ESTIMATING AND ADJUSTING FOR THE INTERVALLING-EFFECT BIAS IN BETA

by

K.J. Cohen, G.A. Hawawini
S.F. Maier, R.A. Schwartz
and D.K. Whitcomb

N° 82/01

Directeur de la Publication :

Jean-Claude THOENIG
Associate Dean: Research and Development
INSEAD

Imprimé par l' INSEAD, Fontainebleau
France

ESTIMATING AND ADJUSTING FOR THE INTERVALLING-EFFECT BIAS IN BETA

by

Kalman J. Cohen
The Fuqua School of Business
Duke University

Gabriel A. Hawawini
INSEAD, Fontainebleau, France

Steven F. Maier
The Fuqua School of Business
Duke University

Robert A. Schwartz
Graduate School of Business Administration
New York University

David K. Whitcomb
Graduate School of Management
Rutgers University

February 1980

Revised October 1981

DL 36

Forthcoming in Management Science

ABSTRACT

Empirical estimates of beta, the appropriate measure of a security's systematic risk, are biased by friction in the trading process which delays the adjustment of a security's price to informational change and hence leads to an "intervalling-effect" bias. In this paper, we present and empirically test two procedures for correcting this bias. These involve the computation of an asymptotic beta as the differencing interval is lengthened without bound, and take account of the depth of the market for a security as measured by its value of shares outstanding. Our results suggest that a substantial corrections is needed to get "true" beta estimates from short differencing interval data.

ESTIMATING AND ADJUSTING FOR THE INTERVALLING-EFFECT BIAS IN BETA*

1. Introduction

Sharpe's (1964) pioneering paper established a new and sophisticated method for quantifying the non-diversifiable, systematic risk of an investment. The relevant measure is beta, the slope parameter of a regression equation that relates the return on an investment to the return on the market portfolio, a portfolio containing the universe of investments held in proportion to their market value. Since its appearance, Sharpe's method has been widely used to measure the riskiness of investments in shares of common stock. Typically, common stock beta estimates are obtained by regressing the continuously compounded rate of return of a stock on that of a market index such as the S&P 500.

One of the earliest sources of data available for estimating betas was the CRSP tape of monthly stock prices that is compiled at Chicago University's Center for Research in Security Prices. For this reason, beta estimates were initially obtained from regressions run on returns computed over monthly time intervals. Increasingly, however, shorter period data have become available, and now betas are being widely computed for returns measured using weekly and even daily differencing intervals.

If the regression assumptions of the Sharpe model are satisfied, the beta parameter should be invariant with respect to the length of the period over which continuously compounded returns are computed. Increasingly, however, the empirical evidence is showing that, for individual stocks, beta changes, and does so systematically, as the length of the differencing interval is varied.[1] This evidence strongly suggests that the standard estimates of beta have been biased and hence, that the riskiness of individual securities has not been appropriately measured. The purpose of this paper is to further identify, and to present a method of adjusting for, what is now known as the "intervalling-effect" bias in beta.

In Cohen-Hawawini-Maier-Schwartz-Whitcomb [hereinafter CHMSW] (1980), we have argued that the fundamental cause of the intervalling-effect bias is friction in the trading process which delays the adjustment of a security's price to informational change. In CHMSW (1980, 1981), we develop an analytical model of the delayed price-adjustment effect. Our primary purpose in the present paper is to implement empirically two approaches to adjusting for the intervalling-effect bias, which are suggested by our previous analyses. Reference to the previous papers will be made at appropriate places in the current text so that requisite proofs can be found, although the empirical logic of the current paper is largely self-contained.

Our first procedure for obtaining unbiased beta estimates involves computing an asymptotic estimator of beta. This is the limit that the ordinary least squares estimator will approach as the differencing interval is increased without bound. Our second procedure involves estimating the extent to which the difference between a security's asymptotic beta and its OLSE beta for any specific differencing interval is related to the value of that security's outstanding shares (which we take as an inverse proxy measure of the security's expected price-adjustment delay). The advantage of the second procedure is that we can infer a security's asymptotic beta, knowing only the beta obtained for some short differencing interval and the market value of the shares outstanding. This is desirable when, due to distributional instability,[2] reasonable estimates of asymptotic beta cannot be made via the more direct route (which requires the use of longer period data).

The empirical findings we report in this paper suggest that substantial adjustments are required to eliminate the intervalling-effect bias in betas estimated from short period data. This emphasizes the practical importance of the procedures considered in this paper. The findings also suggest that price-adjustment delays are quite lengthy, and hence that friction in the trading process has a substantial impact on stock price movements.

The paper is organized as follows: Section 2 briefly reviews the CHMSW theoretical model. In Section 3, we develop the methodology for our empirical tests. Section 4 presents our empirical results. Concluding remarks are contained in Section 5.

2. Theoretical Model of the Intervalling-Effect Bias

In CHMSW (1981) we begin by assuming that true returns are generated by the market model

$$r_{jt} = \alpha_j + \beta_j r_{Mt} + e_{jt} \quad (1)$$

We first show that the OLSE beta estimate derived by regressing j's observed returns on the index observed returns depends on true β_j plus a serial covariances of the index observed returns for all leads up to N periods and the cross-serial covariances between the observed returns of j and M for leads and lags up to N periods. Hence β_j^o is an inconsistent estimator of of β_j.[3]

We next show that the asymptotic estimator

$$\beta_j^* = \lim_{L \to \infty} b_j^o(L) \quad (2)$$

(where $b_j^o(L)$ is an OLSE estimator using differencing intervals of length L) is a consistent estimator of β_j. This result suggests that the intervalling-effect bias diminishes as L increases, and is the basis of one of the adjustment procedures we implement in this current paper ("estimated asymptotic beta").

Proof that the intervalling-effect bias in OLSE beta is systematic and depends in sign and magnitude on the security's "thinness" is given by the following two results. (a) For any security j whose true beta is positive; if the expected price adjustment delay is greater (less) than the weighted average delay in the market index, then $b_j^o(L)$ will underestimate (overestimate) true beta. (b) Observed beta monotonically falls relative to true beta as the expected price-adjustment delay rises across securities. These results lead us empirically to relate the sign and size of security j's intevarvalling effect (measured by the rate of change of OLSE beta as L increases) to j's value of shares outstanding. Indirectly, they suggest that we can infer j's asymptotic beta estimate from its OLSE beta estimate for any L and its value of shares outstanding. For this, we use a three-stage procedure developed in the next section; this provides the second adjustment procedure we implement here ("inferred asymptotic beta").

3. Test Methodology

3.1 The Sample and the Price Data. The sample consists of fifty New York Stock Exchange common stocks selected by stratified random sampling according to the following procedure: The population of common stocks which remained listed on the NYSE throughout the four year period 1/70-12/31/73 was ranked according to the market value of their shares outstanding as of the last trading day of 1971, the mid-point of our sample period,[4] and stratified by value into deciles. A random sample of five commons stocks was obtained from each decile, producing a stratified random sample of fifty common stocks. Firms whose shares have not been publicly held since 1965 were excluded from the sample and replaced by randomly selected alternates belonging to the same decile. For the four year period considered, each of the fifty firms had 1,010 daily price observations. The Standard & Poor's Composite 500 Stock Index was used as the market index. The returns of firm j and the index over differencing intervals of length L days are measured by taking the natural logarithm of price relatives, adjusted for cash and stock dividends.

