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EMPIRICAL METHODS IN CORPORATE FINANCE USED TO CONDUCT EVENT STUDIES

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by

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ABSTRACT

This review discusses the use of security price information in conducting empirical studies of corporate finance. Topics covered include sources of data, the conceptual foundation of modern empirical methods and the critical role of information arrival. A general econometric structure is outlined that encompasses most existing research designs. The review is intended for individuals with backgrounds in economics and econometrics who want to gain an awareness of how and why security price information is used to summarize the corporate experience.

Empirical Methods in Corporate Finance Used to Conduct Event Studies

Rex Thompson

A. Introduction

Empirical work in corporate finance focusses on three primary topic areas: how various decisions and events affect the value of existing corporate debt and equity claims; how corporations choose the mix of financial claims that comprises their capital structure; and the effect of capital structure on a corporation's future decisions. While empirical work in all of the three topic areas is important, this review focusses primarily on the methodology of event studies, the common expression given for the first category. I have chosen this focus because finance distinguishes itself from other branches of applied economics by its emphasis on the role of security markets and the underlying security pricing process. Many empirical investigations into capital structure choice and how capital structure affects future decisions also rely on the use of security prices and are, therefore, indirectly contained in the first topic area[1].

Although experimental research in finance is gaining popularity, particularly in the area of how markets assimilate information (See Cadsby, Frank and Maksimovic [1990] and references), virtually all corporate empirical work to date revolves around the actual experiences of existing corporations, with data collected ex post. While this type of empirical work does not have the benefit of a control experiment, in this review I will call the collection

[1] The branch of corporate empirical work that will not be discussed involves correlating economic and financial decisions with capital structure variables and other, exogenous variables hypothesized to influence these decisions. This type of empirical analysis is done both cross-sectionally and in time series. Logit models are popular estimation methods to infer, say, the importance of ownership structure in determining whether a firm is involved in a control contest (Mikkelson and Partch [1989]), or engages in management turnover (Gilson [1989], Warner, Ross and Wruck [1988]). Logit has been used for estimating the importance of financial variables in predicting bankruptcy (Ohlson [1980], Zmijewski [1984]), takeovers (Palepu [1986]) or the existence of particular bond covenants (Begley [1990]). The econometric methods chosen by researchers are similar to those chosen in other areas of applied economics in which there is a focus on the correlation between decision variables and exogenous variables.

and processing of observational data on corporations an experiment, and treat the lack of control over the independent variables as an inherent limitation of the experimental design.

In event studies the design of experiments follows the traditional structure underlying the scientific method as applied in positive economics. A theory of decision-making within the corporation is proposed that contains a set of refutable predictions for observed phenomena. An experiment is contrived that involves the collection of observational data from past experience. Classical hypothesis tests are performed to determine the conformity between the data and the predictions of the theory. The theory is either supported or rejected according to the results.

Conclusions about competing theories are often couched in terms of which has the best descriptive validity. The concept of descriptive validity is intuitive but somewhat informal as applied in corporate finance[2]. Most researchers acknowledge that all parsimonious theories are to some extent false. Therefore, the goal is to find the best among available theories.

Because the complex environment surrounding the modern corporation often creates a gulf between what theory is able to model and what data are generated by actual experience, many empirical investigations involve aggregating data and summarizing empirical regularities without the clear direction of theory. Empirical regularities, however, form a pool of stylized facts that serves to motivate new theoretical modeling. Thus the empirical work in corporate finance serves two functions: first, to identify the most descriptive among competing theories and, second, to provide motivation for new theoretical analysis. This second function is served, for example, by research into empirical regularities that are considered unexplainable by existing theory. Further, because the researcher is not testing a formal hypothesis when the objective is to identify stylized facts about the

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[2] Unfortunately, formal Bayesian constructs such as the posterior odds ratio for discriminating among competing theories have not yet received significant attention in corporate finance.

corporate experience, this latter area of empirical work is less formal, less structured and less rigorous in its experimental design.

There is a final issue concerning the design of experiments in corporate finance that deserves mentioning before the details surrounding specific applications are explored in later sections. As in all empirical modeling, refinements in methodology frequently come through the careful specification of underlying assumptions about both economic behavior and the nature of the stochastic processes that generate observable variables. Where the assumptions are valid, refinements improve the power of tests and the efficiency of parameter estimates. Where assumptions are invalid or incapable of being tested directly, researchers are forced to evaluate tradeoffs between simple and sophisticated econometric methods. The criterion of *what works best* becomes a matter of judgement and experience. In later sections, I discuss several tradeoffs that have received attention in the literature. In my conclusions, I also offer some thoughts on the potential costs of adopting an informal notion of what works best as a guide to careful empirical modeling.

B. Sources of Data for Empirical Investigations

Many machine readable data sets covering information about corporations are sold by private vendors. In this review, I will highlight only the most commonly available at research Universities. Perhaps the most frequently cited are the files available from the Center for Research in Security Prices (CRSP) and Standard and Poor's. As the name implies, CRSP specializes in data relating to the transactions prices of publicly traded corporate common stock and government securities. On the corporate side, CRSP provides daily transactions prices for all securities traded on the New York and American Stock Exchanges. These data are available from July 2, 1962 along with various types of "header" information about the securities, including dividends per share and number of shares outstanding. CRSP also provides a data base of monthly transactions prices on all NYSE and AMEX securities, starting in December 1925. Daily price quotations for securities traded through NASDAQ are available from CRSP starting in January, 1973. Rate of return files, derived from the price and dividend information are available as are the returns on various security market indexes[3].

The primary source for detailed accounting information about major corporations is the Standard and Poor's Compustat Service, started in 1962. Compustat provides a number of files containing financial, statistical and market information on over 7,100 US and Canadian industrial and nonindustrial companies. The most important for empirical work in corporate finance is the Industrial Full-coverage File, containing approximately 4,800 companies that file reports with the SEC. The annual format has up to 20 years and 320 data items per firm year compiled from annual reports, 10K and 10Q filings, various Standard & Poor's Publications, and other data vendors. Compustat attempts to reproduce major portions of each firm's annual report in a consistent machine readable structure. Footnotes are not included. There is also a 12 year, quarterly format and extensive industry summary information. The existence of data on Compustat is often a screen for firms to be included in empirical studies[4].

Among sources of financial information that are not machine readable, Moody's manuals are frequently referenced for firm and security information as are SEC filings and the audited financial statements published directly by public corporations. The 10K version of the annual report is available at the

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[3] While other security price data bases are available, CRSP is clearly dominant. For example, I could not find an exception to the use of CRSP for some aspect of the experimental design in the over forty-five empirical studies using American companies published in the Journal of Financial Economics in volumes 16 - 26 between 1986 and 1990. There are several exceptions in later volumes and exceptions involving foreign companies.

[4] One oddity of Compustat is that their files contain only the most recent 20 or 12 year history. Older information is dropped from the files when new information is added. To my knowledge there is no systematically compiled source of information deleted from the Compustat tapes. There are over 20 years of data, once compiled by Compustat and in circulation at research Universities, but now no longer available from the company. Many Universities keep back files informally.

SEC in Washington DC and in several regional reading rooms. Since the 10K reports can be purchased, many Universities maintain files on sets of firms such as the S&P 500.

The Wall Street Journal is a standard source for identifying the first public announcement of corporate activities. Securities laws and listing requirements mandate the timely disclosure of material news that may affect the market for a firm's securities. The Wall Street Journal has become the most prominent reporting vehicle for corporations, partly because news reported there is considered to be publicly disclosed by the SEC and other securities regulators. For events covered by the Journal, it is rare that the first public disclosure is not well approximated by a two day window ending on the day the event is reported in the Journal.

