PREDICTED CHANGE IN OPERATIONAL SYNERGY AND POST-ACQUISITION PERFORMANCE OF ACQUIRED BUSINESSES

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The 1980s acquisitions are widely believed to have unwound the conglomerate boom of the 1960s through horizontal mergers, yet alternative forms of unwinding have not been examined. This study tests the explanation that changes in the opportunity to share resources and activities among businesses of the firm may have contributed to post-acquisition performance improvements in the recent acquisition wave. After estimating the sources of competitive performance that are due to these changes within each of 356 manufacturing industries, the study calculates predictions of changes in competitive performance for each acquired business between 1980 and 1984. The predictions are positive and in turn are positively associated with change in competitive performance between 1984 and 1986. This finding highlights the importance of resource sharing and activity sharing in these acquisitions, and leads to the reexamination of theories for the second acquisition wave that are supported by the finding of horizontal acquisitions.

Though there is general agreement that the 1980s acquisition boom was a form of unwinding of the earlier conglomerate acquisition wave of the 1960s, there is debate concerning the form of this unwinding. The interpretation is significant because most studies find poor performance of acquired business units in the first wave and improved performance in the second (Browne and Rosengren, 1987; Porter, 1987; Ravenscraft and Scherer, 1987; Mueller, 1985; Lichtenberg and Siegel, 1989). Knowing more about the characteristics of acquisitions in the second wave may explain why these acquisitions were more successful. This study focuses on the post-acquisition performance of business units which changed ownership in the early 1980s. A distinctive feature is that it considers performance changes which might be expected for each acquired business unit because of increased opportunities to share resources or activities in the acquiring firm relative to the selling firm. It also compares these expectations with the actual changes in performance that were achieved.

Most current theories of the causes for the second boom rest on the finding of horizontal mergers and imply that the diversifying character of the first acquisition boom was the cause of the poor performance of these acquisitions. Researchers have explained the causes of the second boom in terms of agency (Jensen, 1988; Lichtenberg and Siegel, 1989), market failure (Shleifer and Vishny, 1991), tax and antitrust changes (Bhagat, Shleifer, and Vishny, 1990), and excess capacity (Jensen, 1993). Each of these theories has different implications for the specific causes of acquisitions in the second boom, but most tend to suggest that focused, more specialized, or horizontal acquisitions occurred in this second wave. They are supported by the finding that a high proportion of assets in takeovers and LBOs end up managed by firms in the same lines of business (Bhagat *et al.,* 1990:

Jensen, 1993; Kaplan, 1990). With the exception of some research on vertical mergers, the finance research on acquisitions has focused predominantly on horizontal combinations of businesses in acquisitions (McGuckin, Nguyen, and Andrews, 1992). Researchers have not yet investigated whether the positioning of a business in a new portfolio of businesses, and the opportunities for shared activities or resources among businesses that results, are associated with the post-acquisition performance improvements in this second wave.

The proposed rationale for the second acquisition boom is not inconsistent with prior explanations but it does qualify them. Potential agency problems may be greater in conglomerates than in single business firms. However, these agency problems may also be reduced in related diversified firms that follow the strategic planning model which focuses attention on 'interbusiness and interdivisional opportunities and dependencies', as distinct from the financial control model found in conglomerates or the strategic control model found in divisionally managed corporations (Chandler, 1991). Also, some research on agency explanations does not control for changed opportunities in the new firm besides those due to new management (Lichtenberg and Siegel, 1989). The tax policy/antitrust explanations explain the causes of the initial conglomerate boom but assume that the process will reverse toward horizontal or specialized use of assets if these causes are removed. If there are benefits of resource and activity sharing between businesses, why should acquiring firms not take advantage of these opportunities?

Ravenscraft and Scherer (1987) first raised the issue of poor post-acquisition performance and examined lines of business as the unit of analysis because acquisitions often include parts of firms rather than whole firms. By using the business unit as the unit of analysis, the performance of the acquired business is examined directly rather than as part of a selling or acquiring firm. This paper also tracks lines of business which change ownership and their post-acquisition performance. Unlike Ravenscraft and Scherer (1987), who were primarily concerned with performance of acquired business units, this paper posits a relationship between the creation of opportunities for a business unit to share resources and activities with other units in its firm and the subsequent performance of the business unit (Porter, 1985). Therefore it is essential to develop a measure of shared resources and activities for a business unit relative to its parent's portfolio.

This poses a challenge to research design since, as pointed out in Hoskisson and Hitt (1990: 493), a great deal of research on diversification ignores the effect of industry. One effect that is missed is that one should control for industry when examining firm performance (Dess, Ireland, and Hitt, 1990). The other is that shared resources and activities of particular types can contribute to business unit performance in a manner that is unique to a given industry. Davis and Thomas (1993) demonstrate this effect by an intraindustry study of how the diversification into other industries, and the implied shared activities that result, affect the performance of firms that are predominantly in the pharmaceutical industry. Like the Davis and Thomas (1993) study, this study controls for industry effects on performance by using intraindustry analysis, and in so doing it allows for the possibility that the effects of shared activities or resources on performance will be unique to the industry under investigation. In this regard, it is consistent with recent calls that the effects of diversification should be examined at the business unit level, in an intraindustry context, with particular tangible resources in mind (Davis and Thomas, 1993; Davis *et al.*, 1992; Hoskisson and Hitt, 1990). Shared resources and activities are important factors in expecting improved performance in related diversification and their usefulness must be determined within industries.

The paper is divided into five major sections: (1) Theory development; (2) Methods; (3) Measurement; (4) Empirical Results; and (5) Discussion, Conclusion, and Limitations. The Theory development section discusses dimensions of resource and activity sharing between a business unit and its parent and develops hypotheses concerning changes in these dimensions that occur in acquisitions. The Methods section develops models to estimate business unit performance within an industry. A second set of models tests for a change in the prediction of competitive performance which indicates whether the intent of the acquisition was to increase the potential for operational synergy. A third set of models tests the association between the prediction and the subsequent change in competi-

tive performance in order to determine whether the intent is realized. The Measurement section divides the operationalization of shared resources and activities into seven dimensions of relatedness. The variables are defined and the data sources are explained. An important consideration here is that accounting profitability is not available at the business unit level as a measure of competitive performance and so market share is used instead. The empirical relation between a weighted average market share and firm profitability in this sample, as well as other justification, will be reported in the Methods section of the paper. This approach lacks the advantages of market valuation of predicted benefits, such as the instant capitalization of future returns, but it is difficult to link firm-level valuation changes to interbusiness operational changes, and subsequently to *ex post* performance of businesses. Since market valuation may well have been a contrary indicator of post-acquisition performance in the 1960s it may well be useful to have an alternative indicator in this study (Shleifer and Vishny, 1991). The Empirical Results section reviews the findings, while the final section, Conclusion, Limitations and Extensions, discusses the broader implications of the findings.

THEORY DEVELOPMENT

Operational synergy: Interrelationships as sources of competitive performance

Penrose (1959) developed a theory of internal inducement to expand and diversify in order to exploit the existence of a 'pool of unused productive services, resources and special knowledge' that is created within firms through the routinization of activities. These resources are often indivisible and are worth more within the firm than if sold on the market (Rubin, 1973). It follows then that a firm should expand or diversify as a means of using the services of its resources more profitably, and that a firm should expand in directions that 'use the most valuable specialized services of resources as fully as possible' (Penrose, 1959: 71). If a lumpy indivisible resource is valuable in an industry one should then expect diversified firms to be present utilizing their excess capacity in this resource. This is most likely to be the case when the

resource is intangible, not entirely specific to the original industry, and where there are not large costs associated with incremental use (Montgomery and Wernerfelt, 1988). Porter catalogues activities which can be shared between value chains of different business units and calls these *interrelationships* (Porter, 1985, 1987). The opportunity to exploit excess capacity in these activities and the resources that are generated are a likely cause for acquisitions.

Operational synergies can be generated in both horizontal interrelationships and in vertically integrated corporations. The paper respectively considers functional based interrelationships, which correspond primarily to dominant functional activities, and transactional based interrelationships which concern support activities such as procurement and outbound logistics or the use of internal exchange such as backward and forward integration. The following sections argue that the sources of operational synergy should be defined relative to the industry because many theoretical reasons for why interrelationships result in operational synergy derive from characteristics of the environment and technology that businesses in the industry face in common. The sections also discuss previous research which uses these dimensions to determine empirically the effects of interrelationships on performance, the pattern of diversification, and the causes of entry or acquisitions.

Functional interrelationships

R&D, industrial and consumer advertising interrelationships

Intangible resources such as reputation can be shared across businesses more cheaply than they can be bought in the market (Arrow, 1962; Shapiro, 1985; Akerlof, 1970). Sharing skills and outputs of R&D, advertising/promotion know-how, and the fixed costs of plant and equipment, may be far more efficient across businesses within a corporation than purchasing the same in markets (Lemelin, 1982; MacDonald, 1985; Levin, Cohen, and Mowery, 1985; Grabowski and Mueller, 1978; Williamson, 1975; Prahalad and Hamel, 1990). In some cases, benefits come from economies of scope (where doing multiple things is more efficient than doing fewer things), and in others they may come from economies of scale where larger size or volume (e.g., in R&D

or marketing staff) provide increased productivity (Bailey and Friedlaender, 1982).