3.2 Estimation of the Intervalling Effect on Beta Coefficients. A two-pass regression analysis is undertaken to estimate the intervaling effect on each security's beta coefficient.

(1) A first pass based on the market model is used to estimate the beta coefficient of each of the 50 securities in the sample for 14 different lengths of the differencing interval L according to:

$$r_{jLT} = {}_1a_{jL} + {}_1b_{jL} r_{MLT} + {}_1e_{jLT} \tag{3}$$

where:

$j = 1, \ldots , 50;$

$L = 1, \ldots , 6, 8, 10, 12, 14, 15, 16, 18, 20;$

$T = 1, \ldots , 960/L.$

The lower prescript 1 on the RHS of eq. (3) indicates that these are "pass 1" coefficients and residuals. Note that we use only 960 of our 1010 daily returns because 960 is a common multiple for the largest number of the chosen values of L (12 of the 14).

(2) A second pass is used to estimate the intervalling effect on the beta coefficient of each of the 50 securities in the sample. The 14 estimated beta coefficients for each security obtained from the first pass are regressed against the inverse of the length of the 14 corresponding differencing intervals raised to the positive power n according to:

$$ {}_1\hat{b}_{jL} = {}_2a_j + {}_2b_j L^{-n} + {}_2e_{jL} \tag{4} $$

where:

$j = 1, \ldots , 50;$

$L = 1, \ldots , 6,8,10,12,14,15,16,18,12,20;$

$n > 0$

The lower prescript 2 on the RHS of eq. (4) indicates that these are "pass 2" coefficients and residuals.

The justification for eq. (4) stems from CHMSW (1981). It was argued there that the strength of the delayed price-adjustment bias will be reduced as the length of the differencing interval increases. Moreover, in the limit as the length of the differencing interval increases without bound, the OLSE estimator of beta (based on observed returns) will approach an asymptote that is a consistent estimator of true beta. Clearly, data limitations (as well as the underlying stationarity assumption) prevent one from literally estimating OLSE betas based on arbitrarily large differencing intervals. Hence, a functional form [eq. (4)] was devised for which: (a) the dependent variable (the OLSE estimator of beta for a differencing interval of length L) approaches an asymptote (the intercept term) as the independent variable, L, increases without bound; and (b) the difference between the dependent variable and its asymptote monotonically decreases as L increases. Since these desired properties are consistent with the independent variable (1/L) being raised to any positive power, this element of generality was incorporated into eq. (4). In order to use linear regression analysis to estimate the coefficients in eq. (4) , the value of the positive power n must be specified in advance. Since the theory does not indicate what the value of n should be, we determine it experimentally. As we report in Section 4.2 below (see especially footnote 6), we run regressions for various values of n and the value that, on average, produces the best linear fit between ${}_2\hat{b}_{jL}$ and L^{-n} is selected (this turns out to be n = 0.8). In the absence of an intervalling effect on the estimated betas, ${}_2\hat{b}_j$ should be statistically equal to zero regardless of the value of the positive power n. A value different from zero would indicate the presence of an intervalling effect. Securities whose beta coefficients rise (fall) as the differencing interval is lengthened will have negative (positive) estimated slopes ${}_2\hat{b}_j$. Furthermore, the larger the absolute value of the estimated coefficient ${}_2\hat{b}_j$ for any given security, the stronger is the intervalling effect on that security's beta coefficient. In other words, the estimated coefficient ${}_2\hat{b}_j$ can be used as a quantitative proxy variable to measure the intervalling effect on a security's beta.

3.3 The Estimated Asymptotic Beta Coefficient. The estimated asymptotic beta coefficient is given by the intercept of eq. (4), ${}_2\hat{a}_j$, since

$$\lim_{L \to \infty} E({}_1\hat{b}_{jL}) = E({}_2\hat{a}_j) \qquad (5)$$

3.4 Estimation of the Intervalling Effect-Thinness Relationship. A third pass is carried out by regressing the estimated coefficient ${}_2\hat{b}_j$ (the quantitative proxy variable for the intervalling effect) of the 50 securities against the logarithm of the market value of their shares outstanding (the inverse proxy variable for a security's relative price-adjustment delay). The regression equation is:

$$ {}_2\hat{b}_j = {}_3a + {}_3b \cdot \ln V_j + {}_3e_j \tag{6} $$

where j = 1, ..., 50, V_j = market value of shares outstanding at midpoint of sample period (see footnote 4), and 3 is the prescript for the regression pass.

The justification for eq. (6) stems from the results summarized in Section 2: By results proved in CHMSW (1981) and the posited inverse relationship between a security's market value and its expected price-adjustment delay, we predict that the bias will be negative for thin stocks, and that it will increase algebraically to become positive for very thick stocks; hence we expect ${}_3\hat{b} > 0$. The exact functional form for the third pass regressions is not theoretically determinate, but as we report in Section 4.5 below (see especially footnote 9), eq. (6) produced better goodness-of-fit statistics than an alternative functional form that was tried; we also report there that other proxy measures for thinness were tested, but they yielded less satisfactory results.

3.5 Using the Intervalling Effect-Thinness Relationship to Infer Asymptotic Betas. Suppose one wishes to calculate an approximate asymptotic value for the beta coefficient without having to replicate the full intervalling effect study involving the first and second passes (e.g., for a stock where too short a calendar period of data is available). This can be done from a single first pass regression for any value of L for stock k and from knowledge of the third pass intervalling effect - thinness relatationship embodied in eq.(6) (which we shall now assume to have been previously estimated without use of data on this particular stock k). We shall use the term <u>inferred asymptotic beta</u>, denoted by b_k^* , for this estimate of stock k's beta.

It should be noted that the first and second pass regressions, based on eqs. (3) and (4), are run on a stock-by-stock basis. Thus, the empirical results reported in Section 4 really constitute 50 separate and independent tests of the first and second pass regressions. However, the third pass regession, based on eq. (6), is a cross-sectional regression which uses data all stocks in our sample. If the coefficients from eq. (6) estimated from the cross-section of all 50 stocks were then used to obtain inferred asymtotic betas, since data pertaining to stock k would have been used in the cross-sectional third pass regression whose coefficients, in turn, are used obtain the calculated asymptotic beta for stock k. Second, since only one cross-sectional sample would have been used to estimate the third pass regression, there would be no way of knowing how robust the results would be for different samples of stocks.

Fortunately, there is a way of overcoming both of these drawbacks which makes efficient use of all our available data and produces "almost unbiased" [see Lachenbruch (1967)] results. This involves transforming the original sample of stocks into a sequence of hold-out samples, each of which is obtained by deleting one stock from the cross-section used to estimate the third pass regression. This approach to obtaining hold-out samples is analogous to an approach used by Lachenbruch (1967) and Lachenbruch and Mickey (1968) for discriminant analysis and by Allen (1971, 1974) for regression analysis. We use 50 different third pass regressions, each based on a different set of stocks.

