Does Consumption Take a Random Walk? Some Evidence from Macroeconomic Forecasting Data

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DOES CONSUMPTION TAKE A RANDOM WALK? SOME EVIDENCE FROM MACROECONOMIC FORECASTING DATA

Albert Jaeger*

Abstract—Professional forecasts of aggregate U.S. consumption series strongly reject Hall's (1978) random walk hypothesis. Band spectrum regressions show that low-frequency variations in growth rates of expenditures on nondurables and services, defined as cycles taking more than two years to complete, primarily account for the rejection. Consumption growth and professional forecasts of GNP growth are also closely related at the low but not at the high frequencies. Liquidity constraints or durable characteristics of consumption goods may both explain the reported findings.

I. Introduction

HALL'S (1978) interpretation of the life cycle/permanent income hypothesis implies that, to a first approximation, consumption should follow a random walk with drift. The random walk hypothesis (RWH) has been the focus of extensive research efforts over the last twelve years. Most of this research has concluded that the RWH is inconsistent with U.S. data. A small but significant portion of the variation in consumption changes appears to be predictable based on information in lagged variables including lagged income and consumption.[1]

In this paper I apply band spectrum regression analysis to quarterly forecasting data issued by Wharton Econometric Forecasting Associates (WEFA) to provide further evidence on the predictability of consumption variations. Because professional forecasters should have a strong profit-motivated interest to reveal any information that helps predict consumption changes, forecasting data may embody a significant amount of information in a single variable. Test power is therefore likely to be increased relative to the usual strategy of regressing consumption changes on a variety of lagged variables and testing for the statistical significance of the coefficients. Band spectrum regressions proposed by Engle (1974) allow study of the predictability of consumption variations at the high-frequency and the low-frequency ranges of the data. In the time domain it is quite common to exclude specific time periods from regressions because they do not conform to the model underlying the regression. Similarly, it could possibly be the case that the RWH is a better approximation for consumption behavior at some frequencies of the data than at others. Most studies appear to assume that time domain tests of the RWH automatically reveal deviations at the business-cycle frequencies. But deviations may as well occur because within-year movements in consumption are predictable.

The main finding of the paper is that deviations from the RWH are heavily concentrated at the low or business-cycle frequencies, defined as cycles in the data taking more than two years to complete. Moreover, forecasts of GNP growth are found to move closely with actual consumption growth at the business-cycle frequencies, suggesting liquidity constraints as a prime suspect for causing the RWH to fall. As an alternative hypothesis, durable characteristics of goods included in the nondurables and services aggregate may account for the reported predictability of consumption variations. In fact, expenditures on durables also turn out to be predictable at the business-cycle frequencies. Thus, liquidity constraints and durable characteristics of consumption goods may both be consistent with the reported findings. The results indicate, however, that time averaging of consumption data is unlikely to explain rejections of the RWH.

Section II describes the forecasting data for real expenditures on nondurables and services issued by WEFA over 1970III–1987IV. Section III outlines the test procedure, and section IV contains the empirical results. Section V sets out the conclusions.

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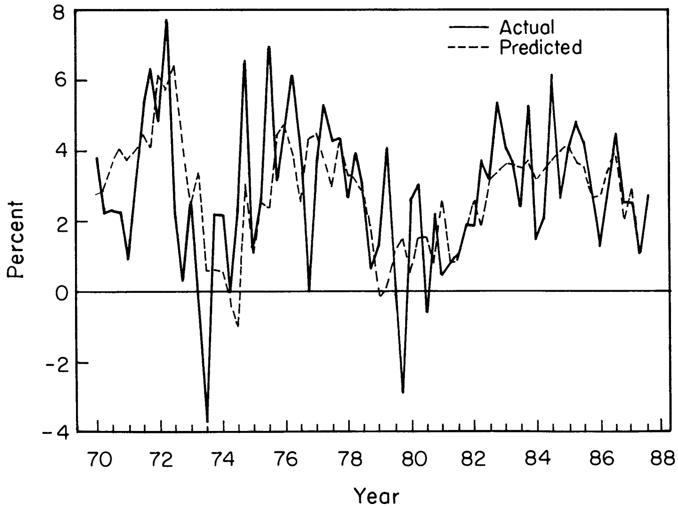
[1] See, for example, Flavin (1981), Hall and Mishkin (1982), Hayashi (1982), and Campbell and Mankiw (1989).