The Wall Street Journal exercises some discretion over what it considers to be material news. Therefore, it is possible that the Journal does not report certain corporate events of interest to researchers. Barclay and Litzenberger (1988) discuss the advantages of using the Dow Jones News Service as an alternative to the Wall Street Journal.

Obviously, many investigations require extensive hand collected data. Accepted practice in published studies is to report detailed collection procedures, leaving the author latitude over whether or not to make data available upon request. Some authors are more generous than others but the profession is sensitive to the tradeoff between the private benefits of maintaining a proprietary data set and the public benefits of independent verification of empirical results. The Journal of Money Credit and Banking is the only journal of which I am aware that requires authors to submit their data for distribution by the journal to interested readers.

Several institutions and individuals have compiled specialized data sets for general use such as the University of Rochester's Merc Database on tender offers and Professor Jay Ritter's Database on Initial Public Offerings. A number of studies contain appendices listing, for example, firm names and key event dates.

C. The Conceptual Foundation of Empirical Methods used in Event Studies

Define the valuation effect of a corporate event as the difference between firm or security value conditional upon the event occurring and value conditional upon the event not occurring. Empirical methods used in event studies involve the various means of estimating the valuation effect, with choices involving tradeoffs surrounding the details of the experimental design. Before examining these details, it is important to review three conceptual issues.

C.1. A limitation in the design of experiments involving management decisions

The market values of corporate securities are derived from a combination of the exogenous environment and the corporate decision process acting within the environment. In testing valuation issues, we would like to separate these forces so as to infer the equivalent of partial derivatives of the value function. What we observe in the data, however, are a collection of financial decisions, all chosen presumably through optimizing processes, in conjunction with the exogenous market structures that are causing firms to make different decision choices. As a result, it is often difficult to disentangle the valuation effects of a management decision, holding constant the economic environment within which the decision is made, from the valuation effects of a change in the economic environment itself. Suppose, for example, that we wish to test a model of dividend irrelevance. To measure the relation between firm value and dividends we would like to have an experiment containing many firms that differ only in the amount of dividends paid. Real data, however, will typically contain observations in which dividend payments are correlated with cash flow. The separate effects of dividends and cash flow can be difficult to untangle.

One way to hold some of the exogenous forces constant is to direct attention to the change in market value associated with a change in corporate policy, or a change in economic environment. This is the approach chosen by the vast majority of empirical work in corporate finance dealing with valuation issues. Structuring the empirical model in terms of value changes simplifies the empirical model because any factors that do not change drop out of the equation. Most empirical work, then, looks at the impact of changes in the exogenous environment and changes in corporate decisions on changes in firm value and changes in the partitioning of firm value among various claimants[5].

Adopting an approach that focusses on changes rather than levels of variables requires the accurate identification of event dates. With accurate event dates it is possible to disentangle various influences on security value as long as changes in these influences are temporally separate. This proviso leads to the second conceptual issue underlying event study methods.

C.2. The role of information arrival

An efficient capital market sets prices based on expectations of the future, and it is difficult to identify when the market forms and changes expectations, particularly about corporate policy. At the time a corporate decision is announced, for example, the price response will be based on the change in expectations that this decision would be made. Any partial anticipation must somehow be accounted for to avoid underestimating the value implications. Define the announcement effect as the change in value resulting from the announcement of a corporate event. In simple environments with only a single possible event, the announcement effect equals the valuation effect times one minus the probability that the event would occur. It is thus attenuated toward zero. For inquiries designed to test the null hypothesis of no effect, attenuation creates a bias against rejection and is not critical to the interpretation of a study that successfully rejects.

The concept of rational prior anticipation opens an important final issue

[5] Christie (1987) discusses the link between what he calls levels models and returns models in the Accounting literature. He identifies situations where the models are equivalent conceptually. Long (1978) looks at the difference in price between two classes of claims in the same corporation that differ in the amount of dividends received. Differencing serves to control for factors that are the same across the two types of securities.

about information arrival. To say that a decision made within a corporation is not perfectly anticipated requires that something about the decision be uncertain in the eyes of investors. There are two possibilities. The first is that investors do not understand the objective function of the decision-maker. But, if the market learns something about the decision-making process, this presumably affects market perceptions of the probabilities of future decisions made within the firm. The second possibility is that investors do not know as much about the exogenous environment surrounding the corporate decision as the corporate decision-maker. In this case the market learns something about private information simultaneously with the decision. In both situations, the implications of theory must be couched in terms of everything that the market learns from a corporate event. Myers and Majluf (1985) have an early discussion of this issue in the context of equity offerings.

C.3. A Tradeoff in Estimation Error

The security price reaction to a corporate event involves several sources of estimation error. I will discuss errors induced by both prior anticipation of the event and failing to identify the event period precisely. The simultaneous arrival of extraneous information about market wide factors and other unrelated firm specific events also induce security price changes that create estimation error. Finally, even in the absence of these other influences, the stock price reaction at the time of announcement represents only an expectation of the ultimate valuation effect. While this estimate is presumably unbiased ex ante, there could be a large difference between what investors expected and what actually happens. The ultimate relevance of a particular event for security holders may not be revealed for a number of years. Over large samples of firms and long time periods, these estimation errors tend to cancel out because they are uncorrelated across the sample. On the other hand, if investors are unfamiliar with an event and a sample of similar events occurs over a short interval of time, the announcement period estimation errors could be very highly correlated. Examples include the market reaction to junk bond issuances and the adoption of antitakover defenses in the mid 1980's and the cluster of LIFO adoptions in 1974. Under these circumstances, an argument can be made for examining stock return performance over intervals that include a learning period for investors.

An alternative approach to estimating the cash flow effects of corporate decisions is to abandon the market reaction to the announcement and focus on changes in cash flow directly. These changes can be estimated relative to a number of benchmarks. In the absence of a financial market to price securities, this approach would be the most natural, but it is fraught with difficulties arising from the openendedness of such a forward looking exercise. Nevertheless, the approach has been used with satisfactory results in a few instances. McNichols (1990) looks at changes in earnings after the announcement of corporate dividend increases with the goal of verifying that the favorable stock price reaction to such increases is a rational response to future expected cash flow increases. Jarrell (1991) and Healey, Palepu and Ruback (1990) look at the future earnings effects of successful corporate acquisitions to ascertain the existence of benefits from acquisitions activity. Even if an event is perfectly anticipated such an exercise can, in principle, uncover the effects of the event[6]. In practice, however, adequately controlling for unrelated influences over long estimation periods makes the forward looking approach of working with realized cash flows difficult to implement. It is used primarily when the evidence based on stock price reactions is considered insufficient to discriminate among competing hypotheses.

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[6] It is important to distinguish between future cash flows and future security price appreciation over long periods. There is no reason to expect a correlation between, say, a good management decision and future abnormal security returns unless there is systematic mispricing of the kind mentioned in the previous paragraph. Future abnormal cash flows relative to a benchmark of normal cash flows is a viable metric of performance regardless of the market pricing process.

D. Details of the Empirical Model

A typical event study starts with hypotheses about how a particular corporate event should affect the value of some of the claims issued against the corporation. If one is interested in the sign of the effect, it is typical to structure the hypothesis in terms of the event's impact on the rate of return process for the corporation's securities. Most investigations focus on common stock returns; occasionally the returns to publicly traded corporate bonds and preferred stock are investigated. The hypothesis that the value of a security has increased consequent on a particular event translates into the hypothesis that the rate of return earned on that security over an interval spanning the first public announcement of the event is more positive than normal. Coupled with the notion that securities markets assimilate new information almost instantaneously, the concept of an abnormal return measured over an event interval is the grist of event study methods.

