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1 A Test of the International CAPM Using Business Cycles Indicators as Instrumental Variables

Bernard Dumas

1.1 Introduction

Previous work by Dumas and Solnik (1993) has shown that a CAPM which incorporates foreign-exchange risk premia (a so-called international CAPM) is better capable empirically of explaining the structure of worldwide rates of return than is the classic CAPM. The test was performed on the conditional version of the two competing CAPMs. By that is meant that moments of rates of return were allowed to vary over time in relation to a number of lagged "instrumental variables." Dumas and Solnik used instrumental variables which were endogenous or "internal" to the financial market (lagged world market portfolio rate of return, dividend yield, bond yield, short-term rate of interest).

In the present paper, I aim to use as instruments economic variables which are "external" to the financial market, such as leading indicators of business cycles. This is an attempt to explain the behavior of the international stock market on the basis of economically meaningful variables which capture "the state of the economy."

The stock market is widely regarded as the best predictor of itself. A large body of empirical work shows that asset prices are predictors of the future level

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of activity or, generally, the future level of economic variables.[1] Several leading indexes of economic activity make use of this property of asset prices.[2]

It may, however, also be true that "external" variables can serve to explain asset returns. Fama and French (1989) show that much of the movement in "internal" variables is related to business conditions; for instance, the term structure spread peaks during recessions. Kandel and Stambaugh (1989) show that expected returns peak at the end of a recession, and Harvey (1991b) shows that the ratio of conditional mean return to variance is countercyclical. We show below that a particular set of leading indicators (which does not include asset prices) predicts the stock markets of four economically developed countries with an in-sample R^2 which is comparable (and in some cases superior) to that of "internal" variables.

From a theoretical standpoint, it should be clear that any intertemporal general-equilibrium model, such as the models of domestic or international business cycles that have appeared recently,[3] would generate asset prices that would be functions of the state variables of the economy. In these models, the conditional expected values of rates of return would be functions of state variables as well. Assuming that the mapping from state variables to asset prices is invertible, conditional expected returns must be functions of asset prices. This explains why the stock market predicts itself; a large enough number of asset prices can serve as proxy variables for the state variables.

In the course of this substitution, however, the model has lost some of its empirical content since the link to the underlying physical economy has been severed. Even if one found that stock returns are related to stock prices in the theoretical way, that would still leave open the question of the contemporaneous relationship of this perfectly working stock market to the economy. Does the stock market move of its own accord or does it remain in line with the conditions of physical production? More is achieved when underlying state variables are identified and expected returns are related to them, than when expected returns are related to asset prices. This paper is a preliminary investigation into the nature of "the state of the economy," as revealed by the behavior of asset returns.

1. Fama and Schwert (1977) show that asset returns predict inflation in the United States. Stambaugh (1988) has extracted the information concerning future economic variables that is contained in bond prices. Several authors have observed that stock prices lead gross national product (GNP): Fama (1981, 1990), Fama and Gibbons (1982), Geske and Roll (1983), and Barro (1990).

2. The list of NBER leading indicators includes, besides exchange rates, (*a*) the yield on a constant-maturity portfolio of ten-year U.S. Treasury bonds, (*b*) the spread between the interest rate on six-month corporate paper and the rate on six-month U.S. Treasury bills, and (*c*) the spread between the yield on a constant-maturity portfolio of ten-year U.S. T-bonds and the yield on one-year U.S. T-bonds. See Stock and Watson (1989). The Department of Commerce list includes, besides money supply, the Standard and Poor's 500 industrials index (see *Survey of Current Business*, current issues).

3. On the international side, see, for example, Backus, Kehoe, and Kydland (1993), Baxter and Crucini (1993), Canova (1993), and Dumas (1992).

Capital asset pricing models can serve as a tool, or sift, in the identification of state variables. First, one finds variables that can serve to condition returns (i.e., that have some power to predict rates of return). Second, one verifies whether the conditional distribution satisfies some asset-pricing restrictions. For instance, can the first moments of returns be made to match time-varying risk premia built on second moments, as the conditional form of the classic CAPM would suggest they should? If not, either the model is incorrect or the variables have been improperly chosen. The search for the relevant state variables, which will account for the time variability of asset returns, is also a search for the relevant model specification.

This paper is organized as follows. Section 1.2 is a short reminder of the "pricing kernel" or marginal-rate-of-substitution approach to CAPM tests. Section 1.3 explores the behavior of worldwide asset returns on the basis of U.S. instrumental variables. Section 1.4 does the same thing on the basis of country-specific instrumental variables. Section 1.5 concludes.

1.2 The "Pricing Kernel" Methodology

The "pricing-kernel" method, or marginal-rate-of-substitution method, initiated by Gallant and Tauchen (1989) and Hansen and Jagannathan (1991), was used in Bansal, Hsieh, and Viswanathan (1993) and generalized by Dumas and Solnik (1993) to test CAPMs.

1.2.1 The International CAPM

Let there be $L + 1$ countries, a set of $m = n + L + 1$ assets—other than the measurement-currency deposit—comprised of n equities or portfolios of equities, L nonmeasurement-currency currency deposits, and the world portfolio of equities which is the mth and last asset. The nonmeasurement-currency deposits are singled out by observing the above order in the list; that is, they are the $(n + 1)$st to $(n + L)$th assets.

The international capital asset pricing model is equation (14) in Adler and Dumas 1983:

$$(1) \qquad E[r_{jt}|\Omega_{t-1}] = \sum_{i=1}^{L}\lambda_{i,\,t-1}\mathrm{Cov}[r_{jt},\, r_{n+i,\,t}|\Omega_{t-1}] + \lambda_{m,t-1}\mathrm{Cov}[r_{jt}, r_{mt}|\Omega_{t-1}],$$

where r_{jt} is the nominal return on asset or portfolio j, $j = 1 \ldots m$, from time $t - 1$ to t, in excess of the rate of interest of the currency in which returns are measured, r_{mt} is the excess return on the world market portfolio, and Ω_{t-1} is the information set which investors use in choosing their portfolios. The time-varying coefficients $\lambda_{i,t-1}$, $i = 1 \ldots L$, are the *world prices of foreign exchange risk.* The time-varying coefficient $\lambda_{m,t-1}$ is the world price of market risk. The model takes into account the fact that investors of different countries view returns differently.

Equation (1) is the result of an aggregation over the several categories of investors. Equation (14) in Adler and Dumas (1983) provides an interpretation of the prices of risk. λ_m is a wealth-weighted harmonic mean of the nominal risk aversions of the investors of the various countries—the world nominal risk aversion, as it were. λ_i is equal to $1 - \lambda_m$ times the weight of country i in the world, where a country's weight is determined by its wealth times one minus its nominal risk tolerance.

By contrast, the classic CAPM ignores investor diversity and assumes, in effect, that everyone in the world translates returns into consumption as do the residents of the reference currency country. Hence, no exchange-risk hedging premium appears. In the above notations, the restriction of the international CAPM to the classic CAPM is stated as

(2) $$\lambda_{i,t-1} = 0 \; i = 1 \ldots L, \forall t.$$

In Dumas and Solnik (1993), a way has been found of writing the international CAPM in a parsimonious way that minimizes the number of parameters to be estimated. Introduce u_t, the unanticipated component of the market's marginal rate of substitution between nominal returns at date t and at date $t - 1$. u_t has the property that

(3) $$E[u_t|\Omega_{t-1}] = 0.$$

Define u_t as

(4) $$u_t = \lambda_{0,t-1} + \sum_{i=1}^{L} \lambda_{i,t-1} r_{n+i,t} + \lambda_{m,t-1} r_{mt}.$$

And define h_{jt} as

(5) $$h_{jt} = r_{jt} - r_{jt} u_t. j = 1, \ldots . m.$$

Then, Dumas and Solnik (1993) show that the international CAPM (1) may be rewritten as

(6) $$E[h_{jt}|\Omega_{t-1}] = 0, j = 1, \ldots m.$$

Equations (3) and (6) are the moment conditions used in the generalized method of moments (GMM) estimation.

1.2.2 Auxiliary Assumptions of the Econometric Analysis

In this subsection, we state two auxiliary assumptions that are needed for econometric purposes. They are identical to the auxiliary assumptions used in Dumas and Solnik (1993).

Assumption 1 of the empirical analysis: the information Ω_{t-1} is generated by a vector of instrumental variables Z_{t-1}.

Z_{t-1} is a row vector of l predetermined instrumental variables which reflect everything that is known to the investor. One goal of this paper is to identify the list of Z variables. Assumption 1 is a strong assumption which does not simply limit the information set of the econometrician: it limits the information set of the investors and, therefore, their strategy space.

Next, we specify the way in which the market prices, λ, move over time. We assume that the variables, Z, can serve as proxies for the state variables and that there exists an exact linear relationship between the λs and the Zs:

Assumption 2:

$$\begin{aligned} \lambda_{0,t-1} &= -Z_{t-1}\delta, \\ \lambda_{i,t-1} &= Z_{t-1}\phi_i,\ i = 1, \ldots L \\ \lambda_{m,t-1} &= Z_{t-1}\phi_m. \end{aligned} \tag{7}$$

Here the δs and ϕs are time-invariant vectors of weights which are estimated by the GMM, under the moment conditions (3) and (6).

Given Assumption 2 and the definition (4) of u_t, we have

$$u_t = -Z_{t-1}\delta + \sum_{i=1}^{L} z_{t-1}\phi_i\, r_{n+i,t} + z_{t-1}\, \phi_m\, r_{mt}, \tag{8}$$

with u_t satisfying (3). Equation (8) serves to define u_t from now on.

