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dissertation entitled

DIVIDEND POLICY: RELATIONSHIPS WITH INVESTMENT AND RISK

presented by

DAVID A. LOUTON

has been accepted towards fulfillment
of the requirements for

Ph.D. degree in Business Administration

Dale L. Domian
Major professor
Dale L. Domian

Date July 31st, 1991

DIVIDEND POLICY: RELATIONSHIPS WITH INVESTMENT AND RISK

By

David A. Louton

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Finance and Insurance
Eli Broad Graduate School of Management

1991

ABSTRACT

DIVIDEND POLICY: RELATIONSHIPS WITH INVESTMENT AND RISK

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David A. Louton

This study consists of two related parts. The first is an examination of the possible empirical relationship between dividends and investment. In particular, simulations are used to examine the limits of the discriminatory power of Smirlock and Marshall's [1983] study employing Granger causality methods on a series of 20 annual observations per firm. Their empirical work is updated using series of 38 annual observations per firm rather than the 20 previously available. Granger causality from dividends to investment, significant at the α=0.05 level, is found in approximately 28 percent of the sample. The implication is that many of the largest domestic firms have been managed in a way that is directly opposed to accepted theory within the field of corporate finance. Although it would be impossible to accurately assess the opportunity cost of such potentially suboptimal decision making, the magnitude of the variables involved suggests that it would be substantial.

The second part of this study consists of tests of the hypothesis that dividend payout causally precedes price

risk. Although causality at statistically significant levels is not found in any substantial proportion of the firms in the sample, there are some interesting observations to be made. Specifically, when longer time series are employed, there is a stronger relationship between changes in OLS beta and changes in dividend payout, than there is between changes in standard deviation of returns and changes in dividend payout. One inference that could be drawn from these findings is that changes in dividend payout policy may contribute to increased systematic risk.

To

Marcie, Shaina, Daniel and Corrie

ACKNOWLEDGEMENTS

I would like to thank the members of my dissertation committee for their critical insights and many helpful suggestions.

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Chapter I

Introduction

Introduction

This study consists of two related parts. The first is an examination of the possible empirical relationship between dividends and investment. In particular simulations are used to examine the limits of the discriminatory power of Smirlock and Marshall's [1983] study employing Granger causality methods on a series of 20 annual observations per firm. Their empirical work is then updated using series of 38 annual observations per firm rather than the 20 previously available. Granger causality from dividends to investment, significant at the α=0.05 level, is found in approximately 28 percent of the sample.

The second part of this study consists of tests of the hypothesis that dividend payout causally precedes price risk. In the process the converse hypothesis is also tested. Although causality at statistically significant levels is not found in any substantial proportion of the firms in the sample, there are some interesting observations to be made. Specifically, when longer time series are employed, there is a stronger relationship between changes in OLS beta and changes in dividend payout, than there is between changes in standard deviation of returns and changes in dividend payout. One inference that could be drawn from these findings is that changes in dividend payout policy may contribute to increased systematic risk.

Assuming perfect capital markets Miller and Modigliani [1961] demonstrate that the value of the firm depends only on investment policy and not on the method of financing investments. Thus, although we would expect higher investment to lead to higher dividends we would not expect to find a similar intertemporal correlation going from dividends to investment. Fama and Miller [1972] call this the separation principle. Although several attempts have been made to test the empirical validity of this proposition (see for example Fama [1974], Smirlock and Marshall [1983] and Partington [1985]), data and methodological problems have prevented an effective resolution of this issue. Since a finding that dividend policy influences investment would clearly imply that suboptimal investment choices are being made, tests of the separation principle are crucially linked to the question of how dividend policy affects value.

A somewhat related question involves the relationship between dividend payout and risk. The importance of controlling for systematic risk in empirical studies of dividend policy has long been understood (see for example Friend and Puckett [1964] and Black and Scholes [1974]). However, although Rozeff [1982] documented a strong negative correlation between dividend payout and risk, little has been done to investigate the specific nature of this relationship, and in particular, its direction. This is the focus of the second part of the current study. Since risk has been shown to be a determinant of share value, this part of the study is essentially another avenue by which the empirical validity of Miller and Modigliani's dividend-irrelevance proposition can be examined. Once again we are only concerned with a specific sort of causality. That is, a causal relationship running from dividend policy to risk is of concern because it has implications for value. In contrast, a causal relationship running from risk to dividend policy, while presenting certain points of interest, does not imply that any suboptimal policy decisions have been made.

Both segments of the current study have in common the dividend policy / value literature, a brief review of which is presented in Chapter II. Table II.1 provides a schematic representation of the development of the literature up to the point where the two investigative fronts in this study became distinctly identifiable as separate sub-topics.

Chapter III provides a description of the Granger causality methodology employed in both parts of this study, along with some observations on its specific requirements and limitations. Chapters IV and V each relate to one of the two empirical questions examined in this study. In each, the literature and methodology relating to the appropriate part of the current study is further developed and empirical results are presented. These two sections are designed to stand alone in the sense that each includes its

own discussion of the conclusions to be drawn from the empirical work.

Chapter II

Review of Literature Common to Empirical Chapters

Review of Dividend Policy and Value Literature

Since Miller and Modigliani's [1961] landmark work demonstrating that dividend policy is irrelevant in perfect capital markets, the dividend policy debate has focused on the documentation of market imperfections and the examination of their implications. Early empirical studies, some prior to Miller and Modigliani, typically regressed share prices on dividends per share and retained earnings (see Graham and Dodd [1934], Gordon [1959], and Benishay [1961]). The consensus arising from these studies was that dividends are significantly more important in explaining prices than are retained earnings. Friend and Puckett [1964] point out that this effect could be explained by a negative correlation between earnings uncertainty and dividend payout ratio. Furthermore, Friend and Puckett [1964], as well as Beaver, Kettler and Scholes [1970], note that the tendency of management to resist dividend cuts could produce just such a negative correlation between earnings uncertainty and dividend payout ratio. As a result of this work it became clear that in future empirical studies of dividend policy, particularly those involving cross-sectional regressions, it would be necessary to control for risk explicitly. With the development of the capital asset pricing model (Sharpe [1964]) the tools with which to operationalize a control of this sort became available.

The first study of dividend policy to control for risk through the capital asset pricing model was conducted by Black and Scholes [1974]. In their classical empirical work on the capital asset pricing model Black, Jensen and Scholes [1972] had found evidence suggesting that the intercept term in the market model is significantly different from zero. As shown by the following quote, the search for an explanation for the non-zero intercept in the market model was a major motivating factor behind Black and Scholes [1974]:

> "... Black, Jensen and Scholes have found evidence that high β securities tend to be overvalued and low β securities tend to be undervalued. One possible interpretation of this result is that high β stocks tend to be low yield stocks, and what is really happening is that low yield stocks are overvalued and high yield stocks are undervalued. If this were the case, then the result should be associated with corporate dividend policy rather than with factors such as capital structure that affect the β of a corporation's common stock."
> (Black and Scholes [1974], p. 8)

Thus, Black and Scholes's study could be seen as an attempt to explain perceived deficiencies in the performance of the capital asset pricing model by including a term capturing dividend policy effects. Black and Scholes attempt to control for the various sorts of bias often present in cross-sectional studies by constructing 25 portfolios with stocks ranked on the basis of both dividend yield and β. The obvious issue of tax effects is avoided by arguing that if corporations are able to adjust the relative supplies of shares at different dividend yields to meet investor demand, then they will respond by doing so until the possibility of any advantage has been removed. Using data spanning the period 1936 through 1966, Black and Scholes find that the dividend policy coefficient is not significantly different from zero. Thus, after adjusting for risk, the expected returns on common stocks in the sample do not appear to be further differentiable on the basis of dividend yield. Although this work does not link dividend policy to the anomalies observed by Black, Jensen and Scholes, it provides more direct evidence regarding the linkage between dividend policy and risk than had previously been available.

Litzenberger and Ramaswamy [1979] use the tax-adjusted capital asset pricing model derived by Brennan [1970] to critique the results presented by Black and Scholes. The Brennan model is derived under assumptions of:

i) proportional individual taxes (non-progressive);
ii) certain dividends;
iii) unlimited borrowing at the riskless rate of interest.

The model can be stated as:

$$E(R_i) - r_f = b\beta_i + \tau(d_i - r_f) \qquad (1)$$

where: $E(R_i)$ = expected before-tax return on security i;

r_f = before-tax return on the risk free asset;

β_i = the systematic risk of security i;

d_i = the dividend yield on security i;

b = the marginal effect of systematic risk;

τ = the marginal effect of taxes.

Litzenberger and Ramaswamy assert that the tests performed by Black and Scholes lack sufficient power to discriminate between hypotheses of the form H_0: τ=0 and H_1: τ=0.5. They concur with Rosenberg and Marathe [1979] that the portfolio technique used to reduce bias, and the estimation method (OLS), were major factors contributing to this problem. Litzenberger and Ramaswamy modify the Brennan model to allow for the taxation of dividend and interest income under a progressive tax scheme. Although the derivation is lengthy (see Litzenberger and Ramaswamy [1979] pp. 165-170), the result is identical to the above model except that an intercept is included and the tax coefficient, τ, takes on a more explicit interpretation as "the weighted average of individual's marginal tax rates less the weighted average of the individual's ratios of the shadow price on the income related borrowing constraint and the expected marginal utility of mean portfolio return" (see Litzenberger and Ramaswamy [1979] p.171). Rather than using portfolio grouping or instrumental variables to control for measurement error in β_i, as in previous studies, Litzenberger and Ramaswamy derive a maximum likelihood estimator to obtain more efficient coefficient estimates incorporating information contained in the estimated sample variance of observed betas. A further refinement introduced by Litzenberger and Ramaswamy is the use of an expected dividend yield based on prior information in ex-dividend months rather than a simple average monthly yield.

The results obtained by Litzenberger and Ramaswamy indicate a strong positive relationship between before-tax expected returns and dividend yields of common stocks. This implies that, after adjusting for risk, the tax effect is significant enough to make dividends undesirable, thus causing investors to require a premium to induce them to hold high dividend yield stocks. Litzenberger and Ramaswamy construct a test to determine whether this effect is absent in non-ex-dividend months, but no significant differences are found.

Miller and Scholes [1982] take issue with Litzenberger and Ramaswamy's handling of the information effect associated with dividend announcements. When the announcement date and the ex-dividend date occur in the same month a potential problem arises because the return contains both the information effect (the timing and magnitude of actual dividends as compared to expected dividends) and the tax effect, if in fact such an effect exists. Litzenberger and Ramaswamy attempted to eliminate this source of bias by introducing a revised dividend variable constructed as follows:

i) If a firm declared prior to month t and went ex-dividend in month t, then the expected dividend yield was computed using the actual dividend paid in t divided by the price at the end of the previous month;

ii) If the firm both declared and went ex-dividend in the same month, then the expected dividend yield was computed using the last regular dividend, going back as far as one year. If no such regular dividend is found, or if the dividend was an extra dividend, then the expected dividend yield was set equal to zero.

Miller and Scholes argue, however, that there is an additional category of firms not taken into account by the screen described above: those that were expected to pay a dividend and did not. They call this the case of "the dog that didn't bark." Two alternative methods of correcting for this possibility are proposed:

i) use the dividend yield from 12 months previous as the expected dividend yield;

ii) include only firms which declared their dividend in advance.

Running the same regressions after screening the data in this fashion Miller and Scholes find that the dividend coefficient is much smaller and statistically insignificant in both cases. Thus, they conclude that the correlation between dividend policy and expected return found by Litzenberger and Ramaswamy is spurious and may actually reflect a signalling phenomenon instead.

Responding to these concerns, Litzenberger and Ramaswamy [1982] reconstructed their original study taking information effects into account in a more explicit way. In order to achieve this, they developed an alternative method of estimating expected dividends using a pooled time series-cross sectional regression with the most recent dividend yield as an explanatory variable, and a system of dummy variables to capture the periodicity of the dividend payments. The prediction rule is constructed in such a way that it relies entirely on information that would be available to investors ex-ante. Since it more closely approximates the system by which individuals are thought to generate expectations, this method has considerably more intuitive appeal than the naive model used in Miller and Scholes. The results obtained by Litzenberger and Ramaswamy using this model suggest once again that the dividend policy coefficient is positive, less than unity, and statistically significant. These findings are consistent with a possible tax-clientele effect. Further evidence presented in this study suggests that the relationship between expected return and dividend yield is non-linear. This is consistent with the findings of Litzenberger and Ramaswamy [1979,1980].

The studies presented here constitute the mainstream of the literature dealing with the relationship between dividend policy and value. The issues dealt with in the current study are off-shoots of this body of literature. As such they are impacted by, and have an impact on, the continuing debate concerning dividend policy and value. Reviews of the literature specific to the dividend-investment and dividend-risk questions are presented in the respective empirical sections in which each of these empirical issues is taken up.

Table II.1

Dividend-Risk	Dividend-Value	Dividend-Investment
	Graham and Dodd [1934]	
	Gordon [1959]	
	Benishay [1961]	
	Miller and Modigliani [1961]	
	Friend and Puckett [1964]	Dhrymes and Kurz [1964]
	Beaver, Kettler and Scholes [1970]	
	Black and Scholes [1974]	Fama [1974]
	Rosenberg and Marathe [1978]	
	Litzenberger and Ramaswamy [1979]	
Kalay [1981]	Miller and Scholes [1982]	
Rozeff [1982]	Litzenberger and Ramaswamy [1982]	
		Smirlock and Marshall [1983]
		Partington [1985]
		Miller and Rock [1985]

Chapter III

Methodology

Modeling and Testing for Causality

The methodology developed by Granger [1969,1980], applied in the context of vector autoregressions on a firm by firm basis, provides a way of testing for both the direction and magnitude of causal relationships between two or more time series. Since this methodology does not require the specification of a structural model it is not subject to many of the criticisms which have plagued ysimultaneous equations models employed in similar situations.

Chow [1983] begins his treatment of Granger causality by noting that: "A favorite saying in regression analysis is that regression can measure the degrees of association between variables but cannot confirm causation" (see Chow [1983], p.212). Nevertheless, in economics and other areas of research this is a topic of sufficient importance that a great deal of effort has been devoted to providing an operationally useful definition of causality. Clearly, one must expect that in order to be operational within the framework of regression analysis any such definition must involve restrictions on both its use and interpretation.

Granger [1969,1980] provides a definition of causality based on three underlying principles which are reiterated and expanded in Granger and Newbold [1986]:

Axiom A: The future cannot cause the past. Strict causality can only occur with the past causing the present or future.

Axiom B: A cause contains unique information about an effect that is not available elsewhere.

Axiom C: All causal relationships remain constant in direction throughout time.

Then, following the notation of Granger and Newbold, if we let $F(B|A)$ denote the conditional distribution of B given A, and we let Ω_t denote all the information in the universe at time t, it is possible to construct a probabilistic definition of causality.

In an analytical sense the proposition that A_t causes B_t is associated with the following inequality (Granger and Newbold equation 7.3.1):

$$F(B_{t+k}|\Omega_t) \neq F(B_{t+k}|\Omega_t - A_t) \quad \text{for all } k>0 \tag{2}$$

If inequality (2) holds, and $\Omega_t - A_t$ denotes all the information in the universe **except** A_t, then A_t is said to "cause" B_t in the Granger [1969,1980] sense.

Although this definition is intuitively pleasing, the fact that we cannot incorporate all the information in the universe into an empirical study means that it can only be made operational in an empirical context after great simplification. Granger [1980] suggests the following solution. Suppose there is available at time t a limited information set J_t consisting of terms of the vector series

Z_t. Then J_t can be considered a proper information set with respect to B_t if B_t is included in Z_t. Suppose also that Z_t does not include any elements of A_t and that the augmented information set J_t' consisting of the union of Z_t and A_t exists. Then we can phrase an operational definition of causality as follows:

$$F(B_{t+k}|J_t') \neq F(B_{t+k}|J_t) \qquad \text{for all } k>0 \qquad (3)$$

In this case we have simply agreed to limit all the information in the universe to a subset J_t' which can reasonably be expected to have a bearing on the situation under study. If inequality (3) holds then A_t can be said to be a _prima facie_ cause of B_t. That is, the series A_t contains unique information which helps to characterize future realizations of B_t. This particular limited form of causality is referred to throughout the literature as 'Granger causality' or 'Wiener-Granger causality'. It is usual to implement equation (3) with k=1.

It should be noted that an important precondition for appropriate implementation of this methodology is that the processes generating time series A_t and B_t are stationary. The type of stationarity referred to here is sometimes called weak stationarity or covariance stationarity. Harvey [1990] defines a covariance stationary process as one which exhibits the following characteristics:

i) The mean is independent of t;

ii) The variance is independent of t;

iii) Each autocovariance, $E(\epsilon_t \epsilon_s)$, depends only on the difference between t and s.

Thus, a stationary process has a mean and variance which are not time dependent, and the covariance between values generated by the process at any two points in time depends only on the time between these two realizations of the process and not on time itself. Among other things, these conditions imply that the time series under consideration must not have trends or fixed seasonal patterns. In general, covariance stationarity can be achieved by differencing, log-differencing, or applying a Box-Jenkins filter with a suitable number of autoregressive, moving average and differencing terms. Non-stationarity can give rise to spurious causality findings if a trend is involved (see Kang [1985]), or can obscure a causal relationship even in the absence of a trend.

Several alternative tests for stationarity have been proposed in the literature. Initially, the possibility of non-stationarity was investigated in a rather ad hoc way by examining autocorrelation coefficients in an attempt to verify that there were no systematic trends in the data. More comprehensive methods of testing for non-stationarity, based on the fact that the autoregressive (AR) representation of covariance stationary processes can contain no roots less than unity, were developed by Dickey and Fuller [1979]. The 'augmented' Dickey-Fuller test[1] is the method of choice in much of the empirical literature (see for example Rose [1988], or Wilcox [1989]). This test may include a drift term (intercept), and, by including additional lags, can be made robust to autocorrelation of order greater than one. The test statistic is computed from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L)Y_{t-i} + \epsilon_t \qquad (4)$$

where Y_t is the series being tested, L is the lag operator, and p is the number of lags of order greater than one included in the test. Then, modeling Y_t as an AR(p+1) process, the hypothesis that one of the p+1 roots of the characteristic equation is one can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$. An alternative test statistic that is sometimes used is $\hat{\beta} \times T$, where T is the number of observations in the time series. The distribution of both these statistics is tabulated in Fuller [1976]. More recently, Schmidt [1990] has shown that the critical values of these statistics are also sensitive to drift, and converge to the t distribution as the drift parameter increases. Using Monte Carlo simulations, he retabulates the critical values by series length and standardized drift. Since the critical values of the test statistics are strictly decreasing with respect to drift, a stationary process exhibiting some drift may not 'look' stationary when evaluated against Fuller's original critical values.

Phillips [1987] has demonstrated that for certain kinds of dependence in the error term in equation (4), such as that generated by an autoregressive integrated moving average process (ARIMA), the Dickey-Fuller statistic may be biased. He suggests modifications which produce statistics with the same asymptotic distribution, but which are robust to ARIMA processes and those exhibiting conditional heteroskedasticity.

Although the modifications suggested by Phillips have been shown to be effective, higher order lags are required in order to detect such differences. Since the lengths of the data series in the current study are at most 38 (i.e. depending on differencing and the number of lags chosen), the possible gains resulting from application of the test suggested by Phillips are outweighed by the obvious decline in estimational efficiency which would result. Under these circumstances the ordinary Dickey-Fuller test (equation (4) with p=1) is a more appropriate choice. Furthermore, to avoid having to compare the results for each firm to a potentially different critical value, zero drift is assumed in evaluating the test statistics. As noted above, this actually amounts to the imposition of a more stringent stationarity condition.

Although Granger's axioms establishing a basis for identifying causality in a multiple regression framework have stood the test of time, there have been several attempts to improve the operational framework for causality testing. For example, Sims [1972] suggests regressing B_t on past **and future** values of A_t, the suspected causal variable. If unidirectional causality exists from A_t to B_t then, by Axiom A, we would expect that the coefficients of the forward shifted A_t series would be insignificantly different from zero. Thus, the hypothesis that A_t causes B_t can then be tested by computing a block F-statistic for the significance of the coefficients of the leads of A_t. Although this approach provides a useful additional perspective on causality testing techniques, is not adopted in the current study because: i.) a data series of greater length would be required to achieve sufficient degrees of freedom for statistical significance; and ii.) the direction of causality can be adequately established in the framework of Granger's original vector autoregressive parameterization of the causality testing model.

Nevertheless, Granger's method of testing for causality has not been without its detractors. Granger and Newbold [1986] note that:

> "It has been suggested, for example, that causation can only be accepted if the empirical evidence is associated with a complete and

> convincing theory explaining how the cause produces the effect. If this viewpoint is taken then 'smoking causes cancer' would not be accepted."
> (Granger and Newbold [1986], p.222)

While this view may impose too restrictive a standard, the possibility that a variable that is in the dataset may proxy for something else that is not in the dataset and is the real cause of observed behavior does impose limitations on the interpretation of results. Granger [1980] suggests an alternative, middle of the road, essentially Bayesian viewpoint. This approach recognizes that in any investigation one generally has some prior belief about the theory under consideration based on past information. If data is gathered, screened and hypotheses tested, then as a result one may update one's belief regarding the validity of the theory in question. It is unlikely, however, that one's posterior probability estimate will go to precisely unity, or for that matter, precisely zero. Rather, the evidence that emerges from the analysis tends to move one's belief some undisclosed positive or negative distance along a continuum, with the result never quite attaining either unconditional extreme. Thus, the results of Granger causality tests are most appropriately viewed simply as evidence, without imposing an 'if and only if' condition. The strength of this evidence should be evaluated not only on the basis of statistical significance, but also in the broader context of appropriateness of model specification given the data environment in question.

This methodology has been widely used in empirical work both in economics (see for example Sims [1972], Thornton and Batten [1985] and Christiano and Ljungqvist [1988]) and in finance (see Smirlock and Marshall [1983] and Bar-Yosef, Callen and Livnat [1987]).

Chapter IV

An Examination of Dividend - Investment Interdependence

An Examination of Dividend - Investment Interdependence

Review of the Literature:

Since Miller and Modigliani [1961] put forward the proposition that in perfect capital markets the investment and financing decisions of firms are independent, there have been many attempts to test the empirical validity of this principle. Some of the significant early work in this area was performed by Dhrymes and Kurz [1967], and Fama [1974]. The conclusions of these studies, however, are very different.

Dhrymes and Kurz [1967] developed a theoretical model consisting of three simultaneous equations representing the dividend, investment and external financing decisions. Their sample consists of 181 firms for which data were available between 1947 and 1960. Data sources consist of balance sheets and income statements appearing in Moody's Manuals. A detailed argument for the use of full information estimation techniques is presented. Although one of the objectives of this study is ostensibly to test the dividend-investment separation principle empirically, the dependence of these relationships is assumed a priori, as evidenced by the following statement:

> "Clearly dividend disbursals and investment outlays represent competing demands on the resources available to the firm; thus it would be quite plausible to suppose that the investment activities of the firm will be affected by its

dividend activities; postponement or curtailment of investment could conceivably result because of inability of the firm to carry out a given investment program, 'optimally' determined by some 'rational' criteria, and at the same time continue to make 'satisfactory' dividend payments."
(Dhrymes and Kurz [1967], p. 435)

This dependence is also explicitly assumed in the specification of the model. Although some theoretical assumptions are necessary within the context of a simultaneous equations model in order to allow for parameter identification, they should not relate to anything integral to the question under study. Allowing presuppositions of this sort to affect the specification of the model constitutes a serious error, and may lead to some bias in the interpretation of results. Dhrymes and Kurz [1967] reject the results obtained from single equation techniques, accepting instead those obtained using a simultaneous equations approach. They conclude that:

> "the dividend impact on investment is quite pronounced and consistently negative and significant (except for 1957 and 1960, both peak years)."
> (Dhrymes and Kurz [1967], p. 460)

The investment term is also found to be significant in the dividend equation. These conclusions are extremely suspect due to the concerns raised above. However, if one accepts the assumptions under which these results were obtained, bi-directional causality is implied.

Fama [1974] argues that the Dhrymes and Kurz model is misspecified. He points out that both the theory and the data used by Dhrymes and Kurz are more consistent with time-series models applied to individual firms. Dhrymes and Kurz, however, use cross-sectional regressions, reestimating the parameters annually. The coefficients of the explanatory variables are therefore the same for all firms. Fama contends that:

> "If dividends are correlated with other explanatory variables in their investment equation, then including dividends in the investment regressions may just be a way to adjust in part for differences among firms in the coefficients of other variables. A similar phenomenon may arise when investment is included in the cross sectional dividend regressions." (Fama [1974], p. 315)

Using Compustat data on 298 firms for which complete information was available for the entire 1946-1968 period, Fama applies both simultaneous and single equation methods to data for individual firms and finds no significant dividend policy effects in either case. In terms of efficiency, the single equation technique is marginally superior. Fama interprets these results to support the conclusion that:

> "...there is no systematic evidence for the type of jointness or interdependence in the year-by-year dividend and investment decisions of firms that requires a simultaneous equations model." (Fama [1974], p. 315)

Thus, Fama rejects both the methodology and the conclusions of Dhrymes and Kurz. Instead he concludes that whatever imperfections are present in the capital market are not sufficient to justify the rejection of the hypothesis that dividend and investment decisions are independently determined.

In a more recent, frequently cited study, Smirlock and Marshall [1983] use Granger [1969,1980] causality methods, discussed above in Chapter III, to test for the presence of a causal relationship between dividends and investment. If we assume symmetric lags, this methodology is best operationalized in the context of a vector autoregression. We can state the two lag specification of the model in vector autoregressive (VAR) form as follows:

$$\mathbf{y}_t = \Lambda + \theta_1 \mathbf{y}_{t-1} + \theta_2 \mathbf{y}_{t-2} + \zeta_t \tag{5}$$

Where:

$$\mathbf{y}_t = \begin{bmatrix} INV_t \\ DIV_t \end{bmatrix} \qquad \Lambda = \begin{bmatrix} \alpha_0 \\ \Gamma_0 \end{bmatrix} \qquad \theta_i = \begin{bmatrix} \alpha_i & \beta_i \\ \delta_i & \Gamma_i \end{bmatrix} \qquad \zeta = \begin{bmatrix} \epsilon_t \\ \mu_t \end{bmatrix}$$

In the bivariate case, this reduces to the following two regression equations:

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

The two lag specification of the model appears justifiable both on the grounds of theory and of data availability. Since the relationship being tested is one which theoretically should not exist at all, and which, if it does exist is most likely to be strictly contemporaneous, it would seem that two lags of the annual data series should be more than sufficient to detect any causal relationship which might exist. Furthermore, in light of the fact that the data series is extremely short for time series work, i.e. n=20, increasing the number of lags in the model is not a viable alternative. Thus, there is nothing to cavil at in the setup of the Granger causality model and the same specification of the model is carried over to the empirical testing performed in the current study.

There may be cause for concern, however, in Smirlock and Marshall's contention that this methodology is appropriate even though, as Granger [1980] points out, it is incapable of identifying causal relationships that are strictly contemporaneous. Smirlock and Marshall dismiss the possibility that there may be a contemporaneous underlying causal relationship on the grounds that:

"As a practical matter, contemporaneous causality from dividends to the investment decision is virtually impossible since a lengthy evolution from planned to actual expenditures has been verified in studies of capital investment." (Smirlock and Marshall [1983], p.1661)

The sample used consists of firms included in the Standard and Poor's 400 index and which met the following criteria for each of the years in the sample period 1958-1977:

i) data were available for dividends, investment and common shares outstanding for every year;

ii) dividends were paid in every year;

iii) the firm had positive investment expenditures in every year;

iv) the firm did not change its fiscal year during the sample period.

These screens resulted in a sample consisting of 20 annual observations for each of 194 firms.

Smirlock and Marshall conduct Granger causality tests on both firm specific and aggregate data. Aggregate data is obtained by simply summing the dividend and investment variables across the firms in the sample for each year in the study. Causality tests are then conducted by estimating equations (6) and (7) above on the individual firm series and on the aggregate series. They report the following fractiles of the F-statistic for block exclusion tests of dividends from equation (6) and investment from equation (7):

Smirlock and Marshall: Firm Specific Tests
Granger Causality F-Statistics
Critical Value of $F_{\alpha=0.05,2,13} = 3.81$

		Dividends	Investment
	10	0.05	0.04
	25	0.18	0.12
Percentile	50	0.59	0.39
	75	1.22	1.07
	90	2.19	2.04

(Smirlock and Marshall [1983], p. 1664, Table II)

In the aggregate case Smirlock and Marshall report much lower F-statistics:

Smirlock and Marshall: Aggregate Tests
Granger Causality F-Statistics
Critical Value of $F_{\alpha=0.05,2,13} = 3.81$

	Dividends	Investment
F-Statistics	0.32	0.04

(Smirlock and Marshall [1983], p. 1663, Table I)

Thus, Smirlock and Marshall find no statistically significant evidence of Granger causality in either direction. For the individual firm data Smirlock and Marshall state unequivocally:

> "The F-statistic corresponding to the null hypothesis of no Granger-causality achieves significance at the 0.05 level for no more firms than would be expected by chance, for either direction of Granger-causality. At the 90th percentile the null hypothesis is **always** [emphasis added] accepted. These results provide strong support for the view that the firm's dividend and investment decisions are separable."
> (Smirlock and Marshall [1983], p.1664)

There are several troubling questions, however, which remain unanswered. First, the small number of degrees of freedom suggest that these tests may lack discriminatory power. The seriousness of this concern is not immediately clear, however, this question is addressed later in the current study by means of simulations. It should be noted that at the time of Smirlock and Marshall's study, additional time series observations were not available, so this problem could not have been easily remedied. A second area of concern is the fact that, although statistically insignificant, the test statistics given are systematically stronger in the direction of Dividend-Investment causality than in the direction of Investment-Dividend causality. The failure of this study to detect what we expect on the basis of theory, i.e. causality running from investment to dividends, casts doubt on its ability to detect that which we may suspect, i.e. causality running in the opposite direction, but which theory does not support. This concern, while possibly also related to the shortage of data, is clearly a very significant one and is sufficient to render Smirlock and Marshall's assertion that "the above results provide strong support for the view that the firm's dividend and investment decisions are separable" insupportable.

Another study conducted around the same time with similar intent but different methodology is Partington [1985]. This study examined the question of potential dividend-investment causality by surveying senior managers of 152 large Australian firms representing a cross-section of the largest 300 firms on the Sydney Stock Exchange Industrial list; 93 responses were obtained. The survey was structured to elicit information regarding **perceived** dividend policies. As with other survey based investigations there are behavioral factors present in this study which make interpretation of the results somewhat difficult at times. In an effort to clarify matters, an attempt is made to gather data relating not only to the frequency and circumstances of different dividend, investment and financing policies, but also the motivations behind them. Partington uses this data to test the null hypothesis that dividends are not determined as a residual. The survey is segmented according to whether or not external financing is seen to be a viable alternative in the case under consideration. In the cases where external financing was raised 39 percent of the executives responding said that there were times when dividends were still given priority and some restrictions were applied to investment spending. In cases where no external financing was raised 39.1 percent responded in this way. Thus, although for the most part Partington's findings support those of Smirlock and Marshall, he finds that for a significant minority of firms there are at times perceived conflicts between dividend and investment policy. He sums up his findings as follows:

"The evidence suggests that independence between

> dividend and investment policies is usual, but not universal. It appears that there are occasions when firms adopt simultaneous dividend and investment policies, or even give dividends priority over investments....Perhaps more surprising, in the light of Miller and Modigliani's [1961] arguments for the primacy of the investment decision, is the evidence that, when a conflict occurs, the dividend decision is more likely to dominate the investment decision." (Partington [1985], pp. 540-541.)

Partington points out that theoretically conflicts of this sort should be resolved by resorting to external financing. The fact that managers apparently do not universally perceive external financing to be an alternative that is available to them at all times is surmised to be due to the presence of market imperfections such as transactions costs and informational asymmetries.

Although Partington's study suggests that dividend-investment independence may not be universal among firms, the small number of observations in the data set and the subjectivity of the survey data make these results far from conclusive. Nevertheless, it is troubling to note that Smirlock and Marshall do not find evidence of the same minority of firms giving dividends priority over investment. In an attempt to resolve this discrepancy we return to a consideration of the previous work of Smirlock and Marshall.

In addition to the problems mentioned earlier, there is another serious obstacle to the interpretation of the work of Smirlock and Marshall; that is, the possibility of dividend-investment dependency in a dividend generating process that is strictly contemporaneous within the context of the temporal screen. As pointed out by Smirlock and Marshall Granger causality methodology is incapable of detecting such dependencies. The current study seeks to demonstrate through a series of simulations that a wholly dependent dividend generating process of the kind proposed by Lintner [1956], and given empirical support in Fama and Babiak [1968], can produce causality test results of a sort indistinguishable from those obtained by Smirlock and Marshall. This is followed up with an empirical test using the longer data series now available.

Simulated Dividends and Investment:

There are numerous alternative approaches which could be taken to simulating dividends and investment while still allowing for the kind of explicit contemporaneous dependence which we wish to model. The objective of the simulation segment of this study is to determine whether it is possible to identify a causal relationship between dividends and investment in a series consisting of only 20 observations. In this context the Lintner model of dividend policy has some attractive features. Specifically, since dividends are always chosen first, with investment determined as the residual, this constitutes the most extreme case of a causal relationship running from dividends to investment. The implication is that if Granger causality methods cannot consistently detect a causal relationship in series of length 20 specifically constructed to conform to the Lintner model, their usefulness in detecting weaker relationships between series of this length is suspect.

Apart from the rather implausible Lintner relationship to be imposed between the simulated dividend and investment series, it is important that the series themselves be simulated along very plausible lines. That is to say, the behavior of the simulated series should have some empirical support. One very straightforward model which meets this description was suggested by Fama and Babiak [1968]. Fama and Babiak began with the following model:

$$D_t - D_{t-1} = \alpha + \beta_1 D_{t-1} + \beta_2 E_t + \beta_3 A_t + u_t \tag{8}$$

D_t : dividends per share during year t

E_t : earnings per share during year t

A_t : depreciation per share during year t

u_t : a random disturbance term

After some empirical testing they conclude that the coefficient of the A_t series is insignificant and they estimate the values of the other coefficients in the model as follows:

$$D_t - D_{t-1} = -0.45 D_{t-1} + 0.15 E_t + u_t \tag{9}$$

$$u_t = 0.2 u_{t-1} + \nu_t \tag{10}$$

While Fama and Babiak simulate earnings as an AR(1) series, a more fundamental approach is taken here. Instead, earnings, E_t, are generated from the following relationships:

$$E_t = r_t K_{t-1} \tag{11}$$

$$I_t = E_t - D_t \tag{12}$$

$$K_t = K_{t-1}(1-\delta) + I_t \tag{13}$$

where: K_t : Capital at time t; $K_0 = 20$

I_t : Investment at time t

r_t : ROA at time t; distributed N(10%,25%)

δ : Depreciation at time t; $\delta = 5\%$

The key relationship here is equation (12) which specifies that in each period investment is determined as the residual of earnings after dividends have been determined. Equations (11) and (13) provide the dynamic link between observations in the simulated time series. The objective here is to provide a set of relationships which allow for a credible simulation of the dividend and investment series, while avoiding complexity on the grounds that it could introduce confounding factors. Note also that $D_0 = 0.05$, and minimum dividends are constrained to be 0.05. The attractions of this parameterization of the simulation model are:

i) Since investment is determined as a residual item only, this is a very clear violation of the separation principle. However, since this relationship is contemporaneous we can demonstrate that it will not be detected in a test for causality.

ii) There is a secondary relationship which is clearly evident in the above equations. This period's dividends affect investment which in turn affects next year's capital. Next year's capital affects next year's earnings which affects next year's dividends. Thus, the Lintner model does imply an indirect underlying causal relationship. Since this relationship via earnings is non-contemporaneous we **can** hope to identify it by means of a causality test if it is strong enough.

Hence, the simulation, as outlined above, constitutes a test of the ability of the methodology employed by Smirlock and Marshall [1983] to detect a violation of the separation principle of the sort implied by the Lintner model of dividend policy. Since managers are widely believed to violate this principle, this represents a critique of the efficacy of the Smirlock and Marshall methodology in identifying this behavior.

Initial Simulation Results:

The above simulation was run with the series length set equal to 20 to match Smirlock and Marshall, and n=10,000.

Initially nine simulations were run, using three values for $\sigma^2(\nu_t)$ (0.001, 0.010, 0.100), and three values for the coefficient of earnings (0.10, 0.15, 0.20). A listing of the code used to generate the simulations is provided in Appendix IVA. Figures IV.1 and IV.2 provide a visual comparison of simulated and actual dividends. In order to achieve stationarity it was necessary to take log first differences of the dividend series, and first differences of the investment series[2]. Selected percentiles of the Dickey-Fuller test statistics on the transformed series are presented in Tables IV.1-IV.3. Results significant at the $\alpha=0.05$ level are designated by an asterisk. In all cases the series are shown to be stationary to within a small margin of random error.

Causality tests were conducted as described in Chapter III above. The regression equations involved in the test were identical to equations (6) and (7) above with n and m, the number of lags, set equal to 2. For series of length 20 this resulted in causality test F-statistics with 2 degrees of freedom in the numerator and 12 degrees of freedom in the denominator. Selected percentiles of these statistics are presented in Tables IV.4-IV.6.

These results demonstrate very clearly that for all values of the earnings coefficient and $\sigma^2(\nu_t)$ covered by the simulation, a causal relationship of the Lintner type cannot be unambiguously identified in a series of length T=20. It is clear that the discriminatory power of the test is positively related to both the earnings coefficient and the $\sigma^2(v_t)$ over the range of values covered in the simulations. This effect is consistent with intuition in the sense that we expect the lagged effects of the built-in contemporaneous dependencies to be more easily identifiable when the signal is stronger. Increases in both the coefficient of earnings and the $\sigma^2(v_t)$ contribute to the strength of the lagged signal in the simulation model.

Further simulation runs included a range of values of the autocorrelation coefficient (-0.2 and 0.0 as well as the original value of 0.2) in equation (10). Selected percentiles of the resulting F-statistics are shown in Tables IV.7-IV.9. We conclude that the results shown earlier are robust to these changed assumptions. That is, even with a strong non-contemporaneous secondary element causality cannot be unambiguously detected in a series of length 20.

Fama and Babiak Revisited:

The evidence from the first series of simulations shows that the variance of the error term, and to some extent also the magnitude of the coefficients have an impact on the discriminatory power of the causality test. Because of this an attempt was made to empirically verify the results of Fama and Babiak [1968].

The current study significantly updates the data set: 254 firms are included for which both dividends and net income were reported for every year during the interval 1952 - 1989. Screens were implemented to exclude banks, utilities, insurance companies, ADR's, limited partnerships and real estate investment trusts; in short, firms for which the regulatory environment would tend to make dividends particularly sticky. The results of estimating equations (9) and (10) on a firm by firm basis are presented in Table IV.10. Histograms are provided in Figures IV.3 - IV.14. Although there are a wide range of values for each coefficient, it is worth noting that the median values of $\hat{\alpha}$ and $\hat{\beta}$ are smaller than those found by Fama and Babiak, and the median value of $\hat{\sigma}$ is larger than expected.

In an effort to resolve this discrepancy the sample period was split into two subperiods, 1952 - 1970 and 1971 - 1989, and the model estimated for each subperiod. These results are presented in Table IV.11. Applying the same screens as before results in somewhat larger samples in both subperiods; 263 firms for 1952 - 1970 and 864 firms for 1971 - 1989. Although the median of $\hat{\alpha}$ and $\hat{\beta}$ in the first subperiod do have the same sign as those provided by Fama and Babiak they are much smaller in magnitude. For the second subperiod the $\hat{\alpha}$ and $\hat{\beta}$ do not appear to be significantly different from zero. However, for both subperiods $\hat{\sigma}$ is many times smaller than it was when estimated for the entire sample period. This suggests the presence of non-linearities and/or non-stationarity in the data. Because the objective of this part of the study is to generate a plausible simulated dividend series rather than to predict actual dividends, these results are accepted with the acknowledgement that although adequate for the purpose used here, it would not be appropriate to use the Fama-Babiak model to predict future dividends. While the estimated parameters allow us to generate a simulated dividend vector that could be drawn from the same distribution as actual dividend realizations, it is unlikely that the values taken by the simulated series will closely parallel the realized values for any one particular firm.

Further Simulation Results:

The fact that the empirically estimated parameters of the dividend generating equation differ so markedly from those reported by Fama and Babiak may cast some suspicion on the validity of the results drawn from the earlier simulation. In order to address this concern several additional simulations were run using, respectively, the median, mode and mean of the estimated $\hat{\alpha}$, $\hat{\beta}$, $\hat{\rho}$ and $\hat{\sigma}$. These simulations were conducted for the entire 1952 - 1989 sample period, and for both of the subperiods (1952 - 1970 and 1971 - 1989). Selected percentiles of the results are shown in Tables IV.12 - IV.17. Histogram representations of these results are presented in Figures IV.15 - IV.32. An examination of these findings reveals that given the empirical relationship between dividends, lagged dividends and contemporaneous earnings, the secondary effects of a contemporaneous causal relationship between dividends and investment (a la Lintner) are no easier to detect than they were under the parameters estimated by Fama and Babiak. In fact a careful comparison of these simulation results with those from the original simulation suggest that even in cases where $\hat{\partial}$ is quite large there is no discernable increase in discriminatory power. Given the findings from the earlier simulation it seems clear that this phenomenon is due to the much lower coefficient of the earnings term in all cases covered in the second series of simulations.

