R&D and Advertising Efficiencies in the Pharmaceutical Industry

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Abstract

R&D and marketing functions play a significant role in gaining a competitive edge over existing and potential rivals of firms and the dual functions continue to stir interests in the academic and professional business settings. This study uses the production function approach to study the concomitant effects of R&D and Advertising expenditures on the revenues of pharmaceutical firms. The most significant insight from this study is that although advertising as a percentage of sales has not increased during the past twenty years, its effectiveness in generating sales has improved dramatically by way of the direct-to-consumers-ads (DTCA) strategy. The study finds that advertising has become more effective over time and is solely responsible for the firm’s collective inputs’ returns-to-scale exceeding one – something managers aspire to and stockholders value highly. The findings of this study also support the notion that advertising replaces R&D investments when those investments fail to live up to their promise. For pharmaceuticals, each percentage increase in R&D and Advertising spending increases sales by one-quarter and one-eighth percent, respectively. The results do not support the hypothesis that pharmaceuticals enjoy constant returns-to-scale.

The study partitioned the pharmaceuticals into two 10-year time periods in order to provide further insights into the R&D and advertising contribution to sales growth. The results rejected the hypothesis that the sales elasticity of advertising remained constant over time. Finally, the results supported a rejection of the hypothesis that firms do not view R&D and advertising as substitutes when making budget allocations.

Keywords: R&D, Advertising, Sales elasticity, Cobb-Douglas function

JEL Classification: L65

1. Introduction

As a part of his seminal work Peter Drucker (2005) recently wrote “The business enterprise has two – and only these two – basic functions: marketing and innovation”. This implies that firms, in an attempt to gain a competitive edge, spend resources on research and development (R&D) and advertising. Hayes and Abernathy (1980) state that “our experience suggests that, to an unprecedented degree, success in most industries today require an organizational commitment to compete in the marketplace on technological grounds – that is, to compete over the long run by offering superior products.” Erickson and Jacobson (1992) state that while R&D is crucial in many industries, a comparative advantage can also be attained through a differentiation strategy based on advertising. It appears that R&D and marketing functions play a significant role in gaining a competitive edge over existing and potential rivals of firms and the dual functions...
continue to stir interests in the academic and professional business settings. In this paper the terms “marketing” and “advertising” are used interchangeably.

The relationship between the inputs R&D and Advertising and the outputs revenues and earnings can be modeled on the Cobb-Douglas production function. This model has been broadly applied to the aggregate output of an economy on the assumption that capital and labor are perfect substitutes as inputs. Economists have conducted thousands of empirical studies of real world production relationships with most discussions of substitution between inputs focusing on the relationship between labor and capital. Variants of the production function convert the output-input relationship into a constant elasticity of substitution form as well as a translog form. This study uses the production function to study the concomitant effects of R&D and Advertising expenditures on the revenues of pharmaceutical firms.

The most significant insight from this study is that although advertising as a percentage of sales has not increased during the past twenty years, its effectiveness in generating sales has improved dramatically by way of the direct-to-consumers-ads (DTCA) strategy. The intent of that strategy has been to have patients ask their healthcare providers for brand names rather than cheaper generics (Aikin et al., 2004). The study finds that advertising has become more effective over time and is solely responsible for the firm’s collective inputs’ returns-to-scale exceeding one – something managers aspire to and stockholders value highly. Finally, the findings also support the notion that advertising replaces R&D investments when those investments fail to live up to their promise.

This paper is organized as follows. Section 2 provides prior research relevant to the topic of this paper including an application of the production function to the field of finance and economics. Section 3 discusses the model and develops hypotheses. Section 4 discusses the sample while Section 5 describes the findings of this study. The final section provides the conclusion and an outline for further research.

2. Literature Review

The literature review provides a glimpse into two strands of extant literature: (i) studies incorporating the production function as a tool of analysis and measurement of output-input relationship, and (ii) studies dealing with impact of R&D and Advertising on some type of measures of performance of firms. Few studies have addressed the two input measures R&D and Advertising concurrently.

