Marketing and R&D Investment of Leader vs. Follower

June 2008

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Abstract

How do a leader and a follower use marketing and R&D differently for resource accumulation, and why? To address the question, we investigate asymmetric incentive structures with respect to marketing and R&D for a leader vs. a follower. In particular, we analyze the resource accumulation paths of Intel and AMD by utilizing 28-year quarterly time series data (1972-1999). In so doing, we adopt Structural Vector-Autoregressive (SVAR) modeling approach, dealing with two methodological challenges, i.e., context dependence and dynamic interdependence. Overall, we find that the leader (Intel) benefits more from its investment in marketing than the follower (AMD), while the follower gains more from its investment in R&D than the leader, consistent with the theoretical prediction. We also find that when the firm's market value unexpectedly increases the leader increases its marketing investment while the follower chooses to invest in R&D. Unlike the conventional First-Mover (Dis)Advantage research which focuses on the timing of entry, our study suggests that a firm, once having entered, may be better off by choosing different resource accumulation paths for marketing and R&D, based on its current market position. Finally, our results imply that there is no single best strategy; context determines what strategy will work best.

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1. Introduction

Marketing and R&D are two vital tools a firm can use to build its competitive advantage.[4] Since the competitive advantage of a firm over its rivals leads to "superior financial returns within its industry over the long run" (Ghemawat and Rivkin 1999, p.49), measuring the impacts of marketing and R&D spending on a firm's financial performance has been one of the popular topics in management and economics research. Previous studies have documented a positive impact of these two types of investments (e.g., Erickson and Jacobson 1992, Dutta et al. 1999). Prior researchers also investigate how the effectiveness of marketing and R&D differs by the type of industry (e.g., Chauvin and Hirschey 1993, Mizik and Jacobson 2003). The overall positive impact of marketing and R&D on financial performance has been repeatedly confirmed in cross-sectional or panel/pooled regression analysis.

The decisions of whether to invest in marketing or R&D and how much to invest in each tool should depend on the resources a firm already possesses and/or intends to build and a firm's position within its industry, however. The Resource-Based View or RBV argues that firms have different ways of accumulating their resources or firm-specific assets (Dierickx and Cool 1989, Teece et al. 1997). Within an industry, for instance, one firm may focus on acquiring the capability of innovation through R&D spending, while another firm may emphasize building the 'market-based assets' such as customer relationships, channel relationships, and partner relationships via marketing spending (Srivastava et al. 1998). The industrial organization literature has discussed how a firm can alter its competitors' economic incentive to imitate by brand proliferation (Schmalensee, 1978) or innovation (Dasgupta and Stiglitz, 1980), suggesting the means by which a firm can exploit its market position.

[4] Drucker (1954, pp. 37-38) pointed out that marketing and innovation are "two basic functions" of modern firms.

Similarly, the returns from investments in marketing and R&D should vary with a firm's resources and market position. Under the conventional assumption of a value-maximizing firm, we expect that firms choose their budget allocations based on the expected financial returns on the firm-specific assets. In other words, each firm must choose a different resource accumulation path. Past studies have shown that intra-industry differences in financial performances are greater than inter-industry ones, implying that firm-specific effects are more important to explain financial performance than industry effects (e.g., Rumelt 1991, McGahan and Porter 1997). These results indicate that resource accumulation paths strongly influence firms' performance. Thus, it would be worth examining 1) how current and past marketing and R&D spending influence intra-industry differences in financial performances over time, and 2) how the expectation on financial performances differently influences future marketing and R&D budget allocation decisions for firms within an industry. This would be an important contribution to strategy literature given that the RBV has been criticized "for its lack of (empirical) studies that consider how resources evolve over time" (Lieberman and Montgomery 1998, p.1112).

In particular, the choice of resource accumulation path must hinge on whether a firm is a leader or a follower in the product market. In the First-Mover Advantage or FMA literature, empirical researchers have focused on the relationship between the order/timing of market entry and financial performances such as market share and profit (Lieberman and Montgomery 1998). However, it is still inconclusive whether it is advantageous or disadvantageous to be a leader (first-mover) or a follower. The first-mover advantages depend on the initial resources captured by a leader, plus the resources subsequently developed by the leader as compared to the quality of resources captured by a follower (Lieberman and Montgomery 1998), and so they are highly context dependent. An examination of resource accumulation paths for a leader vs. a follower in

a specific industry will help our understanding of the mechanism of first-mover advantages from a dynamic perspective.

The purpose of this paper is to explore how asymmetric resources and market positions of a leader and a follower lead to their different investment choices in marketing and R&D, and how these firms benefit from these choices. In so doing, we view financial performance as both an outcome and a cause of marketing and R&D spending decisions. We derive testable predictions from a game-theoretic model, and then test these predictions by addressing the dynamic, interdependent relationship between financial performance and strategic investment decisions with respect to marketing and R&D spending.

To achieve this goal, we examine the resource accumulation paths of Intel and AMD by utilizing 28-year quarterly time series data (1972-1999). Intel and AMD have been regarded as two giants in the microprocessor industry, in which Intel maintained the undisputed leader's position over the period we examine. The microprocessor industry is an ideal industry to analyze the role of marketing and R&D on a firm's performance because both tools have played important roles for the development of the industry. This industry is also ideal to examine the source of FMA because the boundary of the industry is very clearly defined, and so the leader and followers in the industry are clearcut. For data analysis, we use a Structural Vector Auto-Regressive (SVAR) modeling approach, which allows us to examine the firm-specific evolution of resource accumulation, rather than 'on-average' effects of marketing and R&D.

We find that the leader (Intel) benefits more from its investment in marketing than the follower (AMD), while the follower gains more returns from its investment in R&D than the leader. This finding is consistent with the theoretical prediction that a leader may put more weight on marketing to appropriate maximum value from its current market position, while a

follower spends more on R&D to catch up technological gaps and to increase the probability of creating superior next generation products. Likewise, we find that when there is an opportunity for discretionary spending the leader will increase its marketing investment, while the follower chooses to invest in R&D.

We contribute to the literature by proposing a methodology to formally analyze the sources and consequences of FMA. We link the predictions of a game-theoretic model with a SVAR modeling, which allows us to address the asymmetry of the resources a leader and a follower accumulate, and to examine how this asymmetry leads to different strategic investment decisions and financial performances by incorporating a dynamic perspective. We believe this approach is useful to analyze the role of resource accumulation in a specific context and provides a finer lens for the empirical examinations of FMA.

We proceed as follows: In the next section, we discuss asymmetric financial incentive structures for a leader vs. a follower. We also explain two methodological challenges, i.e., context dependence and dynamic interdependence and discuss how we use the SVAR modeling approach to overcome them. In the third section we review the history of the microprocessor industry, focusing on the competition between Intel vs. AMD. Next we explain our data, model, and results. Finally, we discuss managerial implications and suggest directions for future research.

