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Economic Events, Information Structure, and the Return-Generating Process

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Abstract

The parameters of the return process of a firm are determined by two elements—the *natural event structure,* i.e., the process by which nature affects the value of the firm, and the *information structure,* i.e., the process by which information about these events is collected and disseminated to investors. Simple measures of three dimensions of the information structure—the frequency and accuracy of, and the bias in information releases, are derived from the moments of the return distribution.

I. Introduction

The specification of a distribution that accurately models the behavior of stock returns has had a significant impact on the models of asset pricing hitherto developed. Early deviations of the CAPM[1] assume that returns are normally distributed, an assumption at odds with studies[2] that suggest that the empirical distribution of daily returns has fat tails and no finite variance.

More damning to the normal distribution assumption is the positive skewness revealed by most distributions over long periods of time. This empirical fact is consistent with returns following a lognormal diffusion process. Black and Scholes [1] assume that prices follow such a process and derive an option pricing model. The empirical evidence on the return-generating process, however, reveals too many discontinuities in prices for the lognormal diffusion process to be an accurate description of reality.

Observed results are consistent with a stochastic process composed of a mixture of distributions. Several attempts have been made to define this mixture.

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[1] The capital asset pricing model can be derived if one of two conditions hold: (a) returns are normally distributed; or (b) investors have quadratic utility functions.

The general mean-variance framework holds under a wider range of utility functions (see [14]) and distributional assumptions (see [13]).

[2] See Fama [7] for a study of the behavior of stock market prices.

Mandelbrot and Taylor [9] indicate a combination normal-stable distribution. Clark [3] suggests a normal-lognormal mixture, and Blattberg and Gonedes [2] derive a student t from a normal gamma distribution. The work done by Merton [1] and Cox and Ross [4] opened new doors by introducing returns processes that are a mixture of a continuous diffusion and a Poisson process. In light of this discussion, the forces that shape the form of the distribution and define its parameters are of interest to us and will be dealt with here.

In markets in which information is freely available, there are no transaction costs, and all market participants are price takers, prices reflect all available information. However, when information is not freely available and is costly to collect and disseminate, the study of return processes cannot be separated from the process by which information is collected and disseminated to financial markets.

This analysis examines the effect of the information structure on the form and paramaters of the return process and derives simple measures of three dimensions of the structure—the *frequency* and *accuracy* of, and the *bias* in, information releases. It begins by distinguishing between natural events and information events in the first section. In the next three sections, the effect of information structure on the return process parameters is examined. In the final section, implications for limiting distributions are examined.

II. Natural Events and Information Events

The return-generating process for any firm is affected by two forces—events generated by *nature* and the process by which *information* on these natural events is disseminated to the market. In the next few sections, we examine the effects of the *natural event* and the *information* structures on return process parameters and derive simple measures of information efficiency.

We define natural events as any events, decisions, or occurrences that change the true value of the firm. Any of the following, for instance, would qualify as natural events:

(a) a flood, earthquake, or other natural disaster that affects the operations of the firm, positively or negatively;

(b) an outcome of a risky gamble, such as the first sales figures from a new product line; or

(c) a management decision to alter, delete, or modify any or all of the operations of the firm.

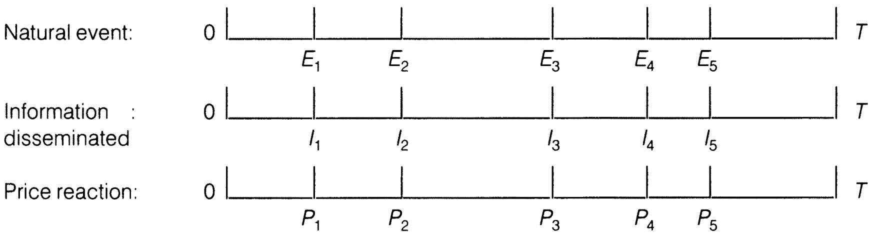
Information events are defined to include all happenings, news releases, or occurrences that change the market value of the firm, but have no effect on the true value of the firm. Either of the following, for instance, would qualify as information events:

(a) an explicit information release, either by the firm or by an external source (such as an analyst or an investment advisor);

(b) a large block trade, either by an insider or by a large institutional investor.