Many researchers use shared functional activities as a rationale for acquisitions and mergers. Stewart, Harris, and Carleton (1984) look at the match in R&D intensity and advertising intensity of the markets of acquiring and acquired firms. Wernerfelt and Montgomery (1986) show that efficient diversifiers (related diversifiers) will be attracted to different kinds of industries (where their resources are potential sources of competitive advantage) than inefficient diversifiers (unrelated diversifiers). Montgomery and Hariharan (1991) also show that firms with certain resources and capabilities (R&D and advertising intensity) enter industries in which those resources and capabilities are also used intensively. The benefits from sharing R&D, industrial marketing, or consumer advertising between businesses will be highly dependent on the technology, product characteristics and industry structure and hence specific to the industry (Dasgupta and Stiglitz, 1980; Kamien and Schwartz, 1975; Comanor, 1967).

Transactional interrelationships

Supplier and customer interrelationships

Katz (1984) and Porter (1985) outline conditions of product substitution and complementarity that affect the decision to share suppliers or customers between businesses. When business units sell complementary products to a common buyer, bundling, shared brand image, shared logistics of distribution, and coordination of product development are advantages (Nayyar, 1990, 1993). The advantages of shared procurement between businesses of the firm can be due to the reduced cost per unit of fixed search costs for price or quality inputs (Nelson, 1970). Search costs are more important in some markets than others depending on the extent of imperfect information in the market. Greater scale of purchasing also provides a stronger negotiating position with suppliers (Adelman, 1949). In addition, businesses which buy similar inputs may use a common technology or production process—some benefits of sharing common suppliers may be linked to the benefits of shared information and knowledge about common production practices.

Lemelin (1982) explains industry patterns of diversification by following Rubin (1973), who argued that lumpy multiuse assets such as common customers, suppliers, or distribution systems could provide a motivation to expand or diversify into industries where those assets could be utilized. MacDonald (1985) uses similar reasoning to analyze changes in the pattern of diversification. In both cases, the variation in the existence of multiuse transactional interrelationships across industries explains variation in diversification and acquisitions.

Forward and backward integration

Theoretical reasons for firms to pursue vertical integration include technical (Stigler, 1958), demand uncertainty (Carlton, 1979), market failure or transaction costs (Williamson, 1975; Klein and Leffler, 1981), and price discrimination (Schmalansee, 1973; Waterson, 1980; Perry, 1978; Vernon and Graham, 1971). Advantages for vertical integration depend to a large degree on industry characteristics such as demand elasticities, the demand elasticities of important supplier or customer industries, the prevalence of specific assets that make internal transactions superior to market-based transactions, the communication among buyers on reputation of firms, and the stage of development of the industry.

Caves and Bradburd (1988) compare theories of risk reduction, transaction costs, and price discrimination as determinants of cross-industry patterns of vertical integration and find support for transaction costs and price discrimination explanations. Both show an element of industry context in the determination of this pattern. Of course, there are also firm-specific elements to many of these, such as firm-specific asset investments or investments in sunk assets to guarantee reputation to avoid the need for vertical integration.

Hypotheses concerning acquisitions

The net change in predicted market share that is due to changes in interrelationships from the acquisition is used to test hypotheses concerning change in operational synergy of acquired businesses. An acquiring firm should only have to pay a price equal to the next-best use of an asset, provided that all firms have identical information about the asset and each other's capabilities. In

this case, the fit of an asset into the portfolio of the acquiring firm characterizes a possibly unique opportunity to the acquirer. The same asset would increase predicted competitive performance, or market share, differently for various firms in the industry and the acquirer should be that firm that increases the predicted market share of the asset the most. Therefore if the search for interrelationships is an important cause of acquisition, the assets (businesses) should be moving to firm portfolios with relatively higher opportunities for operational synergy than the selling firm.

After estimating the importance of relatedness for market share within different industries, the study examines the simple hypothesis that businesses that are acquired move to firms with more operational synergy for the business.

> *Hypothesis 1: Businesses which change ownership between t and t+1 increase their predicted market share from operational synergy.*

If firms are restructuring because businesses can gain competitive performance as parts of other firms, then one would observe that businesses are moving to positions which predict market share gains. However, if the entire firm is acquired, then an acquiring firm may have bought some businesses that it did not want in order to obtain businesses that it did want. If some of these businesses are not resold, then an acquisition could still have occurred in anticipation of synergy for some businesses in the firm but not necessarily for every business in the firm. Thus the appropriate measure of whether restructuring improves expected efficiency is a test of the changes in the expected performance of the different businesses that are involved in the transaction as a group.

> *Hypothesis 2: Businesses which change ownership from one firm to another as a group increase their average predicted market share from operational synergy.*

The previous hypotheses investigate the conjecture that there is a pattern in the types of changes that occurred in acquisitions between *t* and *t+1*. If a business unit has more operational synergy in the acquirer's portfolio than in the sellers, then there is a rationale that the acquirer would be willing to pay more for the asset than

the seller and hence the transaction occurs. If these predictions are positive, it suggests that the *intent* of these acquisitions was to increase the potential for interrelationships between businesses and hence to achieve greater operational synergy in the acquirer's portfolio. While managers may have been motivated to acquire, or sell, businesses because of the potential for operational synergy, one doesn't know if in fact this potential resulted in improved performance of the businesses. Are the predictions in turn associated with improved performance between period *t+1* and *t+2*? If acquisitions which increase the potential for operational synergy are associated with subsequent improvements in performance then one can say that the expectations of operational synergy, as represented by the predictions, are born out in *ex post* performance improvements.

> *Hypothesis 3: The change in market share between t+1 and t+2 will be positively associated with the predicted market share change from operational synergy in acquisitions between t and t+1.*

Similar to the argument for Hypothesis 3, Hypothesis 4 applies to the group of firms that may change ownership as part of one transaction. In this case, is the weighted average of market share changes after the acquisition associated with the prior prediction of market share changes for the group of firms?

> *Hypothesis 4: For businesses which change ownership from one firm to another as a group, the averge change in market share for the group between t+1 and t+2 will be positively associated with the average predicted market share change for the group from operational synergy in acquisitions between t and t+1.*

METHODS

Set 1: Models of relatedness as determinants of competitive performance

In the equations derived below, competitive performance, as measured by market share in a four-digit SIC industry, is regressed on relatedness variables, which are defined for each business in an industry by the relationship between the

business and other businesses in its firm. The identification of a link in specific industries between performance and a relatedness variable establishes the existence of a type of operational synergy in that industry. To test stability of relations, a second equation is estimated on data from two different time periods which allows coefficients to vary across time periods.

The model is estimated independently for each of 356 four-digit SIC manufacturing industries, where i represents different firms that have businesses that are active in the industry. Since all businesses are in the same industry j there is no notation needed for the second element such as $MS_{i,j}$ to distinguish the industry of the businesses under consideration, where i = firm, and j = industry of the business.

Models 1 and 2

$$MS_i = \alpha + \gamma d_i + X\beta + \epsilon_i \qquad \text{(Model 1)}$$

where X is a matrix of relatedness variables, or

$MS_i = \alpha + \gamma d_i + \beta_1$ R&D relatedness$_i$ + β_2 supplier relatedness$_i$ + β_3 customer relatedness$_i$ + β_4 industrial marketing relatedness$_i$ + β_5 consumer advertising relatedness$_i$ + β_6 backward integration$_i$ + β_7 forward integration$_i$ + ϵ_i

Each variable in X is multiplied by a dummy variable d_i, where

$$d_i \quad = 1 \text{ for a multibusiness firm}$$
$$= 0 \text{ for a single-business firm}$$

Given data for two time periods, one can estimate Model 1 under a number of different assumptions. First the parameters are constrained to be equal in the two time periods (for example, $\beta_{1,t} = \beta_{1,t+1}$ is referred to as Model 1). Second, parameters are unconstrained, or allowed to be unequal in each time period (for example, $\beta_{1,t} \neq \beta_{1,t+1}$ in Model 2). Model 2 is specified in Appendix 1. The models are estimated using the seemingly unrelated regressions estimator (SURE) which takes into account the possibility that the errors from the two periods will be correlated (Zellner, 1963). SURE can provide lower variance estimates

than OLS, and provides cross-equation (in this case cross-time period) tests of parameters.[1]

In each period, the models simplify to the following:

$MS_i = \alpha$ for a single-business firm i and
$MS_i = \alpha + \gamma + \beta_{1,i}X_{1,i} + \beta_2X_{2,i} + \beta_3 X_{3,i} + \beta_4 X_{4,i} + \beta_5 X_{5,i} + \beta_6 X_{6,i} + \beta_7 X_{7,i}$

for a multibusiness firm i, where $X_{1,i}$ to $X_{7,i}$ correspond to the seven relatedness variables and β_1 to β_7 correspond to the coefficients on these variables.

The α, or alpha, represents the average market share for a firm with no possible relatedness, i.e. the single business firms. Gamma, or γ, represents a direct general effect of conglomerate diversification, i.e. the average change in market share of diversified firms with no relatedness between businesses. The β, or beta, coefficients represent the unit change in performance associated with a unit change in a relatedness variable. A significant positive estimated β coefficient identifies the existence of a type of synergy in an industry. A significant negative β coefficient identifies the presence of dissynergy.

