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Speculative Dynamics

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This paper presents evidence on the characteristic speculative dynamics of returns on stocks, bonds, foreign exchange, real estate, collectibles, and precious metals. It highlights four stylized facts. First, returns tend to be positively serially correlated at high frequency. Second, they are weakly negatively serially correlated over long horizons. Third, deviations of asset values from proxies for fundamental value have predictive power for returns. Fourth, short term interest rates are negatively correlated with excess returns on other assets. The similarity of the results across markets suggests that they may be due to inherent features of the speculative process

Many recent studies have rejected the hypothesis of constant ex ante returns in a variety of different speculative markets. There is evidence that stock returns for the United States are weakly serially correlated, that dividend yields have predictive power for returns, that the slope of the yield curve predicts long-term bond returns, that interest rate spreads predict excess returns in the foreign exchange market, and more controversially, that asset markets display excess volatility. Research attempting to explain these findings has either challenged the statistical basis of rejections of the constant required return model, or sought to explain varying risk premia with changing risk factors.

An alternative view is that variations in ex ante returns and asset market volatility arise primarily from what we have elsewhere labelled "speculative dynamics"—interactions between different types of traders, some of whom are not rational in the conventional sense of trading on the basis of all publicly available information. Distinguishing conclusively between the speculative dynamics view and the conventional view of asset market fluctuations is inherently very difficult, given the limited amount of data on asset returns and the difficulty of satisfactorily proxying for risk factors.

This paper extends our research on speculative dynamics by introducing a larger and more diverse data set on speculative returns than has previously been analyzed. These data suggest four regularities in asset returns. First, asset returns are positively serially correlated at high frequencies. Second, returns are negatively serially correlated at lower frequencies. Third, there is a tendency toward "fundamental reversion" in asset prices. Finally, when short-term interest rates are high, the excess returns on other assets are low. Not all of these patterns emerge in all markets, but each appears in many different markets. Since risk factors might be expected to operate quite differently in different markets, we tentatively interpret the common patterns as evidence in favour of theories emphasizing speculative dynamics.

This paper is organized as follows. Section one describes the data set covering asset returns in various markets. The second section reports the autocorrelogram of the various returns, emphasizing the similarities across markets. Section three discusses issues relating to fundamental reversion as well as the predictive power of short-term interest rates. The final section concludes by comparing the plausibility of the speculative dynamics and the time-varying returns interpretations of our results, and identifying directions for further research.

1. ASSET-RETURNS DATA

This section describes the data we use in our subsequent analysis. Unlike past studies, which have relied almost exclusively on equity returns in the U.S., our analysis includes returns in a wide range of asset markets. The data are available on diskette from the authors.

Stocks and Bonds: Stock return data for the period 1960–1988 are drawn from Morgan Stanley's *Capital International Perspectives* (MSCI), augmented by data from Ibbotson Associates. For each of the thirteen equity markets in our sample—Australia, Austria, Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom, and United States—we calculate monthly excess returns $R_{j,t}$ as

$$R_{j,t} = \log(P_{j,t} + D_{j,t}) - \log(P_{j,t-1}) - \log(1 + i_{j,t}) \tag{1}$$

where $P_{j,t}$ denotes the end-of-month price index for country j, $D_{j,t}$ dividend payments,[1] and $i_{j,t}$ the monthly short-term nominal interest rate. We chose these thirteen countries because they were the only ones in the *Capital International* universe with data back to 1960. The MSCI price index for each country is a weighted average of the prices for a number of large firms in the country's equity markets. These indices do not correspond to other published indices and often include shares traded on several different exchanges.[2]

Our data on government bond returns are from Ibbotson Associates *World Asset Module*. Short-term yields are Treasury bill or money market yields, except in Italy, Sweden, and Switzerland, where we use the discount rate. The data sample for each country, for both bond and stock returns, is shown in Table 1. For comparability to earlier studies, we also report the results of autocorrelation tests applied to U.S. historical data from Ibbotson Associates (1988).

Foreign Exchange: We compute the excess return to holding foreign currency assuming that investors making such investments hold foreign short-term bonds rather than cash. This implies that the excess return to a U.S. investor holding currency j is:

$$R^*_{US,j,t} = \log(E_{US,j,t}/E_{US,j,t-1}) + \log(1 + i_{j,t}) - \log(1 + i_{US,t}) \tag{2}$$

where the first term is the nominal appreciation of country j's currency relative to the dollar during month t. We focus on the returns to investors in each of five countries—France, Germany, Japan, the U.K., and the U.S.—from holding the currencies of each of the other four countries. This yields 10 bilateral currency returns. Our sample period

1. MSCI computes dividend yields as aggregate dividends paid over the last twelve months divided by price at the end of the reference month. For several countries, dividend yields in the early part of the sample appear to reflect actual dividend payments rather than the sum of the previous year's payments. We adjusted these yields to make them comparable with the later sample. The resulting errors in the measured returns are likely to be smaller than those from omitting dividends altogether.

2. Poterba and Summers (1988) analyzed real (as distinct from excess) returns *excluding* dividends and computed from monthly averages of stock prices as reported by the International Monetary Fund.

TABLE 1

Summary statistics for asset returns

A. *Equity and bond markets*

Country	Sample period: Equities	Sample period: Bonds	Excess return (related to short term yield): Equities Mean	Equities Std. devn.	Long term government bond Mean	Long term government bond Std. devn.
Australia	1969:7	1969:7	1·27	26·17	−2·12	9·78
Austria	1964:11	1971:1	1·60	12·70	3·72	4·06
Belgium	1968:2	1963:10	7·91	16·55	−0·33	4·58
Canada	1968:2	1960:1	2·29	18·55	−0·17	7·22
France	1962:8	1960:1	1·04	20·86	−0·46	5·92
Germany	1960:1	1960:1	2·76	17·98	2·13	5·09
Italy	1964:1	1964:1	−0·31	23·40	0·03	7·56
Japan	1960:1	1966:12	7·11	16·83	0·96	5·00
Netherlands	1966:8	1964:12	6·59	17·51	1·74	6·27
Sweden	1963:10	1963:1	6·38	18·43	−1·20	5·68
Switzerland	1964:1	1964:1	2·58	17·24	1·80	4·51
United Kingdom	1964:1	1964:1	3·87	22·28	−0·27	10·55
United States	1960:1	1960:1	2·62	15·18	−0·45	10·05

B. *Alternative Assets*

	Currency	Gold	Silver	Metals	Houses	Farms	Collectibles
Mean	2·19	−0·81	−5·20	−1·57	0·37	3·29	4·35
Std. devn.	10·16	25·27	48·93	14·11	3·27	9·13	12·32

C. *Correlations for annual U.S. dollar returns*

	U.S. equities	U.S. bonds	Currency	Gold	Houses	Collectibles
U.S. Equities	1·000					
U.S. Bonds	0·403	1·000				
Currency	0·004	0·323	1·000			
Gold	−0·059	−0·164	0·425	1·000		
Houses	−0·036	−0·144	0·566	0·566	1·000	
Collectibles	0·306	−0·084	0·300	0·458	0·821	1·000

Note: Equity and government bond returns are in own currency and are relative to the short term yield. All data are through 1988:12 except for Swedish bond returns, which end in 1988:1. The correlation matrix uses data for the United States only. The currency return is the weighted average dollar excess return to holding the Pound, Mark, Yen and Franc, where the weights are 1975 GNP (in dollars). Currency, gold and silver returns are from 1974–1988. Industrial metals returns are from 1959–1988. House returns are from 1970–1986. Farm returns are from 1912–1986. Collectible returns are from 1968–1988, and average the returns of the available assets each year.

for exchange rates begins in 1974, since exchange rates were fixed in earlier years. End-of-month exchange rate data are from the International Monetary Fund.