We are not ruling out an action that would qualify as both a natural and information event simultaneously, such as a merger motivated by both synergy and information considerations.

To the reader who is mystified by the purpose of this distinction, we should add, that in a world where information is costless, perfect, and instantaneous, information events will indeed coincide with natural events and true value will equal market value. Consider the following:



Our underlying theme is that *markets respond, not to natural events, but to information about these events*. In a world of perfect information, this distinction is irrelevant and price changes will be an instantaneous reflection of natural events.

However, information collection is neither costless nor perfect. In particular,

(a) the *frequency* with which information is collected and disseminated varies across firms;

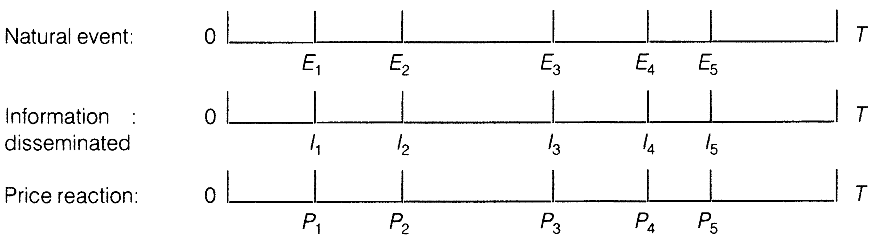
(b) information releases have *noise* in them and convey the impact of events with error, and thus add to the underlying noise in the real event process; and

(c) firms may reveal *bias* in their reporting of news, releasing good news promptly while suppressing bad news.

In the rest of this section, we will examine the implication of these flaws in the information structure for return processes and derive simple measures of the information frequency, noise, and bias.

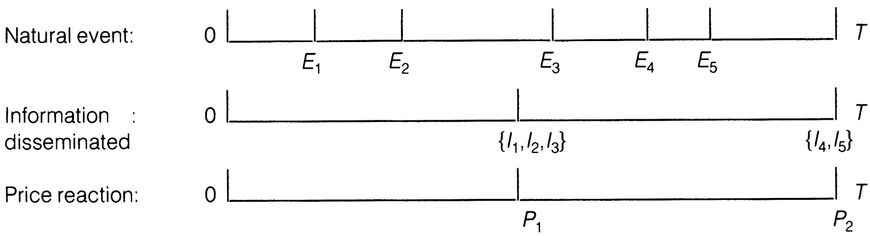
III. Frequency of Information Releases

In the first illustration, we will look at the impact that *frequency of information dissemination* has on price movements. Consider a case in which two firms have similar natural processes, but have information collected and disseminated with different frequencies about them. The first firm, labeled information-rich, has information collected and disseminated instantaneously about events affecting its value.



Its return-generating process will be similar to the true natural process.

The second firm, labeled information-poor, has information released about it infrequently, even though it is affected by the same number of natural events. The only source of information is the firm itself,[3] which releases information every T/2 periods:



In this case, the observed return-generating process will be different from the true natural process. It will have fewer information releases and each release will report on a large number of natural events.

Why is the first firm information-rich and the second information-poor? While this analysis assumes that the information structure is exogenous, it is incomplete insofar as it does not look at the forces that shape the structure. For example, there will be a greater motive for insider trading in the case of the information-poor firm. To the extent that their trades convey information, this will increase the frequency of information releases.

To illustrate the effects of the frequency of information generation on the parameters on the return-generating process, consider the following model. Assume that we observe the return processes of two firms over n observation intervals. They have identical natural event structures, but differ on information structure. The characteristics we will assume for the initial iteration are as follows:

A1: There is one real event per observation interval. The real event has a positive impact on the firm with probability p, in which case the price goes up by υ percent, or has a negative impact with probability $(1-p)$, in which case the price goes down δ percent.