Set 2: Models of change in predicted performance with change in business ownership

The coefficients of Models 1 and 2 are used to calculate a change in predicted market share for a business that undergoes ownership change between t and $t+1$. This is effectively a measurement of whether acquisitions position a business into a firm that will help the business gain market share. In other words, if a business is acquired does its relatedness change as it moves from its old parent to its new parent such that the prediction of market share would be higher for the business as part of the new firm? The intuition would be that its competitive strength as part of the new firm would be greater and that over time its market share would increase.

Since the before and after predictions are not

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[1] The SURE estimator is more efficient than OLS estimators where errors for a business may be correlated over time because of unobserved common characteristics such as managerial skill. SURE estimates with correlated errors across time. Its parameters are unbiased only if unobservable characteristics which may be in the error term are not correlated with the independent variables.

independent samples, a paired *t*-test can be used to test for the difference in predictions within industries. Predictions before and after ownership changes are calculated using Model 1 (and 2). The question arises, how does one test whether ownership change is resulting in predicted increases in performance on average in all industries? Model 3 is estimated across all industries and tests for a difference in prediction before and after ownership change by regressing the difference on a constant term α.[2] Coefficients from Model 1 (or Model 2) are applied to the businesses which change ownership to calculate the prediction of market share for time $t+1$ minus the prediction of market share for time t for each business, or firm i in the jth industry, $MS_{i,j,t+1'} - MS_{i,j,t'}$.

Models 3 and 4

$$MS_{i,j,t+1'} - MS_{i,j,t'}' = \alpha + \epsilon_{i,j} \quad \text{(Model 3)}$$

Using this model to explain prediction changes from Model 1 (and Model 2) one can test whether acquisitions increase predicted market share of acquired businesses (H1) with a positive and signficant α. A Model 4 is specified in Appendix 1 for the group of business units that change ownership in the same acquisition. Model 4 is similar to Model 3 but it uses sales weights of the business units for all variables to estimate a common effect for all the business units in the acquisition.

Set 3: Models of changes in actual vs. predicted performance

To assess whether the predictions examined in Models 3 and 4 are borne out in actual subsequent changes in market share, the actual changes in the subsequent period are regressed on the predicted changes from the acquisition. How quickly would the prediction be realized? It is unlikely that resource sharing would result in rapid adjustment. Not only would the implementation of the acquisition take time as new organizational structures and processes are set up for the acquired firm or business, but the cost savings or improved differentiation that might result from shared activities with the parent would have to be set up and managed successfully in order to be achieved (Haspeslagh and Jemison, 1991). One cannot say how quickly an adjustment would occur, but one can put a range on the period within which most of the adjustment should occur and the direction of change should be in the same direction as the prediction.

The prediction changes indicate how much one would expect market share to change from the acquisition in the long run. The original prediction changes are based on acquisitions that occur between 1980 and 1984, or time t and $t+1$. The paper investigates the subsequent change in market share in 1986, or time $t+2$, to determine the extent to which there is a correspondence between predicted changes and actual changes. A positive association tells one that the prediction from the earlier models is associated with actual subsequent change. A coefficient of 1 would suggest that the prediction is realized entirely within the 2-year time span between 1984 and 1986. A coefficient less than 1 may indicate that some adjustment has occurred and that more will follow, or that some adjustment occurred prior to 1984 and the coefficient represents the end of the adjustment process. Since it is highly unlikely that the 1984–86 window captures all of the adjustment process, the coefficient underrepresents the adjustment that does occur. Nonetheless, since one does not expect adjustment to occur immediately, and the benefits of resource sharing could develop over a lengthy period of time, one would expect that a window which starts on average 2 years after the acquisition and runs for 2 years would capture most of the adjustment that will occur.

In Model 5 the actual change in market share from period $t+1$ to $t+2$ is regressed on a constant plus the predicted change in market share from the acquisition (the dependent variable from Model 3).

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[2] Predictions for acquisitions are derived from a model estimated on the industry with some prediction error. Industries with a high prediction error will also have a high variance of prediction changes. The variance can be retained and used in a weighted least-squares cross-industry analysis of prediction changes which gives greater weight to industries with lower variance in predictions and thereby addresses the problem of heteroskedasticity that would result without this correction. When one has prior information about the source or magnitude of the heteroskedasticity for particular cases or groups of cases it can be corrected. See Kmenta, (1971: 264–266) for more details. Since SURE is a maximum likelihood estimation technique there is no direct analog to prediction error for the estimated equation, and the variance in actual prediction differences by industry would reflect prediction error in the original estimates.

Models 5 and 6

$$MS_{i,j,t+2} - MS_{i,j,t+1} = \alpha +$$

$$\beta[MS_{i,j,t+1} - MS_{i,j,t}] + \epsilon_{i,j} \quad \text{(Model 5)}$$

A version of Model 5 in which the same effect is tested for all the businesses which change ownership in the same transaction is specified in Model 6 through the use of sales-weighted averages of the business unit effects. It is derived in Appendix 1.

MEASUREMENT

Market share as competitive performance

Competitive performance

Market share and change in market share are the only measures of business performance available at the level of disaggregation necessary for intraindustry analysis at the business level of the firm for all manufacturing industries. There is a substantial history in the use of both variables as measures of competitive performance (Buzzell, Gale, and Sultan, 1975; Stigler, 1958). The weighted average market share of a firm's businesses also is significantly related to Tobin's q, a capital market measure of firm value divided by replacement cost (Montgomery and Wernerfelt, 1988; Smirlock, Gilligan, and Marshall, 1984).

In the sample under investigation, there is a significant positive correlation of 7.32 percent between the weighted average market share (weighted by proportion of firm sales), and firm profitability. When the logistic of market share is used, which is the functional form of market share used in this paper, the correlation rises to a statistically significant 19.70 percent. Finally, when the sample is restricted to those firms that have one business which represents 50, 60, 70, 80, and 90 per cent of the firm's sales, to isolate the cases in which the ROI is derived primarily from the market share in one industry, the correlation between the logistic of market share and ROI rises to 23.91, 22.97, 30.34, 30.37 and 37.12 percent respectively.[3]

The study proceeds with the use of market share, while controlling for change in market share, as a measure of business unit competitive performance. What biases are likely to result and how should findings be qualified? While market share may have an association with profitability across all industries, the association is certainly stronger in some than in others. Technologies and production functions which lead to economies of scale, and market conditions which yield benefits from market saturation, are likely conditions for stronger associations (Buzzell *et al.*, 1975). One advantage of using market share as a measure of competitive performance within each industry is that these conditions are held constant for the model and the findings can be interpreted with respect to the industry context. In other words, the findings can be further examined based on additional evidence of whether market share is a relevant measure of competitive performance in the industry.

One concern in using market share as a measure of performance is that Woo (1987) has shown that there are high-profitability low-market-share firms. These firms exploit a small but profitable niche through a focus strategy or they may be profitable because they are growing rapidly in dynamic industries. Using the PIMS data base Venkatraman and Prescott (1990) define two types of competitive environments—emerging and stable with nonfragmented end users—in which there is a particularly weak direct effect in the relationship between market share and profitability. These environments are characterized by rapid growth and nonfragmented end user environments which roughly correspond to the emerging and niche explanations of why the relationship might not hold (Woo, 1987). To determine the sensitivity of the findings to the presence of these two types of industries, 40 industries were dropped that were either growing rapidly or had nonfragmented end users and the coefficient for Model 1 in Table 2 increased

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[3] These correlations are for 1984 and the total sample is based on 733 firms for which COMPUSTAT ROI data could be traced to the Trinet Inc. data set. There were 488, 382,

293, 217, and 145 firms corresponding to the samples with one dominant business constituting respectively 50, 60, 70, 80 and 90 percent of sales. ROI is defined as income before tax divided by assets. All correlations were significant at the 0.05 level. Other characteristics of the sample are described in the Sample and Data subsections of the Measurement section. The full table is available from the author.

slightly.[4] The findings are not sensitive to industries in which the market share–profitability association is weak, but if there is a bias of including these industries it is biased against finding predicted changes in operational synergy.

Market share. Market share data for the focal business is derived from the Trinet Inc. Large Establishment Data Base. Market share of plants in the firm with the same primary SIC code are summed by firm to represent the market share of the focal business in the firm. The logistic transformation of market share is used because the distribution of market share is truncated at 0 and 1. In order to prevent predictions which are less than 0 or greater than 1, the logistic function transforms market share into an 'S-curve' distribution. This S-shaped curve is also commonly applied in models for constrained growth and constrained probability (Wonnacott, 1976) as well as for market share (Borenstein, 1989). $MS_{i,j,t}$ is the logistic transformation of market share ($ms_{i,j,t}$, or $\log(ms_{i,j,t}/1 - ms_{i,j,t})$).

Operationalizing interrelationships as relatedness variables

A number of studies, such as Yip (1982), Wells (1984), and Mahajan and Wind (1988), use the PIMS data base to identify shared activities between a strategic business unit (SBU) and the rest of the firm. There are fewer studies which do so using other data bases such as Montgomery

and Hariharan (1991), which uses the hierarchical logic of the SIC structure to define related diversification of a business unit with respect to the rest of the firm. This extends similar objective measures used by Jacquemin and Berry (1979), Palepu (1985), and particularly Caves, Porter and Spence, (1980) for firm diversification.