The only conclusion to be drawn here is that if in fact the empirical relationship between dividends and investment is purely contemporaneous in the Lintner sense, given the nature of the empirical relationship between dividends and earnings (described in the previous sections) we truly cannot expect to detect any signs of this relationship in a test for Granger causality.

Empirical Tests for Dividend-Investment Causality:

The sample used in testing for dividend-investment causality includes all firms on the Compustat Annual tape for which both dividends and the ending balance of the property, plant and equipment account were reported for every year during the interval 1952 - 1989. Screens were implemented to exclude banks, utilities, insurance companies, ADR's, limited partnerships and real estate investment trusts; again, firms for which the regulatory environment would tend to make dividends particularly sticky. The dividend series used consists of the amount of common stock dividends paid in each year. Since several significant changes in the format and content of sources and uses of funds disclosures required by the Financial Accounting Standards Board occurred during the sample period, consistent investment data was not readily available. In order to avoid the possibility of obtaining test results driven by the method of disaggregating the accounting data for the years in which full information was not disclosed, a simple proxy for net investment was constructed by first differencing the property, plant and equipment account. This had the effect of reducing the length of the series to the 37 years covering 1953 - 1989.

The first attempt to test the hypothesis that dividends and investment are causally related was conducted in the spirit of a replication and extension of the work of Smirlock and Marshall to the significantly longer data series now available. Since Smirlock and Marshall used a log differencing transformation on both the dividend and investment series it was necessary to screen for firms which had strictly positive dividends and investment in all years from 1953 - 1989. However, no firms met these criteria for the period 1953 - 1989. In fact no firms met these criteria for any sample period starting between 1953 and 1974 and ending in 1989. Only one firm passed the screen for sample periods starting between 1975 and 1980 and ending in 1989. Clearly, generalizable results cannot be obtained from a sample consisting of only one firm and a time series of length 15. Thus this particular approach to the problem had to be abandoned[3].

The second approach adopted involved relaxing the screening restrictions to allow firms that had negative or zero investment and zero dividends in some years. This resulted in a sample of 220 firms for which there were no missing observations between 1953 and 1989.

Initially, causality tests were performed on the raw series (levels). Although some indications of a causal relationship were found they were deemed to be inconclusive due to the very weak stationarity test results. Table IV.18 presents selected percentiles of both Dickey-Fuller and F-statistics for the raw series. Histograms of these results are presented in Figures IV.33 - IV.36.

The first differences of these series were found to be stationary in most cases. Table IV.19 presents stationarity test and causality test statistics for the differenced series. It can be seen by examining these results that the

F-statistics for the significance of lagged dividends in predicting investment, i.e. in equation (6), meet the critical value for significance at the $\alpha=0.05$ level all the way down to the 75th percentile. In fact 61 of the 220 firms in the sample exhibit F-statistics greater than the critical value at the $\alpha=0.05$ level. Under the null hypothesis of no causal relationship between dividends and investment we should observe such F-statistics only at the 95th percentile and above. This could be viewed as sampling from a binomial distribution with p=0.05. We can obtain some insight regarding the overall significance of the test results by evaluating the complement of the cumulative binomial probability, $P\{N>k\}$, for the number of significant observations of the F-statistic found. This is the probability, under the null hypothesis, of finding a higher frequency of significant F-statistics than that actually observed in the sample of firms studied. Thus, it could be viewed as a measure of the significance level of the aggregate test results, with a lower probability corresponding to greater significance.

The table below shows the frequency count of F-statistics significant at the $\alpha=0.05$ level for the 220 firms in the sample. These F-statistics are for block exclusion tests of all lags of the variable named. Thus, the F-statistics for dividends relate to tests of the hypothesis that lagged dividends are statistically significant in explaining current investment. The corresponding cumulative binomial probabilities, shown in the column to the right, indicate that the distribution of F-statistics is significantly different from what one would expect under the null hypothesis.

Sample Period 1953-1989
Differenced Series, 220 Firms
$F_{\alpha=0.05,2,29} = 3.33$

F-statistics	Frequency	Binomial P{N>k}
Dividends	61	0.0000
Investment	78	0.0000

An alternative, and potentially more efficient, means of aggregating the statistics derived from the block F tests performed on the individual firms is the χ^2 goodness-of-fit test. In this test a frequency table of the sample F-statistics, rather than a simple proportion, is used to test the hypothesis that the distribution conforms to the F distribution under the null. A χ^2 statistic greater than the critical value indicates rejection of this hypothesis.

χ^2 Goodness-of-Fit Tests
Sample Period 1953-1989
Differenced Series, 220 Firms
$\chi^2_{1-\alpha=0.95,df=19} = 30.14$

F-statistics	χ^2
Dividends	276.9091 *
Investment	468.1818 *

Although the χ^2 test shows only that the distribution of test statistics is significantly different from what it would be under the null hypothesis, the direction of this relationship is clear from the results shown in Table IV.19 and from the binomial test shown above. That is, the test statistics are generally greater than those from the actual F distribution. Thus, although we are not justified in concluding that all firms exhibit Granger causality in the dividend-investment relationship, the test results clearly support the inference that a substantially greater than random proportion of the firms tested do exhibit this behavior. Figures IV.37 - IV.40 provide a visual representation of these results in the form of histograms. Note also that the goodness-of-fit test and Table IV.19 reveal evidence of even stronger causality going from investment to dividends. However, as explained in the introductory section, this is a less interesting result since it is completely in accord with what theory would suggest, and implies no suboptimality in management policy.

One potential concern with the above results is the possibility that the findings could be driven by the firms in the sample which did not exhibit stationarity even in the differenced series. In order to address this issue the sample was segmented according to whether or not firms met the criterion for stationarity. The first group consists of 103 firms which passed the test for stationarity at the

$\alpha=0.05$ level for both the dividend and investment series. The second group consists of 117 firms for which either dividends or investment failed to pass the test for stationarity. The distribution of the causality test F-statistics was then examined separately for each subgroup. Selected percentiles of these distributions are presented in Table IV.20. Figures IV.41 - IV.44 provide histograms showing the same results visually. An examination of Table IV.20 makes it clear that the causality test results presented earlier are not driven by non-stationarity. In fact, the F-statistics from the two subgroups are virtually indistinguishable. Thus, the conclusion that dividends Granger cause investment does appear to be very clearly supported by the data, for a significant proportion of firms in the sample.

At this point it may be of interest to examine the characteristics of firms exhibiting Granger causality in the relationship between dividends and investment. Table IV.21 provides a listing in order from highest to lowest F-statistic of the 61 firms that met or exceeded the critical value for dividend-investment causality at the $\alpha=0.05$ level of significance. These firms do not appear to exhibit any immediately identifiable common characteristics apart from the fact that they are predominantly large manufacturing firms. Given the screening process, they are fairly typical within the sample. It does not appear that there is any significant clustering within industry groups. Perhaps the most remarkable observation to be drawn from Table IV.21 is the evident success of the firms listed; most are household names. Clearly, requiring that firms in the sample release financial statements for all years from 1952 - 1989 does induce some bias toward successful firms. Repeating the study using data from the Compustat Research tape is not a viable alternative since for time series work the series length used in this study, T=37, is already approaching the minimum necessary for reliable inference. Thus, data from firms which were in operation for only a part of the sample period would not be useable. For this reason, we are effectively limited to the conclusions that can be drawn from the current data set. However, even taking into account the survivorship issue it is remarkable that the firms which exhibit the strongest dividend-investment causality are such an entrenched part of the economy. While there are several possible regulatory and/or agency explanations for this phenomenon which could be fruitful directions for future work, they are beyond the scope of this study and are therefore not investigated here.

Conclusions:

While Granger causality techniques can be appropriately used to demonstrate the existence of a causal relationship between two or more time series, it is difficult to prove conclusively that such a relationship does not exist. Pierce and Haugh [1977] have shown that in order to achieve this it is necessary to show that the cross correlations at **all** lags are equal to zero[4]. This result is in keeping with what intuition would suggest.

The current study uses simulations in the initial phase to explore the limitations of the relationships which one can reasonably expect to identify in the context of Granger causality methodology. The conclusion from this part of the study is clear: given the empirical relationship between dividends, lagged dividends and earnings, the methodology employed in this study and the earlier study conducted by Smirlock and Marshall cannot be used to rule out the possibility of a contemporaneous causal relationship. Furthermore, when a series of only 20 observations is used the discriminatory power of the test is very weak. Having established this fundamental limitation the current study proceeds to an empirical test of the potential causal relationship between dividends and investment. Granger causality methodology is employed here as it is in the earlier study by Smirlock and Marshall. However, the availability of additional data makes it possible to significantly update the data set. Using a series of 37 annual observations for each firm (i.e. after differencing property, plant and equipment once), statistically significant evidence of Granger causality from dividends to investment is found in approximately 28 percent of the firms in the sample. These firms do not appear to be clustered in any particular industry group. The results of this study are consistent with the survey results found by Partington in studying 93 Australian firms. Because the current study employs a much larger sample of firms and a more objective methodology the results contribute significantly to the credibility of Partington's conclusions.

In the present study, screens were implemented to exclude banks, utilities, insurance companies, ADR's, limited partnerships and real estate investment trusts; that is, firms for which the regulatory or tax environment would tend to make dividends and/or investment behave in ways other than what one would expect under perfect or close to perfect market assumptions. Given the screens applied to the sample, it is difficult to imagine a particular set of market imperfections which would make it optimal to allow dividends to influence investment for any of the firms included in the sample. If this assessment is accurate the implication is that many of the largest domestic firms have been managed in a way that is directly opposed to accepted theory within the field of corporate finance. Although it would be impossible to accurately assess the opportunity cost of such suboptimal decision making, the magnitude of the variables involved suggests that it would be substantial.

Appendix IV.A

This appendix provides a sample listing of the code used to generate the simulations reported in the first part of this study. All simulations were performed using RATS (Regression Analysis of Time Series) software. On this page a sample of the calling routine is provided. The following pages provide a listing of the steps in the simulation procedure itself.

Sample Calling Routine:

```
* Program to Simulate Dividend-Investment Relationship with
* Contemporaneous Dependence
* SMIRLOCK AND MARSHALL'S APPROACH; MODEL: 1952 - 1989
*
environment noundefinederrors
bma(series=partial)
ieval runs=10000                    ;*  set desired number of
iterations
ieval n=38                          ;*  set desired series
length**
if n .ge. runs
   ieval length = n
else
   ieval length = runs+1
end if
all 0 length
output noecho
source dfunit.ext
source hist200.ext
source smr.ext
output echo
declare vector frc(7)
*
*Run #1: Median Values
clear frcdiv frcinv frcdfdiv frcdfinv bf_div hf_div bf_inv $
     hf_inv bdf_div hdf_div bdf_inv hdf_inv
@smr n runs 63.617 0.0193 0.0035 0.272 frcdiv frcinv $
      frcdfdiv frcdfinv bf_div hf_div bf_inv hf_inv $
      bdf_div hdf_div bdf_inv hdf_inv frc
open copy f_a_med.f38
copy(org=obs,format='(2f12.4)') 1 7 frcdiv frcinv
open copy df_a_med.f38
copy(org=obs,format='(2f12.4)') 1 7 frcdfdiv frcdfinv
open copy a_med.h38
copy(org=obs,format='(8f9.3)') 1 200 bf_div hf_div bf_inv $
     hf_inv bdf_div hdf_div bdf_inv hdf_inv
```

Simulation Procedure:

```
* Procedure to Simulate Dividend-Investment Relationship
* with Contemporaneous Dependence
* SMIRLOCK AND MARSHALL'S APPROACH
*
*
PROCEDURE SMR n runs var_dshk coef_d coef_e a_corr $
frcdiv frcinv frcdfdiv frcdfinv bf_div hf_div bf_inv $
hf_inv bdf_div hdf_div bdf_inv hdf_inv frc
TYPE PARAM n runs
TYPE REAL var_dshk coef_d coef_e a_corr
TYPE SERIES frcdiv frcinv frcdfdiv frcdfinv bf_div $
hf_div bf_inv hf_inv bdf_div hdf_div bdf_inv hdf_inv
TYPE VECTOR frc
LOCAL SERIES roa div inv earn capital dshock f_div $
f_inv df_div df_inv
*
* Define Remaining Simulation Parameters
output noecho
eval mroa = 0.15
eval var_roa = 0.00025
eval dep = 0.05
eval dl = 0.05
eval initcap = 20
eval mindiv = 0.15
eval minratio = 0.5
*
* Set Up Simulation Equations for Random Draw
clear roa div inv earn capital dshock f_div f_inv $
df_div df_inv
set roa = 0.0
set dshock = 0.0
equation simr roa
# constant
associate simr 0 0 var_roa
# mroa
equation(noconstant) simd dshock
# dshock{1}
associate simd 0 0 var_dshk
# a_corr
simulate(setup) 2 n 1
# simr roa
# simd dshock
*
* Run Iterations of Simulation
do loop=1,runs
simulate
do t=1,n
    {
    if t==1
```

```
         {
         eval earn(t)=initcap*roa(t)
         eval div(t)=d1+dshock(t)
         eval inv(t)=earn(t)-div(t)
         eval capital(t)=initcap*(1-dep)+inv(t)
         }
      else
         {
         eval earn(t)=capital(t-1)*roa(t)
         eval div(t)=coef_d*div(t-1)+coef_e*earn(t-1) $
           +dshock(t)
         eval inv(t)=earn(t)-div(t)
         eval capital(t)=capital(t-1)*(1-dep)+inv(t)
         }
      if div(t) .le. mindiv .or. capital(t) .le. $
initcap*minratio
        {
           eval div(t)=mindiv+abs(dshock(t))
           eval inv(t)=earn(t)-div(t)
           if t==1
              eval capital(t)=initcap*(1-dep)+inv(t)
        else
              eval capital(t)=capital(t-1)*(1-dep)+inv(t)
         }
         }
end do t
*
* Transformation of Series and Dickey-Fuller Tests
set div = log(div(t))
smpl 2 n
diff div
diff inv
@dfunit(lags=1,ttest) div
eval df_div(loop) = dfstat
@dfunit(lags=1,ttest) inv
eval df_inv(loop) = dfstat
*
* Granger Causality Tests Performed on Transformed Series
output noregress
smpl 4 n
linreg(noprint) div
# constant div{1 to 2} inv{1 to 2}
exclude(noprint)
# inv{1 to 2}
fetch f_inv(loop) = cdstat
linreg(noprint) inv
# constant div{1 to 2} inv{1 to 2}
exclude(noprint)
# div{1 to 2}
fetch f_div(loop) = cdstat
display(unit=output) loop runs
end do loop
```

```
*
* Sort and Save Selected Fractiles of Simulation Results
smpl 1 runs
order f_div
order f_inv
order df_div
order df_inv
eval frc(1)=0.05
eval frc(2)=0.10
eval frc(3)=0.25
eval frc(4)=0.50
eval frc(5)=0.75
eval frc(6)=0.90
eval frc(7)=0.95
do i=1,7
eval frcdiv(i)=f_div(fix(runs*frc(i)))
eval frcinv(i)=f_inv(fix(runs*frc(i)))
eval frcdfdiv(i)=df_div(fix(runs*frc(8-i)))
eval frcdfinv(i)=df_inv(fix(runs*frc(8-i)))
end do i
*
* Save Data for Histogram of Simulation Output
@hist bf_div hf_div f_div 1 runs
@hist bf_inv hf_inv f_inv 1 runs
@hist bdf_div hdf_div df_div 1 runs
@hist bdf_inv hdf_inv df_inv 1 runs
*
end
```

Table IV.1

Stationarity of Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
Dickey-Fuller Statistics
Coefficient of Earnings = 0.10

Critical Value of $DF_{\alpha=0.05,n=19} = -3.05$
$DF_{\alpha=0.10,n=19} = -2.67$

$\sigma^2(v_t) = 0.001$

		Dividends	Investment
	5	-3.2758*	-2.5181
	10	-3.3800*	-2.8807
	25	-3.5494*	-3.4647*
Percentile	50	-3.7523*	-4.1997*
	75	-3.9602*	-5.0835*
	90	-4.1519*	-6.0159*
	95	-4.2726*	-6.6599*

$\sigma^2(v_t) = 0.010$

		Dividends	Investment
	5	-2.8118	-2.4661
	10	-3.0006	-2.8249
	25	-3.3171*	-3.4337*
Percentile	50	-3.6834*	-4.1786*
	75	-4.0717*	-5.0449*
	90	-4.4122*	-6.0060*
	95	-4.6480*	-6.7157*

$\sigma^2(v_t) = 0.100$

		Dividends	Investment
	5	-2.4894	-2.4368
	10	-2.7224	-2.7726
	25	-3.1421*	-3.3324*
Percentile	50	-3.6709*	-4.0018*
	75	-4.2770*	-4.8196*
	90	-4.8856*	-5.6888*
	95	-5.2727*	-6.3383*

Table IV.2

Stationarity of Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
Dickey-Fuller Statistics
Coefficient of Earnings = 0.15

Critical Value of $DF_{\alpha=0.05,n=19} = -3.05$
$DF_{\alpha=0.10,n=19} = -2.67$

$\sigma^2(v_t) = 0.001$

		Dividends	Investment
	5	-4.4910*	-2.8225
	10	-4.6551*	-3.1502*
	25	-4.9525*	-3.7367*
Percentile	50	-5.3114*	-4.4540*
	75	-5.6912*	-5.2970*
	90	-6.0656*	-6.2203*
	95	-6.2883*	-6.8891*

$\sigma^2(v_t) = 0.010$

		Dividends	Investment
	5	-3.8021*	-2.8160
	10	-4.0453*	-3.1426*
	25	-4.4888*	-3.7187*
Percentile	50	-5.0074*	-4.4234*
	75	-5.5959*	-5.2819*
	90	-6.1466*	-6.1476*
	95	-6.5228*	-6.7921*

$\sigma^2(v_t) = 0.100$

		Dividends	Investment
	5	-2.6852	-2.6260
	10	-2.9433	-2.9405
	25	-3.4699*	-3.4842*
Percentile	50	-4.1260*	-4.1732*
	75	-4.8814*	-4.9822*
	90	-5.6650*	-5.8372*
	95	-6.2063*	-6.4719*

Table IV.3

Stationarity of Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
Dickey-Fuller Statistics
Coefficient of Earnings = 0.20

Critical Value of $DF_{\alpha=0.05,n=19} = -3.05$
$DF_{\alpha=0.10,n=19} = -2.67$

$\sigma^2(v_t) = 0.001$

		Dividends	Investment
Percentile	5	-6.2807*	-2.9948
	10	-6.5272*	-3.3125*
	25	-6.9947*	-3.8881*
	50	-7.5773*	-4.5957*
	75	-8.2240*	-5.4056*
	90	-8.8733*	-6.2976*
	95	-9.2543*	-6.9286*

$\sigma^2(v_t) = 0.010$

		Dividends	Investment
Percentile	5	-5.1451*	-3.0338
	10	-5.5128*	-3.3157*
	25	-6.1411*	-3.8456*
	50	-6.8978*	-4.5336*
	75	-7.7463*	-5.3382*
	90	-8.6599*	-6.2119*
	95	-9.2219*	-6.8509*

$\sigma^2(v_t) = 0.100$

		Dividends	Investment
Percentile	5	-3.0695*	-2.7035
	10	-3.4000*	-3.0053
	25	-4.0463*	-3.5143*
	50	-4.8566*	-4.1515*
	75	-5.8565*	-4.9034*
	90	-6.8788*	-5.7544*
	95	-7.5605*	-6.3213*

Table IV.4

Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
F-Statistics from Granger Causality Tests
Coefficient of Earnings = 0.10

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

$\sigma^2(v_t) = 0.001$

		Dividends	Investment
Percentile	5	0.0182	0.1476
	10	0.0384	0.2317
	25	0.1083	0.4401
	50	0.2694	0.7396
	75	0.5886	1.1631
	90	1.0494	1.7012
	95	1.4396	2.1293

$\sigma^2(v_t) = 0.010$

		Dividends	Investment
Percentile	5	0.0231	0.0838
	10	0.0457	0.1557
	25	0.1228	0.3478
	50	0.3007	0.6845
	75	0.6382	1.1764
	90	1.1581	1.8590
	95	1.5802	2.3785

$\sigma^2(v_t) = 0.100$

		Dividends	Investment
Percentile	5	0.0372	0.0506
	10	0.0730	0.1042
	25	0.1963	0.2771
	50	0.4887	0.6645
	75	1.0186	1.3835
	90	1.7958	2.4192
	95	2.4783	3.2766

Table IV.5

Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
F-Statistics from Granger Causality Tests
Coefficient of Earnings = 0.15

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

$\sigma^2(v_t) = 0.001$

		Dividends	Investment
	5	0.0247	0.1894
	10	0.0501	0.2979
	25	0.1371	0.5542
Percentile	50	0.3428	0.9449
	75	0.7049	1.4979
	90	1.2575	2.1801
	95	1.7282	2.7201

$\sigma^2(v_t) = 0.010$

		Dividends	Investment
	5	0.0252	0.0986
	10	0.0520	0.1888
	25	0.1421	0.4182
Percentile	50	0.3676	0.8234
	75	0.7645	1.4133
	90	1.3515	2.2036
	95	1.9119	2.8237

$\sigma^2(v_t) = 0.100$

		Dividends	Investment
	5	0.0462	0.0476
	10	0.0944	0.0967
	25	0.2569	0.2687
Percentile	50	0.6305	0.6500
	75	1.2896	1.3609
	90	2.2617	2.3563
	95	3.0143	3.1988

Table IV.6

Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
F-Statistics from Granger Causality Tests
Coefficient of Earnings = 0.20

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

$\sigma^2(\nu_t) = 0.001$

		Dividends	Investment
Percentile	5	0.0344	0.2249
	10	0.0719	0.3754
	25	0.1897	0.7138
	50	0.4598	1.2368
	75	0.9875	1.9587
	90	1.7473	2.8500
	95	2.3981	3.5431

$\sigma^2(\nu_t) = 0.010$

		Dividends	Investment
Percentile	5	0.0373	0.1197
	10	0.0734	0.2199
	25	0.2094	0.5030
	50	0.5114	1.0134
	75	1.0640	1.7568
	90	1.8750	2.7071
	95	2.6018	3.4761

$\sigma^2(\nu_t) = 0.100$

		Dividends	Investment
Percentile	5	0.0572	0.0472
	10	0.1201	0.0939
	25	0.3166	0.2585
	50	0.7639	0.6199
	75	1.5742	1.3043
	90	2.7368	2.3339
	95	3.7472	3.1982

Table IV.7

Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
F-Statistics from Granger Causality Tests
Coefficient of Earnings = 0.15, $\sigma^2(v_t)$ = 0.001

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

Autocorrelation Coefficient = -0.2

		Dividends	Investment
	5	0.0264	0.1919
	10	0.0508	0.3045
	25	0.1384	0.5669
Percentile	50	0.3417	0.9582
	75	0.7285	1.4801
	90	1.2799	2.1615
	95	1.7321	2.7034

Autocorrelation Coefficient = 0.0

		Dividends	Investment
	5	0.0240	0.1933
	10	0.0497	0.3056
	25	0.1371	0.5599
Percentile	50	0.3439	0.9535
	75	0.7333	1.4925
	90	1.3263	2.1801
	95	1.7933	2.6960

Autocorrelation Coefficient = 0.2

		Dividends	Investment
	5	0.0247	0.1893
	10	0.0501	0.2979
	25	0.1370	0.5541
Percentile	50	0.3427	0.9449
	75	0.7048	1.4978
	90	1.2575	2.1801
	95	1.7282	2.7201

Table IV.8

Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
F-Statistics from Granger Causality Tests
Coefficient of Earnings = 0.15, $\sigma^2(v_t)$ = 0.010

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

Autocorrelation Coefficient = -0.2

		Dividends	Investment
	5	0.0265	0.1343
	10	0.0548	0.2275
	25	0.1490	0.4925
Percentile	50	0.3676	0.9255
	75	0.7634	1.5350
	90	1.3716	2.3179
	95	1.8770	2.9420

Autocorrelation Coefficient = 0.0

		Dividends	Investment
	5	0.0268	0.1233
	10	0.0542	0.2220
	25	0.1482	0.4591
Percentile	50	0.3719	0.8698
	75	0.7684	1.4565
	90	1.3608	2.2226
	95	1.8278	2.8085

Autocorrelation Coefficient = 0.2

		Dividends	Investment
	5	0.0260	0.1101
	10	0.0540	0.1942
	25	0.1520	0.4274
Percentile	50	0.3701	0.8206
	75	0.7838	1.4054
	90	1.3679	2.1434
	95	1.8870	2.7490

Table IV.9

Simulated Dividends and Investment, T=20
Smirlock and Marshall Approach
F-Statistics from Granger Causality Tests
Coefficient of Earnings = 0.15, $\sigma^2(v_t)$ = 0.100

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

Autocorrelation Coefficient = -0.2

		Dividends	Investment
Percentile	5	0.0377	0.0662
	10	0.0754	0.1391
	25	0.2082	0.3561
	50	0.5231	0.8308
	75	1.1124	1.6664
	90	1.9479	2.8838
	95	2.6655	3.8445*

Autocorrelation Coefficient = 0.0

		Dividends	Investment
Percentile	5	0.0387	0.0582
	10	0.0787	0.1200
	25	0.2233	0.3098
	50	0.5495	0.7300
	75	1.1692	1.4972
	90	2.0479	2.5508
	95	2.8200	3.5224

Autocorrelation Coefficient = 0.2

		Dividends	Investment
Percentile	5	0.0462	0.0475
	10	0.0944	0.0967
	25	0.2569	0.2687
	50	0.6305	0.6500
	75	1.2896	1.3609
	90	2.2616	2.3563
	95	3.0142	3.1987

Table IV.10

Fama and Babiak : Dividend Prediction Model
254 firms with data spanning the years 1952-1989

Fama and Babiak [1968] find evidence supporting a dividend generating model of the form:

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + v_t \tag{10}$$

They estimate $\hat{\alpha}$=-0.45, $\hat{\beta}$=0.15 and $\hat{\rho}$ between -0.2 and 0.2

The current study significantly updates the data set: 254 firms are included for which both dividends and net income were reported for every year during the interval 1952 - 1989. Screens were implemented to exclude banks, utilities, insurance companies, ADR's, limited partnerships and real estate investment trusts.
The results are as follows:

		1952-1989			
		$\hat{\alpha}$	$\hat{\beta}$	$\hat{\rho}$	$\hat{\sigma}$
	5	-.4833	-.0295	-.2455	.0826
	10	-.2829	-.0104	-.1070	.1598
	25	-.0789	-.0012	.0781	1.0004
Percentile	50	.0193	.0035	.2720	7.9760
	75	.1083	.0119	.4050	66.4139
	90	.1800	.0359	.5261	414.7019
	95	.2354	.0627	.5876	1644.3631
	Mean	.0437	.0308	.2310	3881.2000
	* Mode	.0198	.0011	.3338	384.0240
	Number	35	104	4	234

* Note: Estimates of the mode given here are obtained by dividing the range of the distribution into 500 bins of equal size. The mode is then given as the mid-point of the bin containing the most observations. That this method is particularly susceptible to the presence of outliers is obvious by comparing the mode of $\hat{\sigma}$ to the selected percentiles shown. Examination of the entire series reveals that 132 of the estimates of $\hat{\sigma}$ are less than 10.

Table IV.11

Fama and Babiak : Dividend Prediction Model
Subperiod 1: 263 firms with data spanning the years 1952-1970
Subperiod 2: 864 firms with data spanning the years 1971-1989

1952-1970

		$\hat{\alpha}$	$\hat{\beta}$	$\hat{\rho}$	$\hat{\sigma}$
Percentile	5	-.5490	-.0297	-.3934	.0055
	10	-.4094	-.0115	-.3205	.0126
	25	-.2328	.0016	-.1266	.0776
	50	-.0907	.0144	.0702	.5500
	75	.0301	.0415	.2592	3.8581
	90	.0939	.0855	.4126	19.3523
	95	.1483	.1340	.4623	46.2273
	Mean	-.1241	.0290	.0632	16.3529
	* Mode	.0287	.0112	.3707	1.4673
	Number	8	21	4	187

1971-1989

		$\hat{\alpha}$	$\hat{\beta}$	$\hat{\rho}$	$\hat{\sigma}$
Percentile	5	-.7766	-.0155	-.2766	.0000
	10	-.5118	-.0063	-.1479	.0013
	25	-.2260	.0000	.0000	.0306
	50	.0000	.0039	.1792	.5449
	75	.0885	.0128	.3570	11.2811
	90	.1869	.0331	.5129	196.0823
	95	.2554	.0590	.5907	768.1339
	Mean	.1120	.0228	.1713	6174.6181
	* Mode	.0627	.0109	.0013	1554.0890
	Number	309	657	70	841

* For the first subperiod 227 of the estimates of $\hat{\sigma}$ are below 10. In the second subperiod 642 of the estimates of $\hat{\sigma}$ are below 10.

Table IV.12

Stationarity of Simulated Dividends and Investment, T=38
Smirlock and Marshall Approach
Estimated Parameters from 1952-1989 as shown in Table IV.10
Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=37} = -2.95$
$DF_{\alpha=0.10,n=37} = -2.62$

Using Median of Estimated Parameters

		Dividends	Investment
	5	-4.5669*	-1.7478
	10	-5.0506*	-2.2351
	25	-5.9422*	-2.9442
Percentile	50	-6.9621*	-3.7121*
	75	-8.1714*	-4.4917*
	90	-9.5295*	-5.3032*
	95	-10.4544*	-5.8097*

Using Mode of Estimated Parameters

		Dividends	Investment
	5	-4.3620*	-1.6776
	10	-4.8904*	-2.1445
	25	-5.8416*	-2.8571
Percentile	50	-7.0090*	-3.6464*
	75	-8.4439*	-4.4368*
	90	-10.0154*	-5.2050*
	95	-11.0900*	-5.7403*

Using Mean of Estimated Parameters

		Dividends	Investment
	5	-3.1038*	-1.4304
	10	-3.5950*	-1.9432
	25	-5.7589*	-2.7088
Percentile	50	-9.1688*	-3.5302*
	75	-21.0546*	-4.3311*
	90	-418.5514*	-5.1701*
	95	-1239.9369*	-5.6840*

Table IV.13

Stationarity of Simulated Dividends and Investment, T=19
Smirlock and Marshall Approach
Estimated Parameters from 1952-1970 as shown in Table IV.11
Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=18} = -3.05$
$DF_{\alpha=0.10,n=18} = -2.67$

Using Median of Estimated Parameters

		Dividends	Investment
	5	-2.7880	-1.8402
	10	-3.0187	-2.1973
	25	-3.4530*	-2.8079
Percentile	50	-4.0140*	-3.4820*
	75	-4.6830*	-4.2608*
	90	-5.3830*	-5.0819*
	95	-5.9198*	-5.6530*

Using Mode of Estimated Parameters

		Dividends	Investment
	5	-2.8408	-2.7724
	10	-3.1149*	-3.0535*
	25	-3.5937*	-3.5875*
Percentile	50	-4.2277*	-4.2302*
	75	-4.9872*	-5.0106*
	90	-5.8221*	-5.8859*
	95	-6.3916*	-6.4388*

Using Mean of Estimated Parameters

		Dividends	Investment
	5	-2.3473	-2.6032
	10	-2.7809	-2.9487
	25	-3.8092*	-3.5199*
Percentile	50	-5.3204*	-4.1514*
	75	-6.9720*	-4.9017*
	90	-8.7590*	-5.6812*
	95	-10.0393*	-6.2508*

Table IV.14

Stationarity of Simulated Dividends and Investment, T=19
Smirlock and Marshall Approach
Estimated Parameters from 1971-1989 as shown in Table IV.11
Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=18} = -3.05$
$DF_{\alpha=0.10,n=18} = -2.67$

Using Median of Estimated Parameters

		Dividends	Investment
Percentile	5	-2.7061	-1.8098
	10	-2.9625	-2.1816
	25	-3.4010*	-2.7961
	50	-3.9728*	-3.4854*
	75	-4.6312*	-4.2495*
	90	-5.3290*	-5.0858*
	95	-5.8274*	-5.6454*

Using Mode of Estimated Parameters

		Dividends	Investment
Percentile	5	-2.5184	-2.6809
	10	-2.9159	-3.0108
	25	-3.7347*	-3.5861*
	50	-4.8799*	-4.2178*
	75	-6.2477*	-4.9731*
	90	-7.6627*	-5.7677*
	95	-8.5754*	-6.3148*

Using Mean of Estimated Parameters

		Dividends	Investment
Percentile	5	-1.9416	-2.4621
	10	-2.2879	-2.8052
	25	-3.7357*	-3.3660*
	50	-6.0516*	-4.0049*
	75	-11.8095*	-4.7605*
	90	-231.3182*	-5.5144*
	95	-1256.8081*	-6.0646*

Table IV.15

Simulated Dividends and Investment, T=38
Smirlock and Marshall Approach
Estimated Parameters from 1952-1989 as shown in Table IV.10
F-Statistics from Granger Causality Tests

Critical Value of $F_{\alpha=0.05,2,29} = 3.33$
$F_{\alpha=0.10,2,29} = 2.49$

Using Median of Estimated Parameters

		Dividends	Investment
	5	0.0375	0.0372
	10	0.0772	0.0766
	25	0.2131	0.2121
Percentile	50	0.5389	0.5139
	75	1.1852	1.0961
	90	2.1874	1.9658
	95	3.0217	2.7646

Using Mode of Estimated Parameters

		Dividends	Investment
	5	0.0283	0.0372
	10	0.0621	0.0755
	25	0.1705	0.2052
Percentile	50	0.4288	0.4960
	75	0.9306	1.0853
	90	1.7717	2.0248
	95	2.5223	2.8740

Using Mean of Estimated Parameters

		Dividends	Investment
	5	0.0220	0.0205
	10	0.0447	0.0426
	25	0.1131	0.1139
Percentile	50	0.2295	0.2351
	75	0.3945	0.3849
	90	0.5845	0.6161
	95	0.7375	1.0379

Table IV.16

Simulated Dividends and Investment, T=19
Smirlock and Marshall Approach
Estimated Parameters from 1952-1970 as shown in Table IV.11
F-Statistics from Granger Causality Tests

Critical Value of $F_{\alpha=0.05,2,10} = 4.10$
$F_{\alpha=0.10,2,10} = 2.93$

Using Median of Estimated Parameters

		Dividends	Investment
	5	0.0553	0.0546
	10	0.1105	0.1130
	25	0.3101	0.3204
Percentile	50	0.7824	0.7781
	75	1.6599	1.6207
	90	2.9919	2.9717
	95	4.1889*	4.0680

Using Mode of Estimated Parameters

		Dividends	Investment
	5	0.0501	0.0561
	10	0.1063	0.1221
	25	0.2943	0.3252
Percentile	50	0.7185	0.8133
	75	1.5274	1.7579
	90	2.6967	3.2203
	95	3.8389	4.4686*

Using Mean of Estimated Parameters

		Dividends	Investment
	5	0.0519	0.0237
	10	0.1030	0.0507
	25	0.2737	0.1739
Percentile	50	0.6699	0.6516
	75	1.3702	2.0747
	90	2.3937	4.3541*
	95	3.3116	6.4463*

Table IV.17

Simulated Dividends and Investment, T=19
Smirlock and Marshall Approach
Estimated Parameters from 1971-1989 as shown in Table IV.11
F-Statistics from Granger Causality Tests

Critical Value of $F_{\alpha=0.05,2,10} = 4.10$
$F_{\alpha=0.10,2,10} = 2.93$

Using Median of Estimated Parameters

		Dividends	Investment
	5	0.0536	0.0521
	10	0.1054	0.1097
	25	0.3039	0.3049
Percentile	50	0.7442	0.7703
	75	1.6212	1.6245
	90	2.9541	2.9212
	95	4.1061*	4.0601

Using Mode of Estimated Parameters

		Dividends	Investment
	5	0.0523	0.0375
	10	0.1055	0.0767
	25	0.2879	0.2390
Percentile	50	0.6908	0.7906
	75	1.4006	2.1397
	90	2.4884	4.3031*
	95	3.3898	6.3578*

Using Mean of Estimated Parameters

		Dividends	Investment
	5	0.0489	0.0118
	10	0.1019	0.0251
	25	0.2689	0.0690
Percentile	50	0.6211	0.1974
	75	1.2686	0.6212
	90	2.2050	1.6635
	95	3.0245	2.8453

Table IV.18

Empirical Test for Dividend-Investment Causality, T=37
Levels of Variables, 220 Firms
Sample Period 1953-1989

Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=37} = -2.95$
$DF_{\alpha=0.10,n=37} = -2.62$

		Dividends	Investment
	5	4.3022	-2.1104
	10	3.5041	-3.0036*
	25	2.0110	-3.8117*
Percentile	50	0.2742	-4.9418*
	75	-1.4732	-6.1566*
	90	-2.3038	-7.2188*
	95	-2.9957*	-7.4573*

F-Statistics

Critical Value of $F_{\alpha=0.05,2,30} = 3.33$
$F_{\alpha=0.10,2,30} = 2.49$

		Dividends	Investment
	5	0.1342	0.0836
	10	0.2880	0.2201
	25	0.7412	0.6304
Percentile	50	2.0937	1.9333
	75	4.7375*	4.7497*
	90	9.0015*	12.7004*
	95	12.3020*	17.6219*

Table IV.19

Empirical Test for Dividend-Investment Causality, T=37
Differenced Variables, 220 Firms
Sample Period 1953-1989

Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=36} = -2.95$
$DF_{\alpha=0.10,n=36} = -2.62$

		Dividends	Investment
	5	1.4755	-4.2513*
	10	0.1732	-4.8103*
	25	-1.2583	-6.0326*
Percentile	50	-2.9255	-7.0639*
	75	-3.9531*	-8.6787*
	90	-5.1261*	-10.1299*
	95	-6.6050*	-11.1540*

F-Statistics

Critical Value of $F_{\alpha=0.05,2,29} = 3.33$
$F_{\alpha=0.10,2,29} = 2.49$

		Dividends	Investment
	5	0.1209	0.0538
	10	0.2220	0.1785
	25	0.6941	0.6962
Percentile	50	1.7463	2.1340
	75	3.5787*	4.9604*
	90	6.8876*	13.2539*
	95	11.3105*	18.0144*

Table IV.20

Empirical Test for Dividend-Investment Causality, T=37
Differenced Variables, Total of 220 Firms
Sample Period 1953-1989, Firms Segmented by Stationarity

Critical Value of $DF_{\alpha=0.05,n=36} = -2.95$
$DF_{\alpha=0.10,n=36} = -2.62$

Critical Value of $F_{\alpha=0.05,2,29} = 3.33$
$F_{\alpha=0.10,2,29} = 2.49$

Firms with DF ≤ -2.95 for Both Series

		F-Statistics	
		Dividends	Investment
	5	0.1218	0.0538
	10	0.2220	0.1686
	25	0.5138	0.6962
Percentile	50	1.5342	2.4811
	75	3.6759*	5.1046*
	90	6.4768*	13.5594*
	95	9.4618*	27.9175*

Firms with DF > -2.95 for Either Series

		F-Statistics	
		Dividends	Investment
	5	0.1111	0.0451
	10	0.2013	0.2001
	25	0.8818	0.6271
Percentile	50	1.8486	1.8833
	75	3.3448*	4.2910*
	90	6.8017*	12.4258*
	95	11.3105*	15.2892*

Table IV.21

Listing of Firms Exhibiting Dividend→Investment Causality

Critical Value of $F_{\alpha=0.05,2,27} = 3.33$

Sample Period 1953-1989

Company Name	Industry Group	F-Statistic
GOODYEAR TIRE & RUBBER CO	TIRES AND INNER TUBES	23.8718
MOBIL CORP	PETROLEUM REFINING	21.0896
STONE CONTAINER CORP	PAPERBOARD MILLS	19.0714
MAYTAG CORP	HOUSEHOLD APPLIANCES	18.4846
WESTINGHOUSE ELECTRIC CORP	AIR COND,HEATING,REFRIG EQ	16.3007
PENNEY (J.C.) CO	DEPARTMENT STORES	15.1648
ATLANTIC RICHFIELD CO	PETROLEUM REFINING	15.0784
BRISTOL MYERS SQUIBB	PHARMACEUTICAL PREPARATIONS	14.3344
RUBBERMAID INC	PLASTICS PRODUCTS, NEC	13.9674
ARMSTRONG WORLD INDS INC	ABRASIVE,ASBESTOS,MISC MINRL	13.6233
WESTERN UNION CORP-NEW	TELEGRAPH & OTH MESSAGE COMM	12.2324
KROGER CO	GROCERY STORES	11.3105
PITTSTON CO	ARRANGE TRANS-FREIGHT, CARGO	10.2205
WINN-DIXIE STORES INC	GROCERY STORES	9.5607
SAFEWAY INC	GROCERY STORES	9.4618
CHEVRON CORP	PETROLEUM REFINING	8.3954
XEROX CORP	PHOTOGRAPHIC EQUIP & SUPPL	8.3527
RALSTON PURINA CO	GRAIN MILL PRODUCTS	8.1239
AMAX INC	PRIM PRODUCTION OF ALUMINUM	7.7993
FMC CORP	CHEMICALS & ALLIED PRODS	7.5007
AMOCO CORP	PETROLEUM REFINING	7.4169

