# The Rise and Fall of Consumption in the '00s. A Tangled Tale.*

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**Abstract**

U.S. consumption has gone through steep ups and downs since 2000. We quantify the statistical impact of income, unemployment, house prices, credit scores, debt, financial assets, expectations, foreclosures, and inequality on county-level consumption growth for four subperiods: the "dot-com recession" (2001–2003), the "subprime boom" (2004–2006), the Great Recession (2007–2009), and the "tepid recovery" (2010–2012). Consumption growth cannot be explained by a few factors; rather, it depends on a large number of variables whose explanatory power varies by subperiod. Growth of income, growth of housing wealth, and fluctuations in unemployment are the most important determinants of consumption, significantly so in all subperiods, while fluctuations in financial assets and expectations are important only during some subperiods. Lagged variables, such as the share of subprime borrowers, are significant but less important.

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# 1 Introduction

Private consumption accounts for 70 percent of U.S. GDP, and the strong fluctuations in consumer spending during the first decade of the new millennium helped fuel the turbulent business cycles of the period. The past decade was unusually volatile in many dimensions: there were dramatic changes in gross housing wealth, which, after hitting a historic high of $20.7 trillion in 2007, fell to $16.4 trillion in 2011 before recovering to $17.5 trillion in 2012. When house prices dropped, many owners who had fallen behind on their mortgage payments were unable to sell their homes for more than they owed, so foreclosures ballooned from fewer than 800,000 in 2006 to 2.4 million in 2009. Personal real debt per capita rose steeply from $31,000 in 2000 to $56,000 in 2008, when it started to gradually decline, falling to $47,000 in 2012. Consumer confidence eroded dramatically, from an index value of 106 in 2007:Q3 to an exceptionally pessimistic 30 in 2009:Q1, before gradually climbing back to 80 in 2012:Q4. Unemployment shot up from 5 percent in 2007:Q4 to 8.2 percent just a year later, peaking at 9.9 percent in 2009:Q4 before slowly falling to 7.8 percent by the end of 2012. Stock market investors lost a staggering amount, in excess of $5 trillion, as the capitalization of the S&P 500 index dropped from about $13 trillion at the end of 2007 to about $7.8 trillion by the end of 2008. However, the stock market recovered almost all lost ground by the end of 2012.[1]

Using U.S. county-level data, we study consumption growth over the 2001–2012 period.[2] Because consumption patterns were unstable during this period,

[1] Figures on gross housing wealth come from the Federal Reserve Board's annual statistical release. The authors calculate real debt per capita by aggregating individual-level total debt reported by the Equifax Consumer Credit Panel maintained by the Federal Reserve Bank of New York. The population data are from the Census Bureau. Foreclosures are from the Mortgage Bankers Association. The Consumer Confidence index is from the Conference Board. The unemployment rate is from the Bureau of Labor Statistics, and the stock market capitalization is from Standard and Poor's.

[2] Panels with substantial amounts of information are not available at the individual level—the Panel Study of Income Dynamics comes close, but the sample is small. Also, we want to study the role of credit scores, which we obtain from anonymized credit reports that cannot be easily matched with micro datasets containing information on consumption (Mian, Rao, and Sufi (2013) use ZIP-code data for similar reasons). We did not use ZIP-code data because unemployment data are not available for geographical entities smaller than counties

we divide our sample into boom and bust subperiods, namely the "dot-com recession" (2001–2003), the "subprime boom" (2004–2006), the Great Recession (2007–2009), and the "tepid recovery" (2010–2012), and estimate determinants of consumption growth over each of these three-year subperiods.[3] More specifically, we consider the correlation of consumption growth with a large number of concurrent growth variables (income, unemployment, financial assets, housing wealth, and consumer expectations), and a large number of predetermined variables measured in lagged levels (unemployment, income per capita, housing-wealth-to-income, financial-assets-to-income, debt-to-income, share of mortgages foreclosed on, share of total income for individuals earning above the top 5th percentile of income distribution, and the share of subprime borrowers). We examine the stability of relations across subperiods, using rolling regressions and a large battery of tests.

Existing empirical work on consumption patterns during and after the Great Recession focuses on some factors in isolation such as the role of subprime lending, the role of debt overhang, or the role of expectations. We find that consumption growth during this period cannot be explained by a small number of factors. Our explanatory variables mostly have low pairwise correlations, and principal component analysis indicates that one or two common factors cannot capture the variation. Using regression analysis, we find that concurrent growth variables have greater explanatory power for consumption than do predetermined variables. In particular, growth of income, growth of housing wealth, and fluctuations in unemployment were significant throughout the '00s, while fluctuations in financial asset values and expectations were significant only during some subperiods. Among the lagged level variables, only the unemployment rate and the share of subprime borrowers were significant throughout the '00s, while other lagged variables were significant only during

and because we approximate consumption with retail sales which may not accurately reflect the consumption of residents in small geographical areas.

[3]Other authors, see Mian and Sufi (2011), Nakamura and Steinsson (2014), and Petev, Pistaferri, and Saporta-Eksten (2011), use long time intervals. The label 2001–2003 refers to consumption growth that occurred from the year 2000 through 2003 approximated by the difference between annual log-consumption in 2003 and annual log-consumption in 2000. The same convention applies for the other three subperiods.

some subperiods. Each estimated coefficient has the expected sign, with the possible exception of the subprime share, which correlates positively with consumption (driven mainly by the subprime boom, when subprime borrowers were able to increase consumption from a low level).

The contribution of this paper is based on the construction of a large number of variables, which allows us to explore their simultaneous impact on consumption—something that cannot be done using a single short time series. This is particularly important for our sample period, when economic outcomes varied substantially from one part of the United States to another. We outline a theoretical model that helps us interpret the many significant correlations uncovered in terms of shocks to income, wealth, credit, and expectations. Our results indicate that shocks to each of these determinants were important in various guises (e.g., wealth shocks can take the form of house-price shocks or financial wealth shocks), and with varying strength during the '00s.

While our dataset is very comprehensive with respect to the number of variables, much more work is needed to sort out causal effects. For example, an increase in unemployment clearly affects the income of the unemployed (maybe in ways more subtle than reflected in measured income growth, perhaps because it changes the persistence of income shocks). It may also elevate uncertainty for many individuals, change expectations and, by affecting the health of financial institutions, limit credit supply. Our paper helps narrow the range of potential explanations. However, with so many significant correlates of consumption, it also highlights the difficulty of constructing an encompassing structural model that could provide a complete interpretation of the economic fluctuations of the first, volatile decade of this millennium.

The paper is organized as follows: Section 2 outlines the relevant theory of consumption and relates to the existing literature. Section 3 presents our data, and Section 4 describes the economy in the four subperiods we study. Section 5 outlines our empirical specification and describes the results, and Section 6 concludes.

## 2 Theoretical Background

Housing played a central role in economic fluctuations during the '00s, so we frame the discussion around a consumption model with housing. This model descends from the Permanent Income Hypothesis (PIH) of Hall (1978) and the buffer-stock model of Deaton (1991), Carroll (1992), and Carroll (1997). Gourinchas and Parker (2002) find that U.S. consumers typically behave according to the buffer-stock model until about the age of 40, when consumption behavior changes and becomes more in accordance with the PIH, due to accumulated life-cycle savings. However, in order to fully fit the data, the model must include important extensions. In particular, it has to allow for the existence of a large illiquid asset—housing—that generates large consumption commitments as described by Chetty and Szeidl (2007).

Consider the buffer-stock model with nondurables, owner-occupied housing, and downpayment requirements (credit limits) studied by Luengo-Prado (2006). In the model, consumer $j$ derives utility from the consumption of a nondurable good $C$ and the services provided by housing $H$, and maximizes expected utility with respect to $C$ and $H$:

$$\mathrm{E}_0 \left\{ \sum_{t=0}^{T} \beta^t \, U\left(C_{jt}, H_{jt}\right) \right\}, \text{ s.t. } S_{jt} = R_t S_{j,t-1} + Y_{jt} - C_{jt} - q_t \Delta H_{jt} - \chi(H_{jt}, H_{j,t-1}),$$

where the utility function is a CES index, $S$ is financial assets, $q$ is the relative price of housing, $R$ is an interest rate factor, and $Y$ is income. There is a significant cost of relocating, captured by the function $\chi()$, such that consumers do not make marginal adjustments to the housing stock; i.e., consumers adjust their housing consumption only when their desired amount of housing (if there were no adjustment costs) significantly deviates from their current amount of housing.

The consumer faces a collateral constraint $S_{jt} \geq -(1-\theta) q_t H_{jt}$ (where $\theta$ is a required downpayment ratio), which limits borrowing to a fraction of the value of the housing stock. House-price appreciation is fully liquid for consumers for whom the collateral constraint is not binding; however, when house prices fall, many consumers will not be able to borrow because the debt limit binds. Consumers who suffer a transitory income shock may therefore end up disproportionately cutting back on nondurable consumption because it is not optimal to pay the fixed cost of moving in order to free up housing capital. This may make even affluent individuals behave like they are constrained, as they do in the models of "wealthy-hand-to-mouth" consumers (Kaplan and Violante, 2014), and "consumption commitments" (Chetty and Szeidl, 2007). Consumers' debt limits are functions of personal income and credit scores, although it seems that a model with both these features has not yet been studied quantitatively. During the '00s, the tightness of the constraints changed over time, at least for subprime borrowers.

We do not attempt to calibrate the model to the high-dimensional set of regressors used in this paper, but we use it to interpret the patterns discussed in the literature. In simulations of the buffer-stock model, and of the just described housing model, log-income is typically assumed to be the sum of a random walk "permanent income" component and an i.i.d. transitory shock. If there is an above-average permanent income shock, consumers will want to increase consumption of both housing and nondurables, but they may postpone the increase in consumption while accumulating funds for the required downpayment. Foreclosure costs and geographical mobility can be added to the model as in Demyanyk et al. (2017).

This type of model is often simulated with a focus on income shocks but, although we do not attempt here to calibrate the model to the complex patterns of the '00s, the model is consistent with other types of shocks affecting consumption. Shocks to housing wealth have an impact on nondurable consumption through their effect on the budget constraint (and other types of wealth shocks can be included if one allows for risky assets besides housing). The debt limit can be time-varying and stochastic, shocks to expectations can be included, and shocks to uncertainty can be modeled as an increase in the variance of future income shocks. The difference between income and consumption is savings, and Carroll, Slacalek, and Sommer (2012) argue that the changes in the national savings rate in the '00s and earlier can be explained by just three factors that vary substantially over time: credit conditions, unemployment risk (a proxy for uncertainty), and wealth shocks. Their finding is consistent with a very parsimonious buffer-stock model of impatient consumers with a target level of wealth. An increase in unemployment risk has an effect that is similar to a tightening of credit; both factors increase the desired wealth target, so both increase the savings rate. In their model, the precautionary motive diminishes with wealth (the saving rate is a decreasing function of wealth), so a negative exogenous wealth shock reduces consumption and increases savings. However, the authors do not consider the role of housing.

## 2.1 Predicted Consumption Patterns

For easier reference in the empirical section, we provide a numbered list of "Consumption Predictions" based on the previous discussion of the model.

1. Current and expected *income growth* drive current consumption growth in the PIH model and in all subsequent forward-looking models. In Hall's PIH, consumption has a one-to-one reaction to permanent income shocks, but less than that in the buffer-stock model of Carroll (2009), where the marginal propensity to consume (MPC) out of permanent shocks is around 0.8 for standard parameterizations. Estimated MPCs are often much lower; however, "unobserved risk sharing" as in Attanasio and Pavoni (2011) can explain the lower MPC, because unobserved (state-contingent) transfers imply that the "income" entering the budget constraint differs significantly from measured income.[4]

2. *Homeownership*, in combination with downpayments (borrowing limits), lowers the MPC out of permanent income shocks, as demonstrated by Luengo-Prado (2006), because consumers who want to purchase a (bigger) house may put parts of a pay raise aside for a downpayment. If

[4]Luengo-Prado and Sørensen (2008) show, in simulations of the housing model, that unobserved risk sharing is needed in order to match the low MPCs found in state-level data.

house prices are high, this effect may be more pronounced because the required downpayment becomes larger.

3. *Wealth shocks* matter for consumption. De Nardi, French, and Benson (2012) show that a model with shocks to wealth and income expectations can explain the drop in U.S. consumer spending observed during the Great Recession. Using U.S. micro data, Christelis, Georgarakos, and Jappelli (2015) find significant effects of wealth shocks and unemployment on consumption during the Great Recession.

4. More *uncertainty* predicts lower current consumption in the buffer-stock model (Carroll, 1992; Carroll, Slacalek, and Sommer, 2012) and higher MPCs (also in aggregate data, Luengo-Prado and Sørensen, 2008). In our model, higher uncertainty can result from higher income variance, higher variance in house prices, or less risk sharing (which may or may not be reflected in measured income).

5. Tighter *credit constraints* will depress consumption growth because the desired buffer stock increases when the credit limit tightens. Ludvigson (1999) shows theoretically that a predictable tightening of credit limits leads to a decrease in consumption, while Crossley and Low (2014) empirically disentangle the direct effect (being credit constrained in the current period) from the indirect effect (accumulating a larger buffer stock of saving because credit will not be available if needed). Alan, Crossley, and Low (2012) demonstrate that a suitably calibrated life-cycle model with credit constraints can explain the rise in the aggregate savings ratio in the United Kingdom during the Great Recession. Easy mortgage credit followed by tight credit conditions (Demyanyk and Van Hemert, 2011) and housing-wealth gains followed by losses have been suggested as the main explanations of consumption fluctuations in the '00s. Mian, Rao, and Sufi (2013) estimate the consumption elasticity with respect to housing net worth and show that residents in ZIP codes that experienced large wealth losses significantly curtailed their consumption.[5]

[5] Mian and Sufi (2009) show that during the Great Recession, mortgage defaults were

6. *House prices* are typically close to random walks (Li and Yao, 2007), as are stock prices (Fama, 1970). This implies that a positive housing-wealth shock is equivalent to a transitory income gain.[6] If homeowners have little wealth and the collateral constraint is binding, the house-price gain will be illiquid unless it is large enough to enable individuals to borrow against this equity gain. Campbell and Cocco (2007) find a large effect of house prices on consumption in the United Kingdom during 1988–2000, especially for older households; Iacoviello (2011) discusses the literature on housing wealth effects more broadly. Studies using micro data estimate an elasticity of around 10 percent, although the magnitude is likely to depend on the ease with which homeowners can borrow against housing wealth in order to finance their spending. Non-housing-wealth effects on consumption are often found to be smaller.

