Excessive Stock Price Dispersion:

A Regression Test of Cross-Sectional Volatility

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“**Excessive Dispersion of US Stock Prices: A Regression Test of Cross-Sectional Volatility**”,

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Abstract

In this paper we apply a regression test of the volatility of asset prices to a cross-section data set of US stock prices each year between 1932-71. We show that the rejection of *REEM* in the time series domain carries over to a data set consisting of observations on a cross-section of individual share prices within a particular year, and we refer to this phenomena as excess dispersion of stock prices. In nearly all of the years over the period 1932-1971 we find that stock prices are excessively dispersed. This finding is consistent with the existence of a firm specific bubble which drives a wedge between the values of p_t* and p_t. We go on to examine the relationship between the mis-pricing and market fundamentals which we take to be related to past dividends. Assuming that dividend yields proxy for growth expectations we find that investors are unduly optimistic about high growth stocks and too pessimistic about low expected growth stocks. These results support Lakonishok, Shleifer and Vishney’s (1994) contention that contrarian investment strategies outperform the market because market participants have consistently overestimated future growth rates of glamour stocks relative to value stocks.

I Introduction

Following the seminal papers of Shiller (1981) and LeRoy and Porter (1981) there now exists a substantial body of work which has examined whether stock prices are excessively volatile, and Gilles and LeRoy (1991) in a thorough survey of this literature, concludes that there is strong statistical evidence in favour of this documented excess volatility. This work has focused exclusively on the time series behaviour of an aggregate stock price index. In this paper we examine another dimension of volatility and study the cross-section dispersion of individual company share prices. We investigate whether at a particular date, the stock prices of a large sample of US firms are excessively dispersed compared with ex post rational stock prices calculated from the subsequent dividend realisations paid out by these same companies. There are both economic and statistical motivations for testing this "excess dispersion" hypothesis: which is how we refer to the cross-section analogue of the excess volatility thesis.

Inferences on stock price volatility to date have been based almost entirely on a single data set; aggregate US stock prices and dividends since 1870. It would seem useful in its own right to study the hypothesis on a new data set. Furthermore time series tests are inevitably contingent upon assumptions made about the time series properties of the data. Whilst appropriate tests have been developed under different plausible assumptions [Campbell and Shiller (1987), West (1988), and LeRoy and Parke (1992)], it is nevertheless advantageous to side-step these problems and this is possible in a cross-section test.[1]

The economic merit of this new data set is that the evidence about the dispersion of company share prices should contribute to a better understanding of the structure of the documented excess volatility. In particular it allows us to address the question as to whether the reported

[1]/ In fact Kleidon (1986), argues that given a non-stationary dividend series, a cross section volatility test is the only valid test criteria. Board, Bulkley and Tonks (1993) apply a cross-section variance bounds test to a sample of US firms 1926-1970 and find that before 1956 the bound is satisfied, but post 1957 is violated in every year. Of course these arguments rest on the variance of each firm's price at any particular time as being finite in our sample. As a mere technicality this must be true given the finite history of these companies, and further an overwhelming proportion of firms in each cross-section in our sample have been in existence for a relatively short time. The large size of the cross-section then ensures that there is sufficient cross-section variation relative to time series variance to achieve reliable estimates, and justifies using the size of the cross-section as the asymptote in our statistical inference.

excess volatility is purely a macro-phenomena, scaling all share prices by a similar amount, or whether there is also a micro-component affecting the pricing of individual shares, superimposed on the aggregate phenomena. The original papers identifying excess volatility of a stock market index carries no implications for the dispersion of individual stock prices. In section II we discuss the methodology of a cross-section volatility test using regression tests introduced for time series data by Scott (1985) and Campbell and Shiller (1988). Durlauf and Hall (1989), show that this kind of test has higher power than the variance bounds approach which was initially used to test for excess volatility [though Gilles and LeRoy (1991) dispute this]. Campbell and Shiller (1988) point out that these regression tests are equivalent to Fama and French (1988) regressions on the predictability of long run returns.