Table IV.21 Continued

Company Name	Industry Group	F-Statistic
WOOLWORTH CORP	VARIETY STORES	6.9830
NAVISTAR INTERNATIONAL	MOTOR VEHICLES & CAR BODIES	6.8876
FEDERAL PAPER BOARD CO	PAPERBOARD MILLS	6.8017
STANDARD REGISTER CO	MANIFOLD BUSINESS FORMS	6.5244
GERBER PRODUCTS CO	CAN,FROZNPRESRV FRUIT & VEG	6.4768
DANA CORP	MOTOR VEHICLE PART,ACCESSORY	6.4358
KELLOGG CO	GRAIN MILL PRODUCTS	6.3921
MOTOROLA INC	RADIO,TV BROADCAST, COMM EQ	6.3672
FORD MOTOR CO	MOTOR VEHICLES & CAR BODIES	5.9053
MEAD CORP	PAPER AND ALLIED PRODUCTS	5.6400
GATX CORP	TRANSPORTATION SERVICES	5.0330
DOMTAR INC	PAPER MILLS	5.0210
ETHYL CORP	CHEMICALS & ALLIED PRODS	5.0065
PROCTER & GAMBLE CO	SOAP,DETERGENT,TOILET PREPS	4.9738
POLAROID CORP	PHOTOGRAPHIC EQUIP & SUPPL	4.9265
GENERAL ELECTRIC CO	ELECTR, OTH ELEC EQ, EX CMP	4.9171
EAGLE-PICHER INDS	MOTOR VEHICLE PART,ACCESSORY	4.7421
COMINCO LTD	PRIM SMELT,REFIN NONFER METL	4.6039
EDISON BROTHERS STORES	SHOE STORES	4.4718
EXXON CORP	PETROLEUM REFINING	4.4625
DIEBOLD INC	CALCULATE,ACCT MACH,EX COMP	4.4267
QUAKER OATS CO	FOOD AND KINDRED PRODUCTS	4.3980
KENNAMETAL INC	METALWORKING MACHINERY & EQ	4.3527
GRACE (W.R.) & CO	CHEMICALS & ALLIED PRODS	4.2081
SUN CO INC	PETROLEUM REFINING	4.1501
UNISYS CORP	COMPUTER & OFFICE EQUIPMENT	4.0931
GREYHOUND DIAL CORP	EATING PLACES	3.9822
MINNESOTA MINING & MFG CO	CONVRT PAPR,PAPRBRD,EX BOXES	3.9794
BLACK & DECKER CORP	METALWORKING MACHINERY & EQ	3.9555

Table IV.21 Continued

Company Name	Industry Group	F-Statistic
ALCAN ALUMINIUM LTD	PRIM PRODUCTION OF ALUMINUM	3.7500
ASARCO INC	PRIM SMELT,REFIN NONFER METL	3.6759
HERCULES INC	CHEMICALS & ALLIED PRODS	3.6193
HOMESTAKE MINING	GOLD AND SILVER ORES	3.6031
ABBOTT LABORATORIES	PHARMACEUTICAL PREPARATIONS	3.5988
TIMKEN CO	BALL AND ROLLER BEARINGS	3.5787
CROMPTON & KNOWLES CORP	INDUSTRIAL ORGANIC CHEMICALS	3.5512
USG CORP	CONCRETE, GYPSUM AND PLASTER	3.5278
CATERPILLAR INC	CONSTRUCTION MACHINERY & EQ	3.3685
WEST POINT-PEPPERELL	BRDWOVEN FABRIC MILL, COTTON	3.3448
AMETEK INC	INDUSTRIAL MEASUREMENT INSTR	3.3327

Figure IV.1

Simulated Dividend Series, T=20

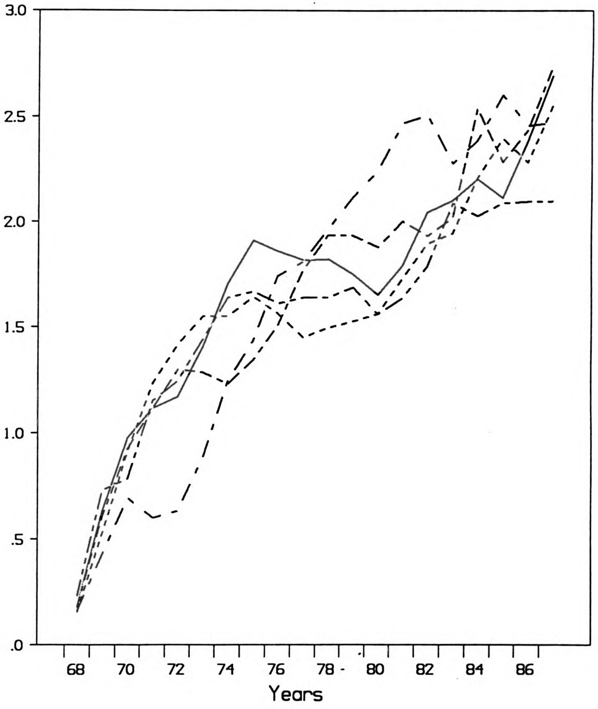
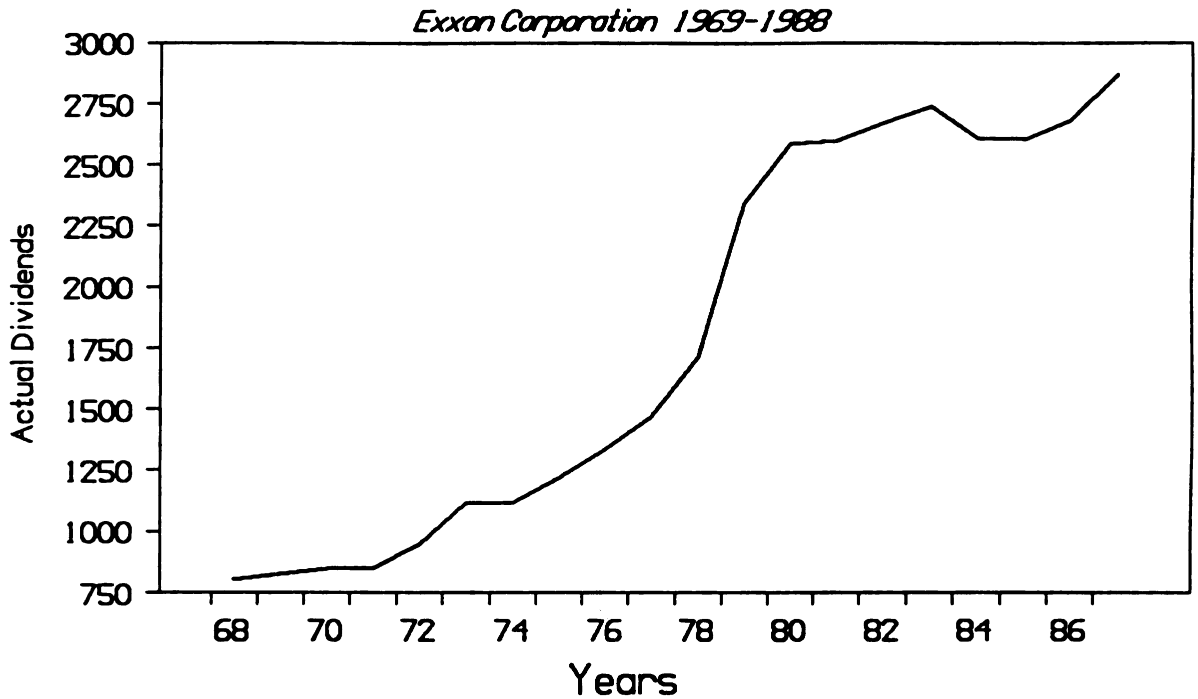


Figure IV.2

Actual Dividend Series, T=20



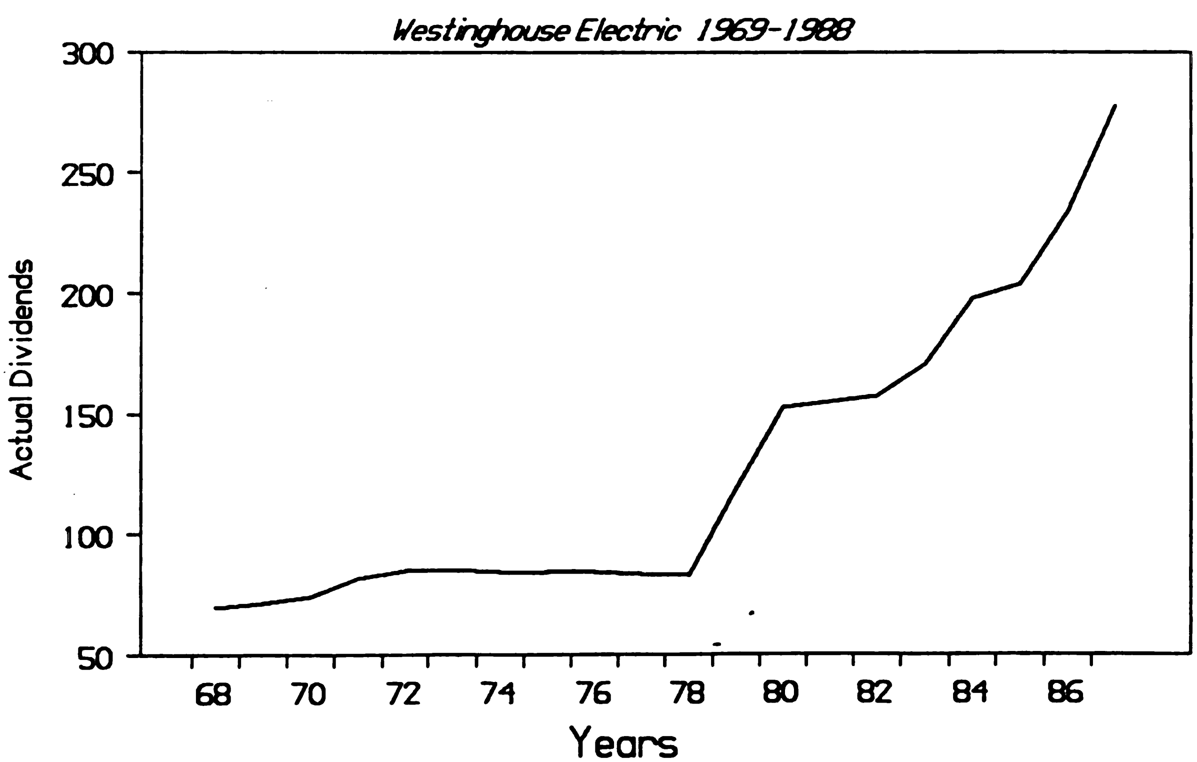


Figure IV.3

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\alpha}$ for 1952 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

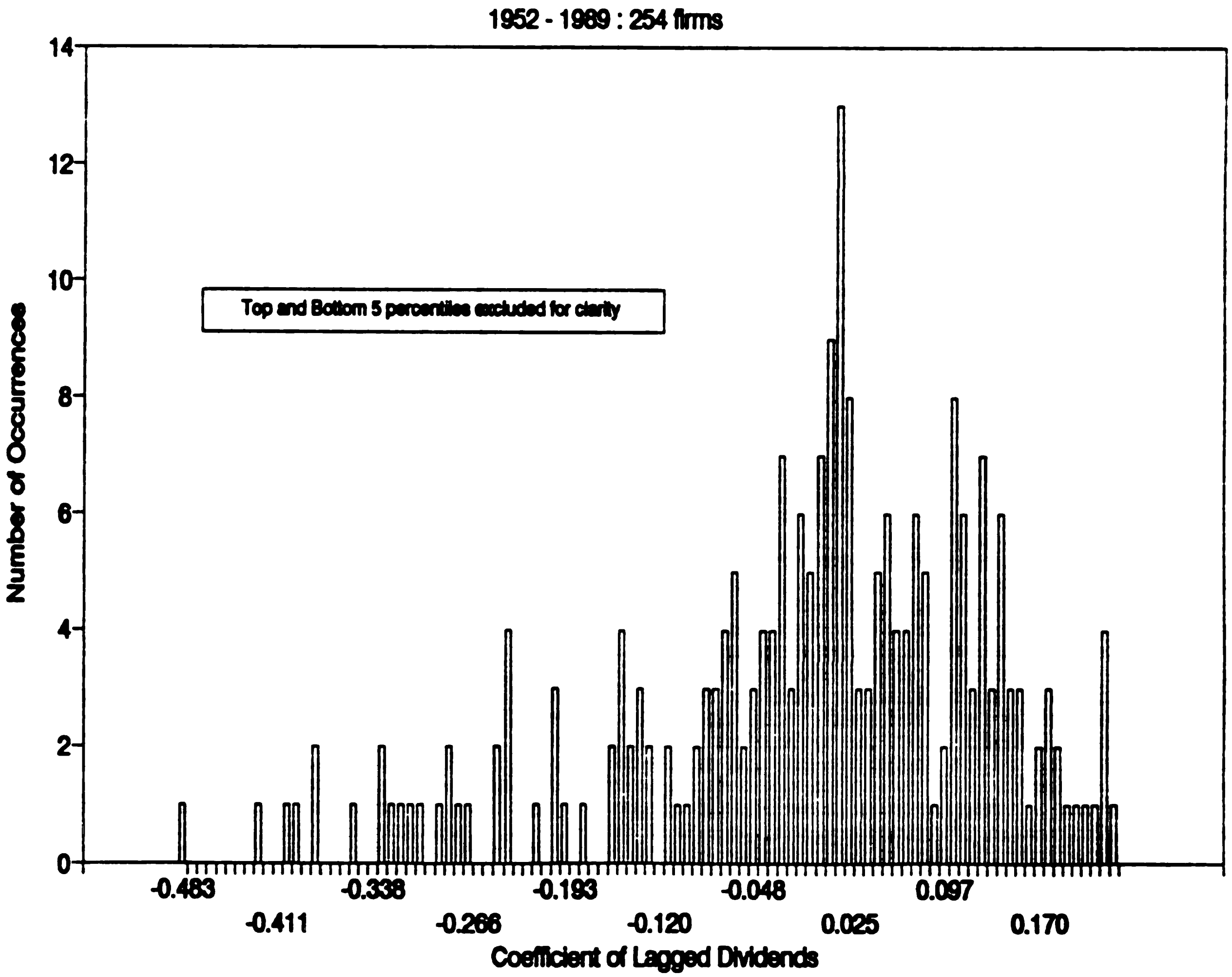


Figure IV.4

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\beta}$ for 1952 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

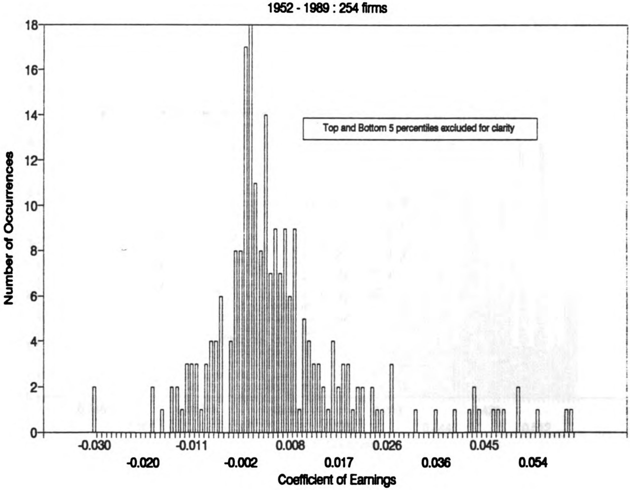


Figure IV.5

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\rho}$ for 1952 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

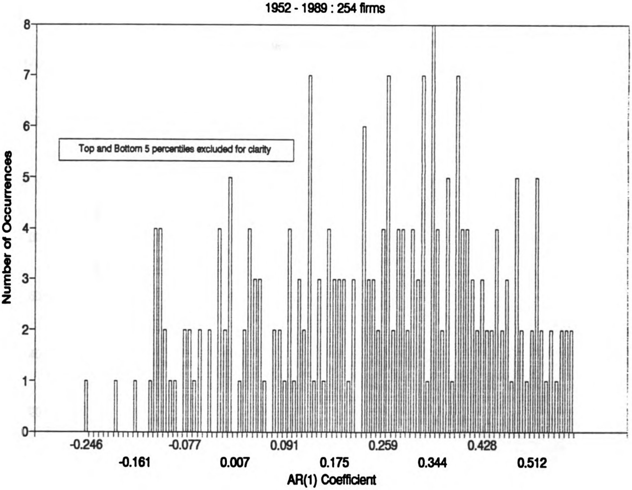


Figure IV.6

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\sigma}$ for 1952 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

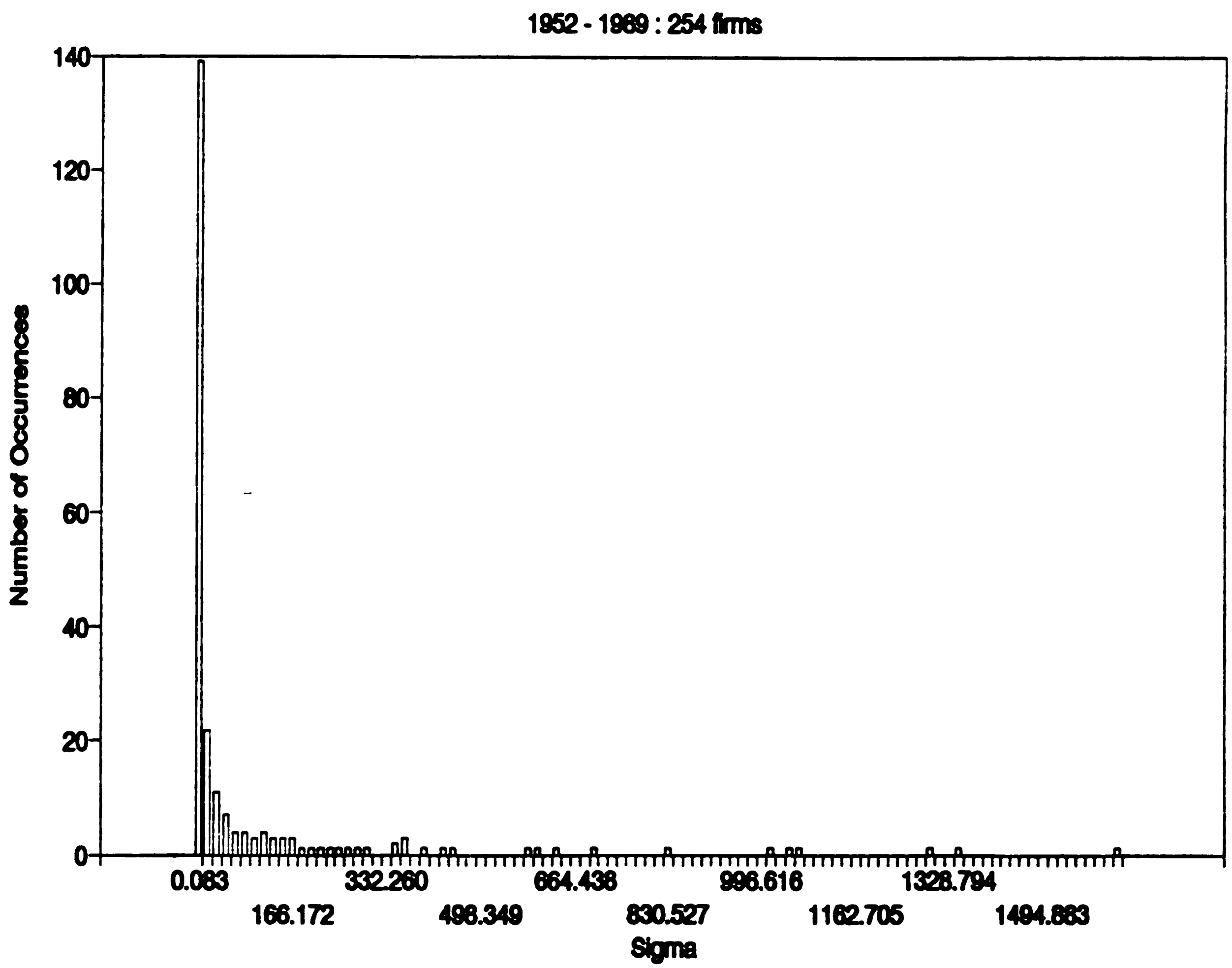


Figure IV.7

Estimation of Fama and Babiak Dividend Prediction Model Frequency Histogram of $\hat{\alpha}$ for 1952 - 1970

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

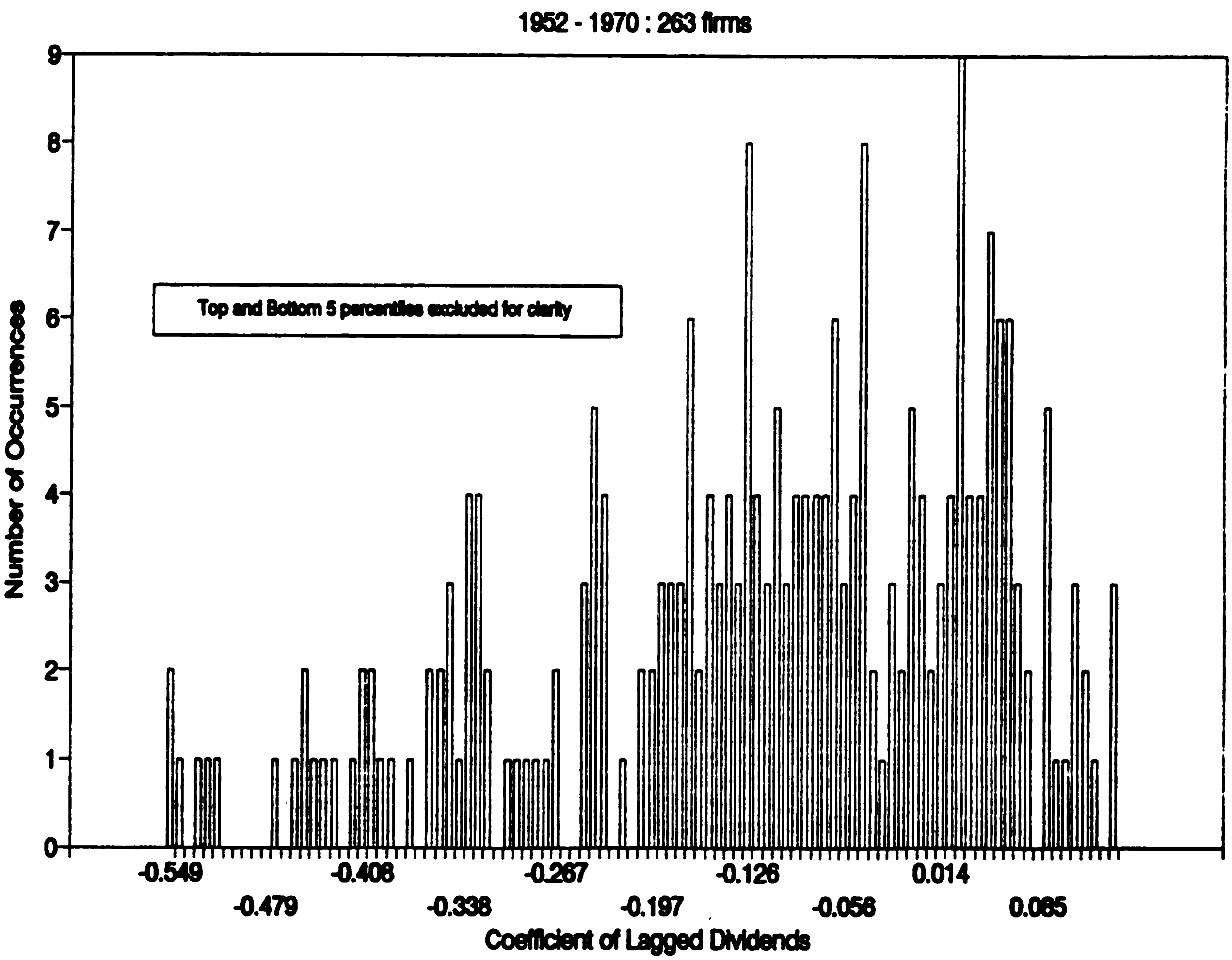


Figure IV.8

Estimation of Fama and Babiak Dividend Prediction Model Frequency Histogram of $\hat{\beta}$ for 1952 - 1970

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \qquad (9)$$

$$u_t = \rho u_{t-1} + \nu_t \qquad (10)$$

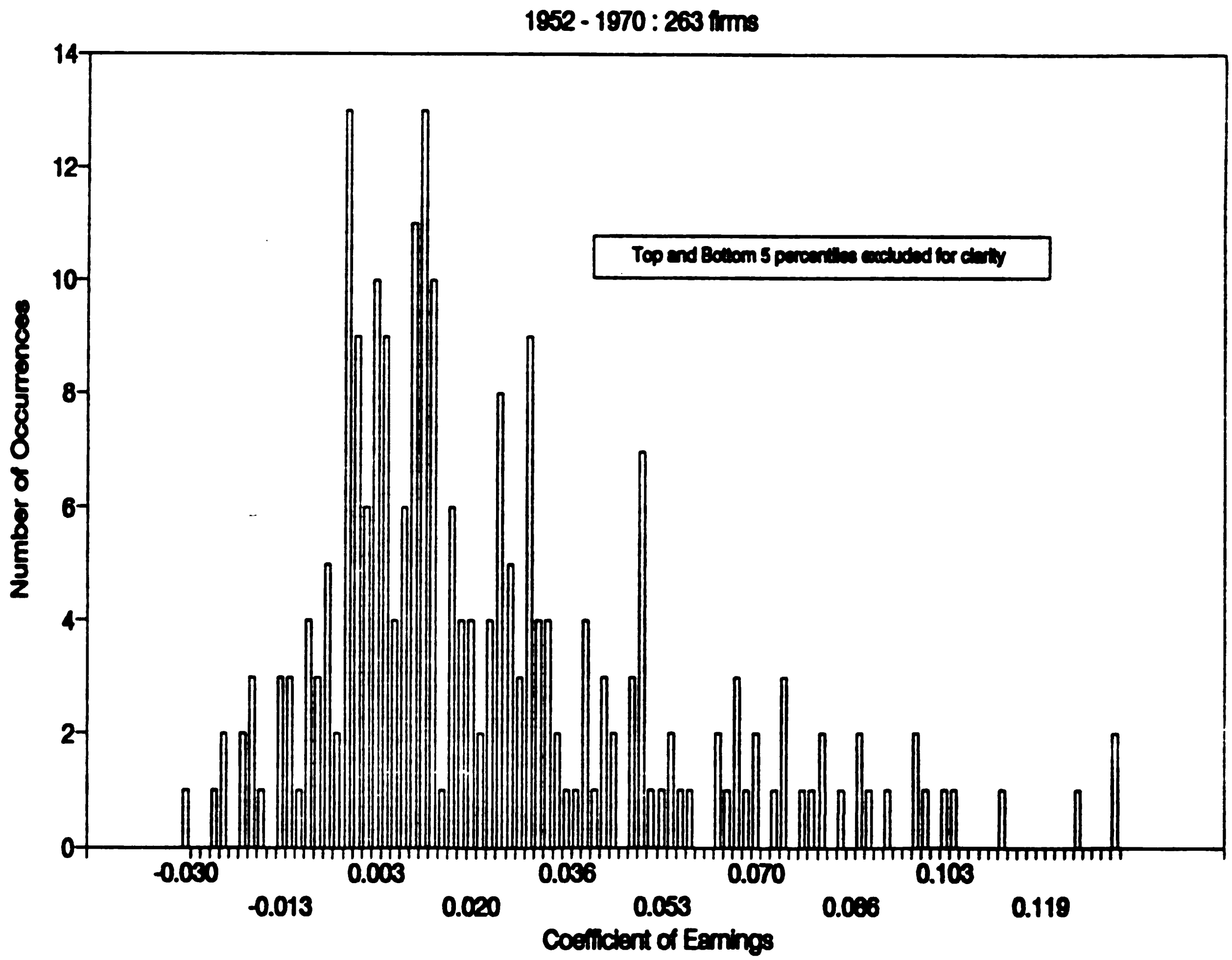


Figure IV.9

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\rho}$ for 1952 - 1970

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

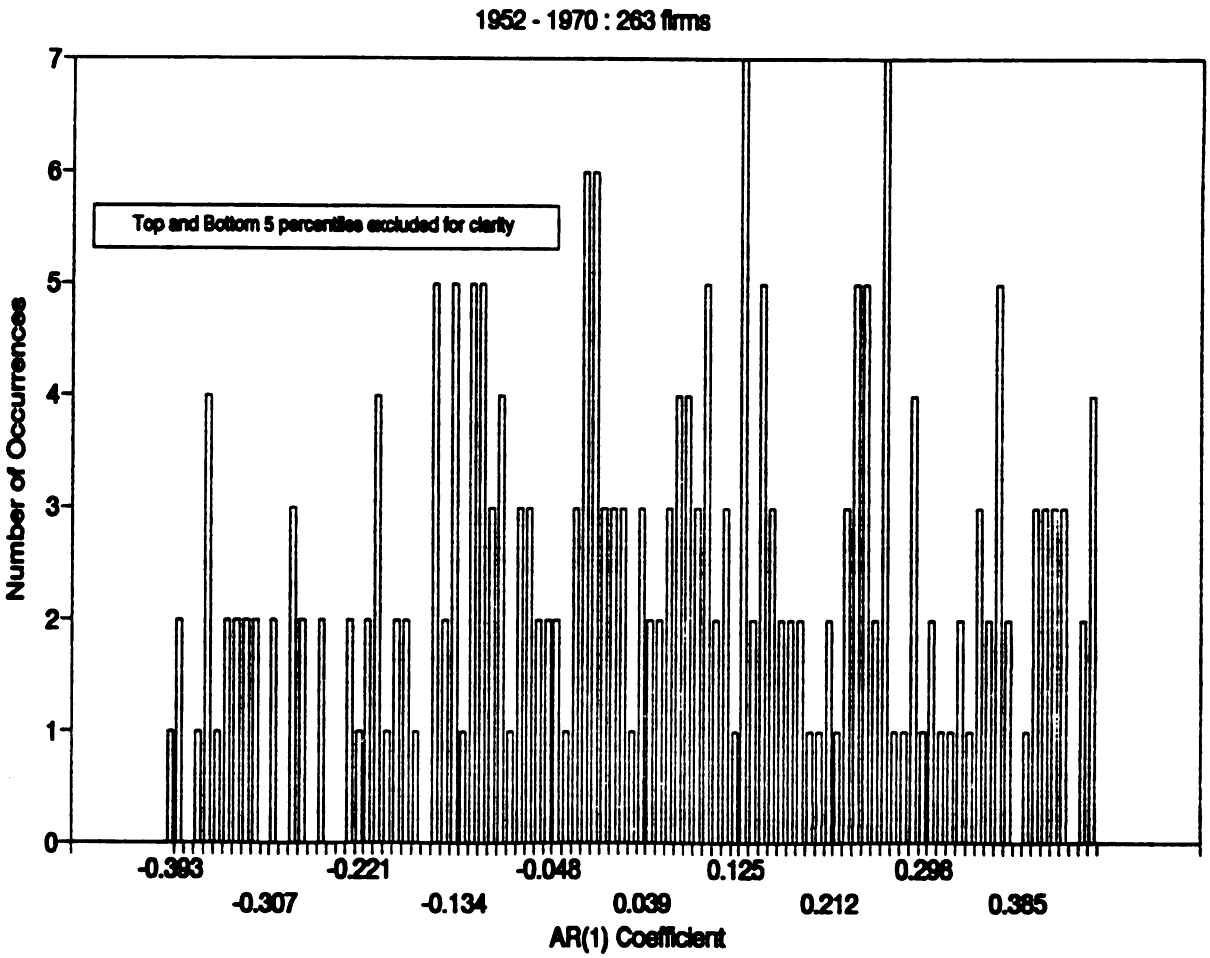


Figure IV.10

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\sigma}$ for 1952 - 1970

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \qquad (9)$$

$$u_t = \rho u_{t-1} + \nu_t \qquad (10)$$

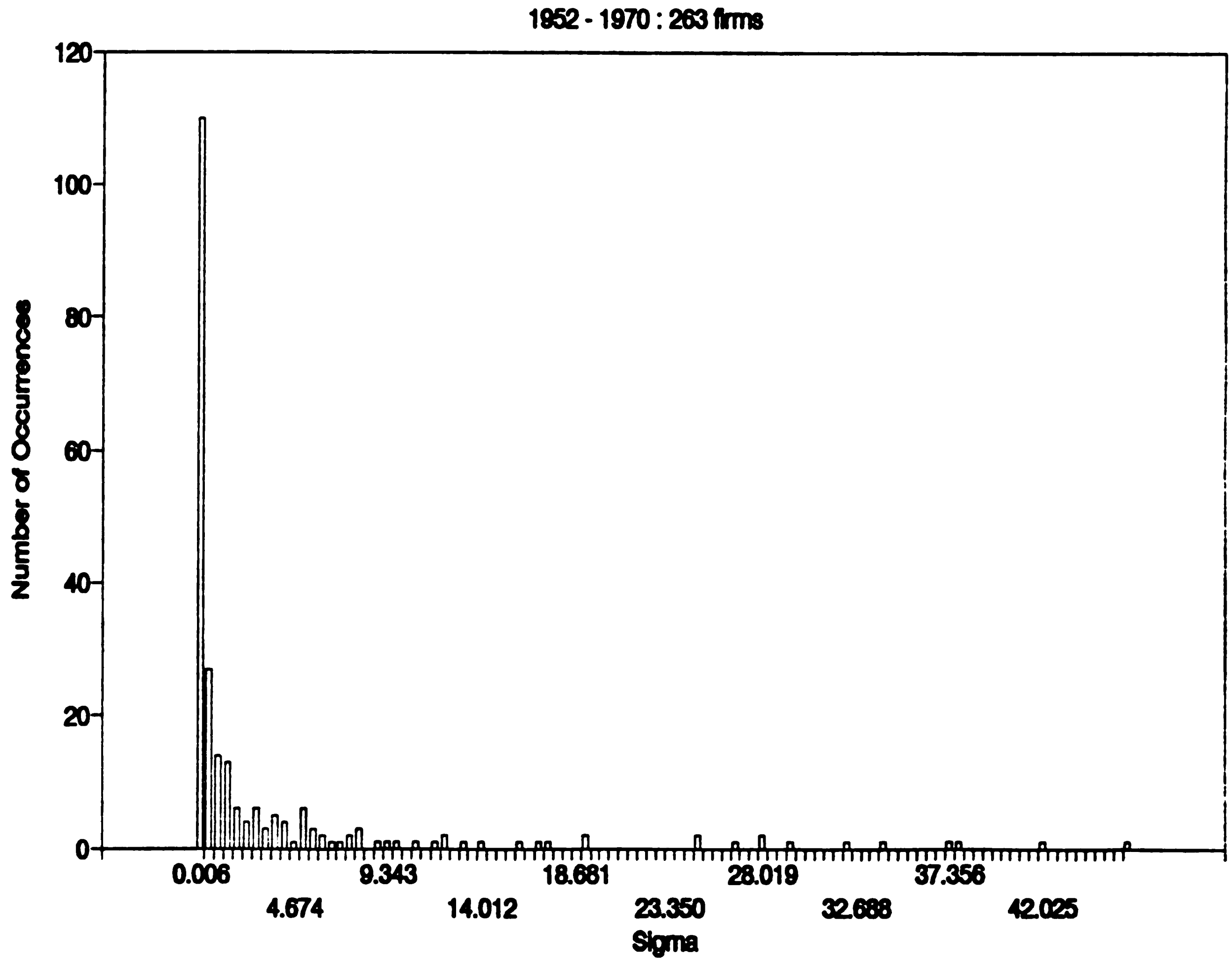


Figure IV.11

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\alpha}$ for 1971 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

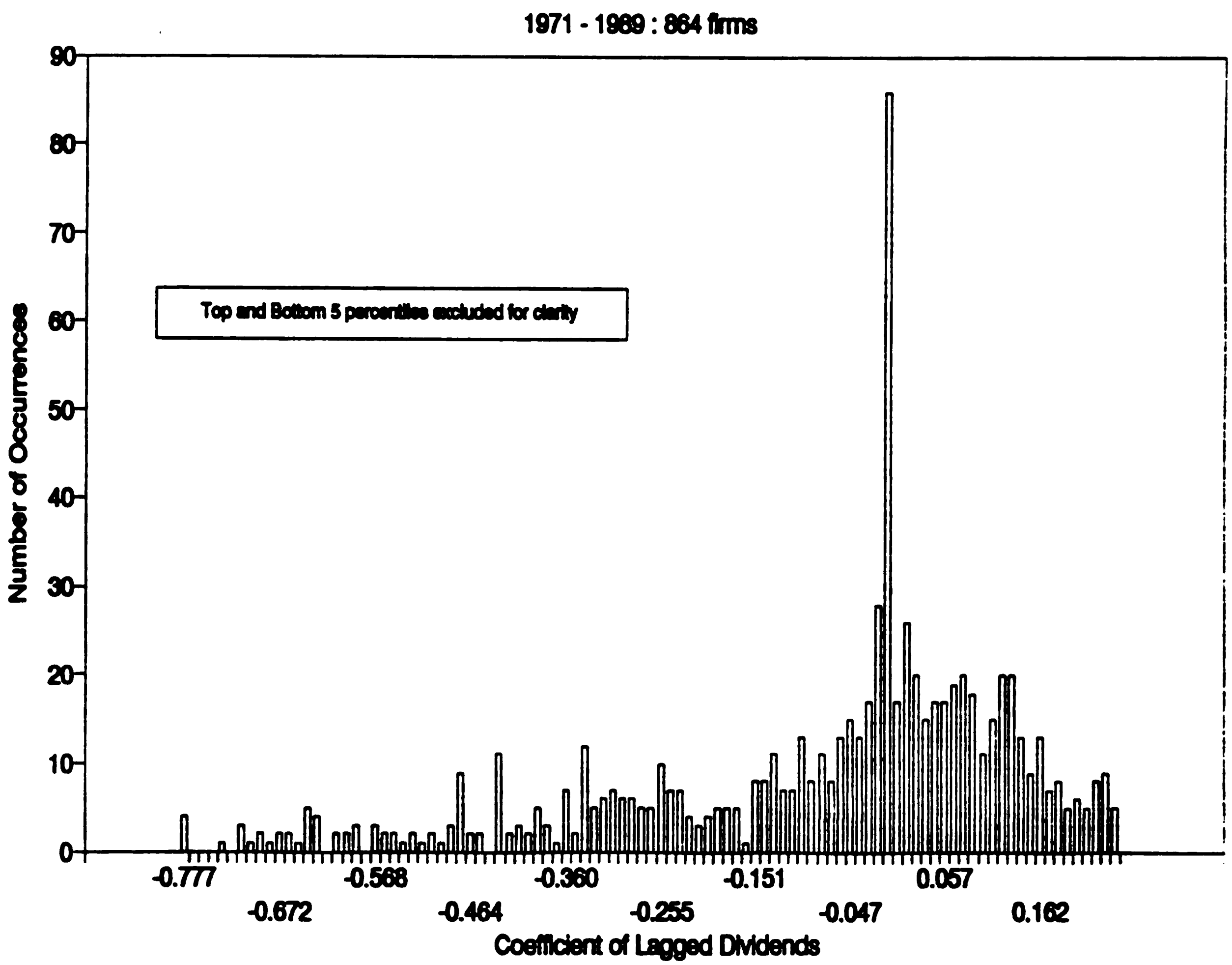


Figure IV.12

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\beta}$ for 1971 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \qquad (9)$$

$$u_t = \rho u_{t-1} + \nu_t \qquad (10)$$

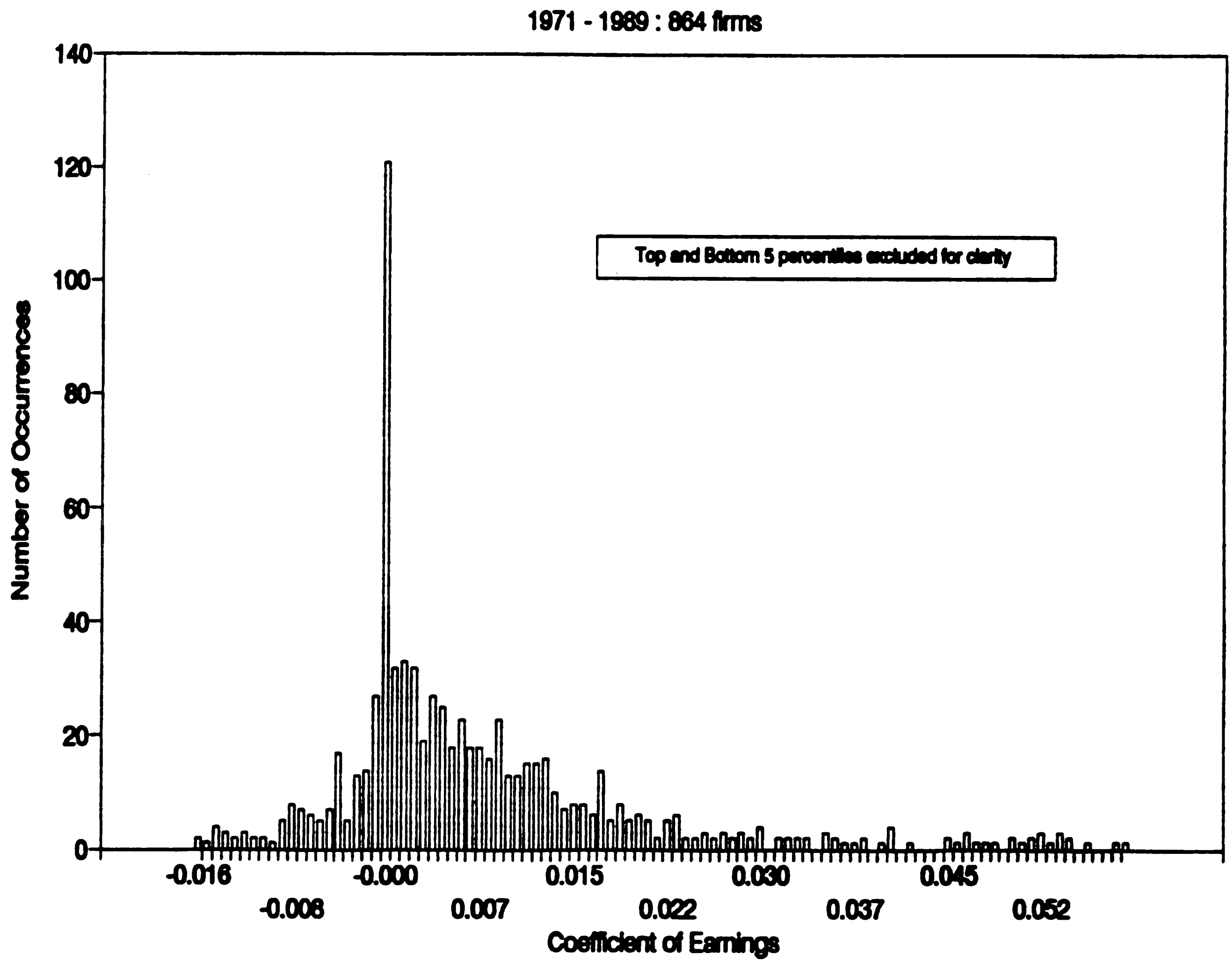


Figure IV.13

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\rho}$ for 1971 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

