ECONOMIC ACTIVITY MEASURES IN NONLINEAR ASSET PRICING

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ABSTRACT

Tests of a nonlinear asset pricing model are presented using an economic activity proxy for the marginal rate of substitution. Recent research has been restricted to quarterly data because the Department of Commerce does not report unfiltered monthly consumption. The proxy introduced here is constructed from retail sales data. A model is tested that allows for seasonal, holiday, and trading day taste shifters in the utility function. The model's restrictions are strongly rejected using one-month real returns on a Treasury bill and a value-weighted stock index. However, there is less evidence against the model when longer-horizon returns are examined.

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1. INTRODUCTION

There is considerable recent evidence of time variation in both expected asset returns and risk measures. Linear asset pricing models have been constructed to incorporate these types of time variation. However, one of the most general models is the proposed by Lucas (1978). This nonlinear formulation is robust to time variation in expected returns, the conditional variance of the joint marginal rate of substitution–returns process, and the conditional covariance between the investor's marginal rate of substitution and asset returns.

Current empirical work concentrates on the not seasonally adjusted data that are reported by the Department of Commerce.[1] The use of seasonally adjusted data is problematic because it is not clear that the filter is consistent with the representative investor's first-order conditions. Furthermore, the use of lagged filtered data as instrumental variables may cause the model's restrictions to be spuriously rejected. Unfortunately, these unfiltered data are only available at the quarterly frequency while there is a rich set of financial data that are available at finer intervals.

This paper introduces two new empirical proxies for personal consumption of nondurable goods that are available at a monthly frequency. These proxies are built from retail sales data. While the model relates asset returns to the utility from the *service flow* from expenditures on consumption goods, these service flows are difficult to observe. Tests of the model have used personal consumption "expenditures." Much of the expenditures data are based on the *Retail Trade Survey,* which is the same source that I use to construct the new proxies.

By extending the model suggested by Miron (1986), taste shifters that allow for deterministic seasonal variation as well as holiday and trading day variation are incorporated in the utility function. Tests with multiple assets suggest that there is strong evidence against the restrictions implied by the model using a one-month horizon. There is considerably less evidence against the model's restrictions when longer horizons are examined.

The paper is organized as follows: In Section 1, the basics of the model are reviewed and the first set of empirical tests is critically reexamined. Some estimation issues are also analyzed. Section 3 details the construction of the new proxies for personal consumption of nondurable goods. Empirical tests of the nonlinear model are presented in Section 4. Some concluding remarks are offered in the final section.

2. ASSET PRICING RESTRICTIONS AND ESTIMATION ISSUES

2.1 The Model

Consider a representative investor maximizing an additively separable utility. The first-order conditions that characterize the solution to this problem can be written

$$E\left[\beta \frac{U'(C_{t+1})}{U'(C_t)} \mathbf{R}_{t+1} - \mathbf{1} \,\middle|\, \mathbf{\Omega}_t\right] = \mathbf{0}, \tag{1}$$

where C_t represents *per capita* real consumption, $\mathbf{R}_{t+1}$ is an n-vector of total real asset returns from t to t+1, β is the representative investor's time discount factor, and $\mathbf{\Omega}_t$ contains all the information about the environment available at time t.

With constant relative risk aversion utility, the following disturbance term is implied:

$$\mathbf{u}_{t+1}(\mathbf{x}, \alpha, \beta) = \beta(C_t/C_{t+1})^{\alpha}\mathbf{R}_{t+1} - \mathbf{1}, \tag{2}$$

where α represents the investor's coefficient of constant relative risk aversion and $\mathbf{x}$ is the consumption and returns data. At the true values of the parameters, the model implies that $E[\mathbf{u}_{t+1} \mid \mathbf{\Omega}_t] = 0$, so

$$E[\mathbf{u}_{t+1}\mathbf{Z}_t] = E\{E[\mathbf{u}_{t+1} \mid \mathbf{\Omega}_t]\mathbf{Z}_t\} = \mathbf{0}, \tag{3}$$

for any set of $\mathbf{Z}_t$ instrumental variables in the investor's information set $\mathbf{\Omega}_t$.

Hansen's (1982) generalized method of moments (GMM) forms a vector of the orthogonality conditions, $\mathbf{g} = \text{vec}(\mathbf{u}'\mathbf{Z})$, where $\mathbf{u}$ is a $T \times n$ matrix of forecast errors for T observations and n assets, and $\mathbf{Z}$ is a $T \times k$ matrix of observations on predetermined instrumental variables. Parameters (α, β) are chosen to make the orthogonality conditions as close to zero as possible by minimizing the quadratic form, $\mathbf{g}'\mathbf{w}\mathbf{g}$, where the $\mathbf{w}$ is a symmetric weighting matrix that defines the metric used to make $\mathbf{g}$ close to zero. Hansen outlines a form of the weighting matrix that guarantees that the estimates are consistent and asymptotically normal.

The minimized value of this quadratic form is distributed χ^2 under the null hypothesis with degrees of freedom equal to the number of orthogonality conditions less the number of parameters to be estimated. This

χ^2 statistic (known as the test of the *overidentifying* restrictions) provides a goodness-of-fit test of the model.[2]

2.2 Selecting Instrumental Variables

In order to estimate the parameters of the utility function and to test the restrictions implied by the asset pricing theory, orthogonality conditions are constructed. The investor's forecast error realized at time $t + 1$ is assumed to be unrelated to information available at time t. If this condition is violated, then the model is rejected. Since all relevant information is unavailable to the econometrician, a subset of information is chosen. These instrumental variables are specified with the purpose of capturing as much of the investor's information environment as is feasible.

This is analogous to linear instrumental-variables regression. In the linear model, instruments are chosen that have the maximum correlation with the actual values of the variables. The case at hand is more complicated because the variable of interest is the joint marginal utility–returns process. This process (and hence correlations with instruments) depends on the utility parameters.

The generalized method of moments does not impose any constraints on instrument selection—other than the requirement that the instruments be predetermined. For example, one could specify a different set of instrumental variables at each point in time (or different instruments for different assets). However, all empirical studies have specified a set of instrumental variables that remains the same through time.[3]

As an illustration of the importance of the instrumental-variables selection, consider the analysis in the seminal paper by Hansen and Singleton (1984). Assuming a monthly decision interval, Hansen and Singleton estimate the econometric model (2) using seasonally adjusted personal consumption expenditures and two assets: NYSE value-weighted stock returns and one-month Treasury bill returns. They find strong evidence against the restrictions implied by the model and these results are widely quoted. Their instrument set includes NLAG (number of lags) lags of the real consumption measure and the real value-weighted stock return. In addition, they state (p. 267):

> Since the nominal risk-free return at time $t + 1$, R^f_{t+1}, is known at time t, we use R^f_{t+1}/R^f_t and NLAG lags of this ratio as instruments in place of NLAG lags of the ex post real return on the bond.

