

TRICKLE-DOWN CONSUMPTION

MARIANNE BERTRAND

University of Chicago, Booth School of Business, NBER, and CEPR

ADAIR MORSE*

University of California at Berkeley, Haas School of Business, and NBER

This version: February 4, 2014

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 levels. We argue that permanent income, wealth effects, or upward local price pressures cannot be the sole explanation for this finding. Instead, we show that the budget shares non-rich households allocate to more visible and more income elastic goods and services rise with top income levels, consistent with status-maintaining and supply-driven-demand 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.

* We thank Chris Carroll, Ulrike Malmendier, and Jonathan Parker for helpful comments. We also would like to thank seminar participants at the AEA, NBER Economics of Household Savings, Chicago Booth, Harvard University, Harvard Business School, Princeton University, EIEF, University of California at Berkeley-Haas, Northwestern-Kellogg, NBER Monetary Economics, NBER Income Distribution and Macroeconomy, INSEAD, and UC Davis Household Finance Conference for helpful comments.

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, Katz and Kearney (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 the median household within a market, whose real income has been essentially stagnant since the mid-1980s, has been increasingly exposed to some 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 the median household. 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 above 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 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 upper 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, and particularly last third, 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 (as suggested by Matlack and Vigdor, 2008), 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 two subsamples of the data that were less exposed to the housing boom: the first half of the sample period (1980-1995) and the subset of states where housing supply is more elastic (Saiz, 2010). 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.

After having found little support in the data for these non-causal explanations for our primary finding, we then consider and test for two causal mechanisms. Why would rising top income levels in a state induce the non-rich to spend more? 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. (2010) 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 just above theirs, generating what they label as "expenditure cascades." Expenditure cascades result in a negative relationship between income inequality 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 the expenditure categories. We find evidence consistent with both explanations, in that the budget shares non-rich households allocate to both more income elastic and 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, 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)). We provide indirect evidence in support of the hypothesis that non-rich income households may have relied on this easier credit and stretched 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. (2010), 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 some 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 80th 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. As is well known, macroeconomic data reveal a steady decline in the personal saving rate from the early 1980s to until the beginning of the Great Recession. Series from the National Income and Product Accounts (NIPAs) show that the personal savings rate dropped from about 10 percent of disposable income in the early 1980s to about 1.5 percent in 2005. A back-of-the envelope analysis suggests that, under the counterfactual of no growth in income inequality, the aggregate personal savings rate would have been 3.5 and 4 percent in 2005. We also argue that the magnitudes of effect we estimate are not inconsistent with the latest work on the relative rise in income and consumption inequality (Aguiar and Bilts (2012) and Attanasio et. al. (2013)).

The rest of the paper is structured as follows. Our CEX dataset is presented in 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 explanations for this primary finding. Section V discusses the relationship between top income levels and the use and supply of credit. Section VI provides our 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.

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 metric. For households with no vehicles, we assign a value of zero.²

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 purchase 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

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 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, Hurst and Roussanov (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 using this second measure as well.

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 categories, or more and less income elastic categories. To do this, we rely on twenty-nine consumption categories following Harris and Sabelhaus' (2000) and Heffetz's (2011) classifications.³ Also, following Aguiar and Bilts (2012), we drop households whose consumption in any of these twenty-nine categories (other than food and shelter) is greater than one-half of total consumption for the year.

Also available in the CEX are households' demographic characteristics and income during the first and last survey quarters. 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. We drop households with zero or negative total income.

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

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. To make sure we capture purchase decisions, we apply the upper end of the estimates, which report that 15-25% of a car's value is lost in the first year of ownership. For example, consumption from \$20,000 new car would be \$5,000 the first year ($=20,000*0.25$) and \$3,750 the second year ($=(20,000-5,000)*0.25$).

³ Harris and Sabelhaus (2000) assign just over 100 classifications to the UCC codes in the CEX. Heffetz (2011) collapses these to 31 categories. We collapse Heffetz's underwear category into clothes, air travel and hotels into travel, cars and car repair into vehicle, bus fares and gasoline into local transport, and three non-health insurances into one. We split out appliances from furniture, health insurance from health, recreational vehicles from recreation, home maintenance from home additions.

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.

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 (even though we will present some complementary analysis on the sample of rich households in Table 1). We use the CPS measures of income at the 80th (or 90th percentile) as our key independent variables in the analysis below. 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 1 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 contains 1.82 adults, .67 children and has an income of \$31,705.

Panel B of Appendix Table 1 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 rich (very rich), which we define 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 only by .02 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. Average 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; average household income at the 90th percentile grew by close to .21 log points over the same period. The top rows 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 $\text{Log}(\text{ConsumptionofRich})$ and $\text{Log}(\text{ConsumptionofVeryRich})$ reported in Appendix Table 1 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:

$$\begin{aligned} \text{Log}(\text{Consumption})_{ist} = & \text{Log}(80^{\text{th}} \text{PercentileIncome})_{st} + \text{Household controls}_{ist} \\ & + \text{Household Income dummies}_{ist} + \text{State}_s + \text{Year}_t + \varepsilon_{ist}, \end{aligned} \quad (1)$$

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. The key independent variable in equation (1) is $\text{Log}(80^{\text{th}} \text{PercentileIncome})$, which is the logarithm of the average of the 80th 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 very 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. All observations in equation (1) are weighted by the CEX population weights. Also, standard errors are clustered at the state-level.

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 $\text{Log}(80^{\text{th}} \text{PercentileIncome})$ (column 1) or $\text{Log}(90^{\text{th}} \text{PercentileIncome})$ (column 2). A 1 percent increase in $\text{Log}(80^{\text{th}} \text{PercentileIncome})$ associates with an increase in non-rich consumption of .265 percent, holding non-rich households characteristics and own income constant. Likewise, a 1 percent increase in $\text{Log}(90^{\text{th}} \text{PercentileIncome})$ associates with an increase in non-rich consumption of .209 percent, all else equal.

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.

While we devote the next section of the paper to a thorough investigation of both non-causal and causal mechanisms for these associations, we provide in the remaining columns of Table 1 some first indications of robustness. One possible confound is that rising top income levels in a state might be associated with a positive shock to local economic conditions. Columns 3 and 4 show that the estimated coefficient on $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ is not statistically affected (in fact, the point estimate goes up) when we allow for differential time trends by state (column 3) and control for the current state unemployment rate (computed from the March CPS; column 4).

Another concern is that the associations in columns 1 to 4 are due to the mis-measurement of household income, and in particular the misclassification of some rich households as non-rich. In column 5, we replicate the specification in column 4 but focus 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 $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ 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 columns 6 and 7 of Table 1. Column 6 adds $\text{Log}(50^{\text{th}}\text{PercentileIncome})$ and $\text{Log}(20^{\text{th}}\text{PercentileIncome})$ (both constructed based on the 3-year averaging method described above) as additional covariates to the specification in column 4. There is no evidence of a statistically significant association between non-rich consumption and either median household income or income at the 20th percentile; moreover, the estimated coefficient on $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ remains unchanged. In column 7, 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 $\text{Log}(50^{\text{th}}\text{PercentileIncome})$ or $\text{Log}(20^{\text{th}}\text{PercentileIncome})$. No statistically or economically significant relationship emerges.⁵

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

⁵ Columns 1 and 2 of Appendix Table A4 respectively replicate columns 4 and 6 of Table 1 using the alternative, rental equivalence-based, definition of shelter expenditures.