Specifically, for each stock k, we run the regression

$$ {}_2\hat{b}_j = {}_3a_k + {}_3b_k \ln V_j + {}_3e_j \qquad (7) $$

that is based on eq. (6) but includes only the 49 observations j = 1,... k-1, k+1, ..., 50. By using the estimated coefficients from eq. (4), equating the error term to zero, and rearranging, we have

$$ {}_2\hat{a}_k = {}_1\hat{b}_{kL} - {}_2\hat{b}_k L^{-n} \qquad (8) $$

Since the regression coefficients ${}_3\hat{a}_k$ and ${}_3\hat{b}_k$ estimated from eq. (7) were not obtained by use of any data pertaining to stock k, it is legitimate to use these coefficients and eq. (7) to infer a value for ${}_2\hat{b}_k$ as follows:

$$ {}_2\hat{b}_k = {}_3\hat{a}_k + {}_3\hat{b}_k \ln V_k \qquad (9) $$

Substituting eq. (9) into eq. (8) we obtain the inferred asymptotic beta for stock k:

$$ b_k^* = {}_1\hat{b}_{kL} - ({}_3\hat{a}_k + {}_3\hat{b}_k \ln V_k)L^{-n} \qquad (10) $$

4. Empirical Results

4.1 Regression Results for the First Pass. Results for the first pass regressions based on eq. (3) are summarized in Table 1. The average value of the estimated betas tends to fall as the length of the differencing interval[5] is shortened (first row). However this is not the case for all securities in the sample, as will be shown in Section 4.2. There is a slight increase in the standard error of the estimated betas as L increases (second row). The average t-statistic falls as L rises (third row), since the number of observations diminishes; for elaboration see Hawawini (1977). The fourth and fifth rows give the across-firms minimum and maximum estimated beta coefficients, respectively. The average R-square deteriorates as L is shortened (sixth row) a result explained by Schwartz and Whitcomb (1977) and Hawawini (1980). The seventh and eighth rows give the minimum and maximum values for R-square, respectively. All intercepts ${}_1\hat{a}_j$ in eq. (3) were insignificantly different from zero at the .05 level of significance.

4.2 Regression Results for the Second Pass. Results for the second pass regressions based on eq. (4) and using the positive power n = 0.8 are presented in Table 2.[6] Note that for the majority of securities, the estimated slope ${}_2\hat{b}_j$ is negative; thus (see section 3.2) estimated betas tend to rise as L increases. Some securities yield estimated slopes ${}_2\hat{b}_j$ insignificantly different from zero. The security with the largest market value in the sample, number 50 (Eastman Kodak), has a significantly positive beta-L relationship. This conforms to the theoretical model (CHMSW (1981); by our sample selection procedure, we would expect few of our stocks to be thicker than the weighted average of S&P 500 stocks.

The estimated asymptotic betas are given by the estimated intercepts ${}_2\hat{a}_j$ in eq. (4) and are reported in the first column of Table 2. Note their high t-statistics compared to L-day betas (see Table 1, third row).

4.3 Comparison of L-day Betas and Asymptotic Beta. Table 3 contains the cross-correlation matrix for estimated and asymptotic betas. The high values of the cross-correlation coefficients indicate that a security which exhibits high estimated beta for a given length L of the differencing interval tends to retain this characteristic when L is changed or in the limit when L is taken to infinity. Not unexpectedly, we usually observe slightly higher correlations for adjacent lengths of the differencing interval L than for nonadjacent values of L. Asymptotic betas are highly correlated with L-day estimated betas, with somewhat higher correlations for large L.

In Table 4, mean-square "errors" are given for estimated L-day betas compared to their respective estimated asymptotic betas. The mean-square error coefficient is computed as follows:

$$MSE\ ({}_1\hat{b}_{jL}) = \sum_{j=1}^{50} ({}_1\hat{b}_{jL} - {}_2\hat{a}_j)^2/50 \qquad (11)$$

The MSE tends to decrease as the length of the differencing interval increases.

Tables 3 and 4 indicate that for our sample, the intervalling-effect bias in beta is substantial for differencing intervals up to 10 days. This, in turn, suggests that price-adjustment delays are nontrivial, and may even extend over a day or more.[7]

4.4 Impact of Intervalling Effect Adjustment on Cross-Sectional Beta - V Relationship. Although financial theory suggests no *a priori* relationship between beta and firm size [see Bowman (1979)], a recent paper in the industrial organization literature [Sullivan (1979)] suggests that, to the extent that large size is associated with market power, large firms may have smaller betas, *ceteris paribus*. Such a relationship would be obscured in short-interval data, however, by the delayed price-adjustment bias, so it is of interest to estimate the beta - V relationship using, in turn, unadjusted one-day interval and asmptotic beta estimates. More importantly for our present purposes, this also provides some evidence as to whether the intervalling effect adjustment is trivial or meaningful.

Our theory (and the results so far) would lead us to expect that the intervalling-effect adjustment would increase the smallest firms' betas the most, thereby rotating the estimated cross-sectional beta - V relationship clockwise. This is what we find. Table 5 reports the results of three regressions, each with the natural logarithm of V_j as the independent variable. With unadjusted one-day beta as the dependent variable, the coefficient is insignificant; but the asymptotic beta estimate is significantly negatively related to ln V_j (although ln V_j not surpisingly explains only a small part of the variance in ${}_2\hat{a}_j$). Evidence that the intervalling-effect adjustment has a meaningful impact on the beta - V relationship is provided by regressing the adjustment ratio $({}_1\hat{b}_{jL} - {}_2\hat{a}_j)/{}_2\hat{a}_j$ on ln V. The slope coefficient is positive and highly significant.

Our finding that the intervalling-effect adjustment rotates the beta -V relationship clockwise is consistent with with the findings of Scholes-Williams and Dimson. However, we find a negative adjusted beta - V relationship, while Dimson finds no association and Scholes-Williams find that their consistent estimators remain larger for portfolios containing more frequently-traded securities. Whether the explanation for these differences lies in the magnitudes of the beta adjustments, the firm size measures used, or the nature of the samples, is unclear.[8]

4.5 Regression Results for the Third Pass. The estimated intervalling-effect coefficients, ${}_2\hat{b}_j$ were regressed on the logarithm of the market value of shares outstanding for the cross-sectional sample of all 50 securities as specified in eq. (6). All 50 securities were used (as opposed to the Lachenbruch holdout sample procedure reported in Section 4.6 below) so as to provide a single estimate for our entire sample; the estimated coefficients could be used to infer asymptotic betas in a different sample of securities.

The resulting equation is:[9]

$$_2\hat{b}_j = -2.637 + .181 \ln V_j \qquad R^2 = .6608 \tag{12}$$
$$(-11.462) \quad (9.670) \qquad\qquad DWS = 2.091$$

where it should be recalled that V_j is measured in thousands of dollars. Eq. (12) is the estimated intervalling effect-thinness relationship. The slope has the predicted positive sign, and both the estimated intercept and slope are significantly different from zero as indicated by the t-statistics given in parantheses. The single variable in V_j explains approximately two-thirds the variation in the dependent variable $_2\hat{b}_j$. All told, these results are quite striking for a third pass regression based on cross-sectional data.

