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Macroeconomic Seasonality and the January Effect

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ABSTRACT

Many financial markets researchers have sought an explanation for the role of January in stock returns. Any explanation of this phenomenon that is consistent with rational pricing must specify a source of seasonality in expected returns. The pervasive seasonality in the macroeconomy is an appealing possibility. A multifactor model that links macroeconomic risk to expected return is found to show substantial seasonality in expected returns. This model accounts for the seasonality in average returns, while the capital asset pricing model cannot.

THE EMPIRICAL SIGNIFICANCE OF January for stock returns continues to puzzle financial economists. Capital-market equilibrium dictates no role for January per se, yet it adds explanatory power to the capital asset pricing model (CAPM), the reigning equilibrium model. As the CAPM is a favored tool for both academic and practical work (for example, in cost-of-capital estimation), both academic economists and financial managers have sought to understand the January effect.

A multifactor model is used here to study the role of macroeconomic uncertainty in determining the January effect. Price is used as an instrumental variable for exposure to seasonal risk. As Bhardwaj and Brooks (1992) show, price subsumes size as an instrumental variable for the January effect.[1] When a set of common time series are used for macroeconomic risk factors, the seasonality in risk exposure is inversely related to price. Seasonality in the model's estimated expected returns accounts for the seasonal in average returns, while the CAPM fails to do so even when its parameters are allowed to vary seasonally.

The rest of the article proceeds as follows. Section I describes the model for returns. Section II describes the factor and returns data, and Section III presents the results. Section IV concludes the article.

I. The Model for Returns

I assume that returns are described by a multifactor model with seasonal expected returns.[2] In particular, I assume that financial market uncertainty

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[1] The results are qualitatively the same when size is used as an instrumental variable.

[2] An example of a similar multifactor model and some theoretical justification for such models is found in Ferson and Harvey (1991).

is described by K stochastic factors, $f_1, f_2, \dots, f_K$, linearly related to returns:

$$r_{it} = E_{t-1}[r_{it}] + \sum_{j=1}^{K} b_{ijt} f_{jt} + \epsilon_{it}. \tag{1}$$

Here r_{it} denotes the return on firm i's stock at date t, and $E_{t-1}[]$ denotes conditional expectation where there are N firms. The factor loading or beta, b_{ijt}, represents firm i's exposure to systematic risk source f_j at date t. In equilibrium, the following risk-return relationship holds:

$$E_{t-1}[r_{it}] = \lambda_{0t} + \sum_{j=1}^{K} b_{ijt} \lambda_{jt}. \tag{2}$$

Note that λ_{jt} is the expected return received for bearing a unit of factor j risk (b_{ijt}) and is known as the price of j-type risk or the jth risk premium. λ_{0t} is the expected return on a portfolio with no factor risk ($b_{ij} = 0$ for all j) and is, therefore, the riskless rate. Seasonal variation (January and non-January) in the betas and risk premia is taken to be the source of seasonality in expected return, so the time subscript on b_{ijt} and λ_{jt} distinguishes January from the rest of the year. Since the betas and risk premia are reduced forms of parameters representing risk aversion and technology, and since there is much evidence to suggest that such parameters display seasonality, this seems to be a plausible specification.[3]

Estimation of the model is straightforward. The betas are estimated by a time-series regression of returns on factors as in equation (1). The risk premia are then estimated from a cross-sectional regression of average returns on estimated betas. While this two-stage technique presents some difficulties for inference due to an errors-in-variable problem (the use of $\hat{b}$ rather than b), the second-stage estimator of λ is consistent and asymptotically normal under weak restrictions on the proces governing the factors and the disturbances.[4] I use a standard error for this estimator, which adjusts for errors in variables; the resulting test statistic yields reliable inferences for the sample size employed here.[5] For comparison purposes, the more traditional Fama MacBeth (1973)-style statistics are also presented.

II. Data

I use the sample period January 1970 to December 1989 for estimation and testing, with monthly data. The 20-year horizon provides 240 monthly observations, enough to allow for reliable parameter estimation in the seasonal subsamples, while covering a short enough time period that stability of parameters within subsamples is a tenable assumption.

[3]See Barsky and Miron (1989), Ferson and Harvey (1992), and Ghysels, Ed. (1993).

[4]See Shanken (1992).

[5]See Kramer (1993).