2. Theory and Methodology

2.1 Asymmetric financial incentive structures for a leader vs. a follower

It has been documented that a leader and a follower have different incentives to innovate. In economics literature, the patent race between a leader and a follower has been extensively studied (for a review, see Reinganum 1989). Some researchers show that a leader has a greater incentive to invest in R&D than a follower because it is motivated to maintain its monopoly rent stream, while others argue a follower has a greater incentive to innovate when the innovation is drastic and gives a follower a chance to displace a leader (Loury 1979, Gilbert and Newbery 1982). While the game-theoretic models proliferate (e.g., Fudenberg et al. 1983, Grossman and Shapiro 1987), empirical examination of the competition in innovation is relatively limited with a few exceptions (e.g., Khanna 1995, Lerner 1997, Sundaram et al. 1996).

In these studies, however, less attention has been paid to another key strategic investment option, i.e., marketing spending (Khanna 1995, Ofek and Sarvary 2003). Yet firms often need to invest in complementary assets such as marketing to profit from own innovation (Teece 1986). Theoretically, it is not clear whether marketing spending has greater benefits for leaders or followers. Some argue that marketing may be helpful for leaders since it creates entry/mobility barriers (e.g., Bain 1956, Schmalensee 1982), while others claim that marketing provides a gateway for followers to access the market (e.g., Benham 1972).

Recently, Ofek and Sarvary (2003) explicitly allow firms to simultaneously undertake marketing and R&D investment and analyze how a leader and a follower have different incentives, using game-theoretic modeling in a multi-period, oligopolistic setting. They assume a fast-changing, technology-intensive market. In each of infinitely many discrete periods, firms invest to generate new products. The higher level of R&D and marketing investments yields

greater chances of success, with diminishing returns to such investments. The outcome of these investments is ex ante uncertain, and the products developed compete in the subsequent period. While the investment in R&D has an impact on a firm's future success, investment in marketing boosts current-period sales as well as increases the chances of future success. Firms maximize their expected discounted economic profits. In each period, firms first simultaneously determine their R&D and marketing investment level, and decide on pricing strategies in the second stage. The successful firm in each period enjoys the lead position, which entails higher than follower per-period profits and bears higher capabilities for next-generation success. The authors show that the leader has a greater incentive to invest in marketing than the follower because the return to marketing in the current period is higher for the leader, as it can leverage its existing stronger appeal to consumers to increase profits. They also show that the follower has a greater incentive to invest in R&D than the leader because the follower wants to increase the probability of acquiring future technological leadership. The follower prefers to forgo current competition in marketing because the basic demand for its product is lower, and so gains from marketing are lower. Their theoretical prediction is appealing, yet, to our knowledge, their assertion has not been thoroughly examined empirically.

If their prediction holds, we can derive the following hypothesis.

HYPOTHESIS 1. *The expected financial return on marketing will be higher for a leader than for a follower, while the expected financial return on R&D will be higher for a follower than for a leader.*

In order to evaluate the effectiveness of marketing and R&D investments, we need to consider which financial performance measures would be suitable for the empirical analysis.

Prior strategy research has extensively used accounting-based financial indicators such as profitability (e.g., ROA) and sales growth (Venkatraman and Ramanujan 1986), which reflect distinct dimensions (Venkatraman and Ramanujan 1985). In particular, Geroski et al. (1997) find that sales growth represents prospects about the long-run profitability of a firm. Therefore, we employ ROA and sales growth, capturing short-run and long-run financial performance of leader and follower in the product market. In spite of the importance of accounting-based financial indicators in practice (e.g., Graham et al. 2005) and in academia (e.g., Lippman and Rumelt 2003), researchers have recognized certain limitations in those indicators (Venkatraman and Ramanujan 1986). Accordingly, we also employ a stock-market based financial indicator, market-to-book ratio, to quantify the financial incentive structure imposed by the stock market (Rumelt 2003).

Thus we expect that leader and follower have asymmetric financial incentive structures in terms of product market and stock market response measures, based on the theoretical prediction made by Ofek and Sarvary (2003). In order to empirically examine the proposed hypothesis, however, one should resolve two methodological challenges: 1) the context dependence problem of game theoretic modeling, and 2) dynamic interdependence between marketing, R&D, and financial performance measures. These issues and our empirical coping strategies will be discussed in the subsequent sections.

2.2 Context dependence and time-series analysis

When conducting an empirical study to examine a theoretical prediction derived from game-theoretic modeling, the biggest challenge is the ‘context dependence’ problem (Sutton 1992). Even though game-theoretic modeling has been successful in explaining how a firm strategically

interacts with its rivals (Teece et al. 1997), it tends to be "rather specific in that the behavior that emerges in equilibrium depends on the precise state of the environment" (Saloner 1991, p.132). Accordingly, different outcomes, or even multiple equilibria can be obtained depending on the assumptions set by a modeler (Teece et al. 1997).

To resolve the context dependence problem, Saloner (1991) suggests a data-driven approach, insisting that researchers should examine whether the data are consistent with the qualitative features derived from the analytic model. Yet, Saloner (1991, p.132) also points out that it is difficult for empirical researchers to find large samples of firms "that face exactly the kinds of environments envisaged by the models". In our case, Ofek and Sarvary (2003)'s theoretical prediction may not apply outside industries characterized as fast-paced, technology-intensive, and more importantly, oligopolistic. This means that it is not effective to examine their theoretical prediction by pooling data from heterogeneous industries with the conventional cross-sectional/panel data analysis approach. Indeed, Camerer (1991, p.146) suggests "(empirical) researchers might have to focus on smaller samples of firms and study each firm more carefully." He also argues that case studies might be a better data source than archival data. However, inference based on a one-shot case study with limited samples may not be generalizable.

To some extent, this dilemma can be overcome by utilizing long time-series data of the firms involved (Camerer 1991). If theorists develop game theoretic models for an industry and empirical researchers examine these models' predictions utilizing long time-series data of that industry, then the sum of models and empirical results will contribute to a rich understanding of a business environment (Saloner 1991). This approach focuses on accommodating the context rather than finding a general principle. However, this approach will be useful to inform

companies how to succeed, where they seek an idiosyncratic solution rather than a general principle (Camerer 1991).

Thus, we will use time-series analysis to investigate the role of asymmetric financial incentive structures for a leader vs. a follower in marketing and R&D investment, thereby overcoming the context dependence problem. To achieve the goal, the choice of an industry is important. In this paper, we analyze the microprocessor industry. This industry possesses fast-paced, technology-intensive, and oligopolistic characteristics, consistent with the basic settings assumed by Ofek and Sarvary (2003). In particular, we focus on the different resource accumulation paths of Intel vs. AMD. We choose Intel and AMD because these two firms are 1) the two dominant microprocessor manufacturers in the US market as well as in the global market, and 2) at the same time, the gap in market power and technological leadership between the two players has been clear.[5] The former characteristic increases the validity of the study, while the latter helps us to identify the leader and the follower. This ease of identification of the leader vs. the follower substantially removes "the subject elements (of identification) that clouds much of the FMA literature" (Lieberman and Montgomery 1998, p.1115).