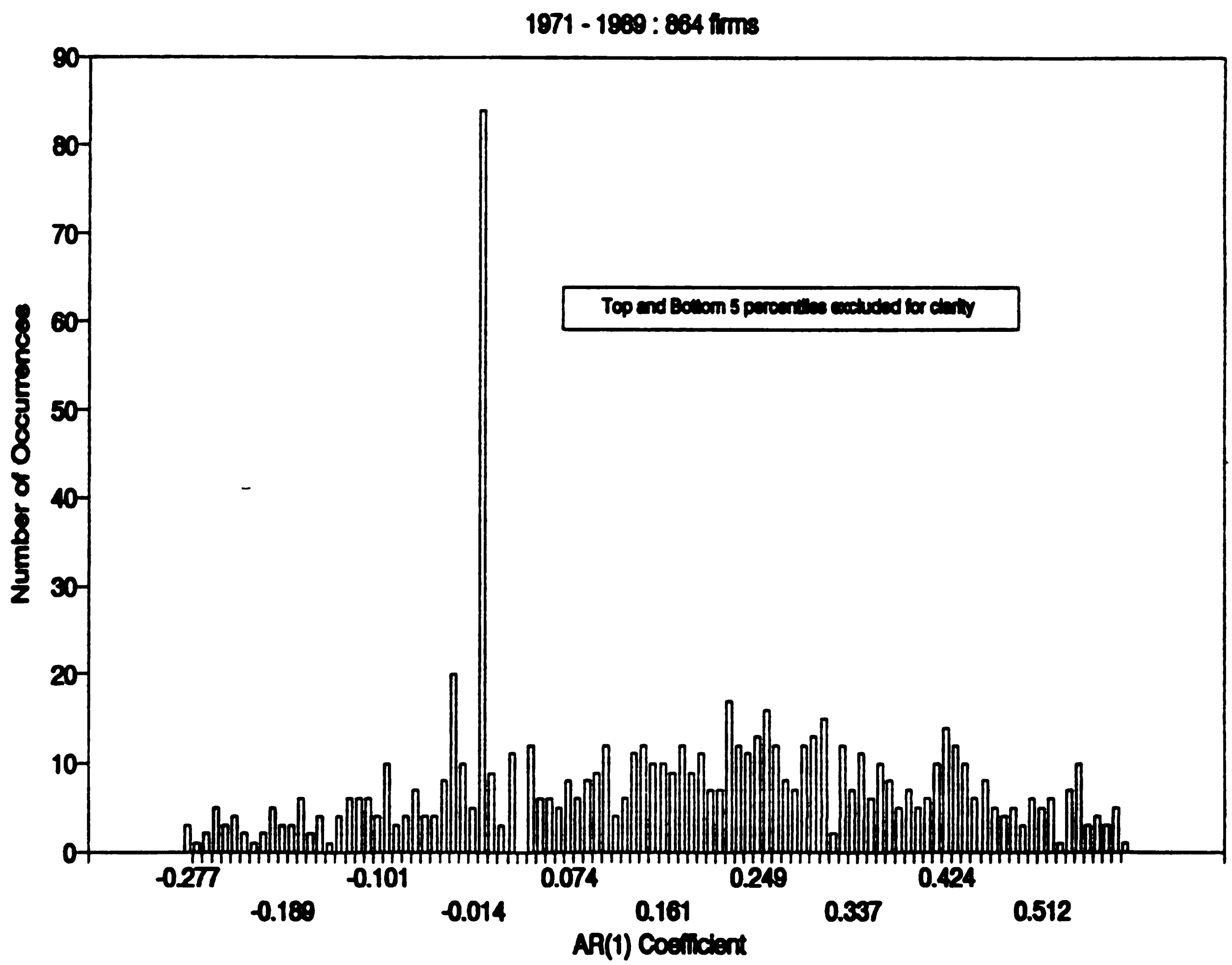


Figure IV.14

Estimation of Fama and Babiak Dividend Prediction Model
Frequency Histogram of $\hat{\sigma}$ for 1971 - 1989

$$D_t - D_{t-1} = \alpha D_{t-1} + \beta E_t + u_t \tag{9}$$

$$u_t = \rho u_{t-1} + \nu_t \tag{10}$$

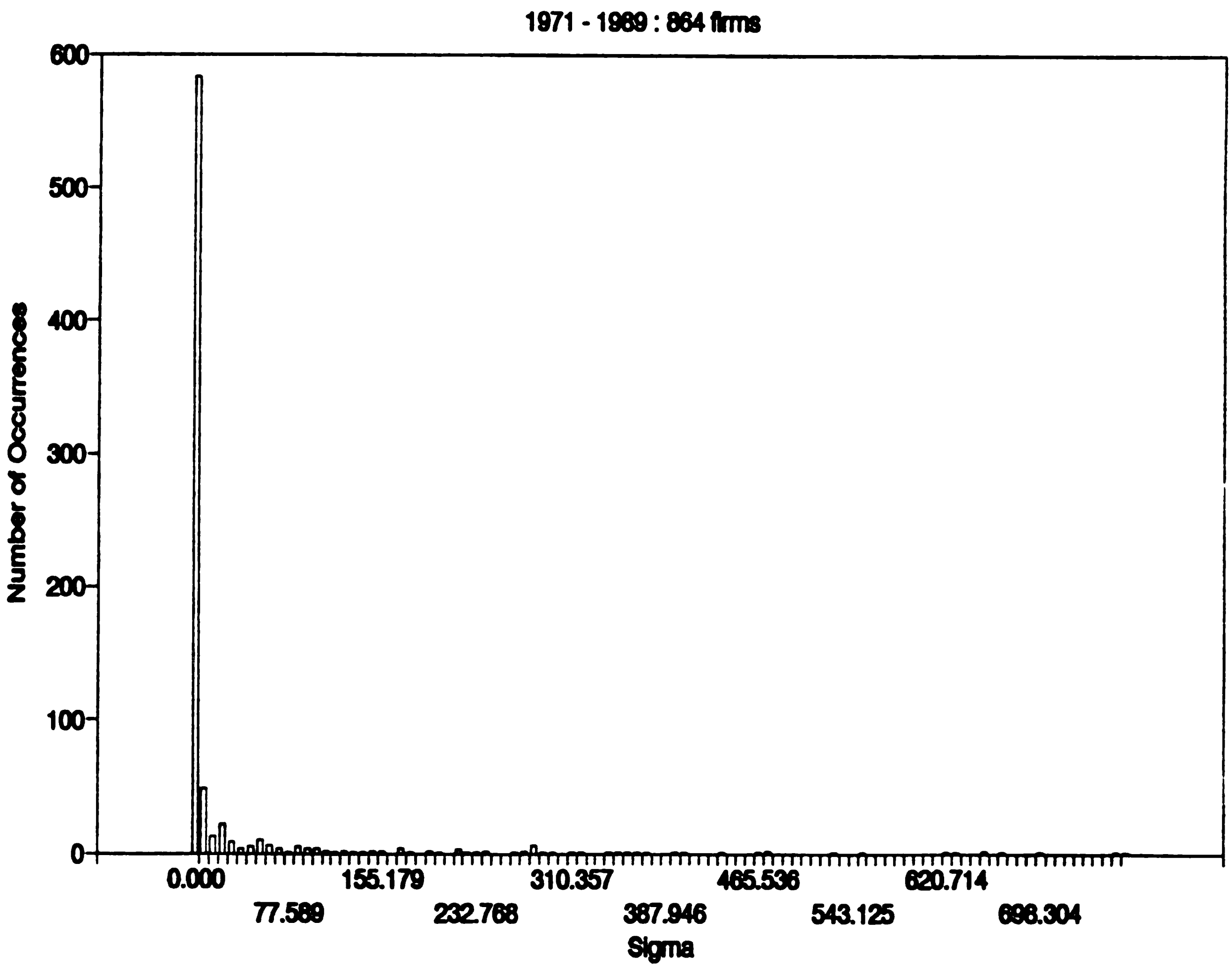


Figure IV.15

**Significance of Dividends in Explaining Investment
Simulation Using Median of Estimated Parameters from 1952-1989
Differenced Series, T=37
Block F Test for Exclusion of Dividends**

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

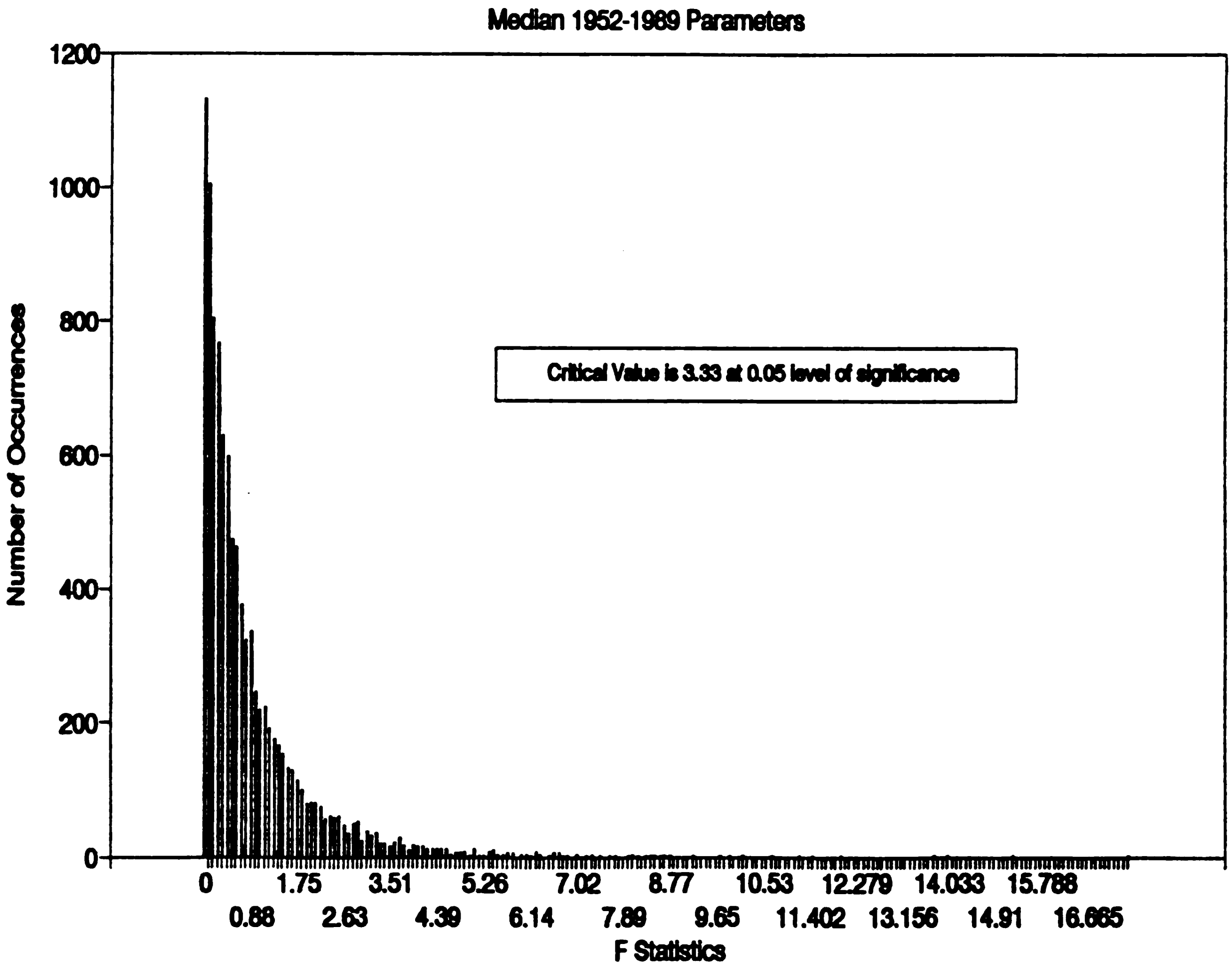


Figure IV.16

Significance of Investment in Explaining Dividends
Simulation Using Median of Estimated Parameters from 1952-1989
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

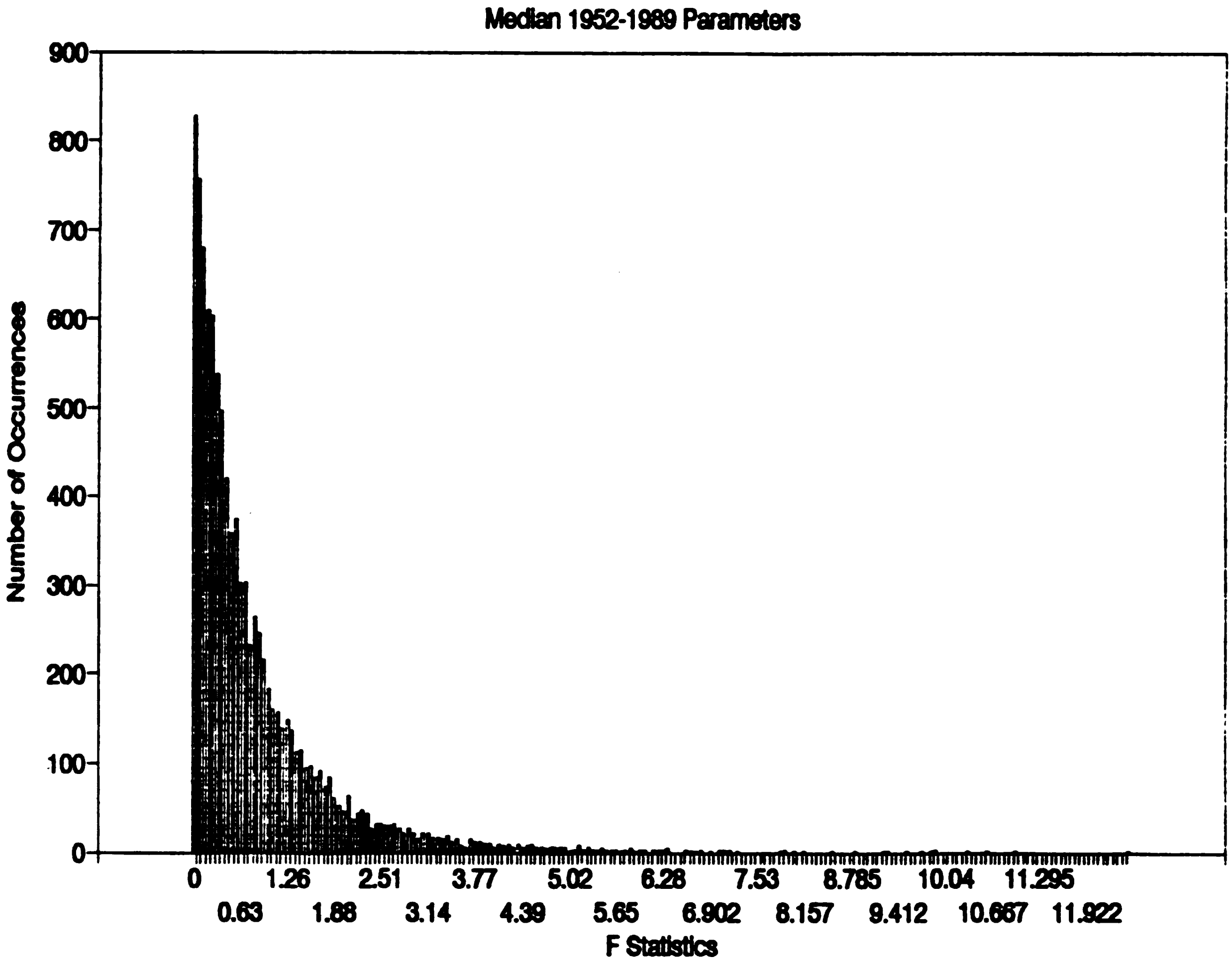


Figure IV.17

Significance of Dividends in Explaining Investment
Simulation Using Mode of Estimated Parameters from 1952-1989
Differenced Series, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \qquad (6)$$

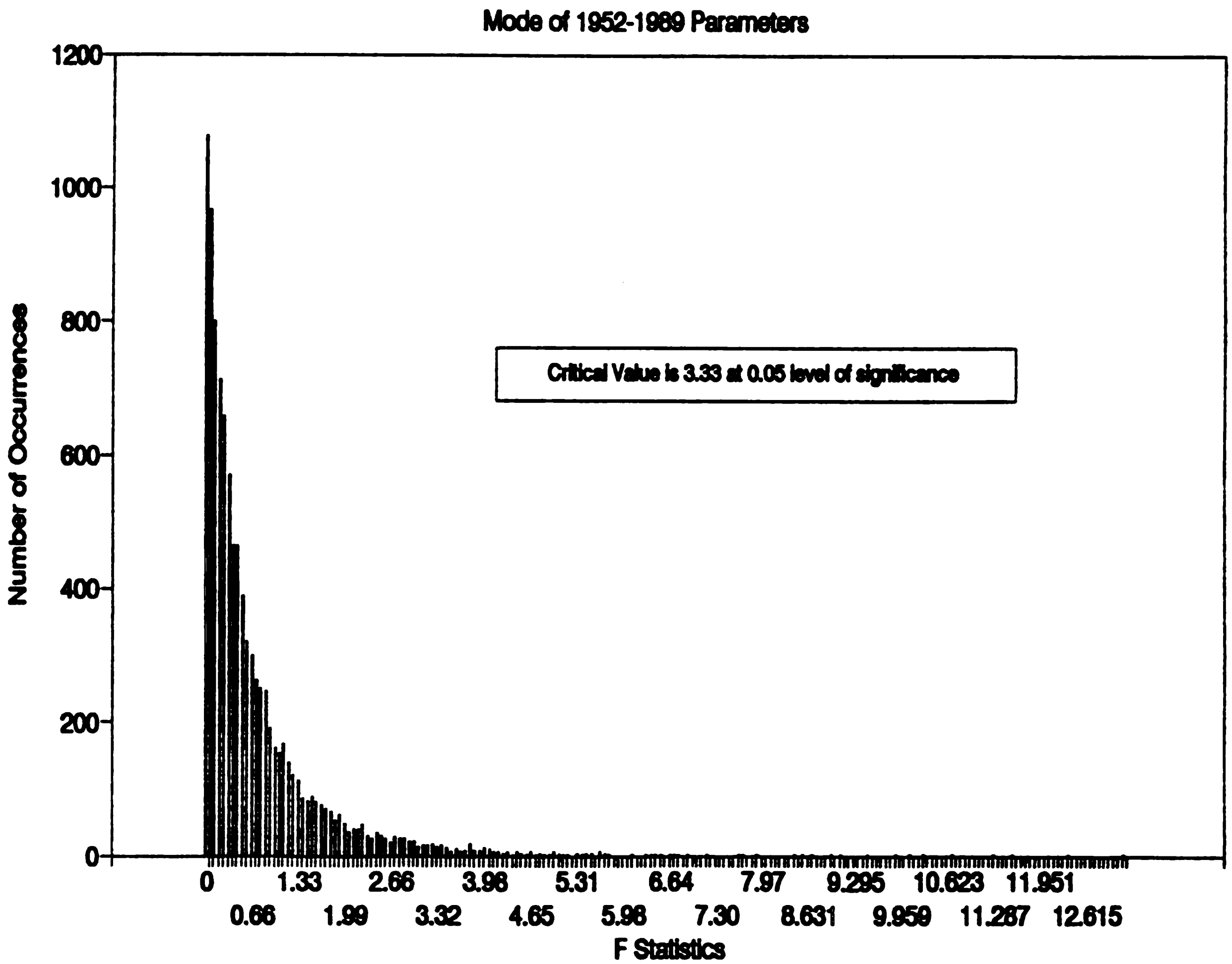


Figure IV.18

Significance of Investment in Explaining Dividends
Simulation Using Mode of Estimated Parameters from 1952-1989
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

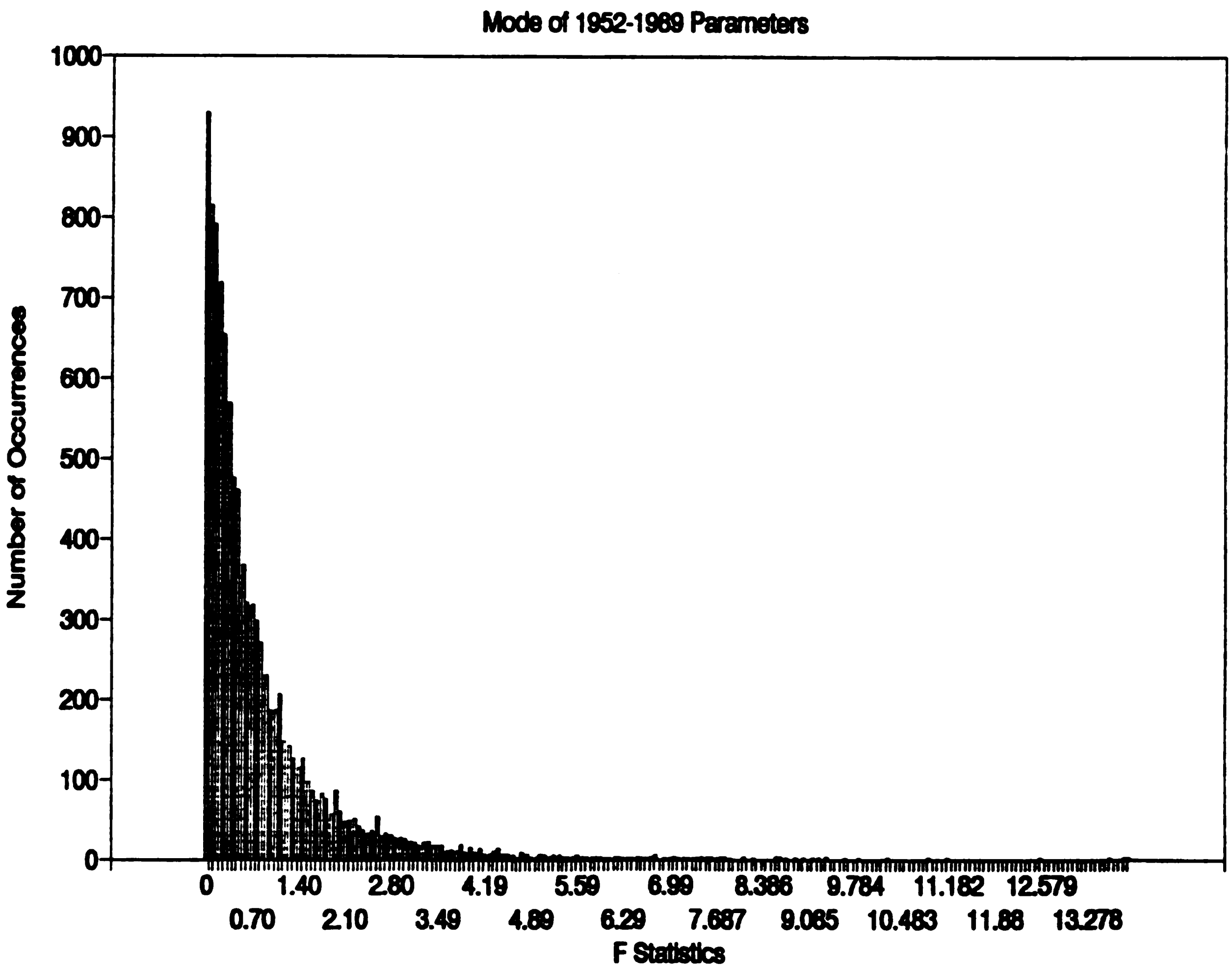


Figure IV.19

Significance of Dividends in Explaining Investment
Simulation Using Mean of Estimated Parameters from 1952-1989
Differenced Series, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \qquad (6)$$

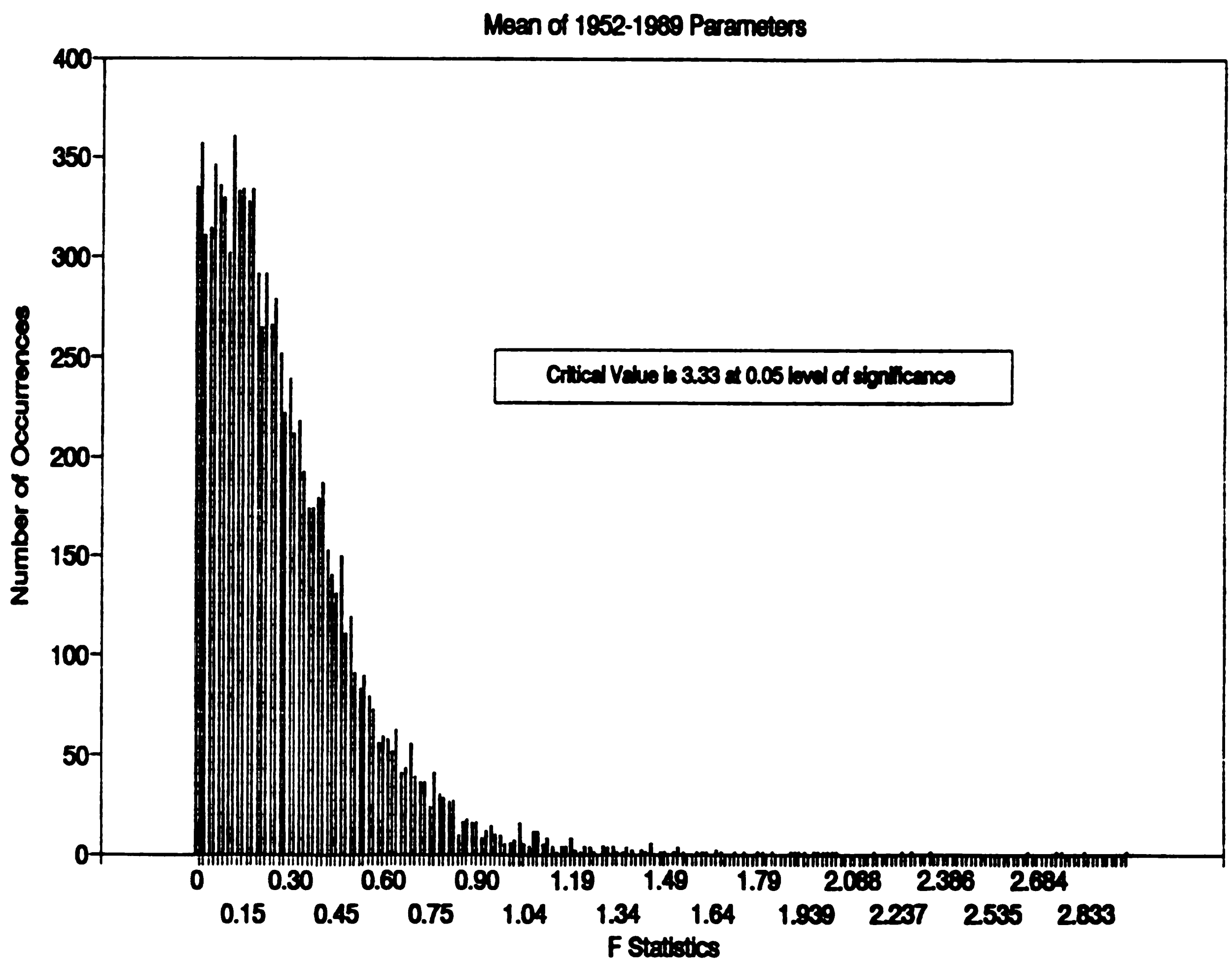


Figure IV.20

Significance of Investment in Explaining Dividends
Simulation Using Mean of Estimated Parameters from 1952-1989
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

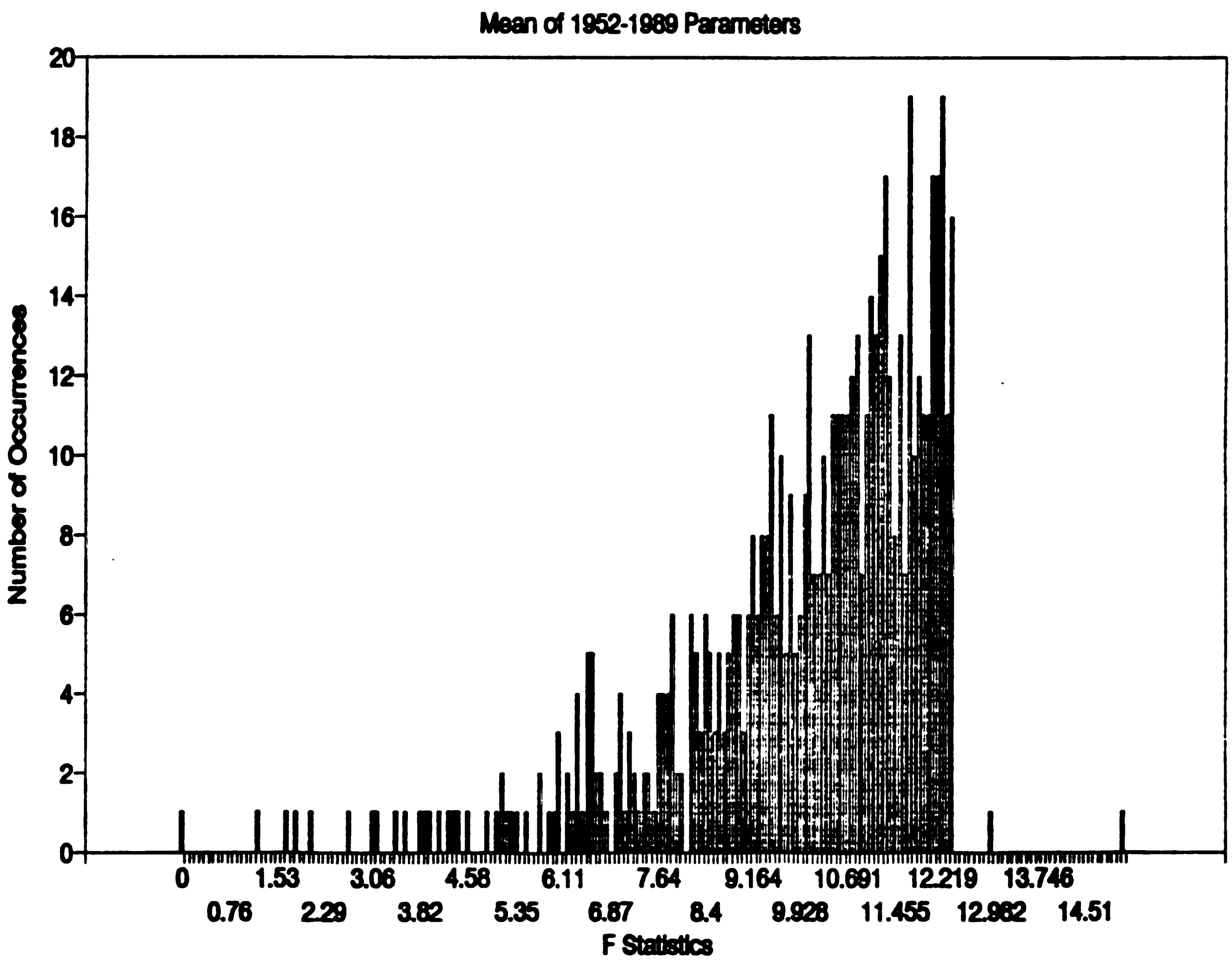


Figure IV.21

Significance of Dividends in Explaining Investment
Simulation Using Median of Estimated Parameters from 1952-1970
Differenced Series, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

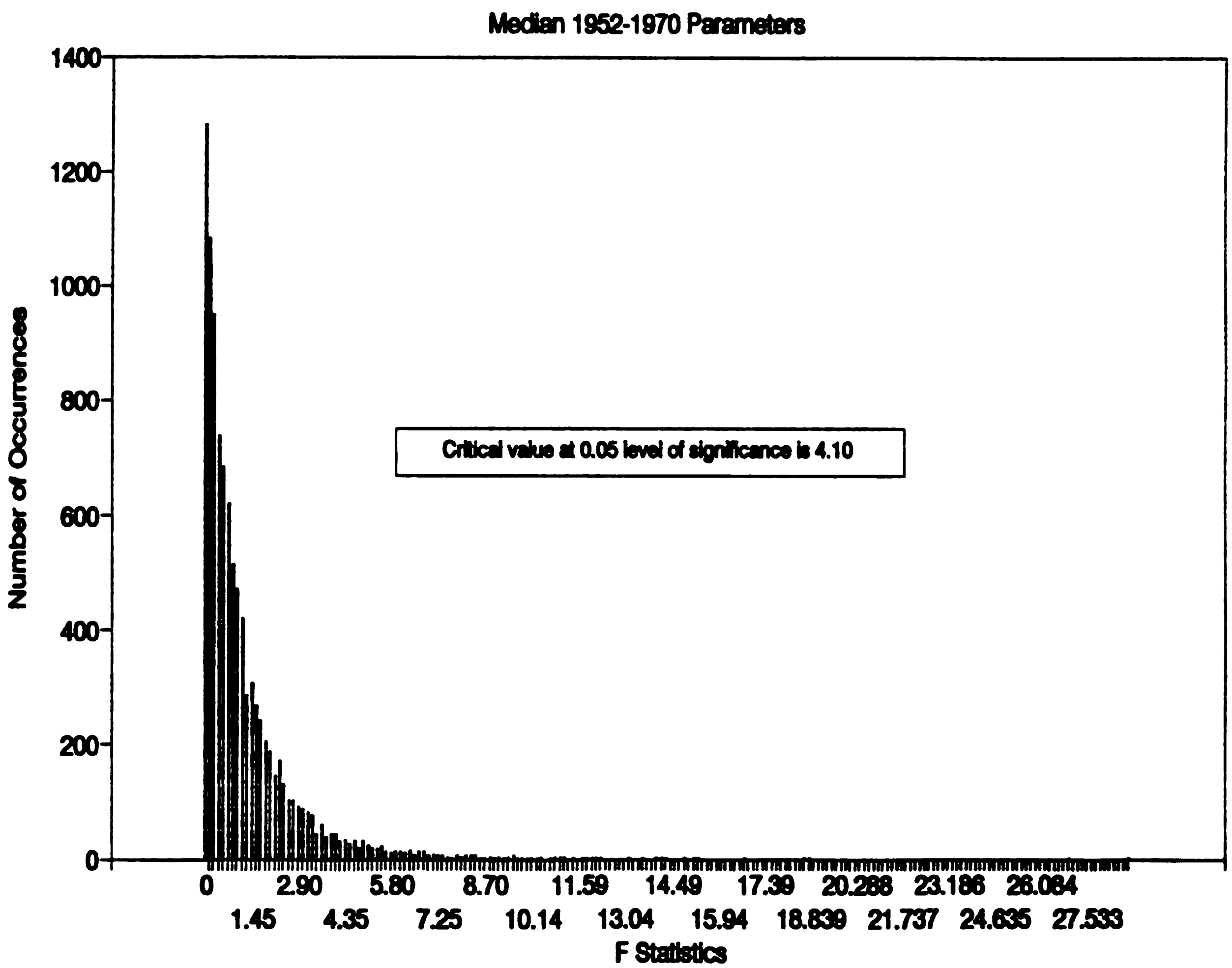


Figure IV.22

Significance of Investment in Explaining Dividends
Simulation Using Median of Estimated Parameters from 1952-1970
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

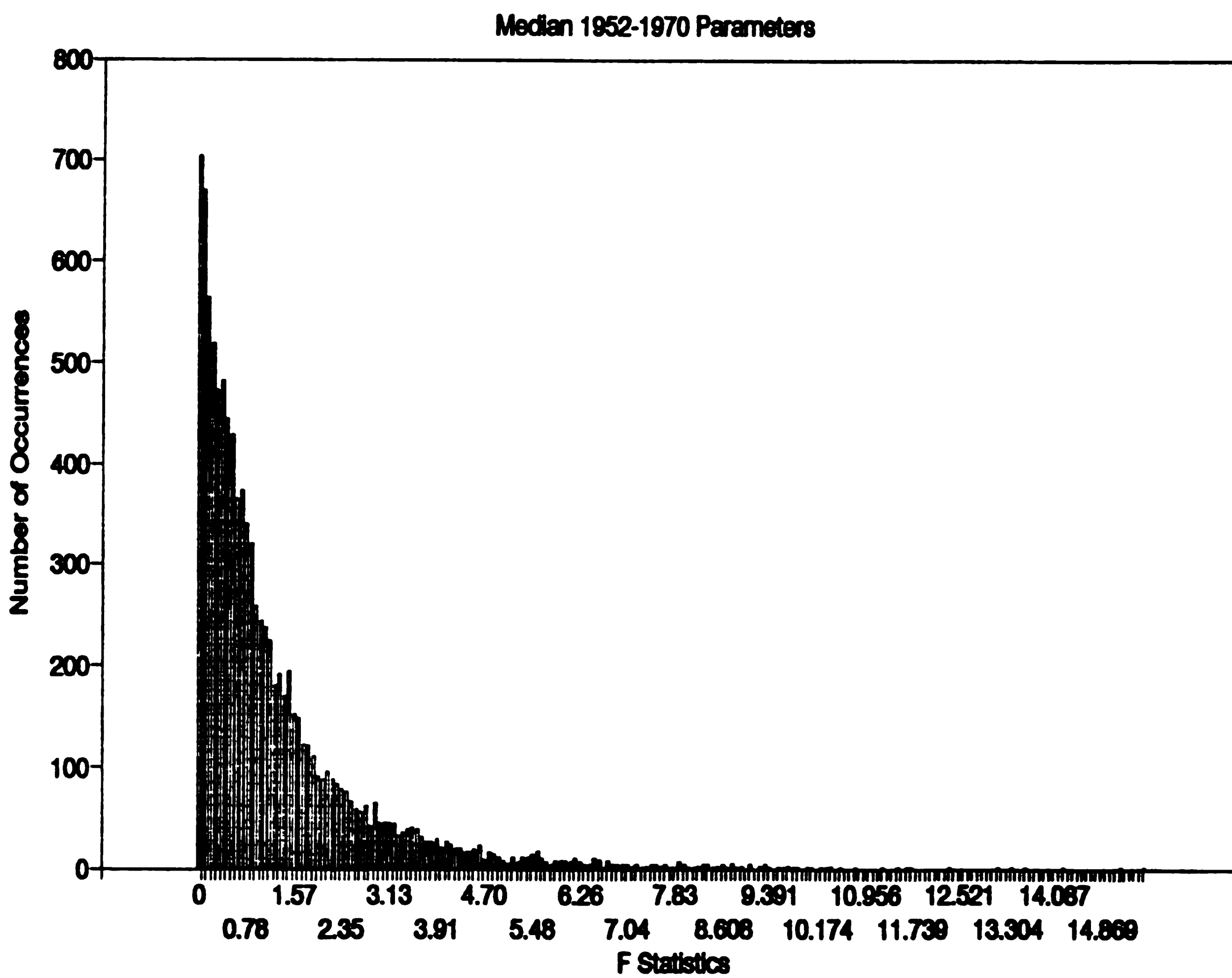


Figure IV.23

Significance of Dividends in Explaining Investment Simulation Using Mode of Estimated Parameters from 1952-1970 Differenced Series, T=37 Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \qquad (6)$$

