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Revisiting the Empirical Inconsistency of the Permanent Income Hypothesis: Evidence from Rural China[#]

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Abstract

Chow (1985) reports strong evidence in favor of the permanent income hypothesis (PIH) using observations from 1953 to 1982 in China. We revisit this issue with rural area household data in China during the post economic reform regime (1978-2009) as well as the postwar US data for comparison. Our in-sample analysis provides strong evidence against the PIH for both countries. Out-of-sample forecast exercises also reveal that consumption changes are highly predictable. Our vector autoregressive (VAR) model analysis also shows significantly positive responses of consumption to income shocks, and non-negligible proportions of variations in consumption are explained by innovations in income.

Keywords: Permanent Income Hypothesis; Consumption; Generalized Method of Moments; Diebold-Mariano-West Statistic; Vector Autoregressive

JEL Classification: E21; E27

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1 Introduction

The permanent income hypothesis (PIH), proposed by Friedman (1957) and restated by Darby (1974) implies that consumption is largely determined by the annuity value of one's lifetime resources.[1] The PIH has been examined by an array of researches, to name a few, Hall (1978), Flavin (1981), Campbell and Mankiw (1990), Sommer (2007), and Carroll, Slacalek, and Sommer (2011), which often finds mixed evidence of the PIH.[2]

The PIH implies that consumption obeys a random walk process (or a martingale process with i.i.d. noise) under quite general framework (Hall, 1978). Put it differently, consumption changes are not predictable. Campbell and Mankiw (1990) empirically test this claim by employing an instrumental variables estimation method, which provides strong, but indirect evidence against the PIH.

In his early study, Chow (1985) reported strong evidence in favor of the PIH using annual observations in China from 1953 to 1982. This paper revisits this issue by investigating the predictability of consumption changes for rural area household data in China as well as the postwar US data for comparison. We use samples from 1978 to

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[1] Wang (2006) proposes a generalized version of the PIH.

[2] Attfield (1980) and Ermini (1993), among others, reported favorable evidence of the PIH when transitory income or measurement error problems are taken care of in the model. DeJuan and Seater, and Wirjanto (2004) and DeJuan and Seater (2007) also find some supporting evidence. Kim (1996) argues that the PIH approximates the postwar US consumption data fairly well. Engsted (2002), however, finds weaker evidence of the PIH when he uses an alternative test to Kim's (1996).

2009, omitting all observations before 1978 when China implemented economic reform toward a market-oriented economy.

We use rural China data excluding urban consumers, because rural consumers have been a dominant majority. About 82% of the consumers resided in rural areas in 1978. Although substantial migration toward urban areas began since 2000, rural consumers maintained the majority even in 2009. Further, the population structure in rural areas is a lot more stable than those in urban areas.

We employ not only the in-sample analysis framework by Campbell and Mankiw (1990) but also out-of-sample forecast exercises using the Diebold-Mariano-West test (Diebold and Mariano, 1995; West, 1996), which is a direct test for predictability of changes in consumption.[3] We obtain very weak evidence of the PIH especially from rural China compared with results from the US.

We further investigate dynamic implications of the PIH on consumption changes over time via the vector autoregressive (VAR) model analysis. We obtain stronger responses of consumption to income shocks in rural China than those from the US data. We also find that income shocks in rural China contribute more to variations in future consumption, while we find a lot weaker contributions of income shocks in the US.

[3] For similar out-of-sample forecast exercises in OECD countries, see Everaert and Pozzi (forthcoming).

The rest of the present paper is organized as follows. Section 2 provides a data description and preliminary test results. In Section 3, we provide our main empirical findings from in-sample and out-of-sample tests. Section 4 presents dynamic aspects of the PIH via a VAR model. Section 5 concludes.

2 Data and Preliminary Analysis

We obtain per capita disposable income (y_t) and consumption expenditure (c_t) of rural households from China Statistical Yearbook (2010). Observations are annual and span from 1978 to 2009. China began their major economic reforms since 1978, so observations prior to 1978 are not used. Per capita disposable income and consumption expenditures of nondurables and services in the US are from the Federal Reserve Bank of St. Louis (FRED). The data is quarterly and covers the period from 1952:Q1 to 2011:Q4. We deflate the data using the consumer price index in each country and all data are expressed in natural logarithms.

