Trickle-Down Consumption

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Abstract

While incomes of the non-rich in the United States have only risen slowly over the last three decades, incomes in the upper part of the income distribution have risen sharply. Concurrently, the average savings rate has been in decline. We ask whether these two trends are related: does rising consumption among (increasingly richer) rich households induce the non-rich to consume more? We find evidence consistent with this, suggesting that up to a quarter of the decline in the savings rate over the last three decades could be attributed to trickle-down consumption. Additional tests argue against permanent income explanations and against upwardly-biased expectations of future income. Consistent with the trickle-down interpretation of our core finding, households exposed to more spending by the rich self-report more financial duress. Likewise, higher top income levels are predictive of more personal bankruptcy filings. Finally, looking to the political economy implications in both federal and state legislations, we find evidence that, holding ideology constant, legislators that represent areas where income inequality is higher are more likely to vote in favor of policies that increase credit availability or decrease the cost of credit.

1. Introduction

Real incomes in the lower and middle portions of the U.S. income distribution have risen much more slowly over the last three decades than those in the upper part of the income distribution. At the same time, the U.S. saving rate has been in constant decline. Are these two trends related? Is rising consumption among (increasingly richer) rich households inducing the non-rich to spend more?

Using the Consumer Expenditure Survey (CEX), we exploit variation across geographic markets and over time to establish that the consumption of the rich (the top quintile of the income distribution) predicts a higher consumption for the non-rich in the local area (usually a state), holding everything else constant including own income. Moreover, we show that this result is robust to accounting for possible state-year unobservable shocks to consumption. In particular, we instrument for consumption among top earning households in a state with consumption among similarly rich households in other states. In this IV specification, we find that a 10 percent increase in consumption by rich households increases consumption by non-rich households by about 2.5 percent, holding non-rich households' disposable income constant. A counterfactual exercise suggests that, had real incomes of the rich grown at the same rate as that of the median household, the average saving rate of non-rich would have been about 1.5 percentage points higher at the end of the 2000s.

We spend the rest of the paper with two goals – trying to understand what drives the correlation behind our core finding and delving into implications to this trickle-down consumption, as both validation and consequence.

What explains this finding? First, we consider the possibility that the rising consumption (and income) by the rich 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. Unfortunately, the CEX is structured as a repeated cross-section and not a panel; we therefore cannot directly control for a given household's future income levels in our core specification. However, we show that our core result is virtually unaffected by the addition of socio-demographic controls such as education or age, which should be predictive of a household's future income holding current income constant.

To offer more direct evidence on permanent income stories, we turn to the PSID (a panel dataset of household incomes). We find no support for a rational expectations story: holding current income constant, rising top income levels in a state do not predict higher future income for the non-rich.

Second, we consider the possibility that non-rich households in states with growing incomes of the rich update to unduly optimistic expectations about their future income growth. To test for this, we use micro data from the Surveys of Consumers that has been carried out at the University of Michigan since the early 1980s. This survey contains questions about expectations about percent change in family income, as well as questions about expectations about future financial well-being. We fail to find any evidence that non-rich households' expectations about future income and financial well-being are positively affected by increases in the income of the rich in their state.

Third, we ask whether the correlation between rich and non-rich expenditures is related to price-level effects. It could be that local goods price inflation drives up expenditures of everyone in the community. Goods price pressure may be caused by the rising incomes of the rich. Irrespective of the cause, the important consideration for our methodology is whether wage inflation for the non-rich follows the goods price inflation. If non-rich wages do not move in tandem with local goods price levels, our result may not be a decision, but just an artifact of price increases locally.

Another price level story concerns home equity. The rich getting rich may drive up house prices, which could in turn fuel consumption out of home equity. Indeed, higher housing expenses account for a non-trivial share of the higher spending by the non-rich living in markets where top income levels are higher. Testing whether our core effects are solely a trickling through of home equity, we find that trickle-down consumption holds not just for homeowners, but for renters and for households in more elastic house price markets, suggesting that our result is not predominantly a home equity story.

Having cast doubt on the above three correlation stories, we look for evidence supporting a causal trickling-down of consumption via the mechanism of particular goods categories. Looking across twenty-nine categories of goods, we find limited evidence of any systematic correlation between good-level responsiveness and an index of how visible consumption of a good is, as defined by Heffetz (2011). It is therefore unclear that pure status-seeking or statusmaintaining considerations drive our core results. On the other hand, we find a rather strong association between this goods-level responsiveness and whether the good can be categorized as a "rich" good, which we define based on the relative budget share of the rich-versus-non-rich for that good. Based on this finding, we conjecture that a "supply-driven demand" explanation may account for at least part of the higher spending ratios by the non-rich living in richer markets. As top income levels rise in a state, the supply of rich goods in that state increases (for example, domestic and business services, salons, health clubs, and recreational services). The non-rich households end up consuming more of those goods without fully scaling back on other consumption.

While we cannot fully assess the welfare implications of these findings, we do provide some evidence suggestive of higher levels of financial duress among non-rich households exposed to higher top income levels. Specifically, in the Consumer Sentiment Survey data, a higher share of non-rich households report being financially worse off the current year compared to last year when the income of the rich in their market is rising. We also find consistent results in a state-year panel of personal bankruptcies. In a specification that controls for both state and year fixed effects, we find a positive relationship between the household income level of the rich and the number of personal bankruptcies in that state, controlling for household income in the middle and lower part of the income distribution.

Finally, we investigate the political economy implications of our findings. First, 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. Consistent with our findings above, and the view that rising income inequality in a geographic market translates into more demand for credit by middle income households (and median voter) and, subsequently, higher financial duress, we find that Republican Congressmen were systematically more likely to vote in favor of H.R. 5334 if income inequality in their congressional district was higher. Second, we study voting patterns on recent payday legislation in Oregon (HB 2203, 2007) and Ohio (HB 545, 2008). The stated goal of these legislations was to protect consumers from what was described as "predatory" lending practices by payday lenders. This was essentially done by slashing the APR that payday lenders could charge from nearly 400% to 20% to 40%. Again, essentially all Democrats voted in favor of payday lending regulation and the observed variation in voting is among Republicans. Again, we find that income inequality in one's congressional district predicts voting outcomes: representatives of districts where income inequality was higher were more likely to favor regulation of payday lending practices.

In summary, our results suggest that the rise in top income levels and the decline in savings by the middle income households over the last 3 decades might be related phenomena. The non-rich living in richer markets also experienced increased exposure to rich goods and increased their consumption of those goods without fully scaling back on other consumption categories. Our analysis of both personal bankruptcy data and voting outcomes on federal and state-level legislations suggest that financial duress, and hence the need for additional cheap credit, might have been particularly pressing for middle income households living in proximity to the very rich.

2. Data

We integrate a number of data sets and sources, with the baseline focus being on the Consumer Expenditure Survey (CEX) of the U.S. Bureau of Labor Statistics (BLS). The CEX is the main source of detailed consumption information for households in the United States, asking household about consumption in hundreds of categories. The CEX consists of two datasets, the Diary Survey and the Interview Survey; to get a picture of annual consumption, we use the latter. For each quarter since 1980 (previously the survey was every decade), the BLS contacts 15,000 addresses in the U.S. to participate in the Interview Survey sample. The BLS surveys each household 5 quarters on a rotational basis, in which one-fifth of the households are replaced each quarter. The success rate is 78 percent on average, and the BLS constructs survey weights to readjust the respondents to be representative of the U.S. population each period.

The first survey is "warm-up" in the sense that the BLS asks households about their expenditures over the last month more for the sake of instructing them to record or remember these items for the subsequent surveys. We use the annual expenditure data reflecting the subsequent four quarters of surveying. We exclude households who fail to complete all four surveys, except in 1980 and 2008 (the beginning and end of our sample), where we annualize answers for respondents truncated two quarters because of the timing of our sample.

We collapse expenditure categories into the set used by Harris and Sabelhaus (2000), further employed by Heffetz (2011). We amend these categories slightly.[1] We exclude savings deposit "expenditures" and gifts, as well as housing and vehicle purchase and selling. Instead, our measures of shelter and vehicle expenditures are a rental equivalence of how much of these items a household decides to consume. For shelter, we include mortgage payments, property taxes, rent and the like. For vehicles, we replace vehicle capital costs (lease payments, car loan servicing, purchases and sales) with the rental equivalence using the Kelly Blue Book depreciation value. We take the car make, model and year from the demographics files and use the Kelly Blue Book rate of 15% depreciation each year to calculate the depreciation-inspired consumption value, replacing the value with zero if the respondent indicates not owning a vehicle.

In addition to the expenditure surveys, the BLS asks households for demographic characteristics, income, assets and liabilities during the first and last surveys and whenever in the middle surveys that the households respond that changes in these items have occurred. The BLS explicitly states that these data are less precise, especially the assets and liabilities data, than the expenditures since the objective of the survey process is to elicit quality expenditure data from households. From these family demographic files, we average household total income and demographics over as many of the survey quarters in which the survey records income. In our analysis, we will want to absorb disposable income. Our definition of disposable income is total income minus non-property taxes, alimony, and childcare.

We drop households whose average income is zero or whose after tax and contributions income is negative. We also follow Aguiar and Bils (2010) and drop households whose expenditure in any of the twenty-nine aggregate expenditure categories (other than food and shelter) is greater than one-half of total expenditures for the year.

Our empirical design calls for assigning individuals in each state to an income percentile bracket for that state-year. To assign household income percentiles for each state-year, we use household income data constructed from the March Current Population Survey (CPS). Included

[1] Our categories are Food Off-Premise; Food On-Premise; Tobacco Products; Alcohol Off-Premise; Alcohol On-Premise; Clothing and Shoes; Jewelry; Barbershops, Beauty Parlors, and Health Clubs; Furniture and Durable Household Equipment; Health Insurance; Business Services; Recreation and Sports Equipment; Other Recreation Services; Religious and Welfare Activities; Interest Paid by Consumers (except on Vehicles and Housing); Housing Additions and Alterations; Recreactional Vehicles & Homes; Appliances; Utilities; Health; Newspapers, Books; Gas, Bridges, Tolls, Mass Transit; Travel; Education; Cars; Laundry and Domestic Services; Home Maintenance; Shelter; Phones.

in the March CPS are all households, including those without labor force participants. We further place no restrictions on age of household head, armed force membership or group living; we however exclude household with any allocated income variables. We define household income as the sum of total money income for all adult household members. Total money income includes income from business, farm rent and government transfers, in addition to wage income. We then use household weights provided in the survey to compute percentiles of the household income distribution in each state-year cell.

Since our study concerns the expenditures of the non-rich, we drop rich households (as defined below) from the CEX dataset once we calculate necessary statistics for them. We end up with an average of 3,918 non-rich households per year.

