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ABSTRACT

Have rising income and consumption at the top of income distribution since the early 1980s induced households in the lower tiers of the distribution to consume a larger share of their income? Using state-year variation in income level and consumption in the top first quintile or decile of the income distribution, we find evidence for such "trickle-down consumption." The magnitude of effect suggests that middle income households would have saved between 2.6 and 3.2 percent more by the mid-2000s had incomes at the top grown at the same rate as median income. Additional tests argue against permanent income, upwardly-biased expectations of future income, home equity effects and upward price pressures as the sole explanations for this finding. Instead, we show that middle income households' consumption of more income elastic and more visible goods and services appear particularly responsive to top income levels, consistent with supply-driven demand and status-driven explanations for our primary finding. Non-rich households exposed to higher top income levels self-report more financial duress; moreover, higher top income levels are predictive of more personal bankruptcy filings. Finally, focusing on housing credit legislation, we suggest that the political process may have internalized and facilitated such trickle-down.

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I. Introduction

Since the early 1980s, real incomes in the lower and middle parts of the U.S. income distribution have risen much more slowly than those in the upper part of the distribution (see Goldin and Katz (2007), Autor, 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 (see Appendix Table A1). 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 the growing local inequality in the United States has been systematically associated with a change in observed 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 state-year level income distribution data from the March Current Population Surveys (CPS). Exploiting within state and year variation in the income and consumption of households in the upper part (top quintile or top decile) of the income distribution, we show that middle income households consume a larger share of their current income when exposed to higher upper income and consumption.[1] This association is robust and economically meaningful. A 10 percent rise in the 90th (80th) percentile of the income distribution within a state increases consumption among middle income households within that state by 2.2 (2.8) percent, *holding those middle income households' own income constant.*

In a second step, we investigate both traditional and more behavioral explanations for this primary finding. The first traditional explanation we consider is Friedman (1957)'s permanent income hypothesis. Specifically, we consider the possibility that rising upper income (and consumption) in a given state-year is 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 disposable income today in those state-years where the rich are richer because they rationally expect their future income to rise. Using the Panel Study of Income Dynamics (PSID), we fail to find support

[1] We define middle income household as households whose income between the 20th and 80th percentile of the income distribution in their state-year cell.

for this explanation. Holding own current household income constant, rising top income levels in a state do not predict higher future income for non-rich households.

In the PSID, we also find no 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 preliminary finding. The housing boom that characterized the second half, and particularly last third, of the period under study may have encouraged households with growing net wealth to save less out of current disposable 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 for our primary finding, 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, even though the effect appears somewhat larger for home owners. Moreover, our primary finding holds in two subsamples of the data that were not or 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).

Having failed to find much support for those traditional explanations, we then turn to more behavioral explanations. First, while we do not see that rising top income levels in a state are predictive of faster future income growth for middle income households in that state, it is possible that middle income households have unduly optimistic expectations about their future income growth when they see some of their co-residents getting richer. To test for this possibility, we use micro data from the University of Michigan's Surveys of Consumers. We fail to find any evidence that non-rich households' expectations about future income are positively affected by increases in the income of the upper decile or upper quintile in their state.

If middle income 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), they may end up spending more out of their disposable income if the local prices of the goods and services they are "committed to" go up. If rising top income levels in a state are associated with rising local prices, such stickiness in middle income households' consumption portfolio may lead to higher spending out of current disposable income. We do 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 qualitatively affect the primary relationship we had uncovered between middle-income households' consumption and top income levels.

We then consider two remaining behavioral explanations for our primary finding. First is the possibility that higher top income levels in a market increases 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" good happens without fully scaling back on the consumption of other goods. A second possibility is that social comparisons (Veblen (1899), Duesenberry (1949)) may explain part of primary finding. While this 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 permanent 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 middle-income households. We test for these 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, even though the patterns appear more robust for the "supply-driven demand" channel than for the "conspicuous consumption" channel.

To get a better sense of the magnitude of the effects, we perform a simple counterfactual exercise. We ask by how much would have middle income households' consumption-out-of-current-income gone down, and hence middle income households' saving rate gone up, had the income levels at the top grown at the same rate as income levels at the median of the distribution since the beginning of our sample period. We estimate that, by 2005, middle income household would have consumed between 2.6 and 3.2 percent less had income levels at the top grown at the same rate as income levels at the median since the beginning of the sample period; this corresponds to between \$1271 and \$1571 less in consumption in 2005 for middle-income households. We argue that this might explain a small, but non-trivial part of the decline in the aggregate personal savings rate. 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 1.5 percent in 2005. A back-of-the envelope analysis suggests that, under the counterfactual, the aggregate personal savings rate would have between 2.6 and 2.8 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 Bils (2012) and Attanasio et. al. (2013)).

The final topic we address relates to the credit environment that may have facilitated the behavioral consumption response we have isolated. 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 middle income households may have relied on this easier credit and thus 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 the trickle-down pressures and responded to these pressures by further easing access to credit, as argued by Rajan (2010). Specifically, 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.

The rest of the paper is structured as follows. Our CEX dataset is presented is Section II. Section III reports our primary finding of a positive relationship between non-rich consumption and income or consumption in the upper part of the local income distribution. Section IV investigates traditional explanations for this primary finding, while Section V investigates more behavioral explanations. Section VI provides some counterfactual analysis and discussion of magnitude of effects. Section VII discusses the relationship between top income levels and the use and supply of credit. We conclude in Section VIII.

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 annual expenditure data of the CEX, reflecting four quarters of surveying for a given household. We exclude households who fail to complete all four surveys, except in 2008 (the end of our sample), where we annualize answers for respondents truncated two quarters because of the end date of our sample.

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 vehicle are rental equivalences of how much service flow of these items a given household decides to consume.[2] In particular, annual shelter consumption is constructed as follows. For renters, we use rent paid; for homeowners, we use the sum of mortgage payments, property taxes and home repair.[3] 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.[4]

[2] We also exclude savings deposit outflows and gifts.
[3] While others (see for example Charles, Hurst and Roussanov (2009)) have instead used the rental equivalence in the CEX or inferred rental equivalences form the CEX asset data, we do not use this approach for housing consumption as it results in many missing values, especially in the earlier years of our sample. The difference between this alternative measure and our current consumption flow measure will be largest for long-time homeowners; specifically, our method will underestimate housing consumption for those who have paid off their mortgages, primarily retirees. Our results hold if we impose an age threshold.
[4] The CEX records purchase prices of cars only if a household buys a car in that year. Like Meyer and Sullivan, we collect original purchases prices of specific makes and models using all purchases in the CEX for the same car. We then apply these values to individuals who own that car but were not surveyed in the purchase years. We fill in missing price information using blue books and dealer guides. We then compute the service flow using the guidelines from Kelley Blue Book that a depreciation

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 (2011) classifications.[5] Following Aguiar and Bils (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, as well as during the middle quarters if a household reports that changes in these demographics or income have occurred. 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 define a household's total annual income as the average of income across the quarters with non-missing income data. We drop households with zero 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.[6] While income distribution by state and year can be constructed within the CEX, we instead use the much larger March Current Population Survey (CPS). Specifically, we start from the full March CPS samples which include all households, including those without labor force participants; we place no restrictions on age of household head, armed force membership or group living but exclude households with any allocated income variables. We define a given household's income as the sum of total money income for all adult household members. Total money income in the CPS includes income from business,

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. This depreciation rate varies by car type. 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).

[5] Harris and Sabelhaus (2000) assign just over 100 classifications to the UCC codes in the CEX. Hefftez (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.

[6] 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.

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.

Since our study concerns the consumption of the non-rich, we drop from the CEX sample all households whose total income is above the 80th percentile in their state-year cell. We will use the CPS measures of income at the 80th (or 90th percentile) as one of the key dependent variables in the analysis below. We also compute average annual total consumption among households in the CEX that are above the 80th (or 90th percentile) of the income distribution in their state-year cell as an alternative dependent variable. From now on, for simplicity, we will refer to those households below the 80th percentile in their state-year cell as "non-rich" households; we will refer to households between the 20th and 80th percentile in their state-year cell as "middle income" and those below the 20th percentile as "low income." We will refer to those households above the 80th (90th) percentile as "rich" ("very rich") households.

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 samples is 49 years old. About 83 percent of the households' heads are white, 55 percent are male and 21 percent have a bachelor or graduate degree. The average household contains 1.83 adults, .67 children and has an income of $31,601.