In Section IV, we report the evidence from these initial cross-section regressions that in most years stock prices are excessively dispersed. In section V we propose an alternative estimation technique which allows for cross-sectional dependence between firms, and the results of this section confirm the earlier ones that stock prices are more dispersed than the efficient markets paradigm would suggest. Given the weight of empirical evidence provided by the volatility tests and return predictability tests, Gilles and LeRoy (1991) and Cochrane (1991) both emphasise in their survey articles that the principal focus of the research agenda should now be to offer explanations for rejections of the efficient markets hypothesis rather than simply report it. With this in mind, in section VI we further investigate the structure and possible determinants of the excess dispersion that we identify.[2] Our results indicate that stocks with low dividend yields are overpriced and stocks with high dividend yields are underpriced. This can be understood in the context of the Gordon Growth model which says that dividend yields proxy for the conditional expectation of the future rate of growth of dividends. These results can be thought of as a cross-sectional analogue to the work of Campbell and Shiller (1988) and Fama and French (1988) who identify dividend yields as a predictor of long run returns in an aggregate time series dataset. Focusing on the mis-pricing allows us to give an interpretation to these excess returns in terms of the present value model.

[2]/ For example Bulkley and Tonks (1989, 1992), Barsky and De Long (1993), Timmermann (1993, 1996), and Donaldson and Kamstra (1996) all suggest that violations of the present value model may be due to agents incorrectly estimating the dividend process.

De Bondt and Thaler (1985) report evidence of excess volatility using company data. They studied the serial correlation in winner and loser portfolios, and demonstrate that stocks which yielded extreme negative returns subsequently deliver positive excess returns on average and interpret this finding as an overreaction to information. Lakonishok, Shleifer and Vishney (1994) suggest that these contrarian investment strategies outperform the market because market participants have consistently overestimated future growth rates of glamour stocks relative to value stocks. Our work complements this research in two respects. First, the focus of our study is mis-pricing, rather than excess returns: the existence of positive or negative excess monthly returns does not directly map into a measure of mis-pricing. The mis-pricing we describe does imply excess returns in the very long run, but it does not necessarily have implications for excess returns over relatively short horizons, such as months or even years. In consequence one cannot infer a mis-pricing measure from forecastable monthly or annual excess returns. Second, we test whether this mis-pricing may be an over-reaction to information about a particular aspect of fundamental values, namely expected dividend growth.

The idea that there are variables in the current information set that can predict future cross-section company returns is not new: Basu (1983) showed that price-earnings ratios help explain the cross-section of average returns on US stocks, and likewise Rozeff (1984) identified dividend yields as a predictor of cross-section average returns. Our contribution in section VI of the paper is to study mis-pricing directly, rather than make inferences indirectly about mis-pricing from evidence on excess returns. Our approach implies excess returns are the consequence of the excessive price dispersion, relative to the present value model, which we identify in sections IV and V.

II Initial OLS Regression Tests of Cross-Sectional Volatility

The standard definition of the realised one period return on share i in time t, $r_{i,t}$, is the return accrued from purchasing the share at price $p_{i,t}$ at date t, selling it at date $t+1$ for $p_{i,t+1}$ and receiving a dividend of $d_{i,t}$ at the end of the holding period. We follow Campbell (1993) who solves an intertemporal representative agent optimisation problem to derive a single factor asset pricing model with the property that the one step ahead conditional expectation of asset returns is approximately constant.[3] Using this approximation we may write expected returns as

$$E_t(r_{i,t}) = \frac{E_t[d_{i,t} + p_{i,t+1}]}{p_{i,t}} - 1 \cong r_i \qquad 1$$

where r_i is a risk adjusted firm specific constant discount rate. The information set at time t in equation (1) includes all current dated variables except for dividends $d_{i,t}$, which are realised between time t and $t+1$.

Multiplying the approximate equality in (1) by $p_{i,t}$ and solving forward gives the present value model for stock prices

$$p_{i,t} = E_t[\sum_{k=0}^{\infty} \delta_i^k d_{i,t+k}] \equiv E_t[p_{i,t}^*] \qquad 2$$

where $\delta_i = [1+r_i]^{-1}$ and $p^*_{i,t}$ is the present discounted value of realised future dividends, which is sometimes termed the ex post rational price for stock i.

