Empirical Estimates of Beta When Investors Face Estimation Risk
Author(s): Peter M. Clarkson and Rex Thompson
Source: *The Journal of Finance*, Vol. 45, No. 2 (Jun., 1990), pp. 431-453
Published by: Blackwell Publishing for the American Finance Association
Stable URL: http://www.jstor.org/stable/2328664
Accessed: 26/11/2009 07:17

THE JOURNAL OF FINANCE • VOL. XLV, NO. 2 • JUNE 1990

Empirical Estimates of Beta When Investors Face Estimation Risk

PETER M. CLARKSON and REX THOMPSON*

ABSTRACT

We examine empirical implications of models of differential information that formalize the following intuition: securities for which there is relatively little information are perceived as relatively more risky because of the greater uncertainty surrounding the exact parameters of their return distributions. The implication that beta risk for low information firms should decline as information increases is confirmed with several data sets. We find such a decline over the first several periods subsequent to initial public offerings and initial listings. There is also an abrupt risk decline at the first annual earnings announcement.

THIS PAPER EXAMINES SEVERAL empirical implications of security return models involving differential information. These models formalize the following intuition: securities for which there is relatively little information are perceived as relatively more risky because of the greater uncertainty surrounding the exact parameters of their return distributions. The research relates to two streams of literature. The first revolves around the new issues and new listings market. It begins with Ibbotson (1975) and includes, for example, Ritter (1984), Beatty and Ritter (1986), McConnell and Sanger (1987), and Muscarella and Vetsuypens (1989). The second is the literature dealing with the effects of differential information on the risk assessment of "low information" firms. This second literature is exemplified by the work of Klein and Bawa (1976, 1977) and Barry and Brown (1984, 1985).

In our examination, we focus on how increased risk associated with low information firms (henceforth called "estimation risk") manifests itself in observed return data. We explore how observed security returns to low information firms appear to researchers in relation to how they appear, ex ante, to investors who base their predictive distribution of security returns on incomplete information about the parameters of the return-generating process. We also examine data on new listings and new issues to exemplify some of the relationships. The data support the most obvious and direct implication of the differential information model: that the expected systematic risk of low information firms decreases as time passes and information increases.

Our evidence, as in Ibbotson, that risk declines with "seasoning" rejects a restrictive null hypothesis that information risk is diversifiable and the under-

* Simon Fraser University and Southern Methodist University, respectively. Comments from workshops at The Ohio State University, Northwestern University, The University of Queensland, and The Australian Graduate School of Management, and especially from C. Barry, G. Richardson, S. Sefcik, the co-editor, David Mayers, and an anonymous referee are gratefully acknowledged.

lying cash flow risk is stationary throughout the seasoning process. An important alternative model also consistent with these findings is that the underlying cash flow covariance risk declines with seasoning. That is, there could be a decline in beta risk as firms season simply because the production processes become less risky and not because investors are sharpening their predictive distribution around a stationary but unknown cash flow process. We offer two pieces of evidence suggesting that information risk contributes to the decline in betas as firms season. First, using an estimate based on annual earnings, we find that seasoning during the first year of listing has only a weak effect on underlying cash flow covariance risk. Second, during the first year of listing, the annual earnings announcement introduces a discrete information event that serves to reduce the subsequent systematic risk of the firm. This second result suggests that the risk reduction is related to information availability.

The paper is organized as follows. In Section I, the differential information model is described and the role of diversification is considered. The implications of the model and the researcher's risk estimates are summarized in Section II. Section III describes several data sets on which the model is estimated and presents the empirical results for these samples. Section IV contains conclusions and a discussion of possible extensions.

I. Beta Measurement with Differential Information

A. The Differential Information Model

Barry (1978), Barry and Brown (1985), Coles and Lowenstein (1988), and Clarkson (1986) have considered beta estimation by investors who face uncertainty over the exact parameters of the joint return distribution. Although somewhat complex analytically, the intuition underlying their results is easy to grasp. Parameter uncertainty enters the investor's estimate of beta whenever parameter estimation error is correlated with the realized market return. This can occur in many simple market settings.

For example, suppose two independently distributed securities, L and H, comprise the entire market. Let σ, ω, and N represent standard deviation of return, market portfolio weight,[1] and amount of information, respectively. Suppose further that the mean return of security H is known ($N_H = \infty$) but that the mean of security L, the low information security, is estimated with N independent observations and diffuse priors. The predictive variance of L's return in the next period will be $\sigma_L^2 + \frac{\sigma_L^2}{N}$, reflecting uncertainty in the mean. This uncertainty enters beta as well. For security L, beta measured without regard for the possible effect of differential information is

$$\beta_a = \frac{\omega_L \sigma_L^2}{\omega_L^2 \sigma_L^2 + \omega_H^2 \sigma_H^2}, \tag{1}$$

[1] For simplicity, we will ignore at this point the effect of differential information on the market portfolio weights, although we include it in our simulations below. It is also included in the more rigorous treatments cited above.

whereas beta adjusted for the effects of differential information is

$$\beta_a = \frac{\omega_L \sigma_L^2 \,[(N+1)/N]}{\sigma_m^2} \tag{2}$$

$$= \beta_u + \gamma, \tag{3}$$

where σ_m^2 denotes the predictive market return variance. Further,

$$\gamma = \frac{1}{N} \frac{\omega_L \sigma_L^2 \,(1 - \omega_L \beta_u)}{\sigma_m^2},$$

$$\sigma_m^2 = \omega_L^2 \sigma_L^2 \,[(N+1)/N] + \omega_H^2 \sigma_H^2.$$

Under the Savage extension of the von Neumann-Morgenstern axioms, the adjusted beta is what investors who maximize expected utility would actually perceive, while the unadjusted counterpart is a logical construct that would be relevant if the differential information were somehow ignored or were inconsequential. It might also appear that data on realized security returns would covary with the market according to the unadjusted beta. This is not the case, in general, as we will argue in Section II.

Equation (3) provides useful insights into the distinction between beta measured with and without regard for differential information. The difference in beta is larger the less information there is about the security. The difference falls at a decreasing rate as information increases and the adjusted beta converges to the unadjusted beta.[2]

B. The Effects of Diversification

Banz (1981) and later Reinganum and Smith (1983) offer the intuition that information effects should be diversifiable. Their logic is based on the idea that the return distribution of a portfolio of low information firms should have a highly predictable comovement with the market and hence such a portfolio should have no penalty for differential information. If there is no penalty for the portfolio, there can be no penalty for the individual securities comprising the portfolio.

Clarkson (1989) explores this argument, finding that within the context of his model the largest adjustments to beta occur in markets where there is a single low information security and an index assumed analogous to a high information security. Continuing, he finds that, where multiple low and high information securities exist, the effects of differential information are reduced. There are two different sources of risk reduction. The first is through an inference of informa-

[2] These conclusions are similar to those obtained by Williams (1977), who considers the CAPM under heterogeneous beliefs. Specifically, he finds that, within his framework, as time passes and information accumulates, investors' subjective means (and portfolios) converge to the corresponding true means (and to the usual portfolio of mean-variance models) at a rate on average steadily decreasing over time. Within the differential information framework, the speed of convergence depends upon details of the market setting such as the relative variances and portfolio weights. Also, a negative market portfolio weight could make the adjusted beta converge from below rather than from above.

tion based on what is known about related securities. For example, a low information security whose return is known to be highly correlated with a high information security effectively reflects the higher information. With many cross-correlated high information securities the market is able to "fill in" the missing information for low information securities. The remaining adjustment for differential information is diminished, and any sensitivity to period of listing or other proxies for firm-specific information would be correspondingly reduced. The second source of risk reduction is through diversification across low information securities. If the uncertainty surrounding expected cash flows is largely uncorrelated across a sample of low information securities, portfolio formation can increase precision and reduce implicit required adjustments to beta. In restricted economies with one or a few low information securities, this diversification is not possible.

