Income Inequality: Does Corporate Income Inequality Parallel Individual Income Inequality?

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Explanations provided to explain the increasing individual income inequality, particularly in the U.S. (Saez (2016)), suggest skills/education-related factors play an important role (De Gregorio and Lee (2002)). Corporate income inequality is also on the rise. The purpose of this paper is to confirm the existence of corporate income inequality and identify specific factors that shed light on this phenomenon. Results indicate corporate income inequality parallels individual income inequality in its existence, increasing degree over recent periods, and in the association with skills-based factors. Further, corporate income inequality is increasing in firms' size suggesting an economies of scale effect. Governments can play a role in addressing both types of inequality.

INTRODUCTION

Income inequality can be examined from two perspectives. On the one hand, research of income inequality has focused on the growing income gap between the top 1% or 10% of individual or household income and the remaining 99% or 90%. Thomas Piketty in his book titled, "Capital in the Twenty-First Century," provides an in-depth analysis of this phenomenon that affects all western societies, but is most acute within the United States (Piketty (2014), pp. 23-24). Notwithstanding the criticism levied on Piketty's work (Delsol et al. (2017)), various explanations are offered to explain individual income inequality (Bentele and Kenworthy (2013); Western and Rosenfeld (2011)). One explanation focuses on the role of education. That is, the widening income disparity is explained by the difference in skills between individuals in the top 1% or 10% income brackets (higher skilled) and the remaining 99% or 90% (lower skilled).

On the other hand, research in corporate income inequality is scarce. Recent articles in the financial press have identified the issue (Ip (2015); Frick (2016); Orszag (2015)) and Furman and Orszag (2015) provide an initial impetus to this emerging area of research. The purpose of this paper is to examine U.S. public company data over the past two decades and determine the following:

1. Is growing income inequality evident across U.S. public companies?
2. If corporate income inequality exists, can specific factors be identified that shed light on explaining the corporate income inequality?

If the results indicate an affirmative answer to both questions, then conclusions can be drawn on whether a parallel exists between individual and corporate income inequality. The research paper is organized as follows:

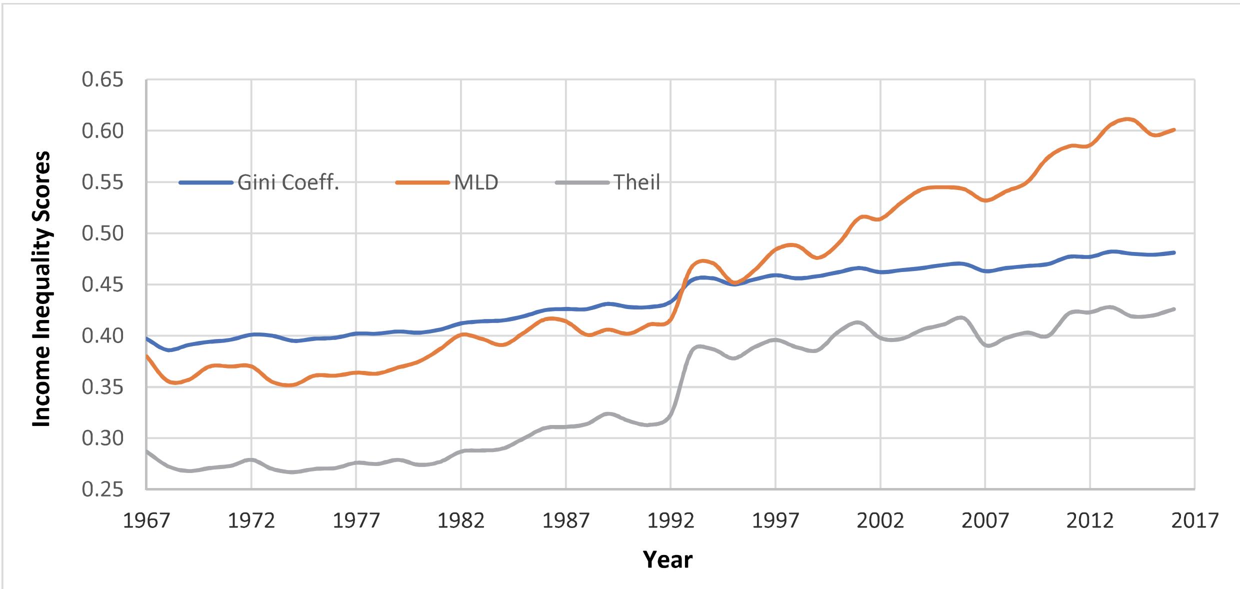
- Literature review and discussion of individual income inequality;
- Literature review and discussion of corporate income inequality;
- Research design;
- Discussion of results; and
- Conclusion.

