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R&D ELASTICITY AND FIRM PERFORMANCE: AN EMPIRICAL ANALYSIS

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ABSTRACT

This paper empirically examines the relationship between the output elasticity of research and development (R&D) and firm financial performance. The purpose of this study is to examine if firms have an incentive to use R&D output elasticity as a metric to help determine R&D investment levels. This study looks at publicly traded United States firms from industries with recognized R&D expenditures. The relationship is examined by first measuring output elasticity of R&D at the firm level by using a random coefficient regression. Second, these firm level elasticities are used in a Quantile regression to determine the relationship between R&D elasticity and firm performance. The results of this study find that higher levels of R&D elasticity are related to higher growth rates of firm revenue, operating income, and operating margin. This study concludes that the R&D elasticity metric positively influences firm performance, and that firms do have an incentive to utilize the measure in their R&D investment decisions.

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I. Introduction

For decades economists have been interested in innovation and its role in economic advancement. Largely, innovation has been credited for bringing about much of the tremendous growth in prosperity seen over the last two-hundred years. Take for example the growth in the United States since the late 1700's. At the time of the revolutionary war, U.S. real GDP per capita[1] was approximately $765, while just over 230 years later it has grown to nearly $43,000, which is approximately a 5500% increase in income (Hulton, 2001; World Bank, n.d.). One obvious explanation for the growth over this time period was the introduction of new technologies as result of the Industrial Revolution. It's this effect of innovation and growth that economists have been actively researching, in order to find out what leads to innovation, and how investment can be more efficient at bringing about these changes.

In his 1942 book, *Capitalism, Socialism, and Democracy* (CSD), Joseph Schumpeter popularized the idea of technology creating economic change and leading to social benefits. A key aspect of CSD was the idea of creative destruction, and the role of firm competition in the development of new innovations. Schumpeter described creative destruction as the force by which old innovations are replaced by newer technologies. While discussing the great technological changes of the late 1800's he states:

> "The opening up of new markets, foreign or domestic, and the organizational development from the craft shop and factory to such concerns as U.S. Steel illustrate the same process of industrial mutation (...) that incessantly

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[1] This Real GDP number is in 1992 dollars.

> revolutionizes the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism. It is what capitalism consists in and what every capitalist concern has got to live in." (Schumpeter, 1942, p. 83)

Broadly, Schumpeter theorizes that economic growth is caused by the interactions of firms trying to maintain a competitive edge. By trying to maximize their profit, firms make investments in innovation for the purpose of gaining a monopolistic advantage. Through this competition, these companies develop new products, new processes, and open entirely new markets, that don't just benefit the firm, but also, indirectly, the rest of society as well. Additionally, through creative destruction, innovations are constantly becoming better and replacing old technology, which increases consumer benefits. In Schumpeter's eyes, it is capitalistic processes such as these that cause sustained economic growth and allow for the great economic advances.

Given the importance of firm investment in innovation, the purpose of this thesis is to examine how firms make the decision to invest in innovation, and to potentially help firms make better decisions regarding this investment. In modern business terms, firms don't invest in "innovation" but in research and development (R&D). As such, for this study innovation will be considered as R&D, where R&D is roughly defined as a company's ability to invent, innovate, and disseminate new technologies, ideas, or processes (McConnell et al., 2009).

The United States had an R&D intensity[2] of 2.9% in 2009, placing the nation 8th in the world (National Science Foundation, 2012). While still in the top of the R&D spenders, U.S R&D intensity has only increased 10.4% since 1995 (Tassey, 2012). This growth rate is less those of than many other developed nations, which have seen growth rates over 20%, and substantially less than in developing Asian nations, which have seen growth rates over 120% (Tassey, 2012). Further, U.S firms play a major role in R&D investment, conducting 71% of all R&D and funding 62% of all other R&D projects. However, these firms invest relatively little into R&D, typically making up less than 6 percent of total revenues for firms that actually conduct R&D (Knott, 2012). These low R&D investment rates are likely a result of the fact that R&D is an uncertain investment with highly variable returns. Instead firms tend to allocate their money relative to expected financial gain, preferring to invest in items such as capital and labor that have proven returns. Consequently, to promote more R&D investment, the financial return from R&D investment needs to be calculated, or more generally, the productivity of R&D. A measure of R&D productivity will both inform firms of what return they are receiving and also help them evaluate their practices to potentially develop higher productivities.

Measuring the returns to R&D is certainly not a new idea. Given the importance of innovation, researchers have been looking for reliable ways of determining the return to R&D for over 60 years (Hall et al., 2009). These methods of measurement have varied significantly over time, from looking at how many patents a firm produces, to taking surveys to rate the effectiveness of an R&D department (Hall et al., 2009).

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[2] In this context, R&D intensity is calculated as total R&D spending divided by total GDP.

However, in more recent times, the measurement of R&D returns has become more statistical, including the use of econometric measures, which utilize production functions. One such measure is the output elasticity of R&D, which measures how much more output a firm generates from additional inputs in R&D. While R&D elasticity has been around for several decades, its use as a measure of R&D productivity for individual firms has become recognized more recently. For instance, in a 2012 *Harvard Business Review* article, it was claimed that if the 20 largest U.S. firms conducted R&D optimally according to their R&D elasticity measurement, then those firms could add one trillion dollars to their collective market capitalization rates (Knott, 2012). Due to this new interest in output elasticity as a measurement of firm-specific R&D productivity, there is a large potential for it to be used to help facilitate investment decisions in the future.

Given the increasing awareness of R&D elasticity as a measurement of R&D productivity, the purpose of this thesis will be to examine whether R&D elasticity is a valuable decision tool. As such, this research project will look at the relationship between R&D elasticity and firm financial performance, as this will determine if the measurement has value to firms. Both logically and economically, if elasticity of R&D[3] is to be used in management circles it must be related to firm performance. If there is no financial gain from having a higher R&D elasticity, then firms will have no incentive to rely on these numbers for decision-making, and thus the measure will be irrelevant for that purpose. Instead the metric will be more for research interests than for real world application. More specifically, as the theoretical measure of elasticity is not perfectly

[3] The terms "output elasticity of R&D," "R&D elasticity," and "elasticity of R&D" will be used interchangeably throughout this study. Additionally, unless otherwise specified, the term of "elasticity" alone should also be considered R&D elasticity.

measureable in practice, this study will look at finding the relationship generated by measureable R&D elasticity. As such, through a thorough empirical study, this thesis will explore the relationship between measurable output elasticity of R&D and firm financial performance, in order to see if firms have the incentive to "care" about elasticity. It is expected that the results of this study will find a statistical relationship between output elasticity of R&D and firm performance, and thus that the measure is a valid tool for application within firms.

Thesis Organization

This thesis will be organized into five primary sections. First the background section will provide information on some relevant R&D ideas and recent R&D productivity research trends. Subsequently, the empirical methods section will include a discussion of the methods of finding the relationship between R&D elasticity and firm performance. This will be followed by a brief review of the data used in this study. Finally, the thesis will then include a presentation of the empirical results and a discussion as to the meaning and implications of those results.

II. Background

Prior to conducting the empirical analysis of this project, it would be beneficial to discuss some background on the subject in order to both give some context for this research and to provide a starting point for later discussions. Given the immense breadth of the research into R&D returns, an in-depth literature review is not possible given the scope of this project. Instead, this background will cover some important aspects of R&D research, including exploring the effects of R&D spillovers on firm incentives, and discussing recent advances in R&D productivity research that are relevant to this topic.

Spillovers from R&D

Spillovers are an important topic for any discussion on firm R&D investment. This is because spillovers from R&D are a primary path for firms and society to receive benefits from R&D, and likely play a large role in firm R&D investment decisions. Simplistically, R&D spillovers are externalities that result from the development of new technologies or new processes, which can occur from any research, including private, government, or academic. Thus, R&D spillovers are the effects of R&D on individuals not directly involved in conducting that R&D. These spillovers are important, as they are necessary for continued economic growth. In “The search for spillovers” (Griliches, 1992), the author discusses two primary points regarding the characteristics of spillovers from the perspective of the endogenous growth theory. The first point is that technological change is a result of conscious decisions and actions of economic agents.

This implies that firms, and other organizations, purposely invest in research to make processes better. This is a simple and important notion, but is not as consequential as the second point. The second point is that without significant spillovers, or other sources of social returns, economic growth would likely slow over time with the onset of diminishing returns (Griliches, 1992). This latter point is the primary reason why spillovers are researched so extensively. Without spillovers, the economic benefits from R&D investment decrease as more investments are made. Instead, with spillovers, as new knowledge is generated it is added to a common "pool" that can then be used to further the research in other sectors. Thus, spillovers prevent diminishing returns to innovation from slowing economic growth.

Many studies have been conducted to try to empirically measure the effect of R&D spillovers on both social and private agents, at both the micro and macro levels. Primarily, studies look to find if spillovers have a significant impact on total-factor productivity or the per capita income of individuals. The results of these studies find that research spillovers are indeed real and do have a significant impact on both of these variables. While estimated spillover returns vary significantly depending on the method of estimation, most studies report between a 10 and 30 percent return from private R&D spillovers (Sveikauskas, 2007). Also, literature reviews on the subject have found that social returns from private R&D investments are normally higher than private returns. Typically, studies find around a 25 percent private return and a 65 percent social return for private R&D, which is a significant difference (Sveikauskas, 2007). This means that as more money is put into R&D, more of the benefits go to society than to the firm conducting the research.

As shown from the spillover research it is clear that firms that conduct R&D do add significant benefits to society. However, this can be counterintuitive to the idea of profit maximization and investment incentives. For a firm the primary purpose of R&D spending is to increase their own profits. As most spillovers from R&D go into the "pool" of knowledge and are accessible by any competitive firms, one question could be: Why do firms conduct research at all if the social returns to spillovers are so high? Any spillovers from research would help rival firms become more competitive and no firm would invest in R&D if rival firms could quickly copy any new products at a lower cost. Additionally, if spillovers are sufficiently high, it may be possible for enough knowledge to be gained from the R&D of rival firms to make R&D investment needless. Thus, spillovers from R&D (in both directions) have a large impact on firm R&D investment decisions.

Clearly, patents and other intellectual property (IP) rights can help incentivize firms to innovate despite the potential for losing some competitiveness. This is because IP laws can help firms limit how their spillovers are used by other firms. If IP rights didn't exist, firms would not receive any monopoly power from their new innovations. Thus, these laws can help explain why there is continued R&D investment in light of potentially harmful spillover effects. In addition to IP laws there is another explanation for firm R&D investment. This explanation is a theory developed by Cohen and Levinthal (1990) called absorptive capacity, which essentially says that R&D is required if firms want to gain from the spillovers of other firms.

Absorptive Capacity

Absorptive capacity is defined as a firm's ability to "recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal, 1990, p. 1). Essentially, absorptive capacity (ACAP) allows firms to more efficiently use spillovers from other firms, in turn allowing them to be more productive in their own research. The proposition behind ACAP is that a firm's level of prior knowledge partially determines how it can use new knowledge. As a simplified example, ACAP is similar to a student needing to know arithmetic and algebra before being able to understand more complex mathematics. Without the prior knowledge, a student will have a difficult time learning the more advanced-level material. Similarly, firms need prior knowledge to utilize available information.

As demonstrated by Cohen and Levinthal, investing in R&D is one of the primary methods that a firm can use to increase its ACAP. By conducting research, firms are creating knowledge that they can apply when assimilating research from other sources. If a firm gets behind in their knowledge level of a certain area, they may preclude themselves from ever entering that area again without a significant investment to overcome the knowledge gap. This theory of absorptive capacity is one likely reason that a firm would benefit from R&D even with own spillovers that could ruin monopoly-pricing powers. Unless a firm continues conducting research in areas of potential future investment, firms will fall behind in their knowledge level, and will inevitably be unable to effectively innovate in those particular areas of research.

R&D and Firm Performance

Now that some background information has been provided on relevant issues regarding firm R&D and the societal gains it causes through spillovers, we will examine some current research about the relationship between R&D and firm financial performance. In general there are two main areas that will be covered in this section. The first area involves the issue of whether spending more on R&D actually helps firms perform better financially. The second area regards firm R&D productivity, and what research shows about its relationship to firm performance.