In a totally unrestricted economy with many high and low information securities, the effects of differential information on beta can be completely eliminated. This limiting argument provides an important null hypothesis for possible tests of the differential information model.[3]

II. Empirical Implications

A. Introduction

The models of estimation risk described in Section I suggest a time series process for investors' subjective probability distributions of returns. In the eyes of investors, return sensitivity to the market return should decline for low information securities as the amount of information increases. The relevant question is, then, whether the subjective probability distributions of investors leave a trace in the data or whether researchers, observing realized returns, ex post, must add a correction for estimation risk.

It is possible to argue very simply why the risk of observed security returns is influenced by the perceptions of investors even though the true, underlying cash flow uncertainty is not. First, the observed return covariance with the market return depends upon the market clearing price at the beginning of the period. Any price penalty resulting from investor perceptions will increase the magnitude of the return covariance.

Second, in repeated experiments, uncertainty in the expected terminal cash flow translates into observed variability in security returns around the average return across the experiments because the beginning price in each experiment is based on the expected terminal price in that experiment. Any randomness in the expected terminal price translates into additional uncertainty in the price change from the beginning to the end of the period. An example might make this clear.

[3] Preliminary empirical evidence on this hypothesis is provided by Brauer (1986). He finds, using a jump-diffusion returns model to gauge the impact of information, that "... portfolios of small firm stocks are no more prone to information surprises than are portfolios of large firm stocks, but that the portfolios of small firm stocks are found to react more severely than portfolios of large firm stocks when surprises do occur." He concludes that these results imply that the relative lack of information associated with small firms must be a source of risk that cannot be diversified away.

Consider a risk-neutral market with two dates and no discounting. A security with true terminal payoff of \$1.00 is sold at the beginning of the period. Suppose investors expect the payoff to be \$1.00 + x, where x represents their estimation error. The selling price will be \$1.00 + x, and the resulting price change over the period will be $-x$. Across repeated experiments, randomness in expectations about the terminal price creates randomness in the price change over the period through its impact on the distribution of selling prices. This randomness will increase the variance of return. It can also increase the systematic risk of the return when estimation risk is not completely diversifiable.

Having argued that uncertainty in investor perceptions should affect observed security uncertainty, we now consider several possible perspectives taken by researchers to estimate the beta risk of low information firms.

B. An OLS Time Series Estimate of Beta for a Stationary Cash Flow Process

Suppose a researcher wishes to compute an OLS market model beta based on a series of realized return observations on a low information security and the market portfolio where the successive time intervals have increasing information. Such a market model might be used to estimate the beta at the end of the interval as in Barry and Brown (1984) or the beta at the beginning of the interval as in McConnell and Sanger (1987). How would the OLS market model beta compare to the adjusted beta, β_a, of equation (2) above? Clarkson (1986) shows that the expected OLS sample beta will approximate the average adjusted beta across the successive time intervals.[4] Thus, the expected market model beta tends to overstate the adjusted beta, as well as the unadjusted beta, at the end of an interval. On the other hand, it tends to understate the adjusted beta at the beginning of the interval. As the amount of information gets large, all beta values converge to the unadjusted beta, β_u.

As Barry and Brown (1984, 1985) argue, betas "measured without regard for differential information" will be too low for low information securities. The beta so measured is the unadjusted beta, β_u. However, as discussed in Subsection *A*, a sample of actual returns on a low information security would not be measured without regard for differential information because the price process provides a continually changing adjustment. Thus, an OLS market model beta based on a sample of prior returns would tend to overstate not only the unadjusted beta but also the adjusted beta.

C. A Cross-Sectional Regression Model

Ibbotson (1975) and Warner (1977) propose a cross-sectional estimation technique for a portfolio of securities separated in time. Consider applying these procedures in a differential information environment. Suppose we have a sample of low information securities, each with information N_i, observed at different

[4] The sample beta is an unbiased estimate of the average adjusted beta if there is no correlation between the risk adjustment and the realized market return. A sufficient assumption would be that the true expected market return is constant over the estimation period. In a setting where the low information security has significant weight in the market portfolio, this independence would be violated, and hence the sample beta is not literally an unbiased estimate of the average.

points in calendar time. For each security there is a realized return and contemporaneous market return. Estimate the Ibbotson "RATS" (returns across time and securities) regression:

$$R_{jt} = \alpha_i + \beta_i R_{mt} + \epsilon_{jt}, \qquad j = 1, \cdots, J, \tag{4}$$

where j denotes the separate securities and i the common information level.

Under the assumption that all the securities have the same underlying cash flow process and the same β_u, with the firms all at the same information level, N_i, they all have the same estimation risk adjustment inherent in their prices and the same increment to covariance risk. Their adjusted betas should be the same, and hence the cross-sectional regression involves a sample of identically distributed returns. Least squares theory implies that the regression β_i is an unbiased estimate of the beta from this process.[5] A series of cross-sectional regressions with N_i increasing uniformly with each cross-section would provide a series of adjusted beta estimates that should decline as information increases. Under the null hypothesis that estimation risk is diversifiable and cash flow risk is constant, the series of adjusted betas should show no tendency to decline as information increases.

D. Estimated Betas in Simulation

Figure 1 presents the results of a simulation designed to illustrate the results of the preceding sections. The market is comprised of two securities with perpetual periodic cash flows. Investors know the mean and variance of the cash flow for security H, while investors only know the variance of the cash flow for security L. The expected cash flow for security L is estimated by accumulating data over time. Time starts after one cash flow has been observed, and this forms the initial estimate of the mean cash flow. The simulation reflects the average of 150 repetitions with the identical true mean cash flows for L. In each repetition, investor estimates converge to the true value over time as observations accumulate.

Realized rates of return are calculated from realized cash flows (assumed to be paid as dividends) and end-of-period market prices that reflect the new information learned over the period about expected future cash flows. The market portfolio weights are based on the assumption of an equal number of L and H securities, although risk differences and estimation error in the expected cash flow for L affect market clearing prices and thus market portfolio weights. Each period, investors have quadratic utility over end-of-period wealth. Risk and mean

[5] It appears that the unbiasedness of the RATS regression model does not extend to the case where firms have different underlying cash flow risk, unless estimation risk is diversifiable. If estimation risk is partly nondiversifiable, the model implies that there should be an association between the risk of the low information security and the total risk of the market portfolio. In equilibrium, this induces positive correlation between the risk of the low information security and the expected return on the market. Although in actual data this correlation is likely to be small if not negligible, it would cause a perhaps trivial upward bias in the RATS beta estimate. When firms have different betas, OLS provides an unbiased estimate of the mean beta under the assumption of an uncorrelated error term. This result is cleverly noted by Ibbotson (1975) and Warner (1977). In the differential information model, the error term is correlated in a cross-sectional regression.