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 and very rich, as defined above. As well 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 .23 log points over the same period. The remaining columns of Panel B show similar growth in both rich and non-rich consumption, even though at a smaller rate than income growth. As we discussed below, Aguiar and Bils (2012) show some systematic and growing overtime under-reporting of consumption in the CEX among top income households. So, it is likely that the level and growth of Log(ConsumptionofRich) and Log(ConsumptionofVeryRich) reported in Appendix Table 1 are biased downwards.

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

III.A. Empirical Methodology

Our research goal is to ask whether, *holding their income constant*, non-rich households spend more when exposed to higher consumption in the upper quintile or decile of their market. We first estimate the following OLS specification in the CEX sample of non-rich households:

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

where i indexes households, s indexes states and t indexes years. The dependent variable is the logarithm of total consumption for a given household in a given state and year. The key independent variable in equation (1) is the logarithm of average consumption among rich households in the same geography and time. Because of small sample sizes in some state-year cells, we compute *Log(ConsumptionofRich)* based on all rich households in a state in the current year (t) and the prior two years (t-1 and t-2). This 3-year averaging also allows us to account for what might be a realistic delay in the trickling-down of consumption from the rich to the non-rich.[7] 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, 7 household head's education categories, 5 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. Most importantly, we control in a very flexible way for household income: we include indicator variables for every $2,000 buckets of disposable income. We also include state dummies to capture any fixed differences across states in the consumption of the non-rich, and year dummies

[7] We replicated the analysis in Table 1 using only the current year to define Log(ConsumptionofRich). The results are qualitatively similar but smaller in magnitude, as one might have expected due to attenuation bias.

to capture aggregate changes over time in the consumption of non-rich. All observations in equation (1) are weighted by year CEX population weights. Also, standard errors are clustered at the state-level.

The econometric specification described under equation (1) is subject to several concerns. First, it is possible that unobserved state-year shocks may induce correlated patterns of consumption between the rich and the non-rich. For example, households in a given state, both rich and non-rich, may have correlated tastes for high-end technology goods; thus both rich and non-rich may be more likely to buy, say, the latest generation *i-Pad* or *i-Phone* when they are released for distribution. A second concern relates to measurement issues with the CEX. As indicated above, 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)). One way to address both of these concerns is to directly use variation in the income of the rich, rather than variation in the consumption of the rich, as our key independent variable of interest. So, we also estimate the following OLS regression:

$$\begin{aligned} &Log(Consumption)_{ist} = Log(80^{th}\,PercentileIncome)_{st} + Household\ controls_{ist} \\ &+Household\ Income\ dummies_{ist} + State_s + Year_t + \varepsilon_{ist}, \qquad (2) \end{aligned}$$

where Log(80th PercentileIncome) is the log 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. All other variables in equation (2) are defined as above.

For completeness, we also present results where we instrument Log(ConsumptionofRich) with top percentiles of the income distribution in a state-year cell. We use Log(80th PercentileIncome) and Log(95th PercentileIncome) as instruments.[8] The exclusion restriction is that the income of the rich is uncorrelated with consumption of the non-rich except through their own consumption after controlling for state and year fixed effects, as well household-level controls (including the flexible controls for household income). One should not rule out the possibility though that non-rich consumption is also *directly* affected by the income of the rich. Several of the explanations for the trickle-down consumption we consider in detail in the later

[8] In the results below, we instrument Log(ConsumptionofVeryRich), the logarithm of average consumption among very rich households, with Log(90thPercentileIncome) and Log(95thPercentileIncome).

sections of this paper, even some of the behavioral explanations, could be consistent with a direct influence of top income levels on non-rich consumption. For example, households may form their expectation about what they will earn in the future not based on what they see their rich neighbors consuming, but what they see them earning (if a paycheck is not often observable, a place of work or occupation might be). Similarly, 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. Other explanations however ultimately rely on higher top income levels translating in higher rich or very rich consumption, such as upward pressures on local prices. So, we stay away from putting a strict "causal" read on these IV results and ultimately defer interpretation of all of these primary findings to Sections IV and V.

III.B. Results

Table 1 presents our analysis of the relationship between non-rich and rich consumption. In particular, column 1 of Panel A presents the results of the estimation of equation (1) above. For brevity, we only report coefficients on the variables of interest in Table 1.

Column 1 shows that the elasticity of consumption of the non-rich to the consumption of the rich is positive and statistically significant at the 1 percent level. A 1 percent increase in consumption of the rich is associated with .182 percent increase in the consumption of non-rich households, holding non-rich households characteristics and own income constant. Column 2 replicates column 1 but focuses on the consumption of the very rich (upper decile) in the market as an alternative independent variable, Log(ConsumptionofVeryRich). Again, we find a positive and statistically significantly elasticity; a 1 percent increase in consumption of the very rich is associated with .073 percent increase in the consumption of non-rich households

Columns 3 to 6 break the non-rich sample into individuals in middle income households (between the 20^{th} and 80^{th} percentiles) and those in low income households (below the 20^{th} percentile of income). This break-down shows that the effect of the consumption of the rich, and in particular the consumption of the very rich, seems to be concentrated among the middle income households.

Panel B of Table 1 reproduces the same regressions as Panel A but uses the ratio of consumption to income as an alternative dependent variable. We continue to absorb income as levels in \$2,000 bucket, hence allowing the ratio of consumption to income among non-rich households to vary flexibly by income bucket. The results are qualitatively similar to those in Panel A. Non-rich households spend a higher share of their current income when exposed to higher rich or very consumption; this relationship is much stronger and much more precisely estimated for middle income households than low income households.

Table 2 presents our analysis of the relationship between non-rich consumption and top income levels in the state-year cell. In particular, Column 1 of Panel A presents the results of the estimation of equation (2) above. The structure of columns 1 to 6 in Table 2 is similar to that of Table 1. The results are very consistent with those in Table 1. We find positive and statistically significant associations between either Log(80thPercentileIncome) (column 1) or Log(90thPercentileIncome) (column 2) and consumption of the non-rich, whether we define the dependent variable as the logarithm of consumption of non-rich households (Panel A) or the ratio of consumption to current income for those households (Panel B). A 1 percent increase in Log(80thPercentileIncome) increases non-rich consumption by .23 percent, everything else constant (Panel A; column 1). Again, these relationships appear stronger and more precisely estimated for middle income households than for low income households.

In columns 7 and 8 of Table 2, we consider the possibility that middle income households' consumption might also be sensitive to changes in income levels at the *bottom* of the income distribution. Is there any evidence of some trickle-up mirroring the trickle-down effect we have focused on so far? To address this, we include Log(20thPercentileIncome) (also constructed based on the 3-year averaging method described above) as an additional control. The point estimates on Log(20thPercentileIncome) is essentially 0 in all specifications in columns 7 and 8. Hence, we see no evidence of a symmetric relationship between the upper and lower parts of the income distribution on the consumption of the middle class.

Finally, Table 3 presents the IV results. As indicated above, we use Log(80thPercentileIncome) and Log(95thPercentileIncome) as instruments for Log(ConsumptionofRich). We use Log(90thPercentileIncome) and Log(95thPercentileIncome) as instruments for Log(ConsumptionofVeryRich). Column 1 of Table 3 presents the first stage regression for Log(ConsumptionofRich). The first-stage F-statistic (20.72) indicates that the instruments are strong predictors of Log(ConsumptionofRich). The second-stage results are reported in columns 2 to 5 (where the dependent variable is Log(Consumption)) and 6 to 9 (where the dependent variable is the ratio of consumption to income). The estimated effects in the IV model are qualitatively similar to those in the OLS model (Table 1) but 50 to 100% larger in magnitude. Omitted positively correlated shocks to tastes between the rich and the non-rich (e.g. all want the new i-Pad when it is released) would have suggested smaller IV estimates. Our preferred interpretation for the larger magnitudes in Table 3 compared to Table 1 is that it reveals the substantial measurement issues with Log(ConsumptionofRich) and Log(ConsumptionofVeryRich).

IV. Traditional Explanations

IV.A. Permanent Income Hypothesis

While we hold current household income constant in all the specifications reported above, it is possible that the non-rich households generating our results are in fact different in terms of their permanent income. In particular, the permanent income hypothesis could explain our results in Section III if non-rich households in markets where top income levels are higher rationally expect their own income to go up in the future. In other words, a higher income level at the 80^{th} percentile in a state today may be systematically related to higher future income for households below the 80^{th} percentile.