We refer to the present value model in equation (2) as the Rational Expectations/Efficient Markets (*REEM*) hypothesis. Under *REEM* the forecast error, $p^*_{i,t} - p_{i,t}$ should be uncorrelated with any information available at date t including $p_{i,t}$. This restriction can be tested using the regression equation

$$p^*_{i,t} = \theta + \gamma p_{i,t} + v_{i,t} \qquad 3$$

where under the null hypothesis of *REEM*, $\theta = 0$, $\gamma = 1$ and $v_{i,t}$ is the forecast error. The time series literature has taken asset i to be a single stock represented by the market portfolio, and Scott (1985) and Durlauf and Hall (1989) test these restrictions on a time series of the Standard

[3]/ Campbell's analysis depends on a log-linearisation of the intertemporal budget constraint assuming that the consumption-wealth ratio is approximately constant. We take the risk free rate to be constant, so that r_i in (1) has no time subscript.

and Poor's 500 market index. We propose to estimate equation (3) on a cross-section dataset of individual share prices, and this will be estimated repeatedly for 40 successive years. In the next section we discuss the computation of the set of ex post rational prices for individual shares constructed from the CRSP data tape.

III Data

We constructed a set of ex post rational stock prices, as implicitly defined in equation (2) for all shares which were quoted for at least two years on the New York or American Stock Exchanges within the period 1926-1992. All share data was obtained from the Centre for Research in Security Prices (CRSP) Tape and this resulted in a maximum number of securities of 2333, though the actual number that we use in any single year will be somewhat smaller. The ex post rational stock price for each share at any date was computed as the present discounted value of all real cash payments. That is, we include not just dividends but all other payments received by shareholders due to capital exchanges, re-organisations mergers or takeovers.

Since we want the main component of the ex post rational prices to be constructed from actual realizations, we restrict attention to years sufficiently far back in time that the discounted value of the terminal price is relatively small. We choose 1971 as the cut-off for our tests, when the terminal price should on average be only 20% of the value of the ex post rational prices under an 8% annual real discount rate.

IV Results for the OLS Regression Tests

To relate our cross-section data to the more familiar times series dataset, we calculated the cross-section means from our dataset of the actual and ex post rational stock prices each year 1926-92. Figure 1 plots a time series of these two sets of cross-section means: each observation is the cross-sectional unweighted average value of actual company real share prices at January 1st each year, and of the company ex post rational real stock prices at the same date. It can be seen that the relative movements in the unweighted means of the actual and ex post rational prices, are broadly similar to movements in the aggregate indices obtained from Standard and Poor's data [cf figure 1 in Grossman and Shiller (1981].

Initially we run a series of cross-section regressions of equation (3), using OLS. In the first two columns of table 1 we report the intercept and slope coefficients of these regressions for each year 1932-71.[5] These results demonstrate a striking rejection of the null hypothesis of *REEM*. It can be seen that the intercept term is consistently significantly positive and the slope coefficient is significantly less than unity for every year except 1932.

To get a single test statistic of the null hypothesis that the slope coefficients in all the cross-section regressions were unity, we compute the average coefficient value over the 40 cross-sections (years) and divide it by an estimate of its standard deviation. If the coefficients were independent across time estimating the standard deviation of their average would be straightforward, but this is unlikely to be the case. However if we are able to assume that they are stationary through time and satisfy a general mixing condition [see McCabe and Tremayne (1993)], then we may use Bartlett's estimator of long run variance to get a statistic that is

[5]/ In section VI of the paper, we need five years of lagged dividends, and therefore in order to be consistent throughout the paper we work with the 1932-71 dataset of 40 years. Inclusion of the earlier five years sets of regressions does not affect the thrust of the results.

asymptotically standard normal [see Kwiatoski, Phillips, Schmidt and Shin (1992), p. 164][6]. We refer to our normalised average coefficient as the "overall t-ratio".

We compute the average intercept and slope coefficients as 0.312, and 0.363, with the overall t-ratio as 7.066 and -6.028 respectively. These summary statistics show a convincing rejection of the null over the whole sample period. However there is a problem which arises in an OLS cross-section test using data on individual stock prices. It is unlikely that the prices of individual firms are independent, and hence we encounter autocorrelation in the error term of equation (3);[7] in general we should expect $\mathrm{Cov}(v_{i,t},\ v_{j,t}) \neq 0 \ \ \forall\, i, j \quad i \neq j$. Of course in large samples autocorrelation is not a problem for parameter consistency unless it generates a correlation between regressors and the error term. However we will show in the next section that in the context of shares prices in the same economy this exactly this type of correlation that is likely to occur.