A. Factors

I choose a set of five factors common in work on the relationship of the macroeconomy to the asset markets (see Burmeister and McElroy (1988), Chen, Roll, and Ross (1986), Chan, Chen, and Hsieh (1985), Ferson and Harvey (1991), Chen (1991), and Estrella and Hardouvelis (1991)). Loadings on the first two factors, default risk and maturity risk, indicate the debt exposure of the firm. The default risk factor is the difference in return on corporate bonds and government bonds (both from Ibbotson and Sinquefeld (1990)), while the maturity-risk factor is the difference in return on government bonds and Treasury bills. Loadings on the second two factors, inflation and consumption growth, show the firm's exposure to macroeconomic forces. The inflation factor is the residual from an integrated moving average (1) (IMA(1)) model (after Ferson and Harvey (1991)), while the consumption factor is simply the growth rate in consumption.[6] The fifth factor, a stock market factor, captures equity market exposure. It is the residual from a regression of the equally weighted Center for Research in Securities Prices (CRSP) index on the first four factors (see Burmeister and McElroy (1988)). Including a stock market factor also means that the model yields the CAPM as a special case.[7]

B. Returns

The sample of returns is taken from the CRSP Monthly Master data tape. For each month in the sample, I group the returns on all companies with return and price data for that month into one of 50 equally weighted portfolios on the basis of the previous month's price. I rebalance the price portfolios monthly, rather than at the end of each year (as is more typical), to avoid inducing turn-of-the-year seasonals. The number of eligible, listed firms for each month varies from 1,285 to 1,651, enough for about 25 to 30 securities per portfolio. As one would expect, the standard deviation of return bears an inverse relation to price across portfolios.

The return on the Treasury bill with maturity closest to one month, taken from Ibbotson and Sinquefeld (1990), is used for the one-period risk-free rate, λ_{0t}. This is subtracted from each portfolio's return to compute the net-risk-free return, R_{it}, used in estimation. An additional benefit of using net-risk-free returns is that although the Treasury bill and stock returns are nominal, as

[6] Both are constructed from seasonally adjusted data. Using seasonally adjusted data decreases the chance of a spurious positive finding, which may be significant when using unadjusted data: as Burmeister and McElroy (1988) point out, any anomaly can be "explained" by choosing a factor that mimics the anomaly. However, the likelihood that seasonally adjusted macroeconomic factors spuriously "explain" the January effect is small. Moreover, no monthly unadjusted series is available for consumption. Even so, Ferson (1990) points out that the growth in seasonally adjusted consumption may serve as a better proxy for marginal utility than the growth in unadjusted consumption.

[7] See Burmeister and McElroy (1991).

Ferson (1990) notes, real returns and net risk-free returns are empirically indistinguishable at one-month intervals.

III. Results

A. January Returns in the Sample

Table I displays statistics describing the differences between the first and tenth price deciles' monthly returns. The average difference between high- and low-priced firms' returns in all months together is economically large (0.31 percent, or about 3.7 percent per year), but statistically insignificant. The average difference in January, however, is large (8.38 percent per month or over 160 percent per year compounded) and significant at all usual significance levels. The same is true for continously compounded rates of return ($\ln(1 + r)$), shown in the second half of the table.

B. Tests for CAPM Excess Returns

Although these statistics suggest the presence of the January effect, they do not demonstrate January-related *excess* returns in the data. I therefore

Table I

Seasonality in Average Returns

Tests for the significance of the mean of the difference in low-priced and high-priced firms' returns, using t-tests for all months together and regressions on a January dummy variable. r_{D1} denotes the return on the decile portfolio containing the lowest-priced firms, while r_{D10} denotes return on the decile portfolio containing the highest-priced firms.

Panel A: Descriptive Statistics: $r_{D1} - r_{D10}$			
Mean	Std. Dev.	Minimum	Maximum
0.0031	0.0462	−0.1554	0.2961

Panel B: Regression of $(r_{D1} - r_{D10})$ on January Dummy		
	Estimate	t-ratio
Constant	−0.0039	−1.4528
January dummy	0.0838	8.9739

Panel C: Descriptive Statistics: $\ln(1 + r_{D1}) - \ln(1 + r_{D10})$			
Mean	Std. Dev.	Minimum	Maximum
0.0021	0.0441	−0.1527	0.2390

Panel D: Regression of $[\ln(1 + r_{D1}) - \ln(1 + r_{D10})]$ on January Dummy		
	Estimate	t-ratio
Constant	−0.0044	−1.7139
January dummy	0.0781	8.6970

document CAPM excess returns for low-priced companies in January and compare the goodness-of-fit of CAPM and multifactor models. One might well suspect that allowing risk and expected return to vary seasonally will trivially "explain" seasonal return. Hence, a CAPM with seasonal risk and return is used in these tests.