Panel A of Table 1 reports the income and expenditure statistics by half decade. All of our data are deflated to 1999 using the CPI deflator from the Bureau of Labor Statistics. In Table 1 and going forward, we define the non-rich (rich) to be all individuals with household incomes less than (greater than) the 80th percentile in their state-year. The threshold for the very rich is the 90th percentile. All statistics are weighted to national representation using CEX weights.

Columns 1 and 2 report real household income and total expenditures for the non-rich in the CEX. On average, the non-rich mark $32,185 and spend almost all of it, $30,723. Columns 3 and 4 show that, excluding those with very low incomes (below the 20th percentile), the non-rich make $47,196 and spend $38,193. As a comparison of the income profile of our CEX sample, middle and low income households on average line up very well with the median national income in column 8. Finally, in columns 5 and 6, we report that the average total expenditures for the rich and very rich are $65,891 and $74,919 respectively.

Panel B of Table 1 breaks down expenditures into twenty-nine goods categories, which are sorted according to a budget share ratio. We calculate the budget share ratio as the average budget share for the goods category across all non-rich individuals over the budget share average for the rich. Thus a higher number means the non-rich spend more on the category than the rich. We then divided in terciles, which we use as splits in the analysis below. Table 1 Panel B reports these budget share ratios, as well as the corresponding average expenditures for each category. As expected, items such as utilities, health and food command higher budget shares for the non-rich, whereas items such as travel, housing additions, and domestic services have a low ratio score for the non-rich relative to the rich.

Before turning to more formal exploration of the data, Figure 1 is an initial glance at the pattern we explore. Figure 1, Panel A plots decade changes in state-level expenditures of the rich and against that of the non-rich. We calculate these decade changes in expenditures by first taking an average of total state-level rich and non-rich expenditures for three years around the decade mark (1980-1982, 1989-1991, 1999-2001 and 2007-2008). We then difference these averages over time to get decade growth measures. The figure pools the periods in the sense that the scatter plot has three dots for each state, one for growth 1980 to 1990, one for growth 1990 to 2000, and one for growth 2000 to 2008. Note that Figure 1 looks materially the same, just with fewer dots, if we plot individual decades separately; no single decade is responsible for the pattern that emerges.

Panel A of Figure 1 shows a positive correlation between the growth in the spending of the rich and non-rich. States with sharper spending growth by the rich experience sharper spending growth by the non-rich. Of course, many things can drive this correlation, the first being the existence of a correlation between the household income growth of the rich and that of the non-rich. To abstract from the role of income, Panel B of Figure 1 plots the relationship between the growth of expenditures (still in dollars) of the rich on the x-axis and the growth of the ratio of expenditures to income of the non-rich on the y-axis. Likewise, Panel C plots the growth in the ratio of expenditures-to-income of the rich against the growth in expenditures-to-income of the non-rich. In all cases, the positive correlation remains. States with faster growth in expenditures of the rich also experience a growth in expenditures of the non-rich, even relative to income.

3. Empirical Methodology

Our goal is to isolate any direct relationship between spending by the rich and the proximate spending of the non-rich. In particular, we focus on non-rich households and ask whether, holding these households' income constant, they spend more as spending by the rich in their relevant market increases.

The dependent variable of interest is the (log of) total expenditures of a non-rich household. The main independent variable is the (log of) total expenditures of the average rich household in the same year-geography. We control for household income non-parametrically by including indicator variables for $2,000 buckets of income. We also year and state fixed effects to remove the patterns of correlation between expenditures of the rich and non-rich that reflect business cycle correlations and to get beyond the raw association across states with always higher or lower expenditures of both the rich and non-rich. The year and state fixed effects force our analysis to identify off state-year variation in patterns of spending by the rich and non-rich. We also include the usual socio-demographic variables – household head's education, household head's race, number of adult household members, number of children, marital status, and a quadratic of age.

This methodology exposes us to the potential for problems of measurement error, attenuation bias and identification off omitted shocks. We address these in turn.

The CEX is generally considered to be very accurate in its expenditure data and nationally representative. At the state-year level, however, using the CEX may pose a legitimate concern, particularly in making an estimate of expenditures for the rich in small states in a single year. It is unlikely that this measurement error is systematic to any factor of concern. However, a bigger problem is in measurement error leading to attenuation bias. For this reason, we focus most of our attention on an econometric specification which takes the expenditures of the rich in a state to be measured as the average of the current year and the two prior years. While directly addressing small sample size issues and attenuation bias problems, this 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.

The other econometric concern we have is that our specification may pick up unobserved state-year shocks that may cause correlated patterns of consumption for the rich and non-rich, beyond national business cycles (picked up by year dummies) and fixed state characteristics (such as common taste patterns). Optimally, we would like to capture variation in the expenditures of the local rich that is uncorrelated with other possible state-year shocks to expenditures among the non-rich. For this, we need an instrument. We propose to instrument spending by top earning households in a state with spending among similarly rich households in other states. Practically, the instrument is constructed as follows. For each state-year, we use CPS data to determine the thresholds of the 80th, 85th, 90th, and 95th percentile of income. Then, we impose these state-year specific thresholds on all households in the entire country for that year. We drop households in the observation state and households below the 80th percentile threshold defined by the observation state. We assign the remaining (out-of-state) people to 80th-

85th, 85th-90th, 90th-95th and 95th-100th buckets according to the thresholds from the observation state.[2] The last step is just to average spending over the four rich quintiles as defined by the observation state for the year. Thus, we use the expenditures of the rich who look like the rich in the observation state but who are not subject to local state-year shocks as the instrument.

A potential problem with our instrument is that we may be (surely are) throwing away variation we care about. Indeed, it is possible that expenditures on certain goods reflect a local trickle down from the rich to everyone else in that market, and that the look-alike rich in every other market may not experience the same timing, magnitude or taste for the consumption of goods those goods. The instrument that we constructed forces us to abstract away from any such local trickle-down effects. On the other hand, the instrument further helps address attenuation bias issues as we can rely on a larger sample of rich households to predict rich spending in a given state and year.

4. Results

4a. Main Results

Table 3 presents the baseline estimation of the effect of the rich's expenditures on that of the non-rich. We only present the coefficients on the main variable of interest. Also included in the estimation are demographic controls for age, education, race and the number of people and children in a household, as well as the income, state, and year fixed effects. All estimates are clustered at the state level and weighted with CEX representative weights.

Column 1 shows that the elasticity of expenditure of the non-rich to the expenditure of the rich in a state-year is significant and positive at 0.074. If we focus instead on the expenditures of the very rich (using a 90th percentile of income cutoff in column 2 instead of the 80th percentile cutoff in column 1), the relation halves in magnitude but remains positively significant. We use the 80th percentile cutoff going forward.

Columns 3 and 4 break the non-rich sample into individuals in very low income households (below the 20th percentile of income) and low and middle income households. The

[2] To be clear, say the observation state is Alabama, which is not a high income state. A person in Connecticut, which is a high income state, might be only at the 65 percentile of income (a non-rich) in Connecticut, but get assigned to the 80th-85th income bucket (a rich person) for the Alabama reference observation.

coefficients show the intuitive result that the correlation between the expenditure of the rich and non-rich is larger for the middle and lower income groups than for very low income households.

Prior research suggests strong peer effects in consumption. In column 5, we try to account for such peer effects by including expenditures of the peer reference group as a control. We define the peer as everyone else in the individuals' quintile income bracket in that state-year. Although including such peer consumption may capture some of the trickle-down mechanism we are trying to isolate (as the peers' own consumption would also be subject to trickle-down), it is still important to assess whether our result is robust to accounting for such peer influences.[3] The estimated elasticity of interest goes down but only slightly, from 0.074 to 0.060.

The final three columns of Table 3 report the sensitivity of expenditures of the non-rich to that of rich after removing shelter expenses from both the right hand side and left hand side total expenditure variables. Shelter is a special case because it is possible, even likely, that as the rich get richer and demand more in terms of housing consumption, they may drive up the prices of housing consumption for everyone else (see Matlack and Vigdor 2008 and our own analysis of local CPI effects below). As columns 6 of Table 3 shows, our main result only slightly diminishes in size, from 0.074 to 0.061, when we remove shelter from total expenditures on both the right and left hand sides of the equation for the full sample. The coefficient remains strongly significant in the full sample and the subsample that focuses on the middle and lower income groups.

While Table 3 establishes a relation between expenditures of the rich and non-rich, Table 4 assesses the robustness of the relationship to the measurement error concerns and omitted variable concerns discussed in Section 3. As in Table 3, we first present results for total expenditures of the non-rich and then for total expenditures minus shelter.

Columns 1-3 redo the analysis with the main independent variable being the three year average (this year and the two prior) of total expenditures of the rich in a state-year. We construct this alternative version of total expenditures of the rich to correct for measurement error induced by the reality that some state-years may have too few rich observations to estimate means properly. Indeed, what we find is that our coefficients in columns 1-3 increase by 70-75 percent relative to the same setup in Table 3, suggesting that the moving average independent

[3] This result holds if we instead let the peer effect enter by including total expenditures for each quintile of the income distribution in the state (i.e., total expenditures of the 0-20% percentile income group, total expenditures of the 20-40th percentile, etc.).

variable removes attenuation bias. This is also true in the specifications reported in columns 5 to 8, where we exclude shelter from total expenditures. In what follows, we will use this moving average of total expenditures of the rich as our main independent variable of interest.

In the remaining columns of Table 4, we further address the possibility of unobserved state-year specific shocks to expenditures that may affect both the rich's and the non-rich's spending. To do this, we use the instrument for total expenditures of the rich as described in the methodology section (Section 3). Column 4 of Table reports the main IV estimate. The estimated coefficient on the instrumented total expenditures of the rich is 0.367, more than double the OLS estimate from column 1. Columns 9 and 10 report similar IV estimates when the dependent variable is total expenditures minus shelter. Again, the IV estimates appear larger than the OLS estimates in columns 5 and 8; they are also more noisy.

4b. Can Permanent Income Considerations Explain our Main Result?

One potential explanation for our results so far is that, while non-rich households exposed to higher top income appear to be spending more than similar households exposed to lower top income, our ability to perfectly match households across states is limited. In particular, while we hold current household income constant in all the specifications reported above, it is possible that the non-rich households we compare are in fact different in terms of their permanent income. The most obvious concern is that non-rich households with markets where top income levels are higher, and increasing so, rationally expect their own income to go up in the future. In other words, a higher income level at the 80th percentile in a state today may be systematically related with higher future income for household below the 80th 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. We can however assess how sensitive our key estimates are to the addition of socio-economic controls which may predict systematically different future income trajectories between households of similar current disposable income. We do this in Table 5. Specifically, we assess the sensitivity of our key estimates in the OLS moving average specification to the removal of education and age as controls. The idea is as follows: if a rise in the income or spending of the rich in a given state attracts more educated people in that state, it is possible that education will be systematically positively correlated with our key independent variable. To the extent that a higher education level in a household predicts higher future income for that household compared to another household of similar current income, the combination of these two forces may lead to our key estimate being biased upwards. The same may apply to age, if younger individuals are more likely to relocate to areas with higher top income levels, and these younger individuals have faster future earnings trajectories. As one can see in Table 5, our key estimates of the relationship between non-rich spending and rich spending are essentially invariant to controlling for age or education.