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.

exists in the data. Our preferred econometric model to show this relationship is an IV specification, where we instrument $\text{Log}(\text{ConsumptionofRich})$ and $\text{Log}(\text{ConsumptionofVeryRich})$ with top percentiles of the income distribution in a state-year cell. (For completeness, we however also report results from an OLS specification at the bottom of Table 2.)

We prefer the IV specification over an OLS one for two reasons. First, concerns about unobserved state-shocks, which are already present in Table 1, 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 for distribution. Likewise, both rich and non-rich consumption might be exposed to changes in local sales taxes.

Second, we prefer the IV specification because of consumption measurement issues with the CEX survey expenditure data. Since we rely particularly on rich consumption measures, the fact that prior research has demonstrated that the CEX especially underestimates consumption among richer households, and increasingly so over time (Garner et al (2006); Aguiar and Bils, (2012)) heightens this problem. Thus, we prefer the IV specification which appeals to the standard practice of addressing mis-measurement of consumption with the instrument of income.

We use $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ and $\text{Log}(95^{\text{th}}\text{PercentileIncome})$ as instruments for $\text{Log}(\text{ConsumptionofRich})$; we use $\text{Log}(95^{\text{th}}\text{PercentileIncome})$ as an instrument for $\text{Log}(\text{ConsumptionofVeryRich})$. We present the two first-stage regressions and report second-stage results for the two dependent variables considered in Table 1: $\text{Log}(\text{Consumption})$ 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 4.4 percent increase in the consumption of the non-rich.

IV. Possible Explanations

The relationships we report 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 variations in the income or consumption of the rich pick up on some un-modeled or unobserved state-year variables. Our goal in this section is to: 1) empirically address some of the main non-causal explanations for the patterns

in Tables 1 and 2 (Sections IV.A. to IV.D) and 2) propose some tests 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 $t+4$.⁷ 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 2. 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, time-varying 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:

$$\begin{aligned} \text{Log}(\text{FutureIncome})_{is,t+j} &= \text{Log}(80^{\text{th}} \text{PercentileIncome})_{st} + \text{Log}(\text{CurrentIncome})_{ist} \\ &+ \text{HouseholdControls}_{ist} + \text{State}_s + \text{Year}_t + \varepsilon_{ist} \end{aligned} \quad (2)$$

where i is a household, s a state, and t a year. The time-varying 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 $\text{Log}(80^{\text{th}}\text{PercentileIncome})$; in Panel B, we use $\text{Log}(90^{\text{th}}\text{PercentileIncome})$. In no specification do we find evidence that higher top income levels in a state in a given year are significantly predictive of higher

⁷ 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.

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).⁸ 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 findings in Tables 1 and 2, 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 some complementary analysis of non-rich households’ self-reported expectations about their future 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 3. 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

⁸ Future income measures in columns 9 to 12 are averages of all non-missing values over the relevant time horizon.

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:

$$\begin{aligned} \text{IncomeChangeExpectation}_{ist} = & \text{Log}(80^{\text{th}} \text{PercentileIncome})_{st} + \text{Individual Controls}_{ist} \\ & + \text{Household Income dummies}_{ist} + \text{State}_s + \text{Year}_t + \varepsilon_{ist}, \end{aligned} \quad (3)$$

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 from 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 (50th and 20th 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 $\text{Log}(80^{\text{th}} \text{PercentileIncome})$ and $\text{Log}(90^{\text{th}} \text{PercentileIncome})$ 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.⁹ Consistent with the evidence in Panels A and B, we do not find that non-rich

⁹ 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?"

households are more optimistic about the future when exposed to higher top income levels. In fact, all the estimate coefficients on $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ and $\text{Log}(90^{\text{th}}\text{PercentileIncome})$ 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 explanation (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 $\log(\text{household income})$ 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 $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ (Panel A of Table 3) or $\text{Log}(90^{\text{th}}\text{PercentileIncome})$ (Panel B of Table 3) are systematically negatively correlated with 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 also control for $\text{Log}(50^{\text{th}}\text{PercentileIncome})$ and $\text{Log}(20^{\text{th}}\text{PercentileIncome})$.

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, Quigley, and Shiller (2005), Campbell and Cocco (2007), Attanasio, Blow, Hamilton, and Leicester (2009), and Carroll, Otsuka, and Slacalek (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), it is possible that a key missing variable in our analysis so far is 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 replicates the specification in column 4 of Table 1. Our goal is to isolate households, time periods, and geographic markets in which or for which we would expect large differences in the sensitivity of non-rich consumption to top income levels under a wealth effect explanation. We then allow for heterogeneity of effects across these groups.

Specifically, in columns 1 and 2, we allow the sensitivity to differ between home owners and renters.¹⁰ While the point estimates indicate moderately larger sensitivities for home owners, the differences are neither large nor statistically significant. In columns 3 and 4, we allow for the sensitivity to differ before and after 1995. To the extent that the rise in home prices started in the middle of the 1990s, a home-equity based explanation for our findings would predict larger effects post-1995. In fact, we tend to find stronger correlations prior to 1995. Finally, in columns 5 and 6, we allow the sensitivity to differ across states with more or less elastic housing supply, using the measure of housing supply elasticity provided by Saiz (2010).¹¹ Markets where housing supply is inelastic have experienced sharper rises in house prices; it is therefore relevant to ask whether our primary finding systematically differs based on the level of house supply elasticity in the market. Contrary to what would have been expected under a home equity channel, the relationship between non-rich consumption and top income levels appears stronger in the states where the housing supply is more elastic.

In summary, because our core results hold both for homeowners and renters, and also hold (and in fact are stronger) prior to the housing boom as well in markets with a more elastic housing supply, we do not believe that a home equity-based wealth channel is the sole 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.

¹⁰ Unfortunately, while the CEX allows us to separate renters from homeowners, there is no variable capturing when a household bought their current house.

¹¹ We use the data from Saiz’s website to construct the housing supply elasticities. Saiz’s data are at the metropolitan level, however, rather than at the state level. We construct supply elasticities within a state by averaging across metro areas in the state, using each metro area population as weight. For metro areas that cover multiple states, we assume that the population is split equally among the states covered in the metro area.

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.¹² 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 $\text{Log}(\text{LocalCPI})$ and both $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ (column 1) and $\text{Log}(90^{\text{th}}\text{PercentileIncome})$ (column 2). In contrast, neither $\text{Log}(50^{\text{th}}\text{PercentileIncome})$ nor $\text{Log}(20^{\text{th}}\text{PercentileIncome})$ are positively related to $\text{Log}(\text{LocalCPI})$.

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 $\text{Log}(\text{LocalCPI})$ in these regressions. $\text{Log}(\text{LocalCPI})$ enters positively in each regression, but the estimates are quite noisy (with significance at most at the 10% level). Controlling for $\text{Log}(\text{LocalCPI})$ 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 5 and 6).

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. In the sub-section below, we do show, however, that non-rich households' budget share for shelter increases substantially when top income levels rise.¹³ While we propose in that sub-section other possible explanations for this finding (e.g. the possibility that non-rich 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 higher local prices per unit of housing.

