The Buffer Stock Model and the Aggregate Propensity to Consume. A panel-data study of US States.

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[Preliminary and Incomplete]

Abstract

We simulate a buffer stock model of consumption at the individual level, aggregate, and estimate regressions on the aggregated (simulated) data. Regressions of consumption on current (or lagged) disposable labor income—using the simulated data—are used to predict the marginal effect of changing persistence of income shocks or changing aggregate uncertainty (variously defined).

Next we estimate a time series model—using observed data—for aggregate disposable labor income for each state. The model allows for varying degrees of persistence and for varying degrees of aggregate uncertainty across states. Finally, we estimate aggregate regressions of consumption on current (or lagged) income, allowing the slope in these regression to depend on persistence and or measures of uncertainty.

We find that the effect of persistence very strongly corresponds to that predicted from the model, while the impact of our aggregate measures of uncertainty matches the theoretical model less well.

KEYWORDS: Buffer stock, Consumption, Precautionary savings.
JEL CLASSIFICATIONS: E21 - Consumption; Saving,

1 Introduction

The buffer-stock model of consumption, pioneered by Deaton (1991) and Carroll (1997), is a promising candidate for replacing the Friedman (1957)-Hall (1978) Permanent Income Hypothesis (PIH) as the benchmark model of consumer behavior. We attempt here to examine if some of the positive predictions of the model hold for U.S. state-level aggregate data.[1]

Hall's (1978) paper shocked the profession by demonstrating that under simple assumptions (rational expectations, quadratic utility, a constant interest rate equal to the rate of time preference, and unlimited borrowing and lending) consumption is a martingale; i.e. a regression of the period t growth of consumption on any variable known at period $t-1$ should return an estimate of zero—regressions using aggregate data, however, consistently return an estimate significantly larger than zero when current growth in consumption is regressed on lagged aggregate income growth—a phenomenon known as "excess sensitivity" (of current consumption to lagged income). The PIH-model also gives closed form solutions to the predicted growth in consumption as a function of innovations to income when income is described by a general Auto Regressive-Moving Average (ARMA) model; for example, if income is random walk consumption is predicted to move one-to-one with income. Empirical work using aggregate data consistently finds a smaller reaction of consumption to income shocks—a phenomenon known as "excess smoothness". Ludvigson and Michaelides (2001) demonstrate that the buffer-stock model under certain conditions of incomplete information can explain at least part of the deviations from the predictions of the PIH model at the aggregate level.

Our goal is to examine how well the buffer-stock model predicts the cross-state variation in the marginal propensities to consume (MPC) out of current and past income; i.e., how well the model predicts the values of the coefficient in a regression of the period t consumption growth rate on the income growth rates in periods t and $t-1$, respectively. Rather than testing if a particular implementation of the model is literally true, we examine if the model predicts the directions in which the coefficients vary with aggregate statistics. Our approach consists of three steps.

[1]The advantage of using state data are the following: states display significant variation in the behavior of aggregate income, the data are collected in a consistent manner, and most institutional features do not vary across states making our results less likely to suffer from left-out variable bias compared to international data. Further, as argued by Ostergaard, Sørensen, and Yosha (2002) and Sørensen and Yosha (2000), the use of panel-data regressions with time-fixed effects will make the results more robust to potential biases that might obtain because the U.S. as whole is unable to borrow internationally at fixed interest rates.

First, we—for each state—estimate a process for aggregate income. State-level income growth is known to be well described by an autoregressive (AR) model of order one. Since the buffer stock model predicts that consumption behavior is different for agents that are subject to more transitory uncertainty, we generalize the process for income to be the sum of an AR-model and a temporary shock. Since we do not observe the actual temporary shocks this is an unobserved component model that we estimate by Maximum Likelihood using a Kalman filter. We find that the AR-model is sufficient for a majority of states but that some—typically agricultural—states are subject to aggregate temporary shocks.

Second, we simulate the buffer stock model for aggregate consumption by simulating individual-level consumption and explicitly aggregating. We assume that (the logarithm of) individual-level income is the sum of aggregate (state-level) income and individual-level idiosyncratic income, where we assume the latter is the sum of a random walk and a temporary shock. (This is the usual assumption in the buffer stock literature.) We further calibrate the standard deviation of the idiosyncratic random walk to have the same value as that chosen in most of the literature, although we further add the possibility of "disastrous" large independently identically distributed (i.i.d.) temporary shocks which happens with low probability. We interpret the probability of the the disastrous i.i.d. shocks as the rate of unemployment—details will be provided in Section refsec:model. We simulate the income and consumption processes for 3,000 consumers, and regress the simulated aggregate series for consumption growth on the simulated aggregate current or lagged income growth. We then repeat the simulations changing the benchmark parameters one at a time in order to examine the predicted marginal effects in empirically relevant directions. For example, we add unemployment to the benchmark model or we add temporary aggregate shocks. We tabulate these results for comparison with the consumption regressions described next. We find clear predicted effects of persistence on the marginal propensity to consume out of current and, in particular, past income. The effect of large infrequent shocks ("unemployment") is strong on the MPC out of current income and (less strongly so) on MPC out of past income. Finally, the model predicts that the standard error of the aggregate income components will affect the MPCs, in particular, if there is a high level of temporary shocks the MPC out of current income will be much lower.

Third, using the panel of U.S. states, we estimate the MPCs by regressing consumption growth on current and lagged income growth, respectively. We include state and time-specific dummy variables (fixed effects) and we allow the estimated MPCs to vary with persistence, unemployment, and aggregate uncertainty.

We find that persistence has strong effects on the marginal MPC out of current income—in the direction predicted by the buffer-stock (and the PIH) model, and on the MPC out of lagged income—also in the direction predicted by the buffer-stock (but *not* the PIH) model. However, we find only weak evidence that temporary aggregate shocks affect the MPCs. The effect of unemployment is consistent with that predicted by our model, although the estimates are not strongly significant.

The remainder of the paper is laid out as follows: Section 2 describes our data while Section 3 treats the estimation of state-level aggregate labor income. Section 4 describes the buffer stock model while Section 5 estimates panel data models for consumption and compares the estimated MPCs to the theoretical results found in Section refsec:model. Section 6 summarizes and points out directions for further research.

2 The Data

We use state-level annual data for 1976-1998 from a variety of sources. Using data from the Bureau of Economic Analysis (BEA) we construct labor income as personal income minus dividends, interest, and rent minus social security contributions. We approximate after-tax labor income by multiplying the resulting series by one minus the tax rate, where we approximate the tax rate by total personal taxes divided by personal income for each state in each year. We will refer to the resulting series as disposable labor income or—for brevity—just as labor income or income. We also, for robustness, used the BEA disposable personal income data by state. We approximate state-level consumption by state-level retail sales published in the Survey of Buying power, in Sales Management (after 1976, Sales and Marketing Management). Retail sales are a somewhat noisy proxy for state-level private consumption, but to our knowledge, it is the best available. The retail sales data are available from 1963—1998. The correlation between annual growth rates of aggregate U.S. total (nondurable) retail sales and aggregate U.S. total (nondurable and services) private consumption from the national income and product account, both measured in real terms and per capita, is 0.83 (0.49). Unemployment rates are from the Bureau of Labor and Statistics (BLS) available since 1976. We also obtained the number of employees in farming and in government from the BEA.

We transform the retail sales and labor income series to per capita terms using population data from the BEA and deflate them using the Consumer Price Index from the BLS.

3 Estimating the Process for Aggregate State Disposable Labor Income

We performed state-by-state Augmented Dickey-Fuller (ADF) tests for unit roots in labor income. These tests reject the unit root null hypothesis for only a few states, at conventional levels of significance. ADF tests provide somewhat weak evidence, since they have low power for samples as short as ours. The overall impression is, nevertheless, that the idiosyncratic component of US state-level labor income is well described as an integrated process.[2] We therefore treat labor income growth as a stationary series.