V Modelling and Estimating Cross-Sectional Dependence

In this section we explicitly allow for the covariance in the error terms in equation (3). We follow standard practice in finance and model the error covariance structure using a factor structure. We assume there are macro economic shocks which affect the return on individual shares by an amount depending on the covariance of each share's return with the factor.

Returning to the definitions of the ex post rational price and actual price, we may redefine $p^*_{i,t}$ and $p_{i,t}$ as

$$p^*_{i,t} = \delta_i\,[d_{i,t} + p^*_{i,t+1}] \qquad 4$$

and

$$p_{i,t} = \delta_i\,[E_t\, d_{i,t} + E_t(p_{i,t+1})] \qquad 5$$

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[6]/ In implementing Bartlett's estimator of long run variance we used a lag truncation parameter of four. Changing the order of lag truncation makes little difference to the test statistic or its significance.

[7]/ Note that time series regressions of (3) also had to deal with the problem of serial correlation.

Combining (4) and (5), the forecast error $v_{i,t}$ in any period t can be written as

$$v_{i,t} = p^*_{i,t} - p_{i,t} = \delta_i [d_{i,t} - E_t d_{i,t}] + \delta_i [p^*_{i,t+1} - E_t(p_{i,t+1})] \qquad 6$$

From the definition of a realised return and its expected value we may obtain an expression for unanticipated returns on an asset. Rearranging this definition to explain unanticipated dividends gives

$$d_{i,t} - E_t d_{i,t} = p_{i,t} [r_{i,t} - E_t r_{i,t}] - [p_{i,t+1} - E_t(p_{i,t+1})] \qquad 7$$

Substituting for unanticipated dividends from (7) into (6), and substituting recursively for $[p^*_{i,t+k} - p_{i,t+k}]$ ultimately yields

$$p^*_{i,t} - p_{i,t} = \sum_{k=0}^{\infty} \delta_i^{k+1} p_{i,t+k} [r_{i,t+k} - E_{t+k}(r_{i,t+k})] \qquad 8$$

Equation (8) is the forecast error in the *REEM* model, which depends on a future stream of unanticipated returns. As we have already noted these unanticipated returns will in general be correlated in the cross-section, and may be modelled using a factor structure. To make this procedure explicit, for the special case of a single factor the returns generating process for share *i* can be written as [8]

$$r_{i,t} = \alpha_i + \beta_i f_t + \omega_{i,t} \qquad 9$$

[8]/ To maintain consistency with Campbell's intertemporal model, which we described in section II, we adopted a single factor structure, where the factor was specified to be the rate of return on the market. In the subsequent empirical work we examined the sensitivity of our results to the adoption of a four factor model with the factors specified as the inflation rate, term premium, default premium and growth in industrial production as in Chen, Roll and Ross (1986). We found little qualitative change in the results.

where α_i and β_i are the factor model parameters, f_t is the factor and $\omega_{i,t}$ is an identically and independently distributed error term with zero mean which represents firm specific shocks. In this factor model the risk of any individual share has two distinct elements; factor risk, to which all firms are subject, but to a varying degree measured by the covariance of the share's return with the factor β_i ; and firm specific risk, $\omega_{i,t}$ which reflects the risk associated with an individual firm's operations.

Unanticipated returns in this factor model are

$$r_{i,t} - E_t\, r_{i,t} = \beta_i\, [f_t - E_t\, f_t\,] + \omega_{i,t} \qquad 10$$

Equation (10) links unanticipated returns at a single date to unanticipated factor movements and firm specific shocks at that date. Using equation (10) in (8) and taking prices over to the right hand side gives

$$p^*_{i,t} = p_{i,t} + \sum_{k=0}^{\infty} \delta_i^{k+1}\, p_{i,t+k} \{ \beta_i\, [\, f_{t+k} - E_{t+k}(\, f_{t+k})]\} + \sum_{k=0}^{\infty} \delta_i^{k+1}\, p_{i,t+k}\, \omega_{i,t+k} \qquad 11$$

where, as was the case with dividends earlier, the information set at time $t+k$ does not include the current value f_{t+k}. Equation (11) demonstrates explicitly the exact structure of the error term in equation (3). The error is composed of two blocks of summation terms. The first block represents the future weighted sum of forecast errors associated with the factor, and the second block is the weighted sum of future firm specific idiosyncratic errors.