4.6 Calculation of the inferred Asymptotic Betas and Comparisons with L-day Betas and Estimated Asymptotic Betas. Applying the procedure discussed in Section 3.5, the inferred asymptotic beta of security k for L = 1 is given by:

$$\hat{b}^*_k = {}_1\hat{b}_{k1} - ({}_3\hat{a}_k + {}_3\hat{b}_k \ln V_k) \tag{13}$$

using eq. (10) for L = 1. The inferred asymptotic betas are reported in the last column of Table 6. Also reported in Table 6 are the estimated coefficients $_3\hat{a}_k$ and $_3\hat{b}_k$ from the third pass regressions excluding k, based on eq. (7).

Inferred asymptotic betas based on daily betas are good estimators of estimated asymptotic betas with an MSE of .059 as shown in Table 4. They are highly correlated with estimated asymptotic betas (.920 in Table 3) as well as with estimated L-day betas as shown in Table 3. The holdout sample procedure that we applied makes efficient use of all available data and produces almost unbiased results. Our results presented in Table 6 indicate that the coefficients of the third pass regression are reasonably stable over different (albeit overlapping rather than independent) samples of NYSE stocks during the period 1970-1973. We do not know, however, if they would be similarly stable over a different universe of stocks and/or different calendar periods.[10]

5. Conclusion

In this paper we have presented tests of our CHMSW (1980, 1981) model that treats the impact of various price-adjustment delays on the measurement of beta. Our model assumes that "true" returns are generated by an underlying unbiased process, and it implies that a security's delayed price-adjustment bias (the extent to which the beta calculated using observed transaction price data differs from the beta for the "true" underlying returns generation process) will tend to vanish as the differencing interval is lengthened. Our formulation also suggests that, for a given differencing interval, true beta will be underestimated for securities with relatively long price-adjustment delays (i.e., for securities with small market values), while, for securities with relatively shorter price-adjustment delays than those of the average security in the market index, beta will be overestimated.

Our empirical tests have generated results that conform well to our theoretical expectations. Our test design consists of three regress passes. In the first pass, betas are estimated for 14 different values of the differencing interval, L, for each of 50 NYSE common stocks. The second pass regressions relate beta to L for each security. The second pass slope coefficient measures the strength of the intervaling effect and the intercept is an estimate of the asymptotic value of beta that is approached as L is increased without bound. Then, the third pass is a cross-sectional test that estimates the intervalling-effect-thinness relationship by regressing the slope of the second pass regressions on the value of shares outstanding for the stocks in the sample. The significance of the third pass test strongly confirms the presence of a delayed price adjustment, and shows that market value is a major determinant of its magnitude and direction.

The analysis also suggests two new approaches to eliminating the delayed price-adjustment bias, and hence to obtaining more meaningful beta estimates from very short period (e.g., daily) returns data. The first, which is based on the second pass regressions, is to estimate the asymptotic value for beta that is approached as L is increased without bound. The adjustment a appears be substantial: a cross-sectional regression shows that the proportional difference between unadjusted one-day beta estimates and estimated asymptotic betas is a significantly related to the logarithm of value of shares outstanding. The other approach, based on the third pass regression, uses the intervalling effect-thinness relationship to "correct" a stock's short period beta by taking account of that stock's value of shares outstanding.

The close association we have observed between the inferred asymptotic betas obtained via the latter approach using a Lachenbruch holdout sample procedure and the estimated asymptotic betas obtained by the former, gives us additional confidence that both correction methods improve the quality of beta estimates obtained from short period data. The comparative value of the second approach, which is based on the intervalling effect-thinness relationship, is that just one time series regression, based on short period data, need be run for a security. That is, with this method, the only additional information beyond the cross-sectional intervalling-effect-thinness relationship needed to adjust the estimated short period beta is the aggregate market value of that security.

FOOTNOTES

* An earlier version of this paper was presented at the Annual National Meeting of the American Finance Association in Chicago, August 29-31, 1978. WE wish to thank our discussant, Richard W. Lang (Federal Reserve Bank of St. Louis) for his helpful comments.

1. Early evidence that average betas of European securities fall as the differencing interval is shortened is reported by Altman-Jacquillat-Levasseur (1974) and Pogue-Solnik (1974). Direct evidence of an intervalling effect on beta for ordinary rates of return is reported by Smith (1978) and for continuously-compounded growth rates by Scholes-Williams (1977), Hawawini (1977, 1980), Hill-Schneeweis (1979), and Dimson (1979). The intervaling effect is simpler, both empirically and theoretically, for continuously compounded returns [see Hawawini (1980)].

2. See Sunder (1980) for evidence on distributional instability and for extensive references.

3. A corollary states a consistent estimator that generalizes the Scholes-Williams (1977) estimator and corrects Dimson's (1979). We do not implement that estimator here, primarily because of the efficiency loss due to measurement error when reasonable values of N are used.

4. Market value of shares outstanding is measured at the midpoint of the four year sample period in order to obtain values close to their actual average over the four years.

5. For compactness, results for the other values of L were omitted from the tables. These omissions do not affect the interpretation of the results.

6. Regressions were run with values of n = 0.1, 0.2, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.2, 2.0. As n dropped the average value of R-square improved and that of the Durbin-Watson Statistics increased from a value smaller than 2 to a value larger than 2. The best average value of the Durbin-Watson Statistics (i.e., closest to 2) was found at n = 0.8, the power that was selected. A two-variable regression was also run with L^{-1} and L^{-2} as independent variables. The goodness-of-fit was poorer than that of a single-variable regression with L^{-1} as the independent variable.

7. For a discussion of the causes of price-adjustment delay and why it may be lengthy, see CHMSW (1980). Note that the impact on beta of any price-adjustment delay will be longer than the length of the delay itself when the observations are temporally contiguous. The effect, however, decays rapidly with increases in the differencing interval once the interval exceeds the length of the maximum price-adjustment delay.

8. Our cross-sectional aymptotic beta - V results are consistent with the findings of Beaver-Kettler-Scholes (1970), Ben-Zion-Shalit (1975), Thompson (1976), and Sullivan (1978), all of which used long-interval betas although the size measures differ considerably.

9. Regressing $_2\hat{b}_j$ on V_j rather than on ln V_j produced an estimated equation with significant coefficients and the predicted sign but with a smaller R-square (.3150). Other proxies for thinness, such as number of shares traded and the logarithm of number of shares traded, were alternatively used as independent variables. The results were similar, but not quite as strong.

10. It would not be meaningful to use inferred asymptotic betas in cross-sectional regressions in ln V (as we did with estimated asymptotic betas in Section 4.4) since ln V was used in calculating inferred asymptotic beta in the first place.

References

Allen, D.M., 1971, "The Prediction Sum of Squares as a Criterion for Selecting Predictor Variables," University of Kentucky, Department of Statistics, Technical Report No. 23.

Allen, D.M., 1974, "The Relationship Between Variable Selection and Data Augmentation and a Method for Prediction," Technometrics, 16. 125-127.

Altman, E., B. Jacquillat and M. Levasseur, 1974, "Comparative Analysis of Risk Measures: France and the United States," Journal of Finance 29 1495-1511.