FIGURE 1.—ACTUAL VS PREDICTED GROWTH OF EXPENDITURES ON NONDURABLES AND SERVICES (1970III–1987IV)



II. The Data

The available one-quarter ahead forecasts of real expenditures on nondurables and services were issued by WEFA over the time period 1970III–1987IV (70 observations). In the following, I refer to real expenditures on nondurables and services as "consumption" if no misunderstanding can arise. Because I intend to test whether the logarithm of consumption follows a random walk, forecasts and realizations of consumption are expressed in growth rates.[2] National income and product account data undergo regular revisions, and there is no obviously correct procedure for calculating predicted and actual growth rates of consumption. The WEFA forecasts of consumption in quarter t are based on information through quarter $t-1$. The forecasting data include the preliminary value of consumption for quarter $t-1$ as known by the forecasters at the time the forecast was made. I use this preliminary value and predicted consumption to calculate the predicted growth rate of consumption expressed at annual rates in percentage points.[3] The realized growth rates of consumption and of the other realized series used in this paper are taken from Citicorp's Citibase data bank.

At this point, the question may arise whether consideration of a single forecasting series for consumption can offer a powerful test of the RWH. Intuitively, one would expect that the smaller the forecast errors of a forecast series, the higher the power against the null hypothesis of a random walk in consumption. McNees (1988, Appendix A) compares mean absolute errors (MAE) for one-quarter ahead forecasts of nondurables and services by six forecasting institutions over 1976II–1987IV. In this comparison, the WEFA forecasts exhibit the lowest error statistic. Thus, at least according to the MAE criterion, WEFA forecasts are likely to provide a stringent test of the RWH. But the track record for consumption of nondurables and services of most of the other forecasting institutions is only marginally inferior to the WEFA forecasts. Roughly similar results can therefore be expected for tests of the RWH based on alternative forecast series.[4]

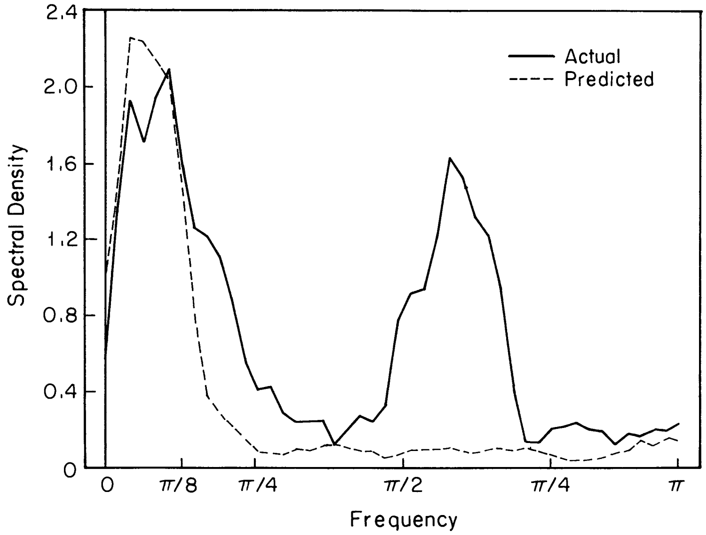
Figure 1 shows the graphs of the actual and predicted growth rates of consumption over

[2] The qualitative results of the paper remain unaffected if levels of consumption instead of logarithms are assumed to follow a random walk.

[3] A similar procedure for calculating predicted growth rates is employed by Fair and Shiller (1989) in a study of the informational content of ex ante forecasts.