Event	Probability	Effect on firm value
Positive	p	$\upsilon\%$
Negative	$(1-p)$	$\delta\%$

In addition, define $u = \log(1+\upsilon)$ and $d = \log(1+\delta)$.

A2: The first firm is information-rich. The real event is reported as and when it occurs with accuracy.

A3: The second firm is information-poor, and reports every t ($t \leq n$) observation intervals on the real events in the preceding t intervals.

[3] We do not consider why the only source of information is the firm. It is possible for one to construct a model with transaction costs and information collection costs to explain why some firms are followed by several analysts and others are not.

Assume that we observe actual returns r_j ($j = 1, 2, 3, \ldots, n$), and that we calculate $R_j = \log(1 + r_j)$. Examining the moments of the return distribution (R_j, $j = 1, 2, 3, \ldots, n$) per observation interval for the information-rich firm reveals the following:

Moment	Value
Mean return	$pu + (1-p)d = E^*$
Variance	$p(1-p)(u-d)^2 = V^*$
Skewness	$p(1-p)(u-d)^3(1-2p) = Sk^*$
Kurtosis	$p(1-p)(u-d)^4(1-3p(1-p)) = Ku^*$
nth moment	$p(1-p)(u-d)^5((1-p)^{n-1} + p^{n-1}(-1)^n)$

Note that these moments are also the true moments of the distribution corresponding to the natural event process.

The information-poor firm releases no information in $(n-t)/n$ of the observation intervals. The returns in those intervals will be equal to the expected returns (E^*) with probability 1. The returns on the day of the information release will depend upon the actual events in the preceding t intervals.[4] The probability of $(t-k)$ up jumps and k down jumps in these t intervals is the following:

Returns	Probability
$((t+k)u + kd) - (t-1)E^*$	$[t!/(k!(t-k)!)]p^{t-k}(1-p)^k$

The moments of the distribution, again calculated on R_j per observation interval, are as follows:

Moment	Value
Mean return	$pu + (1-p)d = E^*$
Variance	$p(1-p)(u-d)^2 = V^*$
Skewness	$p(1-p)(u-d)^3(1-2p) = Sk^*$
Kurtosis	$p(1-p)(u-d)^4(1+3(t-2)p(1-p))$
	$= (1+3(t-2)p(1-p))/(1-3p(1-p))\ Ku^* > Ku^*.$

These results follow directly from the underlying binomial distribution with parameters p, $(1-p)$, u, and d. *The kurtosis increases as the time between information releases increases*. Furthermore, this result can be made even stronger by allowing the time between information releases for the information poor firm to be nondeterministic, i.e., allowing t to follow some probability distribution with mean T and variance σ_t^2. The conclusions are unchanged, with the kurtosis an increasing function of T, and none of the other moments affected. This provides us with the basis for our first two propositions.

Proposition 1. The mean, variance, and skewness in the observed return process are determined by the underlying natural process. They are unaffected by how frequently information about events is collected and disseminated to markets.

[4] The actual return in the interval information released will not only depend upon the reported events over the prior t intervals, but also upon how these reported events deviate from expectations (tE^*).

Proposition 2. The kurtosis in the return process is determined jointly by the event structure and the information structure. As the period between information releases increases, the kurtosis measured over intervals shorter than this period will also increase.

This finding has several implications for both empirical analysis and financial theory. Since observed returns are determined jointly by the event structure and the information structure of the firm, it follows that:

(a) Return parameters estimated over *longer time intervals* are more *precise* estimates of the true parameters of the process than those estimated over shorter time intervals (e.g., daily). While the variance and skewness are unaffected by the frequency of information releases, beta estimates using daily returns will be affected by the informtion structure if the impact of market-wide events on the firm go unreported, and will be lower than their true values for information-poor firms. The nontrading problem has been recognized in empirical analysis, especially in the testing of the small firm effect (see [15], [6], and [12]). Our analysis suggests that an additional correction may have to be made for differences in information structure.