While the relationship between R&D investment and financial returns seems relatively certain, some research says that this isn't the case. For eight years, the annual "Global Innovation 1000" survey conducted by Booz & Company, has found no correlation between R&D spending and financial performance (B.A.H., 2006; Booz & Company, 2012). Specifically, after conducting correlations and regression analyses on various financial variables and R&D spending levels, no relationship was found for a large sample of firms. It is easy to dismiss the results of a study done by a consulting firm that has a division that specializes in making firms more productive at innovating. However, *The Economist* magazine praised the work as being the, "most comprehensive effort to date to assess the influence of R&D on corporate performance" (Economist, 2006). As such, it is likely the study has some merit. While they vary by year, the Booz & Company surveys generally conclude that the reason that no positive results are found is that firms perform R&D differently, or in other words have different R&D productivities (BAH, 2006; Booz & Company, 2012). Thus, there is likely a more complex relationship between R&D productivity and firm performance than just simple correlations.

Despite the findings of the Booz & Company (BC) surveys, it still seems obvious that spending more on R&D will generate better performance, at least to a certain point. Consequently, a 2007 paper by Foray, Hall, and Mairesse directly challenged the findings of the BC surveys. The authors stated that the survey was poorly conducted, with a specific reference to the lack of attention to various problems encountered in the use of accounting data. The study essentially re-estimated the R&D spending and firm performance relationship, but accounted for several items that the BC surveys had neglected to include. After making the adjustments, the authors found a significant relationship between R&D expenditures and firm performance. Specifically, they found that six of the seven financial measures they utilized, including sales and gross margin, were positively impacted by R&D spending.

Given the results of the Foray et al. (2007) study and the results of the eight BC surveys, there is a quite a conflict as to whether R&D really does affect firm performance. Intuitively, the results from Foray et al. (2007) seem more believable given the higher level of econometric expertise of the authors and the potential for bias in the BC surveys. However, the case can still be made for the overall conclusion of the BC surveys, which is that firms differ in their R&D abilities, and thus, that some firms get more returns from R&D than others, leading to the significantly mixed results.

Productivity of R&D

Corresponding to the proposition that firms differ in their R&D productivities, much research has been done in the last several decades to try to measure the returns to R&D spending. While there are several methods available to measure R&D returns, R&D elasticity is one of the more commonly used econometric methods. Typically, researchers look to determine how much return to private R&D is generated by an industry or region, where the elasticity coefficient is the metric that measures this return. The output variable used to determine returns varies by study, but usually firm productivity, revenues, or other finance based metrics are used as proxy variables for output.

Like the results of the spillover research, the results of the estimates of the rate of return to private R&D are normally quite positive. In Fraumeni and Okubo (2005) the results of nine return to R&D studies were summarized, and they found that private returns varied between 7% and 43%. However, the median value was an approximately 22% return. Additionally, more relevant to the work in this paper, some of these studies show that particular industries are more productive with their R&D than others. For instance, in one study it is found that the pharmaceutical industry had a return of 15% while the electrical products industry had a return of 36% (Hall et al., 2009). This holds with the BC proposition that firms differ in their ability to generate returns from R&D.

Carrying the idea of heterogeneous R&D productivities to the next level, it is logical to assume that if industries vary in their returns, that individual firms could vary as well Elasticity of R&D has been used for decades to determine R&D returns, however it has more recently been applied to measure the productivity of R&D at the individual firm level. Typically, estimations that are considered as "firm level" in R&D research are measurements of the average return to R&D for a group of firms or an industry. However, recently there has been more research done on the returns to R&D for individual firms, instead of groups of firms. This is primarily due to the increase in computing power and software options that have become available to researchers in the last decade (Knott, 2008). These individual firm level estimations allow for the differences in productivity of R&D between firms to be measured, which corresponds to the goals of this research project.

One such firm level study was conducted in 2008, and found the output elasticity of R&D at the firm level for many firms in multiple industries (Knott, 2008). The results of this study found that firms do differ significantly in their R&D elasticities, and thus it is likely that firms have varying abilities to generate returns from R&D. In particular, this study compared the idea of innate firm productivity to the idea of absorptive capacity. Instead of the traditional assumption that higher R&D investments lead to higher ACAP, which lead to higher returns from spillovers, the author wanted to determine if firm R&D "intelligence" led to higher spillover returns. The results of this analysis found that when firm ability (R&D elasticity) was taken into account, the measurement for absorptive capacity was no longer significant. Consequently, the study determined that firms do have an innate "intelligence" level that leads some firms to be more productive than others at obtaining returns from spillovers, as was vaguely theorized in multiple Booz & Company surveys (BAH, 2006; Booz & Company, 2012).

In 2012, the same author went further with the idea of innate firm abilities, and recommended that output elasticity of R&D be used as a decision tool within firms to help management optimize R&D investments (Knott, 2012). It was claimed that if firms used R&D elasticity, or their "research quotient[4]" (RQ), they could optimize R&D investments to get the most financial return. In particular, firms are recommended to use RQ as a way to determine if they are investing too much or too little in R&D by finding the point where the marginal benefit of R&D investment equaled the marginal cost. Astonishingly, the author proposed that if the twenty largest firms performed R&D optimally in regard to their RQ's, than their aggregate market values would increase by over one trillion dollars. As such, the author implied through the study that firms with higher R&D elasticities are likely to have better financial performance.

This thesis project will be roughly building on the work of the studies that measured firm specific output elasticity, and will specifically examine the claims made in regard to firm "RQ." It is expected from this study that output elasticity of R&D will be related to firm performance, as proposed by Knott (2012). As mentioned earlier, the findings of this project will potentially help firms determine if elasticity of R&D is a measure that would benefit them. Hopefully, this project will also bring some more academic insight into the relationship between R&D productivity and firm performance, and add to the current literature on firm level R&D.

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[4] The author uses the term research quotient as R&D elasticity is supposedly measuring the "intelligence" level of a firm at conducting R&D, thus it is a firm's "IQ."

III. Empirical Approach

The empirical estimation of the relationship between R&D elasticity and corporate performance will occur in two steps. First, output elasticity of R&D needs to be empirically measured at the firm level. Second, the relationship between R&D elasticity and firm performance needs to be found. Here firm performance will be measured by several commonly used firm financial measures. As per my thesis, it is expected that there will be a relationship found between elasticity and some of these financial measures. However, the estimation of this relationship has quite a few econometric issues that need to be addressed in the analysis stage. These issues, along with the estimation techniques, will be explained in this section.

Stage I: Estimating Firm Production Functions

As mentioned earlier, the output elasticity of a variable is how much more output is produced given an additional input of that variable. As such, it is a fitting variable for the estimation of productivity because it gives the added output attributed to an input. In the case of output elasticity of R&D, this would be the change in output given a change in R&D inputs. As typically found in studies involving productivity, the estimation of elasticity comes from the use of the Cobb-Douglas function, and commonly takes the form:

$$Y = AL^{\alpha}C^{\beta}$$

Where:

- Y = Output
- A = Total Factor Productivity
- L = Labor Input
- C = Capital Input
- α, β = Output Elasticities of Labor and Capital (respectively)

Like all production functions, the Cobb-Douglas function uses a series of inputs to determine what level of output would be produced at those input levels. This function is widely used in economics, because it is relatively easy to understand and estimate, and it has held up reasonably well under empirical scrutiny. Aside from the general economic basis, a benefit of the Cobb-Douglas function that makes it appropriate for this research is that other inputs can be added to the function. In the case of this study, the level of knowledge will be added to the production function so it takes the form:

$$Y = AL^{\alpha}C^{\beta}K^{\lambda}$$

Here K is the level of own knowledge (non-rival) available to the firm, and λ is the output elasticity of knowledge, where, in this case, knowledge will be considered R&D. This is the same model implemented by Griliches in several of his studies, and by connection, by several other R&D researchers as well (Griliches, 1998, Knott, 2008). To statistically determine the elasticity measurements of this model, a regression analysis can be run on a log-transformed version of this function, and the estimated coefficients will represent the respective elasticities. However, even though the estimation of this Cobb-Douglas function seems straightforward, there are actually several econometric issues encountered. The two primary issues that will be discussed here are simultaneity and selection, which can both lead to biased estimates.

First, the issue of simultaneity occurs in production functions when there is a correlation between the inputs in the function and unobserved shocks. This makes the independent variables and the error term in the equation correlated, and thus causes an omitted variable bias. This correlation can happen for many reasons. For instance, if a firm has above average productivity they will get the same output with fewer inputs, making the inputs in the production function seem to have a larger effect on output. As this productivity term isn't directly measured, it is in the error term of the model. Thus, while it seems like the firm is very productive with its inputs, in reality the firm's higher productivity is causing the impact of the production inputs to be overestimated. Hence, the error term (productivity) is correlated with the inputs, and causes their estimated coefficients to be biased. Additionally, shocks to a firm's productivity from other factors, such as market forces or above average gains to innovation, will cause the firm to change their inputs to correspond to the shock. This creates an unobserved variable in the model that can have significant impacts on individual firms, and makes the firms heterogeneous in their decision-making regarding their inputs. This unobserved heterogeneity obviously creates an omitted variable bias in the model, and makes simple OLS estimation inaccurate.

Second, when panel data is used, the issue of selection also arises during the estimation of production functions. Panel data is multi-dimensional data on specific individuals (or panels) collected over a period of time. For firm level research, data is collected on specific firms over a period of years, leading to data that gives the change in variables for the same individual over a period of time. While this type of data is very useful for overcoming numerous assumptions and statistical issues in analysis, it also leads to the selection problem, which results when subjects in the data set drop out. In the case of firm data, a firm exiting the market, and thus no longer participating in data collection, can cause this problem. This leads to a natural bias in firm panel data, where the subjects that are still in the pool are less susceptible to shocks than the firms that have already exited. Normally with firm data, this means that the firms represented in the data have higher capital stocks than average firms, making the data biased towards shockproof firms. As such, these firms will likely be more productive with their inputs, causing the estimations to be upwardly biased, and to thus not be a proper representation of the entire firm population (Arnold, 2005).

While the issue of simultaneity can be somewhat remedied with estimation techniques, it is highly unlikely that all unobserved shocks will be accounted for. As such, the production function estimations will likely have a bias, even if slight. Additionally, not much can be done to remedy the issue of selection except to clean the data set of observations known to be true selection problems. However, as the number of firms is commonly very large in panel analyses, it is almost impossible to make sure that there is no selection bias. As such this bias may influence the results, and at least, make them less generalizable to the population.

Firm Level Estimation

The first step of the analysis requires the gathering of the output elasticity coefficients for each individual firm. For this reason a Random-Coefficient (RC) regression will be performed as it allows for the estimation of random slopes at the individual panel level, without running a separate regression for each panel. In particular, Stata's XTRC command will be used, as this implements a special type of RC model similar to a fixed effects model, which helps control for heterogeneity within each panel and thus overcomes some of the simultaneity problem.

As Random-Coefficient models are used less often than other estimation methods in economic analysis, a brief review of the basics behind this model may be beneficial. Normally, when a regression (such as OLS) is performed on firm panel data, each firm is assumed to have the same general slope and intercept, leading to one regression line through all the panels and their sub-points. However, in reality, this single slope isn't likely to accurately estimate each panel. This seems logical, as each firm has different variables that make them more or less productive, such as management or unique labor or capital inputs. Instead, it's likely that each firm has a unique production function with a slope and intercept that varies from the average group slope. It is these firm specific coefficients that RC regression estimates. Thus, by fitting a line to each specific group, a RC model can estimate the elasticity terms for each unique firm, making it ideal for this research project.

While there are benefits to using an RC model, one obvious issue would be the small sample size at the panel level. As the panel level has many fewer observations than the group level, the estimates are likely to be less statistically sound than if the estimations are made at the higher level. However, as the purpose of the research is to estimate the firm level, this issue will have to be accepted as a necessity for the analysis. Similarly, it should also be noted that output elasticity can not be measured for each year for each firm. This is a simple econometric issue, as a model can't have more parameters than the number of observations. Thus, output elasticity has to be measured over a period of multiple years, which in this analysis is the span of a firm's available data.

The specific Random Coefficient model that will be used in this analysis will be:

Equation 1:

$$\begin{aligned}&\ln(output)_{it} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i}) * \ln(capital)_{it}\\&+(\beta_2 + \beta_{2i}) * \ln(labor)_{it} + (\beta_3 + \beta_{3i}) * \ln(R\,\&\,D)_{it}\end{aligned}$$

Clearly, this is just an implementation of a Cobb-Douglas function with three inputs. As discussed earlier, and as seen in the model, the Random-Coefficient model will generate separate coefficients for both the group level mean coefficients (β) and also the firm level random coefficients (β_i). One issue to consider after the estimation of these coefficients is if there is a substantial difference between the group average and the firm specific estimations. It is expected that there will be significant heterogeneity between coefficients, meaning that firms differ in their abilities to convert inputs to outputs. If the group mean and the random (panel) coefficients are very similar, it would mean that there is little variation in firm productivity levels, and that the elasticity measures are unlikely to help predict firm performance. During the results stage a simple test will be performed to determine if there is heterogeneity between the coefficients.