We also turn to another dataset that is structured as a panel of households to formally test for the possibility that a given household's future income, holding the household's 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 1979 to 2007. We merged onto the PSID, by state-year cell, CPS information about household income level at the 80^{th}, 90^{th}, 50^{th} and 10^{th} percentiles. We focus our analysis on the subset of household-year observations with incomes below the 80^{th} percentile in the household's state-year. We regress the logarithm of future household income (t+1, t+2 or t+3) on the logarithm of current household income, year and state fixed effects, and the logarithms of household income at the 80^{th} (or 90^{th}), 50^{th} and 10^{th} percentile (all averaged over the years t, t-1 and t-2). We also performed additional specifications that further include household fixed effects.

The results from this PSID analysis are reported in Table 6. In Panel A, we use income level at the 80^{th} percentile to define rich income; in Panel B, we use income level at the 90^{th} percentile. In neither specification do we find evidence that increased top income levels in a state in a given year are predictive of higher future income levels for non-rich households in that state in future years (where future is defined as t+1 for columns 1 and 2, t+2 for columns 3 and 4, and t+3 for columns 5 and 6). The same holds if we use as dependent variables the average of future income between t+1 and t+2 (columns 7 and 8) or the average of future income between t+1 and t+3 (columns 9 and 10). In fact, most of the point estimates we estimate are negative (but statistically insignificant).

In summary, while we cannot directly control for permanent income level in the CEX, the analysis we perform in the PSID, and the sensitivity analysis we perform in the CEX, fail 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 3 and 4.

4c. Can Upwardly-Biased Expectations about Future Income Explain our Main Result?

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, 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 thus expenditures 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 these monthly surveys into a single dataset that covers the time period 1980 to 2009. For each state-year cell, we merge in CPS information on key percentiles of the income distribution in that cell.

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 20 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 3.4 percent.

For individuals whose family income is below the 80th percentile in their state-year cell, we then regress answers to these income expectation questions on top income levels in that state-year cell. In particular, we estimate the following regression:

$$\begin{aligned} &IncomeChangeExpectation_{ist} = Log\left(80/90^{th}\,PctileIncome\right)_{st} + Log\left(50^{th}\,PctileIncome\right)_{st} \\ &+Log\left(10^{th}\,PctileIncome\right)_{st} + Actual\ Income\ Change_{i} + Individual\ controls_{ist} \\ &+Household\ Income\ dummies_{ist} + State_{s} + Year_{t} + \varepsilon_{ist}, \end{aligned} \tag{1}$$

where i is an individual, s, a state, and t a year. $Log\left(80/90/50/10^{th}\,Pctile\ Income\right)_{st}$ is the logarithm of average household income at the 80/90/50/10th in state s between year $t-2$ and t.[4]

The coefficient of interest is that on $Log\ \left(80/90^{th}\,Pctile\ Income\right)_{st}$. *Household Income dummies* are dummies for current household income levels of $1,000 increments. 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. $State_s$ are state fixed effects and $Year_t$ are year fixed effects. We also include a variable that captures realized real income growth in the state-year-income percentile cell the survey respondent belongs to (either as dummy variable for positive real income growth or a continuous variable for actual income growth), which we compute from the CPS data.[5] 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 7. 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 various subsamples of the data: all individuals whose household income is below the 80th percentile in their state-year cell (columns 1 and 2), as well those with household income between the 20th and 80th percentiles (columns 3 and 4), between the 50th and 80th percentiles (columns 5 and 6) and between the 20th and 50th percentiles (columns 7 and 8).

In none of the regressions in Table 7 do we find a positive and statistically significant relationship between expectations about future income growth and top income levels. In fact, all

[4] We find qualitatively similar results if we only use year t information to compute Income at the 80/90/50/10th percentile.

[5] Because the Survey of Consumers is not a panel, we do not observe the individual's actual income realization in the next year.

but two of the estimated coefficients on the *Log*(*80th Pctile Income*) or *Log*(*90th Pctile Income*) variables are negative, with some of them statistically significant at standard levels. In other words, we fail to find any systematic evidence that non-rich households have systematically upwardly biased expectations about their future income when exposed to higher top income levels in their market.

For example, across all non-rich households, a 10 percent increase in the income level at the 90th percentile (80th percentile) reduces the likelihood that a given individual expects a rise in his or her real household income in the next year by about 0.7 (1.5) percentage point(s) (Panel A, columns 1 and 2 respectively). Similarly, across all non-rich households, a 10 percent increase in the income level at the 90th percentile (80th percentile) reduces a given individual's expected percent change in household income in the next year by 0.7 (0.8) (Panel B, columns 1 and 2 respectively).

To summarize Tables 6 and 7, we fail to find either rational or behavioral explanations for our earlier CEX findings through future income expectations. In the PSID, we did not find any evidence that current (or current and past) top income levels in a state are predictive of a given household's future income growth once we hold that household's current income level constant. In the University of Michigan's Survey of Consumers, we similarly failed to find evidence that non-rich households might mistakenly perceive higher top income levels in their state as a signal of faster own future income growth. While this evidence remains indirect (and is certainly inferior to the more direct test that could have been performed had the CEX been structured as a panel rather than a repeated cross-section), it runs against the view that either a permanent income channel or an upwardly-biased income expectation channel are responsible for the higher spending levels and ratios we observed in the CEX among non-rich households that are exposed to higher top income levels.

4d. Can Home-Equity Based Borrowing Explain our Main Result?

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 key finding is driven by the same mechanism? To the extent that rising top income levels in a state are associated with rising home prices (see 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 8. Unfortunately, while the CEX allows us to separate renters from homeowners, there is no variable capturing when a household bought their current house. Our findings in column 1 and 2 indicate that our key result is not restricted to the subsample of homeowners, as would have been implied if our effect was primarily driven by the home equity channel identified by Mian and Sufi. We find somewhat smaller, but still statistically significant evidence on trickle-down consumption in the subset of renters.

Two other cuts of the data might be pertinent for assessing the relevance of a home-equity based borrowing channel. In columns 3 and 4, we estimate our core regressions separately for the pre- and post-95 period. 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 find stronger trickle-down consumption pre-1995. In columns 5 and 6, we split the sample into states with inelastic and elastic housing supply elasticities using the measure of Saiz (see Saiz 2011), aggregated to the state-level.[6] 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. We do find significantly larger estimates in markets where housing supply is less elastic. But our effects remain economically large and statistically significant even in the more elastic markets.

In summary, because our core results hold both for homeowners and renters, we do not believe that home-equity appreciation, which might be correlated with the rise in top income levels in a state, is the sole explanation for our finding. But there is some evidence of stronger trickle-down correlations in more inelastic housing markets and among homeowners, which indeed could be due to the impact of rising top income levels in those markets on equilibrium house prices.

4.e. Unpacking the Rise in Expenditure to Income Ratios: Visible Goods and Rich Goods

[6] We use the data from Saiz's website to construct the housing supply elasticities. Saiz's data are at the metropolitan level, howeve, rather than at the state level. Although we cannot perfectly map this finer data to our state-level aggregations, we take the metro areas, which often cover multiple states. (For example, the Kansas City metro area covers two states, Kansas and Missouri. We naively assume that the population is split equally among the states covered in a metro area. Finally, we average the supply elasticities within the state using the population apportioned to that metro area after doing the multiple-state splitting where appropriate.

We return to the CEX and look in finer detail at expenditures by good category to refine our understanding of the trickle-down consumption. We begin by regressing each CEX household expenditure in one of 29 categories of goods on the three-year state average of total expenditures of the rich, absorbing state, year, and income effects. We are interested in knowing which categories of non-rich expenditures explain the sensitivity of total non-rich expenditures to rich expenditures. As the summary statistics in Table 2, Panel B show, however, the mean levels of expenditures vary from very small categories at around $100 per year (e.g., jewelry and non-housing/non-vehicle interest) to very large expenditure items, such as food at home ($8,728). In order to be able to compare the coefficient magnitudes, we need to standardize them in some way.

The usual procedure would just be to standardize expenditures in each of the 29 categories to a 0-1 z-score value by subtracting out the mean and dividing by the standard deviation. For example, if we denote clothing expenditures for individual *i* who exists in CEX year *t* as $c_{it}^{clothing}$, and the mean and standard deviation of clothing expenditures for the year as $\mu_t^{clothing}$ and $\sigma_t^{clothing}$ respectively, then a traditional standardized dependent variable $z_{clothing,it}$ would be:

$$z_{clothing,it} = \frac{c_{it}^{clothing} - \mu_t^{clothing}}{\sigma_t^{clothing}} \tag{2}$$

Because we would like be able to compare the estimates to prior CEX tables, in particular column 1 of Table 4, we further transform expression (2) to the distribution (the location and scale) of total expenditures for the year; i.e.:

$$std_{clothing,it} = \left[\frac{c_{it}^{clothing} - \mu_t^{clothing}}{\sigma_t^{clothing}} \right] * \sigma_t^{total\ \exp enditures} + \mu_t^{total\ \exp enditures}. \tag{3}$$

The resulting variable, for each of the 29 expenditure goods categories, will have the exact mean and standard deviation of the total expenditures variable for the year.

Table 9 presents these results. Each row represents a single estimation of the log of the standardized expenditures of the non-rich in a goods category on the moving average version of the log total expenditures of the rich in the state-year. Included are state, year, and income fixed effects as well as demographic controls. For conciseness, we just report the coefficients, their standard errors (column 2) and the corresponding goods category visibility score and budget share ratios (columns 3 and 4).

To aid in the understanding of these results, we split the table according to what the visibility scores or budget share ratios might predict. One might assert that trickling down of consumption might occur in highly visible goods or in goods for which the non-rich have small budget shares ratios relative to the rich. This need not be exactly the case, but these notions at least provide some frame to evaluate whether our results are intuitive.

Table 9 is thus organized into four sections. The first group consists of goods that neither a visibility split (around the median of 0.56) nor a budget share ratio split (around the natural split of 1) would suggest a possibility for a trickle effect. Intuitively, these are largely necessity goods like utilities and food at home. The coefficients when regressing the standardized versions of expenditures on these goods on rich total expenditures are not significant, as expected, with the exception of health items. Rather than try to ex post rationalize all of these results, like the health coefficient, we just offer our intuition of what we expected and highlight the extent to which the results are consistent with the visibility and budget share ratio notions.

