Did US consumers ‘save for a rainy day’ before the Great Recession?*

André K. Anundsen — Norges Bank

Ragnar Nymoen — University of Oslo

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Abstract

The ‘saving for a rainy day’ hypothesis implies that households’ saving decisions reflect that they can predict future income declines. The empirical relevance of this hypothesis plays a key role in discussions of fiscal policy multipliers and it holds under the null that the permanent income hypothesis is true. We find little support for this hypothesis using time series data for the 100 largest US Metropolitan Statistical Areas for the period 1980q1–2015q4. That is, income is more often found to predict consumption and saving than the converse. Our modus operandi is to investigate the ‘saving for a rainy day’ hypothesis by testing weak exogeneity of income and consumption and by exploring the direction of Granger causality between the two series. We also give evidence that house price changes played a role in the US income and consumption dynamics, before, during and after the Great Recession.

Keywords: *Cointegration; Consumption; Granger causality; Permanent income hypothesis; Household saving*

JEL classification: *C22; C32; C51; C52; E21; E62*

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1 Introduction

Consumer expenditure is by far the largest component of spending in the US economy, and in most other countries as well. Not surprisingly, the study of saving and consumption dynamics is therefore of great importance both for economic policy analysis and economic forecasting. It is well known that the rational expectations permanent income hypothesis (PIH hereafter) due to Hall (1978) is consistent with non-stationarity of income and stationarity of saving, see e.g. Muellbauer and Lattimore (1995, Ch. 3.2). When combined with the famous theoretical result of Hall (1978), stating that consumption follows a first-order Markov-process, we obtain the implication that Granger causation runs from lagged saving to current income and not from saving to consumption. In this paper, we explore the empirical relevance of these theoretical conjectures by testing the direction of Granger causality between consumption and income using quarterly time series data for the 100 largest US Metropolitan Statistical Areas (MSAs) over the period 1980q1–2015q4.

A common ground is represented by the idea that the savings rate may be a stationary variable, even though there are stochastic trends in the time series of both income and consumption. This common ground allows the analysis to be held within a vector autoregressive (VAR) framework. To account for the stochastic trends in income and consumption, we apply econometric methods that are robust to non-stationarity. Under the null that the statistical relationship between consumption and income describes the PIH, a fall in saving anticipates a future increase in income and a rise in saving anticipates future income declines (see Campbell (1987)).[1] This also explains why the result has been dubbed the 'saving for a rainy day' hypothesis, cf. Attanasio (1999).

In his seminal paper, Campbell (1987) referred to (Granger) causation running from the savings rate to income growth – and not the other (Keynesian) way around – as the weak implication of the permanent income hypothesis. Empirically, using aggregate US data for the period 1953–1984, Campbell found that the implication of the PIH for the

[1] Campbell showed this for an infinitely lived consumer with quadratic utility function, equal and constant subjective discount rates and no credit constraints.

direction of Granger causality preserved even if other implications of the PIH fared less well empirically, e.g., consumption (in)sensitivity with respect to income changes (see West (1988)).[2] The conclusion that the PIH is only partly correct, and that it needs to be supplemented by several factors to account for the many features of consumption dynamics that we are trying to understand, is widely agreed, see Romer (2006), Carroll (2009), Jappelli and Pistaferri (2010), Attanasio and Weber (2010), Muellbauer (2016). Nevertheless it is counted as a core element in modern macro (Ljungqvist and Sargent (2004, p. 3)) and it is the centre-piece of DSGE models that developed during the Great Moderation.

Although one-way Granger causality from (the log of) the average propensity to consume to income growth can be regarded a weak implication of the PIH, it has strong implications for the analysis of the income and job recession that followed in the wake of the global financial crisis. For example, the increase in the savings rate preceding the drop in income growth in 2008 and 2009 seems to corroborate the PIH Granger-causality predictions, meaning that consumers had started to adapt to a period with low income growth that they were able to rationally foresee. However, several months earlier real house prices had peaked and started to fall, meaning that the increase in saving that went before the fall in income may have signaled the start of a period of financial consolidation in the US household sector. In that interpretation, the increase in saving may have added to the income recession by depressing aggregate demand.

Our *modus operandi* is to test the implied VAR parameter restrictions of the PIH, as outlined in Campbell (1987). One of the contributions of this paper is to study the empirical relevance of the 'saving for a rainy day' hypothesis using disaggregate data for 100 US MSAs. In addition, we estimate the models both on a sample covering only the Great Moderation period (1980q1–2007q4) and a sample including the Great Recession and the recovery (1980q1–2015q4). Studying both samples allow us to investigate the robustness of our results and to study whether there is a change in the direction and

[2] Campbell (1987, p.1267).

significance of the link between income and consumption. Further, our analysis allow us to shed light on the role of house prices for consumption dynamics before, during and after the Great Recession. More precisely, we estimate separate cointegrated VAR models in consumption, income, house prices and the real interest rate for all 100 MSAs. Thus, we allow for complete heterogeneity in lag length and both short and long-run parameters. Tests for the VAR restrictions implied by the PIH and the relationship between house prices, income and consumption are then conducted for each of the 100 MSAs. As a final exercise, we take the analysis one step further to investigate if our results are robust to controlling for movements in stock prices and credit growth.

The empirical results from the Great Moderation sample strongly suggest that income is Granger causing consumption, while there is little support for Granger causation running in the other direction. Including the financial crisis period in our sample strengthens these result, and overall our findings lead us to reject the 'saving for a rainy day' hypothesis. We also show that house prices played a role in US income and consumption dynamics before, during and after the Great Recession. Moreover, our results suggest a strengthened role of house prices in affecting consumption dynamics after the financial crisis. This suggests that US consumers who saw their retirement funds saved up in the housing market completely wiped out during the housing bust increased their saving to compensate for this loss. These results are robust to controlling for stock prices and credit growth and in contrast to house prices, the link between consumption dynamics and credit growth is invariant to the extension of the data set to include the Great Recession and the period thereafter.

Our findings that the importance of house prices for consumption dynamics has increased in the aftermath of the subprime crisis suggests that the spike in the savings rate following the recent financial crisis may – at least partly – be attributed to a financial consolidation effect. This finding adds insight to the already large literature attempting to explain the puzzle that household saving declined during the Great Moderation. A branch of this literature suggests the easing of credit conditions as an explanation, see e.g. Parker (2000) and Aron et al. (2012). Further, Guerrieri and Lorenzoni (2011), Eggertsson and Krugman (2012) and Hall (2011) find that the tightening of credit standards in the period succeeding the Great Recession can explain the sharp increase in the savings rate. An alternative explanation was highlighted in an earlier contribution by Carroll (1992), who suggested precautionary saving as an explanation for why savings rates tend to increase in recession periods. A more recent study by Alan et al. (2012) reaches a similar conclusion. A final explanation is that the evolution of the savings rate is driven by changes in households' net worth. Consistent with this view, Mian et al. (2013) estimate a sizeable marginal propensity to consume out of housing net worth using US zip code level data for the 2006–2009 period. In a recent paper, Carroll et al. (2012) investigate the relative importance of credit conditions, precautionary saving and the wealth channel in explaining US savings rate dynamics. While their results suggest that all three channels are important, they find that the largest contributor to the recent increase in the savings rate is the drop in household wealth. Our findings are consistent with the view in Carroll et al. (2012) and Mian et al. (2013).

The paper proceeds as follows. In the next section, we outline the implied (and testable) VAR parameter restrictions of the PIH, and we discuss how we will proceed to explore the empirical relevance of these theoretical conjectures. In Section 3, we present the data sets that are used in the econometric analyses. Results from the MSA specific analyses over the Great Moderation are discussed in Section 4. In the same section, we explore how our main conclusions are affected by extending the data set to include the financial crisis period. In Section 5, we analyze whether our results are robust to controlling for credit growth and the evolution of stock prices. We also provide evidence at the aggregate level that is congruent with the MSA evidence. The final section concludes the paper.

2 The 'saving for a rainy day' hypothesis

As shown by Campbell (1987), for an infinitely lived consumer and no credit constraints, saving is given by the discounted sum of anticipated declines in income.[3] The interpretation is that consumers wish to avoid the utility loss of reductions in consumption, so they smooth consumption intertemporally, they 'save for a rainy day'.

Saving can also be expressed as the sum of a linear filter of leads in stationary income changes, and another linear filter of forecast errors, which are $I(0)$ by assumption. Thus, it follows logically that S_t is stationary, $I(0)$. As noted by Muellbauer and Lattimore (1995), stationarity of S_t does not require that income follows a pure random-walk – it holds also in the case where income follows an ARIMA process.

Campbell further noted the implication that, under the null of the PIH, saving should encapsulate the superior information of the agent to the econometrician, meaning that lagged saving should Granger-cause income in the bivariate VAR. This is also consistent with Hall's consumption Euler-equation. Hence, consumption should not be Granger-caused by lagged income, or lagged saving, in the VAR. These implications contradicted the economic interpretation of empirical consumption functions of the Keynesian type, where the existing disequilibrium in saving were a predictor of next period's consumption change, Davidson et al. (1978). Section 2.1 shows briefly how the the two theories can be formulated as two testable models of a VAR with simple first order dynamics. Section 2.2 presents the more general framework that we apply both for the analysis of the MSA level and and aggregate consumption and income data.

2.1 Econometric framework for testing the 'saving for a rainy day' hypothesis

In the following, we measure consumption and income in natural logarithms, where c_t denotes consumption in period t and y_t is income in period t. We assume that both

[3]In addition to the mentioned assumptions, Campbell's derivation assumed quadratic utility function and rational expectations about future income.

consumption and income are integrated of order one, $I(1)$. Due to the non-stationarity of the two series, cointegration represents a common ground between the consumption function approach, which assumes a causal link from income to consumption, and the permanent-income/life-cycle theories, which imply the consumption Euler equation.

Although our econometric analysis makes use of models with longer lags and possible structural breaks, the main hypotheses about saving behavior can be formulated by a first order VAR, reparameterized as an Equilibrium Correction System (EqCM), see Eitrheim et al. (2002):

$$\begin{aligned} \Delta c_t &= \eta_c + \alpha_c[c_{t-1} - \beta_y y_{t-1} - \mu] + \varepsilon_{c,t} \qquad -1 < \alpha_c \leq 0, & (1) \\ \Delta y_t &= \eta_y + \alpha_y[c_{t-1} - \beta_y y_{t-1} - \mu] + \varepsilon_{y,t} \qquad 0 \leq \alpha_y < 1. & (2) \end{aligned}$$

where β_y is the cointegration coefficient, $\mu = \mathsf{E}[c_t - \beta_y y_t]$, while α_c and α_y are the adjustment coefficients which are the focus parameters of the testing of the contesting economic theories of cointegration between income and consumption. In the case of $\beta_y = 1$, the savings rate, $(y - c)$, is $I(0)$. Along a growth path characterized by $\mathsf{E}[c_{t-1} - \beta_y y_{t-1} - \mu] = 0$, the two intercepts η_c and η_y are proportional: $\eta_c = \beta_y \eta_y$.

In the following, we assume that the disturbances, $\varepsilon_{c,t}$, and $\varepsilon_{y,t}$ have a joint normal distribution. Their variances are σ_c^2 and σ_y^2, respectively, and the correlation coefficient is denoted $\rho_{c,y}$.

Consumption function model of the VAR

Underlying the consumption function approach is the idea that consumption is equilibrium correcting, i.e., $-1 < \alpha_c < 0$. Given that this requirement is fulfilled, there are two possibilities for the coefficient α_y: *(i)* $0 < \alpha_y < 1$ or *(ii)* $\alpha_y = 0$. The first case is consistent with hours worked etc. being *demand determined* and that y_t adjusts to past disequilibria. In econometric terms, there is mutual (Granger) causation between income and consumption, see Engle et al. (1983). The second possibility implies that income is *supply determined*. In the context of the VAR, the restriction that $\alpha_y = 0$ implies that income is weakly exogenous with respect to the long-run income elasticity, β_y, see e.g. Johansen (1992). Moreover, for the case of first order dynamics, there is one-way Granger causation from income to consumption, so income is also strongly exogenous.

Interpretation is aided by writing the system (1)-(2) in model form:

$$\Delta c_t = \eta_c + \gamma_c + \pi_c \Delta y_t + \alpha'_c [c_{t-1} - \beta_y y_{t-1} - \mu] + \varepsilon'_{c,t} \tag{3}$$

$$\Delta y_t = \eta_y + \alpha_y [c_{t-1} - \beta_y y_{t-1} - \mu] + \varepsilon_{y,t} \tag{4}$$

where (3) is a conditional consumption function, while (4) is a marginal income equation.[4]

When the testable restriction that $\alpha_y = 0$ holds, (3)-(4) may be expressed as:

$$\Delta c_t = \eta_c + \gamma_c + \pi_c \Delta y_t + \alpha_c [c_{t-1} - \beta_y y_{t-1} - \mu] + \varepsilon'_{c,t} \tag{5}$$

$$\Delta y_t = \eta_y + \varepsilon_{y,t}, \tag{6}$$

Equations (3) and (5) are conditional equilibrium correction equations for c_t, see e.g., Hendry (1995, Chapter 7), Davidson et al. (1978) and Hendry and von Ungern-Sternberg (1981). However, (3) is more general, since (5) rests on the assumption that causation runs from income to consumption, and not the other way around.