LITERATURE REVIEW AND DISCUSSION OF INDIVIDUAL INCOME INEQUALITY

In the United States, the dramatic upswing in individual income inequality has been well documented for over 30 years. The United States Census Bureau (2017) shows in all of their inequality metrics, including the Gini Coefficient, mean logarithmic deviation of income (MLD), Theil index (Figure 1), income share of five quintile groups (Figure 2), and income ratios (Figure 3), that an increasing trend of income inequality exists in the U.S. from 1967 to 2016. Piketty (2014) and Saez (2016) find that the top 10%'s income share steeply increases since the 1980s and exceeds 50% in both 2012 and 2015, even surpassing the highest record of 49.3% in the stock market rapid expansion era of 1928 (Figure 4). By splitting the top 10% income share into 3 groups of top 1%, top 5% minus 1%, and top 10% minus 5% (Figure 5), they state that it is the top 1% decile who make the major contribution to the explosion of income inequality over the recent 30 years (Piketty (2014); Saez (2016)). Other than using the common measures, researchers identify the rising income inequality through different economic aspects. The American Federation of Labor and Congress of Industrial Organizations (AFL-CIO) indicates that the pay ratio between S&P 500 index company CEOs and U.S. workers reached 373:1 in 2014 which is more than 8 times the ratio (42:1) in 1980 (AFL-CIO (2015)). From 1979 to 2015, the wage inequality grew significantly because the wages of the top 1% and top 0.1% of U.S. earners had risen 156.7% and 338.8% respectively while the bottom 90% of wage earners only saw an increase of 20.7% (Mishel and Kroeger, (2016)). All the findings point to rising individual income inequality.

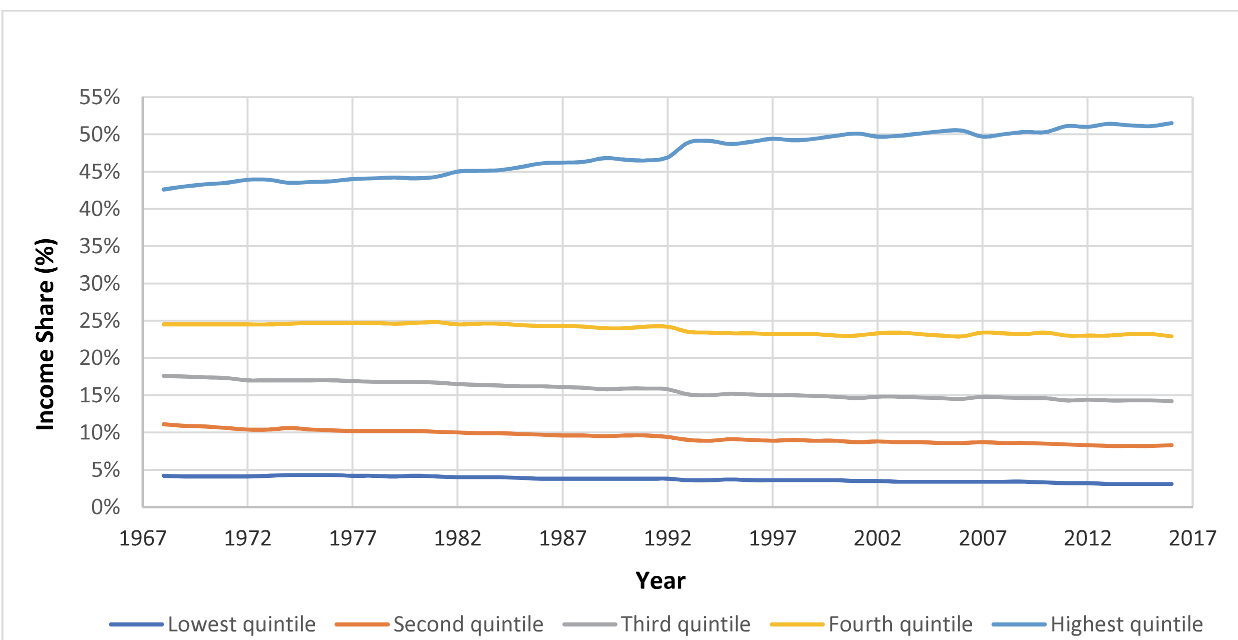
The dramatic upswing of individual income inequality arouses researchers' interests. A variety of studies have been conducted to identify the reasons for the income inequality, such as the decline of unions (Western and Rosenfeld (2011)), macroeconomic volatility (Breen and García-Peñalosa (2005)), government policies (Coburn, (2000)), globalization (Bentele and Kenworthy (2013)), and household income source (Lerman and Yitzhaki (1985)). Of all the explanations for rising inequality, the education-related factors and skilled-based technological change factors are the most prominent. Education-related factors have been considered a significant determinant of income inequality for a long time. By the 1970s, Mincer (1975) had already pointed out the positive effect of education on a worker's annual earnings. Collecting panel data from multiple countries, De Gregorio and Lee (2002) empirically show that education inequality significantly supports the income inequality phenomenon. By using the Gini Coefficient in regression models, Muller (2002) realizes that the model outcomes can be significantly improved by adding education as a covariate; and Jenkins and Jozefowicz (2006) find that the high school attainment rates significantly exaggerate the changes in income inequality over time. After addressing the persistence and endogeneity issues, Coady and Dizioli (2018) identify a strong, consistent, and significantly positive relationship between education inequality and income inequality.