If the goal of the first category was to make sure that we do not find results in goods where no trickling should occur (in the spirit of a placebo), the goal of the next category is to look for results in good for which both visibility and budget shares predict the possibility of trickling. We find a significant elasticity of alcohol off premise, clothing, jewelry, furniture, beauty and fitness services, and recreation services. We do not find an effect for a few other goods one might have expected, mainly recreational items and vehicles, but nevertheless our coefficients are at least somewhat consistent with the intersection of visibility and budget share ratios predictions.

The final two panels assign goods categories to sets for which visibility and budget share ratio theories differ. In these splits, the budget share dissection of expenditure goods categories performs somewhat better. Expenditures by the non-rich on many service items, which the rich consume in greater proportions than the non-rich, such as home maintenance, professional services and domestic services (as well as recreational, health and beauty services from above) have significant elasticities to rich total expenditures.

To investigate further the idea of rich goods and services, as defined by our budget share ratio, Table 10 reports test for which we aggregate all expenditures by a non-rich individual by three budget share ratio splits. For example, the "non-rich goods" group contains the sum of an individual's spending on utilities, food at home, gas and toll, etc. (See Table 1 for the exact goods distribution.) The dependent variable in each column is the ratio of spending relative to total expenditures. Note that there is a mechanical adding-up effect that if there is a positive shift toward some goods, the budget share of other goods must fall.

Across all columns, the results strongly confirm the intuition that the non-rich shift consumption budget shares away from non-rich goods (columns 1 and 4) and towards "intermediate" goods (columns 2 and 5) and rich goods (columns 3 and 6). The non-rich shift 3-4% of their consumption bundles away from the non-rich goods category and towards goods and services consumed by higher income households. A comparison of columns 2 and 5 suggest that the rise in the spending share in the "intermediate goods" category is mainly driven by shelter expenses.

4.f. How Large Are These Effects: A Counterfactual Exercise

We can say more about the economic magnitude of the effect by doing a simple counterfactual exercise. What would have happened had the rich not gotten increasingly richer over the last few decades? For each of the state-year income brackets (80^{th}-85^{th} percentile, 85^{th}-90^{th} percentile, 90^{th}-95^{th} percentile and 95^{th}-100^{th} percentile), we replace the realized growth rate in income with the median growth rate from the population. We then calculate what the new income would imply (using the true relation between the rich's expenditures and income) for rich expenditures. We run our main IV specification (Table 4, column 4) of the log total expenditures of the non-rich on log total expenditures of the rich (Table 4, column 4). We then use the estimated coefficient to predict what total expenditures of the non-rich would have been, replacing the rich's true expenditures with the counterfactual (lower) rich expenditures.

Figure 2 presents these results, showing that, although there is a lot of volatility in the estimate, the non-rich would have been saving an additional $500 per year over the entire period, or over $800 per year nearing the end of the 2000s decade.

5. Evidence on Consequences: Financial Duress and Personal Bankruptcy Filings

While assessing the welfare implications of our findings is beyond the scope of this paper, we present evidence from two separate data sources that are consistent with the hypothesis that non-rich households' financial well-being may be negatively affected by their exposure to higher top income levels. For the first source, we return to the University of Michigan's Survey of Consumers which contains individuals' subjective evaluation about their current financial well-being. For the second source, we turn to a more objective measure by studying the relationship between the number of filed personal bankruptcies in a state and the dynamics of top income in that state. Both analyses suggest that higher top incomes in a market are associated with more financial duress among the non-rich in that market.

5a. Self-Reported Financial Duress

Included in the University of Michigan Survey of Consumers 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. Across all individuals and survey years, about 30 percent of respondents indicate being financially worse off today than a year ago. We then ask whether exposure to higher top income levels is associated with greater self-reported financial duress, holding household income and household characteristics constant. Specifically, we estimate the following OLS regression, which directly follows estimation equation (1) from the prior Michigan analysis:

$$\begin{aligned} &Financially\ Worse\ Off\ \ Today_{ist} = Log\left(80/90^{th}\,PctileIncome\right)_{st} \\ &+Log\left(50^{th}\,PctileIncome\right)_{st} + Log\left(10^{th}\,PctileIncome\right)_{st} \\ &+Individual\ controls_{ist} + Household\ Income\ Dummies_{ist} + State_s + Year_t + \varepsilon_{ist}, \quad (4) \end{aligned}$$

where $Log(80/90^{th}\ Pctile\ Income)_{st}$ is the logarithm of average household income at the in the 80^{th} (or 90^{th}) percentile in state *s* between year *t-2* and *t*, and likewise for the 50^{th} percentile and the 10^{th} percentile.[7] The coefficient of interest is that on $Log\ (80/90^{th}\ Pctile\ Income)_{st}$. *Household income dummies* are dummies for current household income levels of $1,000 increments. 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. $State_s$ are

[7] We find qualitatively similar results if we only use year t information to compute income at the $80/90/50/10^{th}$ percentile.

state fixed effects and $Year_t$ are year fixed effects. Each observation is weighted by household head weight provided in the Surveys. Finally, standard errors are clustered at the state level.

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 decreased expenses or lower debt, interest or debt payments today than a year ago.[8] Across all individuals and survey years, about 10 percent of respondents indicate fewer expenses and debt payments today than a year ago.

Table 11 follows the same structure as Table 7. In particular, as in Table 7, we present results for various subsamples of the data: all individuals whose household income is below the 80th percentile in their state-year cell (columns 1 and 2), as well those with household income between the 20th and 80th percentiles (columns 3 and 4), between the 50th and 80th percentiles (columns 5 and 6) and between the 20th and 50th percentiles (columns 7 and 8).

All regressions in Panels A and B of Table 11 point towards more financial duress, as well as a lower ability to reduce expenses and debt payments, among non-rich households that are exposed to higher top income levels. Consider columns 1 and 2 for example, where the sample includes all households with income levels below the 80th percentile in their state-year cell. A 10 percent increase in the income level at the 90th percentile (80th percentile) increases the likelihood that a given individual reports being worse off financially today than a year ago by a statistically significant 3.4 (5.2) percentage points (Panel A, columns 1 and 2 respectively). Similarly, a 10 percent increase in the income level at the 90th percentile (80th percentile) reduces the likelihood that a given individual reports fewer expenses and lower debt payments today than a year ago by a statistically insignificant 1.2 (statistically significant 1.9) percentage points (Panel B, columns 1 and 2 respectively). The remaining columns of Table 10 show that these findings are robust, and in fact quite stable, across sub-groups of the income distribution.

5b. Personal Bankruptcy Filings

[8] Specifically, we single out the two following reasons for the self-reported current financial well-being (based on variables PAGOR1 and PAGOR2): 1. Decreased expenses: fewer people to be supported by FU; spending less; thrift; not applicable if the individual also mentioned lower prices or lower taxes; 2. Debt, interest or debt payments low or lower: have paid, is paying bills; interest rates lower.

A more objective measure of a household's financial duress is the likelihood to file for personal bankruptcy. It is well-known that personal bankruptcy filings have increased dramatically over the last few decades and a natural implication of our analysis so far is that the rise in top income levels, to the extent it triggers higher expenditure ratios among the non-rich, may help explain part of the increase in the number of personal bankruptcies.

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 households, we can study the relationship between the dynamics of top income level and the number (or rate) of personal bankruptcies in a state-year panel. We report this analysis in Table 12.

Specifically, we obtain information on annual number of personal bankruptcy filings by state for the period 1980 to 2009.[9] 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.[10]

We are interested in whether higher top income levels in a state are predictive of a higher number of personal bankruptcy filings in that state. 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 expenditure 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 expenditure responses. Therefore, in our baseline specification in column 1 of Table 11, we regress the log number of personal bankruptcies in a state s and year t on the logarithm of average top household income levels in that state between year t-3 and t-1, controlling for the logarithm of the number of households in the state. We weight each observation by population size (number of households in the state) and cluster standard errors at the state level.

Maybe not surprisingly given the already-well established trend up in top income levels and trend up in the number of personal bankruptcies, we find a positive correlation between the logarithm of average household income at the 80th percentile in a state between year t-1 and t-3 and the number of personal bankruptcy filings in that state in year t. In column 2, we add state

[9] This data can be found at www.abiworld.org<http://www.abiworld.org>, by clicking on the link "online resources" and then "bankruptcy statistics."

[10] We assign Census information from Census year t to years covering the first 5 years of a decade and Census information from Census year t+1 to the last five years of a decade.

and year fixed effects to the model estimated in column 1. While the estimated R^2 jumps from 0.66 to 0.96, the estimated coefficient on the top income control remains of the same order of magnitude as in column 1. Specifically we find that a 10 percent increase in average income level at the 80th percentile between t-1 and t-3 (column 2, Table 11) raises the number of personal bankruptcy filings in that state in year t by 13 percent.

In column 3, we further control for the logarithm of average income level at the 50th percentile in that state between t-1 and t-3. The estimated coefficient on top income level is economically unchanged. Column 4 replicates column 3 but allows for state specific year trends. Again, the estimated coefficient on top income level is unchanged.

Columns 5 and 6 respectively replicate columns 3 and 4 but further control for the logarithms of current household income at the 80th and 50th percentile in the state. Again, the estimated coefficient on the logarithm of average household income at the 80th percentile between year t-1 and t-3 remains unchanged. Current level of top income does not correlate with current number of bankruptcies. Interestingly, current income level at the 50th percentile is a strong negative predictor of the current number of personal bankruptcies, likely capturing how current income shocks may push already heavily indebted middle-income households into bankruptcy.

Finally, columns 7 and 8 replicate columns 5 and 6 but further control for the logarithm of current income level at the 10th percentile of the income distribution. The findings in those columns are fully consistent with those in columns 5 and 6. The only robust positive predictor of the number of bankruptcy filings in a state is the logarithm of average income level at the 80th percentile in that state between t-1 and t-3, with the point estimate on that variable essentially unchanged compared to the specifications in prior columns. While there is no impact of current income level at the 80th percentile, higher current income levels at the 50th and 10th percentile in a state both reduce the total number of bankruptcy filings in that state in that year.

6. Political Economy Implications

Our results suggest some important political economy implications. In particular, political representatives of areas where the median voter is exposed to higher top incomes may be particularly responsive to policies targeted at increasing access to credit, as well as providing cheaper credit, to this median voter. We test for these political economy implications in two contexts. First, we study voting patterns on the Federal Housing Enterprise Safety and Soundness Act (H.R. 5334) which Congress passed in 1992. Second, we study voting patterns on recent payday legislation in Oregon (HB 2203, 2007) and Ohio (HB 545, 2008).

6.a. Federal Housing Enterprise Safety and Soundness Act of 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 the oversight of that new regulator. 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.[11]

With home ownership rates in the US at about 60 to 70 percent in the United States 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 and cheaper credit would have been particularly strong when middle income households and 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 that represents congressional districts where income inequality, and especially between the gap between the middle and the top of the income distribution, is higher.