7. High *debt*, in the PIH model and its extensions, reflects expected high future income (Campbell, 1987); however, if these income gains do not materialize, as was the case for many individuals during the Great Recession, high debt predicts increased saving and lower consumption. Further, high debt predicts lower consumption in the buffer-stock model if net repayments become higher than expected (lowering cash on hand), perhaps because expected cash-out-refinancing becomes unavailable. Dynan (2012) uses micro data to show that highly leveraged homeowners had larger spending declines during 2007–2009 than did other homeowners.

8. *Expectations* correlate with consumption. The less obvious issue is whether

concentrated in ZIP codes with extensive subprime lending, while Mian and Sufi (2011) show that a large fraction of the rise in U.S. household leverage from 2002 to 2006 (and the subsequent surge in defaults) was due to borrowing against home equity. They find that homeowners extracted 25 cents for every one dollar increase in home equity, amounting to $1.25 trillion in additional household debt from 2002 to 2008. Albanesi, De Giorgi, and Nosal (2017) criticize the view that the lending in the subprime boom was particularly concentrated in the subprime segment, pointing out that low credit scores often are found among the young as part of the life-cycle pattern.

[6] Berger et al. (2015) also point out that a permanent house-price shock is a one-time wealth gain equivalent to a transitory income shock.

consumer expectations have predictive power that is not captured by other variables. Ludvigson (2004) finds that consumer confidence (which we interpret as a synonym for expectations regarding future real income) provides modest predictive power conditional on other observable variables. Carroll, Fuhrer, and Wilcox (1994) find a similar result along with evidence that consumer confidence may determine future income (via a multiplier effect). Barsky and Sims (2012) split expectations into a "news component" and an "animal spirits" component, and find that the effect on future activity is mainly related to the news component.

9. A *foreclosure* implies lack of access to credit and hence a fall in consumption. Also, a foreclosure often involves a slow erosion of credit and possibly a negative wealth shock ahead of the event; see Demyanyk (2017) and Demyanyk et al. (2017).

10. In the buffer-stock model, individuals' consumption is *concave in liquid wealth*, with the strongest curvature around the point where the amount of liquid assets is equal to the desired buffer stock—see Deaton (1991) and Michaelides (2003). We experimented extensively with specifications that allow for concavity in the consumption function, following Mian, Rao, and Sufi (2013), but we did not find significant second-order terms for income or wealth.

11. Falling (rising) *interest rates* benefit net debtors (savers). Keys et al. (2014) use micro data to document a direct effect of mortgage interest rate resets on household consumption. Because our regressions included only four periods, so that the main identifying variation is cross-sectional, we cannot pin down interest rate effects. However, a differential impact of debt during the four subperiods in our sample could be the result of the different prevailing interest rates.

## 2.2 Regionally Aggregated Data, Risk Sharing, and Heterogenous Consumers

The consumption predictions listed above hold for individuals, but they are likely to carry over to the county level if there are common regional components in income. Ludvigson and Michaelides (2001) and Luengo-Prado and Sørensen (2008) demonstrate through simulations that the broad conclusions regarding propensities to consume and the effect of uncertainty predicted by the buffer-stock model and the augmented model with housing carry over to the aggregated data. However, regressions of consumption growth on aggregate and county-level data raise some issues. We show results from cross-sectional regressions, or panel regressions with time fixed effects, of consumption growth rates on various determinants. These regressions utilize variation that is orthogonal to the time series variation in the aggregate U.S. data, which has been more extensively studied. Our regressions would be unidentified if risk sharing between counties was perfect because cross-sectional regressions, or panel regressions with time fixed effects, would be left with only noise in consumption rendering all regressors insignificant.[7]

The predicted patterns for county-level data are similar to those predicted for aggregate time series, as long as consumers react similarly to shocks that affect the county and to shocks that affect the country. This is the case in our model and in the models in the papers cited above. Differences can occur if aggregate results are impacted by general equilibrium effects (such as the interest rate reacting to consumption demand shocks), or if some unmeasured determinants of consumption differ cross-sectionally and correlate with the measured regressors. For example, shocks to expectations of future income growth may differ between counties in a systematic manner or there may be unmeasured transfers between counties. This could be caused by the introduction of a new technology, such as fracking, which affects a significant

[7] The perfect risk sharing model was rejected by Cochrane (1991), Attanasio and Davis (1996), and Hryshko, Luengo-Prado, and Sørensen (2010) using micro data, and by Asdrubali, Sørensen, and Yosha (1996) and Demyanyk, Ostergaard, and Sørensen (2007) using regional data.

number of counties and rationally would change income expectations. In the appendix, we verify that including time series variation in our regressions does not change the results. In particular, we show that inclusion or exclusion of time-fixed effects in a pooled panel regression matters little for the estimated parameters in our most general specification.[8]

Heterogeneity of consumers significantly complicates the interpretation of results from aggregated data, particularly if preferences themselves are heterogenous. Heterogenous time-discount rates have been suggested as an explanation for skewed wealth distributions. Krueger, Mitman, and Perri (2016) show that wealth heterogeneity—in combination with a precautionary savings motive—can help explain the size of the aggregate MPC. The mechanism is that wealth-poor households have to cut back steeply on savings in order to avoid the risk of (near) zero consumption, when hit by a bad income realization. We include an indicator for wealth inequality in our regressions.

Albanesi, De Giorgi, and Nosal (2017) stress that heterogeneity within counties or ZIP codes may preclude the interpretation that county-level regressions capture the behavior of representative individuals. For example, if the counties where many residents have low credit scores are also the counties where many residents have high credit scores (large cities often have very wealthy and very poor population segments) the correlation of average consumption with average credit scores may be quite different from the correlation of average consumption with average credit scores in homogenous counties. We attempt to address this issue by including percentiles of the regressors that we have constructed from micro data, although most of them turned out to be insignificant. Albanesi, De Giorgi, and Nosal (2017) also point out that credit scores correlate with many factors, in particular age. Our extensive data collection is motivated by a desire to hedge against exactly that problem.

Related complementary work examines recent patterns in aggregate consumption through the lens of the theory outlined in this paper. For exam-

[8]The only difference between results with and results without time fixed effects is that the estimated effect of the change in consumer expectations gets smaller and less significant with time fixed effects, which may be a consequence of this variable not being available at the county level.

ple, Petev, Pistaferri, and Saporta-Eksten (2011) use micro data from the Consumer Expenditure Survey and find that the decrease in consumption inequality in the Great Recession is largely explained by wealth shocks that hit the affluent harder than the poor. Pistaferri (2016) sums up the empirical patterns in aggregate consumption over recent decades and asks why consumption growth has remained moderate since the Great Recession. He concludes, based on descriptive time-series evidence, that financial frictions, broadly defined, triggered the Great Recession, while low expectations and high income uncertainty—particularly for the less well-off—are the most likely explanations for the slow recovery.

A burgeoning theoretical literature has found large implications of a slump in consumer spending. We do not review this work, but one example is presented by Eggertsson and Krugman (2012), who demonstrate how debt overhang, affecting a large group of credit-constrained agents, can lead to stagnation resembling that which was observed in the Western world following the 2007–2008 subprime crash. Another example is from Kumhof, Rancière, and Winant (2015), who model the interaction between household debt and income inequality, and show that "excess debt" can trigger a severe recession.

# 3 Variables Included in the Regressions: Motivation and Data Sources

We use multiple datasets and measure most of our variables at the county level, except a few that are available only at higher levels of aggregation. We include all U.S. counties with a population greater than 5,000. For growth variables, we calculate the growth rate over three years for each of the four subperiods: 2001–2003, 2004–2006, 2007–2009, 2010–2012. For stock variables, we use the value in the year prior to the three-year subperiod being examined, with the exception of the measure of foreclosures which is already backward looking (the exact definition appears below).[9]

[9]For example, for the subperiod 2001–2003, stock variables are measured as of year 2000.

*Consumption Growth.* We use total retail sales at the county level, estimated by Moody's Analytics, to proxy for consumption. Total retail sales are defined as the total sales—durables and nondurables—by businesses in the following 13 categories: (1) motor vehicle and parts dealers, (2) furniture and home furnishings stores, (3) electronics and appliance stores, (4) building material, garden equipment, and supply dealers, (5) food and beverage stores, (6) health and personal care stores, (7) gasoline stations, (8) clothing and clothing accessories stores, (9) sporting goods, hobby, book, and music stores, (10) general merchandise stores, (11) miscellaneous store retailers, (12) non-store retailers, and (13) food services and drinking places.

Moody's estimates retail sales in the following way. First, it takes the Census of Retail Trade (CRT) from the U.S. Census Bureau—available at the county level every five years—and matches it with monthly dollar amounts of sales at the national level by industry for 5,000 firms from the Advance Monthly Retail Trade and Food Services Survey (MARTS) (also produced by the Census Bureau). Then, Moody's estimates retail employment in each county broken out by NAICS within the retail industry. From the estimates of retail employment, Moody's creates estimates of retail trade, using the national sales-per-employee ratio. The dollar value of retail trade equals the employment in retail trade (for that county) times the MARTS value (in dollars, for the nation) divided by total employment (for the nation). The quinquennial CRT series are converted into a quarterly frequency. The data are infilled between the survey years and extended after the last survey year (2007) using estimates of retail trade. Services that are incidental to merchandise sales, and excise taxes that are paid by the manufacturer or wholesaler and passed along to the retailer, are included in total sales. The monthly retail trade estimates are developed from samples representing all sizes of firms and kinds of businesses in retail trade and the survey comprises a sample selected from retail employers who made FICA payments.[10] The data are not representative

[10]Retail sales include used cars—which are not typically included in units of cars sold—boats, motorcycles, recreational vehicles, parts, and repairs. Both retail and unit auto sales include fleet-vehicle sales.

of total consumption but retail sales are such a large part of total consumption that it is important to understand its determinants. For simplicity, we refer to the retail sales series as consumption.

We next list the explanatory variables in our regressions. We include a set of contemporaneous growth rates of key variables as well as a more extensive set of predetermined lagged level variables.

*Growth of Income and Lagged Income.* Income growth is expected to be the main driver of consumption growth. We use real per capita income to construct three-year income growth rates. We are not able to estimate transitory components versus permanent components of income with our short samples, but the longer horizon is more informative about the permanent components. We also include lagged income levels. Average income can capture a host of factors. In particular, income-rich individuals may have better access to credit (although this may also be captured by some of our other controls such as the share of subprime borrowers). In that case the impact might change with credit availability. Income levels may also correlate with the life-cycle stage, so high income might signal lower future income growth. The county-level income data come from the Bureau of Economic Analysis.[11]

*Change in Unemployment and Lagged Unemployment.* The unemployment rate correlates with the probability of job loss, and we believe it captures mainly uncertainty as the income decline associated with job loss will be captured by the income variable. We include both the three-year change in the county unemployment rate and the lagged unemployment rate in our analysis—a 1 percentage point change in the unemployment rate could have a different effect on consumption growth when starting from a high unemployment rate level relative to a low level. We use data from the Bureau of Labor Statistics (BLS).

*Growth of Financial Assets and Lagged Financial Assets.* Financial as-

[11] A previous version of this paper used data from the Internal Revenue Service (IRS) and obtained substantially smaller coefficients on the income growth variable. This strongly indicates significant measurement error in the IRS data. The IRS data likely measures adjusted gross income (a tax concept) correctly, but as a measure of average income in the county it appears deficient.

sets can be considered a buffer stock, which can help maintain consumption in the case of unexpected income declines. As demonstrated by, for example, Krueger, Mitman, and Perri (2016), low-wealth consumers had to reduce consumption steeply during the Great Recession. Although financial assets can grow because consumers increase their buffer stock of savings in the face of uncertainty, fluctuations in stock-market prices are likely to drive most of the variation at the county level. These fluctuations play the role of exogenous wealth shocks. We impute financial assets per household at the county level using information from the Survey of Consumer Finances—details are provided in the appendix. We include both the three-year growth rate of real (imputed household-level) financial assets and the lagged ratio of financial-assets-to-income.

*Growth of Housing Wealth and Lagged Housing Wealth.* (Gross) housing wealth is associated with better credit availability because houses can be used as collateral. Further, housing wealth can be realized by selling a house (for instance, in the case of falling income) thereby allowing for greater non-housing consumption. We estimate real per capita housing wealth for counties in each year of our sample following the approach of Mian and Sufi (2011): multiplying median home values by the number of owner-occupied housing units. We use median home values from the 2000 Census and calculate future values by multiplying this initial number by a house-price index (HPI) from CoreLogic normalized to 1 in the year 2000. The HPI is available for only 1,245 counties. When the index is not available for a county, we substitute the corresponding state-level HPI for the missing observation.[12] Similarly, an initial number of owner-occupied housing units at the county level is obtained from the 2000 Census. The number is projected forward using changes in population and homeownership rates (further details are provided in the appendix). We construct three-year growth rates of real housing wealth.

The growth of housing wealth is driven mainly by house-price changes, which are exogenous to the consumer, and its effect should be similar to that

[12] We verified that our results are not sensitive to whether we run regressions on the set of counties with non-missing county-level information on house prices.

of a transitory income shock. The lagged ratio of housing wealth to income in the county is also included to explore the effect of initial differences in housing wealth relative to income. Housing wealth may be borrowed against or liquidated, playing the same role as financial wealth.

*Lagged Debt to Income.* Debt is to some extent the inverse of financial assets, and high debt may indicate a too-low buffer stock if uncertainty increases and/or credit tightens. Debt is also correlated with housing consumption, which owners may decrease in the face of lower-than-expected income. And debt may be excessively large due to unfounded optimism or other "market imperfections" as stressed by Mian and Sufi (2014). To capture the potential effects of debt on consumption growth, we use total debt at the beginning of the three-year subperiod. We use individual-level data available to us from the Equifax Consumer Credit Panel maintained by the Federal Reserve Bank of New York ("Equifax" for brevity hereafter) and aggregate over all individuals in a given county to measure total debt. We calculate the ratio of real debt-to-income by dividing total debt by total income in the county.

*Change in Consumer Expectations.* In the PIH framework, consumption is a function of expected income (and income itself matters only when it deviates from the expected level), so expectations are an important variable. Expectations are likely captured in part by variables such as the unemployment rate, but survey-based information on individuals' expectations may provide further information. We use monthly data on consumer expectations from the Conference Board, available for the nine Census Divisions, which we match with the counties in our sample. The index of expectations is the average of three indices that measure consumers' perceptions about business conditions, employment conditions, and total family income six months hence. We average the monthly data to the annual frequency before calculating the three-year changes (because this is an index, we do not transform the changes to growth rates).