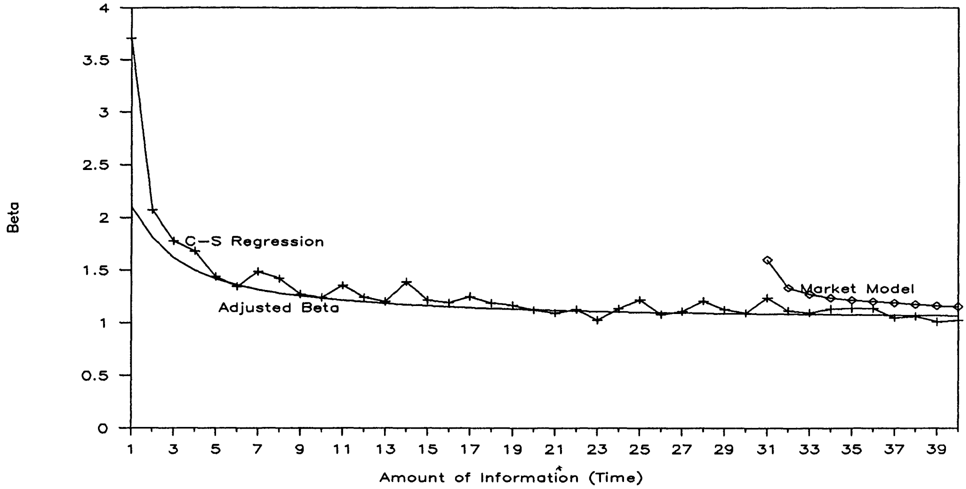

Figure 1. Simulation experiment relating beta to quantity of information. Results are from 150 trials where a new firm is introduced into the market and investors learn about the mean cash flow of the firm over time by observing the current cash flow and updating their estimate of the mean. C-S Regression equals the beta estimate in each time period based on a cross-sectional regression of the 150 firm return-market return pairs. Adjusted Beta equals the average of the 150 adjusted betas based on investor perceptions of the prevailing uncertainty at each time period. See equation (3) of the text. Market Model equals the average market model beta for the 15 firms based on the previous 30 time series observations.

cash flow parameters are set so that the theoretical point of convergence for the adjusted beta is unity.

In the figure are several lines representing different statistics within the market. The solid line shows the average adjusted beta (β_a) based on the ex ante information of investors and standard principles of Bayesian updating. The "◇" line is the average across the 150 trials of the market model beta based upon a time series of realized returns for the preceding 30 observations. The "+" line is the cross-sectional (RATS) beta estimated at each point in time based on the 150 cross-sectional return pairs.

The cross-sectional beta conforms quite closely to the average adjusted beta computed from the investor information available ex ante. The only unusual observation is the first cross-sectional beta, which seems markedly higher than the first average adjusted beta. Both series decline in a similar pattern after period one.[6] The market model betas conform closely to the prediction that, based on historical data, betas will be overstated. The extent of the overstatement declines as the window of time series observations contain increasing amounts of information.

[6] The simulation was replicated a number of times with different true means and variances of cash flow for the low information security. All of the replications showed a tendency for the cross-sectional beta to exceed the average adjusted beta in the first few periods and then track it quite closely. This result is consistent with the bias discussed in the previous footnote.

E. Summary of the Estimation Problem

The preceding discussion has several implications. First, market model beta coefficients based on historical return series will overstate the beta that correctly adjusts for estimation risk at a point in time. Conversely, market model betas based on returns that follow the date of interest will tend to understate this beta. An interesting compromise is to use data that straddle the date of interest—say, an equal number of pre- and post-date observations. Such a compromise will be closer to the beta that correctly adjusts for estimation risk, but, because the adjustment process is nonlinear in the amount of information, one would expect a slight overstatement of beta with this procedure. Finally, a possible benchmark against which the market model can be compared is a cross-sectional regression model based on a set of return pairs from different firms that are all at the same information level. We explore this latter approach in Section III.

III. Empirical Investigation

A. Introduction

The empirical investigation we pursue addresses the relationship between observed beta risk and quantity of information from two perspectives. The first adopts time, or period of listing as in Barry and Brown (1984), as a simple proxy for quantity of information. In this sense we argue that quantity of information is increasing in time. This characterization finds support in Raiffa and Schlaifer (1961), who suggest that a prior distribution reflecting a variety of sources of information can be thought of in terms of "equivalence" to a sample size n.[7] The second considers a discrete change in the quantity of information surrounding an information release, specifically the annual earnings announcement. This particular information release was selected because it is a standard release required of all firms and because it has documented information content. (See, for example, Ball and Brown (1968).)

B. Data

Because the longevity of an information effect is, ex ante, unknown, we focus our attention on the return process of both new issues and new listings. Our primary sample consists of firms which were included in the SEC listing of initial public offerings for the period 1976–1985.[8] The sample was developed in the following manner. Five hundred firms were randomly selected from the SEC list, 50 from each of the 10 years. A firm was retained in the sample if it met the

[7] More formally, Raiffa and Schlaifer point out that there is an equivalent sample information interpretation of Bayesian prior and posterior distributions for parameters of many common processes such as the multinormal.

[8] One potential problem associated with this sample relates to the "Hot Issues" phenomenon documented by Ritter (1984). While there is no a priori reason why this phenomenon should affect systematic risk, as a check we also studied the subsample of firms which fall outside the 15-month window identified by Ritter (January 1980 through March 1981), finding relative magnitudes substantially unaltered.

Table I

Frequency Distribution of Market Value after Offer and S.I.C. Industry Classification for a Sample of 198 New Issues from the Period 1976–1985

Panel A: Market Value

Market Value ($ Million)	Number of Firms
<10	38
10–20	59
20–50	54
50–100	26
>100	21

Panel B: S.I.C. Industry Classification

Division	Industry Group	Number of Firms
A	Agriculture, Forestry, and Fishing	5
B	Mining	33
D	Manufacturing	97
E	Transportation, Communications, Electric, Gas, and Sanitary Services	7
F	Wholesale Trade	2
G	Retail Trade	9
H	Finance, Insurance, and Real Estate	4
I	Services	41

following criteria. First it was required that complete price data for the first 25 days and month end price data for the first 20 months of trading be available in the *Daily Stock Price Record.* The uncertainty surrounding the relationship between time and information leads us to consider both daily and monthly returns. Next it was required that the first post-issue earnings announcement date be available in the *Wall Street Journal Index* and that complete price data be available in the *Daily Stock Price Record* for a period of 15 days before and 15 days after this date. Finally, it was required that trading volume be nonzero for each date on which price data were collected.[9] The final sample consists of 198 firms, with approximately the same attrition rate attributable to each of the above conditions. As indicated in Table I, the sample has a broad base, both in terms of market value and in terms of industry classification. Table II contains a frequency distribution of the initial trading date by year for this sample and of the number of trading days from initial issue to the earnings announcement. Returns are calculated using bid prices,[10] and the CRSP value-weighted index is used as an index of market returns.[11]

[9] Dimson (1979) and Scholes and Williams (1977) (among others) argue that a lack of trading may lead to a bias in beta estimates.

[10] All prices are adjusted for dividends, stock dividends, and stock splits.

[11] The value-weighted index was used to maintain comparability with Banz (1981) and Barry and Brown (1984). As a check, we also used an equally weighted index and found similar results.

Table II

Frequency Distribution of Year of Initial Issue and Number of Trading Days from Date of Initial Issue to First Annual Earnings Announcement for a Sample of 198 New Issues from the Period 1976–1985

Panel A: Year of Initial Issue

Year	Number of Firms
1976	18
1977	18
1978	23
1979	16
1980	15
1981	26
1982	24
1983	22
1984	17
1985	19

Panel B: Number of Trading Days from Issue to Announcement[a]

Number of Trading Days	Number of Firms
0–20	0
21–40	9
41–60	21
61–80	6
81–100	7
101–120	10
121–140	16
141–160	27
161–180	32
181–200	26
201–220	27
221–240	5
241–260	4
261–280	5
281–300	3

[a] The announcement date is taken as the date that the first annual earnings figure appears in the *Wall Street Journal.*

Further to this sample of unseasoned issues, we consider a data set of NYSE new listings. This supplemental sample, which includes a subsample of the firms considered by Barry and Brown (1984), consists of the 692 firms for which complete data are available on both the CRSP daily and monthly return files (1987) for a period of at least 20 months from the date of initial data availability. The initial date must coincide on the two return files. This latter constraint allows us to compare the results of the supplemental sample with the results of the sample of unseasoned securities. Again, the CRSP value-weighted index is used as an index of market returns.