Euler equation model of the VAR

According to the permanent income/life cycle hypothesis, the evolution of consumption is shaped by tastes and life cycle needs. The stochastic permanent income/life cycle hypothesis holds that consumption growth, Δc_t, is not Granger-caused by the lagged income level, hence $\alpha_c = 0$ in (1). Thus, it is assumed that consumption growth is orthogonal to $(c_{t-1} - \beta_y y_{t-1} - \mu)$, the linear and stationary combination of consumption

[4] For the normal distribution the exact parameterization becomes: $\alpha'_c = \alpha_c - \pi_c \alpha_y$, $\pi_c = \rho_{c,y} \dfrac{\sigma_c}{\sigma_y}$, $\gamma_c = -\eta_y \pi_c, \varepsilon'_{c,t} = \varepsilon_{c,t} - \pi_c$.

and income, i.e. the cointegrating relationship.

For the case of $\alpha_c = 0$, the model form of the system (1)-(2) becomes:

$$\Delta c_t = \eta_c + \varepsilon_{c,t} \tag{7}$$

$$\Delta y_t = \eta_y + \gamma_y + \pi_y \Delta c_t + \alpha_y [c_{t-1} - \beta_y y_{t-1} - \mu] + \varepsilon'_{y,t} \tag{8}$$

where (7) is a marginal model for consumption, while (8) is a conditional model for income. [5]

Given $\alpha_c = 0$, cointegration implies that $0 < \alpha_y < 1$, since – as we know from the Engle-Granger representation theorem (Engle and Granger, 1987) – cointegration implies equilibrium correction, and *vice versa.* The interpretation for the case of $\beta_y = 1$, due to Campbell (1987), is that growth in disposable income is negatively related to the lagged savings rate because consumers have superior information about their income prospects. If saving increases "today", this is because consumers expect income to decline in the future. Hence, after first observing a rise in the savings rate, we will observe a fall in income in subsequent periods, since households are 'saving for a rainy day'.

Furthermore, although income is not Granger-causing consumption in (7), this does not preclude contemporaneous correlation, since we can have $\pi_y \neq 0$ without violating the Euler-equation restriction (i.e., $\alpha_c = 0$ and $\Delta c_t \perp (c_{t-1} - \beta_y y_{t-1} - \mu)$).

The theoretical prediction that income is equilibrium correcting carries over to less stylized situations: first, if a proportion of the consumers are subject to liquidity or borrowing constraints, we may find that aggregate income is Granger-causing aggregate consumption, as in Campbell and Mankiw (1989). Still, as long as the remaining proportion of consumers adjust their consumption to expected permanent income, observed aggregate disposable income is negatively related to the aggregate savings rate, so we would still find $\alpha_y > 0$. Second, the orthogonality condition may not hold if the measure of consumption expenditure includes purchases of durables, see e.g. Deaton (1992, p.99–

[5] $\pi_y = \rho_{c,y} \dfrac{\sigma_y}{\sigma_c}$, $\gamma_y = -\eta_y \pi_y$,$\varepsilon'_{y,t} = \varepsilon_{y,t} - \pi_y \varepsilon_{c,t}$.

103), but the implication that $\alpha_y > 0$ still holds. Finally, the basic implication of $\alpha_y > 0$ is unaffected by modifications of the basic Euler equation, e.g., non-constant expected future interest rates (Haug, 1996) and inclusion of demographic variables.

2.2 Generalizations to higher order VARs and allowing for regional heterogeneity

To test for the absence of cointegration between consumption and income, and to explore the direction of equilibrium correction and Granger causality, we develop MSA-specific econometric models.

Our main reference is a VAR(p_j) model of the following form:

$$\boldsymbol{y}_{j,t} = \sum_{s=1}^{p_j} \boldsymbol{A}_{j,s}\boldsymbol{y}_{j,t-s} + \boldsymbol{\Phi}_j \boldsymbol{D}_{j,t} + \boldsymbol{\varepsilon}_{j,t} \tag{9}$$

where the index j represents MSA unit. The vector $\boldsymbol{y}_{j,t}$ comprises real consumption and real disposable income. Deterministic terms (linear trend and a constant) are collected in the vector $\boldsymbol{D}_{j,t}$. House price changes and the real interest rate are also collected in $\boldsymbol{D}_{j,t}$. The disturbances are assumed to follow a multivariate normal distribution, with expectation $\mathbf{0}_{2\times1}$ and covariance matrix $\boldsymbol{\Sigma}_j$, i.e. $\boldsymbol{\varepsilon}_{j,t} \sim MVN(\mathbf{0}_{2\times1}, \boldsymbol{\Sigma}_j)$.

For all areas, we start with a lag length of 5, i.e. $p_j = 5$. Then, we select the lag length (between 1 and 5) that minimizes the Akaike Information Criterium (AIC).[6] Conditional on the optimal lag truncation, p_j^*, we consider (9) on vector equilibrium correction (VECM) form. We follow the recommendation of Johansen (1995) and Harbo et al. (1998) and restrict a deterministic trend to enter the cointegration space in order to achieve a similar test for cointegration rank.[7] Letting $\tilde{\boldsymbol{y}}_{j,t} = \left(\boldsymbol{y}'_{j,t}, trend_j\right)'$, the VECM

[6] Other lag selection criteria also exists, and some researchers prefer the Schwarz Information Criterion (SIC). The main difference between the two criteria is that SIC punishes overparameterization relatively more than AIC, which gives more weight to fit (the likelihood). All of our main findings are robust to using SIC instead of AIC. Detailed results are available upon request.

[7] An alternative to our approach is to exclude the trend from the outset. All our results are robust to excluding the trend from the outset. Detailed results are available upon request.

representation of the VAR model takes the following form:[8]

$$\Delta \boldsymbol{y}_{j,t} = \boldsymbol{\Pi}_j \tilde{\boldsymbol{y}}_{j,t-1} + \sum_{s=1}^{p_j^*-1} \boldsymbol{\Gamma}_{j,s} \Delta \boldsymbol{y}_{j,t-s} + \tilde{\boldsymbol{\Phi}}_j \tilde{\boldsymbol{D}}_{j,t} + \boldsymbol{\varepsilon}_{j,t} \tag{10}$$

where $\tilde{\boldsymbol{D}}_{j,t}$ contains the constant term, the real interest rate and house price changes. All coefficient matrices are redefined conformably.

To determine the rank of the matrix $\boldsymbol{\Pi}_j$, we use the trace test of Johansen (1988). The rank of $\boldsymbol{\Pi}_j$ corresponds to the number of independent linear combinations between the variables in $\tilde{\boldsymbol{y}}_{j,t}$ that are stationary, i.e. the number of cointegrating relationships. When $\boldsymbol{\Pi}_j$ has reduced rank, we can write $\boldsymbol{\Pi}_j = \boldsymbol{\alpha}_j \boldsymbol{\beta}_j'$, where $\boldsymbol{\beta}_j$ is a $(l_j + 1) \times r_j$ matrix and $\boldsymbol{\alpha}_j$ is a $l_j \times r_j$ matrix corresponding to the long-run coefficients and loading factors (adjustment coefficients), respectively. The rank of $\boldsymbol{\Pi}_j$ is denoted by r_j, while $l_j + 1$ refers to the number of endogenous variables (plus the deterministic trend, which is restricted to lie in the space spanned by $\boldsymbol{\alpha}_j$). In all areas, l_j is equal to 2 (real consumption and real disposable income).

Conditional on a non-zero rank, we can estimate the parameters in the cointegration space. In particular, our approach allows us to explore heterogeneities in both long-run income elasticities and the speed of adjustment parameters. Moreover, cointegration implies that there is Granger causality in at least one direction (Granger, 1986). To formally explore the direction of causality, in the Granger sense, consider the reduced rank representation of the VECM. Before exploring the direction of GNC, we test and impose the restriction that $\beta_{trend,j} = 0$. Hence, the VECM used for testing the "rainy day hypothesis" can be written as:

[8] Johansen (1994, 1995) and Harbo et al. (1998).

$$
\begin{pmatrix} \Delta c_{j,t} \\ \Delta y_{j,t} \end{pmatrix} = \begin{pmatrix} \alpha_{c_j} \\ \alpha_{y_j} \end{pmatrix} (c_{j,t-1} - \beta_{y,j} y_{j,t-1}) + \sum_{s=1}^{p_j^*-1} \begin{pmatrix} \Gamma_{11,j,s} & \Gamma_{12,j,s} \\ \Gamma_{21,j,s} & \Gamma_{22,j,s} \end{pmatrix} \begin{pmatrix} \Delta c_{j,t-s} \\ \Delta y_{j,t-s} \end{pmatrix} + \tilde{\boldsymbol{\Phi}}_j \tilde{\boldsymbol{D}}_{j,t} + \boldsymbol{\varepsilon}_{j,t} \tag{11}
$$

where we have normalized the first coefficient in the cointegration space with respect to consumption. A test for GNC from income to consumption in area j amounts to testing the joint hypothesis that $\alpha_{c_j} = \Gamma_{12,j,s} = 0 \ \forall \ s$, while a test for GNC from consumption to income in area j is a test of the joint hypothesis that $\alpha_{y_j} = \Gamma_{21,j,s} = 0 \ \forall \ s$. In our empirical analysis, we shall consider these tests for each of the 100 MSAs covered by our sample.

2.3 Allowing for MSA-specific structural breaks

When building the MSA-specific econometric models, we make use of the *impulse indicator saturation* (IIS) algorithm, which is an integrated part of the *Autometrics* algorithm implemented within OxMetrics (see Doornik (2009) and Hendry and Doornik (2009)) to allow for MSA-specific structural breaks.

The IIS algorithm includes an impulse dummy for each observation in the information set. More precisely, this implies that the baseline VAR in (9) can be modified to:

$$
\boldsymbol{y}_{j,t} = \sum_{s=1}^{p_j} \boldsymbol{A}_{j,s} \boldsymbol{y}_{j,t-s} + \boldsymbol{\Phi}_j \boldsymbol{D}_{j,t} + \boldsymbol{\Psi}_j \boldsymbol{I}_t + \boldsymbol{\varepsilon}_{j,t} \quad t = t_j, \ldots, T \tag{12}
$$

where $\boldsymbol{I}_t$ is a $(T+1-t_j) \times (T+1-t_j)$ matrix of impulse dummies. Since this entails that there are more variables than observations, the model is estimated in blocks to determine which indicators are significant (see Hendry et al. (2008) and Johansen and Nielsen (2009)). If we let the retained indicators for area j be collected in the $(T+1-$

$t_j) \times Q_j$ matrix $\tilde{\boldsymbol{I}}_{j,t}$, with $Q_j < (T + 1 - t_j)$, the IIS robust reparameterization of the VAR takes the following form:

$$\Delta \boldsymbol{y}_{j,t} = \boldsymbol{\Pi}_j \tilde{\boldsymbol{y}}_{j,t-1} + \sum_{s=1}^{p_j^*-1} \boldsymbol{\Gamma}_{j,s} \Delta \boldsymbol{y}_{j,t-s} + \tilde{\boldsymbol{\Phi}}_j \tilde{\boldsymbol{D}}_{j,t} + \tilde{\boldsymbol{\Psi}}_j \tilde{\boldsymbol{I}}_{j,t} + \boldsymbol{\varepsilon}_{j,t} \tag{13}$$

After having estimated (12) employing Autometrics, we follow the same steps as those described in the previous section, i.e. we test down the lag length using the AIC, determine the rank of the matrix $\boldsymbol{\Pi}_j$, and conduct tests for both weak exogeneity and Granger non-causality. Thus, the estimates and tests obtained in this case can be seen as being robustified to MSA-specific structural breaks (Johansen and Nielsen, 2009).

Applying the IIS algorithm, an average of $\alpha^{IIS} \times (T + 1 - t_j)$ indicators will be retained by chance, where α^{IIS} denotes a pre-specified significance level used for the selection of indicators. When applying the IIS algorithm to the VAR model of area j, we set the significance level to 0.1%. As expected from the documented properties of the algorithm (Castle et al., 2012), very few indicators are picked up in the MSA analysis.

3 Data

We have collected quarterly time series data at both the national level and for the 100 largest MSAs in the US. For most of the areas, the data set spans the period 1980q1–2015q4 ($T = 144$).