Traditional tests of the hypothesis of excess returns add the logarithm of price or size to betas in the cross-sectional regression (2) and test its significance. Table II presents the results of such tests, using the value-weighted CRSP index as a market proxy.[8] Price is significant in January using both the asymptotic test statistic and the Fama-MacBeth statistic. The usual January effect is present in this sample, and a CAPM with seasonal expected return cannot account for it.

C. Goodness-of-Fit Tests: The Predictive Least Squares Criterion

Given the fivefold increase in parameters for the multifactor model over the CAPM, the multifactor model might be suspected of trivially improved in-sample performance. Therefore the multifactor model and CAPM are compared in their ability to predict returns ex ante, with and without seasonal parameters.

Rissanen's (1986) predictive least squares (PLS) criterion is a model-selection criterion for regression that performs such comparisons. The PLS criterion is the sum of squared one-step-ahead prediction errors, where the parameters of the model used to predict date t's data are estimated from data through date $t - 1$. The best-fitting model among a set of candidates is the one with the smallest sample value of PLS. This criterion can be thought of as an analytic expression for the common belief that models that overfit provide poor out-of-sample forecasts.

Figure 1 displays the PLS criterion for the full cross-section of 50 price classes for January. The seasonal multifactor model fits at least as well as the other three models for almost every portfolio. Given the conservative small-sample bias of PLS noted by Wei (1992), this is strong evidence in favor of the seasonal multifactor model.

Armed with the knowledge that the seasonal multifactor model outperforms the nonseasonal multifactor model and seasonal and nonseasonal CAPM models, and that the anomaly to be explained is present in CAPM-adjusted returns, I proceed to estimate and test the seasonal multifactor model.

D. Seasonality in Risk

Tests for stable betas show the degree of seasonality in risk. The F-tests are standard likelihood-ratio tests, done two ways. The first set of tests (Table III, Panel A) test the null hypothesis that b_j is the only stable factor

[8] Tests performed using the equally weighted CRSP or the S&P 500 as the market proxy have similar results.