Table 1. A Reexamination of Hansen and Singleton's (1984) Results

NLAG	α	β	χ^2	*DF*	*p-value*
		A. First instrument set			
1	.0857	.9988	14.45	8	.071
	(.1050)	(.0003)			
2	.0513	.9988	15.28	14	.350
	(.0899)	(.0003)			
4	.1261	.9990	39.13	26	.047
	(.0827)	(.0003)			
6	.1147	.9989	52.17	38	.063
	(.0756)	(.0003)			
		B. Second instrument set			
1	.2442	.9991	25.30	8	.001
	(.0947)	(.0003)			
2	.3049	.9993	36.34	16	.003
	(.0795)	(.0003)			
4	.3035	.9994	65.06	32	.001
	(.0708)	(.0003)			
6	.1916	.9992	84.67	47	.001
	(.0632)	(.0002)			

Notes: Generalized method of moments estimation of

$$\mathbf{u}_{t+1} = \beta(C_t/C_{t+1})^{\alpha}\mathbf{R}_{t+1} - 1$$

uses two assets (**R**): real value-weighted stock returns and real one-month Treasury bill returns. In panel A the instrumentation is a constant, NLAG lags of real consumption and real stock returns, the ratio of the contemporaneous nominal bill rate divided by the lagged nominal rate and NLAG lags of this ratio. These are the instruments that Hansen and Singleton say they use in their empirical work. The instruments used in panel B are a constant. NLAG lags of real consumption, real stock returns and real Treasury bill returns, and the ratio of the contemporaneous nominal bill rate divided by the lagged nominal rate and NLAG–1 lags of this ratio. These are the instrument that Hansen and Singleton actually use. The sample is 1959:2–1986:12. The consumption measure is the per capita real consumption of nondurables (seasonally adjusted). The standard errors are in parentheses. The χ^2 statistic is the minimized value of the GMM criterion function and the *p*-value is the probability that the variate exceeds the sample value of the statistic.

The estimation of the model with these instruments is presented in the first panel of Table 1. The χ^2 statistics are much lower than those reported by Hansen and Singleton.

Hansen and Singleton (1984) report a strong rejection for all NLAG (the largest probability value is .0005). Using data from 1959:3–1986:12, the results in Table 1 suggest that there is evidence against the model in only one case (NLAG = 4), where the *p*-value is .047. In the other cases, there is no evidence against the model at the 5% level. Similar results are obtained (not reported) using Hansen and Singleton's (1984) original data.[4]

The reason that the results in the first panel of Table 1 are much different from those reported in Hansen and Singleton (1984) is the instrument selection. Table 1 provides estimates of the model with the instruments that Hansen and Singleton say they use. It turns out that these are *not* the instruments that were used in the empirical estimation in their paper. Hansen and Singleton use NLAG lags of the real consumption and real stock returns. In addition, they use the ratio of the contemporaneous nominal bill rate to the first lag of this rate and NLAG-1 lags of this ratio. Furthermore, NLAG lags of the real Treasury bill rate are also included as instruments. Results based on these instruments are in panel B of Table 1. Similar to the estimates in Hansen and Singleton (1984), the restrictions implied by the model are rejected with a high degree of confidence (highest p-value is .003).[5]

The main difference between two panels of Table 1 is the inclusion of the lagged real return on the Treasury bill as an instrument. The lagged Treasury bill return appears to be a powerful instrument. Ferson and Harvey (1993) show that the lagged Treasury bill return has high correlation with a variety of consumption measures and asset returns. This example illustrates that the estimation is sensitive to the selection of the instrumental variables. That is, one might mistakenly conclude there is little evidence against the model's restrictions if a weak set of instruments is used.[6]

There are two potential problems that one should be aware of when choosing instrumental variables: First, it is possible that the information in the *first* lag of consumption and returns is *not* known to investors and hence the variables are not predetermined. If the investor makes decisions on the first day of each month, information about the consumption and real returns is not officially available for about five weeks.[7] It is possible that the investor may be able to deduce some information about the components of consumption in less than five weeks. For example, some "big-ticket" items such as automobile sales are generally available in less than two weeks. The large retail stores report total sales in less than two weeks after the end of the month. But even with a two-week delay, the immediate lag of consumption would seem to be inadmissible as an instrument.

While nominal asset returns are known at the end of the month, the real returns are not. Consumer price indices are one month old when the information is released. Again it is possible to argue that these prices are known to the investor before they are published. For example, food and gasoline prices are highly visible and these are the most important components of nondurable consumption goods. One strategy to deal with this problem is to check the sensitivity of the empirical results to rolling back the instrument set by one period.

The second issue is potentially more serious. Even if it is possible for investors to deduce the immediate lag in personal consumption and inflation, it is impossible for them to know the prices and consumption for the next 12 months and to run the X-11 seasonal adjustment program on these data. This is roughly what must be believed if you are testing the asset pricing model using revised seasonally adjusted data. The seasonal adjustment filter that the Department of Commerce uses is forward looking. The X-11 applies a series of centered moving averages to the data in order to estimate the seasonal factors.

It is not clear that you want to use this seasonally adjusted data in the asset pricing model. The input to the utility function is *consumption services*. Services are derived from various types of consumption goods: nondurable and durable. The seasonal-adjustment procedure may proxy for the technology that produces consumption services. It seems more appealing to specify a technology transforming the not seasonally adjusted consumption purchases into consumption services that is not forward looking and jointly estimate the parameters of this technology with the parameters of the utility function. This is the approach taken by Miron (1986) and Ferson and Harvey (1992, 1993).

2.3 Measurement Error

Measurement error in the macroeconomic data may cause problems in the econometric analysis. It is likely that the consumption and deflator data are measured with error. There are several potential sources for these errors. Consider the *Retail Trade Survey,* which is a major input for the personal consumption expenditures. The Department of Commerce asks the retailer to estimate sales for the month. If the retailer underestimates sales in this month, then it is possible that the retailer will overestimate sales in the next month. While revisions in the data may reduce the size of the error, it is likely that the measurement error will exhibit *negative* serial correlation. Wilcox (1992) provides a detailed explanation of the construction of the data.

Another source of measurement error is the X-11 filter. The seasonal adjustment program applies a series of centered moving averages to the data to extract the seasonal factors. Since moving averages are used, it is likely that this measurement error will exhibit *positive* serial correlation.

Measurement error is problematic for the empirical analysis. For a single asset, the method of moments estimator approximates:

$$E[u_{t+1}(\mathbf{x}_{t+1}, \alpha, \beta)\mathbf{Z}_t] = \mathbf{0}, \tag{4}$$

where u_{t+1} is a function of parameters and data. The $\mathbf{x}_{t+1}$ represents the consumption and asset returns data. Suppose that the instrument matrix, $\mathbf{Z}_t$, is restricted to lagged values of consumption and real returns. Denote the instrument matrix as $\mathbf{x}_t$. Assume that $\mathbf{x}$ is measured with error:

$$\hat{\mathbf{x}}_{t+1} = \mathbf{x}_{t+1} + \varepsilon_t + 1, \tag{5}$$

where $\hat{\mathbf{x}}$ represents the measured value and ε denotes the measurement error. The observed disturbance, $\hat{u}_{t+1}$, is the true disturbance plus some measurement error:

$$\hat{u}_{t+1} = u_{t+1} + \gamma(\varepsilon_{t+1}). \tag{6}$$

Note that the deviation from the true disturbance is a function of the measurement error, ε, in $\hat{\mathbf{x}}$. Measurement error is not a problem per se. But if the measurement errors are autocorrelated or correlated with the true values of the data, then is possible to spuriously reject the orthogonality conditions.