The empirical model is generally stated as follows. For each security j, let returns follow a stationary stochastic process in the absence of the event of interest. When the event occurs, market participants revise their value of the security, causing a shift in the return generating process.[7] Thus, the conditional return generating process can be written as

$$r_t = x_t B + e_t \qquad (1a)$$

for non-event time periods, and

$$r_t = x_t B + FG + e_t \qquad (1b)$$

in an event period,

where r_t = the return to the security in period t,

x_t = a vector of independent variables not related to the event of interest, such as the return earned on one or more index portfolios in period t,

B = a vector of parameters, such as the security beta, measuring the co-movement between the security return and the independent variables,

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[7] A corporate event might also cause other changes in the return generating process besides a discrete change in security valuation. Several possibilities are discussed below.

F = a row vector of firm characteristics or market conditions hypothesized to influence the impact of the event on the return process,

G = a vector of parameters measuring the influence of F on the impact of the event,

e_t = a mean zero disturbance having variance possibly differing in event and non-event periods, and

the subscript j has been omitted from r, B, F and e.

Hypotheses usually center on G. Where an event spans several periods or takes several periods to be reflected in security prices, FG represents the cumulative shift in the return process and (1b) can be written as

$$\sum_{t=1}^{T} r_t = \sum_{t=1}^{T}(x_t B) + FG + \sum_{t=1}^{T} e_t \qquad (1b')$$

where T is the number of event periods (usually days) required to incorporate FG into prices.

In a simple application, the experiment involves estimating the return process for securities having a particular characteristic or set of characteristics (e.g. common stock in those firms announcing a new equity issue). F is set to unity for each sample firm during the event period and the event's impact is measured by G, a one dimensional event parameter. The null hypothesis is that such an announcement has no impact on the return process, or that G = 0.

The event's impact for a single firm is captured by F times G. It is not possible to disentangle the joint effect of several firm characteristics with data from a single announcement. If, for example, the effect of an event is hypothesized to be a function of leverage and firm size, grouping or regression procedures are required. These involve the aggregation of a sample of firms or of several events within the same firm if firm characteristics are time varying. Aggregation techniques are discussed in Section E.3.

E. Issues in event study methods

Event study methods are the econometric techniques used to estimate and draw inferences about G. The issues are covered in four sections: (1)

modeling and estimating the return process for a single security, (2) modeling and estimating the event's impact, (3) aggregation across securities, and (4) hypothesis testing. Interest in the profession vacillates across the topics, with new ideas and suggestions implemented by researchers according to their needs. Latitude is given researchers to determine the balance between simplicity and sophistication that is appropriate for their specific applications.

E.1. Modeling the return generating process

1.a. Preliminaries

The return generating process for non-event periods is estimated over a time period that does not contain the event. Conventions for choosing this period, called the non-event period, are discussed below. As will also be discussed, conventions for how the process is parameterized varies greatly across applications, creating some confusion as to which is best in any particular case. Generally, researchers choose processes that can be defended as providing forecast errors (unconditional on an event) that have zero means. Tradeoffs between expediency and forecast error variance are frequently made, particularly when large samples will be aggregated.

The general structure of the empirical model in non-event periods is

$$r = xB + e \qquad (2)$$

where r, e and x are the stacked vectors and matrix with typical rows r_t, e_t and x_t. The parameters in B are estimated through regression.

1.b. The return interval

It is common to use daily data for the measurement of rates of return. The primary motivation for daily data is that it is readily available and provides an acceptable range of event periods from one to several days. The use of weekly and monthly data are common where a shorter event period is unnecessary. Intraday data are also used occasionally where an extremely short event period is deemed desirable. It is good methodology to maintain a consistent return interval across any particular application because the parameters of the return process can depend upon the return interval. For example, market model betas estimated with daily data can differ from those estimated with monthly data for the same securities.

1.c. Mean Adjusted Returns

Many event studies include no information in x, using only a column of 1's. G is measured by the difference or cumulative difference between event period returns and the average non-event period return. This mean adjusted returns approach or comparison period returns approach is used by Masulis (1980), for example, in his study of exchange offers.

1.d. The Market Model and Control Portfolios

Most event studies include some information in x, commonly the contemporaneous rate of return on a market index. When a market index and a column of 1's are used, the result is the market model, in which an intercept and slope or beta coefficient are estimated using return data from non-event periods. The announcement effect, FG, is estimated by the market model forecast error cumulated over the event period(s).

x may also include the return on a similar firm or portfolio of similar firms that do not have the event of interest. The purpose of control firms or control portfolios is to reduce sampling variation of the forecast error. To properly interpret the forecast error, it is important that the control firms chosen not be affected by the event under study. As an example, Eisenbeis, Harris and Lakonishok (1984) use the return on an index of bank securities as a control for the returns on banks that elect to become one bank holding companies.

The Center for Research in Security Prices (CRSP) provides an excess returns tape that is used by a number of researchers such as Vermaelen (1981) in his study of common stock repurchases. For each firm, the tape contains a time series of the difference between the return earned on the firm's stock and the return earned on a portfolio of stocks with similar betas.

In principle, adding explanatory variables to the forecast model reduces forecast error variance relative to a mean adjusted returns approach. On the other hand, in applications where security events are not clustered in calendar time and thus can be viewed as independent, the reduction in error variance is often not material, particularly when a large sample of firms is aggregated.

1.e. Multivariate Models

In multivariate extensions to the market model, several portfolio return series are used as regressors to further reduce the sampling variability of the forecast error. Langetieg (1978) considers these issues in his study of mergers. Industry indexes and firm size based portfolios can be used as well as portfolios selected to represent other, unrelated stochastic variation in the economy. Again, the researcher must make the assumption that the regressors chosen are uncorrelated with the timing of the event and its price effect.

1.f. Excess Returns

Some researchers define the return process in excess of the risk free rate available on Treasury Bills. It is more defensible to assume that excess returns follow a fixed stochastic process than to assume the same for raw returns[8]. The reason is that raw returns are typically characterized as containing the risk free return plus a risk premium. Since the former varies over time, raw returns will follow a time varying stochastic process unless

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[8] Recent evidence in the asset pricing literature shows mean excess returns on market indexes to vary over time and hence the assumption of a fixed stochastic process is not entirely descriptive (See, for example, Fama and French [1989] and Campbell [1987]). Market model forecast errors and other measures of abnormal returns to individual securities can still conform to a fixed stochastic process, however, even if mean returns to the market index are time varying. In the context of equilibrium models such as the CAPM, the same cannot generally be said of market model forecast errors in raw returns when the risk free rate is time varying.

the expected value of the risk premium is perfectly negatively correlated with the risk free rate. Evidence shows this assumption to be counter-factual for market indexes. While, the distinction is trivial for daily data because daily risk free returns are so small, the time variation in T-Bill returns can exert a measurable influence over monthly data, although rarely a material one.

1.g. Projection Errors Versus Deviations From an Equilibrium Model

Occasionally, researchers distinguish between forecast models that involve simple projections of security returns on other return variables and models that specify an equilibrium relation between security returns and the returns on, for example, the market index. An equilibrium model imposes restrictions on the intercept of the projection. For example, the traditional Capital Asset Pricing Model implies that the intercept in the unconditional market model measured in excess returns has expected value equal to zero (See Gibbons [1982] and references). Incorporating such a restriction reduces estimation error when the equilibrium model is true.