(b) Relating the kurtosis measured over longer time intervals to shorter time periods gives a *simple measure of the frequency* of information generation about the firm relative to the frequency of natural events. If we define $K^* = K_s/K_1 =$ Measure of information frequency, as the frequency of information releases relative to the frequency of natural events decreases, this ratio will increase. Note also that the disparity in kurtosis between information-rich and -poor firms will decline as the observation period is extended. In our illustration, it will disappear if the observation period is set equal to t intervals.

IV. Error in Information Releases

The frequency of information releases is an important dimension of the information structure. In the following extension, we consider another dimension of the structure, the *accuracy* of the information disseminated. We consider two alternative descriptions of error—the first in the *assessment of probabilities* of natural events occurring, and the second in the *evaluation of impact* of these events.

A. Errors in Assessing Probabilities

A2′: Analysts, in addition to reporting events as and when they occur, attempt to predict the event in the next observation interval. In their predictions, they are assumed to be right a fraction q of the time, and wrong in the remaining fraction $(1-q)$.

The price change in any time interval will include two components:

(a) the expected value of the price change in the next interval, conditioned on the analyst prediction; and

(b) a reaction to the actual event in the interval. This reaction will be small if the analyst prediction for that interval were right, and large if the prediction were wrong.

It is interesting that these actions by analysts *do not alter* any of the moments of the distribution.

B. Errors in Evaluating Impact

A2″: Assume that analysts report real events promptly, but that they do so with error

$$\text{Impact of event} = \begin{cases} u+\varepsilon \text{ with probability } p \\ d+\varepsilon \text{ with probability } (1-p). \end{cases}$$

We assume that $\varepsilon = N(0,\sigma_\varepsilon^2)$.

The error is assumed to arise from incomplete information and the competitive zeal to report news quickly. (If the market learns of the impact through the mechanism of insider trades, this error arises because of the noise with which trades convey information.) We assume that the errors are independent across intervals. The firm is assumed to report news accurately, albeit once every t time intervals. In this case, the variance of the returns will be affected by the error made by analysts in valuing the impact of real events. Evaluating the moments of the returns process, we get: Variance $= V^* + \sigma_\varepsilon^2$.

The other moments are unaffected. This is because we assume that the error is symmetric, i.e., that the size of the error is unaffected by whether the news is good or bad. To the extent that it is not, the other moments will be affected as well. Note that the variance will approach its true value as the period between observation intervals is extended since the true impact of events will be known when the firm releases its information once every t periods: Variance$_t$ $= V^*$. If analysts improve their estimates with time (i.e., σ_ε^2 decreases), the observed variance will approach the true variance much more rapidly. These results can be extended to encompass more general specifications of the error process.

Proposition 3. Errors made by information processors in the assessment of probabilities of events do not affect the observed moments of the return distribution. However, errors made in evaluating the impact of natural events affect the moments of the distribution, though their effect decreases as the return interval is increased.

Extending the observation interval should provide answers on:

(a) The *functioning* of external information sources. If their function is primarily one of forecasting the likelihood of future real events, there should be no effect on the variance if the observation interval is extended. If, however, it is primarily the rapid dissemination of information about real events when they occur, albeit with error, the variance should decline as the observation interval is extended.

(b) A *measure of the error* in the information process can be obtained by relating variances estimated over shorter time intervals to those estimated over longer intervals: $V^* = V_s/V_1$ = Measure of error in the information structure. This statistic can be considered as a measure of the noise added by the information structure to the true noise in the process. To those readers troubled by the "nonproductive" role played by analysts in this process (since they add only noise to it), we would hasten to point out that prompt information is useful to investors, even if it has noise in it, because it enables them to rebalance their portfolios and make better investment decisions in the interim between the firm's information releases.

(c) An interesting extension of this model is a more explicit analysis of the error variance (σ_ε^2). Since this is an aggregate measure of analyst variance, it can be written as

$$\sigma_\varepsilon^2 = \sum_i \sum_j X_i X_j \sigma_{ij},$$

where X_i = Weight given ith analyst in aggregate forecast ($i = 1, 2, 3, \ldots, n$), σ_{ij} = Covariance between forecast errors of ith and jth trader. Clearly, this error will be a function of

—the number of analysts following the stock, and the degree of consensus in their estimates;

—the quality of their individual forecasts (σ_i^2, $i = 1, 2, 3, \ldots, n$); and

—the market's weighting of the forecast errors. An efficient market will choose the weighting scheme that minimizes σ_ε^2.