We first present two scatter plot diagrams of ΔC_t and ΔY_t in each country in Figure 1. If ΔC_t is not predictable, as the PIH implies (e.g., Hall, 1978; Campbell and Mankiw, 1990), one should not find any strong systematic pattern from these diagrams, because the consumption responds only to the extent that there is a change in permanent income. We find a clearly positive relation in both diagrams, which may be at odds with the PIH.

Insert Figure 1 about here

We next implement the augmented Dickey-Fuller (ADF) test for these variables to make sure that our instrument and/or explanatory variables are valid. Results are reported in Table 1.

We chose the number of lags by the Akaike Information Criteria with a maximum 8 and 2 lags, for the US (quarterly) and rural China (annual), respectively. The ADF test rejects the null of nonstationarity only for differenced series with an exception of Y_t in rural China, which may imply a trend stationary process. Overall, our test results imply that consumption and income are integrated series.

Insert Table 1 about here

3 Empirical Findings

3.1 In-Sample Analysis

Campbell and Mankiw (1990) test the empirical validity of Hall's (1978) famous claim that consumption follows a random walk process under the PIH. They assume that a constant fraction of consumers (λ) does not obey the PIH, because they are liquidity constrained, therefore are not capable of smoothing consumption over time.[4] For these consumers, consumption changes should simply reflect income changes, that is, $\Delta C_t = \Delta Y_t$. For the rest of consumers, type 2 consumers, we assume that their consumption is consistent with the PIH, which implies $\Delta C_t = \varepsilon_t$. Aggregating consumptions yields the following estimable equation.

$$\Delta C_t = \lambda \Delta Y_t + u_t, \qquad (1)$$

where $u_t = (1-\lambda)\varepsilon_t$. Campbell and Mankiw (1990) report significantly positive λ estimate using the US data for 1953 to 1986, which implies strong evidence against the PIH. Similarly strong evidence is also reported by Flavin (1981).

We employ Campbell and Mankiw's method for the rural China data. To deal with the Endogeneity bias in (1), we use the iterative efficient Generalized Method of Moments (GMM) estimation method (Hansen, 1982) and report a formal specification test results in Table 2.[5] We also report similar estimates from the US data for 1952 to 2011 in Table 3.

The first column provides sets of instrumental variables used in each regression.[6] The second column reports λ estimates along with their robust standard

[4] They may not be able to access to the credit market because they are not wealthy enough.
[5] Campbell and Mankiw (1990) use the instrumental variable estimator, which is a special case of the GMM, and they didn't report a formal specification test.
[6] Following Campbell and Mankiw (1990), we do not use first lagged variables, because the US data is quarterly and first lagged variables are still likely to be correlated with errors.

errors. The third column reports specification test results along with the p-value of each J test statistic.

As we can see in Tables 2 and 3, all λ estimates are positive and statistically significant at the 5% level, which provides strong empirical evidence against the PIH. Our model specification seems reasonable as the p-value of the J test statistics is less than 0.05 in all regressions.

We also note that the λ estimates are overall bigger in rural China compared with those of the US. The value varies from 0.611 to 0.879 in China, while it ranges from 0.287 to 0.769 in the US. This seems plausible because λ is a fraction of liquidity constrained consumers and households in rural China are more likely to be such consumers.

Insert Tables 2 and 3 about here

3.2 Out-of-Sample Predictability

We next implement a more direct test for the PIH via the out-of-sample forecast test proposed by Diebold and Mariano (1995) and West (1996). We evaluate predictability of lagged variables for consumption changes relative to that of the random walk model, which is consistent with the PIH (Hall, 1978), serving as a benchmark. The test is implemented as follows.

The random walk model of C_t implies,

$$C^R_{t+1|t} = C_t, \tag{2}$$

where $C^R_{t+1|t}$ is the *1*-step ahead consumption forecast by the random walk model given information set at time *t*. The competing model using a vector of lagged variables as the explanatory variables (X_t) is based on the following least squares regression

$$\Delta C_{t+1} = \beta' \Delta X_t + u_t \tag{3}$$

Note that we use difference filter for the consistency of the least squares estimator. Given the least squares coefficient estimate, we construct the *1*-step ahead forecast by such an alternative model $C^A_{t+1|t}$ as follows.

$$C^A_{t+1|t} = \Delta\widehat{C_{t+1}}_{|t} + C_t, \tag{4}$$

where $\Delta\widehat{C_{t+1}}_{|t}$ is the fitted value from (3) and C_t is the actual realized observation at time t.