Stage II: Measuring Firm Performance

Once the elasticity coefficients are estimated for each firm, the relationship between the output elasticity and the firm financial performance can be examined. To do this, seven commonly used financial or accounting measures will be used as dependent variables to measure firm performance. These measures are: sales growth, gross profit growth, gross profit ratio, operating margin, operating income growth, price to book ratio, and shareholder returns. For a summary of all seven measures, please see Table 3.1

While some of these measures are widely understood, others are slightly more vague and would benefit from a more detailed explanation. The simplest measures are sales growth, gross profit growth, and operating income growth. First, sales are simply how much money a firm earns over a period of time. Second, gross profit is how much money remains after all production costs are accounted for, and is a basic measure of firm health after production. Third, operating income is how much money a firm retains after all expenses besides interest and taxes have been paid, meaning it is a measure of overall firm health after the implementation of all business operations.

The other four measures are only slightly more complicated. First, the gross profit ratio is gross profit divided by sales and converted into a percentage. This is used as a measure of a firm's efficiency in manufacturing as it represents the percentage of sales retained after all manufacturing or production costs are subtracted. Second, similar to the gross profit ratio, operating margin calculates what percentage of sales the firm received as profit after all business operations, thus making it a measure of firm efficiency in the entire implementation of firm functions. Third, shareholder returns are the capital gain to a company shareholder over a period. This is calculated as the opening stock price minus the closing stock price for the period, plus any dividends paid during the period, where the period is calculated as one calendar year. Finally, the price to book ratio is the price per share of a firm divided by the book value per share of the firm. In general this measure compares the firm's stock value to the actual asset value of a firm to determine if the firm is overvalued or undervalued compared to its assets.

Table 3.1: Firm Performance Measures

Variable	Calculation	Measurement
Sales	–	Overall income
Gross Profit	Sales – Cost of Goods Sold	Earnings after production.
Operating Income	Gross Profit - Other expenses - Depreciation	Earnings after all expenses except interest and taxes.
Gross Profit Ratio	(Gross Profit / Sales)*100	Measure of production efficiency.
Operating Margin	(Operating Income / Sales)*100	Measure of overall firm efficiency.
Shareholder Returns	Share Value_{T2} – Share Value_{T1} + Dividends per Share over Period	Measure of gains to shareholders over period
Price to Book Ratio	Stock Price / {(Assets – Intangible Liabilities – Liabilities) / Number of Shares}	Measure of the firm's market value compared to its value as an asset

Relating Elasticity to Firm performance

The seven financial measures will be used as the dependent variables in the second step of the analysis to determine if R&D productivity has an effect on firm financial performance. Specifically, R&D productivity will be related to firm performance by using both an Ordinary Least Squares regression and a Quantile Regression. The use of OLS estimation is common in many econometric studies, and will also be used in this analysis as it is statistically sound when performed properly. However, one problem encountered in firm data that could impact the consistency of the OLS estimation is the potential for errors or outliers in the data. As firm panel datasets often contain errors, there is a need to clean the data prior to estimation. However, as these datasets have several hundred thousand observations, and often close to a million data points, manually sorting through the data is not a realistic option. While simple tests can be run to eliminate extreme outliers, it is unlikely to eliminate all errors. Thus, the estimation method needs to control for some of these errors as well. As Median Quantile Regression estimates the conditional median of the response variable, the estimation is not as likely to be skewed by outlier variables as OLS. As such, a Median Regression will be used in addition to OLS, in hope of controlling for some of these outlier data points. It is expected that this Quantile regression will create both more significant and more statistically sound results than just OLS alone.

For each of the seven financial measures, the estimation model will be:

Equation 2:

$$Y_i = \beta_i(OERD) + \beta_i(Size) + \beta_i(Industry) + \varepsilon$$

Where:

- Y = Financial measure for firm i
- OERD = Output Elasticity of R&D for firm i
- Size = Control variable for firm size
- Industry = Dummy variable for industry

The two control variables (firm size and industry) account for variables that may have a significant effect on firm financial status. Without their inclusion, the model has the possibility of containing an omitted variable bias, and thus they will be added to help increase the consistency of the estimators. From the result of previous studies (Hall, 2005) it is expected that there will be a correlation between industry and elasticity, as elasticities are known to vary by industry. Additionally, it is hypothesized that firm size may also impact elasticity and firm financial performance, making the inclusion of a firm size control variable necessary.

IV. Data Selection

One of the most critical aspects of this research project is the selection of the data. Primarily, the data selected has to be accurate in order for any meaningful results to be found. Additionally, as a goal of this paper is to estimate R&D the way a firm would, the data has to be easily attainable by firms. Consequently, the data used in this study will come from publicly released annual financial statements, as they are one of the easiest places to gather information, and are likely to be mostly accurate.

Data Selection Overview

The financial data used in this research project comes from Standard & Poor's Compustat database. Compustat is a database that provides financial information on publicly traded North American firms, with observations from the 1950's until the present. While Compustat collects data on firms in all major industries, the particular firms used in this analysis come from a list used by Foray et al. (2007) which specifies 25 industries that have a history of conducting R&D. For this reason, the data used excludes industries where R&D is uncommon. The industries are selected using their Standard Industrial Classification (SIC) code, which is a series of numbers that correspond to predetermined industries. Firms were selected at the four-digit SIC level[5] to allow for the maximum number of firms in the sample. However, due to a lack of data, two industries

5 SIC codes have four levels that correspond to the precision of the industrial classification. The two-digit level is the second least precise, and represents a major industry class within a particular economic division. Accordingly, the four-digit level is the most precise, and represents specific industries within the larger two digit level.

had to be dropped from the analysis. It should also be noted that all the firms selected for this research are based in the United States. The reason for this limit is primarily because U.S. firms conduct the second most (aggregate) R&D, and more importantly because U.S. firms account for the majority of the Compustat data.

See Table 4.1 for a complete list of the 23 industries used in the analysis. Included in Table 4.1 are simple descriptive statistics generated from the data, along with the number of firms in each industry represented in the data. The industries are represented at the 2-digit SIC level in order to provide a broader perspective than the 4-digit level would provide. As seen, these industries cover a large range of products, and also vary significantly in size. The average revenue ranges from $113 million to nearly $40 billion, and the number of average employees ranges from around 1,000 to 81,000. Therefore, the firms represented in the data are quite heterogeneous in size and financial standing, which is important as this study is examining firm heterogeneity.

Table 4.1: Selected Industries: Summary Statistics and Description

SIC Code	Number of Firms	Average Revenue ($mil)	Average Employees	Description
13	38	3,270.83	16,877	Oil and gas extraction
20	26	3,168.18	14,484	Food and kindred products
21	5	21,059.80	81,221	Tobacco products
22	19	426.1949	8,218	Textile mill products
24	5	282.0811	3,256	Lumber and wood products (except furniture)
25	11	3,369.96	19,519	Furniture and fixtures
26	31	3,469.79	17,983	Paper and allied products
27	12	1,054.16	6,933	Printing, publishing & allied industries
28	283	2,123.61	9,653	Chemicals & allied products
29	29	39,571.76	51,613	Petroleum refining & related industries
30	49	1,179.52	12,075	Rubber & misc. plastic products
32	13	1,114.50	13,122	Stone, clay, glass, & concrete products
33	38	2,024.93	18,074	Primary metal industries
34	53	716.0638	6,418	Fabricated metal (except. machines & transportation equip.)
35	387	1,142.18	7,361	Industrial & commercial machines & computer equip.
36	433	922.3588	5,284	Electrical equip. (except computers)
37	129	8,198.27	38,439	Transportation equipment
38	479	519.4998	3,889	Measuring instruments; photo. goods; watches
39	33	582.4345	4,252	Misc. manufacturing industries
48	46	11,857.33	76,582	Communications
50	21	113.3421	1,167	Durable goods - wholesale
51	8	10,923.08	9,143	Nondurable goods - wholesale
73	316	892.5156	4,472	Business services
Average	**107**	**2,231.65**	**10,390**	–
Total	**2464**	**5,498,780**	**25,601,580**	–

Production Function Data

The first step of the analysis requires the measurement of a production function using inputs for capital, labor, and knowledge. As these values are theoretical in practice, proxy variables need to be selected from the firm data in order to measure these three inputs. For this analysis, the proxy variables that will be used are: net Property Plant, and Equipment (PP&E) for the capital measure, the number of full time workers for the labor measure, and the amount of R&D expenditures for the knowledge variable. These measures were chosen because they are common measures used in production function estimations (Hall et al., 2009). The choice of the proxy variables for this type of firm research is largely dependent on what data is available to the researcher. For instance, while it would be ideal to have data on worker pay to measure the input for labor, not enough data was available to generate a sufficient sample of firms for the estimations. Thus, due to the nature of elasticity estimation at the individual firm level, variables that provide larger data sets take priority over using variables that may be more relevant.

One item of special importance for this research is the measurement of the R&D variable. In general, studies vary in their choice of measuring R&D expenditures as a stock or flow variable, and also about what lag to apply to the variable. Logically, it seems important to take a lag of R&D expenditures, as it likely takes years for R&D investments to impact sales due to the significant amount of time it takes to research new innovations and introduce them to the market. However, due to knowledge depreciation, R&D cannot be measured as an aggregate over the course of the firm's life. A simple example of this depreciation problem can be seen in computer chip manufacturing. It is likely that Intel's R&D expenditures on new computer chip designs in the 1990's have no positive effect on their sales today. Due to depreciation, R&D spending that was once important to their success has since become obsolete owing to the advancement beyond that past research.

To date, research has not been able to find a "one-size fits all" R&D lag variable. As found in Griliches and Mairesse (1984), using various lags on R&D productivity did not significantly affect the measurements. It is likely that the "optimal" lag will depend not just on the industry or type of firm, but also may vary for each individual firm, and potentially on each research project within the firm. As a result of there being no precise lag variable to use, for this research the R&D variable will be measured as the average R&D expenditure over the previous two years. This seems to be a reasonable measure, as it controls for any large research variations. Additionally, it has been found that annual R&D spending in mature firms is roughly equivalent to R&D depreciation (Knott, et al., 2003). Thus, the measure of R&D flows averaged over two years also allows for a rough accommodation of R&D depreciation.

Stage One Data Summary

Initially, data was gathered on all available firms in the industries listed in Table 4.1. This initial dataset consisted of data from 1950 through 2012, and had 7,251 firms and 125,857 firm year observations. However, this dataset consisted of many missing and possibly erroneous data values, and was accordingly cleaned to be more accurate. To clean the data, simple restrictions were applied. These restrictions consisted of dropping all observations that had missing data values, and dropping any observations that posted more profit than revenue or more R&D expenditures than sales[6]. Likewise, in order to

[6] These results were excluded as firms with R&D spending greater than revenues are likely to be R&D labs or other entities funded from an outside source. As such, they are likely to add considerable noise to the calculations.

allow for the Random Coefficient regression, any firms with less than 5 years of observations were dropped from the dataset. All firm years, from 1950 to 2012, were used in the analysis. Table 4.2 contains the detailed summary for the production function data after the restrictions were applied. In summation, the data used in the analysis is an unbalanced panel data that has 2,464 firms, and 37,125 firm year observations over the period of 1950-2012. Within this 62-year span, the average firm had data observations for 16 years, and the minimum and maximum data spans were 5 years and 58 years respectively.

Table 4.2: Production Function Input Data

	Observations	**Mean**	**St. Dev**	**Minimum**	**Maximum**
Revenue ($M)	37,125	2,559.705	13,105.3	-1.632	470,171
Net Property Plant & Equipment ($M)	37,125	981.407	5,687.532	0	152,081
R&D Expense ($M)	37,125	99.63041	521.2036	-0.267	12,183
Employees	37,125	11,029	38,539	0	876,800

After the logarithmic transformation, and the lags placed on the R&D variable, a summary of the final input data is seen in Table 4.3. The logarithmic transformation is needed in order for the estimation coefficients to be interpreted as elasticities. After the transformation, the estimates represent how much (in percentage terms) a one unit change in the independent variable changes the dependent variable, ceteris paribus. Thus, after taking logs, the estimates can be interpreted as the percentage change in revenue from a one percent change in an input.

