline and diesel fuel for motor vehicles.
	Other Transportation	Other Transportation	Hotels etc	0.46	lodging away from home on trips, and housing for someone away at school.
11	Health & Education	Education	Education	0.56	education, from nursery to college, like tuition and other school expenses.
	Health & Education	Health	Health care	0.36	medical care, incl. health insurance, drugs, dentists, doctors, hospitals, etc.
12	Other Nondurables	Other Nondurables	Charities	0.34	contributions to churches or other religious organizations, and other charities.
	Other Nondurables	Other Nondurables	Legal fees	0.26	legal fees, accounting fees, and occupational expenses like tools and licenses.
	Other Nondurables	Other Nondurables	Home insur.	0.17	homeowners insurance, fire insurance, and property insurance.
	Other Nondurables	Other Nondurables	Life insur.	0.16	life insurance, endowment, annuities, and other death-benefits insurance.
	Other Nondurables	Other Nondurables	Laundry	0.34	laundry and dry cleaning.
13	Household Furnishings	Household Furnishings	Furniture	0.68	home furnishings and household items, like furniture, appliances, tools, linen.
14	Entertainment Durables	Entertainment Durables	Recreation 1	0.66	computers, games, TVs, video, audio, musical and sports equipment, tapes, CDs.
15	Vehicles	Vehicle (Limited)	Cars	0.73	the purchase of new and used motor vehicles such as cars, trucks, and vans.

Appendix Table A2: Summary Statistics - CEX Sample, 1980 to 2008

Panel A: All Years

Variable:	**N**	**Mean**	**Std. Dev.**
Household income	77523	31,707	18,959
Age of head of household	77523	49.6	18.2
Head of household is male	77523	0.54	0.50
Head of househols is white	77523	0.83	0.38
Head of household has bachelor or graduate degree	77523	0.20	0.40
Number of children in household	77523	1.82	0.84
Number of adults in household	77523	0.67	1.11
Log(Consumption)	77523	10.15	0.54
Log(ConsumptionofRich)	77523	11.00	0.14
Log(ConsumptionofVeryRich)	77523	11.15	0.16
Log(80thPercentileIncome)	77523	11.16	0.12
Log(90thPercentileIncome)	77416	11.44	0.13
Log(95thPercentileIncome)	77523	11.68	0.14
Log(50thPercentileIncome)	77523	10.52	0.12
Log(20thPercentileIncome)	77523	9.66	0.14

Panel B: Means By Half-Decade

	1980-1984	**1985-1989**	**1990-1994**	**1995-1999**	**2000-2004**	**2005-2008**
Log(ConsumptionofMedian)	10.34	10.39	10.41	10.41	10.38	10.38
Log(ConsumptionofRich)	10.87	10.99	11.01	11.01	11.02	11.07
Log(ConsumptionofVeryRich)	10.97	11.12	11.16	11.16	11.18	11.21
Log(80thPercentileIncome)	11.04	11.12	11.14	11.17	11.20	11.20
Log(90thPercentileIncome)	11.30	11.39	11.42	11.47	11.51	11.51
Log(95thPercentileIncome)	11.51	11.61	11.65	11.72	11.77	11.77
Log(50thPercentileIncome)	10.45	10.52	10.52	10.52	10.54	10.53
Log(20thPercentileIncome)	9.60	9.65	9.66	9.64	9.68	9.67

Note: Data Source is the CEX and the March CPS, 1980 to 2008. The sample is restricted to households whose real household income is below the 80th percentile in the state-year in CPS data. Income and consumption measures are reported in real terms (1999=100). Log(Consumption) is the logarithm of total consumption for a given CEX household in a given state and year. Log(ConsumptionofMedian) is the logarithm of average consumption among CEX households between the 40th and 60th income percentiles in a given state in the current year and prior two years. Log(ConsumptionofRich) is the logarithm of average consumption among rich (e.g. above 80th percentile) CEX households in a given state in the current year and prior two years. Log(ConsumptionofVeryRich) is the logarithm of average consumption among very rich (e.g. above 90th percentile) CEX households in a given state in the current year and prior two years. Log(80/90/95/50/20th PercentileIncome) is the logarithm of the average of the 80/90/95/50/20th percentile of household income distribution in a given state in the current year and the prior two years. Each observation is weighted by the household head weight provided in the CEX Surveys.