1.2.3 Data

We consider the monthly excess return on equity and currency holdings measured in a common currency, the U.S. dollar. The excess return on an equity market is the return on that market (cum dividend) translated into dollars, minus the dollar one-month nominally risk-free rate. The return on a currency holding is the one-month interest rate[4] of that currency compounded by the exchange rate variation relative to the U.S. dollar, minus the dollar one-month risk-free rate.

In this study, we take four countries into account: Germany, the United Kingdom, Japan, and the United States. More precisely, we consider eight assets in addition to the U.S. dollar deposit: the equity index of each country,[5] a deutsche mark deposit, a pound sterling deposit, a yen deposit, and the world index of equities. In the CAPM, we include only three exchange risk premia—as many as we have exchange rates in the data set.

Available index level data cover the period January 1970 to December 1991, which is a 264-data-point series. However, we work with rates of return and in earlier work we needed to lag the rate of return on the world index by one month in the instrumental-variable set; that left 262 observations spanning March 1970 to December 1991. For the sake of comparability, we use here the same time series of returns.

4. These are Eurocurrency interest rates provided by Lombard Odier.

5. These are Morgan Stanley country indexes and the Morgan Stanley world index. See Harvey (1991a) for an appraisal of these indexes.

As we consider below various instrument sets, preliminary statistics will be provided concerning rates of return and their predictability.

1.3 U.S. Instrumental Variables

We first investigate a set of instruments common to all securities. We choose United States business-cycle variables as a common set. In the next section, we explore country-specific variables. The choice of U.S. variables as a common set is justified by figure 1.1, which plots coincident indicators of the business cycle in the four countries of our sample from 1948:01 to 1993:06.[6] It makes it plain that in most upturns and downturns the U.S. economy has led the two European economies of our sample. Japan has had at the most two downturns since the war; the United States has undergone downturns at about the same time. That the United States led other economies is confirmed by figure 1.2, which shows the cross-correlogram of coincident indicators between the United States and other countries.[7] Figure 1.2 reveals that the United States led Japan and Germany by at least twelve months and more strongly led the United Kingdom with a lead time of approximately four months. That fact also explains Harvey's (1991a) finding that U.S. stock market "internal" variables are at least as good predictors of worldwide rates of return as are country-specific "internal" variables.

Below we consider two sets of U.S. economic indicators: the Main Economic Indicators of the Organization for Economic Cooperation and Development (OECD) and the component indicators specifically selected by Stock and Watson (1993) to lead the U.S. cycles and predict recessions. Each time we consider a set of instrumental variables, predictability of returns is assessed by ordinary least squares (OLS), and conformity with the international and classic CAPMs is assessed by means of the GMM.

1.3.1 U.S. Main Economic Indicators (OECD)

I extracted from the OECD Main Economic Indicators (monthly data) the following variables in their seasonally adjusted version for the twenty years of our rate-of-return sample: (i) the U.S. level of total inventories in manufacturing industries (noted INV); (ii) U.S. residential construction put in place (RES); (iii) U.S. total value of retail sales (RSAL); (iv) U.S. percentage of unemployment out of the civilian labor force (UNMP);[8] (v) U.S. commercial bank loans (LOAN); and (vi) the U.S. money supply M3 (noted M3). All of

6. These are the coincident indicators calculated by the Center for International Business Cycle Research (CIBCR) as an overall measure of the overall performance of a country's economy.

7. These represent the correlation between the United States and other countries at various leads and lags, calculated after linear time detrending.

8. Business cycle experts know that unemployment lags the cycle. The use of this variable was not a good idea, but I refrained from making any changes to my original list for fear of accusations of data mining.

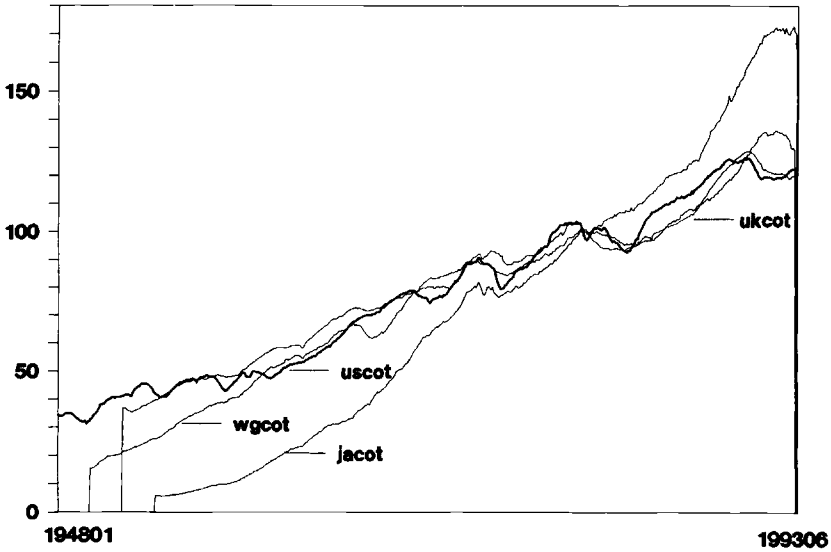

Fig. 1.1 Worldwide business cycles
Source: Center for International Business Cycle Research (CIBCR).
Note: the figure plots the indexes of coincident indicators (JACOT, UKCOT, WGCOT, USCOT) published by the CIBCR for the four countries investigated here.

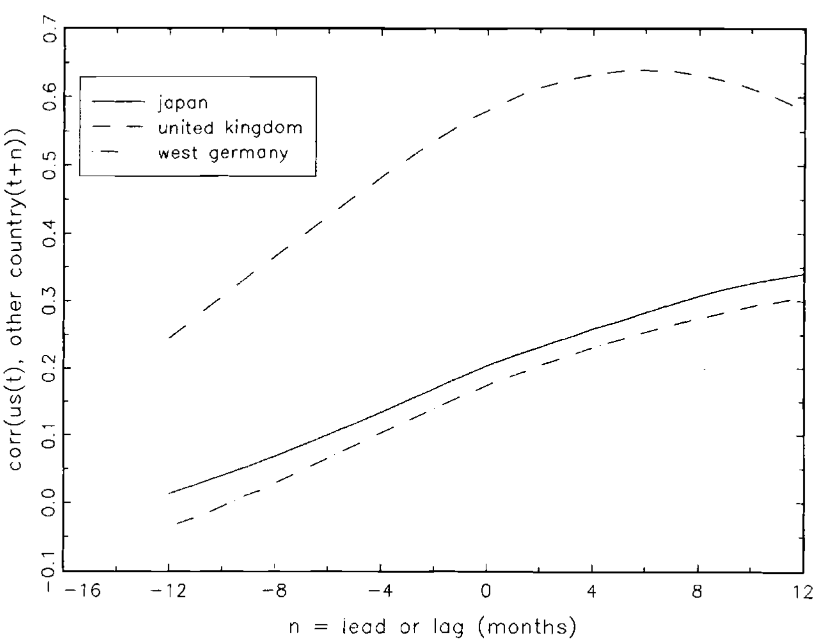

Fig. 1.2 Cross-correlogram of business cycles (1954–1993)
Note: The figure represents the cross-correlations of the U.S. coincident CIBCR indicator (USCOT) with the coincident indicators of other countries, after time detrending.

these were selected as being presumably "forward-looking variables." Series (iv) is naturally stationary. Other series were included in their first difference form. Even though it is properly classified as an "internal" variable, the lagged rate of return on the world market portfolio was added as an instrument in an attempt to capture potential lagged impacts of instruments on returns.[9]

Table 1.1 contains some descriptive statistics on rates of return, instrumental variables, and their ability to predict rates of return. I summarize in table 1.2 the R^2s that have been achieved by main economic indicators (column 2) and, for purposes of comparison, the R^2s that had been achieved by Dumas and Solnik (1993) by means of "internal" variables (column 1). It is observed that the predictive power of the Main Economic Indicators is generally lower than that of the "internal" financial variables. One variable has a consistent ability in predicting rates of return worldwide: the increase in U.S. inventories in manufacturing industries, with a positive increase of that variable being followed by lower returns.

Using these variables as instruments, I proceed to estimate the international and the classic CAPMs. The results appear in tables 1.3 and 1.4, respectively. The international CAPM yields a p-value of 0.0144 and is rejected. The classic CAPM produces a p-value of 0.0064 and is also rejected. It is not clear whether it is legitimate to test a hypothesis when the unrestricted model (in this case the international CAPM) is itself rejected. A Newey-West test does not reject the hypothesis that exchange-rate risk receives a zero price ($\phi_i = 0$, $i = 1 \ldots L$). (See table 1.5, p-value = 0.088.)

1.3.2 U.S. Leading Economic Indicators (National Bureau of Economic Research [NBER])

In a recent article, Stock and Watson (1993) proposed a leading index (called XLI2) which does not refer to financial variables and is instead constructed from the following leading indicators of the U.S. business cycle:[10] (i) housing authorizations (new private housing) in levels (HSBP);[11] (ii) average weekly hours of production workers in manufacturing, in level form (LPHRM); (iii) vendor performance: percentage of companies reporting slower deliveries, in levels (IVPAC); (iv) manufacturers' unfilled orders in the durable goods industries, 1982 dollars, smoothed[12] in growth rate form (MDU82); (v) the capacity utilization rate in manufacturing (Federal Reserve

9. The coefficient of this predictor will be found to be insignificant.

10. All variables are seasonally adjusted. In addition, Stock and Watson (1993) include the trade weighted nominal exchange rate between the United States and other countries as a leading indicator. We do not use it because it is a financial variable (although it obviously has real effects).