C. Empirical Results

C.1. Period of Listing Perspective

C.1.1. Time Pattern of Betas

Figure 2 shows a plot of twenty-five cross-sectional beta estimates corresponding to the first twenty-five days of trading for the sample of 198 new issues. The betas are fit in OLS linear regressions against time in days, the inverse of time in days, and the log of time in days. Since the relationship between information and time is somewhat arbitrary, we consider all three models as a check against sensitivity to model specification. If information is roughly proportional to time, the model with the inverse of time is the most appealing theoretically. All of the models give the impression of a negative relation between the cross-sectional beta estimate and time. They are reported in Panel A of Table III. The relation between beta and the inverse of time is the most significant, with a t-value of 6.922. The intercept, which would correspond to a point estimate of β_u, is 1.068, and the slope, or adjustment for the inverse of time, is 2.099.[12] Standard diagnostic tests fail to reject the hypothesis that the residuals are normal and serially independent.[13] Since the issue of nonsynchronous or infrequent trading arises with daily data (see Scholes and Williams (1977) and Dimson (1979)), we also implement an adjustment to the beta estimates based on the Scholes-Williams approach.[14] The t-value for the model based on the inverse of time is now 7.235, while the t-values for time and the log of time are −4.973 and −6.768. Thus, infrequent trading does not appear to explain the time trend observed in cross-sectional betas.

Panel B of Table III and Figure 3 present the results for the same three models,

[12] We also estimated a nonlinear model of the following form on a firm-by-firm basis. Letting t denote the amount of information available (time from listing), write the realized security return as

$$R_t = \alpha + [\beta_u + \gamma_t]R_m + \epsilon_t. \tag{5}$$

Expressing γ_t as proportional to $1/t$, equation (5) can then be rewritten as

$$R_t = \alpha + \beta_u R_m + \frac{\gamma_0}{t} R_m + \epsilon_t, \tag{6}$$

where γ_0 is a proportionality constant from equation (3). A regression fit to equation (6) then provides a direct estimate of β_u. The estimate of β_a at information level t can be computed by adding the estimate of β_u to the estimate of γ_0 divided by t. The average coefficient estimates for the 198 new issues were virtually identical to those in Table III for the model using the inverse of time.

[13] The test statistic from the chi-square goodness of fit test for normality of the residuals is 1.412 with 2 degrees of freedom. The first-order autocorrelation coefficient for the residuals is −0.091, and the Durbin-Watson test statistic is 2.153.

[14] The adjusted estimate of systematic risk, $\hat{\beta}_t$, is

$$\hat{\beta}_t = \frac{\hat{\beta}_t^- + \hat{\beta}_t + \hat{\beta}_t^+}{1 + 2\hat{\rho}_m},$$

where $\hat{\beta}_t^-$, $\hat{\beta}_t$, and $\hat{\beta}_t^+$ are the OLS estimates of beta using, as the independent variables, the realized market return for the day before, the day of, and the day after the day of interest and where $\hat{\rho}_m$ is the estimation period value of the first-order autocorrelation coefficient of the market return (−0.01587 for our data).

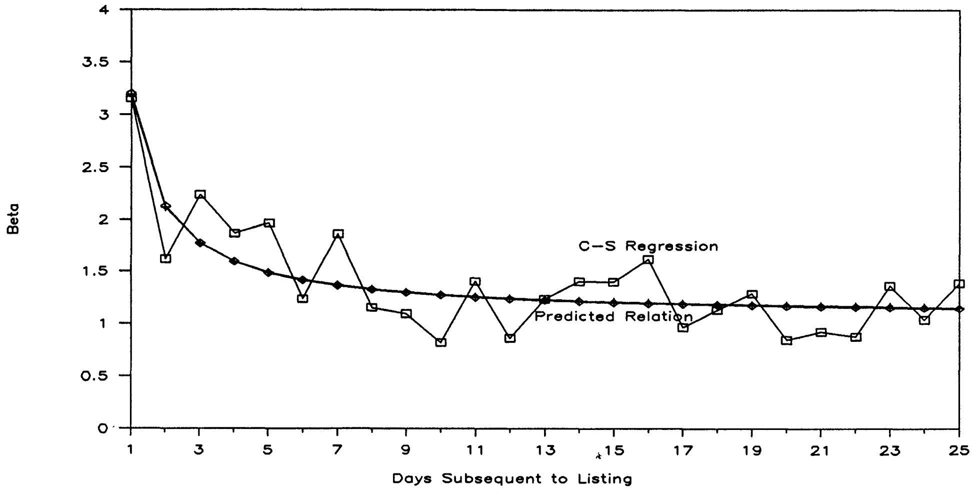

Figure 2. Cross-sectional beta over the interval from day 1 to day 25 after the date of initial listing for a sample of 198 new issues from 1976 to 1985. Cross-sectional betas (C-S Regression) are based on a cross-sectional regression of the 198 firm return-market return pairs. See regression (4) in the text. Predicted Relation is based on the estimated fit between the observed cross-sectional betas and the inverse of time using OLS and WLS. (See Table V for the estimated parameters.) The OLS and WLS predictions are almost identical.

Table III

Fitted Models of the Relation Between the Cross-Sectional Beta Estimate and Variants of Time for a Sample of 198 New Issues from the Period 1976–1985

$$\hat{\beta}_t = \psi_0 + \psi_1 X_t + \nu_t.$$

$\hat{\beta}_t$ is the cross-sectional beta estimate for trading day or month t for the sample of 198 new issues, based on the Ibbotson (1975) "RATS" regression $R_{jt} = \alpha_t + \beta_t R_{mt} + \epsilon_t$ (equation (4) in the text), where R_{jt} is the realized return for firm j for day or month t and R_{mt} is the contemporaneous market return; ψ_0 is the component of $\hat{\beta}_t$ unrelated to the predictor variable; X_t is the predictor variable (time, log time, or 1/time); ψ_1 is the contribution of predictor variable to $\hat{\beta}_t$; ν_t is the error term; and $t = 0$ is the day or month of issue. The relations are based on the cross-sectional beta estimates corresponding to the first twenty-five days of trading and the first twenty months of trading.