To see this problem, expand the expectation in (4):

$$E[\hat{u}_{t+1}(\hat{\mathbf{x}}_{t+1},\alpha,\beta)\hat{\mathbf{x}}_t] = E[(u_{t+1} + \gamma(\varepsilon_{t+1}))(\mathbf{x}_t + \varepsilon_t)] \tag{7}$$

$$= E[u_{t+1}\,\mathbf{x}_t] + E[u_{t+1}\varepsilon_t] + E[\gamma(\varepsilon_{t+1})\mathbf{x}_t] + E[\gamma(\varepsilon_{t+1})\varepsilon_t].$$

If the model is true, then the first term on the right-hand side should be zero. It is possible that the second and third terms are also zero. Serial correlation in ε make it unlikely that the last term is zero. Systematic measurement error in the data or an application of a centered moving-average filter on the consumption and inflation data make it likely that this error term is serially correlated. As a result, the model may be spuriously rejected.[8]

Unfortunately, the true consumption data are unobservable. As a result, it is difficult to correct the errors in the data caused by systematic mismeasurement.[9] However, I take three steps that may alleviate the problem. First, I construct monthly consumption data that are not seasonally adjusted. Second, I allow for systematic holiday and trading day variation that would usually induce negative correlation in the data. Finally, I examine longer-horizon returns to reduce the relative size of the measurement error.

3. NEW CONSUMPTION DATA

3.1 Construction

The components of personal consumption of nondurable goods are presented in Appendix A. The 1986 expenditures are also listed with each component's proportion of the total expenditures. The personal consumption data are available both seasonally adjusted and not seasonally adjusted on a quarterly basis. Unfortunately, the Department of Commerce does not report (nor calculate) the not seasonally adjusted monthly consumption.

In order to build a proxy for the not seasonally adjusted consumption of nondurables, one must use the input series that the department employs. Most of these input series originate from the *Retail Trade Survey*. Appendix B lists the published components of retail sales of nondurables. It is evident that there is substantial overlap of the components of retail sales of nondurables and personal consumption expenditures on nondurables. Appendix B also lists the 1986 dollar expenditures for each component of the retail sales.

Unlike the personal consumption expenditures, the retail sales do not have matching deflators. In the far right column of Appendix B is the closest urban Consumer Price Index (CPI) available. The CPIs are available in seasonally adjusted and not seasonally adjusted formats. Unfortunately, there is only partial coverage of the components of retail sales. Furthermore, some of the deflators are only available on a monthly basis from 1967:1.

Two proxies for personal consumption of nondurable goods are proposed. The first is simply the aggregate measure of nondurable retail sales. This measure is deflated by the CPI for nondurables. The second measure excludes some of the *durable* components of the nondurable retail sales. For this variable, only three components are used: food stores' sales,[10] eating and drinking places' sales, and gasoline service

Table 2. A Comparison of Personal Consumption and Retail Sales

Frequency	*Adjustment*	*Span*	*Obs*	β_0	β_1	$\bar{R}^2$
Quarterly	NSA	1959:1–1986:4	115	.0007	.9044	.99
				(.0011)	(.0090)	
Annual (real)	NSA	1959–1986:4	28	.0056	.7737	.85
				(.0021)	(.0634)	
Annual (nominal)	NSA	1959–1986:4	28	.0014	.9760	.92
				(.0041)	(.0570)	

Notes: Ordinary least squares estimation of

$$\Delta \text{Cons}_t = \beta_0 + \beta_1 \Delta \text{Sales}_t + \varepsilon_t$$

where ΔCons and ΔSales represent the logarithmic first difference in real personal consumption of nondurables and real nondurable retail sales, respectively. In the first regression, both measures are deflated by the CPI for nondurables (not seasonally-adjusted). The monthly not seasonally adjusted retail sales are aggregated to a quarterly measure to compare with the quarterly not seasonally adjusted personal consumption. In the second regression, the retail sales and not seasonally adjusted consumption are aggregated to an annual frequency. Both measures are deflated with the CPI for nondurables (seasonally adjusted). The third regression is similar to the second except the sales and consumption data are not deflated by the CPI. Standard errors are in parentheses.

stations' sales. Liquor stores' and drug stores' sales had to be excluded because the CPIs for these two components were only available from 1967:1. The three components in this second measure account for 60% of the total retail sales of nondurables. Among the excluded components are shoes and clothing. It is unlikely that all the consumption services from shoes or clothing occur within one month.

To test how closely retail sales and personal consumption expenditures move together, the monthly not seasonally adjusted retail sales are aggregated to a quarterly frequency and compared in a linear regression to the quarterly not seasonally adjusted personal consumption expenditures. The regression measures how well the logarithmic first difference in retail sales explains the quarterly rate of change in consumption growth. The regression results over the 1959:2–1986:4 period are presented in Table 2. The R^2 of this regression is extremely high (99%), suggesting that the retail sales closely move with personal consumption expenditures.

A second comparison is also presented in Table 2. The monthly seasonally adjusted retail sales are compared with the monthly seasonally adjusted personal consumption expenditures. This regression spans the 1967:1–1987:4 period. The correlation between these measures is also quite high.

Finally, Figure 1 plots the variables used in the first regression. The top panel is particularly striking. The quarterly growth in retail sales move in the same direction as the quarterly growth in personal consumption in *every* quarter. The lower panel shows the difference between the consumption and retail sales variables plotted in the upper panel. The difference is small and on average close to zero. This analysis suggests that the retail sales measure will be a satisfactory proxy for personal consumption expenditures.

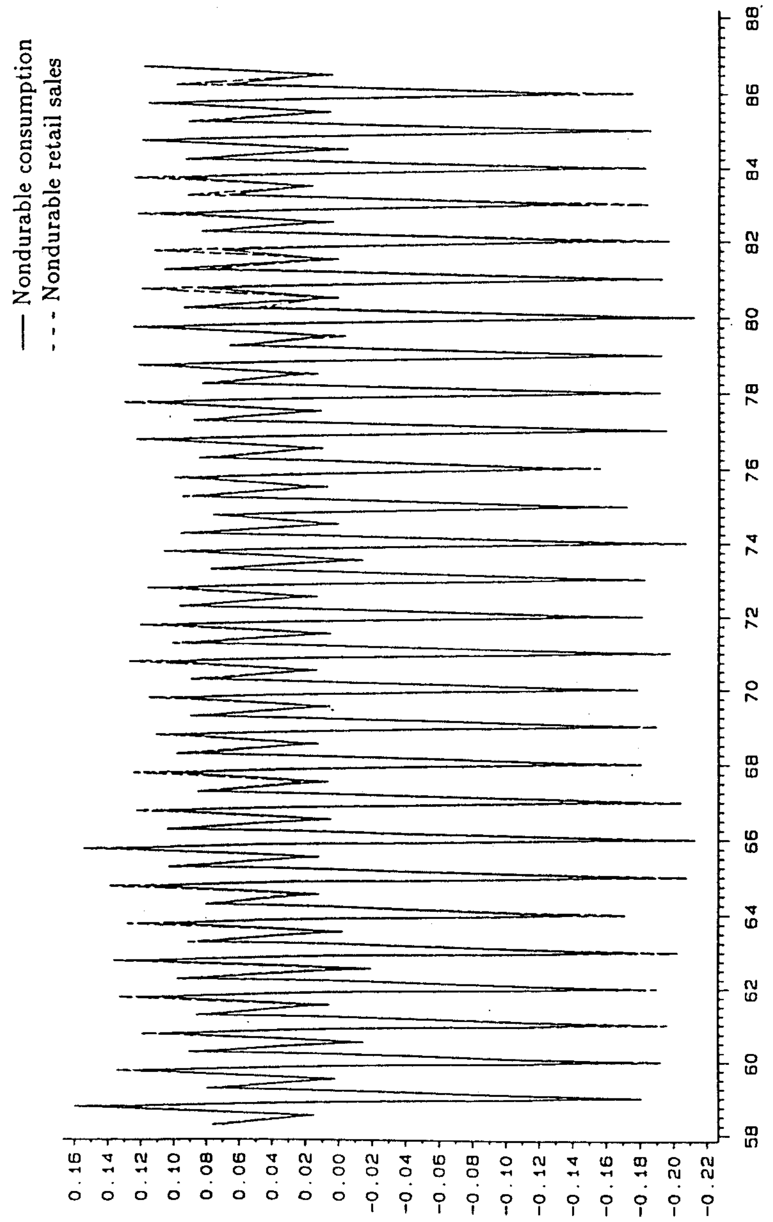
3.2 Seasonal, Holiday, and Trading Day Factors