11. Observe that we use some of Stock and Watson's variables in level form, others in first-difference form. The issue of stationarity arises. There is no evidence that the level variables are nonstationary. However, there is a question of consistency in the comparisons; here we have housing authorizations in levels, whereas construction put in place—an MEI variable—was used in first-difference form in section 1.3. Further investigation is needed.

12. The series described as "smoothed" were passed through the filter $(1 + 2L + 2L^2 + L^3)$.

Table 1.1 **Summary Statistics Using U.S. Main Economic Indicators (MEIs) As Instrumental Variables (number of observations = 262)**

Securities	Mean of Excess Return	Standard Deviation of Excess Return
German stock market	0.0050726679	0.062362157
British stock market	0.0065975649	0.077541166
Japanese stock market	0.0090457824	0.065944529
U.S. stock market	0.0024764962	0.046825699
Deutsche mark	0.0017136374	0.034912228
British pound	0.0017428969	0.031856602
Japanese yen	0.0027198626	0.033234643
World stock market	0.0031789237	0.043619171

Instruments	Mean	Standard Deviation	Correlations						
Constant	1.00000	0.00000							
$rm,t-1$	0.0361454	0.521389	1.0	−0.15	0.11	0.026	0.13	−0.054	0.054
inv	0.00521380	0.0105418	−0.15	1.0	−0.21	−0.086	−0.18	0.14	0.11
res	0.00644040	0.0253341	0.11	−0.21	1.0	0.20	0.25	0.14	0.27
rsal	0.00633719	0.0132688	0.026	−0.086	0.20	1.0	0.038	0.097	0.15
unmp	6.69847	1.38235	0.13	−0.18	0.25	0.038	1.0	−0.25	0.14
loan	0.00774770	.00643937	−0.054	0.14	0.14	0.097	−0.25	1.0	0.41
M3	0.00733305	.00353889	0.054	0.11	0.27	0.15	0.14	0.41	1.0

Ordinary Least Squares with Heteroscedasticity Consistent Standard Errors (securities returns regressed on instruments; consistency is achieved by the Newey-West [NW] procedure)

German Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.00569285	0.0216447	0.263013	0.0222965
$rm, t-1$	0.00669026	0.00859968	0.777966	0.00746890
inv	−0.368126	0.243561	−1.51143	0.384939
res	0.0937675	0.152453	0.615060	0.167409
rsal	−0.326319	0.289070	−1.12886	0.295759
unmp	0.00189927	0.00285244	0.665842	0.00308242
loan	−0.0120132	0.618495	−0.0194233	0.698068
M3	−1.37839	1.10329	−1.24934	1.26840

R-squared is 0.236371

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
−0.018 −0.031 0.067 0.059 0.0027 −0.041 0.066 0.030

U.K. Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.00456223	0.0230321	0.198082	0.0275204
$rm, t-1$	0.00693558	0.00955990	0.725486	0.00921879

(continued)

Table 1.1 (continued)

World Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
inv	−0.553277	0.451608	−1.22513	0.475126
res	0.126568	0.242514	0.521900	0.206631
rsal	−0.553975	0.360443	−1.53693	0.365052
unmp	0.00330507	0.00330871	0.998899	0.00380460
loan	−0.684188	0.682991	−1.00175	0.861619
M3	−1.29185	1.27644	−1.01207	1.56557

R-squared is 0.0378930

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
0.065 −0.11 0.043 0.0099 −0.041 −0.017 0.856 −0.067

Japanese Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.00782489	0.0253743	−0.308378	0.0233101
$rm, t-1$	0.0136144	0.00992300	1.37201	0.00780844
inv	−0.862245	0.230546	−3.74001	0.402438
res	0.0640068	0.174230	0.367371	0.175019
rsal	−0.268500	0.357431	−0.751195	.309204
unmp	0.00178737	0.00316203	0.565262	0.00322255
loan	−0.352924	0.598969	0.589220	0.729803
M3	1.01683	1.20467	0.844073	1.32606

R-squared is 0.0456416

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
−0.057 −0.019 0.036 0.030 0.062 0.075 −0.015 0.051

U.S. Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.006669039	0.0168837	−0.396264	0.0165100
$rm, t-1$	0.00231443	0.00607610	0.380906	0.00553053
inv	−0.579509	0.195591	−2.96286	0.285037
res	0.00226372	0.119716	0.0189091	0.123962
rsal	−0.112179	0.234005	−0.479386	0.219002
unmp	0.00337828	0.00223428	1.51203	0.00228245
loan	−0.383116	0.444596	−0.861718	0.516902
M3	−0.935501	0.823839	−1.13554	0.939217

R-squared is 0.0504767

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.024 −0.064 −0.026 −0.049 −0.016 0.054 −0.020 −0.11

Deutsche Mark				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.0258594	0.0111676	2.31557	0.0123199
$rm, t-1$	0.00801109	0.00404676	−1.97963	0.00412691
inv	−0.385613	0.148917	−2.58945	0.212696
res	0.0204019	0.0911840	0.223744	0.0925011
rsal	−0.201447	0.159687	−1.26152	0.163420
unmp	−0.00275891	0.00157580	−1.75080	0.00170318
loan	0.268681	0.402691	0.667214	0.385715
M3	−0.586607	0.605239	−0.969215	0.700848

R-squared is 0.0488795

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
0.028 0.10 −0.0038 0.021 −0.0049 0.034 0.049 0.056

British Pound				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.0338504	0.0104436	3.24125	0.0111803
$rm, t-1$	−0.00303430	0.00378204	−0.802292	0.00374519
inv	−0.233203	0.109419	−2.13128	0.193023
res	0.0888226	0.0846396	1.04942	0.0839452
rsal	−0.220981	0.136461	−1.61937	0.148305
unmp	−0.00339392	0.00139092	−2.44005	0.00154564
loan	0.222244	0.318936	0.696829	0.350038
M3	−1.21933	0.543510	−2.24344	0.636023

R-squared is 0.0592174

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
0.066 0.067 −0.017 0.028 −0.084 −0.047 0.037 0.00080

Japanese Yen				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.0110907	0.0120695	0.918900	0.0118473
$rm, t-1$	−0.000429227	0.00397897	−0.107874	0.00396862
inv	−0.365841	0.111626	−3.27740	0.204538
res	0.113531	0.0832779	1.36328	0.0889533
rsal	−0.213294	0.169312	−1.25977	0.157152
unmp	−0.000364428	0.00168879	−0.215793	0.00163785
loan	0.00795930	0.290915	0.0273595	0.370921
M3	−0.470191	0.575398	−0.817156	0.673967

R-squared is 0.0294043

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
0.048 0.041 0.080 0.068 −0.0037 0.096 −0.051 −0.052

(*continued*)

Table 1.1 (continued)

World Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.00802493	0.0160887	−0.498793	0.0153149
$rm, t-1$	0.00598386	0.00545754	1.09644	0.00513018
inv	−0.622000	0.183153	−3.39607	0.264404
res	0.0297202	0.117849	0.252190	0.114989
rsal	−0.293711	0.211799	−1.38674	0.203149
unmp	0.00311797	0.00202408	1.54044	0.00211723
loan	−0.00729195	0.440082	−0.0165695	0.479484
M3	−0.672124	0.776432	−0.865657	0.871228

R-squared is 0.584330

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.011 −0.049 0.021 −0.041 −0.013 −0.067 0.098 −0.095

Table 1.2 **Summary of Predictive Ability of Instruments**

	R^2%				
	Dumas-Solnik	OECD Main Economic Indicators (table 1.1)	NBER XL12 Components (table 1.6)	NBER XL12 Delayed 1 Month	NBER XL12 Delayed 2 Months
Number of instruments (including constant)	6	8	7	7	7
German stock market	5.97	2.36	4.28	3.69	2.65
British stock market	10.28	3.79	12.18	10.20	5.03
Japanese stock market	7.93	4.56	9.27	7.86	7.40
U.S. stock market	9.60	5.05	7.96	4.55	4.42
Deutsche mark	10.63	4.89	4.07	4.52	3.12
British pound	11.24	5.92	3.14	3.62	2.61
Japanese yen	7.74	2.94	3.63	3.29	2.68
World stock market	11.33	5.84	10.17	5.86	4.99

	CIBCR Country Leading Indexes (LDTs) (table 1.9)	CIBCR Leading Index (LDT) Components
Number of instruments (including constant)	5	(number of instruments varies)
German stock market	2.76	2.19 (7)
British stock market	0.50	2.84 (9)
Japanese stock market	0.82	6.43 (7)
U.S. stock market	0.93	8.93 (10)
Deutsche mark	2.23	6.75 (16)
British pound	0.72	9.56 (18)
Japanese yen	0.06	10.39 (16)
World stock market	0.90	18.26 (30)

Table 1.3 **Estimation of the International CAPM with U.S. Main Economic Indicators as Instrumental Variables (number of observations = 262; number of factors = 4; degrees of freedom = 32)**