Unfortunately, because the CEX is structured as a repeated cross-section and not as a panel, we cannot add future income controls to the analysis we have performed so far. Instead, we turn to another dataset that is structured as a panel to formally test for the possibility that a given household's future income, holding the household's own current income constant, is systematically positively related to current top income level in the household's geographical market. This panel data set is 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.[9] By state-year cell, we merge the PSID micro data into the CPS-constructed variables on the 80th, 90th, 50th and 20th percentiles of the household income distribution in each state-year cell (3-year averages, as in Section III). We focus our analysis on the subset of household-year observations with incomes below the 80th percentile in the household's state-year. 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:

$$\begin{aligned} &Log(FutureIncome)_{is,t+j} = Log(80thPercentileIncome)_{st} + Log(CurrentIncome)_{ist} \\ &+HouseholdControls_{ist} + State_s + Year_t + \varepsilon_{ist} \end{aligned} \tag{3}$$

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 4. In Panel A, we use Log(80thPercentileIncome); in Panel B, we use Log(90thPercentileIncome). In no specification do we find evidence that increased top income levels in a state in a given year are significantly predictive of higher future income levels for non-rich households in that state in future years (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).[10] 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

[9] 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.

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

(50th and 20th percentiles). These findings are also robust to the inclusion of household fixed effects (columns 3 and 6).

In summary, while we cannot directly control for permanent income level in the CEX sample, the analysis we perform in the PSID fails to find evidence that higher top income levels in a state are systematically predictive of higher future income for the non-rich, holding their current income constant. In other words, a permanent income explanation does not appear to rationalize the findings we reported in Tables 1 to 3.

IV.B. Precautionary Saving Motive

In columns (13) and (14) of Table 4, we also 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 saving 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 disposable income.

In the PSID, we define the standard deviation of log(household income) between t+1 and t+4. We then estimate equation (3) above using this alternative dependent variable. We fail to find support for the view that either Log(80thPercentileIncome) (Panel A of Table 4) or Log(90thPercentileIncome) (Panel B of Table 4) are systematically negatively correlated with a lower 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 Log(50thPercentileIncome) and Log(20thPercentileIncome).

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. Given the results in Tables 1 to 3, we further constrain that sample to the subgroup of middle income households. Panel A of Table 5 replicates the specification under equation (1) (with log rich consumption as the main independent variable), and Panel B of Table 5 replicates the specification of equation (2) (with log rich income as the main independent variable). 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 either to rich consumption or to rich income 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.[11] 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 trickle-down consumption pre-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).[12] Markets where housing supply is inelastic have experienced sharper rises in house prices; it is therefore relevant to ask whether our key finding systematically differs based on the level of house supply elasticity in the market. In Panel A, but not Panel B, we do find

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

[12] 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.

significantly larger estimates in markets where the housing supply elasticity is lower. But our effects remain economically large and statistically significant even in the more elastic markets.

In summary, the rise in home equity might be correlated with the rise in top income levels in a state. Indeed we find some evidence of stronger trickle-down correlations in more inelastic housing markets and, to a lesser, among homeowners. However, because our core results hold both for homeowners and renters, and also hold (and in fact are stronger) prior to the housing boom, we do not believe that a home-equity, net wealth channel is the sole explanation for our primary finding.

V. Behavioral Explanations

V.A. Upwardly-Biased Expectations about Future Income

While we find no evidence that higher current top incomes in a market are predictive of higher future income for the non-rich in that market (Table 4), it is possible that the non-rich's expectations about their future income are systematically biased upwards when they are exposed to the increasing incomes and consumption of proximate top income earners. To investigate this possibility, 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. In particular, the Index of Consumer Expectations is an official component of the Index of Leading Indicators developed by the U.S. Department of Commerce. 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 average across all individuals and years, the expected percent change in family income in the next year is 5.6 percent.

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

$$\begin{aligned} &IncomeChangeExpectation_{ist} = Log(80thPercentileIncome)_{st} + Individual\ Controls_{ist} \\ &+ HouseholdIncomedummies_{ist} + State_s + Year_t + \varepsilon_{ist} \end{aligned} \quad (4)$$

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 6. 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 present results for two subsamples of the data: all individuals whose household income is below the 80th percentile in their state-year cell (columns 1 to 4), and middle income households (e.g. those with household income between the 20th and 80th percentiles) (columns 5 and 6), 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 6 do we find a positive and statistically significant relationship between expectations about future income growth and top income levels. In fact, all the estimated coefficients on Log(80thPercentileIncome) and Log(90thPercentileIncome) are negative. In other words, we fail to find any evidence that non-rich households have systematically upwardly biased expectations about their future income when exposed to higher top income levels in their market. If anything, an increase in the income level at the 80th percentile reduces the likelihood that an individual expects his or her family income to rise.[13]

V.B. Local Price Pressures and Sticky Consumption

If middle income 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 disposable income when the local prices rise for the goods and services to which they are "committed" . If rising top income levels in a state are associated with higher local prices, such stickiness in middle income households' consumption portfolio may lead to higher spending out of current disposable income, without middle income households making much active changes to their real consumption.

To analyze the effect of local prices, we download the MSA-level local CPI indices from the BLS.[14] In columns (1) and (2) of Table 7, we first show that there is indeed a strong positive correlation between the state CPI index and top income levels in that state. Specifically, in a state-year panel regression that covers all state-years included in our CEX sample, we find a positive correlation between Log(LocalCPI) and both Log(80thPercentileIncome) and Log(90thPercentileIncome). In contrast, neither Log(50thPercentileIncome)or Log(20thPercentileIncome) are systematically related to Log(LocalCPI). To the extent that house price variation within state and time is an important component of the variation in Log(LocalCPI) within state and time, the correlations we observe in columns (1) and (2) of Table 7 are related to Matlack and Vigdor (2008)'s finding of a positive relationship between income inequality and housing costs in Census data.

In the remaining columns of Table 7, we replicate the specifications under equations (1) and (2) but now directly controlling for Log(LocalCPI) in the regressions. Given the results in Tables 1 to 3, we restrict the sample to the subgroup of middle income households. Log(Local

[13] The results in Table 6 could also be viewed as an alternative test, and additional rejection, of a permanent income hypothesis explanation for our primary finding.

[14] 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.

CPI) enters positively in each regression but the estimates are noisily estimated. While controlling for the local CPI tends to somewhat reduce the magnitude and precision of the estimated coefficients on Log(80^{th}/90thPercentileIncome) (columns 4 and 5) and Log(Consumptionof(Very)Rich) (columns 6 and 7), the coefficients remain economically large. For example, a comparison of column (4) in Table 7 and column (3) in Table 2 shows that estimated coefficient on Log(80thPercentileIncome) goes from .279 (s.e.=.110) to .239 (s.e.=.133) after controlling for Log(Local CPI).

In summary, while it is possible that some of the higher consumption to income ratios among the non-rich exposed to higher top income levels may be the consequence of upward local price pressures interacting with the non-rich's inability to reduce their consumption, our analysis in Table 7 suggests that such local price effects is not the sole explanation for our findings. In the sub-section below, we do show, however, that middle-income households' budget share for shelter increases substantially when top income levels rise. While we propose in that sub-section other possible explanations for this finding (e.g. the possibility that non-rich demand for housing might be increasing with top income levels), we however cannot and 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.

V.C. Budget Share Analysis: Income Elasticity and Visibility

In order to further build our understanding of what drives the non-rich consumption response, in this section we analyze how the budget shares of the non-rich across 29 consumption categories respond to top income levels.

In particular, we are interested in testing two specific behavioral hypotheses. One 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" good happens without fully scaling back on the consumption of other goods, either because of self-control problems or because much of the other consumption is already "committed to". To test for the hypothesis, we ask whether the sensitivity of budget shares to top income levels varies in a systematic way with the income elasticity of the consumption categories. Column 1 of Appendix Table A4 reports income elasticity estimates for each of the 29 consumption categories we have constructed. These elasticity estimates are the coefficients on disposable income in the CEX from a population-weighted regression of log consumption in that category on log(income), a quadratic of age, and dummies for race, education, number of children and number of people in the household.