[4] I also analyzed forecasts of consumption issued by the Bureau of Economic Analysis (BEA). BEA forecasts give similar results as the WEFA series. The two sets of results are not strictly comparable, however, because the observation for the first quarter in 1981 is missing in the BEA series and the sample period is shorter. Other quarterly forecasting series were not available for this study.

FIGURE 2.—SPECTRAL DENSITIES OF ACTUAL AND PREDICTED CONSUMPTION GROWTH



1970III–1987IV. Visual inspection of the graphs points to two noteworthy features of the data. The forecasts appear to track the actual series reasonably well as far as movements in growth rates stretched over several years are concerned. But there appears to be substantial short-run variation in the actual series which is not captured well by the forecasting series. These impressions from figure 1 are vividly confirmed by the sample spectral densities of the series plotted in figure 2.[5] Both power spectra exhibit a peak at the lower frequencies around $\pi/8$ usually associated for quarterly data with business cycle fluctuations. Note that the peak in the spectrum for the actual growth rate at the business cycle frequencies is prima facie evidence against the RWH. There is a second conspicuous peak in the spectrum of the actual growth rate of consumption indicating a cycle in the series that takes less than 1 year to complete. This high-frequency cycle is close to $\pi/2$, and it may well represent an artifact of the seasonal adjustment filter Census X-11. The gain of the linearized Census X-11 filter for quarterly data shows that the filter removes frequency bands around the seasonal frequencies $\pi/2$ and π completely and the filter can amplify some of the remaining high-frequency cycles (Laroque (1977, p. 115)).

III. The Test Procedure

I take the random walk theory of consumption to imply

$$\Delta c_t = \epsilon_t \tag{1}$$

where Δc_t is the growth rate of consumption adjusted for constant mean growth, and ϵ_t is a regression disturbance orthogonal to all information available at time $t-1$.[6] An important implication of equation (1) is that forecasts of the mean-adjusted consumption growth rate based on information available at $t-1$, denoted by $\Delta c_{t,f}$, should not be correlated with actual consumption growth. Thus, in the bivariate regression:

$$\Delta c_t = \beta\, \Delta c_{t,f} + u_t \tag{2}$$

the coefficient estimate of β should be statistically insignificant and the coefficient of determination R^2 should be zero.

In the time domain, researchers routinely test a model's validity by re-estimating the regression over different sample periods. A conceptually similar investigation may be implemented in the frequency domain using band spectrum regres-

[5] The sample spectral densities are based on a rectangular window of width 5 in the frequency domain. The area under the plots is equal to 1/2 of the variance of the series.

[6] To be accurate, equation (1) says that consumption is a martingale. I follow popular terminology by employing the more restrictive but presumably more charming term "random walk."

sions proposed by Engle (1974).[7] From the point of view of frequency domain analysis, a time series is perceived as the sum of cycles with different time lengths. For quarterly data, the high frequencies comprise the cycles which take only a few quarters to complete whereas the low frequencies comprise the cycles which may take a larger number of quarters to complete. The frequency domain view could be of particular interest for studying the RWH because predictability of consumption growth may occur at low and/or high frequencies of the data. Rejecting the RWH because high-frequency movements in consumption growth are predictable may warrant a different economic policy interpretation than a rejection due to predictability of low-frequency movements. In the empirical section, I will report regression results for equation (2) based on (a) the whole frequency band, (b) the low or business-cycle frequencies, and (c) the high frequencies. The two restricted frequency bands of interest are defined as follows: High-frequency movements include all cycles that take less than two years to complete (frequencies $\geq \pi/4$ in figure 2), whereas low-frequency movements include all cycles taking more than two years to complete (frequencies $< \pi/4$ in figure 2).