Generalized Method of Moments (GMM) Results, Stage 20			
Coefficients	Value	Standard Error	t-statistic
	Linear form for $\lambda_{0,t-1}$ (see equation [7])		
Constant	−0.7624	0.3710	−2.0553
$rm,t-1$	0.0567	1.3231	0.0428
inv	27.9459	15.0797	1.8532
res	2.1540	2.1545	0.9998
rsal	−6.2960	4.9054	−1.2835
unmp	0.0185	0.0055	3.3873
loan	−2.7934	9.7046	−0.2878
M3	−34.0587	14.2208	−2.3950
	Linear Forms for Market Prices of Risk, $\lambda_{m,t-1}$ and $\lambda_{i,t-1}$		
Constant			
$\lambda m,t-1$	53.8784	24.1627	2.2298
$\lambda 1,t-1$	45.0855	20.5153	2.1977
$\lambda 2,t-1$	−30.7942	20.7468	−1.4843
$\lambda 3,t-1$	−23.0563	9.9523	−2.3167
$rm\,(-1)$			
$\lambda m,t-1$	−160.2995	86.3428	−1.8565
$\lambda 1,t-1$	87.9048	83.4154	1.0538
$\lambda 2,t-1$	39.4347	75.9711	0.5191
$\lambda 3,t-1$	17.2105	34.7671	0.4950
inv			
$\lambda m,t-1$	−1390.1074	733.0540	−1.8963
$\lambda 1,t-1$	718.7262	727.4729	0.9880
$\lambda 1,t-1$	−229.0456	561.8708	−0.4076
$\lambda 1,t-1$	−148.8943	256.9847	−0.5794
res			
$\lambda m,t-1$	−206.5363	138.6434	−1.4897
$\lambda 1,t-1$	78.9526	159.1203	0.4962
$\lambda 2,t-1$	140.8913	169.2117	0.8326
$\lambda 3,t-1$	7.2748	82.5645	0.0881
rsal			
$\lambda m,t-1$	−157.2546	223.5246	−0.7035
$\lambda 1,t-1$	−99.0278	253.8506	−0.3901
$\lambda 1,t-1$	−59.7750	222.6823	−0.2684
$\lambda 1,t-1$	−206.2905	140.8505	−1.4646
unmp			
$\lambda m,t-1$	−0.8447	0.3391	−2.4906
$\lambda 1,t-1$	−0.4295	0.2883	−1.4897
$\lambda 2,t-1$	0.5240	0.2841	1.8446
$\lambda 3,t-1$	0.4676	0.1505	3.1062

(continued)

Table 1.3 (continued)

Generalized Method of Moments (GMM) Results, Stage 20			
Coefficients	Value	Standard Error	t-statistic
	Linear Forms for Market Prices of Risk, $\lambda_{m,t-1}$ and $\lambda_{i,t-1}$		
loan			
$\lambda m,t-1$	705.1855	645.9489	1.0917
$\lambda 1,t-1$	117.8120	796.5030	0.1479
$\lambda 2,t-1$	−311.7085	734.6841	−0.4243
$\lambda 3,t-1$	−594.0021	371.0511	−1.6009
M3			
$\lambda m,t-1$	283.5984	1168.9769	0.2426
$\lambda 1,t-1$	−2710.4280	1559.4271	−1.7381
$\lambda 2,t-1$	350.1110	1346.4438	0.2600
$\lambda 3,t-1$	99.3373	664.8671	0.1494

Note: Number of iterations: 2; weighing matrix updated 20 times; chi-square : 51.923974; RIGHT TAIL p-value : 0.014421; degrees of freedom : 32.

Table 1.4 **Estimation of the Classic CAPM with U.S. Main Economic Indicators as Instrumental Variables (number of observations = 262; number of factors = 1; degrees of freedom = 56)**

Generalized Method of Moments Results, Stage 31			
Coefficients	Value	Standard Error	t-statistic
	Linear form for $\lambda_{0,t-1}$ (see equation [7])		
Constant	−0.0590	0.1727	−0.3416
$rm,t-1$	−0.2638	0.5272	−0.5003
inv	8.0625	11.0876	0.7272
res	1.4246	1.2198	1.1679
rsal	−6.7746	3.1070	−2.1804
unmp	0.0023	0.0026	0.8853
loan	−0.3844	3.0409	−0.1264
M3	−2.0035	7.9628	−0.2516
	Linear Form of Market Price of Covariance Risk, $\lambda_{m,t-1}$		
Constant	−2.0280	7.9695	−0.2545
$rm,t-1$	14.2907	30.0824	0.4751
inv	−344.1557	126.6979	−2.7163
res	113.9686	72.0067	1.5828
rsal	−343.5483	121.5828	−2.8256
unmp	0.1899	0.1152	1.6485
loan	−81.3205	306.1997	−0.2656
M3	−379.7604	541.0834	−0.7019

Note: Number of iterations: 4; weighing matrix updated 31 times; chi-square : 85.755252; RIGHT TAIL p-value : 0.006427; degrees of freedom : 56.

Table 1.5 **Tests of Hypotheses**

Instruments	Specification	χ^2 Difference	Degrees of Freedom	p-value
U.S. MEI 8 instruments	linear	85.750564 $-\underline{51.923974}$ 33.826590	24	0.088
U.S. NBER 7 instruments	linear	86.702953 $-\underline{39.961045}$ 46.741908	21	0.001

Note: Statistics in this table test the hypothesis: $\phi_i = 0$, $i = 1, 2, 3$ against the alternative that the international CAPM holds. The various tests differ only in the set of the instrumental variables used.

Board), in first difference form (IPXMCA); and (vi) an index of help-wanted advertising in newspapers (the Conference Board), in growth rates (LHELL).

Table 1.6 reports the results of multiple OLS (and heteroscedasticity corrected) regressions of rates of return on these variables.[13] For purposes of comparison, the overall performance (R^2s) is transcribed in table 1.2. This set of instruments predicts stock returns worldwide about as well as the financial or internal variables used by Dumas and Solnik do. They predict currencies less well. The outstanding contribution to predictability is that of the indicator IVPAC (vendor performance) whose t-statistics in regressions of the various securities rates of return are, respectively, −2.72, −4.23, −2.96, −4.05, −0.138, −1.42, −1.62, −4.30. The signs are as expected: an increase in the number of firms reporting slower deliveries is followed by lower returns on securities. The larger values of t occur for stock returns. The forecasting of currencies presumably requires bilateral instrumental variables; U.S. business-cycle variables by themselves are insufficient. Another valuable contribution is that of HSBP (housing starts), also with the anticipated sign.

Many time series (280 series, precisely) were mined by Stock and Watson to select variables and their lags in order to make up an index that predicts the three-month increments in their U.S. index of coincident indicators (XCI, defined in Stock and Watson 1989). It turns out, however, that these variables (without lags) also predict U.S. and other stock returns about as well as internal variables do. That is not the result of data mining.[14]

13. The indicated variables were used in a vector autoregression (VAR) form by Stock and Watson to predict increments in their index of coincident indicators (XCI). I use here the raw variables, in the form described, without the VAR form and without lags. I did reconstruct the implied VAR coefficients that Stock and Watson used but found that the VAR form predicts securities returns with approximately the same degree of success as do the raw variables.

14. The correlations between monthly securities returns and one-month increments in the XCI are as follows:

German stock market	−0.074
British stock market	−0.073
Japanese stock market	0.046

Table 1.6 **Summary Statistics with U.S. NBER Variables as Instruments**

Instruments	Mean	Standard Deviation	Correlations					
Constant	1.00000	0.00000						
hsbp	121.004	32.6542	1.0	0.34	0.49	0.44	0.41	0.48
lphrm	40.2859	0.607544	0.34	1.0	0.45	0.38	0.30	0.23
ivpac	53.3844	13.0493	0.49	0.45	1.0	0.58	0.23	0.29
mdu82	0.00139399	0.0102974	0.44	0.38	0.58	1.0	0.27	0.31
ipxmca	−0.0164122	0.772366	0.41	0.30	0.23	0.27	1.0	0.49
lhell	−0.000517679	0.0316811	0.48	0.23	0.29	0.31	0.49	1.0

Ordinary Least Squares (OLS) with Heteroscedasticity Consistent Standard Errors (securities returns regressed on instruments; consistency is achieved by the Newey-West [NW] procedure)

German Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.390731	0.276101	−1.41518	0.285232
hsbp	0.000343379	0.000136858	2.50901	0.000149806
lphrm	0.0102116	0.00712679	1.43284	0.00722220
ivpac	−0.00107297	0.000393827	−2.72446	0.0000389195
mdu82	0.0304419	0.444454	0.0684928	0.469395
ipxmca	−0.00305786	0.00572859	−0.533789	0.00584667
lhell	−0.113002	0.159433	−0.708775	0.146780

R-squared is 0.0428200

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.031 −0.039 0.049 0.053 −0.0062 −0.036 0.056 0.036

U.K. Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.534844	0.308444	−1.73401	0.339701
hsbp	0.000559973	0.000184360	3.03739	0.000178414
lphrm	0.0147479	0.00770939	1.91298	0.00860139
ivpac	−0.00227316	0.000537946	−4.22562	0.000463518
mdu82	0.379958	0.548411	0.692834	0.559033
ipxmca	−0.0170324	0.0136970	−1.24351	0.00696319
lhell	−0.181394	0.159830	−1.13492	0.174810

R-squared is 0.121848

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.016 −0.15 0.038 −0.027 −0.050 −0.013 0.043 −0.0079

Japanese Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.253508	0.320174	−0.791781	0.293657
hsbp	0.000750459	0.000148571	5.05119	0.000154231
lphrm	0.00563301	0.00822220	0.685097	0.00743553
ivpac	−0.00102859	0.000346998	−2.96424	0.000400692
mdu82	−0.288754	0.449197	−0.642822	0.483261
ipxmca	−0.00251334	0.00529847	−0.474353	0.00601938
lhell	−0.166150	0.141414	−1.17492	0.151116