The MSAs included in our MSA data set cover all but four of the 50 US states and are spread out in different geographical regions. To ease the exposition, we shall follow the Census Bureau and divide the US into four major regions (West, Midwest, South and East) when discussing some of our results.[9] The geographical divide of the four regions

[9]The estimation and testing are, however, carried out for each MSA.

is presented in Figure 1.[10]

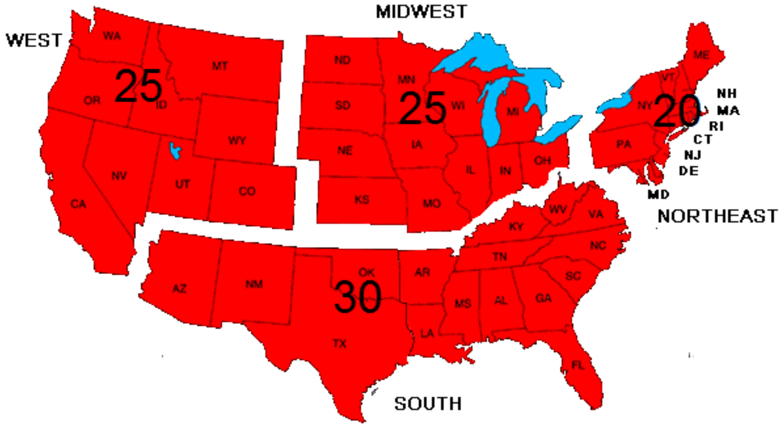


Figure 1: Main geographical regions in the US

With reference to Figure 1, 25 of the MSAs included in our sample belong to the West, 20 to the East, 30 to the South and 25 to the Midwest.

The income data, $y_{j,t}$, measure personal disposable income in billions of USD. Disaggregate consumption data are not available at the MSA level (in fact it is not even available at the state level). For that reason, we use data on retail sales in billions of USD as a proxy for consumption, $c_{j,t}$. That said, as pointed out by Sorensen and Luengo-Prado (2008), the correlation between aggregate US retail sales and non-durable consumption is very high. Thus, in the absence of data on MSA level consumption, we take this to be a relatively good proxy. Similar data have been used in e.g. Case et al. (2012), Sorensen and Luengo-Prado (2008) and Dejuan et al. (2004), who all consider state level consumption in the US. We follow Case et al. (2012) and use the retail sales data supplied by Moody's (formerly supplied by Regional Financial Associates). House price data are collected from the FHFA, and all series are deflated by the corresponding MSA level CPI measure, which has also been collected from Moody's. Finally, MSA-specific real interest rates are constructed by subtracting the MSA level CPI inflation from the nominal 3-month T-bill. In the empirical analysis, all variables, except the real

[10]Whereas our approach is to consider MSA-specific econometric models, we have also done our analysis using panel data methods when splitting the US into the four major census regions. While this has the cost of imposing more homogeneity, it comes at the gain of increased efficiency. The results from the panel analysis resemble our MSA results. Details are available upon request.

interest rate, are included in log form.

The discussion in Section 2 is based on the premise that the time series for income and consumption contain unit roots. To investigate the empirical relevance of this assumption, we have tested the order of integration of the data series using standard ADF tests (Dickey and Fuller, 1979) for each of the areas. In particular, we started with a lag length of 5, including a deterministic trend in the ADF regressions. Then, the optimal lag truncation was chosen by a sequence of t-tests. The average order of integration is close to one for both series.[11] Based on these results, we feel confident in continuing our analysis under the modeling assumption that both series are integrated of order one.

4 MSA-based evidence about rainy day behavior

4.1 Cointegration results for the MSA data set

In this section, we present the results from the MSA-specific econometric analysis using data for the Great Moderation (1980q1–2007q4). In the first step of our estimation approach, the IIS algorithm picks up a little more than 1 dummy on average (confer the last row in the first column of Table 1). Based on AIC, we find the average optimal lag truncation to be just below 4, and the hypothesis of co-trending is supported for a majority of the areas (66%) when we use a 1% significance level. While detailed results for the individual MSAs are presented in Table A.1–A.4 in Appendix A, Table 1 reports a summary of the average results across each of the four census regions illustrated in Figure 1.

As is evident from Table 1, we find clear evidence in a majority of the areas that the residuals are well behaved, i.e. there are no sings of autocorrelation, heteroskedasticity nor departures from normality. It is also evident that the average rank is very close to one, which is also what we will impose for the rest of the analysis. Imposing the reduced rank restriction and normalizing the cointegrating vector with respect to consumption

[11] Detailed results from the unit root tests at the MSA level are available upon request.

Table 1: Averages and percentages of key model features for Great Moderation sample (1980q1–2007q4), ordered by census region

Region	Dummies (avg.)	p^* (avg.)	Rank($\mathbf{\Pi}$) (avg.)	Auto. (%)	Norm. (%)	Hetero. (%)	$\beta_{trend} = 0$ (%)
West	1.36	3.16	0.48	100.00	100.00	76.00	76.00
East	0.90	3.75	0.95	100.00	100.00	100.00	70.00
South	0.48	4.28	1.08	96.00	100.00	100.00	44.00
Midwest	1.43	4.13	0.97	96.67	96.67	86.67	73.33
All	1.07	3.85	0.87	98.00	99.00	90.00	66.00

Notes: Columns 2-4 report the average number of dummies, Dummies (avg.), included in the econometric models within each of the four major regions, as well as the average optimal lag truncation, p^* (avg.) and average number of cointegrating relationships, Rank($\mathbf{\Pi}$). Columns 5-7 report the percentage number of times where we cannot reject absence of autocorrelation, non-normality and heteroskedasticity. The final column displays the percentage number of areas where we find support for co-trending, i.e. $\beta_{trend} = 0$. The final row in each column reports the same figures for all the MSAs covered by the sample (all areas). Detailed results for the individual MSAs are reported in Table A.1–A.4 in Appendix A.

($\beta_{c,j} = 1 \ \forall \ j$), we obtain estimates of the long-run income elasticity. While detailed results for the individual MSAs are reported in Table A.5–A.8, Figure 2 plots the point estimates for the long-run income elasticity for all of the areas included in our sample – in descending order.

The average long-run income elasticity across all areas is 0.84, and the standard error of this mean group estimate is 0.03, see the second and fourth column in Table 2.[12] Note that the hypotheses about the adjustment coefficients and the direction of Granger causality between income and consumption (our parameters of interest) are independent of whether $\beta_y = 1$ or not. For this reason, we continue the analysis with as few restrictions as possible.

To have a first look at the empirical relevance of the weak implication of the PIH (implying that $\alpha_{c,j} = 0$ and $\alpha_{y,j} > 0$), Figure 3 plots the distribution of the point estimate of the two adjustment parameters across the 100 MSAs.[13]

It is clear that in a majority of the areas, we find that $\alpha_{c,j} < 0$, which is consistent with a consumption function approach and at odds with the 'rainy day' hypothesis. In the cases where a positive point estimate is obtained, we cannot reject the hypothesis that the parameter is equal to zero. The average estimated speed of adjustment in the consumption equation is found to be -0.12, see Column 5 in Table 2. Looking at the

[12]In calculating the mean group estimates, we have excluded the outliers where the estimated income elasticity was negative or above 2. This is only the case for 7 areas, meaning that mean group estimates are based on the remaining 93 MSAs.

[13]Again, detailed results for each MSA can be found in Table A.5–A.8 in Appendix A.

adjustment coefficient associated with the income equation, it is found to be positive in a majority of the cases, and in the cases where the point estimate is negative, weak exogeneity is not rejected by the data. The average estimate, around 0.03, is substantially lower (in absolute value) than the adjustment parameter in the consumption equation. Hence, results thus far suggest mixed support for the 'saving for a rainy day' hypothesis as an empirically relevant description of US consumption behavior. In the next section, we shall explore the direction of Granger causality in more detail by conducting formal tests for both weak exogeneity and Granger non-causality for each of the MSAs in the sample.

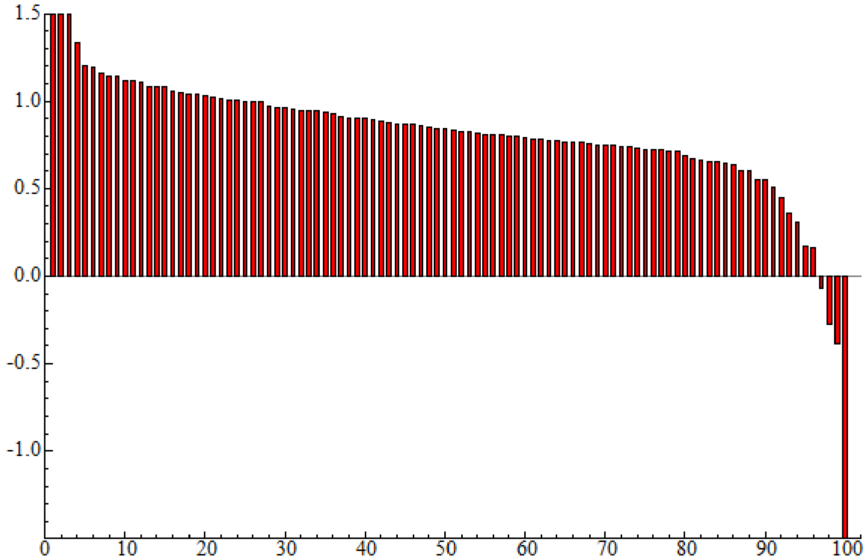
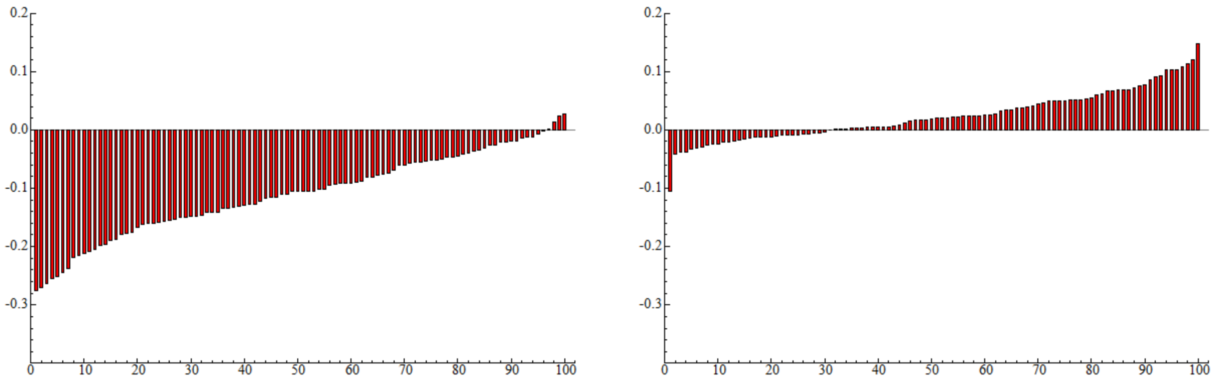


Figure 2: Estimated long-run income elasticities ($\beta_{y,j}$) for all MSAs for Great Moderation sample (1980q1–2007q4), in descending order



(a) $\alpha_{c,j}$

(b) $\alpha_{y,j}$

Figure 3: Adjustment parameter in consumption equation ($\alpha_{c,j}$) and in income equation ($\alpha_{y,j}$) for Great Moderation sample (1980q1–2007q4), in descending order

Table 2: Summary of cointegration results for Great Moderation sample (1980q1–2007q4)

	$\hat{\beta}_y^{IIS}$			$\hat{\alpha}_c^{IIS}$			$\hat{\alpha}_y^{IIS}$		
Region	Mean	Median	Standard error	Mean	Median	Standard error	Mean	Median	Standard error
West	0.8786	0.8663	0.0367	-0.1132	-0.1036	0.0138	0.0295	0.0397	0.0077
East	0.7345	0.7386	0.1621	-0.1150	-0.1178	0.0134	0.0245	0.0025	0.0125
South	0.8322	0.7960	0.0453	-0.1227	-0.1268	0.0179	0.0166	0.0204	0.0100
Midwest	0.8750	0.8728	0.0281	-0.1170	-0.1101	0.0127	0.0282	0.0204	0.0072
All	0.8397	0.8406	0.0253	-0.1171	-0.1101	0.0072	0.0250	0.0209	0.0045

Notes: The table reports the average long-run income elasticities of consumption ($\hat{\beta}_y^{IIS}$), the adjustment parameter in the consumption equation ($\hat{\alpha}_c^{IIS}$) and the adjustment parameter in the income equation ($\hat{\alpha}_y^{IIS}$), grouped by census region. The table also reports the median and the standard error for each of these coefficients. The final row in each column reports the same figures for all the MSAs covered by the sample (all areas). Detailed results for the individual MSAs can be found in Table A.5–A.8 in Appendix A.