Beaver, W., T. Kettler, and M. Scholes, 1970, "The Association Between Market Determined and Accounting Determined Risk Measures," The Accounting Review, 654-82.

Ben-Zion, U. and S.S. Shalit, 1975, "Size, Leverage and Dividend Record as Determinants of Equity Risk," Journal of Finance 30, 1015-26.

Bowman, R.G., 1979 "The Theoretical Relationship Between Systematic Risk and Financial (Accounting) Variables," Journal of Finance 34, 617-30.

Cohen, K.J., G.A. Hawawini, S.F. Maier, R.A. Schwartz, and D.K. Whitcomb, 1980, "Implications of Microstructure Theory for Empirical Research on Stock Price Behavior," Journal of Finance 35, 249-257.

Cohen, K.J., G.A. Hawawini, S.F. Maier, R.A. Schwartz, and D.K. Whitcomb, 1981, "Friction in the Trading Process and the Estimation of Systematic Risk," Working Paper.

Cohen, K.J., S.F. Maier, W.L. Ness, Jr., H. Okuda, R.A. Schwartz, and D.K. Whitcomb, 1977, "The Impact of Designated Market Makers on Security Prices: I. Empirical Evidence," Journal of Finance, 33, 149-167.

Dimson, E., 1979, "Risk Measurement When Shares are Subject to Infrequent Trading," Journal of Financial Economics, 7, 197-226.

Hawawini, G.A., 1977, "On the Time Behavior of Financial Parameters: An Investigation of the Intervaling Effect," Ph.D Dissertation, New York University.

Hawawini, G.A., 1980, "Intertemporal Cross Dependence in Securities' Daily Returns and the Short-Run Intervaling Effect on Systematic Risk," Journal of Financial and Quantitative Analysis, 15, 139-150.

Hill, J. and T. Schneeweis, 1979, "The Effect of Interval Selection on the Parameters of the Market Model as Applied to Bond Returns", The Financial Review, Fall, 34-51.

Lachenbruch, P.A., 1967, "An Almost Unbiased Method of Obtaining Confidence Intervals for the Probability of Misclassification in Discriminant Analysis," Biometrics, 23, 639-645.

Lachenbruch, P.A., and M.R. Mickey, 1968, Estimation of Error Rates in Discriminant Analysis," Technometrics, 10, 1-11.

Pogue, G. and B. Solnik, 1974, "The Market Model Applied to European Common Stocks: Some Empirical Results," Journal of Financial and Quantitative Analysis, 9, 917-44.

Scholes, M. and J. Williams, 1977, "Estimating Beta from Non-synchronous Data," Journal of Financial Economics, 5, 309-27.

Schwartz, R.A. and D.K. Whitcomb, 1977, "Evidence on the Presence and Causes of Serial Correlation in Market Model Residuals," Journal of Financial and Quantitative Analysis, 12, 291-313.

Sharpe, W.F., 1964, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," Journal of Finance 19, 425-442.

Smith, K., 1978, "The Effect of Intervaling on Estimating Parameters of the Capital Asset Pricing Model," Journal of Financial and Quantitative Analysis, 13, 313-344.

Sullivan, T., 1979, "The Cost of Capital and the Market Power of Firms," Review of Economics and Statistics 58, 209-17.

Sunder, S., 1980, "Stationarity of Market Risk: Random Coefficients Tests for Individual Stocks," Journal of Finance, 35, 883-896.

Thompson, D.J. II, 1976, "Sources of Systematic Risks in Common Stocks," Journal of Business 49, 184-205.

TABLE 1

SUMMARY STATISTICS FOR FIRST PASS REGRESSIONS

$$\hat{r}_{jL} = {}_1\hat{a}_{jL} + {}_1\hat{b}_{jL}\, r_{ML}$$

L (days)	1	2	3	4	5	10	15	20	$({}_2\hat{a}_j)$[e]	(b_j^*)[f]
Avg$({}_1\hat{b}_{jL})$[d]	.963	1.047	1.036	1.072	1.140	1.262	1.307	1.381	1.334	1.396
$\sigma({}_1\hat{b}_{jL})$	.462	.471	.466	.472	.486	.525	.564	.624	.571	.566
Avg $t({}_1\hat{b}_{jL})$[a]	10.478	9.380	7.901	7.662	7.537	6.439	5.535	5.531	22.057	——
Min$({}_1\hat{b}_{jL})$[b]	.279	.245	.270	.239	.327	.374	.334	.253	.348	.542
Max$({}_1\hat{b}_{jL})$[c]	2.144	2.202	2.184	2.229	2.403	2.844	2.887	2.950	2.929	2.780
Avg(R^2)	.1095	.1644	.1756	.2023	.2361	.3048	.3283	.4045	——	——
Min(R^2)	.0204	.0456	.0557	.0655	.0767	.0955	.0700	.1714	——	——
Max(R^2)	.3916	.4861	.4978	.5171	.5081	.5248	.5963	.6973	——	——

Notes:

a. All ${}_1\hat{a}_{jL}$ are insignificantly different from zero at the .05 significance level.

b. All Min $({}_1\hat{b}_{jL})$ belong to the same company (Union Electric).

c. All Max $({}_1\hat{b}_{jL})$ belong to the same company (Monogram Industries).

d. All averages are for 50 securities.

e. Estimated asymptotic betas [see eq. (4)]. Included for convenience; see Table 2.

f. Inferred daily asymptotic beta [see eq.(13)]. Included for convenience; see Table 6.