State-level income data (see Ostergaard, Sørensen, and Yosha 2002) are typically well approximated by first order autoregressive AR models of order 1. Nonetheless, some states are highly dependent on agriculture—an industry that is subject to large temporary shocks (typically weather, but also outbreaks of livestock deceases in the state—or in other locations, affecting prices). Since temporary uncertainty is important for the consumption behavior of buffer-stock savers it is potentially important to capture such temporary components of the income process and we, therefore model, state-level labor income as the sum of a "permanent component" — which follows an AR(1) model after differencing—and a "temporary component"—white noise shocks.

We assume that the growth rate of real per capita disposable labor income, $\Delta \log Y_{it}$, in state i follows the model

$$\Delta \log Y_{it} \; = \mu_i + \log G_{it} + \sigma_{Wi} \left(W_{it} - W_{it-1} \right) \, , \tag{1}$$

where W_{it} is a temporary shock (an i.i.d. variable) with variance one and σ_{Wi} is a parameter, μ_i is a state specific constant, and the permanent component of the growth rate follows the AR(1)

[2] Panel unit root tests are not attractive for these series since they are highly correlated across states. Ostergaard, Sørensen, and Yosha (2002) show that panel unit root tests for disposable income—when aggregate income is subtracted, making the data less correlated—provide little evidence against the unit root hypothesis. Disposable income is highly correlated with labor income state-by-state.

model:

$$\log G_{it} = a_i \log G_{it-1} + \sigma_{Gi}\, \epsilon_{it} \ , \tag{2}$$

where ϵ_{it} are i.i.d. mean zero innovations with variance one and σ^2_{Gi} is a parameter. The larger the parameter a_i the stronger the impact of past shocks on current income. We say that shocks are *more persistent* the larger a_i. Some states (in particular agricultural states) are subject to temporary shocks (weather, in the case of agriculture); We refer to states with a higher value of σ^2_{Wi} as states with higher "temporary uncertainty."

The model is deceptively simple, although it is known that the model will follow an ARMA(2,1) model, it is complicated to utilize that knowledge for estimations. Instead, we estimate the model by Maximum Likely, using a Kalman Filter approach that allows us to estimate the model directly allowing for the unobserved W_{it} component.

Maximum Likelihood estimation of the income processes.
Let $y_{it} = \Delta \log(Y_{it})$ denote the growth rate of state-level labor income. We apply a Kalman filter technique to evaluate the likelihood function recursively, assuming the initial observation is generated by the long-run stationary distribution implied by the model. The general workings of Kalman filters are described in econometric textbooks. In terms of the technical details we parameterize the filter in terms of a transition equation for state i of the form $x_{it} = A_i x_{i,t-1} + w_{it}$ where

$$A = \begin{pmatrix} a_i & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{pmatrix} \ ,$$

and $w_t' = (u_{it}, v_{it}, v_{it})$. The measurement equation is $y_{it} = (1,1,0)x_{it}$. Here a_i is the persistence parameter, $u_{it} = \sigma_{Gi}\epsilon_{it}$, and $v_{it} = \sigma_{Wi} W_{it}$. The remaining parts of the Kalman filter implementation are standard and we leave out the details.

Although it is fairly straight forward to estimate the model using the Kalman filter, the estimations resulted in local minima for the likelihood function for a low number of states. These local minima always were found for $\hat{\sigma}_{Wi} = 0$—since the standard deviation cannot be negative this value is at the boundary of the parameter space, a situation that sometimes complicates inference. We, therefore, hedged against local minima by performing grid-searches. Basically we chose a grid for $\sigma_{Wi} = 0$ and optimized over the remaining two parameters; this grid search revealed the likelihood function to have one global maximum and no other local maxima for all states.[3]

The results from the estimation are presented in Table 1. The estimates, $\hat{\sigma}_{Wi} = 0$, of the standard deviation of the aggregate transitory shocks is non-zero for 17 states and significant at conventional levels for only a few. However, the states with relatively large transitory shocks are typically agricultural (Iowa, Nebraska, North Dakota,....) and since our prior is that agricultural states will be subject to temporary shocks we find it important to examine if the states with a large estimated component of temporary uncertainty show different MPCs.

The parameter a_i is interpreted as a measure of persistence. Assuming for the sake of argument that $\sigma_{Wi} = 0$ then permanent income (the interest rate times the present value of the income shock plus the change in the expected value of future income) will increase one-to-one with income, while the change in permanent income will be higher the higher a_i. We find the lowest values of a_i to be around 0 for Iowa, Montana, Nebraska, North and South Dakota; while the largest value of 0.97 is found for Oklahoma followed by Hawaii with 0.76. In general, it looks like income shocks tend to be more persistent in oil-states such as Alaska and Wyoming, but, in general, we cannot conjecture what are the economic reasons behind the large differences across states.

4 Uncertainty and Aggregate Consumption in Theory

In this section, we present the specification of the buffer stock model that we use to illustrate the effects on persistence and uncertainty on aggregate consumption. The specification is standard with the exception of the income process that allows for transitory aggregate shocks (as explained before), which is not common in the literature. In order to explore the aggregate implications of the buffer stock model, we simulate it and perform explicit aggregation.

[3]We experimented with a few grid searches for the other parameters, but those all indicated that no other problems with local minima exists.

4.1 The model

Consumer j's problem is to maximize the present discounted value of expected utility from consumption of a nondurable good, C. Let $\beta < 1$ and R be the discount factor and the interest factor respectively. A is a risk-less financial asset. In period t, agent j holds past financial assets gross of interest, RA_{jt-1}, receives Y_{jt} units of income and chooses nondurable consumption, C_{jt}. The maximization problem can be written as:

$$\max_{C_{jt}} \ \mathrm{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t \, U(C_{jt}) \right\}$$
$$\text{s.t. } A_{jt} = RA_{jt-1} + Y_{jt} - C_{jt}.$$

Utility is assumed to be CRRA, $U(C_{jt}) = \frac{C_{jt}^{1-\rho}}{1-\rho}$, since for $\rho > 0$ the agent is risk-averse and has a precautionary motive for saving.

In the literature, buffer stock saving behavior has been derived from two different assumptions. Deaton (1991) explicitly imposes a no borrowing constraint ($A_{jt} > 0$) but assumes that agents always receive positive income. Carroll (1997), on the other hand, endogenously generates a no borrowing constraint by assuming that with a very small probability, p, an individual may receive zero income (a transitory disastrous state) implying that the agent will optimally never want to borrow to avoid $U'(0) = -\infty$. In this paper, we use Deaton's specification as our benchmark, with p, the probability of the disastrous state, set to zero. We also consider the case where p is different from zero and impose different lower bounds for the transitory shock. A positive lower bound may be interpreted as an income replacement program (unemployment benefit, welfare, disability payments, etc.). We will refer to the disastrous state as unemployment.

Income is assumed to be exogenous to the agent and stochastic. Notice that it is the only source of uncertainty in the model. We will assume that:

$$Y_{jt} = P_{jt} V_{jt} W_t,$$
$$P_{jt} = G_t P_{jt-1} N_{jt}.$$

Labor income Y_{jt} is the product of permanent income, P_{jt}, an idiosyncratic transitory shock, V_{jt}, and an aggregate transitory shock, W_t. G_t can be thought of as the growth in permanent income attributable to aggregate productivity growth in the economy which is common to all agents. N_{jt} is a permanent idiosyncratic shock. We assume that $\log N_{jt}$, $\log V_{jt}$ and $\log W_t$ are independent and identically distributed with mean $-\sigma_N^2/2$, $-\sigma_V^2/2$ $-\sigma_W^2/2$, and variances σ_N^2, σ_V^2 and σ_W^2 respectively.[4] $\log G_t = \mu_G + a \log G_{t-1} + u_t$ is assumed to be an $AR(1)$ process with persistence a, mean μ_G, and variance $\sigma_G^2 = \sigma_u^2/(1-a^2)$.