4.2 Weak exogeneity and Granger non-causality

Using the optimal lag truncations of the VAR models, as found in the previous section, together with the estimated cointegrating vectors, we derive the vector equilibrium correction representation of the CVAR models (confer (11)). The VECM for each area is estimated by FIML, and Table 3 summarizes the main results regarding tests for both weak exogeneity and Granger non-causality.[14]

As is evident by inspecting the second and third column, weak exogeneity of consumption with respect to the cointegrating vector is rejected in a majority of the cases (84%), while weak exogeneity of income is rejected only for 33% of the MSAs. These findings are at odds with the weak implication of the PIH, and further support for this claim is provided by the results in Column 4 and Column 5, where we report the percentage number of times where we find evidence that income is Granger-causing consumption (87%) and the percentage number of times where we find evidence that consumption is Granger-causing income (56%). The Granger causality tests for house prices suggest that house prices Granger-cause consumption in 60% of the areas, suggesting that house prices may be important for consumption dynamics in some MSAs. The same figure for income is around 38%.

[14]Note that the reported results are based on the MSAs where the estimated long-run income elasticity was "meaningful"– defined as $0 < \hat{\beta}_{y_j} < 2$. This holds for all, except 7 areas, meaning that tests for weak exogneity and GNC are based on 93 MSAs.

Table 3: Tests for weak exogeneity and Granger non-causality for Great Moderation sample (1980q1–2007q4)

Region	$\alpha_c \neq 0$	$\alpha_y \neq 0$	$y \underset{GC}{\rightarrow} c$	$c \underset{GC}{\rightarrow} y$	$ph \underset{GC}{\rightarrow} c$	$ph \underset{GC}{\rightarrow} y$
West	79.17	37.50	91.67	75.00	45.83	37.50
East	94.12	29.41	82.35	47.06	76.47	29.41
South	86.96	26.09	86.96	34.78	56.52	43.48
Midwest	79.31	37.93	86.21	62.07	65.52	37.93
All	83.87	33.33	87.10	55.91	60.22	37.63

Notes: Column 2–4 report the percentage number of times where weak exogeneity of consumption is rejected ($\alpha_c \neq 0$) and the percentage number of times where weak exogeneity of income ($\alpha_y \neq 0$) is rejected , as well as the percentage number of times where we find that income Granger-causes consumption $\left(y \underset{GC}{\rightarrow} c\right)$ and vice versa $\left(c \underset{GC}{\rightarrow} y\right)$. The final two columns report the percentage number of times where we find that house prices Granger-cause consumption $\left(ph \underset{GC}{\rightarrow} c\right)$ and income $\left(ph \underset{GC}{\rightarrow} y\right)$.

4.3 Including the financial crisis period

We have seen that the 'saving for a rainy day' hypothesis receives mixed support over the Great Moderation period. The empirical evidence is clearly supportive to the interpretation that consumption represents the main equilibrium correction mechanism.

In this section, we check if the assessment changes when we extend the sample to include the financial crisis period and the ensuing income and job crisis, i.e. the sample now covers the period from 1980q1 to 2015q4. The distribution of long-run income elasticities is plotted in Figure 4.

In Figure 5, we plot the estimated long-run elasticities from the Great Moderation sample against the estimated long-run elasticities obtained on the full sample and the correlation coefficient of the long-run elasticities from the two samples is a little more than 0.7. It is clear that the coefficients are very stable, which is a reassuring finding.

The estimated adjustment parameters in the consumption and income equation from the full sample analysis are illustrated in Figure 6. It is evident that the adjustment parameter in the consumption function is negative in most areas and, resembling the results from the Great Moderation sample. The distribution of the adjustment parameter

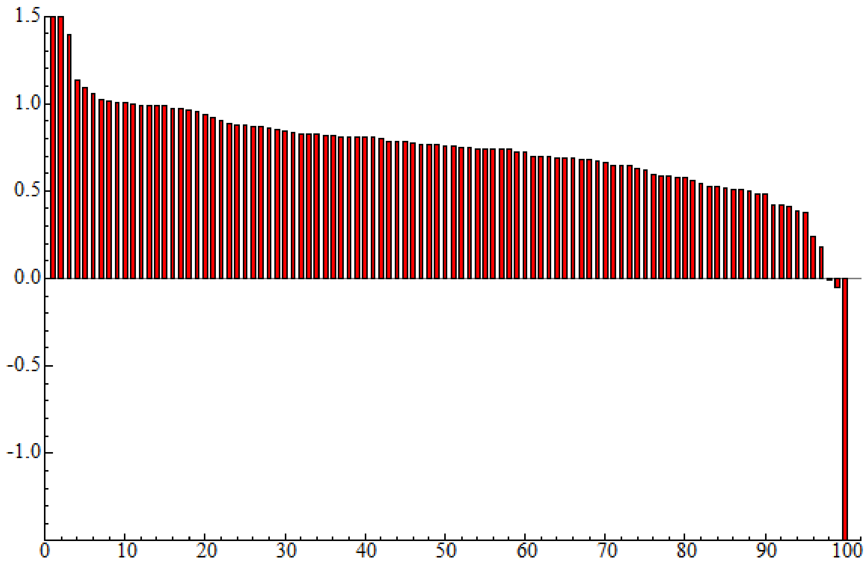


Figure 4: Estimated long-run income elasticities ($\beta_{y,j}$) for all MSAs for full sample (1980q1–2015q4), in descending order

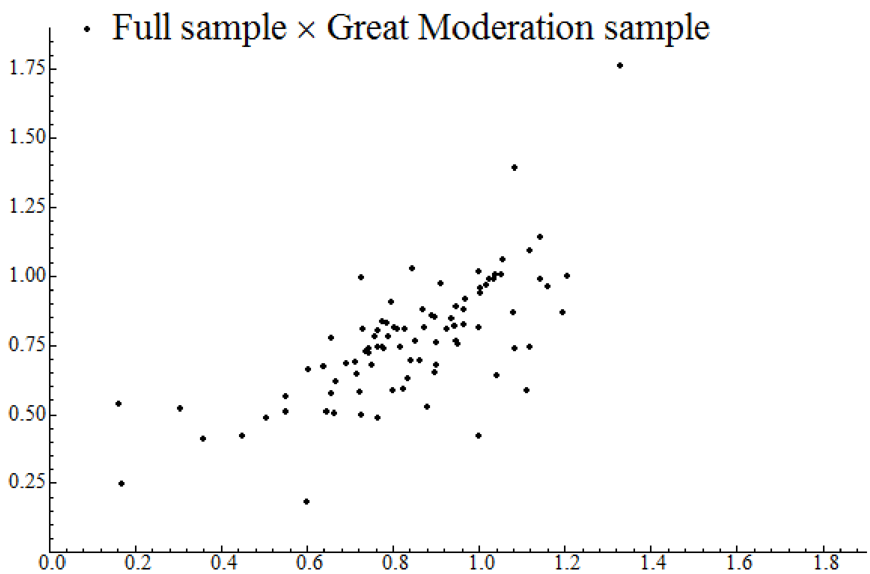
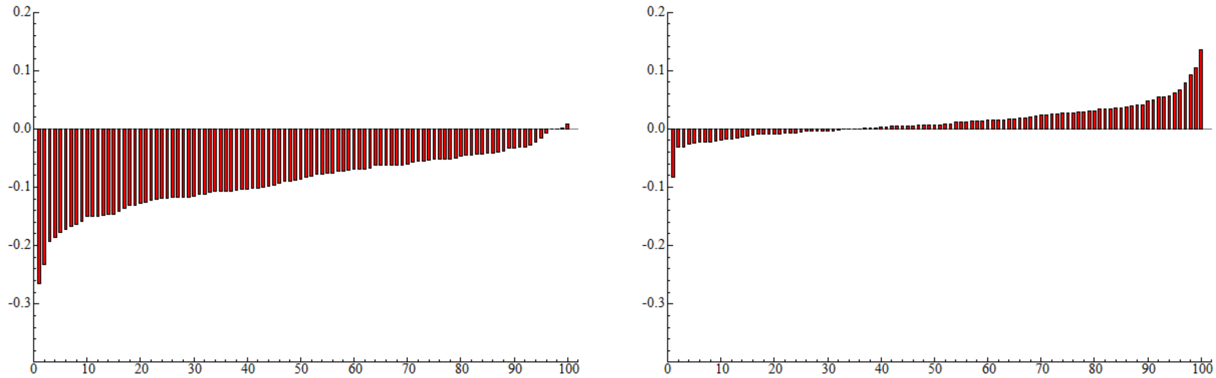


Figure 5: Estimated long-run income elasticities ($\beta_{y,j}$) from Great moderation sample (1980q1–2007q4) versus full sample (1980q1–2015q4)



(a) α_c (b) α_y

Figure 6: Adjustment parameter in consumption equation (α_c) and in income equation (α_y) for full sample (1980q1–2015q4), in descending order

in the income equation is also similar to the Great Moderation sample.[15]

Based on the above results, it is clear that the inclusion of the financial crisis period in the estimation sample does not alter our main conclusions. Overall, our results are strengthened when the sample is extended. This is also seen from the mean and median estimates for long-run income elasticity and the adjustment parameters, which are summarized in Table 4.[16] Comparing these results to the results obtained on the Great Moderation sample, we see that there are no significant changes in results.

To formally explore how the inclusion of the financial crisis period affects the tests for weak exogeneity and Granger non-causality, Table 5 reports average results across the four major census regions.[17]

There are several interesting observations in Table 5. First, the average number of dummies retained by the IIS algorithm (confer the final column) increases slightly compared to the Great Moderation sample. Second, the main results regarding weak exogeneity and Granger causality are maintained – in fact results are further strengthened when the financial crisis period is included, i.e. the rejection of the weak implication of the PIH is stronger when we include the financial crisis period. Finally, the evidence that

[15]Also for this extended sample do we find that the null cannot be rejected for the cases where the point estimates suggest $\hat{\alpha}_c > 0$ and $\hat{\alpha}_y > 0$.

[16]Detailed results for the individual MSAs from the full sample analysis are available upon request.

[17]Again, detailed results for the individual MSAs are available upon request.

Table 4: Summary of cointegration results from full sample analysis (1980q1–2015q4)

	$\hat{\beta}_y^{IIS}$			$\hat{\alpha}_c^{IIS}$			$\hat{\alpha}_y^{IIS}$		
Region	Mean	Median	Standard error	Mean	Median	Standard error	Mean	Median	Standard error
West	0.7920	0.7807	0.0959	-0.0829	-0.0760	0.0106	0.0064	0.0047	0.0044
East	0.6860	0.6988	0.0433	-0.0992	-0.0998	0.0088	0.0090	0.0129	0.0040
South	0.7452	0.6847	0.0594	-0.0966	-0.0881	0.0116	0.0123	0.0059	0.0064
Midwest	0.8325	0.8091	0.0458	-0.0899	-0.0960	0.0089	0.0229	0.0117	0.0073
All	0.7702	0.7622	0.0274	-0.0919	-0.0881	0.0050	0.0134	0.0078	0.0031

Notes: The table reports average long-run income elasticity ($\hat{\beta}_y^{IIS}$), the adjustment parameter of the consumption equation ($\hat{\alpha}_c^{IIS}$) and the adjustment parameter of the income equation ($\hat{\alpha}_y^{IIS}$), grouped by census region. The table also reports the median and the standard error for each of these coefficients. The final row in each column reports the same figures for all the MSAs covered by the sample (all areas).

Table 5: Tests for weak exogeneity and Granger non-causality for full sample (1980q1–2015q4)

Region	$\alpha_c \neq 0$	$\alpha_y \neq 0$	$y \underset{GC}{\rightarrow} c$	$c \underset{GC}{\rightarrow} y$	$ph \underset{GC}{\rightarrow} c$	$ph \underset{GC}{\rightarrow} y$	Dummies
West	91.30	8.70	86.96	69.57	69.57	56.52	3.84
East	100.00	5.00	95.00	55.00	90.00	35.00	1.40
South	100.00	12.00	96.00	44.00	76.00	60.00	1.72
Midwest	89.66	44.83	96.55	68.97	79.31	51.72	3.70
All	94.85	19.59	93.81	59.79	78.35	51.55	2.78

Notes: Columns 2-4 report the percentage number of times where weak exogeneity of consumption ($\alpha_c \neq 0$) is rejected and the percentage number of times where weak exogeneity of income ($\alpha_y \neq 0$) is rejected, as well as the percentage number of times where we find that income Granger-causes consumption $\left(y \underset{GC}{\rightarrow} c\right)$ and vice versa $\left(c \underset{GC}{\rightarrow} y\right)$. Columns 5-6 report the percentage number of times where we find that house prices Granger-cause consumption $\left(ph \underset{GC}{\rightarrow} c\right)$ and income $\left(ph \underset{GC}{\rightarrow} y\right)$. The final column reports the average number of dummies that were retained by the IIS algorithm. The final row in each column reports the same figures for all the MSAs covered by the sample (all areas).

house prices Granger-cause consumption is stronger than what we found for the Great Moderation sample. This is consistent with the view that the fall in house prices during the subprime crisis led to increased saving by US consumers to counteract the negative impact on their accumulated wealth of the housing crash, i.e. that there are sizeable housing wealth effects on consumption, see also Carroll et al. (2012) and Mian et al. (2013).[18]

5 Extensions

5.1 Controlling for asset prices

Our results suggest that house prices play an important role for consumption dynamics and that the link between house prices and consumption has increased after the recent financial crisis. Housing wealth is one the main components of household wealth, which might directly influence their consumption and saving decisions. For instance, Carroll et al. (2003) do not find precautionary responses when they exclude home equity from

[18]Household expectations might have played a similar role during the Great Depression period. Romer (1990) argues that households' perception of future income uncertainty increased significantly after the crash in the stock market in 1929, which led to the postponement of durable goods purchases.

household wealth. To analyze the link between wealth and consumption in a bit more detail, we consider a version of our model, where we extend the model to also include the real S&P500 index to control for financial wealth.