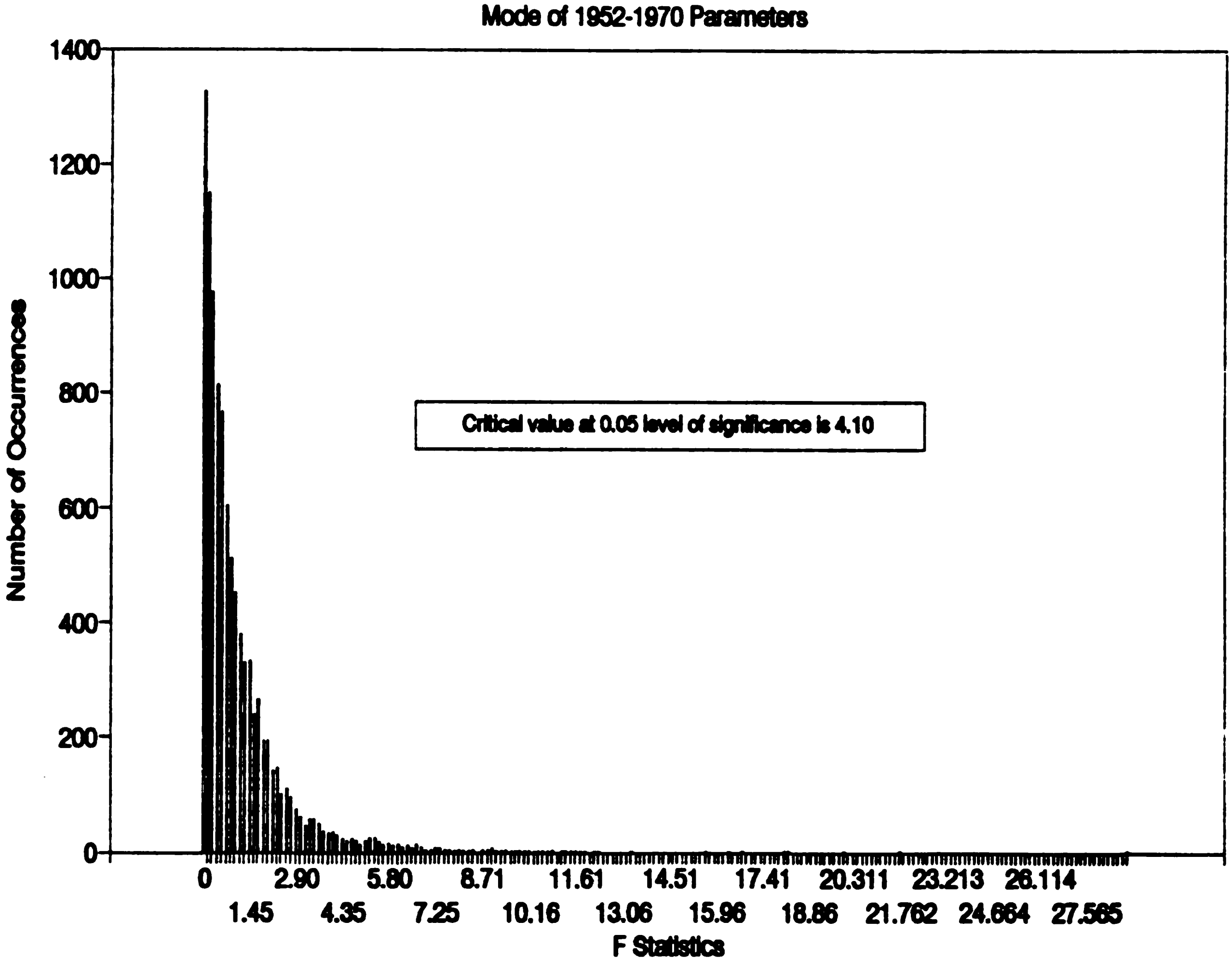


Figure IV.24

Significance of Investment in Explaining Dividends
Simulation Using Mode of Estimated Parameters from 1952-1970
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

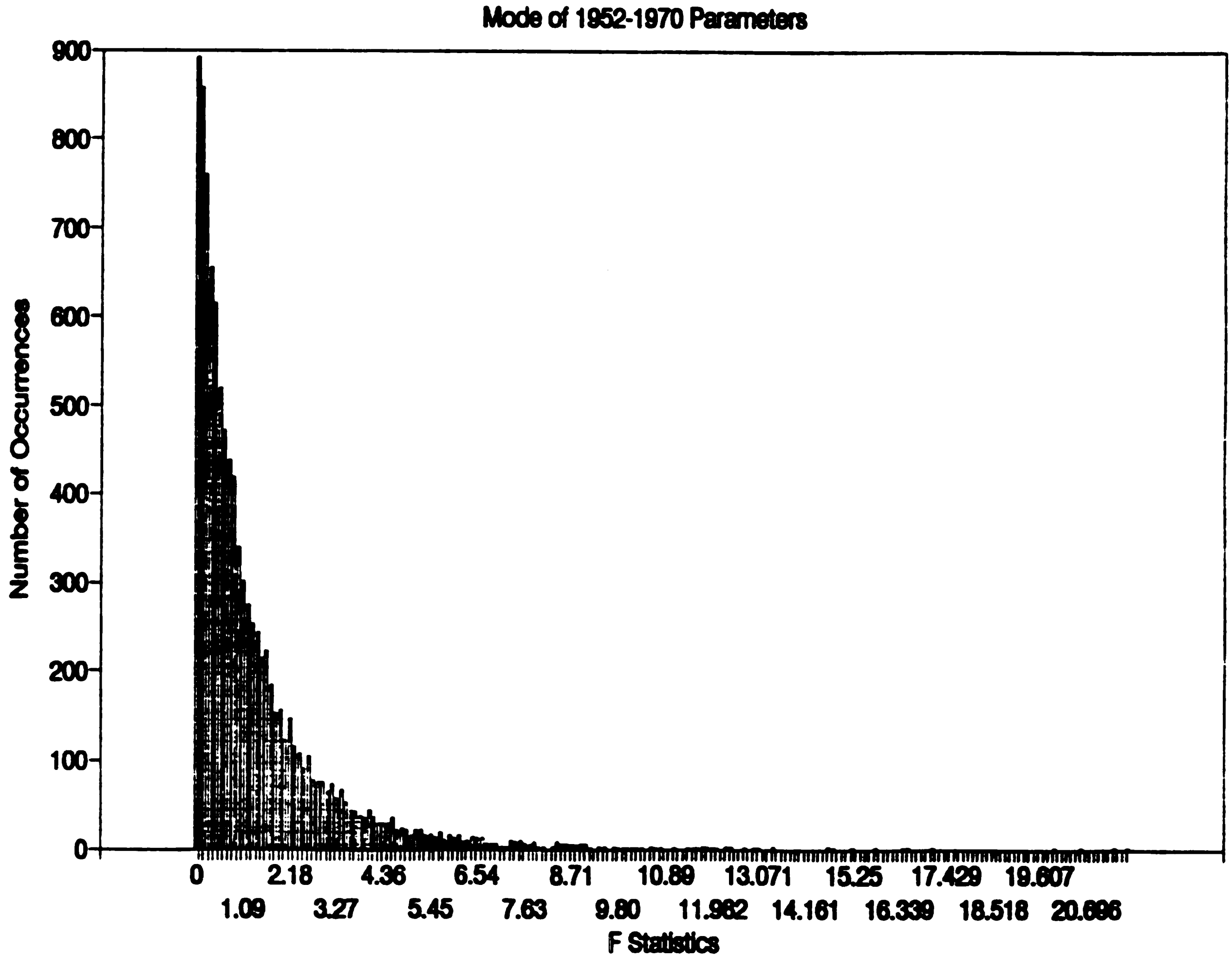


Figure IV.25

Significance of Dividends in Explaining Investment
Simulation Using Mean of Estimated Parameters from 1952-1970
Differenced Series, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

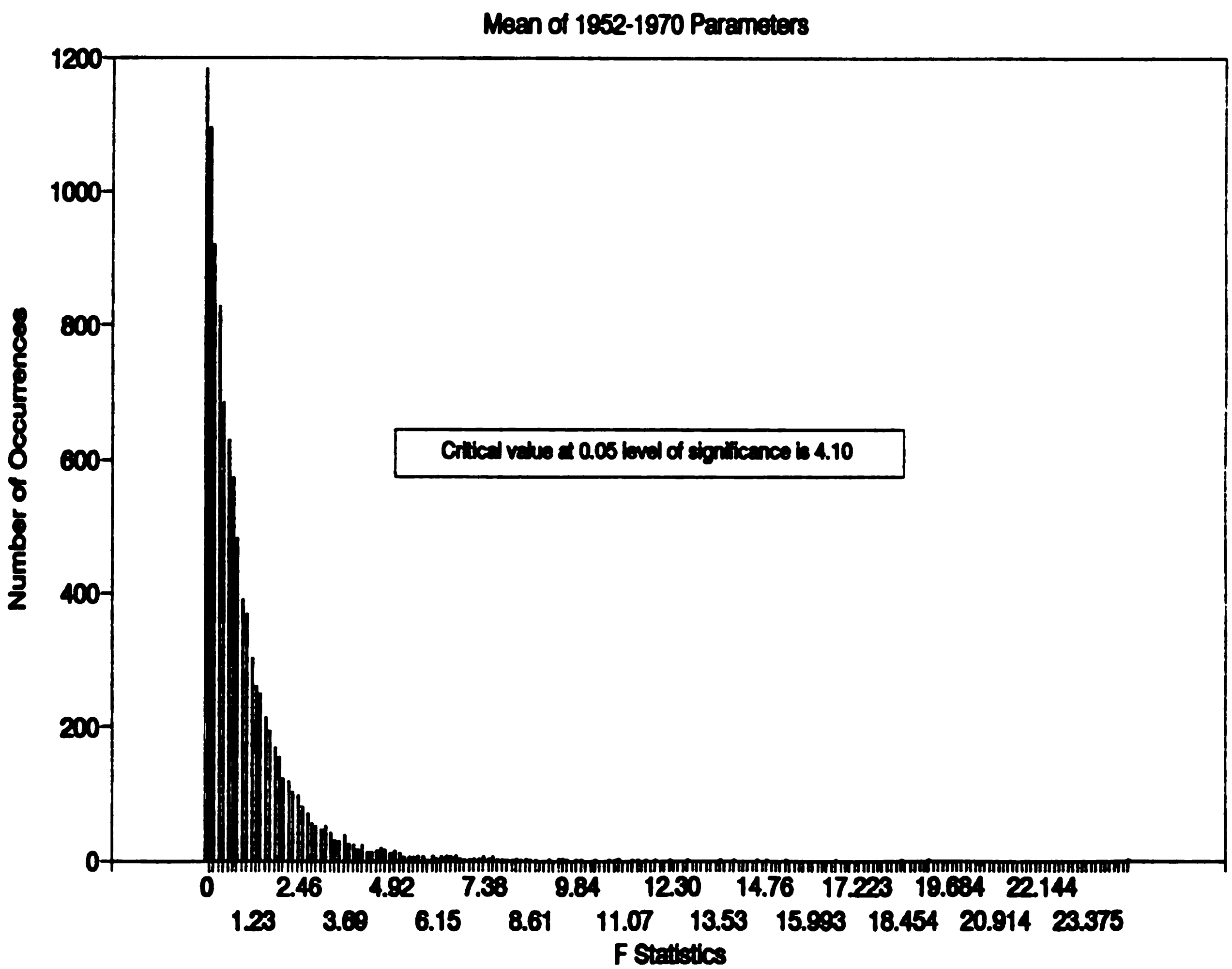


Figure IV.26

Significance of Investment in Explaining Dividends
Simulation Using Mean of Estimated Parameters from 1952-1970
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \qquad (7)$$

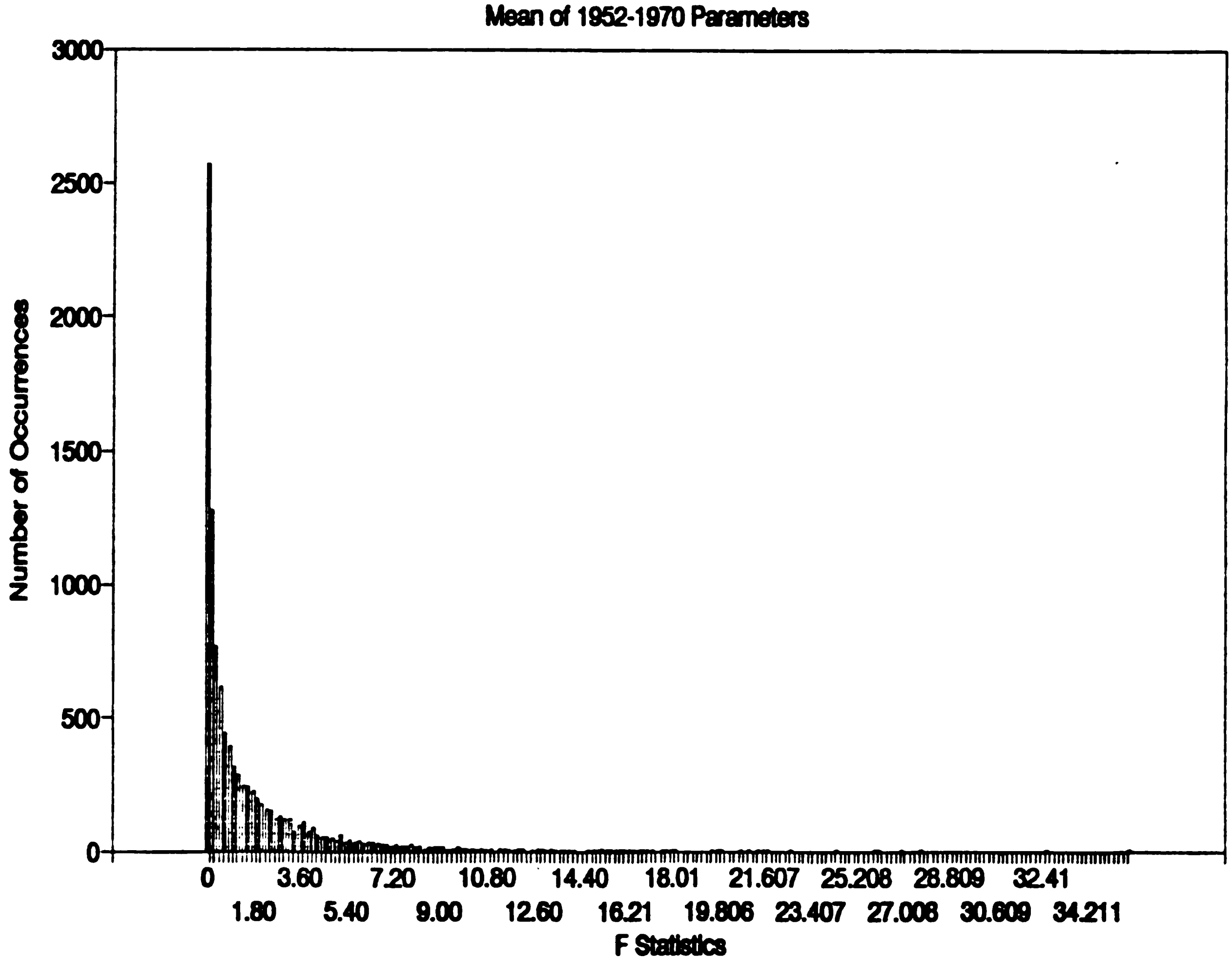


Figure IV.27

Significance of Dividends in Explaining Investment
Simulation Using Median of Estimated Parameters from 1971-1989
Differenced Series, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

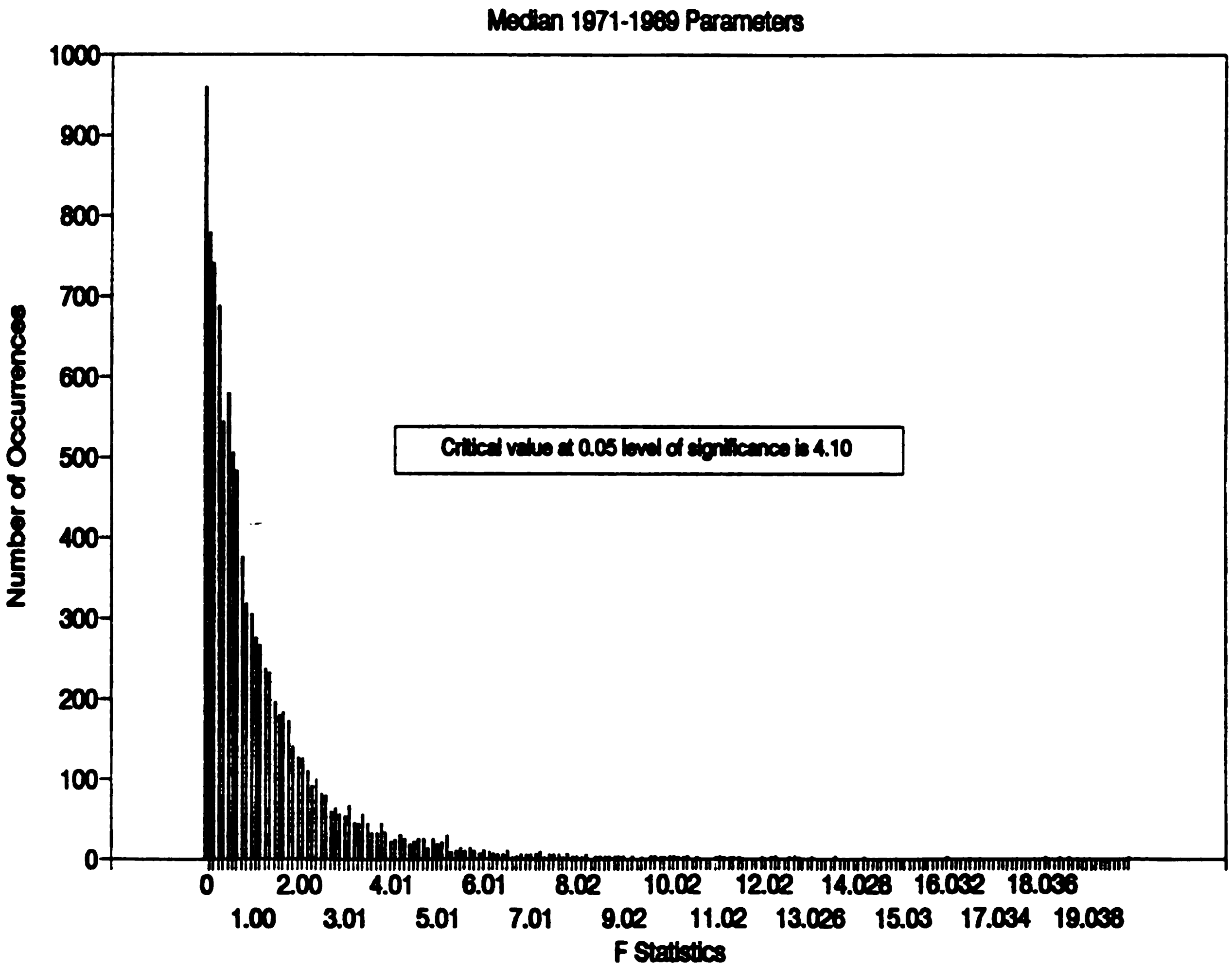


Figure IV.28

Significance of Investment in Explaining Dividends
Simulation Using Median of Estimated Parameters from 1971-1989
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

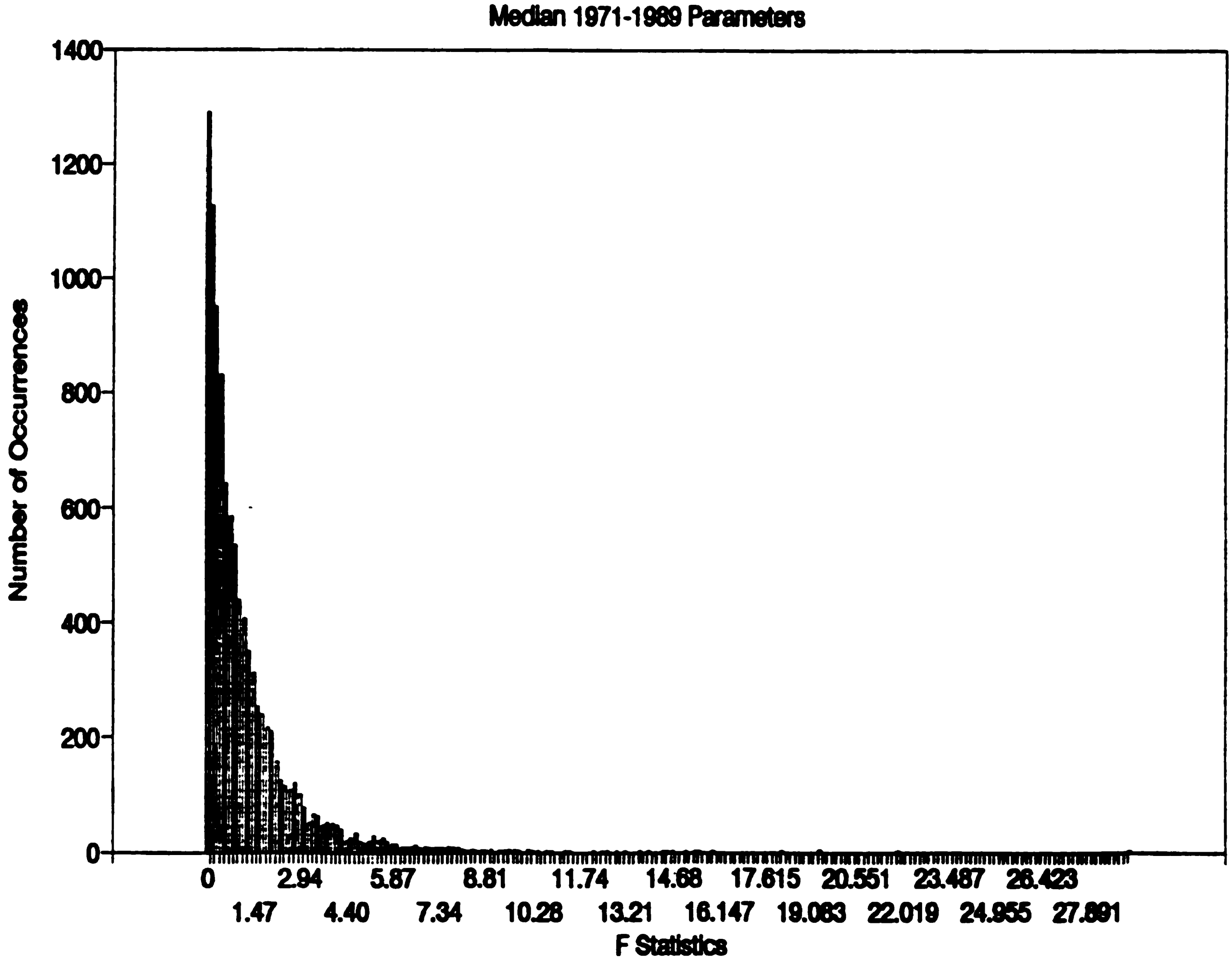


Figure IV.29

Significance of Dividends in Explaining Investment
Simulation Using Mode of Estimated Parameters from 1971-1989
Differenced Series, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

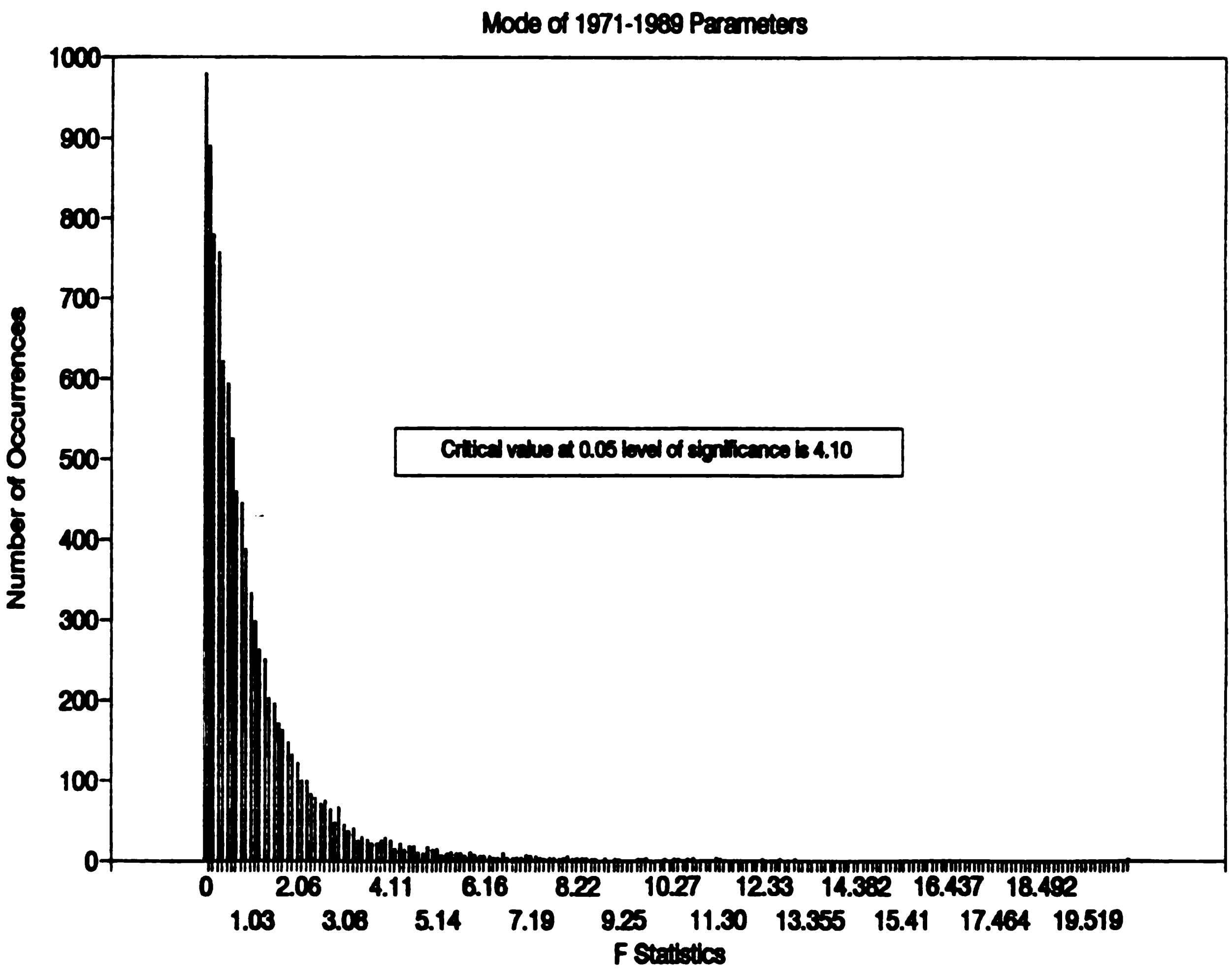


Figure IV.30

Significance of Investment in Explaining Dividends
Simulation Using Mode of Estimated Parameters from 1971-1989
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

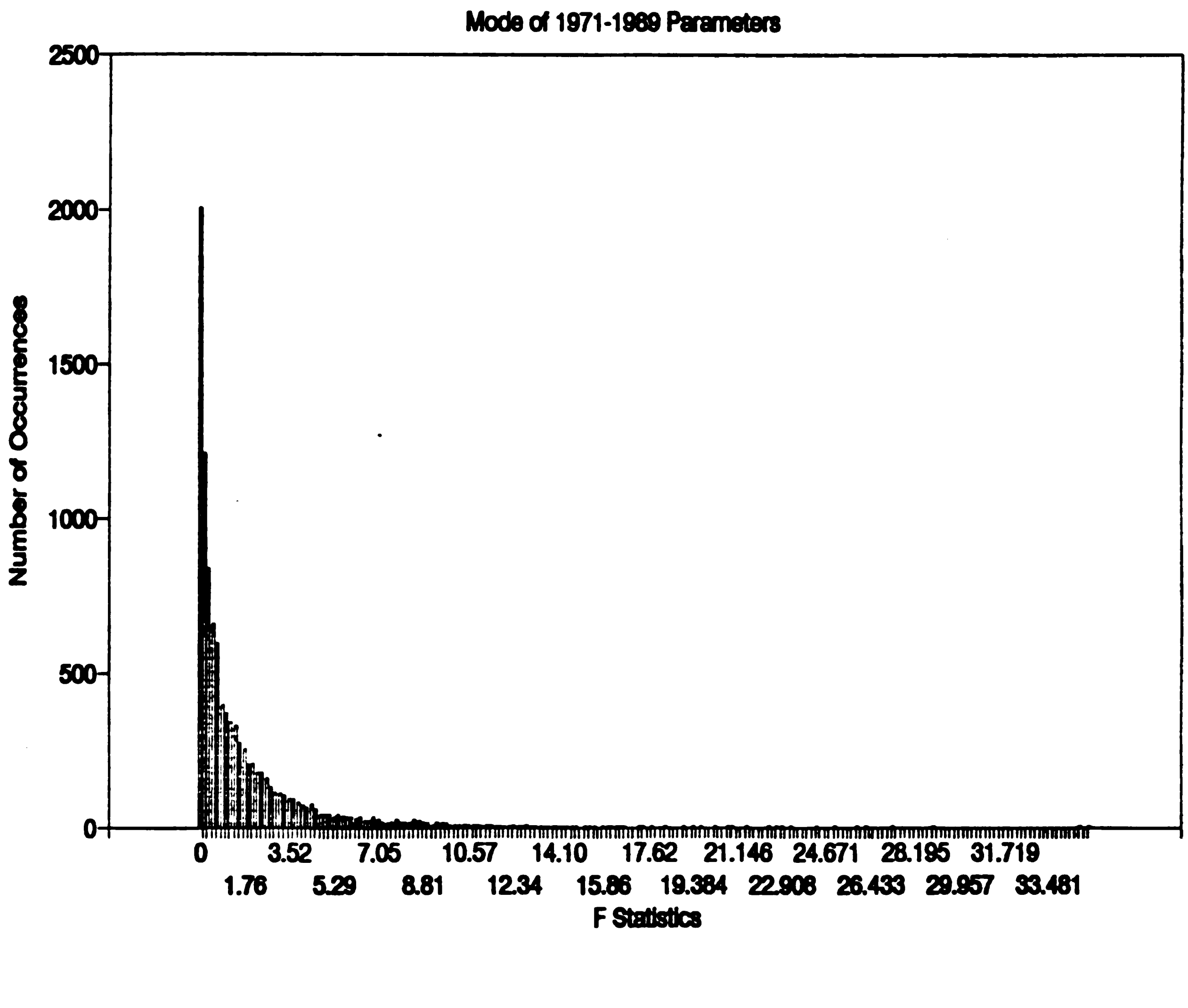


Figure IV.31

Significance of Dividends in Explaining Investment Simulation Using Mean of Estimated Parameters from 1971-1989 Differenced Series, T=37 Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \qquad (6)$$

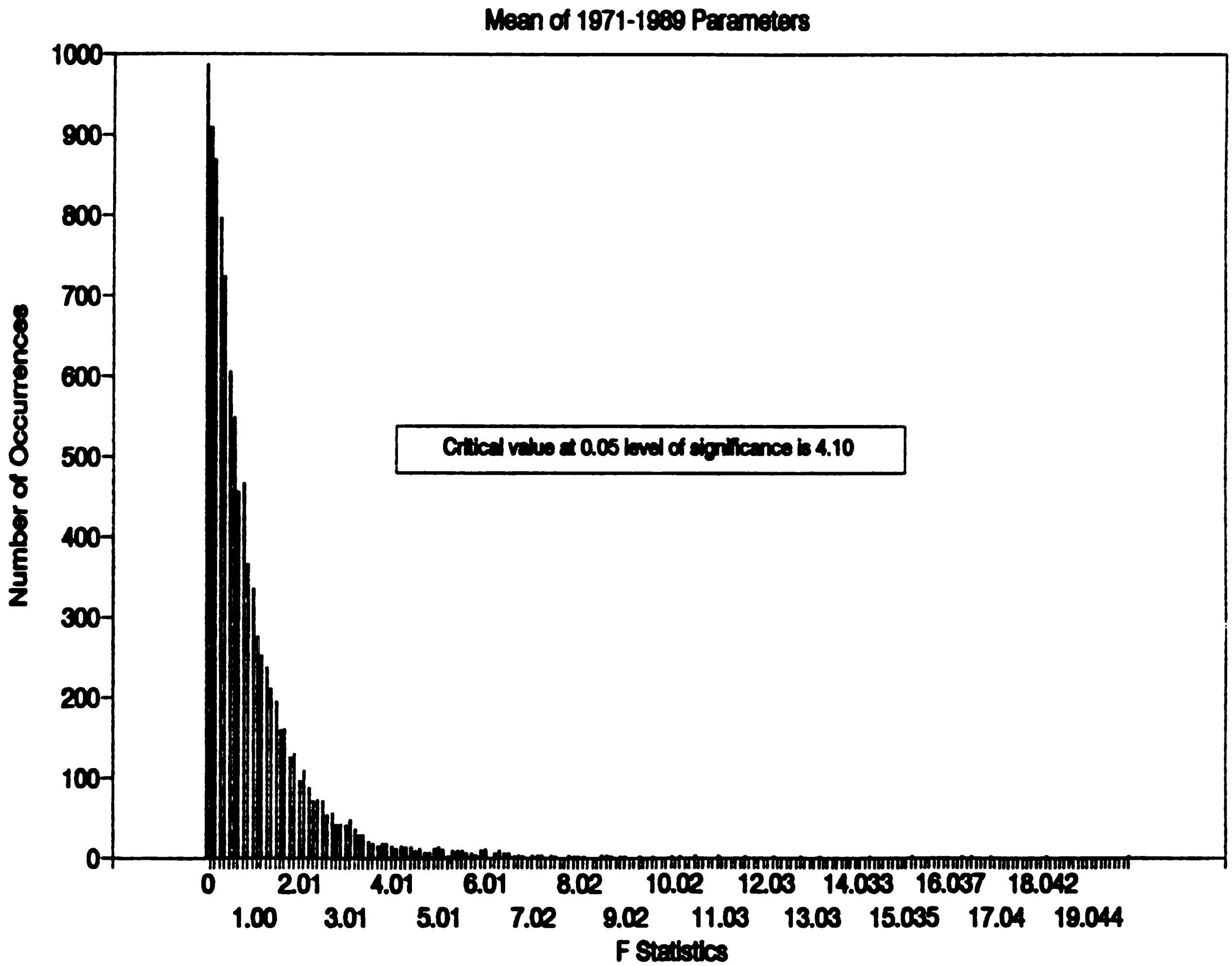


Figure IV.32

Significance of Investment in Explaining Dividends
Simulation Using Mean of Estimated Parameters from 1971-1989
Differenced Series, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \tag{7}$$

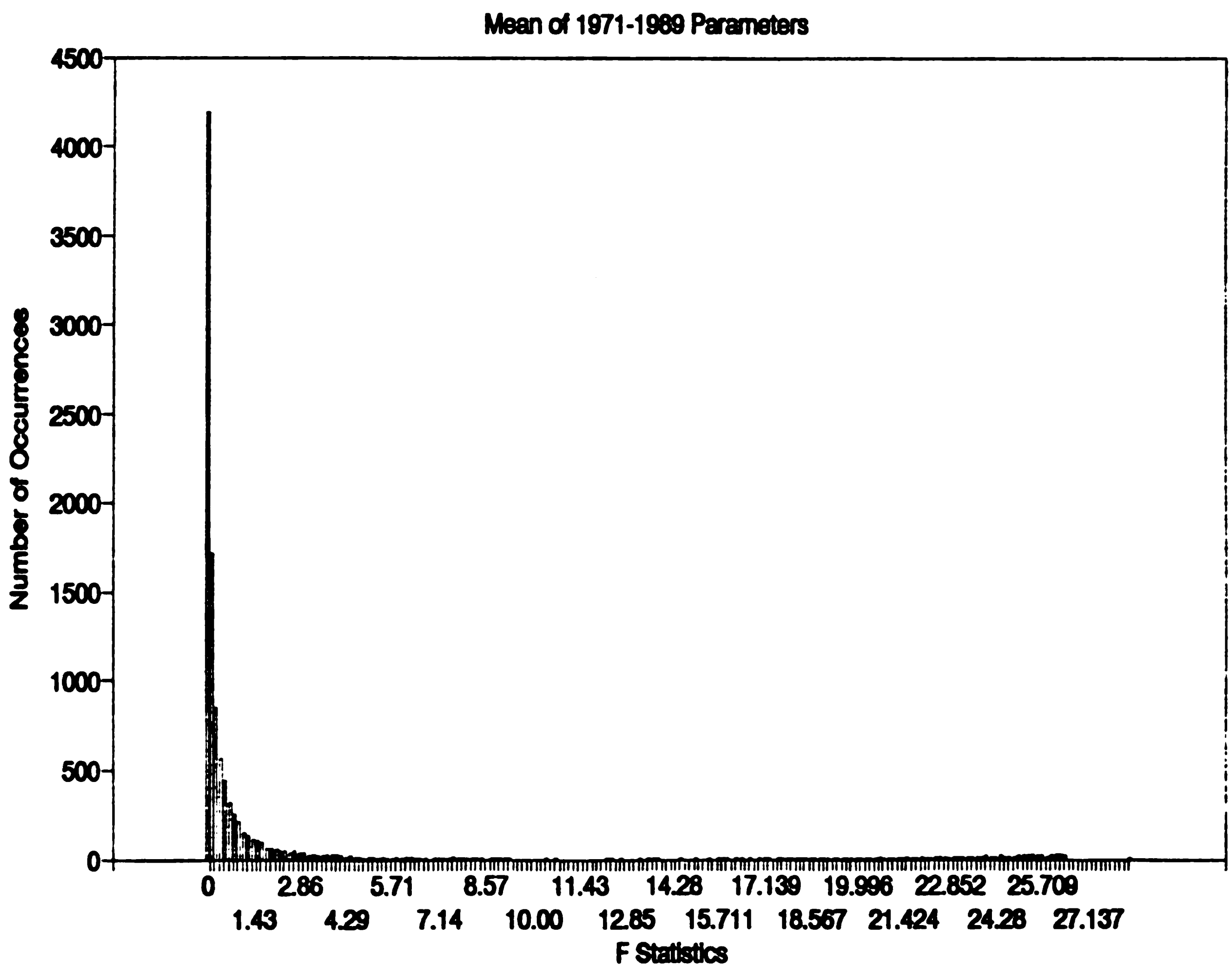


Figure IV.33

Dickey-Fuller Test for Stationarity of Dividends
Levels of Variables, T=37

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \qquad (4)$$

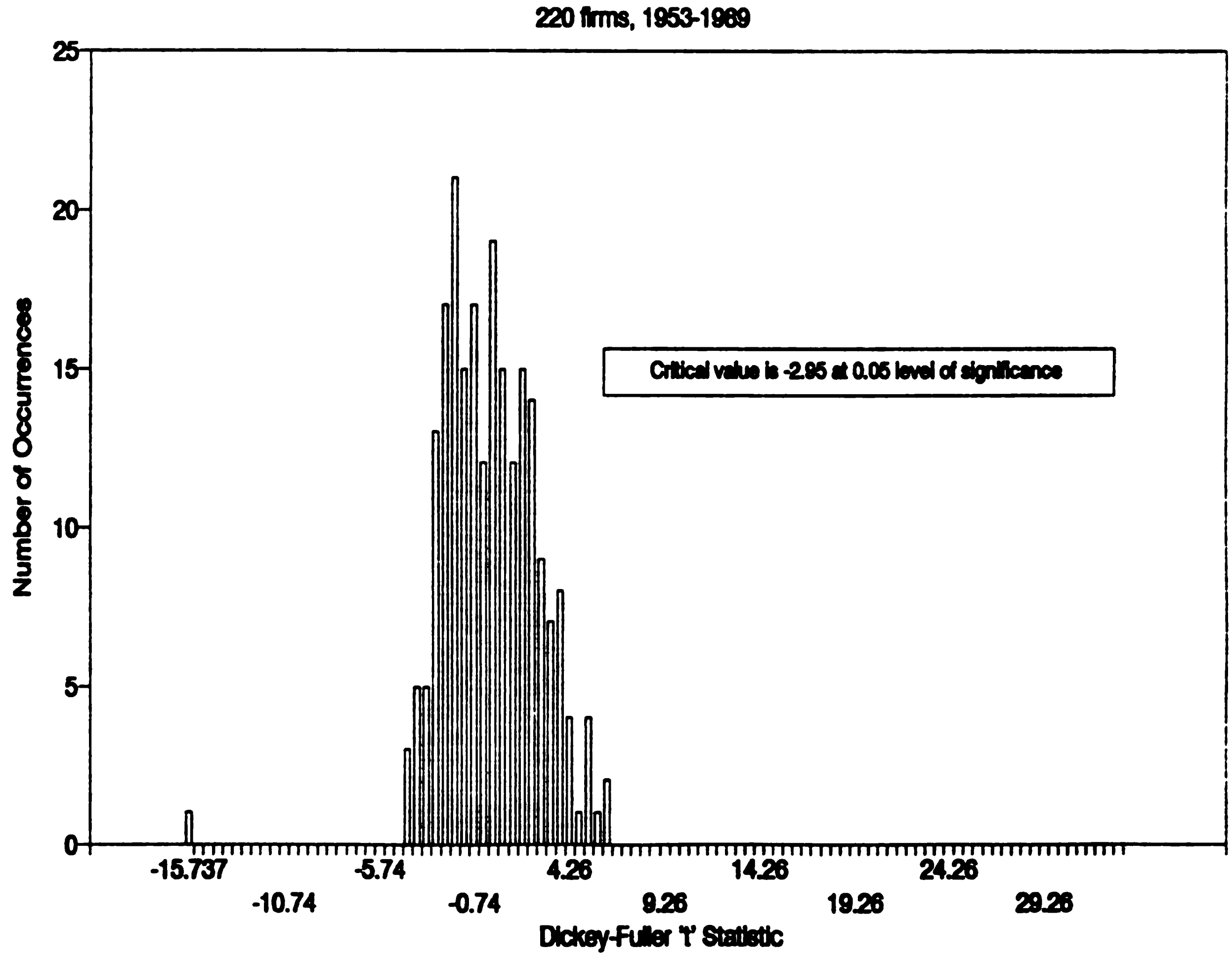


Figure IV.34

Dickey-Fuller Test for Stationarity of Investment Levels of Variables, T=37

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \qquad (4)$$

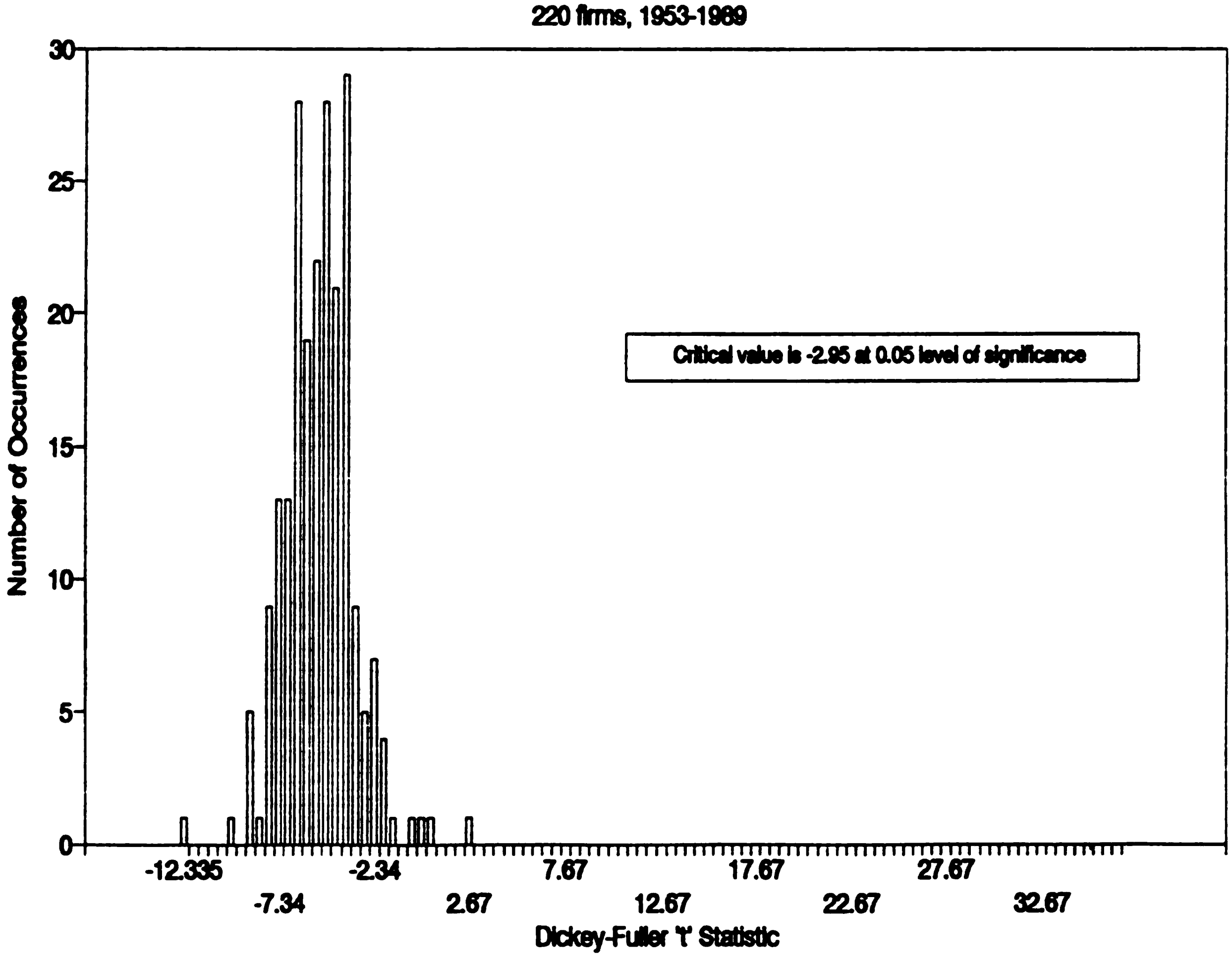


Figure IV.35

Significance of Dividends in Explaining Investment Levels of Variables, T=37
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \qquad (6)$$