Davis and Duhaime (1992) conceptually criticize reliance on the hierarchical structure of the SIC to determine relatedness, though research by Hoskisson *et al.* (1993) finds construct reliability and validity between an entropy classification measure using the SIC and subjective measures originally developed by Rumelt (1974). However, both Davis and Duhaime (1992) and Hoskisson *et al.* (1993) rely on SEC 10-K business segment data and argue that an advantage of the segment data is that managers, who know the true similarity among business units, decide which business units to put into which segments. This reasoning assumes that managers use the segment reporting internally, which they need not do, and misses the criticism of the segment reporting program made at the inception of the program, which is that managers will group businesses into segments that reveal as little information as possible to outside competitors (Scherer, 1979). Further, except for primary and secondary SIC codes representing product lines little is known about the actual plants and lines of business that are included within the segment (Davis and Duhaime, 1992). This is a problem for research on diversification which requires detailed knowledge of the diversity of the firm.

One solution to these problems is to merge detailed business unit data from Trinet Inc. with empirically derived flows between industries as found in the input–output tables and the Scherer technology flow matrix (Scherer, 1982) to determine relatedness. The advantage is that similarity between industries that is used for defining related diversification is no longer derived on the basis of a taxonomic hierarchical structure such as the SIC code but is defined empirically through data bases which are designed to determine relationships between industries.

These product and R&D flows between industries are used to represent the flows that might exist between businesses of the firm. If a firm has two businesses which are in industries which have some level of transaction in input–output tables, this approach assumes that those two businesses

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[4] The coefficient increased from 0.00025 to 0.00026, which is still significant at the 0.99 confidence level. Industries that were above two standard deviations from the mean of industry growth and end user fragmentation were dropped. Growth in industry sales between 1972 and 1982 from the Census of Manufacturers was adjusted for inflation with the producer price index for each industry to determine industry growth rate. End user fragmentation was calculated from the input–output data base by multiplying the proportion of output sold to an industry by the Herfindahl index of concentration for that industry. When summing these one has a measure of buyer industry concentration similar to that used in Lustgarten (1975). The Herfindahl index is used as a measure of concentration rather than four-firm concentration because it reflects the broader distribution of sales within the industry. Nineteen high-growth industries were dropped, corresponding to four-digit SIC codes 2067, 2296, 2631, 2812, 2813, 2816, 2819, 2865, 2869, 2895, 2992, 3313, 3331, 3334, 3412, 3559, 3565, 3586, and 3624. Twenty-one nonfragmented end user industries were dropped, corresponding to 2121, 2257, 2279, 2283, 2429, 2517, 2661, 2831, 2833, 2911, 2999, 3259, 3322, 3333, 3497, 3533, 3573, 3671, 3678, 3792, and 3795.

of the firm transact with each other to the degree represented by the average proportion of sales of one industry to the other (Lemelin, 1982; MacDonald, 1985; Caves and Bradburd, 1988). While this is obviously not always the case, it is true on average for the businesses of the industry as a whole, which imposes a constraint on the overall level of misrepresentation.

There are two ways in which the use of industry flows to reflect transactions within firms could lead to errors in variables, though there are constraints on the potential bias from these errors. First, the FTC and input–output data are available at a level between the three- and four-digit level, thus some groups of four-digit industries are constrained to have common measures of variables. Since the industry flows are defined to represent the total flows at the industry level, even where the industry level consolidates some four-digit SIC industries, these flows are constrained not to be biased at any particular four-digit SIC industry level. Industry estimates should not be biased from this source. Second, four-digit SIC data are used to define the effects of relatedness at the business unit level and a business in a large firm may have to work with different businesses in order to share a variety of activities. This would tend to overexaggerate the benefits of operational synergy, so a sales-weighted average of the sharing is used which implicitly reduces the effect of sharing in a large firm for a particular business. If operational synergy derives from multiple or different business units these flows receive less weight than the same flows in a smaller firm due to the difficulties of managing these relationships.

Transactional-related diversification

Product flows from 1977 input–output tables can be merged with detailed sales data on the businesses of the firm, or sales by each four-digit SIC product (Trinet Inc. data for 1980 and 1984), to create transactional relatedness variables such as backward and forward integration (Caves and Bradburd, 1988). Supplier and customer interrelationships such as a business unit's interaction with similar supplier or customer industries as other business units in the firm, as derived from input–output tables, are used to calculate measures of transactional relatedness such as customer and supplier relatedness (Lemelin, 1982).[5] A weighted average of the flows or interaction with other businesses of the firm is used so that flows from many businesses in a multibusiness firm receive less weight due to the difficulty of managing these flows.

The input–output tables are constructed as rows that represent flows from producing industries into consuming industries. Alternatively columns represent the input purchases of one industry from other industries. A subset of these tables known as total intermediate inputs includes all direct sales to other industries. When every element of this matrix is divided by column totals the elements in one column are the proportion of an industry's total inputs that are purchased from each row industry. This matrix is labeled $Input_{(x,y)}$. When every element is divided by row totals, the elements in one row then reflect the proportions of an industry's sales sold to each column industry. This matrix is labeled $Output_{(x,y)}$. It should be noted that $Output_{(x,y)}$ is not the transpose of $Input_{(x,y)}$. These tables of input coefficients and output coefficients can then be used in conjunction with firm-level data to define transaction-related diversification variables. Variables are defined with respect to the ith firm in the jth industry. The ith firm has businesses in a focal industry, where $j = f$, and in other industries where $j \neq f$, for example $j = k$. The notation is as follows:

i = firm
j = industry
   where $j = f$, the industry is the focal industry
   where $j \neq f$, the industry is a nonfocal industry (ex. $j = k$)
$_{i,j}$ = where $j = f$, the focal business of firm i
$_{i,j}$ = where $j \neq f$, other businesses of firm i (ex. $j = k$)

[5] Production relationships are not explicitly identified, but to some extent the use of common materials between two businesses may be correlated with the production process. The SIC system itself categorizes establishments into industries by 'products made, raw materials consumed, or manufacturing process used' (*Standard Industrial Classification Manual*, 1957: 431). Similar sources of supply may also suggest manufacturing process similarity of even a more specific nature than categories of production process such as batch, continuous flow or job shop would suggest. This implies that one should interpret the results for supplier relatedness, or purchasing from common suppliers, more broadly as partly reflecting production relatedness.

$p_{i,j}$ = the proportion of a firm's nonfocal sales for each nonfocal business, or,

$$= sales_{i,j} / \sum_{j=1; j \neq f}^{n} sales_{i,j},$$

defined for $j \neq f$.

The matrix with coefficients as proportions of column totals, $Input_{(x,y)}$, is used to calculate supplier similarity, which in turn is combined with firm-level data to calculate supplier relatedness. To get an index of supplier similarity between one industry, where $x = f$, and another industry, where $y = k$, the difference between columnn f and column k is squared and summed over all elements. If columns f and k are noted as industry vectors $Input_{(x,f)}$ and $Input_{(x,k)}$ with n elements in each, corresponding to the proportion industires f and k buy from each manufacturing industry x, the following equation for supplier diversity is useful for deriving a measure of supplier similarity:

$$supplier\ diversity_{(f,k)} = \sum_{x=1}^{n} (Input_{x,f} - Input_{x,k})^2$$

from which a matrix supplier diversity$_{(x,y)}$ is constructed from every combination of $x = f$ and $y = k$.

The maximum value in $Input_{(x,f)}$ and $Input_{(x,k)}$ is 1, so supplier diversity ranges from 0 to 2 and is high when industry f and industry k buy from different types of industries. Thus an index of supplier similarity between two industries is the following:

$$supplier\ similarity_{(x,y)} = 2 - supplier\ diversity_{(x,y)}$$

In the same manner, an index of customer similarity$_{(x,y)}$ can be constructed using the matrix, with coefficients representing proportions of row tables or $Output_{(x,y)}$. Lemelin (1982) utilized a measure of customer similarity based on correlations between rows of $Output_{(x,y)}$.

One can interact these industry matrices of supplier similarity$_{(x,y)}$, and customer similarity $_{(x,y)}$, as well as $Input_{(x,y)}$ and $Output_{(x,y)}$, with the relative sales of each business in the firm to construct a focal business measure of supplier relatedness, customer relatedness, forward integration, and backward integration.

