

The Rise and Fall of Consumption in the '00s

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Abstract:

U.S. consumption has gone through steep ups and downs since 2000, but the causes of these fluctuations are still imperfectly identified. We quantify the relative statistical impact of income, unemployment, house prices, credit scores, debt, expectations, foreclosures, inequality, and refinancings on 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). We document that the explanatory power of different factors varies by subperiods, implying that a successful modeling of this entire decade needs to allow for multiple determinants of consumption. Unemployment, income, and debt are important determinants of consumption during all four periods.

JEL Classifications: E21, E37

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The authors thank Danny Kolliner for outstanding research assistance.

This paper presents preliminary analysis and results intended to stimulate discussion and critical comment. The views expressed herein are those of the authors and do not indicate concurrence by the Federal Reserve Bank of Boston, the Federal Reserve Bank of Cleveland, the principals of the Board of Governors, or the Federal Reserve System.

This paper, which may be revised, is available on the web site of the Federal Reserve Bank of Boston at <http://www.bostonfed.org/economic/ppdp/index.htm>.

This version: October 16, 2015

1 Introduction

In the first decade of the new millennium, U.S. consumer spending oscillated strongly and provided much fuel for business cycle fluctuations, as private consumption makes up the bulk of gross domestic product (GDP).¹ 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 fell, many owners who fell 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 increased steeply from \$31,000 in 2000 to \$56,000 in 2008, when it started to gradually decline, reaching \$47,000 in 2012. Consumer confidence eroded steeply 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 recovering, ending 2012 at 7.8 percent. 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 had recovered almost all lost ground by the end of 2012.²

Using county-level data, this paper provides empirical evidence on the relative statistical impact of these factors on consumption growth over the 2001–2012 period. Despite recent influential research that has pinpointed partial explanations of the fluctuations in consumption during the subprime boom

¹In 2014, the consumption share of GDP was 68 percent.

²Figures on gross housing wealth come from the Federal Reserve Board’s annual statistical release. The authors calculated 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.

and the Great Recession—in particular, the role played by housing wealth, subprime lending, and debt overhang—the role of other potential drivers of consumption remains mostly unexplored. This paper adds to the literature by considering the effect of many variables on consumption in a multiple-regression framework. This is potentially important because studies which consider individual determinants of consumption may suffer from omitted-variable bias. In particular, regressions of consumption growth on house-price growth may be biased because house-price growth correlates with other potentially important explanatory variables.

We document how consumption growth during the 2001–2012 period correlated with income, unemployment, debt, income inequality, consumer expectations, housing wealth, access to credit, cash-out refinancings, and foreclosures. We perform regressions of three-year consumption growth rates on its various determinants at the county level, with some variables measured at a higher level of geographic aggregation. Four subperiods are considered separately: the “dot-com recession” (2001–2003), the “subprime boom” (2004–2006), the Great Recession (2007–2009), and the “tepid recovery” (2010–2012).³ We find that income, debt overhang, and unemployment significantly influenced consumption in all subperiods, while other individual variables significantly correlated with consumption in certain subperiods.

An ideal statistical model of consumption should be at the household level, include exogenous variation in all potential shifters of consumption, and the same model should be able to fit all subperiods with high explanatory power. Further, dynamic adjustment should be fully modeled. No current work has gotten close to that ideal.⁴ Because exogenous or instrumental variables are not available, we perform ordinary least squares (OLS) estimations. While our

³The 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.

⁴Most closely related is the work of Mian and Sufi (2011) that examines the role of house-price appreciation during the subprime boom using instrumental-variables estimation, but that paper includes only a few, among many potentially important, variables which might affect consumption. Like many papers examining the Great Recession, Mian and Sufi’s paper examines only a short period of time.

results may be contaminated by endogeneity bias, they are informative, and for many variables the bias is likely to be small. For example, we use lagged values for stock variables, such as debt, because these values are predetermined, and thus closer to the exogenous drivers of the ideal model.

We do not attempt to pin down dynamics. We found numerous significant variables and estimating a large amount of lags would render the analysis nontransparent. We therefore follow the example of Mian and Sufi (2011) and estimate regressions cross-sectionally over multiple years (three years in our case). Further, the sensitivity of consumption to its correlates is unstable over the years we study. We find, for example, that the stock of debt correlates positively with consumption growth in the dot-com recession, and negatively in other subperiods. Our interpretation is that debtors benefitted from falling interest rates in the dot-com recession, were hurt by increasing interest rates in the subprime boom, and by low income realizations and tightened credit conditions in the Great Recession and the tepid recovery (even if some debtors with high credit scores benefitted during the latter subperiods when interest rates fell steeply). This interpretation could be tested in a very large dataset by including interactions of debt with interest rates and interactions of debt with credit conditions, and maybe higher-order interactions, but our dataset is not large enough to pin down such interactions, which is why we display results separately by subperiod. Nonetheless, our specification is much richer than any other studies that we are aware of for the 2000s and presents a clear warning against relying on past statistical relations for forecasting when the economic environment changes.

We use (mainly) county-level data because 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 which cannot be easily matched with micro datasets with 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.

The results of this study are not structural and the “effects” (“impacts” or similar terms) of regressors are to be understood in the statistical sense. The results, however, can be used as a guide for structural analysis. For example, we find that high unemployment growth is robustly related to low consumption growth. This suggests that economic policy which reduces unemployment will increase consumption. However, without exogenous shifters of unemployment or the aid of a well-tested structural model, we do not know for certain which deep structural variables, related to unemployment, shift consumption. Likely, consumption falls both for individuals who lose their job and for individuals who do not experience unemployment but who face higher earnings uncertainty when the probability of job loss is higher. Moreover, high unemployment could be a result of lower consumption rather than a cause of reduced spending. A full understanding would disentangle these potential factors, but we believe it is important to know that unemployment has a strong impact on consumption growth in the statistical sense.

For structural economic models to be useful for policy recommendations, the models should capture important features of the data, and this study provides statistical relations that such models should be able to match. Below, we list papers that have focused on matching particular features of, in particular, the Great Recession, but we believe there is a danger of misspecification if one tries to match only, say, debt overhang and not a more expansive range of empirical patterns.⁵

Our results are potentially important for guiding fiscal and monetary policy even if our estimates are not structural. For example, if debt overhang explains a large fraction of the variation in consumption, an interest rate policy that lowers debt service may be a powerful stabilizer, but if lowering unemployment is more important for consumption growth, fiscal policy—in the form of increased public purchases—may be more effective. Because we do not formulate a full model we do not attempt to suggest optimal policy; nonetheless,

⁵One may raise the objection that only a model can determine what are “important” empirical patterns, but structural modeling is still in its infancy and we select our regressors based on intuition guided by our reading of recent research on consumption.

in the absence of having a general consensus on an encompassing model, we believe that it is important to know which variables correlate strongly with consumption growth.

Analyzing all the variables simultaneously, we are able to measure their partial contributions to consumption growth in each of the four subperiods. Based on a partial R^2 analysis, unemployment has the highest explanatory power throughout the entire sample period, income growth and debt overhang have consistent but lower explanatory power, and other factors have high explanatory power only in some subperiods. The share of income received by the top 5 percent of households was important in the dot-com recession while consumer confidence was an important spur to consumer spending in the subprime boom. During the Great Recession, unemployment and housing wealth were important for consumption growth while income growth, foreclosures, debt overhang, and cash-out refinancings were relevant during the tepid recovery. Further, income inequality and access to credit were important in some of the four subperiods.

The paper is organized as follows: Section 2 relates our findings to the existing body of literature and Section 3 outlines the relevant theory of consumption. Section 4 describes our data and Section 5 describes the economy in the four subperiods we study. Section 6 outlines our empirical specification and describes the results, while Section 7 concludes.

2 Previously Established Patterns

In the first decade of the twenty-first century, the U.S. economy was dominated by the boom and bust in housing values and a boom and bust in subprime mortgages (Demyanyk and Van Hemert, 2011). Easy mortgage credit followed by tight credit conditions and housing wealth gains followed by wealth losses are two prime candidates for explaining the patterns in consumer spending observed during this period. 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. Iacoviello (2011) discusses the literature on housing wealth effects more broadly and points out that regressions of aggregate consumption on housing wealth may find correlations that are driven by omitted variables. 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. Nonhousing wealth effects on consumption are often found to be smaller.

Mian and Sufi (2009) focus on the easy credit conditions associated with the peak in subprime lending in the years 2004–2006 and the subsequent bust and debt overhang. They show that during the Great Recession, mortgage defaults were concentrated in ZIP codes with extensive subprime lending. Mian and Sufi (2011) show that a significant fraction of the rise in U.S. household leverage from 2002 to 2006 (and the subsequent surge in defaults) was due to borrowing against gains in home equity by existing homeowners. Using instrumental variables estimation, they find that homeowners extracted 25 cents for every one dollar increase in home equity, and that this type of home equity-based borrowing accounted for \$1.25 trillion in additional household debt from 2002 to 2008, potentially leading to a severe debt overhang that depressed consumer spending in the recovery from the Great Recession.

However, a more detailed sorting out of the determinants of the consumption bust that happened in the Great Recession is still work in progress. For example, 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 more than the poor. Dynan (2012) uses micro data to show that highly leveraged homeowners had larger spending declines between 2007 and 2009 than did other homeowners. Uncertainty about jobs and income also increased in the Great Recession. Alan, Crossley, and Low (2012) demonstrate that a suitably calibrated life-cycle model with credit constraints is able to explain the rise in the aggregate savings ratio in the United Kingdom during the Great Recession, particularly if young consumers faced a significant increase in uncertainty. The recession was also associated with depressed expectations

for future income, and 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. Christelis, Georgarakos, and Jappelli (2015) find significant effects of wealth shocks and unemployment on consumption during the Great Recession using U.S. micro data, consistent with our findings.