The regression results reported below are based on a technique for performing band spectrum regressions proposed by Harvey (1978). Put briefly, the time series data are first transformed to the frequency domain by using a real finite Fourier transform matrix (Z) with dimension $T \times T$, where T is the number of observations. The elements of the matrix are described in Harvey (1978, p. 509). Equation (2) can be written in the frequency domain as

$$c^* = \beta c_f^* + u^* \tag{3}$$

where $c^* = Z\,\Delta c_t$, $c_f^* = Z\,\Delta c_{t,f}$, and $u^* = Zu_t$. All transformed series consist of real numbers. Band spectrum regressions for the low-frequency range then simply correspond to running ordinary least squares (OLS) regressions using only the first quarter of the transformed data whereas the regression for the high-frequency range is based on the remaining three quarters of the transformed data series. All the usual statistical properties of parameter estimates known from time-domain regressions will hold for the frequency-domain regressions. Moreover, if regression (3) includes all frequencies, it is equivalent to regression (2) in the time domain.

A caveat has to be raised at this point. Band spectrum regressions restricted to specific frequency bands require the right-hand side regressor in equation (2) to be orthogonal to the error term at all leads and lags. This strong assumption is unlikely to be met if forecasters adapt their forecasts based on past forecast errors. In particular, the forecast error of last period may plausibly be correlated with the forecast for the current period.[8] To account for this problem at least partially, I also report results based on instrumental variable (IV) regressions done in two steps. In the first step, the forecast for period t is regressed on forecasts of various macroeconomic variables dated $t-1$ or earlier. Because these forecasts are based on information available in period $t-2$ or earlier they should be uncorrelated with the forecast error in period $t-1$. In the second step, the band spectrum regressions are implemented as outlined above but use the estimates from the IV regressions as the right-hand side regressor. The IV approach may provide only a partial remedy, however, because forecast errors dated $t-2$ or earlier may still be correlated with the instrumented right-hand side regressor in equation (2).

IV. Empirical Results

Table 1 reports the results of regressing the realized growth rate of expenditures on nondurables and services on its predicted growth rate. The table has five columns. The first gives the frequency range included in the regression. The second indicates the estimation method used. The third and fourth columns report the regression coefficient β of equation (3) at different frequency ranges with t-statistics in parentheses and the R^2-statistic, respectively. Finally, the fifth column gives the degrees of freedom (DF) of the

[7] Engle (1974) applied band spectrum regressions to test whether the marginal propensity to consume out of transitory and permanent income differs. Engle (1978) tests for the stability of price equations across frequency bands.

[8] The correlation between predicted consumption growth and the prediction error in the previous period is -0.23. Assuming forecast errors to be serially uncorrelated, the critical value at the 5% level for this correlation is approximately -0.24. See, e.g., Brockwell and Davis (1987, p. 400).

TABLE 1.—REGRESSION OF REALIZED ON PREDICTED GROWTH RATE OF EXPENDITURES ON NONDURABLES AND SERVICES

Frequencies	Estimation	β	R^2	DF
All	OLS	0.655 (4.463)	.224	69
All	IV	0.692 (3.473)	.153	65
Low	OLS	0.776 (4.313)	.522	17
Low	IV	0.817 (3.388)	.432	15
High	OLS	0.143 (0.450)	.004	51
High	IV	−0.337 (0.600)	.008	49

Notes: Numbers below regression coefficients are t-statistics. DF denotes the number of degrees of freedom in the regression. Instruments used for the IV regressions are four lags of predicted real growth rates of expenditures on nondurables and services, expenditures on durables, and GNP, respectively. The sample period is 1970III–1987IV.

TABLE 2.—REGRESSION OF REALIZED GROWTH RATE OF EXPENDITURES ON NONDURABLES AND SERVICES ON PREDICTED GNP GROWTH RATE

Frequencies	Estimation	β	R^2	DF
All	OLS	0.269 (4.059)	.193	69
All	IV	0.311 (3.341)	.143	65
Low	OLS	0.379 (4.927)	.588	17
Low	IV	0.425 (3.891)	.501	15
High	OLS	−0.055 (0.455)	.004	51
High	IV	−0.221 (1.090)	.008	49

Notes: See table 1.

regression. The IV regressions use as instruments four lags of the predicted growth rate of nondurables and services, of expenditures on durables, and of real GNP, respectively.