This formulation implies that the growth rate of individual labor income follows an MA(1) process, $\Delta \log Y_{jt} = \log G_t + \log N_{jt} + \log V_{jt} - \log V_{jt-1} + \log W_t - \log W_{t-1}$, which is consistent with the microeconomic evidence (see for example MaCurdy 1982, Abowd and Card 1989). It can be shown that under appropriate conditions, aggregate income growth can be written as $\Delta \log Y_t = \log G_t + \log W_t - \log W_{t-1}$. Note that aggregate income growth inherits the properties of the aggregate income shocks.

4.2 Solution Method and Calibration

It is well known that a closed-form solution of the model presented does not exist and one must rely on computational methods to solve it. Following Deaton (1991), the model is first reformulated in terms of cash-on-hand, $X_{jt} \equiv RA_{jt-1} + Y_{jt}$.[5] Given the homogeneity property of the utility function, all variables can be normalized by permanent income to deal with non-stationarity as proposed by Carroll (1997). The first order condition of the problem becomes:

$$U'(c_{jt}) = \max\{U'(x_{jt}), \beta R \mathrm{E}_t[(G_{t+1}N_{jt+1})^{-\rho}U'(c_{jt+1})]\}, \tag{3}$$

where $c_{jt} = C_{jt}/P_{jt}$ and $x_{j,t+1} = (G_{t+1}N_{j,t+1})^{-1}R(x_{jt} - c_{jt}) + V_{j,t+1}W_{t+1}$.[6]

Equation (3) can be solved numerically to obtain an optimal normalized consumption function for given values of the parameters of the model. In other words, the numerical technique delivers a consumption function $c(x)$: normalized consumption as a function of normalized cash on hand.[7]

[4]This guarantees that $EE_tV_{jt} = E_tV_{jt} = E_tW_t = 1$.

[5]The budget constraint becomes $A_{jt} = X_{jt} - C_{jt}$ and the liquidity constraint $C_{jt} \leq X_{jt}$. Combining the definition of cash-on-hand and the budget constraint we can write an expression for the evolution of cash-on-hand: $X_{jt+1} = R(X_{jt} - C_{jt}) + Y_{jt+1}$.

[6] A necessary condition for the individual Euler equation to define a contraction mapping is $\beta R E_t[(G_{t+1}N_{j,t+1})^{-\rho}] < 1$. This is the "impatience" condition common to buffer-stock models which guarantees that borrowing is part of the unconstrained plan.

[7]We use Euler equation iteration to solve equation (3). First x is discretized. Also, the different income shocks

Remember that in this specification of the model uncertainty arises from stochastic income alone. Obviously a good calibration of the income process is essential to obtain quantitative predictions. We use the previous estimates from state-level income data to calibrate the aggregate shocks, G and W. Idiosyncratic income shocks are taken from previous studies (see for example Carroll and Samwick 1997, Gourinchas and Parker 2001). In our benchmark calibration, we set $\rho = 2$, $\beta = 0.9524$, which implies a discount rate of 5%, $\sigma_V = 0.1$ and $\sigma_N = 0.1$, standard values in the literature. For the aggregate shocks, we start with $\sigma_W = 0$ (no aggregate transitory shocks) and $\log G_t = a \log G_{t-1} + u_t$, with $a = 0.39$, $\mu_G = 0.0165$ and $\sigma_u = 0.0265$ (the average values for our state-level income data). For the case with unemployment, we set $p = 0.03$ and consider to different replacement rates 30% of income and 0.

4.3 Consumption Functions and Simulation Results

As it is well know, under this specification, the consumption function is nonlinear. Figure 1 depicts the optimal consumption functions for a case with G assumed to be an i.i.d process and certain variations of the parameters.[8] Note that the MPC out of cash-on-hand is higher for the cash-on-hand poor. Also, in the baseline case with no unemployment, MPC out of cash-on-hand is equal to 1 while the liquidity constraint is binding. When $p > 0$ and no replacement income is allowed agents optimally choose to never borrow. The figure illustrates that when uncertainty increases (either by increasing the probability of the disastrous state from zero to $p = 0.03$, decreasing unemployment insurance or increasing the variance of the transitory shock), the consumption functions shift down because of the precautionary motive for saving. Figure 2 shows the changes in the MPC out of normalized cash-on-hand for the baseline case and the case with unemployment. The MPC is clearly higher in the baseline case for the cash-on-hand poor. More transitory uncertainty, lower MPC for the cash-on-hand poor.

Since the consumption functions are nonlinear, one must aggregate explicitly to obtain aggregate implications.[9] Moreover, since normalized consumption and cash-on-hand are not what

are approximated by 10-point discrete Markov processes à la Tauchen (1986). Interpolation is used between points in the x grid. More details on how to solve this equation can be found, for example, in the appendix of Ludvigson and Michaelides (2001).

[8] We show the i.i.d. case instead of the case with persistence of our baseline calibration because with persistence, the optimal policy function has 10-branches, one for each shock in our 10-point Markov discrete approximation of G, which will make the figure too busy to illustrate this point

[9] We simulate 3,000 consumers for 200 periods. 3,000 consumers were enough to maintain the aggregate results. We simulate 215 periods but drop the first 15 periods to guarantee that our results do not depend on the initial conditions. Using a different number of periods would change the standard error in the regressions considered

we would typically observe in aggregate data we focus on the relationship between per capita aggregate consumption and income. Using the optimal consumption functions, we calculate aggregate consumption and aggregate income as averages over consumers and report the results from the regression of consumption growth on current or lagged income growth. In particular, we run the following two regressions to determine the sensitivity of consumption to current and lagged income in our simulated data:

$$\Delta \log C_t = \mu + \alpha \Delta \log Y_t + \varepsilon_t,$$

$$\Delta \log C_t = \upsilon + \beta \Delta \log Y_{t-1} + \epsilon_t.$$

$\hat{\alpha}$ will be the estimated aggregate MPC out of current income and $\hat{\beta}$ the MPC out of lagged income.

Table 2 presents results comparing an explicitly aggregated buffer stock model to the closed-form predictions from a representative-agent PIH model (where the representative agent receives the aggregate income process). We study the effects of persistence, unemployment and changes in transitory and permanent uncertainty on the MPCs out of current and lagged income. The table presents the aggregate MPCs, the marginal effects of changing the parameters of our simulations on these MPCs as well as the average saving rate for the buffer stock model.[10] For the PIH model we only present the MPC out of current income since the MPC out of lagged income is always 0.

In our baseline simulations there are no aggregate transitory shocks and aggregate permanent shocks are assumed to be persistent. This implies that the PIH representative consumer only receives persistent permanent shocks. In this case, the PIH predicts an MPC out of current income higher than 1.[11] The predicted MPC out of lagged income is 0 because the agent is not subject to borrowing constraints and adjusts consumption immediately to income shocks. Things are different in the buffer stock model. Agents cannot borrow. Moreover, they do have some assets because of prudence but not very many due to impatience (the average saving rate

below but not the point estimates, at least not considerably.

[10]The average saving rate is defined as the average of cash-on-hand minus consumption over cash-on-hand across consumers.

[11]The MPC out current income can be calculated as:

$$\frac{cov(\Delta c_t, \Delta y_t)}{var(\Delta y_t)} = \frac{R}{R-a} \Big/ \frac{1}{1-a^2},$$

assuming that Δy_t follows an AR(1) process with persistence a.

is low 6.93%). This means that individuals cannot increase consumption as much as a PIH consumer would do when facing a persistent positive permanent shock and sensitivity to lagged income appears.