Commodities: The excess return to holding gold and silver is

$$R_{gold,t} = \log\left(P_{gold,t}/P_{gold,t-1}\right) - \log\left(1+i_{US,t}\right) \qquad (3)$$

where $P_{gold,t}$ is the end-of-month closing price. We study monthly data from 1974–1988, the period when gold is actively traded in a speculative market. We also study the return to holding other metals for the 1959–1988 period. Their returns are defined as the monthly logarithmic difference in the Commodity Research Bureau's industrial metals price index, which includes copper, lead and steel scrap, tin, and zinc.

Real Assets: We also analyze returns on houses and various collectibles. We measure excess holding returns under the assumption that these assets provide no service flow:

$$R_{j,t} = \log(P_{j,t}/P_{j,t-1}) - \log(1+i_{US,t}). \tag{4}$$

Constant-quality house price indices are from Case and Shiller (1989).[3] The data on collectibles, provided annually by Salomon Brothers for 1967–1988, cover oriental carpets, stamps, Chinese ceramics, rare books, coins, diamonds, and old master paintings.

We also computed the return to holding farms by generalizing (4) to include a service flow term:

$$R_{farm,t} = \log(P_{farm,t} + D_{farm,t}) - \log(P_{farm,t-1}) - \log(1+i_{US,t}) \tag{5}$$

where $D_{farm,t}$ is aggregate farm income divided by aggregate farm value, then multiplied by the farm price index. The price is the average farm value per acre. Data on average value per are, 1912–1986, were obtained from the Department of Agriculture (1981 and updates). Farm income data are from Colling and Irwin (1989).

2. AUTOCORRELATION OF ASSET RETURNS

This section presents empirical evidence on the autocorrelation properties of asset returns. Analyzing many markets increases the statistical power of our tests, although in some cases the limited data span makes our findings relatively imprecise. The various markets should share any patterns that are common to the process of speculation, although risk considerations may differ across markets.

Table 1 presents summary statistics on asset returns. The first panel focuses on equity and bond returns and shows substantial disparity in the mean returns across nations. Table 1 also shows the correlation between U.S. dollar returns on different classes of assets. The correlation between equity and bond returns is 0·403. The foreign exchange portfolio—a 1975 GNP-weighted average of the returns on the poind, franc, yen, and mark—exhibits a correlation of only 0·004 with U.S. equity returns, and its correlation with U.S. bond returns is 0·323. The real assets we analyze are highly correlated with each other, but negatively correlated with many other asset returns. Gold, houses and collectibles all exhibit cross-correlations of over 0·45, but the correlation between them and either stocks or bonds is small and usually negative. These findings suggest that our analysis of many different assets provides substantial evidence on the behaviour of speculative prices beyond that contained in equity returns.

2.1. *The characteristic autocorrelogram of speculative returns*

Tables 2 through 4 present autocorrelograms for the various returns. We report the first order autocorrelation as well as the average autocorrelation over several distinct twelve month intervals. In each case, the reported autocorrelations have been corrected for small sample bias as described in the appendix.

Table 2 presents the autocorrelations for stocks and bonds, Table 3 for foreign exchange and precious metals, and Table 4 for real assets. When we analyse data from

3. In order to avoid autocorrelation induced by measurement error, Case and Shiller formed an A and B price index for each city, using separate houses in each index. Our autocorrelations correlate contemporaneous values of the A series with lags of the B series. The results are very similar when the two series are reversed.

TABLE 2

Autocorrelations for stock and bond returns

Asset	Autocorrelations—excess returns relative to short-term treasury bills Months averaged in autocorrelations								
	1	1–12	13–24	25–36	37–48	49–60	61–72	73–84	85–96
Corporate equities (1960–1988)									
Australia	0·028	0·002	−0·022	0·007	0·012	0·003	−0·013	0·004	0·034
Austria	0·116	0·070	−0·040	−0·002	−0·007	−0·024	0·007	0·012	−0·014
Belgium	0·200	0·018	0·006	0·040	0·009	0·016	−0·022	0·033	−0·014
Canada	0·057	0·002	−0·032	−0·004	0·007	0·007	−0·014	0·019	0·039
France	0·083	0·007	−0·021	0·023	0·003	0·000	−0·001	0·030	0·022
Germany	0·138	0·029	−0·042	0·002	0·006	−0·003	−0·024	−0·003	0·044
Italy	0·138	0·044	−0·040	0·000	−0·017	0·019	0·031	−0·013	0·031
Japan	0·085	0·020	−0·025	0·019	0·004	−0·016	0·010	0·017	−0·013
Netherlands	0·114	0·021	−0·015	0·004	0·010	0·002	−0·022	−0·005	0·036
Sweden	0·134	0·038	−0·041	0·022	0·001	0·000	0·002	−0·011	0·035
Switzerland	0·046	0·017	−0·019	−0·017	0·020	−0·007	−0·019	0·008	0·022
U.K.	0·091	0·002	−0·015	−0·015	0·011	0·009	−0·005	0·010	0·019
U.S.	0·077	−0·002	−0·029	0·004	0·017	0·019	−0·016	0·000	0·041
Average	0·101	0·021	−0·026	0·006	0·006	0·019	−0·007	0·008	0·022
	(0·030)	(0·004)	(0·009)	(0·006)	(0·014)	(0·016)	(0·008)	(0·011)	(0·005)
United States	0·106	0·021	−0·017	−0·005	−0·011	−0·006	0·000	0·012	0·013
(1926–1988)	(0·036)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)
Long-term bonds (1960–1988)									
Australia	0·078	0·036	−0·013	−0·032	−0·010	0·012	0·014	0·022	0·008
Austria	0·360	0·119	−0·046	−0·067	−0·003	0·013	−0·010	0·060	0·056
Belgium	0·191	0·110	0·006	−0·005	−0·006	−0·023	−0·022	−0·025	0·012
Canada	0 116	0·032	−0·008	−0·007	−0·015	−0·020	0·011	0·002	0·004
France	0·230	0·086	−0·009	−0·011	−0·012	−0·039	0·004	−0·003	0·047
Germany	0·477	0·106	−0·033	−0·041	−0·055	−0·029	−0·024	0·003	0·051
Italy	0·514	0·115	−0·003	−0·026	−0·049	0·018	−0·018	0·078	−0·010
Japan	0·132	0·062	−0·028	−0·036	−0·024	0·024	0·056	0·008	−0·032
Netherlands	0·291	0·043	−0·026	−0·017	−0·015	0·013	−0·001	0·006	0·023
Sweden	0·116	−0·007	0·004	−0·006	−0·015	0·031	0·008	0·004	−0·006
Switzerland	0·266	0·083	−0·010	−0·045	−0·014	−0·020	0·030	−0·012	0·010
U.K.	0·299	0·026	0·003	−0·039	−0·014	0·031	0·036	0·017	0·006
U.S.	0·030	0·027	−0·012	−0·005	0·008	−0·016	0·000	−0·006	−0·003
Average	0·238	0·064	−0·013	−0·026	−0·017	−0·002	0·006	0·012	0·013
	(0·015)	(0·004)	(0·005)	(0·005)	(0·005)	(0·005)	(0·005)	(0·005)	(0·005)
United States	0·033	0·023	−0·010	0·001	0·009	−0·010	0·004	0·000	0·000
(1926–1988)	(0·036)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)	(0·011)