A burgeoning theoretical literature has found that there are large implications to a slump in consumer spending. While we will not offer a detailed review of this work, one example is Eggertsson and Krugman (2012), who demonstrate how debt overhang, affecting a large group of credit-constrained agents, can lead to stagnation resembling that observed in the western world following the 2007–2008 subprime crash. Another is Kumhof, Ranci ere, and Winant (2015), who model the interaction between household debt and income inequality, and show that “excess debt” can trigger severe recessions.

3 Theoretical Background

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 to be more in accordance with the PIH, due to accumulated life-cycle savings. However, in order to fully fit the data, important extensions are necessary, in particular, allowing for the existence of a large illiquid asset—housing—which generates large consumption commitments in the sense of Chetty and Szeidl (2007).

Consider the buffer-stock model with nondurables, owner-occupied housing, and downpayment requirements studied by Luengo-Prado (2006). 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 :

$$E_0 \left\{ \sum_{t=0}^{\infty} \beta^t U(C_{jt}, H_{jt}) \right\}, \text{ s.t. } S_{jt} = R_t S_{j,t-1} + Y_{jt} - C_{jt} - q_t \Delta H_{jt} - \chi(H_{jt}, H_{j,t-1}),$$

where the utility function typically is a CES index, S is financial wealth, q is the relative price of housing, R is an interest rate factor, and Y is income. There is a significant cost to relocate, captured by the function $\chi()$, so that consumers do not make marginal adjustments to 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, 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 cutting back disproportionately 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 in the models of “wealthy hand-to-mouth” consumers (Kaplan, Violante, and Weidner, 2014) and “consumption commitments” (Chetty and Szeidl, 2007). The consumer’s debt limit itself is a function of personal income and credit scores, although a model with both these features seems not yet to have been studied quantitatively. During the 2000s, the tightness of the constraint gyrated strongly, at least for subprime borrowers.

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 would like to increase consumption of both housing and nondurables, but the increase in consumption may be postponed while funds for the required downpayment are accumulated. Foreclosure costs and geographical mobility can be added to the model as in

Demyanyk et al. (2013).

3.1 Predicted Consumption Patterns

For easier reference in the empirical section, we provide a numbered list of the model’s “Consumption Predictions.”

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 MPC is around 0.8 for standard parameterizations. Home-ownership leads to even lower MPCs, as demonstrated by Luengo-Prado (2006).
2. More uncertainty predicts lower current consumption in the buffer-stock model (Carroll, 1992) 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).
3. 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). Using a mid-1990s Canadian dataset, they find that among recent job losers, a quarter was unable to borrow and therefore unable to smooth consumption. We expect the numbers to be similar in the United States although the severity of the constraints likely varied over our sample, as credit was eased during the subprime boom and then tightened in the Great Recession.

4. 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.
5. An implication of the budget constraint is that net debtors will benefit from falling interest rates, while net savers will benefit from higher interest rates. In other words, debt will, everything else equal, predict increasing consumption in an environment of falling interest rates and *vice versa* in an environment of increasing interest rates. Keys et al. (2014) use micro data to document a direct effect of mortgage interest rate resets on household consumption.
6. In the PIH model, high debt is a reflection of 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, as discussed in connection with credit. Kaplan, Violante, and Weidner (2014) discuss how “wealthy hand-to-mouth” consumers may have significant, but illiquid, wealth and therefore high MPCs.
7. Expectations correlate with consumption. The less obvious issue is whether consumer expectations have predictive power that is not captured by other variables. Ludvigson (2004) finds that consumer confi-

⁶A permanent house-price shock is a one-time wealth shock equivalent to a transitory income shock. Only if the *growth* of house prices is integrated (rendering the house-price itself twice integrated) will house-price shocks correspond to permanent income shocks.

dence (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 some 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.

8. A foreclosure implies lack of access to credit and hence a fall in consumption, although a foreclosure often involves a slow erosion of credit and possibly a negative wealth shock ahead of the event; see Demyanyk (2014) and Demyanyk et al. (2013).

We experimented extensively with specifications that allow for concavity in the consumption function, following Mian, Rao, and Sufi (2013), but we were not able to obtain robustly significant results.⁷

Luengo-Prado and Sørensen (2008) show that the consumption model with housing can fit U.S. state-level MPCs well if significant risk sharing, as in Attanasio and Pavoni (2011), is added to the model. The standard one-good risk-sharing model (see Mace, 1991; Cochrane, 1991) predicts that all consumers have perfectly coordinated consumption—a model which was rejected by Cochrane (1991), Attanasio and Davis (1996), and Hryshko, Luengo-Prado, and Sørensen (2010) using micro data, and Asdrubali, Sørensen, and Yosha (1996) and Demyanyk, Ostergaard, and Sørensen (2007) using regional data.

⁷The model does not have clear predictions regarding concavity of aggregated consumption. At the individual level, consumption is concave in transitory income shocks, 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). Transitory *shocks* will be correlated with relatively high income *levels* because the income level in a given year reflects the most recent income shock—an example is someone who wins the lottery; see the discussion in Friedman (1957) in the setting of the PIH. However, according to the buffer-stock model, consumers with transitory low income may have higher MPCs due to the concavity of the consumption function. Jappelli and Pistaferri (2014) find much lower MPCs for more affluent households using an Italian survey that directly asked about the consumer’s response to transitory shocks.

Under imperfect risk sharing and correlated income shocks, consumption will be partly coordinated, and the consumption patterns predicted at the individual level will survive aggregation, as explicitly demonstrated by Ludvigson and Michaelides (2001) and Luengo-Prado and Sørensen (2008).

4 Data

We use multiple datasets. For growth variables, we calculate the growth rate over three years for each of the four subperiods: 2001–2003, 2004–2006, 2007–2009, and 2010–2012. For stock variables, we use the value in the year before the three-year subperiod being considered, with the exception of foreclosures which are already a backward-looking measure (the exact definition appears below).⁸ Most of our data are measured at the county level, and we include all U.S. counties with a population over 5,000.

Consumption Growth. We use total retail sales at the county level from Moody’s to proxy for consumption. Total retail sales are the total of 13 industries including both durables and nondurables: (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 Analytics estimates retail sales in the following way. First, they match the Census of Retail Trade (CRT) from the U.S. Census Bureau available at the county-level every five years 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), which is also produced by the Census Bureau. Then, they estimate retail employment in each county

⁸For example, for the subperiod 2001–2003, stock variables are measured as of year 2000.

broken out by NAICS within the retail industry. From the estimates of retail employment, they create 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 is composed of a sample selected from retail employers who made FICA payments.⁹ The data are not representative 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.

Income Growth. The county-level data come from the Internal Revenue Service (IRS). We use real per capita adjusted gross income to construct three-year income growth rates. We are not able to estimate transitory versus permanent components of income with our short samples, but the longer horizon is more informative about the permanent components.

Income Inequality. We calculate the share of income for individuals earning more than the top 5 percent in total income using data from the Current Population Survey (CPS). This variable is available only at the state level.

Change in Unemployment Rate. We use data from the Bureau of Labor Statistics (BLS) to construct the change in the county unemployment rate over the three years of each of the subperiods in our analysis.

⁹Retail 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.

Growth of Housing Wealth. 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 only for 1,245 counties. Whenever the index is not available for a county, we substitute the missing observation for the county-level HPI with the corresponding state-level HPI.¹⁰ 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.¹¹ We construct three-year growth rates of housing wealth.

Debt Overhang. To capture the potential effects of debt on consumption growth, we use total debt at the beginning of the three-year subperiod and label it “debt overhang.” We use individual-level Equifax data available to us from the Consumer Credit Panel maintained by the Federal Reserve Bank of New York (“Equifax” for brevity hereafter) and aggregated over all individuals in each county to measure total debt. The logarithm of real per capita debt is used in the regressions.

Share of Subprime Borrowers. Individuals with relatively low credit scores—in Equifax, those with credit scores below 661—are considered risky

¹⁰We verified that our results are virtually the same if we run regressions on the set of counties with non-missing county-level information on house prices.

¹¹For each county c and year t we calculate:

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

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

and usually referred to as “subprime borrowers.”¹² Such borrowers experienced a significant easing of access to credit during the subprime boom, with a reversal when the Great Recession broke. An easing of credit is likely to boost consumption, particularly for consumers with low credit ratings, and we interpret a significant coefficient on the subprime ratio as capturing a change in credit conditions, similarly to Mian and Sufi (2009). We use Equifax data to calculate the fraction of individuals in a county/year whose credit scores (Equifax Risk Scores) were below 661.

Fraction of Borrowers in Foreclosure. We calculate this fraction as the number of consumers who experienced at least one foreclosure in the previous 24 months relative to the number of all consumers in the Equifax data sorted by county and year. The choice of the past 24-months is dictated by data availability. 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).

Consumer Expectations Growth. We use monthly data on consumer expectations from the Conference Board, available for nine Census Divisions, which we match with the counties in our sample. Our index of expectations is the average of three indexes 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 growth rates.

Growth of Cash-Out Refinancings. We calculate this as the number of cash-out refinance originations scaled by the number of outstanding mortgages in a county, and use the county’s three-year growth rate in our regressions. The data are from Black Knight Financial Services, Inc.

¹²See, for example, <http://investor.equifax.com/releasedetail.cfm?ReleaseID=881777>.

5 Descriptive Statistics

The empirical analysis uses county-level data. There is large variation in consumption growth, income growth, and so on across counties, even within states, but in order to provide uncluttered illustrations, most figures depict state-level patterns.