1.h. Estimation window

There is discretion over the choice of non-event estimation period for most empirical investigations. Typically, prior periods of about 250 days for daily data or 60 months for monthly data are used[9]. Alternatives are to use post event period data or to center the non-event period around the event. Once the non-event period is chosen, the relevant parameters of the return generating process are estimated.

The primary concern with using prior period data is that the event could

[9] The predominant use of prior data probably results from two influences. Prior data were used by the first event studies published; for example by Fama, Fisher, Jensen and Roll (1969) in their study of stock splits. These early studies were concerned with the possibility of forming a trading rule to beat the market by investing in securities after corporate events. Therefore, they were careful to base their analysis on information known to the market before the event. In addition, using prior data allows researchers to process the greatest number of recent events.

be caused in part by prior period return performance. In such cases, forecast errors in event periods based on prior period parameter estimates can contain biases because the non-event period does not provide an unbiased estimate of what the security return would have been absent the event. Post event period data are preferred in these cases. For example, Mikkelson (1981, footnote 13) in his examination of the effects of calling convertible debt uses post announcement returns to estimate the normal return on equity because debt is typically called after a period of positive stock price performance.

E.2. Modeling the Event Effect

2.a. Forecast errors versus multiple regression event parameters

Most event studies use a non-event period to estimate a forecast model and estimate the event's impact from forecast errors in the event period. An alternative characterization of the conditional return generating process under the same assumptions combines the event and non-event periods into a single model for security j of the form

$$r_j = xB_j + D_j \otimes F_jG + e_j$$

where now the vectors r, e and x contain both the event and non-event data while D is a column of indicators having zeros for non-event periods and 1/T in the event periods[10]. The model can be written more compactly as

$$r_j = X_jB_j^* + e_j \qquad (3)$$

where $X_j = [x, D_j \otimes F_j]$, and

$B_j^* = [B_j, G]'$

This characterization will be referenced later during the discussion of aggregation across firms because it is a convenient econometric format. Binder (1985) and Thompson (1985) discuss the versatility of models like

[10] Another characterization would be to view D as a matrix of zero-one variables, letting each column indicate a single event period (say, day). G equals the sum of the individual event period effects. This approach maintains an algebraic equality between forecast errors from a two step approach and the individual event period multiple regression event parameters.

equation (3).

2.b. Risk Changes During and After the Event

Events may influence the return process other than through a shift in the level of security prices. For example, theory might imply an increase in beta risk or residual risk for a sample of firms. Both permanent and transitory changes have been investigated. Permanent changes in risk parameters can be estimated by comparing pre and post event return data, either estimating two separate market models or combining pre and post event data into a switching regimes model. Mandelker (1974), and Dodd and Ruback (1977) contain two of the first estimates of risk shifting around mergers and successful tender offers. More recently, Dann, Masulis and Mayers (1991), Hertzel and Jain (1991) and Bartov (1991) estimate risk changes around stock repurchases.

Transitory risk changes involve a shock to risk parameters during the event period itself. If the event period is just a few days, it is difficult to estimate risk parameters for individual firms unless the event recurs periodically. For example, Kalay and Loewenstein (1985) document increases in both total risk and beta risk during dividend announcement periods by comparing risk parameters estimated during non-dividend announcement periods and risk parameters estimated over a set of sequential dividend announcements. In a slightly different context, Brown, Harlow and Tinic (1988) examine transitory risk changes around major corporate events. Where each firm has only a single event, the approach taken involves cross-sectional aggregation of individual firm events. Cross-sectional risk estimation is discussed in Section 3.c.3.

2.c. Security Value Changes Versus Abnormal Rates of Return

Some economic theories focus more directly on firm value changes than on rates of return. While the two processes are closely tied, the distinction is most relevant when the researcher wishes to average or aggregate results across a sample of securities. The sign of the average abnormal security value change can differ from the sign of the average abnormal security return when the sample securities vary in market values. For example, testing whether mergers create value across bidders and targets involves aggregating effects across firms that likely differ in size. Based on average abnormal returns, the estimated effects are positive, but based on average abnormal value changes, the results are less supportive of an increase in combined value. The difference in inference is caused by the fact that targets have large average positive abnormal returns but small size, while bidders have small average abnormal returns but large size. Malatesta (1983) evaluates abnormal value changes for combinations of merging firms, while Bradley, Desai and Kim (1988) look at tender offer pairs. Dann (1981) combines the abnormal value change of debt and equity in considering the effects of corporate common stock repurchases.

2.d. Multiple Events and Multiple Event Dates

Some research considers several events within a single return generating process. Most researchers, such as Mikkelson and Ruback (1985) in their examination of interfirm equity investments, assume that a single non-announcement period applies to all events; each event is then compared to the same forecast model.

Where multiple events share common event dates an additional complexity is introduced. Schipper and Thompson (1983) discuss the effects of several regulatory changes on a common sample of corporations. In their problem, each regulatory change evolves over a set of dates, some of which are common with the dates of other regulatory changes. If the impact of the regulatory changes are estimated singly, the impact of one regulatory change may affect the estimate of the impact of another wherever the two changes share a common event date. The solution to this problem is a multivariate extension to model (2) above in which the event indicators are a set of columns with each column pertaining to a single regulatory change. The model is estimated jointly with each event parameter estimated holding constant the effects of the other regulatory changes.

2.e. Inaccurate Event Dates

Precise identification of event dates is important because the standard deviation of cumulative forecast errors increases with about the square root of the number of time periods over which the errors are cumulated[11]. Detecting an effect when one is present is facilitated by identifying the shortest possible interval containing the event. Where an event unfolds through a series of announcements or potential information leaks, there is a tradeoff between reducing estimation error by focussing on the most important information dates and attenuation caused by missing some of the true market reaction. Attempting to trace a slow diffusion of information about an event is the exception rather than the rule unless a series of event dates can be identified objectively such as in Mikkelson and Ruback's (1985) investigation of corporate control contests.

The highest signal to noise ratio is often found in extremely short time intervals. For example, Barclay and Litzenberger (1988) use intraday data to examine the effects of new equity issues. Their investigation focusses on the first fifteen minutes to a few hours of trading, so an accurate announcement time is required. They use the Dow Jones News Service, which time stamps each announcement.

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[11] For example, a typical common stock daily return forecast error (residual) from the market model might have a standard deviation of about 2.5% (See Brown and Warner [1985, Table 1]). Since security returns are almost serially uncorrelated, the cumulated forecast error for, say, 10 days would have a standard deviation of about the square root of 10 times 2.5%, or about 8%. An empirical study with 100 independent firms would detect a 1% average event effect rather easily if the exact event day could be pinpointed for each firm. The average forecast error would have a standard deviation of about .25%, making a 1% average event effect about 4 standard deviations from the null hypothesis. On the other hand, with a 10 day event window, the average forecast error would have a standard deviation of about .8%, making a 1% average event effect only 1.25 standard deviations from the null hypothesis. Reference to the cumulative normal distribution reveals that a t-statistic greater than 2 would occur only about 23% of the time if projection errors are roughly normal. With a two day event window, a 1% average event effect would be detected about 79% of the time.

Estimation error in parameters of the forecast model is also more important with longer event windows. Estimation error in the intercept of the market model, for example, cumulates additively over the event window.