R-squared is 0.0926722

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.020 −0.071 −0.0020 −0.011 0.043 0.073 0.0095 0.077

U.S. Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.235663	0.215653	−1.09279	0.210016
hsbp	0.000251501	0.000108271	2.32289	0.000110302
lphrm	0.00660721	0.00542312	1.21834	0.00531770
ivpac	−0.00109923	0.000271581	−4.04752	0.000286564
mdu82	0.0564726	0.361858	0.156063	0.345615
ipxmca	−0.00219562	0.00430679	−0.509805	0.00430490
lhell	−0.187171	0.117017	−1.59952	0.108074

R-squared is 0.0795992

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.034 −0.090 −0.028 −0.052 −0.022 0.032 −0.0042 −0.088

Deutsche Mark				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.328134	0.137363	−2.38880	0.159854
hsbp	0.000193983	6.49824e-05	2.98516	8.39562e-05
lphrm	0.00766495	0.00353697	2.16710	0.00404757
ivpac	−3.82105e-05	0.000276595	−0.138146	0.000218118
mdu82	−0.328321	0.241348	−1.36036	0.263065
ipxmca	−0.00438420	0.00321052	−1.36557	0.00327667
lhell	−0.0215355	0.0852959	−0.252481	0.0822604

R-squared is 0.0407542

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
−0.022 0.071 −0.010 0.018 −0.039 −0.00073 0.028 0.096

(*continued*)

Table 1.6 (continued)

British Pound				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.332575	0.133099	−2.49870	0.146574
hsbp	0.000103983	5.95071e-05	1.74741	7.69820e-05
lphrm	0.00828977	0.00341368	2.42840	0.00371133
ivpac	−0.000231653	0.000163528	−1.41660	0.000199999
mdu82	0.0712808	0.212960	0.334714	0.241212
ipxmca	−0.000255775	0.00267844	−0.0954940	0.00300448
lhell	−0.0733277	0.0714012	−1.02698	0.0754270

R-squared is 0.0313697

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.056 0.073 −0.016 0.036 −0.093 −0.046 −0.011 0.038

Japanese Yen				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.159703	0.166350	−0.960047	0.152527
hsbp	0.000187078	6.24738e-05	2.99450	8.01082e-05
lphrm	0.00389288	0.00423289	0.919674	0.00386205
ivpac	−0.000316085	0.000194594	−1.62433	0.000208121
mdu82	−0.134085	0.244464	−0.548487	0.251008
ipxmca	−0.00347325	0.00299366	−1.16020	0.00312649
lhell	0.0734632	0.0826545	0.888798	0.0784901

R-squared is 0.0362787

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.039 0.018 0.065 0.067 −0.015 0.094 −0.061 −0.030

World Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	−0.304620	0.201082	−1.51490	0.193269
hsbp	0.000392649	9.90945e-05	3.96237	0.000101506
lphrm	0.00789062	0.00511004	1.54414	0.00489366
ivpac	−0.00108092	0.000251444	−4.29886	0.000263713
mdu82	−0.0322675	0.322532	−0.100044	0.318056
ipxmca	−0.00401874	0.00432539	−0.929105	0.00396162
lhell	−0.172625	0.102169	−1.68960	0.0994560

R-squared is 0.101723

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.0092 −0.096 0.0014 −0.048 −0.031 0.051 0.015 −0.036

There is, of course, an issue concerning the precise timing of releases of economic data. Internal variables are observed in real time in the financial markets, whereas some economic variables are released several weeks after the end of the month. In the statistical analysis, we have simply used the data pertaining to month $t - 1$ to predict rates of return over the month $(t - 1, t)$. That procedure is not congruent with actual release dates. However, the variable that is most effective in bringing about predictive performance is vendor performance IVPAC. IVPAC is released by the National Association of Purchasing Managers a mere two days after the end of the month.

Even if economic data are released with some delay by statistical agencies and would, therefore, be available to external observers at that time only, it is also true that the investors, whose information set we are trying to represent, are not external observers and do not await actual releases. They enjoy the benefits of early estimates.

Furthermore, financial market prices and flows of goods and services act as aggregators of information faster than statistical agencies do. My goal in this paper is not to show that external economic variables are superior in their predictive ability to internal financial variables. I use them because I believe that their message is more meaningful. I am comfortable with the idea that news about economic variables may be "released" through the channel, inter alia, of financial market prices. Even then, I am interested in identifying the relevant economic variables.

The reader may nonetheless wish to know how the results would have been affected by a different assumption on the timing of releases. In order to provide that information to him or her, I have shown in table 1.2 the levels of R^2s attained when the Stock and Watson variables are delayed further by one and also two months. Not surprisingly, the predictive performance for stock returns deteriorates gradually.[15] The predictive performance for currencies, which was poor in the first place, is not markedly affected.

Tables 1.7 and 1.8 report on the tests of the two CAPMs based on the Stock and Watson leading variables. The overidentifying restrictions of the international CAPM are marginally accepted with a p-value of 0.067, and the classic CAPM is rejected with a p-value of 0.03.[16] A Newey-West test of the hypothesis of zero price on foreign-exchange risk is reported in table 1.5 and shows rejection (p-value = 0.0005). Foreign-exchange-risk premia are significant.

U.S. stock market	−0.027
Deutsche mark	−0.075
British pound	−0.073
Japanese yen	0.026
World stock market	−0.032

15. In my opinion, the gradual deterioration in predictive power that occurs confirms that earlier results were not pure chance and that they was some bona fide predictive power in the first place.

16. When the Stock-Watson instruments are lagged one month further, the international CAPM is marginally rejected (p-val = 3.9 percent) and the domestic CAPM is marginally accepted (p-val = 9.17 percent).

Table 1.7 **Estimation of the International CAPM with U.S. NBER Instrumental Variables (number of observations = 262; number of factors = 4; degrees of freedom = 28)**

Generalized Method of Moments (GMM) Results, Stage 19			
Coefficients	Value	Standard Error	t-statistic
	Linear form for $\lambda_{0,t-1}$ (see equation [7])		
Constant	7.2346	3.9152	1.8478
hsbp	0.0176	0.0234	0.7530
lphrm	−0.1811	0.0957	−1.8915
ivpac	0.0030	0.0053	0.5681
mdu82	11.3602	5.6840	1.9986
ipxmca	−0.0063	0.0077	−0.8162
lhell	−1.5675	1.8945	−0.8274
	Linear Forms for Market Prices of Risk, $\lambda_{m,t-1}$ and $\lambda_{m,t-1}$ and $\lambda_{i,t-1}$		
Constant			
$\lambda m,t-1$	−244.6722	300.3837	−0.8145
$\lambda 1,t-1$	−421.7032	230.8744	−1.8265
$\lambda 2,t-1$	361.2365	233.2194	1.5489
$\lambda 3,t-1$	−32.8439	151.6363	−0.2166
hsbp			
$\lambda m,t-1$	6.3348	2.0582	3.0779
$\lambda 1,t-1$	−1.7197	1.8737	−0.9178
$\lambda 2,t-1$	−1.0261	1.6096	−0.6374
$\lambda 3,t-1$	2.2875	0.9770	2.3414
lphrm			
$\lambda m,t-1$	4.0333	7.6146	0.5297
$\lambda 1,t-1$	11.0753	5.9827	1.8512
$\lambda 2,t-1$	−7.8050	5.9297	−1.3162
$\lambda 3,t-1$	0.9961	3.8104	0.2614
ivpac			
$\lambda m,t-1$	0.4265	0.3275	1.3021
$\lambda 1,t-1$	−0.1739	0.4019	−0.4327
$\lambda 2,t-1$	−0.7289	0.3564	−2.0453
$\lambda 3,t-1$	−0.4764	0.1738	−2.7418
mdu82			
$\lambda m,t-1$	−1518.8104	512.2532	−2.9650
$\lambda 1,t-1$	762.5102	432.8288	1.7617
$\lambda 2,t-1$	583.1863	426.5617	1.3672
$\lambda 3,t-1$	−105.5570	259.2887	−0.4071
ipxmca			
$\lambda m,t-1$	−0.6235	0.4303	−1.4488
$\lambda 1,t-1$	−1.1746	0.5937	1.9785
$\lambda 2,t-1$	−0.2372	0.4885	−0.4856
$\lambda 3,t-1$	0.3153	0.1770	1.7812

Table 1.7 (continued)

Generalized Method of Moments (GMM) Results, Stage 19			
Coefficients	Value	Standard Error	t-statistic
lhell			
$\lambda m,t-1$	−200.9777	114.8282	−1.7502
$\lambda 1,t-1$	−227.7343	111.1008	−2.0498
$\lambda 2,t-1$	354.0376	126.1874	2.8056
$\lambda 3,t-1$	−171.5884	56.9768	−3.0116

Note: Number of iterations: 2; weighing matrix updated 19 times; chi-square: 39.961045; RIGHT TAIL p-value : 0.066658; degrees of freedom: 28.