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. Spending on durables fell particularly strongly during the Great Recession, by an astonishing 21 percent. Durable spending increased in the tepid recovery but, as for 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 is consistent with the model of Browning and Crossley (2009). Services were one of the fastest growing components in the dot-com recession and the subprime boom, but the consumption of services has been virtually unchanged 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 drop 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 regres-

sions) 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 relatively high growth rates during the two recessions and relatively low growth rates in 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 over 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 had consumption growth less than 5 percent, while 1,050 counties experienced a decline larger than 15 percent. The tepid recovery was not uniformly distributed either: 20 states had 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 provides a map of the U.S. states indicating 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. One state had negative consumption growth between 0 and -5 percent, four states between -5 and -10 percent, 27 states between -10 and -15 percent, and a staggering 19 states had consumption falling by more than 15 percent.

Figure 4 shows the distribution of changes in the unemployment rate and the growth rate of state-level income, debt overhang, and consumer expectations. Comparing Figure 3 and Panel A of Figure 4, we see that while some

¹³A similar plot of the non-winsorized data is provided in the Appendix.

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

states had negative growth in both consumption and income during the dot-com recession, five states had rising income but declining consumption. All states experienced a sharp fall in consumption during the Great Recession, but income did not show the same pattern. During this subperiod, 17 states had positive income growth, and of these states three had real per capita income growth of more than 5.5 percent. In the tepid recovery, income growth was high for a large fraction of states: 15 states had income growth larger than 5.5 percent.

Consumer “overborrowing” during the subprime boom is sometimes blamed for the severity of the recession that followed and for the slowness of the tepid recovery (e.g., Mian and Sufi, 2009; Dynan, 2012). In Panel B of Figure 4, we display the growth rates of debt because these seem more informative than the debt-level used in our main regressions. All but 10 states had debt growing by more than 14 percent during the dot-com recession while debt continued to grow across the country during the subprime boom. By the time consumption plummeted in all states and counties in the Great Recession, only 15 states deleveraged to an extent that their debt was shrinking on average. Yet, in the tepid recovery debt was shrinking in all states. Further, although not visible in the figure, 45 states deleveraged by more than 10 percent, and 20 of these states deleveraged by more than 15 percent. In terms of debt levels (used in the regressions, but not depicted), California had relatively high debt levels in the dot-com recession and the subprime boom while most states in the West and the Northeast had high debt levels in Great Recession and the tepid recovery.

The trends in unemployment are even more pronounced; see Figure 4, Panel C. In the dot-com recession, unemployment increased more than 1.5 percentage points in 32 states, mainly those outside the Southeast and the Rocky Mountains. In the subprime boom, almost all states outside of the Midwest increased employment while, in the Great Recession, every state had higher unemployment. During the tepid recovery, the change in unemployment was quite scattered across states.

Changes in consumer expectations (see Figure 4, Panel D) were small dur-

ing 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 displays the income share of the top 5 percent in Panel A. Overall this share has been increasing over time with a bit of a reversal during the tepid recovery. Figure 5, Panel B displays the share of consumers in foreclosure. As extensively documented, foreclosure rates were historically high and widespread during the Great Recession, but there is also significant variation in foreclosure rates across states in other subperiods.

Variation in housing wealth across states and subperiods is depicted in Panel C of Figure 5. For housing wealth, the difference in our sample between the two recessions was dramatic: in the dot-com recession, states either had rapidly growing or fairly constant housing wealth while in the Great Recession, no state had significant growth in housing wealth and 38 states had housing wealth declining by more than 15 percent. During the tepid recovery, 16 states had housing wealth declining by more than 15 percent.

States with large fractions of subprime borrowers are mostly concentrated in the South. These fractions are more stable over time than any other measure we used in our analysis; see Figure 5, Panel D.

We use the observed variation in all the county- or state-level variables listed and an array of other variables not included in the figures to assess the *contribution* of each factor in explaining the changes in county-level consumption during the four subperiods considered.

6 Specification and Results

The volatility of the 2001–2012 period precludes the use of panel-data estimations that pool the years: we find quite different parameter estimates across subperiods and, therefore, we split the sample into four subperiods. One possi-

bility would be to run regressions at the annual frequency with lags in order to pinpoint the exact pattern of the adjustment to shocks, but we are interested in using a nested framework to test the impact on consumption of the variables suggested in the literature. This involves a large number of regressors, and dynamic regression would then entail a very large number of estimated coefficients, possibly leading to a confusing and unstable picture. Instead we follow Nakamura and Steinsson (2014) and Petev, Pistaferri, and Saporta-Eksten (2011), and use long time intervals with three-year growth rates. Such regressions, where the constant captures the aggregate growth rate of consumption, can also be seen as measuring which variables generate deviations from perfect risk sharing.¹⁵

We regress consumption growth on an array of macroeconomic variables such as income, unemployment, debt, income inequality, consumer confidence, housing wealth, access to credit, and foreclosures. For robustness, we run regressions on a variety of other variables to make sure we do not omit any important determinants of consumption growth. For the sake of brevity, the variables that do not explain consumption growth above and beyond those listed above are not included in the paper with the exception of the lagged level of housing wealth and the change in debt—these are both stock-variables in the households’ asset portfolio and it seems natural to treat them symmetrically but, as these variables are not statistically significant, we relegated them to an appendix table, Table A.1.

We do not have instruments which would allow us to give clear causal results of, say, a change in the unemployment rate separate from changing income expectations due to a structural change in productivity with the latter being the deep structural variable. For example, Philippon and Midrigan (2011) construct a model where tighter credit conditions cause declining consumption and increased unemployment, so that in the model unemployment is a result of credit tightening and in a structural sense “everything” is caused

¹⁵Cochrane (1991) and Hryshko, Luengo-Prado, and Sørensen (2010) estimate the impact on risk sharing of unemployment and house-price appreciation, respectively, using long time intervals.

by credit tightening. Similarly, house-price growth may be a function of income growth, which itself may be a function of aggregate demand shocks or of productivity supply shocks, and we are not able to sort this out. Yet we talk about the “effect” of each variable without repeatedly signalling this caveat—our descriptive approach does not uncover deep structural forces but rather provides stylized facts.

We estimate the following cross-sectional regressions over U.S. counties:

$$\Delta^3 \log(C_{c,t}) = \alpha + \beta_1 \widetilde{\Delta^3 \log(X_{c,t})} + \beta_2 \widetilde{W_{c,t-3}} + \beta_3 \Delta^3 \widetilde{UR_{c,t}} + \beta_4 \widetilde{Foreclosure_{c,t}} + \epsilon_{ct}, \quad (1)$$

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; $\Delta^3 \log(X_{c,t})$ is the three-year growth rate of county-level variables (or state- or census region-level variables for which county-level data are not available); $\Delta^3 UR_{c,t} = UR_{c,t} - UR_{c,t-3}$ is the change in the unemployment rate over the subperiod; $Foreclosure_{c,t}$ is the share of consumers who had at least one foreclosure in the past 24 months relative to the number of all consumers, measured at the end of the subperiod. $W_{c,t-3}$ are county-level lagged variables—we prefer to include the lagged value for most of our stock values. Other stock variables, such as the subprime fraction of consumers, are slowly changing, and the interpretation is cleaner when using the predetermined value.

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: $\widetilde{\Delta \log(X_{c,t})} = \Delta \log(X_{c,t}) - \frac{1}{N} \sum_{c=1}^N \Delta \log(X_{c,t})$, where c indexes counties and N is the total number of counties in our sample. Lagged and concurrent variables are demeaned in a similar way. Our data have significant outliers (see Figure A.1 in the Appendix) and we therefore winsorize all variables at 2 percent and 98 percent to make sure our results are not driven by outliers. Most results are quite robust to winsorizing but there are exceptions. For example, the estimated effect of income growth varies more across subperiods when using non-winsorized data. Standard errors were estimated robustly and clustered at the state level which resulted in larger standard errors than

plain robust estimation of the standard errors. Our main results are presented in Table 2. The results are discussed for each individual regressor.

Constant. The constant measures average county-level consumption growth because the regressors are demeaned. Consumption declined weakly (1 percent) over the dot-com recession, recovered by 7 percent during the subprime boom, and fell steeply (12 percent) over the Great Recession, highlighting how this recession was much more severe than the dot-com recession. During the tepid recovery, consumption grew by 10 percent, almost regaining the ground lost during the Great Recession. Yet, as Petev, Pistaferri, and Saporta-Eksten (2011) point out, it is atypical for consumption to be depressed so long after the onset of a recession. These spending patterns are driven by aggregate effects, for example, the drop in the Great Recession is consistent with a U.S.-wide increase in uncertainty, a drop in income expectations, and a loss of wealth; however, without more degrees of freedom, we cannot test this and we move on to the estimated determinants of county differences. The effects of most economic variables differ between subperiods.

Income. At about 10 percent, the elasticity of per capita consumption with respect to per capita income is quite robust across subperiods with high statistical significance. Compared to Consumption Prediction # 1, this value is low, which may indicate that county-level income shocks are considered transitory by consumers. Cross-county shopping, and a substitution of state-level variables for some county-level variables, might also add to a downward bias in the elasticities. Further, the IRS income data are likely to be a noisy measure of labor income, and this may partly explain the very low elasticities found here.¹⁶

Unemployment. For a consumer, job loss is typically associated with a large negative income shock. However, our regressions control for income, 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,

¹⁶Luengo-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 3 when adding substantial (not directly measured) risk sharing.

Consumption Prediction # 2. The effect of rising or falling unemployment is also estimated with high stability across subperiods and with even higher precision than was found for income. The economic interpretation of the coefficient -0.01 is that a 1 percentage point increase in unemployment will decrease consumption by 1 percent. Clearly, changing unemployment, whether increasing or decreasing, was a strong predictor of consumption throughout the entire period.