Note. Each entry reports the average autocorrelation for the 1 or 12 months in the indicated time period. The autocorrelations are bias-adjusted, by adding $1/(T-j)$ to each entry, where T is the length of the time period, and j is the autocorrelation. The standard error of the individual correlations is $(T-k)^{-0.5}$, as in Kendall (1973). The standard error of the average autocorrelation, shown in parentheses, adjusts the predicted standard error for the cross-correlation of the assets, as indicated in the text.

several countries, we also report the average autocorrelation at each frequency. We view this as a summary indication of the autocorrelation pattern, not as a deep parameter which characterizes behaviour in all markets. To indicate the precision of this average, we calculate its standard error assuming that the estimated statistics (such as the average of twelve autocorrelations) exhibit a constant pairwise correlation π across countries,

TABLE 3

Autocorrelations for exchange rates and metals

Asset	Autocorrelations—excess returns relative to short-term treasury bills Months averaged in autocorrelations								
	1	1–12	13–24	25–36	37–48	49–60	61–72	73–84	85–96
Exchange Rates (Interest Rate Adjusted)									
United States									
France	−0·015	0·059	0·026	−0·011	−0·013	−0·035	−0·019	−0·024	0·024
Germany	0·002	0·046	0·014	−0·016	0·004	−0·028	−0·027	−0·016	0·019
Japan	0·088	0·047	−0·031	0·036	−0·028	−0·023	0·014	−0·032	0·017
UK	0·103	0·052	0·026	−0·022	−0·038	−0·054	0·008	0·018	0·025
Japan									
France	0·005	0·030	−0·070	0·042	−0·040	0·027	0·031	−0·008	0·035
Germany	0·012	0·012	−0·068	0·065	−0·026	0·003	0·032	−0·019	0·050
UK	0·101	0·031	−0·017	0·004	−0·049	−0·001	0·025	−0·012	0·030
United Kingdom									
France	0·184	0·015	0·033	−0·014	−0·006	−0·012	−0·039	0·009	0·016
Germany	0·122	0·018	0·020	−0·027	−0·004	0·012	−0·037	0·016	0·019
Germany									
France	0·068	0·020	−0·035	−0·015	0·013	0·006	0·043	0·001	−0·025
Average	0·067	0·033	−0·010	0·004	−0·019	−0·011	0·003	−0·007	0·021
	(0·043)	(0·015)	(0·007)	(0·007)	(0·015)	(0·011)	(0·009)	(0·024)	(0·025)
Metals									
Gold	0·020	0·051	0·017	0·026	0·007	−0·019	−0·007	0·004	0·033
	(0·075)	(0·022)	(0·023)	(0·024)	(0·025)	(0·026)	(0·027)	(0·029)	(0·031)
Silver	−0·102	0·002	−0·022	−0·013	−0·002	0·007	0·013	0.012	0·030
	(0·075)	(0·022)	(0·023)	(0·024)	(0·025)	(0·026)	(0·027)	(0·029)	(0·031)
Industrial metals	0·269	0·061	0·029	0·018	−0·015	0·044	0·026	0·001	−0·026
	(0·053)	(0·015)	(0·016)	(0·016)	(0·016)	(0·017)	(0·017)	(0·017)	(0·018)

Note. Each entry reports the average autocorrelation for the 1 or 12 months in the indicated time period The autocorrelations are bias-adjusted by adding $1/(T-j)$ to each entry, where T is the length of the time period and j is the autocorrelation. The sample period for eaxchange rates, gold and silver is 1974–1988. The sample for industrial metals is 1959–1988. The standard error of the individual correlations is $(T-k)^{-0\cdot 5}$, as in Kendall (1973). The standard error of the average autocorrelation adjusts the predicted standard error for the cross-correlation of the assets, as indicated in the text.

and if they have constant variance σ^2, then the expected value of their *sample* cross-sectional variance is $\sigma^2(1-\pi)$ where σ^2 denotes the variance of the statistic for a single nation. Replacing the expected sample variance with its actual value, we estimate π as $1-s^2/\sigma^2$. In the case of monthly stock return autocorrelations, for example, the estimated cross-sectional correlation is 0·265. The variance of the sample mean for N observations on different countries, each with variance σ^2 but with cross correlation π, is $\sigma^2(1+(N-1)\pi)/N$ or 0·00093.[4]

Very small deviations of returns from the martingale assumption can imply large deviations of asset prices from fundamental values. Summers (1986) and Poterba and Summers (1988) consider an example in which the transitory component of stock prices has a standard deviation of 30%, a half-life of three years, and accounts for three quarters of the variance in stock returns. Nonetheless it induces an expected autocorrelation of only −0·007 in monthly returns.

4. We also tried estimating the autocorrelations in different countries simultaneously in a seemingly-unrelated-regression framework, and constraining these parameters to be identical across nations. In the case of monthly stock returns, the constrained SUR estimate of the first order autocorrelation was below the average reported in Table 2, but still significantly different from zero (the estimate was 0·031 (0·015)). For bonds, the results again yielded strong rejection of the null of serial independence (0·156 (0·015)). The hypothesis of a constant autocorrelation across countries, however, is strongly rejected in both cases.

TABLE 4

Autocorrelations for alternative assets

Asset	Autocorrelation 1 Year	2 Year	3 Year	Observations
House Prices—Average	0·206	0·083	0·053	—
	(0·032)	(0·033)	(0·062)	
Atlanta	0·062	0·034	0·008	65
Chicago	0·391	0·185	0·081	65
Dallas	0·129	0·036	0·063	65
San Francisco	0·243	0·075	0·058	66
Farm Prices	0·727	0·442	0·306	76
	(0·116)	(0·118)	(0·120)	
Collectibles—Average	0·365	0·011	−0·103	—
	(0·160)	(0·153)	(0·152)	
Oriental Carpets	0·725	0·163	−0·105	11
	(0·316)	(0·333)	(0·354)	
Stamps	0·573	0·324	0·105	20
	(0·229)	(0·236)	(0·243)	
Chinese Ceramics	0·114	−0·182	−0·183	21
	(0·224)	(0·229)	(0·236)	
Rare Books	−0·070	−0·115	0·159	13
	(0·289)	(0·302)	(0·316)	
Coins	0·242	−0 056	−0·091	21
	(0·224)	(0·229)	(0·236)	
Diamonds	0·515	−0·050	−0·239	21
	(0·224)	(0·229)	(0·236)	
Old Master Paintings	0·456	−0·007	−0·364	21
	(0·224)	(0·229)	(0·236)	

Note Each entry reports the autocorrelation for the year indicated. House price data are quarterly from 1970:1 to 1986:2 (1986:3 for San Francisco), see Case and Shiller (1989) for a description. Farm price data are annual from 1912–1986; the capital gain is from Department of Agriculture (1988); rental income is from Colling and Irwin (1989). Data on other assets are annual from 1967 or later and were supplied by Salomon Brothers. The standard errors for the averages take account of the cross-correlation between assets. For the collectibles, the theoretical standard deviation is assumed to be that for the asset with the fewest observations (11).