2.3 Dynamic interdependence and Structural Vector Auto-Regressive (SVAR) modeling

When we quantify the financial incentive structures using longitudinal or time-series data, dynamic interdependence among marketing, R&D, and financial performance measures (e.g., accounting profit, stock price) should be taken into consideration (see Figure 1). First, marketing and R&D spending may improve current financial performances (contemporaneous effect) and future performances (carry-over effect). Second, financial performance measures may influence

[5] In 1999, Intel's revenue was $29.39 billion and AMD's revenue was $2.86 billion. In terms of technological gap, Intel can be regarded as having been superior to AMD at least until 1999 (Ofek and Sarvary 2003).

the future budget of marketing and R&D (feedback effect) and the current spending level of marketing and R&D (earnings management effect[6]). In addition, there may be autocorrelations in discretionary spending (e.g., firm-specific budgeting rules) as well as in financial performance measures (e.g., self-enforcement, momentum). Third, marketing and R&D may also be positively interrelated. The effectiveness of marketing is likely to increase when the R&D function successfully introduces innovative or improved products (Dutta et al. 1999). Further, marketing is important not only for recovering past R&D investments but also for reserving financial resources for future innovation activities. R&D may also contribute to increased cash flows, which can be used to invest in marketing in the future. For more details, see Shin (2006).

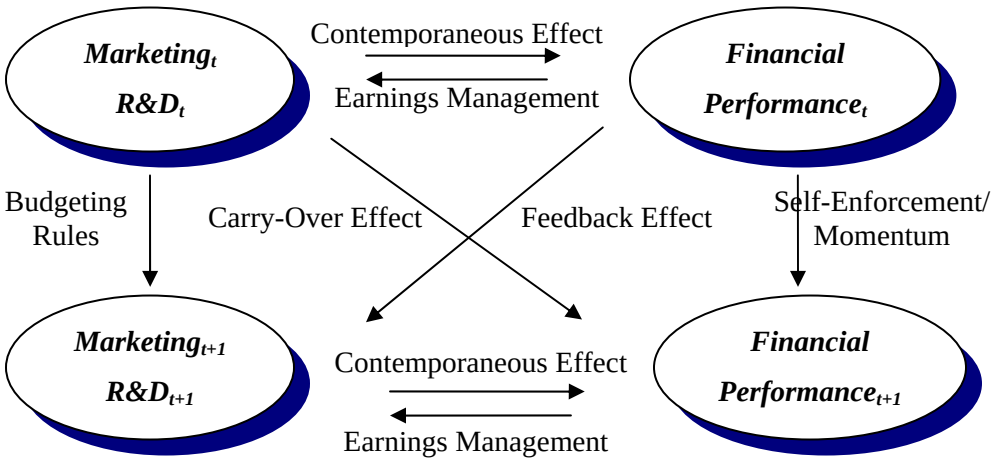

Figure 1: Dynamic Interdependence among Marketing, R&D, and Financial Performances

Considering the feedback effect and earnings management effect, coupled with the theoretical prediction made by Ofek and Sarvary (2003), we expect an asymmetric behavior of a

[6] In accounting/finance literature, marketing/R&D spending is called 'discretionary spending', meaning it is often cut down to artificially boost accounting profits, i.e., earnings management. Regarding the earnings management literature, see Trueman and Titman (1988) for an analytical model, DeGeorge et al. (1999) for an empirical analysis, and Graham et al (2005) for a large scale survey. For a literature review, see Stlowy and Breton (2004).

leader vs. a follower when they face an increase in financial outcomes. Graham et al. (2005) report that managers are willing to sacrifice real economic gains to boost earnings, and thus, to improve firm values. Then positive shock in earnings or firm values may encourage managers to increase their discretionary spending in order to realize real economic gains. If marketing (R&D) is useful for a leader (follower), then the positive shock in financial performance measures will lead to an increase in marketing (R&D). Thus we expect

HYPOTHESIS 2. *When there is an unexpected increase in financial performance measures, a leader will increase marketing spending more than a follower, while a follower will increase R&D spending more than a leader*.

Such dynamic, interdependent relationships result in 'chain reactions' in the system (Dekimpe and Hanssens 1995). Therefore, ignoring the endogeneity due to the simultaneity among focal variables may lead to biased and inconsistent estimates (Greene 2003). One way of dealing with simultaneity is to use instrument variables or IV method. Yet the heterogeneity bias problem cannot be resolved even with IV method in a dynamic linear panel model setting (Pesaran and Smith 1995). Specifically, if there exists heterogeneity across firms in their strategic positions, then their marketing and R&D decisions may lead to different responses from customers and investors. Then, our estimates will be biased in spite of using IV method. Another way to address simultaneity is to apply Vector Auto-Regressive (VAR) modeling approach. VAR model, originally designed by Sims (1980), is an N-equation, N-variable linear system of equations in which each variable is explained by its own lagged values, plus current and past values of the remaining N-1 variables. This simple framework provides a systematic way to capture rich dynamics in multiple time series (Stock and Watson 2001). In particular, by

applying Impulse Response Function (IRF) analysis, one can fully examine the impact of one endogenous variable on any other endogenous variable in the system. IRF analysis systematically traces the incremental effect of a one-unit shock (i.e., unexpected change) in an endogenous variable on other endogenous variables, capturing the consequence of chain reactions among variables (Enders 2004).

Originated in the field of economics, VAR modeling has been used in diverse management disciplines including accounting (e.g., Bar-Yosef et al. 1996), finance (see Campbell et al. 1997, pp.279-286 for a review), and strategy (e.g, Nair and Filer 2003), though its use in strategy is still limited.[7] In marketing discipline, VAR framework has provided valuable insights into dynamic effects on diverse financial performance measures of marketing mix variables including advertising, distribution, promotion, and product (for a review, see Dekimpe and Hanssens 2004). These studies, however, focus on the dynamic impacts of marketing on financial performances. Our study goes beyond previous studies; in addition to examining the long-term effects of marketing on financial performance, we are interested in investigating 1) *the long-term impact of R&D on financial performance*, 2) *the role of financial resources on marketing and R&D budgeting (through feedback effect and earnings management effect)*, and 3) *the positive interdependence between marketing and R&D*, considering *the role of asymmetric financial incentive structures of the leader vs. follower with respect to marketing and R&D spending*.