*Share of Foreclosed Mortgages.* Foreclosure, an extreme outcome of excessive housing debt, is costly for consumers and shuts the homeowner out of credit markets at least temporarily (typically seven years in the United States, with the ramifications lessening over time). This variable is not a lagged variable, nor a growth rate. The measure available to us from Equifax is the number of consumers who experienced at least one foreclosure in the previous 24 months relative to the number of all consumers, aggregated by county and year. Because of the backward-looking nature of the raw data, this variable is measured at the end of the subperiod (i.e., for each subperiod $t-2$ to $t$, foreclosure is measured as of time $t$).

*Lagged Share of Income of the Top 5 Percent.* Higher-income individuals have lower MPCs (see, for example, the discussion in Pistaferri, 2016), so income inequality could certainly affect consumption. The idea that inequality can amplify the impact of aggregate shocks is discussed by Krueger, Mitman, and Perri (2016), and this variable likely picks up such effects (our use of aggregated data complicates the interpretation of the level-variables in particular). Using data from the Current Population Survey (CPS), we calculate the share of total income accounted for by the collective income of the top 5 percent of earners. This variable is available only at the state level.

*Lagged Share of Subprime Borrowers.* An easing of credit availability is likely to boost consumption, particularly for consumers with low credit ratings, and, like Mian and Sufi (2009), we would interpret a significant coefficient on the subprime ratio as capturing a change in credit conditions. Individuals with relatively low credit scores—in Equifax, those with credit scores below 661—are considered risky and usually referred to as "subprime borrowers." We use Equifax data to calculate the fraction of individuals in a county/year whose credit scores (Equifax Risk Scores) were below 661.

# 4 Descriptive Statistics

The empirical analysis uses county-level data and we report summary statistics by period at this level of aggregation in Table 1. There is large variation in the variables across counties.

In our analysis, retail sales are used to proxy for consumption. To assess the quality of the data, Figure 1 shows the growth rates of real per capita aggregate U.S. total, nondurable, durable, and services expenditures together with the growth rates of county-level retail sales aggregated to the U.S. economy. Nondurable consumption grew at about 1 percent during the dot-com recession, accelerated to over 8 percent during the subprime boom, fell 4.5 percent in the Great Recession, and grew by about 7 percent in the tepid recovery. Consumption of durables fell particularly dramatically during the Great Recession, by an astonishing 21 percent. Durable consumption increased during the tepid recovery but, as with most components, the increase was tepid in the sense that it did not make up for ground lost during the Great Recession. The strong collapse in durables consumption is consistent with the model of Browning and Crossley (2009). Services were one of the fastest-growing components during the dot-com recession and the subprime boom, but the consumption of services has changed little since then. Total consumption was less volatile than its components.

Goods is the combination of nondurables and durables. Overall, retail sales match goods consumption quite well. For example, the decline in retail sales during the Great Recession was about 13 percent while goods consumption dropped about 10 percent. The difference between retail sales and goods consumption is smaller in the other subperiods. Our regressions are cross-sectional and focus on the relative importance of consumption determinants across counties, but it is reassuring that the growth rates are similar in the aggregate.

Figure 2 provides evidence of cross-county variation in consumption growth rates in a box-and-whisker plot, where the top and bottom of the boxes are the 75th and 25th percentiles, respectively. The data for this plot (and our regressions) is winsorized at 2 percent and 98 percent.[13] The interquartile ranges span about 10 percentage points in each subperiod, and some counties have consumption growth rates that are far different from those of other counties, as shown by some county-observations falling outside the "whiskers."[14] The counties with atypical growth rates are mostly counties that had rela-

[13] A similar plot of the non-winsorized data is provided in the appendix.

[14] The length of the whiskers is 1.5 times the interquartile range.

tively high growth rates during the two recessions and relatively low growth rates during the subprime boom and the tepid recovery. Even during the subprime boom when aggregate consumption grew at a fast pace of 6.1 percent per year, some counties had negative growth rates of more than 20 percent. Natural disasters, such as Hurricane Katrina in 2005, which hit the Gulf Coast and, in particular, New Orleans, generated large negative outliers which will have undue influence in the absence of winsorizing.

Our data provide further details not readable from the figure: in the Great Recession, 2,618 out of 2,768 counties saw consumption growth of less than 5 percent, while 1,050 counties experienced a decline greater than 15 percent.

## 4.1 State-Level Maps of the Variation in Regressors

We next depict variation in consumption growth and the explanatory variables with a set of state-level maps for uncluttered illustrations.

Figure 3, Panel A, uses a map of the U.S. states to indicate the geographical distribution of consumption (retail sales) growth rates. During the dot-com recession, 25 states had negative consumption growth. During the subprime boom, only Michigan had negative three-year consumption growth, likely due to contraction in the automobile industry. During the Great Recession, all states had declining consumption growth, but the decline was not uniform. Although not visible from the figures, one state had negative consumption growth between 0 percent and –5 percent, four states between –5 percent and –10 percent, 27 states between –10 percent and –15 percent, and a staggering 19 states had consumption falling by more than 15 percent. The tepid recovery was not uniformly distributed either: 20 states saw weak consumption growth (positive growth rates smaller than 8 percent), while consumption grew quite rapidly at rates above 8 percent in the remaining states.

Figure 3, panel B, shows the distribution of changes in the unemployment rate. In the dot-com recession, unemployment increased in all states except Hawaii and Montana, increasing by more than three percentage points in six states, and by more than 1.5 percentage points in 32 states, mainly those outside the Southeast and the Rocky Mountains. In the subprime boom, all states except Mississippi increased employment while, in the Great Recession, every state had higher unemployment, with 37 states seeing unemployment rate increases of more than three percentage points. During the tepid recovery, unemployment rates went down in all but five states, but the recovery was quite uneven across states in this dimension.

Figure 4 shows the growth rates of state-level income, housing wealth, and financial assets as well as the change in consumer expectations. In Panel A, we see that 13 states experienced income losses during the dot-com recession. While some states had negative growth of both consumption and income during this period, five states had rising income but declining consumption. Income grew in all states but three (Michigan, Nebraska, and South Dakota) during the subprime boom , while consumption grew in all states except Michigan. All states experienced a sharp fall in consumption during the Great Recession, but income did not show the same pattern. During this subperiod, 18 states had negative income growth, while four states had significant real per capita income growth (Alaska, Nebraska, North Dakota, and South Dakota, with income gains greater than 8 percent). In the tepid recovery, income growth was positive for all states except Delaware; nine states saw income gains of more than 8 percent, including a high of 32 percent in North Dakota, likely due to growth in fracking.

Variation in housing wealth across states and subperiods is depicted in Panel B of Figure 4. For housing wealth, the difference in our sample between the two recessions was dramatic: during the dot-com recession, states saw either rapidly growing or fairly constant housing wealth while in the Great Recession, no state had significant growth of housing wealth, and 38 states had housing wealth declining by more than 15 percent. During the tepid recovery, 16 states had housing wealth decline by more than 15 percent. As expected, financial assets decrease during both recessions and increase during the subprime boom and the tepid recovery (see Figure 4, Panel C), with significant variation across states (and across counties) in each period.

Changes in consumer expectations (see Figure 4, Panel D) were small during the dot-com recession, indicating that consumers felt that the recession was relatively mild. The picture was drastically different during the Great Recession, when consumer expectations collapsed by more than 26 percent in all states except those in the New England Census Division. Consumer expectations improved across the board during the subprime boom and the tepid recovery.

Figure 5 depicts the patterns in state-level debt-to-income, income inequality, frequency of foreclosures, and fraction of subprime borrowers. In Panel A of Figure 5, we display debt-to-income levels at the beginning of each period by state. California had relatively high debt levels at the start of the dot-com recession and the subprime boom, while most states in the West and the Northeast had high debt levels at the beginning of the the Great Recession and the tepid recovery. Debt-to-income levels increased over time during our sample period (because this variable is lagged, our maps do not depict the deleveraging that happened after the Great Recession ended).

Figure 5 displays the income share of the top 5 percent in Panel B. Overall, this share has been increasing over time with a bit of a reversal during the tepid recovery. Figure 5, Panel C displays the share of consumers in foreclosure. As extensively documented, foreclosure rates were historically high and widespread during the Great Recession, but there was significant variation in foreclosure rates across states in other subperiods. States with large fractions of subprime borrowers were mostly concentrated in the South. These fractions were more stable over time than any other measure we used in our analysis; see Figure 5, Panel D.

Figure 6 shows the across-state variation in the remaining lagged (beginning of period) variables: income per capita, unemployment rates, housing-wealth-to-income, and financial-assets-to-income. The figure shows that the distribution of income per capita has remained relatively stable, while unemployment rates have varied significantly over the business cycle. Housing-wealth-to-income and financial-assets-to-income also vary with the business cycle, and financial assets have become relatively more important over time, perhaps reflecting the aging of the population.

## 4.2 Correlation Matrices, Principal Components, Time-Series versus Cross-Sectional Variation

We show full correlation matrices and principal components by subperiod, and we evaluate how much of the variation in the data is along the time dimension versus the cross-sectional dimension. For brevity, most of the detailed tables are relegated to the appendix, with a brief summary here.

### 4.2.1 Correlation Matrices

The lagged variables are not highly correlated with the growth-rate variables and, in order to highlight the more significant correlations, we display one correlation matrix for lagged variables and one for growth-rate variables (with the exception that the backward-looking number of foreclosures is included in both tables).

The correlations between the lagged variables in Table 2 are, in general, low. The largest correlations are between the ratio of financial assets-to-income and the ratio of debt-to-income, subprime share, and average income, implying that consumers with a high ratio of financial-assets-to-income also have high debt and high income, while they are unlikely to have subprime credit scores. The debt-to-income ratio correlates positively with income, suggesting that wealthier households with good credit hold financial assets and debt at the same time. The only other correlation numerically above 0.50 is the negative correlation between average income and the subprime share.

The correlations between the growth-rate variables in Table 3 are all numerically below 0.35 in absolute value; the highest correlation (in absolute value) is the negative correlation between growth of housing wealth and foreclosure. This is not surprising because in a situation where the owner cannot make the mortgage payments, the house can usually be sold for more than the mortgage balance if house values have increased. The second highest correlation is between the growth of financial assets and the growth of housing wealth, maybe because both fell steeply during the Great Recession.

#### 4.2.2 Principal Components

We examine if the variation in the regressors is common, in the sense that it can be captured by a few principal components. Our analysis of covariances indicates that the variation in the data cannot be fully captured by a few principal components. We provide a detailed discussion in Appendix A.4.

#### 4.2.3 Time-Series versus Cross-Sectional Variation

In Appendix A.5, we examine how much of the variation in three-year consumption growth can be explained just by time-dummies in a pooled regression. For this regression, the adjusted R-square is 0.38, while it is 0.46 in a pooled regression with time dummies and all other regressors. This implies that the partial R-square for all non-time-dummy regressors is only 0.08. However, the partial R-square for the three time dummies is only 0.02, indicating that the majority of the variation is explained by the time-series patterns in the regressors. The amount of variation that is explained by cross-sectional variation in the regressors may be somewhat underestimated because these results were done imposing pooling across time, an issue that we explore in the next section.

# 5 Regression Specification and Results

We estimate, cross-sectionally, or as a panel, the following regressions over U.S. counties:

$$\Delta^3 \log(C_{c,t}) = \mu_t + \beta' \widetilde{X_{c,t}} + \epsilon_{ct}, \tag{1}$$

where $\Delta^3 \log(C_{c,t}) = \log(C_{c,t}) - \log(C_{c,t-3})$ is the three-year growth rate of county-level consumption proxied by real per capita total retail sales; $X_{c,t}$ denotes the county-level[15] variables used. In all regressions, but one, we demean all independent variables in order to permit the constant to capture average consumption growth over each three-year interval in the following way: $\widetilde{X_{c,t}} = X_{c,t} - \frac{1}{N}\sum_{c=1}^{N} X_{c,t}$, where $c$ indexes counties and $N$ is the total number

[15]Or state- or census region-level variables for which county-level data are not available.

of counties in our sample. $\epsilon_{ct}$ is a generic error term. Our data have significant outliers (see Figure A.2 in the appendix), and we therefore winsorize all variables at 2 percent and 98 percent to make sure the results are not driven by these outliers. We find that the overall pattern of the results is robust to winsorizing. Standard errors are robustly clustered at the state level—resulting in larger values than obtained if standard White robust estimates were used.

## 5.1 Rolling Regressions

We study whether the relationships between consumption and our regressors are constant over the sample period. We cross-sectionally regress (three-year) consumption growth on all regressors for each year and plot the estimated coefficients for each regressor over time in Figure 7.[16] In order to highlight the relative importance of each regressor, we plot the standardized coefficients (obtained by dividing each regressor by its cross-sectional standard deviation in the given year), and we include two-standard-deviations bands. In Panel (a), we display the rolling coefficients for the "growth-rate regressors," which are contemporaneous with the dependent variable, consumption growth. Expectations seem to matter more in the recoveries, while the growth of housing wealth becomes particularly important during the Great Recession (where growth is negative). Overall, the rolling regressions support our strategy of using data for 2001–2003, 2004–2006, 2007–2009, and 2010–2012—capturing two recessions and two recoveries.

In Panel (b), we display the rolling coefficients for the "lagged regressors," dated at the beginning of each three-year interval. It it clear from the figures that the regressors have different impacts over time. In particular, several regressors are especially significant in 2006, where the regression captures the period 2004–2006 (the expansion that followed the dot-com recession). In particular, the lagged ratio of financial-assets-to-income and the lagged debt-to-income ratio are relatively more important during that period.

One can directly observe that the growth-rate regressors on average are

[16]The regressions are performed for overlapping three-year periods: 2001–2003, 2002–2004, and so on.

more important than the lagged-level variables in explaining consumption growth. All lagged-level regressors have many years where they are not significant (the $x$-axis being inside the confidence bands), and the normalized coefficients are often small (with the lagged financial wealth ratio being an exception in 2006).

## 5.2 Period-by-period Regressions

In Table 4, we show the results from four separate regressions, one for each of our subperiods. It is immediately clear that some coefficients are not stable over time, while others are. Consumption growth rates are very different across the four periods: at nil during the dot-com recession, 8 percent during the subprime boom, –11 percent in the Great Recession and 11 percent in the tepid recovery—although 11 percent is fairly high, it returns consumption only to the level of 2006. We do not comment on the other estimated coefficients, but postpone discussion until after testing for pooling and tabulating pooled estimates. Formal tests for pooling together with the observed differences in the coefficients over time are informative about the stability of the estimated coefficients.