IV.E. Possible Causal Mechanisms

In the prior four sub-sections, we failed to find much empirical support for several explanations for the correlations we observed in Tables 1 and 2. In these explanations, consumption of the rich and non-rich may be related, but non-causally so. In particular, we considered permanent income, precautionary savings, wealth effects and local price pressures explanations, and concluded that none of

¹² 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. A few states have no MSA covered by the BLS CPI indices; for those, we apply the region average.

¹³ Columns 3 and 4 of Appendix Table A4 replicate columns 4 and 6 of Table 1 but exclude shelter expenses from total consumption. The elasticity of non-rich households' total consumption excluding shelter to top income levels is about 2/3 the size of the elasticity of their total consumption to top income levels. (p-values on $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ are below 0.10 in both columns for both panels.)

these appears to be the sole explanation for the positive correlation we observe between non-rich consumption and top income levels (or rich consumption).

In this section, we propose and test for two channels through which rising income and consumption at the top of income distribution might cause the non-rich to spend more. One hypothesis is that a non-rich consumption response might be driven by social comparisons and relative income considerations. The 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. (2010) propose a variant where a given household’s consumption is directly positively affected by the consumption of the households whose permanent income is just above theirs, generating what they label as “expenditure cascades”. Expenditure cascades generate a negative relationship between income inequality 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 the consumption induced by such 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 propose to ask whether the sensitivity of budget shares to top income levels varies in a systematic way with the visibility of the consumption categories. We use Heffetz (2011) to assign a visibility index to a given consumption category. Heffetz (2011)’s index was based on answers to a household telephone survey. For a list of goods and services, survey respondents were asked to answer the following question: *“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 is based on averaging those answers across survey respondents. Column 2 of Appendix A5 reports the visibility index for each of the 29 consumption categories.

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 test for 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. Column 1 of Appendix Table A5 reports income elasticity estimates for each of the 29 consumption categories we have constructed. 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.

To proceed with the testing of these two hypotheses, in a first step, we estimate the following demand system in the CEX subsample:

$$W_{ist}^k = \beta^k \text{Log}(80\text{thPercentileIncome})_{st} + \sum_{l=1}^5 \log\left(\frac{P_t^l}{P_t}\right) + \log\left(\frac{P_{st}}{P_t}\right) \quad (4)$$

$$+ \text{HouseholdControls}_{ist} + \text{HouseholdIncomeDummies}_{ist} + \text{State}_s + \text{Year}_t + \varepsilon_{ist}$$

where W_{ist}^k is consumption share (as a ratio of total consumption) on good k (with $k=1$ to 29) 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; p_{st} is the local CPI; and all other variables are defined as above. We estimate the demand system of equation (4) in three additional forms, following the usual flow of our analysis. We replace $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ with $\text{Log}(90^{\text{th}}\text{PercentileIncome})$. Then, in the spirit of Table 2, we perform two IV estimations of the demand system: one where we instrument $\text{Log}(\text{ConsumptionofRich})$ with $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ and $\text{Log}(95^{\text{th}}\text{PercentileIncome})$, and one where we instrument $\text{Log}(\text{ConsumptionofVeryRich})$ with $\text{Log}(95^{\text{th}}\text{PercentileIncome})$. Once we estimate these demand systems, the second step is to test how well each vector of estimated coefficients β^k lines up with the income elasticity and visibility measures presented above.

Appendix Table 5 reports the first step estimated β^k across the specifications; in particular, column 4 reports the estimates on $\text{Log}(80^{\text{th}}\text{PercentileIncome})$, column 5 on $\text{Log}(90^{\text{th}}\text{PercentileIncome})$, column 8 on $\text{Log}(\text{ConsumptionofRich})$ and column 9 on $\text{Log}(\text{Consumption ofVeryRich})$, with bolded coefficients being statistically significant at least at the 10 percent level. Finally, in columns 6, 7, 10 and 11, we scale the estimated coefficients by the mean budget share from column 3, to provide a better sense

of magnitude. Column 3 of the table reports these mean budget shares among non-rich households in our sample for each of the 29 consumption categories.

Some intuition emerges from the first stage results on categories in Appendix Table 5. We find a large positive estimate for the shelter share across all four specifications. For example, the estimate in column 6 is consistent with the interpretation that a 10% increase in $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ increases the shelter budget share by about a 5 percent (column 6). While scoring quite high on the visibility index (.5), the income elasticity of shelter consumption is only moderate (.32). Other categories for which we estimate large percent increase in budget shares (in at least some of the specifications) include “food away from home”, “salons, fitness and clubs,” and “clothing,” all of which score high on both the visibility index and in terms of income elasticity.

A more systematic investigation of the relationship between the budget share responses and the income elasticity or visibility of the categories is presented in Table 7. The dependent variables are the estimated budget share sensitivities to top income and rich consumption, scaled by mean budget shares (e.g. the coefficients from columns 6, 7, 10, and 11 in Appendix Table A5). The even columns exclude the shelter category. In each regression, we weight the category by the inverse of the square of the standard error of the coefficient estimate.

The results in Table 7 are very consistent across specifications. All the estimated coefficients on income elasticity and visibility are positive and statistically significant. In other words, we find more positive changes in budget shares in response to higher top income levels (and to higher rich consumption) for those goods and services that are more income elastic, as well as for those that are more visible. While not a direct proof of the validity of a causal interpretation of the patterns we report in Tables 1 and 2, the patterns in Table 7 are consistent with the two possible causal pathways we had conjectured for the non-rich consumption behavior in Tables 1 and 2: status-seeking (or status-maintaining) consumption, and supply-driven consumption induced by exposure to richer co-residents.

VI. Use and Supply of Credit

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 middle-income 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. (2010) 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 2009.¹⁴ 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.¹⁵ We are interested in whether higher top income levels in a state are predictive of a higher rate of 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 $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ (or $\text{Log}(90^{\text{th}}\text{PercentileIncome})$) as our independent variable of interest.¹⁶ The results of this analysis are

¹⁴ This data can be found at www.abiworld.org, by clicking on the link "online resources" and then "bankruptcy statistics."

¹⁵ 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.

¹⁶ Since $\text{Log}(80/90^{\text{th}}\text{PercentileIncome})$ is based on averaging between year t and t-2, two-year lagged $\text{Log}(80/90^{\text{th}}\text{PercentileIncome})$ is based on averaging between year t-2 and t-4.

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.¹⁷

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 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 $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ 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 $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ in a state. The estimated coefficient on $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ is the same as in column 5 (1). Finally, in column 11, we further control for two-year lagged $\text{Log}(50^{\text{th}}\text{PercentileIncome})$ and $\text{Log}(20^{\text{th}}\text{PercentileIncome})$. While statistical significance drops below the 5 percent level ($p=.07$), the point estimate on our main variable of interest remains unchanged.

¹⁷ 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.

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 A3). 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):

$$\begin{aligned} \text{Financial Worse Off Today}_{ist} = & \text{Log}(80\text{thPercentileIncome})_{st} + \text{IndividualControls}_{ist} \quad (5) \\ & + \text{Household Income Dummies} + \text{State}_s + \text{Year}_t + \varepsilon_{ist} \end{aligned}$$

Besides 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, interest or debt payments today than a year ago.¹⁸ About 7 percent of respondents indicate higher expenses and debt payments today than a year ago (Appendix Table A3).

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-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.

¹⁸ 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.