We may view equation (11) as a regression equation and the usual concern in time series analysis with regard to the standard errors would be bias arising from the use of generated regressors [Pagan (1983)]. However in our cross-sectional analysis, provided that the standard errors are adjusted for heteroscedasticity, inference using the regression in (11) may proceed along the usual lines. This is because the asymptote which determines the accuracy of the cross-sectional standard errors is the number of stocks, whereas that for the parameters in the generated regressors is the number of months. When these asymptotes both become large, which is generally the case for our dataset, the standard error biases vanish.

It can be seen that the first block of terms in the error (11) is autocorrelated in the cross-sectional dimension. In estimating equation (11) there are two alternative methods which may be adopted to overcome this problem. The first approach includes as regressors future values of $\{\delta_i^{k+1} p_{i,t+k} \beta_i\}$ up to a truncation point. In practice these future terms were found to be highly collinear, and therefore instead we approximated the first block of terms in equation (11) by the first term in this block $\{\delta_i p_{i,t} \beta_i\}$.[9]

In table 2 we report the effects of including this additional variable as a single extra regressor. It can be seen that the inclusion of this additional explanatory variable increases the value of the slope coefficient on price relative to the unadjusted OLS results, but the new values are still generally significantly different from unity. The summary statistics in this case were that the mean values of the intercept and slope coefficients were 0.284 and 0.540, with overall t-ratios as 6.493 and -4.54 respectively, comfortably rejecting the null hypothesis. As noted above, extra terms in the forward sum in the error term in (11) were added and were instrumented. The slope coefficients on the current price were somewhat lower so these results still indicate rejection of the null of *REEM*.

Our second method recognises the importance of the future terms in this first block, but rather than freely estimating the regression, where we would obtain future factor shocks as estimated coefficients, we instead construct a prior estimate of this discounted sum of terms. Using data on the factor we estimate the weighted sum of the forecast errors in this first block up to a suitable truncation point, and deduct this weighted sum from the dependent variable $p^*_{i,t}$.[10] This

[9]/ The extra terms require instruments because they are correlated with the error term. An Arrelano-Bond (1991) dynamic IV procedure was tried but it gave estimates that were qualitatively similar to the simple approximation in the sense that the results indicated a rejection of REEM. The standard errors in the IV case were of course much higher than in the simple case that we present.

[10]/ For our purposes truncating the sum at k=20 was thought to provide a reasonable approximation.

corrected variable may now be regressed on price, so that under the null of *REEM* the slope coefficient will give a consistent estimate of unity and an intercept of zero.

This second modification applied to implement equation (11) adjusts the dependent variable $p^*_{i,t}$ and requires estimates of both the factor loadings and the one-step-ahead forecast errors of the factor. The former parameter values were obtained from the time series regression in equation (9) using all the monthly observations that were available for each stock. In keeping with the assumption in equation (1) that rates of return are approximately unforecastable, we estimated the series of annual one-step-ahead forecast errors as the difference between the market rate series and its average value over the years 1926-1992.

Broadly speaking, the results in tables 1-3 all indicate that the slope coefficient in the cross sectional regression of $p^*_{i,t}$ on $p_{i,t}$ is less than unity and for the later (earlier) years the intercept is typically positive (negative). A slope coefficient less than unity coupled with a positive intercept implies that prices are excessively dispersed, indicating a micro-component to excess volatility. Stocks with high $p^*_{i,t}$'s are overpriced, and have prices higher than are warranted by the subsequent dividend realisations. Similarly a stock with a low $p^*_{i,t}$ is underpriced, and has a price lower than is in fact warranted. The negative intercepts before 1955 combined with the low value of the slope coefficient would appear to suggest that all stocks were overpriced for these years.