The Cobb-Douglas production function of individual firms and the aggregate economy measures the relationship between inputs and outputs in terms of efficiency and returns to scale. Economists have conducted many empirical studies of real world production relationships. Most discussion of substitution between inputs has focused on the relationship between labor and capital. Nicholson (1985) makes a case for substitution among other inputs. He was specifically interested in the nature of relationship between energy and capital in production. He suggested that energy and capital were complements in production instead of substitutes. Use of more sophisticated equipment necessarily involves using more energy to power the equipment. Berndt and Wood (1975) indicated this was indeed the case for many industries.
The impact of financing constraints on the productivity of R&D investment using an augmented Cobb-Douglas function has been studied by Millet-Reyes (2004). Demand for R&D is motivated by technological feasibility and market potential. On the supply side R&D intensity, measured by the ratio of R&D to Sales (both in monetary units), is affected by availability of capital. The study found that financially constrained firms are smaller and less R&D intensive but generate a rate of return on R&D higher than larger firms. Millet-Reyes measured inter-firm efficiencies but did not address economies of scale arising from R&D inputs.

The current study also uses a Cobb-Douglas function to model the relationship between annual sales and its various inputs in several industries. However, the inputs complement rather than substitute each other in that setting. In addition, the study looks for economies of scale within industries and across time.

Since the early 1970s drug advertising has been overseen by the FDA, and advertising has grown into a $5 billion business (Pickert, 2008). That supports earlier findings that advertising plays an increasingly significant role in the budgeting process at pharmaceutical firms. Kotler et al. (2009) reported that 69% of senior managers described relations between marketing and R&D as collegial, but only 34% of mid-level managers viewed the relationship that way. Companies with barriers between marketing and R&D are more likely to miss out on the kinds of breakthrough products and market-research finds that can drive growth and profits for years. The current study provides an opportunity to find support for the notion that both departments enjoy equal recognition in the board rooms.

Erickson and Jacobson (1992) explored the extent to which R&D and advertising expenditures generate a comparative advantage that allows firms to earn “supra-normal” profits for a sample of industrial companies for the period 1972 through 1986. Their results suggested substantially lower accounting and stock market returns to R&D and advertising than indicated in prior research. Once the effects of firm-specific factors and the influence of profitability on discretionary spending were taken into account neither R&D nor Advertising expenditures increased the market value of the firm more than other types of discretionary investments or expenditures. The isolating mechanisms necessary to prevent imitation by competitors appear, on the average, insufficient for these expenditures to generate a comparative advantage allowing for supra-normal returns. Obtaining a comparative advantage through R&D or advertising depends crucially on the specific nature of the expenditure and how it interacts with the firm’s asset and skill base so as to prevent imitation by competitors.

Ho et al (2005) examine the effects of R&D and advertising expenditures on holding period returns of manufacturing and non-manufacturing firms between 1962 and 2001. In their study they find the coefficient of the product of R&D and advertising to possess a negative sign indicating that firms with superior performance use one or the other of the inputs. They thus argue their findings are in support of the resource based theory which postulates that firms prioritize their investments so as to reap maximum benefits from their core competence – not surprisingly that is R&D investment in manufacturing and advertising in non-manufacturing environments.
Effects of R&D and advertising on earnings of pharmaceutical firms have been estimated separately. Bhagwat et. al. (2001) showed that a one percent increase in R&D investment resulted in a one-quarter percent increase in EPS (earnings per share) for publicly traded pharmaceutical companies for the period 1989-98. They found that the degree of R&D leverage – i.e., the earnings elasticity of R&D – remained unchanged during that period which contradicts the notion that there have been unfair price increases in the drug industry. The authors suggested that the rising drug prices simply reflected the rising costs of developing new drugs. Using a similar approach, Bhagwat and DeBruine (2004) studied the degree of advertising leverage – i.e., the earnings elasticity of advertising – in manufacturing and service industries. With respect to the pharmaceutical industry, they found the degree of advertising leverage to be one-quarter percent implying a boost in EPS by a quarter percent for every one percent increase in advertising budgets of publicly traded pharmaceutical firms during 1989 - 2000. They also observed that the degree of advertising leverage decreased with size and over time. However, neither study looked at the complementary nature of those two inputs on the productivity of firms.