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.¹⁹

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 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 102nd 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 80th, 50th and 10th percentile of the distribution for each congressional

¹⁹ 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."

district. We define income inequality within a congressional district as the difference between $\log(\text{family income})$ at the 80th (or 90th) percentile and $\log(\text{family income})$ 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 90th and 50th 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 50th and 20th percentile), and log (population) in the congressional district. The point estimate on the gap between the 80th and 50th 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 $\text{Log}(\text{Consumption})$ under the assumption that $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ or $\text{Log}(90^{\text{th}}\text{PercentileIncome})$ had grown at the same rate as $\text{Log}(50^{\text{th}}\text{PercentileIncome})$. We perform the calculation of these counterfactual growth rates using the change in average $\text{Log}(50^{\text{th}}\text{PercentileIncome})$ by year in our CEX sample. We use the estimates from Table 1 of the sensitivity of $\text{Log}(\text{Consumption})$ for non-rich households to either $\text{Log}(80^{\text{th}}\text{PercentileIncome})$ (column 1) or $\text{Log}(90^{\text{th}}\text{PercentileIncome})$ (column 2) to compute counterfactual $\text{Log}(\text{Consumption})$.

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 ($\text{Log}(80^{\text{th}}\text{PercentileIncome})$), while Panel B presents the counterfactual for column 2 of Table 1 ($\text{Log}(90^{\text{th}}\text{PercentileIncome})$). We report gaps between actual and counterfactual consumption both in log points (column 1) and dollar figures (column 2).²⁰ For 1990, we estimate that $\text{Log}(\text{Consumption})$ by non-rich households would have been between .8 (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 2.6 and 3.1 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 \$1732 and \$2068 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 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.²¹ 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

²⁰ 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.

²¹ 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.

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 4.9 (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 middle-income 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 A1), this is roughly equivalent to a .21 percent increase in consumption for median-income household for every 1 percent 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 project was whether the rise in income inequality and the decline in the personal savings rate over the last 3 decades were related phenomena. We proposed to 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 appear to spend a higher share of that income. We considered a series of non-causal explanations for this finding and found little support for them in the data. Instead, we showed evidence consistent with two possible causal pathways: status-seeking (or status-maintaining) consumption, and supply-driven consumption induced by exposure to richer co-residents.

In future work, it would be worthwhile to follow through with the supply-driven demand explanation. In particular, we would like to complement this study with evidence from marketing databases to assess how the composition of stores (as well as what is supplied in those stores), and the composition of advertising, relate to top income levels in a market.

Our analysis of personal bankruptcies, self-reported financial duress, and voting patterns on federal policies to expand credit supply suggest that the use of credit might have been particularly large for households living in proximity to richer co-residents, corroborating the causal pathways we propose. If some of this credit translated in bad credit, rising income inequality might have been a contributing factor in the recent financial crisis.

References

- Aguiar, Mark and Mark Bilts, 2012. "Has Consumption Inequality Mirrored Income Inequality." NBER WP #16807.
- Attanasio, Orazio P., Laura Blow, Robert Hamilton, and Andrew Leicester, 2009. "Booms and Busts: Consumption, House Prices and Expectations." *Economica*, Vol. 76(301), pp: 20-50.
- Attanasio, Orazio, Erik Hurst and Luigi Pistaferri, 2013. "The Evolution of Income, Consumption, and Leisure Inequality in the US, 1980-2010." NBER Chapters, in: Improving the Measurement of Consumer Expenditures. Cambridge, MA: National Bureau of Economic Research, Inc.
- Autor, David, Lawrence Katz, and Melissa S. Kearney, 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*, Vol. 90(2), pp: 300–23.
- Campbell, John Y., and João F. Cocco, 2007. "How Do House Prices Affect Consumption? Evidence from Micro Data." *Journal of Monetary Economics*, Vol. 54(3), pp: 591-621.
- Carroll, Christopher D., 1992. "The Buffer Stock Theory of Saving: Some Macroeconomic Evidence." *Brookings Papers on Economic Activity*, 1992(2), pp: 61-156.
- Carroll, Christopher D., Misuzu Otsuka, and Jiri Slacalek, 2011. "How Large Are Housing and Financial Wealth Effects? A New Approach." *Journal of Money, Credit, and Banking*, Vol. 43(1), pp: 55–79.
- Case, Karl E., John M. Quigley, and Robert J. Shiller, 2005. "Comparing Wealth Effects: The Stock Market versus the Housing Market." *Advances in Macroeconomics*, Vol. 5(1), pp: 1-32.
- Charles, Kerwin, Erik Hurst, and Nick Roussanov, 2009. "Conspicuous Consumption and Race." *Quarterly Journal of Economics*, Vol. 124(2), pp: 42-67.
- Chetty, Raj and Adam Szeidl, 2007. "Consumption Commitments and Risk Preferences." *Quarterly Journal of Economics*, Vol. 122(2), pp: 831-877.

Cutler, David M. and Lawrence F. Katz, 1991. "Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980s." *American Economic Review*, Vol. 82, pp: 546–551.

Diamond, Rebecca, 2013. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000." Working Paper.

Duesenberry, James S., 1949. Income, Saving, and the Theory of Consumer Behavior. Harvard University Press: Cambridge, MA.

Dynan, Karen E. and Donald L. Kohn, 2007. "The Rise in U.S. Household Indebtedness: Causes and Consequences," in Christopher Kent and Jeremy Lawson, eds., The Structure and Resilience of the Financial System. Reserve Bank of Australia: Sydney, Australia.

Fay, Scott, Erik Hurst, Michelle J. White, 2002. "The Household Bankruptcy Decision." *American Economic Review*, Vol. 92(3), pp: 706-718.

Frank, Robert H., Adam Seth Levine and Oege Dijk, 2010. "Expenditure Cascades." Working Paper.

Friedman, Milton, 1957. A Theory of the Consumption Function. Princeton University Press: Princeton, NJ.

Garner, Thesia I. , George Janini, William Passero, Laura Paszkiewicz, and Mark Vendemia, 2006. "The CE and the PCE: a comparison." *Monthly Labor Review*, September Volume, pp: 20-46.

Goldin Claudia, and Lawrence F. Katz, 2007. "Long-Run Changes in the U.S. Wage Structure: Narrowing, Widening, Polarizing." *Brookings Papers on Economic Activity*. Vol. 2007(2), pp: 135-165.

Handbury, Jessie, 2012. "Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities." Working Paper.

Handbury, Jessie and David E. Weinstein, 2012. "Is New Economic Geography Right? Evidence from Price Data." Working Paper.

Harris, Ed and John Sabelhaus, 2000. "Consumer Expenditure Survey Family-Level Extracts, 1980:1–1998:2." NBER website. (www.nber.org/data/ces_cbo.html)

Heffetz, Ori, 2011. "A Test of Conspicuous Consumption: Visibility and Income Elasticities." *Review of Economics and Statistics*, Vol. 93(4), pp: 1101–1117.

Hurst, Erik and Frank Stafford, 2004. "Home is Where the Equity Is: Liquidity Constraints, Refinancing and Consumption." *Journal of Money, Credit and Banking*, Vol. 36(6), pp: 985 - 1014.

Krueger, Dirk and Fabrizio Perri, 2006. "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory." *Review of Economic Studies*, Vol. 73(1), pp: 163–193.

Luttmer, Erzo F. P., 2005. "Neighbors as Negatives: Relative Earnings and Well-Being." *Quarterly Journal of Economics*, Vol. 120(3), pp: 963–1002.