One criticism of VAR modeling is that it is first specified and estimated in a reduced form, and then its structural form is recovered using the estimates in an ad-hoc way (e.g.,

[7] Nair and Filer (2003) is one of a few exceptions, but they rather focus on estimating cointegration relationship (i.e., long-run equilibrium) among firms within a strategic group by checking "speed of adjustment" coefficients from the cointegrating vector. In contrast, our paper aims to study individual firm level incentive structure as well as dynamic interdependence among marketing, R&D, and financial measures by using IRF analysis.

Choleski decomposition), which causes the result to be dependent on the pre-imposed ordering of variables. Accordingly, Koop et al. (1996) develop Generalized Impulse Response Function (GIRF) method, which is insensitive to the ordering (Pesaran and Shin 1998). However, GIRF is also a data-driven approach, and thus, less appropriate for a policy simulation (Pauwels 2004). To address this issue, we adopt Structural Vector Auto-Regressive (SVAR) modeling approach (Sims 1986), which imposes identification restrictions on the contemporaneous relationships among endogenous variables based on economic reasoning (see Appendix 1). We discuss the procedure in the fourth section.

In sum, SVAR modeling is well suited for our research goal of examining the proposed hypotheses with firm-specific longitudinal data, while at the same time resolving issues such as the context dependence of game theoretic modeling as well as dynamic, interdependent relationships among focal variables.

3. History of the Microprocessor Industry[8]

The microprocessor industry is a large and growing industry, whose global market value was $3.6 billion in 1991 (Gruber 2000) and exceeded $30.5 billion in 2004 (Semiconductor Industry Association 2005). Unique properties of this industry include: 1) The short product life-cycle leads to the continual introduction of next-generation products (Norton and Bass 1987); 2) In each generation, a number of firms almost simultaneously introduce their cutting-edge products, while (typically) only one firm succeeds in attaining supra-normal profits (Ofek and Sarvary 2003); 3) Due to the high level of manufacturing complexity, the market has been dominated by

[8] See Collis and Pisano (1999), Gruber (2000), Yager (2004), and Gordon (2007) for excellent reviews of the histories of Intel, AMD, and the evolution of the microprocessor industry.

a few gigantic global companies (Gruber 2000); and 4) Unlike other high-tech industries in which leadership shifts occur frequently across generations, one company, Intel, has retained its technological leadership (Ofek and Sarvary 2003).

Founded in 1968, Intel developed the first commercial microprocessor, the 4004, in 1971. During the 1970s, Intel was a leader in the DRAM market. Facing intense competition from Japanese DRAM producers in the early 1980s, Intel shifted its focus to the microprocessor market. Intel's x86 chips were a huge success, and Intel benefited from the expansion of the PC industry thereafter.

AMD's growth is partly owing to Intel. To secure a steady chip supply, IBM requested Intel to contract with another manufacture as a secondary source. To comply, Intel licensed its chip designs to other manufacturers including AMD. AMD, founded in 1969, agreed to discard its own architecture in 1982 and produced Intel's 286 chips under the licensing agreement. Intel, however, cancelled the agreement in 1986, refusing to reveal its design of 386 chips to AMD. AMD sued Intel in 1987 and the relationship between Intel and AMD became bitter. In 1991, the Supreme Court of California decided that Intel should pay over $1 billion for the violation of contract. However, the right to use the derivatives of Intel's design was still in dispute until the Court made a final ruling in 1996. Before the final ruling, AMD dealt with uncertainty by developing its own design. In 1996, the Court decided that AMD had no legal right to Intel's Pentium chips. Consequently, AMD began to improve its own design capabilities, considerably reducing the performance gap vs. Intel. In 1999, AMD introduced Athlon, the first chip developed by its own design free from Intel's technology. The performance of Athlon was comparable to Intel's chips in terms of speed and stability, which provided mid-sized manufacturers with a more affordable option (Yager 2004). In 2000, Athlon went down in

history by becoming the first chip to break the 1 GHz (1 billion clock cycles per second) barrier. This is often regarded as the turning point after which there is no more technology gap between Intel and AMD.

While the fierce competition in the mid-1990s resulted in falling prices and shortened product life cycle (Aizcorbe 2005), the market position of the two giants has been rather stable: Intel's market share was consistently over 70% in the 1990s, while AMD's market share was fluctuating around 15% during the same time (Gordon 2007). Interestingly, the way these companies used marketing and R&D was quite different. In a B2B setting like the microprocessor industry, managing customer relationship with one's distribution channel — in this case, with PC manufacturers — is imperative (Dutta et al. 1999). Accordingly, Intel has offered diverse incentive programs, including volume discount, to build customer loyalty. Moreover, Intel has launched the "Intel Inside" campaign to create brand equity since 1990. As for R&D, both Intel and AMD have spent extensively to innovate their products as well as to improve their manufacturing processes. For example, Intel spent over $1 billion in the third quarter of 1999, while AMD spent $158 million during the same quarter. During the analysis period (1972-1999), Intel's R&D intensity ranges between 2–5%, with AMD between 1–8%.

In particular, as shown in Figure 2, the two firms show different patterns of R&D/marketing spending behavior. Intel has given relatively more attention to marketing, while AMD has spent relatively more on R&D activities. Moreover, Intel focused more on R&D during its early stage (until 1973), but after then it has shifted its emphasis from R&D to marketing. In contrast, AMD has radically increased its emphasis on R&D since the early 1980s. In the next section, we will examine what makes the leader (Intel) and the follower (AMD) to

choose different resource accumulation paths regarding marketing and R&D by analyzing the time-series data.

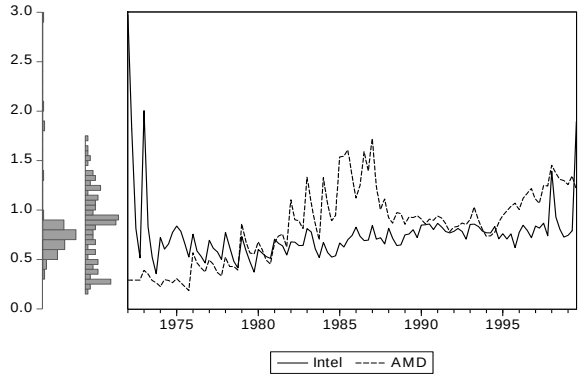

Figure 2: R&D Spending(t)/Marketing Spending(t) Pattern of Intel vs. AMD (1972-1999)

4. Data, Model, and Results

4.1 Data

For the empirical analysis, we obtain the quarterly financial data of Intel and AMD over the time periods between 1972:1Q and 1999:3Q (i.e., T=111) from the COMPUSTAT and CRSP database.