We obtain the following loss function,

$$d_t = L(\varepsilon^R_{t+1|t}) - L((\varepsilon^A_{t+1|t}),$$

where $L(\varepsilon^j_{t+k|t})$, $j = R, A$ is a loss function and forecast errors are,[7]

[7] We use the conventional squared error loss function, $(\varepsilon^j_{t+1|t})^2$, $j = R, A$.

$$\varepsilon^R_{t+1|t} = C_{t+1} - C^R_{t+1|t}, \qquad \varepsilon^A_{t+1|t} = C_{t+1} - C^A_{t+1|t}$$

The Diebold-Mariano-West statistic (*DMW*) with the null of equal predictive accuracy, $H_0\colon Ed_t = 0$, is given,

$$DMW = \frac{\bar{d}}{\sqrt{\widehat{Avar}(\bar{d})}} \qquad (5)$$

where $\bar{d} = \frac{1}{T - T_0}\sum_{t=T_o+1}^{T} d_t$, and $\widehat{Avar}(\bar{d})$ is the asymptotic variance of $\bar{d}$, $\frac{1}{T - T_0}\sum_{j=-q}^{q} k(j,q)\hat{\Gamma}_j$, where $k(\cdot)$ denotes a kernel function where $k(\cdot) = 0$, $j > q$, and $\hat{\Gamma}_j$ is the j^{th} autocovariance function estimate.[8] Since the DMW statistic is severely under-sized with asymptotic critical values when competing models are nested, we use critical values by McCracken (2007) to correct it.[9]

We carried out forecasting recursively by sequentially adding one additional observation from P percent initial observations toward the end of observations. We re-estimate coefficients (β) for each recursive sample. The ratio of the root mean square prediction error (*RRMSPE*) is defined as the root mean square error of the random walk model relative to that of the competing model. Therefore, a greater value of *RRMSPE* than one implies some evidence against the PIH, because the explanatory variables have predictive power. We seek for more rigorous evidence via the *DMW* statistics with McCracken's (2007) critical values.

[8] Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.
[9] Note that the alternative model nests the random walk model when β is a null vector.

We report out-of-sample forecast exercise results in Tables 4 and 5 for rural China and the US, respectively. All *RRMSPE* values exceed one for both rural China and the US. We reject the null of equal predictability of the *DMW* test at any conventional significance level. Our results are quite robust to size of initial split ratio.[10] Again, we obtain very strong empirical evidence against the PIH via more direct out-of-sample forecast analysis.

Insert Tables 4 and 5 about here

4 Vector Autoregressive Analysis

4.1 Impulse-Response Function

We supplement our analysis on the predictability of consumption changes by the vector autoregressive (VAR) model analysis. That is, we propose the following conventional VAR model for the consumption and income growth rates.

$$x_t = A(L)x_{t-1} + B\epsilon_t, \tag{6}$$

where $x_t = [\Delta Y_t, \Delta C_t]'$, B is a lower-triangular matrix, and ϵ_t is a vector of orthogonalized structural income and consumption shocks. The shape of B implies that

[10] The forecast performance may depend of the size of initial number of observations used in the estimation relative to the remaining observations for evaluations. That is, if one uses the first half observations for estimation, the split ratio is 0.5. We report results with three split sizes in each Table.

income is not contemporaneously affected by unexpected consumption changes. We used two lags by the Akaike Information Criteria and construct nonparametric bootstrap confidence bands from 5,000 bootstrap simulations using empirical distributions. We report the accumulated responses of the level variables, Y_t and C_t, to each structural shock in Figure 2.

Note that Hall's (1978) extension of the PIH predicts that consumption responds to income changes only by the extent of the change in permanent income. In rural China, consumption increases about 0.5% at the impact when there is a 1% income shock. After growing rapidly for about two years, consumption growth slows down and stabilizes to around 2% overall increase from the beginning. Similar but a lot weaker responses are observed in the US, which implies stronger evidence against the PIH in rural China. We also note that the response function estimates are significant at the 5%.