The first pervasive characteristic of the results in Tables 2–4 is positive serial correlation over horizons shorter than one year. For most of the assets we consider, the first-order monthly autocorrelation is positive, and the average is usually statistically significant. The values range from 0·020 for gold and 0·067 for exchange rates to 0·101 for common stocks, 0·238 for bonds, and 0·269 for industrial metals.[5] These results differ from earlier findings on European equity markets, surveyed in Hawawini (1984), in large part because the additional precision afforded by data on many countries yields greater confidence in rejecting the null hypothesis. While these findings appear in many markets, they are not universal. Schwert (1989), for example, finds negative serial correlation in daily U.S. stock returns before 1917. An obvious issue for future research is whether differences in data construction, or variation in market structure through time or across markets, can explain some of the differences in the stochastic properties of returns.

While some have argued that non-trading effects may account for positive autocorrelation in monthly equity returns, this explanation is implausible in the case of foreign

5. For gold and silver, which exhibit particularly large price moves on a small number of days in the sample, the results are sensitive to the precise definition of the monthly return. For example, one could define calendar months, or monthly returns from the 15th of one calendar month to the 15th of the next calendar month, etc. The results we report, for the Friday-to-Friday returns between Fridays closest to month-ends, are very close to the average over all possible intervals.

exchange, gold or bonds. Even in the case of equities, our focus on monthly data makes non-trading biases unlikely; Lo and McKinlay (1988) find little support for non-trading as the explanation of positive autocorrelation in weekly U.S. equity returns since 1962.[6]

The estimated monthly autocorrelations are not only statistically but also substantively significant, often implying negative expected returns. If the monthly risk premium in a given market is μ, the ex ante risk premium on an asset will be negative if $\rho_1^* R_t < -\mu$, which occurs with probability $\Phi(-\mu/\rho_1\sigma)$, where Φ is the distribution function for returns. For stocks, if one takes the risk premium to be 0·7% per month and the standard deviation of returns to be 5% per months, negative expected returns would be observed more than 10% of the time. For bonds, where the standard deviation is only slightly smaller but the risk premium is much smaller, the calculation is even more dramatic.

Substantial autocorrelation at short horizons is particularly difficult to reconcile with traditional asset-pricing models. As we expand the return interval, the risk premium increases linearly while the standard deviation of returns rises with the square root of the interval length. For k-period returns, therefore, the chance of a negative expected return is $\Phi(-k^{0\cdot 5}\mu/\rho_k\sigma)$, where ρ_k is the autocorrelation coefficient for this horizon. The probability of a negative expected return is therefore higher if an autocorrelation coefficient of a given absolute value is observed at high frequencies.

Positive autocorrelation is not confined to one-month returns. By subtracting one-twelfth of the first month's autocorrelation from the average autocorrelation over the (1–12)-month interval, one finds that average autocorrelations between two and twelve months are positive for all of the assets. For equities, the one-month autocorrelation is 0·101 and the average over the next eleven months is 0·013. For bonds, the corresponding values are 0·238 and 0·047, while for foreign exchange the average autocorrelation at months 2–12 is 0·029. For both stocks and bonds, markets in the United States exhibit below-average degrees of positive autocorrelation. These findings strengthen earlier results (for example Poterba and Summers (1988) and Lo and MacKinlay (1988)) of positive serial correlation in U.S. equity returns.

For collectibles, farms, and real estate, data limitations prevent us from calculating monthly return autocorrelations. Nevertheless, the returns on these assets show positive serial correlation at an annual frequency. For house prices, the annual autocorrelation averages 0·206 for the four cities, while for farm returns and collectibles, the autocorrelations are even larger.

The results in Tables 2–4 also suggest the presence of negative autocorrelation at longer lags, although the evidence on this point is less compelling than that for positive high-frequency autocorrelation. For both stocks and bonds, the average of the 13th–24th autocorrelations is statistically significantly negative.[7] The correlation is also negative in U.S. historical data on equity returns. For bonds, the negative serial correlation persists, with negative average autocorrelations at twelve-month windows up to 60 months. For exchange rates, the average autocorrelation in the second year is negative and approximately equal to its standard error, paralleling earilier findings by Huizinga (1986). The

6. At higher frequencies, for example in daily returns, there may be non-trading biases even in recent years, when stock exchange volume has been far higher than in earlier decades. For the period since 1982, when S&P futures contracts have been traded, daily and weekly returns on the S&P 500 index exhibit more positive autocorrelation than the analogous futures returns. The interpretation of this result is tempered, however, by the finding that the difference between spot and futures prices forecasts index returns no better than returns on S&P futures.

7. The negative autocorrelations for stocks during the post-1960 period are noteworthy, since Kim, Nelson and Startz (1989) and others have emphasized the sensitivity (noted in Poterba and Summers (1988)) of evidence for mean-reversion in U.S. stock prices to inclusion of the Depression period.

negative autocorrelation is somewhat more pronounced at longer lags. There is also more pronounced evidence of negative autocorrelation at longer lags, notably between three and four years. There is little evidence of negative autocorrelation in the returns to holding metals, houses, or farmland, although Case and Shiller (1990) present evidence that annual real returns in the housing market are negatively autocorrelated at longer horizons.

3. PREDICTING RETURNS USING INFORMATION ON FUNDAMENTALS

The previous results suggest that asset returns are partly predictable on the basis of lagged returns. In this section, we examine the extent to which returns over various horizons can be forecast using information on the deviation of price from estimates of fundamental value, as well as lagged values of short-term interest rates.

3.1. *The predictive power of fundamentals*

We begin by examining whether the deviation between actual prices and crude proxies for fundamental values have forecast power for returns. We study returns over horizons of one, twelve, and forty-eight months by estimating regression equations of the form:

$$r_{t+k} = \alpha_k + \beta_k(z_t - p_t) + \nu_{t+k} \tag{6}$$

where r_{t+k} is the return from period t to period $t+k$ and $(z_t - p_t)$ is the difference between the logarithm of a potentially noisy measure of fundamental value (z_t) and the asset price. We interpret β_k as the *fraction of the deviation from the price fundamental* which is eradicated over a k-month horizon. If the current market price is one percent below the price fundamental z_t, then returns over the next month will be higher by $0{\cdot}01\beta$.