Appendix Table A3: Top Income Levels and Non-Rich Consumption - Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Log(Consumption)*					
Log(80thPercentileIncome)		0.343	0.306	0.319	0.344	0.345
		[0.132]*	[0.136]*	[0.126]*	[0.134]*	[0.134]*
Log(80thPercentileIncome) * 1980s	0.296					
	[0.113]*					
Log(80thPercentileIncome) * 1990s	0.308					
	[0.120]*					
Log(80thPercentileIncome) * 2000s	0.217					
	[0.118]					
Fraction employed in finance		0.895				
		[0.426]*				
Fraction of state-year pop who moved into state in prior year				0.299		
				[0.360]		
Fraction of state-year pop who moved to another state in prior year				-0.247		
				[0.254]		
Gini coefficient for household income					-0.092	
					[0.160]	
Log(80thPercentileIncome)-Log(20thPercentileIncome)						-0.012
						[0.069]
Additional controls:						
Fraction employed in each one-digit industry	No	No	Yes	No	No	No
Unemployment rate	Yes	Yes	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77523	77523	77523	73536	77523	77523
R-squared	0.59	0.59	0.59	0.59	0.59	0.59

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample includes all CEX households whose income is below the 80th percentile in the state-year cell measured in the CPS. Income and consumption measures are in real terms (1999=100). The dependent variable is Log(Consumption), the logarithm of total consumption for a given CEX household in a given state and year. Log(80th PercentileIncome) is the logarithm of the 80th percentile income in a given state, averaged over the current year and the prior two years from CPS data. Household income F.E.s are dummies for $2000 buckets of total household income from the CEX. CEX household controls include a quadratic in age of head, dummies for the head’s gender, race and education, and dummies for the number of adults and children in the household. Unemployment rate is the state unemployment rate in the current year (computed from the March CPS). Fraction employed in finance is the fraction of the labor force in a given year-cell that is employed in the financial sector (defined as IND1990 code=701 or 702 or 710 or 711; from March CPS). Fraction employed in each one-digit industry are dummies for the fraction of the labor force in each one-digit IND1990 code in a given-year cell (from March CPS). Population inflows and outflows, as well inequality measures, Gini coefficient on household income and Log(80thPercentielIncome)-Log(20th PercentileIncome), are also computed from the March CPS (population inflows and outflows cannot be computed for 1985 and 19995). Each observation is weighted by the household head weight provided in the CEX Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Appendix Table A4: Top Income Levels and Non-Rich Consumption - Geography Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent Variable:						*Log(Consumption)*					
States excluded from sample:	*CA*	*NY*	*CA and NY*	*Fast growth*	*Slow growth*	*Rust belt*	*Sun belt*	*Coasts*	*East Coast*	*West Coast*	*High Polarization*
Log(80thPercentileIncome)	0.360	0.230	0.241	0.358	0.349	0.356	0.452	0.325	0.272	0.358	0.261
	[0.137]*	[0.098]*	[0.100]*	[0.147]*	[0.136]*	[0.153]*	[0.155]**	[0.181]	[0.141]	[0.141]*	[0.177]
Additional controls:											
Unemployment rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68031	71671	62179	70952	66471	57494	50556	37037	52227	62333	39669
R-squared	0.60	0.60	0.60	0.60	0.59	0.59	0.61	0.59	0.59	0.60	0.59

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample includes all CEX households whose income is below the 80th percentile in the state-year cell measured in the CPS. Income and consumption measures are in real terms (1999=100). The dependent variable is Log(Consumption), the logarithm of total consumption for a given CEX household in a given state and year. Log(80th PercentileIncome) is the logarithm of the 80th percentile income in a given state, averaged over the current year and the prior two years from CPS data. Household income F.E.s are dummies for $2000 buckets of total household income from the CEX. CEX household controls include a quadratic in age of head, dummies for the head’s gender, race and education, and dummies for the number of adults and children in the household. Unemployment rate is the state unemployment rate in the current year (computed from the March CPS). Fast growth states are NV, AZ, CO, UT, ID and GA. Slow growth states are OH, PA and CT. Rust belt states are PA, IL, IN, OH, MI and WI. Sun belt states are CA, FL, GA, NV, LA, TN, OK, AK, TX and AZ. High polarization states are AK, CA, CO, CT, DE, IL, IN, MD, MA, MI, NJ, NY, NC, OR, SC and VA (see Lindley and Machin, 2004). Each observation is weighted by the household head weight provided in the CEX Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Appendix Table A5: Summary Statistics - PSID Sample, 1980 to 2006