Means, standard deviations, and autocorrelations of the logarithmic first difference in the retail sales measures and seasonally adjusted personal consumption of nondurables is provided in Table 3. Miron (1986) and Ferson and Harvey (1992) have observed that the personal consumption of durables is the most volatile of all the categories. The alternative measure of retail sales (RSA) strips out the *durable* categories of the nondurables (shoes and clothing). Table 3 shows that the standard deviation of this alternative measure is less than half of the standard deviation of retail sales of all nondurables.

The seasonal autocorrelations indicate that both series exhibit strong seasonal patterns. The seasonal in the measure of all nondurable retail sales is stronger than the seasonal in the alternative measure because of the large seasonal (around Christmas) in the purchase of shoes and clothing.

There is a large negative first-order autocorrelation in all three variables. This could be caused by several factors. One possibility is trading day variation. A large proportion of retail sales occurs on the weekend. The number of weekends varies between four and five each month. This could induce negative correlation in these series. A second potential cause is holiday variation. The Easter holiday is a lunar holiday, which occurs in March or April.

In order to explore the importance of seasonal, holiday, and trading day variation, some regression results are presented in Table 4. Suppose the natural logarithm of the measure of interest follows:


— Nondurable consumption
- - - Nondurable retail sales
Date
58 60 62 64 66 68 70 72 74 76 78 80 82 84 86 88
0.16 0.14 0.12 0.10 0.08 0.06 0.04 0.02 0.00 -0.02 -0.04 -0.06 -0.08 -0.10 -0.12 -0.14 -0.16 -0.18 -0.20 -0.22

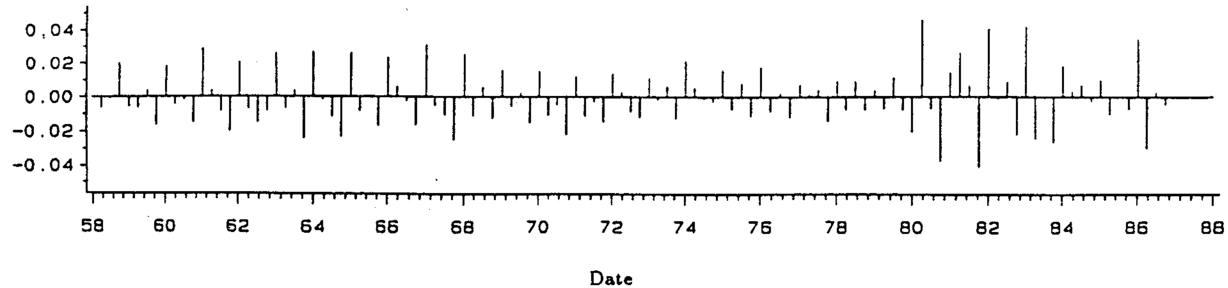


Figure 1. Comparison of consumption and retail sales. In the top panel, monthly not seasonally adjusted retail sales are aggregated to a quarterly frequency and compared to the not seasonally adjusted personal consumption of nondurables. The retail sales are deflated by the CPI for nondurable goods (not seasonally adjusted). The sample is 1959:2–1986:4. The bottom panel presents the difference between the growth in nondurable personal consumption and retail sales.

Table 3. Summary Statistics for Consumption and Retail Sales

Variable	*Obs.*	*Mean*	*Std dev.*	ρ_1	ρ_2	ρ_3	ρ_4	ρ_6	ρ	ρ_{24}	ρ_{36}
CN	335	.001048	.007809	–.36	.03	.11	–.07	–.01	–.04	–.24	–.05
RS	335	.001996	.128481	–.32	–.25	.02	.02	–.04	.92	.86	.82
RSA	335	.000898	.059752	–.39	–.09	.13	–.23	–.28	.79	.58	.51

Notes: CN is the logarithmic first difference in real personal consumption expenditures on nondurable goods. This measure is seasonally adjusted. RS denotes the logarithmic first difference in retail sales of nondurable goods. This measure is deflated by the CPI for nondurables. RSA represents the logarithmic first difference in retail sales of food stores, food away from home, and gasoline service stations. Each component is deflated by the CPI that is closest to the sales category. All data are not seasonally adjusted. The approximate standard error on the autocorrelations is .054.

Table 3, 1 page

$$Y_t = ct + \delta_0^* H_t + \sum_{i=1}^{7} \delta_i^* \mathrm{TD}_t + \sum_{i=8}^{19} \delta_i^* \mathrm{SD}_t + \varepsilon_t^*, \tag{8}$$

where Y represents the logarithm of the consumption or sales measure, t denotes a time trend, H is a weighting variable for the Easter holiday, TD are dummy variables that account for trading day variation, and SD are dummy variables that represent the seasonal variation.

The Easter variable is not a simple dummy variable that switches on if the holiday is in April rather than March. This reflects the fact that most consumer shopping takes place *before* the holiday. If Easter occurred on April 1, then shopping took place in March and a simple dummy variable in April would not pick up the variation. Furthermore, an Easter occurring on April 14 will have more of an effect on April sales than an Easter occurring on April 3. Following Liu (1980), a weighting variable is constructed. It is assumed that shopping is equally distributed over eight days[11] prior to and including the Easter holiday. If Easter occurs on April 8, then the variable gives 1.0 to April and 0.0 to March. If Easter occurs on April 2, 0.25 weight is given to April and 0.75 is assigned to March. Appendix C gives a complete listing of the Easter holidays from 1958 to 1987.