Table 1.8 **Estimation of the Classic CAPM with U.S. NBER Instrumental Variables (number of observations = 262; number of factors = 1; degrees of freedom = 49)**

Generalized Method of Moments Results, Stage 8			
Coefficients	Value	Standard Error	t-statistic
	Linear form for $\lambda_{0,t-1}$ (see equation [7])		
Constant	2.5886	1.8490	1.4000
hsbp	0.0087	0.0162	0.5388
lphrm	−0.0709	0.0469	−1.5126
ivpac	0.0056	0.0037	1.5079
mdu82	1.5476	3.2085	0.4823
ipxmca	−0.0082	0.0051	−1.6022
lhell	−1.4689	1.0460	−1.4044
	Linear Form of Market Price of Covariance Risk, $\lambda_{m,t-1}$		
Constant	−124.5130	117.8852	−1.0562
hsbp	2.4277	0.7155	3.3930
lphrm	3.3990	2.9848	1.1388
ivpac	−0.6296	0.1319	−4.7728
mdu82	61.8821	202.6053	0.3054
ipxmca	0.1011	0.1378	0.7339
lhell	−99.3850	44.9423	−2.2114

Note: Number of iterations: 4; weighing matrix updated 8 times; chi-square: 69.235898; RIGHT TAIL p-value: 0.029985; degrees of freedom: 49.

1.4 Worldwide Instrumental Variables

In tests of conditional CAPMs, it is crucial to predict well the market rate of return and, in tests of the international conditional CAPM, it is important to predict well the rates of return on currencies. Exchange rates are bilateral variables. Their prediction should not logically be based on unilateral instrumental variables, such as U.S. leading indicators. In this section, I consider instrumental variables reflecting the business cycles of the four countries of our sample. I use leading indexes of the four countries' cycles simultaneously.

Every month the Center for International Business Cycle Research (CIBCR) publishes a leading index of the business cycle for eleven countries. The growth rate of the index provides advance warning of a growth cycle upturn or downturn.[17] I used the leading indicators of Japan (JALDT), the United Kingdom (UKLDT), the former West Germany (WGLDT), and the United States (USLDT), in their growth rate form, as instrumental variables. The forecasting performance of the five variables (including a constant) is reported in table 1.9. R^2s are very low, of the order of 1 percent or 2 percent. It did not seem worthwhile to pursue a test of any CAPM.

The fact that a leading index shows poor forecasting performance for stock returns does not preclude the component series of the index from faring many times better. For instance, the Stock and Watson XLI2 (experimental leading index) predicts returns very poorly, but we reported in section 1.3.2 that its components provide the best forecasting basis that we have found so far. This remark applies even more in the case of the CIBCR indexes since they are meant to be qualitative predictors of upturns and downturns, not quantitative predictors of the subsequent movement in the business cycle.

Accordingly, I have also investigated the predictive ability of the series which compose the country leading indexes of the CIBCR. For each country, I used as instruments every component series that was available on a monthly basis. Then, for example, German stock returns were predicted on the basis of German instruments alone, but the deutsche mark/dollar return was predicted on the basis of German and U.S. instruments; the worldwide stock returns were predicted on the basis of all country instruments put together. In table 1.2 the column headed CIBCR leading index (LDT) components contains the R^2s obtained by this method. The number of instruments is large; yet the forecasting performance reached for stocks is no better than that of the NBER component series. For currencies, the performance is better (R^2s of the order of 10 percent). However, due to their large number, these instruments cannot be used to test CAPMs by the GMM.

Instruments ought to be selected in each country for the purpose of predicting increments in business-cycle coincident indicators. This would be a replication of the Stock and Watson procedure with worldwide data. Then the

17. Descriptions of various leading indicators are available in Lahiri and Moore (1991) and Moore (1992).

Table 1.9 **Summary Statistics with the CIBCR's Country Leading Indexes as Instruments**

Instruments	Mean	Standard Deviation	Correlations			
Constant	1.000000	0.000000				
JALDT	0.003146	0.013503	1.00	0.29	0.37	0.25
UKLDT	0.001078	0.006056	0.29	1.00	0.23	0.22
WGLDT	0.001533	0.005653	0.37	0.23	1.00	0.28
USLDT	0.002531	0.009265	0.25	0.22	0.28	1.00

Ordinary Least Squares with Heteroscedasticity Consistent Standard Errors (securities returns regressed on instruments; consistency is achieved by the Newey-West [NW] procedure)

German Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.006115	0.004093	1.493955	0.004043
JALDT	−0.528313	0.307287	−1.719281	0.313727
UKLDT	0.856442	0.673679	1.271291	0.669450
WGLDT	1.028668	0.699139	1.471335	0.745461
USLDT	−0.742447	0.391963	−1.894175	0.438001

R-squared is 0.027619

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36)::
0.01 −0.02 0.08 0.08 −0.04 −0.03 0.05 0.05

U.K. Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.007672	0.006315	1.214889	0.005085
JALDT	−0.045286	0.480511	−0.094246	0.394588
UKLDT	−0.828986	1.006346	−0.823758	0.841997
WGLDT	−0.234803	0.911190	−0.257689	0.937598
USLDT	0.127008	0.705268	0.180084	0.550892

R-squared is 0.005056

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.01 −0.08 0.06 0.00 −0.05 −0.00 0.07 −0.03

Japanese Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.007704	0.004565	1.687841	0.004318
JALDT	0.128434	0.308548	0.416253	0.335046
UKLDT	0.502277	0.691403	0.726461	0.714943
WGLDT	−0.487162	0.745188	−0.653744	0.796118
USLDT	0.451507	0.458765	0.984179	0.467765

(continued)

Table 1.9 (continued)

R-squared is 0.008194

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.05 0.0 0.06 0.05 0.08 0.08 −0.02 0.07

U.S. Stock Market

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.002766	0.003427	0.807155	0.003064
JALDT	0.094160	0.240852	0.390946	0.237778
UKLDT	0.072221	0.450946	0.160154	0.507384
WGLDT	−0.842245	0.582581	−1.445712	0.564994
USLDT	0.247814	0.331390	0.747801	0.331966

R-squared is 0.009287

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.05 −0.03 0.01 0.00 −0.00 0.03 −0.03 −0.05

Deutsche Mark

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.002498	0.002209	1.130873	0.002270
JALDT	−0.093262	0.180581	−0.516453	0.176112
UKLDT	0.345475	0.321228	1.075484	0.375799
WGLDT	0.344474	0.477226	0.721825	0.418468
USLDT	−0.549694	0.232381	−2.365488	0.245874

R-squared is 0.022317

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.04 0.09 0.02 0.05 −0.00 0.03 0.03 0.08

British Pound

Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.002029	0.001968	1.030766	0.002087
JALDT	0.057912	0.152396	0.380009	0.161934
UKLDT	−0.191978	0.292474	−0.656395	0.345546
WGLDT	0.246833	0.383650	0.643380	0.384779
USLDT	−0.252616	0.219688	−1.149884	0.226080

R-squared is 0.007217

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.10 0.08 0.02 0.06 −0.05 −0.00 0.02 0.03

Japanese Yen				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.002853	0.002193	1.300887	0.002184
JALDT	−0.036799	0.171975	−0.213981	0.169500
UKLDT	−0.013601	0.340779	−0.039911	0.361690
WGLDT	−0.087413	0.378062	−0.231214	0.402756
USLDT	0.051806	0.231718	0.223571	0.236642
R-squared is	0.000616			

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.07 0.05 0.08 0.10 0.02 0.10 −0.06 −0.04

World Stock Market				
Coefficients	Value	NW Standard Error	t-statistic	OLS Standard Error
Constant	0.003171	0.003181	0.996848	0.002855
JALDT	0.109950	0.219190	0.501620	0.221523
UKLDT	0.113356	0.435592	0.260235	0.472700
WGLDT	−0.730282	0.514128	−1.420427	0.526371
USLDT	0.260565	0.325975	0.799338	0.309273
R-squared is	0.009033			

residual auto correlations (rho1~rho2~rho3~rho4~rho8~rho12~rho24~rho36):
0.10 −0.03 0.04 −0.00 −0.01 0.05 −0.01 −0.03

selected instruments could be investigated for the ability to forecast securities returns. This will be left for future research.

1.5 Conclusion

This preliminary investigation was meant to highlight the links that exist between predicted activity levels and conditionally expected stock returns. The following conclusions emerge from it:

1. The nonfinancial leading indicators selected by Stock and Watson (1993) for the purpose of predicting United States business cycles also seem to offer some potential for the prediction of worldwide stock returns. Outstanding contributions to predictive power were made by the variables IVPAC (vendor performance) and HSBP (housing authorizations). Furthermore, the signs of these variables' coefficients made intuitive sense. IVPAC is an especially valuable predictor since its value is released a mere forty-eight hours after the end of the month.

2. Using the Stock and Watson instrument set, the international conditional CAPM was marginally not rejected while the classic conditional CAPM was rejected.

3. Other sets of instrumental variables that I have tried so far (U.S. Main Economic Indicators, CIBCR country leading indexes) have not proven as successful both in regard to their power of prediction and in regard to their ability to discriminate between asset-pricing models.

Other more subtle clues could be gathered from the data and could point the way toward future research. The first issue that I would like to raise concerns the link between predictability of returns and the power of asset-pricing tests. The OECD Main Economic Indicators (MEIs), as used here, have lower predictive power than did the Stock and Watson leading series, while these series in turn had a lower predictive ability than did the "internal" variables used by Dumas and Solnik and others (see table 1.2). In tests of asset prices, the MEIs rejected both the classic and the international models, while the Stock-Watson variables rejected one model and marginally did not reject the other. In Dumas and Solnik (1993), the discrimination between the two asset-pricing models was much sharper (the classic CAPM was rejected while the international one had a p-value of 22 percent). As we improve the degree of predictability, should we expect better discrimination between models? Since our goal is not to predict but to identify state variables of the economy and to determine which asset-pricing model is correct, how much importance should we give to the predictive power (the R^2) of the instruments?