Relating the measure of error obtained in (b) to these factors should give us a better understanding of how important each is in determining aggregate error.

V. Bias in Information Releases

The final dimension of the information structures is its *bias*. We have assumed so far that neither the firms nor external sources suppress information intentionally. While the competitive urges may make this a reasonable assumption for the latter, it is not realistic for the former. Firms have a propensity to release good news promptly and bad news at their convenience. Markets anticipating such behavior build it into returns. In this extension, we consider the game-playing firm and implications for return behavior:

A3′: Assume that the information-poor firm releases good news a fraction j of the time as soon as it occurs, and bad news a fraction k of the time as soon as it occurs, and that $j > k$, i.e., that the firm is more likely to delay bad news than good.

In any period, therefore, the firm can report

Report	Probability
tu	$j(1-j)^{t-1}p^t$ for $t = 1, 2, 3, \ldots, \infty$
td	$k(1-k)^{t-1}(1-p)^t$ for $t = 1, 2, 3, \ldots, \infty$
0 (no news)	$1 - \sum_j j(1-j)^{t-1}p^t - \sum_k k(1-k)^{t-1}(1-p)^t$.

Since $j > k$, the probability of large negative information releases increases relative to that of large positive releases. Note also that no news release conveys information to the market. A greater propensity to release good news than bad news introduces a negative bias in the observed skewness. Consequently, skewness measured over short time intervals will be lower than that measured over longer intervals. Two special cases deserve mention. The first is the case where

$j = 1, k = 1$, which corresponds to the non-game-playing firm. The second is the case where $j = 1, k = 0$, i.e., the firm always reports good news, but never reports bad news. In this case, no news is bad news, and the market reacts accordingly.

Proposition 4. If firms release good news promptly, but delay the release of bad news, skewness measured over short time intervals will be less than that measured over longer time intervals.

This behavior has some interesting implications for financial theorists:

(a) It may help us understand the *weekend phenomenon*. Cross-sectional examination of Monday returns should provide us with valuable information about the process of information releases. If firms release good news promptly, but delay bad news releases for weekends, the negative returns on Mondays should be caused by a few firms having large negative returns. An alternative is that no news is bad news, and that Monday is on an average a no-news day. The implication is that the negative returns on Mondays are caused by a large number of firms having no information releases and, hence, small negative returns. Note, though, that the transactions costs of exploiting this anomaly will be greater under the first alternative.

(b) This aspect of the information structure has a significant impact on the credibility of information releases in financial markets. As the bias increases, firms will find it more difficult convincing financial markets to believe them and will have to resort to costly signals to make their point.

(c) A simple *measure of a firm's bias* towards good news is obtained by comparing the skewness measured over short time intervals with that measured over longer intervals: Measurement of information bias $= Sk^* = Sk_s/Sk_l$. As the bias increases, this ratio should decrease. In the illustrations we have used, the event structure for firms is held constant while the information structure is varied. However, differences in return process parameters across firms can be caused by a different event structure, a different information structure, or both. This study takes the information structure as a given and looks at its effect on the return-generating process. It does not look at the determinants of the structure, or several related issues such as:

—Do firms have a motive to attract more coverage by external analysts?

—Does the natural event structure itself affect the information structure? If so, how?

We will defer discussion of these issues to a companion paper.

VI. Limiting Processes

These conclusions can be extended to more general processes by defining the limiting process for the event structure defined in A1. If, in A1, as $n \rightarrow \infty$, $p \rightarrow 0$ in such a way that $np = \lambda$ is a constant, then the limiting distribution is a Poisson distribution with arrival rate λ. The expected jump size will be E^*, and the variance in the jump process will be $\lambda V^{**} = V^*$, where E^* and V^* are as defined earlier and V^{**} is the variance/jump. The observed distribution for the information-rich firm described in A2 will have similar parameters. While the observed return process for the information-poor firm described in A3 will also have a Poisson distribution, the parameters will be different. In particular, the arrival rate will be λ/t and the jump process will have mean E^* and variance λV^{**}.