We also undertook a number of additional sensitivity tests to assess the robustness of our results. First we divided the cross-sectional sample alphabetically into four equal groups and performed the cross-sectional tests on each sample. The results for each of the sub-samples were almost identical to those for the full sample. To motivate a second sensitivity test note that the construction of the ex post rational series is dependent on the discount rate applied to each firm's dividend series. As we explained in the previous section we took the average realised real return over the companies lifetime as the appropriate firm specific discount rate. This annualised value averaged across stocks was 11.55%, and is rather high in comparison with the average real return of 8.8% on the S&P500 over the same period. The reason for the difference is probably because our sample average is unweighted, and gives undue weight to small stocks which on average have performed well over our sample period. To determine whether our results are sensitive to the value of the firm specific discount rate we re-calculated the ex post rational price series for each firm using a 10% lower discount rate for each stock, and re-estimated the cross-sectional regressions. The qualitative results were again not greatly affected by this new discount rate.

In these tests one interpretation of our principal result that the slope coefficient on price is less than unity could be that there is an additive stock specific component in the stock price that drives a wedge between the observed price and its *REEM* value. Provided that this wedge is uncorrelated across firms, then its existence will cause downward bias on the slope coefficient in the regression of $p^*_{i,t}$ on $p_{i,t}$ which is in fact what we find.

In summary what our results in this section show is that across a sample of firms the stock price is not always an unbiased predictor of subsequent dividend realisations. The time series literature obtained this result by looking at successive observations on the stock price index. We show it holds true also when the data set consists of a large number of firms in a single year.

VI Predictability of Mis-pricing

We now investigate the source of the mis-pricing identified in the previous section, by relating it to key elements in the information set. We measure mis-pricing as the difference between $p^*_{i,t}$ and $p_{i,t}$. The ex post rational price is the present value of dividend realisations and therefore the difference in the ex post rational and the actual stock price relative to the actual stock price can be interpreted as a long run rate of return [Campbell and Shiller (1988)]. Under the null hypothesis of *REEM,* we would expect this variable to be unforecastable using current information, but the results of section IV show that this is not so: high price stocks are overpriced and low price stocks are underpriced. Here, we investigate the hypothesis proposed by Lakonishok, Shleifer and Vishny (LSV) (1994) that stock mis-pricing is due to excessively dispersed earnings growth forecasts. LSV (1994) argued that the correlation between market-to-book and subsequent returns could be explained as a consequence of high earnings growth expectations, resulting in high market-to-book, typically being over-optimistic. In our context this hypothesis would imply stocks with high earnings growth expectations would have market prices above their ex post rational values. We can test this hypothesis if we assume that current dividend yields are a proxy for earnings growth expectations [for example via the Gordon Growth model], and then examining whether the percentage mis-pricing $(p_{it}^*-p_{it})/p_{it}$ is explained by the dividend yield. From (3) and including $d_{i,t-1}/p_{i,t}$ as a regressor we have

$$\frac{p^*_{i,t} - p_{i,t}}{p_{i,t}} = \lambda + \pi \frac{d_{i,t-1}}{p_{i,t}} + \frac{v_{i,t}}{p_{i,t}} \qquad 12$$

Under the null hypothesis of efficient markets $\pi = \lambda = 0$, but under the LSV hypothesis π should be positive. It is important to note that the error term in (12) $v_{i,t}$, is the same error as before except for the price term in the denominator, and as a result we use the same correction as for $p^*_{i,t}$ in equation (11).

The results of running the regression in (12) for each year between 1932-1971 are given in table 4. It can be seen that the coefficient π on dividends is positive in all but the first year and is significantly different from zero in 27 years. The intercept coefficient λ is significantly negative in most years. As a supplementary exercise, five additional lagged dividends over price terms were added to the right hand side of equation (12). The results given in table 5 appear to have no systematic sign or magnitude across years. We may examine the long run effect of dividends on mis-pricing implied by this regression, by summing the individual lagged dividend coefficients. Table 6 shows that the long run effect is significantly positive in nearly all years. In fact the long run effects are quite stable and qualitatively similar to their static counterparts (the estimates of π) given in table 4.