Inequality: Income share of the top 5 percent. High-income consumers typically have high wealth (which we cannot directly measure) and might be able to better withstand negative income shocks in the sense of maintaining a higher level of nondurable consumption by adjusting their asset holdings. We find that consumption indeed fell less in counties where the wealthy had a higher income share during both recessions, significantly so in the dot-com recession, while the point estimates are negative and insignificant in the subprime boom and in the tepid recovery. More work is needed to uncover whether this pattern is due to wealth holdings or to wealthy individuals' income being less volatile—although the results of Petev, Pistaferri, and Saporta-Eksten (2011) indicate that the wealthy were buffeted by severe wealth shocks in the Great Recession. Having controlled for income, we believe this variable captures lower uncertainty, Consumption Prediction # 2, for the well-to-do, who typically do not work in sectors, such as construction, where the probability of job loss is high in recessions.

Housing Wealth. Mian, Rao, and Sufi (2013) find that housing wealth had large effects on consumption in the Great Recession, and we confirm this result. We find strong positive effects on consumption growth in the subprime boom and strong negative effects during the Great Recession (the positive coefficient in the Great Recession is interacting with negative changes in housing wealth during that subperiod). There is an insignificant positive effect in the dot-com recession and in the tepid recovery. We surmise that the pattern in the tepid recovery is a reflection of many homeowners being underwater—owing more on their mortgage than their house is worth—and/or tighter credit constraints such that the wealth gain from any house-price increase was illiquid

and could not be borrowed against. According to Consumption Prediction # 4, the propensity to consume out of increasing housing wealth should be small, so the magnitude of the housing wealth coefficients in the subprime boom and the Great Recession may indicate that consumers expected house-price appreciation to continue in the subprime boom but expected continuing depreciation in the Great Recession.

Debt Overhang. Debt overhang has a significant negative relationship with consumption growth except in the dot-com recession where the effect is positive. (Dynan (2012) found negative effects of debt overhang in the Great Recession using micro data.) Our interpretation is that the interest rate declines during the dot-com recession made debt service less burdensome (Consumption Prediction # 5). This allowed indebted consumers to increase consumption, as in the textbook model of interest rate effects on net debtors—the change in conventional, first lien mortgage rates over the subperiods is displayed in Figure 6. During the subprime boom, interest rates increased, and the burden of carrying debt became heavier, depressing consumption. When the recession hit and credit conditions became much tighter, consumption was depressed due to credit constraints (and other factors), even as interest rates continued to decline. We interpret this pattern as reflecting that, during the Great Recession, a large number of consumers needed to pay down debt and limit consumption. Consumers with good credit and stable jobs should have been able to refinance into lower interest rates and increase consumption (and this heterogeneity may explain the lower significance), but implicit in Consumption Prediction # 6 is that life-cycle consumer debt reflects expected future savings (a function of income) so that a downward revision of expected future income makes debtors increase their current saving rate. Consumption Predictions # 5 and # 3, concerning interest rates and credit, are still relevant but it appears that what debtors gained from lower interest rates was outbalanced by the credit and income effects in the Great Recession, and that consumer deleveraging during the tepid recovery contributed to its slow speed.

Subprime Credit. As a direct indicator of credit conditions, Consumption Prediction # 3, we include the share of subprime borrowers defined as the

fraction of individuals whose Equifax credit scores are below 661. We interpret this measure as capturing changes in the amount of credit available to marginal borrowers with impaired credit. The subprime boom stands out, with the fraction of subprime borrowers being an important predictor of consumption during those years. This finding strongly agrees with the results in Mian and Sufi (2009)—they mainly consider home equity lending in isolation, but we show that the general easing of credit has strong overall significance even after all our other variables have been included.¹⁷

Cash-Out Refinancings. Another indicator of overall credit conditions is the share of cash-out mortgage refinancings. Homeowners with good credit were able to refinance into lower rates during the tepid recovery, but this was not possible for unemployed individuals or individuals with bad credit, underwater mortgages, or other impediments; our interpretation is that counties with relatively more cash-out refinancings had better access to credit beyond what is already captured by the fraction of subprime borrowers. (We alternatively considered the number of individuals with very high credit scores, but this was not significant—likely because a good credit score was a necessary but not a sufficient condition for being able to refinance during the tepid recovery.) The theoretical underpinnings for the importance of this variable are found in Consumption Predictions # 3 and # 5, regarding interest rates and credit.¹⁸

Foreclosure. A foreclosure is costly and severely limits future access to credit, as summarized in Consumption Prediction # 8. In the run-up to foreclosure, many consumers may cut back consumption, hoping to avoid losing their houses and, indeed, the number of foreclosures in a county correlates negatively

¹⁷The 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.

¹⁸It is quite possible that people who were able to refinance in the tepid recovery are better financial planners than those who were not (we thank Michael Haliassos for bringing up this point). Indeed, all the credit indicators will capture such heterogeneity in addition to changes in credit conditions. We believe that changes in credit conditions dominated during our sample period, but we cannot verify this without micro data which includes information on both credit and personality traits.

with consumption growth in all subperiods except the Great Recession. During the Great Recession, a large number of foreclosures resulted from collapsing house prices, and it seems that falling house prices during this subperiod leave no further explanatory power for foreclosure.

Consumer Confidence. Expectations are at the core of rational expectations consumer models. Even if our measure of expected economic performance is available for only nine Census Divisions, it is significant during the subprime boom, but not otherwise. This suggests that consumers act on their expectations and increase consumption more when economic conditions are expected to improve, Consumption Prediction # 7. 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 downwards. It is virtually impossible to know if the effect of confidence is due to rational forecasting of expected future income or fear of some negative tail event.

The variables in our statistical model are able to explain between 4 and 12 percent of the county variation in consumption growth, based on the adjusted R^2 . Retail sales are an imperfect measure of consumption and, due to cross-county shopping, retail sales in one county may reflect consumption that occurred in neighboring counties. This noisy data will tend to depress the explanatory power of our variables and will make it hard to find significant effects. These imperfections, however, simply add to the error term and, because they are unlikely to be systematically correlated with our regressors, do not lead to biases. The total R^2 was particularly low in the dot-com recession and the tepid recovery.

6.1 Univariate Regressions

The paper is novel in estimating the effect of a large number of variables simultaneously. We examine if the results are different when consumption growth is regressed on the variables one-by-one. These results are presented in Table 3. As one might expect, the coefficient to income is higher than in the multivari-

ate regression, but only in the subprime crisis is the estimated coefficient much larger, at 0.28, which indicates that counties that did relatively badly in the subprime crisis did so along many dimensions, making the explanatory variables highly correlated. The coefficient to unemployment is quite similar to the coefficient estimated in the multivariate regression, and the income share of the top 5 percent is still significant in the dot-com recession. Housing wealth has much larger coefficients with high statistical significance in Table 3, which suggests that regressions of consumption growth on housing wealth without controls may suffer from omitted variable bias if not carefully designed. The role of debt overhang is quite robustly estimated, although the coefficients are somewhat larger when no controls are included, especially in the Great Recession. The subprime fraction is significant only in the subprime boom as before, while cash-out refinancings are still significant in the Great Recession and the tepid recovery. Foreclosure is now very significant throughout with much larger coefficients which, in conjunction with the previous results, indicates that foreclosure itself is a function of income, credit, and house price shocks. Consumer confidence, as before, is most important in the dot-com recession and the subprime boom.

6.2 Economic Significance

To assess the economic significance of the results, in Figure 7 we plot: (i) the average values of each variable used in our estimation, (ii) the estimated coefficient multiplied by one standard deviation of the variable (calculated cross-sectionally for each relevant subperiod) indicating economic significance, and (iii) partial R^2 s for each variable showing the share of variance explained by each variable.

The left panel of Figure 7 shows the average value of the regressors across all counties for each subperiod. While this average value technically does not help pin down our cross-sectional estimates, it helps paint a picture of the variation over our sample period. Combined with the estimated parameters, we obtain an indicator of aggregate effects. Over the subperiods considered, per capita

income growth varies from a low of -6.6 percent during the Great Recession to a high of 12.3 percent during the tepid recovery. Figure 7's middle panel is directly informative of the impact of each variable in explaining differences in consumption growth across counties, as it shows the estimated coefficient multiplied by the cross-sectional standard deviation of the relevant regressor in each subperiod. The effect of income growth is fairly stable over time: a county with income growth that is a one standard deviation higher than the average is predicted to have 0.5 – 0.8 percent higher consumption growth. A one-standard-deviation change in unemployment explained more than 1 percentage point of the change in consumption during each subperiod.¹⁹ Our inequality measure is fairly constant over time and has some explanatory economic significance in the recessions but not in the subprime boom or the tepid recovery.

Not surprisingly, changes in housing wealth contributed significantly to consumption patterns during the subprime boom and the Great Recession. Debt overhang, while quite stable, predicted large negative changes in consumption in all subperiods except the dot-com recession. The share of subprime borrowers added significantly to consumption growth in the subprime boom only. While the average fraction of subprime borrowers is fairly stable over time, it is not important for explaining variation in consumption across counties outside the subprime boom. A county with a one-standard-deviation higher proportion of such borrowers had a 1 percent higher consumption growth rate during the subprime boom, while the effect is lower during the other three subperiods. The total amount of debt at the beginning of the period is associated with stronger consumption growth during the dot-com recession—interest rates were falling. However, in the other subperiods high debt is associated with shrinking consumption. Debt contributes significantly to explaining the variation in consumption growth across counties, although its importance has been declining. Debt that is one-standard-deviation higher at the beginning of the subperiod increases consumption growth by more than 1 percent in 2001–

¹⁹The left-hand column depicts averages across counties, while our results are identified from the deviation from these averages, so our interpretations of the numbers in the middle panel of Figure 7 are only suggestive.

2003, while it lowers consumption by about 1 percent in other subperiods.