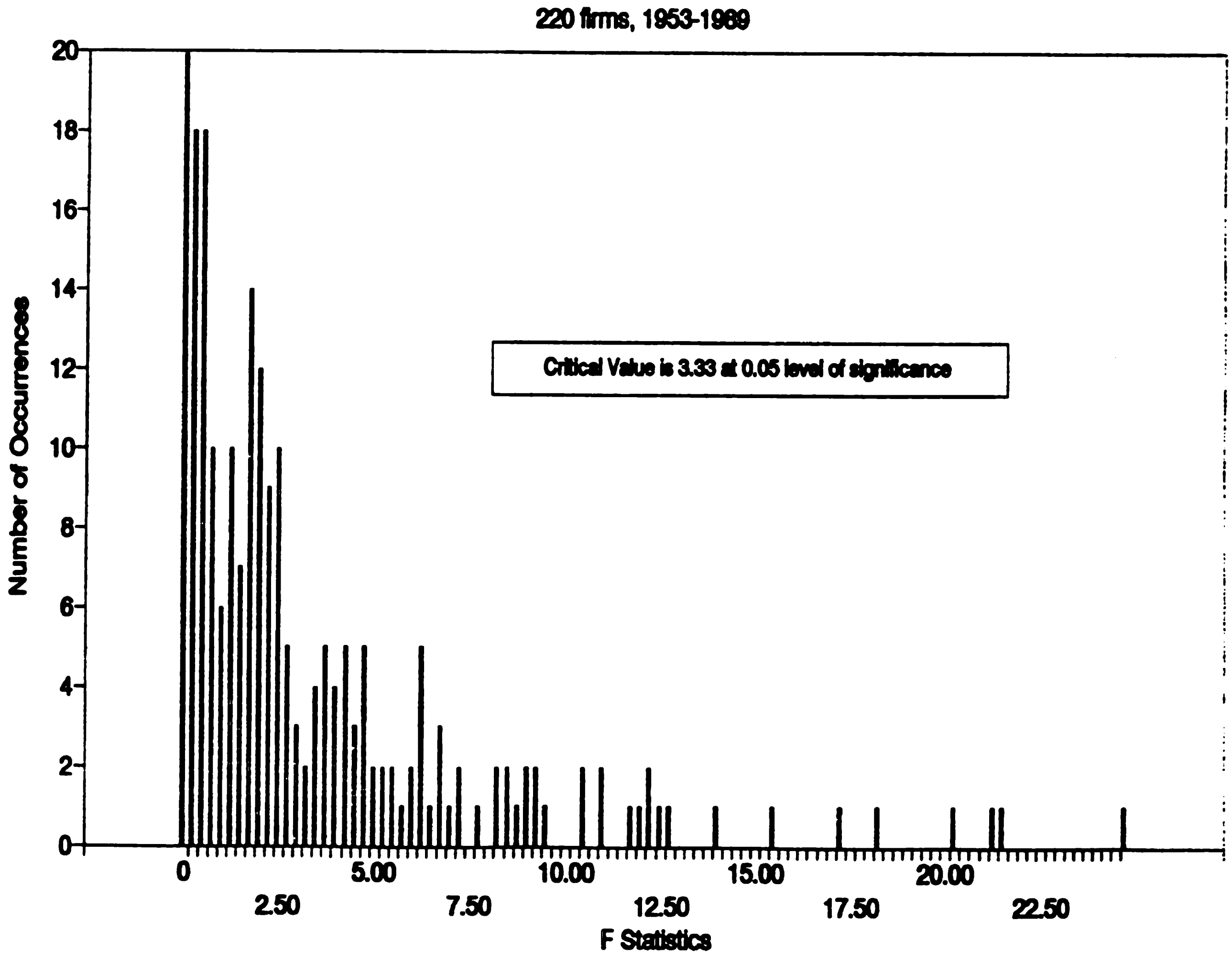


Figure IV.36

Significance of Investment in Explaining Dividends
Levels of Variables, T=37
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \qquad (7)$$

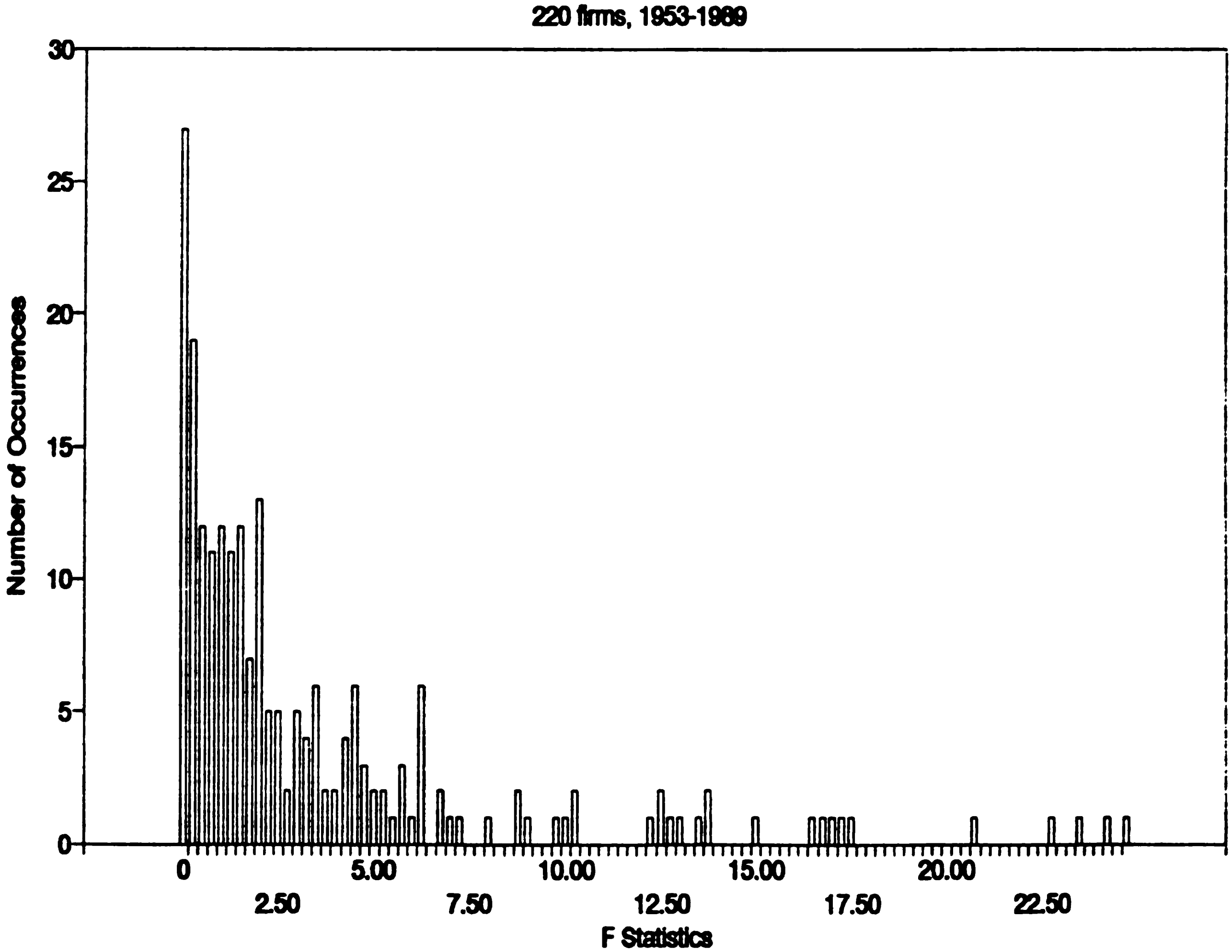


Figure IV.37

Dickey-Fuller Test for Stationarity of Dividends Differenced Series, T=36

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \tag{4}$$

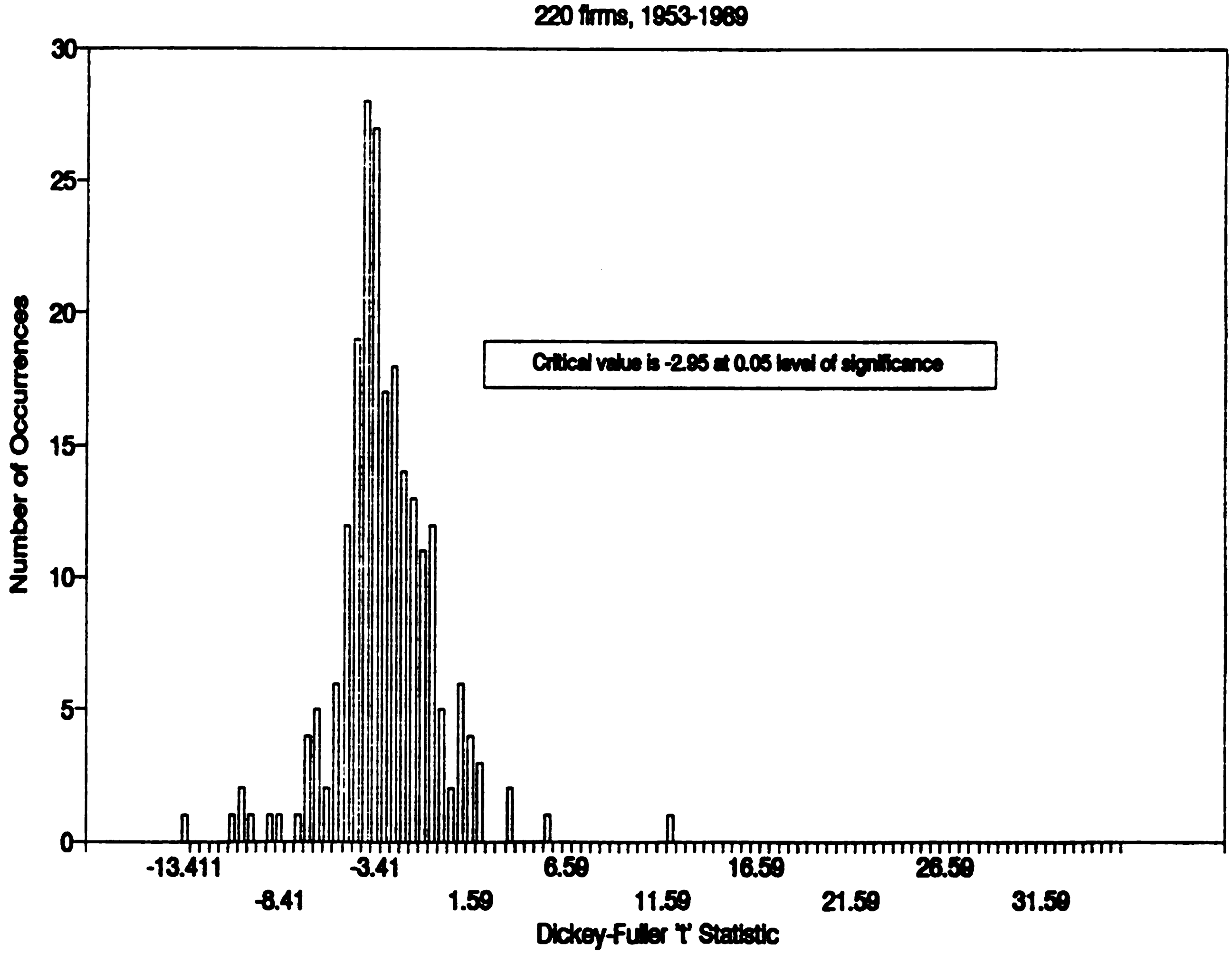


Figure IV.38

Dickey-Fuller Test for Stationarity of Investment Differenced Series, T=36

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \qquad (4)$$

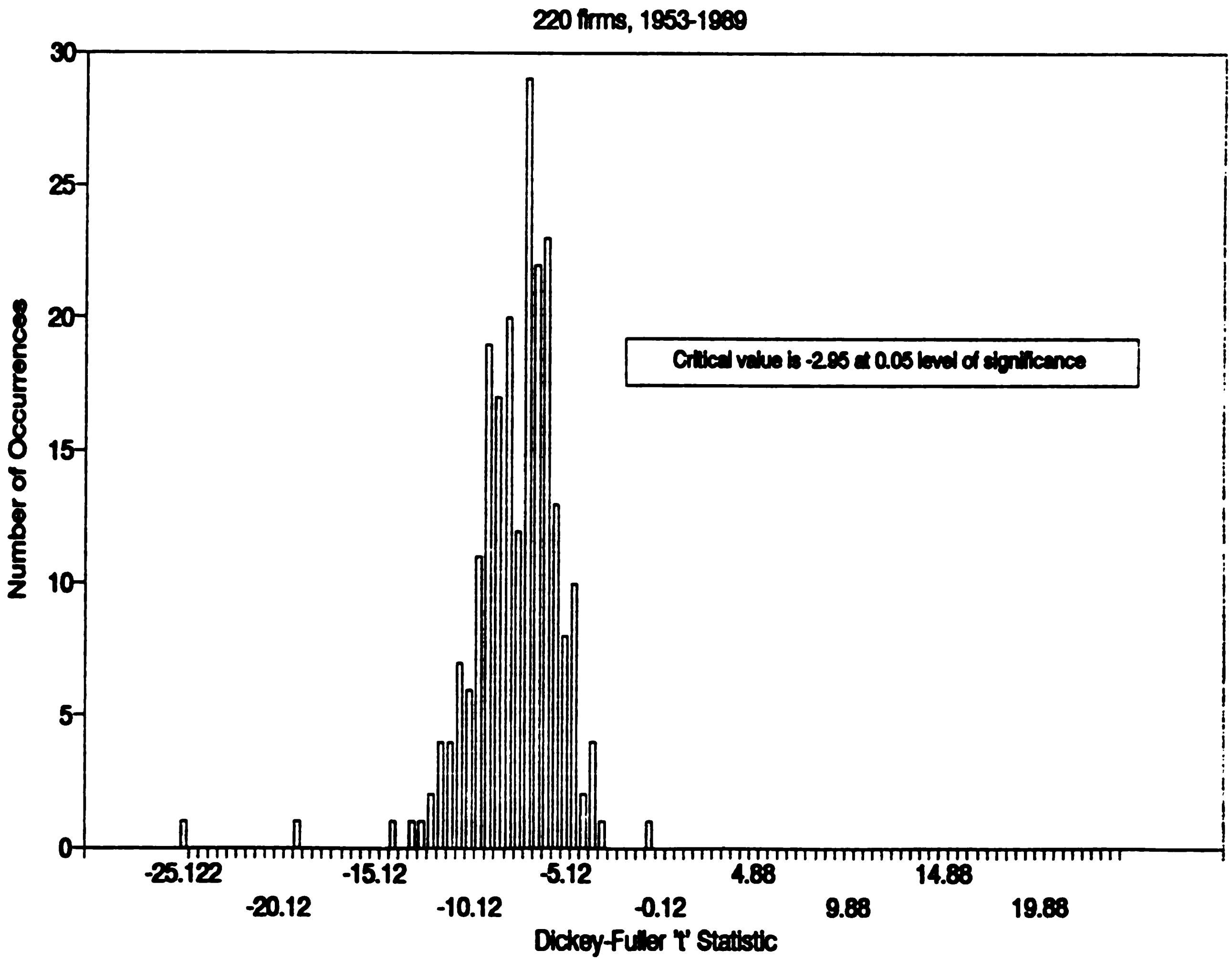


Figure IV.39

Significance of Dividends in Explaining Investment
Differenced Series, T=36
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \qquad (6)$$

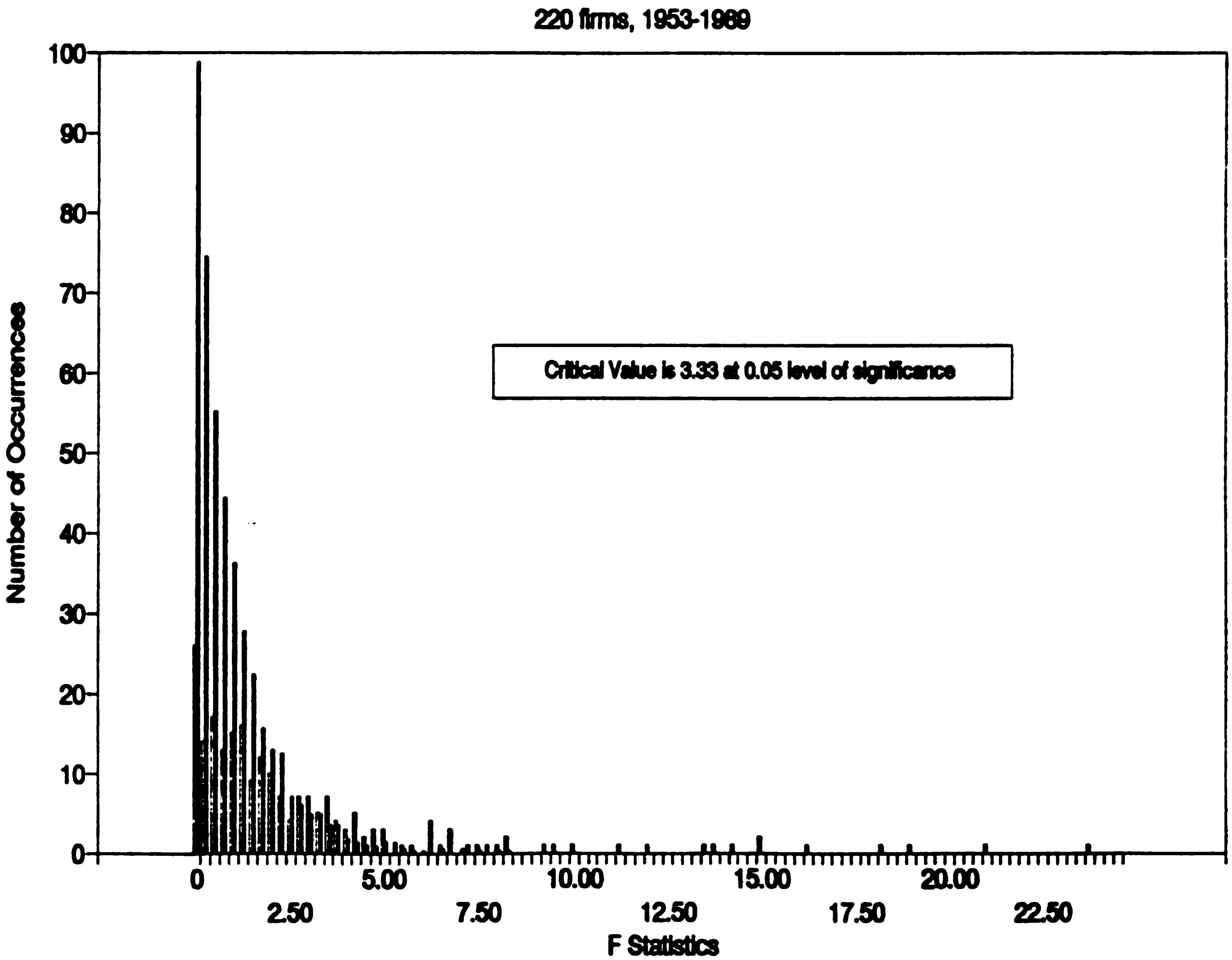


Figure IV.40

Significance of Investment in Explaining Dividends
Differenced Series, T=36
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \qquad (7)$$

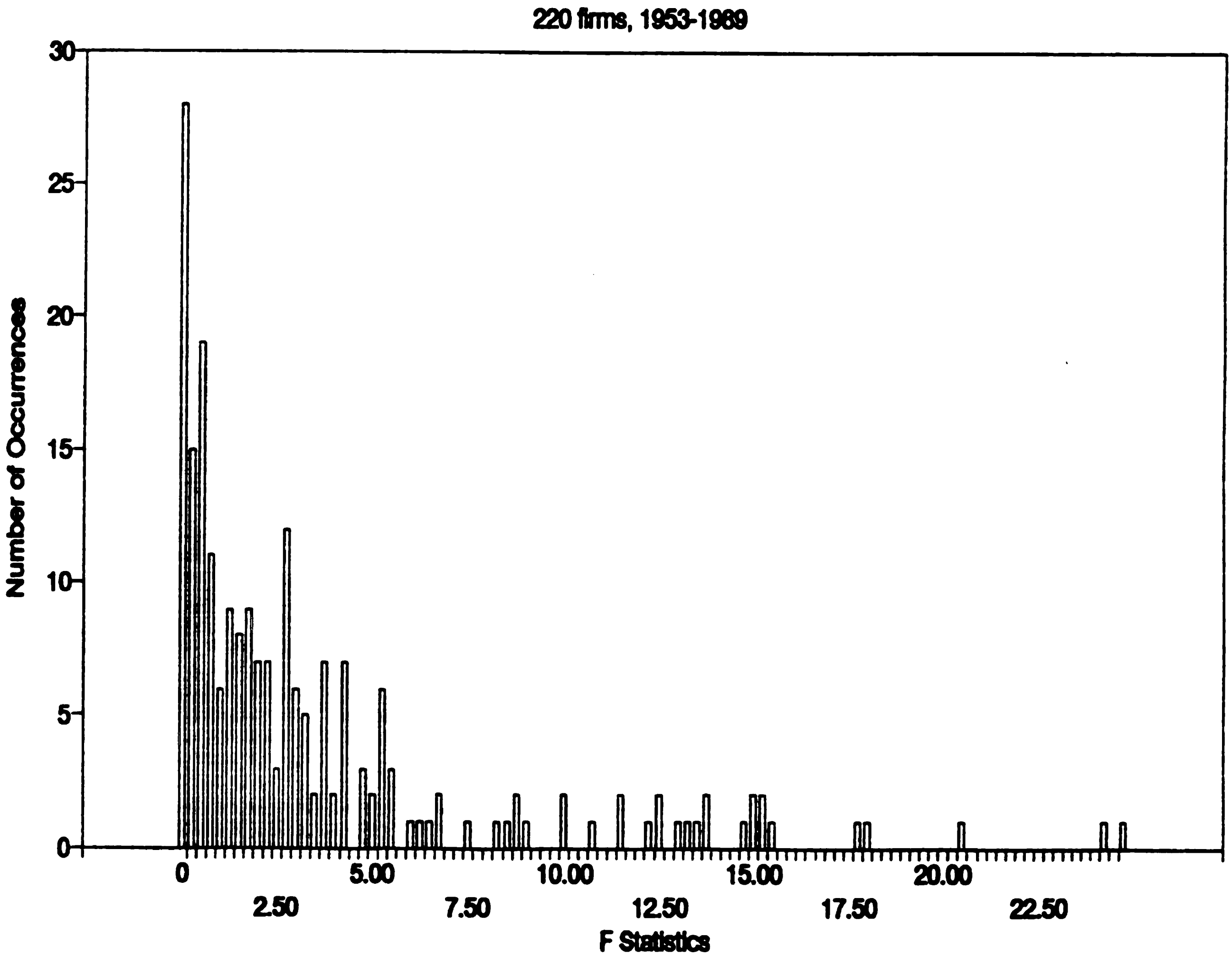


Figure IV.41

Significance of Dividends in Explaining Investment
Subsample Exhibiting Stationarity at α=0.05 Level
Differenced Series, T=36
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \quad (6)$$

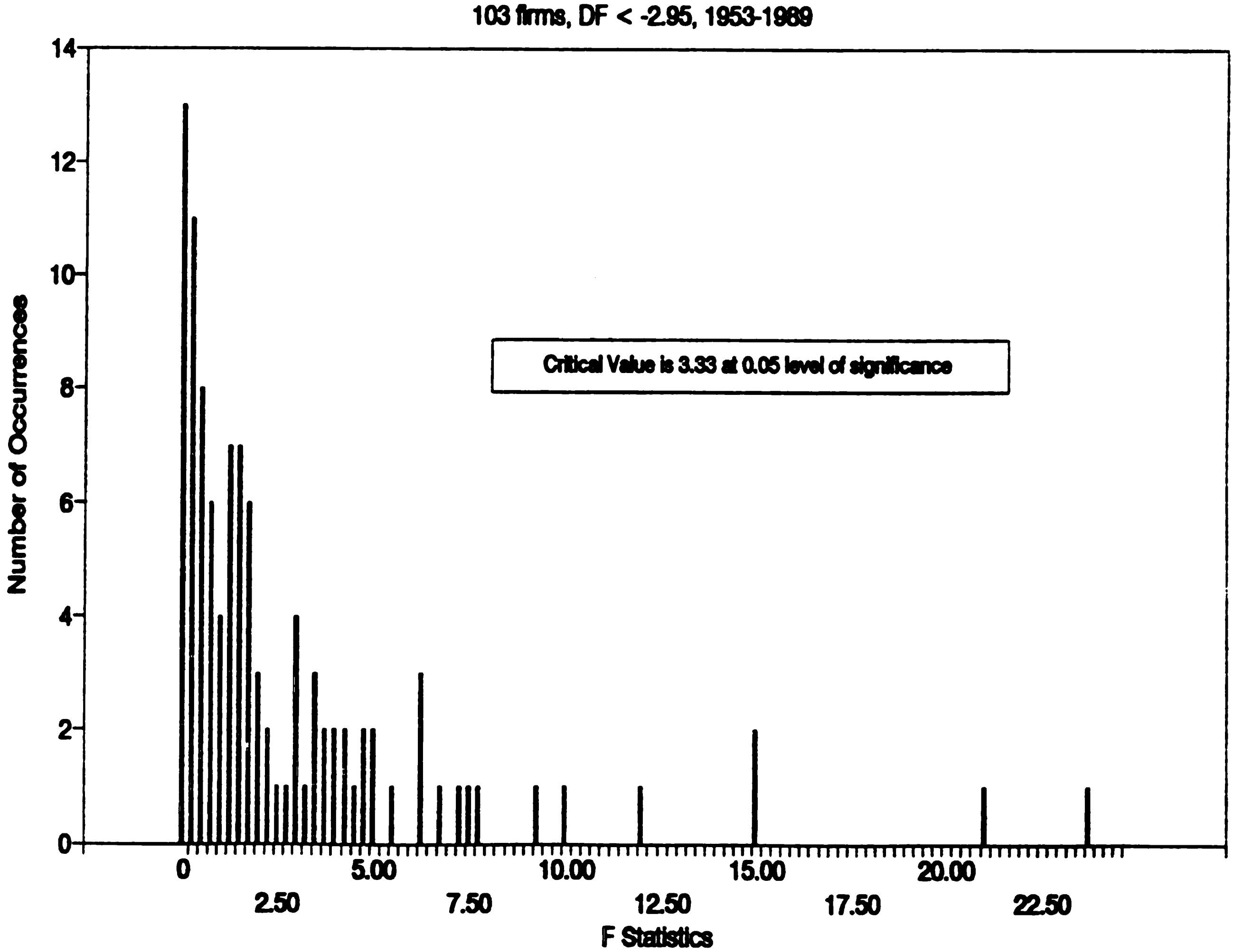


Figure IV.42

Significance of Investment in Explaining Dividends
Subsample Exhibiting Stationarity at α=0.05 Level
Differenced Series, T=36
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \qquad (7)$$

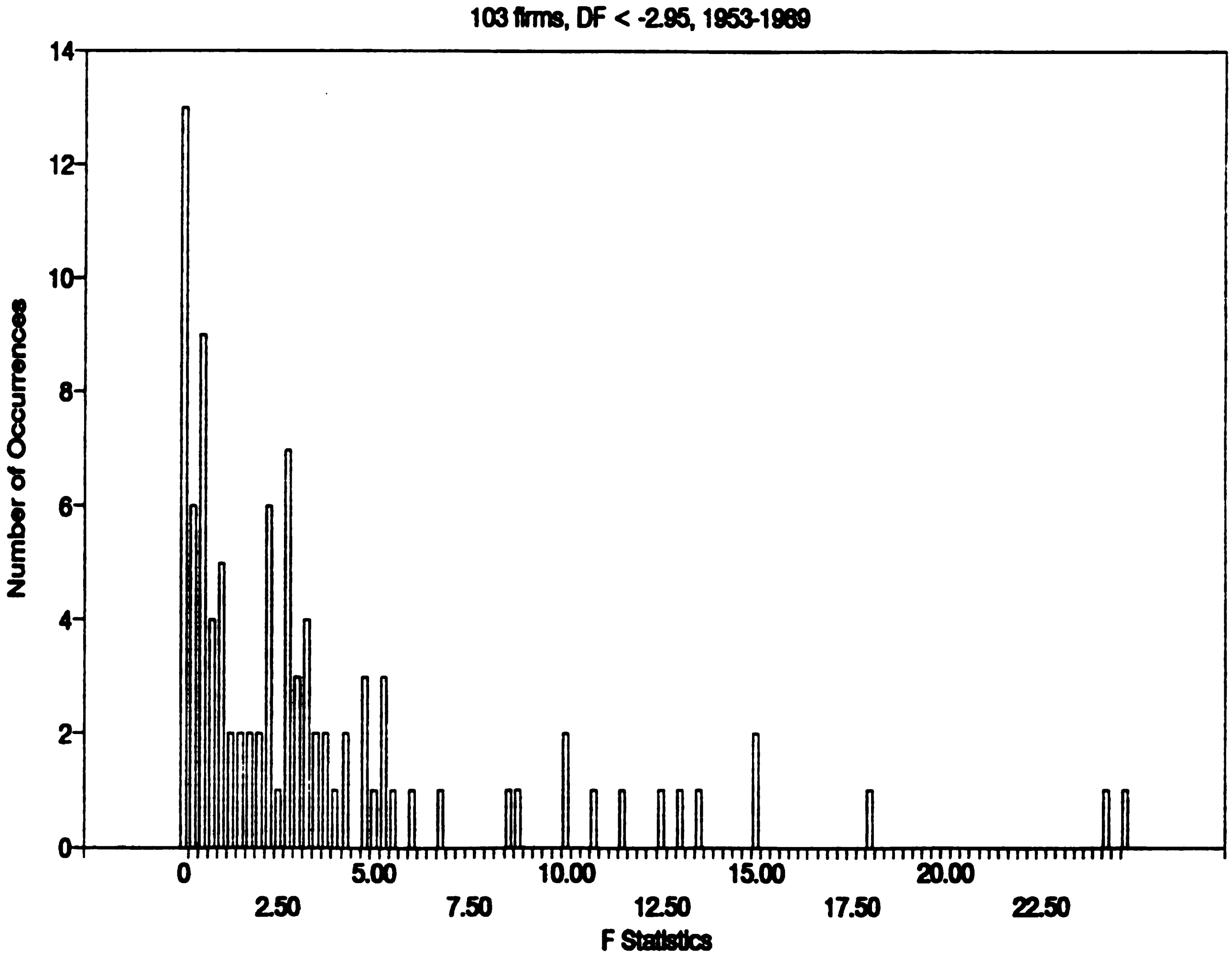


Figure IV.43

Significance of Dividends in Explaining Investment
Subsample Failing to Exhibit Stationarity at α=0.05 Level
Differenced Series, T=36
Block F Test for Exclusion of Dividends

$$INV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i INV_{t-i} + \sum_{j=1}^{2} \beta_j DIV_{t-j} + \epsilon_t \tag{6}$$

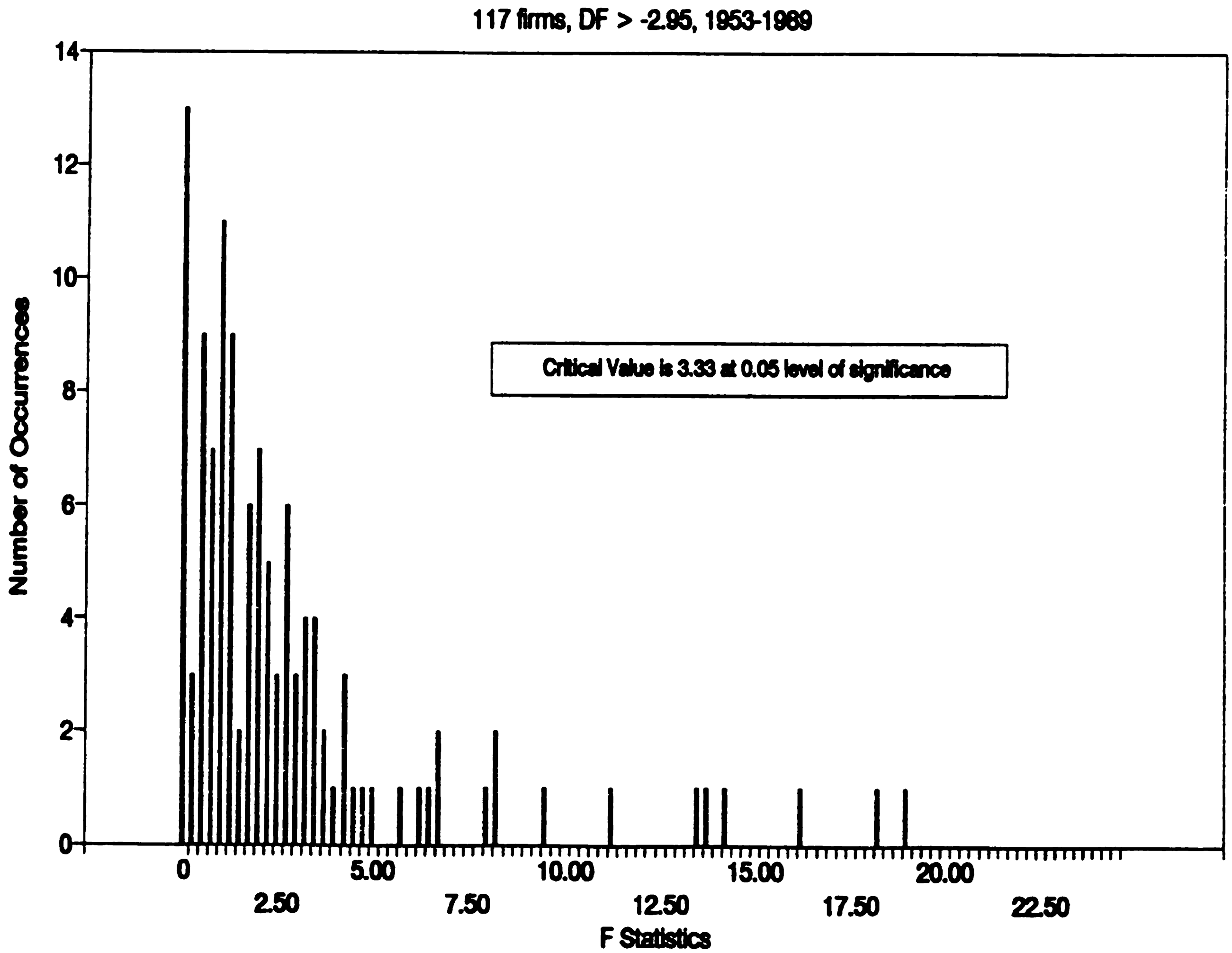
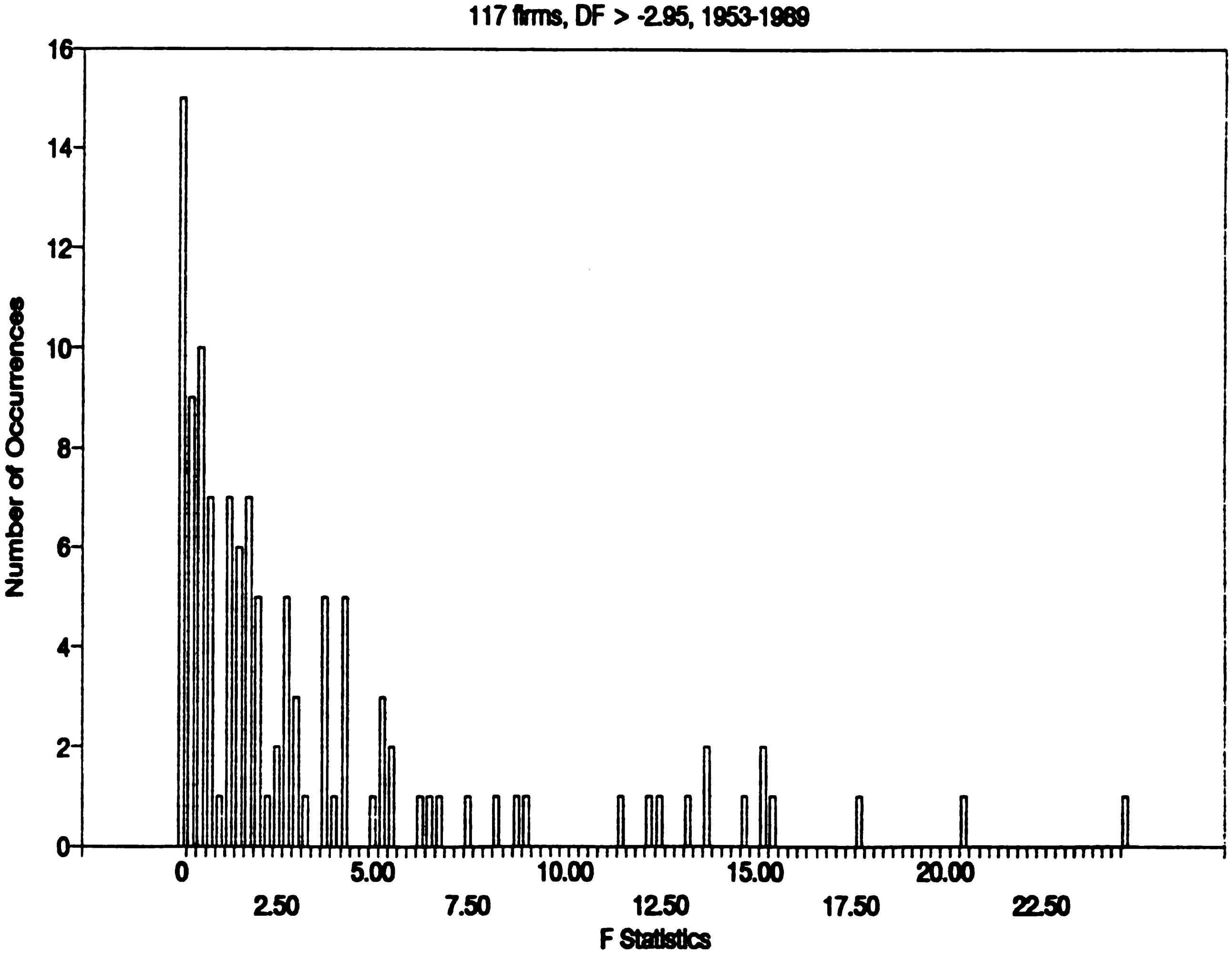


Figure IV.44

Significance of Investment in Explaining Dividends
Subsample Failing to Exhibit Stationarity at α=0.05 Level
Differenced Series, T=36
Block F Test for Exclusion of Investment

$$DIV_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j DIV_{t-j} + \sum_{i=1}^{2} \delta_i INV_{t-i} + \mu_t \qquad (7)$$



Chapter V

Causality Tests of the Relationship Between Dividend Payout and Risk

Causality Tests of the Relationship Between Payout and Risk

Review of the Literature:

Kalay [1981] was the first to conduct a specific empirical test of the hypothesis that dividend payout and earnings uncertainty are negatively correlated. Since earnings is an accounting variable, and price is not a function of earnings alone, measures of earnings uncertainty are far removed from measures of price risk. Nevertheless, this study is relevant to the investigation at hand because the strong correlation believed to exist between earnings and price suggests that the relationship between dividend payout and price risk may be similar to that observed between dividend payout and earnings uncertainty.