Combining the positive estimates of π in (12) with the finding of a negative intercept λ means that when dividend yields are high (low expected dividend growth) stocks are undervalued: $p_{i,t}$ tends to be less than $p^*_{i,t}$. When dividend yields are low stocks are overvalued: $p_{i,t}$ tends to be greater than $p^*_{i,t}$. Interpreting the dividend yield as a proxy for expected earnings growth then these results imply that investors appear to be unduly optimistic about high expected growth stocks and too pessimistic about low expected growth stocks. Put another way it appears that investors' beliefs about future company growth prospects are too widely dispersed!

Fama and French (1988) document a similar positive relationship between market dividend yields and a measure of long run excess returns, but in the time series domain. They explain this finding in terms of a time varying risk premium. It is difficult to see how this explanation of mis-pricing can apply to our cross-section results. We would expect macroeconomic phenomena such as a time varying risk premium to affect all stocks in the cross-section. However we identify both underpricing of some stocks and overpricing of others in the same time period. Therefore unlike previous work based on aggregate time series analysis, our rejection of efficient markets may not be circumscribed by falling back on an aggregate time-varying risk premium: a microeconomic theory is required to explain our results.

VII Time Varying Risk Premia

In this section we examine the sensitivity of our results to time varying risk premia on the assets. We start by extending the factor model in equation (9) to the case of a time varying risk premia by writing the one step ahead conditional expectation of asset returns as

$$E_t r_{i,t} = \alpha_i + \beta_i E_t f_t \qquad 13$$

Rearranging equation (13) and iterating forward to solve for the current price as we did in section II to obtain equation (2) in the case of a constant discount rate, we may similarly get an expression for prices with a time varying risk premia

$$p_{it} = E_t\left(\sum_{k=0}^{\infty} d_{i,t+k} \prod_{k=0}^{\infty} \frac{1}{1+\alpha_i + \beta_i E_{t+k}(f_{t+k})}\right) \equiv E_t(p_{i,t}^{**}) \qquad 14$$

We follow Shiller (1981) and take a linear approximation around $d_{i,t+k} = E\, d_j$ and $E_{t+k}(f_{t+k}) = E\, f$, so that the term in brackets in (14) defined as $p^{**}_{i,t}$ can be written approximately as

$$p_{it}^{**} \cong \left(p_{it}^{*} - \frac{E\, d_i}{E\, r_i} \sum_{k=0}^{\infty} \delta_i^{\,k+1} \beta_i [E_{t+k}\, f_{t+k} - E\, f]\right) \qquad 15$$

A crucial question is how good an approximation is (15) to (14)? We proceed as before and adopt a single factor model as in equation (9), where the single factor, f_t is taken to be the market return. In section II above, we assumed that $E_t\, f_t$ was constant through time and supported this by noting that although there was predictability in the market rate in our sample, this predictability was not strong. In this section we approximate f_t by an *AR(2)* process since this was found to be empirically adequate. Adopting an *AR(2)* process for f_t, we can examine the adequacy of the linear approximation in (15) by means of some numerical simulations under various scenarios. Explicitly, we simulate a dividend and risk premia series assuming parameter values for their respective data generation processes and we then examine the correlation coefficient of the implied $p^{**}_{i,t}$ and its linear approximation given on the right hand side of equation (15).

The parameter scenarios were as follows. The coefficients of the *AR(2)* process and the intercept for the market rate were calibrated to accord with our data and were set to 0.0 and -0.2 and 0.075 respectively; β was set alternately as "low" (0.4), and then "high" (1.3). (Note: the median beta in our sample was around 0.8). The (log of) dividends were assumed to follow a random walk with drift. The drift took "low" and "high" values of 1% and 4% respectively. The standard deviation of the dividend growth innovations was set "low" and "high" at 0.2 and 0.8 respectively (the median value for the latter in our data was 0.5).