Maki, Dean M. and Michael G. Palumbo, 2001. "Disentangling the Wealth Effect: A Cohort Analysis of Household Saving in the 1990s." Federal Reserve Board FEDS Paper, #2001-21.

Matlack, Janna L. and Jacob L. Vigdor. 2008. "Do rising tides lift all prices? Income Inequality and Housing Affordability." *Journal of Housing Economics*, Vol. 17(3), pp: 212-224.

Meyer, Bruce D. and James X. Sullivan, 2010. "Five Decades of Consumption and Income." NBER Working Paper # 14827.

Mian, Atif and Amir Sufi, 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis." *Quarterly Journal of Economics*, Vol. 124(4), pp: 1449-1496.

Mian, Atif and Amir Sufi, 2011. "House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis." *American Economic Review*, Vol. 101(5), pp: 2132-2156.

Moffitt, Robert A., and Peter Gottschalk, 2002. "Trends in the Transitory Variance of Earnings in the United States." *Economic Journal*, Vol. 112, pp: C68–C73.

Moretti, Enrico, 2012. The New Geography of Jobs. Houghton Mifflin Harcourt Publishing: New York, NY.

Piketty, Thomas and Emmanuel Saez, 2003. "Income Inequality in the United States: 1913-1998." *Quarterly Journal of Economics*, Vol. 118 (1), pp: 1-39.

Rajan, Raghuram, 2010. Fault Lines: How Hidden Fractures Still Threaten the World Economy. Princeton University Press: Princeton, NJ.

Saiz, Albert, 2010. "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics*, Vol. 125(3), pp: 1253-1296.

Veblen, Thorstein, 1899. The Theory of the Leisure Class: an Economic Study of Institutions. Reprinted 1994, Penguin Books: New York, NY.

White, Michelle J., 2007. "Bankruptcy Reform and Credit Cards." *Journal of Economic Perspectives*, Vol. 21(4), pp: 175-99.

Table 1: Top Income Levels and Non-Rich Consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:							
<i>Dependent Variable:</i>							
<i>Log(Consumption)</i>							
Sample:		All Non-Rich			Non-Rich	All Non-Rich	Rich
Definition: household income x:		x < 80th %ile			x < 60th %ile	x < 80th %ile	x > 80th %ile
Log(80thPercentileIncome)	0.265 [0.114]*		0.343 [0.135]*	0.342 [0.136]*	0.355 [0.149]*	0.331 [0.149]*	
Log(90thPercentileIncome)		0.209 [0.092]*					
Log(50thPercentileIncome)						0.000 [0.132]	0.136 [0.151]
Log(20thPercentileIncome)						0.012 [0.095]	-0.062 [0.108]
Unemployment Rate				-0.073 [0.265]	-0.119 [0.265]	-0.062 [0.241]	-0.602 [0.372]
State and Year F.E.s	Yes						
State-specific time trends	No	No	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes						
Household controls	Yes						
Observations	77531	77531	77531	77531	58401	77531	20775
R-squared	0.59	0.59	0.59	0.59	0.53	0.59	0.38
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B:							
<i>Dependent Variable:</i>							
<i>Ratio of Consumption to Income</i>							
Sample in CEX:		All Non-Rich			Non-Rich	All Non-Rich	Rich
Definition: household income x:		x < 80th %ile			x < 60th %ile	x < 80th %ile	x > 80th %ile
Log(80thPercentileIncome)	0.366 [0.168]*		0.469 [0.214]*	0.469 [0.214]*	0.468 [0.215]*	0.514 [0.227]*	
Log(90thPercentileIncome)		0.294 [0.131]*					
Log(50thPercentileIncome)						-0.114 [0.174]	0.105 [0.083]
Log(20thPercentileIncome)						0.065 [0.134]	-0.04 [0.066]
Unemployment rate				-0.023 [0.337]	-0.026 [0.382]	0.006 [0.291]	-0.38 [0.217]
State and Year F.E.s	Yes						
State-specific time trends	No	No	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes						
Household controls	Yes						
Observations	77531	77531	77531	77531	58401	77531	20775
R-squared	0.55	0.55	0.55	0.55	0.53	0.55	0.19

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. In columns 1-4 and 6, the sample includes all households whose income is below the 80th percentile in the state-year cell. In column 7, the sample is restricted to household whose income is above the 80th percentile in the state-year cell. In column 5, the sample is restricted to households whose income is below the 60th percentile in the state-year cell. 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(80/90/50/20th 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%.

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)
<i>Dependent Variable:</i>	<i>Log (Consumption of Rich)</i>	<i>Log (Consumption)</i>	<i>Ratio of Consumption to Income</i>	<i>Log (Consumption of Very Rich)</i>	<i>Log (Consumption)</i>	<i>Ratio of Consumption to Income</i>
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 [0.111]			0.674 [0.183]**		
Log(ConsumptionofRich)		0.435 [0.134]**	0.611 [0.219]**			
Log(ConsumptionofVeryRich)					0.304 [0.135]*	0.437 [0.209]*
Unemployment Rate	-0.299 [0.297]	-0.001 [0.173]	0.083 [0.231]	0.077 [0.309]	-0.033 [0.214]	0.039 [0.272]
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	77531	77531	77531	77424	77424	77424
R-squared	0.86	0.594	0.567	0.84	0.593	0.567
First Stage F-Statistic	37.33			13.62		
OLS Coefficient		0.189 [0.054]**	0.257 [0.088]**		0.071 [0.030]*	0.092 [0.047]