Variable:	**N**	**Mean**	**Std. Dev.**
Household income	55627	28,820	17,784
Age of head of household	55627	43.17	17.56
Head of household is male	55627	0.65	0.48
Head of househols is white	55627	0.55	0.50
Head of household is married	55627	0.47	0.50
Number of children in HH	55627	0.95	1.26
Number of adults in HH	55627	2.71	1.60

Note: Data Source is the PSID, 1980 to 2006. Summary statistics are reported for the sample in columns 1 to 3 of Table 3, e.g., the PSID sample of households with household income below the 80th percentile in their state-year cell and households for which household income in t+1 is observed in the data. Household income is reported in real terms (1999=100).

Appendix Table A6: Summary Statistics - Michigan Surveys of Consumers, 1980 to 2008

Variable:	**N**	**Mean**	**Std. Dev.**
Household income	126706	32183.0	17896.5
Age	126706	46.74	17.83
Male	126701	0.42	0.49
White	126706	0.82	0.38
Married (living with partner)	126706	0.58	0.49
Number of children in HH	126706	0.71	1.10
Number of adults in HH	126706	1.82	0.73
Expect real income to go up in the next year (Y=1)	126182	0.17	0.38
Expected percent change in household income in the next year	117539	5.61	17.87
Index of consumer expectations	126706	78.89	44.67
Worse off financially than a year ago (Y=1)	126556	0.32	0.47
More expenses/more debt, int. and debt payments than a year ago (Y=1)	126706	0.07	0.26

Note: Data Source is University of Michigan Surveys of Consumers, 1980 to 2008. Statistics correspond to estimations in Table 5 for the Michigan Survey of Consumers. Sample is restricted to respondents whose real household income is below the 80th percentile in the state-year cell. Household income is reported in real terms (1999=100). Each observation is weighted by the household head weight provided in the Surveys.

Appendix Table A7: Top Income Levels on Non-Rich Consumption:
Robustness to Alternative Definition of Shelter Consumption

	(1)	(2)	(3)	(4)
Panel A:				
Dependent Variable:	*Log(Consumption)*		*Log(Consumption Minus Shelter)*	
Shelter Defined as:	*Rental Equivalence*		*Shelter Excluded*	
Sample:	All Non-Rich			
Log(80thPercentileIncome)	0.422	0.389	0.240	0.296
	[0.132]**	[0.157]*	[0.124]	[0.143]*
Log(50thPercentileIncome)		0.016		-0.064
		[0.125]		[0.106]
Log(20thPercentileIncome)		0.018		0.004
		[0.101]		[0.084]
Unemployment Rate	-0.300	-0.275	-0.155	-0.172
	[0.279]	[0.254]	[0.262]	[0.247]
State and Year F.E.s	Yes	-0.275	-0.155	-0.172
State-specific time trends	Yes	[0.254]	[0.262]	[0.247]
Household Income F.E.s	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	75477	75477	77523	77523
R-squared	0.58	0.58	0.56	0.56
Panel B:	(1)	(2)	(3)	(4)
Dependent Variable	*Ratio of Consumption to Income*		*Ratio of (Consumption Minus Shelter) to Income*	
Shelter Defined as:	*Rental Equivalence*		*Shelter Excluded*	
Sample:	All Non-Rich			
Log(80thPercentileIncome)	0.576	0.573	0.287	0.376
	[0.208]**	[0.242]*	[0.149]	[0.160]*
Log(50thPercentileIncome)		-0.064		-0.141
		[0.188]		[0.125]
Log(20thPercentileIncome)		0.066		0.046
		[0.157]		[0.093]
Unemployment Rate	-0.541	-0.493	-0.129	-0.129
	[0.390]	[0.353]	[0.266]	[0.245]
State and Year F.E.s	Yes	Yes	Yes	Yes
State-specific time rend	Yes	Yes	Yes	Yes
Household Income F.E.s	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	75477	75477	77523	77523
R-squared	0.54	0.54	0.51	0.51