First, note that decreasing persistence to 0 lowers the MPCs out of current and lagged income in the buffer stock model but only the MPC out of current income in the PIH model. Table 2 shows that in our simulations, the marginal effect of increasing persistence on aggregate MPC out of current income is 0.95 in the PIH model while it is only 0.33 in the buffer stock model. The marginal effect of persistence on lagged income is 0 in the PIH and 0.27 in the buffer stock.[12]

We then add unemployment (a disastrous state) to our simulations. We use a probability of unemployment of 3% and consider both a case with an unemployment benefit that replaces 30% of average income and a case with no unemployment benefit. We can see that adding unemployment (which implies increasing uncertainty) decreases the MPCs in the buffer stock model due to precautionary saving (the average saving rate goes up dramatically). The decrease in current MPC (and the increase in the saving rate) is more substantial if no income-replacement program is present.[13] In the PIH model the MPCs are not affected since unemployment is modeled as a idiosyncratic phenomenon.

Next, we change uncertainty by changing the standard deviation of the different income shocks one at a time. In the PIH, these changes do not affect the MPCs but in the buffer stock model they do. We start with the idiosyncratic shocks by reducing their standard deviations by half (one at a time). Because of less uncertainty, agents should require less saving which in principle should result in higher MPCs. As we can see from the table, the average saving rate does go down. However, with persistent permanent shocks less saving implies that agents cannot adjust consumption as much as they would like to in response to a positive permanent shock. Moreover, agents are the liquidity constraint more often, resulting in a lower MPC out of current income but a higher MPC out of lagged income instead.

Finally, we introduce more aggregate uncertainty by changing the standard deviation of the

[12] These marginal effects are calculated as the change in the MPC divided by the change in the parameter that we are altering, in this case the persistence parameter: persistence is decreasing from 039, the average observed in the data, to 0, the i.i.d. case

[13] Note that in this case there is no sensitivity to lagged income growth since the agent optimally chooses not to borrow.

aggregate shocks (one at a time). We increase the standard deviation in this case.[14] More aggregate permanent uncertainty results in a higher MPC out of current income in this simulations. Since agents hold more assets because of the higher uncertainty (the saving rates goes up to 7.42%), they can also adjust more promptly to persistent positive permanent income shocks. They are also constrained less often and the MPC out of lagged income decreases slightly.

Introducing aggregate transitory uncertainty lowers both MPCs due to the precautionary saving motive. Note that in this case the MPC out of current income decreases in the PIH model as well.[15]

We must say that the purpose of these simulations is not to replicate the exact size of MPCs out of current and lagged income that we see in the data. The MPCs out of current income are much larger in our simulated data than their empirical counterparts, while the MPCs out of lagged income are generally smaller. Ludvigson (1999) and Luengo-Prado (2001) showed that introducing incomplete information and durable goods respectively can bring the MPC's for the buffer stock model closer to their empirical counterparts. In our empirical implementation, we study if differences in persistence, income variance and unemployment rates in a panel of U.S. states change MPC out of current and lagged income in the direction predicted by the buffer stock model.

5 Panel-data Estimation of the MPCs

Let $c_{it} = \Delta \log C_{it}$ denote the growth rate of state-level consumption. In our implementation we regress c_{it} on y_{it} and lagged income growth y_{it-1}, respectively. Aggregate policy and aggregate interest rates affect consumption. It is not obvious how to best capture such aggregate effects using exogenous regressors and we therefore follow Ostergaard, Sørensen, and Yosha (2002) and perform all regressions in terms of the deviations from the average value in each time period.[16] In symbols, we regress $c_{it} - \bar{c}_{.t}$ on $y_{it} - \bar{y}_{.t}$ and $y_{it-1} - \bar{y}_{.t-1}$, respectively, where $\bar{c}_{.t} = \frac{1}{N} \Sigma_{i=1}^{N} c_{it}$ is the time-specific mean of consumption growth and similarly for the other variables. Removing time-

[14] We hope this causes no confusion. For convergence reasons we decrease uncertainty when changing idiosyncratic shocks but increase uncertainty when changing the permanent shocks.

[15] Intuitively, the MPC depends only on persistence of shocks in the PIH model, so the effect of higher transitory uncertainty comes from the fact that the temporary shocks get larger relatively to the persistent shocks, thereby lowering the persistence of shocks.

[16] Empirically, it matters little if we adjust the data by subtracting average values of the variables or if we subtract aggregate values. The method chosen here is the most straightforward in terms of implementation.

specific means is equivalent to including a dummy variable for each time-period. We will refer to such time dummies as time-fixed effects, denoted ν_t, as is usual in the panel-data literature. We also want our results to be robust to differences between the states. For instance, some states may have higher consumption growth due to demographic factors that we cannot control for. We therefore also remove state specific averages; i.e., we use data in the form (for a generic variable x): $z_{it} = x_{it} - \bar{x}_{.t} - \bar{x}_{i.} + \bar{x}_{..}$, where $\bar{x}_{i.} = \frac{1}{T}\Sigma_{t=1}^{T} x_{it}$ is the state-specific mean of x and the last term is the overall average across states and time, which is added to keep the mean of z_{it} equal to 0. Using variables in this form is equivalent to including state-specific (and, as before, time-specific) dummy variables. In the language of panel-data econometrics we include a state-fixed effect (also referred to as a "cross-sectional fixed effect"). We will use the shorter panel-data econometric notation and write our regressions as

$$c_{it} = \mu_i + v_t + \alpha y_{it} + \varepsilon_{it} \ ,$$

where the μ_i terms symbolize the inclusion of cross-sectional fixed effects and the ν_t terms symbolize the inclusion of time-fixed effects. In the above regressions, α is measuring the marginal propensity to consume (MPC). The main focus of our empirical work is to examine if the MPC changes in the way predicted by theory in the face of uncertainty. If X is a variable that might affect the MPC, we examine if the MPC changes with X by estimating the regression

$$c_{it} = \mu_i + v_t + \alpha y_{it} + \zeta(X_{it} - \bar{X}_{.t})(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..}) + \varepsilon_{it},$$

where μ_i is a cross section fixed effect, v_t is a time fixed effect.

In this regression, the MPC is $\alpha + \zeta(X_{it} - \bar{X}_{.t})$, where we have subtracted the time-specific average of X_{it} in order to remove any aggregate effects. The term $\zeta(X_{it} - \bar{X}_{.t})$ is multiplied by $(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..})$ rather than just y_{it} since the inclusion of the fixed effects in the regression implies that *de facto* the term y_{it} multiplying α has the form $(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..})$ and since we are interested in how α change as a function of X, the income-term multiplying X therefore has to have that same form. We subtract the time-specific average $\bar{X}_{.t}$ from the X variable—the effect of that is that the ζ-coefficient will not pick up variations in the MPC over time. We do not subtract the state-specific average from the X variable. The whole point of the exercise is to gauge if the MPC varies across states and, indeed, many of the "X-variables" that we utilize are constant over time (and would become trivially zero if the state-specific average was subtracted).

In our implementation we will most often include more than one interaction variable and each of them will be treated as explained here. Our regressions using lagged income are done in the exact same fashion, substituting y_{t-1} for y_t everywhere.

Empirical Results.

We perform two types of panel regressions. We first examine if the aggregate MPCs vary across states that potentially have more uncertain or less uncertain labor income on average. While we do not in this paper attempt to calibrate individual level uncertainty, we conjecture that states with a (relatively) large number of farmers might display more income uncertainty than states with large numbers of government employees. We therefore use the interaction variables "farm share" (number of employed—including proprietors—in farming divided by total population of the state) and "government share" (correspondingly for government employees). Our second set of regressions utilize directly the estimated parameter values for the time series processes for each state and the results obtained can be directly compared to the theoretical simulation results tabulated earlier—these regressions serve to more directly evaluate the ability of the buffer stock model to predict the impact of aggregate uncertainty.