## 5.3 Tests of Pooling of Subperiods

Typically, regressions are pooled across years, most often without testing. Because of our large cross-sectional dimension, we can perform the regressions by subperiods, but it is of interest to know for which variables the data accept pooling. If the years can be pooled, the information can be more compactly summarized and the parameter estimates may be more precisely estimated. We therefore test if our regressors can be pooled across all subperiods and, if not, across some subperiods. Our testing strategy is somewhat unusual and is a variant of the general-to-specific testing strategy. A general-to-specific testing strategy would start with 42 regressors (13 variables interacted with a dummy for each of the four periods), which would be quite unwieldy and, due to the many variables, would allow for a large number of testing paths (sequential tests after dropping insignificant variables). We chose the following strategy: we depart from the pooled panel specification of Table A.3 and estimate, for each variable $X^k$, $k = 1, \ldots, K$, included in $X$, (where $K$ is the number of regressors), the regression

$$\begin{aligned} \Delta^3 \log(C_{c,t}) &= \mu_t + \beta_0^k \widetilde{X_{c,t}^k} + \beta_1^k \widetilde{X_{c,t}^k} \times D_{2006} \\ &+ \beta_2^k \widetilde{X_{c,t}^k} \times D_{2009} + \beta_3^k \widetilde{X_{c,t}^k} \times D_{2012} + \sum_{i=1, i \neq k}^{K} \alpha_i \widetilde{X_{c,t}^i} + \epsilon_{ct}, \end{aligned} \tag{2}$$

where $D_t$ is a dummy for year $t$ and $\alpha$ and $\beta$ are parameters. We then perform a number of tests, starting, for each variable, by testing if $\beta_1^k = \beta_2^k = \beta_3^k = 0$. If the null cannot be rejected, that variable $k$ can be pooled across the years of the sample. If that is not the case, we test other obvious hypotheses, such as, $\beta_1^k = \beta_2^k$ (years 2006 and 2009 can be pooled for variable $k$), or $\beta_0^k - \beta_1^k = 0$ (the effect of variable $k$ is zero in year 2006 so that the 2006 effect can be dropped for this variable), and so on. Table 5 summarizes our tests but does not give details about the tests that are rejected, including a large number of $t$-tests. The resulting non-rejected model can potentially depend on the order of the tests, but in general, we found our results to be robust.

## 5.4 Pooled Regressions Estimates

Our most parsimonious specification is presented in Table 6. We discuss the impact of each regressor in turn (skipping the time dummies, which were already discussed). In general, the picture that emerges from the pooled regressions is similar to what can be gleaned from the period-by-period regressions with a few exceptions, that are discussed below. We start with the growth variables, which are generally easier to interpret.

**The role of contemporaneous regressors**

*Income Growth.* This variable is the most significant predictor of consumption growth. The pooled coefficient, at 0.22, is somewhat lower than Consumption Prediction # 1. Luengo-Prado and Sørensen (2008) find MPCs around 0.33

for nondurable state-level retail sales during 1970–1998, which they were able to match using the model with housing described in Section 2 when adding substantial (not directly measured) risk sharing. However, the magnitude appears reasonable considering that our multivariate regressions control for a number of variables that are correlated with income.

*Change in Unemployment.* The impact of a change in the unemployment rate is highly significant and pooled over the four subperiods. For a consumer, job loss is typically associated with a large negative income shock; however, our regressions control for income growth, and our preferred interpretation of unemployment, in the context of the model, is that high unemployment in a county is associated with high income uncertainty, Consumption Prediction #4. The effect of unemployment is also estimated with high significance. The economic interpretation of the coefficient –0.82 is that a one percentage point increase in the unemployment rate will decrease consumption by 0.82 percent. Clearly, changing unemployment, whether an increase or decrease, was a strong predictor of consumption throughout the entire period.

*Growth of Housing Wealth.* Mian, Rao, and Sufi (2013) find that housing wealth had substantial effects on consumption during the Great Recession, and we confirm this result for all periods with an elasticity of 0.07. The estimate is notably smaller than the 0.25 magnitude that Mian, Rao, and Sufi (2013) find, but it is similar to the values reported in Christelis, Georgarakos, and Jappelli (2015). According to Consumption Prediction # 6, the propensity to consume out of increasing housing wealth should be small and comparable to that of a transitory income shock. The coefficient is indeed smaller than the estimated coefficient for income growth (a combination of permanent and transitory components), but it is larger than the value predicted by the PIH model (equal to the real interest rate if house price shocks are expected to be one-off). This could indicate that consumers typically expect house price appreciation (or depreciation) to continue over time or it could reflect a relaxation of credit constraints.

*Growth of Financial Assets.* The fluctuations in county-level financial asset values are dominated by exogenous fluctuations in stock prices.[17] At 0.20, the estimated elasticity is very large during the dot-com recession, significant at 0.06 during the subprime boom and the tepid recovery, and insignificant during the Great Recession. It is hard to pin down why the elasticities change—the magnitude of 0.06 is similar to that of housing-wealth effects, but the lack of stability is more puzzling. Possibly, this imputed variable correlates with unmeasured variables, such as expectations about financial returns, leading to biased estimates, but we are not able to narrow this down further with our data.

*Change in Consumer Expectations.* Expectations are at the core of forward-looking behavior. Although our measure of expected economic performance is available only for the nine Census Divisions, it is significant during the subprime boom, when higher confidence is associated with higher consumption growth, but not otherwise. This suggests that consumers act on their expectations and increase consumption more when economic conditions are expected to improve, Consumption Prediction # 8. On average, from Table 1, consumer expectations did not change a lot during the subprime boom period, but there was large variation across Census Divisions, which is why the coefficient is pinned down precisely for this period. The coefficient of 0.13 for this period, where the standard deviation of the variable was 0.12, implies that a one-standard-deviation difference in expectations explained about a 1.5 percent difference in consumption growth. Measurement error in this confidence measure may be particularly high due to the limited geographical variation available, and our estimates are therefore likely to be biased toward zero. Our results for this variable are more tentative than for other variables due to the data constraints.

### The role of lagged regressors

Correlations of (lagged) level variables with consumption growth are sometimes hard to interpret because they may proxy for permanent or "structural"

[17] At the individual level, asset holdings may change due to idiosyncratic decisions, but idiosyncratic fluctuations will average out in aggregated data.

features of counties.[18] For example, some counties may be dominated by poor immigrants, or they may be agricultural or oil-rich, and it is not feasible to control for the large number of potentially important determinants of consumption growth captured by the structural features of counties. The interpretation that follows is therefore somewhat speculative. Nevertheless, as previously discussed, the MPC can be very different for the poor than for the wealthy, and this difference will be captured by lagged level variables. Moreover, some argue that debt overhang is the root cause of the Great Recession, and growth variables will correlate with lagged levels if there is mean reversion, leading to omitted-variable bias if lagged level variables are not controlled for. However, in our data the inclusion (or exclusion) of lagged variables does not seem to greatly affect the estimated coefficients on the growth/change variables just discussed.

*Lagged Income.* The elasticity of consumption growth with respect to lagged income per capita is –0.04 during the subprime boom and insignificant in other subperiods. This coefficient is particularly hard to interpret because it may capture a relation between income levels and consumption growth at the individual level or it may capture features of wealthy counties that we do not otherwise capture. The fact that this variable is significant only during the subprime boom suggests that it may capture access to credit.

*Lagged Unemployment.* The lagged unemployment rate predicts consumption growth over the subsequent three years with a negative sign. An increase of 1 percentage point in unemployment leads to a 0.27 percent decline in consumption growth in all subperiods. We interpret this coefficient as capturing income uncertainty over the following three years as unemployment reverts slowly to its county-specific mean.

*Lagged Housing Wealth/Income.* The ratio of housing wealth to income correlates positively with consumption growth in the Great Recession and tepid recovery. Our interpretation is that residents in counties with a higher level of housing wealth had better access to mortgage loans.

[18] This is particularly true for the credit scores that become insignificant if county dummies are included. (We do not report the details of these regressions that produce similar results.)

*Lagged Financial Assets/Income.* This variable is significant only in 2001–2003, with a positive sign. Individuals with a larger buffer stock may be able to better weather recessions (keeping in mind that the large fall in the value of financial assets in both recessions is captured by the *change* in financial assets). The clear result of Krueger, Mitman, and Perri (2016), that a low level of assets is associated with a higher propensity to consume, is hard to find in our data—in particular, we did not find significant results from interacting wealth levels with income.

*Lagged Debt/Income.* We find that debt was a drag on the recovery from the dot-com recession, but the variable is significant only during this period. There is a very high positive correlation of this variable with the ratio of financial-assets-to-income, likely because well-off individuals generally live in larger houses and hold larger mortgages. The high correlation makes it difficult to identify any debt overhang, although more severe debt will be captured by foreclosures. Dynan (2012), using micro data, found negative effects of debt overhang in the Great Recession. While our results do not disprove an effect of debt overhang, they do show that researchers need to be very careful in interpreting correlations of consumption growth with a single variable in the absence of natural experiments providing variation that is orthogonal to that of other variables.

*Share of Mortgages Foreclosed.* Foreclosure predicts negative consumption growth as expected from Consumption Prediction # 9. The variable is highly significant for the recovery periods of 2004–2006 and 2010–2012, and this very specific type of debt-overhang dampens recovery. In the run-up to foreclosure, many consumers may cut back consumption, hoping to avoid losing their houses. The coefficient of –2.51, together with standard deviations of about 0.25 across counties in Table 1, implies that counties with a one-standard deviation higher share of mortgages in foreclosure had about 0.6 percent lower consumption growth.

*Income Share of the Top 5 Percent.* The income share of the well-off likely correlates with skewness in wealth, and their low MPCs have been suggested as an explanation for the slow recovery after the Great Recession, see Krueger, Mitman, and Perri (2016). We cannot rule out this theory, but we found this variable to be significant only for the dot-com recession (a one-standard deviation increase in the income share of the high-income people during this period correlated with a 1 percent greater consumption growth). We experimented with other measures of income skewness within counties and found no significant results. The income share of the top 5 percent correlates positively with the share of subprime borrowers, and the lack of results for income skewness is, we believe, more a testament to the challenge of sorting out many simultaneous disparate determinants.

*Subprime Share.* The subprime boom has been labeled as such because of the easing of credit to subprime individuals during 2003–2006. Surprisingly, we find a positive correlation of this variable with consumption growth in all periods, although the period-by-period regressions have this variable significant only in the subprime boom. Our interpretation is that the variable was important only in the subprime boom, and tests for pooling can accept a null hypothesis due to high standard deviations rather than similarity of coefficients.[19]

A low credit score typically indicates low credit and low consumption levels, which, for given income, may correlate with higher future consumption growth. However, from the rolling regressions, the subprime share correlates more clearly with consumption growth in the subprime boom, when credit became more readily available for subprime borrowers. This finding agrees with the results in Mian and Sufi (2009)—they consider home equity lending mainly in isolation, but we show that the general easing of credit has strong overall significance even after all our other variables have been included.[20]

[19] In accordance with the results in Table 6, counties with a one-standard deviation higher share of subprime borrowers experienced a 0.5 percent higher consumption growth.

[20] The result does not imply that more subprime borrowers will lead to higher consumption, which we do not test. It implies that these borrowers had faster growing consumption, likely due to being able to catch up when their impaired credit rates were less important for lenders.

# 6 Conclusion

We explain statistically the variation in consumption growth across U.S. counties during the first 12 years of this century. Using a rich dataset, we document the explanatory power of numerous economic variables during four subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012). We find that contemporaneous growth variables explain most of the variation in consumption: growth of income, housing wealth, and fluctuations in unemployment were important determinants of consumption in all periods, while fluctuations in financial assets and expectations were important during some subperiods. Lagged unemployment rates and the share of subprime borrowers were important determinants of consumption throughout the sample, with negative and positive coefficients, respectively. Other lagged variables were important only in some subperiods.

Our study contributes to a large body of literature that empirically uncovers, or theoretically models, determinants of consumption growth during the '00s. Our results imply that consumption growth cannot be explained by only a few variables or factors. Further work might include the collection of even more detailed data in order to address issues of aggregation, it might focus on more rigorous identification of causality, or it might involve models that encompass the facts uncovered here.

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Figure 1: Real Per Capita Growth of U.S. Retail Sales and Consumption Components

This figure compares three-year growth rates of real consumption components and aggregated total retail sales, calculated as $\Delta^3 \log(C_t) = 100 \times [\log(C_t) - \log(C_{t-3})]$ for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012). The growth rate of total personal consumption is labeled *Consumption*; its two sub-components are *Goods* and *Services*. *Goods* is the sum of *Durables* and *Nondurables*. *Durables* consist of personal expenditures on motor vehicles and parts; furnishings and durable household equipment; recreational goods and vehicles; and other durable goods. *Nondurables* are goods in the following categories: food and beverages purchased for off-premises consumption; clothing and shoes; gasoline, fuel oil, and other energy goods; and other nondurable goods. We also plot the growth rates of *Services* which consist of the following household consumption expenditures: housing and utilities; health care; transportation; recreation; food services and accommodations; financial services and insurance; and other services. The data sources are Moody's Analytics and the Bureau of Economic Analysis.

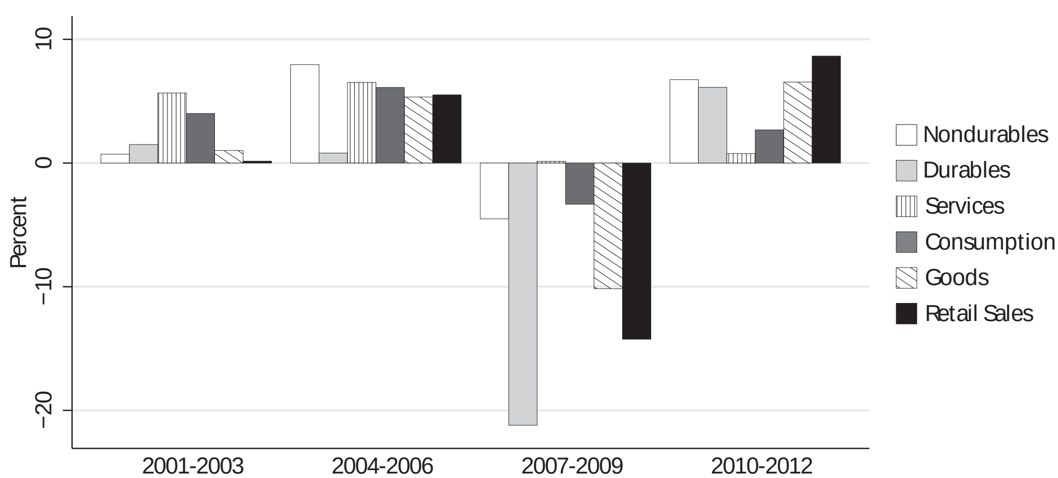


Figure 2: Cross-County Variation in Retail Sales Growth

This figure displays three-year growth rates of real per capita county-level consumption growth, proxied by total retail sales, calculated as $\Delta^3 \log(C) = 100 \times [\log(C_t) - \log(C_{t-3})]$ for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012). The data source is Moody's Analytics. The data are winsorized at 2 percent and 98 percent.