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. The sample is all households whose real household income is below the 80th percentile in the state-year cell. Log(Consumption) is the logarithm of total consumption for a given household in a given state and year. Log(ConsumptionofRich) is the logarithm of average consumption among rich (e.g. above 80th percentile) 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) households in a given state in the current year and prior two years. Log(80/95th PercentileIncome) is the logarithm of the average of the 80/95th 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 is the state unemployment rate in the current year. Each observation is weighted by the household weight provided in the CEX Surveys. All numbered columns report second-stage results. The columns before columns 1-2 and before columns 3-4 report the first stage regression for the subsequent two columns. The last two rows report OLS estimates [standard errors] on Log(ConsumptionofRich) (columns 1 and 2) and Log(ConsumptionofVeryRich) (columns 3 and 4). 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)
<i>Dependent Variable:</i>	<i>Log(HH income) in t+1</i>			<i>Log(HH income) in t+2</i>			<i>Log(HH income) in t+4</i>		<i>Log (average HH income) between t+1 and t+2</i>		<i>Log (average HH income) between t+1 and t+4</i>		<i>S.D. of Log(HH income) between t+1 and t+4</i>	
Log(HH income)	0.689 [0.007]**	0.689 [0.007]**	0.17 [0.015]**	0.625 [0.008]**	0.625 [0.008]**	0.073 [0.015]**	0.547 [0.009]**	0.547 [0.009]**	0.636 [0.007]**	0.636 [0.007]**	0.585 [0.007]**	0.585 [0.007]**	-0.102 [0.006]**	-0.102 [0.006]**
Log(80thPercentileIncome)	0.019 [0.096]	0.121 [0.159]	0.012 [0.213]	-0.116 [0.083]	0.021 [0.147]	0.016 [0.176]	-0.210 [0.122]	-0.095 [0.126]	-0.017 [0.080]	0.041 [0.139]	-0.056 [0.084]	0.027 [0.114]	0.161 [0.042]**	0.112 [0.086]
Log(50thPercentileIncome)		-0.047 [0.250]	0.223 [0.293]		-0.066 [0.186]	0.126 [0.246]		-0.095 [0.181]		-0.009 [0.185]		-0.048 [0.154]		0.051 [0.106]
Log(20thPercentileIncome)		-0.068 [0.094]	-0.023 [0.114]		-0.089 [0.087]	-0.082 [0.109]		-0.03 [0.098]		-0.06 [0.073]		-0.042 [0.069]		-0.003 [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)
<i>Dependent Variable:</i>	<i>Log(HH income) in t+1</i>			<i>Log(HH income) in t+2</i>			<i>Log(HH income) in t+4</i>		<i>Log (average HH income) between t+1 and t+2</i>		<i>Log (average HH income) between t+1 and t+4</i>		<i>S.D. of Log(HH income) between t+1 and t+4</i>	
Log (HH income)	0.689 [0.007]**	0.689 [0.007]**	0.17 [0.015]**	0.625 [0.008]**	0.625 [0.008]**	0.073 [0.015]**	0.546 [0.009]**	0.547 [0.009]**	0.636 [0.007]**	0.636 [0.007]**	0.585 [0.007]**	0.585 [0.007]**	-0.102 [0.006]**	-0.102 [0.006]**
Log(90thPercentileIncome)	0.014 [0.095]	0.053 [0.126]	0.022 [0.167]	-0.116 [0.084]	-0.042 [0.126]	-0.027 [0.178]	-0.25 [0.132]	-0.217 [0.147]	-0.029 [0.082]	-0.024 [0.107]	-0.069 [0.086]	-0.045 [0.094]	0.139 [0.046]**	0.065 [0.074]
Log(50thPercentileIncome)		0.008 [0.214]	0.214 [0.269]		-0.01 [0.173]	0.163 [0.258]		0.006 [0.176]		0.049 [0.153]		0.014 [0.129]		0.093 [0.090]
Log(20thPercentileIncome)		-0.071 [0.096]	-0.021 [0.119]		-0.102 [0.091]	-0.089 [0.116]		-0.061 [0.098]		-0.072 [0.073]		-0.055 [0.068]		-0.005 [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. See text for details. 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)
<i>Dependent Variable:</i>	<i>Expect Real Income to Go Up in the Next Year (Y=1)</i>			
<i>Sample:</i>	All Non-Rich			
Log(80thPercentileIncome)	-0.054 [0.029]	-0.091 [0.056]		
Log(90thPercentileIncome)			-0.055 [0.030]	-0.071 [0.045]
Log(50thPercentileIncome)		0.025 [0.071]		0.008 [0.065]
Log(20thPercentileIncome)		0.017 [0.038]		0.017 [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)
<i>Dependent Variable:</i>	<i>Expected Percent Change in Household Income in the Next Year</i>			
<i>Sample:</i>	All Non-Rich			
Log(80thPercentileIncome)	-3.015 [1.637]	-2.821 [2.670]		
Log(90thPercentileIncome)			-1.913 [1.609]	-0.589 [2.003]
Log(50thPercentileIncome)		-0.713 [2.714]		-2.44 [2.389]
Log(20thPercentileIncome)		0.547 [1.241]		0.797 [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)
<i>Dependent Variable:</i>	<i>Index of Consumer Expectations</i>			
<i>Sample:</i>	All Non-Rich			
Log(80thPercentileIncome)	-15.926 [6.891]*	-20.933 [9.158]*		
Log(90thPercentileIncome)			-20.33 [6.432]**	-25.39 [8.154]**
Log(50thPercentileIncome)		2.043 [11.004]		4.977 [10.720]
Log(20thPercentileIncome)		3.665 [5.372]		2.076 [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. See text for details. 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

<i>Dependent Variable:</i>	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Log(Consumption)</i>					
Sample:	All Non-Rich					
Log(80thPercentileIncome)	0.321 [0.149]*		0.244 [0.124]		0.389 [0.149]*	
Log(90thPercentileIncome)		0.279 [0.139]		0.170 [0.104]		0.326 [0.138]*
Log(80thPercentileIncome)*Homeowner	0.070 [0.037]					
Log(90thPercentileIncome)*Homeowner		0.055 [0.035]				
Log(80thPercentileIncome)*(Year<=1995)			0.133 [0.070]			
Log(90thPercentileIncome)*(Year<=1995)				0.154 [0.080]		
Log(80thPercentileIncome)*(Housing supply elasticity<1)					-0.280 [0.295]	
Log(90thPercentileIncome)*(Housing supply elasticity<1)						-0.269 [0.247]
Unemployment Rate	-0.065 [0.274]	-0.082 [0.279]	-0.148 [0.273]	-0.171 [0.273]	-0.035 [0.272]	-0.043 [0.269]
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	75646	75646	77531	77531	75409	75409
R-squared	0.60	0.60	0.59	0.59	0.59	0.59

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. In all regressions, the 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). 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. 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 the state unemployment rate in the current year. Also included in columns 1 and 2 is a dummy variable for whether the CEX respondent is a homeowner. 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 6: Local Price Channel

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Dependent Variable:</i>	<i>Log(Local CPI)</i>		<i>Log(Consumption)</i>			
<i>Sample:</i>	State-year panel		All Non-Rich			
<i>Estimation</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>IV</i>	<i>IV</i>
Log(80thPercentileIncome)	0.539 [0.108]**		0.333 [0.159]*			
Log(90thPercentileIncome)		0.312 [0.089]**		0.282 [0.138]		
Log(50thPercentileIncome)	-0.252 [0.117]*	-0.097 [0.110]				
Log(20thPercentileIncome)	0.093 [0.062]	0.081 [0.063]				
IV Log(ConsumptionofRich)					0.431 [0.146]**	
IV Log(ConsumptionofVeryRich)						0.403 [0.153]**
Log(Local CPI)			0.274 [0.171]	0.296 [0.156]	0.159 [0.116]	0.229 [0.125]
Unemployment Rate	0.077 [0.211]	0.118 [0.213]	-0.074 [0.289]	-0.089 [0.295]	-0.001 [0.198]	-0.015 [0.236]
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	No	No	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Observations	553	553	68149	68149	68149	68105
R-squared	0.95	0.95	0.60	0.60	0.60	0.59

Note: Data Source: CEX, March CPS, and BLS (Local CPI), 1980 to 2008. See text for details of sample construction. 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 6, 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). Log(Consumption) is the logarithm of total consumption for a given household in a given state and year. Log(ConsumptionofRich) is the logarithm of average consumption among rich (e.g. above 80th percentile) 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) 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. Columns 3-4 are OLS estimates; columns 5 and 6 are IV estimates (see 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: Expenditure Share Sensitivities to Top Income Levels and Rich Consumption:
Relationship to Income Elasticity and Visibility of the Expenditure Category**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Dependent Variable</i>	<i>Estimated Coefficient on Log(80thPercentileIncome) Relative to Budget Share</i>		<i>Estimated Coefficient on Log(90thPercentileIncome) Relative to Budget Share</i>		<i>IV Estimated Coefficient on Log(Rich Consumption) Relative to Budget Share</i>		<i>IV Estimated Coefficient on Log(Very Rich Consumption) Relative to Budget Share</i>	
<i>Sample</i>	All	Excluding Shelter	All	Excluding Shelter	All	Excluding Shelter	All	Excluding Shelter
Elasticity	3.635	3.634	4.308	4.306	4.039	4.038	3.390	3.390
	[1.218]**	[1.242]**	[1.361]**	[1.388]**	[1.462]*	[1.490]*	[1.423]*	[1.451]*
Visibility	2.465	2.465	2.883	2.883	2.558	2.558	2.004	2.004
	[0.714]**	[0.728]**	[0.795]**	[0.811]**	[0.899]**	[0.917]**	[0.953]*	[0.971]*
Observations	29	28	29	28	29	28	29	28
R-squared	0.63	0.63	0.66	0.66	0.51	0.51	0.39	0.39