We observe that income negatively responds to a consumption shock, which is insignificant at the 5% but significant at the 10% (not reported here) in rural China. On the other hand, significantly positive responses are observed for the US. That is, unexpectedly high consumption growth rates in rural China may reduce their income over time, which may happen if economic capacity shrinks as the saving declines. On the contrary, consumption is a virtue, not a vice, in the US.

Insert Figure 2 here

4.2 Variance Decomposition Analysis

We next implement the variance decomposition analysis to illustrate how much variations of consumption changes in the future can be explained by exogenous shocks to each variable. Results are reported in Tables 6 and 7, for rural China and the US, respectively.

We again observe very different patterns. In rural China, both income shocks and consumption shocks play virtually equally important roles in explaining future changes in consumption. In the US, a little less than 25% contributions of income shocks are observed for all time horizons we consider. These findings imply a weaker evidence of the PIH in rural China compared with the US, while we fail to see strong empirical evidence of the PIH in any of these countries.

Insert Tables 6 and 7 about here

5 Concluding Remarks

This paper revisits the empirical inconsistency of the Permanent Income Hypothesis using rural area household data in China along with the postwar US data as a benchmark. We view rural area residents as representative consumers in China since this group of consumers has been a dominant majority until recently. Further, rural China and the US make good contrasting groups of consumers. We present strong evidence against the PIH in contrast to the work by Chow (1985) who reported favorable evidence using mostly the pre-economic overhaul regime data.

Our in-sample analysis based on Campbell and Mankiw (1990) implies a lot weaker evidence in favor of the PIH when the rural China data is used instead of the US data. The λ point estimate ranges from 0.611 to 0.879 for rural China, while much smaller values were obtained when we use the US data, which seem reasonable because λ is a fraction of consumers who are liquidity constrained.

Our out-of-sample forecasting exercises directly deal with the predictability issue from the PIH. We obtain very strong results against the PIH in the sense that explanatory variables have substantial predictive contents for consumption growth, which is robust to the choice of sample split.

Our dynamic analysis with VAR framework also provides empirical results that are consistent with previous findings. Consumption responds to an income shock highly significantly in both countries, but we observed a lot stronger responses from rural China than the US. The variance decomposition analysis shows that roughly 50% of consumption changes are explained by income shocks in rural China, while income shocks explain less than 25% in the US.

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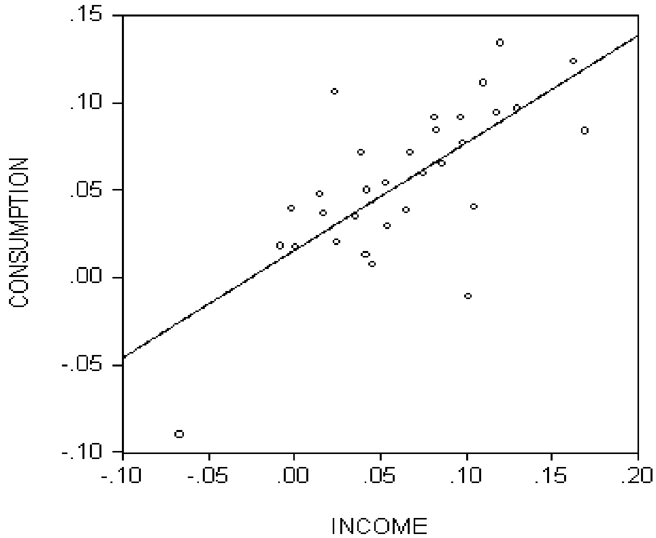
Figure 1. Scatter Plot Diagrams of ΔC_t and ΔY_t