FIGURE 1
THREE MEASURES OF INCOME INEQUALITY IN U.S. FROM 1967 TO 2016



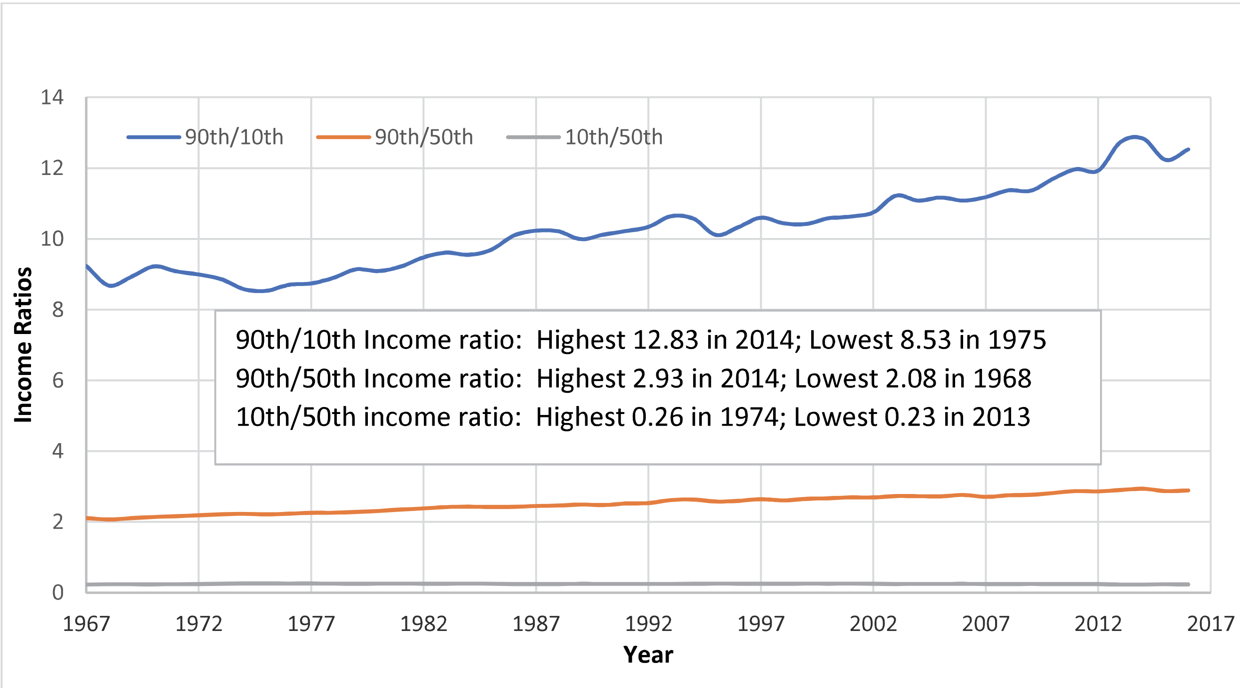
Source: Income and Poverty in the United States: 2016, United States Census Bureau, Table A2

FIGURE 2
INCOME SHARE BY QUINTILES IN U.S. FROM 1967 TO 2016



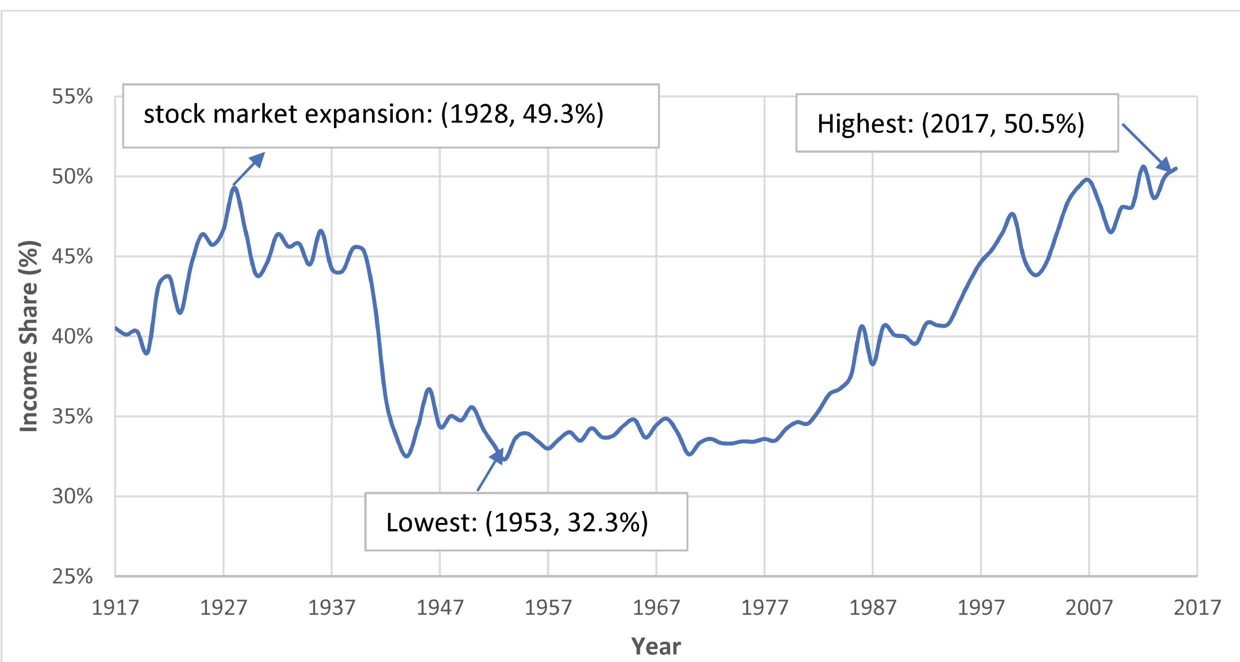
Source: Income and Poverty in the United States: 2016, United States Census Bureau, Table A2