As a background for interpreting the panel data regressions we, in Table 3, present the correlations of our regressors: unemployment, the share of farmers in total employment, the share of government employment, and the estimated persistence and standard deviations of aggregate permanent and transitory shocks to income found in section 3. Unemployment has low correlation with the other regressors, while the share of agriculture is strongly correlated with persistence of income as well as with both parameters for aggregate uncertainty. The share of government is not highly correlated with other regressors, while persistence also is highly (negatively) correlated with the variance of the permanent shocks. Finally, we observe that there is a high positive correlation between permanent and temporary shocks.

In Table 4, we show the results of regressing consumption growth on current income in column (1). In column (2), we add unemployment and in the remaining columns we add interaction terms for Share of Agriculture and Share of Government in the state.

Empirically we found that state-level unemployment, U_{it}, strongly predicts consumption growth and we therefore include unemployment together with current and lagged income in most regressions. A (non-tabulated) panel data regression of income on lagged unemployment and lagged income reveals that current unemployment is associated with lower future income growth, so unemployment may affect current consumption because it signals higher future income (unemployment would be significant in a PIH-model because high unemployment signals lower future income) or because it affects individual level uncertainty (and thereby precautionary saving). Likely both, so we will not focus our attention on interpreting the coefficient to unemployment. However, we keep it in all regressions to guard against left-out variable bias.

The MPC from a simple regression of consumption growth on current income is 0.19. This is clearly lower than the coefficients near one found in Table 1—our benchmark version of the buffer stock model is therefore not the full truth. Before examining how the MPC varies with covariates we consider the effect of adding unemployment. The unemployment rate is highly significant and we therefore keep it in the following regressions to guard against left-out variable bias.

Our main focus is on the interaction effects.[17] In column (3), we allow the MPC to depend on unemployment but the estimated coefficient is clearly not significant. In column (4), we let the MPC depend on the share of agriculture in the state, finding a clearly significant coefficient. From column (5) we see that the MPC is clearly lower in states with a large government sector, and, finally, in column (6), we attempt to simultaneously estimate the effect of all three covariates on the MPC. Unemployment is significant in the latter regression but (confirmed by untabulated permutations of the set of regressors) the coefficient is not robustly significant and the regressions, in our interpretation, do not support a strong effect of unemployment on the MPC out of current income. The effects of agriculture and government, on the other hand, seem to estimated significantly. Those coefficients are also of a significant size in term of economic interpretation: increasing the share of government by ten percentage points is predicted to increase the MPC from about 0.1 to about 0.5! Our preliminary interpretation is that "farm states" differ due to aggregate shocks being more uncertain and less persistent—we will examine this in detail below. States with a large government sector do not seem to have particularly different dynamic behavior of aggregate labor income so our conjecture is that the significantly lower MPC has to do with lower idiosyncratic uncertainty of government employees (and suppliers). A serious attempt to verify this conjecture will, however, take us much too far afield in the present paper.

[17]Since these are based on interaction variables from an initial regression, they are obviously measured with error, which in the case of just one mismeasured regressor lead to bias towards zero—in the case of more mismeasured regressors the direction of the bias may be conjectured to be towards zero. It is fairly straightforward to adjust for these problems as is done in, for example, Kalemli-Ozcan, Sørensen, and Yosha (2003).

Table 5 examines the same specification in terms of the MPC out of lagged income ("excess sensitivity"). It appears that higher unemployment states may have higher excess sensitivity but it is obvious that this is not a robust finding. It is, however, robustly the case that farming states display lower sensitivity to lagged income, while the effect of the share of government seems robustly estimated to be negligible.

In Table 6, we examine the effect of unemployment, aggregate persistence, "permanent" and "temporary" uncertainty on the MPC out of current income. Unemployment is not near significant in any of the regressions, but because unemployment is not highly correlated with the other regressors there is no reason for leaving it out. The effect of persistence on the MPC is highly significant with an estimated coefficient that is very robust to the exact choice of specification. In column (3), we further include standard deviation of the innovation to the AR-component, σ_{Gi} (labelled "st.dev. persist. innov." in the table); in column (4), we show the results including the standard deviation of the temporary shock, σ_{Wi} (labelled "st.dev. temp. innov." in the table), together with persistence and unemployment; and in column (5), we include both parameters of aggregate uncertainty with unemployment and persistence. The results of this table reveals a very clear significant impact of persistence on the marginal propensity to consume out of current income as predicted by both the PIH and the buffer stock model. Unemployment is not significant—which may be because it is not a good measure of uncertainty—and the parameters of uncertainty seems to be too correlated with each other and with persistence so that we basically cannot identify their impact, if any, on the MPC.

In Table 7, we shift the attention to regressions on lagged income. Persistence is clearly significant with an estimated coefficient that is slightly smaller than in the regressions on current income but still large in economic terms. The effect of unemployment is also significant with robustly determined negative coefficient—comparing with Table 5, where unemployment was not significantly estimated– implying that unemployment is not robust to leaving out persistence, but since the effect of persistence is estimated robustly and precisely it seems clear that the effects of both persistence and unemployment can be considered well determined. As we find above, the data do not allow for estimating the effect of the uncertainty parameters with any robustness.

Comparing the empirical findings of the panel data estimation with the predictions of the buffer stock (and PIH) model in Table 2, we see that the buffer stock model and the data strongly agrees on a clear effect of persistency of shocks on the MPCs, with the correct sign: more persistence higher MPCs. The PIH also predicts a strong effect on the MPC out of current income but the one found out of lagged income. The estimated effect is somewhat larger than predicted by the model, though. The effect of unemployment on the MPCs is also robustly estimated and with the right sign as long as persistence is included in the regressions—as clearly it should be. Our interpretation is that the measured unemployment rate captures increases in individual level income risk beyond that capture by the aggregate uncertainty parameters. The panel data regressions were not able to pin down robust estimates of the effect of aggregate uncertainty as measured by these parameters.

All in all, our regressions notch up a quite spectacular successes for the buffer stock model in finding a clear, strongly significant, effects of persistence and unemployment on the MPC out of current and past income. Effects that are consistent with predictions of the buffer stock model.

6 Conclusion

The contributions of our paper are theoretical and empirical. Based on simulating suitably calibrated versions of the buffer stock model we document that the persistence of aggregate shocks have large effects on the marginal propensities to consume out of current and lagged shocks to labor income. We also document large effects of aggregate uncertainty and individual level uncertainty—in particular from low probability severe shocks, which we interpret as the effect of job loss.

Estimating fixed-effect panel data regressions, we showed that there could be large difference in the aggregate propensities to consume between states with different industrial structures—specifically we found much large propensities to consume in states with a large government sector than in states with a large agricultural sector. Attempting to estimate the effects of (estimated) differences in the time series properties of state-level income, we document large effects of persistence of aggregate shocks on the marginal propensities to consume—consistent with the model. Slightly less robustly, we identify large effect of unemployment on the marginal propensities to consume, which also confirm the predictions of the model. Finally, we were not able to pin down effects of aggregate uncertainty measured as the variance of innovation to state-level income. Likely, this latter non-finding is due to these estimates of uncertainty being too correlated (among themselves and with other variables).

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Table 1: Parameters of Time Series Process for State Level Disposable Income.