Product Market Response Measures: To capture the contemporaneous profitability implication, we obtain a comprehensive profitability measure, **Return on Asset (ROA)**, by using Net Income before Extra-ordinary Items (NI before EI) divided by Total Asset.[9] To represent the expectations about the long-run profitability, we compute Sales Growth (SG) at

[9] Note that NI before EI is similar to Operating Income in our data. NI before EI includes non-operation items such as Gains (Losses) on Securities and Interests. But the importance of those items is limited. For instance, Intel reports that the adjustment due to non-operation items account for 2-3% during 2002-2004, meaning that Operating Income and NI before EI are very close to each other (Intel's Form 10-K, 2005).

time t by computing [(Sales(t+1)-Sales(t))/Sales(t)] where Sales(t) refers to Sales in dollar value at time t.

Stock Market Response Measure: In economics and management literature, popular proxy measures of firm value include Tobin's Q (e.g., Dutta et al. 1999), stock return (e.g., Erickson and Jacobson 1992), market value of common equity (e.g., Chauvin and Hirschey 1993), and market-to-book ratio (e.g., Joshi and Hanssens 2004). We use **Market-to-Book ratio (MB)**, which is computed as the product of Stock Price and Outstanding Shares divided by Shareholder's Equity.

Marketing and R&D Spending: To measure the marketing inputs, we rely on Sales, General, Administrative Spending (SGA). Dutta et al. (1999) use SGA as a proxy for diverse marketing activities since SGA contains abundant information regarding market research, advertising, cooperative marketing program funds (e.g., the "Intel Inside" program), distribution (e.g., sales force compensation), and other related sales efforts. This information is particularly relevant to marketing activity of microprocessor manufacturers playing in a B2B setting. However, SGA contains R&D-related components such as R&D costs and purchased in-process R&D. Therefore, we separate these costs from SGA, which together are used as a proxy of R&D inputs, i.e., **R&D Spending (RD)**. As a result, we obtain **Marketing Spending (MKT)** as SGA minus R&D. One important issue here is whether the MKT variable is a valid measure for our empirical analysis. We examine the validity of MKT in diverse aspects and conclude that MKT is a reasonably good (but not perfect) proxy for marketing spending (see Appendix 2). Both **RD** and **MKT** variables are scaled by using Total Asset, meaning that they are R&D and marketing intensity measures, respectively.

Table 1 contains descriptive statistics for our focal endogenous variables discussed so far. Note that the variance of MKT is twice bigger than that of R&D for both Intel and AMD. This suggests that marketing spending fluctuates more possibly due to the earnings management motivation of executives.

	Intel (T=110)					**AMD (T=110)**				
Variable	**ROA**	**SG**	**MB**	**RD**	**MKT**	**ROA**	**SG**	**MB**	**RD**	**MKT**
Mean	0.04	0.08	4.14	0.03	0.04	0.01	0.07	2.51	0.04	0.06
Median	0.04	0.08	3.59	0.03	0.04	0.01	0.06	2.11	0.04	0.05
Max	0.09	0.47	11.57	0.05	0.09	0.08	1.54	8.96	0.08	0.11
Min	-0.05	-0.16	1.58	0.02	0.01	-0.07	-0.62	0.45	0.01	0.03
Std.Dev.	0.02	0.11	2.03	0.01	0.02	0.03	0.20	1.54	0.01	0.02

Table 1: Descriptive Statistics

4.2 Model

Unit Root Test: Before specifying our VAR model, we first perform unit root tests to see if our focal variables are stationary or evolving (i.e., non-stationary). The unit root test results suggest that all variables are stationary, which allows us to set up our *VAR model in level* (i.e. no adjustment is necessary) for both Intel and AMD cases (see Appendix 3). The unit root test results also suggest that there is no structural break in our data over the analysis period (1972-1999), which allows us to analyze data without dividing it into sub-periods.

Model Specification: Next, we specify our structural-form VAR model. As described in Figure 3, the model captures both contemporaneous and lagged relationships among focal variables. In particular, the B matrix captures the contemporaneous relationships. To construct the B matrix, we derive identification restrictions based on the following assumptions: 1) firm

value (MB) has no contemporaneous effect on product market response measures (SG, ROA) and discretionary spending (MKT, RD); 2) growth (SG) does not influence current discretionary spending (MKT, RD); 3) profitability (ROA) has neither contemporaneous effect on growth (SG) in an accounting sense nor contemporaneous effect on current R&D spending budgeting decision (RD); 4) marketing (MKT) does not have a contemporaneous effect on R&D, considering the relative importance of R&D over marketing in the microprocessor industry; and 5) R&D (RD) does not have a contemporaneous effect on growth (SG).

$$Bx_t = \Gamma_0 + \sum_{p=1}^{P} \Gamma_p x_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_i^2 I), \quad i = 1,2,...,5$$

$$where\ B = \begin{bmatrix} 1 & b_{12}^0 & b_{13}^0 & b_{14}^0 & b_{15}^0 \\ 0 & 1 & 0 & b_{24}^0 & 0 \\ 0 & b_{32}^0 & 1 & b_{34}^0 & b_{35}^0 \\ 0 & 0 & b_{43}^0 & 1 & b_{45}^0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \Gamma_p = \begin{bmatrix} \varphi_{11}^p & \varphi_{12}^p & \varphi_{13}^p & \varphi_{14}^p & \varphi_{15}^p \\ \varphi_{21}^p & \varphi_{22}^p & \varphi_{23}^p & \varphi_{24}^p & \varphi_{25}^p \\ \varphi_{31}^p & \varphi_{32}^p & \varphi_{33}^p & \varphi_{34}^p & \varphi_{35}^p \\ \varphi_{41}^p & \varphi_{42}^p & \varphi_{43}^p & \varphi_{44}^p & \varphi_{45}^p \\ \varphi_{51}^p & \varphi_{52}^p & \varphi_{53}^p & \varphi_{54}^p & \varphi_{55}^p \end{bmatrix}, x_t = \begin{bmatrix} MB_t \\ SG_t \\ ROA_t \\ MKT_t \\ RD_t \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \varepsilon_{MB_t} \\ \varepsilon_{SG_t} \\ \varepsilon_{ROA_t} \\ \varepsilon_{MKT_t} \\ \varepsilon_{RD_t} \end{bmatrix}$$

Figure 3: Identification of the Structural-Form VAR Model

The parameters in the B matrix can be interpreted as follows: first, current firm value (MB) is influenced by current accounting numbers (SG and ROA) through b^0_{12} and b^0_{13} (Varaiya et al. 1987) as well as current discretionary spending level (MKT, RD) through b^0_{14} and b^0_{15}; second, current sales growth (SG) is affected by current level of marketing spending (MKT) through b^0_{24}; third, current profitability (ROA) is influenced by current sales growth (SG) through b^0_{32} (Cho and Pucik 2005)[10]. Moreover, ROA is influenced by current discretionary spending (MKT, RD) through b^0_{34} and b^0_{35} because discretionary spending directly reduces current earnings; fourth, current marketing (MKT) is influenced by current profitability (ROA) via b^0_{43}, representing firms' earnings management behavior. Specifically, we assume that

[10] Cho and Pucik (2005) empirically show that growth influences profitability, but not vice versa.

managers adjusting their current marketing spending level consider its effects not only on the top line (revenue) but also on the bottom line (ROA). Thus, b^0_{43} captures *'earnings management effect'* as described in Figure 1, representing managers' incentives to report reasonable profits or to meet analysts' earnings forecasts (e.g., Graham et al. 2005); and finally, current marketing (MKT) is also affected by current R&D (RD) through b^0_{45}, but not vice versa. Note that we assign the causal priority to R&D over marketing because of the nature of the microprocessor industry. For instance, if there is an unexpected increase in R&D spending for some reason (e.g., a price shock in crucial equipments that should be purchased for R&D during this period), managers would be willing to cut down the current period's marketing spending under the budget constraint for discretionary spending. But, if there is an unexpected need for increasing marketing (e.g., fee increase for TV advertising spot), managers would cut down other parts of marketing spending (e.g., purchase fewer market research reports), rather than adjust R&D spending.