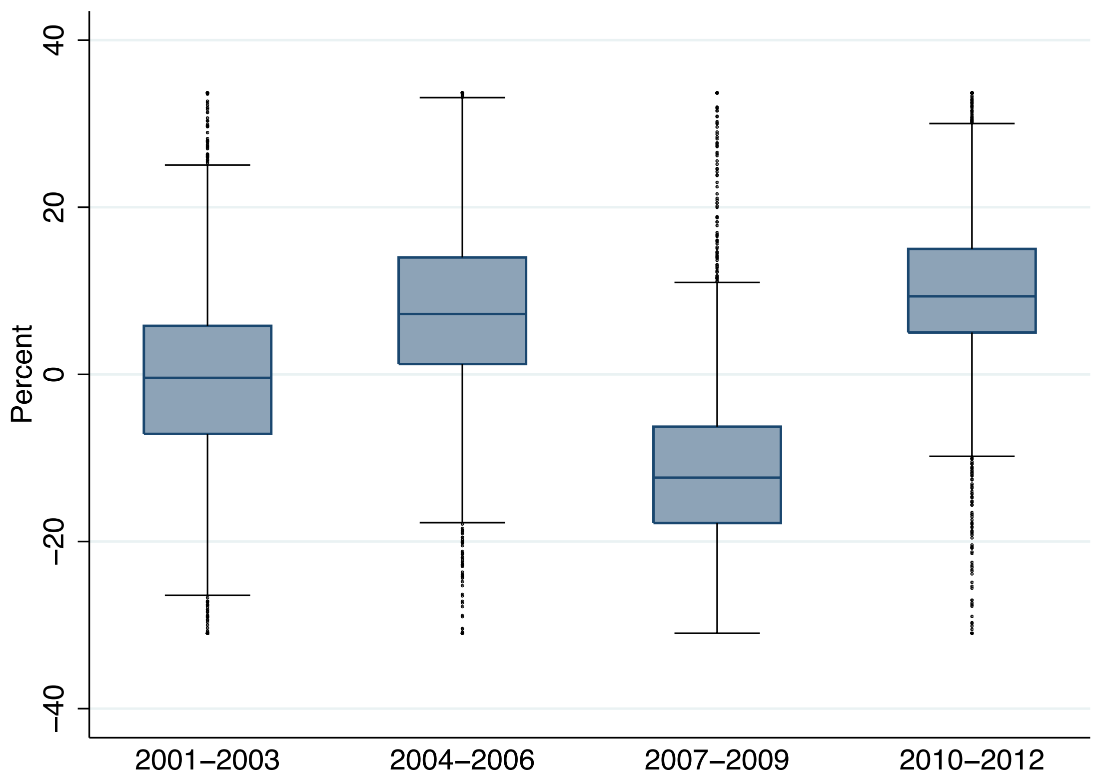


Figure 3: State Consumption Growth and Unemployment Rate Change by Subperiod

This figure displays three-year growth rates of real per capita consumption proxied by total county-level retail sales aggregated to the state level and calculated as $\Delta^3 \log(C_t) = 100 \times [\log(C_t) - \log(C_{t-3})]$ (from Moody's Analytics), and the change in unemployment rate (from the Bureau of Labor Statistics) for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012).

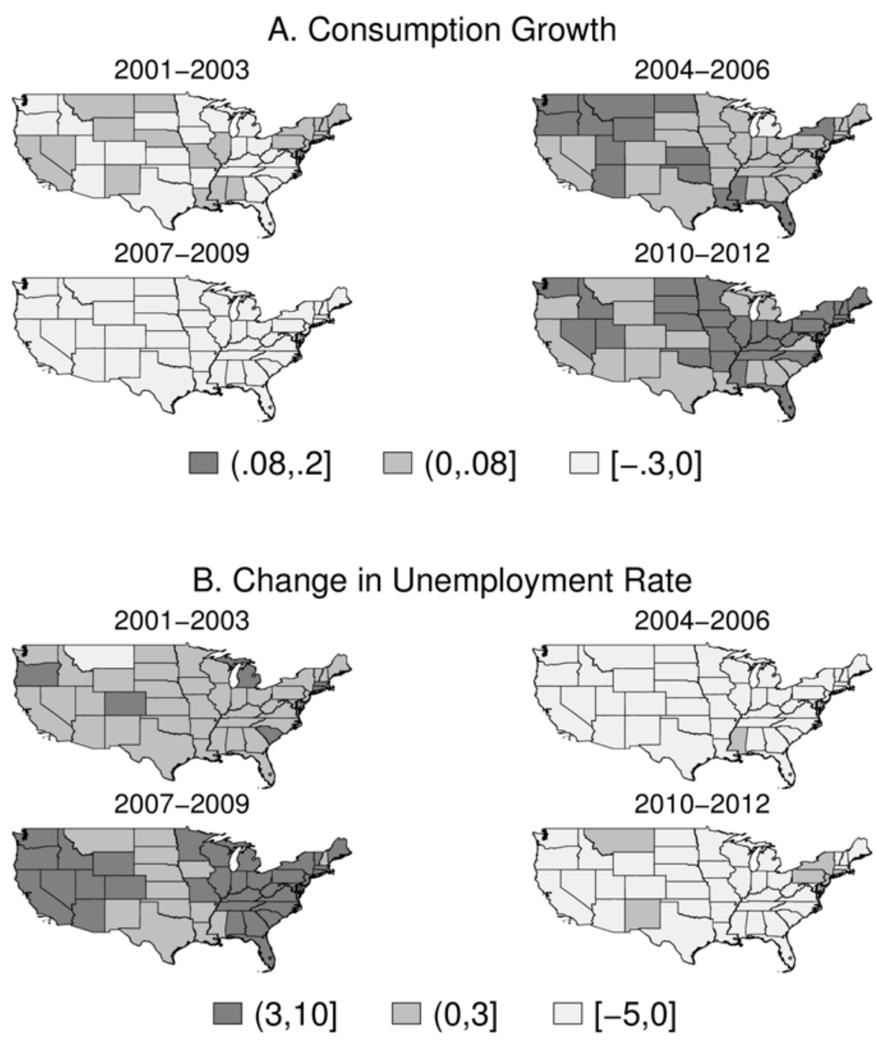


Figure 4: Income, Housing Wealth, and Financial Assets Growth and Change in Consumer Expectations by Subperiod

This figure displays three-year *Growth of Income* (real per capita from the Bureau of Economic Analysis), *Growth of Housing Wealth* (gross real housing wealth constructed from CoreLogic and Census 2000 data), *Growth of Financial Assets* (imputed by the authors using the Survey of Consumer Finances), and *Change in Consumer Expectations* (from the Conference Board) for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012).

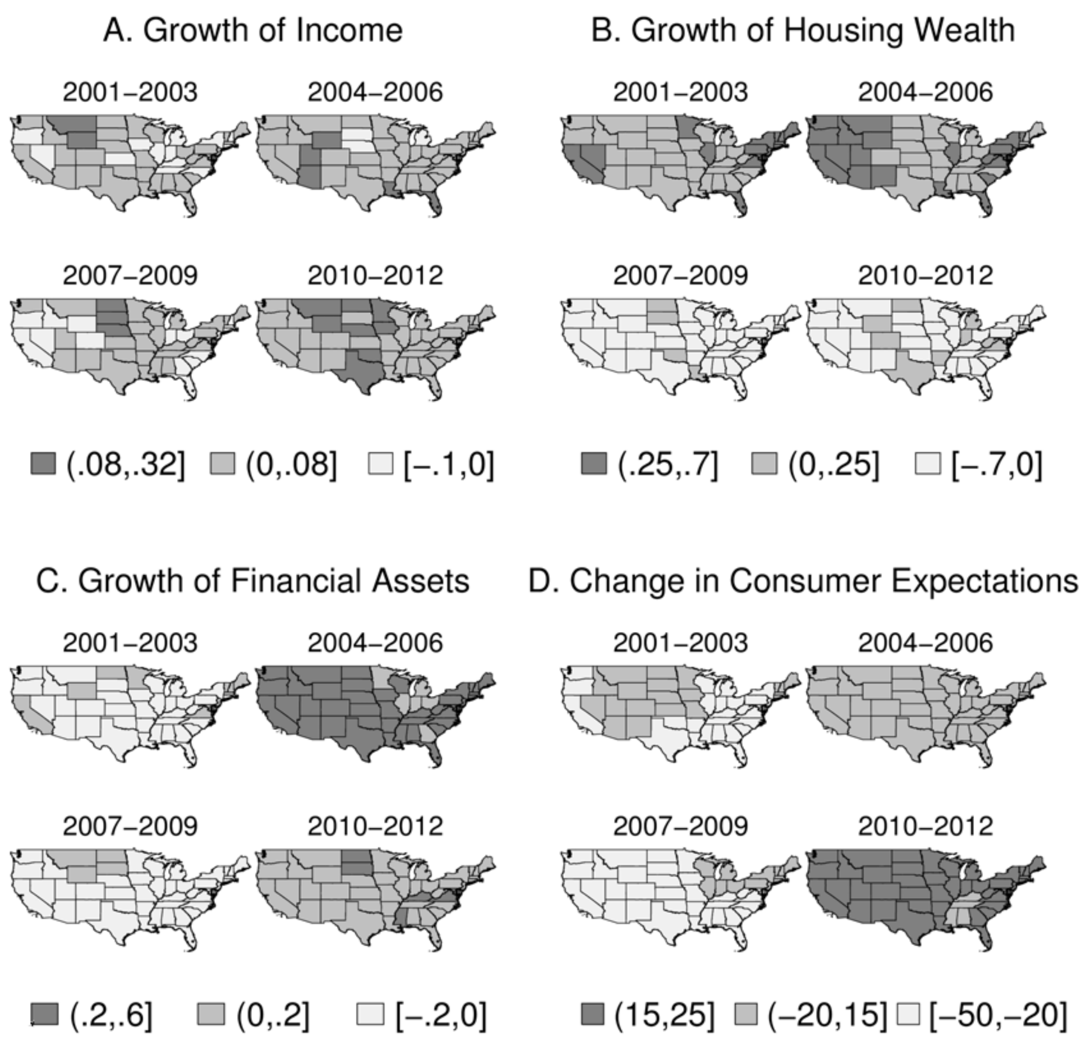


Figure 5: Debt to Income, Inequality, and the Shares of Foreclosures and Subprime Borrowers by Subperiod (Beginning of the Period)

This figure displays *Debt/Income* (gross real per capita debt from Equifax relative to BEA income; beginning of period), *Income Share, Top 5%* (from the CPS; beginning of the period), *Foreclosure Share* (or the share of consumers, in percent, who had at least one foreclosure in the last 24 months measured at the last year of each subperiod from Equifax), and *Subprime Share* (the share of individuals, in percent, in a state whose credit score is lower than 661 in Equifax; beginning of period) for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012).

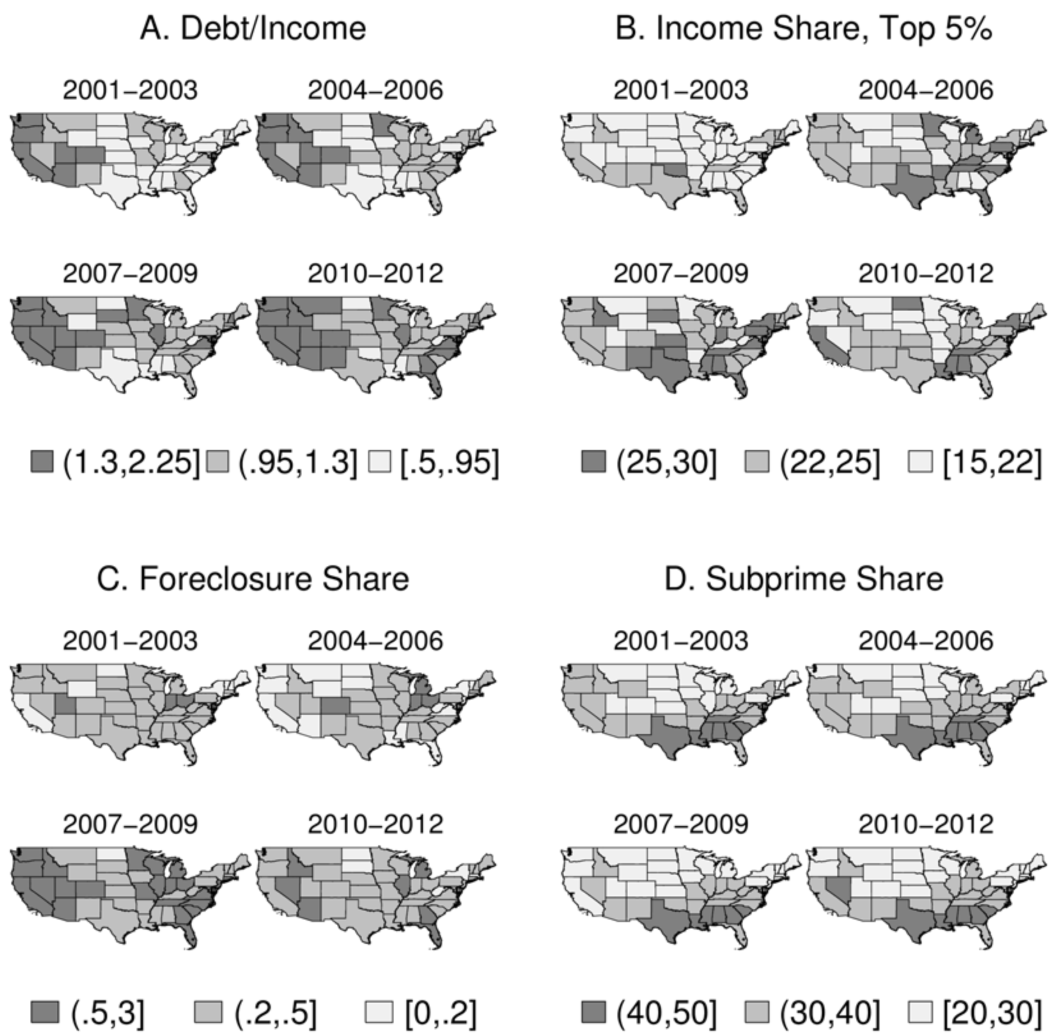


Figure 6: Log. Income, Unemployment Rate, Housing Wealth/Income, and Financial Asset/Income (Beginning of the Period)

This figure displays *Logarithm of Income* (real per capita from the Bureau of Economic Analysis; beginning of period), *Unemployment rate* (from the Bureau of Labor Statistics; beginning of period), *Housing Wealth/Income* (a ratio constructed from CoreLogic, Census 2000, and BEA income data; beginning of period), and *Financial Assets/Income* (a ratio of imputed financial assets using the SCF to BEA income; beginning of period) for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012).