TABLE 2
SUMMARY STATISTICS FOR SECOND PASS REGRESSIONS

$$ {}_1\hat{b}_{jL} = {}_2\hat{a}_j + {}_2\hat{b}_j (L)^{-.8} $$

FIRM	${}_2\hat{a}_j$	$t({}_2\hat{a}_j)$	${}_2\hat{b}_j$	$\lvert t({}_2\hat{b}_j)\rvert$	R-SQUARED	DURBIN-WATSON STATISTICS	b_j^*
1	.967	17.859	-.936	4.306	.6071	1.906	1.379
2	.889	18.047	-.897	4.033	.5754	2.011	1.293
3	1.035	20.909	-.738	5.477	.7104	1.531	1.230
4	.689	23.613	-.839	4.725	.5793	1.917	.705
5	2.314	18.872	-1.150	3.438	.4962	2.061	2.255
6	1.457	42.393	-.659	3.021	.4320	2.205	1.961
7	1.501	34.562	-.612	5.166	.6898	1.462	1.770
8	2.541	26.464	-1.296	4.949	.6712	1.760	2.363
9	2.362	32.389	-.869	4.369	.6140	1.680	2.393
10	1.152	20.476	-.380	2.481	.3392	2.276	1.561
11	.973	17.446	-.313*	1.401	.1406	1.729	1.473
12	1.360	25.206	-.483	3.200	.4605	1.804	1.606
13	1.928	29.917	-.706	4.013	.5731	1.723	2.060
14	1.306	11.294	-.759	2.408	.3257	1.619	1.387
15	2.929	30.422	-.405	4.007	.5723	2.056	2.780
16	1.003	24.463	-.476*	1.583	.1727	1.763	1.485
17	1.766	21.825	-.486	2.122	.2729	2.402	1.982
18	2.345	37.531	-.384	5.187	.6916	2.018	2.255
19	1.170	18.811	-.617	3.635	.5240	2.024	1.201
20	.885	15.888	-.520	3.420	.4937	1.796	.964
21	1.567	16.181	-.367	2.904	.4127	1.893	1.566
22	1.659	18.118	-.789	4.763	.6541	1.858	1.232
23	1.897	12.457	-.454*	1.094	.0907	2.845	2.015
24	1.236	11.697	-.268	2.785	.3927	1.755	1.214
25	2.257	23.970	-.429*	1.834	.2189	1.458	2.234
26	1.226	22.726	-.621	4.221	.5975	1.850	1.212
27	1.004	13.221	-.858	3.767	.5419	1.578	.979
28	1.160	22.005	-.685	4.762	.6504	2.586	.963
29	.764	21.239	-.414	4.217	.5972	1.857	.793
30	.810	21.491	-.079*	.769	.0469	1.981	1.160
31	1.543	13.149	-.191*	.597	.0288	1.969	1.743
32	.554	21.437	-.289	4.099	.5833	1.733	.715
33	2.068	15.233	-.276*	1.667	.1881	1.997	2.102
34	1.673	21.274	-.391*	1.826	.2173	1.418	1.672
35	1.367	18.575	-.714	3.854	.5532	1.615	1.119
36	1.899	25.005	-.105*	.506	.0209	2.183	2.214
37	.597	18.847	-.312	3.623	.5225	1.623	.634
38	.596	14.683	-.087*	.786	.0489	2.162	.802
39	.968	11.991	-.041*	.187	.0029	2.106	1.068
40	.348	15.106	-.117*	1.858	.2235	2.374	.512

TABLE 2
(Continued)

$F_{I_{R_M}}$	$_2\hat{a}_j$	$t(_2\hat{a}_j)$	$_2\hat{b}_j$	$\|t(_2\hat{b}_j)\|$	R-SQUARED	DURBIN-WATSON STATISTICS	b_j^*
41	.971	19.293	-.350	2.551	.3517	1.597	.974
42	1.168	26.981	-.286	4.963	.6724	2.293	.810
43	1.008	27.651	-.010	2.112	.2710	2.194	1.021
44	1.050	25.719	.050*	.458	.0166	2.226	1.272
45	1.247	34.759	-.125	4.350	.6120	2.405	1.024
46	.850	18.604	-.131	2.513	.3448	2.455	.592
47	.925	19.892	-.206*	1.864	.2246	1.862	.639
48	1.359	29.639	.053*	1.223	.1108	1.659	1.133
49	.827	22.829	.122*	.224	.0042	2.089	.696
50	.897	30.905	.432	5.453	.7124	2.045	.896

Notes: 1. Asterisks indicate coefficients not significantly different from zero at the .05 significance level.

2. b_j^* data included for convenience; see Table 6.

TABLE 3

CROSS CORRELATION MATRIX FOR ESTIMATED BETAS

	${}_1\hat{b}_{j,1}$	${}_1\hat{b}_{j,2}$	${}_1\hat{b}_{j,3}$	${}_1\hat{b}_{j,4}$	${}_1\hat{b}_{j,5}$	${}_1\hat{b}_{j,10}$	${}_1\hat{b}_{j,15}$	${}_1\hat{b}_{j,20}$	${}_2\hat{a}_j$	b_j^*
${}_1\hat{b}_{j,1}$	1.000									
${}_1\hat{b}_{j,2}$	.987	1.000								
${}_1\hat{b}_{j,3}$	.977	.975	1.000							
${}_1\hat{b}_{j,4}$	.948	.974	.953	1.000						
${}_1\hat{b}_{j,5}$	.937	.959	.948	.978	1.000					
${}_1\hat{b}_{j,10}$	.891	.921	.906	.963	.952	1.000				
${}_1\hat{b}_{j,15}$	.857	.864	.882	.881	.888	.891	1.000			
${}_1\hat{b}_{j,20}$	.848	.869	.876	.907	.902	.955	.891	1.000		
${}_2\hat{a}_j$	.882	.901	.908	.934	.931	.962	.962	.966	1.000	
b_j^*	.867	.891	.870	.896	.876	.897	.878	.886	.920	1.000

TABLE 4

MEAN-SQUARE ERRORS FOR ESTIMATED BETAS[a]

	${}_1\hat{b}_{j,1}$	${}_1\hat{b}_{j,2}$	${}_1\hat{b}_{j,3}$	${}_1\hat{b}_{j,4}$	${}_1\hat{b}_{j,5}$	${}_1\hat{b}_{j,10}$	${}_1\hat{b}_{j,15}$	${}_1\hat{b}_{j,20}$	${}_2\hat{a}_j$	b^*_j
${}_2\hat{a}_j$	.210	.144	.147	.112	.083	.031	.030	.032	.000	.055
b^*_j	.266	.187	.206	.168	.139	.079	.084	.084	.055	.000

Notes:

a. Mean-Square Errors are computed according to eq. (11) and analogous equations.

${}_2\hat{a}_j$ = estimated asymptotic beta coefficient [see eq.(4)].

b^*_j = inferred daily asymptotic beta coefficient [see eq.(13)].

TABLE 5

RESULTS OF BETA - V REGRESSIONS

$$\hat{y}_j = \hat{c} + \hat{d} \ln V_j \qquad j = 1,\ldots,50$$

Eq	$\hat{y}_j$	c	t(c)	d	t(d)	R^2	DWS
1.	${}_1\hat{b}_{j1}$	1.1443	2.137	-.0157	-.361	.0027	1.957
2.	${}_2\hat{a}_j$	2.8638	4.594	-.1266	-2.493	.1147	1.871
3.	$\frac{{}_2\hat{b}_j - {}_2\hat{a}_j}{{}_2\hat{a}_j}$	-1.151	-6.554	.0717	5.011	.3434	1.546

TABLE 6

SUMMARY STATISTICS FOR THIRD PASS REGRESSIONS

$${}_2\hat{b}_k = {}_3\hat{a}_k + {}_3\hat{b}_k \ln V_j; \; j = 1,\ldots,k-1,k+1,\ldots,50$$