FIGURE 3
INCOME RATIO BETWEEN SELECTED QUANTILES IN U.S. FROM 1967 TO 2016



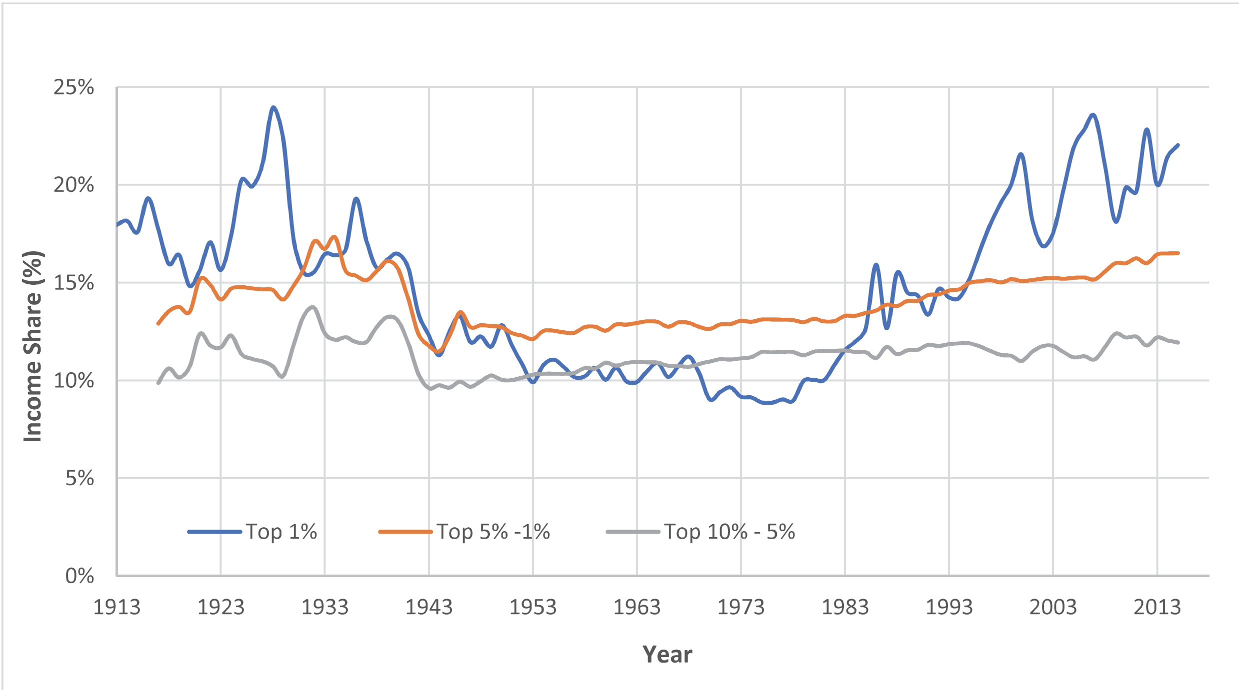
Source: Income and Poverty in the United States: 2016, United States Census Bureau, Table A2

FIGURE 4
THE TOP 10% DECILE INCOME SHARE, 1917 – 2015



Source: Emmanuel Saez (2016), UC Berkeley, Figure 1

FIGURE 5
DECOMPOSING THE TOP 10% INCOME SHARE INTO 3 GROUPS, 1913 – 2015



Source: Emmanuel Saez (2016), UC Berkeley, Figure 2

Additional research demonstrates that not only education factors, but also skilled-based technology changes should be jointly investigated in explaining income inequality. For example, Johnson (1997) points out that it is the demand shift toward high-skilled workers that causes growing income inequality. The U.S. Census Bureau (2010) reported a significant positive relationship between educational and individual income levels over time (see Table 1). Such results indeed reflect a consistently growing demand for high-skilled employees in the U.S. economy (Strauss, (2011)), which lifts the income inequality in the overall population. By looking at the "other 99%" of the U.S. citizens, Autor (2014) further concludes that it is the dramatic growth in the skill-based wage premium attached to the higher education groups that shapes the overall income inequality. Acemoglu (1998) shows that the increase of college graduates in the short run may reduce income inequality, but in the long-run income inequality rises because it increases the skill premium through inciting skill-based technical change. Galor and Moav (2000) argue that it is the increase in technological progress that improves education attainment and enlarges the wage discrepancy. They define such joint phenomena as ability-biased technological transition (Galor and Moav, (2000)). Acemoglu and Autor (2010) suggest that income inequality widens because new technology replaces moderately-skilled workers. Dabla-Norris (2015) state that technological progress and the associated elevation of skill premium contribute to the overall income inequality.