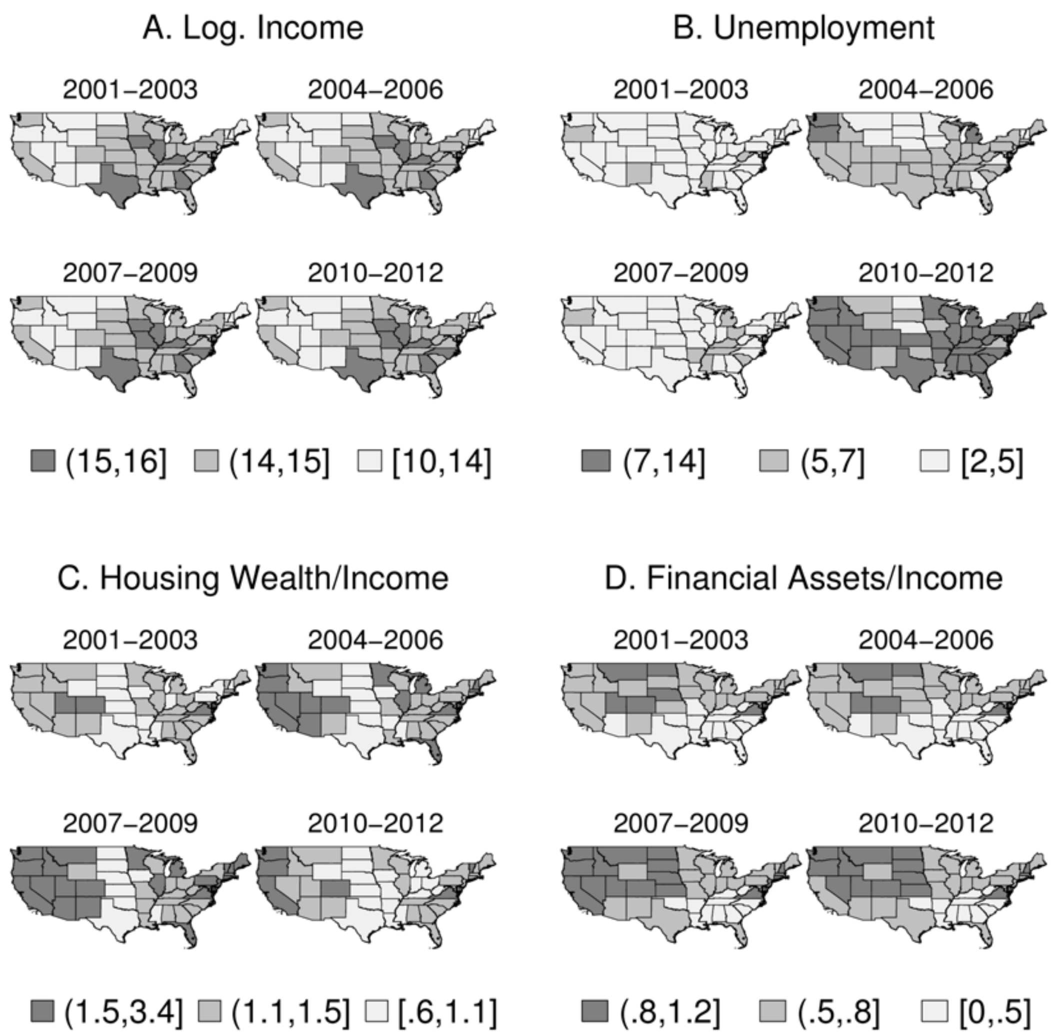
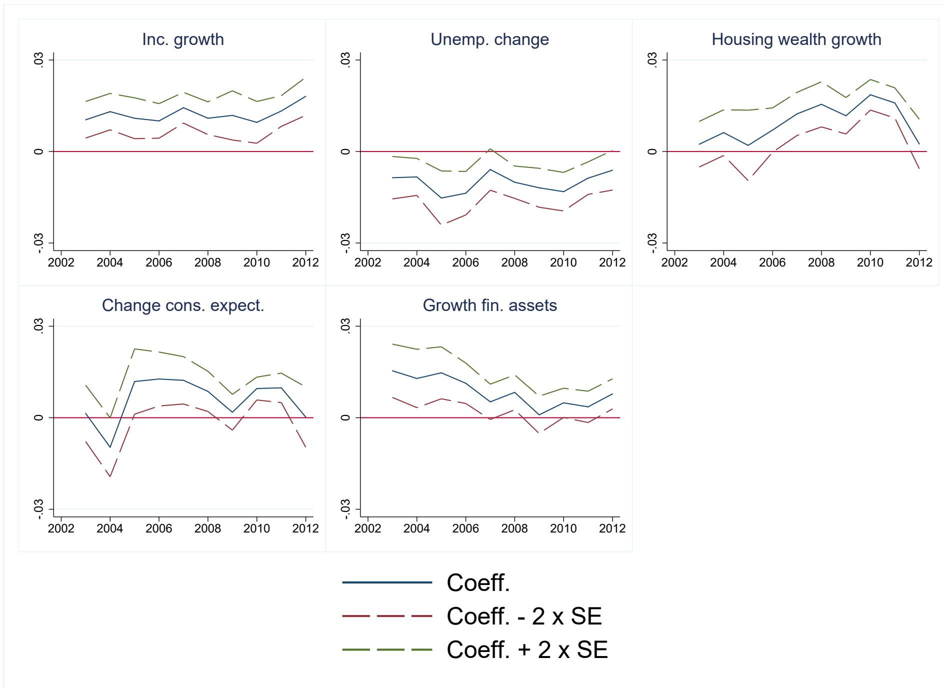
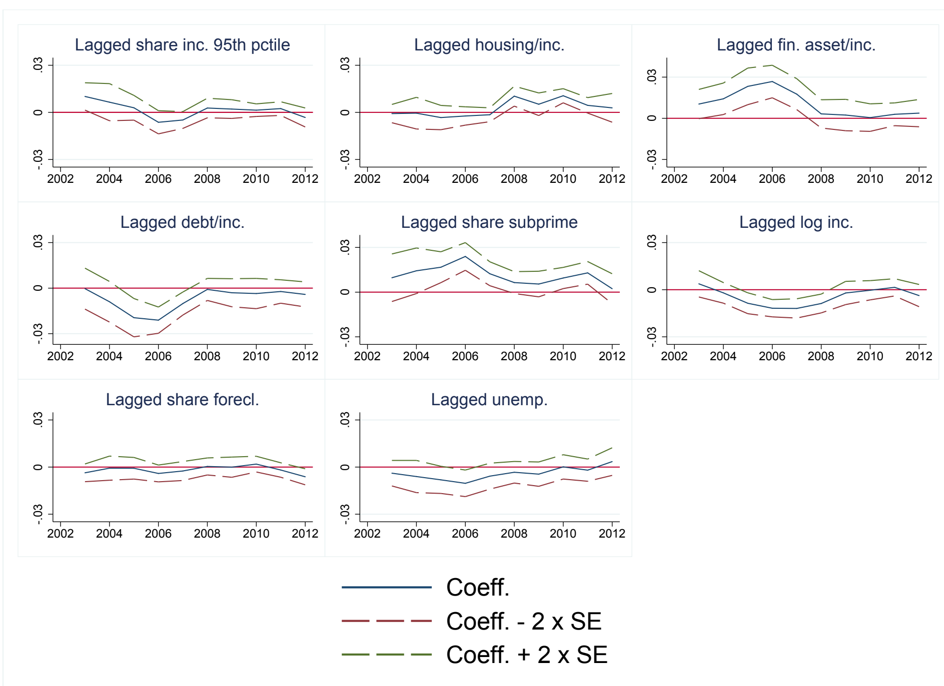


Figure 7: Slope Coefficients from Rolling Regressions




(a) Coefficients from cross-sectional regressions: growth variables




(b) Coefficients from cross-sectional regressions: lagged variables

*Note*: Each panel depicts slope coefficients (solid line) from cross-sectional regressions of three-year consumption growth on eight lagged variables and five growth variables for each of those variables for years 2001–2012. Each regressor was normalized by its standard deviation in a given year. Dotted lines depict a 95% confidence interval.

Table 1: Descriptive Statistics

| | 2001–2003 | | 2004–2006 | | 2007–2009 | | 2010–2012 | |
|---|---|---|---|---|---|---|---|---|
| Variable | mean | sd | mean | sd | mean | sd | mean | sd |
| Growth of Consumption (Retail Sales), % | –0.25 | 10.70 | 8.28 | 11.10 | –10.80 | 8.99 | 10.55 | 9.64 |
| Growth of Income, % | 1.74 | 5.53 | 3.70 | 5.52 | 2.35 | 6.26 | 4.99 | 5.45 |
| Change in Unemployment Rate | 1.72 | 1.14 | –1.08 | 1.02 | 4.15 | 1.78 | –1.23 | 1.35 |
| Growth of Housing Wealth, % | 11.75 | 9.02 | 13.09 | 11.27 | –18.89 | 10.88 | –10.53 | 6.84 |
| Growth of Financial Assets | –2.76 | 4.50 | 23.25 | 7.20 | –6.77 | 6.20 | 14.89 | 9.39 |
| Change in Consumer Expectations (Regional) | –23.05 | 3.41 | 3.31 | 11.31 | –42.50 | 9.42 | 27.15 | 5.94 |
| Lagged Income Per Capita | 10.35 | 0.20 | 10.37 | 0.20 | 10.40 | 0.21 | 10.43 | 0.20 |
| Lagged Unemployment Rate , % | 4.44 | 1.59 | 6.14 | 1.86 | 5.04 | 1.66 | 9.04 | 2.43 |
| Lagged Ratio Housing Wealth/Income,% | 1.17 | 0.31 | 1.30 | 0.39 | 1.44 | 0.49 | 1.15 | 0.37 |
| Lagged Ratio Financial Assets/Income | 0.48 | 0.18 | 0.46 | 0.18 | 0.55 | 0.21 | 0.51 | 0.20 |
| Lagged Ratio Debt/Income | 0.48 | 0.23 | 0.61 | 0.26 | 0.69 | 0.29 | 0.71 | 0.31 |
| Lagged Share of Income, top 5 Percent, % | 21.33 | 1.64 | 23.82 | 2.29 | 24.07 | 1.99 | 23.32 | 1.77 |
| Lagged Share Subprime, % | 34.79 | 8.71 | 35.09 | 8.69 | 34.40 | 8.68 | 34.29 | 8.94 |
| Share of Mortgages Foreclosed (24 Months),% | 0.27 | 0.22 | 0.26 | 0.22 | 0.44 | 0.32 | 0.29 | 0.23 |

*Note*: *Growth of Consumption (Retail Sales)* is defined as $\Delta^3 \log(C_{c,t}) = \log(C_{c,t}) - \log(C_{c,t-3})$, the three-year growth rate of consumption proxied by real per capita total county-level retail sales. *Growth of Income* is defined similarly using real per capita county-level income. *Change in Unemployment Rate* is $\Delta^3 UR_{c,t} = UR_{c,t} - UR_{c,t-3}$, the change in unemployment rate over the subperiod. *Growth of Housing Wealth* equals growth of (No. of owner occupied housing $\text{units}_{c,t} \times$ Median home $\text{value}_{c,t}$), which is defined in more details in Section 3. *Growth of Financial Assets* is the three-year growth rate of imputed financial assets. *Growth of Consumer Expectations (Regional)* is the three-year change in a consumer confidence index measured at the Census Divisions level. *Lagged Income Per Capita* is the logarithm of income per capita at the beginning of the period. *Lagged Housing Wealth/Income* is the ratio of county-level gross housing wealth divided by total income in the county at the beginning of the period. *Lagged Financial Assets/Income* is the ratio of imputed household financial assets in the county divided by per-capita income. *Lagged Debt/Income* is the ratio of county debt to county income at the beginning of the period. *Lagged Share of Income, top 5 Percent* is the share of real income that belongs to the richest 5 percent of people in a state. *Lagged Subprime Fraction* is a fraction of individuals residing in a county with credit scores less than 661 at the beginning of the subperiod. *Share of Mortgages Foreclosed (24 Months)* is the share of mortgages in foreclosure relative to all outstanding mortgages in a county over the last two years, measured at the end of each subperiod. All variables have been winsorized at 2 percent and 98 percent.

Table 2: Correlation Matrix. Lagged Variables.

| | Unemp. | Inc.Top5% | Housing R. | Fin. R. | Debt R. | Subpr. | Income | Forecl. |
|---|---|---|---|---|---|---|---|---|
| Unemployment | 1.00 | | | | | | | |
| Top 5% Inc. Share | 0.16 | 1.00 | | | | | | |
| Housing W. Ratio | 0.15 | –0.03 | 1.00 | | | | | |
| Fin. Ass. Ratio | –0.36 | –0.16 | 0.17 | 1.00 | | | | |
| Debt Ratio | –0.13 | –0.04 | 0.20 | 0.74 | 1.00 | | | |
| Subprime Share | 0.37 | 0.25 | –0.17 | –0.75 | –0.40 | 1.00 | | |
| Income | –0.45 | –0.07 | –0.14 | 0.58 | 0.47 | –0.55 | 1.00 | |
| Foreclosure | 0.01 | 0.02 | 0.04 | 0.24 | 0.39 | –0.06 | 0.14 | 1.00 |

*Note*: The table shows the correlation between the level variables included in our regressions.