The second hypothesis we are interested in testing relates to the possibility that the 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 of this relative income model 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," and 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 A4 reports the visibility index for each of the 29 consumption categories.

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

$$W^{k}{}_{ist} = \beta^{k} Log(80thPercentileIncome)_{st} + \sum_{l=1}^{5} \log\left(\frac{p_t^l}{P_t}\right) + \log\left(\frac{p_{st}}{P_t}\right) \qquad (5)$$
$$+HouseholdControls_{ist} + HouseholdIncomeDummies_{ist} + State_s + Year_t + \varepsilon_{ist}$$

where $W^{k}{}_{ist}$ 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 food, shelter, transportation, clothing and other goods; p_{st} is the local CPI; and all other variables are defined as above.

In a second step, we study the relationship between the vector of estimated coefficients on β^k and the income elasticity and visibility measures presented above. For these regressions, we weigh each category by the inverse of the square of the standard error of β^k.

Given the results in Tables 1 to 3, we again restrict this analysis to the subsample of middle-income households. We also perform an alternative specification of the demand system under equation (5) where we use *Log(90thPercentileIncome)* instead *Log(80thPercentileIncome).* The results of this analysis are presented in the remaining columns of Appendix Table 4 (first step) as well as in Table 8 (second step).

Column 3 of Appendix Table A4 reports mean budget shares among middle-income households in our sample for each of the 29 consumption categories. The estimated coefficients on β^k are reported in columns 4 (Log(80thPercentileIncome) and 5 (Log(90thPercentileIncome), with bolded coefficients statistically significant at least at the 10 percent level. Finally, in columns 6 and 7, we normalize the estimated coefficients by the mean budget share from column 3, to provide a more intuitive sense of magnitude. About a third of the estimated coefficients are statistically significant. There is broad consistency between the estimated coefficients whether we use Log(80thPercentileIncome) or Log(90thPercentileIncome).

Consistent with our prior findings, we find a large positive estimate is for the shelter share of budget. The estimate is consistent with the interpretation that a 10% increase in Log(80thPercentileIncome) increases the shelter budget share by .01 (column 4), about a 5 percent increase (column 6). While scoring quite high on the visibility index (.5), the income elasticity of shelter consumption is only moderate (.66). Other categories with similarly large percent increase in budget shares include "alcohol away from home" (not statistically significant), and "salons, fitness and clubs" (statistically significant), both of which score high on both the visibility index and in terms of income elasticity. The largest percent decrease in budget share in for "education," with a 10% increase in Log(80thPercentileInome) reducing the education budget share by about 11 percent; education expenses, while quite visible, are only moderately income elastic.

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 8. We consider two dependent variables. In columns 1 to 4, the dependent variable is the estimated budget share sensitivities to rich consumption, normalized to mean budget shares (the coefficients from Appendix A4, column 6) . In columns 5 to 8, the dependent variable is a dummy variable that equals 1 if the estimated coefficients are positive. We present results for both the model that uses Log(80thPercentileIncome) (Panel A) and one that uses Log(90thPercentileIncome) (Panel B). We also present results where we use the continuous measures of income elasticity and visibility (columns 1, 3, 5 and 7) and others where we use dichotomous versions (columns 2, 4, 6 and 8). For these dichotomous versions, we define as "more visible" goods and services that score .5 or above on the visibility index; we define as "more income elastic" goods and services with income elasticities of .75 or above (the sample mean).[15] Finally, we also present results with and without shelter. In each regression, we weigh the category by the inverse of the square of the standard error of the coefficient estimate.

[15] For ease of reading, Appendix Table A5 lists the goods and services across these dichotomous classes.

The results in Table 8 are broadly consistent across specifications. All the estimated coefficients on income elasticity and visibility are positive. In other words, we find more positive changes in budget shares in response to higher top income levels for those goods and services that are more income elastic and more visible. The mapping to income elasticity however appears more robust than the mapping to visibility, particularly in Panel B.

In summary, the evidence reported in this section suggests that both supply-driven demand and status-seeking, or status-maintaining, explanations might play a role in explaining middle income households' consumption behavior changes when exposed to higher top income levels.

VI. Economic Magnitude

To get a better sense of the magnitude of the trickle-down effects on middle-income households' consumption, we perform a simple counterfactual exercise. We ask how much lower would have middle income households' consumption-out-of-current-income been, and hence how much larger middle income households' saving rate, had the 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 change (decrease) in Log(Consumption) under the assumption that Log(80thPercentileIncome) or Log(90thPercentileIncome) had grown at the same rate as Log(50thPercentileIncome). We perform the calculation of these counterfactual growth rates using the change in average Log(50thPercentileIncome) by year in our CEX sample. We use the estimates from Table 2 of the sensitivity of Log(Consumption) for middle income households to either Log(80thPercentileIncome) (column 3) or Log(90thPercentileIncome) (column 4) to compute counterfactual Log(Consumption).

The results of this counterfactual analysis are presented in Table 9. We report results for 4 different years: 1990, 2000, 2005 and 2008. Panel A presents the counterfactual for column 3 of Table 2 (Log(80thPercentileIncome), while Panel B presents the counterfactual for column 4 of Table 2 (Log(90thPercentileIncome). We report gaps between actual and counterfactual consumption both in log points (column 1) and dollar figures (column 2).[16] For 1990, we estimate that Log(Consumption) by middle income households would have been between .7

[16] The dollar figures are obtained by multiplying column 1 by average consumption (in $1999) across all middle-income households in a CEX in a given year.

(Panel A) and 1.1 (Panel B) percent lower under the counterfactuals. By 2000, the (positive) gap between actual and counterfactual log consumption grows to between 2.1 (Panel A) and 2.8 percent (Panel B). By 2005, we estimate that middle income household would have consumed between 2.6 and 3.2 percent less had income levels at the top grown at the same rate as income levels at the median since the beginning of the sample period; this corresponds to between $1271 and $1571 less in consumption in 2005 for middle-income 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 middle income households in the US in each year.[17] This defines the additional savings that would have occurred in each of the years listed in the Table under the counterfactuals. We report this number in column 4 of Table 9, with the actual personal savings figures from the NIPA data in column 3. Both are reported in billions of dollars; also, for comparability, both are reported in nominal terms. Finally, in columns 5 and 6, respectively, we report the actual personal savings rate from the NIPA data and the counterfactual rate. To compute the counterfactual rate, we take the actual aggregate personal savings from NIPA (column 3) and add the additional savings under the counterfactual (column 4); we then divide by aggregate disposable income from the NIPA data. We estimate that the personal savings rate in 2000, which was 2.9 percent, would have been between 3.6 (Panel A) to 3.8 (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 2.6 and 2.8

[17] We use 1990, 2000 and 2010 Census data on total number of households in the US and assume that the number of middle income households is 3/5 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.

percent. Hence, a small but 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 columns 3 of Table 2, we estimate about a .22 percent increase in consumption for the median-income household for every 1 percent increase in income at the 90^{th} percentile. Given that median income household is essentially stagnant over the period under study (see Appendix Table A1), this is the same a .22 percent increase in consumption for median-income household for every 1 percent increase in the income gap between the 90^{th} and 50^{th} 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 50^{th} and 90^{th} percentile would translate in a .78 percent increase in the consumption gap between the 50^{th} and 90^{th} 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 50^{th} and 90^{th} percentile would translate in a .57 percent increase in the consumption gap between the 50^{th} and 90^{th} percentile. In the CEX, we estimate an elasticity of consumption of income for households above the 90^{th} 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 that the elasticity of consumption to income above the 90^{th} percentile was above .75. Hence, our estimates are consistent, under reasonable assumptions, with the current evidence on the relative rise of income and consumption inequality.

VII. 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 middle-income households to stretch their personal finances, facilitating the trickling-down of consumption we have documented. 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 the trickle-down pressures and responded to these pressures by further easing credit supply.

VII.A. 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 in 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.[18] We then merge this data by state-year to the CPS measures of income percentiles discussed above, and to Census information on the number of households by state and decade.[19] We are interested in whether higher top income levels in a state are predictive of a higher rate of personal bankruptcy filings in that state going forward. We do not expect a rise in top income levels in a given year in a state to immediately translate into a higher number of bankruptcies. Unlike the consumption responses documented above, which could theoretically take place quite rapidly, the bankruptcy response, if it exists, would likely be based on an accumulation of past consumption responses. Therefore, we propose to use two-year lagged Log(80thPercentileIncome) (or Log(90thPercentileIncome)) as our independent variable of interest.[20] The results of this analysis are presented in Table 10. 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 10). 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

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

[19] We assign Census information from Census year T to years covering the first 5 years of a decade starting in year T and Census information from Census year T+1 to the last five years of a decade starting in year T.