Note: Data Source: CEX, March CPS, and BLS (for Local CPI and category-specific CPI), 1980 to 2008. The unit of observation is an expenditure category. The dependent variables in columns 1-4 are constructed based on the estimated coefficients on Log(80thPercentileIncome) and Log(90thPercentileIncome) for each expenditure category following the estimation of the demand system equation (4) in the text on sample of non-rich households (households whose real income is below the 80th percentile in their state-year cell). The dependent variables in columns 5-8 are based on an IV estimation of the demand system equation (4) where we instrument Log(ConsumptionofRich) with Log(80thPercentileIncome) and Log(95thPercentileIncome) (columns 5 and 6) and instrument Log(ConsumptionofVeryRich) with Log(95thPercentileIncome) (columns 7 and 8). The estimated coefficients for each expenditure category are reported in Appendix Table A4. In all regressions, each observation is weighted by the inverse of the square of the standard error of the estimated coefficient. Income elasticity and visibility index (from Heffetz 2011) for each expenditure category are reported in Appendix Table A5. * significant at 5%; ** significant at 1%.

Table 8: Personal Bankruptcy Filings and Top Income Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Dependent Variable:</i>	<i>Log (Number of Personal Bankruptcy Filings/Population)</i>										
<i>Sample:</i>	All years				1980, 1985, 1990, 1995, 2000, 2005 and 2009				All years		
Log(80thPercentileIncome) (t-2)	1.06 [0.406]*		0.994 [0.365]**		1.018 [0.343]**		1.289 [0.474]**		0.896 [0.261]**	1.024 [0.347]**	1.167 [0.639]
Log(90thPercentileIncome) (t-2)		1.321 [0.355]**		0.917 [0.379]*		0.839 [0.395]*		1.144 [0.485]*			
Log unemployment rate (t)				0.176 [0.048]**	0.183 [0.050]**	0.164 [0.088]	0.168 [0.090]	0.217 [0.047]**	0.171 [0.049]**	0.171 [0.049]**	0.171 [0.049]**
Log(80thPercentileIncome) (t)				-0.209 [0.286]	-0.181 [0.300]	0.051 [0.535]	0.054 [0.535]	-0.414 [0.258]	-0.109 [0.320]	-0.045 [0.298]	-0.045 [0.298]
Log(50thPercentileIncome) (t)				-0.426 [0.381]	-0.398 [0.380]	-0.82 [0.621]	-0.735 [0.613]	-0.14 [0.265]	-0.573 [0.415]	-0.605 [0.415]	-0.605 [0.415]
Log(20thPercentileIncome) (t)				-0.145 [0.238]	-0.126 [0.235]	0.052 [0.337]	0.047 [0.333]	-0.361 [0.131]**	-0.169 [0.228]	-0.218 [0.204]	-0.218 [0.204]
Log(50thPercentileIncome) (t-2)											-0.621 [0.858]
Log(20thPercentileIncome) (t-2)											0.514 [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 80thP	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. The dependent variable is the logarithm of the number of bankruptcy filings per capita. 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. 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)
<i>Dependent Variable:</i>		<i>Worse Off Financial than a Year Ago (Y=1)</i>		
	All Non-Rich			
Sample:				
Log(80thPercentileIncome)	0.228 [0.065]**	0.226 [0.090]*		
Log(90thPercentileIncome)			0.25 [0.059]**	0.244 [0.076]**
Log(50thPercentileIncome)		0.058 [0.103]		0.049 [0.100]
Log(20thPercentileIncome)		-0.061 [0.056]		-0.049 [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)
<i>Dependent Variable:</i>		<i>More Expenses/More Debt, Int. and Debt Payments than a Year Ago (Y=1)</i>		
	All Non-Rich			
Sample:				
Log(80thPercentileIncome)	0.031 [0.026]	0.026 [0.035]		
Log(90thPercentileIncome)			0.043 [0.022]	0.048 [0.027]
Log(50thPercentileIncome)		0.006 [0.038]		-0.01 [0.035]
Log(20thPercentileIncome)		-0.001 [0.023]		0.004 [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. See text for details. 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

	<i>Dependent Variable: Yes Vote</i>				
	(1)	(2)	(3)	(4)	(5)
Log(80thPercentileIncome)-Log(50thPercentileIncome)	1.077		1.053	1	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.

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 information. 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 3 of Table 2, 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	-0.008	-516.5	276.7	29.8	0.065	0.072
2000	-0.022	-1,336.1	213.1	116.5	0.029	0.045
2005	-0.026	-1,731.9	143.2	180.4	0.015	0.035
2008	-0.027	-1,868.3	592.3	221.1	0.054	0.074
Panel B:	Counterfactual Analysis for Column 4 of Table 2, 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	-665.9	276.7	38.4	0.065	0.074
2000	-0.028	-1,688.8	213.1	147.3	0.029	0.049
2005	-0.031	-2,067.9	143.2	215.5	0.015	0.039
2008	-0.032	-2,190.0	592.3	259.2	0.054	0.077

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. See text for details. Figures in column (2) are in real dollars. Figures in columns (3) and (4) are in billions of nominal dollars.

Appendix Table A1: Summary Statistics - CEX Sample, 1980 to 2008

Panel A: All Years

Variable:	N	Mean	Std. Dev.
Household income	77531	31,706	18,959
Age of head of household	77531	49.58	18.19
Head of household is male	77531	0.54	0.50
Head of households is white	77531	0.83	0.38
Head of household has bachelor or graduate degree	77531	0.20	0.40
Number of children in HH	77531	0.67	1.11
Number of adults in HH	77531	1.82	0.83
Log(Consumption)	77531	10.15	0.54
Log(ConsumptionofRich)	77531	11.00	0.14
Log(ConsumptionofVeryRich)	77531	11.15	0.16
Log(80thPercentileIncome)	77531	11.16	0.12
Log(90thPercentileIncome)	77531	11.44	0.13
Log(95thPercentileIncome)	77531	11.68	0.14
Log(50thPercentileIncome)	77531	10.52	0.12
Log(20thPercentileIncome)	77531	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 cell. See text for details of sample construction. Income and consumption measures are reported in real terms (1999=100). Log(Consumption) is the logarithm of total consumption for a given household in a given state and year. Log(ConsumptionofMedian) is the logarithm of average consumption among 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) 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) 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 A2: 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 households 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) in Table 5, e.g. the 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 A3: Summary Statistics - Michigan Surveys of Consumers, 1980 to 2008

Variable:	N	Mean	Std. Dev.
Household income	126706	32183.01	17896.52
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. 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 A4: Top Income Levels on Non-Rich Consumption:
Robustness to Alternative Definition of Shelter Consumption**