The regression results based on all frequencies confirm the widely reported finding that a significant portion of the variation in realized consumption growth is predictable. According to the R^2-statistic for the OLS regression the variance explained by the forecast amounts to about 20% of the total variance. The estimation results for restricted frequency ranges indicate, however, that the rejection of the RWH is essentially a low-frequency phenomenon. About 50% of the variance of consumption growth is explained at the low frequencies, whereas the R^2-statistics for the regressions including only high frequencies are small and the t-statistics in the regressions are insignificant. The use of OLS or IV regressions does not affect the results.[9]

The results in table 1 naturally raise the question why consumption growth is strongly predictable at the business-cycle frequencies. The dominant explanation for rejections of the RWH holds that consumption growth is predictable because liquidity constraints tie consumption growth to movements in income growth. WEFA forecasts of predicted income growth may provide some suggestive evidence on the relevance of liquidity constraints. Because forecasting data on dispos-

[9] The results remain qualitatively unaffected if the sample is split in 1979II, or if the cut-off point for the restricted frequency bands is $\pi/2$ instead of $\pi/4$.

TABLE 3.—REGRESSION OF REALIZED ON PREDICTED GROWTH RATE OF EXPENDITURES ON DURABLES

Frequencies	Estimation	β	R^2	DF
All	OLS	1.149 (9.608)	.568	69
All	IV	1.031 (3.996)	.186	65
Low	OLS	1.019 (4.874)	.578	17
Low	IV	1.153 (3.891)	.537	15
High	OLS	1.212 (8.280)	.569	51
High	IV	0.876 (2.119)	.057	49

Notes: See table 1.

able household income are not available, I use WEFA forecasts of growth in real gross national product (GNP). The pertinent regression in the time domain is

$$\Delta c_t = \beta \Delta y_{t,f} + u_t \tag{4}$$

where $\Delta y_{t,f}$ is the mean-adjusted WEFA prediction of real GNP growth. The results in table 2, which has a similar organization as table 1, show that predicted GNP growth explains about the same amount of variance at the different frequencies as predicted consumption growth. These results indicate that the ability of forecasters "to beat the random walk" is in fact closely related to co-movements of consumption and income growth around the business-cycle frequencies.

The main alternative interpretation of the failure of the RWH holds that some of the goods included among the nondurables and services aggregate possess durability characteristics. If the adjustment of the stock of durables to income movements is spread out over time, the results in table 2 may actually reflect the durables accumulation process rather than liquidity constraints (see, for example, Bernanke (1985)). But this alternative interpretation suggests that growth rates of expenditures on durables should also be predictable at the business-cycle frequencies. I therefore used band spectrum regressions to investigate whether WEFA forecasts of the growth rate of expenditures on durables explain variations in the realized growth rates. The results are collected in table 3. Variations in expenditures on durables appear to be predictable at all frequencies but in particular at the low frequencies.[10] Hence, the hypothesis that durability characteristics account for the rejection of the RWH cannot be dismissed as an alternative explanation to liquidity constraints.

Another possibility to account for the rejection of the RWH is to invoke the time averaging of consumption data (see Christiano, Eichenbaum, and Marshall (1991)). If the logarithm of consumption follows a random walk at a time interval smaller than a quarter, quarterly consumption will be a time average. Working's (1960) famous result implies that the growth rate of time-averaged quarterly consumption follows:

$$\Delta c_t = \epsilon_t + \alpha \epsilon_{t-1} \tag{5}$$

where α is 0.221 if monthly consumption is a random walk. By exploiting information contained in ϵ_{t-1}, the maximum R^2 a forecaster can achieve is $\alpha^2/(1 + \alpha^2)$ or about 0.046 for α equal to 0.221. According to this calculation, time averaging can account only for about 20% of the amount of predicted variance reported for nondurables and services in panel A of table 1.

I finally investigated whether the use of forecasting data and the specific sample period 1970III–1987IV are crucial for the reported find-

[10] This finding is clearly at odds with Mankiw (1982) and Startz (1989) who argue that U.S. expenditures on durable consumption goods are well approximated by a random walk with drift. Part of the low frequency predictability of durables reported in table 3 can be traced to predicted GNP growth. But other types of information, for example, consumer surveys, must also be of significant help in predicting growth in durables.