At the other logical extreme is the case where the actual event date falls within an interval of time, but the exact date is uncertain. This situation is examined by Ball and Torous (1988) in studying stock splits and stock dividends. They contrast the standard approach of cumulating abnormal returns in an event window with a maximum likelihood procedure based on the assumption that the event takes place on a single, but unknown, day within the event window. Forecast errors are assumed to be mean zero on all days except the true event day. The procedure estimates the event effect and the probabilities that each day in the interval is the true event day. Maximum Likelihood provides more efficient estimates of the event effect than cumulating forecast errors when the underlying assumptions are true.

f. Infrequent Trading

The low trading frequency of some securities introduces new complexities into the measurement of the event's impact. In general, it is desirable to measure the impact over an interval that includes significant trading volume on both sides of the event because transactions represent market clearing phenomena and are thus most likely to reflect information accurately. Bid-asked spreads with no volume may be stale relative to the market's assessment of value. In some data sets (e.g. CRSP), it is not possible to tell whether a particular closing price represents a transaction made after an announcement. In cases where low volume exists the event window is typically widened, although for common stock traded on the organized exchanges, it is rare that a two day event window would not capture sufficient volume to include the announcement effect. In markets with infrequent trading, the forecast model can include leading and lagging values of the return on the market index in the spirit of Scholes and Williams (1977) and Dimson (1979).

The greatest concern over infrequent trading involves the use of bond and preferred stock returns where transactions can be separated by several days, even up to a month. In these cases, researchers view multiple day returns as the aggregation of several single day returns with care taken to determine over what interval each return is measured. Handjinicolaou and Kalay (1984) compute a premium between their bond returns and the returns on comparison Treasury Bonds measured over identical time intervals. The mean of the underlying daily premium series is then used to compute abnormal premiums in the event periods[12]. Marais, Schipper and Smith (1989) estimate a forecast model and work with forecast errors by assuming that multiple day returns are the summation of independently and identically distributed daily returns. Where an event day has no trade, the forecast error cumulates until the next trade.

2.g. Market Microstructure Issues.

Although event study methods presume that transactions are made at equilibrium prices, the distinction between transactions made at the bid and the asked can exert an influence in applications where an event creates an order flow imbalance. Normally, one would expect a bid-asked bounce to cancel out across a sample of firms but some events create a bias. Grinblatt, Masulis and Titman (1984) discuss the market for stock that has recently announced a split. Trading off the exchange in the "when issued" market causes the predominance of exchange trades to take place at the bid during periods shortly before the ex date. This can cause an apparent positive market reaction at the ex date as the stock resumes trading at both bid and asked prices. Lease, Masulis and Page (1991) consider the role of order imbalances in measuring the effect of seasoned equity offerings. They argue that some purchase orders are temporarily diverted to a primary market causing a preponderance of sell orders to be observed in the secondary market. The effect is to create an artificial negative impact on offering day returns. One solution is to use the average of the closing bid and asked quotes, assuming that the specialist uses volume between the event and the close to set equilibrium spreads.

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[12] The premium between a corporate bond and Treasury Bond controls for term structure variation. Their model could be extended to control for other market information such as the return on a stock market index.

2.h. Partial Anticipation

The potential importance of partial anticipation of events was discussed in Section C.2. In an early effort to formally model the effects of partial anticipation, Malatesta and Thompson (1985), assumed that market participants hold constant beliefs about the likelihood that a merger will occur each month. In their model, a merger announcement engenders a surprise equal to (1-p) times the true valuation effect of a merger, where p is the prior probability that a merger will occur. Non-announcement months, on the other hand, are associated with a surprise of -p times the valuation effect of a merger. The difference between returns in announcement and non-announcement periods provides an unbiased estimate of the event's full valuation effect.

Subsequent researchers such as Acharya (1988, 1993) have extended the logic of prior anticipation to include models of the prior probability formation process. Observable firm characteristics are used to build a forecast model of event announcements and their probability. In his discussion, Acharya makes an important point about the effects of partial anticipation when the probability of an event is not constant over time. If a researcher simply differences the returns in announcement and non-announcement periods, in general a downward biased estimate of the valuation effect results. This is because events typically occur in periods where they are more likely and do not occur in periods where they are less likely. Thus the average surprise in event periods is less than one minus the average surprise in non-event periods and the difference in surprises is less than one.

3. Aggregating Results Across Firms

3.a. General considerations

In order to streamline the discussion, I first treat concepts in aggregation that apply to cases in which prior anticipation is not of paramount importance. Either the researcher is interested in modeling the announcement effect specifically rather than the valuation effect or the event is sufficiently unanticipated that the difference between the two measures is immaterial. Where I do not wish to distinguish between valuation effects and announcement effects, I will use the term "event effect" to capture both concepts. Prior anticipation is introduced again in Section 3.b.3.

Aggregation across firms can be viewed as a mechanism for estimating G within a pooled system of equations with a typical equation for firm j as in (3). Most studies use a two step process. First, the separate models in (3) are estimated on a firm by firm basis, ignoring the separate influences of the elements in each F_j. The first step estimates the event effect for each firm, typically with a forecast error, and also provides residual variance and covariance information from the non-event periods. Next, viewing each separate firm as an observation, the event effect is modeled as

$$\gamma = FG + \epsilon \qquad (4a)$$

where γ = a column vector of length J with typical element γ_j,

γ_j= an estimate of the event effect for firm j[13]

F = a matrix of firm characteristics with typical row F_j as defined in equation (3),

G = the influence of F on the event effect as defined in (3),

ϵ = a column of estimation errors of γ around FG.

To help visualize the second step, suppose there are J firms that have undergone a stock repurchase and K (K < J) firm characteristics such as leverage and ownership concentration that are hypothesized to explain the effect of stock repurchases on equity values. Equation (4a) then has the following representation:

$$\begin{bmatrix} \gamma_1 \\ \cdot \\ \cdot \\ \gamma_J \end{bmatrix} = \begin{bmatrix} f_{1,1} & \cdots & f_{K,1} \\ & & \cdot \\ & & \cdot \\ f_{1,J} & \cdots & f_{K,J} \end{bmatrix} \begin{bmatrix} g_1 \\ \cdot \\ \cdot \\ g_K \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \cdot \\ \cdot \\ \epsilon_J \end{bmatrix} \qquad (4b)$$

[13] Using the notation from equations 1b and 3, γ_j is an estimate of F_jG. Where a single event period (month or day) is used, γ_j would be the forecast error for that period. Where a series of periods are included, γ_j would generally be estimated by the cumulative forecast error over the event periods. An alternative estimation approach is to estimate the model in equation (3) directly, with the event indicator variable, D, having the value 1/T for each of the T announcement days in the event window.

The simplest way to estimate equation (4) is with OLS cross-sectional regression, letting the regression provide an estimate G and its standard deviation. Such an approach can be enhanced, however, by recognizing that the error variance and covariance in the estimates of the individual event effects result from variability and covariability in the time series of individual security returns.

3.b A digression on time series measures of variability.

In an ideal experiment, created in the laboratory, it would be natural for firms to have constant residual variance across event and non-event periods. A model of the event's impact would be added to the system in the form of FG. Security returns and regression coefficients generated in repeated simulations of the experiment, holding F and G constant, would have sampling variability consistent with the residual variance-covariance matrix estimated in non-event periods. The perspective of such an ideal experiment is the one taken by most researchers in the field.