Note: Data Source: CEX and the March CPS, 1980 to 2008. The sample includes all households whose income is below the 80th percentile in the state-year cell. Income and consumption measures are in real terms (1999=100). Odd columns and even columns follow the specification of columns 4 and 6, respectively, of Table 1. In panel A, columns 1 and 2, the dependent variable is Log(Consumption), the logarithm of total consumption for a given household in a given state and year. In panel B, columns 1 and 2, the dependent variable is the ratio of consumption to income for a CEX household. The only difference in columns 1 and 2 from the main estimates in Table 1 is that the measure of shelter here uses the rental equivalence estimate (a direct survey answer for CEX homeowners) rather than the flow of payments for housing for the shelter measure used elsewhere in the paper. Renters shelter consumption does not change. In columns 3 and 4 of both panels here, the dependent variable excludes consumption spent on shelter from the measure of total consumption. Log(80/90/50/20th PercentileIncome) is the logarithm of the average of the 80/90/50/20th percentile of household income distribution in a given state in the current year and the prior two years. Household income F.E.s are dummies for $2000 buckets of total household income. Household controls include a quadratic in age of head, dummies for the head’s gender, race and education, and dummies for the number of adults and children in the household. Unemployment rate is the state unemployment rate in the current year (computed from the March CPS). Each observation is weighted by the household head weight provided in the CEX Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Appendix Table A8: Demand System Estimation: Budget Share Regressed on Demand System Variables and IV(LogRichConsumption)

	Clothing / Jewelry	Housing	Food at home	Food away	Alcohol tobacco	Personal Care	Communication & Media	Entertainment Services	Utilities	Other Transportation	Health & Education	Other Non-durable	Home Furnishings	Entertainment Durables	Vehicles
IV(LogRichConsumption)	0.011	0.062	-0.003	0.036	-0.004	0.006	-0.001	0.002	-0.035	-0.043	-0.021	-0.008	-0.004	0.004	-0.002
	[0.007]*	[0.036]*	[0.051]	[0.014]**	[0.008]	[0.004]	[0.005]	[0.009]	[0.016]**	[0.017]***	[0.018]	[0.007]	[0.020]	[0.005]	[0.012]
Log Food Price Index	0.007	-0.737	0.331	0.322	-0.046	-0.013	0.067	0.057	0.063	0.104	0.037	-0.007	0.055	0.067	-0.321
	[0.049]	[0.362]**	[0.273]	[0.106]***	[0.061]	[0.022]	[0.047]	[0.073]	[0.103]	[0.136]	[0.208]	[0.096]	[0.188]	[0.075]	[0.091]***
Log Clothing Price Index	0.046	0.047	-0.053	-0.097	0.022	0.011	0.027	-0.010	-0.044	-0.049	0.001	0.023	0.027	-0.028	0.036
	[0.012]***	[0.070]	[0.067]	[0.018]***	[0.016]	[0.004]**	[0.010]***	[0.016]	[0.028]	[0.030]	[0.039]	[0.015]	[0.044]	[0.015]*	[0.014]***
Log Housing Price Index	-0.064	1.077	0.231	0.103	-0.076	0.033	-0.156	-0.124	-0.124	-0.348	-0.333	-0.262	-0.297	0.002	0.375
	[0.078]	[0.567]*	[0.338]	[0.124]	[0.081]	[0.030]	[0.055]***	[0.075]	[0.120]	[0.178]*	[0.259]	[0.138]*	[0.227]	[0.077]	[0.134]***
LogTransport Price Index	0.035	-0.414	-0.416	-0.146	0.088	-0.020	0.048	0.068	0.119	0.284	0.169	0.171	0.148	-0.009	-0.132
	[0.041]	[0.255]	[0.119]***	[0.043]***	[0.036]**	[0.008]**	[0.022]**	[0.027]***	[0.035]***	[0.080]***	[0.085]**	[0.051]***	[0.097]	[0.026]	[0.041]***
Log Other Price Index	-0.008	-0.029	-0.143	-0.155	0.022	-0.007	0.025	0.027	-0.006	0.021	0.117	0.083	0.061	-0.018	0.035
	[0.013]	[0.084]	[0.048]***	[0.022]***	[0.015]	[0.005]	[0.010]**	[0.014]*	[0.026]	[0.027]	[0.029]***	[0.017]***	[0.034]*	[0.016]	[0.015]**
Log Local CPI	0.000	0.000	0.000	-2.238	0.000	-2.408	0.000	0.000	21.788	3.169	1.330	0.000	39.290	0.000	0.000
	[0.042]	[0.166]	[0.240]	[4.265]	[0.042]	[2.853]	[0.036]	[0.034]	[24.251]	[5.009]	[8.456]	[0.040]	[23.922]	[0.026]	[0.075]
Unemployment Rate	-0.039	0.123	0.041	-0.024	0.013	0.000	0.005	0.007	0.072	-0.028	0.009	0.020	-0.103	-0.004	-0.090
	[0.018]**	[0.050]**	[0.073]	[0.023]	[0.012]	[0.006]	[0.011]	[0.015]	[0.035]**	[0.036]	[0.049]	[0.013]	[0.050]**	[0.012]	[0.018]***
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68101	68101	68101	68101	68101	68101	68101	68101	68101	68101	68101	68101	68101	68101	68101
R-squared	0.349	0.289	0.451	0.324	0.179	0.201	0.282	0.326	0.255	0.425	0.298	0.202	0.250	0.034	0.397