To shed more light on the importance of the financial market interaction with consumption and the robustness of the link we established between house prices and consumption, Table 6, reports results from tests for GNC from house prices and stock prices to both consumption and income, for the Great Moderation sample and for the full sample.[19]

First, we notice that our finding of a strong link between house prices and consumption, which has increased after the financial crisis, is maintained. Furthermore, we also establish a link between stock prices and consumption, but the evidence for this link is weaker than for the link between house prices and consumption. The finding that income Granger causes consumption is maintained in this extension.[20]

Table 6: Tests for Granger non-causality from house prices and stock prices to income and consumption

Region	$ph \underset{GC}{\rightarrow} c$	$ph \underset{GC}{\rightarrow} y$	$S\&P500 \underset{GC}{\rightarrow} c$	$S\&P500 \underset{GC}{\rightarrow} y$
Great moderation sample:				
West	40.00	36.00	40.00	0.00
East	70.59	23.53	52.94	11.76
South	60.87	39.13	34.78	8.70
Midwest	71.43	42.86	60.71	28.57
All	60.22	36.56	47.31	12.90
Full sample:				
West	59.09	54.55	59.09	9.09
East	90.00	35.00	45.00	15.00
South	75.00	54.17	54.17	12.50
Midwest	82.76	48.28	68.97	27.59
All	76.84	48.42	57.89	16.84

Notes: Column 2–3 report the percentage number of times where we find that house prices Granger-causes consumption $\left(ph \underset{GC}{\rightarrow} c\right)$ and income $\left(ph \underset{GC}{\rightarrow} y\right)$. Column 4–5 report the percentage number of times where we find that stock prices Granger-causes consumption $\left(S\&P500 \underset{GC}{\rightarrow} c\right)$ and income $\left(S\&P500 \underset{GC}{\rightarrow} y\right)$.

[19]Detailed results are reported in Section A of the online appendix, but all main results are invariant to this extension of the information set.

[20]See Section A of the online appendix for details.

5.2 Controlling for credit growth

In the presence of liquidity constraints, the sensitivity of consumption to income may decrease in strength, see e.g., Ludvigson (1999). For this reason, we investigate the robustness of our results to controlling for credit growth in the empirical analysis. MSA-level data for credit growth are only available from 1990q1, which restricts our sample somewhat. The inclusion of credit growth (and therefore also the reduction of the sample) has no material impact on our results and we still find Granger causality from income to consumption in a majority of the MSAs .[21]

Table 7 reports results from tests for GNC from house prices and credit to consumption and income, both for the Great Moderation sample and for the full sample. Also in the case where we control for credit growth, the role of house prices for consumption dynamics is found to increase after the financial crisis. A link between consumption growth and credit is established in about 30% of the areas and this link has been relatively stable across the two samples.

5.3 Macro evidence

Macro time series of private income and consumption have features similar to the typical MSA series in that there are clear signs of both unit-root non-stationarity and intermittent structural breaks. To investigate if aggregate cointegration evidence and Granger causality is congruent with the picture that emerged from the analysis of the MSA-data, we redid the analysis using aggregate data for consumption and income.

Consistent with the average MSA results, we found evidence of cointegration. The zero restriction on the trend coefficient in the cointegration relationship is not rejected, which is similar to the analysis of the MSA data, where the co-trending restriction was accepted in about 70% of the MSAs.

[21]Detailed results are reported in the online appendix, Section B. Since credit data are only available from 1990q1, we also redid the original analysis on a similar sample and results are robust to considering this alternative sample period.

Table 7: Tests for Granger non-causality from house prices and credit growth to income and consumption

Region	$ph \underset{GC}{\rightarrow} c$	$ph \underset{GC}{\rightarrow} y$	$Credit \underset{GC}{\rightarrow} c$	$Credit \underset{GC}{\rightarrow} y$
Great moderation sample:				
West	32.00	48.00	36.00	8.00
East	55.56	38.89	50.00	38.89
South	35.00	25.00	45.00	55.00
Midwest	29.63	29.63	33.33	40.74
All	36.67	35.56	40.00	34.44
Full sample:				
West	72.73	63.64	40.91	13.64
East	90.00	50.00	35.00	5.00
South	82.61	52.17	43.48	39.13
Midwest	79.31	44.83	51.72	17.24
All	80.85	52.13	43.62	19.15

Column 2–3 report the percentage number of times where we find that house prices Granger-causes consumption $\left(ph \underset{GC}{\rightarrow} c\right)$ and income $\left(ph \underset{GC}{\rightarrow} y\right)$. Column 4–5 report the percentage number of times where we find that credit growth Granger-causes consumption $\left(Credit \underset{GC}{\rightarrow} c\right)$ and income $\left(Credit \underset{GC}{\rightarrow} y\right)$.

The results strongly indicate that equilibrium correction is just as significant in consumption as it is in income. The macro results are robust to using data on total retail sales instead of personal consumption expenditures. In general, the aggregate analysis is in line with the MSA evidence, and a detailed description of the aggregate analysis is given in Appendix B.

6 Conclusion

We started this paper by asking whether US consumers saved for a rainy day during the Great Moderation period. To test this hypothesis, we have concentrated on the so-called weak implication of the permanent income hypothesis, which entails that consumption growth does not respond to deviations from a long-run relationship between income and consumption. The statistical implication of this is that consumption is weakly exogenous with respect to any long-run cointegrating relationship that exists between income and consumption. Our econometric analysis on the Great Moderation sample (1980q1–

2007q4) give little support for this hypothesis, and indicate that consumption responds to deviations from the long-run cointegrating relationship between income and consumption in a majority of the areas. Including the financial crisis period in the estimation sample, this result is strengthened, and the same is true for the results from the aggregate time series.

The VAR models that we use for testing include lagged growth rates in real house prices. In the MSA models we find significant effects of these conditioning variables, first on the 1980q1–2007q4 sample and even stronger effects when the financial crisis and Great Recession is included. On both samples, the overall direction of the effect is that lagged house price changes are positively related to consumption growth. The macro model corroborated the existence of such a relationship. Our finding therefore suggests that the large declines in housing equity in the aftermath of the subprime crash have strongly dampened consumer spending in the US. A similar conclusion is reached by Aron et al. (2012), Carroll et al. (2012) and Mian et al. (2013).

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Appendix A: Detailed econometric results by MSA

Table A.1: Specification results for West region for Great Moderation sample (1980q1–2007q4)

MSA and state	Dum.	p^*	$Rank(\mathbf{\Pi}_i)$	*Auto.*	*Norm.*	*Hetero.*	p(co-trend)	$p\left(y \underset{GC}{\rightarrow} c\right)$	$p\left(c \underset{GC}{\rightarrow} y\right)$	p(c is WE)	p(c is WE)
ALBUQUERQUE NM	1	5	1	0	0.3439	0.0619	0.0549	0.0030	0.0674	0.0005	0.0529
ANAHEIM CA	2	2	0	0	0.9922	0.0940	0.4853	0.1354	0.0038	0.3436	0.0113
BOISE CITY ID	0	2	0	0	0.2132	0.7151	0.0111	0.0001	0.5053	0.0222	0.5352
BOULDER CO	1	2	0	0	0.1254	0.0000	0.4390	0.0320	0.0012	0.2244	0.1397
COLORADO SPRINGS CO	0	4	0	0	0.4700	0.5193	0.0512	0.0994	0.0494	0.0962	0.0368
DENVER CO	2	4	1	0	0.8615	0.0196	0.0122	0.0149	0.0605	0.0025	0.0825
EUGENE OR	0	2	0	0	0.3525	0.0000	0.0989	0.0008	0.0591	0.0037	0.2097
LAS VEGAS NV	0	2	0	0	0.6945	0.0208	0.9277	0.0000	0.0067	0.0000	0.4734
LOS ANGELES CA	0	4	0	0	0.0634	0.9198	0.1763	0.0030	0.1948	0.0070	0.1171
OAKLAND CA	1	2	0	0	0.5952	0.0007	0.0063	0.0283	0.0726	0.0387	0.2565
OXNARD CA	1	3	0	0	0.2327	0.0491	0.8472	0.1720	0.0041	0.1565	0.0072
PHOENIX AZ	3	3	1	0	0.6513	0.0079	0.3971	0.0000	0.0018	0.0001	0.1725
PORTLAND WA OR	1	4	1	0	0.6636	0.0107	0.0013	0.0003	0.0097	0.0015	0.2271
PROVO UT	0	2	1	1	0.6014	0.3275	0.0490	0.0000	0.6023	0.0001	0.9058
RIVERSIDE CA	4	4	1	0	0.1629	0.0901	0.0000	0.0040	0.0186	0.0480	0.0056
SACRAMENTO CA	1	4	0	0	0.1314	0.0152	0.5955	0.0151	0.0375	0.2616	0.0196
SALT LAKE CITY UT	0	2	0	0	0.3339	0.0020	0.0346	0.0525	0.0041	0.5056	0.0119
SAN DIEGO CA	5	4	2	0	0.1533	0.6920	0.0000	0.0000	0.6282	0.0000	0.3686
SAN FRANCISCO CA	0	3	2	0	0.8135	0.0759	0.7737	0.0000	0.2490	0.0000	0.6156
SAN JOSE CA	1	4	0	0	0.2791	0.0014	0.1088	0.0408	0.0527	0.0352	0.0070
SEATTLE WA	3	2	0	0	0.5807	0.0829	0.9338	0.0026	0.0098	0.0006	0.1511
SPOKANE WA	2	4	1	0	0.5286	0.9161	0.0000	0.0000	0.0122	0.0000	0.5054
TACOMA WA	2	4	0	0	0.1159	0.1950	0.0773	0.0019	0.0389	0.0001	0.2688
TUCSON AZ	2	2	0	0	0.1825	0.0560	0.1190	0.0000	0.0703	0.0031	0.9481
URBAN HONOLULU HI	2	5	1	0	0.1022	0.4187	0.0006	0.0007	0.7169	0.0027	0.7423

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the West region of the US. The first three columns report the number of dummies picked up by the IIS algorithm, Dum., the selected lag length (based on AIC), p_i^*, and the cointegration rank, $Rank\left(\mathbf{\Pi}\right)$. The next three columns report the p-value from tests for no autocorrelation (Auto.), normality (Norm.) and homoskedasticity (Hetero.). The next column reports the p-value for the test of whether the trend can be excluded from the cointegration space, p(co-trend). The final four columns report p-values from tests for GC from income to consumption ($p\left(y \underset{GC}{\rightarrow} c\right)$), GC from consumption to income ($p\left(c \underset{GC}{\rightarrow} y\right)$), as well as tests for weak exogeneity of consumption, p(c is WE), and income, p(y is WE).