As a measure of risk, Kalay [1981] uses the "size adjusted average squared deviation from the best prediction of next period earnings (given past and current earnings)" (see Kalay [1981], p.440). Such a measure of risk has several advantages: i) they are scale free and thus comparable to payout; and ii) by taking the squared deviation from predicted earnings, negative earnings can be dealt with in a natural way. Predicted earnings are drawn from two alternative models. The first is a random walk with an additive drift parameter; the second is a first order moving average process in the first differences. Kalay derives an earnings uncertainty measure for each of these processes, however, the only difference between them is the method of obtaining predicted earnings. He calls these risk measures U_1 and U_2 respectively.

Payout ratio is estimated as an earnings weighted average of past payout ratios. Kalay contends that this is an appropriate way of reducing bias due to observations with very small earnings per share. Thus, an implicit assumption in this study is that over time individual firms try to maintain some target dividend payout ratio.

Kalay's sample consists of 474 firms from the Compustat Industrial File screened such that each firm reported annual earnings per share and annual dividends per share in every year from 1949 through 1972. Kalay conducts both cross-sectional and time series tests using differenced series. Cross-sectional tests, in this case, consist of computing Spearman rank correlation coefficients between payout and each measure of earnings uncertainty used.

Spearman Rank Correlation
Earnings Uncertainty and Payout Ratio, 474 Firms

Uncertainty Measure	Rank Correlation
U_1	-0.1238
U_2	-0.2040

(Kalay [1981], p.441, Table 1)

In both cases the sample rank correlation is negative and significantly different from zero; U_1 is significant at the 0.05 level and U_2 is significant at the 0.01 level. These results suggest that firms with higher earnings uncertainty have lower payout ratios.

Chi-squared tests of the independence of changes in uncertainty and changes in payout at the individual firm level were conducted using the time series of payout and uncertainty for each firm.

Chi Squared Test
Earnings Uncertainty and Payout Ratio, 474 Firms

Uncertainty Measure	χ^2
U_1	-0.1238
U_2	-0.2040

Critical values 0.05 and 0.10 levels of significance are 3.84 and 2.71 respectively. (Kalay [1981], p.442, Table 2)

These tests suggest that dividend payout and earnings uncertainty are unrelated. Kalay speculates that this discrepancy between time series and cross-sectional results may reflect a failure in the cross-sectional tests to control for other variables which are potentially correlated with earnings uncertainty, in particular, leverage.

Rozeff [1982] found similar results in a cross-sectional regression. The objective of this study was to identify possible links between dividend policy and various proxies for agency costs. Since the study was not directed at the relationship between dividend payout and risk this issue is dealt with only in passing. In order to control for risk a measure of β was included in the regression. The sample used by Rozeff consists of 1000 firms listed in the

Value Line Investment Survey of June 5th, 1981 and spanning the years 1974-1980. Firms in the following industry categories are excluded: regulated firms (gas, telephone, electrical utilities, air transport, railroad, banking, insurance, savings and loan, and investment companies), foreign firms, and firms involved in petroleum exploration. Rozeff employs a smoothing process to estimate each firm's 'target' payout ratio as an arithmetic average of the actual payout ratios recorded during the period of the study. This variable is then regressed on several growth variables, Value Line beta, measures of inside ownership, and total number of stockholders. Regression results are as follows (see Rozeff [1982], p.256):

Variable	Coefficient Estimate	t-statistic
Constant	47.810	12.83
Percent Inside Ownership	-0.090	-4.10
Average Revenue Growth	-0.321	-6.38
Value Line Forecast Growth	-0.526	-6.43
Value Line Beta	-26.543	-17.05
ln(number of stockholders)	2.584	7.73

Regression $R^2 = 0.48$ F-statistic = 185.47

One of the more striking results of this study is the large, strongly significant, negative coefficient of Value Line beta. Rozeff's view of this is as follows:

> "There are many reports in the literature that beta is negatively related to dividend payout, but explanations of this phenomenon are in short supply. The author's view is that high beta firms are more likely to require costly external financing, other things equal. Hence, they

> intentionally choose lower dividend payout policies. This explanation relies on the fact that beta incorporates operating and financial leverage."
> (Rozeff [1982], p. 257)

An alternative explanation, consistent with the signalling and clientele literature, would be that changes in dividend policy affect the frequency and magnitude of price changes and therefore contribute to risk. Although Rozeff's study did not address the possibility of an omitted leverage variable, and the use of a 'target' payout ratio may to some extent obscure the true relationship between payout and risk, the presence of strong statistical significance in the context of a smoothed dependent variable may suggest the existence of a causal underlying relationship. That is, the smoothing process may proxy for the explicit use of lags. The current study seeks to investigate this possibility.

<u>Dividend Payout and Risk</u>:

The hypothesis that dividend payout causally precedes risk is tested via Granger [1969,1980] causality methodology. Leverage concerns of the sort raised by Kalay are not an issue here since only firm specific time series tests are performed and thus the potential problem of leverage differences inducing bias in cross-sectional results does not arise. However, as discussed below, leverage may pose problems in the sense that if we find a causal relationship between risk and payout, but a leverage variable is not included in the test, we cannot preclude the possibility that leverage rather than risk is the true causal factor.

Two risk variables, OLS beta and standard deviation of returns, are used in the initial work. The possible outcomes can be summarized as follows:

i) a) **payout causes OLS beta**: since systematic risk has been demonstrated to be a determinant of value, this finding would imply that dividend policy is a relevant concern.

b) **payout causes standard deviation of returns**: this finding may indicate that a potential for agency problems (as in Jensen and Meckling [1976]) exists, particularly if a) above is found not to be true, since managers are likely to be more concerned about a firm's total risk than are shareholders.

ii) a) **OLS beta causes payout**: this would support the costly external financing explanation put forward by Rozeff and cited above.

b) **standard deviation of returns causes payout**: once again this raises potential agency concerns, although by itself it is not conclusive.

iii) **no causal relationship**: this does not rule out the possibility of a strictly contemporaneous causal relationship.

Furthermore, it should be noted that sections i.) and ii.) above are not mutually exclusive since causality can be bi-directional.

The Model:

Tests for the presence of a causal relationship between risk and payout were carried out using the methodology proposed by Granger [1969,1980] and discussed in section III. In the bivariate case with symmetric lags this reduces to two regression equations of the form:

$$RISK_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i RISK_{t-i} + \sum_{j=1}^{n} \beta_j PAYOUT_{t-j} + \epsilon_t \qquad (14)$$

$$PAYOUT_t = \Gamma_0 + \sum_{j=1}^{n} \Gamma_j PAYOUT_{t-j} + \sum_{i=1}^{n} \delta_i RISK_{t-i} + \mu_t \qquad (15)$$

As discussed in section III the operational definition of this methodology requires that the dataset used approximates the universe of information available at time t that could have a bearing on the variables involved. Obviously, if a much longer series were available it would be theoretically preferable to conduct this test with many more explanatory variables, and more lags, included in the equations. Data limitations and power considerations prohibit this in the current study. However, the results of Rozeff [1982] lend some support to the choice of the bivariate model. In

Rozeff's cross-sectional regression of target payout on a variety of explanatory variables, OLS beta emerged with a t statistic nearly three times that of any other variable in the equation. One remaining issue is that Rozeff did not include a measure of leverage in his study. Since leverage is known to be strongly correlated with OLS beta any findings showing significance of this variable would be confounded by the fact that it could be proxying for leverage. On the other hand, the results of a test using a trivariate model, with both risk and leverage measures included, are not likely to prove illuminating due to the multicollinearity problems which would arise. As in most cases where potential explanatory variables are known to be correlated, the order of precedence must be established on theoretical grounds. Since it appears to be more plausible that changes in leverage precede changes in risk measures than that changes in risk measures precede changes in leverage, risk variables rather than leverage variables are used in the current study. Thus, the specification of the model in the current study seeks to strike a balance between theoretical and practical considerations by including a limited number of the most relevant variables.

In the context of equations (14) and (15), testing the hypothesis that PAYOUT causally precedes RISK amounts to a test of the significance of the β and δ coefficients in these equations. If β proves to be statistically significant while δ does not, we would reject the null hypothesis in favor of the alternative hypothesis that PAYOUT 'Granger causes' RISK.

There is, however, an important underlying assumption in the development of this model which constitutes a precondition for its application; that is, the series must be stationary. Stationarity and techniques for testing for its presence are discussed in section III above.

The Sample:

The sample used for the initial tests included all firms that met the following criteria:

a) listed on both the Annual Compustat tape <u>and</u> the CRSP Daily tape for the period 1969 through 1988;

b) fiscal year-end in December throughout the sample period;

c) no firms with more than one class of common stock;

d) no missing payout observations.

This screening process resulted in a sample of 506 firms. Imposing the non-singularity requirement necessary in order to make estimation of the test equations feasible further reduced the sample to 483 firms. Of the cases of singularity, 21 were attributable to firms with zero payout over the entire sample period and 2 were attributable to firms with zero payout over all but one year of the sample period. For purposes of this study the payout variable is defined as:

$$\text{PAYOUT} = \frac{\text{COMMON DIVIDENDS}}{\text{(NET INCOME - PREFERRED DIVIDENDS)}}$$

The items on the right hand side of the above equation correspond to the following Compustat item numbers:

18 Income Before Extraordinary Items

19 Preferred Dividends

21 Common Dividends

Risk variables used are OLS beta and standard deviation of returns. These were computed from returns series on the CRSP Daily Tape using non-overlapping daily series for each calendar year. Firms for which data were not available for the full year were excluded from the sample.

<u>**Initial Test Results**</u>: First, in order to address the stationarity issue discussed above, Dickey-Fuller [1979] test statistics were computed for each of the series involved in the study. The following results were obtained by comparing these test statistics to the appropriate critical values[5]:

Dickey-Fuller Test Statistics
Levels of Variables
(Percent of Sample Firms Significant)

Series	Level of Significance 0.01	0.025	0.05
PAYOUT	36.36%	47.43%	60.28%
STD DEV	76.68	86.36	91.70
OLS BETA	49.41	66.80	77.27

In an effort to a achieve a higher proportion of sample firms exhibiting stationarity at a significant level, the series were first differenced.

Dickey-Fuller Test Statistics
First Differences
(Percent of Sample Firms Significant)

Series	Level of Significance 0.01	0.025	0.05
PAYOUT	61.07%	72.92%	80.04%
STD DEV	69.96	86.17	93.48
OLS BETA	56.92	74.31	89.53

Table V.1 gives selected percentiles of these test statistics. Significant test statistics are denoted by an asterisk. Histograms showing these results are provided in Figures V.1 - V.3. Note that for some firms this transformation appears to have induced a unit root where there was none before. Thus, for the STD DEV series, a lower percentage of firms exhibit stationarity at the 0.01 level of significance after the transformation than before the transformation. Nevertheless, at the 0.05 level, the transformation helps more than it hurts. Indeed, since a substantial **majority** of firms appear to exhibit stationarity in all three series with the differencing transformation, it is the transformed rather than the raw series which are used in the subsequent causality tests.

Selected percentiles of the F-statistics resulting from the causality tests performed on these series are provided in Table V.1. These tests were performed as described above with two lags on both the payout and risk variables. Thus, the degrees of freedom for the F-tests involved are 2 in the numerator and 12 in the denominator.

Although the results are slightly slanted towards significance of lagged PAYOUT in the second test, they are not grounds for acceptance of the hypothesis that dividend payout Granger causes risk at a statistically significant level. In fact if we apply the critical value of 3.81 for significance at the $\alpha=0.05$ level with 2 degrees of freedom in the numerator and 12 degrees of freedom in the denominator, under the null hypothesis of no causal relationship, we can view this as repeated sampling from the binomial distribution with $p=0.05$. This can be used to obtain some insight regarding the overall significance of the test results by evaluating the complement of the cumulative binomial probability, $P\{N>k\}$, for the number of significant observations of the F-statistic found.

The table below shows the frequency count of F-statistics significant at the $\alpha=0.05$ level for the 483 firms in the sample. These F-statistics are for block exclusion tests of all lags of the variable named. Thus, the F-statistics for OLS beta relate to tests of the hypothesis that lagged OLS beta is statistically significant in explaining current dividend payout. The resulting cumulative binomial probabilities are as follows:

Sample Period 1969-1988
Differenced Series, 483 Firms
$F_{\alpha=0.05,2,12} = 3.81$

F-statistics	Frequency	Binomial P{N>k}
Payout(Beta)	22	0.6242
OLS Beta	28	0.1802
Payout(SDev)	46	0.0000
Std. Dev.	31	0.0670

These are the probabilities, under the null hypothesis, of finding a higher frequency of significant F-statistics than that actually observed in the sample of firms studied. They could therefore be viewed as measures of the significance levels of the aggregate test results. A lower cumulative binomial probability would correspond to greater significance in the test results.

Alternatively, the χ^2 goodness-of-fit test provides a useful means of measuring the aggregate significance of the sample F-statistics. In this test a frequency table of the sample F-statistics, rather than a simple proportion, is used to test the hypothesis that the distribution of the sample statistics conforms to the F distribution under the null. A χ^2 statistic greater than the critical value indicates rejection of this hypothesis.

χ^2 Goodness-of-Fit Tests
Sample Period 1969-1988
Differenced Series, 483 Firms
$\chi^2_{1-\alpha=0.95,df=19} = 30.14$

F-statistics	χ^2
Payout OLS Beta	26.8551 10.6232
Payout Std. Dev.	46.3168 * 22.8799

The direction of the relationship between the test statistics and the F distribution under the null hypothesis is clear from Table V.1 and from the binomial test shown above. It is evident from these results that when standard deviation of returns is used as the risk variable the null hypothesis is rejected in a significant proportion of sample firms. It appears that in these firms changes in dividend payout precede changes in price risk, but do not necessarily precede changes in market risk. As noted earlier, findings of this sort could be construed as evidence supporting signalling and/or clientele effects.

Segmenting the results of both tests further by means of histograms (see Figures V.4 through V.7), this observation comes through even more clearly. There is evidence of the originally hypothesized relationship between the PAYOUT and STD DEV series but none between the PAYOUT and OLS BETA series.

At this stage it may be helpful to examine the various factors which may contribute to the lack of clearly interpretable results:

i) **The temporal screen may be too coarse.** That is, the observations may be spaced too far apart. Even in the presence of a clear uni-directional causal relationship this could lead to findings of bi-directional causality, or, if the underlying relationship is contemporaneous within the context of the temporal screen, no causality. While quarterly data is available, its information content is suspect due to the common practice of paying dividends quarterly while only making changes in dividends annually. Thus, with existing data one **may** establish a prima facie case supporting causality. However, one cannot establish a case for its rejection.

ii) **The series may be too short.** Since the current Compustat tape includes only 20 annual observations per firm, the payout series is necessarily limited. After first differencing, and including an intercept, the degrees of freedom for the unrestricted model are reduced to 12. This raises concerns regarding the power of the test. As evidenced by the simulation results in the earlier section, a moderately strong non-contemporaneous causal relationship can be consistently detected with series of this length. However, with a stronger contemporaneous element to the relationship, and more noise, the discriminatory power of the test drops precipitously. This concern is addressed later in the current study through the use of a back-dated Compustat tape which provides 18 additional observations for firms in operation for the entire 38 years covered by both tapes.

iii) **Stationarity conditions may not have been adequately met.** It is noteworthy that a weak causal relationship between PAYOUT and STD DEV is hinted at while the same did not hold true when OLS BETA was used as the risk variable. It is possible that this phenomenon is attributable at least in part to the weaker stationarity of the OLS BETA series. If this does not provide a satisfactory explanation for the discrepancy, then this would suggest that the agency dimension of this problem could be a fruitful area for further investigation.

iv) **Results may be obscured by firms with 'sticky' dividends.** Specifically, highly regulated firms such as utilities, banks, and insurance companies for which market imperfections may be viewed as particularly pronounced may exhibit behavior which is not representative of other less regulated firms.

v) **An alternative specification of the PAYOUT variable may be more appropriate.** That is, changes in the dividend payout ratio may not be an appropriate proxy for changes in dividend policy. Specifically, since PAYOUT incorporates two sources of variance, dividend policy effects may be confounded with earnings effects or totally obscured.

Tests with Extended Data Series:

Although all of the concerns listed above may bear further consideration, augmentation of the data series to improve the power of the test appeared to hold the most promise. Using the Compustat Backdata tape in conjunction with the current tape series of 38 annual observations covering the period 1952-1989 were constructed. Since the CRSP Daily tape only contains data going back as far as 1962, risk series were constructed using monthly return observations from within each year. These data were obtained from the CRSP monthly tape. Although this approach may result in less accurate risk observations than those obtainable from daily data, the greater degrees of freedom available with the longer series should improve estimational efficiency. It is not clear which effect predominates.

In addition screens were implemented to exclude banks, utilities, insurance companies, ADR's, limited partnerships and real estate investment trusts; that is, firms for which the regulatory environment would tend to make dividends particularly sticky. Also, firms with zero dividend payout over the entire sample period were excluded in order to avoid cases of singularity. This resulted in a data set consisting of 115 firms for which payout and risk data were available for the entire 38 year sample period.

Initially, stationarity tests were performed on the series. Since a large proportion of the firms in the sample exhibit stationarity in the raw series, the results of these tests and the related causality tests using the raw series are presented in Table V.2. Although the results are consistent with those for the larger sample shown in Table V.1, they are still far from conclusive.

Since stationarity is accepted in a far greater proportion of cases when the differenced series are used, the causality tests performed on these series would appear to be more relevant. The results of these tests are presented in Table V.3 and the accompanying histograms in Figures V.8 - V.14. Although the results are still far from conclusive, if we return to the application of the binomial distribution presented earlier, it is clear that the relationship between dividend payout and standard deviation of returns observed earlier is still present in a significant proportion of firms.

Sample Period 1952-1989
Differenced Series, 115 Firms
$F_{\alpha=0.05,2,28} = 3.33$

F-statistics	Frequency	Binomial P(N>k)
Payout(Beta)	6	0.3525
OLS Beta	3	0.8321
Payout(SDev)	12	0.0050
Std. Dev.	8	0.1126

Once again, the χ^2 goodness-of-fit test provides a convenient means of comparing the distribution of these F statistics with the distribution of the F statistics under the null hypothesis of no causal relationship between the variables.

χ^2 Goodness-of-Fit Tests
Sample Period 1953-1989
Differenced Series, 115 Firms
$\chi^2_{1-\alpha=0.95,df=19} = 30.14$

F-statistics	χ^2
Payout	27.7826
OLS Beta	20.4783
Payout	18.7391
Std. Dev.	14.5652

These results, although statistically insignificant, represent a reversal of the results obtained over the shorter 1969-1988 sample period in the sense that dividend payout appears to have stronger significance in explaining OLS Beta than in explaining standard deviation. This suggests that the unusually high frequency count on the

PAYOUT F-statistics in the second section of the first of the two tables on the previous page is an aberration, and the distribution of the test statistics overall closely matches the F distribution under the null hypothesis. Thus, over the longer sample period, the test results do not support the hypothesis that dividend payout Granger causes risk.

Conclusion:

Although the results of the tests performed do not lead to an unambiguous acceptance of the hypothesis that dividend payout Granger causes risk, the available data does not allow for unambiguous rejection. Perhaps the most notable result in this study is the evident reversal of the relationship between dividend payout and OLS beta and dividend payout and standard deviation of returns. It should be noted that although the χ^2 statistic for dividend payout in the causality test of dividend payout and OLS beta is not significant at the $\alpha=0.05$ level it is significant at the $\alpha=0.10$ level. Thus, there is evidence in support of an empirical relationship between dividend payout and risk. Specifically, at the $\alpha=0.10$ level we would reject the null hypothesis in favor of the hypothesis that dividend payout Granger causes OLS beta.

The results obtained with shorter time series suggested that changes in dividend payout precede changes in volatility more often than changes in systematic risk. Such findings would imply that changes in dividend payout contribute (at least in some firms) to increased non-systematic risk. This interpretation is consistent with the signalling and clientele effect literature but does not necessarily have any immediate implication for firm value. However, the results obtained with the longer data series have more serious implications. If in fact dividend payout Granger causes systematic risk, even in a minority of firms, then dividend policy does affect firm value, at least for these firms.

In order to confirm and possibly further illuminate this phenomenon a thorough attempt should be made to identify the unique characteristics of the current statistically significant subset of the sample, i.e. in terms of dividend policy, leverage, market capitalization, etc. In particular it may be helpful to compare these results to those obtained from causality tests for a relationship between dividend policy and leverage. Although it is possible that the results observed in this study are driven by disparities in leverage it appears unlikely since leverage differences should be closely related to beta.

Table V.1

Empirical Test for Causality between Payout and Risk, T=19
Differenced Variables, 483 Firms
Sample Period 1969-1988

Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=19} = -3.05$
$DF_{\alpha=0.10,n=19} = -2.67$

		PAYOUT	OLS Beta	Std. Dev.
	5	-1.4184	-2.7075	-2.8470
	10	-2.4508	-2.9971	-3.0760*
	25	-3.3324*	-3.3224*	-3.5610*
Percentile	50	-4.1846*	-3.9311*	-4.0282*
	75	-4.9337*	-4.5831*	-4.5505*
	90	-5.8435*	-5.4442*	-5.0939*
	95	-7.0387*	-5.8287*	-5.4398*

F-Statistics

Critical Value of $F_{\alpha=0.05,2,12} = 3.81$
$F_{\alpha=0.10,2,12} = 2.76$

Causality Test of Payout and OLS Beta

		Payout	OLS Beta
	5	0.0459	0.0504
	10	0.0931	0.1040
	25	0.2759	0.2788
Percentile	50	0.6344	0.6804
	75	1.5962	1.4606
	90	2.7530	2.8473
	95	3.5122	3.9760*

Causality Test of Payout and Std. Dev.

		Payout	Std. Dev
	5	0.0425	0.0412
	10	0.0769	0.0812
	25	0.3307	0.2508
Percentile	50	0.8975	0.6613
	75	1.9622	1.4868
	90	3.3737	2.9178
	95	5.3519*	4.1002*

Table V.2

Empirical Test for Causality between Payout and Risk, T=38
Levels of Variables, 115 Firms
Sample Period 1953-1989

Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=38} = -2.95$
$DF_{\alpha=0.10,n=38} = -2.62$

		PAYOUT	OLS Beta	Std. Dev.
	5	0.6868	-2.9437*	-2.1006
	10	-1.0129	-3.1155*	-2.3502
	25	-2.1350	-3.3843*	-2.8287
Percentile	50	-2.8931	-4.0455*	-3.7241*
	75	-4.0271*	-4.8744*	-4.3042*
	90	-4.7311*	-5.5325*	-4.7671*
	95	-5.1224*	-5.7530*	-5.2189*

F-Statistics

Critical Value of $F_{\alpha=0.05,2,31} = 3.33$
$F_{\alpha=0.10,2,31} = 2.49$

Causality Test of Payout and OLS Beta

		Payout	OLS Beta
	5	0.0425	0.0485
	10	0.1012	0.0911
	25	0.3602	0.2323
Percentile	50	0.7630	0.5428
	75	1.7098	1.1065
	90	2.4885	1.8500
	95	3.3644*	2.4814

Causality Test of Payout and Std. Dev.

		Payout	Std.Dev.
	5	0.1037	0.1010
	10	0.2373	0.1326
	25	0.5924	0.4389
Percentile	50	1.2964	0.8697
	75	2.3795	1.7325
	90	3.7173*	3.3222
	95	4.6893*	4.9369*

Table V.3

Empirical Test for Causality between Payout and Risk, T=37
Differenced Variables, 115 Firms
Sample Period 1953-1989

Dickey-Fuller Statistics

Critical Value of $DF_{\alpha=0.05,n=37} = -2.95$
$DF_{\alpha=0.10,n=37} = -2.62$

		PAYOUT	OLS Beta	Std. Dev.
	5	-3.4821*	-5.2902*	-4.9601*
	10	-4.1742*	-5.6527*	-5.3364*
	25	-5.0150*	-6.3314*	-5.6848*
Percentile	50	-6.1568*	-7.1034*	-6.2449*
	75	-6.9773*	-8.0589*	-7.1372*
	90	-8.3398*	-9.0011*	-7.7847*
	95	-9.6348*	-9.6435*	-8.2933*

F-Statistics

Critical Value of $F_{\alpha=0.05,2,30} = 3.33$
$F_{\alpha=0.10,2,30} = 2.49$

Causality Test of Payout and OLS Beta

		Payout	OLS Beta
	5	0.0263	0.0264
	10	0.0910	0.0769
	25	0.3081	0.2552
Percentile	50	0.7488	0.6242
	75	1.6695	1.2752
	90	2.6629	2.0306
	95	3.0172	2.5481

Causality Test of Payout and Std. Dev.

		Payout	Std. Dev.
	5	0.0383	0.0285
	10	0.0795	0.0906
	25	0.3505	0.2817
Percentile	50	0.8190	0.6906
	75	1.6625	1.4749
	90	3.1456	2.7328
	95	5.9608*	3.7035*

Figure V.1

Dickey-Fuller Test for Stationarity of Dividend Payout Differenced Series, T=19

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \tag{4}$$

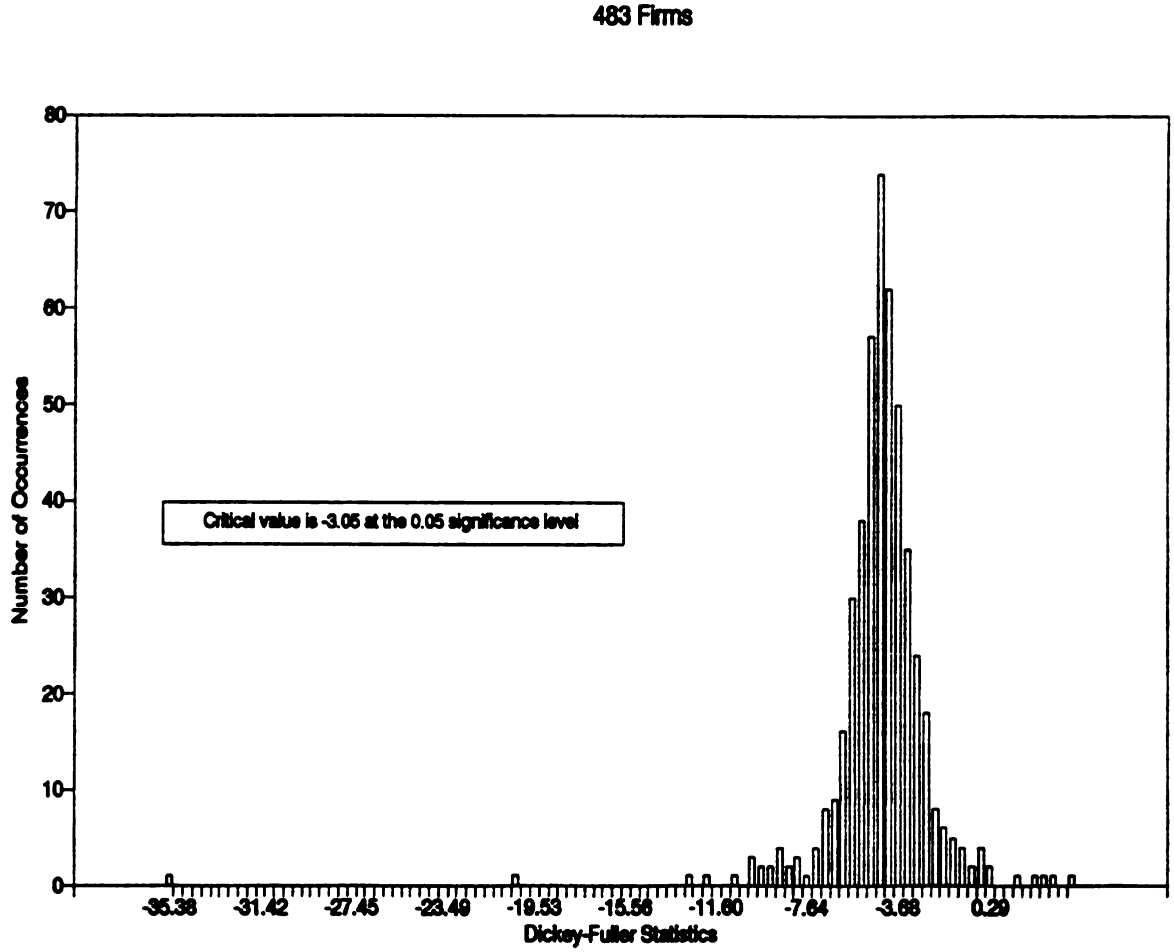


Figure V.2

Dickey-Fuller Test for Stationarity of OLS Beta Differenced Series, T=19

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \tag{4}$$

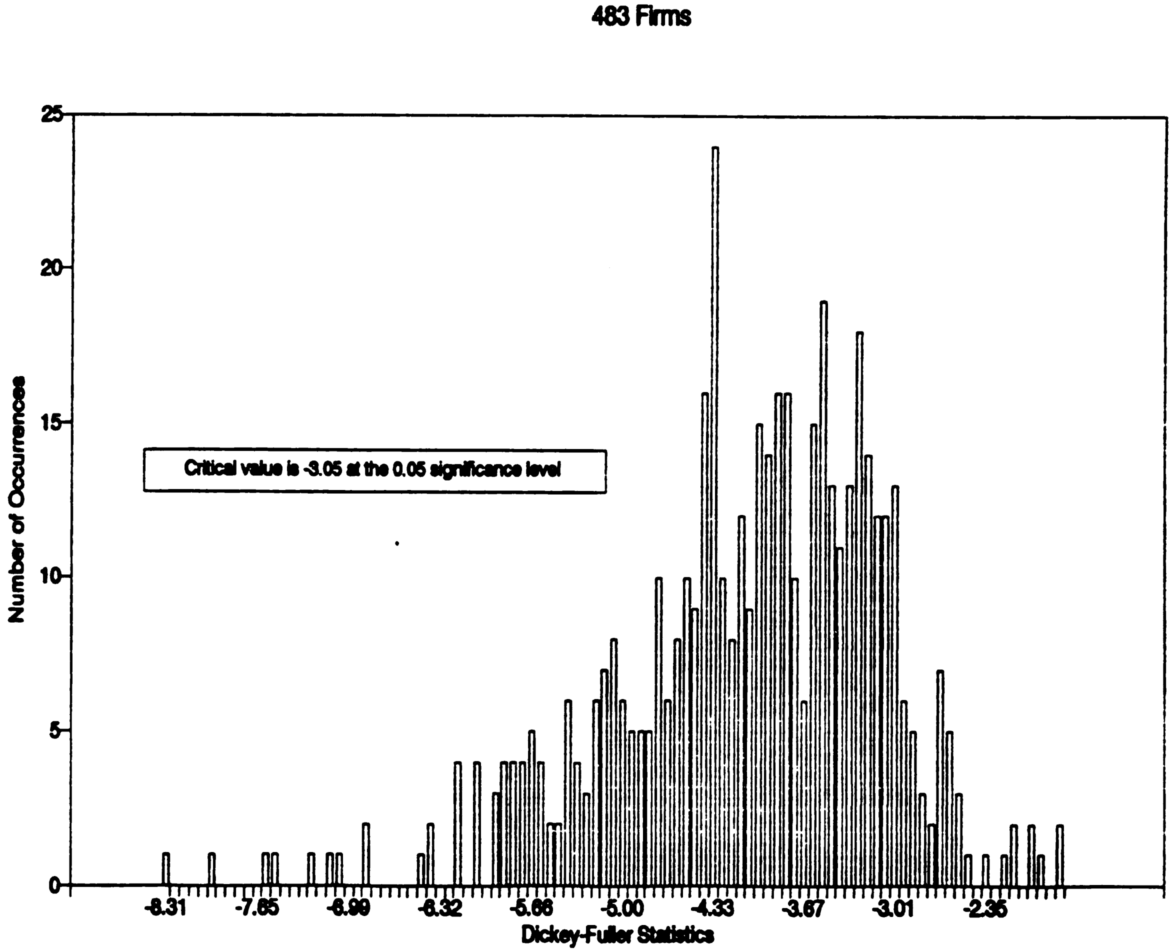


Figure V.3

Dickey-Fuller Test for Stationarity of Standard Deviation Differenced Series, T=19

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \qquad (4)$$

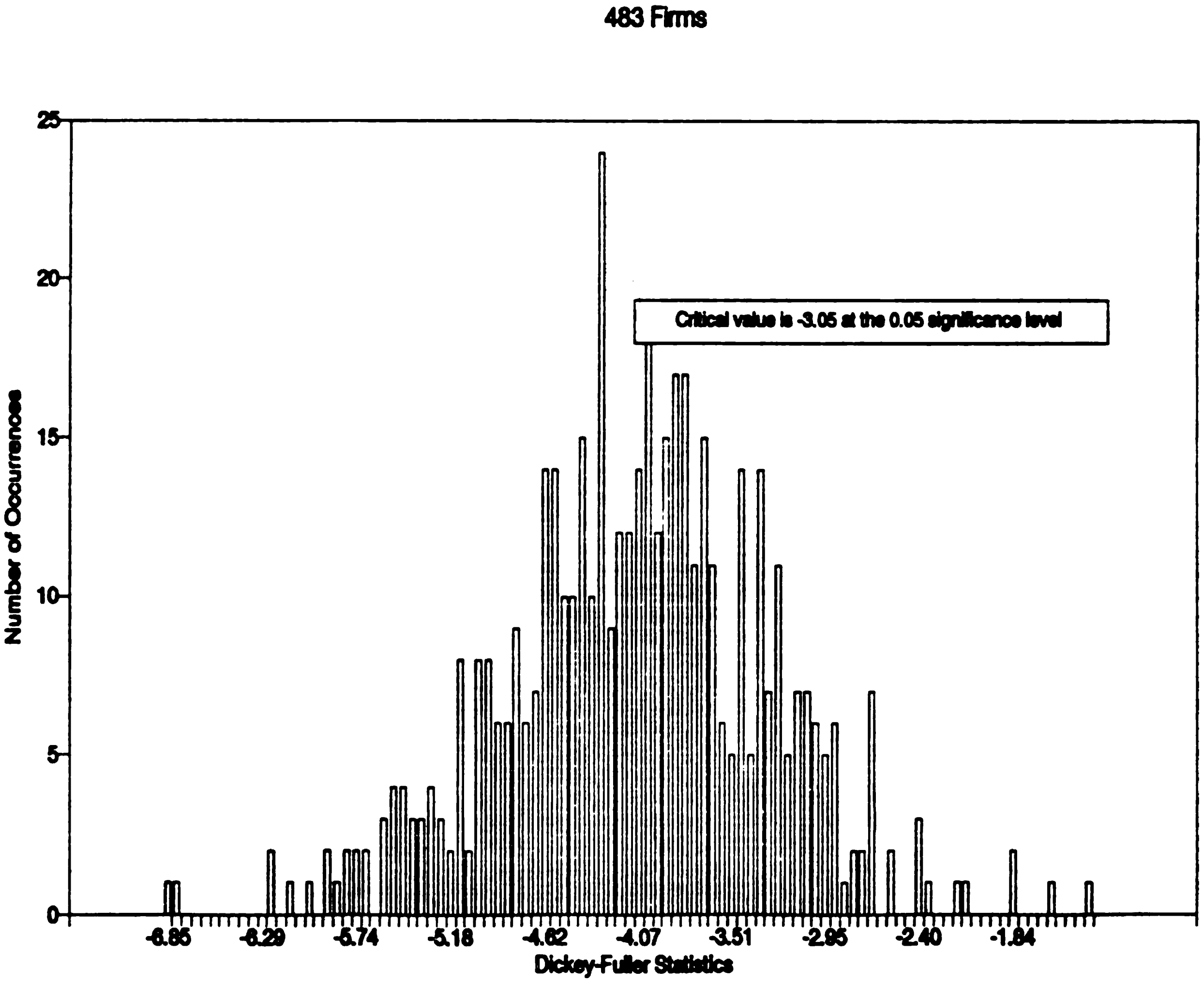


Figure V.4

Significance of Dividend Payout in Explaining OLS Beta Differenced Series, T=19
Block F Test for Exclusion of Dividend Payout

$$BETA_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i BETA_{t-i} + \sum_{j=1}^{2} \beta_j PAYOUT_{t-j} + \epsilon_t \qquad (14)$$

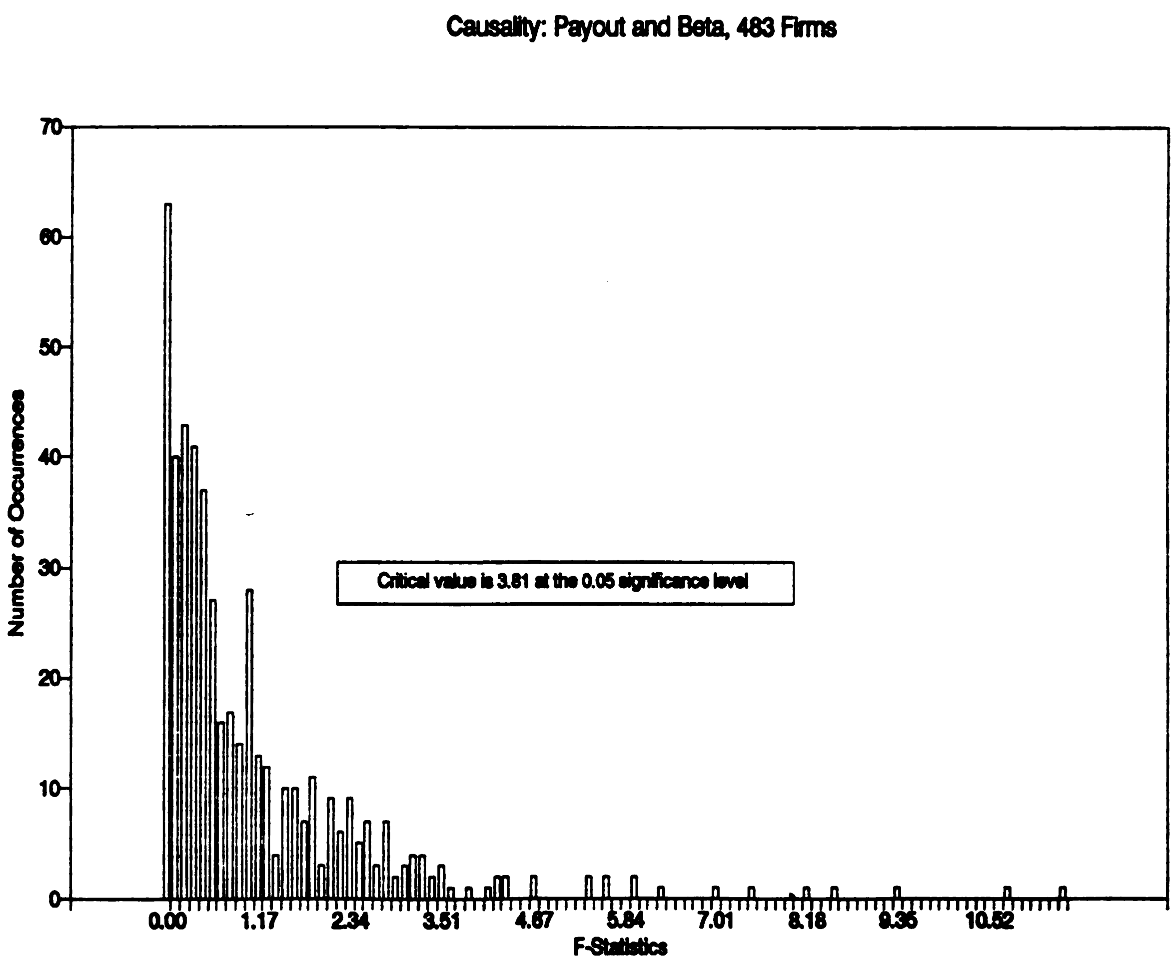


Figure V.5

Significance of OLS Beta in Explaining Dividend Payout
Differenced Series, T=19
Block F Test for Exclusion of OLS Beta

$$PAYOUT_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j PAYOUT_{t-j} + \sum_{i=1}^{2} \delta_i BETA_{t-i} + \mu_t \qquad (15)$$