To test the null hypothesis that returns are unpredictable, we compute the bias-corrected t-statistic for β_k using Newey-West (1987) standard errors. (The bias correction is described in the appendix.) We also use Monte Carlo simulations to find the empirical distribution of the t-statistic of β_k under the null hypothesis. We report the p-value associated with the hypothesis that the bias-corrected t-statistic equals zero.[8]

Imprecise measures of price fundamentals will bias our tests *against* finding that the divergence between price and the measured fundamental can forecast returns. Nevertheless, under the null hypothesis that asset returns cannot be predicted using lagged information, none of our variables should exhibit any forecast power.

For equities, we measure the price fundamental as a constant multiple of the real dividend. The variable $(z_t - p_t)$ is therefore the logarithm of the dividend-price ratio, and equation (6) resembles equations estimated by Campbell and Shiller (1988) and Fama and French (1988). In the bond market, the efficient markets hypothesis and the assumption of a constant risk premium imply that the long-term interest rate is a weighted average of expected future short-term rates. If short rates are a random walk, the long rate should equal the short rate, and the fundamental value of the long-term bond is therefore the reciprocal of the short rate. Since the actual price of the long-term bond is the reciprocal of the long rate, we define $(z_t - p_t)$ as the logarithm of the long rate divided by the short rate. The resulting specification resembles the term structure tests of Shiller, Campbell and Schoenholtz (1983) and Mankiw and Summers (1984).

The fundamental value of the exchange rate depends on the long-run real exchange rate at which a sustainable trade balance can be achieved. Rather than attempting to

8. Hodrick (1990) and Nelson and Kim (1990) discuss the potential biases in estimating equations similar to (6), and present Monte Carlo evidence using a somewhat different specification of the null hypothesis.

model changes in terms of trade, we simply assume that the real exchange rate consistent with long-run trade balance is a constant. The logarithmic difference between the fundamental and the current exchange rate is therefore just minus the logarithm of the real exchange rate. We use the same approach with metals, so the price deviation is minus the logarithm of the real price.[9]

Table 5 presents evidence on the forecast power of differences between fundamentals and prices in world equity markets. The first column considers the forecastability of one month returns; the results are relatively weak. The estimated coefficient on $z_t - p_t$ has a p-value less than 0·10 for only three of the thirteen countries, although the cross-country average (reported in the penultimate row) has a p-value of 0·02. The point estimates, however, suggest substantively important links between the dividend-price ratio and subsequent returns. The average value of β_1, 0·75, implies that the ex ante risk premium is negative whenever dividend yields are less than approximately forty percent below their average value. It also suggests that about three-quarters of one percent of any deviation between the current price and our dividend-based fundamental is corrected in the first month after such a deviation appears.

The centre columns in Table 5 report regressions for twelve-month returns. The patterns of coefficients is similar to the one-month returns. On average, approximately 15% of a deviation from the price fundamental is erased over the subsequent year. Since the average value of β_{12} is about seventeen times the average for β_1, the evidence suggests that the dividend-price ratio's forecast power for one-period returns grows slightly as the horizon grows. In four of the thirteen countries, the coefficient has a p-value less than 0·10; the p-value for the average, however, is 0·01.[10] The most notable outlier is Japan, where the coefficient is negative and statistically significant. For the United States, the forecast power of the dividend-price ratio appears to have fallen over time.[11] Within our post-1960 sample, however, there is limited evidence of parameter instability. We experimented by allowing for a parameter shift in the middle of our data sample, and in nine of the thirteen stock markets we analyze, the null hypothesis of parameter constancy was not rejected at standard levels.

The final columns in Table 5 present evidence for 48-month returns. Although the sample size for these regressions is limited, the results suggest some predictive power of dividend-price ratios. The average correction to deviations between the current price and our simple measure of fundamentals is forty-one percent over a four-year horizon. This confirms Fama and French's (1988) earlier findings based on U.S. time-series data.

These results are nevertheless much weaker than might have been expected in light of earlier findings for the United States. These discrepancies may be attributed to several features. First, our corrections for small-sample bias significantly reduce the average

9. We also experimented with allowing the fundamental value for equities, exchange rates, and metals to vary with the long term real interest rate The qualitative conclusions were similar to those we report below, although this modification typically raised the standard errors of our estimated coefficients.

10. We also applied the seemingly-unrelated-regression methodology, constraining the coefficient on the dividend-price ratio to be the same across all nations. In this framework we did not calculate Newey–West standard errors or make out small-sample adjustment, but the results may nevertheless be of interest. If the twelve-month equations are estimated by OLS, the resulting average coefficient is 24·23 and our estimated standard error for the average is 2 94. Constraining the β_{12} parameter to be identical across countries yields a value of 15·62 (0·84), strongly rejecting the null hypothesis of no effect. The data also reject the hypothesis of a common coefficient, however.

11. The power of the dividend-price ratio to forecast U.S. multiperiod returns is only slightly smaller for the post-1945 period than for the 1926–1988 period, in contrast to the finding of long-horizon negative serial correlation in returns, which is much weaker for the latter period. However, for the period since 1960, shown in Table 5, the forecast power of dividend-price ratios is distinctly lower than in the longer sample.

TABLE 5

Forecasting excess stock returns using dividend-based fundamentals

	1 Month			12 Month			48 Month		
Country	β_1	p-value	$\bar{R}^2$	β_{12}	p-value	$\bar{R}^2$	β_{48}	p-value	$\bar{R}^2$
Australia	2·30 (1·74)	[0·10]	0·014	32·77 (7·80)	[0·01]	0·240	85·07 (11·62)	[0·01]	0·572
Austria	−1·69 (0·90)	[0·95]	0·004	−8·74 (12·79)	[0·68]	−0·002	35·25 (56·08)	[0·41]	0·032
Belgium	−0·62 (0·91)	[0·71]	−0·004	−0·46 (8·88)	[0·52]	0·015	26·04 (31·47)	[0·37]	0·202
Canada	1·30 (1·81)	[0·23]	0·004	27·07 (12·28)	[0·08]	0·132	43·91 (16·65)	[0·14]	0·249
France	0·48 (0·86)	[0·28]	0·005	8·94 (6·05)	[0·17]	0·101	45·42 (17·80)	[0·13]	0·440
Germany	−0·04 (1·03)	[0·50]	0·000	11·04 (10·30)	[0·24]	0·091	40·60 (21·54)	[0·21]	0·395
Italy	0·59 (1·21)	[0·31]	−0·001	18·81 (10·08)	[0·12]	0·063	5·20 (40·33)	[0·51]	0·000
Japan	−1·10 (0·41)	[0·99]	0·002	−13·19 (4·56)	[0·97]	0·034	−56·71 (24·22)	[0·90]	0·098
Netherlands	0·46 (1·29)	[0·36]	0·002	11·95 (12·11)	[0·26]	0·089	71·09 (24·46)	[0·10]	0·461
Sweden	−0·23 (0·97)	[0·57]	−0·002	12·32 (10·21)	[0·22]	0·083	51·64 (40·52)	[0·29]	0·278
Switzerland	2·70 (1·64)	[0·06]	0 014	28·20 (11·18)	[0·06]	0·122	73·58 (33·52)	[0·17]	0·291
United Kingdom	5·11 (1·62)	[0·01]	0·018	43·90 (11·62)	[0·01]	0·268	94·39 (17·98)	[0·02]	0·516
United States	0·54 (1·00)	[0·29]	0·002	11·43 (8·99)	[0·21]	0·080	20·06 (21·17)	[0·35]	0·202
Average	0·75 (0·35)	[0·02]		14·16 (2·79)	[0·01]		41·20 (8·31)	[0·03]	
U.S. 1926–1988	0·01 (0·78)	[0·47]	0·003	17·44 (8·46)	[0·06]	0·077	66·58 (14·45)	[0·01]	0·296