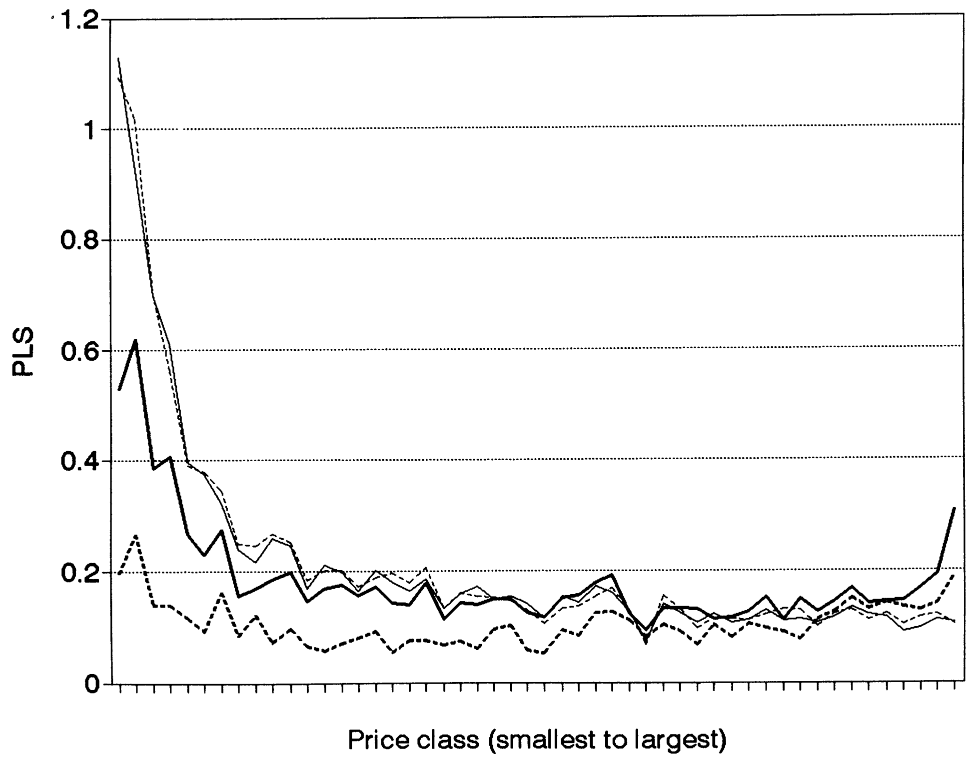

Figure 1. PLS criterion for January. PLS goodness-of-fit criterion for four models: CAPM, CAPM with seasonal parameters, multifactor model, and multifactor model with seasonal parameters, across price portfolios. Models are fitted to January observations. A smaller value of PLS implies a better fitting model. —CAPM, —Seasonal CAPM, ----Multifactor, and ----Seasonal Multifactor.

Table II

Tests for Excess Returns: CAPM Models

Risk-premium estimates and test statistics for the significance of the logarithm of price in cross-section regressions, using the value-weighted CRSP index as the market proxy. Beta denotes the estimated market beta, $\hat{\lambda}$ denotes the risk premium estimate, AN denotes the asymptotically normal test statistic, and FM the Fama-MacBeth (1973) test statistic (distributed Student t), both for the null hypothesis that λ is zero.

	January			February–December		
	$\hat{\lambda}$	AN	FM	$\hat{\lambda}$	AN	FM
ln(Price)	−0.0009	−2.3113	−3.8702	0.0001	1.6697	1.6703
Beta	0.0640	2.8004	3.4750	0.0013	0.3520	0.3617

Table III

Tests for Seasonal Stability in Risk

p-Values for the null hypothesis that January and February–December coefficients are the same. The alternative is that all coefficients are seasonal. Default denotes the beta for the default factor (the difference between corporate bond and government bond returns), Maturity denotes the beta for the maturity factor (the difference between government bond returns and one-month Treasury bill returns), Inflation denotes the beta for the inflation factor (the innovation from an IMA(1) model), Bus. Cycle denotes the beta for consuption growth, and Market denotes the beta for the residual market factor (the residual from a regression of the equally weighted CRSP index on the other four factors). D1 denotes the return on the lowest-price decile portfolio, D10 denotes the return on the highest-price decile.

	Default	Maturity	Inflation	Bus. Cycle	Market
Panel A: H_0, Only b_{ij} Stable; Factor (j)					
Portfolio (i)					
D1	0.0011	0.0671	0.0114	0.0109	0.3022
D5	0.0176	0.0525	0.3949	0.0342	0.1092
D10	0.1546	0.5363	0.4675	0.1146	0.1046
Panel B: H_0, Only b_{ij} Seasonal; Factor (j)					
Portfolio (i)					
D1	0.0008	0.0003	0.0161	0.0004	0.0002
D5	0.0332	0.0534	0.0493	0.0529	0.0379
D10	0.1892	0.1884	0.2543	0.3084	0.5215

beta, while the second set of tests (Table III, Panel B) test the null hypothesis that b_j is the only seasonal factor beta. All have as the alternative that every factor beta is seasonal.

Two features are apparent in the results. First, the lowest-priced firms have the strongest seasonality in betas. Second, more than one factor is responsible for this seasonality. There is pervasive and significant seasonality in the macroeconomic risk of low-priced companies.

E. Estimated Expected Returns Versus Average Returns: Evidence for an Equilibrium January Effect in the Multifactor Model

Average net-risk-free returns, $\overline{R}_i$, and estimated expected returns (or model predicted return), $\sum_{j=1}^{K}\hat{b}_{ij}\hat{\lambda}_j$, for price classes in January and February-December are displayed in Figure 2. Since expected return in the multifactor model is $\sum_{j=1}^{K} b_{ijt}\lambda_{jt}$, comparing average return and estimated expected return should provide a clue as to whether expected-returns seasonals mirror average-returns seasonals. An inverse relationship between estimated expected returns and price is clear in January but is absent during the rest of the year. The seasonality in expected return predicted by the model mimics the seasonality in average return, implying that the model captures the seasonality in returns. The next task is to test this formally.