k	${}_3\hat{a}_k$	$t({}_3\hat{a}_k)$	${}_3\hat{b}_k$	$t({}_3\hat{b}_k)$	R-SQUARED	b_k^*
1	-2.6316	-10.901	.18077	9.2324	.64458	1.379
2	-2.6153	-11.005	.17955	9.3084	.64832	1.293
3	-2.6505	-11.169	.1822	9.4577	.65555	1.230
4	-2.6226	-11.069	.18011	9.3632	.65100	.705
5	-2.5490	-11.211	.17462	9.4590	.65561	2.255
6	-2.6605	-11.271	.18293	9.5443	.65965	1.961
7	-2.6693	-11.347	.18359	9.6108	.66276	1.770
8	-2.5181	-11.640	.17238	9.8121	.67197	2.363
9	-2.6088	-11.103	.17910	9.3856	.65208	2.393
10	-2.6931	-11.761	.18526	9.9582	.67845	1.561
11	-2.6943	-11.878	.18529	10.0530	.68255	1.473
12	-2.6648	-11.453	.18317	9.6872	.66629	1.606
13	-2.6287	-11.213	.18060	9.4791	.65657	2.060
14	-2.6198	-11.208	.17996	9.4730	.65628	1.387
15	-2.6682	-11.550	.18337	9.7650	.66984	2.780
16	-2.6467	-11.366	.18183	9.6016	.66233	1.485
17	-2.6403	-11.336	.18138	9.5728	.66099	1.982
18	-2.6478	-11.426	.18183	9.6445	.66432	2.255
19	-2.6294	-11.313	.18072	9.5575	.66027	1.201
20	-2.6366	-11.319	.18115	9.5584	.66031	.964
21	-2.6469	-11.430	.18176	9.6463	.66410	1.566
22	-2.6189	-11.514	.18020	9.7354	.66849	1.232
23	-2.6383	-11.340	.18124	9.5722	.66096	2.015
24	-2.6481	-11.523	.18174	9.7167	.66764	1.214
25	-2.6383	-11.346	.18123	9.5749	.66109	2.234
26	-2.6307	-11.397	.18096	9.6294	.66363	1.212
27	-2.6274	-11.886	.18112	10.0620	.68296	.979
28	-2.6315	-11.520	.18117	9.7401	.66871	.963
29	-2.6365	-11.342	.18117	9.5692	.66082	.793
30	-2.6370	-11.658	.18065	9.8057	.67168	1.160
31	-2.6350	-11.445	.18071	9.6347	.66387	1.743
32	-2.6354	-11.356	.18092	9.5689	.66081	.715
33	-2.6350	-11.359	.18088	9.5702	.66087	2.102
34	-2.6405	-11.367	.18161	9.5911	.66184	1.672
35	-2.6578	-11.955	.18358	10.9550	.68584	1.119
36	-2.6250	-11.383	.17989	9.5674	.66074	2.214
37	-2.6381	-11.333	.18132	9.5534	.66008	.634
38	-2.6224	-11.330	.17971	9.5195	.65848	.802
39	-2.6181	-11.353	.17930	9.5316	.65905	1.068
40	-2.6254	-11.290	.18004	9.4907	.65712	.512

TABLE 6
(Continued)

k	$_3\hat{a}_k$	$t(_3\hat{a}_k)$	$_3\hat{b}_k$	$t(_3\hat{b}_k)$	R-SQUARED	b_k^*
41	-2.6558	-11.438	.18300	9.6575	.66492	.974
42	-2.6512	-11.369	.18254	9.5896	.66178	.810
43	-2.6150	-11.241	.17912	9.4318	.65431	1.021
44	-2.6069	-11.237	.17838	9.4166	.65358	1.272
45	-2.6346	-11.233	.18097	9.4494	.65515	1.024
46	-2.6656	-11.283	.18374	9.5116	.65811	.592
47	-2.7215	-11.618	.18863	9.8382	.67313	.639
48	-2.6513	-11.032	.18245	9.2727	.64657	1.133
49	-2.6426	-10.924	.18168	9.1695	.64144	.696
50	-2.6001	-10.290	.17802	8.5778	.61022	.896
All firms	-2.6366	-11.462	.18115	9.6703	.66081	

<u>Note</u>: The b_k^* were computed from eg. (13).

LIST OF INSEAD RESEARCH WORKING PAPERS

80/01 "Identifying cognitive style determinants of retail patronage, by Christian PINSON, Arun K. JAIN and Naresh K. MALHOTRA, January 1980.

80/02 "Dimensions culturelles des conceptions de management - une analyse comparative internationale", par André LAURENT Février 1980.

80/03 "Cognitive style and effective communication", by Arun K. JAIN, Naresh K. MALHOTRA and Christian PINSON, Dec. 1979.

80/04 "Accomodative cognitive style differences in consumer reduction of alternatives", by Naresh K. MALHOTRA, Christian PINSON and Arun K. JAIN, October 1979.

80/05 "Stability and reliability of Part-Worth utility in conjoint analysis : a longitudinal investigation", by Arun K. JAIN, Naresh K. MALHOTRA and Christian PINSON, September 1979.

80/06 "The expected future spot exchange rate, the forward rate, and the trade balance", by Charles A. WYPLOSZ, March 1980.

80/07 "Decline and adjustment: Public intervention strategies in the European clothing industries", by José de la TORRE, July 1980.

80/08 "The uncommon market: European policies towards a crisis industry - clothing in the 1970's", by José de la TORRE and Michel BACCHETTA, May 1980.

80/09 "Stratport: a decision support system for strategic planning", by Jean-Claude LARRECHE and V. SRINIVASAN, April 1980, Revised October 1980.

80/10 "A new approach to market segmentation strategy: a banking application", by Arun K. JAIN, Christian PINSON and Naresh K. MALHOTRA, March 1980.

80/11 "The exchange and interest rate term structure under risk aversion and rational expectations", by Charles A. WYPLOSZ, Revised Version, September 1980.

80/12 "Individual cognitive differences in MDS analysis of perceptions", by Arun K. JAIN, Naresh K. MALHOTRA and Christian PINSON, July 6-12, 1980.

80/13 "STRATPORT: A Model for the evaluation and formulation of Business Portfolio Strategies", by Jean-Claude LARRECHE and V. SRINIVASAN, April 1980, Revised November 1980.

80/14 "Les styles cognitifs : une nouvelle approche de la segmentation des marchés, by Christian PINSON, Naresh K. MALHOTRA and Arun K. JAIN, Septembre 1980.

80/15 "Cognitive styles: A new approach to market segmentation", by Christian PINSON, Naresh K. MALHOTRA and Arun K. JAIN, March 1980.

81/01 "Eurobanking, open market operations and the monetary base" by Herwig LANGOHR, August 1980.

81/02 "Alternative approaches to the theory of the banking firm: a note" by Herwig LANGOHR, September 1980.

81/03 "Why does beta shift when the length of securities returns varies?" by Gabriel HAWAWINI, December 1980.

81/04 "Forward market and the cooperative firm" by Gabriel HAWAWINI, January 1981.

81/05 "On some propositions regarding the behavior of the labor-managed firm under uncertainty" by Gabriel HAWAWINI, Jan. 1981.

81/06 "Impact of the investment horizon on the association between securities' risk and return: theory and tests" by Gabriel HAWAWINI and Ashok VORA, February 1981.

81/07 "New evidence on beta stationarity and forecast for Belgian common stocks" by Gabriel A. HAWAWINI and Pierre A. MICHEL, February 1981.

81/08 "Industrial policy in the European economic community : Crisis and change", by Kenneth S. COURTIS, June 1980.

81/09 "Dogmatism as a moderator of banking behavior and attitudes", by Arun K. JAIN, Christian PINSON and Naresh K. MALHOTRA, March 1981.

81/10 "Investment horizon, diversification, and the efficiency of alternative beta forecasts", by Gabriel A. HAWAWINI and Ashok VORA, March 1981.

81/11 "Organizational Development & Change", by Claude FAUCHEUX, Gilles AMADO and André LAURENT, April 1981.