Let WDt represent the number of days of the week (i.e., Mondays, Tuesdays,..., Sundays) in month t. The effects of the trading day factors in month t can be written:

$$\sum_{i=1}^{7} \lambda_i \mathrm{WD}_{it}, \tag{9}$$

where i indexes the day of the month. Following Liu (1980), the trading day effects are restricted to vary around zero.[12] For n observations, the λ_i are normalized to satisfy. This implies:

$$\frac{1}{n}\sum_{t=1}^{n}\left[\sum_{i=1}^{7} \lambda_i \mathrm{WD}_{it}\right] = \frac{1}{n}\sum_{i=1}^{7} \lambda_i \sum_{i=1}^{n} \mathrm{WD}_{it} = 0. \tag{10}$$

For a large sample size, $(\Sigma_{t=1}^{n} \mathrm{WD}_{it})/n$ is approximately the same for all weekdays i. It then follows from (10) that $\lambda_1 + \lambda_2 + \ldots + \lambda_7 = 0$. Then (10) can be rewritten:

$$\sum_{i=1}^{6} \delta_i^* \mathrm{TD}_{it}, \tag{11}$$

where $\mathrm{TD}_{it} = \mathrm{WD}_{it} - \mathrm{WD}_{7t}$ and $\delta_i^* = \lambda_i$. Following Bell and Hillmer (1983) an additional term, $\delta_7^* \mathrm{TD}_{7t}$, is included. The variable is defined to be:

$$\mathrm{TD}_{7t} = \sum_{i=1}^{7} \mathrm{WD}_{it}. \tag{12}$$

The parameter on this term represents the average of daily effects and is used to adjust for the length of the month. A listing of the number of weekdays in each month from 1959 to 1987 is provided in Appendix D.

Equation (8) is estimated in first difference form in Table 4. The formulation assumes that the holiday, trading day, and seasonal effects are constant over time. The model could be easily modified to allow for linear or quadratic trends over time. The regressions are estimated for three series: personal consumption expenditures on nondurables (seasonally adjusted), retail sales of nondurables (not seasonally adjusted), and the alternative measure of retail sales (not seasonally adjusted).

The first column in Table 4 shows the parameter estimates for personal consumption of nondurables. There is a strong "Easter effect" in these data as well as trading day variation. The X-11 fails to remove all of the seasonality as evidenced by 5 of 11 seasonal dummies having coefficients more than two standard errors from zero. The second and third columns of Table 4 report the parameter estimates for the two measures of retail sales. The Easter effect is significant in both regressions but much more important for the broader measure of retail sales. The trading day variation seems similar across the two series. The coefficients on the seasonal dummies are much larger for the broader measure of retail sales, indicating that this series is much more seasonal than the sales of food stores, restaurants, and gasoline service stations.

One of the puzzling aspects of the monthly seasonally adjusted data is the negative first-order serial correlation. This negative correlation is especially problematic for those tests of the linear version of the consumption model at the monthly level using returns that are properly time aggregated from daily data.[13] If the measured monthly consumption were an "average" of daily consumption, then one would expect positive serial

Table 4. Seasonal, Holiday and Trading Day Factors in Consumption

Coefficient (t-statistic)	Dependent Variable		
	CN	RS	RSA
$\hat{c}$	.00106 (4.11)	.00108 (2.73)	.00074 (2.50)
$\hat{\delta}_0$	.00710 (5.65)	.02917 (11.07)	.00983 (4.85)
$\hat{\delta}_1$	–.00309 (–4.24)	–.00667 (5.23)	–.00790 (–8.33)
$\hat{\delta}_2$	.00231 (3.49)	–.00064 (–0.49)	–.00423 (–5.21)
$\hat{\delta}_3$	–.00146 (–1.95)	–.00433 (–3.02)	.00283 (–2.51)
$\hat{\delta}_4$	.00026 (0.35)	.00362 (2.55)	.00226 (1.90)
$\hat{\delta}_5$	–.00028 (–0.41)	.01134 (9.05)	.01267 (13.23)
$\hat{\delta}_6$	.00171 (2.17)	.01115 (7.24)	.01295 (13.08)
$\hat{\delta}_7$	–.00735 (–4.18)	.02821 (16.18)	.02937 (12.76)
$\hat{\delta}_8$	–.01991 (–4.30)	.01936 (5.13)	.00206 (3.12)
$\hat{\delta}_9$	–.00107 (–0.59)	.04933 (19.47)	.02854 (11.92)
$\hat{\delta}_{10}$	–.01100 (–4.91)	.07369 (28.50)	.05101 (13.50)
$\hat{\delta}_{11}$	.00133 (0.67)	.09888 (37.47)	.07536 (31.17)
$\hat{\delta}_{12}$	–.00652 (–2.58)	.11388 (37.41)	.10272 (29.19)
$\hat{\delta}_{13}$	.00105 (0.53)	.08036 (32.96)	.09450 (37.84)
$\hat{\delta}_{14}$	.00025 (0.13)	.10351 (40.18)	.08702 (35.56)
$\hat{\delta}_{15}$	–.00780 (–3.11)	.09253 (30.29)	.06630 (19.04)

(continued)

Table 4. (Continued)

Coefficient (t-statistic)	Dependent Variable		
	CN	RS	RSA
$\hat{\delta}_{16}$	−.00066 (−0.34)	.10093 (47.96)	.05573 (24.54)
$\hat{\delta}_{17}$	−.00734 (−2.92)	.15438 (48.78)	.05731 (17.23)
$\hat{\delta}_{18}$	−.00008 (−0.05)	.34526 (119.17)	.09481 (37.35)
$\bar{R}^2$	.13	.99	.97

Notes: Least squares estimation of:

$$(1 - L)Y_t = c + \delta_0(1 - L)H_t + \sum_{i=1}^{7} \delta_i(1 - L)\mathrm{TD}_t + \sum_{i=8}^{18} \delta_i(1 - L)\mathrm{SD}_t + \varepsilon_t,$$

where L is the lag operator. Y represents logarithm of (CN) real personal consumption of nondurables (seasonally adjusted); (RS) real retail sales of nondurable goods (not seasonally adjusted); or (RSA) real retail sales of food, food away from home, and gasoline service stations. TD represents the trading days in the month. SD are seasonal dummies. The t-statistics reported are based on standard errors that have been corrected for a first-order moving average process and conditional heteroscedasticity.

correlation in the growth rate. But the observed growth rates have significant negative serial correlation. Holiday and trading day variation contributes to the negative first-order serial correlation. But this type of variation does not explain all of the negative autocorrelation. Each of the regressions in Table 4 exhibits negative first-order autocorrelation in the residuals. This indicates that there is something else causing this correlation structure. A likely candidate is measurement error.[14]

4. MODEL SPECIFICATION AND EMPIRICAL RESULTS

4.1 The Econometric Model

The econometric specification extends the model suggested by Miron (1986). In his study of quarterly not seasonally adjusted data, Miron incorporates deterministic seasonal taste shifters, in the form of dummy variables, into the utility function. If the service flow from consumption is characterized by (8), then by substituting into (2) the following econometric model is implied:

$$\mathbf{\upsilon}_{t+1} = \beta(C_t/C_{t+1})^{\alpha}(e^{\mathbf{X}_{t+1}\delta})^{1-\alpha}\,\mathbf{R}_{t+1} - \mathbf{1}, \tag{13}$$

where

$$\mathbf{X}_{t+1}\delta = \delta_0(1-L)H_{t+1} + \sum_{i=1}^{7}\delta_i(1-L)\mathrm{TD}_{t+1} + \sum_{i=8}^{18}\delta_i(1-L)\mathrm{SD}_{t+1}.$$

The e denotes the natural exponent, L is the lag operator, H is the holiday variable, TD are the trading-day dummies, and SD are the seasonal dummy variables. Notice that the δ parameters in (13) are not the taste shifter coefficients but the difference in the taste shifter coefficients.[15] There are a total of 21 parameters (including the fundamental parameters of the utility function).