Estimation: Since it is not easy to directly estimate our structural-form VAR model, we multiply both sides of the model by B^{-1} and obtain the reduced-form VAR model as shown in Figure 4 (also see Appendix 1.1 for a detailed explanation). Then we estimate the reduced-form model using Ordinary Least Squares (OLS) method, which provides us with consistent and efficient estimates. As for the number of lags (p), we choose one lag for AMD and seven lags for Intel (see Appendix 4.1 for the detailed lag length selection procedure). We also include three exogenous control variables, i.e., Real GDP, S&P 500 index, and Seasonal Dummy (see Appendix 4.2 regarding the control variables specification).

$$x_t = \Pi_0 + \sum_{p=1}^{P} \Pi_p x_{t-p} + e_t, \quad e_t \sim N(0, \Sigma_e)$$

$$where\ x_t = \begin{bmatrix} MB_t \\ SG_t \\ ROA_t \\ MKT_t \\ RD_t \end{bmatrix}, \Pi_p = \begin{bmatrix} \pi_{11}^p & \pi_{12}^p & \pi_{13}^p & \pi_{14}^p & \pi_{15}^p \\ \pi_{21}^p & \pi_{22}^p & \pi_{23}^p & \pi_{24}^p & \pi_{25}^p \\ \pi_{31}^p & \pi_{32}^p & \pi_{33}^p & \pi_{34}^p & \pi_{35}^p \\ \pi_{41}^p & \pi_{42}^p & \pi_{43}^p & \pi_{44}^p & \pi_{45}^p \\ \pi_{51}^p & \pi_{52}^p & \pi_{53}^p & \pi_{54}^p & \pi_{55}^p \end{bmatrix}, e_t = \begin{bmatrix} e_{MB_t} \\ e_{SG_t} \\ e_{ROA_t} \\ e_{MKT_t} \\ e_{RD_t} \end{bmatrix}$$

Figure 4: Reduced-Form VAR Model in the Levels with p Lags

Structural Decomposition: Now we need to recover the parameters of the structural form (the B matrix in Figure 3) using the estimated residual matrix from the reduced-form VAR model described in Figure 4. Note that we have the following relationship between the residual matrix and structural shock matrix:

$$e_t = B^{-1} \cdot \varepsilon_t \ or\ B \cdot e_t = \varepsilon_t$$
$$where\ \varepsilon_t \sim N(0, \sigma_i^2 I)\ and\ e_t \sim N(0, \Sigma_e)$$

Figure 5: Relationship between Structural Shock Matrix (ε_t) and Residual Matrix (e_t)

Using this relationship, we estimate the B matrix by maximum likelihood method. We then derive impulse response functions (IRFs) using the estimated B matrix as well as estimated coefficients matrices from the reduced-form VAR model in Figure 4 (see Appendix 1.2 for the detailed procedure). IRFs describe the response of endogenous variables to the shocks on endogenous variables over certain time periods.

IRF Analysis: Next we perform IRF analysis, which is a useful tool to quantify the dynamic effect of a focal variable on the other endogenous variable. Specifically, we compute two forecasts, one based on information set without a shock in the focal variable (e.g., marketing), and another with a shock. The difference between the two forecasts captures the incremental effect of unexpected movements or shocks over time (Dekimpe and Hanssens 1995).

This feature is especially beneficial in investigating the behavior of the firm value or stock price since we often assume investors react only to shocks, i.e., unexpected deviations from their expectations (e.g., Erickson and Jacobson 1992, Pauwels et al. 2004). We compute impulse response functions up to 20 periods, i.e., 20 quarters or 5 years in our data. We define short-term and long-term effects based on a 'fiscal year' concept, following Shin (2006).[11] Specifically, we regard the sum of IRF values within the first 4 periods (i.e., 1 fiscal year) as the short-term effect, while we refer to the sum of IRF values beyond 4th period until IRF values converges to zero as the long-term effect. The total effect can then be obtained by adding the short-term effect and long-term effect. We apply a '|*t-stat*| >1.645' criterion to identify statistically significant IRF values, which means that we sum all the IRF values whose significance is greater than this cutoff.[12]

4.3 Results

Dynamic impacts of marketing and R&D: In HYPOTHESIS 1, we hypothesize that *the expected financial return on marketing will be higher for a leader than for a follower, while the expected financial return on R&D will be higher for a follower than for a leader.* We examine the hypothesis via IRF analysis. Table 2 presents the results. To enhance the comparability of the findings, we compute unit-free elasticities, accounting for scale differences

[11] If the effect persists due to the non-stationarity of endogenous variables, then we call it **persistent effect**, following Dekimpe and Hanssens (1995). Persistent effect can be quantified by the non-zero asymptotic value of IRF coefficients. But we do not observe persistent effects since all endogenous variables in our data are stationary.

[12] For pure forecasting purposes, all IRF values should be summed up regardless of their significance level. Researchers, however, often apply statistical criterion to assess the dynamic effects of focal variables in a more conservative way. Prior studies in economics (e.g., Pesaran, Pierse and Lee 1993) and management (e.g., Dekimpe, Hanssens, Silva-Risso 1999) conventionally adopt a *'|t-stat|>1'* criterion, considering the multicollinearity problem which is inherent in VAR model specification with a number of lagged variables. Our criterion is stricter than the conventional one. Our criterion can be interpreted as the lower bound for the 90% significance level, considering the multicollinearity problem in VAR method.

across variables and across firms. For example, we find that Intel's marketing has a short-term effect on ROA (0.83). This means that if Intel unexpectedly increases its marketing spending by 10% (i.e., a 10% marketing shock), then Intel's ROA will be increased by 8.3%.