Table 4.3: Logarithmic Production Function Input Data

	Observations	Mean	St. Dev	Minimum	Maximum
Revenue	37,125	18.53032	2.514038	0	26.87636
Net Property Plant & Equipment	37,125	16.76032	2.949181	0	25.74768
R&D Expense (2 year lag)	37,125	15.12437	2.771959	0	23.22331
Employees	37,125	6.94408	2.303116	0	13.68403

As the panel data in this analysis is unbalanced, it brings up the issue of why certain firms may be missing values. Unbalanced panel data results when firms have an unequal time dimension, meaning that firm year observations are missing from the data. For instance, Firm ABC may have 15 years of data, while Firm XYZ has 17 years of data. This difference in the number of observations of firms can create a bias in the data, depending on the reason for the missing data. If the data is missing for random reasons, than there should be no particular bias in the data. However, it could be the case that data is missing for non-random reasons meaning that there is some form of bias. Common examples would be a firm going bankrupt and exiting the market, or reentering the market after going private for a period of time. These examples lead to a dropped observations or time gaps within panels. Occurrences like these can lead to attrition or selection bias, where the data are biased toward firms with higher capital stocks.

Another potential area of bias in the input data could be non-random sampling. As the data comes from a data set of publicly traded firms, the firms in this research are much larger than the average firm. For instance, looking at Table 4.2 the average revenue of the firms in the data is near $2.56 billion, meaning these firms are all quite large. In one respect this bias is needed for the research because normally only larger firms conduct R&D or count R&D in their financial statements. Often if a firm's R&D expenses are below a certain amount, they will expense it with other related items, and thus there will be no clear R&D data available. For R&D to be examined there is a need to oversample large firms, as these firms actually declare their R&D spending. However, this clearly makes the sample of firms biased, and not representative of the average company. Additionally, the data only represents those firms that are publicly traded. While this may not be likely to affect the estimation results, it will still be hard to generalize results from this research to a small non-public firm conducting R&D.

Stage Two Data Summary

The data used to measure the dependent variables in the second step of the analysis were also gathered through Compustat. These variables were calculated according to the calculations found in Table 3.1. However, due to the multi-year aspect of the elasticity measures, and to allow for a comparison across firms, an average annual growth rate was found for these measures. Thus, all of the dependent variables except for the price to book ratio were measured as the average percent change per year for each firm. This is necessary to allow for a comparison between firms. Additionally, as the price to book ratio is the only variable not measured as a growth rate, it was calculated as the average price to book ratio a firm had over the span of available data years.

Similar to the controls for the input variables, the data for the dependent variables was also cleaned of obvious outliers. In general, these controls consisted of limiting percent changes in the data to 5000%(+/-), as values higher or lower than this are extremely unlikely to be accurate. The summary statistics of these dependent variables are seen in Table 4.4. Finally, the control variable for firm size used in the second step regressions were measured as the percent of industry revenue that a particular firm earns within its industry, where the industry is the two-digit SIC level. Like the dependent variables, the firm size control variable was also averaged over time.

The averaging of the data over the available firm years for the dependent variables was needed to allow for the regression in the second step. After the random coefficients regression, there will be only one elasticity data point per firm, regardless of the number of firm year observations. For this reason it is necessary to limit all the dependent variables to one variable per firm as well. As such, after the first stage estimation, the data set was reduced to 2464 observations, and no longer has a year dimension.

Table 4.4: Dependent Variable Data

Variable	Obs.	Mean	Std. Dev.	Min	Max
Sales	2464	25.9473	46.291	-36.409	726.664
Operating Income	2464	16.242	134.492	-1077.932	902.715
Operating Margin	2464	-41.239	152.404	-1415.822	857.273
Gross Profit	2464	31.006	65.141	-872.344	744.927
Gross Profit Ratio	2464	5.456	47.578	-796.469	584.439
Price to Book Ratio	1958	4.631	17.845	-303.115	293.079
Shareholder Returns	2351	73.246	243.623	-1467.469	3200

As seen in Table 4.4, even with controls for outliers there are still some extreme observations. This supports the use of Quantile regression in addition to OLS to hopefully control for some these outliers. All the dependent variables with the exception of the price to book ratio are denominated in average annual percent changes. Thus, for the sales variable, the mean change of sales for each firm was about 26%, which means that on average the firms in the data experienced an average increase in sales growth of 26% per year. While this seems to be a high value, it isn't unbelievable considering the sample of firms in the data. As the firms in question are larger than average, their growth rates had to have been higher than average at some point in their life span. Consequently, their average growth rates should be high as well, as is represented in the data.

V. Empirical Results

Prior to a full discussion of the results of this thesis, it would be beneficial to give a basic account of what results were found. The results from both the stage one estimation of R&D elasticity, and the stage two firm performance estimations are found in this section. Additionally, both the OLS and Quantile regression results will be compared and there will a brief discussion on the interpretation of the results.

Stage One Results

First, the R&D coefficients were estimated for all the firms in the data set. As stated earlier, this estimation was conducted using a Random Coefficient model, meaning there are separate results for both the entire group of firms and for individual firms. The summary statistics for the group mean estimation of the firm production function is found in Table 5.1. As seen, the average output elasticity of R&D for the entire set of 2464 firms is 0.227, which is significant at the 0.01 level, and falls within normal range of R&D elasticities found by other studies (Hall et al., 2009: Sveikauskas, 2007).

Table 5.1: Group Level Random-Coefficient Results:

Variable	Coefficients	Standard Error	Z-Score
Property Plant and Equipment	0.2597**	0.0180	14.43
Employees	0.5402**	0.0259	20.84
R&D (with lag)	0.2272**	0.0130	17.51
Constant	6.8086**	0.2678	25.42
Number of Observations	37125		
Number of Groups	2464		
Group (min, max)	(5, 57)		
Group Average	15.1		
Prob > Chi^2	0		

**=Significant at .01 level

One item to note from Table 5.1 is that R&D elasticity has the smallest effect on revenue of all three inputs. The greatest effect on output comes from the labor input and second largest comes from capital inputs. This means that firms generally gain more from increasing their capital or labor inputs, compared to increasing their R&D inputs. This finding, combined with the fact that firms typically invest more in capital and labor, is consistent with the idea of firm profit maximization. It can also be seen that the group experiences slight increasing returns to scale, as the coefficients of the three inputs variables sum to 1.025. However, in practical terms this result is not significantly different from 1, which means the average firm effectively receives constant returns.

While the Random Coefficient regression results give the elasticity coefficients for each firm, it also allows for the elasticities to be measured at the industry level. In Figure 5.1, the average R&D elasticity by industry is seen. Additionally Table 5.2 displays the same results with the precise productivity measurements and an industry description. The industry with the highest returns to R&D is the Textile mill products sector (SIC 22), and the lowest return is the Petroleum refining sector (SIC 29). This is relevant, as these findings contrast with a general intuition that would point to the more technology focused industries (SIC 35 and 36 in particular) as having the highest R&D elasticity. These industries, with firms such as Apple and Intel, are normally considered the most innovative of all industries, both by other scholars and by the general population (Hall et al. 2009). However, from the findings of this study, these industries have roughly average R&D elasticities.

Figure 5.1: R&D Elasticity by SIC Code

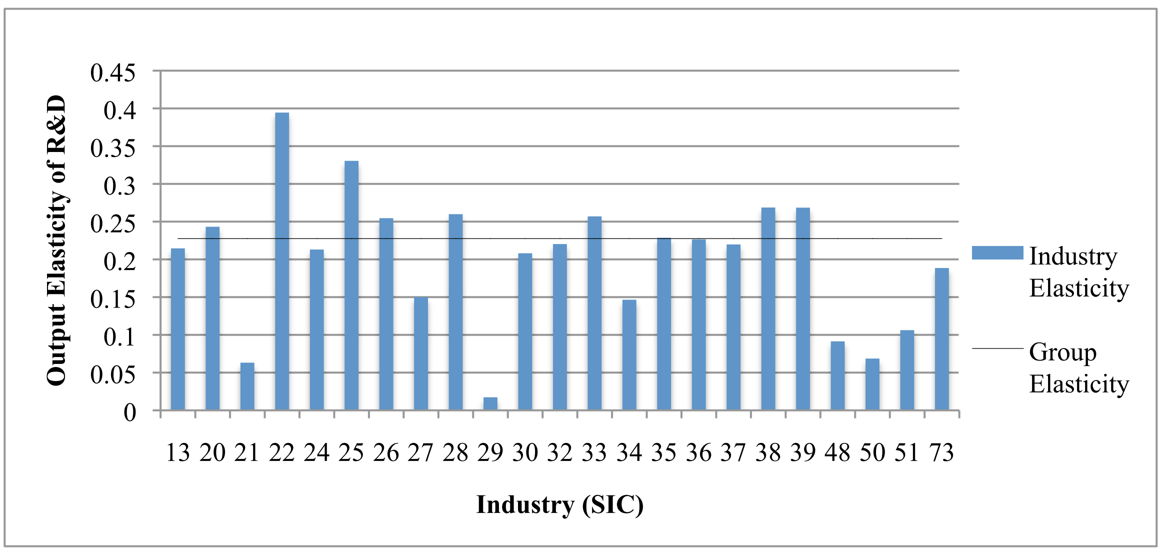
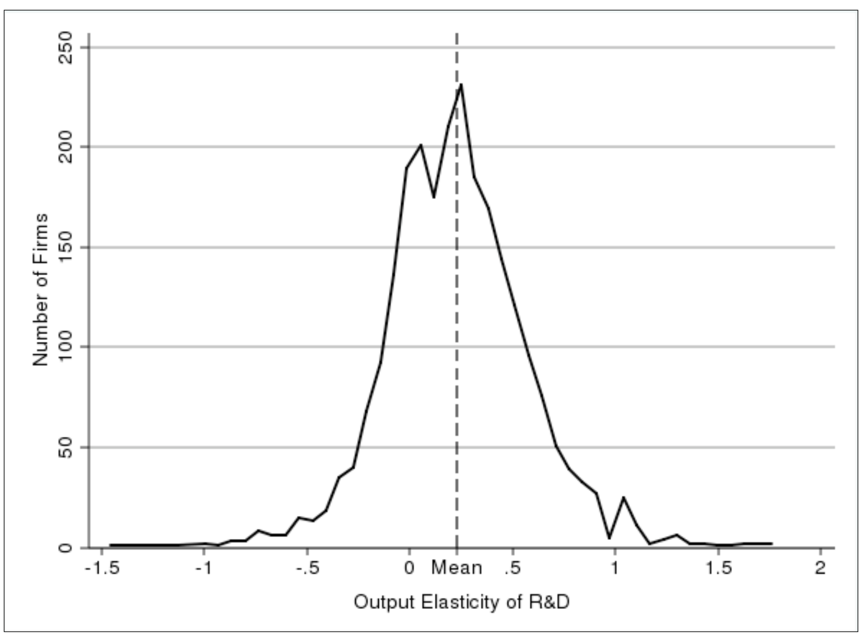


Table 5.2: R&D Elasticity by SIC with Industry Description

SIC Code	R&D Elasticity	Industry Description
13	0.213	Oil and gas extraction
20	0.243	Food and kindred products
21	0.063	Tobacco products
22	0.394	Textile mill products
24	0.213	Lumber and wood products (except furniture)
25	0.331	Furniture and fixtures
26	0.255	Paper and allied products
27	0.150	Printing, publishing & allied industries
28	0.260	Chemicals & allied products
29	0.017	Petroleum refining & related industries
30	0.208	Rubber & misc. plastic products
32	0.220	Stone, clay, glass, & concrete products
33	0.257	Primary metal industries
34	0.147	Fabricated metal (except. machines & transportation equip.)
35	0.229	Industrial & commercial machines & computer equip.
36	0.227	Electrical equip. (except computers)
37	0.220	Transportation equipment
38	0.269	Measuring instruments; photo. goods; watches
39	0.268	Misc. manufacturing industries
48	0.091	Communications
50	0.069	Durable goods - wholesale
51	0.106	Nondurable goods - wholesale
73	0.189	Business services

The results of the firm specific R&D elasticity measurements are seen in Figure 5.2. In particular, Figure 5.2 plots the R&D elasticity of all 2464 firms in a histogram to allow for an overview of all the firm estimates. As seen in the graph, the group elasticity (denoted "mean") is roughly at the median of all the elasticities. In addition, this graph gives an informal test of the heterogeneity of the R&D elasticity terms. As seen, the results are relatively heterogeneous, and have a standard deviation of 0.3556, which is significant considering that the range of values is only from approximately -1.5 to 1.75. Even with this informal visual test of elasticity heterogeneity, it can be concluded that R&D productivity varies enough between firms to potentially impact financial performance.