(a) Rural China



(b) US

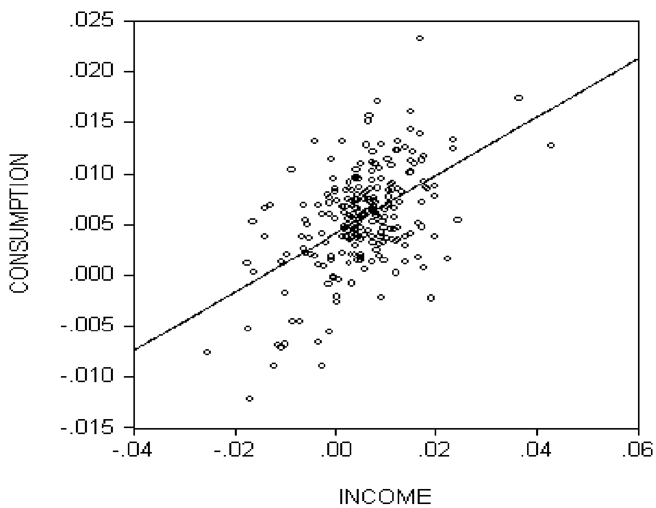
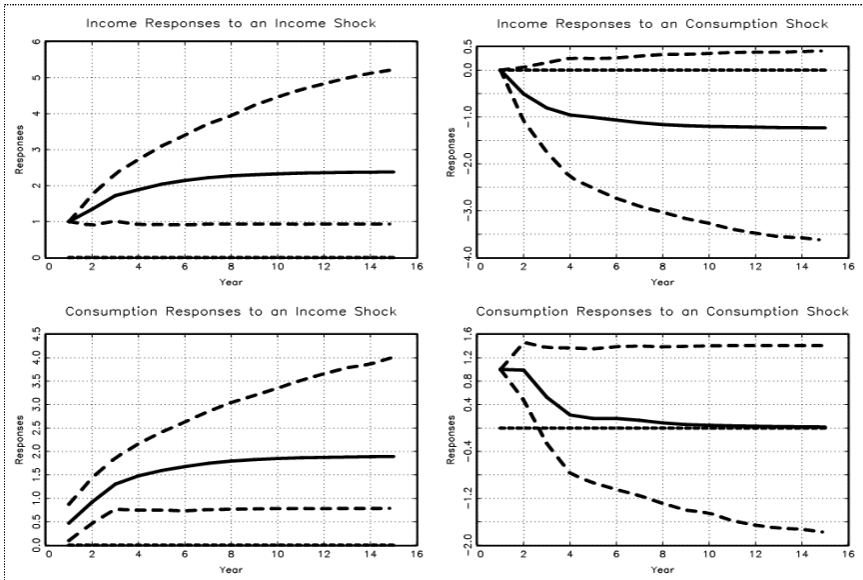
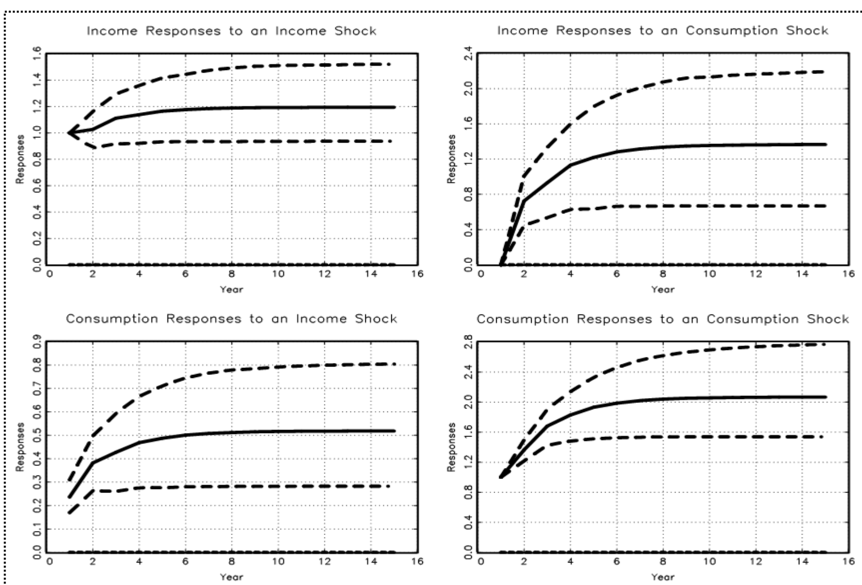


Figure 2. Orthogonalized Impulse Response Function Estimates

(a) Rural China



(b) US



Note: 95% confidence bands are constructed by 5,000 nonparametric bootstrap simulations. ΔY_t is ordered first so that it is not contemporaneously affected by innovations in ΔC_t. Responses are accumulated to make statistical inferences on the level variables, Y_t and C_t, instead of the growth variables.