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

income negatively correlates with bankruptcy filings. Adding these contemporaneous controls however does not change our estimates of interest.[21]

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

VII.B. Self-Reported Financial Duress

A key limitation of the analysis in Table 10 is that, given its aggregate nature, it does not allow us to "zoom in" on middle income households. In Table 11, we thus complement the analysis from Table 10 with a look into 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

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

duress, holding household income and household characteristics constant. Specifically, we estimate the following regression, which directly mirrors equation (4):

$$\begin{aligned} &Financial\ Worse\ Off\ Today_{ist} = Log(80thPercentileIncome)_{st} + IndividualControls_{ist} \\ &+ Household\ Income\ Dummies + State_s + Year_t + \varepsilon_{ist} \end{aligned} \quad (6)$$

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.[22] About 7 percent of respondents indicate higher expenses and debt payments today than a year ago (Appendix Table A3).

Table 11 follows the same structure as Table 5. In particular, as in Table 5, we present results for two subsamples of the data: all individuals whose household income is below the 80th percentile in their state-year cell (columns 1 to 4), and those with household income between the 20th and 80th percentiles (columns 5 and 6). We also present results that further control for income level at the 50th and 20th percentiles of the state-year income distribution.

All regressions in Panel A of Table 11, 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 most are not statistically significant at standard levels.

In summary, the evidence in Tables 10 and 11 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 among the non-rich in the state. While this evidence is

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

only indirect, these results are consistent with greater reliance on credit, up to the point of financial distress, among middle-income households exposed to higher top income levels.

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

Our results point to some possible political economy implications. In particular, political representatives of 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 last section, we provide some suggestive evidence of such political economy implications in the context of the Federal Housing Enterprise Safety and Soundness Act (H.R. 5334), which Congress passed in 1992.

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

With home ownership rates in the US being between 60 to 70 percent at the time this Act was passed, it is reasonable to argue that the population that was targeted by this expanded housing lending 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 middle income households and median voter's demand for more credit would have been particularly strong where middle income households and the median voter are 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

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

with more income inequality, and in particular districts with a large gap between the middle and the top of the income distribution.

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

Ideology was a clear determinant of voting on H.R. 5334. Among Democrat Congressmen that expressed a vote, 257 voted in favor while only 2 voted against. There is therefore essentially no variation to exploit among Democrats. However, voting was more divided among Republican Congressmen. While 111 Republicans voted in favor of this new legislation, 52 voted against. In Table 12, 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 12, we regress the likelihood of voting in favor of H.R. 5334 on income inequality in the district. We absorb ambient differences in economic conditions across states with state fixed effects. The estimated relationship between a yes vote and income inequality is positive and statistically significant (p=0.04). A one standard deviation increase in income inequality (0.08) increases the likelihood of a Republican voting in favor of H.R. 5334 by about 8 percentage points. When we measure inequality based on the gap between the 90^{th} and 50^{th} percentile (column 2), we continue to find a positive relationship between district inequality and a yes vote, but the relationship is no longer statistically significant.

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

While the evidence in Table 12 should only be viewed as suggestive, the associations found in this table help in proposing an additional mechanism by which middle income households with stagnating real income may have been made to keep up with the increasingly rich: 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.

VIII. Conclusion

The question that originally motivated this paper is whether rising income inequality and the decline in the personal savings rate over the last 3 decades are related phenomena. We proposed to exploit within 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 income constant, middle income households that are exposed to higher top income levels in their market appear to spend a higher share of that income. Moreover, we failed to find support for more traditional explanations for this fact (such as permanent income hypothesis, precautionary savings motive or wealth effects).

A more behavioral analysis of these middle-income households' consumption patterns instead suggested the possibility that the extra consumption might be related to an increase supply of "rich" goods within their market, and maybe also a desire to keep up with richer co-residents through more "visible" spending. We also found a large increase in the shelter budget share with rising top income levels; because our data does not allow us to directly study the quantity of housing that is demanded, we do not rule out that local upward housing price pressures may have resulted in higher expenses for this quite rigid expenditure category.

In future work, it would be worthwhile to follow through with the supply-driven demand explanation by complementing 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.

Both our analysis of the personal bankruptcy data and of voting on federal policies to expand credit supply suggest that the use of credit might have been particularly large for middle income households living in proximity to the rich. If some of this credit translated in bad credit, rising income inequality might have been a contributing factor in the recent financial crisis.

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Table 1: Effect of Rich Consumption on Non-Rich Consumption

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			*Log(Consumption)*			
Sample:	All		Middle Income		Low Income	
Log(ConsumptionofRich)	0.182		0.215		0.074	
	[0.036]**		[0.036]**		[0.064]	
Log(ConsumptionofVeryRich)		0.073		0.100		0
		[0.026]**		[0.025]**		[0.043]
State and Year F.E.s	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	78739	78161	60152	59720	18587	18441
R-squared	0.62	0.62	0.45	0.45	0.48	0.48
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			*Ratio of Consumption to Income*			
Sample:	All		Middle Income		Low Income	
Log(ConsumptionofRich)	0.206		0.206		0.165	
	[0.044]**		[0.044]**		[0.116]	
Log(ConsumptionofVeryRich)		0.067		0.091		-0.001
		[0.033]*		[0.025]**		[0.078]
State and Year F.E.s	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	78739	78161	78739	59720	18587	18441
R-squared	0.5	0.5	0.5	0.38	0.32	0.32

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. In columns 1 and 2, the sample includes all households whose real household income is below the 80th percentile in the state-year cell. In columns 3 and 4 (Middle Income), the sample is restricted to households whose real income is between the 20th and 80th percentile in the state-year cell. In columns 5 and 6 (Low Income), the sample is restricted to household whose real income is below the 20th 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. Household income F.E.s are 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. 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: Effect of Top Income Levels on Non-Rich Consumption

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	*Log(Consumption)*							
Sample:	All		Middle Income		Low Income		Middle Income	
Log(80thPercentileIncome)	0.234		0.279		0.112		0.286	
	[0.112]*		[0.110]*		[0.139]		[0.127]*	
Log(90thPercentileIncome)		0.184		0.226		0.078		0.211
		[0.093]		[0.096]*		[0.108]		[0.109]
Log(20thPercentileIncome)							-0.008	0.021
							[0.065]	[0.065]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78739	78739	60152	60152	18587	18587	60152	60151
R-squared	0.62	0.62	0.45	0.45	0.48	0.48	0.45	0.45
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	*Ratio of Consumption to Income*							
Sample:	All		Middle Income		Low Income		Middle Income	
Log(80thPercentileIncome)	0.316		0.343		0.174		0.36	
	[0.146]*		[0.125]**		[0.249]		[0.140]*	
Log(90thPercentileIncome)		0.254		0.283		0.122		0.271
		[0.120]*		[0.109]*		[0.193]		[0.120]*
Log(20thPercentileIncome)							-0.018	0.017
							[0.066]	[0.067]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78739	78739	60152	60152	18587	18587	60152	60152
R-squared	0.5	0.5	0.38	0.38	0.32	0.32	0.38	0.38

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. In columns 1 and 2, the sample includes all households whose real household income is below the 80th percentile in the state-year cell. In columns 3, 4, 7 and 8 (Middle Income), the sample is restricted to households whose real income is between the 20th and 80th percentile in the state-year cell. In columns 5 and 6 (Low Income), the sample is restricted to household whose real income is below the 20th 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(80/90/20th PercentileIncome) is the logarithm of the average of the 80/90/20th percentile of household income distribution in a given state in the current year and the prior two years. Household income F.E.s are 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. 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 3: Effect of Rich Consumption on Non-Rich Consumption: IV Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	First Stage Regression for Columns (2) and (6)								
Dependent Variable:	*Log(ConsumptionofRich)*	*Log(Consumption)*				*Ratio of Consumption to Income*			
Sample:	All	All	Middle Income	Low Income	Middle Income	All	Middle Income	Low Income	Middle Income
Log(80thPercentileIncome)	0.585								
	[0.199]**								
Log(95thPercentileIncome)	0.24								
	[0.201]								
Log(ConsumptionofRich)		0.282	0.339	0.138		0.395	0.422	0.245	
		[0.133]*	[0.139]*	[0.146]		[0.175]*	[0.164]*	[0.266]	
Log(ConsumptionofVeryRich)					0.213				0.275
					[0.097]*				[0.108]*
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78739	78739	60152	18587	59720	78739	60152	18587	59720
R-squared	0.81								
First Stage F-Statistic	20.72								