The second issue concerns the choice of instrumental variables. In this respect it is important to avoid the pitfalls of data mining. That is the reason why I never modified my list of MEI indicators and why I chose to work with the Stock and Watson variables which have been preselected to predict activity and not to predict stock returns. This defense against accusations of data mining is all the stronger as the correlations between stock returns and activities levels are small (see note 14). As we attempt to predict worldwide stock returns, should we be content to use U.S. variables, such as those of Stock and Watson, on the grounds that the U.S. business cycle seems to lead other cycles? Or can we hope to attain greater predictability by using country-specific indicator variables? If so, should these variables be selected on the basis of their ability to predict local levels of activity?

A third issue that will deserve more scrutiny is the influence of time lags. Time lags are both of economic and statistical significance. Economically speaking, only innovation in a data series is capable of constituting news. News is the primary moving force behind realized returns. It is not clear, however, to what extent the past information and the lag structure that were identified as giving the best prediction of activity levels should also be relevant as determinants of conditionally expected returns. We did observe here (note 13) that the use of the Stock and Watson lags did not improve the predictability of returns.

Finally, from the point of view of the statistical specification, Thierry Wizman will point out in his comment that the levels, the first differences of indicator variables, and their first differences at different lags do not convey the same information concerning the stage of the business cycle the economy is in and do not have the same power to predict returns. How does one determine which specification is preferable for our purposes?

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Comment Campbell R. Harvey

The Contribution

Bernard Dumas's paper is important because it bridges finance and macroeconomics. I am sure that it will cause researchers to reevaluate the way that they specify the representative investor's conditioning information. Indeed, the idea of this paper is to explore the behavior of international stock market returns with "economically meaningful" variables. These variables will be called "external" or "macro" variables. This is in contrast to previous research which focuses on "internal" variables which are usually lagged financial returns. The paper poses and answers two questions: Do the external variables predict returns? and How does the use of external variables change the tests of the international CAPM?

Why Have Researchers Avoided Using Macro Variables?

Let me begin my discussion with an explanation of why previous research has focused on the use of financial variables as instruments. First, financial variables are available at time $t - 1$ (last day of month) and can be legitimately used to predict returns over the next month. This is in contrast to the variables used by Dumas. None of the macro variables is available on the last day of the month—not even the number of manufacturers reporting slower deliveries.

In conditional asset-pricing tests, it is crucial to have instruments that are strictly predetermined. None of the variables used in his asset-pricing tests are predetermined. In addition, it is hard to make the argument that all investors know the data before they are released. While they might in some countries, it is not the case in the United States. These macro data are very carefully protected before their release (usually at 8:30 A.M. EST). In addition, the innovations in the announcements affect both returns and volatility (see Harvey and Huang 1993). Hence, the values of the macro variables are not know in advance.

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The Advantages of Financial Variables as Instruments

Financial variables, on the other hand, are known on the last day of the month. In addition, asset-pricing theory suggests that financial variables should capture expectations of economic growth. A good example is interest rates. The price of the j-period discount bond, Q_j, is

$$Q_t^j = E[m_{t+j}|\Omega_{t-1}],$$

where m_{t+j} is the marginal rate of substitution between t and j, and Ω_{t-1} is the set of conditioning information that investors use to set prices at time $t - 1$. Hence, the term structure of interest rates is an ex ante measure of the marginal rate of substitution, and there has been considerable previous research confirming the relation between the term structure and the business cycle.

Most finance researchers avoid the use of macro variables. Even in consumption-based asset-pricing studies it is not unusual to project personal consumption growth rates (a macro variable) on a set of stock returns and use the resultant portfolio (a maximum correlation portfolio) for asset pricing.

The first reason research has avoided these variables has already been mentioned—the data are generally not available at the end of the month. Aside from violating the econometric assumptions, we lose the important link between asset pricing and real-world asset allocation.

Second, the data are filtered with Census X-11 seasonal adjustment program. This algorithm applies a series of centered moving averages, that is, it uses data in the future to determine the seasonal weights. In addition, the moving average changes in an ad hoc way through time. The use of future data for the seasonal weights makes even a one-year lag of the data technically nonpredetermined in the econometric sense.

Third, the macro data are subject to revisions. These revisions are often very substantial—especially when the data are first differenced. Technically, one should be using the first release of the data (unless one is willing to accept the assumption that economic agents know the data in advance).

Fourth, and most importantly, economic news is filtered by investors in forming expectations. The filter is applied to the innovation in the macro release (i.e., not the first difference as Dumas uses, but the deviation of the actual release from the market consensus expectation). In addition, the filter simultaneously considers many news events. The weights in the filter are potentially time-varying. That is, sometimes a decrease in unemployment is "bad" news if participants believe that there will be an increase in inflationary pressures, and sometimes a decrease in unemployment is good news! The filter is possibly nonlinear and fundamentally unobservable. It is unlikely that it can be proxied by a linear regression of returns on macro variables. The advantage of the financial variables is that this complicated process is collapsed into the predetermined asset price.

Predictability of Asset Returns

Expected equity returns are influenced by expected real activity. This is the main idea of Fama (1981, 1990) and Schwert (1990). Variables that forecast expected real activity should also forecast equity returns. Well-known examples are term structure variables and default risk measures.

Stock and Watson (1992) swept 280 economic series to isolate 7 which predict real activity. Data snooping is definitely an issue here. Although economic series were not swept for their ability to predict stock returns, there is a correlation between expected stock returns and expected real activity which has been documented in previous research.

Dumas identifies a number of series which "predict" stock returns: housing authorizations, growth in inventories, and the percentage of manufacturers reporting slower deliveries. If the data have been snooped, then we are stacking the deck against the asset-pricing model. Remember, the conditional asset-pricing model generates fitted expected returns. These model-fitted returns should mimic the statistical predictability in unrestricted regressions of asset returns on instruments. If the unrestricted regressions use snooped series, then it is no surprise that the asset-pricing model is rejected—it cannot be expected to explain snooped variation by changes in risk premiums and conditional betas!

The Econometric Model

The model is identical to Dumas and Solnik 1993. Let

$$E[r_{j,t}|\boldsymbol{\Omega}_{t-1}] = \boldsymbol{\Lambda}'_{t-1}E[r_{j,t}(\boldsymbol{f}_t - E[\boldsymbol{f}_t|\boldsymbol{\Omega}_{t-1}]|\boldsymbol{\Omega}_{t-1}],$$

where $\boldsymbol{\Lambda}$ = vector of prices of risk and $\boldsymbol{f}$ = factors (world excess return, FX excess returns).

A general way to test this model is to note

$$E[r_{j,t}|\boldsymbol{\Omega}_{t-1}] = E[r_{j,t}u_t|\boldsymbol{\Omega}_{t-1}],$$

where u_t is the relative innovation in the marginal rate of substitution (MRS). In terms of the Dumas and Solnik 1993 model,

$$u_t = \lambda_{0,t-1} + \boldsymbol{\Lambda}'_{t-1}\boldsymbol{f}_t,$$

where $\lambda_{0,t-1}$ is an intercept term.

However, some assumptions are required. Specifically, $\lambda_{0,t-1}$ is "whatever term is needed to bring about" equality. More precisely,

$$\lambda_{0,t-1} = -\boldsymbol{\Lambda}'_{t-1}E[\boldsymbol{f}_t|\boldsymbol{\Omega}_{t-1}].$$

Some interpretation of this term would add to the paper.

The econometric assumptions include

$$\lambda_{0,t-1} = -\boldsymbol{Z}_{t-1}\boldsymbol{D}$$

and

$$\Lambda_{t-1} = Z_{t-1}\Phi,$$

where D and Φ are coefficient matrices and Z is the matrix of information variables. This amounts to assuming that the prices of risks are linear in the information set. For the tests, the innovation in the MRS is defined

$$u_t = -Z_{t-1}D + Z_{t-1}\Phi' f_t,$$

where the assumptions on the prices of risk are substituted into the definition of the innovation in the MRS.

However, the economic model imposes restrictions on the meaning of λ_0 and Λ. These restrictions are not imposed in the estimation. For example, in the case of the classic CAPM, $\Lambda = \lambda$, which is the conditionally expected excess return on the market divided by the conditional variance. That is, the coefficient has an economic definition which is not imposed in the estimation.

Dumas provides a "general test"—but we lose the ability to give intuitive interpretations to results. It is hard to answer questions like What are the model pricing errors? How well does the model do in accounting for the predictability in the asset returns? How well does the model explain the cross-section of expected returns? What do the fitted risk premiums look like? What do the fitted conditional covariances look like? What are the conditional betas? and What is the forecasted premium and covariance for the next period?

The cost of a general test is the inability to answer many of these questions. The approach is limited to verdicts such as "model rejected." In my opinion, the generality is not worth the cost. The model could be rejected but provide a useful approximation to the behavior of returns. It is impossible to measure the quality of the approximation using the approach in this paper. Nevertheless, this is only a comment on the econometric implementation. The main idea of the paper, to explicitly introduce macroeconomic variables into the conditioning information set, is a provocative one and is worthy of future research.