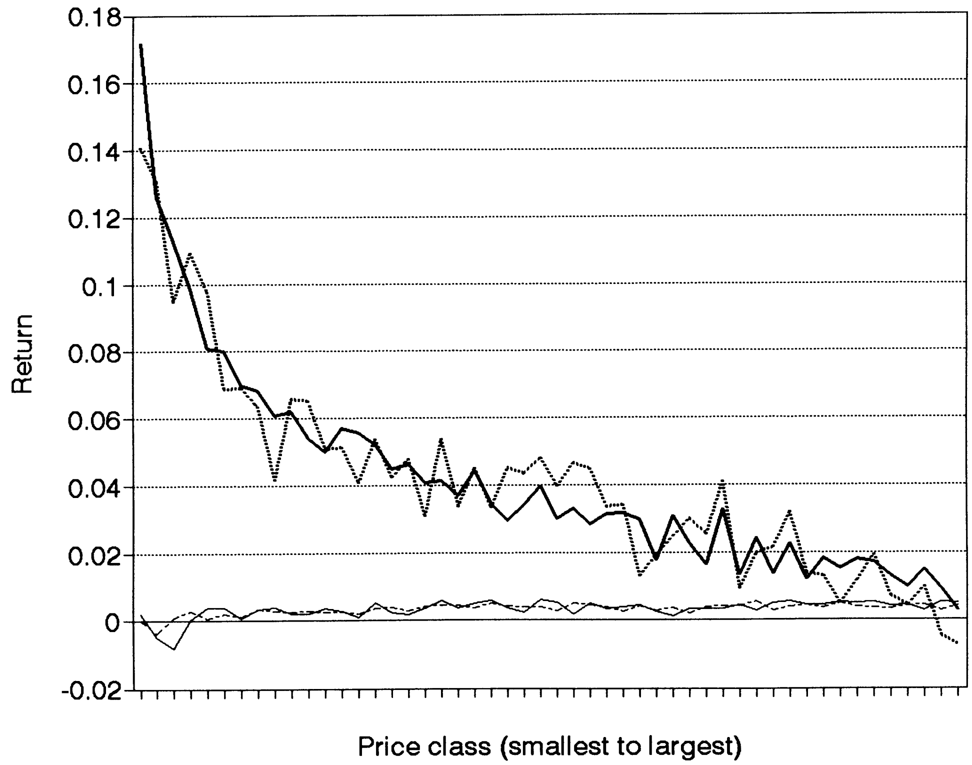

Figure 2. Average versus predicted return. Average return and estimated expected return (from the seasonal multifactor model) across price portfolios. —January average, ······January predicted, —February–December average, and ----February–December predicted.

Table IV

Tests for Excess Return: APT Model

Test statistics for the significance of the logarithm of price in cross-section regressions. Default denotes the beta for the default factor (the difference between corporate bond and government bond returns), Maturity denotes the beta for the maturity factor (the difference between government bond returns and one-month Treasury bill returns), Inflation denotes the beta for the inflation factor (the innovation from an IMA(1) model), Bus. Cycle denotes the beta for consumption growth, and Market denotes the beta for the residual market factor (the residual from a regression of the equally weighted CRSP index on the other four factors). $\hat{\lambda}$ denotes the risk-premium estimate, AN denotes the asymptotically normal test statistic, and FM denotes the Fama-MacBeth (1973) test statistic (distributed Student t), both for the null hypothesis that λ is zero.

	January			February–December		
	$\hat{\lambda}$	AN	FM	$\hat{\lambda}$	AN	FM
ln(Price)	0.0022	0.4338	0.7687	0.0011	1.0995	1.2038
Default	0.0082	1.7167	2.2520	−0.0005	−0.1784	−0.1935
Maturity	0.0070	0.4702	0.6796	0.0024	0.3908	0.4220
Inflation	−0.0061	−3.0675	−4.5407	0.0017	1.5765	1.7054
Bus. Cycle	0.0010	0.3284	0.3969	−0.0021	−1.0234	−1.1162
Market	−0.0212	−1.0558	−1.6985	0.0174	1.4839	1.6004

Tests for the significance of price in the second-stage regression are repeated for the seasonal multifactor model. The results are presented in Table IV. The January significance of price is eliminated entirely when the multifactor model is applied. The accumulated evidence provides strong support for a role of macroeconomic seasonality in the seasonals of low-priced firms.

IV. Conclusions

A multifactor model with seasonal risk and risk premia accounts for the January effect. Seasonals in estimated risk and estimated expected returns are inversely related to price, as predicted. These results support the conjecture that expected-returns shifts are responsible for January seasonals in low-priced company returns. There is evidence that risk is priced, supporting the model specification. Furthermore, there is no evidence for a January effect in excess returns from the multifactor model.

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