Note: Data Source: CEX and the March CPS, 1980 to 2008. See text for details of sample construction. In columns 1, 2 and 6, the sample includes all households whose real household income is below the 80th percentile in the state-year cell. In columns 3, 5, 7 and 9 (Middle Income), the sample is restricted to households whose real income is between the 20th and 80th percentile in the state-year cell. In columns 4 and 8 (Low Income), the sample is restricted to household whose real income is below the 20th 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(80/95th 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. Each observation is weighted by the household head weight provided in the CEX Surveys. All columns except column 1 report second-stage results. Column 1 is the first stage regression for the second stage regressions in columns 2 and 6. The first stage regressions for the specifications in columns 3, 4, 7 and 8 is similar to that in Column 1 on the restricted samples. In columns 5 and 9, we use Log(90th PercentileIncome) and Log(95thPercentileIncome) as instruments for Log(ConsumptionofVeryRich). Standard errors are clustered at the state level. * significant at 5%; ** significant at 1%.

Table 4: Do Higher Top Income Levels Today Predict Higher or More Stable Future Income for the Non-Rich?

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent Variable:	*Log(HH income) in t+1*			*Log(HH income) in t+2*			*Log(HH income) in t+4*		*Log (average HH income) between t+1 and t+2*		*Log (average HH income) between t+1 and t+4*		*S.D. of Log(HH income) between t+1 and t+4*	
Log(HH income)	0.689	0.689	0.17	0.625	0.625	0.073	0.547	0.547	0.636	0.636	0.585	0.585	-0.102	-0.102
	[0.007]**	[0.007]**	[0.015]**	[0.008]**	[0.008]**	[0.015]**	[0.009]**	[0.009]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.006]**	[0.006]**
Log(80thPercentileIncome)	0.019	0.121	0.012	-0.116	0.021	0.016	-0.21	-0.095	-0.017	0.041	-0.056	0.027	0.161	0.112
	[0.096]	[0.159]	[0.213]	[0.083]	[0.147]	[0.176]	[0.122]	[0.126]	[0.080]	[0.139]	[0.084]	[0.114]	[0.042]**	[0.086]
Log(50thPercentileIncome)		-0.047	0.223		-0.066	0.126		-0.095		-0.009		-0.048		0.051
		[0.250]	[0.293]		[0.186]	[0.246]		[0.181]		[0.185]		[0.154]		[0.106]
Log(20thPercentileIncome)		-0.068	-0.023		-0.089	-0.082		-0.03		-0.06		-0.042		-0.003
		[0.094]	[0.114]		[0.087]	[0.109]		[0.098]		[0.073]		[0.069]		[0.043]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household F.E.s	No	No	Yes	No	No	Yes	No	No	No	No	No	No	No	No
HH time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55870	55870	55870	55377	55377	55377	42293	42293	64993	64993	71596	71596	50468	50468
R-squared	0.65	0.65	0.79	0.57	0.57	0.78	0.51	0.51	0.64	0.64	0.62	0.62	0.1	0.1
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent Variable:	*Log(HH income) in t+1*			*Log(HH income) in t+2*			*Log(HH income) in t+4*		*Log (average HH income) between t+1 and t+2*		*Log (average HH income) between t+1 and t+4*		*S.D. of Log(HH income) between t+1 and t+4*	
Log (HH income)	0.689	0.689	0.17	0.625	0.625	0.073	0.546	0.547	0.636	0.636	0.585	0.585	-0.102	-0.102
	[0.007]**	[0.007]**	[0.015]**	[0.008]**	[0.008]**	[0.015]**	[0.009]**	[0.009]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.006]**	[0.006]**
Log(90thPercentileIncome)	0.014	0.053	0.022	-0.116	-0.042	-0.027	-0.25	-0.217	-0.029	-0.024	-0.069	-0.045	0.139	0.065
	[0.095]	[0.126]	[0.167]	[0.084]	[0.126]	[0.178]	[0.132]	[0.147]	[0.082]	[0.107]	[0.086]	[0.094]	[0.046]**	[0.074]
Log(50thPercentileIncome)		0.008	0.214		-0.01	0.163		0.006		0.049		0.014		0.093
		[0.214]	[0.269]		[0.173]	[0.258]		[0.176]		[0.153]		[0.129]		[0.090]
Log(20thPercentileIncome)		-0.071	-0.021		-0.102	-0.089		-0.061		-0.072		-0.055		-0.005
		[0.096]	[0.119]		[0.091]	[0.116]		[0.098]		[0.073]		[0.068]		[0.042]
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household F.E.s	No	No	Yes	No	No	Yes	No	No	No	No	No	No	No	No
HH time-varying 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 time-varying 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 5: Home Equity Channel

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	**Effect of Rich Consumption on Non-Rich Consumption**					
Dependent Variable:	*Log(Consumption)*					
Sample:	Middle Income					
Log(ConsumptionofRich)	0.186		0.168		0.199	
	[0.037]**		[0.045]**		[0.037]**	
Log(ConsumptionofVeryRich)		0.08		0.059		0.084
		[0.024]**		[0.038]		[0.023]**
Log(ConsumptionofRich)*Homeowner	0.042					
	[0.025]					
Log(ConsumptionofVeryRich)*Homeowner		0.031				
		[0.021]				
Log(ConsumptionofRich)*(Year<=1995)			0.091			
			[0.037]*			
Log(ConsumptionofVeryRich)*(Year<=1995)				0.077		
				[0.045]		
Log(ConsumptionofRich)*(Housing supply elasticity<1)					0.123	
					[0.035]**	
Log(ConsumptionofVeryRich)*(Housing supply elasticity<1)						0.093
						[0.027]**
State and Year F.E.s	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	59139	58728	60152	59720	58434	58002
R-squared	0.47	0.46	0.45	0.45	0.45	0.45
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B:	**Effect of Top Income Levels on Non-Rich Consumption**					
Dependent Variable:	*Log(Consumption)*					
Sample:	Middle Income					
Log(80thPercentileIncome)	0.293		0.224		0.275	
	[0.114]*		[0.109]*		[0.113]*	
Log(90thPercentileIncome)		0.237		0.16		0.225
		[0.096]*		[0.097]		[0.099]*
Log(80thPercentileIncome)*Homeowner	0.04					
	[0.034]					
Log(90thPercentileIncome)*Homeowner		0.031				
		[0.029]				
Log(80thPercentileIncome)*(Year<=1995)			0.09			
			[0.054]			
Log(90thPercentileIncome)*(Year<=1995)				0.119		
				[0.062]		
Log(80thPercentileIncome)*(Housing supply elasticity<1)					0.011	
					[0.082]	
Log(90thPercentileIncome)*(Housing supply elasticity<1)						-0.006
						[0.052]
State and Year F.E.s	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	59139	59139	60152	60152	58434	58434
R-squared	0.46	0.46	0.45	0.45	0.45	0.45

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 between the 20th and 80th percentile in the state-year cell (Middle Income). 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(80/90th 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 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: Expectations about Future Income Growth and Top Income Levels

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Expect Real Income to Go Up in the Next Year (Y=1)*					
Sample:	All				Middle Income	
Log(80thPercentileIncome)	-0.054	-0.091			-0.069	
	[0.029]	[0.056]			[0.065]	
Log(90thPercentileIncome)			-0.055	-0.071		-0.055
			[0.030]	[0.045]		[0.057]
Log(50thPercentileIncome)		0.025		0.008	0.007	-0.005
		[0.071]		[0.065]	[0.074]	[0.071]
Log(20thPercentileIncome)		0.017		0.017	0.017	0.017
		[0.038]		[0.039]	[0.045]	[0.046]
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126177	126177	126177	126177	105748	105748
R-squared	0.1	0.1	0.1	0.1	0.1	0.1