Panel A: Daily Data					
X_t	ψ_0	t_{ψ_0}	ψ_1	t_{ψ_1}	R^2
Time	1.965	11.252**	−0.044	−3.771**	0.355
Log Time	2.532	12.459**	−0.493	−5.963**	0.590
1/Time	1.068	13.901**	2.099	6.922**	0.662
Panel B: Monthly Data					
X_t	ψ_0	t_{ψ_0}	ψ_1	t_{ψ_1}	R_2
Time	2.449	14.550**	−0.085	−4.022**	0.650
Log Time	2.907	13.507**	−0.636	−4.680**	0.697
1/Time	1.201	9.637**	2.002	3.541**	0.508

** Significant at the 1% level.

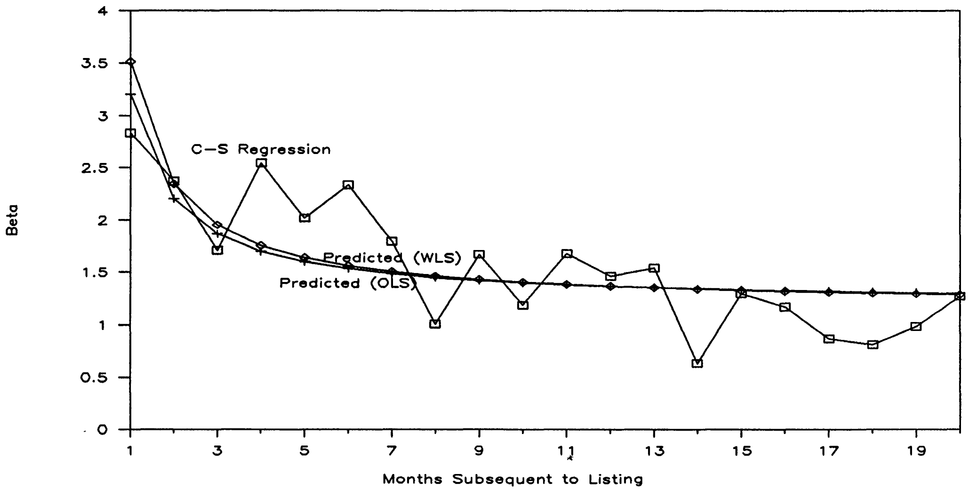

Figure 3. Cross-sectional beta over the interval from month 1 to month 20 after the date of initial listing for a sample of 198 new listings from 1976 to 1985. Cross-sectional betas (C-S Regression) are based on a cross-sectional regression of the 198 firm return-market return pairs. See regression (4) in the text. Predicted relation is based on the estimated fit between the observed cross-sectional betas and the inverse of time using OLS and WLS. (See Table V for the estimated parameters.)

with the dependent variable changed to the cross-sectional beta estimates corresponding to the first 20 months of trading for the sample of 198 new issues and with time measured in months. Consistent with Ibbotson's (1975) suggestion, we adjust the market return in the first month of trading to reflect only that portion over which the security traded. Once again, the results give the impression of a negative relation. The t-value for the inverse of time is 3.541, while the t-values for time and the log of time are -4.022 and -4.680, respectively. Here the model with the inverse of time does not provide the best fit, although no model appears to be clearly superior. Standard diagnostic tests again fail to reject the hypothesis that the residuals are normal and serially independent.

The supplemental sample of NYSE new listings supports the conclusions drawn from the new issues. The relations between the cross-sectional beta estimates and variants of time are reported in Table IV. Panel A presents the results for daily betas corresponding to the first 25 days of trading. The t-value for the inverse of time is 2.293. Results for the monthly cross-sectional beta estimates corresponding to the first 20 months of data availability on the CRSP monthly return file are found in Panel B. The t-value for the inverse of time is 2.819.

Comparing the coefficients in Tables III and IV reveals that the adjusted betas for new issues start at a higher level and decline faster than the adjusted betas for new listings. For example, with daily data fit to the model based on the inverse of time, the adjusted beta at time equals one ($t = 1$) is 3.167 for the new issues and only 1.388 for the new listings. Based on the relative slopes and their standard errors, the difference in slopes is significant, while the long run unadjusted betas are not significantly different. These results are as predicted by the

Table IV

Fitted Models for Relation Between the Cross-Sectional Beta Estimate and Variants of Time for a Sample of 692 New Listings on the NYSE over the Period 1963–1987

$$\hat{\beta}_t = \psi_0 + \psi_1 X_t + \nu_t.$$

$\hat{\beta}_t$ is the cross-sectional beta estimate for trading day or month t for the sample of 692 NYSE new listings, based on the Ibbotson (1975) "RATS" regression $R_{jt} = \alpha_t + \beta_t R_{mt} + \epsilon_t$ (equation (4) in the text), where R_{jt} is the realized return for firm j for day or month t and R_{mt} is the contemporaneous market return; ψ_0 is the component of $\hat{\beta}_t$ unrelated to the predictor variable; X_t is the predictor variable (time, log time, or 1/time); ψ_1 is the contribution of predictor variable to $\hat{\beta}_t$; ν_t is the error term; and $t = 0$ is the day or month of initial listing. To be included in the sample, each firm required complete data on the CRSP monthly and daily return files for a period of at least 20 months, with the date of initial data availability on the two return files coinciding. The relations are based on the cross-sectional beta estimates corresponding to the first twenty-five days and the first twenty months of trading on the NYSE.

Panel A: Daily Data					
X_t	ψ_0	t_{ψ_0}	ψ_1	t_{ψ_1}	R^2
Time	1.250	24.951**	−0.007	−2.091*	0.123
Log Time	1.327	18.811**	−0.073	−2.534*	0.184
1/Time	1.117	37.279**	0.271	2.293**	0.149
Panel B: Monthly Data					
X_t	ψ_0	t_{ψ_0}	ψ_1	t_{ψ_1}	R^2
Time	1.271	31.495**	−0.009	−2.734*	0.254
Log Time	1.331	25.271**	−0.074	−0.3190**	0.326
1/Time	1.129	45.246**	0.249	2.819*	0.268

* Significant at the 5% level.
** Significant at the 1% level.

differential information model since new NYSE listings typically have a trading history in the OTC markets or on smaller exchanges.

C.1.2. Sensitivity Considerations

Examination of the standard errors of estimate for the individual daily cross-sectional betas for the new issues data reveals a declining pattern over time. In particular, the first day of trading has a much larger standard error than subsequent days.[15] Further, days 21–25 have about 80% of the standard error, on average, as days 2–6 (0.548 vs. 0.672). A reduction in the standard error of estimate for beta is consistent with the differential information model because the model predicts that both nonsystematic and systematic risk declines as information increases.

Table V presents the results of some sensitivity analysis relating to the effects of heteroskedasticity and the importance of the first few time periods in the series for the new issues data. The table compares the results of OLS regressions with Weighted Least Squares (WLS) that incorporate the standard errors of estimate for the individual cross-sectional betas. Results are for the model based

[15] The standard error for the first day is 3.289, while none of the other standard errors exceeds 0.800.

Table V

Comparisons of Weighted Least Squares and OLS for Daily and Monthly Cross-Sectional Beta Estimates Fitted Against the Inverse of Time over Different Time Intervals for 198 New Issues from the Period 1976–1985

$$\hat{\beta}_t = \psi_0 + \psi_1(1/t) + \nu_t.$$

$\hat{\beta}_t$ is the cross-sectional beta estimate for trading day or month t for the sample of 198 new issues, based on the Ibbotson (1975) "RATS" regression $R_{jt} = \alpha_t + \beta_t R_{mt} + \epsilon$ (equation (4) in the text), where R_{jt} is the realized return for firm j for day or month t and R_{mt} is the contemporaneous market return; ψ_0 is the component of $\hat{\beta}_t$ unrelated to the predictor variable, the inverse of time $(1/t)$; ψ_1 is the contribution of predictor variable to $\hat{\beta}_t$; ν_t is the error term; and $t = 0$ is the day or month of issue. The relations are based on the cross-sectional beta estimates corresponding to different time intervals from the first twenty-five days of trading and the first twenty months of trading. Weighted Least Squares incorporates the standard errors of estimate for the individual cross-sectional betas. t-Values are in parentheses.