The results of estimating (13) using the Treasury bill and value-weighted stocks are presented in Table 5.[16] In the first panel, only the seasonal taste shifters are included. This model is similar to Miron (1986).[17] However, the results are somewhat different. First, the risk aversion coefficients are smaller and more precisely estimated. All the estimates have the sign predicted by economic theory. Second, the coefficients of the seasonal taste shifters are in most cases significantly different from zero (not reported). Third, the model is rejected with a high degree of confidence.[18] This means, of course, that the parameter estimates are likely inconsistent.

The results are similar using both proxies for personal consumption. Consistent with the observation that the broader measure of retail sales has a larger seasonal pattern, 10 of 11 seasonal shifters are significantly different from zero, whereas the narrower measure has only 7 of 11 shifters significantly different from zero. The inferences are not sensitive to the number of lags of the variables used in the estimation.[19]

The second panel of Table 5 presents the estimates using seasonal, holiday, and trading day shifters. The coefficients on the shifter variables are generally significantly different from zero. The risk aversion parameter is more precisely estimated (three to four standard errors from zero) and has the correct sign. As with panel A, the time discount factor is always less than unity. But also similar to panel A, the model is rejected with a high degree of confidence.

Table 5. Estimation with Seasonal, Holiday, and Trading Day Taste Shifters

Consumption measure	*NLAG*	α	β	χ^2	*DF*	*p-value*
A. Model with seasonal shifters						
RS	4	.0155 (.0081)	.9990 (.0002)	60.59	35	.005
RS	6	.0184 (.0080)	.9988 (.0002)	74.16	47	.007
RSA	4	.0141 (.0095)	.9990 (.0003)	61.05	35	004
RSA	6	.0182 (.0094)	.9991 (.0003)	76.27	47	.004
B. Model with seasonal, holiday, and trading day shifters						
RS	4	.1499 (.0418)	.9993 (.0002)	74.91	43	.002
RS	6	.0961 (.0367)	.9990 (.0002)	89.23	55	.002
RSA	4	.3046 (.0901)	.9998 (.0003)	76.92	43	.001
RSA	6	.2396 (.0804)	.9996 (.0003)	91.85	55	.001

Notes: Generalized method of moments estimation of Equation (13), where in panel A:

$$X_{t+1}\delta = \sum_{i=8}^{18} \delta_i(1-L)\mathrm{SD}_{t+1},$$

and in panel B:

$$X_{t+1}\delta = \delta_0(1-L)H_{t+1} + \sum_{i=1}^{7} \delta_i(1-L)\mathrm{TD}_{t+1} + \sum_{i=8}^{18} \delta_i(1-L)\mathrm{SD}_{t+1}.$$

4.2 Longer Horizon Estimation

The final step is to consider longer horizon estimation. According to (2), the price of an asset that matures in more than a month is set to reflect the marginal rate of substitution in consumption from today to the asset's maturity. It is possible to estimate the model in the form:

$$\mathbf{v}_{t+m} = \beta^m (C_t/C_{t+m})^{\alpha} (e^{\mathbf{X}_{t+m}\delta})^{1-\alpha}\, \mathbf{R}_{t+m} - \mathbf{1}, \tag{14}$$

where

$$\mathbf{X}_{t+m}\delta = \delta_0(1 - L^m)H_{t+m} + \sum_{i=1}^{7} \delta_i(1 - L^m)\mathrm{TD}_{t+m} + \sum_{i=8}^{7+S} \delta_i(1 - L^m)\mathrm{SD}_{t+m},$$

where S represents the number of (differences in) seasonal taste shifter parameters that are identified. Note that for some values of m, some parameters are not identified. For example, if $m = 6$, then only 6 of the seasonal taste shifters are identified. If $m = 12$, then the model relates annual growth in consumption to 12-month asset returns and none of the seasonal shifters are identified. As m is increased, the importance of the trading day shifters should diminish. That is, the number of Saturdays in a month will change from 4 to 5 but the number of Saturdays over longer horizons will be less variable.

It is potentially important to look at longer horizon returns because the measurement error problem may be less severe. Harvey (1988) argues that by looking at longer horizons, the size of the measurement error relative to the growth in consumption should be reduced.[20] One strategy would be to look at nonoverlapping three-month consumption and returns. This is equivalent to the tests using quarterly data presented in Miron (1986) and Ferson and Harvey (1992). However, more powerful tests may be possible using overlapping data.[21]

Tests of (14) are presented in Table 6 for two- to five-month horizons. The Treasury asset is the return on an m-period Treasury bill that is held to maturity. The equity is an m-period return on the value-weighted stock index. The instrument set includes four lagged values of the one-month consumption ratio, the real one-month Treasury bill return, and the real one-month stock return. To avoid overlapping the consumption and returns data with the instruments, the "first" lag in the instrument set is actually the $(m + 1)$th lag. The model parameterization is restricted to seasonal taste shifters. Since overlapping data are used, the disturbance in (14) will follow a moving-average process. The estimation routine corrects for the moving-average process.[22]

The results in Table 6 suggest that there is less evidence against the model's restrictions when longer horizons are examined. For the two-month horizon, the model is rejected at the 6.4% level for the broad measure of nondurables and at the 4.9% level for the narrow measure. In the two- to five-month horizons, there is little evidence against the model in terms of the test of the overidentifying restrictions. Similar to

Table 6. Longer-Horizon Estimation of the Asset Pricing Model

Horizon	*Consumption measure*	α	β	χ^2	*DF*	*p-value*
2	RS	.0223	.9991	47.31	34	.064
		(.0195)	(.0003)			
2	RSA	–.0094	.9991	48.68	34	.049
		(.0207)	(.0003)			
3	RS	.0705	.9992	34.67	33	.388
		(.0818)	(.0003)			
3	RSA	.1190	.9996	35.06	33	.370
		(.0888)	(.0003)			
4	RS	.0379	.9994	28.33	32	.653
		(.0656)	(.0003)			
4	RSA	.0189	.9994	29.57	32	.591
		(.0327)	(.0004)			
5	RS	.0151	.9992	29.90	35	.756
		(.0261)	(.0003)			
5	RSA	–.0082	.9990	27.55	35	.811
		(.0253)	(.0004)			

Notes: Generalized method of moments estimation of Equation (14), where

$$X_{t+m}\delta = \sum_{i=1}^{S} \delta_i (1 - L^m)\mathrm{SD}_{t+m}.$$

The e in Equation (14) denotes the natural exponent, L is the lag operator, SD are the seasonal dummy variables, and S represents the number of shifters that are identified. Two assets (**R**) are used: real value-weighted stock returns and real one-month Treasury bill returns. The instrumentation is a constant, four lags of the one-month real consumption ratio, four lags of the one-month Treasury bill and stock returns, and a set of dummy variables corresponding to the shifter variables. The sample is 1959:2–1986:12. RS denotes the consumption measure that is constructed from retail sales of nondurable goods. RSA denotes the alternative measure that does not include clothing and shoes. The standard errors are in parentheses. The estimation accounts for the moving average in the disturbance induced by overlapping data. The χ^2 is the minimized value of the GMM criterion function and the p-value is the probability that the variate exceeds the sample value of the statistic.