Overall, there is strong evidence supporting the rise of individual income inequality over the past few decades. In addition, education and skill-based qualities are one set of factors that are associated with the rise of individual income inequality.

TABLE 1
MEAN EARNINGS ($) BY EDUCATIONAL LEVELS (2007-2009)

Educational level	Mean Earnings		
	2009	2008	2007
All persons	$42,469	$42,588	$42,064
Not a high school graduate	20,241	21,023	21,484
High school graduate only	30,627	31,283	31,286
Some college, no degree	32,295	32,555	33,009
Associate's	39,771	39,506	39,746
Bachelor's	56,665	58,613	57,181
Master's	73,738	70,856	70,186
Professional	127,803	125,019	120,978
Doctorate	103,054	99,697	95,565

Source: SAUS, table 232; Statistical Abstract of the United States -- published by the US Census Bureau, “Statistical Abstracts of the United States: 2010.”

LITERATURE REVIEW AND DISCUSSION OF CORPORATE INCOME INEQUALITY

Research in corporate income inequality is scarce. Ip (2015) graphically depicts the return on equity (ROE) of S&P 500 non-financial firms from the 1960’s to 2014. From the early 1990’s, the ROE gap between the top 10% and median firms increased, and widened substantially from 2000 onwards. Furman and Orszag (2015) depict the same ROE picture as Ip (2015), and suggest the top firms are “earning super-normal returns on capital.” That is, the top earning firms are performing much better than their counterparts in previous years.

One explanation for the super-normal returns in particular industries is the greater concentration of firms within the industry. A greater concentration of firms within an industry results in a market that resembles an oligopoly rather than a competitive market. Generally, firms in an oligopolistic market earn above-normal returns. Furman and Orszag (2015) cite studies by other researchers that identify higher market concentrations. For example, Shields (2010) and Fuglie et al. (2012) find increased market concentration in agriculture-related industries. Further, Vogt and Town (2006), the U.S. Federal Communications Commission (2014), and Corbae and D’Erasmo (2011) find greater market concentration in the hospital, wireless communication, and U.S. banking industries respectively. McAfee and Brynjolfsson (2008) state in their research about U.S. public companies that, “Since the mid-1990s, a new competitive dynamic has emerged — greater gaps between the leaders and laggards in an industry, more concentrated and winner-take-all markets, and more churn among rivals in a sector.”

Orszag (2015) provides an opinion on the growing gap in return on invested capital for U.S. publicly traded companies. First, he states that, “the top 10 percent of publicly traded nonfinancial firms earned 20 percent or more on their invested capital in the 1980s, and 100 percent or more in 2014.” Second, he states that these high-return firms are predominantly from the health care and information technology sectors. Firms operating in both of these sectors derive their value from high levels of technology-related and education-related skills.

Other studies support the link between high levels of technology/education/skill and higher returns. Manyika, Pinkus, and Ramaswamy (2016) state that companies employing advanced digital technologies are the leaders in productivity and profitability. McAfee and Brynjolfsson (2008) find the leaders in information technology tend to be the leaders in profitability and stock returns.

Overall, recent articles provide graphical evidence of growing income inequality between firms. Among a variety of factors, the growing corporate income inequality is associated with greater market concentration and firms displaying higher levels of knowledge/education/skill.

Another important characteristic of business enterprises is the ability to take advantage of economies of scale. Economies of scale refers to the ability of large firms to earn a higher return per dollar of invested capital when compared to smaller firms (Hall and Weiss (1967)). Hall and Weiss (1967) build on the work of Baumol (1959) and examine 341 of the largest industrial corporations over the period from 1956 to 1962. Their research model employs the after-tax rate of return on year-end equity (i.e., invested capital) as the dependent variable. The independent variables include proxies for size (i.e., reciprocal of total year-end total assets), concentration (i.e., weighted-average of concentration ratios), growth (i.e. percentage change in production output), and time (i.e., dummy variables representing each year of the study). The authors find that there is a positive relationship between profits and size to the extent suggesting firms seek greater size to overcome barriers to entry in the marketplace.