Foreclosures had a negative impact on consumption in every subperiod besides the Great Recession—foreclosures likely were important in the Great Recession but since these were across the board during this subperiod, our regressions cannot capture this; micro data are needed to fully sort this out. Changes in consumer expectations, which vary greatly over time, play a strong role during the subprime boom when expectations were positive: consumption is about 1.6 percent higher in regions with one-standard-deviation more optimistic expectations than the average. The estimated impact was negligible during other subperiods, even if expectations were quite negative in both recessions. Finally, in counties with a large share of cash-out refinancings—which we take to be an indicator of excellent access to credit—consumers spending was particularly strong during the tepid recovery. A one standard deviation increase in cash-out refinancings contributed to 0.8 percent higher consumption growth during this subperiod.

6.3 Marginal Explanatory Power: Partial R^2 Analysis

In the third panel of Figure 7, we plot the partial R^2 for each variable in order to assess how much each variable is contributing to the model's fit. The partial R^2 s (multiplied by 100) and the contribution to the R^2 (the partial R^2 as a share of the total R^2) are displayed in Table 4.²⁰ In the dot-com recession and the tepid recovery, unemployment had the most predictive power—with partial R^2 s each contributing 15-22 percent of the total R^2 . It appears that monetary policy was particularly effective in the dot-com recession—with falling interest rates and easy credit, debtors could refinance into cheaper loans and benefit from the increase in debtors' effective wealth.

Overall, unemployment growth was the most important determinant of consumption growth throughout the full sample period. During the subprime boom, growth in consumer confidence was the most important, while inequal-

²⁰These partial R^2 s do not sum to the total R^2 unless the regressors are orthogonal because each of them only measures the incremental explanatory effect of the relevant variable so, for example, if all the regressors were highly correlated, each partial R^2 would be very small.

ity and debt-overhang was important in the dot-com recession. In the tepid recovery, income growth, foreclosures, and cash-out refinancings were all important determinants of consumer spending.

7 Conclusion

We explain the variation in consumption growth across U.S. counties during the first twelve years of this century. Using a rich dataset, we document the explanatory power of numerous economic variables during each of four sub-periods: 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 income, house prices, unemployment, consumer confidence, and cash-out refinancings as well as the (lagged) level of debt, income inequality, the fraction of borrowers that are subprime, and the fraction of mortgages in foreclosure all help explain consumption growth during our sample period, albeit the importance of each factor differs in each subperiod. The role of income and, especially, housing wealth is much reduced in multiple regressions compared to univariate regressions of consumption on these variables. This indicates that researchers need to be very careful when interpreting the results of regressions which do not control for other potential determinants of consumption.

Unemployment variation has the largest explanatory power for consumption growth throughout our sample. Optimistic consumer expectations were important during the subprime boom, while housing wealth was an important determinant of consumption in the subprime boom and in the Great Recession. Debt overhang was very significant in the dot-com recession but had a lesser role in other subperiods. The fraction of subprime borrowers significantly predicted consumption growth during the subprime boom, while income growth, foreclosures, and cash-out refinancings were important in the tepid recovery. Overall, many of the patterns found are specific for certain subperiods, and any full modeling of the boom and bust of the cycles that took place between 2000 and 2012 needs to account for these complicated patterns. We do not calibrate a structural model, but our results provide important facts for

structural models to match. Several factors in our data are likely causal for consumption growth while others are not. For example, debt overhang is likely to be a predetermined causal determinant, while unemployment may capture income uncertainty, income expectations, more complicated interactions, or nonlinearities.

Our study contributes to a large body of literature that either empirically uncovers or models determinants of consumption growth during the last decade or so. Our main contribution lies in quantifying the relative impact of a variety of factors that affected the economy during this period. 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 on the formulation of models calibrated to 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.

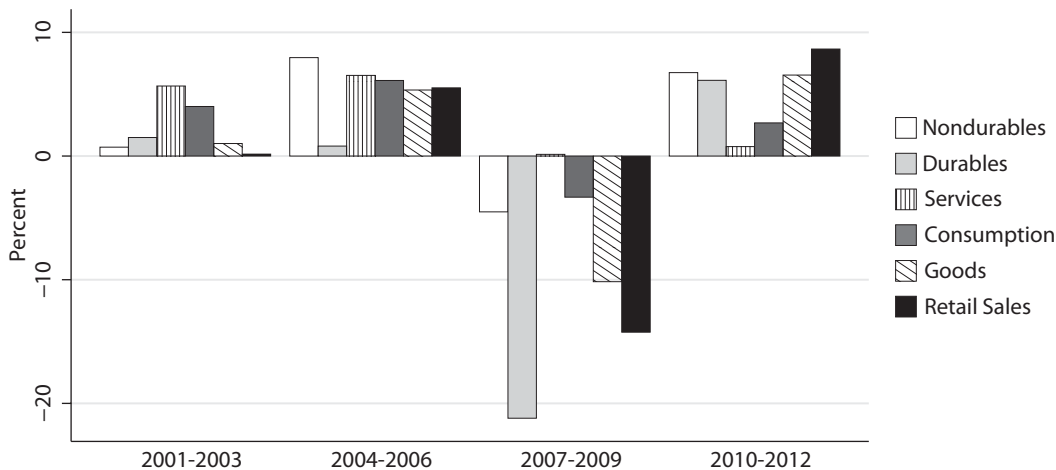


Figure 2: Cross-County Variation in Retail Sales Growth

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.

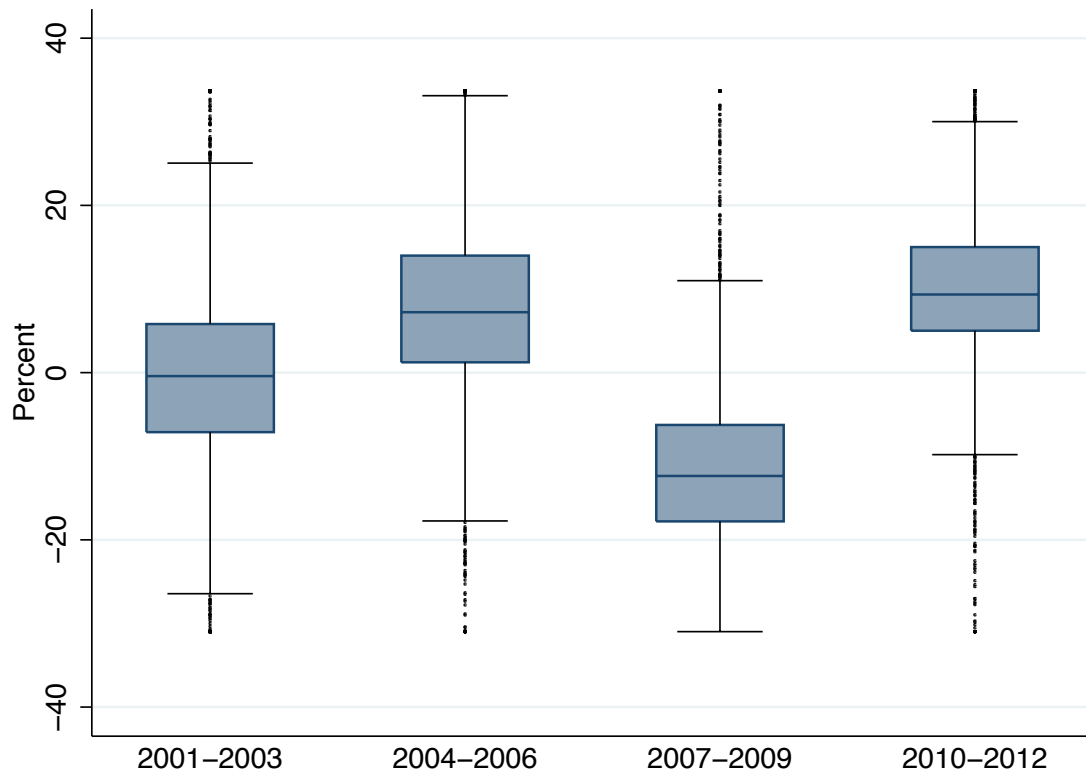


Figure 3: State Consumption Growth by Subperiod

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 $\Delta^3 \log(C_t) = 100 \times [\log(C_t) - \log(C_{t-3})]$ 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.

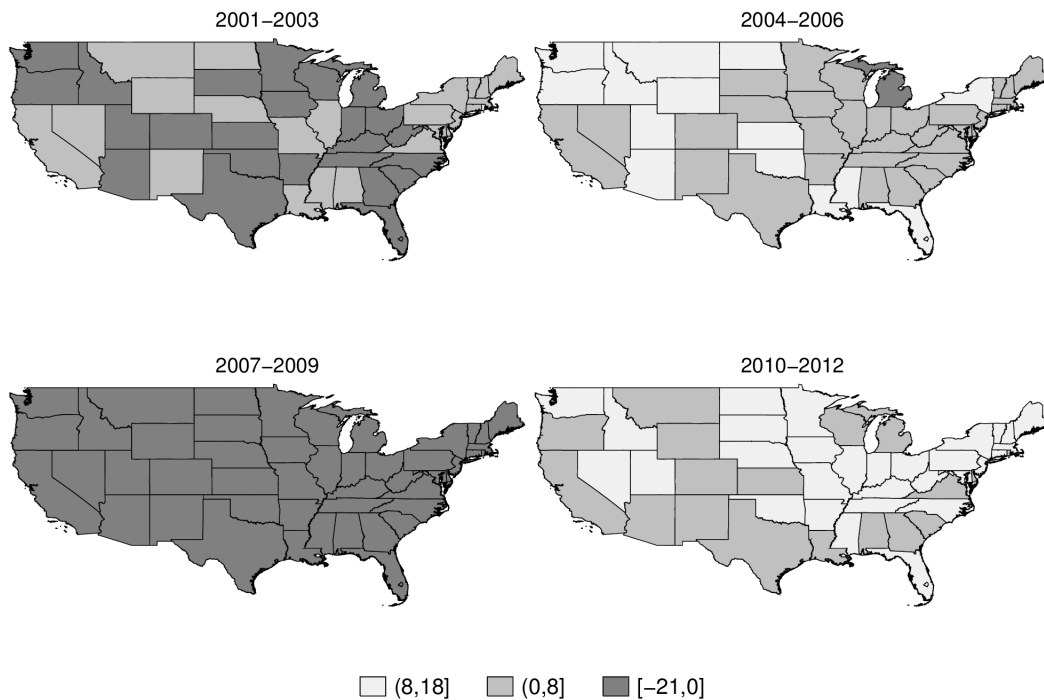


Figure 4: Change in State Unemployment Rate and Growth Rates of State Income, Debt, and Consumer Expectations by Subperiod

This figure displays three-year *Income Growth* (real per capita and from the Bureau of Economic Analysis (BEA)), three year growth of *Debt* (gross real per capita debt aggregated from Equifax data), *Change in Unemployment Rate* (from the BLS), and *Growth of 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).