Table 5, the estimates of the time discount factor are all less than unity and in all but one case two standard errors from unity. Most of the coefficients on the seasonal taste shifters (not reported) are significantly different from zero. The point estimates of the risk aversion coefficient are of a similar magnitude as the ones reported in Table 5, but there is one case with the wrong sign. In contrast to the results reported in Table 5, the standard errors of the risk aversion coefficient are larger. As a result, none of the coefficients are significant at conventional levels.

One possible reason that the model's restrictions are not rejected in the longer horizon is the lack of power. The GMM test of the overidentifying restrictions tests against an unspecified alternative. I now consider two specific alternatives. First, the coefficient of constant relative risk aversion is different for stocks and Treasury bills.[23] Second, there is a "structural" change in risk aversion after November 1979.[24]

Both of these alternatives are tested with a method suggested by Gallant and Jorgenson (1979), Eichenbaum, Hansen, and Singleton (1988), Eichenbaum and Hansen (1990), and Newey and West (1987b). Initially, the model is estimated in an unrestricted form. In the first case, there are "risk aversion parameters" for each asset. In the second case, the risk aversion parameter is allowed to shift after 1979:11. The optimal weighting matrix is saved. Next, the model is estimated in the restricted form (14) using seasonal taste shifters. The weighting matrix is constrained to be the (saved) unrestricted estimate. The following test statistic is calculated:

$$\chi_q^2 = \mathbf{g}_r'\mathbf{w}_{ur}\mathbf{g}_r - \mathbf{g}'_{ur}\mathbf{w}_{ur}\mathbf{g}_{ur}, \tag{15}$$

where r represents restricted, ur represents unrestricted, and q is the number of parameter restrictions (degrees of freedom), which is one in our case.[25]

The results of these tests are provided in Table 7. The results of the testing the null hypothesis that risk aversion is independent of the asset examined indicate that there is no evidence against the null hypothesis (the smallest p-value is .42). The point estimates of the risk aversion parameter in the unrestricted case (not reported) are similar for the Treasury bill and the stock portfolio. However, like the results in Table 6, the parameter is rarely significant at conventional levels so it is not surprising that we cannot reject the null in this case.

The second set of χ^2 statistics in Table 7 tests the structural stability of the model. With the alternative hypothesis, the risk aversion parameter is allowed to take a different value after November 1979. The results suggest that there is no evidence of a structural shift.[26]

Table 7. Specification Tests for the Longer-Horizon Estimation

		H_0: $\alpha^{stock} = \alpha^{bill}$		H_0: $\alpha^{59:2-79:10} = \alpha^{79:11-86:12}$	
Horizon	*Consumption measure*	χ^2	*p-value*	χ^2	*p-value*
2	RS	0.60	.420	0.85	.356
2	RSA	0.26	.609	1.15	.283
3	RS	0.38	.536	0.01	.944
3	RSA	0.01	.907	0.01	.944
4	RS	0.10	.752	2.68	.102
4	RSA	0.35	.554	1.17	.291

Notes: Generalized method of moments estimation of Equation (14), where

$$X_{t+m}\delta = \sum_{i=1}^{S} \delta_i (1 - L^m)\text{SD}_{t+m},$$

with two sets of restrictions on the coefficient of relative risk aversion. The e in Equation (14) denotes the natural exponent, L is the lag operator, SD are the seasonal dummy variables, and S represents the number of shifters that are identified. Two assets (**R**) are used: real value-weighted stock returns and real one-month Treasury bill returns. The instrumentation in the first test is a constant, four lags of the one-month real consumption ratio, four lags of the one-month Treasury bill and stock returns, and a set of dummy variables corresponding to the shifter variables. In the second test, the instruments are augmented with a dummy variable that takes the value of one from 1979:11 to 1986:12 The sample is 1959:2–1986:12. RS denotes the consumption measure that is constructed from retail sales of nondurable goods. RSA denotes the alternative measure that does not include clothing and shoes. The estimation accounts for the moving average in the disturbance induced by overlapping data. Both χ^2 statistics have one degree of freedom and the p-value is the probability that the variate exceeds the sample value of the statistic.

5. CONCLUSIONS

Tests of a nonlinear asset pricing model have been presented based on a new measure of economic activity. Results are presented using two monthly measures for not seasonally adjusted consumption of nondurables goods. These proxies are built from retail sales. The first proxy matches as many of the categories of personal consumption expenditures of nondurables as possible. It is shown that if these retail sales are aggregated to a quarterly frequency, they have a 99% correlation with not seasonally adjusted consumption of nondurables. An alternative consumption proxy is also presented that strips out some of the *durable* nondurables (i.e., food and clothing).

The restrictions implied by the consumption-based asset pricing model are tested using these new data with a model that gives explicit consideration to deterministic shifts in the investor's utility that result from seasonal, holiday, and trading day factors. The evidence indicates that these shifters are potentially important when the model is tested with one-month returns.

Consistent with the research on the model, the restrictions implied by the model are strongly rejected using one-month Treasury bill returns on a one-month stock return. However, there is less evidence against the model when longer horizon returns are examined. These results are consistent with the hypothesis that measurement error may be less of a problem in the consumption and deflator data in longer horizons.

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NOTES

1. See Miron (1986), Singleton (1988), English, Miron, and Wilcox (1989), Ferson and Harvey (1992, 1993).
2. See Hansen and Singleton (1984, p. 1277) for the interpretation of this test.
3. Hansen (1985) and Hansen and Singleton (1988a, 1988b) explore the issue of "optimal instrumental variables" selection. Hansen and Singleton (1988a) implement an optimal selection criteria for linear asset pricing models that have moving-average errors.
4. I thank Lars Hansen for providing me with his original data. The main differences (other than sample size) between the data used in Table 1 and the data used by Hansen and Singleton (1984) are that I use the most recent revisions in the consumption and price deflator data and I use returns that are not rounded. [The returns published in Ibbotson and Sinquefield (1979) are rounded to two significant digits while if you purchase the data on diskette from Ibbotson Associates, Inc., the data are provided in four significant digits.] A version of Table 1 using the original data is available on request.
5. Let me emphasize that there are *no* incorrect results in Hansen and Singleton (1984). My analysis verifies, given the proper set of instruments, their results. This discussion is meant to raise some issues about instrument selection; it should not be construed as a criticism of Hansen and Singleton's path-breaking work.
6. One might interpret the test at the unconditional level as an extreme example. In this case, only a constant is included as an instrument. When the asset returns are augmented to include real returns on portfolios of government bonds, corporate bonds, and the smallest decile of NYSE stocks, there is little evidence against the restrictions implied by the model at the unconditional level. There are only overidentifying restrictions when more than two assets are used in the estimation. Results (not reported) using

three to five assets show that the smallest p-value is .625 (using five assets). However, the estimates of the risk aversion parameter are large and imprecise. Also see Ferson and Harvey (1992).