81/12 "The Pricing of Risky Assets on the Belgian Stock Market" by Gabriel HAWAWINI and Pierre A. MICHEL, May 1981.

81/13 "A Test of the Generalized Capital Asset Pricing Model" by Gabriel HAWAWINI and Ashok VORA, May 1981.

81/14 "On the History of Yield Approximations" by Gabriel HAWAWINI and Ashok VORA, May 1981.

81/15 "Pitfalls of the Global Product Structure" by William H. DAVIDSON and Philippe C. HASPESLAGH, May 1981.

81/16 "Adjusting Beta Estimates: Real Gains or Illusions?" by Gabriel A. HAWAWINI and Ashok VORA, June 1981.

81/17 "Do European Industrial Marketers Budget Differently? an International Comparison via the Advisor Model" by David WEINSTEIN and Gary L. LILIEN, June 1981.

81/18 "The Internationalisation of Manufacturing in the Automobile Industry - Some Recent Trends" by Yves L. DOZ, April 1981.

81/19 "Portfolio Planning: Use and Usefulness" by Philippe HASPESLAGH, May 1981.

81/20 "Production Decisions in the Mixed Firm" by Claude VIALLET, Octobre 1981.

81/21 "Foreign Investment and Economic Development: Conflict and Negotiation", by José de la TORRE, April 1981.

81/22 "Forecasting Country Political Risk" by José de la TORRE and David H. NECKAR, March 1981.

81/23 "The Impact of Inflation on Real Variables: A General Equilibrium Approach", by Antonio M. BORGES, November 1981.

81/24 "An Assessment of the Risk and Return of French Common Stocks", by Gabriel A. HAWAWINI, Pierre A. MICHEL and Claude J. VIALLET, November 1981.

81/25 "Mode de vie et style de vie : Quatre observations sur le fonctionnement des termes" par Jean-François BERNARD-BECHARIES et Christian PINSON.

81/26 "Simulating an Oil Shock with Sticky Prices" by Francesco GIAVAZZI, Mehmet ODEKON and Charles WYPLOSZ, November 1981.

81/27 "Decomposing the Impact of Higher Energy Prices on Long-Term Growth" by Antonio M. BORGES and Lawrence H. Goulder.

81/28 "Forecasting for Industrial Products" by David WEINSTEIN.

EURO-ASIA CENTRE

INSEAD

Institut Européen d'Administration des Affaires
European Institute of Business Administration
Europäisches Institut für Unternehmensführung
Institut Privé d'Enseignement Supérieur
Boulevard de Constance
77305 Fontainebleau Cedex, France
Telephone (6) 422 48 27 Telex 690389F

E A C RESEARCH PAPERS

N°1. A Contribution to the Study of Entrepreneurship Development in Indonesia.

Philippe LASSERRE. April 1979 (corrected version 1980). 72, 7 p. (limited distribution)

N°2. The Transfer of Technology from European to Asean Enterprises : Strategies and Practices in the Chemical and Pharmaceutical Sectors.

Philippe LASSERRE and Max BOISOT. February 1980. 109, VI p.

EURO-ASIA CENTRE

INSEAD

Institut Européen d'Administration des Affaires
European Institute of Business Administration
Europäisches Institut für Unternehmensführung
Institut Privé d'Enseignement Supérieur
Boulevard de Constance
77305 Fontainebleau Cedex, France
Telephone (6) 422 48 27 Telex 690389F

E A C BRIEFING PAPERS

N°1. Strategies and Practices of Transfer of Technology from European to Asean Enterprises.

Philippe LASSERRE and Max BOISOT. April 1980. 30 p.

N°2. The Partners of Foreign Investors in Indonesia : the Tip of the Ethnic Iceberg. (working draft)

Stephen C. HEADLEY. December 1980. 21 p.

N°3. Foreword to Government-Business Relations in Indonesia. (working draft)

Stephen C. HEADLEY. December 1980. 17 p.

N°4. Personnel Management in Indonesia : How ? (working draft)

Stephen C. HEADLEY. December 1980. iv, 16 p.

N°5. Can you work for Honda and remain yourself ? The Cultural Dimensions of Indonesian Management. (working draft)

Stephen C. HEADLEY. December 1980. 17 p.

N°6. The Context of Management Development in Malaysia.

Bryony Conway. December 1980. 17 p.

N°7. Racial Balance in Management.

Bryony Conway. December 1980. 13 p.

EURO-ASIA CENTRE

INSEAD

Institut Européen d'Administration des Affaires
European Institute of Business Administration
Europäisches Institut für Unternehmensführung
Institut Privé d'Enseignement Supérieur
Boulevard de Constance
77305 Fontainebleau Cedex, France
Telephone (6) 422 48 27 Telex 690389F

E A C REPRINTS

N°1. Japanese Organizational Behaviour : A Psychocultural Approach.

Henri-Claude de BETTIGNIES. February 1981.
Reproduced from : Management Research: A Cross-Cultural Perspective.
Edited by Desmond Graves. Amsterdam, London, New York: Elsevier Scientific Publishing Company, 1973. pp. 75-93.

N°2. The Transfer of Management Know-How in Asia : An Unlearning Process.

Henri-Claude de BETTIGNIES. February 1981.
Reproduced from : Breaking down Barriers: Practice and Priorities for International Management Education.
Edited by Bob Garratt and John Stopford. London: Gower for the Association of Teachers of Management, 1980. pp. 293-310.

N°3. Korean Management in the 1980's : The International Challenge.

Henri-Claude de BETTIGNIES. February 1981.
Reproduced from : The Korean Journal of International Business. Vol. 1.
International Management Institute, Korea University; Seoul, Korea, July 1980. pp. 119-125.

N°4. La Sociologie des organisations : Le cas du Japon

Henri-Claude de BETTIGNIES. February 1981.
Reproduced from : Les Etudes Japonaises en France.
Colloque, oct. 1979.
Paris : Association pour l'Etude de la Langue et la Civilisation Japonaise, 1980. Compte-rendu du Colloque tenu à Paris les 8-13 oct. 1979 sous les auspices de la Maison Franco-Japonaise, à Tokyo et la Fondation du Japon. pp. 118-130.

N°5. Analyse des craintes françaises.

Henri-Claude de BETTIGNIES. February 1981.
Reproduced from : Revue Française de Gestion. N° 27-28, sept-oct. 1980.
Numéro spécial : Le Japon Mode ou Modèle ? pp. 16-23.

N°6. L'Indonésie et ses Potentiels

Philippe LASSERRE. May 1981.
Reproduced from : Marchés Internationaux N° 51, mai 1981. pp. 83-98.

N°7. Transferts de Technologie : des mariages difficiles.

Philippe LASSERRE. May 1981.
Reproduced from : Revue Française de Gestion, N° 30 mars-avril 1981. pp. 97-103

N°8. The Industrialising Countries of Asia : Perspectives and Opportunities.

Philippe LASSERRE. July 1981.
Reproduced from : Long Range Planning Vol 14 N° 3, June 1981. pp. 36-43.

N°9. Le Japon prépare ses managers de demain à l'école de l'Occident.

Jacques de RUGY. July 1981.
Reproduced from : France Japon éco N°9, automne 1981, pp. 10-21.