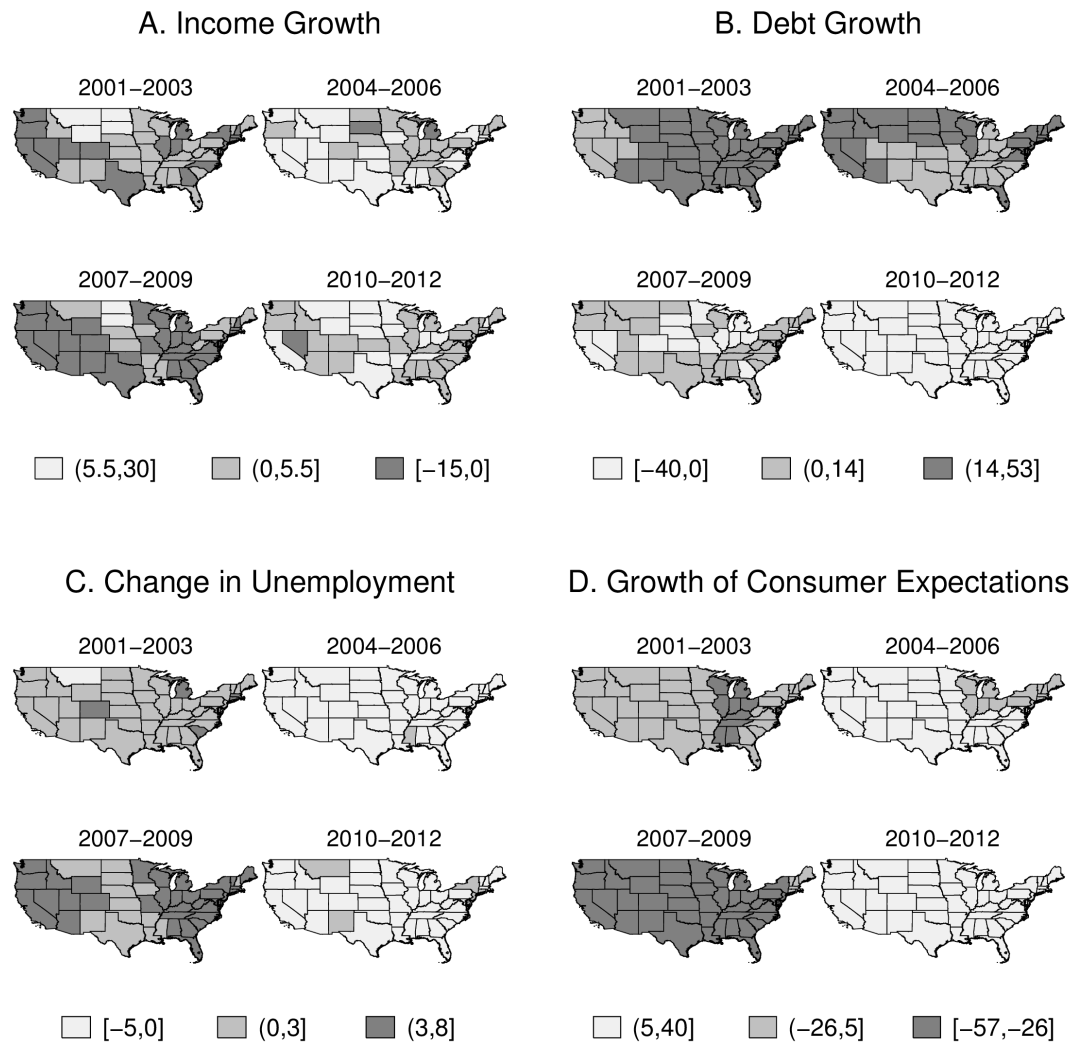


Figure 5: Growth Rate of State Income Inequality, Housing Wealth, and Shares of Foreclosures and Subprime Borrowers by Subperiod

This figure displays *Share of Income, Top 5%* which is taken at the beginning of each subperiod (from the CPS), *Share in Foreclosure*, which equals 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 (Equifax), *Growth of Housing Wealth* (constructed from CoreLogic and Census 2000 data), and *Lagged Subprime Fraction*, which equals the share of individuals, in percent, in a state whose credit score is lower than 661 (from Equifax).

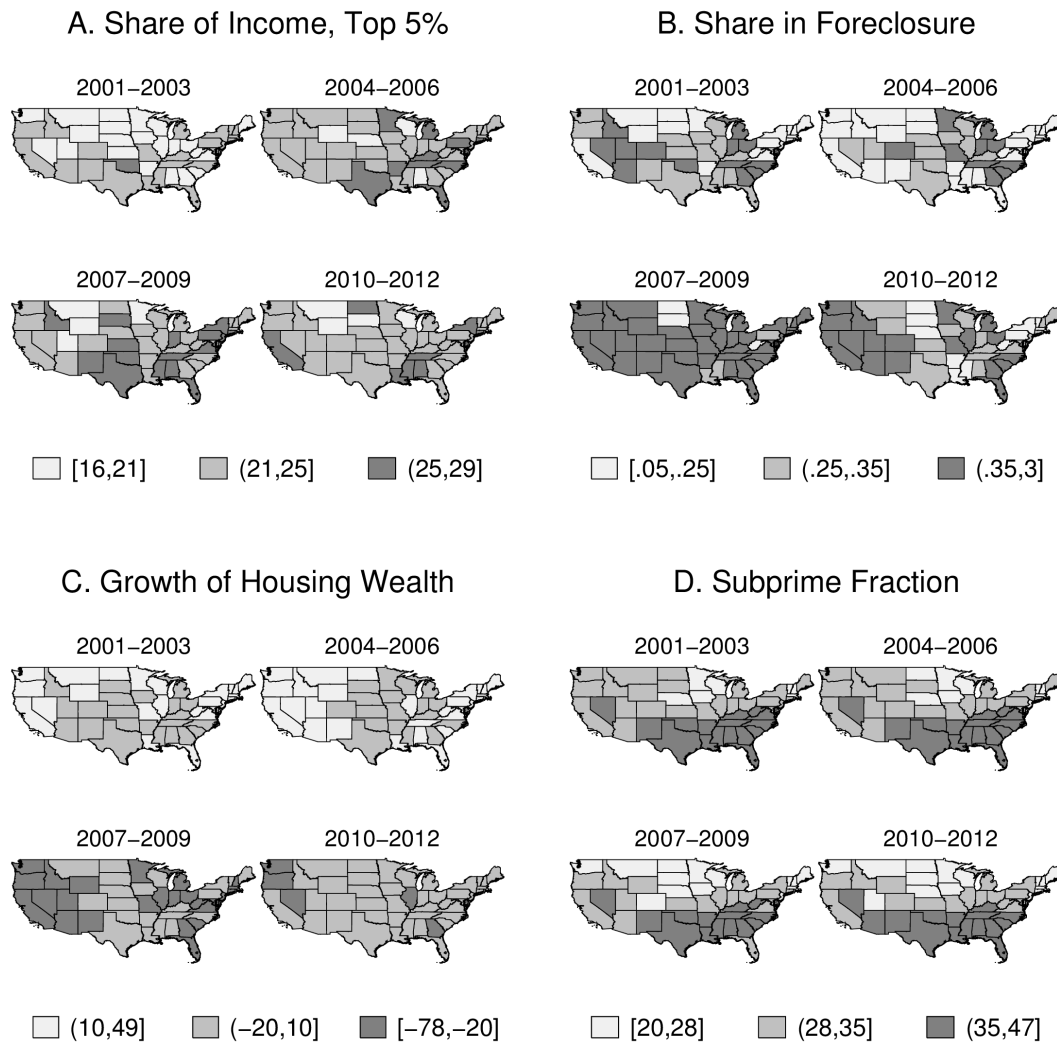


Figure 6: Change in Mortgage Rates

The figure displays the change in mortgage rates at origination (from Black Knight) for the dot-com recession (2001–2003), the subprime boom (2004–2006), the Great Recession (2007–2009), and the tepid recovery (2010–2012). The sample consists of fixed-rate conventional first-lien mortgages originated during each of the subperiods.