Table 3: Correlation Matrix. Growth/Change Variables.

| | Foreclosure | Income | Unempl. | Housing W. | Fin Assets | Expectations |
|---|---|---|---|---|---|---|
| Foreclosure | 1.00 | | | | | |
| Income | –0.25 | 1.00 | | | | |
| Unemployment | 0.19 | –0.26 | 1.00 | | | |
| Housing Wealth | –0.35 | 0.26 | –0.25 | 1.00 | | |
| Fin. Assets | –0.23 | 0.20 | –0.18 | 0.27 | 1.00 | |
| Expectations | –0.06 | 0.12 | –0.12 | 0.08 | 0.05 | 1.00 |

*Note*: The table shows the correlation between the growth/change variables included in our regressions as well as foreclosure rates.

Table 4: Determinants of Consumption. Period-by-Period Regressions.

| | 2001–2003 | 2004–2006 | 2007–2009 | 2010–2012 |
|---|---|---|---|---|
| Growth of Income | 0.19*** | 0.18*** | 0.19*** | 0.33*** |
| | (3.40) | (3.47) | (2.88) | (5.69) |
| Change in Unemployment | –0.75** | –1.34*** | –0.67*** | –0.45* |
| | (–2.42) | (–3.76) | (–3.65) | (–1.85) |
| Growth of Housing Wealth | 0.03 | 0.06* | 0.11*** | 0.04 |
| | (0.63) | (1.90) | (3.84) | (0.60) |
| Growth of Financial Assets | 0.25*** | 0.14*** | 0.01 | 0.08*** |
| | (3.45) | (3.34) | (0.31) | (3.11) |
| Change in Consumer Expectations | 0.04 | 0.11*** | 0.02 | 0.00 |
| | (0.31) | (2.82) | (0.60) | (0.04) |
| Lagged Income Per Capita | 0.02 | –0.06*** | –0.01 | –0.02 |
| | (0.88) | (–4.19) | (–0.55) | (–1.03) |
| Lagged Unemployment Rate | –0.24 | –0.56** | –0.27 | 0.14 |
| | (–0.94) | (–2.40) | (–1.14) | (0.78) |
| Lagged Ratio Housing Wealth/Income | –0.00 | –0.01 | 0.01 | 0.01 |
| | (–0.26) | (–0.77) | (1.41) | (0.62) |
| Lagged Ratio Financial Assets/Income | 0.06* | 0.15*** | 0.01 | 0.02 |
| | (1.91) | (4.43) | (0.41) | (0.75) |
| Lagged Ratio Total Debt/Income | –0.00 | –0.08*** | –0.01 | –0.01 |
| | (–0.04) | (–4.78) | (–0.64) | (–0.98) |
| Share of Mortgages Foreclosed (24 Months) | –1.56 | –1.75 | –0.02 | –2.52** |
| | (–1.27) | (–1.49) | (–0.02) | (–2.37) |
| Lagged Share of Income of Top 5% | 0.62** | –0.28* | 0.11 | –0.18 |
| | (2.28) | (–1.68) | (0.69) | (–1.05) |
| Lagged Share of Subprime | 0.11 | 0.28*** | 0.06 | 0.03 |
| | (1.19) | (5.06) | (1.24) | (0.45) |
| Constant | –0.00 | 0.08*** | –0.11*** | 0.11*** |
| | (–0.30) | (22.30) | (–39.04) | (30.68) |
| R-squared | 0.06 | 0.14 | 0.10 | 0.06 |
| Observations | 2,770 | 2,769 | 2,766 | 2,767 |
| No. clusters | 51 | 51 | 51 | 51 |

*Note*: Cross-sectional regressions over U.S. counties based on the following regression specification for each subperiod: $\Delta^3 \log(C_{c,t}) = \mu_t + \beta' \widetilde{X_{c,t}} + \epsilon_{ct}$, where $\Delta^3 \log(C_{c,t}) = \log(C_{c,t}) - \log(C_{c,t-3})$ is the three-year growth rate of real per capita county-level consumption proxied by total retail sales, and $X_{c,t}$ is the vector of variables indicated in the first column. $\widetilde{X}_{c,t} = X_{c,t} - \frac{1}{N}\sum_{c=1}^{N} X_{c,t}$, for any variable $X$ where $c$ indexes counties and $N$ is the total number of counties in our sample. All variables have been winsorized at 2 percent and 98 percent. t-statistics based on standard errors clustered by state are reported in parentheses. *** (**) [*] indicate significance at the 1 (5) [10] percent level.

Table 5: Determinants of Consumption. Tests for Pooling

| | P-value | | P-value |
|---|---|---|---|
| ***Step 1. Adding interaction terms one-by-one*** | | ***Step 2. Conditional on step 1 outcomes:*** | |
| Lagged Unemployment Rate (fraction) | | Lagged Share of Income of Top 5 Percent | |
| pool all subperiods | 0.30 | pool 2004-06, 2007-09, and 2010-12 | 0.36 |
| Lagged Ratio Housing Wealth/Income | | Growth of Income | |
| drop 2004-06 | 0.32 | pool all subperiods | 0.60 |
| pool 2007-09 and 2010-12 | 0.73 | Change in Unemployment | |
| Lagged Ratio Financial Assets/Income | | pool all subperiods | 0.77 |
| pool 2007-09 and 2010-12 | 0.82 | ***Step 3. Conditional on step 2 outcomes:*** | |
| drop 2004-06 | 0.94 | Lagged Ratio Total Debt/Income | |
| Lagged Ratio Total Debt/Income | | drop 2001-03 | 0.72 |
| pool 2007-09 and 2010-12 | 0.30 | Lagged Share Subprime | |
| Lagged Income Per Capita | | pool all subperiods | 0.69 |
| drop 2007-09 and 2010-12 | 0.40 | Lagged Income Per Capita | |
| Share of Mortgages Foreclosed (24 Months) | | drop 2001-03 | 0.72 |
| drop 2007-09 and 2010-12 | 0.40 | Change in Consumer Expectations | |
| Change in Unemployment | | drop 2001-03 | 0.72 |
| pool all subperiods | 0.09 | ***Step 4. Conditional on step 3 outcomes:*** | |
| Growth of Housing Wealth | | Lagged Ratio Housing Wealth/Income | |
| pool all subperiods | 0.95 | drop 2001-03 | 0.73 |
| Growth of Financial Assets | | Growth of Financial Assets | |
| drop 2007-09 | 0.97 | pool 2004-06 and 2010-12 | 0.62 |
| Change in Consumer Expectations | | ***Step 5. Conditional on step 4 outcomes:*** | |
| drop 2007-09 and 2009-12 | 0.60 | Lagged Share of Income of Top 5 Percent | |
| Foreclosure | | drop 2004-06, 2007-09, and 2010-12 | 0.22 |
| pool 2004-06 and 2010-12 | 0.56 | ***Step 6. Conditional on step 5 outcomes:*** | |
| drop 2001-03 and 2007-09 | 0.72 | Lagged Ratio Financial Assets/Income | |
| | | drop 2007-09 and 2010-12 | 0.39 |
| | | Lagged Ratio Total Debt/Income | |
| | | drop 2007-09 and 2010-12 | 0.39 |

*Note*: The table displays select p-values from testing restrictions. In step 1, tests are performed by adding year-interactions for each variable one-by-one. The p-values of non-rejected hypotheses are displayed. Based on the results of step 1, interaction terms are added, and the tests are done in a sequential manner as indicated by the labels. The results conditional on the outcomes of step 6 are reported in Table 6.

Table 6: Determinants of Consumption After Sequential Testing

| **Lagged Levels** | coeff. | t-stat | **Contemporaneous Growth Rates/Changes** | coeff. | t-stat |
|---|---|---|---|---|---|
| *Per Capita Income:* | | | *Per Capita Income:* | | |
| 2004–06 | –0.04 *** | (–2.73) | pooled (all years) | 0.22 *** | (8.57) |
| *Unemployment Rate:* | | | *Unemployment Rate:* | | |
| pooled (all years) | –0.27 ** | (–2.37) | pooled (all years) | –0.82 *** | (–5.69) |
| *Housing Wealth/Income:* | | | *Housing Wealth:* | | |
| pooled (2007–09, 2010–12) | 0.01 ** | (2.21) | pooled (all years) | 0.07 *** | (3.69) |
| *Financial Assets/Income:* | | | *Financial Assets:* | | |
| 2001–03 | 0.06 ** | (3.02) | 2001–03 | 0.20 *** | (3.17) |
| | | | pooled (2004–06, 2010–12) | 0.06 *** | (2.83) |
| *Debt/Income:* | | | *Consumer Expectations:* | | |
| 2004–06 | –0.03 ** | (–2.42) | 2004–06 | 0.13 *** | (2.75) |
| *Share of Foreclosed Mortg.:* | | | | | |
| pooled (2004–06, 2010–12) | –2.59 *** | (–3.44) | | | |
| *Inc. Share Top 5 Percent:* | | | | | |
| 2001–03 | 0.65 ** | (2.40) | | | |
| *Share Subprime:* | | | | | |
| pooled (all years) | 0.08 ** | (2.10) | | | |
| *Time Dummies:* | | | | | |
| Year=2001–03 | –0.00 | (–0.38) | Year=2007–09 | –0.11 *** | (–41.38) |
| Year=2004–06 | 0.08 *** | (18.55) | Year=2010–12 | 0.11 *** | (28.98) |
| R-squared | 0.47 | | Observations | 11,072 | |

*Note*: Panel regressions over U.S. counties based on the following regression specification for each subperiod: $\Delta^3 \log(C_{c,t}) = \mu_t + \beta' \widetilde{X_{c,t}} + \epsilon_{ct}$, where the variables are defined in the notes to Table 4 and the main text. The coefficients are constrained according to the tests described in Table 5 and the main text. All variables have been winsorized at 2 percent and 98 percent. *** (**) [*] indicate significance at the 1 (5) [10] percent level.

# A Appendix

## A.1 Imputing Financial Assets

To impute financial assets at the county level, we first use the Survey of Consumer Finances (SCF) to predict household-level holdings of financial assets. Using the estimated coefficients from this initial regression, we use county-level counterparts for each regressor to predict financial assets at the county level. The list of regressors in the SCF predicting-equation is dictated by county-level data availability—e.g., certain interactions of variables are not readily available at the county level. In particular, we estimate the following regression:

$$\begin{aligned}\log(A_i) \quad = \quad & \alpha + \sum_{j=1}^{3} \beta_j D_j^{race} + \sum_{j=1}^{4} \gamma_j D_j^{education} + \sum_{j=1}^{4} \delta_j D_j^{age} + \zeta D^{rich} \\ & + \eta \log(Y_i) + \theta \log(H_i) + \sum_{j=1}^{4} \vartheta_j \log(M_i) \times D_j^{age} + \sum_{j=1}^{4} \kappa_j D^{no\ M} \times D_j^{age} \\ & + \sum_{j=1}^{4} \lambda_j \log(F_i) \times D_j^{age} + \sum_{j=1}^{4} \nu_j D^{no\ F} \times D_j^{age} + \varepsilon_i \,, \end{aligned} \tag{3}$$

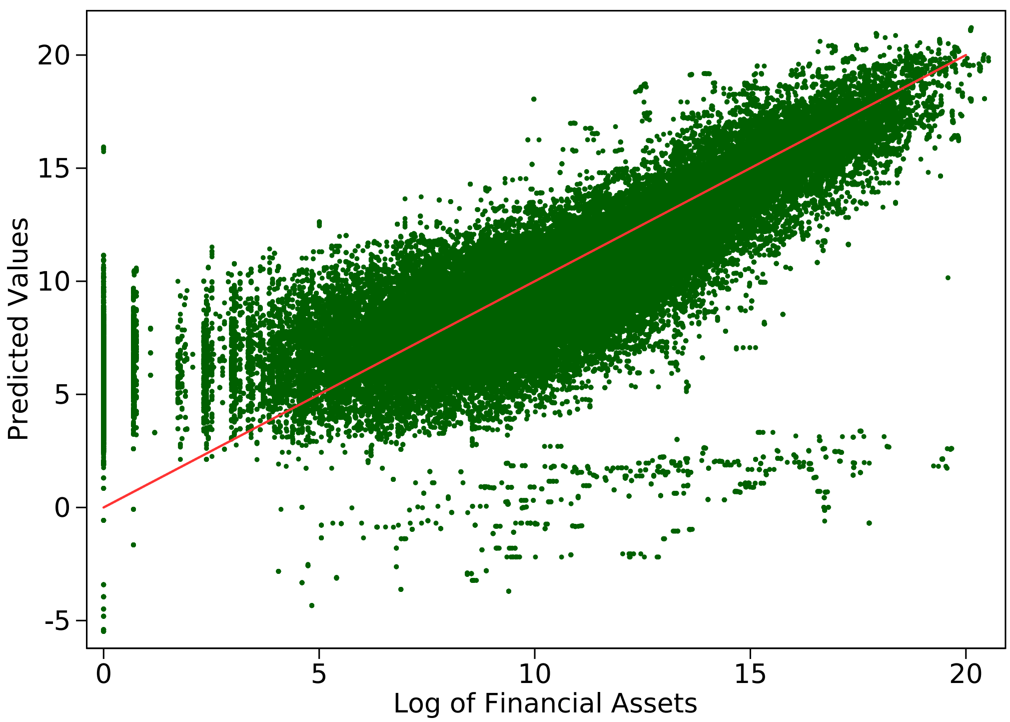
where $A$ denotes financial assets (the sum of transaction accounts, mutual funds, stocks, bonds, quasi-liquid retirement accounts, savings bonds, the cash value of life insurance, other managed assets, and other financial assets). $Y$ is household income, $H$ is home value, $M$ is mortgage balance, and $F$ is other debt. (We replace the logarithm of any of these variables with a zero in the case of zero holdings of that particular measure.) $D^x$ denotes a dummy variable classifying a household according to characteristic $x$. In particular, households are classified according to the head's race, education, and age group. We use three racial groups: white (omitted category), black, and other race; four education groups: less than high school, high school graduates, some college (the omitted group), and college or more; and four age groups: 18–34, 35–49, 50–64 (omitted), and 65+. We further keep track of whether a household is income-rich with a dummy $D^{rich}$ equal to one if household income is above \$150,000 (in 2009 dollars) and zero otherwise. This variable captures the fact that a significant fraction of financial assets are held by income-rich households. $D^{no\ M}$ and $D^{no\ F}$ are dummies for whether a particular household has no mortgage or no other debt.