7. This is the reporting lag today. In the early years of the data, there was a longer delay.

8. Wallis (1974) is the first to make this point in the context of causality tests in linear regression models.

9. If the errors are not related to asset returns, one could form mimicking portfolios such as the ones in Breeden, Gibbons, and Litzenberger (1989).

10. Some food may be considered durable. Also, food stores sell items other than food that are may be durable.

11. Following Liu (1980), the duration of the Easter weighting was determined by estimating a seasonal time series model with trading day and Easter transfer functions. Durations of the Easter weighting from 1 (simple dummy variable) to 14 were estimated. The model with the smallest standard error of the residuals had a duration of 8 days.

12. Liu (1980) argues that this transformation should be imposed if the data are going to be seasonally adjusted. Furthermore, the transformation may reduce extreme collinearity in the parameter estimates. This is an important consideration in the econometric estimation (in the next section) because of the large parameterization.

13. See Grossman, Melino, and Shiller (1987) and Hansen and Singleton (1988a).

14. Heaton (1993) shows that ignoring durability could also lead to negative autocorrelation in the monthly consumption data.

15. Consider a model with only seasonal taste shifters. Some of the coefficients in (8) can be identified by setting a reference month to zero and estimating:

$$\mathbf{\upsilon}_{t+1} = \beta(C_t/C_{t+1})^{\alpha}(e^{\mathrm{SD}_{t+1}\delta})^{1-\alpha}\,\mathbf{R}_{t+1} - \mathbf{1},$$

where

$$\boldsymbol{\delta}^* = \begin{pmatrix} -\delta_{12}^* \\ \delta_2^* \\ \delta_3^* - \delta_2^* \\ \delta_4^* - \delta_3^* \\ \vdots \\ \delta_{12}^* - \delta_{11}^* \end{pmatrix}.$$

16. The stock returns index is the value-weighted return on the New York Stock Exchange compiled by the Center for Research in Security Prices (CRSP) at the University of Chicago. The Treasury bill data are the same data used by Fama (1984) and updated by CRSP. The data are holding period returns on the Treasury bill that is closest to 30 days to maturity at the end of the month. The holding period is standardized to 30.4 days. The data used here are converted from continuous to discrete time. These asset data are available from 1959:3 to 1986:12.

17. Miron (1986) examines quarterly data and also includes a quadratic time trend in (8).

18. These differences could be due to the fact that I use a larger sample (328 observations), I use multiple assets (Miron uses only one asset, the discount rate on a three-month Treasury bill), and there is an error in the degrees of freedom calculation (and the p-values) in Miron's table. Ferson and Harvey (1992) reject the model using multiple assets and not seasonally adjusted quarterly data.

19. The first panel is also estimated with the instruments rolled back one period (not reported). The results are similar.

20. This is also noted in Breeden, Gibbons, and Litzenberger (1989).

21. Harvey (1988) finds no evidence against the restrictions implied by the model using two-, three-, and four-quarter overlapping horizons, while there is strong evidence against the model using the one-quarter horizon.

22. The algorithm uses the weighting matrix suggested by Hansen (1982) as the default. If the weighting matrix is not positive definite, then the matrix suggested by Newey and West (1987a) is used.

23. In testing the capital asset pricing model, Harvey (1989) finds that estimates of reward to risk parameters do not seem to be independent of the asset examined. This can be interpreted as evidence of misspecification.

24. This is the month that the Federal Reserve changed its operating procedures. However, it is not clear that risk aversion should be related to Fed procedures. As a result, it is best to interpret this as evidence of a more general specification problem.

25. The second test can be considered a test of structural stability. Ghysels and Hall (1990) develop a different methodology to test the stability of the parameter estimates. Applying their tests indicates that in many cases where the overidentifying restrictions are not rejected, there is evidence of instability in the parameter estimates.

26. Harvey (1989) provides results that suggest that the reward-to-risk ratio changes through time. With some assumptions on the consumption process, this ratio can be interpreted as the coefficient of relative risk aversion. If risk aversion is changing through time, then (2) and (13) are misspecified.

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Appendix A. The Components of Personal Consumption of Nondurable Goods

Category	*1986*[a]	*% of Total*[b]
Nondurable goods	877.2	100.0
Food	444.9	50.7
Food purchased for off-premise consumption	305.9	34.9
Purchased meals and beverages	130.9	14.9
Food furnished employees (including military) and food produced and consumed on farms	8.0	0.1
Addenda: Food excluding alcoholic beverages	394.5	45.0
Alcoholic beverages purchased for off-premise consumption	31.8	3.6
Other alcoholic beverages	18.5	2.1
Clothing and shoes	158.0	18.0
Shoes	24.0	2.7
Women's and children's clothing and accessories except shoes	91.2	10.4
Men's and boy's clothing and accessories except shoes	42.8	4.9
Gasoline and oil	100.3	11.4
Fuel oil and coal	21.5	2.5
Other	152.6	17.4
Tobacco Products	23.7	2.7

Category	*1986*[a]	*% of Total*[b]
Toilet articles and preparations	20.7	2.3
Semidurable house furnishings	12.8	1.5
Cleaning and polishing preparations, and miscellaneous household supplies and paper products	24.3	2.8
Drug preparations and sundries	22.3	2.5
Nondurables toys and sport supplies	21.8	2.5
Stationary and writing supplies	6.3	0.1
Net foreign remittances	3.2	0.0
Magazines, newspapers, and sheet music	11.8	1.3
Flowers, seeds, and potted plants	5.6	0.1

Notes: [a]Consumption data in billions of 1982 dollars.
[b]Percentages may not sum to 100 due to rounding.

Appendix B.
The Components of Nondurable Retail Sales

Category	*1986*[a]	*% of Total*[b]	*Closest CPI Match*[c]
Nondurable goods stores	886.6	100.0	Nondurables
General Merch. group stores	155.3	17.5	—
Food stores	296.0	33.4	Food
Gasoline service stations	86.6	9.8	Gasoline, motor oil and coolant
Apparel and accessory stores	80.8	9.1	Apparel commodities
Eating and drinking places	145.0	16.4	Food away from home
Drug and proprietary stores	49.3	5.6	Medical care commodities[d]
Liquor stores	19.8	2.2	Alcoholic beverages[d]
Other	53.6	6.0	—

Notes: [a]Billions of 1986 dollars.
[b]Percentages may not sum to 100 due to rounding.
[c]There are no deflators available for retail sales. The CPI is chosen that has the closest association with the sales category.
[d]Monthly price deflators only available from 1967:1.

Appendix C. The Easter Holiday: 1958–1987

Year	*Date*
1958	April 6
1959	March 29
1960	April 17
1961	April 2
1962	April 22
1963	April 14
1964	March 29
1965	April 18
1966	April 10
1967	March 26
1968	April 14
1969	April 6
1970	March 29
1971	April 11
1972	April 2
1973	April 22
1974	April 14
1975	March 30
1976	April 18
1977	April 10
1978	March 26
1979	April 15
1980	April 6
1981	April 19
1982	April 11
1983	April 3
1984	April 22
1985	April 7
1986	March 30
1987	April 19