As noted by Christie (1993), however, a number of researchers have observed that forecast errors seem to have higher variance in event periods than otherwise. In fact, a comparison of variance between event and non-event periods is an approach to testing whether or not an event has information content (See Beaver [1968]). How to incorporate increased variance during event periods into the inference problem is an interesting issue that is not altogether completely resolved in the literature. For example, Christie (1993) advocates including increased variance while Sefcik and Thompson (1987) describe a scenerio where increased variance should be ignored. Many different arguments have been offered as motivation for particular variance estimation procedures and empirical evidence shows that the choice can affect inferences.

To clarify the issues, reconsider the ideal experiment described above. If data generated by such an experiment were studied, ex post, it is likely that a researcher would find increased variance in event periods. Increased variance will be observed whenever the researcher omits explanatory variables from F. These variables enter the residual of the event periods.

Viewing the inference problem in terms of omitted variables is quite general; the issues center on what statistical properties the omitted variables are assumed to possess. To focus on significance measures, assume that the omitted variables are uncorrelated with the included variables so the remaining regression coefficients are still unbiased. In this sense the model is correctly specified.

If the omitted variables are orthogonal to the included variables, regression coefficients are unaffected by whether or not the omitted variables are in the model. It is clear in such a case that increased variabliity should be ignored in assessing the estimation error of coefficients on the included variables. This is because the increased variability does not contribute estimation error. An important application is where inferences are to be drawn about the mean impact of an event on a particular sample of firms. The mean impact across a sample is, in a trivial sense, always orthogonal to any other potential explanatory variables[14]. Therefore, a test of the mean impact should not include increased variance in the event period because this increased variance does not contribute to the estimation error of the mean.

There is a second, equally interesting, perpective, however, that argues in favor of accounting for the increased variance caused by omitted variables. Suppose the realizations of the omitted variables are viewed as drawings from an underlying population of possible realizations such that any sample is orthogonal only in expectation. In this case we might wish to draw inferences unconditionally, treating the omitted variables as additional error that may be spuriously correlated with the included variables in this particular realization of the experiment. If we assume that the omitted variables are drawn independently across the sample from a common population, then the

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[14] If a model is structured with an intercept and any other variables defined in terms of deviations from means, the intercept will always be the mean of the sample regardless of which variables are included in the regression.

increased variance in the event periods captures the noise added by the sampling variability of the omitted variables.

In any case, the use of non-event time series variability is a common feature of event study methods and I will discuss it carefully. One approach to combining time series information with increased variability in event periods is suggested by Collins and Dent (1984). They suggest scaling the covariance matrix estimated in non-event periods, say S, by the factor $(J-1)^{-1}\ \underline{\epsilon}'S^{-1}\underline{\epsilon}$, where $\underline{\epsilon}$ is the vector of estimated residuals in the event periods for the sample of J firms. In the discussion that follows I will ignore this scalar for convenience although in specific applications such an adjustment can be defended.

3.c. When Firm Events are Dispersed in Time (No Event Clustering)

The assumption that security returns are serially uncorrelated simplifies both the forecast model of non-event returns and the cross-sectional aggregation of results[15]. If security returns are serially uncorrelated, forecast errors across firms are essentially cross-sectionally uncorrelated whenever the events of interest are dispersed in calendar time. Except when events are clustered in calendar time, a cross-sectional independence assumption is virtually universal in the literature. Interest in residual variance-covariance information in non-event periods centers on heteroscedasticity adjustments.

Measures of individual firm variances are typically estimated in the non-event periods under the assumption of stationarity[16]. Where heteroscedasticity

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[15] The critical assumption is that security residuals (forecast errors) are serially uncorrelated. There is some evidence of serial correlation in daily forecast errors, primarily due to serial correlation in index returns (See Scholes and Williams [1977] for reasons why). Researchers such as Ruback (1982) have proposed corrections to standard errors for the slight serial correlation that exists.

[16] A process for residual variance can also be incorporated. For example, Christie (1987) discusses a model in which residual variance is a function of leverage and, indirectly, a function of firm size. Where forecast errors are used to compute γ_j, Patell (1976) suggests a correction for the increased variability of forecast errors but this is typically not material.

heteroscedasticity is small or uncorrelated with the (squared) explanatory variables in the model of the event effect, OLS cross-sectional regression can be defended as an unbiased procedure. In richer contexts, accounting for heteroscedasticity is commonly included in the experimental design.

3.c.1 Tests for an average effect

The average event effect is couched within (4) by setting F as a column of ones, ignoring all other firm characteristics. Such a model is usually not a complete specification of (4) but rather a simple model of inherent interest. Time series estimates of variability are combined with estimates of individual firm event effects in a number of ways. I will discuss the three most common approaches, giving each a cross-sectional regression interpretation.

The first is to estimate the mean effect and its significance through a weighted least squares regression (WLS) of the individual firm estimates on the column of ones. Let σ_j be an estimate of the standard error of γ_j around the true event effect for firm j[17]. Then the weighted least squares regression coefficient, which is an estimate of the mean event effect[18], is

$$\frac{\sum_{j=1}^{J} \gamma_j/\sigma_j^2}{\sum_{j=1}^{J} 1/\sigma_j^2} \qquad (5)$$

The standard error of the coefficient is the square root of the inverse

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[17] If equation (3) is used to calculate γ, the standard error of γ would come from the same regression and be used for σ. Where a forecast model is used, σ would come from the standard error of the residuals, adjusted for the number of forecast errors cumulated to compute γ with a possible correction for the fact that it is an out of sample forecast error.

[18] Weighted least squares does not generally lead to an unbiased estimate of the average event effect because the individual abnormal returns are weighted. A sufficient condition for unbiasedness, however, is that the deviations of the true individual firm effects from the true mean effect are uncorrelated with the inverse of the residual variances.

of the denominator and thus a t-ratio is often based on the ratio of the numerator to the square root of the denominator. The standard deviation of residuals from the WLS cross-sectional regression could also be used to estimate the standard error of the coefficient. This measure includes the increased variance created by the omitted explanatory variables discussed earlier.

A second approach is to test significance of the average event effect by using the time series estimates of variability to construct an estimate of variability for the arithmetic mean. This is equivalent to an OLS regression of forecast errors on a column of ones. To test for significance of the mean event effect, compute the statistic

$$\frac{\sum_{j=1}^{J} \gamma_j}{\left(\sum_{j=1}^{J} \sigma_j^2\right)^{1/2}} \qquad (6)$$

The standard errors from OLS cross-sectional regressions are often ignored in actual applications because they fail to account for heteroscedasticity.

A final approach is to compute standardized residuals by dividing the forecast error for each firm by the time series estimate of its standard error as in weighted least squares. These standardized residuals are then averaged and inferences drawn under the assumption that each standardized residual is a mean zero, t-distributed random variable; an assumption that follows from the null hypothesis that there is no event effect for any firm. Estimation is analogous to an OLS regression of standardized residuals on a column of ones.

The average standardized residual, has standard deviation approximately equal to $1/\sqrt{J}$ if there is no time series heteroscedasticity in the event periods. Some researchers use the standard deviation from the cross-sectional regression for hypothesis tests rather than the theoretical standard deviation of $1/\sqrt{J}$. This latter measure includes any increased variation in the event periods caused by omitted explanatory variables as discussed above.

The three test procedures just described combine the same information in slightly different ways and thus can lead to different inferences. Which statistic is emphasized depends on what assumptions about the event effect are being maintained and what specifically is being tested or estimated. Suppose, for example, that the event effect is assumed to be the same for all firms and the hypothesis being tested is that this common event effect is zero. Then weighted least squares (the first procedure) is the natural choice because it provides an unbiased and efficient estimate of the common event effect. OLS (the second procedure) provides an unbiased estimate, but is less efficient than WLS.