Table A.2: Specification results for East region for Great Moderation sample (1980q1–2007q4)

MSA and state	Dum.	p^*	$Rank(\mathbf{\Pi}_i)$	*Auto.*	*Norm.*	*Hetero.*	p(co-trend)	$p\left(y \underset{GC}{\rightarrow} c\right)$	$p\left(c \underset{GC}{\rightarrow} y\right)$	p(c is WE)
ALBANY NY	0	4	1	0	0.5023	0.1557	0.0000	0.0183	0.0086	0.0147
BOSTON MA	1	4	2	0	0.7291	0.7120	0.0252	0.0000	0.1199	0.0000
BRIDGEPORT CT	1	2	0	0	0.0799	0.0834	0.0146	0.0566	0.5561	0.0217
BUFFALO NY	2	4	2	0	0.3049	0.0275	0.0583	0.0016	0.1724	0.0001
CAMBDEN NJ	2	4	2	0	0.5790	0.0553	0.0931	0.1289	0.0000	0.0088
DUTCHESS COUNTY NY"HARRISBURG PA	0	4	1	1	0.0920	0.2753	0.6851	0.0000	0.2776	0.0000
HARTFORD CT	2	4	0	1	0.3689	0.0435	0.4450	0.0187	0.0417	0.0052
MANCHESTER NH	0	2	1	0	0.5762	0.1508	0.0007	0.0048	0.0502	0.0012
NASSAU NY	1	4	1	1	0.1252	0.1021	0.0019	0.0002	0.1344	0.0002
NEWARK PA NJ	0	4	1	0	0.4971	0.0676	0.4799	0.0012	0.0918	0.0001
NEW HAVEN CT	0	4	0	0	0.1524	0.0172	0.3157	0.0068	0.1163	0.0002
NEW YORK NJ NY	0	2	1	0	0.0373	0.2725	0.0000	0.0059	0.0039	0.0062
OCEAN CITY NJ	1	4	0	0	0.0856	0.0584	0.0017	0.1409	0.0286	0.0113
PHILADELPHIA PA	0	2	0	1	0.0689	0.1297	0.0589	0.2850	0.0079	0.1215
PITTSBURG PA	1	4	1	0	0.4022	0.1503	0.5955	0.0002	0.1438	0.0000
PORTLAND ME	5	5	1	1	0.1156	0.1439	0.0000	0.0008	0.0004	0.5848
PROVIDENCE MA RI	1	4	1	1	0.2966	0.3362	0.0630	0.0000	0.0000	0.0001
SYRACUSE NY	0	4	2	0	0.2536	0.1138	0.6729	0.0000	0.1554	0.0000
TRENTON NJ	1	5	2	0	0.3843	0.3948	0.9939	0.3877	0.0188	0.0751

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the East region of the US. The first three columns report the number of dummies the IIS algorithm, Dum., the selected lag length (based on AIC), p_i^*, and the cointegration rank, $Rank\left(\mathbf{\Pi}\right)$. The next three columns report the p-value from tests for no autocorrel normality (Norm.) and homoskedasticity (Hetero.). The next column reports the p-value for the test of whether the trend can be excluded from the cointegration space, p(co-trend). columns report p-values from tests for GC from income to consumption ($p\left(y \underset{GC}{\rightarrow} c\right)$), GC from consumption to income ($p\left(c \underset{GC}{\rightarrow} y\right)$), as well as tests for weak exogeneity of consumptio and income, p(y is WE).

Table A.3: Specification results for South region for Great Moderation sample (1980q1–2007q4)

MSA and state	Dum.	p^*	$Rank(\mathbf{\Pi}_i)$	*Auto.*	*Norm.*	*Hetero.*	p(co-trend)	$p\left(y \underset{GC}{\rightarrow} c\right)$	$p\left(c \underset{GC}{\rightarrow} y\right)$	p(c is WE)	p(c is WE)
ATLANTA GA	0	4	2	0	0.8918	0.1554	0.7615	0.0005	0.2821	0.0000	0.5286
AUSTIN TX	0	4	1	0	0.8699	0.7293	0.0316	0.1054	0.0014	0.9437	0.0000
BALTIMORE MD	0	4	0	0	0.7785	0.3226	0.2708	0.0001	0.4416	0.0004	0.1715
BIRMINGHAM AL	1	5	2	0	0.5322	0.4618	0.0001	0.0001	0.3098	0.0000	0.9666
CHARLOTTE SC NC	1	5	2	0	0.4587	0.0167	0.0004	0.0231	0.0339	0.0018	0.4199
CINCINNATI IN KY OH	1	4	1	0	0.0752	0.4433	0.0000	0.0010	0.0662	0.0000	0.4285
COLUMBUS GA AL	1	4	2	0	0.3200	0.9825	0.0036	0.0007	0.5923	0.0000	0.6942
DALLAS TX	0	5	0	0	0.5776	0.1101	0.0983	0.3894	0.0013	0.1894	0.0078
FORT LAUDERDALE FL	3	5	0	1	0.2298	0.0460	0.8845	0.0136	0.0001	0.0110	0.5308
FORT WORTH TX	0	5	0	0	0.7662	0.2386	0.6183	0.1057	0.0015	0.3308	0.0010
GREENSBORO NC	3	5	2	0	0.7450	0.1917	0.1434	0.0001	0.0080	0.0001	0.0140
GREENVILLE SC	2	4	0	0	0.2064	0.0315	0.5970	0.0496	0.0000	0.1453	0.0007
HOUSTON TX	0	3	0	0	0.3182	0.7278	0.1477	0.0078	0.9306	0.0007	0.5402
JACKSONVILLE FL	1	4	1	0	0.2547	0.0709	0.9719	0.0056	0.0181	0.0044	0.0266
LITTLE ROCK AR	1	4	1	1	0.2748	0.5929	0.0014	0.0002	0.1045	0.0015	0.1411
LOUISVILLE IN KY	3	4	2	0	0.7700	0.4821	0.0133	0.0002	0.6138	0.0000	0.6319
MEMPHIS AR MS TN	1	5	1	0	0.0829	0.3444	0.2926	0.0000	0.4217	0.0000	0.5312
MIAMI FL	2	2	0	0	0.6787	0.0097	0.0784	0.0032	0.9240	0.0987	0.7288
NASHVILLE TN	3	2	0	0	0.1187	0.0527	0.1842	0.0105	0.0366	0.0201	0.0458
NEW ORLEANS LA	4	5	1	0	0.8446	0.2730	0.0007	0.0000	0.0002	0.0000	0.4721
OKLAHOMA CITY OK	1	4	1	1	0.2549	0.6866	0.4204	0.0133	0.0000	0.6199	0.0000
ORLANDO FL	3	4	0	0	0.8849	0.0057	0.5833	0.0037	0.0553	0.0050	0.4372
RALEIGH NC	2	4	2	0	0.7678	0.0080	0.3092	0.1308	0.0065	0.0111	0.0044
RICHMOND VA	3	4	2	0	0.9989	0.0424	0.0064	0.0657	0.0027	0.3323	0.0002
SAN ANTONIO TX	0	4	0	0	0.3095	0.0277	0.3138	0.0029	0.0557	0.0434	0.0308
TAMPA FL	2	4	2	0	0.0515	0.0035	0.2977	0.0000	0.0497	0.0001	0.3637
VIRGINIA BEACH NC VA	0	4	2	0	0.0989	0.1289	0.0107	0.0000	0.5384	0.0001	0.7603
WASHINGTON WV MD VA	3	4	2	1	0.0066	0.5664	0.3463	0.0000	0.1919	0.0000	0.9955
WEST PALM BEACH FL	2	4	0	0	0.3555	0.3280	0.2015	0.0143	0.2213	0.0010	0.8888
WILMINGTON NJ MD DE	0	5	0	0	0.1405	0.1842	0.0018	0.0027	0.0256	0.0023	0.7002

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the South region of the US. The first three columns report the number of dummies picked up by the IIS algorithm, Dum., the selected lag length (based on AIC), p_i^*, and the cointegration rank, $Rank(\mathbf{\Pi})$. The next three columns report the p-value from tests for no autocorrelation (Auto.), normality (Norm.) and homoskedasticity (Hetero.). The next column reports the p-value for the test of whether the trend can be excluded from the cointegration space, p(co-trend). The final four columns report p-values from tests for GC from income to consumption ($p\left(y \underset{GC}{\rightarrow} c\right)$), GC from consumption to income ($p\left(c \underset{GC}{\rightarrow} y\right)$), as well as tests for weak exogeneity of consumption, p(c is WE), and income, p(y is WE).

Table A.4: Specification results for Midwest region for Great Moderation sample (1980q1–2007q4)

MSA and state	Dum.	p^*	$Rank(\mathbf{\Pi}_i)$	*Auto.*	*Norm.*	*Hetero.*	p(co-trend)	$p\left(y \underset{GC}{\rightarrow} c\right)$	$p\left(c \underset{GC}{\rightarrow} y\right)$	p(c is WE)	p(c is WE)
AKRON OH	0	4	2	1	0.1866	0.9122	0.0006	0.0350	0.1165	0.0018	0.3137
ANN ARBOR MI	0	5	0	1	0.4621	0.4675	0.0335	0.0353	0.8008	0.0028	0.3020
CHICAGO IL	0	4	2	0	0.1817	0.1003	0.0047	0.0000	0.3959	0.0000	0.7674
CLEVELAND OH	2	5	1	1	0.5297	0.9678	0.0005	0.0010	0.0410	0.0001	0.1633
DAYTON OH	1	4	0	0	0.1171	0.9765	0.0029	0.1516	0.1716	0.0253	0.2542
DES MOINES IA	2	5	2	0	0.0525	0.4703	0.0303	0.0000	0.0647	0.0000	0.5879
DETROIT MI	0	4	1	0	0.9051	0.7871	0.0006	0.0566	0.0033	0.6511	0.0009
FARGO MN ND	1	5	1	0	0.5307	0.0371	0.0004	0.8274	0.1336	0.7345	0.0072
FORT WAYNE IN	1	4	1	0	0.3574	0.2443	0.0432	0.0025	0.0311	0.0006	0.2560
GARY IN	0	4	1	0	0.5455	0.6106	0.0014	0.0000	0.3989	0.0000	0.7799
GRAND RAPIDS MI	0	2	0	0	0.3690	0.3874	0.0536	0.0026	0.0038	0.1484	0.0503
INDIANAPOLIS IN	0	4	1	0	0.7423	0.1389	0.0032	0.0218	0.1543	0.0069	0.4873
KANSAS CITY KS MO	1	4	1	0	0.7138	0.4208	0.0323	0.0008	0.1347	0.0001	0.7114
LANSING MI	0	3	1	1	0.9847	0.1592	0.0006	0.0165	0.2991	0.0144	0.2832
MADISON WI	0	5	1	0	0.0637	0.3342	0.0525	0.0023	0.0188	0.0000	0.0729
MILWAUKEE WI	0	4	1	0	0.4164	0.1111	0.1488	0.0004	0.0486	0.0000	0.3507
MINNEAPOLIS WI MN	1	5	1	0	0.1683	0.2880	0.2538	0.0008	0.9508	0.0002	0.8868
OMAHA IA NE	1	4	1	0	0.8860	0.8919	0.0076	0.0128	0.2727	0.0013	0.3850
PEORIA IL	0	5	1	1	0.4488	0.1233	0.0000	0.0349	0.1001	0.0038	0.0815
ROCHESTER MN	0	5	2	0	0.1321	0.4902	0.0092	0.8616	0.0055	0.5044	0.0004
ST LOUIS IL MO	1	5	2	0	0.6343	0.0787	0.0000	0.0000	0.3839	0.0000	0.2553
SIOUX FALLS SD	0	4	0	0	0.3307	0.9204	0.3662	0.0259	0.2588	0.0053	0.4999
SPRINGFIELD IL	0	5	1	1	0.4193	0.7792	0.7483	0.0000	0.0710	0.0000	0.0151
TOLEDO OH	0	4	1	0	0.4802	0.6300	0.0006	0.0089	0.1023	0.0011	0.3932
WICHITA KS	1	4	2	0	0.3095	0.9145	0.0128	0.0000	0.9189	0.0000	0.9078

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the Midwest region of the US. The first three columns report the number of dummies picked up by the IIS algorithm, Dum., the selected lag length (based on AIC), p_i^*, and the cointegration rank, $Rank(\mathbf{\Pi})$. The next three columns report the p-value from tests for no autocorrelation (Auto.), normality (Norm.) and homoskedasticity (Hetero.). The next column reports the p-value for the test of whether the trend can be excluded from the cointegration space, p(co-trend). The final four columns report p-values from tests for GC from income to consumption ($p\left(y \underset{GC}{\rightarrow} c\right)$), GC from consumption to income ($p\left(c \underset{GC}{\rightarrow} y\right)$), as well as tests for weak exogeneity of consumption, p(c is WE), and income, p(y is WE).