To perform this analysis, we obtained individual voting records on H.R. 5334. We then map each congressional district from the 102nd Congress (which was in session when this bill was passed in 1992) into the 1990 census tracts that cover this district. We then use 1990 census

[11] Rajan (2011) 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."

information to construct measures of median household income and 80^{th} percentile household income for each congressional district. We define income inequality within a congressional district as the difference between log (household income) at the 80^{th} percentile and log(household 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 voted in favor of this new legislation, 52 voted against. In Table 13, 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 13, we regress the likelihood of voting in favor of H.R. 5334 on income inequality in the district and median income in the district. We observe a positive but statistically insignificant correlation between a yes vote and income inequality. In column 2, we further control for state fixed effects. The estimated relationship between a yes vote and income inequality becomes much larger (1) and marginally significant (p=0.06). 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. Further controlling for log (population) in the congressional district (column 3) does not change this result. In column 4, we also control for the share of employment in finance in each congressional district. This share enters positively, possibly consistent with the view that lobbying pressures by the financial sector, or consideration for the positive economic impact of this legislation on the financial sector, may also have influenced voting. The estimated coefficient on income inequality remains economically large (0.8) but becomes less statistically significant (p=0.18).

6.b. State-Level Payday Lending Legislation: The Case of Ohio and Oregon

In recent years, a few states passed legislation whose stated goal was to protect consumers from what was described as “predatory” lending practices by payday lenders. We focus on two such legislations recently adopted in Ohio and Oregon. H.B. 545, which was passed in Ohio in 2008, slashed the APR that payday lenders could charge to 28 percent, down from 391 percent and prohibited loan terms of less than 31 days. Similarly, H.B. 2203 which was passed in

Oregon in 2007 capped the APRs that payday lenders could charge at 36%, limited origination fees to 10% and required a minimum 31-day maturity.[12]

Given our findings above, how do we expect political representatives' voting on these bills to be affected by the level of income inequality within their district? To the extent that a higher level of income inequality is associated with a higher dependence on those expensive payday loans among one's low and middle income constituents, one may expect that representatives that experience greater income disparities within their district might be more willing to reduce such "predatory" lending and hence vote in favor of such legislation, which will effectively reduce the financial burden on their constituents. This reasoning of course might be a bit naïve and strongly relies on the assumption that the total supply of credit will not be affected by the restrictions imposed on payday lenders. In practice, studies (see for example, Zinman 2010) of the impact of these bills have shown that these legislations may have in fact made vulnerable consumers worse off, with former payday lenders shifting into plausibly inferior substitutes to payday loans as payday lenders shut down their branches in states where the price they can charge are capped. Hence, while the naïve reasoning would predict a positive relationship between income inequality in one's district and support for these bills, a less naïve reasoning would predict a negative relationship. In practice, the naïve reasoning seemed to dominate the political debate, with the strongest political proponents of these bills stressing how good the interest caps would be for vulnerable consumers.

To empirically investigate these effects, we collect data on individual votes (both in the State House and the State Senate on the Oregon and Ohio bills. To obtain measures of median income and income inequality by congressional district, we mapped each district into census tracts and used tract-level information from the 2000 census to compute income distribution by congressional district.

Just as with H.R. 5334, voting on these payday lending legislations was strongly influenced by party affiliation. In Oregon, all Democrats voted in favor of restricting payday lending; in Ohio, only 5 Democrats voted against while 52 voted in favor. We observe more variation in voting among Republicans. In Ohio, 46 Republicans voted "yes" while 25 voted

[12] However, both of these bills also limited the number of payday loans a given borrower could make (in Ohio, to a maximum to four loans per year; in Oregon, by establishing a waiting period between payday loans).

“no”; in Oregon, 11 Republicans voted “yes” while 27 voted “no.” In Table 14, we therefore again focus our analysis on voting patterns among Republicans.

In column 1 of Table 14, we regress the likelihood of voting in favor of payday lending regulation on income inequality in the district and median income in the district. We observe a positive and statistically insignificant correlation between a yes vote and income inequality.

The magnitudes are comparable to those in Table 13. A one standard deviation increase in income inequality (0.10) increases the likelihood of a Republican voting in favor of payday regulation by about 10 percentage points. Further controlling for whether the representatives sit in the house or the senate and for whether this is the Ohio or Oregon bill (column 2) does not change this result. Further controlling for log (population) in the congressional district (column 3) does not change this result either. Hence, these findings support the naïve voting perspective outlined above. They are consistent with the view that higher income inequality within one’s congressional district may have made more constituents dependent on payday loans and created a political will to protect those constituents from too much financial burden.

7. Conclusion

The question that motivated this paper is whether rising income inequality and the decline in the personal savings rate over the last 3 decades were related phenomena. We proposed to use a state-year panel data analysis to inform our thinking on this question. The evidence we have put together suggests that there might indeed be an economically important link. Holding income constant, middle and lower income households that are exposed to higher top income levels in their market appear to spend a higher share of that income. While higher shelter expenses contribute for a non-trivial part of this higher spending out of income, middle and lower income households expose to higher consumption by the rich also appear to consume more “rich” goods, maybe because they are exposed to a higher supply of those goods in their market. In future work, we would like to complement this study with 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.

One alternative explanation for our findings that we cannot formally rule out so far is that of a reverse causality, where higher consumption by middle and low income households in a state raise top income levels in that state. While we do not an instrument for top income level variation, we feel that the separate analysis we perform by rich versus non-rich goods does not fit well under this reverse causality explanation.

Both our analysis of the personal bankruptcy data and of voting on federal and state-level legislations suggest that financial duress, and hence the need for additional cheap credit might have been particularly pressing for middle income households living in proximity to the very rich. To the extent that such policies to increase access to credit (such as H.R.5334) may have also translated in a lot of bad credit, rising income inequality may have been a critical component in the recent financial crisis.

References

Aguiar, Mark and Mark Bils. 2011. “Has Consumption Inequality Mirrored Income Inequality”, NBER WP #16807.

Harris, Ed and John Sabelhaus. 2005. “Consumer Expenditure Survey Family-Level Extracts,1980:1–2003:2.” NBER website. (www.nber.org/data/ces cbo.html, July 2007)

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

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

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

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

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

Zinman, Jonathan. 2010. “Restricting Consumer Credit Access: Household Survey Evidence on Effects Around the Oregon Rate Cap.” *Journal of Banking and Finance*, 34 (3): 546-556.

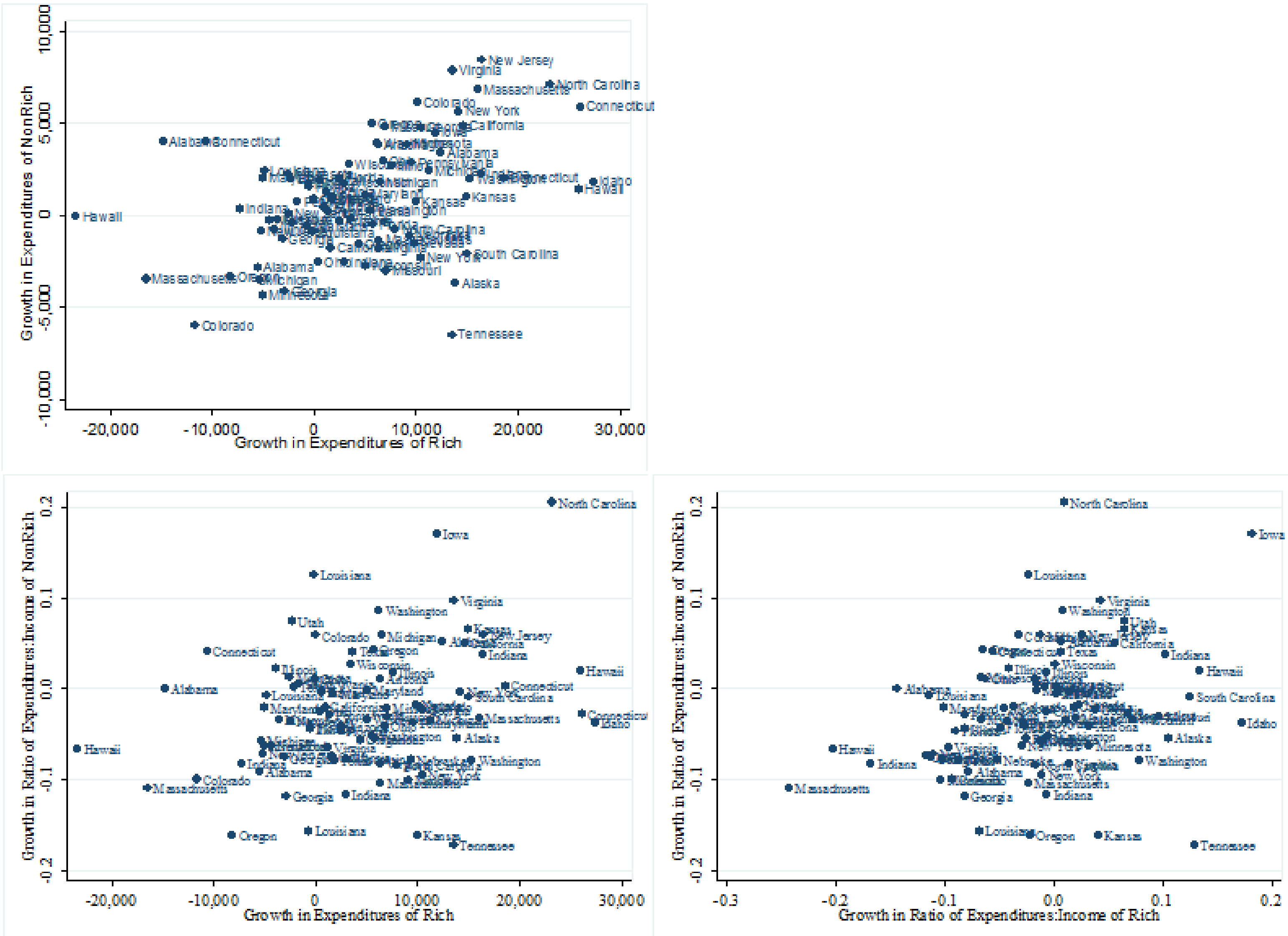

Figure 1: State-Decade Growth in Expenditures of NonRich plotted Against State-Decade Expenditures of Rich