Alternatively, suppose we do not wish to maintain the assumption that the event effect is the same for all firms but we wish an unbiased estimate of the mean effect and a test for significance. Then OLS is the obvious choice, although WLS might be more efficient under some assumptions[19].

The third procedure provides a statistic with a convenient sampling distribution under the null hypothesis that all firms have a zero event effect. While the two previous procedures also provide test statistics with convenient sampling distributions under this null hypothesis, the relative power of the three procedures to reject the null hypothesis when it is false depends on the nature of the alternative. Many empirical studies report more than one of these procedures because the economic hypotheses are not sharpened to the point where the procedures can be clearly ranked on the basis of efficiency or power.

3.c.2 Tests for general cross-sectional relationships

Inquiries into general cross-sectional models involve extending (4) to include more information in F. The researcher provides a model relating the event effect to firm specific characteristics such as leverage, firm size, or beta. Equation (4b) represents such a structure. Estimation is by

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[19] See the previous footnote for conditions under which WLS is unbiased. Where it is unbiased, the efficiency of WLS relative to OLS depends on how large the differences are across the true individual firm event effects relative to the amount of heteroscedasticity in the residuals across firms.

regression. As in tests for a mean effect, weighted least squares based on the residual variance in the first step forecast model is a common approach to control for heteroscedasticity across firms. It is also common to use a heteroscedasticity consistent estimator for the cross-sectional covariance matrix of residuals as suggested in White (1980). Dann, Masulis and Mayers (1991), for example, adopt both procedures.

Where general models are estimated, typically the residuals from the cross-sectional regression are used to estimate the covariance matrix of the model's coefficients, ignoring the time series variability measures available from the forecast models for each firm. As discussed above, cross-sectional variance measures include variation that time series measures do not: the variation caused by omitted explanatory variables in the cross-sectional model of the event effect. The researcher has to decide whether the increased variation should be included during hypothesis testing.

3.c.3 Event specific market risk measures

When events are temporally separated, it is possible to estimate a beta coefficient for the event returns apart from the individual beta coefficients of the firms during non-event periods. A cross-sectional regression is run of forecast errors or raw security returns on a market index return that is matched pair-wise in calendar time. If forecast errors from a market model are used, such a cross-sectional beta identifies the average increase in beta during the event for the firms under investigation. The concept of a cross-sectional beta was first suggested by Ibbotson (1975) in his study of new stock issues and was later adopted by Clarkson and Thompson (1990) to study the question of how beta changes as securities season.

3.c.4 Incorporating prior anticipation.

Most economic models that link event effects to firm characteristics focus on the complete valuation effect including any partial anticipation component. Inferences drawn from cross-sectional econometric models often rely on the assumption that there is no correlation between the degree of surprise in the event and the firm characteristics used in the second step of the model[20]. Rational market participants, however, will use firm characteristics to help forecast the likelihood of corporate events. If, for example, events are more likely for firms with high leverage, the announcement effect will be more attenuated for highly levered firms. The forecast error for these firms may be lower even though the economic importance of the event is higher[21].

Lanen and Thompson (1988) give several examples where rational prior anticipation destroys the relation between a firm characteristic and the announcement effect even though there is a linear relation between the same firm characteristic and the valuation effect. Their first example (p. 314) clearly shows the problem: "As a stylized example, consider the association between the stock reaction to LIFO adoptions and the firm specific tax benefits as assumed here to be known by investors prior to the adoptions. If the tax benefits are large, the likelihood of a LIFO adoption is also large and thus the market surprise will be small. Obviously, there will also be a small market reaction to a LIFO adoption if the tax benefits are small. Our model shows that the association between stock reaction and tax benefits depends upon where, between these extreme tax benefits, the sample is drawn."

Careful modeling of the information arrival process can incorporate partial anticipation. Eckbo, Maksimovic and Williams (1990) develop a model of mergers that includes formal recognition of partial anticipation. The model has three essential parts, which, in a simplified form are as follows: First, observable firm characteristics, which, to be consistent with the notation in equation (4), I will denote as F, and a characteristic observable

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[20] Another obviously critical assumption underlying cross-sectional regression is that the right hand side variables are measured without error.

[21] Researchers are careful to state the necessary assumptions for their estimation approaches. For example, Holthausen (1981 p. 80) and Barclay and Litzenberger (1988, footnote 11) state sufficient econometric conditions to interpret their cross-sectional regressions. It is often more difficult to provide good economic justification for these conditions.

only to the manager, denoted η, summarize the effect of a merger. η enters directly while F enters through coefficients, denoted G. Second, the objective function of the manager is such that the merger takes place iff $y = FG + \eta$ exceeds zero. Third, investors, are assumed to know the probability distribution of η and thus by observing F and knowing G they can determine the probability of a merger, prob(y>0). The linear structure in equation (4) is replaced by a nonlinear model of the form

$$\gamma \;=\; [1-\text{prob}(y>0)]\cdot E(y|y>0) + \epsilon. \tag{7}$$

As before, the researcher is interested in estimating G. This can be accomplished by assuming a distribution for η and fitting (7) with nonlinear optimization[22].

3.d. Events Clustered in Calendar Time

3.d.1 Introduction

When firms share common event dates, any cross-correlation of security returns transfers to the security forecast errors in the event period. Cross-correlation has often been found to be important, particularly for studies with industry clustering. The covariance matrix or a quadratic form in the covariance matrix can be estimated from data in the non-event periods. It is much more important to include common sources of variation in the specification of the return generating process, such as a market index, when there is event clustering.

Once the major sources of common variation are included in the return generating process, there is a potential tradeoff to be considered in using additional residual covariance information. Where covariances are expected to be small, the estimation error involved in estimating a large covariance matrix can outweigh the asymptotic benefits. This issue is discussed carefully by Bernard (1987) who offers a nice synthesis and relevant

[22] Eckbo, Maksimovic and Williams assume that η is mean zero and normal, allowing maximum likelihood estimation.

references. In my discussion, I will assume that the researcher wishes to incorporate covariance information because it is felt to be material in the application at hand. I will also emphasize portfolio approaches to estimation where the amount of covariance information explicitly estimated can be greatly reduced.

In one of the first applications, Collins and Dent (1979) couched their hypothesis in terms of the difference between the impact of a common event on two types of firms. To estimate the significance of the difference in average event period forecast errors, they identified a pre-test period within which a time series of average differences in forecast errors could be computed. The event period difference was then compared to the distribution so estimated in order to assess statistical significance[23].

Most studies involving common event <u>dates</u> also involve common <u>events</u> such as regulatory changes, macroeconomic changes, or, as in the case of Eckbo (1985) and Eisenbeis, Harris and Lakonishok (1984), the effect of firm specific events on other firms in the same industry. In such cases, it is possible to combine the individual firms into a seemingly unrelated regressions (SUR) framework and estimate the entire system jointly. This is the approach advocated by Binder (1985) and Schipper and Thompson (1983) in the case of regulatory changes and French, Ruback and Schwert (1983) for studying macroeconomic effects.

One useful fact about the firms affected by a common event is that the degree of surprise is constant across the sample. This is not to say that a common event affects all firms equally; the attenuation due to partial anticipation is, however, constant across the sample. An example will clarify the issues.

Let there be three firms, i, j, and k that are potentially affected by

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[23] This logic can be extended to the investigation of various kinds of cross-sectional relationships. Hughes and Ricks (1984) use a prior period to determine the significance of a regression coefficient by running the same regression repeatedly in non-event periods and ascertaining the likelihood of observing the regression coefficient estimated in the event period.

events a, b, and c. The events are mutually exclusive and equally likely, for example, the three possible outcomes from the resolution of a control contest. Assume a payoff structure as indicated in Table 1.