Supplier relatedness for the focal business, where $j = f$, in a firm i would be the following if firm i has a business in any other industry, for example $j = k$. In this example, one is interested in the relationships between industry f and industry k and thus the x and y in the above industry matrices correspond to f and k (Figure 1). More generally, since firm i can have nonfocal businesses in every other industry in addition to f, one is interested in the rows of these matrices corresponding to $x = f$, and $y \neq f$, where y can be any number from 1 to n, the number of manufacturing industries. Again, $P_{i,j}$, defined only for nonfocal businesses where $j \neq f$, is the percentage of business$_{i,j}$'s sales as a proportion of the sum of sales of businesses in firm i not including the sales of the focal business. Variables are defined with respect to each firm with a business active in a focal industry f. Once defined, these variables can be thought of as having subscripts $_{i,j}$, as f in turn varies from 1 to n. Supplier similarity$_{j,f}$ represents a column corresponding to the focal industry, with all elements interacted with respect to each jth industry. Supplier interrelationships are represented by the *supplier relatedness* of other businesses in firm i with respect to a focal business for which $j = f$ is defined by the following equation:

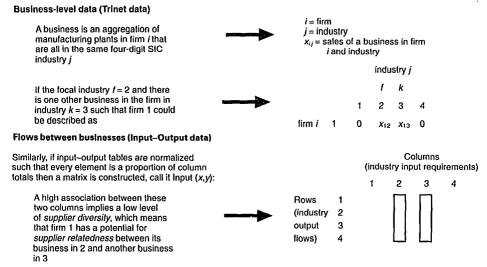$$supplier\ relatedness_{(i,f)} = \sum_{j=1; j \neq f}^{n} P_{i,j} \cdot supplier\ similarity_{j,f}$$

The summation is from $j = 1$ to n for $j \neq f$, or all possible industries in which firm i may have a business other than the focal business.
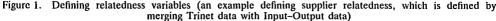
Customer similarity$_{f,j}$ represents a row corresponding to the focal industry, with all elements interacted with respect to each jth industry. Customer interrelationships are represented by *customer relatedness* of other businesses in firm i with respect to a focal business for which $j = f$ is defined by the following equation:

$$customer\ relatedness_{(i,f)} = \sum_{j=1; j \neq f}^{n} P_{i,j} \cdot customer\ similarity_{f,j}$$

The summation is from $j = 1$ to n for $j \neq f$, or all possible industries in which firm i may have a business other than the focal business.

Indexes of backward and forward integration for a firm i with a business in industry j use $Input_{(x,y)}$ and $Output_{(x,y)}$ respectively and can be

Figure 1. Defining relatedness variables (an example defining supplier relatedness, which is defined by merging Trinet data with Input–Output data)

defined in the following manner: $\text{Input}_{(x,y)}$ = an element in the matrix with coefficients representing proportions of intermediate input (column) totals. $\text{Input}_{j,f}$ represents a column corresponding to the industry of the focal industry f, with all elements interacted with respect to each jth industry.

$$backward\ integration_{(i,f)} =$$
$$\sum_{j=1;\, j \neq f}^{n} P_{i,j} \cdot \text{Input}_{j,f}$$

The summation is from $j = 1$ to n for $j \neq f$, or all possible industries in which firm i may have a business other than the focal business.

$\text{Output}_{(x,y)}$ = an element in the matrix with coefficients representing proportions of inter-mediate output (row) totals. $\text{Output}_{f,j}$ represents a row corresponding to the industry of the focal industry f, with all elements interacted with respect to each jth industry.

$$forward\ integration_{(i,f)} =$$
$$\sum_{j=1;\, j \neq f}^{n} P_{i,j} \cdot \text{Output}_{f,j}$$

The summation is from $j = 1$ to n for $j \neq f$, or all possible industries in which firm i may have a business other than the focal business.

Both measures of vertical integration represent the maximum amount of integration that a firm in an industry j can have.[6] For *backward integration* this assumes that if it has another business in k then it buys all its inputs from industry j from its own business in j. A similar assumption follows for *forward integration*.[7] Similar measures of forward and backward integration are used in Lemelin (1982), MacDonald (1985), and Caves and Bradburd (1988).

Functional-related diversification

The marketing functional relatedness variables are derived by combining marketing expense to sales ratios for industries from the 1977 FTC line of

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[6] This measure of vertical integration is very similar to a measure used in Caves and Bradburd (1988), although they restricted their sample to industries in which 80 percent of output is sold to intermediate producers. Using Standard and Poor's Register instead of Trinet they identify 'company names that appear on its list for both a given sampled industry and any customer industry accounting for more than (approximately) 4 percent of shipments' (Caves and Bradburd, 1988: 267). These firm data are then aggregated to an industry measure which represents the proportion of firms in an industry which is vertically integrated.

[7] Since only plants that are producing in U.S. manufacturing industries are considered in this data set, flows between plants in the same firm that are in different countries or in nonmanufacturing industries would not be considered in the vertical integration measure.

business data with previously derived variables on customer and consumer similarity from the Input–Output tables. These expense ratios are multiplied by customer similarity between businesses for the industrial marketing relatedness variable and final consumer similarity for the consumer relatedness variable (MacDonald, 1985).[8] Tables on R&D flows and spillovers (Scherer, 1982) between industries are used to identify the R&D dollars that are available to a business because of its proximity to other businesses in the firm. For the R&D relatedness variable, the R&D expense to sales of adjacent businesses is multiplied by their sales and then the R&D coefficient to determine the proportion of this R&D which is available to the focal business. R&D flows are calculated using Scherer's Technology Flow Matrix (Scherer, 1982). Scherer's matrix is in turn derived from FTC line of business, Input–Output and patent data.

To identify common industrial channels between two businesses, or the exploitation of an industrial marketing interrelationship, the variable *industrial marketing relatedness* is defined. Customer similarity$_{(f,j)}$ between the focal business, $j = f$, and another business in the firm, for example $j = k$, is multiplied by the non-media marketing to sales ratio of business k's industry. Customer similarity$_{f,j}$ represents a row corresponding to the industry of the focal industry f, with j elements corresponding to each other industry's customer similarity to industry f. When summed across businesses of the firm this creates a measure of the potential for sharing industrial marketing expenses within the firm that will help a focal business in an industry where $j = f$.

industrial marketing relatedness$_{(i,f)}$ =
$$\sum_{j = 1; j \neq f}^{n} P_{i,j} \cdot \text{customer similarity}_{f,j}$$
$\cdot$ non-media marketing/sales$_j$

The summation is from $j = 1$ to n for $j \neq f$, or all possible industries in which firm i may have a business other than the focal business.

An index of *consumer advertising relatedness* is derived to operationalize a consumer advertising interrelationship between two businesses. The index uses a measure of similarity between two businesses in terms of the degree to which they sell to final consumer demand. The share of origin industry output going to final consumer demand was used in MacDonald (1985). The output that is sold to consumer demand is a column in the input–output tables. To calculate the proportion that each industry sells to consumers as a proportion of the domestic market, the domestic output sold to consumers is divided by row totals minus net exports which represents the domestic market. The percentage of sales that are sold directly to final consumer demand for two industries x and y is noted as CD_x and CD_y and the difference between these two indexes is squared. This weights larger differences much more than closer differences and is the same functional form, except it is the squared difference of scalars rather than vectors, as the customer and supplier similarity indexes defined earlier. Finally, the maximum squared difference between two scalars that vary from 0 to 1 is 1, and the squared difference is subtracted from 1 to derive a measure that increases with similarity of sales to the final consumer.

$$\text{consumer similarity}_{(x,y)} = 1 \cdot (CD_x - CD_y)^2$$

If $x = f$, the focal industry, then this measure of consumer similarity between the focal industry and each other industry represented by $y = j$ is then interacted with the media advertising/sales ratio of the respective industry j, and summed across businesses of the firm to derive consumer advertising relatedness for a focal business in firm i for which $j = f$.

consumer advertising relatedness$_{(i,f)}$ =
$$\sum_{j = 1; j \neq f}^{n} P_{i,j} \cdot \text{consumer similarity}_{f,j} \cdot \text{media}$$
advertising/sales$_j$

The summation is from $j = 1$ to n for $j \neq f$, or all possible industries in which firm i may have a business other than the focal business.

A measure of *R&D relatedness* is derived to operationalize an R&D interrelationship in the R&D support function that could be shared between two businesses. Scherer (1982) calculated a technology flow matrix which identifies the flows from origin industry R&D into other industries of

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[8] Unfortunately the FTC decomposition of marketing expense does not conform exclusively to whether marketing is directed to industrial users vs. final consumer demand. Many consumer marketers use promotions and many industrial marketers advertise in trade publications which would be a type of media expense. However, the bulk of media expense is to final consumer demand and the bulk of promotion expense is directed to industrial marketing.

use. This matrix is calculated using the patents that are attributed to businesses in one industry that are used in other industries. Scherer devises a method which, roughly, flows industry origin R&D through to other industries of use in proportion to the number of patents filed by firms in one industry that are used in other industries. Thus his diagonal elements correspond to what he conjectures to be process R&D and off diagonal elements correspond to product R&D. Firms undertake process R&D to be used in their own industries and much of product R&D is for products in other industries. Scherer was primarily interested in the net R&D available to an industry and whether there was a significant difference between this and the actual R&D that the industry originated. This difference was used in a study of the productivity of R&D.