When we use our measures of product market response, we find the positive total effect of marketing on profitability (0.83) for Intel, but none for AMD. This is consistent with the theoretical prediction that, in order to exploit its technological advantage a leader will have more incentive to spend on marketing than a follower. In addition, we observe that Intel's R&D spending has a positive effect on sales growth and ROA, which represents the capability of R&D to improve the quality of product holding the unit cost fixed and/or to achieve cost reduction given an unchanged price (Darby and Zucker 2006). As expected, R&D spending shows both short- and long-term effects, with long-term effects generally bigger. The finding that the short-term effect (of Intel's R&D) on sales growth is bigger than the long-term one is interesting, but not unreasonable given that R&D aims not only at achieving a 'pure' innovation but also at improving the value of products via product modification and/or cost reduction. In contrast, AMD's marketing and R&D has no effect on sales growth or on ROA.

IRF Analysis		**Intel**		**AMD**	
Impact of marketing and R&D on financial performances		**Marketing**	**R&D**	**Marketing**	**R&D**
Product Market Response	Sales Growth	ST: - LT: -	**ST: 0.91** **LT: 0.79**	ST: - LT: -	ST: - LT: -
	ROA	**ST: 0.83** LT: -	**ST: 0.45** **LT: 3.40**	ST: - LT: -	ST: - LT: -
Stock Market Response	Market-to-Book Ratio	**ST: 0.25** LT: -	**ST: -** **LT: 0.47**	ST: - LT: -	**ST: 1.03** **LT: 1.10**

(ST: Short-term effect, LT: Long-term effect, Total Effect = ST + LT)

Table 2: Dynamic Impacts of Marketing and R&D on Financial Performance Measures

As for stock market response, we find that investors react favorably to a positive shock or an unexpected increase in Intel's marketing (0.25), but not to a shock in AMD's marketing. Moreover, the magnitude of the total effect of AMD's R&D is considerable (2.13), much bigger than the effect of Intel's R&D (0.47). This would be a good reason for AMD's executives to increase their R&D in spite of the ineffectiveness of its R&D on growth and profitability. This finding can be interpreted as follows: Wall Street sees the R&D focus of AMD as a 'right' move considering its market position, and so they react favorably to it. This implies that 1) *in order to maximize shareholder value, firms should carefully observe the implicit directions given by Wall Street and send the appropriate signals by deploying the conforming strategy to investors* (Sundaram et al. 1996), and 2) *the conforming strategy may depend on the firm's market position.* An alternative explanation is that investors may regard an unexpected increase in R&D by AMD as a signal of good cash flow or of 'deep pockets' (Erickson and Jacobson 1992). But if this is so, then an unexpected increase in spending on marketing by AMD should have a similar effect, which is not the case in our analysis.

In sum, our findings do not fully support our prediction that there would be different incentive structures which influence a leader to spend more on marketing and a follower to spend more on R&D. When we use a stock-market response measure our Hypothesis 1 is supported. However, when we use product-market response measures, we find Intel has a greater incentive to conduct marketing than AMD, as predicted, while Intel has greater incentive to conduct R&D than AMD as well. Our finding on R&D is against Ofek and Sarvary's (2003) base model, but they also note that when a leader has a relative innovative advantage over a follower (i.e. a leader can achieve a greater R&D results than a follower with the same amount of R&D investment), then higher R&D productivity tends to induce greater leader R&D effort because an incremental

spending on R&D induces a greater chance of success for a leader than for a follower. Perhaps our result reflects Intel's superior R&D productivity.

Impacts of financial performance on discretionary spending: In HYPOTHESIS 2, we hypothesize that *when there is an unexpected increase in product market response or stock market response, a leader will increase marketing spending more while a follower will increase R&D spending more*. Via IRF analysis, we investigate the over-time response of firms to an unexpected change in profitability and firm value. For example, in Table 3, we find that Intel responds by increasing its marketing spending by 0.4% when there is a 10% shock in firm value.

IRF Analysis	**Intel**		**AMD**	
Impact of financial performances on marketing and R&D	**ROA**	**Market-to-Book**	**ROA**	**Market-to-Book**
Marketing	**ST: -0.47** **LT: -0.08**	**ST: 0.04** LT: -	**ST: 0.03** **LT: 0.03**	ST: - LT: -
R&D	**ST: -0.11** LT: -	ST: - LT: -	ST: - LT: -	**ST: 0.13** LT: -

(ST: Short-term effect, LT: Long-term effect, Total Effect = ST + LT)

Table 3: Dynamic Impacts of Financial Performance on Marketing and R&D

Interestingly, we find that a 10% negative shock in profitability (ROA) would have increased marketing (5.5%) more than R&D spending (1.1%) in Intel's case (see Table 3). In other words, Intel's managers would have reacted to an unexpected decrease in profitability by increasing marketing spending more than R&D. This behavior might be due to the fact that Intel had less restrictive budget constraint in terms of cash flows during the data span. Thus, Intel might not have responded to a positive ROA shock; however, it might have reacted to a negative shock by increasing its marketing and R&D spending, mainly in order to meet the analysts' target stock price (see Table 2). As for AMD, we find a 10% shock in profitability would have increased

marketing by 0.3%, but not R&D. Note that AMD often reported negative earnings during the data span but nevertheless kept focus on R&D (see Figure 1). Thus, cash-strapped AMD seemed to invest in building complementary assets to R&D only when it had some financial flexibility.

Further, we find that a 10% shock in Intel's firm value (MB) would have increased its marketing (0.4%), while a 10% shock in AMD's firm value would have increased its R&D (1.3%). In sum, these findings suggest that 1) product and stock market response measures are important drivers of the marketing and R&D budgets, 2) the leader (follower) tends to increase its marketing (R&D) efforts when its firm value increases, consistent with our HYPOTHESIS 2, and that 3) Intel increases its marketing and R&D when it has a negative shock in profitability in order to maintains its stock price, while AMD increases its marketing but maintain its planned level of its R&D investment when there is a chance for discretionary spending.

Robustness checks: The biggest question for SVAR modeling would be whether the identifying assumptions are appropriate. To address the issue, we compare our main results to those derived from the Generalized IRF (GIRF) approach. We find that the results are qualitatively similar, implying that our identifying assumptions are reasonable (see Appendix 5.1 for details). Second, we use the '$|t\text{-}stat| > 1.645$' criterion to compute short- and long-term effects. Instead, we apply a stricter criterion, i.e., '$|t\text{-}stat| > 1.96$', and find that the results are substantially similar across criteria (see Appendix 5.2 for details). Third, a maximum likelihood method we used does not guarantee the attainment of global optimum, and so we try different starting values. We find that this procedure makes no difference, implying that we are likely to achieve global maximum. In sum, we conclude that our empirical findings are robust.