The current study – using more recent data than those earlier studies – finds results that are not inconsistent with the earlier findings. However, its approach and methodology are different in that it focuses on the inputs’ impact on sales rather than EPS and performs a cross-sectional analysis using panel data. The focus is on sales because investments in R&D and advertising have a more direct impact on sales than on EPS. In addition, company-specific factors may have contributed to the results reported in those earlier studies that pooled all company-year observations, and a cross-sectional analysis using panel data overcomes that concern. The objective of the current study is to measure the concomitant effects of R&D and advertising and determine whether and how the two inputs complement each other.

3. Model and Hypothesis Development

3.1. Model

At many firms, R&D and advertising departments compete for limited funds in the annual budgeting process. Senior executives eventually decide on the allocation of funds to those departments. This study attempts to evaluate the optimality of those decisions – defined as producing a given level of sales with the least amount of total inputs. As such, it models the department costs as production factors and arranges them using the so called Cobb-Douglas production function represented as

\[ \text{Sales}_i = A \cdot \text{XRD}_i^{\beta_1} \cdot \text{XAD}_i^{\beta_2} \cdot \text{OOE}_i^{\beta_3} \]  \hspace{1cm} (A > 0)  \hspace{1cm} (1)

where Sales\(_i\) represent the firm’s annual net sales, XRD\(_i\) is the firm’s annual R&D expense, XAD\(_i\) is the firm’s annual advertising expense, and OOE\(_i\) are the firm’s annual other operating expenses. In production function parlance, the parameter A is known as the “efficiency parameter” and the parameters \(\beta_1, \beta_2, \beta_3\) as the “returns-to-scale parameters” for the respective production factors. Taking natural logarithms of both sides of Equation (1) obtains

\[ \ln(\text{Sales}_i) = \ln(A) + \beta_1 \ln(\text{XRD}_i) + \beta_2 \ln(\text{XAD}_i) + \beta_3 \ln(\text{OOE}_i) \]  \hspace{1cm} (2)
and represents an intrinsically linear regression model. $\beta_1$ in Equation (2) represents the degree of R&D leverage on sales ($DRL_{Sales}$) – also called the sales elasticity of R&D – or the growth in sales given the growth in R&D. Similarly, $\beta_2$ represents the degree of advertising leverage on sales ($DAL_{Sales}$) or the sales elasticity of advertising. Finally, $\beta_3$ represents the degree of other operating expenses leverage on sales ($DOL_{Sales}$). To illustrate those identities consider the Bhagwat and DeBruine (2004) derivation that starts as follows:

\[
DAL_{Sales} = \frac{\%\Delta Sales}{\%\Delta XAD} \tag{3a}
\]

which can be rewritten as

\[
DAL_{Sales} = \frac{\Delta Sales \times \partial \ln(Sales)}{\partial Sales} \div \frac{\Delta XAD \times \partial \ln(XAD)}{\partial XAD} \tag{3b}
\]

and reduced to

\[
DAL_{Sales} = \frac{\partial \ln(Sales)}{\partial \ln(XAD)}. \tag{3c}
\]

Finally, Equation (3c) can be transformed into

\[
\ln(Sales) = \alpha + \beta \ln(XAD) \tag{3d}
\]

Thus, the slope $\beta$ in Equation (3d) represents the degree of advertising leverage on sales ($DAL_{Sales}$) or the sales elasticity of advertising.

### 3.2. Hypothesis Development

Increases in R&D and advertising expenditures create higher sales. Outside investors look for early indications of whether such growth is generating increased efficiencies and thus increased profits. Tracking marginal returns of the input factors provides one of the earliest signals about the revenue generating prospect of those inputs. In the Cobb-Douglas model this returns-to-scale question is answered by regarding the sum of the exponents of the input factors. In a pure competition environment with no barriers to entry or exit the returns-to-scale parameters equal to 1. However, in an industry with high barriers to entry or exit there could well be increasing or decreasing returns to scale. Not surprisingly, the firm wants investors to believe that its industry is enjoying increasing returns to scale. This leads to the first hypothesis:

Hypothesis 1: $DRL_{Sales} + DAL_{Sales} + DOL_{Sales} = 1$

Due to changes in the industrial and regulatory environment, pharmaceutical firms have resorted to direct advertising. As illustrated in Table 2 advertising intensities did not increase from the earlier time period (1988-1996) to the later time period (1999 – 2008), implying that those direct advertising dollars were not just added to the traditional advertising budget. The direct-to-consumers-ads (DTCA) strategy encourages patients to ask their healthcare providers for brand names rather than cheaper generics (Aikin et al., 2004). If that strategy is more effective then
more of the revenue generation comes to depend on advertising, and that should translate into an increase in DAL$Sales$ over time. This leads to the second hypothesis:

Hypothesis 2:  $(DAL^{Sales})_{t+1} = (DAL^{Sales})_{t}$

As observed in Table 2 comparing two 10-year time periods, average R&D intensity is higher in the later period but average advertising intensity is not. Firms may well be converting advertising dollars into R&D projects in order to increase their revenues – i.e., firms view R&D and advertising as substitutes and over time adjust the amount allocated to each department in order to maximize their effect. This leads to the third hypothesis:

Hypothesis 3: $(DRL^{Sales} + DAL^{Sales})_{t+1} = (DRL^{Sales} + DAL^{Sales})_{t}$

4. Sample Selection and Descriptive Statistics

This study employs the Standard and Poor COMPUS TAT database to select financial data on firms that reported R&D and advertising expenditures during the 21-year window from 1988 to 2008. We limited our sample to those firms that reported data in at least four consecutive years. The resulting set of firms consisted of 12 pharmaceutical firms (SIC 2834), 6 cosmetics firms (SIC 2844), and 8 automobile manufacturers (SIC 3711). Data obtained included net sales, R&D and advertising expenditures as well as operating income after depreciation – all on an annual basis. The data are not inflation adjusted, and R&D (advertising) intensity is defined as the ratio of R&D (advertising) to sales.

Table 1 shows a wide distribution of R&D and advertising intensity among the different industries. Auto manufacturers – by far the largest firms in the set – outspent the other two industries on both R&D and advertising – on R&D more than twice what the pharmaceutical firms spent and more than eight times what the cosmetic firms spent, while on advertising they spent about three times what the pharmaceutical firms spent but only slightly more than the cosmetics firms. However, the auto manufacturers are by far the lowest in terms of advertising intensity – half that of the pharmaceutical firms and about one-fifth that of the cosmetics firms. The cosmetics firms had the lowest R&D intensity of all three industries.

Table 1 reports the simple average for the three industries included in the study. Those industries are made up of very different-sized firms. For example, the median annual sales amount for the 12 pharmaceutical firms is $8,356 million or about 60% of the annual average sales reported for firms in that industry. Similarly, the median annual sales amount for the 6 cosmetics firms is $807 million or just 40% of the annual average sales reported for firms in that industry. In contrast, the median annual sales amount for the 8 vehicle manufacturers was virtually identical to the average annual sales reported for firms in that industry. However, differences in firm size will not affect the subsequent analysis because this study uses a cross-sectional log linear model on panel data (by firm). The relationship between median and average values for R&D and advertising expenditures are similar to that of the sales in each of the industries.

Table 2 provides further descriptive statistics on R&D and Advertising expenditures in different time periods. The study partitioned the firms into two 10-year time periods – from 1988 through
1997 and from 1999 through 2008. The first time period contains 12 firms while the second time period contains just 8 of the 12, evidence of significant merger activity in the 1990s. Average annual sales more than tripled and R&D intensity increased. Surprisingly, advertising intensity decreased slightly during that time.

5. Results

This study analyzes panel data (observations organized by company and by year) and employs a fixed-effect cross-sectional model that is specifically designed to find relationships that are common across different companies while ignoring firm-specific variables – for example, the firms included are of different sizes which may give them other efficiencies that are not the particular focus of this study. The following log-linear model establishes the relationship between Sales and the three input factors R&D, Advertising, and other operating expenses:

\[
\ln(\text{Sales}_{i,t}) = \ln(A) + \beta_1 \ln(\text{XRDi}_{i,t}) + \beta_2 \ln(\text{XADi}_{i,t}) + \beta_3 \ln(\text{OOE}_{i,t}) + \mu_i + \epsilon_{i,t} \quad (4)
\]

The coefficients \(\beta_1, \beta_2, \beta_3\) of this cross-sectional regression model represent the elasticity of the identified independent variables while \(\mu_i\) captures the variability among firms – i.e. company-specific variables – that are assumed constant over time. This study estimates the coefficients for all observations in the pharmaceutical, cosmetics, and auto manufacturing industries.