Figure 5.2: R&D Elasticity Histogram



Stage Two Results

After elasticity was estimated OLS estimation was performed on the elasticity estimations using equation 2. The results of these estimations are seen in Table 5.3. The results show that both operating income and operating margin are positively affected by R&D elasticity. However, R&D elasticity does not seem to have a significant statistical relationship to any of the other variables using the OLS estimation. It should be noted that the last two dependent variables, shareholder returns and the price to book ratio, have a different number of observations from the other variables. These fewer observation resulted from there being less data available for these measurements. With the goal of preserving as many observations as possible, instead of reducing the amount of observations for the first five variables, these estimations were run with the available data. It is not expected that the observation differences will have a significant effect on the comparability of the coefficients. For complete regression outputs of all seven regressions, please see Appendix A.

Table 5.3: OLS Estimation

Dependent Variable	R&D Elasticity Coefficient	Standard Error.	T - value	Observations
Revenue	-0.6918	2.8981	-0.24	2464
Operating income	21.0773**	8.1725	2.58	2464
Operating Margin	38.1992**	11.2656	3.39	2464
Gross Profit	-1.1989	4.2628	-0.28	2464
Gross Profit Ratio	-2.0120	3.6113	-0.56	2464
Shareholder Returns	-13.6517	12.7834	-1.07	2351
Price to Book Ratio	-2.1443	1.4394	-1.49	1958

**=significant at .01 level

Table 5.4 displays the results of the Median Quantile regression. As seen in the table, four of the seven dependent variables now have a significant relationship to elasticity, including revenue, operating income, operating margin, and gross profit. Additionally, with the exception of the gross profit ratio, all of these variables are positively related to R&D output elasticity. With the exception of the gross profit and gross profit ratio results, the findings are more in line with the expectations of this research project. For the full regression output of all seven of the Quantile regressions, please see Appendix B.

Table 5.4: Quantile Estimation Results

Dependent Variable	R&D Elasticity Coefficient	Standard Error	T - value	Observations
Revenue	2.5811**	0.9210	2.8	2464
Operating Income	9.9358**	2.5169	3.95	2464
Operating Margin	15.6538**	3.5709	4.38	2464
Gross Profit	1.1967	1.3475	0.89	2464
Gross Profit Ratio	-0.5134**	0.2296	-2.24	2464
Shareholder Returns	4.2406	9.6022	0.44	2351
Price to Book Ratio	0.0294	0.1362	0.22	1958

OLS to Quantile Results Comparison

The differences between the OLS and Quantile regression results bring up the issue of which results to rely on. The Quantile regression results are obviously more representative of the thesis, but to dismiss the OLS results on those grounds alone would be poor research. It was assumed previously that the Quantile estimation would be the more reliable measure, but this assumption needs to be tested prior to completely excluding the OLS results.

In general, there are two interrelated reasons that Quantile regression may be more reliable than OLS regression. These reasons are 1) if there are outliers in the dependent data, or 2) if the data have a distribution that is non-normal. First, Quantile regression is more robust against outliers, because unlike OLS, which estimates the conditional mean of the dependent variable, Quantile regression estimates the conditional median. Additionally, Quantile regression does not assume a normal error distribution as OLS does. Consequently, for the results to be "better" than OLS, the data for the dependent variables should contain significant outliers or be non-normal. As stated earlier, and as was informally seen in Table 4.4, it is assumed that the dependent data contain significant outliers, meaning Quantile regression is likely to be more robust for the first reason. However, the aspect of normality can also be examined. To test the non-normality assumption a Shapiro-Wilk test can be utilized to determine if the dependent variable data come from a normally distributed population. The results from this test are seen in Table 5.5. As the null hypothesis of the Shapiro-Wilk test is that the data is from a normal distribution, given high z-values, the null can be easily rejected. Thus, all of the dependent variables are likely to be non-normally distributed. Given that both of the reasons for Quantile regression being more robust than OLS are satisfied, the results that will be accepted as "true", and the results from the Quantile regression estimation will be discussed from now on.

Table 5.5: Shapiro-Wilk Normality Test Results

	Observations	W	V	z	Prob > z
Revenue	2464	0.469	760.704	17.003	0.000
Operating Income	2464	0.816	263.536	14.286	0.000
Operating Margin	2464	0.833	239.77	14.044	0.000
Gross Profit	2464	0.548	647.831	16.591	0.000
Gross Profit Ratio	2464	0.355	924.341	17.502	0.000
Shareholder Returns	2351	0.762	327.125	14.816	0.000
Price to Book Ratio	1958	0.407	690.053	16.615	0.000

Coefficient Interpretation

As we are using Median Quantile regression, it would be beneficial to review how the coefficients should be interpreted. Median regression specifies the change in the median dependent variable as a function of the independent variables. Thus, the results are roughly interpreted the same as OLS estimates, except that the coefficients represent the median change, not the average change. For instance, for the revenue results, the coefficient of 2.58 means that the median firm will experience a 2.58% increase in revenue growth for each additional percent increase in elasticity, all else equal.

Another issue regarding the result interpretation is that the dependent variable in this analysis is a growth rate for all variables except for the price to book ratio. This means the coefficients represent the increase in the growth rate of the variables. Continuing the example of the revenue findings, this can be interpreted as a one percent increase in R&D elasticity leading to revenue growth that is 2.58% higher than they had previously. For instance, if the median firm has an average revenue growth rate of 10%, it will grow at 10.258% if R&D elasticity is increased one percent. The results for the other three statistically significantly variables can be interpreted in a similar fashion.

Potential of Error

As previously mentioned in the empirical analysis section, the results of this study have may be influenced by a simultaneity bias. This bias is caused when both the dependent and an independent variable influence each other simultaneously. In this particular case, firm revenue (output) both influences, and is influenced by, R&D investment. Consequently, there is a significant issue of which direction causality flows in this analysis. For instance, it is likely that R&D investment influences future revenues, but it is also likely that R&D investment depends on past and present revenues, along with the expectation of future revenues. For this reason, there is a potential for a bias in this study, where higher R&D investments are falsely attributed to higher revenues, when it is the actually the case that there are more R&D investments due to higher revenues.

Due to the issue of simultaneity, the results found in this study cannot be considered to be unbiased. To help control for some bias a lag was taken of the R&D variable. However, this isn't likely to control for all of the bias. This is because R&D investments often take several years to generate more output, and because R&D processes are likely to be slow to start or stop due to the numerous costs involved. Thus, even with a lag included, the timing of R&D investment and output relationship can't be accurately measured, leading to the simultaneity bias in the results. In turn, this bias is likely to impact the results of the firm performance analysis. Consequently, while the results in this section are believed to be as accurate as possible considering the scope of this project, some caution is certainly warranted.

VI. Discussion

Have the results found by this study proved the thesis? Given that the primary purpose of this study was to determine if measureable R&D elasticity is related to firm financial performance, the answer is likely yes. However, another aspect of this project was to determine if firms have an incentive to utilize R&D elasticity as a tool to decide the amount of R&D investment. Thus, a question that needs to be answered is: Do the results found in this study provide adequate incentive for firms to care about their R&D elasticities?

In economics, it is generally assumed that firms are trying to maximize their profits. Because of this profit incentive, firms are always trying to become more efficient, and get more output with less input. Thus, for firms to be incentivized to use R&D elasticity during investment decisions, the effects have to go beyond just increasing revenues or decreasing costs. This is because higher revenues or lower costs are often associated with respective increases in cost or decreases in revenue. Consequently, the variables used in the study of the most interest to firms would be operating margin, operating income, gross profit, and gross profit ratio, as these variables measure firm efficiency and profit levels.

For the purpose of this discussion it will be assumed that the relationships found in the analyses are both authentic and causal, and thus that the simultaneity bias along with the other sources of error don't have a meaningful impact on the results. If this assumption is made then it can be said that as R&D elasticity increases, the median firm will:

- Receive more income.
- Receive more overall profit after operations.
- Be more efficient in its total operations.
- Be less efficient in production.

With the exception of the last statement, these results clearly give the impression that firms have an incentive to want higher levels of elasticity. However, there is also a structural relationship between these variables that is relevant to discuss.

The first structural implication has to deal with the magnitude of the operating margin result. As previously stated, it is known that operating margin equals operating income divided by revenue. Given this relationship, if revenue goes down or operating income goes up, then the operating margin will increase. However, from the results it is known that all three of these variables increase with higher elasticity. Consequently, it has to be that R&D elasticity has a greater effect on firm operating income than on revenue. In other words, it likely the case that R&D productivity has a larger effect on firm operating income than on revenues, meaning elasticity makes firms more efficient instead of just increasing sales, which is highly desirable for firms.

A second structural relationship found from the results involves the negative gross profit ratio term. In general, negative gross profit ratio could be interpreted as a firm becoming less efficient in the production of their products. Clearly, this is contrary to the operating income result, and creates a disincentive for firms to use elasticity as a metric. However, based on the structural relationship between the variables, it can be seen that this negative relationship might not negatively affect firms. As gross profit ratio is calculated as gross profit divided by sales, if gross profit ratio is decreasing, than clearly either sales are increasing or gross profit is decreasing. Consequently, as the results show an increase in sales and no significant change in gross profit, it is likely that the negative gross profit ratio results from the revenue increase. This means that the gross profit ratio decreases “naturally.” As such, the negative coefficient for gross profit ratio doesn’t necessarily imply that the firm is less efficient, but instead that revenue is increasing more than gross profit.

Combining the basic findings with the structural relationships, it can be clearly seen that the thesis of this study holds, and that R&D elasticity positively affects firm performance. In particular it was found that an increase in measureable R&D elasticity increases the growth rates of firm revenue, operating income, and operating margin. More significantly, it was found that elasticity has a greater effect on operating income growth than on revenue growth, meaning R&D elasticity is more related to increased firm efficiency. Consequently, from these results it can be stated that firms have adequate incentives to used R&D elasticity as a decision tool, due to its positive relationship to firm performance.

However, one issue not yet discussed is the non-significant relationship found between elasticity and shareholder returns and the price to book ratio. Simply stated, it seems as if there is no relationship between elasticity and investor expectations about firms. In general, it wasn’t expected that the results would show any sort of relationship for these variables because it is assumed that the efficient market hypothesis holds. For instance, if there was a significant relationship found for shareholder returns it would be possible for investors to use R&D elasticity in a trading strategy to make a profit, which would go against efficient markets. Similarly, for the price to book ratio, it is generally unexpected that the efficiency of R&D spending will substantially affect investor expectations of a company's value. In any case, if a firm is incentivized solely by profit maximization, the insignificant findings for these measures are not expected to impact a firm's incentive to use the R&D elasticity metric.

Sources of the Results

Now that the thesis of this project has been proven, the second issue of why R&D elasticity actually affects firm performance can be discussed. Obviously, elasticity impacts firm performance because it measures how much output a firm receives from their production inputs. Simply stated, the higher it is, the more efficient a firm becomes. However elasticity is only a measure of efficiency, not the cause, meaning that elasticity is representative of separate occurrences within a firm that lead higher efficiency.

There are likely to be many causes of the relationship between elasticity and firm performance, but one that will be discussed here is the effect of elasticity on higher R&D investments. Studies have shown that firms with higher R&D spending generally have better financial performance (Foray, 2007). Additionally, other studies have theorized that higher R&D elasticities increase R&D investment, due to the greater marginal benefits (Knott, 2008). Given these ideas it could be theorized that firms with higher elasticities have higher spending on R&D, in turn causing better performance. The root cause of this relationship is that higher R&D elasticities might create the incentives for firms to invest more in R&D.

Firms invest in R&D to either enhance production processes or to develop new or better products. Consequently, the goal of R&D is to increase the financial performance of the firm. While debatable, some studies have found a relationship between R&D spending and performance, such as Foray et al. (2007), which found that firms that spend more on R&D have higher financial performance on average. However, as this study is measuring the productivity of R&D, instead of the amount of R&D spending, the same effect cannot be directly attributed to R&D elasticity. Instead it could be hypothesized that firms that have higher R&D productivities are incentivized to conduct more R&D and thus have better financials.

A relationship between higher R&D efficiencies and higher investment incentives makes economic sense, as firms want to invest to maximize their returns. As such, firms should invest until the marginal benefit of R&D investment equals the marginal cost of R&D investment, which will occur at a higher level in firms with greater R&D productivities. Thus, assuming firms are profit maximizing, firms with higher R&D elasticities should invest more than firms with lower elasticities.