Other studies primarily confirm the Hall and Weiss (1967) study's results. Buzzell, Gale, and Sultan (1975) cite economies of scale as a key reason for higher rates of returns for firms with larger market share. Kumbhakar et al. (2015) investigate scale economies among Norwegian electricity distribution companies and find evidence to support economies of scale and technical progress. They also find that the potential for economies of scale is greater among small firms and firms can realize economies of scale following a merger or acquisition. Bena and Li (2014) argue that companies can achieve economies of scale in production of innovation if the merging firms have related research and development activities. The merger would reduce the cost of development activities by avoiding duplication and by sharing inputs which can boost corporate earnings. Overall, the economies of scale can be realized in all facets of business from procurement, manufacturing, marketing, and other processes. The economies of scale ultimately affects the profitability and growth of a firm.

In summary, income inequality can be examined from the individual and corporate perspectives. The depth of research from the individual perspective outweighs that from the corporate perspective. The effect of economies of scale likely impacts the degree of corporate inequality.

RESEARCH DESIGN

Sample Selection

The sample consists of firms contained in the COMPUSTAT Annual Industrial File over the period 1997 to 2016. A data cleansing process is required to determine the firms in the final sample. This process is summarized in Table 2. Only firms across a broad spectrum of industries with a complete data set are included in the sample.

Hypotheses and Research Model

The hypotheses of this research study build on the individual income inequality research that links individual income inequality with education and job skills. For example, De Gregorio and Lee (2002) find that educational factors are associated with a more equal income distribution. That is, they find educational attainment increases with income and that educational attainment is highly persistent. From a corporate perspective, higher investments in intangible assets, plant and equipment, and research and development costs are expected to be associated with higher firms' operating earnings. In addition, the economies of scale effect means a larger firm possesses a greater likelihood of earning higher profits. Thus, firms' size is expected to be positively associated with corporate income inequality.

TABLE 2
NUMBER OF UNIQUE FIRMS (OBSERVATIONS) AFTER EACH STEP OF DATA CLEANSING

Year	Number of unique firms (observations)			
	in Raw data	Remove firms without operating income after depreciation	Remove firms without two consecutive years of data	Final data for Model
97-98	3,364	3,124	2,839	2,762
98-99	3,654	3,409	3,113	3,022
99-00	3,888	3,594	3,391	3,304
00-01	4,111	3,766	3,577	3,487
01-02	4,293	3,899	3,746	3,661
02-03	4,524	4,055	3,865	3,774
03-04	4,709	4,188	4,018	3,905
04-05	4,945	4,327	4,136	4,025
05-06	5,253	4,443	4,280	4,153
06-07	5,768	4,572	4,370	4,227
07-08	6,002	4,702	4,461	4,321
08-09	6,314	4,858	4,620	4,471
09-10	6,752	5,127	4,777	4,613
10-11	7,304	5,437	5,026	4,830
11-12	7,782	5,925	5,302	5,072
12-13	8,097	6,294	5,810	5,523
13-14	8,277	6,390	6,075	5,763
14-15	8,378	6,364	6,127	5,827
15-16	8,294	6,103	6,030	5,757

Firms grow in size in two different ways. First, a firm can grow internally by reinvesting its earnings from operations. Second, a firm can grow through acquisitions. Firms that grow by acquiring other businesses will have goodwill on their balance sheets if they pay a premium for these acquired businesses. In either case, a firm's growth increases its size which enables the firm to take advantage of economies of scale. Larger firms would have a greater ability to innovate and invest in research and technology that leads to different products and services. Porter (1985) describes this process of innovation through strategies to create a competitive advantage. Thus, a firm's growth and economies of scale provides a springboard for the firm to develop a competitive advantage through the successful launching of its new products and services. Further, such a firm's performance would exceed that of an average firm and the performance gap would increase over time if it continues to take advantage of economies of scale, innovate, and develop competitive advantages.

Taken together, the research questions for this study are presented in the following form:

H_1: The corporate income inequality gap of firms classified in the top 10% of operating earnings and the remaining 90% is increasing over time.

H_2: The likelihood of a firm that is classified in the top 10% of operating earnings is positively associated with firm size.

H_3: The likelihood of a firm that is classified in the top 10% of operating earnings is positively associated with its investment in plant and equipment, intangible assets, research development costs, and goodwill.

The first hypothesis is addressed by a descriptive comparison of the median operating income of firms in the 10% and the remaining 90%. This gap is expected to increase over time if corporate income inequality mirrors individual income inequality. Hypotheses 2 and 3 are tested by the following regression model:

$$TEN_{it} = a + \beta_1 (INTANG_{i(t-1)} / TA_{i(t-1)}) + \beta_2 (PE_{i(t-1)}/ TA_{i(t-1)}) + \beta_3 (SIZE_{i(t-1)}) + \beta_4 (LEV_{i(t-1)}) + \beta_5 (SIZE_{i(t-1)} * RD_{i(t-1)}) + B_6 (GDW_{i(t-1)} / TA_{i(t-1)}) * (RE_{i(t-1)} / TA_{i(t-1)}) + \varepsilon_{it} \quad (1)$$

where:

TEN_{it} = the dependent variable, an indicator variable, equal to 1 if the firm is in the top 10% of operating earnings after depreciation expense for all firms during year t, otherwise equals 0;
$INTANG_{i(t-1)} / TA_{i(t-1)}$= the firm's intangible assets scaled by total assets at time t-1;
$PE_{i(t-1)} / TA_{i(t-1)}$= the firm's plant and equipment assets scaled by total assets at time t-1;
$SIZE_{i(t-1)}$= the natural log of the firm's total assets at time t-1;
$LEV_{i(t-1)}$= the firm's total liabilities scaled by total assets at time t-1;
$RD_{i(t-1)}$= the firm's research and development costs scaled by total assets at time t-1;
$GDW_{i(t-1)}/ TA_{i(t-1)}$= the firm's goodwill scaled by total assets at time t-1; and
$RE_{i(t-1)}/ TA_{i(t-1)}$= the firm's retained earnings scaled by total assets at time t-1.

Equation 1 is a logistic regression model identifying the important factors that relate to a company's propensity of being in the top 10% of operating earnings after depreciation expense (OIAD). The firms who possess the top 10% of the OIAD are assigned as Group 1 and the remaining firms are categorized as Group 0 for each year of the study. Thus, the dichotomous variable of whether a firm is in the top 10% earnings group is the dependent variable (TEN). It is well-acknowledged that the logistic regression approach relies on a logit transformation of the dependent variable, thus it possesses several features on modeling the binary outcomes of this study (see Gujarati 2003, pp. 596-597). For example, the logit model's predictor coefficients are interpreted in a manner similar to that of a multiple regression model.

In the model setup, TEN = 1 suggests the firm is in the top 10% of OIAD in year (t) and TEN = 0 means the firm is not in the top 10% of OIAD group. For the predictor variables (X's), a positive coefficient β indicates that the changes of X values and the logits of TEN are in the same direction. A negative coefficient β suggests the opposite effect. The "odds" expresses the probability of occurrence, that is TEN_t =1 relative to the probability of non-occurrence, TEN_t =0. Consequently, a positive coefficient β means that the probability of TEN_t =1 increases as the X_t value increases.

A stepwise selection with backward elimination of covariates by the SAS program is utilized to select the significant predictor variables in the logistic regression. In this study, a firm's performance in the previous year is used as the predictor variables (X_{t-1}). An entering significance level of P =0.30 is used to explore the effects of covariates which means the model will only include those predictor variables with P value < = 0.30.

The predictor variables (X_{t-1}) include the firm's intangible assets, property, plant and equipment, research and development costs, goodwill, size, and leverage. The model includes the main effects of predictor variables and the effects of two-way interaction between certain predictor variables. For example, SIZE * RD indicates the interaction between the firm's size and research and development costs.

DISCUSSION OF RESULTS

Descriptive Statistics

Table 3 provides the descriptive statistics for the variables included in model (1) for the years 1998, 2006, and 2016. The descriptive statistics for all years 1998 to 2016 inclusive are provided in Appendix 1. For the years 1998 to 2016, several trends are present in the data. First, the percentage of intangible assets to total assets has increased over the study period. The average ratio (mean) of intangible assets to total assets stood at 5.8% in 1998. By 2006, this ratio increased to 11.6% and by 2016 the ratio stood at 14.6%. Certainly, intangible assets have been employed to a greater extent in the firms' business operations over time. Second, firms' size (i.e., defined by the book value of total assets) increased by 1.88 times from 1998 to 2016. The variable SIZE is defined as the natural log of lagged total assets. The mean natural log of total assets increased from 19.349 to 19.980 between 1998 and 2016. The exponential function is the inverse of the natural log function. Thus, the mean total assets for 1998 equals $253,025,289 and for 2016 the figure is $475,558,281. The interaction variable (SIZE*RD) describes the interaction of firms' size and research and development expenditures (R&D). The mean increased from 0.836 in 1998 to 3.602 in 2016. Factoring out the effect of the SIZE variable, firms' average R&D expenditures increased over 4:1 during the study period. Overall, during the 1998 to 2016 period firms grew in size and increased their investment in knowledge-based expenditures.

TABLE 3
DESCRIPTIVE STATISTICS: 1998 TO 2016

Fiscal Year = 1998			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	2,762	0.100	0.300
INTANG/TA	2,762	0.058	0.118
PE/TA	2,762	0.276	0.258
SIZE	2,762	19.349	2.813
LEV	2,762	5.464	63.182
SIZE * RD	2,762	0.836	2.414
(GDW/TA) * (RE/TA)	2,762	-0.002	0.095
Fiscal Year = 2006			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	4,153	0.100	0.300
INTANG/TA	4,153	0.116	0.181
PE/TA	4,153	0.222	0.247
SIZE	4,153	19.640	3.338
LEV	4,153	3.792	23.489
SIZE * RD	4,153	1.101	4.937
(GDW/TA) * (RE/TA)	4,153	-0.055	0.808
Fiscal Year = 2016			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	5,757	0.100	0.300
INTANG/TA	5,757	0.146	0.211
PE/TA	5,757	0.204	0.260
SIZE	5,757	19.980	3.271
LEV	5,757	6.878	193.351
SIZE * RD	5,757	3.602	93.659
(GDW/TA) * (RE/TA)	5,757	-0.049	0.839

See "Hypotheses and Research Model" section for a description of the variables.