Figure 2: Counterfactual Exercise

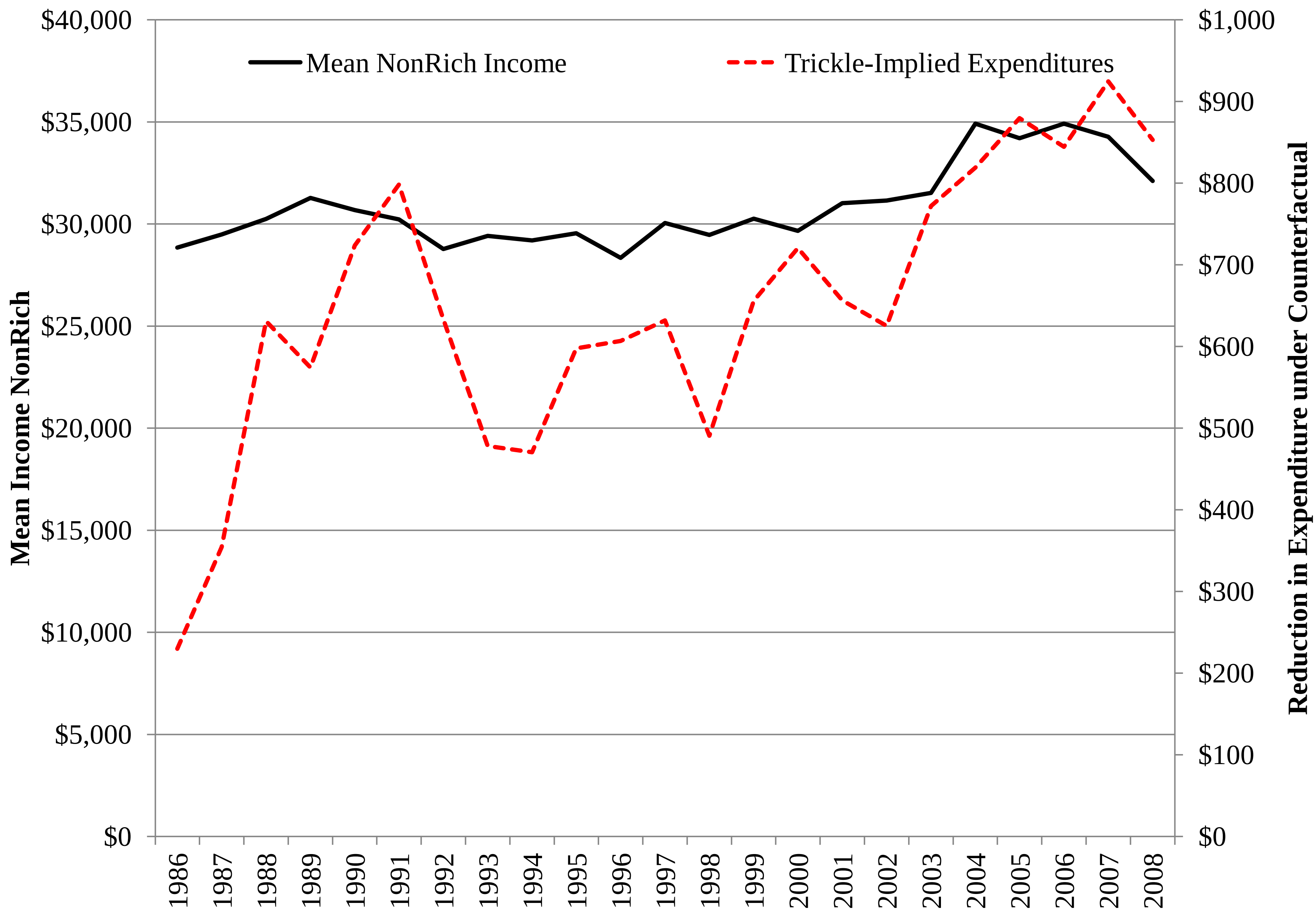

Table 1: Summary Statistics for Consumer Expenditure Survey Data

Panel A reports the income and expenditure statistics by half decade breakdown. Columns 1 and 2 report real (to 1999 dollars) household income and total expenditures for the non-rich in the CEX. Non-rich is defined to be households with income less than the 80th income threshold for the state-year. Columns 3 and 4 limit the sample to individuals in between the 20th and 80th percentiles of state-year household income. Columns 5 and 6 report the average total expenditures for the rich (over 80th percentile) and very rich (over 90th percentile) respectively. All statsitsics using CEX data are weighted to national representation using CEX weights. Columns 7, 8, and 9 report the 20th, 50th, and 80th percentiles from the Current Population Survey.

Panel A: Consumer Expenditure Survey Data

	Income of Non-Rich Households	Total Expenditures of Non-Rich	Income of Middle & Low Income Households	Expenditures of Middle & Low Income Households	Total Expenditures of Rich	Total Expenditures of Very Rich	CPS -Income 20th%ile	CPS -Income 50th%ile	CPS -Income 80th%ile
Means	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1980-1984	29,313	29,403	42,872	36,349	59,228	66,042	24,102	43,687	68,846
1985-1989	30,924	30,449	45,430	38,044	64,652	73,620	24,864	46,034	72,554
1990-1994	30,929	30,616	45,602	38,031	64,335	72,160	25,044	45,942	74,140
1995-1999	31,144	30,867	47,709	38,553	66,488	77,844	26,348	48,249	78,922
2000-2004	34,826	31,512	51,413	39,434	69,340	79,009	28,051	51,709	84,679
2005-2008	36,922	31,683	50,887	38,870	72,655	82,322	27,544	50,911	85,399
All Years	32,185	30,723	47,196	38,191	65,891	74,919	26,072	47,950	77,724

Panel B: Breaking Down Expenditures of the NonRich according to Budget Share Splits

Expenditures are the weighted average, annual spending, deflated to 1999 dollars. The budget share ratio is the average budget share in each goods category across all non-rich individuals divided by the budget share average for the rich. Thus a higher number means the non-rich spend more on the category than the rich. We then divided in terciles, which we use as splits in the analysis.

	Mean Expenditure	Budget Share Ratio		Mean Expenditure	Budget Share Ratio		Mean Expenditure	Budget Share Ratio
"Non-Rich Goods"			"Intermediate Goods"			"Rich Goods"		
Health	980	1.140	Other Rec. Services	824	0.758	Housing Additions	437	0.428
Gas, Transit	1440	1.144	Clothing and Shoes	1,041	0.843	Education	439	0.434
Interest Paid	68	1.155	Alcohol Off-Premise	139	0.894	Rec Vehicles & Homes	252	0.450
Food at Home	8,728	1.296	Business Services	295	0.906	Travel	260	0.546
Utilities	1679	1.325	Cars	2,863	0.909	Jewelry	111	0.560
Phones	766	1.356	Media	381	0.924	Food Off-Premise	353	0.577
Health Insur.	826	1.485	Shelter	5,586	0.964	Religion & Welfare	534	0.657
Tobacco	307	2.178	Barber, Health Clubs	262	0.993	Furniture & Durables	591	0.658
			Alcohol at Home	171	1.013	Domestic Services	416	0.668
			Appliances	180	1.017	Home Maintenance	656	0.731
						Recreation & Sports Eq.	525	0.735

Table 3: The Effect of Rich Households' Spending on Non-Rich Households' Spending - OLS

Dependent Variable:	Log Total Expenditures					Log Total Minus Shelter		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	All Non-Rich	All Non-Rich	Middle & Low Income Group	Very Low Income Group	All Non-Rich	All Non-Rich	Middle & Low Income Group	Very Low Income Group
LogExpenditures Rich	0.0743***		0.106***	0.0274	0.0600***			
	[0.0213]		[0.0205]	[0.0295]	[0.0178]			
LogExpenditures Very Rich		0.0344***						
		[0.0127]						
LogExpenditures of Peer					0.190***			
					[0.0205]			
LogExpenditure (Total Minus Shelter) of Rich						0.0609***	0.0893***	0.0241
						[0.0215]	[0.0209]	[0.0284]
Own Household Income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96333	103500	53008	43325	96333	96332	53008	43324
R-squared	0.589	0.616	0.364	0.453	0.591	0.563	0.352	0.429

Notes:

1. The dependent variable for columns 1-6 is the log of total annual expenditures for an individual. In column 7, the dependent variable is the log total expenditures minus shelter.

2.The sample for columns 1, 5, 6, 7 is all individuals in the CEX between 1980 and 2008 who are beneath the 80th percentile of income in the state (using CPS thresholds for the state-year). Columns 3 and 4 divide these Non-Rich Households into the Very Low Income Households (defined to be less than the 20th percentile) and the Middleand Low Income Households (from 20th percentile to 80th percentile). The definition of and sample threshold for Very Rich in Column 2 is that of all individuals above/below the 90th percentile of state-year income.

3. Each estimation contains the following controls: quadratic of age, race dummies for up to two household members, education levels, and dummies for number of adults and children.

4. We absorb income in the estimations by including dummies for $2000 buckets of total household income.

5. All estimations include year and state fixed effects, and errors are clusters by state. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively

Table 4: The Effect of Rich Households' Spending on Non-Rich Households' Spending - Moving Average & IV

Dependent Variable	Log Total Expenses				Log Expenses Minus Shelter					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	IV	OLS	OLS	OLS	OLS	IV	IV
Sample:	All Non-Rich	Middle & Low Income Group	Very Low Income Group	All Non-Rich	All Non-Rich	Middle & Low Income Group	Very Low Income Group	All Non-Rich	All Non-Rich	All Non-Rich
LogExpenditures Rich - 3 Year Average	0.137***	0.193***	0.0668	0.367***				0.108**	0.222*	
	[0.0418]	[0.0444]	[0.0585]	[0.117]				[0.0503]	[0.130]	
LogExpenditure (Total Minus Shelter) of Rich - 3 Year Average					0.138***	0.200***	0.0743			0.206
					[0.0424]	[0.0447]	[0.0551]			[0.290]
Own Household Income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82746	45592	37149	82746	82745	45592	37153	82745	82745	82745
R-squared	0.588	0.362	0.450	0.587	0.561	0.348	0.424	0.561	0.560	0.561

Notes:

1. The dependent variable is the log of total annual expenditures in columns 1-4, and log total expenditures minus shelter in columns 6-9.

2.The sample is all individuals in the CEX between 1980 and 2008 who are beneath the 80th percentile of income in the state (using CPS thresholds for the state-year). Columns 2 and 3 as well as 6 and 7 divide these Non-Rich between Very Low Income Households (defined to be less than the 20th percentile) and Middle and Low Income Households (from 20th percentile to 80th percentile).

3. The main independent variables are calculated as three year averages (including the current year and the two prior years) of the expenditures of the rich in the state-year.

4. Estimation in columns 1-3 and 5-8 is OLS. Estimation in columns 4 and 9-10 is IV, where the instrument for the log expenditures of the rich in a state-year is the log expenditures for individuals defined to be rich according to the state-year threshold for the observation in question but who reside outside of the state in question.

5. Each estimation contains the following controls: quadratic of age, race dummies for up to two household members, education levels, and dummies for number of adults and children.