However, for this relationship to work it also has to be assumed that R&D has frictions. At the hypothetical R&D investment marginal cost / marginal benefit equilibrium point, the return to R&D should be equal for all firms. Consequently, it shouldn't be possible for there to be a relationship between R&D returns and the amount spent on R&D if firms are at this point. However, if there are frictions for R&D investments, firms can't invest efficiently. For instance, it could be that research costs or communication errors within R&D departments prevent firms from adjusting R&D

spending fast enough to match changing R&D returns. If frictions are assumed, it can be hypothesized that higher R&D elasticities will be correlated to higher R&D investments.

To explore this idea a simple test will be conducted. To do this, a Median Quantile regression will be estimated between the dependent variable of R&D intensity[7] and the independent variable of R&D elasticity. Like the previous tests, dummy variables for industry and a firm size control variable will be included. The results from this simple test are seen in Table 6.1[8]. From the results, it is seen that there is a significant and positive relationship between having higher elasticity and having higher R&D investment rates. Thus, it seems plausible that being more productive at R&D does create an incentive to invest more in R&D.

Table 6.1: Median Quantile Regression: R&D Intensity Dependent

Variable	Coefficient	Standard Error	t-value
R&D Elasticity	0.3408^{+}	0.1761	1.94
Observations	2464		
Pseudo R2	0.1507		

+ = Significant at .1 level

While it's likely not the only reason why higher R&D elasticities are related to greater firm performance, the relationship between higher R&D expenditures and higher R&D elasticity can explain some of the results found in this paper. In particular, investing more in R&D will increase the likelihood of both having monopolistic pricing power and having more efficient production processes. In turn this will lead to higher revenues, profitability, and efficiency. Thus, higher productivity creating an incentive for

[7] R&D intensity is calculated as R&D spending divided by total revenues.
[8] Please see Appendix C for the full results of this regression.

more R&D investment could be one potential path for elasticity to lead to higher firm performance.

One issue with this relationship could be that a dual causality is occurring. For instance, higher R&D investment rates could be causing the firms to have higher R&D elasticities. It makes logical sense, and is similar to the idea of absorptive capacity, that the more a firm conducts R&D, the better they will become at conducting R&D. However, considering profit maximization, if firms did experience significant R&D efficiency gains from conducting more R&D spending, it would be expected that firms would spend more than they currently do in order to reap the additional benefits. Thus, while there is a potential for higher R&D intensities to create higher R&D elasticities, it is more likely that the reverse is true, and that higher elasticities incentivize more research spending.

VII. Conclusion

From a broad perspective, this thesis was an introductory investigation into how to increase firm investment in R&D. Increasing firm investment in R&D is important as it not only increases firm performance, but is also a primary driver of economic growth. Due to imperfect information about R&D productivities, firms have a general aversion to investing in R&D. For this reason, R&D has made up proportionally small amounts of firm budgets in recent decades. To incentivize R&D investment, what firms require is a method to determine the productivity of their R&D programs, to allow for more efficient R&D investments. Consequently, the purpose of this thesis was to examine if R&D elasticity is related to firm performance, in hopes of determining if it is an adequate metric for use in R&D investment decisions. After empirical estimation, the general thesis of this study was proven. It was found that higher levels of R&D elasticity are related to higher growth rates for firm revenue, operating margin, and operating income.

The findings from this study have shown that firms now have a relatively reliable variable that can be used to measure their R&D performance, which has major implications. First, firms now can compare their performance to other firms to determine if they are falling behind, which will allow them to adjust their R&D investments accordingly. Second, with such a measure, firms can now determine if changes they make to their R&D processes make them more efficient, which will lead to more repeatable processes of improvement. Thus, what has changed over the last decade with the introduction of the measurement of R&D elasticity at the firm level is that firms now have a metric to help them both invest optimally, and become more efficient at R&D.

While this study has answered some relevant questions about the relationship between firm performance and R&D elasticity, it has also left many questions unanswered. The primary unanswered question is: What can firms do to have a higher elasticity? This will likely be a question that future studies into R&D productivity will attempt to answer. The investigation into the determinants of R&D elasticity could have significant implications for both firms and society. If determined, the findings could lead to many more innovations, and in turn, advances in societal wellbeing.

This study fits into the overall field of R&D literature by synthesizing some of the more recent findings to be more applicable for firm decision making. The results showed that firms with higher measureable elasticities do have better performance. While the results of this study have the potential to be highly biased, they are believed to be reasonably accurate given the constraints of the data and the available statistical methods. For this reason, it is the conclusion of this study that having higher measureable R&D elasticity does increase firm performance, and that firms should be adequately incentivized to use R&D elasticity as a tool to help determine their R&D investments.

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Appendix A: Ordinary Least Squares Regression Results

1. Dependent Variable: Revenue

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	-0.692	2.898	-0.24	0.811	-6.375	4.991
Firm Size	-842.829	282.874	-2.98	0.003	-1397.527	-288.131
Sic - 13	11.712	6.119	1.91	0.056	-0.286	23.710
Sic - 20	8.561	9.020	0.95	0.343	-9.126	26.248
Sic - 21	(omitted)					
Sic - 22	1.340	4.265	0.31	0.753	-7.023	9.703
Sic - 24	1.130	5.335	0.21	0.832	-9.332	11.592
Sic - 25	4.160	5.149	0.81	0.419	-5.936	14.256
Sic - 26	4.991	5.366	0.93	0.352	-5.530	15.513
Sic - 27	3.966	4.189	0.95	0.344	-4.249	12.182
Sic - 28	23.646	4.726	5.00	0.000	14.378	32.914
Sic - 29	2.312	4.503	0.51	0.608	-6.518	11.142
Sic - 30	6.174	4.904	1.26	0.208	-3.442	15.790
Sic - 32	-0.457	5.594	-0.08	0.935	-11.426	10.512
Sic - 33	9.523	8.806	1.08	0.280	-7.745	26.790
Sic - 34	6.172	4.976	1.24	0.215	-3.585	15.928
Sic - 35	14.906	4.400	3.39	0.001	6.278	23.533
Sic - 36	13.516	4.535	2.98	0.003	4.623	22.410
Sic - 37	7.954	4.179	1.90	0.057	-0.242	16.149
Sic - 38	10.486	3.597	2.92	0.004	3.433	17.539
Sic - 39	5.491	4.496	1.22	0.222	-3.325	14.306
Sic - 48	17.701	6.931	2.55	0.011	4.110	31.293
Sic - 50	21.288	7.900	2.69	0.007	5.798	36.779
Sic - 51	43.064	21.175	2.03	0.042	1.541	84.587
Sic - 73	17.308	4.283	4.04	0.000	8.910	25.707
Constant	12.808	3.354	3.82	0.000	6.232	19.385

Number of observations	2464
F(24, 2439)	5.15
Prob > F	0
R-squared	0.0164
Root MSE	46.135

2. Dependent Variable: Operating Income

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	21.077	8.172	2.58	0.010	5.052	37.103
Firm Size	1480.434	888.262	1.67	0.096	-261.391	3222.260
Sic - 13	24.281	17.115	1.42	0.156	-9.279	57.842
Sic - 20	9.861	19.393	0.51	0.611	-28.168	47.890
Sic - 21	0.000	(omitted)				
Sic - 22	-15.364	17.366	-0.88	0.376	-49.418	18.690
Sic - 24	-6.793	14.356	-0.47	0.636	-34.943	21.357
Sic - 25	52.165	69.990	0.75	0.456	-85.081	189.411
Sic - 26	21.924	17.173	1.28	0.202	-11.752	55.600
Sic - 27	18.289	23.686	0.77	0.440	-28.157	64.736
Sic - 28	5.457	15.681	0.35	0.728	-25.293	36.206
Sic - 29	19.650	15.020	1.31	0.191	-9.803	49.104
Sic - 30	18.135	24.361	0.74	0.457	-29.634	65.904
Sic - 32	20.528	25.760	0.80	0.426	-29.986	71.041
Sic - 33	27.973	29.838	0.94	0.349	-30.537	86.483
Sic - 34	30.124	22.984	1.31	0.190	-14.946	75.195
Sic - 35	-2.452	15.578	-0.16	0.875	-32.999	28.096
Sic - 36	-0.780	14.944	-0.05	0.958	-30.084	28.524
Sic - 37	34.587	16.128	2.14	0.032	2.961	66.213
Sic - 38	12.196	14.641	0.83	0.405	-16.515	40.906
Sic - 39	19.465	32.075	0.61	0.544	-43.432	82.361
Sic - 48	-24.712	18.427	-1.34	0.180	-60.845	11.422
Sic - 50	-63.989	39.038	-1.64	0.101	-140.540	12.562
Sic - 51	-27.853	19.693	-1.41	0.157	-66.469	10.764
Sic - 73	-24.339	16.605	-1.47	0.143	-56.900	8.222
Constant	7.791	13.800	0.56	0.572	-19.271	34.852

Number of observations	2464
F(24, 2439)	2.67
Prob > F	0
R-squared	0.0205
Root MSE	133.76

3. Dependent Variable: Operating Margin

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	38.199	11.266	3.39	0.001	16.108	60.290
Firm Size	6253.570	1231.512	5.08	0.000	3838.652	8668.488
Sic - 13	-32.157	54.453	-0.59	0.555	-138.936	74.622
Sic - 20	-19.360	53.195	-0.36	0.716	-123.673	84.952
Sic - 21	(omitted)					
Sic - 22	-43.788	56.862	-0.77	0.441	-155.292	67.715
Sic - 24	-63.176	65.626	-0.96	0.336	-191.864	65.513
Sic - 25	-103.731	65.114	-1.59	0.111	-231.416	23.954
Sic - 26	-1.874	63.116	-0.03	0.976	-125.640	121.892
Sic - 27	-105.194	64.066	-1.64	0.101	-230.823	20.436
Sic - 28	-55.159	52.692	-1.05	0.295	-158.485	48.167
Sic - 29	8.347	52.768	0.16	0.874	-95.129	111.822
Sic - 30	-43.484	56.069	-0.78	0.438	-153.431	66.462
Sic - 32	26.339	77.748	0.34	0.735	-126.121	178.799
Sic - 33	-51.355	54.556	-0.94	0.347	-158.335	55.626
Sic - 34	-80.890	56.300	-1.44	0.151	-191.289	29.510
Sic - 35	-67.740	52.388	-1.29	0.196	-170.469	34.990
Sic - 36	-73.312	52.364	-1.40	0.162	-175.995	29.370
Sic - 37	-52.440	53.565	-0.98	0.328	-157.478	52.597
Sic - 38	-57.515	52.184	-1.10	0.270	-159.844	44.814
Sic - 39	-77.685	56.415	-1.38	0.169	-188.310	32.941
Sic - 48	-51.977	53.148	-0.98	0.328	-156.197	52.242
Sic - 50	-157.625	71.002	-2.22	0.027	-296.856	-18.394
Sic - 51	-177.473	79.792	-2.22	0.026	-333.940	-21.006
Sic - 73	-100.531	52.547	-1.91	0.056	-203.573	2.512
Constant	13.435	51.810	0.26	0.795	-88.162	115.031

Number of observations	2464
F(24, 2439)	6.28
Prob > F	0
R-squared	0.0393
Root MSE	150.11

4. Dependent Variable: Gross Profit

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	-1.199	4.263	-0.28	0.779	-9.558	7.160
Firm Size	-799.202	303.838	-2.63	0.009	-1395.010	-203.394
Sic - 13	1.916	22.498	0.09	0.932	-42.202	46.034
Sic - 20	-7.447	23.017	-0.32	0.746	-52.581	37.688
Sic - 21	(omitted)					
Sic - 22	-19.117	21.123	-0.91	0.366	-60.537	22.304
Sic - 24	-14.359	21.845	-0.66	0.511	-57.196	28.479
Sic - 25	-18.757	21.069	-0.89	0.373	-60.072	22.558
Sic - 26	-16.803	20.960	-0.80	0.423	-57.904	24.298
Sic - 27	-15.520	20.822	-0.75	0.456	-56.350	25.311
Sic - 28	0.427	21.185	0.02	0.984	-41.116	41.970
Sic - 29	-21.526	20.771	-1.04	0.300	-62.257	19.205
Sic - 30	-15.055	20.920	-0.72	0.472	-56.077	25.968
Sic - 32	-23.294	21.226	-1.10	0.273	-64.916	18.328
Sic - 33	-19.921	23.458	-0.85	0.396	-65.920	26.078
Sic - 34	-13.146	21.161	-0.62	0.534	-54.641	28.349
Sic - 35	1.573	20.977	0.07	0.940	-39.562	42.708
Sic - 36	-4.381	20.854	-0.21	0.834	-45.274	36.513
Sic - 37	-5.784	20.997	-0.28	0.783	-46.957	35.389
Sic - 38	-2.930	20.891	-0.14	0.888	-43.897	38.037
Sic - 39	-14.901	21.000	-0.71	0.478	-56.081	26.280
Sic - 48	-6.392	22.062	-0.29	0.772	-49.654	36.871
Sic - 50	-5.657	21.341	-0.27	0.791	-47.504	36.191
Sic - 51	-7.768	21.899	-0.35	0.723	-50.711	35.176
Sic - 73	1.679	21.060	0.08	0.936	-39.618	42.976
Constant	34.993	20.624	1.70	0.090	-5.449	75.434