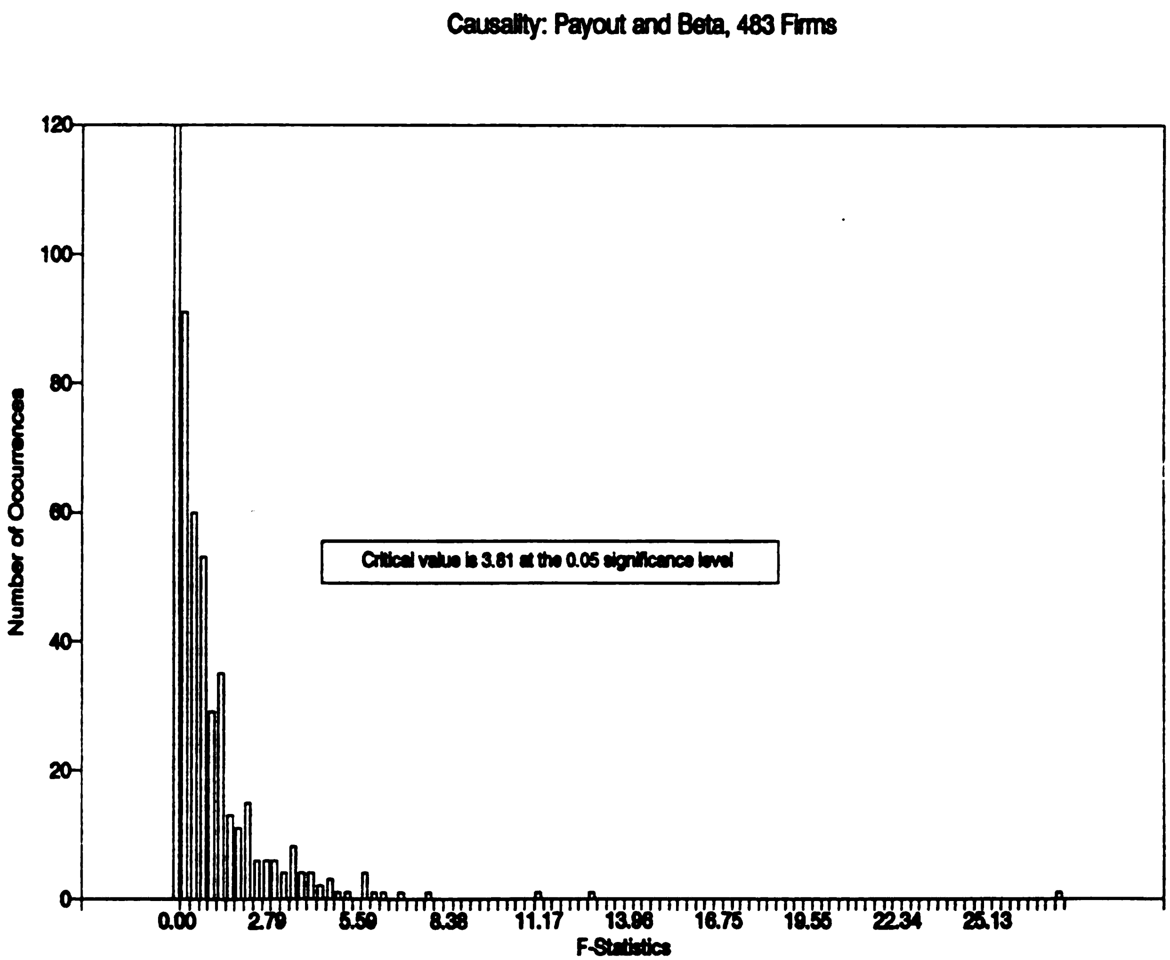


Figure V.6

Significance of Dividend Payout in Explaining Std. Deviation Differenced Series, T=19
Block F Test for Exclusion of Dividend Payout

$$SDEV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i SDEV_{t-i} + \sum_{j=1}^{2} \beta_j PAYOUT_{t-j} + \epsilon_t \qquad (14)$$

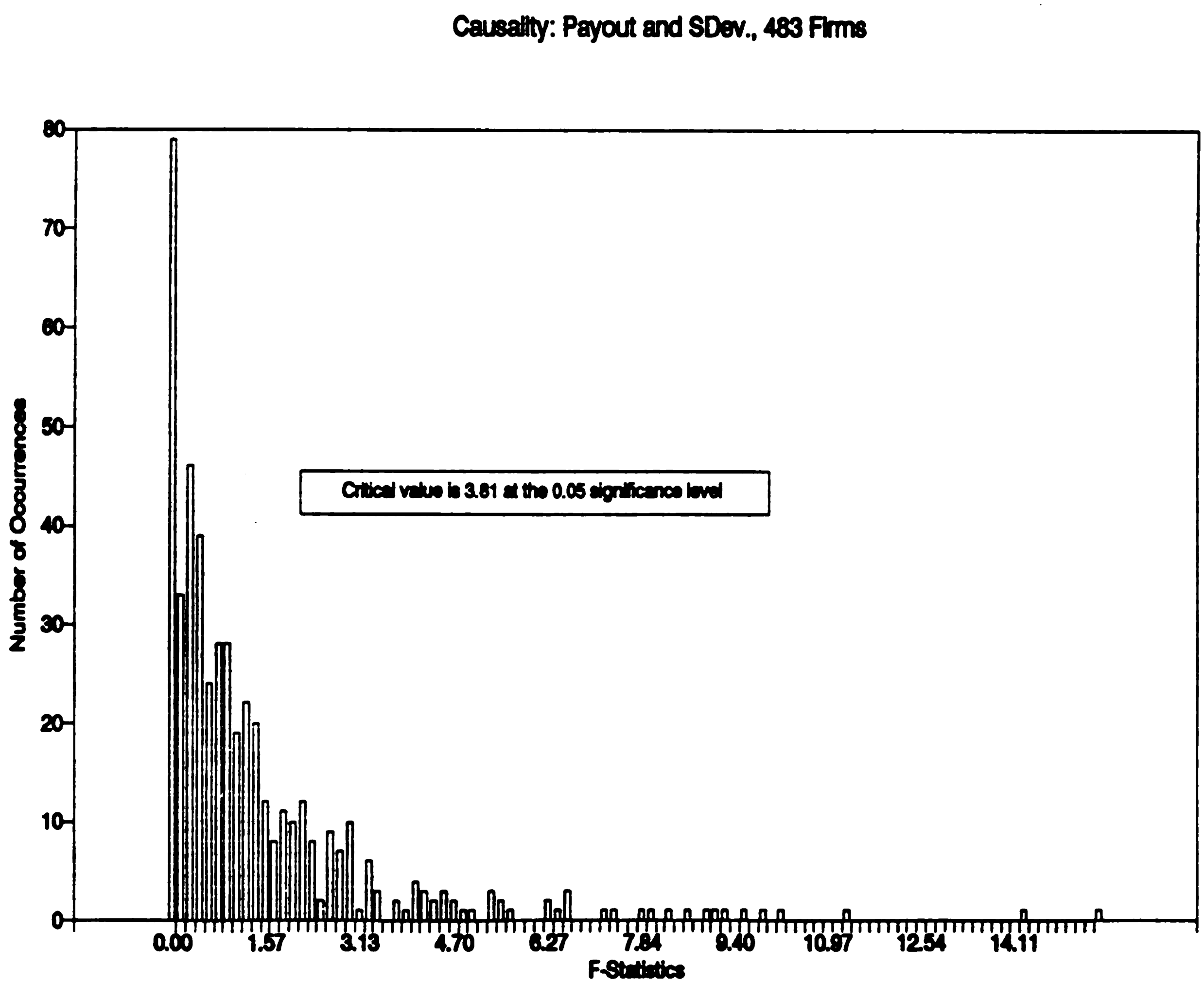


Figure V.7

Significance of Std. Deviation in Explaining Dividend Payout Differenced Series, T=19
Block F Test for Exclusion of Std. Deviation

$$PAYOUT_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j PAYOUT_{t-j} + \sum_{i=1}^{2} \delta_i SDEV_{t-i} + \mu_t \tag{15}$$

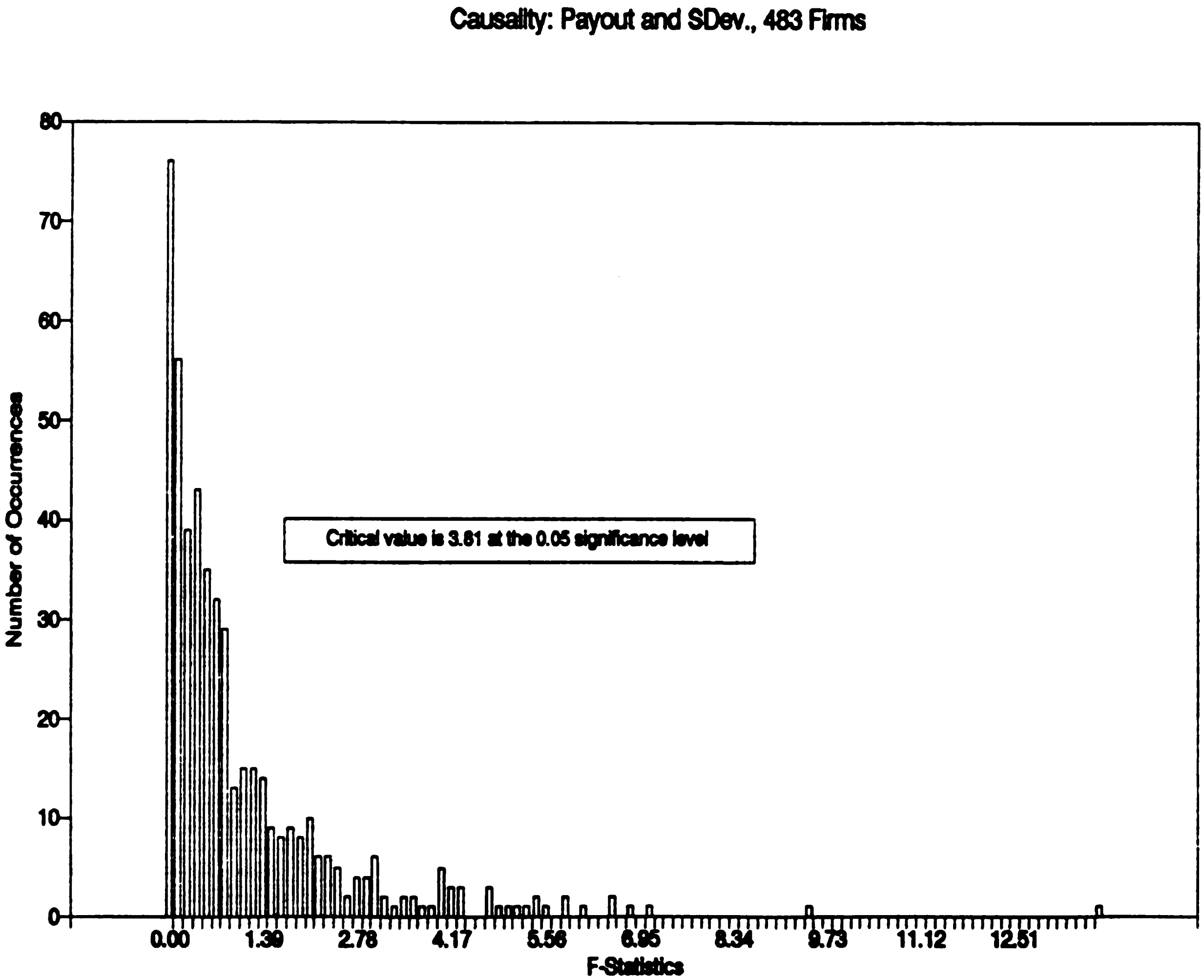


Figure V.8

Dickey-Fuller Test for Stationarity of Dividend Payout Differenced Series, T=37

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \tag{4}$$

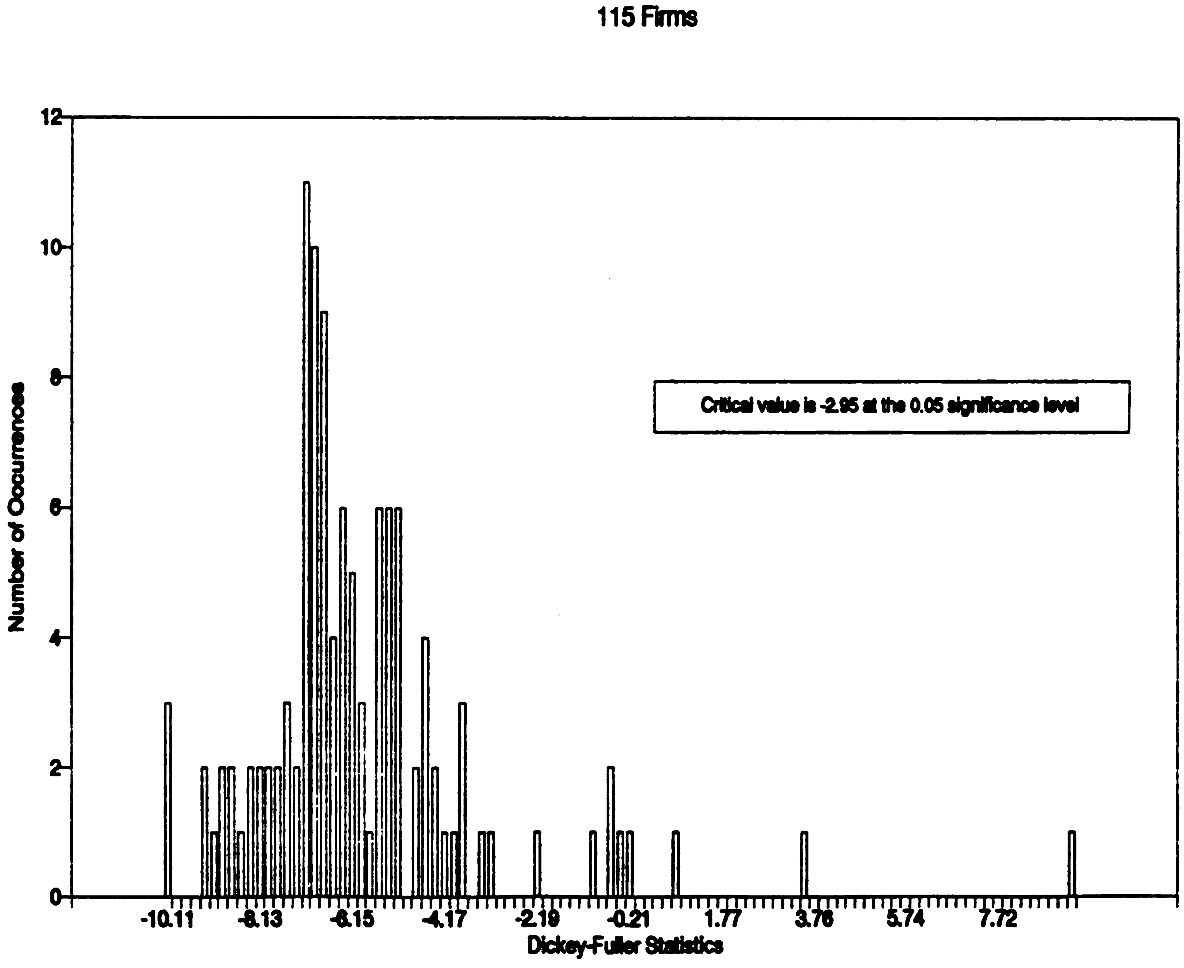


Figure V.9

Dickey-Fuller Test for Stationarity of OLS Beta Differenced Series, T=37

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \qquad (4)$$

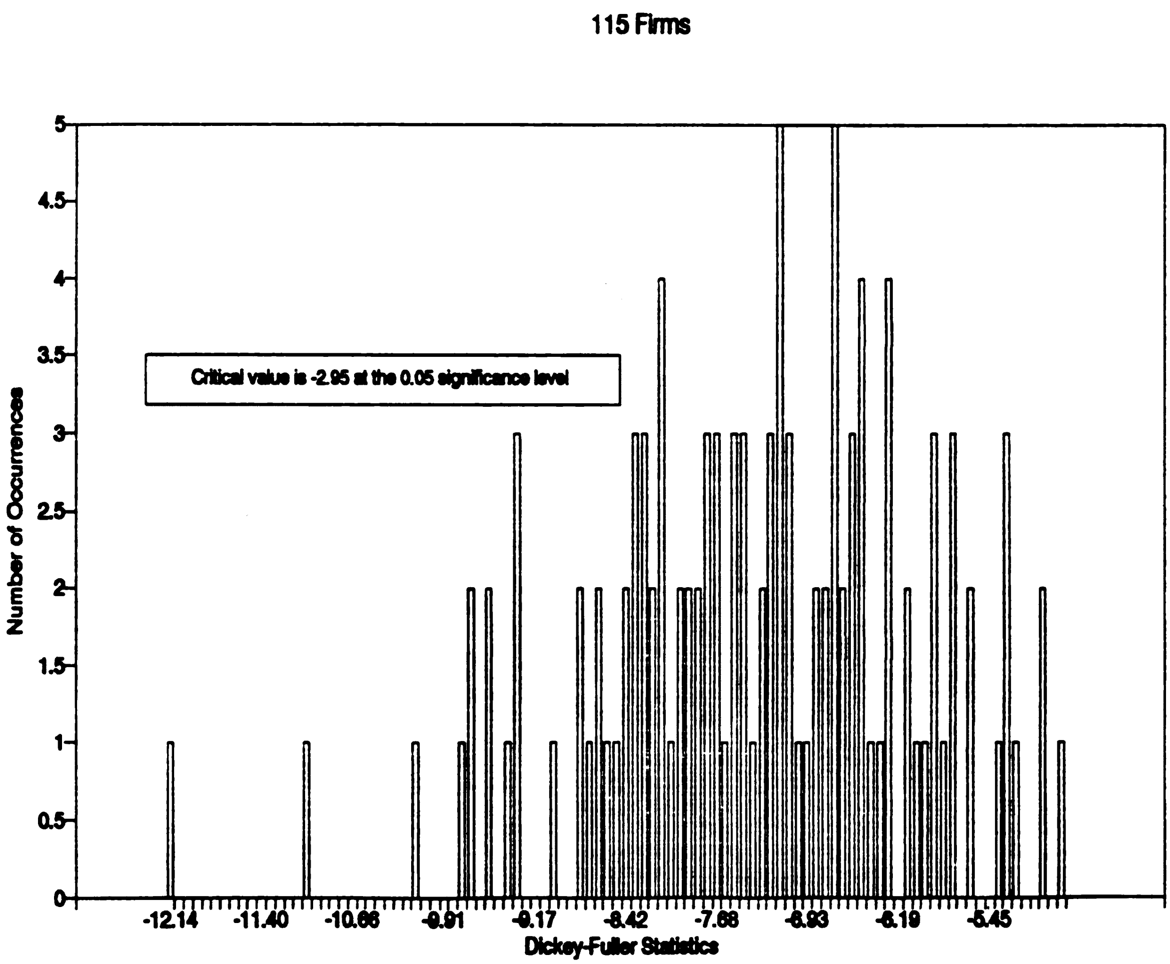


Figure V.10

Dickey-Fuller Test for Stationarity of Standard Deviation Differenced Series, T=37

The hypothesis that one of the p+1 roots of the characteristic equation is unity can be tested by computing a 't-like' statistic consisting of $\hat{\beta}/SE(\hat{\beta})$ from the following regression:

$$(1-L)Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \Gamma_i (1-L) Y_{t-i} + \epsilon_t \qquad (4)$$

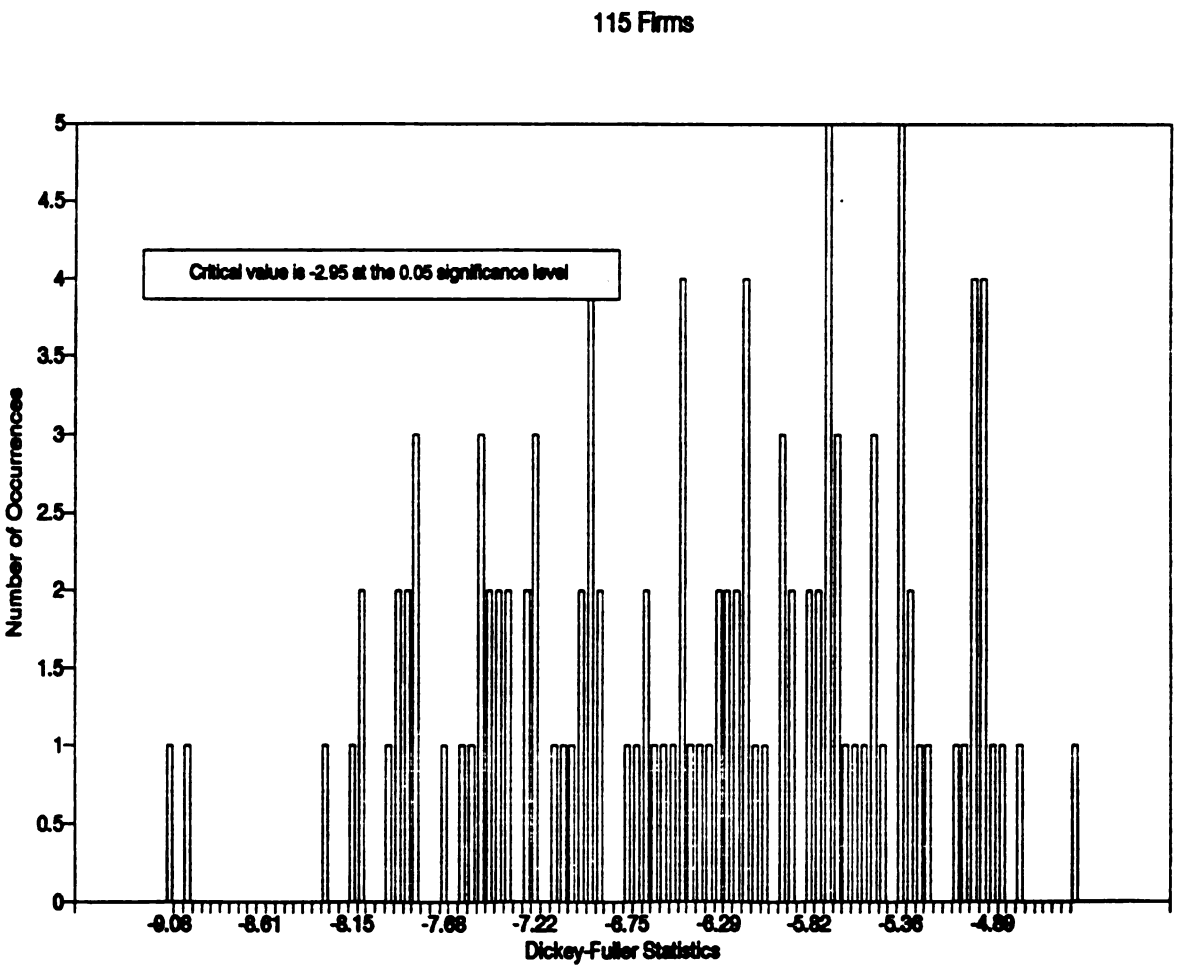


Figure V.11

Significance of Dividend Payout in Explaining OLS Beta Differenced Series, T=37
Block F Test for Exclusion of Dividend Payout

$$BETA_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i BETA_{t-i} + \sum_{j=1}^{2} \beta_j PAYOUT_{t-j} + \epsilon_t \quad (14)$$

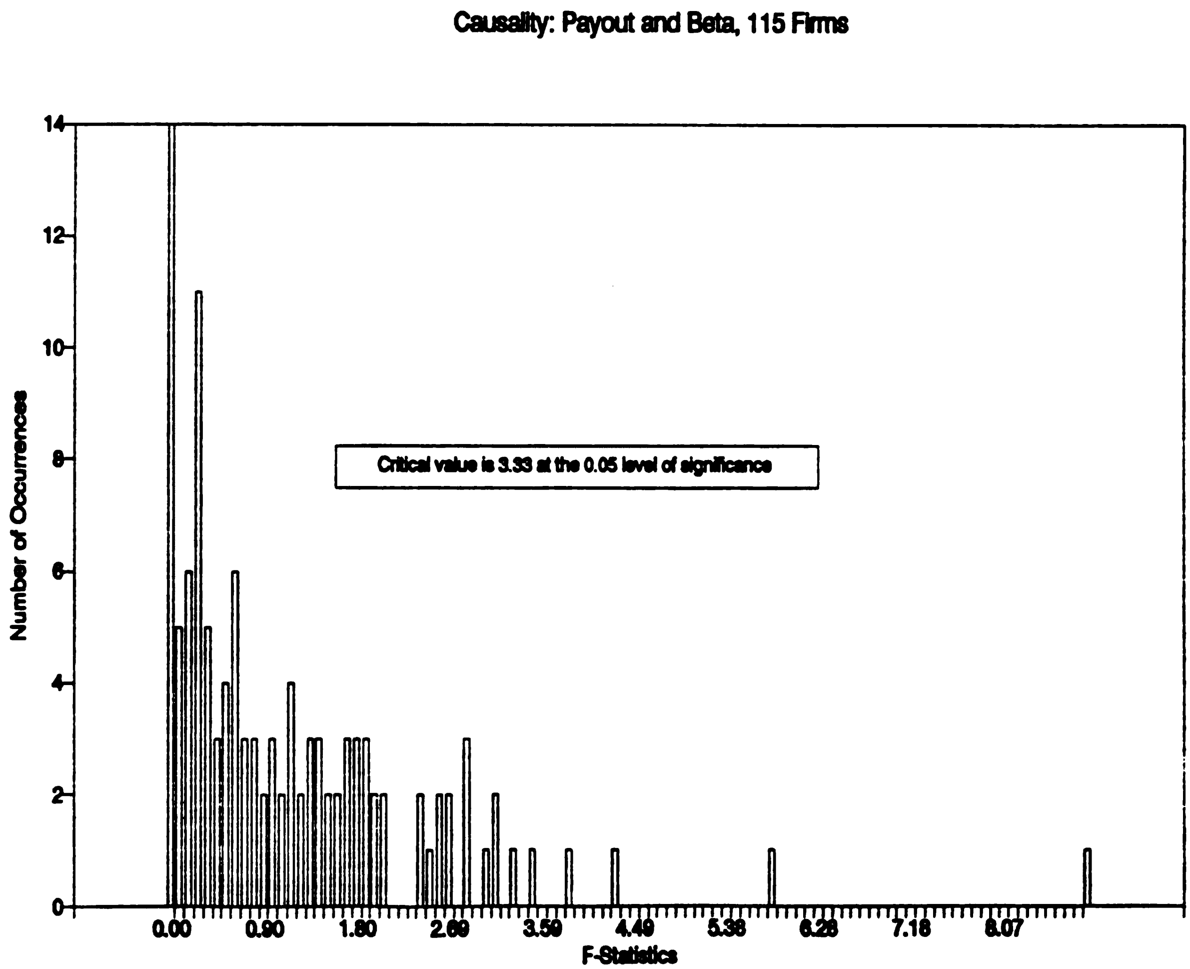


Figure V.12

Significance of OLS Beta in Explaining Dividend Payout
Differenced Series, T=37
Block F Test for Exclusion of OLS Beta

$$PAYOUT_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j PAYOUT_{t-j} + \sum_{i=1}^{2} \delta_i BETA_{t-i} + \mu_t \qquad (15)$$

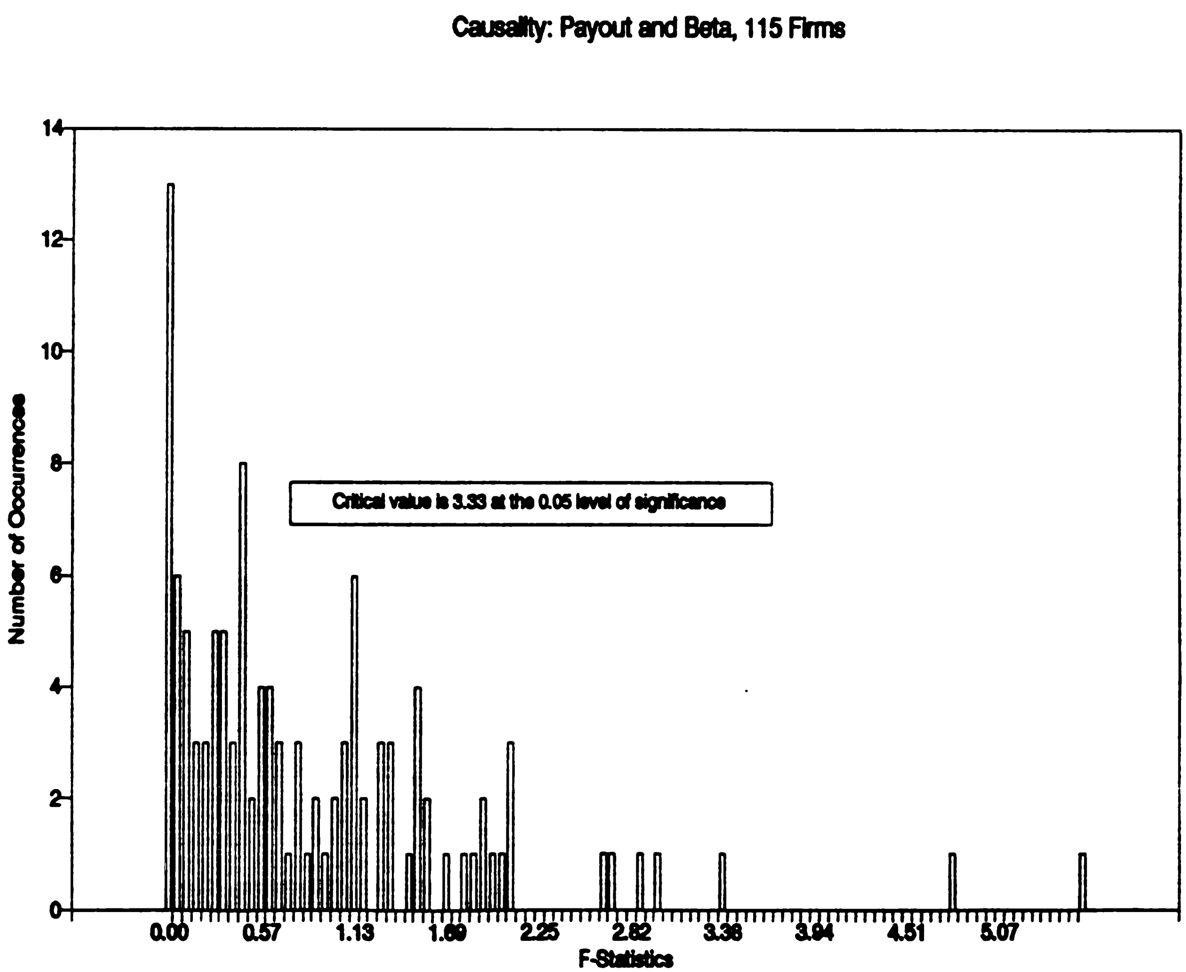


Figure V.13

Significance of Dividend Payout in Explaining Std. Deviation
Differenced Series, T=37
Block F Test for Exclusion of Dividend Payout

$$SDEV_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i SDEV_{t-i} + \sum_{j=1}^{2} \beta_j PAYOUT_{t-j} + \epsilon_t \tag{14}$$

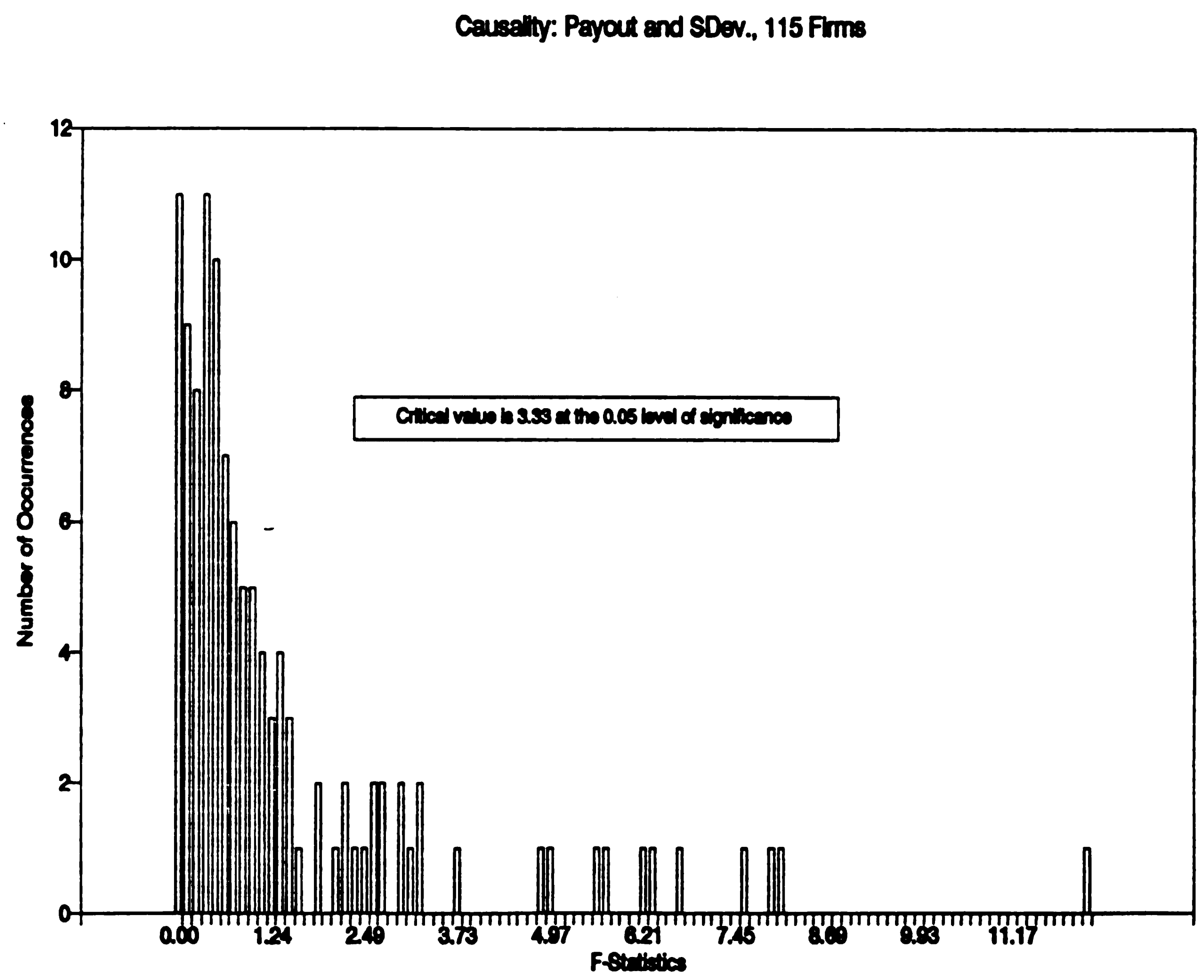
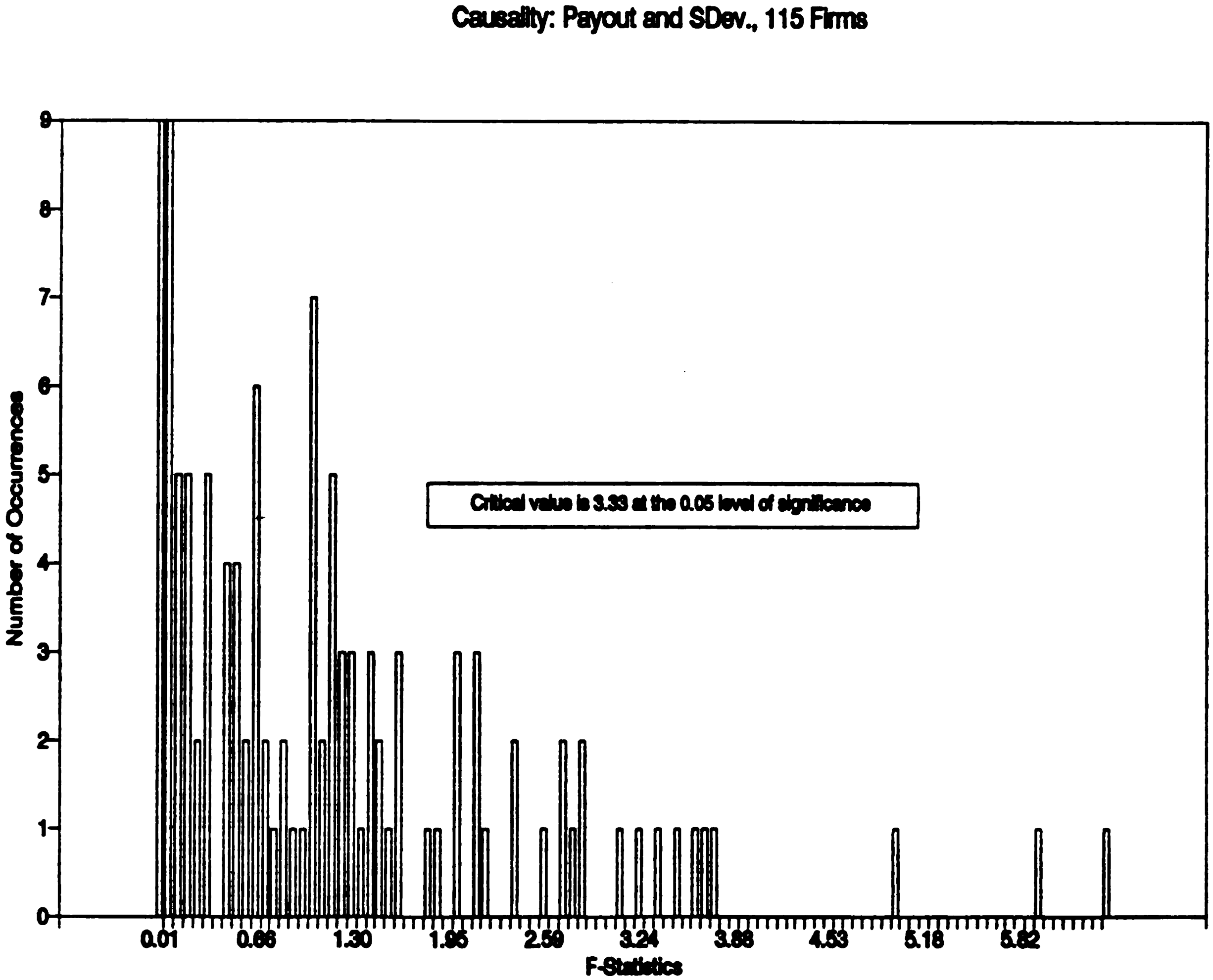


Figure V.14

Significance of Std. Deviation in Explaining Dividend Payout
Differenced Series, T=37
Block F Test for Exclusion of Std. Deviation

$$\text{PAYOUT}_t = \Gamma_0 + \sum_{j=1}^{2} \Gamma_j \text{PAYOUT}_{t-j} + \sum_{i=1}^{2} \delta_i \text{SDEV}_{t-i} + \mu_t \qquad (15)$$



Endnotes

1. This is essentially the test suggested by Dickey and Fuller [1979], p.431, but without the time trend term.

2. The 'augmented' Dickey-Fuller test used in much of the empirical literature was used to confirm the stationarity of the series. This is essentially the test suggested by Dickey and Fuller [1979], p. 431, but without the time trend term. The tables in Fuller [1976], and Schmidt [1990] only provide critical values for selected sample sizes. However, the changes in critical value from sample size T to T-1 become more pronounced as T declines, making interpolation difficult. Fortunately, Peter Schmidt was willing to provide a Monte Carlo simulation routine capable of producing critical values for any sample size, thus resolving the difficulty.

3. It is interesting to note that Smirlock and Marshall report 194 firms which pass this screen over the sample period 1958 - 1977. This suggests that the investment variable used in their study was constructed with the intention of obtaining a proxy for gross rather than net investment. Unfortunately, the published version of Smirlock and Marshall's study is vague on this point and repeated attempts to obtain clarification from the authors have been unsuccessful. Had information specifying the exact construction of their investment variable been available, it would have been interesting and perhaps instructive to follow up on the attempt to replicate their study with the data currently available.

4. Pierce and Haugh [1977] p. 274, Theorem 4.2, derive seven equivalent conditions, any one of which could be used to demonstrate the absence of a causal relationship if sufficient data are available to apply it in a practical context.

5. See note 2.

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