Panel A: Daily Data

Time Interval (Days)	OLS ψ_0	OLS ψ_1	Weighted Least Squares ψ_0	Weighted Least Squares ψ_1
1–25	1.068	2.099	1.058	2.141
	(13.901)**	(6.922)**	(12.852)**	(4.350)**
2–25	1.064	2.139	1.055	2.170
	(11.208)**	(3.579)**	(11.459)**	(3.419)**
3–25	0.918	3.818	0.925	3.746
	(9.531)**	(4.931)**	(9.524)**	(4.459)**

Panel B: Monthly Data

Time Interval (Months)	OLS ψ_0	OLS ψ_1	Weighted Least Squares ψ_0	Weighted Least Squares ψ_1
1–20	1.201	2.002	1.173	2.339
	(9.637)**	(3.541)**	(8.788)**	(3.008)**
2–20	1.039	3.328	1.020	3.616
	(7.153)**	(3.060)**	(6.778)**	(3.101)**
3–20	0.911	4.578	0.807	5.694
	(5.325)**	(3.009)**	(4.582)**	(3.275)**

** Significant at the 1% level.

on the inverse of time, with Panel A showing daily data and Panel B showing monthly data.

The most dramatic effect is the drop in significance of the inverse of time when WLS is used instead of OLS on the entire series of 25 daily observations. The t-value on the inverse of time falls from 6.922 to 4.350. As a check against the importance of the first few observations in the series, the model was re-estimated after dropping the first observation and then the first and second observations. The significance and general fit of the model seem to reflect the original WLS. For example, with daily data, WLS shows a slope coefficient of 2.170 with a t-value of 3.419 when the first observation is dropped, rising to a slope of 3.746 and t-value of 4.459 when the first two observations are dropped. OLS generally yields slopes slightly lower and t-values slightly higher than WLS.

With monthly data, the impact of using WLS is less dramatic. All t-values for both methods exceed three, with no general tendency for WLS to show lower significance than OLS. Dropping the first observations does not alter the significance of OLS as it does with daily data. The standard error of estimate for the first monthly observation is closer to the standard errors of the other months,[16] reducing the impact of the first observation and the contribution of WLS.

Finally, we find, in a similar fashion, that neither WLS nor dropping the first observation significantly alters the impression of the fitted relations for the NYSE sample of new listings. For example, with daily data, WLS shows a slope coefficient of 0.282 with a t-value of 2.207 for the model with the inverse of time based on the entire series of 25 daily observations (as opposed to 0.271 and 2.293 for OLS). With the first observation dropped, the slope coefficient is 0.421 and its t-value is 1.807. For the monthly data, the WLS model with the inverse of time has a slope coefficient of 0.262 with a t-value of 2.774 based on the entire series of 20 monthly observations (compared with 0.249 and 2.819 for OLS) and a slope coefficient of 0.391 and t-value of 2.212 with the first observation dropped.

We conclude from these results that the decline in betas over time for both new issues and new listings appears significant and is not driven by the first few observations. The dramatic significance of the OLS regressions for the daily new issues data, however, overstates the fit of the model, although the point estimates of the parameters seem reasonable.

C.1.3. Market Model Betas

The differential information model predicts that, if information is increasing in time, a beta estimate based on a sample of historical return observations will tend to overstate beta relative to its value appropriately adjusted for the degree of differential information. Extrapolating from the fitted model based on the inverse of time, the estimate of β_u based on daily data is 1.068 and is 1.201 based on monthly data. From the daily data, at time equal to the end of our observations, $t = 26$, the estimate of β_{a26} from the fitted model with the inverse of time would be 1.149. In contrast, a researcher using the first 25 trading days to compute estimates of beta for each firm from the market model would have determined the average $\hat{\beta}_{OLS}$ to be 1.562.[17] Similarly, from the monthly data, the estimate of β_{a21} would be 1.296 based on the fitted model with the inverse of time. A researcher, using the first 20 months to estimate beta for each firm from the market model, would have found the average $\hat{\beta}_{OLS}$ to be 1.437. Thus, the researcher would have overestimated the point estimate of beta for day 26 and for month 21 as the model predicts. Attempts to use historical market model betas for abnormal return calculations would thus tend to understate average abnormal returns for low information firms.

[16] The standard error for the first month is 1.126, with the standard errors of the remaining months ranging from 0.398 to 1.017.

[17] This average market model beta is the average of the betas estimated from traditional time series market models. For daily data, the range of betas is −4.98 to 12.49, with an average R^2 of 0.04. For monthly data, the range is −0.52 to 5.03, with an average R^2 of 0.16.

Consistent with these results, we also find that researchers would tend to overestimate the point estimates of beta at the end of the observation period for the sample of NYSE new listings. Average beta estimates for day 26 and for month 21, based on the simple market model and computed from the first 25 trading days and the first 20 trading months, respectively, would have been 1.185 and 1.236, while, extrapolating from the fitted models based on the inverse of time, the estimates of the adjusted betas would be 1.127 and 1.141, respectively.

C.1.4. Alternative Explanations for Declining Beta Estimates

Our results, while consistent with the predictions of the differential information model, could be caused by other factors. For example, the decline in estimated betas could be consistent with a decline in the underlying cash flow covariance risk of new listings and new issues. Another possible factor is the general regression tendency of estimated betas first described by Blume (1975). In this subsection we take a rough cut at the possible importance of these two influences.

To gain some appreciation for how important a decline in cash flow risk might be, we develop an estimate of the effects of seasoning based on the first annual earnings figure. For the sample of 198 new issues, we estimate the following model:

$$\frac{E_j}{P_j} = \alpha + \psi_0 R_{mj} + \psi_1 \frac{R_{mj}}{A_j} + e_j, \qquad j = 1, \cdots, 198, \tag{7}$$

where E_j is the first annual earnings per share subsequent to issue for firm j, P_j is the initial share price for firm j, R_{mj} is the annual market return for the year corresponding to the annual earnings for firm j, and A_j is the length of time in days between the issue date and the end of the year corresponding to the first earnings for firm j subsequent to issue. Thus, A_j indicates the age of the earnings relative to the issue date. If cash flow risk falls with seasoning, we would expect ψ_1 to be positive. A positive ψ_1 implies that the beta risk of the earnings for new issues declines with the amount of seasoning (A_j). The form of the model follows the reasoning in footnote 12 and equation (6).

Based on the 198 new issues, the estimate of ψ_0 is 0.651 with a t-value of 2.673. The estimate of ψ_1 is 0.533 with an insignificant t-value of 0.805. Thus, although the estimate for the effect of seasoning is positive, the effect on earnings does not appear to be material in the first months of trading.[18]

Blume (1975) shows that high beta firms tend to have lower betas in subsequent periods and that low beta firms tend to have higher betas, irrespective of the period of listing. Our samples have average market model betas exceeding unity, and hence a decline in beta would be consistent with regression toward the mean. Alternatively, the form of the adjustment process for differential information holds for any true beta value. Therefore, we repeat the analysis in Table III after partitioning the sample of 198 new issues on the basis of OLS market model beta. For both daily and monthly data, the sample is split in half at the median OLS beta estimate.

[18] We also estimated equation (7) using total annual earnings as the dependent variable. The estimate of ψ_1 was again insignificant with a t-value of 0.817.

Results for daily data are shown in Panel A of Table VI. The low beta subsample has a t-value on the inverse of time of 3.270 with a model R^2 of 0.472. The average OLS market model beta for the subsample is 0.721. The high beta subsample has a t-value on the inverse of time of 5.891 and model R^2 of 0.598. The average beta for this subsample is 2.403.

Results for monthly data are in Panel B of Table VI. The low beta subsample generates a slope coefficient on the inverse of time having a t-value of 3.120 and model R^2 of 0.643. Alternatively, the high beta subsample has insignificant results, with a t-value for the inverse of time of 1.706. Nevertheless, the coefficient of 2.297 is the correct sign and not significantly different from the corresponding coefficient for the low beta subsample, assuming that the subsamples are independent. Thus, we would conclude that there is little within this crude test of sensitivity to average OLS beta to indicate that the adjustment process can be explained by a general regression tendency toward the mean.