Number of observations	2464
F(24, 2439)	4.41
Prob > F	0
R-squared	0.0093
Root MSE	65.155

5. Dependent Variable: Gross Profit Ratio

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	-2.012	3.611	-0.56	0.577	-9.094	5.070
Firm Size	-111.197	183.935	-0.60	0.546	-471.882	249.488
Sic - 13	-13.321	18.475	-0.72	0.471	-49.549	22.908
Sic - 20	-17.139	18.373	-0.93	0.351	-53.168	18.891
Sic - 21	(omitted)					
Sic - 22	-20.821	18.386	-1.13	0.258	-56.874	15.232
Sic - 24	-15.882	18.471	-0.86	0.390	-52.103	20.339
Sic - 25	-20.906	18.322	-1.14	0.254	-56.834	15.023
Sic - 26	-16.857	18.406	-0.92	0.360	-52.951	19.236
Sic - 27	-19.275	18.324	-1.05	0.293	-55.208	16.658
Sic - 28	-18.110	18.856	-0.96	0.337	-55.086	18.865
Sic - 29	-22.239	18.197	-1.22	0.222	-57.922	13.444
Sic - 30	-19.696	18.286	-1.08	0.282	-55.555	16.162
Sic - 32	-21.416	18.292	-1.17	0.242	-57.287	14.454
Sic - 33	-30.605	21.227	-1.44	0.149	-72.229	11.019
Sic - 34	-25.165	19.170	-1.31	0.189	-62.756	12.425
Sic - 35	-16.184	18.250	-0.89	0.375	-51.972	19.604
Sic - 36	-15.282	18.236	-0.84	0.402	-51.041	20.478
Sic - 37	-14.965	18.306	-0.82	0.414	-50.862	20.932
Sic - 38	-14.463	18.246	-0.79	0.428	-50.242	21.315
Sic - 39	-19.460	18.227	-1.07	0.286	-55.202	16.282
Sic - 48	-16.913	18.830	-0.90	0.369	-53.838	20.011
Sic - 50	-21.653	18.308	-1.18	0.237	-57.554	14.249
Sic - 51	-20.411	18.702	-1.09	0.275	-57.085	16.263
Sic - 73	-13.279	18.408	-0.72	0.471	-49.376	22.817
Constant	22.150	18.133	1.22	0.222	-13.409	57.709

Number of observations	2464
F(24, 2439)	2.52
Prob > F	0.0001
R-squared	0.0045
Root MSE	47.704

6. Dependent Variable: Shareholder Returns

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	-13.652	12.783	-1.07	0.286	-38.720	11.416
Firm Size	-1644.487	3045.458	-0.54	0.589	-7616.583	4327.609
Sic - 13	-39.807	94.571	-0.42	0.674	-225.260	145.646
Sic - 20	2.996	110.593	0.03	0.978	-213.875	219.866
Sic - 21	-137.925	99.015	-1.39	0.164	-332.091	56.242
Sic - 22	-3.445	95.259	-0.04	0.971	-190.246	183.356
Sic - 24	(omitted)					
Sic - 25	4.358	109.911	0.04	0.968	-211.177	219.893
Sic - 26	-89.605	96.579	-0.93	0.354	-278.994	99.784
Sic - 27	-119.670	95.087	-1.26	0.208	-306.134	66.794
Sic - 28	-31.180	93.282	-0.33	0.738	-214.104	151.744
Sic - 29	-113.381	96.731	-1.17	0.241	-303.069	76.307
Sic - 30	-58.972	93.015	-0.63	0.526	-241.374	123.429
Sic - 32	60.856	134.393	0.45	0.651	-202.686	324.397
Sic - 33	-82.368	98.020	-0.84	0.401	-274.584	109.847
Sic - 34	-55.163	101.543	-0.54	0.587	-254.286	143.961
Sic - 35	-49.482	92.204	-0.54	0.592	-230.293	131.329
Sic - 36	-44.821	92.251	-0.49	0.627	-225.723	136.082
Sic - 37	-95.165	92.889	-1.02	0.306	-277.319	86.989
Sic - 38	-50.116	92.502	-0.54	0.588	-231.512	131.279
Sic - 39	-117.365	100.351	-1.17	0.242	-314.152	79.423
Sic - 48	-45.696	116.959	-0.39	0.696	-275.052	183.659
Sic - 50	-83.593	100.180	-0.83	0.404	-280.045	112.859
Sic - 51	13.948	184.183	0.08	0.940	-347.233	375.128
Sic - 73	-64.488	92.765	-0.70	0.487	-246.399	117.424
Constant	129.643	91.816	1.41	0.158	-50.406	309.692

Number of observations	2351
F(24, 2326)	1.48
Prob > F	0.0615
R-squared	0.0089
Root MSE	243.78

7. Dependent Variable: Price to Book Ratio

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	-2.144	1.439	-1.49	0.136	-4.967	0.679
Firm Size	29.127	237.684	0.12	0.902	-437.017	495.270
Sic - 13	2.142	2.162	0.99	0.322	-2.098	6.381
Sic - 20	-0.081	1.619	-0.05	0.960	-3.256	3.093
Sic - 21	-16.857	8.456	-1.99	0.046	-33.440	-0.274
Sic - 22	-0.115	1.200	-0.10	0.924	-2.469	2.238
Sic - 24	(omitted)					
Sic - 25	4.078	2.702	1.51	0.131	-1.222	9.378
Sic - 26	-0.578	1.907	-0.30	0.762	-4.318	3.163
Sic - 27	-13.656	13.352	-1.02	0.307	-39.841	12.529
Sic - 28	7.641	2.710	2.82	0.005	2.326	12.956
Sic - 29	-0.591	1.899	-0.31	0.756	-4.315	3.133
Sic - 30	0.995	2.098	0.47	0.636	-3.120	5.109
Sic - 32	2.380	3.535	0.67	0.501	-4.553	9.312
Sic - 33	0.846	2.041	0.41	0.679	-3.157	4.849
Sic - 34	0.875	2.035	0.43	0.667	-3.115	4.865
Sic - 35	3.499	2.403	1.46	0.146	-1.214	8.212
Sic - 36	4.922	2.230	2.21	0.027	0.549	9.296
Sic - 37	0.643	2.788	0.23	0.818	-4.825	6.111
Sic - 38	3.174	2.340	1.36	0.175	-1.414	7.762
Sic - 39	3.284	3.066	1.07	0.284	-2.729	9.297
Sic - 48	2.443	2.770	0.88	0.378	-2.989	7.876
Sic - 50	-0.105	1.784	-0.06	0.953	-3.604	3.393
Sic - 51	14.653	14.175	1.03	0.301	-13.147	42.453
Sic - 73	7.065	2.630	2.69	0.007	1.908	12.222
Constant	1.078	2.177	0.50	0.621	-3.192	5.348

Number of observations	1958
F(24, 1933)	6.8
Prob > F	0
R-squared	0.0269
Root MSE	17.713

Appendix B: Median Quantile Regression Results

1. Dependent Variable: Revenue

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	2.581	0.921	2.80	0.005	0.775	4.387
Firm Size	-302.487	202.644	-1.49	0.136	-699.859	94.884
Sic - 13	4.723	7.148	0.66	0.509	-9.294	18.740
Sic - 20	-3.699	7.296	-0.51	0.612	-18.007	10.608
Sic - 21	-3.292	8.574	-0.38	0.701	-20.104	13.521
Sic - 22	-1.929	7.468	-0.26	0.796	-16.574	12.716
Sic - 24	(omitted)					
Sic - 25	1.439	8.051	0.18	0.858	-14.348	17.226
Sic - 26	-2.301	7.233	-0.32	0.750	-16.484	11.881
Sic - 27	1.828	7.950	0.23	0.818	-13.761	17.417
Sic - 28	6.240	6.773	0.92	0.357	-7.041	19.520
Sic - 29	-0.449	7.274	-0.06	0.951	-14.712	13.814
Sic - 30	-0.669	7.047	-0.09	0.924	-14.487	13.149
Sic - 32	-4.074	7.896	-0.52	0.606	-19.559	11.410
Sic - 33	-3.121	7.138	-0.44	0.662	-17.119	10.877
Sic - 34	-2.911	7.024	-0.41	0.679	-16.685	10.862
Sic - 35	1.719	6.755	0.25	0.799	-11.527	14.966
Sic - 36	2.092	6.750	0.31	0.757	-11.145	15.329
Sic - 37	0.146	6.843	0.02	0.983	-13.273	13.565
Sic - 38	4.249	6.747	0.63	0.529	-8.982	17.480
Sic - 39	1.230	7.207	0.17	0.864	-12.901	15.362
Sic - 48	8.227	7.049	1.17	0.243	-5.595	22.050
Sic - 50	8.261	7.435	1.11	0.267	-6.319	22.841
Sic - 51	15.892	8.432	1.88	0.060	-0.644	32.427
Sic - 73	5.965	6.764	0.88	0.378	-7.299	19.228
Constant	11.731	6.711	1.75	0.081	-1.429	24.891

Raw sum of deviations	47879.48 (about 15.118814)
Min sum of deviations	47012.3
Number of Observations	2464
Pseudo R2	0.0181

2. Dependent Variable: Operating Income

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	9.936	2.517	3.95	0.000	5.000	14.871
Firm Size	316.817	561.042	0.56	0.572	-783.351	1416.985
Sic - 13	22.127	19.236	1.15	0.250	-15.594	59.848
Sic - 20	-1.219	19.707	-0.06	0.951	-39.863	37.425
Sic - 21	6.127	24.975	0.25	0.806	-42.847	55.101
Sic - 22	-1.210	20.271	-0.06	0.952	-40.961	38.540
Sic - 24	(omitted)					
Sic - 25	4.863	21.803	0.22	0.824	-37.890	47.617
Sic - 26	5.872	19.484	0.30	0.763	-32.335	44.079
Sic - 27	14.866	21.526	0.69	0.490	-27.346	57.077
Sic - 28	4.119	18.167	0.23	0.821	-31.505	39.743
Sic - 29	11.860	19.602	0.61	0.545	-26.579	50.298
Sic - 30	12.794	18.955	0.67	0.500	-24.375	49.963
Sic - 32	-3.249	20.952	-0.16	0.877	-44.334	37.835
Sic - 33	21.933	19.219	1.14	0.254	-15.755	59.622
Sic - 34	14.478	18.889	0.77	0.443	-22.562	51.518
Sic - 35	8.390	18.117	0.46	0.643	-27.137	43.917
Sic - 36	13.206	18.104	0.73	0.466	-22.295	48.707
Sic - 37	16.629	18.372	0.91	0.365	-19.397	52.654
Sic - 38	12.218	18.094	0.68	0.500	-23.264	47.700
Sic - 39	20.351	19.398	1.05	0.294	-17.687	58.389
Sic - 48	-4.616	18.972	-0.24	0.808	-41.820	32.587
Sic - 50	-1.249	20.094	-0.06	0.950	-40.652	38.153
Sic - 51	-17.787	22.918	-0.78	0.438	-62.728	27.154
Sic - 73	4.679	18.144	0.26	0.797	-30.900	40.259
Constant	7.775	17.995	0.43	0.666	-27.512	43.062

Raw sum of deviations	187728.3 (about 20.430145)
Min sum of deviations	186419.9
Number of Observations	2464
Pseudo R2	0.007