5. Discussions

We investigate asymmetric resource accumulation paths of a leader vs. a follower and the associated incentive structures which lead them to use marketing and R&D differently. In so doing, we develop Structural VAR modeling approach to examine the theoretical prediction, dealing with two methodological challenges; dynamic interdependence among focal variables and context dependence of game theoretic modeling. When we use a stock-market based financial measure, we find that the leader benefits more from its investment in marketing than the follower, while the follower gains more from its investment in R&D than the leader. We also find that the leader will increase its marketing investment when there is an unexpected increase in stock market response, while the follower chooses to invest in R&D. Both are consistent with our predictions.

We also find interesting twists to our predictions. When we use product market responses as financial measures, we find that Intel has a greater incentive to conduct marketing and R&D than AMD. We attribute this finding to Intel's greater R&D productivity. Further, an unexpected profitability increase leads AMD to spend more on marketing, but does not change its planned level of R&D. Intel responds to an unexpected negative profitability shock by increasing its marketing and R&D in order to please investors. We interpret these responses as results of AMD's cash constraints and Intel's deep pockets.

We show that our proposed methodology will be a useful tool for empirical analysis of FMA because this methodology allows us to explicitly address the role resources play for strategic decisions by a leader and a follower. Also, Resource-Based View or RBV, which is often criticized for a lack of empirical support (Porter 1991), can benefit from the use of time series analysis and, in particular, SVAR modeling. Saloner (1991, p.134) points out that "Which

resources and core competences are worth developing depends, in part, on the extent to which the firm is able to capture the rents from them". By examining individual firm-level time series data, we show that in the microprocessor industry the 'complementary asset' accumulated through marketing is a valuable resource for the leader, while the 'technological asset' obtained by R&D is an imperative resource for the follower (e.g., Teece et al. 1997). To our knowledge, this study is the first paper to combine RBV and game theoretic modeling using SVAR framework with individual firm-level data, which can be a conceptual and methodological contribution.

This finding has managerial implications for future resource accumulation paths. We find that Intel's marketing and R&D contributed to its financial performance, albeit in different ways. Intel's managers should direct their marketing strategy to maintain current high profitability by setting premium prices, which would be possible through improving brand image and fostering channel relationship. Intel should also deploy R&D to improve its sales growth (via product refinement) and profitability (via cost reduction) in the short- and long-term. In contrast, AMD's managers may want to increase R&D as far as its discretionary spending budget permits. We recommend this strategy even though AMD's R&D investment has no effect on its ROA because its R&D investment does contribute to increasing its firm value. In sum, AMD should focus on R&D, which may eventually give them a technological advantage and subsequent profit (*next-generation customer acquisition strategy*). This move will be rewarded by investors who perceive an unexpected increase in R&D investment as a signal that AMD is pursuing the right strategy.

This study has broader implications for researchers and managers. First and foremost, this study shows that there is no single best strategy. Context determines what strategy will work

best, and so researchers need to be careful not to draw overly general conclusions from an atomistic approach. Also, this study shows that market structure shapes strategy, and vice versa. The market leader should choose its strategy by utilizing its current market position, while the follower should take the strategy which will alter market structure and lead the firm to a favorable position.

However, there are certain limitations at the current stage of study, which we leave for future study. First, only one industry is examined. Future study may consider the expansion of a dataset into other technology-intensive industries. However, in the analysis of leader-follower asymmetry, researchers need to find a clever way to set the boundary of industry and to identify a leader when there are frequent shifts in technological leadership.

Second, VAR modeling is a reduced form approach; it is regarded as less reliable than the structural modeling approach for policy simulation (Stock and Watson 2001). To alleviate this concern, we apply Sims (1986)'s SVAR approach using identification assumptions derived from economic reasoning. Future study may impose more 'structures' based on further behavioral/economic assumptions to examine the dynamic impacts of marketing and R&D. It is more difficult, however, to model the competition among major players in marketing and R&D investment because researchers need to construct each firm's objective function properly.[13] In addition, the role of myopic investors in the manager's decision-making should also be considered if a stock price-based performance measure is used (e.g., Stein 1989).[14] These

[13] One challenge is how to operationalize the 'economic profit', which should be maximized by a firm. As explained in Shin (2006), both accounting and finance constructs have their pros and cons. Note that we are able to use multiple measures instead of choosing only one, benefiting from the flexibility of VAR framework.

[14] Since managers are sometimes willing to sacrifice real economic values for more selfish concerns (Graham et al. 2005), the observed data may not reflect the optimal outcomes. Then systematic bias due to real earnings management may deter consistent estimation. Moreover, managers' utility function may not be aligned with their firms' profit maximization principle, which complicates modeling.

concerns reflect the difficulty of analyzing the relationship among endogenous variables in a complex system using so-called 'structural modeling approach'.

Third, one may want to apply fixed- or random-effect dynamic panel specification with IV/GMM method to investigate the research questions raised in this paper. In this case, the heterogeneity problem across individual firms should be addressed. Note that N-T asymptotics in a panel data setting is often achieved by large N and small T. In order to obtain large N, however, neither does it make sense to combine Intel and AMD, a pairing for which the revenue ratio is about ten to one, nor to combine Intel and Genentech, which are operating in totally different market environments. Moreover, when the heterogeneity problem across units exists, instrument variables cannot resolve the endogeneity problem as long as we estimate dynamic panel model with lag terms (Pesaran and Smith 1995).[15] This could be problematic when a researcher wants to capture the chain reactions among marketing, R&D and financial performance. On the contrary, our empirical strategy is to utilize large T of time series data first, and then increase N for generalization, following suggestions made by Saloner (1991) and Camerer (1991). However, note that our analysis is built on the implicit assumption that there is no structural change over the periods analyzed. Even though unit root test results suggest that we do not have structural change in our data, this 'no structural change' assumption inherent in time series analysis may be as critical as 'no heterogeneity across units' in cross-section or panel data analysis. Access to proprietary data having large T over relatively short time span (e.g., monthly data for 10 years) may be the only way to resolve the problem.

[15] To resolve the problem, Pesaran and Smith (1995) propose the Mean Group Estimator or MGE approach; the key idea is to estimate parameters for each individual unit when there exists heterogeneity across individual units. Indeed, this approach is consistent with our VAR modeling approach in spirit.

Fourth, our dataset is not perfect.[16] In particular, the use of SGA minus R&D as a proxy of marketing is one of the weaknesses in this paper even though we performed robustness checks. In addition, firms may acquire other firms in order to secure access to technology, which is not reflected in their own R&D spending. Moreover, our data do not have qualitative aspects of marketing and R&D (e.g., advertising media effectiveness, expertise of R&D personnel), which may be an inherent problem with a secondary data. How to deal with these issues would also be a challenging problem for future study.

In spite of these short-comings, we hope that this study provides a new methodology to analyze the nature of FMA and the role resources play in strategic decisions. We also hope that this study provides insights for top-level managers who need to determine the level of marketing and R&D spending, while considering both customer response and investor response in order to accumulate appropriate resources and compete successfully in a high-tech, capital-intensive, and fast-paced industry.

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