The results of the regression differ by industry as illustrated in Table 3. A 1.0% increase in R&D expenditures results in a 0.231% increase in pharmaceutical sales, a 0.084% increase in cosmetics sales, and a 0.086% increase in automobile sales. Similarly, a 1% increase in advertising expenditures results in a 0.126% increase in pharmaceutical sales, a 0.048% increase in cosmetics sales, and a 0.018% increase in automobile sales. Not surprisingly, the DRL\text{Sales} and DAL\text{Sales} are more significant for the pharmaceuticals industry than for the other industries. On the other hand, even though cosmetics had an advertising intensity twice that of pharmaceuticals, its DAL\text{Sales} was about two-thirds that of pharmaceuticals. One explanation could be that the cosmetics market is more saturated than the market for pharmaceuticals. An alternative explanation would suggest that the advertising strategy applied by pharmaceuticals is much more effective than the advertising strategy of cosmetics firms. The results in Table 3 show that the average DRI\text{Sales} exceeds the average DAL\text{Sales} for each industry. Because cosmetics firms have the highest advertising intensity of the three industries included in this study, those firms appear to have the most to gain in terms of improving their sales (and bottom-line) by shifting some of their advertising budget to the R&D department.

Inspecting Table 3 reveals that in terms of returns-to-scale the cosmetics and pharmaceuticals enjoy increasing returns-to-scale (\(\beta_1 + \beta_2 + \beta_3 > 0\)) while automobiles display decreasing returns-to-scale over the same time period. The cosmetics industry is the highest at 1.077, pharmaceuticals is next at 1.038, followed by automobiles at 0.995. These results support a rejection of the first hypothesis that pharmaceuticals have constant returns-to-scale. Given the state of the automobile industry, it is not surprising to have those firms be least effective at using R&D and advertising for growing sales during the time period studied.
In order to investigate changes over time, this study partitions the pharmaceutical data into two 10-year time periods – 1988 through 1997 and 1999 through 2008. Table 4 reveals the results and show that $\beta_1$ decreased by 0.015 and $\beta_2$ increased 0.186, respectively. Thus, the contribution from R&D remained virtually the same while the contribution from advertising increased by over 400 percent! A Chow test applied to the two groups ($F_{2,138} = 3.65; \text{Prob} > F = .0285$) rejects the second hypothesis that the sales elasticity of advertising remained unchanged over time.

Earlier the study found that pharmaceuticals enjoy increased returns-to-scale as the sum of the parameters $\beta_1 + \beta_2 + \beta_3 = 1.038 > 1$. Inspecting the results on the partitioned data, for the earlier time period (1988 – 1997) the sum of the parameters equaled 0.994 while for the later time period (1999 – 2008) that sum equaled 1.150. Removing the third parameter, the sum of the first two parameters ($\beta_1 + \beta_2$) increased from 0.2983 during the earlier time period to 0.4692 during the later time period – an increase of almost 60%. This result supports a rejection of the third hypothesis that R&D and advertising are not viewed as substitutes when firms decide on how to optimize their revenue and profits.

6. Conclusions

R&D and advertising both contribute to higher sales for pharmaceutical firms. This study compared the inputs’ contribution to sales across several industries that report both R&D and advertising expenditures to COMPUSTAT. For pharmaceuticals, each percentage increase in R&D and Advertising spending increases sales by one-quarter and one-eighth percent, respectively. The results supported a rejection of the first hypothesis that pharmaceuticals enjoy constant returns-to-scale.

The study partitioned the pharmaceuticals into two 10-year time periods in order to provide further insights into the R&D and advertising contribution to sales growth. The results rejected the second hypothesis that the sales elasticity of advertising remained constant over time. Finally, the results supported a rejection of the third hypothesis that firms do not view R&D and advertising as substitutes when making budget allocations.

The study noted that the 12 firms during the first period merged into 8 during the second period, suggesting that efforts at increasing returns-to-scale was a driving force during that time. As illustrated in Table 4, the sales elasticity of advertising increased significantly between the two time periods and appears to be solely responsible for the pharmaceuticals’ increasing returns-to-scale. To the extent that this can be attributed to the direct-to-consumer-ads campaigns, consumers can expect an increase in similar television commercials as the pharmaceutical firms may increase their reliance on successful strategies such as direct-to-consumer-ads for old and new drugs in order to stimulate demand and drive profits. Further research into this question is needed to provide support for this statement.