	(1) persistence	(2) std.dev. AR-term	(3) std.dev. Temp. shocks
Alabama	0.48 (0.15)	2.21 (0.26)	0.00 (0.68)
Alaska	0.51 (0.22)	4.05 (0.92)	0.84 (1.15)
Arizona	0.46 (0.15)	2.37 (0.28)	0.00 (0.82)
Arkansas	0.25 (0.16)	3.44 (0.40)	0.00 (1.91)
California	0.54 (0.20)	1.70 (0.35)	0.51 (0.30)
Colorado	0.46 (0.15)	1.77 (0.21)	0.00 (0.59)
Connecticut	0.43 (0.15)	2.06 (0.24)	-0.00 (0.56)
Delaware	0.46 (0.15)	2.19 (0.25)	0.00 (0.52)
Florida	0.45 (0.15)	2.30 (0.27)	0.00 (0.56)
Georgia	0.45 (0.15)	2.37 (0.28)	0.00 (0.91)
Hawaii	0.81 (0.12)	1.57 (0.35)	0.85 (0.21)
Idaho	0.32 (0.39)	2.99 (1.15)	1.46 (0.87)
Illinois	0.38 (0.25)	2.28 (0.51)	0.40 (0.82)
Indiana	0.22 (0.16)	3.27 (0.38)	0.00 (1.46)
Iowa	0.00 (0.32)	4.11 (1.72)	2.10 (1.75)
Kansas	0.27 (0.32)	2.83 (0.79)	0.27 (2.80)
Kentucky	0.30 (0.15)	2.51 (0.29)	0.00 (1.43)
Louisiana	0.47 (0.26)	1.92 (0.50)	0.42 (0.64)
Maine	0.36 (0.29)	2.53 (0.66)	0.18 (2.82)
Maryland	0.57 (0.18)	1.96 (0.38)	0.19 (0.84)
Massachusetts	0.47 (0.14)	2.15 (0.25)	0.00 (0.62)
Michigan	0.40 (0.15)	3.10 (0.36)	0.00 (0.62)
Minnesota	0.10 (0.16)	3.50 (0.41)	0.00 (4.19)
Mississippi	0.39 (0.15)	2.70 (0.31)	0.00 (0.78)
Missouri	0.26 (0.16)	2.77 (0.32)	0.00 (1.97)
Montana	-0.00 (0.22)	3.72 (0.41)	0.48 (2.24)
Nebraska	-0.17 (0.40)	4.43 (2.14)	-0.72 (7.41)
Nevada	0.43 (0.24)	2.14 (0.52)	0.75 (0.45)
New Hampshire	0.32 (0.16)	2.63 (0.31)	-0.00 (0.83)
New Jersey	0.30 (0.29)	2.13 (0.56)	0.38 (1.02)
New Mexico	0.42 (0.15)	1.93 (0.22)	0.00 (0.81)
New York	0.48 (0.23)	1.79 (0.45)	0.77 (0.33)
North Carolina	0.39 (0.15)	2.53 (0.29)	-0.00 (1.14)
North Dakota	0.00 (0.28)	8.51 (3.32)	4.56 (3.31)
Ohio	0.42 (0.15)	2.32 (0.27)	0.00 (0.65)
Oklahoma	0.78 (0.24)	1.11 (0.58)	1.11 (0.31)
Oregon	0.42 (0.22)	2.61 (0.53)	0.08 (4.72)
Pennsylvania	0.59 (0.14)	1.72 (0.20)	0.00 (0.31)
Rhode Island	0.46 (0.15)	2.05 (0.24)	0.00 (0.74)
South Carolina	0.61 (0.19)	2.01 (0.43)	0.45 (0.45)
South Dakota	0.00 (0.16)	6.08 (1.71)	-2.46 (2.11)
Tennessee	0.43 (0.15)	2.55 (0.30)	-0.00 (0.59)
Texas	0.41 (0.39)	1.94 (0.77)	0.51 (0.93)
Utah	0.53 (0.14)	1.83 (0.21)	0.00 (0.30)
Vermont	0.27 (0.16)	2.73 (0.32)	-0.00 (5.20)
Virginia	0.53 (0.16)	2.07 (0.24)	-0.00 (0.50)
Washington	0.49 (0.15)	2.03 (0.24)	-0.00 (0.56)
West Virginia	0.56 (0.18)	2.13 (0.39)	0.26 (0.66)
Wisconsin	0.46 (0.15)	2.25 (0.26)	-0.00 (0.50)
Wyoming	0.54 (0.14)	2.66 (0.31)	0.00 (0.55)

Notes: y_{it} is the log of per capita disposable income (deflated by the CPI) in state i. Model: $\Delta y_{it} = v_i + \alpha_i \Delta y_{it-1} + u_{i,t} + e_{i,t} - e_{i,t-1}$ where v_t is a time fixed effect, u_{it} is a Normally distributed iid innovation and e_{it} (an iid innovation to the level of y_{it}) is Normally distributed iid and independently of the u_{it} innovations. The Table reports the estimates of α_i in column (1), 100 times the standard deviation of u_{it} is reported in column (2), and the standard deviation of e_{it} is reported in column (3). The model is estimated by Maximum Likelihood using a Kalman Filter. Standard Errors in parentheses. Sample 1964-1998.

Table 2: Sensitivity to Current and Lagged Income in Simulated Data

	Buffer Stock					PIH	
	MPC		Marginal effect		Average Saving	MPC	Marginal effect
	Current	Lagged	Current	Lagged	Rate	Current	Current
Baseline	1.08	0.106	–	–	6.93%	1.37	–
	(0.03)	(0.080)			(0.002)		
No persistence	0.95	-0.001	-0.33	-0.27	6.63%	1	0.95
	(0.01)	(0.068)			(0.000)		
Unemployment							
Replacement	1.01	0.054	-2.05	-1.71	26.74%	1.37	0.00
	(0.03)	(0.078)			(0.00)		
No replacement	0.89	0.063	-6.12	-1.43	45.41%	1.37	0.00
	(0.03)	(0.070)			(0.003)		
More aggregate uncertainty							
$\sigma_u = 0.035$	1.10	0.103	2.39	-0.29	7.42%	1.37	0.00
	(0.02)	(0.081)			(0.002)		
$\sigma_w = 0.004$	1.05	0.099	-7.52	-1.60	6.94%	1.28	-22.50
	(0.03)	(0.079)			(0.002)		
Less Idiosyncratic uncertainty							
$\sigma_N = 0.05$	1.08	0.157	-0.01	1.02	4.50%	1.37	0.00
	(0.02)	(0.078)			(0.001)		
$\sigma_V = 0.05$	1.07	0.160	-0.09	1.09	2.25%	1.37	0.00
	(0.02)	(0.077)			(0.001)		

Reported coefficients:
α for current income from the regression: $\Delta \log C_t = \mu + \alpha \Delta \log Y_t + \varepsilon_t$.
β for lagged income from the regression $\Delta \log C_t = \upsilon + \beta \Delta \log Y_{t-1} + \epsilon_t$.
We assume that $\log \Delta Y_{jt} = \log G_t + \log W_t - \log W_{t-1} + \log N_{jt} + \log V_{jt} - \log V_{j,t-1}$, where $\log G_t = \mu_G + a_i \log G_{t-1} + u_t$. Baseline parameters: $\mu_G = 0.0165$, $\mathrm{sd}(u_t) = 0.0265$, $a_i = 0.39$. $\mu_W = 1$ and $\sigma_W = 0$; $\mu_N = \mu_V = 1$, $\sigma_N = \sigma_V = 0.1$. Regressions for 200 periods. Aggregate consumption and income are averages over 3,000 individuals. The interest rate is 2%, the discount rate is 5%. The coefficient of risk aversion $\rho = 2$ and the unemployment probability is 0. In the case with unemployment, $p = 0.03$ and the replacement rate is 30% when present. Reported averages over 100 samples. Standard errors in parentheses.