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Comment Thierry A. Wizman

Most theories of asset pricing link the common movement in expected returns across different assets to a very small set of possible forces. These forces include (a) changes in volatility of dividends, volatility in dividend growth, or some broader measure of business-cycle risk (Fama and French 1989); (b) changes in risk aversion of a representative agent as aggregate wealth rises or falls (Marcus 1989); and (c) the risk of exogenous shifts in the demand of "noise traders" which must be accommodated by rational utility-maximizing traders (DeLong, Shleifer, Summers, and Waldmann 1990). The first two forces, and sometimes the third, are commonly associated with the cycle of boom and bust. For example, the degree of risk aversion may be higher in a recession, as might fundamental risk and noise-trader risk. Thus, it seems natural that we would want to use variables that are directly linked to the performance of the *real* economy in describing the behavior of excess returns through time. However, much of the literature on asset pricing has sought to link expected returns not to the underlying physical economy, but rather to other asset *price* variables such as interest rates, term structure spreads, quality spreads, and dividend yields. Professor Dumas seeks to restore the link with *quantity* variables in the context of the classic and international CAPM models of asset pricing. It is with this premise that the paper is at its most innovative and where the most potential for a new research agenda lies. I will structure my remarks around two issues: first, how to improve the power of the tests; second, how to make the premise of this approach and the motivations for using this model more convincing.

Choosing a Set of Instruments

As we know, the power of certain "internal" variables such as interest rates, dividend yields, interest-rate spreads, and quality spreads in predicting "in-sample" stock market returns has been established largely by repeated trial and error over the course of many papers (Keim and Stambaugh 1986; Campbell 1987; Campbell and Shiller 1988; Fama and French 1989; Chen 1991). In terms of R^2, the best that empirical economists can usually do in a multivariate predictive equation of monthly U.S. stock returns regressed on financial variables is about 12 percent (Harvey 1989; Hardouvelis and Wizman 1992). With

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quarterly returns, similarly specified equations yield R^2s of about 36 percent (Pesaran and Timmerman 1990). However, because some justifiable data-mining went into finding the set of explanatory variables that yield high R^2s, part of the multiple correlation may be spurious. As a result, the predictive equations typically used as a basis for testing the conditional form of the CAPMs may imbed statistical error, and this will bias the tests toward rejection. It makes sense, therefore, to select an alternative criterion, apart from the predictive power for stock market returns, for choosing state variables. One obvious criterion, given the arguments made above, is to choose variables with a direct relation to the real business cycle. Of course, if the test of the CAPM or international CAPM is to have some power, it would be nice if the same instruments help predict excess returns as well. Choosing a set of instruments that fulfill both criteria is the difficult part of the exercise Professor Dumas undertakes, because it requires the researcher to impose some discipline in his search. Specifically, we want to avoid introducing bias anew in the asset-pricing tests by mining the data for the best (highest R^2) predictive equation using a new set of "external" or "quantity" variables.

To Professor Dumas's credit, he handled the choice of instruments well, in my view. Instead of taking the reader through various specifications of stock returns regressed on various "external" variables on a hunt for the best fit, the author chooses to start with two *established* sets of nonfinancial variables. Although the point is not emphasized in the paper, the use of an established set of variables helps to deflect the criticism that any correlation between the stock market and these external variables is spurious. The two sets of candidate variables chosen are the OECD's main economic indicators for the United States (OECD-MEI) and the component indicators selected by Stock and Watson (1992) to lead the U.S. business cycle.

One suggestion here is that future research does not need to restrict its list of "external" variables to *leading* indicators only. Presumably, it is knowledge about the *phase* of the business cycle that helps us to predict stock returns. If this is so, including a corresponding predetermined set of *coincident* or *lagging* business indicators may provide a more powerful test of the orthogonality conditions implied by the conditional CAPMs because it would improve the fit of the predictive equation without sacrificing statistical integrity by overly mining the data. For example, industrial production indices, which are *coincident* indicators, have previously been shown also to help predict monthly stock returns. Also, the direction of exogenous fiscal and monetary policy may provide information on the current and future course of the economy over and above the indicators. Darrat (1990), for example, shows that changes in the cyclically adjusted budget deficit help forecast stock returns.

Transforming the Data

The first conclusion that the author draws is that while the Stock-Watson variables have the potential to predict not only U.S. but also international stock returns, the OECD-MEI variables do not share this property. At first, one might believe that this difference in predictive power is due to the temporal relation that these sets of variables have with respect to the U.S. business cycle: the Stock-Watson variables lead the cycle, while the OECD variables may lead, coincide, or slightly lag (as in the case of unemployment rates) the cycle. On second thought, however, the difference in predictive power may be an artifact of the way Professor Dumas transforms the variables, particularly the OECD-MEI variables. Specifically, my concern is with how stationarity of the instruments is achieved. As we know, stationarity is important if regressions of returns on the state variables are to have the standard asymptotic distributions. However, it is possible that a variable which carries information about the phase of the business cycle when it is expressed in *levels* or *de-trended level* loses this information when it is transformed into a first-difference, and only the most recent value of this first-difference is substituted in place of the level or de-trended level. This may be especially true of quantity variables measured in current dollars, since high-frequency changes in inflation rates may introduce noise in a measure of real economic activity (as in the case of *retail sales*). If the transformed variables no longer serve as summary statistics for the *phase* of the business cycle, they are rendered useless as state variables for the purpose of the exercise in Professor Dumas's paper.

To illustrate my point, notice that in table 1.1 of Professor Dumas's paper, where he reports the contemporaneous correlations between the six macroeconomic variables in the OECD-MEI, the correlations are relatively low. The average absolute value of cross-correlation among the set of instruments excluding the market return is 0.18. In table 1.6, on the other hand, the author reports the correlations among the Stock-Watson variables. Here, the correlations are higher. The average absolute value of the macroeconomic variables is 0.40. In light of my discussion above, these results are not surprising: three of the Stock-Watson variables are expressed in levels (housing authorizations, manufacturing hours, vendor performance), while the three that are expressed in growth rates (unfilled orders, capacity utilization, help wanted) are not measured in current dollars. In contrast, of the OECD-MEI variables, all but the unemployment rate are measured in current dollars. A strong indication that the method of transformation matters is seen in table 1.6: the predictive power of the Stock-Watson variables comes exclusively from the three variables measured in levels.

How can we improve the power of the OECD-MEI and Stock-Watson variables for U.S. and international stock market returns, while preserving stationarity? One possibility is to use de-trended levels in place of first-differences (growth rates) for the variables that are currently in first-difference (growth rate) form. Given the philosophical objections to using de-trended data in a unit-root world, another possibility is to use a higher-order lag specification in the predictive equations. That is, generalize the specification to include many lag values of the one-month first-difference (growth rate) on the right-hand side of the predictive equations. (Stock and Watson, for example, used five lags of their leading indicator variables in predicting U.S. recessions.) Although this will recover the low-frequency information previously lost, it will also expand the list of instrumental variables beyond what may be computationally feasible in the asset-pricing tests. The last (and probably best) possibility is to use longer-horizon first-differences or growth rates instead of the one-month first-differences or growth rates. Personal experience and intuition suggest that using the twelve- or eighteen-month growth rates of the macroeconomic variables would provide the greatest explanatory power for stock returns, since this periodicity closely matches the duration of U.S. business cycle downturns. If this is the case, we should be able to improve the R^2s of the predictive equations without surrendering computational ease and with a minimal amount of data mining. This would make the asset-pricing tests in Professor Dumas's paper more powerful and their results more convincing.

Having experimented with methods of transforming an established set of "external" variables, another way to make both the results and premise of this line of research more convincing is to address the issue of structural stability of the predictive equations. Professor Dumas does not address this issue, but it is important nonetheless. It turns out that when financial or "internal" variables such as interest rates, term structure spreads, and quality spreads are used to predict stock returns, most of the explanatory power comes from the period 1975–85 when the financial variables were most volatile. Moreover, in general, financial variables which have strong explanatory power in one part of the sample period do not always have explanatory power in another part. This may have to do with changes in monetary policy or changes in financial institutions over the postwar period. Finding that the properly transformed "external" variables (OECD-MEI and Stock-Watson) have a stable relationship to future stock returns and exchange-rate returns would strengthen Professor Dumas's case for using them over "internal" financial variables.

Additional Diagnostics and Experiments

The second principal finding in Professor Dumas's paper is that using the Stock-Watson instrument set, the conditional international CAPM was marginally not rejected while the conditional classic CAPM was rejected. This suggests that allowing for foreign exchange risk in a world with preferred local habitats matters. Also, recall that the specification in the theoretical section of Professor Dumas's paper is well motivated if the conditional covariances of the asset excess returns with the market return and exchange-rate returns move through time. What also motivates the specification is that the prices of risk are conditioned on the "external" variables. Given this, an interesting agenda for future research is to examine whether exchange-rate risk does in fact move significantly over time and whether these risks move with or are independent of world business cycles. Moreover, does one sort of exchange-rate risk, say, yen risk, move differently than, say, DM risk? These are important questions that may help to motivate empirical work using the ICAPM model over the traditional CAPM.

What also motivates Professor Dumas's specification is the idea that the prices of the various sources of risk are conditioned on the business cycle. Although Professor Dumas reports the coefficients from the estimated linear projection of the prices of risk on the instruments, a plot of the fitted values of the risk prices as they relate to international recessions and recoveries would be particularly helpful in ascertaining whether the prices of the various exchange-rate risks move in relation to business cycles in the various countries. Do the prices attached to yen risk, say, vary more with the cycle than prices attached to DM risk? Conducting these exercises would strengthen the premise of Professor Dumas's model by examining the nature of preferred habitats and how they might weaken or strengthen over time.

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