TABLE 4.—REGRESSION OF REALIZED GROWTH RATE OF EXPENDITURES ON NONDURABLES AND SERVICES ON AGGREGATE INCOME GROWTH RATE

Frequencies	β	R^2	DF
	A. GNP Growth		
All	0.332 (3.027)	.070	117
Low	0.649 (4.272)	.375	29
High	−0.164 (1.035)	.012	87
	B. Disposable Income Growth		
All	0.475 (3.407)	.088	117
Low	0.781 (2.869)	.241	29
High	0.275 (1.687)	.029	87
	C. Labor Income Growth		
All	0.408 (3.089)	.073	117
Low	0.527 (2.454)	.157	29
High	0.231 (1.236)	.017	87

Notes: The income growth rates are first regressed on twice-lagged growth rates of consumption on nondurables and services and on the growth rate of the income aggregate. The sample period is 1954I–1984IV.

ing that most evidence against the RWH is concentrated at the business-cycle frequencies. The following analysis is closely related to the approach introduced by Campbell and Mankiw (1989) for testing the RWH in the time domain. In the first step, aggregate income growth is regressed on lagged income growth rates and lagged consumption growth rates where the lags run from $t-2$ to $t-6$.[11] The estimated values from the first-step regression are interpreted as predictors of aggregate income movements which are uncorrelated with the current innovation in consumption growth. In the second step, the growth rate of expenditures on nondurables and services is regressed on the predictor of income movements at the different frequency ranges. Three different aggregate income concepts are used: real GNP, real disposable income, and the real labor income series constructed by Blinder and Deaton (1985). Because the Blinder-Deaton labor income series is available only up to 1984IV, the time range for all series is chosen as 1954I to 1984IV. Taking into account the lags lost through the IV regression, a total number of 118 observations is available for the band spectrum regressions. The regression results are collected in table 4. While there is now some evidence for predictability of high frequency movements in consumption based on disposable income and labor income, the qualitative findings of the paper remain unaffected. The co-movements of expenditures on nondurables and services and aggregate income are again heavily concentrated at the business-cycle frequencies.

[11] Campbell and Mankiw (1989) use twice-lagged instruments to avoid estimation problems due to time-averaged data. The use of twice-lagged instruments in this paper may also be appropriate in view of the orthogonality assumption for band spectrum regressions.

V. Summary and Conclusions

The paper examined professional forecasting data to provide further evidence on discrepancies between the RWH and aggregate consumption behavior. Hall's (1978, p. 986) seminal article concluded that a forecast obtained by extrapolating the current level of consumption adjusted for trend can not be improved under a strict interpretation of the life cycle/permanent income hypothesis. Professional forecasters should have a particularly strong incentive to contradict Hall's conclusion. I report that the testable restrictions imposed by the RWH are strongly rejected by the WEFA forecasts of consumption growth at the business-cycle frequencies.

Further empirical analyses indicated that consumption growth is closely related to predictable GNP growth around the business-cycle frequencies. This finding is consistent with recent work on aggregate consumption behavior which stresses liquidity constraints as the key mechanism for causing deviations from the RWH. But I also found that the growth rate of expenditures on durables is predictable at the low frequencies, suggesting that durability characteristics of goods included among expenditures on nondurables and services could as well account for the failure of the RWH. Time averaging of consumption data does not provide a full explanation of the findings.

The results of this paper may be helpful to clarify two minor issues on testing the RWH. First, the use of seasonally adjusted data is unlikely to account for rejections of the RWH. Seasonal adjustment filters like Census X-11 will in general not distort the business-cycle frequencies which were found to contain most of the evidence contradicting the RWH. Second, changing the sampling interval may have substantial influence on the outcome of tests of the RWH. For example, monthly observations may provide weaker evidence against the RWH than, say, annual observations because for monthly observations a much larger portion of the frequency range corresponds to high-frequency movements.

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