Table 1. ADF Test Results

Rural China

Variable	ADF_c	ADF_t
C_t	0.053	-2.113
Y_t	-0.166	-3.438*
ΔC_t	-3.553*	-3.474†
ΔY_t	-3.342*	-3.170†

US

Variable	ADF_c	ADF_t
C_t	-1.839	-0.688
Y_t	-2.093	-0.503
ΔC_t	-4.966*	-5.280*
ΔY_t	-9.416*	-14.62*

Note: ADF_c and ADF_t denote the ADF t-statistic with an intercept and with an intercept and time trend, respectively. We chose the number of lags by the Akaike Information Criteria with a maximum 8 lags for quarterly US data, while a maximum 2 lags were used for annual rural China data.

Table 2. GMM Estimation Results: Rural China

Instruments (Z)	λ (s.e.)	J (p-value)
None (OLS)	0.730 (0.092)	
$\Delta Y_{t-1}, \Delta Y_{t-2}$	0.731 (0.163)	0.908 (0.341)
$\Delta Y_{t-1}, \ldots, \Delta Y_{t-4}$	0.611 (0.245)	3.257 (0.354)
$\Delta C_{t-1}, \Delta C_{t-2}$	0.766 (0.140)	2.322 (0.128)
$\Delta C_{t-1}, \ldots, \Delta C_{t-4}$	0.730 (0.235)	4.070 (0.254)
$\Delta Y_{t-1}, \Delta Y_{t-2}, \Delta C_{t-2}, \Delta C_{t-2}$	0.778 (0.118)	2.831 (0.418)
$\Delta Y_{t-1}, \ldots, \Delta Y_{t-4}, \Delta C_{t-1}, \ldots, \Delta C_{t-4}$	0.879 (0.133)	5.409 (0.610)

Note: Annual observations span from 1978 to 2009. This table reports iterative efficient GMM estimates of $\Delta C_t = \lambda Y_t + u_t$, using an array of instrumental variables Z. Numbers in parentheses in column 2 are standard errors for the λ estimate. Numbers in parentheses in column 3 are p-values for the J-test statistic that follows the chi-square distribution. All λ estimates are significant at the 5% level. The J-test supports the specification of our model at any conventional significance levels.

Table 3. GMM Estimation Results: US Nondurable and Services

Instruments (Z)	λ (s.e.)	J (p-value)
None (OLS)	0.287 (0.045)	
$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	0.769 (0.282)	1.240 (0.538)
$\Delta Y_{t-2}, \ldots, \Delta Y_{t-6}$	0.447 (0.157)	4.989 (0.288)
$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	0.628 (0.137)	5.885 (0.053)
$\Delta C_{t-2}, \ldots, \Delta C_{t-6}$	0.664 (0.132)	8.291 (0.082)
$\Delta Y_{t-2}, \ldots, \Delta Y_{t-4}, \Delta C_{t-2}, \ldots, \Delta C_{t-4}$	0.487 (0.112)	9.902 (0.078)
$\Delta Y_{t-2}, \ldots, \Delta Y_{t-6}, \Delta C_{t-2}, \ldots, \Delta C_{t-6}$	0.505 (0.094)	13.06 (0.160)

Note: Observations are quarterly and span from 1952:Q1 to 2011:Q4. This table reports iterative efficient GMM estimates of $\Delta C_t = \lambda Y_t + u_t$, using an array of instrumental variables Z. Numbers in parentheses in column 2 are standard errors for the λ estimate. Numbers in parentheses in column 3 are p-values for the J-test statistic that follows the chi-square distribution. All λ estimates are significant at the 5% level. The J-test supports the specification of our model at the 5% significance level.