Proposition 5. If the limiting distribution for the event structure is Poisson, the parameters of the jump process will be determined jointly by the underlying natural event process and the process by which information is collected and desseminated to financial markets.

	Parameters of the jump process	
Parameter	Information-rich firm	Information-poor firm
Frequency of jumps	λ	λ/t
Variance/Jump	V^{**}	tV^{**}
Total variance in process	$\lambda V^{**} = V^*$	$\lambda V^{**} = V^*$
Expected jump size	E^*	E^*

An interesting question that is raised by this difference is whether investors care about the frequency of jumps and the variance/jump. The answer lies, I believe, in how easily the jump risk can be diversified away. If large portfolios of the information-poor firms have fewer jumps and higher variance/jump than comparative portfolios of information-rich firms, investors may be justified in demanding compensation for the greater jump risk. Since small firms tend to be information-poor, further analysis of this question may help us understand the small firm effect better.

It is also interesting that the underlying limited distribution to the event structure described in A1 can be a continuous diffusion process, if as $n \rightarrow \infty$, $u \rightarrow 0$, and $d \rightarrow 0$. The observed distribution for the information-rich firm also will follow a continuous diffusion process. However, the observed return distribution for the information-poor firm can still take on the manifestations of a jump process if information releases are sufficiently infrequent.

Proposition 6. If the limiting distribution for the event structure is a continuous diffusion process, the observed distribution will also follow the same process if and only if information dissemination is continuous. The observed distribution will become more discontinuous as the period between information releases increases.

This has important implications for asset pricing models that use a combination of a continuous diffusion and a Poisson process to derive equilibrium relationships. One application that comes to mind is *option pricing*. Tests of the Black-Scholes model, which assumes that stock prices follow a lognormal diffusion process, have shown that it works well for options listed on the CBOE. However, the stocks that have options listed on the CBOE are generally information-rich. As option trading on information-poor stocks increases, it will be interesting to see if the model continues to work as well as it has in the past.

VII. Conclusion

In this paper, we have examined the determinants of the returns process for a firm. The parameters of the process are determined by two elements: (1) the *natural event structure*, i.e., the process by which nature affects the value of the

Summary of Hypothesized Relations

Information Structure	Returns process: Variance	Returns process: Skewness	Returns process: Kurtosis	Jump process: # Jumps	Jump process: Jump Variance
(1) Infrequency	0	0	+	–	+
(2) Error	+	0	0	0	+
(3) Bias	0	–	0	0	0

\+ indicates a positive relationship.
0 indicates no relationship.
– indicates a negative relationship.

firm; and (2) the *information structure,* i.e., the process by which information is collected and disseminated about the firm. Three dimensions of the information structure—the *frequency* and *accuracy* of, and the *bias* in information releases—are identified and simple measures of information efficiency are derived from the moments of observed return distributions.

Several interesting implications emerge from this analysis. The observed moments of the distribution are determined jointly by the information and event structure. In particular, (1) the *variance* is determined jointly by the event structure and the *accuracy* of the information structure, (2) the *skewness* is determined jointly by the event structure and the *bias* in the information structure, (3) the *kurtosis* is determined jointly by the event structure and the *frequency* of information releases relative to natural event frequency. Furthermore, if the true returns process has a jump component in it, the parameters of the jump process will be determined jointly by both the information and event structures. Information-poor firms will have fewer jumps and more jump variance than information-rich firms.

These results are interesting for several reasons. *Anomalies,* such as the small firm effect and the weekend effect, may be better explained if differences in the information structure are allowed for. An investigation of the dimensions of the information structure may also provide us with valuable insight into the *determinants* of the structure. An empirical examination of the questions raised in this study is included in a companion paper [5].

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