Scherer publishes origin R&D, used R&D (private and public where public includes R&D that is used in products for final demand) and the percent of process R&D in used R&D for 210 FTC-level industries. Unfortunately he did not calculate and publish the flow matrix at this level of disaggregation but only published it at the 48 origin industry by 57 receiving industry level. This table gives a roughly 2.5-digit flow of R&D from the originating industry (row) to the receiving industry (column) which is called $\text{Flow}_{(o,r)}$. With the 210-industry FTC data, at roughly 3.5-digit level, one can disaggregate the R&D flow from one 2.5-level industry to another into a flow from one 3.5-level industry by using the proportion of 3.5-level industry R&D to total process R&D of its 2.5-level group. Process R&D, or the diagonal element, is the largest component of R&D use. Using these available data, a measure is constructed of the amount of R&D which would be available to a business by virtue of R&D spillovers from other businesses in the firm.

$$R\&D \ relatedness_{(i,f)} =$$
$$\ln \left[\sum_{j=1; j \neq f}^{n} sales_{i,j} \cdot R\&D/sales_j \right] \cdot [\text{Flow}_{o,r} /$$
$$\sum_{j=1}^{s} R\&D \ origin_j] \cdot [R\&D \ used_f /$$
$$\sum_{i=1}^{t} R\&D \ used_j]$$

The first term is the industry R&D/sales ratio for the jth industry times the actual sales of the jth business of firm i, the result is an estimate of the R&D originated in the jth business of firm i. The term $\text{Flow}_{o,r}$ is the proportion of a dollar of R&D from the 2.5-digit originating industry group o which spills over to the 2.5-digit receiving industry group r. Since only a subset of this R&D comes from the originating industry j, as distinct from the industry group of which j is a member, this flow is divided by the total R&D from the originating group of industries, or the sum from 1 to s where s is the number of 3.5-digit industries in the 2.5-digit industry group of which the jth business of firm i is a member, $\sum_{j=1}^{s} R\&D \ origin_j$. The summation in the last term is from 1 to t, where t is the number of 3.5-digit receiving industries in the 2.5-digit receiving industry group that includes the industry of the focal business, where $j = f$. When these conversions are summed across all the businesses of the firm for which where $j \neq f$, the result is the R&D available to the focal business, where $j = f$, from spillovers within the firm.

The entire expression is logged. The prospect that there is a critical level of R&D available to a business increases as the pool of R&D activities in other businesses increases. However, the spillover to a focal business should increase at a decreasing rate since the probability that the firm is using all other business R&D in the focal business decreases.

Validity

The validity of the seven dimensions of relatedness developed here are tested with respect to the entropy classification measure used in Hoskisson *et al.* (1993). A construct using these measures was substituted for the DR dimension in the entropy measure and the two constructs are shown to have a 0.56 correlation at the 0.999 confidence level (see Appendix 2 for detailed explanation). A significant 0.5 correlation is often considered as demonstrating construct validity. Since the entropy classification measures are shown to be significantly correlated with the Rumelt (1974) categories in Hoskisson *et al.* (1993), and the measures used here are significantly correlated with the entropy classification measure, this shows convergent validity for the measures used here with the subjective measures developed by Rumelt (1974) (Venkatraman and Grant, 1986: 79).

Data

The Trinet Inc. Large Establishment Data Base comprises plant-level data on sales and market share for plants with over 20 employees. The original files of over 350,000 plants were restricted to manufacturing which reduced the sample size to roughly 150,000 plants. The 1981 and 1985 Trinet tapes correspond to 1980 and 1984 respectively. The Trinet data set includes four-digit SIC plant-level data on number of employees, sales, market share and parent firm, for every plant in the United States with over 20 employees. Trinet Inc. defines an establishment as a single physical location where goods or services are produced. It estimates that its Large Company Data Base 'covers 90–95% of all establishments with 20 or more employees in the manufacturing industries' (Trinet Inc., 1986).

Trinet reports that the Federal Trade Commission has extensively studied the Trinet Large Establishment Data Base and published a comparison which found a 92 percent correlation between its own figures and Trinet's for the sales of the top four companies in each of over 900 four-digit SIC codes.

In addition to the Trinet data for 1980 and 1984, the primary data used to construct the transactional relatedness variables are the 1977 Input–Output data. While these data do not temporally correspond with the Trinet data, there is substantial research showing the temporal stability of the Input–Output tables (Burt, 1988).

Together with the Trinet data, the 1977 FTC expense-to-sales ratios are primarily used to calculate functional interrelationship variables. These ratios are used to identify the relative promotional, advertising, and R&D intensity of different industries. The FTC data constitute a strong effort to break down direct promotion, media advertising and R&D expenses by line of business. Unfortunately the FTC data are not available after 1977. While there may be changes in the industry ratios over time, this would be a problem only if the relative ranking among industries in their expense-to-sales ratios was unstable between 1977 and 1982; the use of expense-to-sales ratios means that inflation would not affect the applicability since the ratios are multiplied by the true sales for 1980 and 1984 to represent the marketing or R&D expenditure in that year.

An alternative approach to calculating expense ratios using Compustat may be more timely but would have the problem that expenses of businesses from multiple industries often comprise the segment that is classified as corresponding primarily to one SIC code. There is a trade-off between timeliness and a greater probability that industry ratios would comprise data from other industries. This paper prefers the line of business clarity of the FTC at the penalty of applying ratios of functional intensity from 1977 to data from 1980 and 1984. The Scherer 1982 Technology Flow matrix uses 1974 FTC survey of R&D by line of business, the 1972 Input–Output data—a sample of 15,112 U.S. Patents from June 1976 to March 1977 which give industry origin and use.

Sample

An important methodological consideration concerns which industries to examine. There are two constraints on the number of industries. The first is that the industries are restricted to manufacturing industries because the quality of the Input–Output and FTC data deteriorate beyond manufacturing industries. Therefore, businesses which are solely distribution or extraction businesses that may be parts of diversified firms are excluded. Second, industries had to be dropped in the analysis if there were insufficient cases in the Trinet data base to estimate Models 1 and 2. There had to be sufficient cases in the Trinet data base to have adequate degrees of freedom with nine independent variables. In some cases, particularly with forward integration in some final consumer industries, there was insufficient variation to estimate the full model, so a model without forward integration was estimated. If the model was still singular after dropping the forward integration variable, then the industry was not included in the results. As a result, 85 manufacturing industries were dropped but these constitute only 6.13 percent of manufacturing sales.[9]

[9] Notes on whether the industry had insufficient cases or resulted in singular estimation are available. The four-digit SIC codes for these 85 industries are the following: 2043, 2044, 2061, 2062, 2067, 2074, 2083, 2097, 2098, 2111, 2121, 2131, 2141, 2251, 2253, 2254, 2259, 2279, 2284, 2292, 2296, 2297, 2323, 2351, 2363, 2371, 2381, 2384, 2385, 2386, 2387, 2395, 2429, 2499, 2511, 2646, 2771, 2794, 2795, 2823, 2875, 2895, 2999, 3021, 3031, 3041, 3142, 3151, 3161, 3171, 3253, 3262, 3263, 3316, 3317, 3332, 3333, 3341, 3483, 3565, 3581,

The FTC and the Input–Output tables are defined for a broader level industry than four-digit, so the Input–Output and FTC relationships for two industries are often lumped together.[10] Since the Department of Commerce and the FTC essentially believe that the FTC and Input–Output characteristics of some four-digit industries are similar, the paper uses broader level data as the FTC and Input–Output data for industries that have been lumped into that category. In these cases there is a 'one-to-many' correspondence between FTC or Input–Output categories and SIC four-digit categories.

The sample of business units which changed ownership between 1980 and 1984 is derived by selecting those business units which have a different parent company code in the Trinet data base in 1984 than they did in 1980. Business units in which not all plants changed ownership were dropped from the change of ownership sample. These constitute plant-level facilities changes rather than a decision to acquire or divest business units.

EMPIRICAL RESULTS

Model 1 is estimated for each four-digit industry and it is impossible to report all the estimates here. As an example, in SIC 2013, sausage making, the significant coefficients are positive in R&D relatedness, supplier relatedness, and customer relatedness, while industrial marketing relatedness has a negative coefficient. The estimated coefficients are used to calculate the prediction changes with ownership changes. A likelihood ratio test of whether the seven relatedness variables explain a significant proportion of variance in market share reveals that in 84 percent of the industries the relatedness

variables are important for explaining variance in market share.[11]

The market share prediction changes for the set of businesses which change ownership can be descriptively analyzed to assess whether changes are positive. The first descriptive statistic reports the number of industries in which changes are positive; the second reports the number and identity of industries in which these changes are significantly positive. The paper also reports tests of whether the number of events associated with positive changes and positive significant changes is greater than one would expect by chance alone. Finally, the results of the hypothesis tests are discussed.

The descriptive results in Table 1 are consistent with the hypothesis that market share predictions increase with business ownership changes.[12] Examination of business ownership changes shows that market share predictions increased in 86 percent of the industries in Model 1. Of those industries with significant changes, 100 percent were positive. There are significant positive changes in predicted market share associated with business ownership changes in 92 out of 356 industries, or 26 percent of industries. The predictions from Model 2 are quite similar to those from Model 1. This confirms that predictions are not sensitive to a model which allows coefficients to change over time.

With so many tests it is important to establish that the number of significant tests is not occurring by chance. A test using the large sample normal approximation to the binomial rejects the hypothesis that the number of positive changes and significant positive changes could have occurred by chance alone (Table 1).