Note: Each column presents estimates from a demand system. The dependent variable is the annual consumption for a CEX household in the category labeled by the column divided by total annual consumption for that household. Included variables in the demand system are food log price index, clothing log price index, housing log price index, transportation log price index, and other goods log price index as well as the local CPI, aggregated from the MSA to the state using county population weights and scaled to 100 in 1980. All indices are from the Bureau of Labor Statistics. The main independent variable of interest is IV Log(RichConsumption), the instrumented logarithm of consumption of the rich (above the 80th percentile) in a given state in the current year and the prior two years. The instruments are Log(80th Percentivel Income) and Log (95th Percentile Income), both averaged over the current and prior two years. Household income F.E.s are dummies for $2000 buckets of total household income. Household controls include a quadratic in age of head, dummies for the head's gender, race and education, and dummies for the number of adults and children in the household. Also included as a control is the state unemployment rate in the current year. Each observation is weighted by the household head weight provided in the CEX Surveys. Standard errors are clustered at the state level. * significant at 1%; ** significant at 5%; *** significant at 10%.

Appendix Table A9: Top Income Levels and Non-Rich Consumption: Heterogeneity of Effect Based on State Income Segregation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Log(Consumption)*					
Sample:	All Non-Rich					
Subsample:	Income segregation is:		Segregation of poverty is:		Segregation of affluence is:	
	Low	High	Low	High	Low	High
Log(80thPercentileIncome)	0.344	0.274	0.379	0.272	0.472	0.213
	[0.159]*	[0.125]	[0.136]*	[0.152]	[0.150]**	[0.150]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38635	38888	36269	41254	35771	41752
R-squared	0.60	0.58	0.60	0.58	0.61	0.58

Source: CEX and the March CPS, 1980 to 2008 Measures of income segregation, segregation of poverty and segregation of affluence are from Chetty et al. (2014) and available at http://www.equality-of-opportunity.org/. Households whose income is below the 80th percentile in the state-year cell are split based on whether they are below ("Low") or above ("High") the sample median for each of the respective income segregation measures. Income and consumption measures are in real terms (1999=100). The dependent variable, Log(Consumption), is the logarithm of total consumption for a given household in a given state and year. Log(80th PercentileIncome) is the logarithm of the average of the 80th percentile of household income distribution in a given state in the current year and the prior two years. Household income F.E.s are dummies for $2000 buckets of total household income. Household controls include a quadratic in age of head, dummies for the head's gender, race and education, and dummies for the number of adults and children in the household. Also included as a control is the state unemployment rate in the current year (computed from the March CPS). Each observation is weighted by the household head weight provided in the CEX Surveys. All regressions are estimated using OLS. Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.