6. We absorb income in the estimations by including dummies for $2000 buckets of total household income.

7. All estimation include year and state fixed effects, and errors are clusters by state. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5: The Effect of Rich Households' Spending on Non-Rich Households' Spending - Sensitivity to Socio-Demographic Controls

	(1)	(2)	(3)
Dependent Variable:	Log Total Expenditures of Non-Rich		
	Original	Without education	Without education & age
LogExpenditures Rich - 3 Year Average	0.137***	0.142***	0.140***
	[0.0418]	[0.0414]	[0.0419]
Own Household Income F.E.s	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes
Individual controls (except column header)	Yes	Yes	Yes
Observations	82746	82746	82746
R-squared	0.588	0.574	0.567

Notes:

1. The dependent variable is the log of total annual expenditures. The columns differ only in the exclusion of education (columns 2 and 3) and age (column 3) as controls. Column 1 is the original column 1 from table 4.

2.The sample is all individuals in the CEX between 1980 and 2008 who are beneath the 80th percentile of income in the state (using CPS thresholds for the state-year).

3. The main independent variables are calculated as three year averages (including the current year and the two prior years) of the expenditures of the rich in the state-year.

4. Each estimation contains the following controls: race dummies for up to two household members and dummies for number of adults and children.

5. We absorb income in the estimations by including dummies for $2000 buckets of total household income.

6. The estimations are OLS and include year and state fixed effects, and errors are clusters by state. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Do Higher Top Income Levels Today Predict Higher Future Income for the Non-Rich?

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	*Log(hh income) in t+1*		*Log(hh income) in t+2*		*Log(hh income) in t+3*		*Log (average hh income) between t+1 and t+2*		*Log (average hh income) between t+1 and t+3*	
Log (hh income) in t	0.442	0.073	0.445	0.09	0.365	-0.011	0.363	0.109	0.31	0.076
	[0.014]**	[0.016]**	[0.015]**	[0.016]**	[0.014]**	[0.011]	[0.015]**	[0.014]**	[0.014]**	[0.012]**
Log hh income at the 80th pctile	-0.068	-0.019	-0.612	-0.776	-0.897	-0.914	-0.162	-0.315	-0.183	-0.343
(t, t-1, t-2)	[0.285]	[0.483]	[0.334]	[0.350]*	[0.343]*	[0.600]	[0.369]	[0.469]	[0.404]	[0.497]
Log hh income at the 50th pctile	-0.271	-0.12	0.558	0.872	0.819	0.803	-0.179	0.314	-0.22	0.329
(t, t-1,t-2)	[0.317]	[0.501]	[0.391]	[0.424]*	[0.496]	[0.564]	[0.439]	[0.525]	[0.469]	[0.529]
Log hh income at the 10th pctile	0.26	0.291	-0.043	-0.183	-0.224	0.021	0.184	0.083	0.234	0.155
(t, t-1,t-2)	[0.206]	[0.247]	[0.232]	[0.266]	[0.292]	[0.245]	[0.256]	[0.220]	[0.256]	[0.201]
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
hh F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	81413	81413	77250	77250	62376	62376	89378	89378	89939	89939
R-squared	0.17	0.4	0.16	0.42	0.12	0.45	0.15	0.45	0.14	0.51

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	*Log(hh income) in t+1*		*Log(hh income) in t+2*		*Log(hh income) in t+3*		*Log (average hh income) between t+1 and t+2*		*Log (average hh income) between t+1 and t+3*	
Log (hh income) in t	0.442	0.073	0.445	0.09	0.365	-0.011	0.363	0.109	0.31	0.076
	[0.014]**	[0.016]**	[0.015]**	[0.016]**	[0.014]**	[0.011]	[0.015]**	[0.014]**	[0.014]**	[0.012]**
Log hh income at the 90th pctile	-0.296	-0.033	-0.437	-0.305	-0.743	-0.594	-0.326	-0.3	-0.319	-0.344
(t, t-1, t-2)	[0.261]	[0.375]	[0.277]	[0.428]	[0.344]*	[0.334]	[0.327]	[0.475]	[0.388]	[0.467]
Log hh income at the 50th pctile	-0.087	-0.11	0.385	0.466	0.673	0.536	-0.048	0.287	-0.114	0.313
(t, t-1,t-2)	[0.270]	[0.458]	[0.378]	[0.509]	[0.484]	[0.436]	[0.385]	[0.530]	[0.448]	[0.553]
Log hh income at the 10th pctile	0.222	0.289	-0.032	-0.144	-0.24	0.016	0.152	0.075	0.206	0.145
(t, t-1,t-2)	[0.190]	[0.245]	[0.234]	[0.284]	[0.280]	[0.229]	[0.244]	[0.223]	[0.247]	[0.207]
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
hh F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	81413	81413	77250	77250	62376	62376	89378	89378	89939	89939
R-squared	0.17	0.4	0.16	0.42	0.12	0.45	0.15	0.45	0.14	0.51

Note: Data source is PSID. We merge information on household income levels at the 80th, 90th, 50th and 10th percentiles from the CPS. The sample is restricted to household-year observations where the household's income is below the 80th percentile in the household's state -year cell. Standard errors, in brackets, are clustered at the state level. See text for details.

Table 7: Expectations about Future Income Growth and Top Income Levels

	Panel A							
	Dependent Variable: Expect Real Income to Go Up in the Next Year (Y=1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample: Individuals whose household income is:	All Non-Rich		Middle and Low Income Households		Middle Income Households		Low Income Households	
Log hh income at the 90th pctile	-0.07		-0.043		-0.254		0.079	
(t, t-1, t-2)	[0.062]		[0.088]		[0.120]*		[0.098]	
Log hh income at the 80th pctile		-0.157		-0.152		-0.245		-0.108
(t, t-1, t-2)		[0.074]*		[0.108]		[0.145]		[0.134]
Log hh income at the 50th pctile	-0.065	0.017	-0.118	-0.016	-0.108	-0.095	-0.104	0.059
(t, t-1, t-2)	[0.085]	[0.104]	[0.110]	[0.140]	[0.155]	[0.187]	[0.145]	[0.187]
Log hh income at the 10th pctile	0.091	0.079	0.108	0.092	0.196	0.194	0.026	-0.001
(t, t-1, t-2)	[0.063]	[0.064]	[0.081]	[0.083]	[0.100]	[0.103]	[0.104]	[0.106]
Real income up in the next year	0.005	0.005	0.004	0.004	0.004	0.005	0.003	0.003
	[0.002]	[0.002]*	[0.003]	[0.003]	[0.005]	[0.005]	[0.004]	[0.004]
Own household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.022	1.207	1.107	1.382	2.607	2.326	0.326	0.948
	[0.466]*	[0.427]**	[0.686]	[0.601]*	[0.852]**	[0.792]**	[0.794]	[0.721]
Observations	129938	129938	89269	89269	44276	44276	44993	44993
R-squared	0.1	0.1	0.09	0.09	0.1	0.1	0.09	0.09

	Panel B							
	Dependent Variable: Expect Percent Change in Household Income in the Next Year							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample: Individuals whose household income is:	All Non-Rich		Middle and Low Income Households		Middle Income Households		Low Income Households	
Log hh income at the 90th pctile	-6.833		-0.715		-8.15		7.046	
(t, t-1, t-2)	[4.092]		[4.667]		[6.877]		[5.268]	
Log hh income at the 80th pctile		-8.482		-3.613		-6.724		-0.277
(t, t-1, t-2)		[4.495]		[5.102]		[7.893]		[7.335]
Log hh income at the 50th pctile	9.824	11.795	2.925	5.585	8.188	7.626	-4.315	1.807
(t, t-1, t-2)	[5.469]	[5.299]*	[7.560]	[7.168]	[11.899]	[12.192]	[6.567]	[6.811]
Log hh income at the 10th pctile	-5.226	-5.471	-3.835	-4.239	-5.455	-5.386	-1.925	-2.979
(t, t-1, t-2)	[3.108]	[3.102]	[3.796]	[3.650]	[5.497]	[5.445]	[4.317]	[4.129]
Pct change in hh income in the next year	2.075	2.218	1.92	1.907	-0.218	-0.045	3.843	3.757
	[2.248]	[2.249]	[2.273]	[2.268]	[3.320]	[3.244]	[3.188]	[3.225]
Own household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	34.747	32.981	21.054	28.803	58.068	45.59	-4.556	23.729
	[31.779]	[34.931]	[30.175]	[33.860]	[40.387]	[44.803]	[47.226]	[50.879]
Observations	124577	124577	86590	86590	43101	43101	43489	43489
R-squared	0.07	0.07	0.06	0.06	0.06	0.06	0.06	0.06

Note: Data source is the University of Michigan Surveys of Consumer, 1980 to 2009. All regressions are estimated using OLS. Standard errors are in brackets. Own Income F.E.s are dummies for current household income levels of $1,000 increments. 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. Each observation is weighted by household head weight provided in the Surveys. Standard errors are clustered at the state level. See text for details.

Table 8: The Effect of Rich Households' Spending on Non-Rich Households' Spending- the Role of Housing Equity

	(1) Owners	(2) Renters	(3) <=1995	(4) >1995	(5) Inelastic Housing Supply	(6) Elastic Housing Supply
LogExpenditures Rich - 3 Year Average	0.166***	0.0957**	0.184**	0.0779	0.258**	0.111**
	[0.0522]	[0.0465]	[0.0773]	[0.0491]	[0.0701]	[0.0444]
Own Household Income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51123	29771	32440	50306	19553	61443
R-squared	0.534	0.590	0.601	0.586	0.570	0.593

1. The dependent variable is the log of total annual expenditures.

2. The sample is all individuals in the CEX between 1980 and 2008 who are beneath the 80th percentile of income in the state (using CPS thresholds for the state-year).

3. The main independent variable is calculated as three year averages (including the current year and the two prior years) of the expenditures of the rich in the state-year.

4. Each estimation contains the following controls: quadratic of age, race dummies for up to two household members, education levels, and dummies for number of adults and children.