Note: Each entry reports estimates of the coefficient β_k from the regression:

$$R_{t,k} = \alpha_k + \beta_k(z_t - p_t) + \nu_{t,k}$$

where z_t is the logarithm of the real dividend. Data are from 1960–1988. The coefficients are bias-adjusted. Numbers in parentheses are standard errors, calculated using the Newey–West procedure. The standard error of the average accounts for cross correlation of the coefficients, as in the text. Numbers in brackets are p-values for the null hypothesis that the coefficient is zero, based on the Monte Carlo distribution of the adjusted t-statistic.

regression coefficients. Second, taking account of the leptokurtotic distribution of the t-statistic under the null hypothesis further reduces the confidence of our findings. Finally, it appears that the relation between future returns and past values of the dividend-price ratio is weaker in other markets than it is for the U.S. This is particularly evident for the Japanese stock market, where high values of the dividend yield have negative and statistically significant effects on future returns.

Table 6 considers the forecastability of returns in the bond market. The results are less consistent than those from the equity markets and provide weaker evidence on the forecast power of fundamental-price deviations. For one-month returns, the yield spread has statistically significant explanatory power in five of the thirteen bond markets, and the cross-country average is also statistically significant. The coefficient implies about the same amount of mean reversion as for the equity market: eight-tenths of one percent of a fundamental-price disparity is corrected over a one-month horizon.

TABLE 6

Forecasting long-term excess holding returns with yield spreads

Country	β_1	1 Month p-value	$\bar{R}^2$	β_{12}	12 Month p-value	$\bar{R}^2$	β_{48}	48 Month p-value	$\bar{R}^2$
Australia	0·11	[0·45]	−0·004	−7·66	[0·66]	0·009	−26·45	[0·69]	0·029
	(1·17)			(12·21)			(34·76)		
Austria	1·33	[0·01]	0·023	3·27	[0·41]	−0·002	3·03	[0·50]	−0·004
	(0·55)			(9·16)			(17·16)		
Belgium	3·40	[0·01]	0·036	25·82	[0·10]	0·061	43·04	[0·37]	0·020
	(1·04)			(12·64)			(53·00)		
Canada	0·65	[0·10]	0·002	3·96	[0·29]	0·007	−3·22	[0·59]	0·006
	(0·49)			(4·68)			(12·13)		
France	2·10	[0·00]	0·042	3·07	[0·37]	−0·001	−9·26	[0·71]	0·015
	(0·53)			(5·92)			(10·53)		
Germany	−0·05	[0·58]	−0·003	−1·65	[0·73]	0·007	−5·87	[0·81]	0·031
	(0·17)			(1·82)			(3·95)		
Italy	0·43	[0·13]	0·003	−0·23	[0·52]	−0·003	−20·16	[0·69]	0·043
	(0·39)			(6·58)			(26·95)		
Japan	0·76	[0·05]	0·011	−0·11	[0·51]	−0·004	−17·19	[0·81]	0·092
	(0·45)			(5·46)			(11·63)		
Netherlands	0·07	[0·40]	−0·003	−2·99	[0·73]	0·019	−13·63	[0·89]	0·125
	(0·31)			(3·22)			(6·03)		
Sweden	0·44	[0·09]	0·002	−0·84	[0·59]	0·001	−10·01	[0·92]	0·226
	(0·31)			(2·65)			(3·78)		
Switzerland	0·22	[0·18]	−0·001	−1·28	[0·59]	0·002	−12.52	[0·96]	0·136
	(0·24)			(3·79)			(3·66)		
United Kingdom	−0·14	[0·54]	−0·003	−2·33	[0·60]	−0·002	−53·98	[0·91]	0·203
	(0·88)			(6·32)			(22·00)		
United States	1·72	[0·02]	0·012	15·41	[0·05]	0·081	−6·49	[0·62]	0·004
	(0·77)			(6·00)			(16·52)		
Average	0·85	[0·01]		2·65	[0·19]		−10·21	[0·78]	
	(0·18)			(1·94)			(7·99)		
U.S. 1926–1988	0·13	[0·16]	0·004	1·62	[0·01]	0·055	5·57	[0·04]	0·124
	(0·13)			(0·45)			(1·63)		

Note. Each entry reports estimates of the coefficient β_k from the regression:

$$R_{t,k} = \alpha_k + \beta_k * (z_t - p_t) + \nu_{t,k}$$

where z_t is the logarithm of the reciprocal of the short term interest rate. Data are from 1960–1966; see Table 1 for specifics. The coefficients are bias-adjusted. Numbers in parentheses are standard errors, calculated using the Newey–West procedure. The standard error of the average accounts for cross-correlation of the coefficients. Numbers in brackets are p-values for the null hypothesis that the coefficient is zero, based on the Monte Carlo distribution of the adjusted t-statistic.

At the 12-month horizon, only two of the thirteen countries evidence statistically significant links between yield differentials and subsequent returns. At the 48-month horizon, most of the coefficients are *negative*, contrary to the prediction of our earlier analysis, although we cannot reject the null of no effect. The results for the long-horizon U.S. bond returns in the last row of the table do suggest some forecast power, but with only about six percent of fundamental-price deviations corrected over a 48-month horizon.

Table 7 presents the results of relating currency returns to the deviation between real exchange rates and our estimate of their fundamental value. There is little evidence of predictability in these returns. Most of the coefficients are small and have large standard errors. The average correction is only nine percent after one year, and thirty-two percent after four years, both with very large standard errors.

Table 7 also presents results for commodity metals. The statistical confidence of these results is again low but the point estimates are consistent with the earlier findings.