Table: The closeness of the linear approximation

ρ_1	ρ_2	β	σ_d	drift
.97	.88	.4	.2	.01
.98	.94	.4	.8	.01
.92	.73	.4	.2	.04
.97	.92	.4	.8	.04
.89	.81	1.3	.2	.01
.84	.72	1.3	.8	.01
.75	.47	1.3	.2	.04
.84	.78	1.3	.8	.04
.92	.77	.8	.5	.025

Regressions of $p^{**}_{i,t}$ on its linear approximation gave a slope coefficient that was (in nearly all cases) insignificantly different from unity and an intercept that was (in most cases) insignificant from zero. Overall, the table suggests that we should expose our results here to a sensitivity analysis where we exclude high beta stocks from the regression. Finally note that when time varying discount rates of the kind we have modelled exist, the linear approximation is a significant improvement over the fixed discount rate $p^*_{i,t}$.

For the empirical work, we compute the same ex post price as in section V but make new adjustments to the dependent variable $(p^{**}_{i,t} - p_{i,t})$ to ensure that it is uncorrelated with the information set and is not correlated across stocks. Equation (15) above implies that the forecast error $(p^{**}_{i,t} - p_{i,t})$ can be approximated as follows

$$u_{it} \cong v_{it} - \frac{E\,d_i}{E\,r_i} \sum_{k=0}^{\infty} \delta_i^{\,k+1} \left\{ \beta_i \left(E_{t+k}(f_{t+k}) - E(f) \right) + \omega_{i,t+k} \right\} \qquad 16$$

where $v_{i,t}$ is defined in equation (6) above, and as before, the new error u_{it} has two components the second of which is in terms of idiosyncratic errors $\omega_{i,t+k}$ and hence is uncorrelated across stocks and is uncorrelated with elements of the information set. The first component involves firm *i's* beta, average discount rate and the forecast errors in predicting f_{t+k} using information dated at time t. As before, we obtain a prior estimate of this first component by constructing the forecast errors from the data assuming an *AR(2)* process for the factor f_t (Recall that an *AR(2)* model was found to be empirically adequate for the annual market rate). Using these forecast error estimates we corrected the dependent variable in the same manner as before.

We regressed the corrected $p^{**}_{i,t}$ on $p_{i,t}$ and the results are given in tables 7 and 8. Inspecting these tables we see that the results for the time varying risk premia case are little different to those for the fixed discount rates. Repeating the regressions analogous to those in table 4 above [corrected $(p^{**}_{i,t} - p_{i,t}) / p_{i,t}$] in table 9 we find that only three of these early years do we fail to reject the *REEM*. The results from these regressions are broadly similar as before with the exception that the p-values are lower in the time varying discount rate case.

VIII Conclusions

The result that there are movements in stock prices which are excessive relative to movements in fundamentals, has proved remarkably robust with respect to a number of tests, applied to a time series index of stock prices. In this paper we have applied a regression test of volatility to a cross-section data set, specifically testing Campbell's constant discount rate present value model. We have shown that the rejection of *REEM* carries over to a data set consisting of observations on a cross-section of individual share prices within a particular year, and we have referred to this phenomena as excess dispersion. In nearly all of the years over the period 1932-1971 we have found that stock prices were excessively dispersed: firms with high p^*'s have prices higher than are warranted by the subsequent dividend realisations; firms with a low p^*'s have stock prices that are lower than are in fact warranted. This finding is consistent with the existence of a firm specific bubble, driving a wedge between the values of p_t^* and p_t. When we ammended our regression test to allow for the cross-correlation of security prices, and for the existence of firm specific time varying discount rates, the dramatic rejection of the null hypothesis still obtained.

We went on to examine the relationship between the mis-pricing and market fundamentals which we took to be related to past dividends. Assuming that dividend yields proxy for growth expectations we found that investors are unduly optimistic about high growth stocks and too pessimistic about low expected growth stocks. Hence the mis-pricing we have identified is not just a macroeconomic phenomena whereby all shares are either underpriced or overpriced by a similar amount, and cannot be explained away by the existence of time varying risk premia.. Our results suggest that there is a microeconomic source of mis-pricing. Within the same time period those stocks with high dividend yields tend to be undervalued, and when dividend yields are low the stocks are overvalued. We would agree with Lakonishok, Shleifer and Vishney (1994) that these results can be explained by market participants having a preference for glamour or high expected growth stocks pushing up their prices, and a corresponding reluctance by investors to hold low growth securities, which depresses the prices of these stocks.

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