Table A.5: Cointegration results for West region for Great Moderation sample (1980q1–2007q4)

MSA and state	$\hat{\beta}_y^{IIS}$	$se\left(\hat{\beta}_y^{IIS}\right)$	$\hat{\alpha}_c^{IIS}$	$se\left(\hat{\alpha}_c^{IIS}\right)$	$\hat{\alpha}_y^{IIS}$	$se\left(\hat{\alpha}_y^{IIS}\right)$	Likelihood
ALBUQUERQUE NM	1.0845	0.0311	-0.1578	0.0414	0.0684	0.0331	675.9548
BOISE CITY ID	1.0845	0.0571	-0.0261	0.0440	0.0503	0.0363	682.8870
BOULDER CO	0.9464	0.0514	-0.1022	0.0383	0.0232	0.0340	596.2837
COLORADO SPRINGS CO	0.6569	0.0695	-0.0415	0.0249	0.0418	0.0234	641.9990
DENVER CO	0.9632	0.0282	-0.0504	0.0435	0.0606	0.0367	660.9940
EUGENE OR	0.7803	0.1310	-0.1162	0.0199	0.0622	0.0149	699.2242
HONOLULU HI	2.5041	0.0918	0.0140	0.0422	0.0046	0.0303	633.1040
LAS VEGAS NV	0.9997	0.0278	-0.1219	0.0277	-0.0180	0.0231	637.1365
LOS ANGELES CA	0.9993	0.1234	-0.0813	0.0277	0.0346	0.0232	690.1868
OAKLAND CA	0.6473	0.0471	-0.0917	0.0579	0.0377	0.0472	670.1707
OXNARD CA	0.9516	0.0664	-0.0517	0.0376	0.0681	0.0276	666.5681
PHOENIX AR	1.0022	0.0245	-0.2154	0.0631	0.0500	0.0392	699.3391
PORTLAND WA OR	0.8172	0.0494	-0.1318	0.0369	0.0371	0.0222	683.4505
PROVO UT	1.1195	0.0228	-0.1336	0.0403	-0.0029	0.0330	606.5022
RIVERSIDE CA	1.1416	0.0857	-0.0448	0.0230	0.0522	0.0172	684.3179
SACRAMENTO CA	0.7992	0.0689	-0.0366	0.0355	0.0541	0.0271	682.2644
SALT LAKE CITY UT	1.0796	0.0675	-0.0189	0.0213	0.0522	0.0171	668.7008
SAN DIEGO CA	0.7579	0.0284	-0.2183	0.0478	-0.0323	0.0383	703.5785
SAN FRANCISCO CA	0.5516	0.0286	-0.2119	0.0516	-0.0197	0.0476	664.1219
SAN JOSE CA	0.7251	0.0563	-0.0895	0.0336	0.1032	0.0368	665.3136
SANTA ANA CA	0.8704	0.0866	-0.1537	0.0406	0.0508	0.0313	663.4214
SEATTLE WA	0.8622	0.0218	-0.2695	0.0670	-0.0268	0.0617	656.9314
SPOKANE WA	0.7754	0.0505	-0.1507	0.0459	-0.0320	0.0353	655.0228
TACOMA WA	0.8059	0.0469	-0.1049	0.0391	0.0018	0.0304	675.7661
TUCSON AZ	0.6651	0.0524	-0.0957	0.0377	-0.0084	0.0292	666.9054

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the West region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run income elasticity and the speed of adjustment parameters, along with the estimated standard errors. The final column shows the likelihood.

Table A.6: Cointegration results for East region for Great Moderation sample (1980q1–2007q4)

MSA and state	$\hat{\beta}_y^{IIS}$	$se\left(\hat{\beta}_y^{IIS}\right)$	$\hat{\alpha}_c^{IIS}$	$se\left(\hat{\alpha}_c^{IIS}\right)$	$\hat{\alpha}_y^{IIS}$	$se\left(\hat{\alpha}_y^{IIS}\right)$	Likelihood
ALBANY NY	-2.1258	0.0661	-0.0076	0.0269	-0.0093	0.0364	592.6765
BOSTON MA	0.5041	0.0504	-0.1562	0.0344	-0.0381	0.0298	672.1524
BRIDGEPORT CT	0.3573	0.0394	-0.0473	0.0415	0.0073	0.0386	640.8102
BUFFALO NY	1.1597	0.0502	-0.2083	0.0478	0.1075	0.0519	658.3250
CAMBDEN NJ	0.9659	0.0689	-0.0910	0.0374	0.1035	0.0292	672.6637
EDISON NJ	0.7386	0.0504	-0.1178	0.0372	0.0024	0.0331	589.8010
HARRISBURG PA	0.9426	0.1153	-0.0693	0.0212	0.0439	0.0152	672.7667
HARTFORD CT	0.3062	0.0958	-0.0739	0.0296	-0.0064	0.0242	608.5671
MANCHESTER NH	0.8232	0.0738	-0.1097	0.0347	-0.0116	0.0361	593.5354
NASSAU NY	0.8516	0.0621	-0.1601	0.0434	0.0504	0.0535	652.4390
NEWARK PA NJ	0.6379	0.1005	-0.1499	0.0332	-0.0082	0.0262	671.8479
NEW HAVEN CT	-0.2717	0.1290	-0.0320	0.0346	-0.0124	0.0260	595.9654
NEW YORK NJ NY	0.7299	0.0858	-0.0601	0.0226	0.0025	0.0281	672.6928
OCEAN CITY NJ	16.0739	0.1539	-0.0017	0.0272	0.0016	0.0228	514.6028
PHILADELPHIA PA	0.1704	0.0354	-0.1979	0.0540	-0.0137	0.0464	663.7053
PITTSBURG PA	1.1972	0.0630	-0.0193	0.0482	0.0910	0.0432	712.1982
PORTLAND ME	0.4503	0.0877	-0.1323	0.0301	-0.0288	0.0204	601.1006
PROVIDENCE MA RI	0.8406	0.0683	-0.1558	0.0306	0.0057	0.0243	687.4641
SYRACUSE NY	1.2076	0.0693	-0.0779	0.0467	0.1195	0.0499	595.9447
TRENTON NJ	0.6028	0.0789	-0.1287	0.0345	-0.0100	0.0331	597.6906

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the East region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run income elasticity and the speed of adjustment parameters, along with the estimated standard errors. The final column shows the likelihood.

Table A.7: Cointegration results for South region for Great Moderation sample (1980q1–2007q4)

MSA and state	$\hat{\beta}_y^{IIS}$	$se\left(\hat{\beta}_y^{IIS}\right)$	$\hat{\alpha}_c^{IIS}$	$se\left(\hat{\alpha}_c^{IIS}\right)$	$\hat{\alpha}_y^{IIS}$	$se\left(\hat{\alpha}_y^{IIS}\right)$	Likelihood
ATLANTA GA	0.8050	0.0216	-0.1771	0.0417	0.0176	0.0287	666.6898
AUSTIN TX	1.3299	0.0891	0.0008	0.0153	0.0324	0.0109	659.3953
BALTIMORE MD	0.8728	0.0466	-0.1663	0.0476	0.0454	0.0368	680.6307
BIRMINGHAM AL	0.9128	0.0507	-0.1595	0.0304	0.0010	0.0210	706.4453
CHARLOTTE SC NC	0.8465	0.0332	-0.0885	0.0409	0.0160	0.0296	691.4948
CINCINNATI IN KY OH	0.7642	0.0516	-0.1479	0.0408	-0.0211	0.0316	705.8901
COLUMBUS OH	0.9470	0.1483	-0.2443	0.0219	0.0170	0.0141	539.9304
DALLAS TX	0.7746	0.0242	-0.0548	0.0558	0.0859	0.0441	684.6702
FORT LAUDERDALE FL	1.0567	0.1009	-0.1406	0.0377	0.0224	0.0273	715.8443
FORT WORTH TX	0.8284	0.3959	-0.0463	0.0172	0.1126	0.0138	694.9175
GREENSBORO NC	0.6017	0.0458	-0.0566	0.0353	-0.0237	0.0281	699.8741
GREENVILLE SC	1.0423	0.0667	-0.0522	0.0421	0.0717	0.0236	691.6424
HOUSTON TX	0.7113	0.0222	-0.1414	0.0472	0.0209	0.0438	665.1756
JACKSONVILLE FL	0.9365	0.0322	-0.1157	0.0435	0.0765	0.0358	686.5959
LITTLE ROCK AR	-0.0650	0.3536	-0.0210	0.0073	-0.0063	0.0054	699.4705
LOUISVILLE IN KY	0.8900	0.0462	-0.2053	0.0385	-0.0154	0.0312	712.8161
MEMPHIS AR MS TN	0.7365	0.0247	-0.2550	0.0533	-0.0238	0.0425	697.1416
MIAMI FL	0.6562	0.5579	-0.0352	0.0092	0.0055	0.0070	683.0976
NASHVILLE TN	0.8965	0.0249	-0.1046	0.0403	0.0674	0.0366	680.2769
NEW ORLEANS LA	0.8356	0.0968	-0.1792	0.0411	0.0204	0.0329	681.3190
OKLAHOMA CITY OK	0.8989	0.0992	-0.0125	0.0288	0.0923	0.0220	686.6427
ORLANDO FL	1.0177	0.0491	-0.1101	0.0352	0.0236	0.0293	695.7634
RALEIGH NC	1.0239	0.0212	-0.0907	0.0419	0.0670	0.0297	682.7236
RICHMOND VA	1.0381	0.0515	-0.0258	0.0314	0.0690	0.0219	695.6206
SAN ANTONIO TX	0.9676	0.0472	-0.0536	0.0293	0.0502	0.0249	687.2917
TAMPA FL	0.9271	0.1802	-0.1887	0.0110	-0.0380	0.0090	701.2222
VIRGINIA BEACH NC VA	0.8093	0.0561	-0.1336	0.0317	0.0083	0.0300	636.8337
WASHINGTON WV MD VA	0.7447	0.0256	-0.1970	0.0449	0.0002	0.0361	724.0693
WEST PALM BEACH FL	0.7164	0.0308	-0.1060	0.0337	0.0034	0.0311	690.3714
WILMINGTON NJ MD DE	0.7858	0.0343	-0.1061	0.0439	0.0120	0.0363	651.4845

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the South region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run income elasticity and the speed of adjustment parameters, along with the estimated standard errors. The final column shows the likelihood.

Table A.8: Cointegration results for Midwest region for Great Moderation sample (1980q1–2007q4)

MSA and state	$\hat{\beta}_y^{IIS}$	$se\left(\hat{\beta}_y^{IIS}\right)$	$\hat{\alpha}_c^{IIS}$	$se\left(\hat{\alpha}_c^{IIS}\right)$	$\hat{\alpha}_y^{IIS}$	$se\left(\hat{\alpha}_y^{IIS}\right)$	Likelihood
AKRON OH	1.0342	0.0777	-0.1623	0.0477	0.0336	0.0324	686.5644
ANN ARBOR MI	-0.3881	0.2789	-0.0217	0.0086	-0.0059	0.0086	606.2434
CHICAGO WI IN IL	0.6903	0.0268	-0.2522	0.0574	-0.0127	0.0527	689.2220
CLEVELAND OH	0.7662	0.1274	-0.0763	0.0287	-0.0201	0.0232	703.4433
DAYTON OH	1.1173	0.1640	-0.0598	0.0275	0.0182	0.0178	687.5985
DES MOINES IA	0.7452	0.0451	-0.1761	0.0329	0.0204	0.0334	677.6496
DETROIT MI	2.2143	4.7449	-0.0126	0.0037	0.0753	0.0033	664.9436
FARGO MN ND	0.9027	0.0641	-0.0135	0.0451	0.1481	0.0678	481.5662
FORT WAYNE IN	0.8684	0.0867	-0.1411	0.0193	0.0387	0.0154	660.1483
GARY IN	1.1427	0.0296	-0.1870	0.0531	-0.0088	0.0464	670.2280
GRAND RAPIDS MI	1.1101	0.0930	0.0272	0.0330	0.0261	0.0280	662.6120
INDIANAPOLIS IN	0.7899	0.0507	-0.1022	0.0348	0.0225	0.0298	669.2469
KANSAS CITY KS MO	0.7226	0.0686	-0.0939	0.0322	-0.0057	0.0224	715.0453
LANSING MI	0.8799	0.4613	-0.0813	0.0093	0.0247	0.0093	641.3315
MADISON WI	0.1636	0.1096	-0.0404	0.0119	-0.0129	0.0093	642.4513
MILWAUKEE WI	0.5497	0.0737	-0.1488	0.0278	0.0270	0.0239	699.8976
MINNEAPOLIS WI MN	0.7646	0.0563	-0.1458	0.0255	0.0046	0.0259	678.3875
OMAHA IA NE	1.0036	0.0549	-0.1046	0.0345	0.0243	0.0296	682.0332
PEORIA IL	0.7254	0.0644	-0.1282	0.0494	0.0530	0.0394	672.7146
ROCHESTER NY	0.9994	0.1295	0.0247	0.0356	0.1038	0.0454	573.7023
ST LOUIS IL MO	0.7960	0.0311	-0.2376	0.0625	-0.0409	0.0521	722.1888
SIOUX FALLS SD	0.6666	0.3355	-0.0560	0.0062	0.0163	0.0076	490.0670
SPRINGFIELD MA	1.0528	0.2310	-0.2758	0.0219	-0.1059	0.0171	567.9967
TOLEDO OH	0.8999	0.0816	-0.1268	0.0392	0.0241	0.0311	683.2239
WICHITA KS	0.7504	0.0555	-0.2639	0.0466	0.0043	0.0352	677.4428

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the Midwest region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run income elasticity and the speed of adjustment parameters, along with the estimated standard errors. The final column shows the likelihood.