C.2. Information Release Perspective

The differential information model suggests that the adjustment to beta is increasing in the inverse of the quantity of available information. An instantaneous increase in the quantity of information resulting from an information

Table VI

Fitted Models of the Relation Between the Cross-Sectional Beta Estimate and the Inverse of Time for Subsamples of 198 New Issues from the Period 1976–1985 Partitioned on the Basis of OLS Market Model Beta

$$\hat{\beta}_t = \psi_0 + \psi_1(1/t) + \nu_t.$$

$\hat{\beta}_t$ is the cross-sectional beta estimate for trading day or month t for the sample of 198 new issues, based on the Ibbotson (1975) "RATS" regression $R_{jt} = \alpha_t + \beta_t R_{mt} + \epsilon_t$ (equation (4) in the text), where R_{jt} is the realized return for firm j for day or month t and R_{mt} is the contemporaneous market return; ψ_0 is the component of $\hat{\beta}_t$ unrelated to the predictor variable, the inverse of time $(1/t)$; ψ_1 is the contribution of predictor variable to $\hat{\beta}_t$; ν_t is the error term; and $t = 0$ is the day or month of initial listing. The relations are based on the cross-sectional beta estimates corresponding to the first twenty-five days of trading and the first twenty months of trading. The market model beta estimates, $\hat{\beta}_{OLS}$, are also based on the first twenty-five trading days and the first twenty trading months.

Panel A: Daily Data

X_t	ψ_0	t_{ψ_0}	ψ_1	t_{ψ_1}	R^2
	High Beta Sample n = 99, $\hat{\beta}_{OLS} > 1.641$, avg. $\hat{\beta}_{OLS} = 2.403$				
1/Time	1.722	6.174**	3.017	5.891**	0.598
	Low Beta Sample n = 99, $\hat{\beta}_{OLS} < 1.641$, avg. $\hat{\beta}_{OLS} = 0.721$				
1/Time	0.398	1.492	1.892	3.270**	0.472

Panel B: Monthly Data

X_t	ψ_0	t_{ψ_0}	ψ_1	t_{ψ_1}	R^2
	High Beta Sample n = 99, $\hat{\beta}_{OLS} > 1.395$, avg. $\hat{\beta}_{OLS} = 2.354$				
1/Time	1.829	5.804**	2.297	1.706	0.285
	Low Beta Sample n = 99, $\hat{\beta}_{OLS} < 1.395$, avg. $\hat{\beta}_{OLS} = 0.520$				
1/Time	0.203	0.927	2.406	3.120**	0.643

** Significant at the 1% level.

release will lead to a shift in the parameters of the relation between the adjustment to beta and the inverse of time at the point in time when the information release occurs. The relation can be written as

$$\gamma_t \alpha \begin{cases} \dfrac{1}{t} & \text{if } t < t^*, \\ \dfrac{1}{t + \delta} & \text{if } t \geq t^*, \end{cases} \tag{8}$$

where t^* represents the point of information release, δ represents the time equivalent of the quantity of information contained in the information release, and γ_t is the adjustment in beta for differential information of quantity t.

This relationship, translated back into its impact on adjusted beta, is as follows. The information release causes a discrete jump in the average information accumulation pattern, which leads to a discontinuity in the relation between the adjustment to beta and time. The parameters of the relation between adjusted beta and the inverse of time are then altered relative to the pre-release relation. After the release the relation is no longer linear in the inverse of time. Reference to a Taylor's expansion of the relation around any given $1/t$ after t^* reveals that the slope of a linear projection on the relation should decrease and the intercept should increase after the information release.[19] The information increase essentially creates two relations for the beta adjustment process:

$$\beta_{at} = \begin{cases} \psi_0 + \psi_1(1/t) & \text{if } t < t^*, \\ \theta_0 + \theta_1(1/t) & \text{if } t \geq t^*, \end{cases} \tag{9}$$

with $\theta_0 > \psi_0$ and $\theta_1 < \psi_1$.

To examine the impact of an information release on the adjustment of beta, we compare the relation between the cross-sectional beta estimates, $\hat{\beta}_t$, and the inverse of time from the pre-announcement period, regime 1, with its counterpart from the post-announcement period, regime 2. The model adopted for this purpose is

$$\beta_t = \psi_0 + \psi_1(1/t) + \psi_2 Y_t + \psi_3(1/t) Y_t + \mathscr{E}_t, \tag{10}$$

[19] To see how a linear approximation predicts a higher intercept and lower slope after an information release, write the adjusted beta after the information release as

$$\beta_{at} = \psi_0 + \psi_1 \frac{1}{(t + \delta)},$$

where ψ_0 and ψ_1 are intercept and slope coefficients in the adjustment process that would be observed in a regression on $1/t$ in the absence of an information release (in the pre-event period). Expressing adjusted beta as a function of $1/t$ after an information release and expanding around any arbitrary t^* reveals the linear approximation:

$$\beta_{at} \approx \theta_0 + \theta_1 \frac{1}{t},$$

where $\theta_0 = \psi_0 + \dfrac{\delta}{(t^* + \delta)^2}$ and $\theta_1 = \psi_1[t^*/(t^* + \delta)]^2$. Thus, for any positive δ and t^*, the intercept increases and the slope decreases as the result of an information event.

where $Y_t = 0$ for the pre-announcement period and $Y_t = 1$ for the post-announcement period. This formulation yields the same coefficients as fitting separate regressions for the pre- and post-announcement periods. By setting $Y_t = 0$ in equation (10), we have $E(\hat{\beta}_t) = \psi_0 + \psi_1(1/t)$, while setting $Y_t = 1$ yields $E(\hat{\beta}_t) = (\psi_0 + \psi_2) + (\psi_1 + \psi_3)(1/t)$. The model predicts that $\psi_2 > 0$ and $\psi_3 < 0$.

Since the model suggests that the magnitude of a shift in the cross-sectional betas at the time of the information release will depend on the relative importance of the release (i.e., on both the quantity of information available prior to the release and the incremental quantity contributed by the release), the sample of 198 new issues is partitioned into three groups based on the number of trading days from the date of issue to the annual earnings announcement date. If, indeed, information is increasing in time, then the importance of the announcement would be expected to diminish, on average, as the time between listing and the announcement increases.

Panel A of Table VII reports the results of the tests for homogeneity of the complete relation.[20] The central observations from day −2 through +2 are omitted to avoid contamination by the information event itself, resulting in 26 observations per firm. Firms are aligned in event time for the estimation of β_t. The time variable in equation (10) is the average time between listing and the announcement date for the sample of firms.[21]

For the overall sample of 198 firms, the test ratio is 5.983, significant at the 1% level for the F with 2 and 22 degrees of freedom.[22] The results suggest a shift in the relation between the cross-sectional beta estimates and the inverse of time in the predicted direction because ψ_2 and ψ_3 have the correct signs. The t-values for ψ_2 and ψ_3, the differences between the pre- and post-announcement intercepts and slopes, are presented in Panel B of the same table. The t-value of −1.490 does not allow us to reject the simple hypothesis of a common regression slope. The t-value for ψ_2 is 2.040, significant at the 5% level. The joint test of homogeneity derives its power from combining the two hypotheses of common slope and intercept.