Table 3: Correlation Matrix

	U	farmsh	govt. sh	persist	std.dev. AR	std. dev. temp
U	1.00	-0.39	0.20	0.35	-0.29	-0.27
farmsh		1.00	0.05	-0.66	0.73	0.64
govt. sh			1.00	0.29	0.07	0.18
persist				1.00	-0.75	-0.40
std.dev AR					1.00	0.76
std.dev temp						1.00

Table 4: Sensitivity to Current Labor Income: Non-Durable Retail Sales

	(1)	(2)	(3)	(4)	(5)	(6)
μ_i	yes	yes	yes	yes	yes	yes
v_t	yes	yes	yes	yes	yes	yes
$\Delta \log(Y_{it})$	0.11	0.06	0.06	0.18	0.03	0.12
	(3.38)	(1.84)	(1.61)	(4.27)	(0.78)	(2.72)
U_{it}	-	–0.62	–0.62	–0.53	–0.63	–0.59
	-	(6.55)	(6.44)	(5.60)	(6.76)	(6.29)
Interaction terms:						
U_{it}	-	-	0.05	-	-	–15.31
	-	-	(0.02)	-	-	(4.10)
Farm share	-	-	-	–3.00	-	–5.11
	-	-	-	(4.00)	-	(5.27)
Govt. share	-	-	-	-	4.22	4.54
	-	-	-	-	(5.03)	(5.54)

Notes: Model: $c_{it} = \mu_i + v_t + \alpha y_{it} + \gamma U_{it} + \delta X_{it} + \zeta(X_{it} - \bar{X}_{.t})(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..}) + \varepsilon_{it}$ where μ_i is a cross section fixed effect, v_t is a time fixed effect, and X is one of the variables vol. of income (interaction term only), share of farm employment, inequality, or unemployment (interaction term only), resp. t-statistics in parentheses. Sample 1976–1998

Table 5: Sensitivity to Lagged Labor Income: Non-Durable Retail Sales

.

	(1)	(2)	(3)	(4)	(5)	(6)
μ_i	yes	yes	yes	yes	yes	yes
v_t	yes	yes	yes	yes	yes	yes
$\Delta \log(Y_{it})$	0.14	0.11	0.15	0.23	0.10	0.22
	(3.83)	(3.05)	(3.74)	(4.48)	(2.67)	(4.25)
U_{it}	-	–0.63	–0.58	–0.54	–0.63	–0.53
	-	(6.62)	(5.94)	(5.50)	(6.61)	(5.45)
Interaction terms:						
U_{it}	-	-	6.78	-	-	0.14
	-	-	(2.28)	-	-	(0.04)
Farm share	-	-	-	–2.64	-	–2.67
	-	-	-	(3.17)	-	(2.44)
Govt. share	-	-	-	-	1.18	1.29
	-	-	-	-	(1.00)	(1.07)

Notes: Model: $c_{it} = \mu_i + v_t + \alpha y_{it} + \gamma U_{it} + \delta X_{it} + \zeta(X_{it} - \bar{X}_{.t})(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..}) + \varepsilon_{it}$ where μ_i is a cross section fixed effect, v_t is a time fixed effect, and X is one of the variables vol. of income (interaction term only), share of farm employment, inequality, or unemployment (interaction term only), resp. t-statistics in parentheses. Sample 1976–1998

Table 6: Sensitivity to Current Income: Non-Durable Retail Sales

	(1)	(2)	(3)	(4)	
μ_i	yes	yes	yes	yes	yes
v_t	yes	yes	yes	yes	yes
$\Delta \log(Y_{it-1})$	0.31	0.31	0.29	0.28	0.27
	(6.08)	(6.16)	(5.57)	(5.26)	(5.12)
U_{it}	–0.46	–0.46	–0.46	–0.46	–0.46
	(4.73)	(4.78)	(4.78)	(4.79)	(4.81)
Interaction terms:					
U_{it}	-	–3.92	–3.06	–2.57	–2.42
	-	(1.07)	(0.82)	(0.69)	(0.65)
persistence	0.85	0.98	1.19	1.20	1.03
	(5.44)	(4.99)	(4.63)	(5.14)	(3.78)
st.dev. persist innov.	-	-	2.51	-	–7.04
	-	-	(1.27)	-	(1.20)
st.dev. temp. innov.	-	-	-	4.36	12.69
	-	-	-	(1.76)	(1.72)

Notes: Model: $c_{it} = \mu_i + v_t + \beta y_{i,t-1} + \gamma U_{it} + \delta X_{it} + \zeta(X_{it} - \bar{X}_{.t})(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..}) + \varepsilon_{it}$ where μ_i is a cross section fixed effect, v_t is a time fixed effect, and X is one of the variables vol. of income (interaction term only), share of farm employment, inequality, or unemployment (interaction term only), resp. t-statistics in parentheses.

Table 7: Sensitivity to Lagged Income: Non-Durable Retail Sales

	(1)	(2)	(3)	(4)	
μ_i	yes	yes	yes	yes	yes
v_t	yes	yes	yes	yes	yes
$\Delta \log(Y_{it-1})$	0.17	0.17	0.18	0.18	0.19
	(3.72)	(3.76)	(3.73)	(3.86)	(4.00)
U_{it}	–0.55	–0.56	–0.56	–0.57	–0.60
	(5.72)	(5.85)	(5.85)	(5.94)	(6.18)
Interaction terms:					
U_{it}	-	–7.54	–8.01	–8.47	–8.32
	-	(2.07)	(2.15)	(2.27)	(2.21)
persistence	0.46	0.68	0.58	0.51	0.73
	(3.30)	(3.86)	(2.72)	(2.51)	(3.22)
st.dev. persist innov.	-	-	–1.18	-	10.62
	-	-	(0.67)	-	(2.04)
st.dev. temp. innov.	-	-	-	–3.16	–15.80
	-	-	-	(1.40)	(2.38)

Notes: Model: $c_{it} = \mu_i + v_t + \beta y_{i,t-1} + \gamma U_{it} + \delta X_{it} + \zeta(X_{it} - \bar{X}_{.t})(y_{it} - \bar{y}_{.t} - \bar{y}_{i.} + \bar{y}_{..}) + \varepsilon_{it}$ where μ_i is a cross section fixed effect, v_t is a time fixed effect, and X is one of the variables vol. of income (interaction term only), share of farm employment, inequality, or unemployment (interaction term only), resp. t-statistics in parentheses.