The SCF is available every three years (we use 2004, 2007, 2010, and 2013). We estimate the predicting-equation year-by-year with all financial variables in 2009 dollars. For SCF survey years, we impute county-level financial assets per household by using the estimated coefficients in equation (3) for that particular year and the corresponding county-level values for that year. A $D^x$ variable in the predicting-equation at the county level is replaced with the proportion of households/individuals in that category in a given county. Our data sources are as follows: (1) race: Census Bureau (CB) and American Community Survey (ACS); (2) education: CB and ACS; (3) age: CB; (4) income: median income from CB and ACS ; (5) rich: percent of individuals with incomes above a threshold: CB; (6) home values: median home values from the CB and ACS adjusted by CoreLogic price indices; (7) mortgage by age: Consumer Credit Panel from Equifax (CCP); (8) other debt by age: CCP.

For years that fall outside SCF survey years, we use either the closest value (e.g., the SCF 2004 for year 2003), or a weighted average of the two closest years (e.g., the SCF 2004 and the SCF 2007 for year 2006 with weights 1/3 and 2/3, respectively). Using different weighting schemes (e.g., just using the closest year) does not affect the results significantly. We also adjust (inflate/deflate) the predicted county-level financial assets outside SCF years using the aggregate real growth rate of financial assets in the Flow of Funds (available at higher frequencies). However, this adjustment washes out when time dummies are included in the consumption regressions.

Figure A.1 plots the predicted values for financial assets compared to the actual values in the SCF regressions (all years pooled together), illustrating the relatively good fit of the predicting equation. The average adjusted R-squared across years is roughly 0.5. In 2004, the bottom 10 counties in terms of predicted financial assets per household (all bellow $2,000) are: Issaquena County, MS; Sioux County, ND; Buffalo County, SD; Jefferson County, MS; Zavala County, TX; Holmes County, MS; East Carroll Parish, LA; Humphreys County, MS; Starr County, TX. The top 10 counties (all with assets above $65,000) are: Fairfax County, VA; Hamilton County, IN; Morris County, NJ; Loudoun County, VA; Marin County, CA; Hunterdon County, NJ; Pitkin County, CO; Falls Church City, VA; Douglas County, CO; Los Alamos County, NM.

Figure A.1: Predicting Financial Assets in the Survey of Consumer Finances




*Note*: The figure depicts predicted values for the logarithm of financial assets in the SCF relative to the original values, pooling the years 2004, 2007, 2010, and 2014 together. The solid line is the 45 degree line.

## A.2 Imputing Housing Wealth

For each county $c$ and year $t$, we calculate:

$$\textit{Housing Wealth}_{c,t} \quad = \quad \textit{No. owner-occupied units}_{c,t} \times \textit{Median home value}_{c,t},$$

where $\textit{No. owner-occupied units}_{c,t} = \textit{No. owner-occupied units}_{c,2000} \times$ $\left(1 + \%\Delta \textit{Population}_{a,(t,2000)}\right) \times \left(1 + \%\Delta \textit{Homeownership rate}_{a,(t,2000)}\right)$ and $\textit{Median home value}_{c,t} = \textit{Median home value}_{c,2000} \times \left(1 + \%\Delta \textit{House Prices}_{c,(t,2000)}\right)$.

A variable $\%\Delta x_{c,(t,2000)}$ refers to the percentage change in variable $x$ in county $c$ (house prices) between years $t$ and 2000, and $\%\Delta x_{a,(t,2000)}$ refers to the percentage change in variable $x$ at the aggregate level (homeownership rate or population), where $t > 2000$.

## A.3 Correlation Matrix

A full correlation matrix of all regressors included in our analysis is presented in Table A.1.

Table A.1: Correlations for All Regressions.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Lagged Unemployment | 1.00 | | | | | | | | | | | |
| (2) Lagged Share Income of Top 5% | 0.16 | 1.00 | | | | | | | | | | |
| (3) Lagged Housing Wealth-to-Income | 0.15 | –0.03 | 1.00 | | | | | | | | | |
| (4) Lagged Financial Assets-to-Income | –0.36 | –0.16 | 0.17 | 1.00 | | | | | | | | |
| (5) Lagged Debt-to-Income | –0.13 | –0.04 | 0.20 | 0.74 | 1.00 | | | | | | | |
| (6) Lagged Share of Subprime | 0.37 | 0.25 | –0.17 | –0.75 | –0.40 | 1.00 | | | | | | |
| (7) Lagged Log Income | –0.45 | –0.07 | –0.14 | 0.58 | 0.47 | –0.55 | 1.00 | | | | | |
| (8) Share Foreclosed, past 2 years | 0.01 | 0.02 | 0.04 | 0.24 | 0.39 | –0.06 | 0.14 | 1.00 | | | | |
| (9) Income Growth | –0.03 | –0.04 | –0.01 | –0.06 | –0.15 | 0.00 | –0.13 | –0.25 | 1.00 | | | |
| (10) Change Unemployment | –0.16 | 0.05 | 0.12 | –0.02 | 0.06 | 0.05 | 0.01 | 0.19 | –0.26 | 1.00 | | |
| (11) Growth Housing Wealth | 0.03 | –0.02 | –0.05 | –0.13 | –0.17 | –0.01 | –0.03 | –0.35 | 0.26 | –0.25 | 1.00 | |
| (12) Growth Financial Assets | –0.07 | 0.04 | 0.01 | –0.07 | –0.09 | –0.02 | 0.02 | –0.23 | 0.20 | –0.19 | 0.27 | 1.00 |
| (13) Growth Consumer Expectations | 0.01 | 0.01 | –0.05 | 0.10 | 0.03 | –0.10 | 0.03 | –0.06 | 0.12 | –0.12 | 0.08 | 0.05 |

## A.4 Principal Component Analysis

We examine if the variation in our set of regressors can be captured by a low number of linear combinations. Such would likely be the case if a few major forces, such as credit or house prices, were driving most of the variation in all regressors. Table A.2 displays the fraction of variance explained by each principal component, in order, for the periods 2001–2003, 2004–2006, 2007–2009, and 2010–2012. We find that the share of variance explained by the largest principal component is 0.25 for 2001–2003 and 2010–2012, 0.26 for 2004–2006, and 0.30 for 2007–2009. The second principal component explains a fraction of 0.20 of the variance for 2007–2009 and 0.17 for the other periods. The third principal component explains 10–12 percent of the variance in all years. The greater picture that emerges is one of many different influences, with no common linear component explaining most of the variation, although the Great Recession period 2007–2009 has 60 percent of the variation explained by three linear components. This analysis cannot cope with long lags in any relations or with non-linearities, but the empirical patterns do not seem to support models where a few variables, such as credit or housing, explain the main part of what is going on. In factor analysis, the Kaiser-Meyer-Ohlin statistic (gauging the proportion of the variance that may be common) is often used to test if the dataset is "suited for factor analysis;" i.e., whether a few factors can capture the variation in all variables. For our sample, the value of the statistic is 0.6, a fairly low value indicating that our data are not well suited for the principal component analysis. In conclusion, the variation in our regressors cannot well be reduced to a significant lower dimension of

Table A.2: Fraction of Variance Explained by Principal Component

| Variance Expl.: | 2001–2003 | | 2004–2006 | | 2007–2009 | | 2010–2012 | | Pooled | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | cum. | | cum. | | cum. | | cum. | | cum. |
| Pr. Comp. #: | | | | | | | | | | |
| 1 | 0.25 | 0.25 | 0.26 | 0.26 | 0.30 | 0.30 | 0.25 | 0.25 | 0.26 | 0.26 |
| 2 | 0.17 | 0.42 | 0.17 | 0.43 | 0.20 | 0.49 | 0.17 | 0.42 | 0.17 | 0.43 |
| 3 | 0.10 | 0.52 | 0.11 | 0.54 | 0.11 | 0.60 | 0.12 | 0.54 | 0.12 | 0.54 |
| 4 | 0.09 | 0.61 | 0.10 | 0.64 | 0.08 | 0.68 | 0.09 | 0.63 | 0.09 | 0.63 |
| 5 | 0.08 | 0.69 | 0.07 | 0.71 | 0.07 | 0.75 | 0.08 | 0.70 | 0.08 | 0.71 |
| 6 | 0.07 | 0.75 | 0.06 | 0.77 | 0.05 | 0.80 | 0.07 | 0.77 | 0.07 | 0.77 |
| 7 | 0.06 | 0.81 | 0.05 | 0.83 | 0.04 | 0.84 | 0.06 | 0.83 | 0.06 | 0.83 |
| 8 | 0.05 | 0.86 | 0.05 | 0.87 | 0.04 | 0.88 | 0.05 | 0.88 | 0.05 | 0.88 |
| 9 | 0.04 | 0.90 | 0.04 | 0.91 | 0.04 | 0.92 | 0.05 | 0.92 | 0.03 | 0.91 |
| 10 | 0.04 | 0.94 | 0.03 | 0.95 | 0.03 | 0.95 | 0.03 | 0.95 | 0.03 | 0.94 |
| 11 | 0.03 | 0.97 | 0.02 | 0.97 | 0.02 | 0.97 | 0.02 | 0.97 | 0.03 | 0.97 |
| 12 | 0.02 | 0.99 | 0.02 | 0.99 | 0.02 | 0.99 | 0.02 | 0.99 | 0.02 | 0.99 |
| 13 | 0.01 | 1.00 | 0.01 | 1.00 | 0.01 | 1.00 | 0.01 | 1.00 | 0.01 | 1.00 |

*Note*: The table shows the fraction of variance explained by the explanatory variables of our study. For each year, the first row shows the fraction of variance explained by the first principal component (which is the linear combination of the regressors which maximizes this value). The second row shows the fraction of variance explained by the second largest principal (which is the maximum variance explained by a linear combination of the variables after orthogonalizing from the first principal component). And so forth for the other rows. The variables included are described in Section 3.

variables capturing common influences.

## A.5 Time-series versus Cross-Sectional Variation

We show results from multiple regressions pooled for the years 2003, 2006, 2009, and 2012. Our panel regressions highlight how much of the explanatory power is driven by time-series variation and how much by cross-sectional variation. The first column in Table A.3 shows results for a regression without time fixed effects while, in the second column, we drop the constant and include dummies for each year. The regressors, but not consumption growth, in the second column have been demeaned in each year, so that the estimated coefficients for the time dummies equal average consumption growth in the respective three-year period.

The R-square of the regression without time dummies is 0.44, while the adjusted R-square of the regression with the time dummies is 0.46. When including the time dummies, we capture only a small incremental fraction of the total variation in the panel, even if the consumption growth rates are very different across the four periods. The consumption growth rate was nil during the dot-com recession, 8 percent during the sub-prime boom, –11 percent in the Great Recession, and 11 percent in the tepid recovery. A growth rate of 11 percent is fairly high, but it only brings consumption back to the level of 2006. If we regress consumption on time dummies only, the R-square is 0.38, so the partial R-square for all regressors is a low 0.08 percent. The conclusion of this exercise is that the majority of the variation in the panel is the variation across time but this time-series variation is almost all captured by the (non-demeaned) regressors.

Table A.3: Determinants of Consumption: The Role of Fixed Effects

| Fixed Effects: | None | Year |
|---|---|---|
| Growth of Income | 0.17*** | 0.19*** |
| | (5.33) | (6.69) |
| Change in Unemployment | –0.83*** | –0.66*** |
| | (–5.13) | (–4.18) |
| Growth of Housing Wealth | 0.08*** | 0.07*** |
| | (6.38) | (3.42) |
| Growth of Financial Assets | 0.09*** | 0.10*** |
| | (4.36) | (4.62) |
| Change in Consumer Expectations | 0.19*** | 0.10*** |
| | (13.45) | (3.57) |
| Lagged Income Per Capita | –0.01 | –0.01 |
| | (–0.92) | (–1.34) |
| Lagged Unemployment Rate (fraction) | –0.20 | –0.26* |
| | (–1.43) | (–1.94) |
| Lagged Ratio Housing Wealth/Income | 0.00 | 0.00 |
| | (0.64) | (1.02) |
| Lagged Ratio Financial Assets/Income | 0.04** | 0.05*** |
| | (2.37) | (2.99) |
| Lagged Ratio Total Debt/Income | –0.02* | –0.02* |
| | (–1.73) | (–1.86) |
| Share of Mortgages Foreclosed (24 Months) | –1.32** | –1.39** |
| | (–2.06) | (–2.62) |
| Lagged Share of Income of Top 5 Percent | –0.13 | 0.00 |
| | (–1.19) | (0.03) |
| Lagged Share Subprime | 0.15*** | 0.14*** |
| | (3.26) | (3.18) |
| Year=2001–2003 | | –0.00 |
| | | (–0.37) |
| Year=2004–2006 | | 0.08*** |
| | | (16.87) |
| Year=2007–2009 | | –0.11*** |
| | | (–36.11) |
| Year=2010–2012 | | 0.11*** |
| | | (28.10) |
| Constant | 0.11 | |
| | (1.14) | |
| R-squared | 0.44 | 0.46 |
| Partial R-square for regressors, not time-dummies | | 0.08 |
| N | 11072 | 11072 |

*Note*: Parameters from all variables have been winsorized at 2 percent and 98 percent. *** (**) [*] indicate significance at the 1 (5) [10] percent level.

## A.6 Non-Winsorized Consumption

In Figure A.2, we show the three-year consumption growth rate proxied by the growth of total real per capita retail sales, calculated as $\Delta^3 \log(C_{c,t}) = 100 \times [\log(C_{c,t}) - \log(C_{c,t-3})]$ for county $c$ and each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012), using the data sample that has not been winsorized and includes outliers. Many of these outliers occur in small counties which may be affected by cross-border shopping or natural disasters. Upon inspecting the data, we found the largest outliers in Gulf Coast counties with large drops in consumption in subperiods where major hurricanes hit, followed by consumption recoveries during the following subperiods. The results in the main body of this paper are therefore obtained from data where all variables are winsorized at 2 percent and 98 percent in order to hedge against the results being driven by outliers. Most results are quite robust to winsorizing but, in particular, the effect of income growth varies much more across subperiods if the variables are not winsorized.

Figure A.2: County Retail Sales Growth: Not Winsorized

This figure shows the three-year growth of the real per capita consumption growth, proxied by total retail sales, calculated as $\Delta^3 \log(C_t) = 100 \times (\log(C_t) - \log(C_{t-3}))$ for each of the subperiods: the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012). The data source is Moody's Analytics.