Endnotes

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References


Table 1. Distribution of R&D (XRD) and Advertising (XAD) – select industries (1988 – 2006)

<table>
<thead>
<tr>
<th>Industry Description</th>
<th>SIC</th>
<th># of Firms</th>
<th>Average Sales</th>
<th>XRD</th>
<th>XRD Intensity</th>
<th>XAD</th>
<th>XAD Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pharmaceuticals</td>
<td>2834</td>
<td>12</td>
<td>14,118</td>
<td>1,899</td>
<td>0.1368</td>
<td>754</td>
<td>0.0497</td>
</tr>
<tr>
<td>Cosmetics</td>
<td>2844</td>
<td>6</td>
<td>13,908</td>
<td>391</td>
<td>0.0179</td>
<td>1,348</td>
<td>0.1067</td>
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<tr>
<td>Automobiles</td>
<td>3711</td>
<td>8</td>
<td>94,546</td>
<td>3,916</td>
<td>0.0391</td>
<td>2,010</td>
<td>0.0217</td>
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Table 2. Distribution of R&D (XRD) and Advertising (XAD) – Then vs. Now (Pharmaceuticals)

<table>
<thead>
<tr>
<th>Time Period</th>
<th># of Firms</th>
<th>Sample Size</th>
<th>Average Sales</th>
<th>XRD</th>
<th>XRD Intensity</th>
<th>XAD</th>
<th>XAD Intensity</th>
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<tbody>
<tr>
<td>1988 - 1997</td>
<td>12</td>
<td>92</td>
<td>6,430</td>
<td>671</td>
<td>0.1298</td>
<td>395</td>
<td>0.0507</td>
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<tr>
<td>1999 - 2008</td>
<td>8</td>
<td>63</td>
<td>25,550</td>
<td>3,735</td>
<td>0.1456</td>
<td>1,262</td>
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Table 3. Effects of XRD and XAD on Sales – select industries (1988 – 2006)

<table>
<thead>
<tr>
<th>Industry Description</th>
<th>Sample size</th>
<th>( \beta_1 ) (t-stat)</th>
<th>( \beta_2 ) (t-stat)</th>
<th>( \beta_3 ) (t-stat)</th>
<th>Intercept (t-stat)</th>
<th>Overall ( R^2 )</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pharmaceuticals</td>
<td>160</td>
<td>0.2307 (17.00)</td>
<td>0.1259 (8.19)</td>
<td>0.6815 (32.97)</td>
<td>0.9396 (13.71)</td>
<td>0.9951</td>
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<td>Cosmetics</td>
<td>90</td>
<td>0.0843 (4.74)</td>
<td>0.0483 (2.71)</td>
<td>0.9442 (35.57)</td>
<td>0.1037 (0.73)</td>
<td>0.9950</td>
<td>2,181</td>
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<td>Automobiles</td>
<td>103</td>
<td>0.0857 (2.76)</td>
<td>0.0182 (0.69)</td>
<td>0.8910 (22.47)</td>
<td>0.5342 (2.55)</td>
<td>0.9986</td>
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Table 4. Effects of XRD and XAD on Sales – Then vs. Now (Pharmaceuticals)

<table>
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<th>Time Period</th>
<th>Sample size</th>
<th>$\beta_1$ (t-stat)</th>
<th>$\beta_2$ (t-stat)</th>
<th>$\beta_3$ (t-stat)</th>
<th>Intercept (t-stat)</th>
<th>Overall $R^2$</th>
<th>F</th>
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<tbody>
<tr>
<td>1988 - 1997</td>
<td>92</td>
<td>0.2622 (9.22)</td>
<td>0.0361 (2.27)</td>
<td>0.6959 (17.99)</td>
<td>1.1055 (7.20)</td>
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<tr>
<td>1999 - 2008</td>
<td>63</td>
<td>0.2473 (7.86)</td>
<td>0.2219 (5.35)</td>
<td>0.6809 (12.91)</td>
<td>0.1662 (0.69)</td>
<td>0.9850</td>
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Chow test results for $H_3$

<table>
<thead>
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<th>Then vs. Now</th>
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<td>$F_{2,138} = 3.65$</td>
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