Appendix B: Macro evidence

In this appendix we show that the evidence from modelling the aggregate time series of private consumption and private disposable income goes in the same direction as the MSA results. The evidence support a log-linear cointegrating relationship, and the implied equilibrium correction involves consumption adjusting to past changes in the savings rate. The result is show to be robust to changes in the real house price index, and in the stock market index, and to the real interest rate. The main sample in this appendix in 1980q1-2007q4, i.e. the volatile 1980s and including the Great Moderation. All data series used for the aggregate macro time series are taken from the FRED data base of the St. Louis Fed. The income data measure private disposable income, while the consumption data are personal consumption expenditures. House prices are measured by the FHFA house price index. All variables are considered in real terms, and the nominal-to-real transformations are achieved by deflating by the CPI. The real interest rate is the nominal 3-month T-bill less CPI inflation. We have also collected aggregate retails sales data (similar to those used for the MSA level analysis) to explore how this alternative operationalization affects the aggregate results. While a similar robustness cannot be done with respect to the MSA analysis due to data availability, we take it as reassuring that the qualitative results from the aggregate analysis are relatively invariant to the operationalization of the consumption variable.

This data set is analyzed in B.1. In B.2 we show how the main results are affected by extendending the sample by 34 quarters, so that the Great Recession in included, with 2016(2) as the last observation.

Cointegration and modelling of aggregate savings dynamics

We tested the null hypothesis of no cointegration between aggregate c_t and y_t using a fourth order VAR , with an unrestricted constant (allowing the necessary trends in the two variables), and a restricted deterministic trend that picks up a drift in the mean of the savings rate (denoted μ above), if present. This gives the same representation of deterministic trends in the VAR as in the MSA cointegration analysis. As conditioning economic variables we include three lagged growth rates of the real house price index (ph) and of the consumer price deflated SP500 stock exchange index (sp), and the lagged level of the real interest rate (R). Hence, also this part of the aggregate VAR is consistent with the MSA data analysis.

Estimation using the the sample period 1980q1-2007q4 indicated that the VAR residuals were well behaved, with the exception of a significant non-normality test. When indicator variables were selected by the IIS algorithm in Autometrics, only one indicator variable was found, for the first observation, 1980q2. [22] Inclusion of that indicator removed the non-normality in the VAR residuals, implying that the VAR is well behaved if we remove the first observation.

The Johansen trace-statistic supported one cointegrating relationship. If we use the whole sample, it is estimated as

$$c = 0.98y + 0.0007Trend \qquad \text{(B.1)}$$

with very little change if the indicator variable is used. The corresponding α parameters (with standard errors in brackets) are: $\widehat{\alpha}_c = -0.26(0.07)$ and $\widehat{\alpha}_y = 0.16(0.1)$ indicating significant equilibrium correction in consumption change, and maybe also in income.

As already mentioned, the Trend in (B.1) was included for purpose of testing no-cointegration. Conditional on cointegration rank one, it can be removed: the test statistic is $\chi^2(1) = 0.52$ with a p-value of 0.5. Nevertheless, is of interest to test the robustness of the estimation result for α_c and α_y (our main parameters of interest) to a specification that allows for a break (rather than a smooth trend) in the mean of the savings rate. Both the time graph of the savings rate, and estimation of a regime-switching model for $c_t - y_t$ suggests a possible change in the mean of the savings rate around 1993q1. To take

[22] A significance level of 0.1 % was used, consistent with the MSA analysis.

account of a shift, we specified a step-function that reduces the unconditional expectation of the savings rate permanently by 3 percentage points, beginning in 1993q1.[23]

Using $c_{t-1} - y_{t-1} - \mu_{[T_1 T_2]}$ in the cointegrated VAR (also known as vector equilibrium model, VECM) we obtain $\widehat{\alpha}_c = -0.19(0.04)$ and $\widehat{\alpha}_y = 0.06(0.07)$, which is consistent with cointegration, and with equilibrium correction occurring in consumption rather than in income.

As noted, three lags of housing price growth and in real S&P500 are included in the VAR. They are jointly significant in the VECM as the exclusion test of $\chi^2(12) = 31.047{*}{*}$ shows.

Further interpretation is made difficult by the correlation between the VAR residuals, which is 0.33. Hence, we estimated a simultaneous equation model using FIML, which is reported in equation (B.2) and (B.3):

$$\begin{aligned}
\Delta c_t \;=\;& \underset{(0.0668)}{0.3031}\ \Delta c_{t-3} + \underset{(0.0618)}{0.06879}\ \Delta y_{t-1} - \underset{(0.0247)}{0.1794}\ ECM_{t-1} \\
&+ \underset{(0.0584)}{0.104}\ \Delta ph_{t-1} + \underset{(0.0564)}{0.04037}\ \Delta ph_{t-2} + \underset{(0.00763)}{0.01404}\ \Delta sp_{t-1} \\
&+ \underset{(0.00762)}{0.02224}\ \Delta sp_{t-2} - \underset{(0.00027)}{0.0007336}\ R_{t-1} - \underset{(0.00442)}{0.02922}\ \mathrm{I{:}1980(2)}_t
\end{aligned} \tag{B.2}$$

[23]Specifically, we subtract $\mu_{[T_1 T_2]}$ from $c_t - y_t$. $\mu_{[T_1 T_2]}$ takes one value when $t < T_1$ and $t > T_2$ and another when $(T_1, T_2) = (1_{T_1,t} + 1_{T_1+1,t} \ldots + 1_{T_2,t})$, where $1_{T_1+j,t}$ is an indicator equal to unity only when $t = T_1 + j$. T_1 is 1993q1 and T_2 is the end period of the sample.

$$
\begin{aligned}
\Delta y_t \;=\;\; & \underset{(0.206)}{0.5561}\ \Delta c_t \;+\; \underset{(0.125)}{0.3018}\ \Delta c_{t-1} \;-\; \underset{(0.0984)}{0.1662}\ \Delta y_{t-1} \\
& +\; \underset{(0.0649)}{0.144}\ ECM_{t-1} \;+\; \underset{(0.0968)}{0.06336}\ \Delta ph_{t-1} \;-\; \underset{(0.0927)}{0.1496}\ \Delta ph_{t-2} \\
& -\, \underset{(0.0121)}{0.01204}\ \Delta sp_{t-1} \;-\; \underset{(0.0127)}{0.01207}\ \Delta sp_{t-2} \;+\; \underset{(0.00042)}{0.0006469}\ R_{t-1} \\
& +\, \underset{(0.00208)}{0.005953}
\end{aligned}
\tag{B.3}
$$

To simplify the expressions we have used

$$ECM_{t-1} = c_{t-1} - y_{t-1} - \mu_{[T_1 T_2]}$$

in the two equations. The sample is the same 1980(1)-2007(4). Using the cointegrated VAR as the unrestricted reduced form, the test on the model's over-identifying restrictions is $\chi^2(13) = 10.574$ with a p-value of 0.6, so the restrictions are not rejected.

The FIML residuals are practically orthogonal, sine the correlation coefficient is -0.04. This is mainly due to the appearance of Δc_t in the income equation B.3). With the aid of that variable we can obtain a re-parameterization by subtracting Δc_t on both sides of the equality sign in B.3), so that the first part of the equation would be:

$$\text{change in savings rate} = \underset{(0.206)}{-0.44}\ \Delta c_t + \ldots$$

and the rest of the equation is unchanged. Hence, the relationship in (B.3) can be interpreted as a 'savings equation', with approximate adjustment coefficient $-(0.44 \cdot 0.18) + 0.14 = -0.21$ with respect to the past savings rate.

However, $y - c$ in our data is only an approximation to the aggregate level saving rate.[24]

[24] We use the variable PSAVERT from the FRED database (divided by 100) as the measured saving rate.

When we regressed the change in the measured personal saving rate on the exogenous variables of (B.2)-(B.3) and one lagged change, we obtained a coefficient of ECM_{t-1} of -0.19^{**}, which is well in line with the mentioned approximate -0.21 reduced form coefficient of the model. Of course, that result alone is consistent with the rainy-day hypothesis, but empirically we also find strong equilibrium correction in consumption (B.2): The t-value of $\alpha'_c = 0$ is -7.3 (the point estimate is -0.18). That result is inconsistent with the permanent income hypothesis, but consistent with the results obtained on the MSA data set. Conversely, if we, in the same reduced form, use change in income as regressand, and replace ECM_{t-1} by the lagged savings rate, the estimated coefficient is small in magnitude and it is statistically insignificant (t-value of -0.3). The lagged change in the saving rate is more significant with a t-value of -1.9. Hence, also this evidence gives only weak support to the hypothesis that the lagged values of savings will have predictive power for income.

The FIML estimated model also indicates that house prices and the stock market variables, which we have seen were significant in the cointegrated VAR, mainly "work through" the consumption function. This is confirmed in Table B.1 which shows that the two exclusion tests are significant when in the "consumption function" in (B.2), and insignificant in (B.3). The last row of the table shows that that the same is found for the lagged interest rate, it has not effect in (B.3), but is strongly significant in the δc_t equation.

The discussion in Romer (2006) showed that small (numerical) and statistically insignificant effects of the real interest rate on US consumption is a common finding. Since we use private disposable income, where non-labor income may capture the income effect of the interest rate, the negatively signed coefficient of the real interest rate is consistent with a substitution effect.

Table B.1: Exclusion test of the simultaneous equation model for the Great Moderation sample, 1980q1-2007q4

	Δc equation (B.2)	Δy equation (B.3)
Housing price change	$\chi^2(2) = 6.92^{**}$	$\chi^2(2) = 2.6$
Stock market change	$\chi^2(2) = 16.3^{**}$	$\chi^2(2) = 0.0$
Interest rate level	$\chi^2(1) = 7.4^{**}$	$\chi^2(1) = 0.0$

Note: **: Significant at 1 % level.

Robustness tests

As noted above, the results about consumption adjusting to past saving, and past saving only weakly predicting income is robust to use of the observed aggregate saving rate in the empirical system. In order to check the robustness of the aggregate modelling results we estimated the model using a sample that ends in 2016(2), which increases the number of observations by 34, including the Great Recession and after.

The estimation result for the focus parameter α_c is a little lower in magnitude, it is -0.13 but the t-value of $\alpha_c = 0$ is highly significant also on the extended sample: it is -7.9. The implied approximate adjustment coefficient for the change in the savings rate becomes -0.27, showing robustness of the result on the Great Moderation sample, which was -0.23.

Regarding the effects of the conditioning variables there are some changes, as Table B.2 shows. First, the significance of the housing market and stock market variables are *not* weakened, if anything they are more significant when data from the the Great Recession is included. Second, and in the opposite direction, the significance of the real interest rate effect seems to be lost, in particular in the consumption equation.

Table B.2: Exclusion test of the simultaneous equation model for the extended sample 1980q1-2016q2

	Δc equation	Δy equation
Housing price change	$\chi^2(2) = 27.1^{**}$	$\chi^2(2) = 5.1$
Stock market change	$\chi^2(2) = 25.4^{**}$	$\chi^2(2) = 3.0$
Interest rate level	$\chi^2(1) = 0.06$	$\chi^2(1) = 3.3$

Note: **: Significant at 1 % level.

One possible explanation for why the coefficient of the real interest rate is estimated to zero on the extended sample, may be that scope for inter temporal substitution has become reduced by raised credit constraints during and after the financial crises. However when lags of real credit change is included in the model, their estimated coefficients are small in numerical value, and statistically insignificant in both equations. The estimated coefficients of the already including variables are robust with respect to credit growth rates as conditioning variables. In particular the sensitivity of consumption to income, as measured by α_c, is numerically and statistically unaffected by the inclusion of credit growth rates as conditioning variables.

Data definitions and sources

Table B.3: The macro time series from FRED data base

Variable in FRED database	Series ID	Units
Real disposable personal income	DPIC96	Billions of Chained 2009 Dollars
Real personal consumption expenditures	PCECC96	Billions of Chained 2009 Dollars
3-month treasury bill	TB3MS	Percent
All-transactions house price index for the United States	USSTHPI	Index 1980 Q1=100
Personal saving rate	PSAVERT	Percent
Personal consumption expenditures	PCECTPI	Index 2009=100
Total population: all ages including Armed Forces Overseas	POP	Thousands
Price index for personal consumption expenditures	PCECTPI	Index
Consumer price index for all urban consumers	CPIAUCSL	Index
Total Credit to Households and Non-Profit Institutions	QUSHAMUSDA	Index

Note: https://fred.stlouisfed.org/ was accessed on 14 October 2016.

The time series y_t and c_t in the text are the natural logarithms of real disposable income and real personal consumption. Total population was used to create per capita versions of the income and consumption time series, without any notable changes in the main results.

The time series for real house price growth, Δrph_t, was constructed by extending USSTHPI back from 1974(4) to 1960(1) by CPIAUCSL. The extended nominal series was deflated by PCECTPI, and rph_t is the natural logarithm of this variable.

The real interest variable is TB3MS minus the annual rate of inflation constructed from PCECTPI.

We also made use of Retail Sales from U.S. Census Bureau. The units are million Dollars. This data was obtained from www.FreeLunch.com - http://www.economy,com/freelunch. Access date 11 November 2016, The fixed price series was obtained by deflating by PCECTPI. The S&P500 data series was downloaded from the same source.