Table 4. Out-of-Sample Forecast: Rural China

Split Ratio	Explanatory Variables	*RRMSPE*	*DMW*
0.50	ΔY_t	1.6670	6.4453*
	$\Delta C_{t-1}, \Delta C_{t-2}$	1.5121	5.5638*
	$\Delta Y_{t-1}, \Delta Y_{t-2}$	1.6606	6.5673*
	$\Delta C_{t-1}, \Delta C_{t-2}, \Delta Y_{t-1}, \Delta Y_{t-2}$	1.6377	5.3142*
0.66	ΔY_t	1.8764	7.1839*
	$\Delta C_{t-1}, \Delta C_{t-2}$	1.6249	10.288*
	$\Delta Y_{t-1}, \Delta Y_{t-2}$	1.7243	9.3049*
	$\Delta C_{t-1}, \Delta C_{t-2}, \Delta Y_{t-1}, \Delta Y_{t-2}$	1.7647	10.931*
0.81	ΔY_t	1.9118	10.956*
	$\Delta C_{t-1}, \Delta C_{t-2}$	1.5886	11.565*
	$\Delta Y_{t-1}, \Delta Y_{t-2}$	1.6889	29.985*
	$\Delta C_{t-1}, \Delta C_{t-2}, \Delta Y_{t-1}, \Delta Y_{t-2}$	1.7863	16.006*

Note: Out-of-sample forecasting was recursively implemented by sequentially adding one additional observation from *P*% initial observations toward the end of observations. Split ratio denotes the number for *P*, that is, 0.66 implies that 66% initial observations are used to start recursive forecasting. *RRMSPE* denotes the ratio of the root mean squared prediction error of the random walk hypothesis to the competing model. *DMW* denotes the test statistics of Diebold and Mariano (1995) and West (1996). * denotes rejection of the null hypothesis of equal predictability at the 1% significance levels.

Table 5. Out-of-Sample Forecast Analysis: US

Split Ratio	Explanatory Variables	*RRMSPE*	*DMW*
0.50	ΔY_t	1.8411	10.322*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	2.0158	10.806*
	$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.9177	10.602*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4} \Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	2.0068	10.642*
0.65	ΔY_t	1.7986	9.8501*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	2.0615	10.660*
	$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.8993	9.9372*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4} \Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	2.0824	10.892*
0.81	ΔY_t	1.4856	5.4806*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	1.7480	6.9882*
	$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.5825	5.9971*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4} \Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.7572	7.1435*

Note: Out-of-sample forecasting was recursively implemented by sequentially adding one additional observation from *P*% initial observations toward the end of observations. Split ratio denotes the number for *P*, that is, 0.66 implies that 66% initial observations are used to start recursive forecasting. *RRMSPE* denotes the ratio of the root mean squared prediction error of the random walk hypothesis to the competing model. *DMW* denotes the test statistics of Diebold and Mariano (1995) and West (1996). * denotes rejection of the null hypothesis of equal predictability at the 1% significance levels.

Table 6. Variance Decomposition of $\hat{E}_t(\Delta C_{t+k})$: Rural China

k	Income	Consumption	Standard Error
1	68.165	31.834	0.0312
2	52.974	47.025	0.0354
3	50.480	49.519	0.0400
4	50.916	49.083	0.0413
5	50.465	49.534	0.0415
6	50.187	49.812	0.0416
7	50.003	49.996	0.0417
8	49.943	50.057	0.0418
9	49.917	50.082	0.0418
10	49.903	50.096	0.0418

Note: The variance decomposition is based on a bivariate VAR with ΔY_t and ΔC_t. ΔY_t is ordered first. $\hat{E}_t(\Delta C_{t+k})$ denotes the least squares projection for *k*-period ahead consumption changes using available information at time *t*.

Table 7. Variance Decomposition of $\widehat{E}_t(\Delta C_{t+k})$: U.S.

k	Consumption	Income	Standard Error
1	78.5724	21.4276	0.0042
2	75.1206	24.8794	0.0046
3	76.2049	23.7951	0.0047
4	76.1455	23.8545	0.0048
5	76.2113	23.7887	0.0048
6	76.2157	23.7843	0.0048
7	76.2212	23.7788	0.0048
8	76.2223	23.7777	0.0048
9	76.2228	23.7772	0.0048
10	76.2230	23.7770	0.0048

Note: The variance decomposition is based on a bivariate VAR with ΔY_t and ΔC_t. ΔY_t is ordered first. $\widehat{E}_t(\Delta C_{t+k})$ denotes the least squares projection for k-period ahead consumption changes using available information at time t.