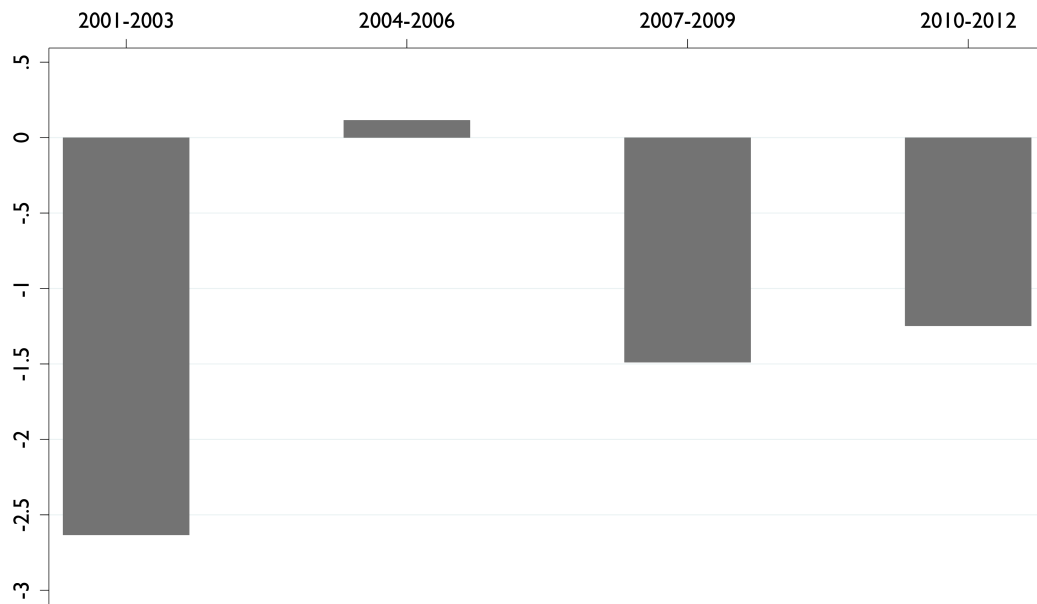


Figure 7: Average Value, Economic Significance, and Partial R Squared

The first panel of this figure displays the average value of the variables used in the regressions. We plot the growth rate of the unemployment rate in this panel but we use the change in the unemployment rate in our regressions (and the other panels of this figure). For clearer exposition, we multiplied *Income Growth* by 5, *Share in Foreclosure* by 100, *Growth of Share of Cash-Out Refinancings* by 10, and divided *Lagged Debt overhang* by 20. The second panel of this figure displays the estimated coefficient for each variable multiplied by one standard deviation (calculated for each time interval in the sample). The third panel of the figure displays the partial R^2 for each variable in each subperiod. Debt overhang is calculated as the logarithm of total real per capita state-level debt at the beginning of the subperiod (from Equifax).

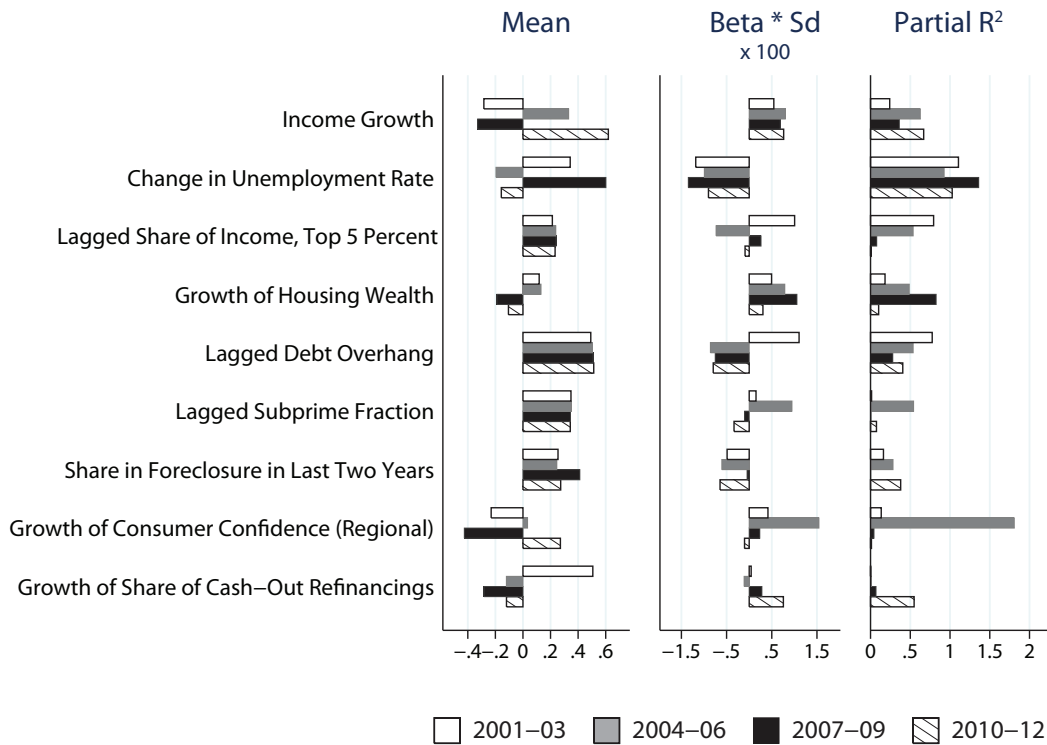


Table 1: Descriptive Statistics

Variable	2001–2003		2004–2006		2007–2009		2010–2012	
	mean	sd	mean	sd	mean	sd	mean	sd
Growth of Consumption (Retail Sales), %	-0.82	10.71	7.43	10.27	-11.90	9.56	9.65	8.80
Income Growth, %	-5.67	6.43	6.63	8.96	-6.57	7.29	12.39	7.67
Change in Unemployment Rate	1.72	1.14	-1.08	1.02	4.15	1.78	-1.23	1.35
Lagged Share of Income, top 5 Percent, %	21.33	1.64	23.82	2.29	24.07	1.99	23.31	1.77
Growth of Housing Wealth, %	11.77	9.04	13.10	11.28	-18.90	10.90	-10.53	6.86
Lagged Debt Overhang	9.83	0.57	10.03	0.55	10.17	0.56	10.27	0.54
Debt Growth, %	19.56	13.76	14.75	14.53	9.09	11.77	-9.88	10.49
Lagged Subprime Fraction, %	34.79	8.71	35.09	8.69	34.40	8.67	34.25	8.91
Growth of Share of Cash-Out Refinancings, %	5.30	3.36	-1.30	3.81	-2.94	2.26	-1.22	1.08
Share in Foreclosure in Last Two Years, %	0.27	0.22	0.26	0.22	0.44	0.32	0.29	0.23
Growth of Consumer Confidence (Regional)	-23.05	3.41	3.32	11.31	-42.50	9.41	27.16	5.94

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. *Income Growth* is defined similarly using real per capita total county-level gross adjusted 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. *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. *Growth of Housing Wealth* equals growth of (No. of owner occupied housing units $_{c,t} \times$ Median home value $_{c,t}$), which is defined in more details in Section 4. *Lagged Debt Overhang* is logarithm of real per capita total county debt at the beginning of each subperiod. *Debt Growth* is defined as $\Delta^3 \log(D_{c,t}) = \log(D_{c,t}) - \log(D_{c,t-3})$, where $D_{c,t}$ is per capita total county debt in year t . *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 in Foreclosure in Last Two Years* is a 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. *Growth of Consumer Confidence (Regional)* is the three-year growth in consumer confidence index measured at the Census Divisions level. *Growth of Share of Cash-Out Refinancings* is the three-year growth rate of a share of cash-out refinancings relative to the number of all outstanding mortgages. All variables have been winsorized at 2 percent and 98 percent.

Table 2: Determinants of Consumption. Period-by-Period Regressions.

	2001–2003	2004–2006	2007–2009	2010–2012
Income Growth	0.08** (2.08)	0.09*** (2.95)	0.09* (1.92)	0.10*** (3.12)
Change in Unemployment Rate	−0.01*** (−3.18)	−0.01*** (−3.45)	−0.01*** (−3.75)	−0.01*** (−3.40)
Lagged Share of Income, top 5 Percent	0.62** (2.10)	−0.32 (−1.52)	0.13 (0.71)	−0.05 (−0.34)
Growth of Housing Wealth	0.05 (1.51)	0.07** (2.28)	0.10*** (2.74)	0.04 (0.79)
Lagged Debt Overhang	0.02*** (2.95)	−0.02*** (−2.98)	−0.01* (−1.91)	−0.01** (−2.19)
Lagged Subprime Fraction	0.02 (0.27)	0.11** (2.44)	−0.01 (−0.27)	−0.04 (−1.18)
Growth of Share of Cash-Out Refinancings	0.01 (0.11)	−0.03 (−0.32)	0.12 (1.24)	0.63*** (3.22)
Share in Foreclosure in Last Two Years	−2.09 (−1.59)	−2.61** (−2.49)	−0.14 (−0.13)	−2.63** (−2.40)
Growth of Consumer Confidence (Regional)	0.12 (0.88)	0.14*** (3.05)	0.02 (0.62)	−0.02 (−0.21)
Constant	−0.01 (−1.52)	0.07*** (17.57)	−0.12*** (−37.13)	0.10*** (30.65)
Adj. R sq.	0.04	0.12	0.09	0.05
No. obs.	2,772	2,770	2,766	2,761
No. clusters	51	51	51	51

Note: Cross-sectional regressions over U.S. counties based on the following regression specification for each subperiod:

$$\Delta^3 \log(C_{c,t}) = \alpha + \beta_1 \Delta^3 \widetilde{\log}(X_{c,t}) + \beta_2 \widetilde{W}_{c,t-3} + \beta_3 \Delta^3 \widetilde{UR}_{c,t} + \beta_4 \widetilde{Foreclosure}_{c,t} + \epsilon_{ct},$$

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, $\Delta^3 \log(X_{c,t})$ is a vector of the following variables: *Income Growth* (real per capita total county-level income), *Growth of Housing Wealth* (defined in Section 4), *Growth of Consumer Confidence* in a region, and *Growth of Share of Cash-Out Refinancings* in a county. $W_{c,t-3}$ are county- or state-level lagged variables: *Lagged Share of Income, top 5 Percent* (state), *Lagged Debt Overhang* (log of real per capita total county-level debt at the beginning of the subperiod) and *Lagged Subprime Fraction* (the fraction of individuals residing in a county with credit scores less than 661 at the beginning of the subperiod). $\Delta^3 UR_{c,t} = UR_{c,t} - UR_{c,t-3}$ is the change in the unemployment rate over the subperiod, and *Foreclosure* $_{c,t}$ is the share in foreclosure in last two years measured at the end of the subperiod. We demean all independent variables in order for the constant to capture average consumption growth over each three-year interval in the following way: $\widetilde{X}_{c,t} = X_{c,t} - \frac{1}{N} \sum_{c=1}^N X_{c,t}$, for any variable X where c indexes counties and N is the total number of counties in our sample. Consumption, income, debt, and housing wealth are real per capita total aggregates at the county-level. t-statistics based on standard errors clustered by state are reported in parentheses. All variables have been winsorized at 2 percent and 98 percent. *** (**) [*] indicate significance at the 1 (5) [10] percent level.