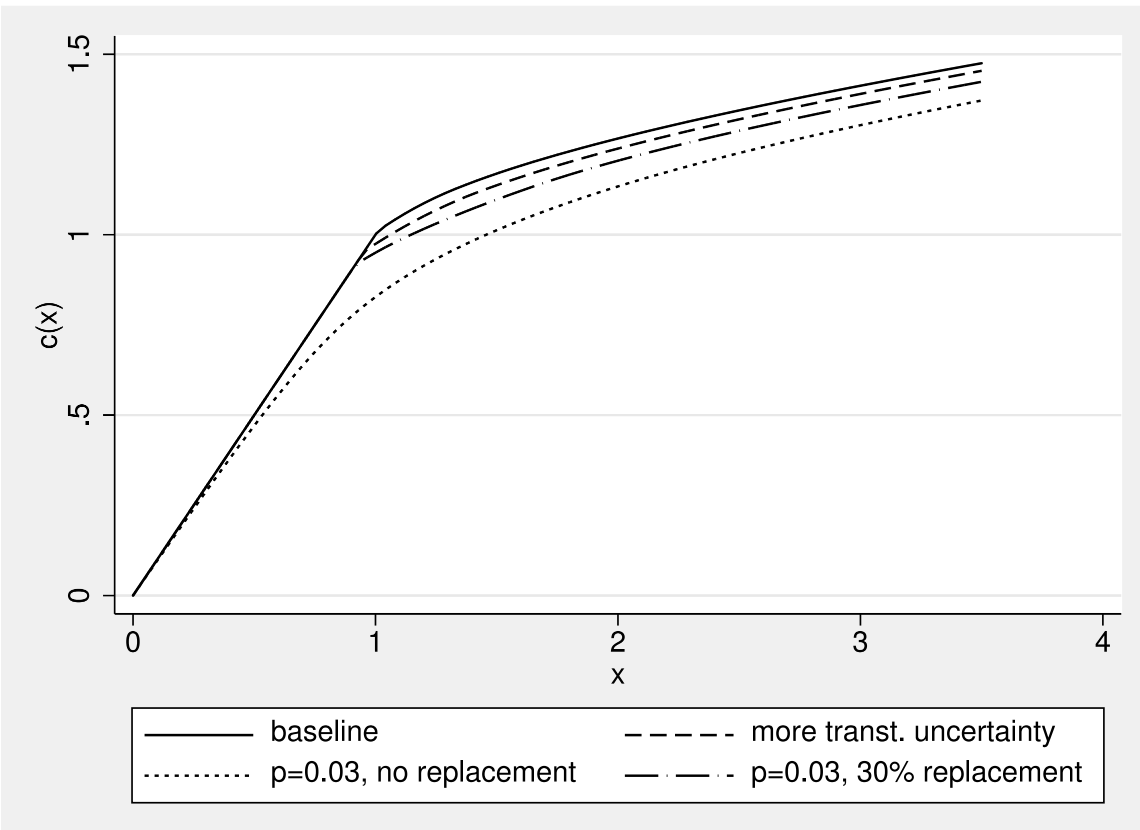

Figure 1: Consumption Functions

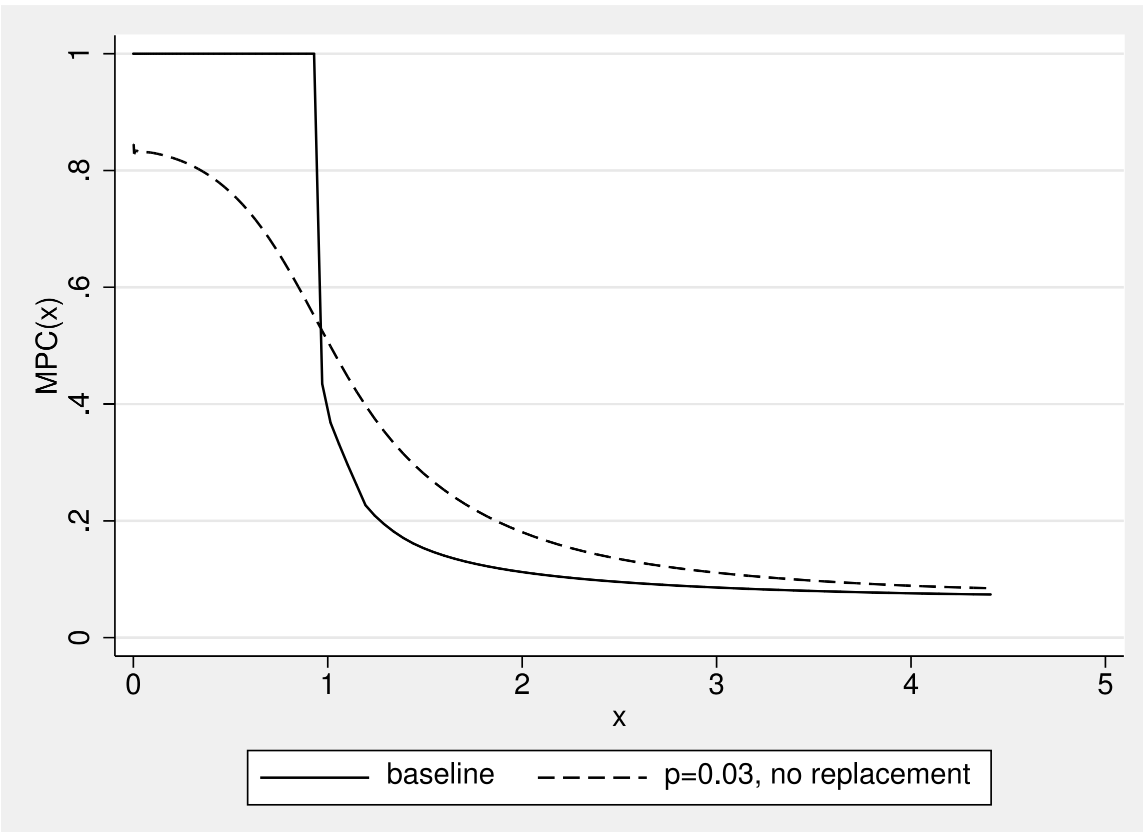

Figure 2: Marginal Propensity to Consume

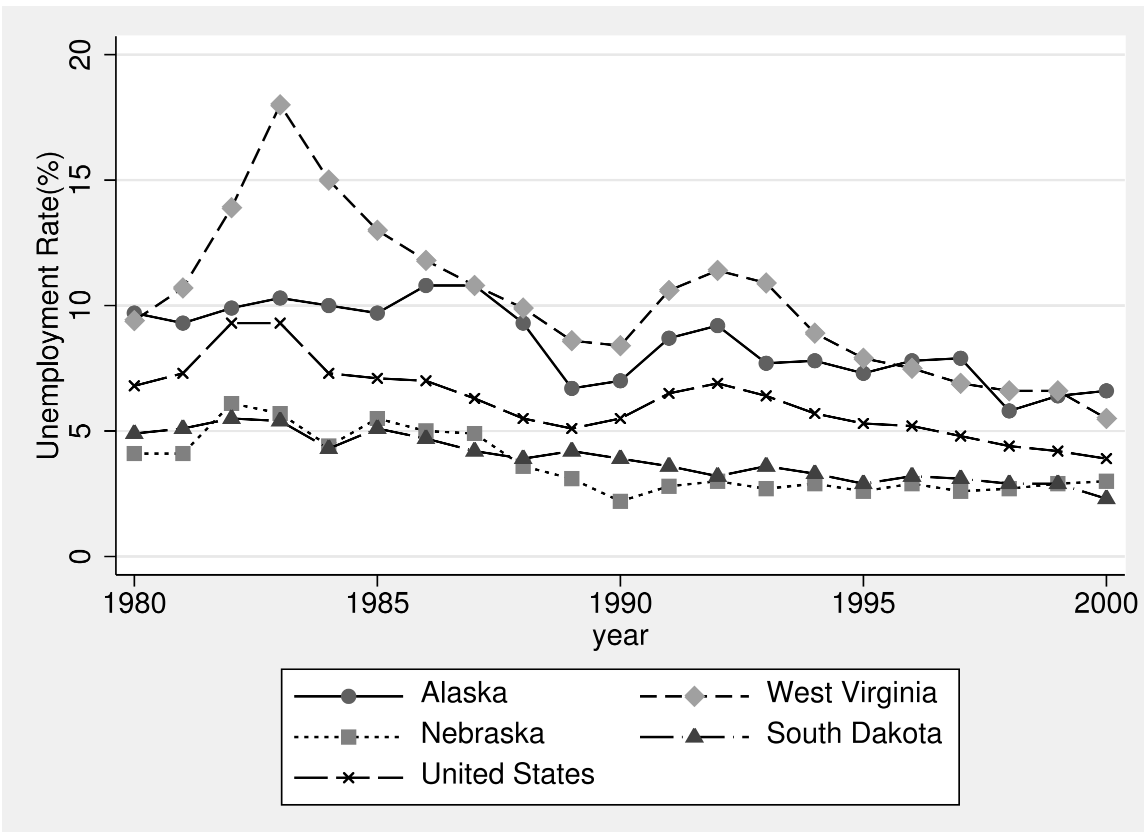

Figure 3: Unemployment Rate