3. Dependent Variable: Operating Margin

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	15.654	3.571	4.38	0.000	8.651	22.656
Firm Size	3369.323	718.616	4.69	0.000	1960.162	4778.485
Sic - 13	65.109	27.447	2.37	0.018	11.287	118.930
Sic - 20	66.566	28.089	2.37	0.018	11.486	121.646
Sic - 21	74.617	35.458	2.10	0.035	5.086	144.149
Sic - 22	58.817	28.872	2.04	0.042	2.200	115.433
Sic - 24	(omitted)					
Sic - 25	64.760	31.064	2.08	0.037	3.845	125.676
Sic - 26	64.812	27.792	2.33	0.020	10.314	119.310
Sic - 27	-6.051	30.519	-0.20	0.843	-65.898	53.795
Sic - 28	62.094	25.942	2.39	0.017	11.224	112.964
Sic - 29	79.944	27.955	2.86	0.004	25.127	134.762
Sic - 30	67.576	27.049	2.50	0.013	14.534	120.617
Sic - 32	53.057	30.422	1.74	0.081	-6.599	112.713
Sic - 33	41.009	27.424	1.50	0.135	-12.768	94.787
Sic - 34	62.123	26.951	2.31	0.021	9.273	114.973
Sic - 35	52.824	25.872	2.04	0.041	2.090	103.558
Sic - 36	43.928	25.853	1.70	0.089	-6.768	94.623
Sic - 37	67.372	26.229	2.57	0.010	15.938	118.806
Sic - 38	60.009	25.841	2.32	0.020	9.336	110.682
Sic - 39	50.676	27.697	1.83	0.067	-3.635	104.987
Sic - 48	53.926	27.072	1.99	0.046	0.840	107.013
Sic - 50	2.126	28.641	0.07	0.941	-54.038	58.289
Sic - 51	6.631	31.477	0.21	0.833	-55.093	68.355
Sic - 73	28.804	25.907	1.11	0.266	-21.998	79.607
Constant	-68.154	25.688	-2.65	0.008	-118.525	-17.782

Raw sum of deviations	227627.8 (about -6.3943453)
Min sum of deviations	223764.7
Number of Observations	2464
Pseudo R2	0.017

4. Dependent Variable: Gross Profit

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	1.197	1.347	0.89	0.375	-1.446	3.839
Firm Size	-209.999	304.129	-0.69	0.490	-806.377	386.379
Sic - 13	7.658	10.459	0.73	0.464	-12.851	28.168
Sic - 20	1.702	10.672	0.16	0.873	-19.226	22.630
Sic - 21	-3.211	13.398	-0.24	0.811	-29.482	23.061
Sic - 22	-0.659	10.938	-0.06	0.952	-22.109	20.790
Sic - 24	(omitted)					
Sic - 25	1.680	11.773	0.14	0.887	-21.407	24.766
Sic - 26	-1.724	10.571	-0.16	0.870	-22.452	19.005
Sic - 27	3.938	11.626	0.34	0.735	-18.860	26.735
Sic - 28	7.702	9.914	0.78	0.437	-11.739	27.143
Sic - 29	-3.649	10.646	-0.34	0.732	-24.524	17.226
Sic - 30	1.515	10.312	0.15	0.883	-18.707	21.737
Sic - 32	-6.504	11.556	-0.56	0.574	-29.164	16.156
Sic - 33	-0.738	10.446	-0.07	0.944	-21.221	19.745
Sic - 34	-0.378	10.279	-0.04	0.971	-20.535	19.779
Sic - 35	4.704	9.889	0.48	0.634	-14.688	24.097
Sic - 36	5.599	9.882	0.57	0.571	-13.779	24.978
Sic - 37	3.952	10.019	0.39	0.693	-15.693	23.598
Sic - 38	7.698	9.878	0.78	0.436	-11.672	27.067
Sic - 39	4.879	10.548	0.46	0.644	-15.805	25.563
Sic - 48	5.347	10.286	0.52	0.603	-14.823	25.517
Sic - 50	3.457	10.870	0.32	0.750	-17.858	24.772
Sic - 51	10.046	12.327	0.81	0.415	-14.128	34.219
Sic - 73	9.870	9.902	1.00	0.319	-9.546	29.287
Constant	12.443	9.825	1.27	0.205	-6.823	31.710

Raw sum of deviations	69970.89 (about 17.821482)
Min sum of deviations	69143.3
Number of Observations	2464
Pseudo R2	0.0118

5. Dependent Variable: Gross Profit Ratio

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	-0.513	0.230	-2.24	0.025	-0.964	-0.063
Firm Size	-27.974	45.608	-0.61	0.540	-117.408	61.460
Sic - 13	-4.114	1.778	-2.31	0.021	-7.601	-0.627
Sic - 20	-4.179	1.817	-2.30	0.022	-7.741	-0.617
Sic - 21	-4.275	2.282	-1.87	0.061	-8.750	0.200
Sic - 22	-4.350	1.864	-2.33	0.020	-8.006	-0.695
Sic - 24	(omitted)					
Sic - 25	-5.066	2.005	-2.53	0.012	-8.997	-1.135
Sic - 26	-4.844	1.799	-2.69	0.007	-8.373	-1.316
Sic - 27	-4.502	1.977	-2.28	0.023	-8.378	-0.625
Sic - 28	-4.520	1.683	-2.69	0.007	-7.821	-1.220
Sic - 29	-5.279	1.810	-2.92	0.004	-8.829	-1.729
Sic - 30	-5.242	1.753	-2.99	0.003	-8.679	-1.805
Sic - 32	-6.084	1.966	-3.09	0.002	-9.939	-2.228
Sic - 33	-4.767	1.776	-2.68	0.007	-8.250	-1.284
Sic - 34	-4.479	1.747	-2.56	0.010	-7.904	-1.054
Sic - 35	-4.520	1.679	-2.69	0.007	-7.812	-1.228
Sic - 36	-3.932	1.678	-2.34	0.019	-7.222	-0.642
Sic - 37	-3.995	1.701	-2.35	0.019	-7.331	-0.659
Sic - 38	-4.191	1.677	-2.50	0.013	-7.479	-0.903
Sic - 39	-3.982	1.791	-2.22	0.026	-7.495	-0.470
Sic - 48	-2.981	1.754	-1.70	0.089	-6.420	0.458
Sic - 50	-6.577	1.852	-3.55	0.000	-10.208	-2.946
Sic - 51	-8.153	2.029	-4.02	0.000	-12.131	-4.175
Sic - 73	-3.812	1.681	-2.27	0.023	-7.109	-0.516
Constant	5.511	1.668	3.30	0.001	2.240	8.781

Raw sum of deviations	33971.18 (about 1.0786654)
Min sum of deviations	33872.71
Number of Observations	2464
Pseudo R2	0.0029

6. Dependent Variable: Shareholder Returns

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	4.241	9.602	0.44	0.659	-14.589	23.070
Firm Size	1229.245	2394.888	0.51	0.608	-3467.093	5925.582
Sic - 13	137.000	80.111	1.71	0.087	-20.097	294.096
Sic - 20	90.973	81.807	1.11	0.266	-69.448	251.395
Sic - 21	(omitted)					
Sic - 22	143.634	82.058	1.75	0.080	-17.280	304.549
Sic - 24	177.284	97.367	1.82	0.069	-13.651	368.219
Sic - 25	137.949	87.579	1.58	0.115	-33.791	309.689
Sic - 26	85.876	81.074	1.06	0.290	-73.109	244.862
Sic - 27	95.205	87.848	1.08	0.279	-77.063	267.473
Sic - 28	121.190	76.648	1.58	0.114	-29.116	271.496
Sic - 29	107.863	80.805	1.33	0.182	-50.594	266.320
Sic - 30	97.070	78.907	1.23	0.219	-57.665	251.806
Sic - 32	95.476	87.227	1.09	0.274	-75.576	266.527
Sic - 33	86.347	79.824	1.08	0.279	-70.187	242.882
Sic - 34	118.377	79.052	1.50	0.134	-36.642	273.397
Sic - 35	111.910	76.483	1.46	0.144	-38.072	261.892
Sic - 36	118.060	76.452	1.54	0.123	-31.862	267.981
Sic - 37	100.167	77.242	1.30	0.195	-51.304	251.637
Sic - 38	111.367	76.412	1.46	0.145	-38.476	261.210
Sic - 39	57.488	80.295	0.72	0.474	-99.969	214.945
Sic - 48	68.947	78.858	0.87	0.382	-85.693	223.588
Sic - 50	58.418	82.204	0.71	0.477	-102.783	219.619
Sic - 51	11.985	94.871	0.13	0.899	-174.055	198.025
Sic - 73	102.276	76.517	1.34	0.181	-47.772	252.324
Constant	-64.694	76.031	-0.85	0.395	-213.790	84.402

Raw sum of deviations	329112.8 (about 44.603775)
Min sum of deviations	327186.5
Number of Observations	2351
Pseudo R2	0.0059

7. Dependent Variable: Price to Book Ratio

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	0.029	0.136	0.22	0.829	-0.238	0.296
Firm Size	18.824	28.884	0.65	0.515	-37.823	75.471
Sic - 13	25.933	1.067	24.30	0.000	23.839	28.026
Sic - 20	25.208	1.089	23.14	0.000	23.071	27.344
Sic - 21	(omitted)					
Sic - 22	25.013	1.087	23.00	0.000	22.881	27.145
Sic - 24	25.190	1.323	19.04	0.000	22.595	27.786
Sic - 25	26.570	1.192	22.28	0.000	24.231	28.909
Sic - 26	25.180	1.076	23.39	0.000	23.069	27.291
Sic - 27	25.135	1.184	21.22	0.000	22.812	27.458
Sic - 28	27.473	1.017	27.02	0.000	25.479	29.467
Sic - 29	25.257	1.087	23.24	0.000	23.125	27.389
Sic - 30	25.414	1.052	24.15	0.000	23.350	27.478
Sic - 32	25.114	1.162	21.60	0.000	22.834	27.393
Sic - 33	25.725	1.072	24.01	0.000	23.623	27.826
Sic - 34	25.371	1.055	24.05	0.000	23.302	27.440
Sic - 35	26.504	1.015	26.12	0.000	24.514	28.494
Sic - 36	27.333	1.014	26.96	0.000	25.344	29.321
Sic - 37	25.743	1.026	25.09	0.000	23.731	27.755
Sic - 38	27.082	1.014	26.71	0.000	25.094	29.070
Sic - 39	25.502	1.069	23.85	0.000	23.406	27.599
Sic - 48	25.743	1.051	24.50	0.000	23.682	27.804
Sic - 50	25.474	1.088	23.42	0.000	23.341	27.607
Sic - 51	25.531	1.245	20.51	0.000	23.090	27.971
Sic - 73	29.240	1.015	28.81	0.000	27.249	31.231
Constant	-24.918	1.007	-24.74	0.000	-26.893	-22.943
Raw sum of deviations	12042.74 (about 1.6511225)					
Min sum of deviations	11689.06					
Number of Observations	1958					
Pseudo R2	0.0294					

Appendix C: R&D Intensity Regression Results

Dependent Variable: R&D Intensity

Variable	Coefficient	Std. Error	t-Stat	P-Value	95% CI	
R&D Elasticity	0.341	0.176	1.94	0.053	-0.004	0.686
Firm Size	3.905	40.075	0.10	0.922	-74.680	82.490
Sic - 13	0.857	1.364	0.63	0.530	-1.818	3.532
Sic - 20	-0.081	1.394	-0.06	0.954	-2.815	2.654
Sic - 21	0.384	1.755	0.22	0.827	-3.058	3.826
Sic - 22	0.008	1.419	0.01	0.996	-2.774	2.790
Sic - 24	(omitted)					
Sic - 25	0.900	1.540	0.58	0.559	-2.120	3.919
Sic - 26	0.269	1.380	0.19	0.845	-2.438	2.976
Sic - 27	1.482	1.520	0.97	0.330	-1.498	4.462
Sic - 28	7.642	1.292	5.92	0.000	5.109	10.175
Sic - 29	0.304	1.389	0.22	0.826	-2.419	3.028
Sic - 30	1.136	1.345	0.84	0.398	-1.501	3.773
Sic - 32	0.236	1.509	0.16	0.876	-2.722	3.195
Sic - 33	0.353	1.362	0.26	0.796	-2.319	3.024
Sic - 34	0.568	1.340	0.42	0.672	-2.060	3.196
Sic - 35	4.040	1.288	3.14	0.002	1.514	6.567
Sic - 36	5.561	1.287	4.32	0.000	3.037	8.085
Sic - 37	1.849	1.305	1.42	0.157	-0.711	4.408
Sic - 38	6.510	1.287	5.06	0.000	3.987	9.033
Sic - 39	1.575	1.376	1.14	0.253	-1.124	4.273
Sic - 48	1.700	1.344	1.26	0.206	-0.936	4.335
Sic - 50	0.835	1.420	0.59	0.557	-1.950	3.620
Sic - 51	0.030	1.613	0.02	0.985	-3.133	3.193
Sic - 73	12.143	1.290	9.41	0.000	9.613	14.672
Constant	0.211	1.279	0.16	0.869	-2.298	2.720
Raw sum of deviations	15580.81 (about 4.9625325)					
Min sum of deviations	13233.52					
Number of observations	2464					
Pseudo R2	0.1507					

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