Table 3: Determinants of Consumption. Coefficients from Regressions on Each Regressor at a Time.

	2001–2003	2004–2006	2007–2009	2010–2012
Income Growth	0.11*** (2.65)	0.15*** (3.90)	0.28*** (6.03)	0.12*** (2.70)
Change in Unemployment Rate	−0.01*** (−3.28)	−0.02*** (−3.33)	−0.01*** (−7.61)	−0.01*** (−2.70)
Lagged Share of Income, top 5 Percent	0.70*** (2.73)	−0.17 (−0.44)	0.03 (0.13)	−0.20 (−0.96)
Growth of Housing Wealth	0.12*** (3.96)	0.15*** (2.67)	0.20*** (6.32)	0.14*** (2.51)
Lagged Debt Overhang	0.01 (1.49)	−0.03*** (−4.35)	−0.03*** (−3.85)	−0.02** (−1.99)
Lagged Subprime Fraction	−0.03 (−0.37)	0.23*** (3.79)	0.03 (0.51)	−0.02 (−0.24)
Growth of Share of Cash-Out Refinancings	0.01 (0.03)	0.16 (1.34)	0.51*** (3.25)	0.91*** (4.25)
Share in Foreclosure in Last Two Years	−3.67*** (−2.73)	−7.67*** (−3.60)	−5.31*** (−6.27)	−4.48*** (−4.14)
Growth of Consumer Confidence (Regional)	0.26* (1.89)	0.23*** (3.67)	0.02 (0.52)	0.02 (0.22)

Note: Each entry in each row contains a regression coefficient of consumption growth in a given subperiod on the regressor in each respective row, with no controls for other variables. t-statistics based on standard errors clustered by state are reported in parentheses. All variables have been winsorized at 2 percent and 98 percent. *** (**) [*] indicate significance at the 1 (5) [10] percent level.

Table 4: Partial R^2 and Contribution to R^2

Partial R^2				
	2001-2003	2004-2006	2007-2009	2010-2012
Income Growth	0.24	0.63	0.36	0.67
Change in Unemployment Rate	1.11	0.93	1.36	1.03
Lagged Share of Income, top 5 Percent	0.79	0.54	0.08	0.01
Growth of Housing Wealth	0.18	0.49	0.83	0.10
Lagged Debt Overhang	0.78	0.54	0.28	0.41
Lagged Subprime Fraction	0.01	0.54	0.01	0.07
Growth of Share of Cash-Out Refinancings	0.00	0.01	0.07	0.55
Share in Foreclosure in Last Two Years	0.16	0.28	0.00	0.38
Growth of Consumer Confidence (Regional)	0.13	1.81	0.04	0.01

Contribution to R^2				
	2001-2003	2004-2006	2007-2009	2010-2012
Income Growth	0.06	0.05	0.04	0.14
Change in Unemployment Rate	0.26	0.08	0.15	0.22
Lagged Share of Income, top 5 Percent	0.18	0.05	0.01	0.00
Growth of Housing Wealth	0.04	0.04	0.09	0.02
Lagged Debt Overhang	0.18	0.05	0.03	0.09
Lagged Subprime Fraction	0.00	0.05	0.00	0.02
Growth of Share of Cash-Out Refinancings	0.00	0.00	0.01	0.12
Share in Foreclosure in Last Two Years	0.04	0.02	0.00	0.08
Growth of Consumer Confidence (Regional)	0.03	0.15	0.00	0.00

Note: This table shows partial R^2 and contribution to the total R^2 (the partial R^2 as a percent of the total R^2) for each of the explanatory variables used in the baseline regression specification. The partial R^2 s are multiplied by 100. See previous table for variable definitions.

A Appendix

In Figure A.1, we show the three-year consumption growth 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*. Many of the 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. We therefore winsorized all variables at 2 percent and 98 percent for our regressions to make sure our results are not driven by outliers—most results are quite robust to winsorizing but, for example, the effect of income growth varies much less across subperiods with winsorized data.

Figure A.1: County Retail Sales Growth. Not Winsorized

This figure shows the three-year growth in 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.

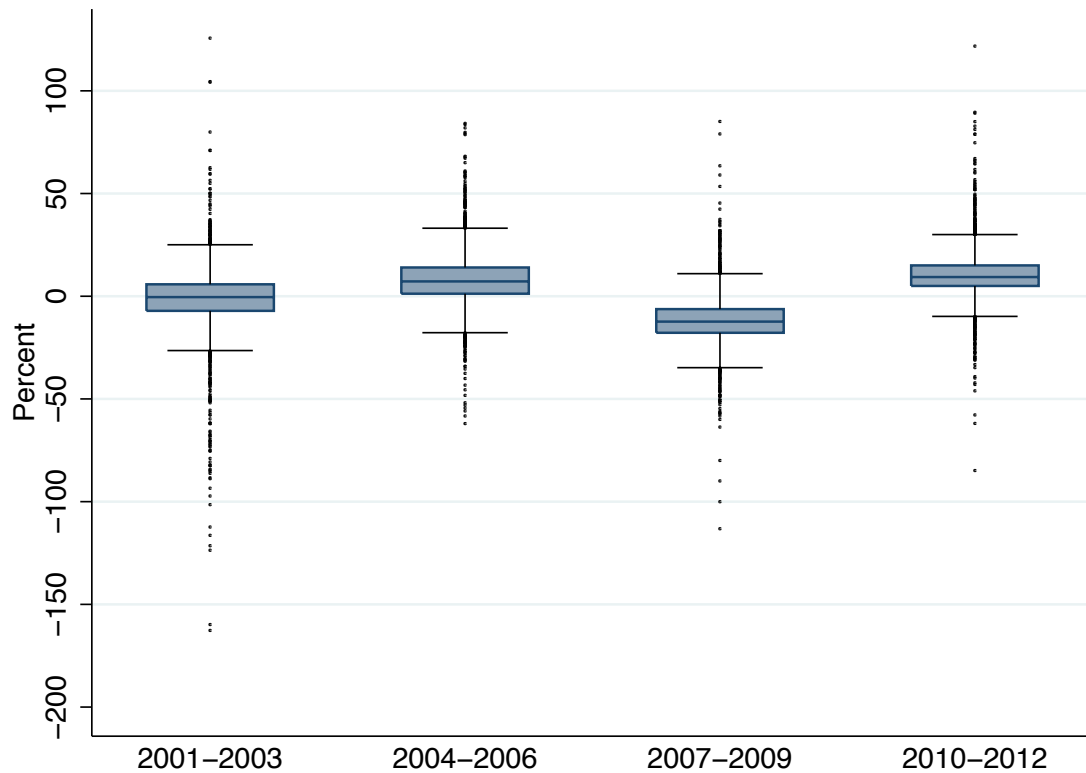


Table A.1: Determinants of Consumption. Period-by-Period Regressions.
Change in Debt and Lagged Level of Housing Wealth Included

	2001–2003	2004–2006	2007–2009	2010–2012
Income Growth	0.08** (2.07)	0.09*** (2.89)	0.09* (1.95)	0.09*** (2.85)
Change in Unemployment Rate	−0.01*** (−3.13)	−0.01*** (−3.58)	−0.01*** (−3.94)	−0.01*** (−3.74)
Lagged Share of Income, top 5 percent	0.61** (2.10)	−0.31 (−1.49)	0.12 (0.72)	−0.08 (−0.46)
Growth of Housing Wealth	0.06 (1.38)	0.08** (2.27)	0.12*** (4.26)	0.05 (1.00)
Lagged Level of Housing Wealth	−0.01 (−0.42)	−0.01 (−0.82)	0.02* (1.71)	0.01 (1.22)
Growth of Debt	−0.00 (−0.14)	0.01 (0.50)	0.02 (1.02)	0.03 (1.45)
Lagged Debt Overhang	0.02** (2.38)	−0.01** (−2.34)	−0.01** (−2.01)	−0.01* (−1.82)
Lagged Subprime Fraction	0.01 (0.18)	0.11** (2.50)	0.03 (0.65)	−0.00 (−0.00)
Growth of Share of Cash-Out Refinancings	0.02 (0.13)	−0.03 (−0.38)	0.17* (1.77)	0.69*** (3.46)
Share in Foreclosure in Last Two Years	−2.12 (−1.63)	−2.61** (−2.45)	0.09 (0.10)	−2.39** (−2.20)
Growth of Consumer Confidence (Regional)	0.12 (0.83)	0.13*** (2.98)	0.04 (1.11)	−0.01 (−0.13)
Constant	−0.01 (−1.53)	0.07*** (17.74)	−0.12*** (−38.86)	0.10*** (31.02)
Adj. R sq.	0.04	0.12	0.09	0.05
No. obs.	2,772	2,770	2,766	2,761
No. clusters	51	51	51	51

Note: See notes to Table 2. t-statistics based on standard errors clustered by state are reported in parentheses. All variables have been winsorized at 2 percent and 98 percent.