TABLE 7

Forecasting excess exchange rate and precious metal returns

Country		1 Month			12 Month			48 Month	
	β_1	p-value	$\bar{R}^2$	β_{12}	p-value	$\bar{R}^2$	β_{48}	p-value	$\bar{R}^2$
				A. Exchange Rate Returns					
United States									
France	−0·98	[0·80]	0·003	−1·88	[0·59]	0·129	34·43	[0·49]	0·455
	(1·03)			(14·21)			(34·94)		
Germany	−1·44	[0·88]	−0·002	−9·44	[0·70]	0·071	−9·32	[0·67]	0·252
	(1·03)			(14·10)			(33·66)		
Japan	0·58	[0·40]	0·007	29·72	[0·28]	0·212	150·63	[0·01]	0·715
	(1·79)			(21·58)			(13·82)		
United Kingdom	0·61	[0·35]	0·019	18·74	[0·27]	0·272	122·56	[0·06]	0·813
	(1·28)			(13·17)			(19·17)		
Japan									
France	−1·29	[0·78]	−0·003	−0·17	[0·56]	0·111	−28·81	[0·77]	0·286
	(1·16)			(10·86)			(24·39)		
Germany	−1·64	[0·83]	−0·004	−8·97	[0·74]	0·051	−67·42	[0·91]	0·024
	(1·15)			(10·31)			(20·32)		
United Kingdom	0·22	[0·53]	0·009	21·28	[0·26]	0·222	96·30	[0·10]	0·592
	(1·42)			(14·12)			(18·90)		
United Kingdom									
France	−0·87	[0·68]	−0·002	−9·06	[0·72]	0·024	24·30	[0·49]	0·366
	(1·66)			(11·69)			(24·75)		
Germany	−1·46	[0·82]	−0·004	−9·81	[0·75]	0·032	−24·63	[0·74]	0·187
	(1·41)			(10·11)			(28·18)		
Germany									
France	4·05	[0·06]	0·033	63·00	[0·05]	0·452	21·15	[0·49]	0·086
	(2·28)			(17·43)			(21·42)		
Average	−0·22	[0·67]		9·34	[0·17]		31·92	[0·16]	
	(0·46)			(4·48)			(7·84)		
				B. Precious Metal Returns					
Gold	0·94	[0·33]	0·012	27·05	[0·17]	0·235	133·19	[0·06]	0·871
	(1·97)			(13·06)			(20·98)		
Silver	2·92	[0·16]	0·017	27·49	[0·20]	0·188	109·00	[0·22]	0·451
	(2·51)			(14·68)			(32·75)		
Metal index	−0·18	[0·55]	0·000	14·05	[0·19]	0·094	29·69	[0·37]	0·150
	(0·93)			(10·51)			(35·31)		

Note. The regressions are similar to those in Table 5. The fundamental is a constant in each case. The price is the logarithm of the real exchange rate or the logarithm of the real metal price. Data are from 1974–1988, except for the metal index (1959–1988).

For both gold and silver, the estimated coefficients on 48-month returns imply that deviations between prices and fundamental values are more than eradicted over this interval. The small samples preclude us from estimating similar equations for real assets. Case and Shiller (1990) report evidence that rental-to-price ratios positively predict future returns in the cities for which they have data. If the discount rate is constant, the rental-to-price ratio can be interpreted as a constant multiple of the fundamental-price ratio.

3.2. *Short-term interest rates and return predictability*

A final empirical regularity concerns the relationship between short-term interest rates and excess returns. Froot (1990) documents that the level of short rates forecasts the excess return on foreign exchange, some commodities, as well as U.S. stocks and bonds.

TABLE 8

Forecasting excess returns using short term interest rates

	Stocks		Bonds	
Country	β_1	$\bar{R}^2$	β_1	$\bar{R}^2$
Australia	1·310	0·002	−0·008	0·000
	(1·781)		(1·043)	
Austria	−4·332	0·009	−2·093	0·003
	(2·657)		(2·239)	
Belgium	0·425	0·000	−3·431	0·024
	(1·865)		(1·386)	
Canada	−1·949	0·009	−0·048	0·000
	(1·303)		(0·732)	
France	0·520	0·000	−1·279	0·009
	(1·326)		(0·742)	
Germany	−1·859	0·006	−0·724	0·002
	(1·276)		(0·803)	
Italy	0·987	0·004	−0·560	0·004
	(0·965)		(0·485)	
Japan	−3·943	0·024	−4·364	0·093
	(1·370)		(0·734)	
Netherlands	−1·951	0·005	−0·978	0·002
	(1·754)		(1·284)	
Sweden	2·199	0·011	−1·365	0·015
	(1·199)		(0·643)	
Switzerland	−1·859	0·001	0·338	0·000
	(3·008)		(2·139)	
United Kingdom	0·551	0·000	2·246	0·013
	(1·676)		(1·154)	
United States	−1·652	0·007	0·212	0·000
	(1·044)		(0·693)	
Average	−0·889		−0·927	
	(0·481)		(0·335)	
U.S.	−1·245	0·004	−0·236	0·001
1926–1988	(0·753)		(0·303)	

Note. Each entry reports estimates of the coefficient β_1 from the regression:

$$R_{t+1} = \alpha_1 + \beta_1 i_t + \nu_{t+1}$$

where i_t is the short term interest rate Data are from 1960–1988. Standard errors are in parentheses. The standard error of the average accounts for cross-correlation of the coefficients, as in the text.

He finds that a one hundred basis-point rise in the short rate is associated with a three hundred basis-point decline in the annual excess return to other assets. We examine the robustness of this finding using our data on stock and bond returns outside the United States.

Table 8 reports regression results relating the one-month excess return on bonds and stocks to the once-lagged short-term interest rate. In ten of the thirteen bond markets, and seven of the thirteen equity markets, the coefficient on the lagged short rate is negative. The average coefficient for equity markets is −0·89, and that for bond markets is −0·93. These findings are less dramatic than those reported in Froot (1990), but taken with his evidence on other asset markets, they suggest yet another source of return predictability.

4. ALTERNATIVE EXPLANATIONS FOR ASSET RETURN PATTERNS

One explanation of the stylized patterns in asset returns which we documented above is that they are caused by changes in risk factors over time. Such an argument is difficult to rule out, since any failure of an asset-pricing model can always be attributed to the mis-measurement of risk. Changing required returns appear unlikely, however, to explain our empirical findings.

First, traditional models in financial economics have difficulty justifying substantial risk premia, let alone variation in these risk premia. Mehra and Prescott (1985) show that the average excess return on the U.S. stock market since 1926 is too large to be consistent with plausible estimates of risk aversion and the observed riskiness of stock returns. Frankel (1985) argues that risk premia of more a few basis-points are not supported by standard capital asset pricing models. Yet our results suggest that positive autocorrelation in returns implies large swings in ex-ante returns.

Second, changing risk factors would not naturally produce the observed autocorrelation patterns, particularly positive autocorrelation at high frequencies.[12] One would expect increases in risk that raise future ex-ante returns to be capitalized as a current negative excess return. For simple specifications of the risk process, this would lead to *negative* autocorrelation at high frequencies. While it is possible to find processes for risk factors consistent with the observed autocorrelation in returns (Poterba and Summers (1988), footnote 27), they do not agree with the empirical work on the evolution of volatility, such as Poterba and Summers (1986) or French, Schwert and Stambaugh (1987).[13]

Third, since returns on the assets analyzed in the last section are only weakly correlated, a single risk factor is unlikely to account for the statistical regularities in all markets. Some assets are affected primarily by nominal factors while others are influenced primarily by real factors; some represent large shares of investors' wealth others represent small shares; some yield variable cash flows while others are a source of stable income; some have finite horizons while others do not. It would be remarkable if a common risk factor could account for the common patterns in returns on all assets.[14] Indeed, it is not even clear how risk should affect all the assets we analyse. In the case of foreign exchange, for example, risk affects both currencies being exchanged, and so does not even have a predictable effect on the level of exchange rates.[15]

A fourth difficulty with the required returns explanation is the weak empirical association between variations in ex post returns and changes in measurable aspects of risk. Campbell and Shiller (1989) find that while dividend yields have predictive power for subsequent dividend growth in long-period U.S. data, they do not have predictive power for interest rates or other determinants of risk premia. Cutler, Poterba and Summers (1989) have trouble explaining more than half of the variation in U.S. stock returns on the basis of news, even after controlling for changes in volatility.[16]

In contrast to the time-varying risk explanation, the similarity of these speculative patterns in a wide range of asset markets suggests the possibility that they are best

12. Marcus (1989) argues that changes in stock prices change the wealth of investors, affecting their risk aversion and thus expected returns. Whatever the merits of this argument in the case of stocks, it is much less likely to apply in the case of inside assets like bonds, or assets like gold and metals that comprise only a small fraction of the representative investors' portfolio.