	(1)	(2)	(3)	(4)
Panel A:				
		<i>Log(Consumption)</i>	<i>Log(Consumption Minus Shelter)</i>	
<i>Dependent Variable:</i>				
<i>Shelter Defined as:</i>		<i>Rental Equivalence</i>	<i>Shelter Excluded</i>	
<i>Sample:</i>		<i>All Non-Rich</i>		
Log(80thPercentileIncome)	0.420 [0.133]**	0.382 [0.160]*	0.235 [0.127]	0.287 [0.146]
Log(50thPercentileIncome)		0.026 [0.127]		-0.054 [0.108]
Log(20thPercentileIncome)		0.014 [0.103]		-0.001 [0.086]
Unemployment Rate	-0.31 [0.285]	-0.286 [0.260]	-0.160 [0.264]	-0.179 [0.250]
State and Year F.E.s	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes
Household Income F.E.s	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	75486	75486	77530	77530
R-squared	0.58	0.58	0.56	0.56
Panel B:	(1)	(2)	(3)	(4)
		<i>Ratio of Consumption to Income</i>	<i>Ratio of (Consumption Minus Shelter) to Income</i>	
<i>Dependent Variable</i>				
<i>Shelter Defined as:</i>		<i>Rental Equivalence</i>	<i>Shelter Excluded</i>	
<i>Sample:</i>		<i>All Non-Rich</i>		
Log(80thPercentileIncome)	0.565 [0.214]*	0.560 [0.250]*	0.387 [0.170]*	0.387 [0.170]*
Log(50thPercentileIncome)		-0.051 [0.192]		-0.148 [0.124]
Log(20thPercentileIncome)		0.056 [0.160]		0.046 [0.096]
Unemployment Rate	-0.606 [0.406]	-0.565 [0.372]	-0.148 [0.251]	-0.148 [0.251]
State and Year F.E.s	Yes	Yes	Yes	Yes
State-specific time trend	Yes	Yes	Yes	Yes
Household Income F.E.s	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	75486	75486	77531	77531
R-squared	0.54	0.54	0.51	0.51

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. 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). Log(Consumption) is the logarithm of total consumption for a given household in a given state and year. 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 A5: Top Income Levels, Rich Consumption and Non-Rich Expenditure Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
	Estimated Coefficient on:				Estimated Coefficient Relative to				Estimated Coefficient Relative to			
	Income				Budget Share on:				IV		IV	
Consumption Category:	Elasticity	Visibility Index	Budget Share	Log(80thPctile Income)	Log(90thPctile Income)	Log(80thPctile Income)	Log(90thPctile Income)	Log(Consumption Rich)	Log(Consumption VeryRich)	Log(Consumption Rich)	Log(Consumption VeryRich)	
Food Away from Home	0.427	0.620	0.046	0.025***	0.027***	0.51	0.55	0.035**	0.036**	0.76	0.78	
Food at Home	0.115	0.510	0.268	0.012	0.011	0.05	0.05	0.004	-0.003	0.01	-0.01	
Tobacco Products	0.060	0.760	0.012	-0.002	-0.002	-0.19	-0.19	-0.003	-0.003	-0.26	-0.26	
Alcohol Away from Home	0.323	0.600	0.004	-0.001	0.000	-0.22	0.00	0.000	0.001	0.00	0.24	
Alcohol at Home	0.174	0.610	0.005	-0.001	0.000	-0.18	0.00	-0.002	-0.002	-0.37	-0.37	
Clothing	0.426	0.710	0.030	0.007	0.008	0.22	0.26	0.009	0.010***	0.30	0.33	
Jewelry	0.464	0.670	0.003	0.001	0.001	0.32	0.32	0.002	0.002	0.73	0.73	
Salons, Fitness Clubs	0.323	0.600	0.009	0.006**	0.005*	0.71	0.59	0.006*	0.006	0.70	0.70	
Furniture	0.477	0.680	0.016	0.000	0.001	0.00	0.06	0.004	0.007	0.26	0.45	
Health Insurance	0.128	0.260	0.032	-0.009	-0.013	-0.31	-0.44	-0.012	-0.012	-0.38	-0.38	
Business Services	0.278	0.260	0.009	-0.007***	-0.003	-0.76	-0.33	-0.006**	-0.003	-0.70	-0.35	
Recreation and Sports Eq.	0.423	0.660	0.014	-0.006	-0.005	-0.37	-0.31	-0.008*	-0.008	-0.56	-0.56	
Other Recreation Services	0.427	0.580	0.026	-0.004	0.002	-0.15	0.07	-0.001	0.002	-0.04	0.08	
Charity	0.293	0.340	0.005	0.004	0.003	0.25	0.19	0.006	0.007	1.20	1.40	
Interest Paid (non-durables)	0.178	0.260	0.002	-0.004***	-0.005***	-1.73	-2.17	-0.005***	-0.005**	-2.32	-2.32	
Home Improvement	0.447	0.500	0.009	0.006	0.001	0.61	0.10	0.000	-0.004	0.00	-0.46	
Recre. Vehicles & Homes	0.201	0.660	0.004	-0.004	-0.005	-1.03	-1.28	0.001	0.004	0.27	1.09	
Appliances	0.215	0.680	0.005	-0.005*	-0.005**	-0.94	-0.94	-0.007**	-0.007*	-1.35	-1.35	
Utilities	0.156	0.310	0.061	-0.032**	-0.026*	-0.56	-0.46	-0.039**	-0.035**	-0.64	-0.57	
Health	0.249	0.360	0.031	0.005	0.002	0.17	0.07	0.006	0.006	0.19	0.19	
Media	0.331	0.570	0.011	0.000	-0.001	0.00	-0.09	0.000	0.001	0.00	0.09	
Gas, Tolls, Mass Transit	0.250	0.390	0.045	-0.019**	-0.016**	-0.40	-0.34	-0.016*	-0.010	-0.36	-0.22	
Travel	0.305	0.460	0.007	0.000	0.002	0.00	0.27	0.002	0.004*	0.29	0.57	
Education	0.381	0.560	0.010	-0.007	-0.013*	-0.61	-1.14	-0.013	-0.015	-1.28	-1.47	
Cars	0.388	0.730	0.086	-0.047**	-0.041***	-0.42	-0.36	-0.050***	-0.041**	-0.58	-0.48	
Domestic Services	0.412	0.340	0.013	-0.010**	-0.008***	-0.80	-0.64	-0.010**	-0.007*	-0.79	-0.55	
Home Maintenance	0.274	0.310	0.019	0.008	0.003	0.42	0.16	0.010	0.009	0.53	0.48	
Shelter	0.318	0.500	0.191	0.085**	0.077**	0.46	0.42	0.084**	0.065*	0.44	0.34	
Phones	0.202	0.470	0.028	0.000	0.001	0.00	0.04	-0.001	-0.002	-0.04	-0.07	

Note: "Income Elasticity" (column 1) is 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. "Visibility Index" (column 2) is the scoring of Heffetz (2011) from a phone survey to measure of how noticeable expenditure items of one's contemporaries are. "Budget Share" (column 3) reports mean budget shares for each expenditure category in the sample of non-rich households (where each household is weighted using the CEX weight). Estimated coefficients refer to the estimated betas from the demand system in equation (4). See text for details. Estimated coefficients that are statistically significant at least at the 10 % level are reported in bold.