As indicated in the table, the shift appears to be more pronounced among securities in the shorter period of listing classes. As an additional test, we observed that the first annual earnings announcement was the first post-issue article appearing in the *Wall Street Journal* for 67 of the 198 firms in the sample. For this subset, which includes 46 of the firms from the first period of listing class,

[20] The test statistic for overall model homogeneity is

$$F = \frac{(SSE(R) - SSE(F))/2}{SSE(F)/(n_1 + n_2 - 4)},$$

where *SSE(R)* is the error sum of squares for the regression in equation (10) based on the combined data set (observations from regime 1 and regime 2 are pooled), *SSE(F)* is the sum of the error sum of squares for the regressions run separately for the pre- and post-announcement periods, and n_1 and n_2 are the number of pre- and post-announcement observations (13). The F has 2 and 22 degrees of freedom.

[21] We also performed all of the tests using the average of the inverse of time rather than the inverse of the average time as the time variable in equation (10). This did not change any inferences.

[22] The results are unaffected by the adjustment for infrequent trading discussed in the previous section.

Table VII

Tests for Differences Between Pre- and Post-Announcement Relations Between the Cross-Sectional Beta Estimate and the Inverse of Time for a Sample of 198 New Issues over the Period 1976–1985

$$\hat{\beta}_t = \psi_0 + \psi_1(1/t) + \psi_2 Y_t + \psi_3(1/t)\ Y_t + \mathscr{E}_t.$$

$\hat{\beta}_t$ is the cross-sectional beta estimate for trading day t for the sample of 198 new issues, based on the Ibbotson (1975) "RATS" regression $R_{jt} = \alpha_t + \beta_t R_{mt} + \epsilon_t$ (equation (4) in the text), where R_{jt} is the realized return for firm j for day or month t and R_{mt} is the contemporaneous market return; $Y_t = \begin{cases} 0 & \text{if } t < t^* \\ 1 & \text{if } t \geq t^*, \end{cases}$ and t^* is the point in time when information release occurs. The relation is based on the cross-sectional beta estimates corresponding to trading days −15 through −3 and +3 through +15 relative to the announcement day, t^*. The central observations from days −2 to +2 are omitted to avoid contamination by the information event itself. The announcement considered in this study is the first annual earnings announcement by the 198 new issues. The announcement date is taken as the date that the earnings figure appears in the *Wall Street Journal*. Results are presented for the overall sample of 198 new issues and for the sample partitioned into three classes (T) on the basis of the number of trading days from the date of issue to the annual earnings announcement date, with $T = 1$ corresponding to those firms listed for the shortest time before the announcement date.

Panel A: Test of Overall Model Homogeneity

	Period of Listing Class (T)			
	1	2	3	Overall
F Ratio	7.047**	3.690*	1.771	5.983**

Panel B: Tests for Differences in Intercepts and Slopes

	Period of Listing Class (T)			
	1	2	3	Overall
t_{ψ_2}	2.582**	1.747*	1.116	2.040*
t_{ψ_3}	−1.957*	−1.459	−0.628	−1.490

* Significant at the 5% level.
** Significant at the 1% level.

the test statistic for overall model homogeneity is 6.093 and is significant at the 1% level. The t-values for ψ_2 and ψ_3 are 2.617 and −1.628, respectively.

IV. Concluding Remarks

In summary, the results of our tests are generally consistent with the predictions of the differential information model. Discrete information events appear to shift the adjustment process as the model predicts. Market model regressions tend to overstate betas when time series data before the date of interest are used. Similarly, market model regressions will tend to understate beta if data are taken after the date of interest.

Barry and Brown (1984) calculate beta estimates based on historical data to document a positive period of listing effect, while McConnell and Sanger (1987) use data observed after each day of interest to document negative post-listing abnormal returns. The bias in beta estimation procedures tends to mitigate against both sets of results. Therefore, whatever explanation exists for the interesting and somewhat contradictory anomalies uncovered in these studies probably lies outside the differential information model.

The decline in betas as firms season is not conclusive evidence that estimation risk is partly nondiversifiable. It rejects a restrictive null hypothesis that cash flow risk is stationary and estimation risk is diversifiable. However, the decline in betas could be caused by a decline in cash flow risk. Definitive tests to discriminate between these alternatives are left for further research. That the first earnings announcement appears to reduce the beta risk of new issues suggests that information plays a role in the process. It seems implausible that cash flow risk, if it were declining over time, would drop discretely at an information release date that lags the cash flow process by several months.

Why uncertainty about low information securities might not be entirely diversifiable remains conjectural. A possible explanation is that low information firms are often involved in productive activities that are related to the current state of technology in the economy. Information about the earning capacity of these firms reveals information about the entire state of technology and is thus partly nondiversifiable. In other words, portfolios of low information securities cannot diversify across important components of the missing information, and hence investors are forced to bear estimation risk when investing in them. However, this explanation would appear to predict the existence of estimation risk for possibly prolonged periods of time. Our results indicate that the bulk of any adjustment is relatively short-lived, perhaps within a year of listing. However, this perception may be due to the short-term perspective taken in our empirical work.

REFERENCES

Ball, R. and P. Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159–178.

Banz, R., 1981, The relationship between returns and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Barry, C. B., 1978, Effects of uncertain and nonstationary parameters upon capital market equilibrium conditions, *Journal of Financial and Quantitative Analysis* 13, 419–433.

——— and S. Brown, 1984, Differential information and the small firm effect, *Journal of Financial Economics* 13, 283–294.

——— and S. Brown, 1985, Differential information and security market equilibrium, *Journal of Financial and Quantitative Analysis* 20, 407–422.

Beatty, R. and J. Ritter, 1986, Investment banking, reputation, and the underpricing of initial public offerings, *Journal of Financial Economics* 15, 213–232.

Blume, M., 1975, Betas and their regression tendencies, *Journal of Finance* 30, 785–795.

Brauer, G. A., 1986, Using jump-diffusion return models to measure differential information by firm size, *Journal of Financial and Quantitative Analysis* 21, 447–458.

Clarkson, P., 1986, Capital market equilibrium and differential information: An analytical and empirical investigation, Unpublished Ph.D. dissertation, University of British Columbia.

———, 1989, Differential information: Should it be priced?, Working Paper, Simon Fraser University

Coles, J. and U. Lowenstein, 1988, General equilibrium and portfolio composition in the presence of uncertain parameters and estimation risk, *Journal of Financial Economics* 22, 279–303.

Dimson, E., 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Ibbotson, R., 1975, Price performance of common stock new issues, *Journal of Financial Economics* 2, 235–272.

Klein, R. and V. Bawa, 1976, The effect of estimation risk on optimal portfolio choice, *Journal of Financial Economics* 3, 215–231.

——— and V. Bawa, 1977, The effect of limited information and estimation risk on optimal portfolio diversification, *Journal of Financial Economics* 5, 89–111.

McConnell, J. and G. Sanger, 1987, The puzzle in post-listing common stock returns, *Journal of Finance* 42, 119–140.

Muscarella, C. and M. Vetsuypens, 1989, A simple test of Baron's model of IPO underpricing, *Journal of Financial Economics* 24, 125–135.

Raiffa, H. and R. Schlaifer, 1961, *Applied Statistical Decision Theory* (Harvard University, Boston).

Reinganum, M and J. Smith, 1983, Investor preference for large firms: New evidence on economies of size, *Journal of Industrial Economics* 32, 213–227.

Ritter, J., 1984, The "hot" issue market of 1980, *Journal of Business* 57, 215–240.

Scholes, M. and J. Williams, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics* 5, 309–327.

Warner, J., 1977, Bankruptcy, absolute priority, and the pricing of risk debt claims, *Journal of Financial Economics* 4, 239–277.

Williams, J., 1977, Capital asset prices with heterogeneous beliefs, *Journal of Financial Economics* 5, 219–239.