5. We absorb income in the estimations by including dummies for $2000 buckets of total household income.

6. All estimation are OLS and include year and state fixed effects. Errors are clusters by state. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 9: Effect of Rich Households' Spending on Non-Rich Households' Spending by Category

29 Regressions with Dependent Variable:	(1) Independent Variable: Log Total Expenditures of Rich Coefficient	(2) Standard Error	(3) Visibility Score	(4) Budget Share Ratio
Low Visibility/Non-Rich Goods				
Utilities	-0.1380	[0.105]	0.31	1.325
Phones	-0.0080	[0.0565]	0.30	1.356
Gas, Tolls, Mass Transit	-0.0008	[0.0297]	0.39	1.144
Food On-Premise	0.0204	[0.0240]	0.51	1.296
Interest Paid (excluding vehicles/mortgages)	0.0415**	[0.0197]	0.26	1.155
Health Insurance	0.0547*	[0.0316]	0.20	1.485
Health	0.0775**	[0.0316]	0.36	1.140
High Visibility/Rich Goods				
Alcohol Off-Premise	0.0448*	[0.0235]	0.60	0.894
Beauty, Health Clubs	0.0813*	[0.0433]	0.60	0.993
Clothing and Shoes	0.105**	[0.0434]	0.71	0.843
Jewelry	0.0376***	[0.0127]	0.67	0.560
Furniture and Durables	0.0680**	[0.0297]	0.68	0.658
Other Recreation Services	0.113***	[0.0326]	0.58	0.758
Recreation and Sports Equipment	0.0451	[0.0296]	0.66	0.735
Recreational Vehicles & Homes	0.0097	[0.00887]	0.66	0.450
Cars	0.0136	[0.0384]	0.73	0.909
Newspapers, Books	0.0606	[0.0458]	0.57	0.924
Food Off-Premise	0.0473	[0.0429]	0.62	0.577
High Visibility/Non-Rich Goods				
Alcohol On-Premise	0.0620*	[0.0347]	0.61	1.013
Appliances	0.0344*	[0.0189]	0.68	1.017
Tobacco Products	0.0362	[0.0305]	0.76	2.178
Low Visibility/Rich Goods				
Shelter	0.148***	[0.0393]	0.50	0.964
Home Maintenance	0.0571***	[0.0195]	0.31	0.731
Professional Services	0.0801***	[0.0160]	0.26	0.906
Domestic Services	0.0640**	[0.0273]	0.34	0.668
Religious and Welfare Activities	0.0273	[0.0541]	0.34	0.657
Housing Additions and Alterations	0.0076	[0.0117]	0.50	0.428
Travel	0.0102	[0.0186]	0.46	0.546
Education	0.0029	[0.0237]	0.56	0.434

Notes:

1. Each coefficient in column 1 (with standard error in column 2) corresponds to a single estimation. We regress total

2.The sample is all individuals in the CEX between 1980 and 2008 who are beneath the 80th percentile of income in the

3. Each estimation contains the following controls: quadratic of age, race dummies for up to two household members, education levels, and dummies for number of adults and children.

4. We absorb income in the estimations by including dummies for $2000 buckets of total household income.

5. The estimations are OLS and include year and state fixed effects, and errors are clusters by state. ***, **, and * denote

6. Column 3 is the goods visibility score from Heffetz (2010).

7. Column 4 is the budget share ratio defined as the average budget share of the non-rich expenditures on the goods category dividied by the budget share of the rich on the goods.

Table 10: The Effect of Rich Households' Spending on Non-Rich Households' Spending- "Rich Goods" vs. "Non-Rich Goods"

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Ratio of Expenditures to Total Expenditures in:			Ratio of Expenditures to Total Expenditures minus Shelter in:		
Split by:	Budget Share of Non-Rich Relative to Rich			Budget Share of Non-Rich Relative to Rich		
	"Non-Rich Goods"	"Interm. Goods"	"Rich Goods"	"Non-Rich Goods"	"Interm. Goods"	"Rich Goods"
LogExpenditures Rich: 3 Year Average	-0.0397***	0.0251*	0.0146*	-0.0310**	0.00922	0.0218**
	[0.0136]	[0.0125]	[0.00850]	[0.0146]	[0.00896]	[0.00960]
Household Income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85138	85138	85138	85137	85137	85137
R-squared	0.339	0.261	0.119	0.315	0.250	0.137

Notes:

1. Each set of three columns represents a split of each person's expenditures into three. This budget share splits assigns each expenditure category into a high, medium, or low ranking according to what percent on average the expenditure category comprises the budget share of the nonrich relative to the rich.

2. The dependent variable for columns 1-3 is expenditures in the budget share tertile split relative to total expenditures for each individual. Columns 4-6 have the same dependent variable except that shelter is removed from the numerator (in the medium budget share split) and the demoninator (in all splits).

3.The sample is all individuals in the CEX between 1980 and 2008 who are beneath the 80th percentile of income in the state (using CPS thresholds for the state-year).

4. Each estimation contains the following controls: quadratic of age, race dummies for up to two household members, education levels, and dummies for number of adults and children.

5. We absorb income in the estimations by including dummies for $2000 buckets of total household inco

6. All estimation include year and state fixed effects. Errors are clusters by state. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 11: Current Financial Well-Being and Top Income Levels

	Panel A							
Dependent Variable:	*Worse Off Financially than a Year Ago (Y=1)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample: Individuals whose household income is:	All Non-Rich		Middle and Low Income Households		Middle Income Households		Low Income Households	
Log hh income at the 90th pctile	0.335		0.276		0.276		0.262	
(t, t-1, t-2)	[0.091]**		[0.106]*		[0.115]*		[0.140]	
Log hh income at the 80th pctile		0.528		0.52		0.557		0.478
(t, t-1, t-2)		[0.112]**		[0.123]**		[0.148]**		[0.160]**
Log hh income at the 50th pctile	0.067	-0.129	0.207	-0.034	0.176	-0.099	0.255	0.042
(t, t-1, t-2)	[0.115]	[0.155]	[0.140]	[0.166]	[0.169]	[0.217]	[0.178]	[0.207]
Log hh income at the 10th pctile	-0.021	0.007	-0.117	-0.082	-0.094	-0.054	-0.119	-0.087
(t, t-1, t-2)	[0.079]	[0.085]	[0.090]	[0.092]	[0.114]	[0.118]	[0.109]	[0.113]
Own household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130307	130307	89410	89410	44317	44317	45093	45093
R-squared	0.07	0.07	0.05	0.05	0.05	0.05	0.05	0.05

	Panel B							
Dependent Variable:	*Fewer Expenses/Lower Debt, Int. and Debt Payments than a Year Ago (Y=1)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample: Individuals whose household income is:	All Non-Rich		Middle and Low Income Households		Middle Income Households		Low Income Households	
Log hh income at the 90th pctile	-0.115		-0.115		-0.099		-0.118	
(t, t-1, t-2)	[0.061]		[0.079]		[0.099]		[0.104]	
Log hh income at the 80th pctile		-0.189		-0.199		-0.1		-0.267
(t, t-1, t-2)		[0.073]*		[0.095]*		[0.127]		[0.116]*
Log hh income at the 50th pctile	0.068	0.142	0.049	0.132	0.059	0.068	0.055	0.197
(t, t-1, t-2)	[0.075]	[0.079]	[0.094]	[0.100]	[0.111]	[0.140]	[0.125]	[0.136]
Log hh income at the 10th pctile	0.004	-0.007	0.033	0.021	-0.018	-0.02	0.059	0.037
(t, t-1, t-2)	[0.036]	[0.036]	[0.047]	[0.046]	[0.068]	[0.069]	[0.070]	[0.070]
Own household income F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130444	130444	89480	89480	44359	44359	45121	45121
R-squared	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.01

Note: Data source is the University of Michigan Surveys of Consumer, 1980 to 2009. All regressions are estimated using OLS. Standard errors are in brackets. Own Income F.E.s are dummies for current household income levels of $1,000 increments. 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. Each observation is weighted by household head weight provided in the Surveys. Standard errors are clustered at the state level. See text for details.

Table 12: Personal Bankrupcy Filings and Top Income Levels

	Dependent Variable: Log (Number of Personal Bankruptcy Filings)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log average HH income at 80th pctile	**1.719**	**1.311**	**1.569**	**1.466**	**1.757**	**1.626**	**1.552**	**1.619**
(t-1, t-2, t-3)	**[0.432]****	**[0.464]****	**[0.791]**	**[0.552]***	**[0.745]***	**[0.533]****	**[0.724]***	**[0.531]****
Log average HH income at 80th pctile			-0.278	-1.101	0.776	-0.002	1.066	0.235
(t-1, t-2, t-3)			[0.918]	[0.572]	[0.785]	[0.588]	[0.783]	[0.633]
Log aver HH income at the 80th pctile					-0.18	-0.055	-0.252	-0.065
(t)					[0.333]	[0.284]	[0.337]	[0.285]
Log aver HH income at the 50th pctile					-1.464	-1.932	-0.804	-1.181
(t)					[0.459]**	[0.339]**	[0.424]	[0.357]**
Log aver HH income at the 10th pctile							-0.769	-0.954
(t)							[0.249]**	[0.245]**
Log (Number of HHs)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.s*Year	No	No	No	Yes	No	Yes	No	Yes
Constant	-20.677	-20.668	-20.752	-64.171	-16.838	-74.346	-17.482	-67.845
	[4.576]**	[8.126]*	[8.078]*	[8.813]**	[8.244]*	[8.818]**	[8.304]*	[7.923]**
Observations	1530	1530	1530	1530	1530	1530	1530	1530
R-squared	0.66	0.96	0.96	0.97	0.96	0.97	0.96	0.97

Note: Data is a state-year panel of number of personal bankrupty filings. All regressions are estimated using OLS. Each observation is weighted by the number of HHs in the state. Standard errors are in brackets and clustered at the state level. See text for details.

* significant at 5%; ** significant at 1%

Table 13: Republican Congressmen's Voting on H.R. 5334

	Dependent variable: Yes Vote			
	(1)	(2)	(3)	(4)
Log(hhincome at the 80th pctile)- Log(hh income at the 50th pctile)	0.201	1.053	1.000	0.796
	[0.509]	[0.564]	[0.564]	[0.600]
Log (hh income at the 50th pctile)	-0.105	-0.030	0.028	-0.225
	[0.151]	[0.206]	[0.211]	[0.329]
Log(population)			-0.524	-0.502
			[0.420]	[0.420]
Share finance				4.434
				[4.445]
State F.E.s	No	Yes	Yes	Yes
Constant	1.649	0.656	7.07	9.364
	[1.697]	[2.247]	[5.612]	[6.065]
Observations	163	163	163	163
R-squared	0.01	0.33	0.34	0.34

Note: Included in the table are all republican congressmen that expressed a vote on H.R. 5334. Measures of income inequality, median income, population and share of employment in finance in each congressional district were obtained by mapping 102nd Congress' congressional district lines into 1990 census tract information. Standard errors are in brackets. See text for details.

Table 14: Republican Congressmen's Voting on H.B. 545 (Ohio) and H.B. 2203 (Oregon)

	Dependent Variable: Yes Vote		
Log(household income at the 80th pctile)-			
Log(household income at the 50th pctile)	1.06	1.024	0.93
	[0.466]*	[0.450]*	[0.445]*
Log (household income at the 50th pctile)			
	0.865	0.639	0.63
	[0.257]**	[0.259]*	[0.254]*
Log (population)			0.754
			[0.355]*
House F.E.	No	Yes	Yes
State F.E.	No	Yes	Yes
Constant	-9.333	-6.75	-16.141
	[2.850]**	[2.872]*	[5.250]**
Observations	109	109	109
R-squared	0.11	0.19	0.22

Note: Included in the table are all Republican Congressmen that expressed a vote on H.B. 545 (Ohio, 2008) and H.B. 2203 (Oregon, 2007).Measures of income inequality, median income, population and share of employment in finance in each congressional district were obtained by state-level congressional district lines into 2000 census tract information. Standard errors are in brackets. See text for details.