Table 1: The Structure of a Common Event

Event	Firm	Payoff	Economic Impact	Announcement Effect
	i	$20	$20 - 5	$20 - 10
a	j	6	6 - 12	6 - 10
	k	0	0 - 15	0 - 10
	i	10	10 - 10	10 - 10
b	j	4	4 - 13	4 - 10
	k	20	20 - 5	20 - 10
	i	0	0 - 15	0 - 10
c	j	20	20 - 5	20 - 10
	k	10	10 - 10	10 - 10

Prior to announcement of which event is chosen, each firm has the same value of $10. Suppose event b is the outcome. For each firm, what is the valuation effect of event b and what is the announcement effect? Earlier we defined the valuation effect as the difference between firm value conditional upon the event occurring and value conditional upon the event not occurring. In this context, then, the valuation effect of event b is the payoff minus the expected payoff from the other two events. These are shown in column four of Table 1. For event b, the valuation effect is $0 for firm i, -$9 for firm j, and $15 for firm k. The announcement effect was defined as the change in value resulting from the announcement of an event. Column five in Table 1 shows the announcement effect to be $0 for firm i, -$6 for firm j, and $10 for firm k. For each firm, prior anticipation has attenuated the announcement effect toward zero by 1/3. This is the prior probability that the event would occur, and since the prior probability is the same for all firms, the attenuation is also the same.

With common events, cross-sectional relationships will be preserved in the following sense: Let G represent the true influence of a particular firm characteristic on the valuation effect of the event, as described in equation (1) above. Let p represent the prior probability that the event would occur.

Then the cross-sectional relation between firm characteristics and the announcement effect will be (1-p)G. The sign of the relation is preserved[24].

SUR systems become very large in typical applications involving several hundred firms. If the individual firm parameters are of little interest in themselves because the researcher is focussing on hypotheses about G, the size of the models can be reduced to the number of parameters in G, typically on the order of one to five, regardless of the number of firms. This is accomplished through portfolio aggregation.

3.d.2. Portfolio approaches

A popular and powerful estimation approach for large systems of firms is to group firms into portfolios. For a given sample of firms, the average forecast error is equivalent to the forecast error from an equally weighted portfolio of the sample. This equivalence also applies to other forecast model parameters such as the average beta. Thus a simple approach to estimating the average effect of a common event is to create a portfolio of firms and compute the portfolio forecast error. Moreover, the residual variance of a portfolio includes any effects of cross-correlation of individual firm residuals. Thus a simple approach to estimating the statistical significance of a mean effect is to create a portfolio of firms and compare the portfolio forecast error in the event period to the portfolio's estimated standard error derived from the non-event periods.

Portfolio approaches can be used to test various hypotheses for samples of firms all influenced by a common event. For example, assume a sample of J firms conforming to equation (3) above, each with K different firm characteristics in Fj for the jth firm. As before, the elements in G

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[24] As indicated in the example of Table 1, both the valuation effect and the announcement effect of an event involve the relation between that particular event and any other events whose probabilities are changed. A clean interpretation of announcement effects requires modeling the prior probability and consequences of all affected events. Obviously this is an extremely difficult task and many topics in corporate finance are studied over and over as new refinements to the event possibilities are modeled.

represent the importance of the K firm characteristics in determining the impact of the event across the sample. With common events, the researcher would typically like to include information about the full covariance matrix of the residuals. This can be accomplished by creating K portfolios that separate the effects of each type of characteristic.

Let W equal a matrix of portfolio weights with K rows and J columns, chosen by the researcher to satisfy the constraint

$$W\ F \ = \ I_{KxK} \tag{7}$$

where, as in equation (4), F is a JxK matrix of firm characteristics with typical row F_j. The kth portfolio created with these weights has all of its characteristics summing to zero except the kth, which sum to unity. K seemingly unrelated regressions can be run in the form

$$R_k = XB^* + e_k \tag{8}$$

where the notation is the same as in equation (3) except that R_k is the column of rates of return to the portfolio constructed with weights equal to the kth row in W. For the k^{th} portfolio, the influence of everything but the k^{th} characteristic is zeroed out, leaving only the k^{th} element in G to be estimated. The distribution of the residuals in (8), e_k, incorporates all of relevant variance-covariance information about the original sample. X is the same for each portfolio, so the system involves identical explanatory variables.

Popular portfolio weighting schemes come from the regression literature. OLS weights would set $W = (F'F)^{-1}F'$ while GLS weights would set $W = (F'S^{-1}F)^{-1}F'S^{-1}$ with S the estimated covariance matrix of residuals for the original sample of firms, typically estimated over the same sample period. Notice that OLS weights do not require any covariance information about the sample firms. The only covariance information necessary to test hypotheses about G is contained in the covariance matrix of the K portfolios. Portfolios can be based on WLS weights as well. WLS represents an appealing compromise between the non-stochastic, but inefficient, weights implicit in OLS and the asymptotic efficiency of full GLS. Sefcik and Thompson (1986) discuss portfolio approaches in more detail.

4. A Final Hypothesis Testing Issue: Normality of Estimation Errors

Evidence dating back to Fama (1965) indicates that daily security return distributions have fatter tails than the normal and studies such as Brown and Warner (1985, Table 1) show daily abnormal returns to be generally skewed right. Various nonparametric statistical procedures are included in empirical examinations to confirm that results are not sensitive to outliers; for example, a percent positive or percent negative test based on the assumption of cross-sectional independence. Hite and Vetsuypens (1989) use several simple nonparametric tests in their study of divisional management buyouts. Corrado (1989) discusses more elaborate nonparameteric procedures based on ranks. Where inferences are reversed with nonparametric tests, researchers focus on outliers to better understand which test is preferred.

An alternative approach is to explain outliers and eliminate them from the sample, then base inferences on normal theory applied to the rest of the sample. Where sample trimming has occurred, most researchers point it out and leave the interpretation up to the reader. For example, Weinstein (1977) treats the influence of an outlier in his study of bond rating changes by reporting all results but emphasizing his interpretation on a sample that omits an influential outlier.

F. Concluding Remarks

A number of investigations into the empirical methods surrounding event studies have concluded that minor variations in econometric methods have little impact on inferences (e.g. Brown and Warner [1980,1985], and Malatesta [1986]). Researchers are left with discretion over the choice of estimation window, projection model, raw versus excess returns, forecast error versus event parameter and the form of hypothesis tests. Where these decisions are made ex ante, this discretion seems harmless although latitude can be manipulated, however unintentionally, to generate significant results in any specific application. If a researcher can choose an estimation window between 200 and 300 days, choose an event window between 1 and 5 days, select a projection model with 3 or 4 different types of explanatory variables, use raw or excess returns, pick parametric or nonparametric tests and exercise judgement over modeling how the event affects different firms, it is likely that something of interest will turn up in the data. Credibility is added to the findings of empirical investigations when the methods chosen can be defended on the basis of objective econometric or economic criteria, however minor the improvement in the estimation method on average.

Notwithstanding the concern over latitude in experimental design, there has been little debate over design details, possibly because there is little abuse in practice. Sensitivity analysis is usually requested by reviewers and routinely provided by researchers to minimize the chance that an extremely unusual set of results, based on a particular research design will be reported. One is left with the problem of how to interpret conflicting results across methods, however. Generally it is agreed that all results are reported and the interpretation of conflicting results left to the reader.

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