Predictions are positive on average for business ownership changes, and there is strong support for Hypothesis 1 (H1) that businesses which change ownership increase their predicted market share from changes in operational synergy. Using weighted least squares, prediction changes are regressed on a constant term to test H1.[13] The coefficient on the constant term is positive and

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3582, 3586, 3632, 3633, 3636, 3641, 3647, 3671, 3672, 3673, 3692, 3716, 3761, 3764, 3792, 3795, 3914, 3915, 3942, 3953, 3955, 3962, 3963, 3995. A breakdown by percent of sales in each two-digit SIC industry is available from the author.
[10] The FTC reports data on 270 3.5-level industries when there are approximately 450 four-digit industries. In this case, the same FTC-level data are assigned to multiple four-digit industries according to the FTC instructions. For many of the FTC-level industries there are missing data where disclosure requirements preclude publishing data. Where data are not disclosed three-digit industry average of expense ratios is substituted. There are unique input–output data for 370 manufacturing industries and a key that links four-digit industries to the appropriate aggregate.

[11] These results are available from the author.
[12] Horizontal acquisitions would not upwardly bias the predicted change in market share since with no change in relatedness variables there would be no predicted change in market share from a horizontal acquisition.
[13] The variance of the change in the dependent variable within industries is used to weight predicted changes. Where

Table 1. Breakdown of number of industries by sign of the average percentage change in predicted market share from business ownership change

Two models:
(1) Coefficients restricted over time
(2) Coefficients unrestricted over time

Type of change	Total industries	Positive changes		Negative changes	
		No. positive	% of total	No. negative	% of total
Model 1	356	307[b]	86.2	49	13.8
Model 2	356	278[b]	78.1	78	21.9
Significant changes					
Model 1	92[a]	92[b]	100	0	0
Model 2	83[a]	82[b]	98.8	1	1.2

Large-sample normal approximation to the binomial rejects the hypothesis that the number of events occurred by chance at the following levels with 99 percent confidence:
(For test of significant changes the original tests are at the 95% confidence level)
[a] Rejects the null hypothesis that this number of significant events could have occurred by chance.
The number of significant tests out of 356 tests = 27.4, or 28 significant events.
(For test of sign the original tests are at the 50% confidence level)
[b] Rejects the null hypothesis that this number of significant tests could have occurred by chance.
The number of significant tests out of the following tests is:
$356 \approx 199.9$, or 200 positive or negative events.
92 tests = 57.2 (58) or 58 positive or negative events.
83 tests = 52.1 (53) or 53 positive or negative events.

significant (Model 3), with values of 0.00025 and 0.00020 respectively for predictions from Model 1 and Model 2 (Table 2). These can be interpreted as an average prediction of 0.025 percent and 0.02 percent of the market from operational synergy changes associated with business ownership change.[14] The positive coefficients support H1 and reject the null that there is no significant relation.

Acquisitions often involve groups of businesses

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the variance within industries is greater the cases for that industry are given less weight. The variance represents error in the underlying regression since these predictions are point estimates with an underlying prediction error from the equation. All predictions within the industry come from the same equation and thus the variance in the predictions reflects the underlying prediction error.
[14] The constant, α, in Models 3 and 4 is approximately equal to the average percentage change in market share. It is equal to $\ln(((MS_{t+1}/(1 - MS_{t+1}))/(MS_t/(1 - MS_t)))$ or $e^\alpha = (MS_t+1/MS_t)((1 - MS_t)/(1 - MS_{t+1}))$. Thus for small α, or small average MS, α is approximately equal to $MS_{t+1}/MS_t - 1$, the proportional increase in market share which can be converted to the percentage change in market share. Percentage change in market share is preferred to actual change in market share because market share points have different significance in different industries.

Table 2. Average change of predicted market share with business ownership changes (weighted least-squares estimates)

Two models estimated:
(1) SURE with coefficients restricted over time
(2) SURE with coefficients unrestricted over time

Coefficient · 100 equals change in market share

Type of model	Constant	*t*-statistic
Model 1 Restricted (market share)	0.00025***	(25.95)
Model 2 Unrestricted (market share)	0.00020***	(19.67)

*** Significant two-tailed test with 99% confidence.
Source of estimation technique: J. Kmenta, *Elements of Econometrics*, 1971, pp. 264–266.

changing ownership simultaneously and, since the logic of rational firms implies that businesses changing ownership as a group would have a net increase in predicted market share, one needs to test this hypothesis as well. Consistent with Hypothesis 2 (H2), businesses which change ownership from firm *a* to firm *b* increase a sales-weighted average predicted market share from operational synergy for the *group* of businesses involved in the acquisition. The coefficient on the constant in Model 4, corresponding to the average prediction for the group of businesses involved in each transaction, shows an average change in predicted market share of 0.01208 and 0.01118 respectively from Models 1 and 2 (Table 3). This corresponds to an approximate predicted change of 1.21 percent and 1.12 percent of the market. The coefficients are significant, reject the null, and are of the expected sign to support H2.

There are also reasons to expect that the benefits of operational synergy, and thereby acquisitions which increase operational synergy, would be greater in some industries than in others. A summary of the percentage of significant prediction increases in two-digit SIC groups is an aggregate evaluation of this conjecture. For example, one might expect that the fragmented

structure of the apparel and textile groups would result in fewer opportunities for fruitful interrelationships between businesses of diversified firms than in the machinery industry. This prior is borne out in the list of two-digit groups, with the highest percentage of industries with significant positive prediction changes in market share: printing, rubber/miscellaneous plastics, fabricated metal, machinery, electrical machinery, and measuring devices (Table 4).[15]

Both the frequency of industries in which significant predictions are positive, and the rejection of the null hypotheses for H1 and H2, support the hypotheses that managers seek to increase the potential for operational synergy in business ownership changes and in acquisitions of multiple businesses.

Are these expected gains in operational synergy realized in improved performance of the busi-

Table 3. Average change of predicted market share with business ownership changes for groups of businesses acquired in the same transaction (sales-weighted average of predictions for the group of businesses)

Two models estimated:
(1) SURE with coefficients restricted over time
(2) SURE with coefficients unrestricted over time

Coefficient · 100 equals change in market share

Type of model	Constant	t-statistic
Model 1 Restricted (market share)	0.01208***	(6.22)
Model 2 Unrestricted (market share)	0.01118***	(5.85)

*** Significant two-tailed test with 99% confidence.
Source of estimation technique: J. Kmenta, *Elements of Econometrics*, 1971, pp. 264–266.

Table 4. Significant positive changes in percent market share with business ownership changes (proportion of four-digit SIC industries in each two-digit SIC category of industries)

SIC	Industry	Positive change in % market share		
		N	No.	Proportion
20	Food	36	6	0.167
22	Textiles	19	3	0.158
23	Apparel	22	2	0.091
24	Lumber/wood	14	3	0.214
25	Furniture	13	2	0.154
26	Paper	16	2	0.125
27	Printing	14	7	0.500
28	Chemicals	25	6	0.240
29	Petroleum	4	0	0.000
30	Rubber/plastics	3	2	0.667
31	Leather	7	0	0.000
32	Stone/glass	23	5	0.217
33	Primary metals	21	4	0.190
34	Fabr. metals	35	15	0.429
35	Machinery	40	15	0.375
36	Elec. machinery	28	10	0.357
37	Transportation	13	3	0.231
38	Meas. devices	13	5	0.385
39	Miscellaneous	10	2	0.200

[15] The predicted changes in market share from Models 1 and 2 with business ownership changes are reported for every industry and are available from the author. The respective tests of significance from paired t-tests in industries are also reported.

nesses at a later date? There is a strong significant association between predicted market share and subsequent change in market share between 1984 and 1986. When Model 5 is estimated, a change in predicted market share of 1 percent is associated with a 0.027 percent change in subsequent market share which is significant at the 99 percent level (Table 5). If coefficients are allowed to vary over time in the original prediction (Model 2) then a 1 percent increase is only associated with a 0.010 percent change, which is significant at the 90 percent level. These results support H3, that predictions of changes in market share will be realized in subsequent increases in market share for acquired businesses, though the link between predicted change and actual change is not very strong.

Do groups of businesses which change ownership together also show a relationship between predicted market share and subsequent changes in market share? When a sales-weighted average of subsequent market share changes for the group of businesses changing ownership is regressed on the predictions for the group, as described in Model 6, there is a significant and strong association between the weighted average of predicted market share and subsequent change in the weighted average market share. A change in predicted market share of 1 percent is associated with a change in subsequent market share of 0.32 percent, which is significant at the 99 percent level (Table 5). If coefficients are allowed to vary over time in the original prediction (Model 2), then the association is reduced to 0.084 per cent, which is significant at the 95 percent level. These results are strong support for Hypothesis 4, that predictions of changes in market share for businesses which change ownership as a group will be realized in subsequent increases in market share for the group of acquired businesses.