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Expected Percent Change in Household Income in the Next Year*					
Sample:	All				Middle Income	
Log(80thPercentileIncome)	-3.015	-2.821			-2.63	
	[1.637]	[2.670]			[2.809]	
Log(90thPercentileIncome)			-1.913	-0.589		-0.12
			[1.609]	[2.003]		[2.264]
Log(50thPercentileIncome)		-0.713		-2.44	0.372	-1.561
		[2.714]		[2.389]	[2.669]	[2.504]
Log(20thPercentileIncome)		0.547		0.797	-0.226	0.08
		[1.241]		[1.289]	[1.473]	[1.524]
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117534	117534	117534	117534	99629	99629
R-squared	0.07	0.07	0.07	0.07	0.06	0.06

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. In columns 5 and 6 (Middle Income), the sample is restricted to households whose real income is between the 20th and 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 7: Local Price Channel

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Log(Local CPI)*		*Log(Consumption)*			
Sample:	State-year panel		Middle Income			
Log(80thPercentileIncome)	0.528			0.239		
	[0.110]**			[0.133]		
Log(90thPercentileIncome)		0.321				0.184
		[0.088]**				[0.111]
Log(50thPercentileIncome)	-0.217	-0.069				
	[0.121]	[0.112]				
Log(20thPercentileIncome)	0.08	0.067				
	[0.062]	[0.062]				
Log(ConsumptionofRich)			0.221			
			[0.041]**			
Log(ConsumptionofVeryRich)					0.088	
					[0.029]**	
Log(Local CPI)			0.031	0.079	0.069	0.088
			[0.055]	[0.066]	[0.065]	[0.061]
State and Year F.E.s	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	554	554	51911	51911	51617	51911
R-squared	0.95	0.95	0.44	0.44	0.44	0.44

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 between the 20th and 80th percentile in the state-year cell (Middle Income). 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. 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. Each observation in columns 3 to 6 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 8: Expenditure Share Sensitivities to Top Income Levels: Relationship to Income Elasticity and Visibility of the Expenditure Category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	**Log(80thPercentileIncome)**							
Dependent Variable:	*Estimated Coefficient on Log(80thPercentileIncome) Relative to Budget Share*				*Estimated Coefficient on Log(80thPercentileIncome) is Positive (Y=1)*			
Sample:	All		Exclude Shelter		All		Exclude Shelter	
Income elasticity	0.709		0.709		0.386		0.386	
	[0.242]**		[0.246]**		[0.277]		[0.282]	
Visibility	1.306		1.306		1.039		1.04	
	[0.519]*		[0.529]*		[0.595]		[0.606]	
More income elastic (Y=1)		0.564		0.565		0.382		0.382
		[0.144]**		[0.147]**		[0.169]*		[0.172]*
More visible (Y=1)		0.361		0.36		0.36		0.359
		[0.164]*		[0.167]*		[0.192]		[0.196]
Observations	29	29	28	28	29	29	28	28
R-squared	0.38	0.51	0.38	0.51	0.17	0.31	0.17	0.32
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	**Log(90thPercentileIncome)**							
Dependent Variable:	*Estimated Coefficient on Log(90thPercentileIncome) Relative to Budget Share*				*Estimated Coefficient on Log(90thPercentileIncome) is Positive (Y=1)*			
Sample:	All		Exclude Shelter		All		Exclude Shelter	
Income elasticity	0.873		0.873		0.673		0.673	
	[0.241]**		[0.245]**		[0.260]*		[0.265]*	
Visibility	1.365		1.366		0.705		0.706	
	[0.529]*		[0.539]*		[0.571]		[0.582]	
More income elastic (Y=1)		0.594		0.596		0.524		0.525
		[0.160]**		[0.163]**		[0.167]**		[0.170]**
More visible (Y=1)		0.303		0.302		0.082		0.081
		[0.184]		[0.187]		[0.192]		[0.196]
Observations	29	29	28	28	29	29	28	28
R-squared	0.44	0.45	0.44	0.46	0.25	0.31	0.25	0.31

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 are constructed based on the estimated coefficients on Log(80thPercentileIncome) (Panel A) and Log(90thPercentileIncome) (Panel B) for each each expenditure category following the estimation of the demand system equation (5) in the text on the sub-sample of middle income households (households whose real income is between the 20th and 80th percentile in the state-year cell). 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 A4. "More visible" equals 1 for the subset of expenditure categories with a visibility index larger or equal to .5. "Less income elastic" equals 1 for the subset of expenditure categories with an income elasticity of consumption of the category larger or equal to .75. For ease of reading, see appendix Table A5 for lists of more/less visible and more/less income elastic categories under these definitions. * significant at 5%; ** significant at 1%.

Table 9: 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	-307.560	276.700	13.312	0.065	0.068
2000	-0.021	-805.440	213.100	52.688	0.029	0.036
2005	-0.026	-1271.250	143.200	99.338	0.015	0.026
2008	-0.028	-1295.670	592.300	115.003	0.054	0.064
	(1)	(2)	(3)	(4)	(5)	(6)
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	-419.780	276.700	18.168	0.065	0.069
2000	-0.028	-1066.720	213.100	69.780	0.029	0.039
2005	-0.032	-1571.150	143.200	122.773	0.015	0.029
2008	-0.034	-1562.710	592.300	138.706	0.054	0.066

Notes: Source: Author's calculation, CEX, NIPA, and Census (for number of households). Reported in the Table are estimated changes in middle-income households' consumption and the aggregate personal savings rate using the estimates of columns 2 and 3 of Table 2 under the counteractual 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.

Table 10: Personal Bankruptcy Filings and Top Income Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent Variable:	*Log (Number of Personal Bankruptcy Filings/Population)*										
Sample:			All years				1980, 1985, 1990, 1995, 2000, 2005 and 2009			All years	
Log(80thPercentileIncome) (t-2)	1.06		0.994		1.018		1.289		0.896	1.024	1.167
	[0.406]*		[0.365]**		[0.343]**		[0.474]**		[0.261]**	[0.347]**	[0.639]
Log(90thPercentileIncome) (t-2)		1.321		0.917		0.839		1.144			
		[0.355]**		[0.379]*		[0.395]*		[0.485]*			
Log unemployment rate (t)					0.176	0.183	0.164	0.168	0.217	0.171	0.171
					[0.048]**	[0.050]**	[0.088]	[0.090]	[0.047]**	[0.049]**	[0.049]**
Log(80thPercentileIncome) (t)					-0.209	-0.181	0.051	0.054	-0.414	-0.109	-0.045
					[0.286]	[0.300]	[0.535]	[0.535]	[0.258]	[0.320]	[0.298]
Log(50thPercentileIncome) (t)					-0.426	-0.398	-0.82	-0.735	-0.14	-0.573	-0.605
					[0.381]	[0.380]	[0.621]	[0.613]	[0.265]	[0.415]	[0.415]
Log(20thPercentileIncome) (t)					-0.145	-0.126	0.052	0.047	-0.361	-0.169	-0.218
					[0.238]	[0.235]	[0.337]	[0.333]	[0.131]**	[0.228]	[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<http://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 11: Current Financial Well-Being and Top Income Levels

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Worse Off Financial than a Year Ago (Y=1)*					
Sample:	All				Middle Income	
Log(80thPercentileIncome)	0.228	0.226			0.234	
	[0.065]**	[0.090]*			[0.093]*	
Log(90thPercentileIncome)			0.25	0.244		0.239
			[0.059]**	[0.076]**		[0.074]**
Log(50thPercentileIncome)		0.058		0.049	0.031	0.032
		[0.103]		[0.100]	[0.107]	[0.100]
Log(20thPercentileIncome)		-0.061		-0.049	-0.06	-0.049
		[0.056]		[0.057]	[0.060]	[0.060]
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126551	126551	126551	126551	105985	105985
R-squared	0.07	0.07	0.07	0.07	0.06	0.06

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*More Expenses/More Debt, Int. and Debt Payments than a Year Ago (Y=1)*					
Sample:	All				Middle Income	
Log(80thPercentileIncome)	0.031	0.026			0.034	
	[0.026]	[0.035]			[0.041]	
Log(90thPercentileIncome)			0.043	0.048		0.061
			[0.022]	[0.027]		[0.027]*
Log(50thPercentileIncome)		0.006		-0.01	-0.022	-0.043
		[0.038]		[0.035]	[0.048]	[0.041]
Log(20thPercentileIncome)		-0.001		0.004	0.02	0.027
		[0.023]		[0.023]	[0.028]	[0.027]
Household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State and Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126701	126701	126701	126701	106090	106090
R-squared	0.01	0.01	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. In columns 5 and 6 (Middle Income), the sample is restricted to households whose real income is between the 20th and 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 12: Republican Congressmen's Voting on H.R. 5334

	Dependent Variable: Yes Vote				
	(1)	(2)	(3)	(4)	(5)
Log(80thPercentileIncome)-Log(50thPercentileIncome)	1.077		1.053	1	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]
Log(share finance)					
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%.