13. In principle it may be easier to explain these patterns in multi-factor asset pricing models, although there is little empirical evidence to support this proposition.

14. For equities, changes in dividends may precede increases in risk premia and induce spurious positive autocorrelation in ex-post returns. Even if this were correct, it is difficult to see how analogous explanations could operate in the case of gold, long-term bonds, or foreign exchange.

15. Theories of exchange rate determination that rely on asset substitutability, for example, imply that the effect of exchange rate risk will depend on the relative supplies of assets across countries and savings propensities in different countries, variables which are likely to change over time.

16. Meese and Rogoff (1983) report similar findings in their study of the foreign exchange market. In an earlier version of this paper (available on request), we added measures of market volatility to our equations predicting future equity returns. The coefficient on the lagged dividend-price ratios was virtually unchanged.

explicable as a consequence of the speculative process itself. Shiller (1984), Black (1986), Campbell and Kyle (1987), DeLong, Shleifer, Summers, and Waldmann (1990), among others, discuss models of asset pricing that permit prices to deviate from the rational discounted value of future cash flows.

Research directed at formalizing the dynamics of speculative markets is just beginning. Our own preliminary efforts to formalize the role of "feedback traders" are presented in Cutler, Poterba and Summers (1990). We outline a model of asset market equilibrium in which interactions between rational investors, who base demand on expected future returns, and feedback traders, who base demand on realized past returns, can produce the stylized facts we document here.

The difference between the risk and feedback-trading approaches is best illustrated by considering periods of very high or low prices, such as U.S. stock market peak in 1987, the Japanese market peak in 1990, or the U.S. trough in 1974. The conventional approach posits that market peaks are times when risk is low, so that investors rationally lower their required returns, while troughs are times of very high required returns, in response to large market risks. The feedback trading approach instead posits that peaks are caused by over-optimism on the part of some investors, who drive prices up to levels from which future returns are depressed. As we note in Cutler, Poterba and Summers (1990), qualitative discussions of dramatic price fluctuations often lay much more stress on feedback traders than on changing risk factors.

Further research is needed to explore models of speculation. Genotte and Leland (1990) argues that if positive feedback trading becomes sufficiently important, it is possible for market to have multiple equilibria, with discontinuous responses of prices to fundamentals. The effect of learning, with traders switching to trading strategies which have been profitable, could generate important dynamics in these models. Perhaps the greatest need, however, is to develop testable implictions of these models. It may be possible to make predictions, for example, about the amount of positive feedback trading and market volatility or volume. Such testable predictions are vital if the literature on alternatives to traditional asset pricing models is to advance beyond the realm of speculation.

APPENDIX: DERIVATION OF SMALL-SAMPLE BIAS

This appendix details our calculation of the small-sample bias in the β_k and autocorrelation coefficients. We assume that $z_t - p_t$ (denoted μ_t) is a first-order autoregression: $\mu_{t+1} = \phi\mu_t + \eta_{t+1}$. We further assume that the true relation between one-period returns and fundamental-price ratios is given by: $r_{t+1} = \tilde{\beta}_1\mu_t + \nu_{t+1}$. Because positive shocks to returns raise prices, and therefore lower $z_t - p_t$, η_{t+1} and ν_{t+1} are negatively correlated: $\nu_{t+1} = \rho_{\nu\eta}\eta_{t+1} + \zeta_{t+1}$, $\rho_{\nu g\eta} < 0$.

With these assumptions, the coefficient in a regression of r_{t+j} on μ_t is $\tilde{\beta}_j = \tilde{\beta}_1\phi^{j-1}$, and its bias is:

$$\begin{aligned}\text{Bias}(\tilde{\beta}_j) = E[\hat{\tilde{\beta}}_j - \tilde{\beta}_j] &= \textstyle\sum_{t=1}^{T} \mu_t * R_{t+j} / \sum_{t=1}^{T} (\mu_t)^2 - \tilde{\beta}_1 * \phi^{j-1} \\ &= \tilde{\beta}_1 * (E[\hat{\phi}_{j-1}] - \phi^{j-1}) \\ &\quad + \rho_{\nu\eta} * [(E[\hat{\phi}_j] - \phi^j) - \phi * (E[\hat{\phi}_{j-1}] - \phi^{j-1})] \end{aligned} \tag{A.1}$$

where $\hat{\phi}_{j-1}$ is the $(j-1)$-st autocorrelation of μ_t. The expectation of $\hat{\phi}_j$, given in Kendall (1973), is:

$$E[\hat{\phi}_j] = \phi^j - [(1+\phi)/(1-\phi) * (1-\phi^j) + 2j\phi^j]/(T-j). \tag{A.2}$$

The coefficient β_k in equation (6) is: $\beta_k = \sum_{j=1}^{k} \tilde{\beta}_j$. Thus, the bias of β_k is the sum of the biases for $\tilde{\beta}_j$: Bias $(\hat{\beta}_k) = \sum_{j=1}^{k}$ Bias $(\hat{\tilde{\beta}}_j)$. Summing equation (A.1):

$$\text{Bias}\,(\hat{\beta}_k) = -[\tilde{\beta}_1 + \rho_{\nu\eta}(1-\phi)] * \left[\frac{k-1+k\phi-(2k-1)\phi^k}{(1-\phi)*(T-k)}\right]$$

$$-\frac{\rho_{\nu\eta}}{T-k} * \left[\left(\frac{1+\phi}{1-\phi}\right) * (1-\phi^k) + 2k\phi^k\right]. \quad \text{(A.3)}$$

We estimate $\hat{\tilde{\beta}}_1$, $\hat{\phi}$, and $\hat{\rho}_{\nu\eta}$ for each data set, and use (A 3) to find the bias in the longer-horizon regression coefficients

The bias in the return autocorrelation (ρ_k) follows directly from (A.2). If returns are serially uncorrelated, $E[\hat{\rho}_k] = -1/(T-k)$. Following a referee's suggestion, we explored the sensitivity of this result to non-normal return distributions by drawing returns from the empirical distribution for the U.S. With 348 observations, and thus a one month theoretical bias of −0·0029, the estimated one month bias using this procedure was −0·0026.

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