In sum, the average change is a statistically significant change of 0.02 per cent of the market for businesses, and 1.21 per cent on average for the group of businesses that are bought and sold together. The dominant pattern of positive average industry changes and the significant average change across industries support the general propositions that acquisitions result in an increase in *predicted* market share, from operational synergy for the businesses involved. In addition, these predicted changes are strongly associated with subsequent changes in market share for acquired businesses and groups of businesses. Of any given predicted change, 2.7 per cent of this prediction is subsequently realized for businesses separately, but 32.1 percent is realized for groups of businesses sold in the same transaction. The actual improvement in market share from acquisitions that is due to change in the operational synergy is the product of predicted changes and the association between predicted and actual; this is 0.001 percent for businesses taken separately and 0.388 percent for groups of businesses in the same transaction.[16]

Table 5. Actual market share changes from 1984 to 1986 regressed on predicted market share changes

Model 5 refers to business ownership changes
Model 6 refers to groups of businesses changing ownership together

Restricted models derive predictions from models with coefficients restricted over time
Unrestricted models derive predictions from models with coefficients restricted over time

Type of model	Constant	Coefficient on prediction
Businesses		
Model 5—restricted	0.0731***	0.0271***
(*t*-statistic) $n = 3048$	(9.18)	(3.76)
Model 5—unrestricted	0.0803***	0.0097*
(*t*-statistic) $n = 3048$	(10.43)	(1.82)
Groups of businesses		
Model 6—restricted	−0.0009	0.3208***
(*t*-statistic) $n = 122$	(−0.54)	(4.35)
Model 6—unrestricted	0.0006	0.0837**
(*t*-statistic) $n = 122$	(−0.33)	(2.47)

*** Significant two-tailed test with 99% confidence.
** Significant two-tailed test with 95% confidence.
* Significant two-tailed test with 90% confidence.

CONCLUSION, LIMITATIONS, AND EXTENSIONS

Two important conclusions are made concerning the characteristics of the 1980s acquisition wave

[16] The calculation for these figures is simply $0.0271 \times 0.00025 = 0.00001$ or 0.001 percent for businesses or $0.3208 \times 0.01208 = 0.00388$ or 0.388 percent for groups of businesses.

based on this sample of acquired business units from 1980 to 1984. First, the finding of positive market share predictions complements event studies that find net gains in shareholder wealth in acquisitions but adds to these findings because these predictions are explicitly the result of an *operational* synergy that is made possible by the acquisition. Second, while previous research suggests that the *ex post* performance of acquired businesses in the second wave of acquisitions is better than the first, this research confirms this finding and explains part of the source of improved performance in terms of operational synergy.

Both conclusions help distinguish between alternative theories which seek to explain the characteristics of the second acquisition boom and thereby its causes. Alternative theories concerning agency, tax policy, antitrust and excess industry capacity as causes for the 1980s acquisitions are not directly rejected. Nonetheless, many of these theories use the finding that acquisitions result in horizontal combinations as support for their theories. Since the findings in this paper distinguish between acquired businesses in terms of the degree to which they move to firms in which there is greater potential for interrelationships, they represent an alternative explanation to a group of theories which rest on evidence of horizontal combinations for support (Morck, Shleifer, and Vishny, 1990; Kaplan, 1990; Jensen, 1993). Horizontal acquisitions would not affect the measures of operational relatedness, and hence the predictions used here. The findings also stress the importance of recognizing differences between types of diversifying acquisitions which have generally been overlooked in the finance research. In addition, by showing that these businesses improve their postacquisition performance, it uses predictive validity to support the results.

While a strength of the paper is its business unit level of analysis, an associated limitation is that it uses market share as a measure of competitive performance. The concern that market share may not be a good measure of competitive performance in some industries is partially addressed by the research design which uses intraindustry estimation and allows one to report results on an industry-by-industry basis. Where there are strong concerns about the limitations of market share as a measure of competitive performance, one can isolate the cases in which the concern is greatest; industries where the direct link between market share and profitability was known to be weak were dropped from the sample and the findings were not sensitive to this change. In addition, the business unit level of analysis requires some simplifying assumptions concerning the use of industry Input–output and R&D flows to measure potential transactions within firms because information on these transactions is not publicly available. There is considerable noise in the use of these measures for individual firms, though as a broad representation of the flows within firms that are active in an industry there are constraints which make the representation accurate.

A disadvantage of this method is that the potential for operational synergy in an industry is derived from current practice. Atypical or unusual combinations of businesses will not be estimated as likely sources of operational synergy. This may miss pioneer moves by some firms which seek to exploit new technologies or new markets via interrelationships with other businesses. If there are other synergies that are exploited that are operational in nature then the extent to which operational synergy is important in motivating acquisitions is underestimated. Thus the finding that operational synergy is an important cause of acquisitions and predictor of *ex post* performance is, if anything, biased to underrepresent the true degree to which operational synergy is important in acquisitions.

These findings focus on the acquired *business* as it moves from the seller's to the acquirer's portfolio and are not comparable to research which associates strategic acquisitions with market valuation of the target and acquired *firm* (Singh and Montgomery, 1987; Lubatkin, 1987; Chatterjee, 1986; Seth, 1988; Shelton, 1988). Previous research in general does not find a relationship between related acquisitions and acquiring firm shareholder valuation, and the reasons include the following: (1) the market prices away publicly known potential synergies (Barney, 1988); (2) the event window is too short (Balakrishnan, 1988); and (3) relatedness is not measured in a manner that represents opportunities to the buying firm that exceed the value to the next highest bidder (or potential bidder) (Barney, 1988). It may be possible to use the multiple dimensions of industry-specific interrelationships

derived here, for which the market for corporate control may be less efficient, to determine the predicted operational synergy associated with the acquiring firm. This could then be compared with any other firm in the acquiring firm's industry and thus identify a unique relatedness available to the acquiring firm. Defined in this way, research could begin to address the call for conducting less aggregate research on mergers and acquisitions, in which relatedness will be expected to lead to abnormal returns for bidding firms when those 'cash flows are private and unique, inimitable and unique, or unexpected' (Barney, 1988).

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APPENDIX 1: DERIVATION OF MODELS TO TEST PREDICTIONS WHEN MULTIPLE BUSINESSES CHANGE OWNERSHIP AS A GROUP

Derivation of Model 2: Estimate of market share with unconstrained parameters over time

$$MS_{i,t} = \alpha_t + \gamma_t d_{i,t} + X\beta_t + \epsilon_{i,t}$$
$$MS_{i,t+1} = \alpha_{t+1} + \gamma_{t+1} d_{i,t+1} + X\beta_{t+1} + \epsilon_{i,t+1}$$

Derivation of Model 4: Estimate of effect of predicted market share for groups of businesses which change ownership in the same transaction

For the group of businesses sold by one firm to another, the predicted change in market share for each business ownership change is used to calculate a sales-weighted average of prediction changes. Consistent with the hypothesis that restructuring should improve expected performance of businesses involved in each acquisition of a group of businesses, one expects this test to be significant and positive.

$$\sum_{j=1}^{n} P_{i,j} \cdot MS'_{i,j,t+1} - \sum_{j=1}^{n} P_{i,j} \cdot MS'_{i,j,t} = \alpha + \epsilon_i \qquad \text{(Model 4)}$$

The summation is for the sum across all businesses j which change ownership as a group, and $P_{i,j}$ weights them by their sales-weighted average in the group. The dependent variable is the difference

in average market share predictions (from Model 3), of a group of acquired businesses sold by firm $i = 1$ to firm $i = 2$. Using this model to test prediction changes from Model 1 (and Model 2), one can test H2, that the group of businesses on average increase predicted market share, with a positive and significant a.

Derivation of Model 6: Estimate of relation between predicted market share changes and actual market share changes for groups of business which change ownership in the same transaction

In Model 6, a sales-weighted average of the actual market share changes of the group of businesses which change ownership between time $t+2$ and $t+1$ are regressed on the weighted average of their predictions from the acquisition (the dependent variable in Model 4).

$$\sum_{j=1}^{n} P_{i,j} \cdot MS_{i,j,\,t+2} - \sum_{j=1}^{n} P_{i,j} \cdot MS_{i,j,t+1} = \alpha + \beta [\sum_{j=1}^{n} P_{i,j} \cdot MS'_{i,j,t+1} - \sum_{j=1}^{n} P_{i,j} \cdot MS'_{i,j,t}] + \epsilon_i$$

(Model 6)

APPENDIX 2: VALIDITY TEST OF MEASUREMENTS OF SEVEN DIMENSIONS OF OPERATIONAL RELATEDNESS

The clustering method suggested by Hoskisson *et al.* (1993, Appendix A) was followed as closely as possible to test for the validity of the measures used here with respect to previous measures of relatedness. Three sets of five clusters were created. The first, HClus, uses the means of the clusters as reported in Table 1 of Hoskisson *et al.* (1993) for seed points. The other two use hierarchical average linkage clustering to determine seed points which were then used in a nonhierarchical clustering algorithm (FASTCLUS) as described in Hoskisson *et al.* (1993, Appendix A). The second, DRClus, uses the variables specialization, related and unrelated defined by Hoskisson *et al.* (1993). The third, 7DClus, uses a seven-dimensional construct based on the seven relatedness variables used in this paper and substitutes this construct for DR.

The HClus/DRClus correlation shows that the procedure using variable means reported in Hoskisson *et al.* (1993, Table 1), as seeds is 0.77 correlated (*p*-value = 0.000) with the cluster construct derived using the same procedure on the data in this paper's sample of 774 firms (Hoskisson *et al.*, 1993, Appendix A). The DRClus/7DClus significant correlation of 0.56 shows a correlation (*p*-value = 0.000) between the entropy classification measure of diversification (Hoskisson *et al.*, 1993) using DR, as the dimension of relatedness, and a measure of diversification which substitutes a construct based on the seven relatedness variables used in this paper for the DR dimension. The seven relatedness variables at the business unit level were aggregated to one firm-level measure using sales weights.