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

Panel A: All Years

Variable:	**N**	**Mean**	**Std. Dev.**
Household income	78739	31601.29	18549.47
Age of head of household	78739	49.34	18.10
Head of household is male	78739	0.55	0.50
Head of housohols is white	78739	0.83	0.38
Head of household has bachelor or graduate degree	78739	0.21	0.41
Number of children in HH	78739	0.67	1.10
Number of adults in HH	78739	1.83	0.83
Log(Consumption)	78739	10.18	0.54
Log(ConsumptionofRich)	78739	11.06	0.13
Log(ConsumptionofVeryRich)	78161	11.21	0.16
Log(80thPercentileIncome)	78739	11.15	0.12
Log(90thPercentileIncome)	78739	11.44	0.13
Log(95thPercentileIncome)	78739	11.68	0.14
Log(50thPercentileIncome)	78739	10.51	0.12
Log(20thPercentileIncome)	78739	9.65	0.14

Panel B: Means By Half-Decade

	1980-1984	**1985-1989**	**1990-1994**	**1995-1999**	**2000-2004**	**2005-2008**
Log(ConsumptionofRich)	10.93	11.04	11.06	11.05	11.08	11.11
Log(ConsumptionofVeryRich)	11.05	11.18	11.20	11.23	11.23	11.27
Log(80thPercentileIncome)	11.04	11.11	11.14	11.17	11.20	11.20
Log(90thPercentileIncome)	11.29	11.38	11.42	11.46	11.51	11.51
Log(95thPercentileIncome)	11.50	11.60	11.65	11.71	11.76	11.76
Log(50thPercentileIncome)	10.44	10.51	10.52	10.51	10.53	10.53
Log(20thPercentileIncome)	9.59	9.64	9.65	9.63	9.67	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(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	28820.26	17784.39
Age of head of household	55627	43.17	17.56
Head of household is male	55627	0.65	0.48
Head of househols is white	55627	0.55	0.50
Head of household is married	55627	0.47	0.50
Number of children in HH	55627	0.95	1.26
Number of adults in HH	55627	2.71	1.60

Note: Data Source is the PSID, 1980 to 2006. Summary statistics are reported for the sample in columns (1) to (3) 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
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 obervation is weighted by the household head weight provided in the Surveys.

Appendix Table A4: Effect of Rich Consumption and Top Income Levels on Non-Rich Expenditure Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Estimated Coefficient on:		Estimated Coefficient Relative to Budget Share on:	
Consumption Category:	Income Elasticity	Visibility Index	Budget Share	Log(80thPercentileIncome)	Log(90thPercentileIncome)	Log(80th PercentileIncome)	Log(90thPercentileIncome)
Food Away from Home	1.241	0.620	0.05	-0.01	0.00	-0.11	-0.03
Food at Home	0.234	0.510	0.24	0.05	**0.05**	0.22	**0.21**
Tobacco Products	-0.240	0.760	0.01	**-0.0067**	**-0.0072**	**-0.63**	**-0.68**
Alcohol Away from Home	1.148	0.600	0.00	0.0024	0.0025	0.53	0.56
Alcohol at Home	0.883	0.610	0.01	-0.0007	-0.0019	-0.12	-0.36
Clothing	0.748	0.710	0.03	0.0000	0.0024	0.00	0.08
Jewelry	0.788	0.670	0.00	0.0001	0.0004	0.04	0.12
Salons, Fitness Clubs	0.755	0.600	0.01	**0.0047**	**0.0047**	**0.55**	**0.55**
Furniture	1.006	0.680	0.02	-0.0067	-0.0060	-0.39	-0.35
Health Insurance	0.539	0.260	0.03	-0.0004	-0.0052	-0.01	-0.18
Business Services	0.957	0.260	0.01	-0.0006	-0.0010	-0.06	-0.11
Recreation and Sports Eq.	1.153	0.660	0.02	**-0.0106**	**-0.0113**	**-0.66**	**-0.70**
Other Recreation Services	0.982	0.580	0.03	-0.0030	0.0021	-0.11	0.08
Charity	0.865	0.340	0.02	0.0026	-0.0030	0.16	-0.19
Interest Paid (non-durables)	0.396	0.260	0.00	-0.0022	-0.0026	-0.95	-1.11
Home Improvement	0.787	0.500	0.01	0.0011	-0.0001	0.12	-0.01
Recre. Vehicles & Homes	0.256	0.660	0.00	0.0011	-0.0016	0.27	-0.41
Appliances	0.512	0.680	0.01	-0.0020	-0.0019	-0.38	-0.36
Utilities	0.482	0.310	0.06	**-0.0282**	-0.0162	**-0.50**	-0.29
Health	0.727	0.360	0.03	-0.0084	-0.0092	-0.28	-0.31
Media	0.710	0.570	0.01	**-0.0056**	**-0.0044**	**-0.49**	**-0.38**
Gas, Tolls, Mass Transit	0.510	0.390	0.05	**-0.0234**	**-0.0188**	**-0.49**	**-0.40**
Travel	1.084	0.460	0.01	-0.0008	0.0005	-0.10	0.07
Education	0.674	0.560	0.01	**-0.0127**	**-0.0154**	**-1.11**	**-1.35**
Cars	1.129	0.730	0.11	**-0.0456**	**-0.0400**	**-0.40**	**-0.35**
Domestic Services	1.009	0.340	0.01	-0.0062	-0.0051	-0.50	-0.41
Home Maintenance	1.073	0.310	0.02	0.0089	0.0046	0.47	0.24
Shelter	0.661	0.500	0.18	**0.1002**	**0.0850**	**0.54**	**0.46**
Phones	0.393	0.470	0.03	-0.0024	-0.0018	-0.09	-0.07

Note: "Budget Shares" are the mean budget shares for each expenditure category in the sample on middle income households across years (where each household is weighted using the CEX weight). "Estimated Coefficients" refer to the estimated betas from the demand system in equation (5). See text for details. Estimated coefficients that are statistically significant at least at the 10 % level are reported in bold.

Appendix A5: Consumption Categories: More and Less Visible; More and Less Income Elastic

Less Visible	*More Visible*	*Less Income Elastic*	*More Income Elastic*
Interest Paid (non-durables)	Shelter	Tobacco Products	Salons, Fitness Clubs
Health Insurance	Home Improvement	Food at Home	Home Improvement
Business Services	Food at Home	Recre. Vehicles & Homes	Jewelry
Utilities	Education	Phones	Charity
Home Maintenance	Media	Interest Paid (non-durables)	Alcohol at Home
Charity	Other Recreation Services	Utilities	Business Services
Domestic Services	Salons, Fitness Clubs	Gas, Tolls, Mass Transit	Other Recreation Services
Health	Alcohol Away from Home	Appliances	Furniture
Gas, Tolls, Mass Transit	Alcohol at Home	Health Insurance	Domestic Services
Travel	Food Away from Home	Shelter	Home Maintenance
Phones	Recre. Vehicles & Homes	Education	Travel
	Recreation and Sports Eq.	Media	Cars
	Jewelry	Health	Alcohol Away from Home
	Appliances	Clothing	Recreation and Sports Eq.
	Furniture		Food Away from Home
	Clothing		
	Cars		
	Tobacco Products		

Note: Reported in the table are the groupings of consumption categories used for the analysis reported in Table 8. The categories listed under "Less Visible" are those we mapped into a visibility index strictly less than .5 (using Heffetz 2011); the categories listed under "More Visible" are those we mapped into a visibility index larger or equal to .5 (using Heffetz 2011). The categories listed under "Less Income Elastic" are those for which we estimated an income elasticity of consumption of the category strictly less than .75; categories listed under "Less Income Elastic" are those for which we estimated an income elasticity of consumption of the category larger or equal to .75.