Other variables have changed over time as evidenced by the descriptive statistics. The share of plant and equipment assets (P&E) to total assets has declined from 27.6% to 22.2% to 20.4% over the 1998, 2006, and 2016 periods respectively. This result is not surprising when coupled with the greater importance of intangible assets over the same period. The interaction variable goodwill and retained earnings represents firms' ability to grow through acquisition. A firm with goodwill on its balance sheet must have acquired another business. Goodwill is always a positive number. Retained earnings can be positive or negative. The mean for this statistic is negative throughout the study period with the most negative result, not surprising, occurring in 2008 (i.e. start of Great Recession) with a value of -0.213.

Thus, firms on average operated with a deficit (negative retained earnings) over the study period. Firms' leverage fluctuated over the study period but remained above total assets (i.e. ratio greater than 1:1) throughout. Given the low borrowing costs over the past twenty years, this result is not surprising.

Table 4 provides the Pearson correlations for 2016, 2006, and 1998. The most consistent finding is that the SIZE variable has a positive correlation of approximately 0.50 with the dependent variable throughout the study period. This result indicates that the firms in the top 10% of OIAD are more likely to employ economies of scale.

Primary Results

Figure 6 shows the firms' median OIAD for the top 10% and remaining 90%. The gap between the two groups dipped around the Great Recession period (2008), however the trend is clearly an increasing gap between the top corporate earners and all other firms. Table 5 presents the results for the logistic regression equation of model (1) for the years 1998, 2006, and 2016 respectively. The regression results for each year of the study are contained in Appendix 2. From these results, the SIZE variable is significant and positive for each year at either the 0.01 or 0.05 level of significance. This result supports the firms' use of economies of scale to drive higher operating profits.

Further, although plant and equipment assets are still important to the top firms' operating earnings, their importance has declined over the study period as evidenced by the decline in the β_2 coefficient. On the one hand, the variable LEV shows no significance over the last five years of the study period. On the other hand, the interaction variable GDW*RE is highly positive and significant over the study period. These two results suggest top OIAD firms have positive retained earnings and grow through acquisitions. Overall, the results over the study period suggest that the firms with the highest operating profits take advantage of economies of scale. Also, firms are relying on more intangible assets and investments in R&D to drive the highest operating profits. Further, the top corporate earners tend to grow through acquisitions.

TABLE 4
PEARSON CORRELATION COEFFICIENTS

Panel A -- Pearson Correlation Coefficients (2016, N = 5757)

	TEN	INTANG/TA	PE/TA	SIZE	LEV	SIZE * RD	(GDW/TA) * (RE/TA)
TEN	1						
INTANG/TA	0.0995 <.0001	1					
PE/TA	0.0618 <.0001	-0.1821 <.0001	1				
SIZE	0.4621 <.0001	0.1114 <.0001	0.1331 <.0001	1			
LEV	-0.0090 0.4955	-0.0128 0.3323	-0.0021 0.8741	-0.0179 0.1736	1		
SIZE * RD	-0.0116 0.3804	-0.0192 0.1444	0.0219 0.0965	-0.0999 <.0001	-0.0011 0.933	1	
(GDW/TA) * (RE/TA)	0.0331 0.0121	-0.0995 <.0001	0.0372 0.0047	0.0823 <.0001	0.0004 0.9735	0.0001 0.9952	1

TEN_{it} = the dependent variable, an indicator variable, equal to 1 if the firm is in the top 10% of operating earnings after depreciation expense for all firms during year t, otherwise equals 0;
$INTANG_{i(t-1)}$ / $TA_{i(t-1)}$= the firm's intangible assets scaled by total assets at time t-1;
$PE_{i(t-1)}$/ $TA_{i(t-1)}$= the firm's plant and equipment assets scaled by total assets at time t-1;
$SIZE_{i(t-1)}$ = the natural log of the firm's total assets at time t-1;
$LEV_{i(t-1)}$ = the firm's total liabilities scaled by total assets at time t-1;
$RD_{i(t-1)}$ = the firm's research and development costs scaled by total assets at time t-1;
$GDW_{i(t-1)}$ / $TA_{i(t-1)}$ = the firm's goodwill scaled by total assets at time t-1; and
$RE_{i(t-1)}$ / $TA_{i(t-1)}$ = the firm's retained earnings scaled by total assets at time t-1.

TABLE 4 (CONTINUED)
PEARSON CORRELATION COEFFICIENTS

Panel B -- Pearson Correlation Coefficients (2006, N = 4153)

	TEN	INTANG/ TA	PE/TA	SIZE	LEV	SIZE * RD	(GDW/TA) * (RE/TA)
TEN	1						
INTANG/TA	0.0158 0.3099	1					
PE/TA	0.0873 <.0001	-0.16592 <.0001	1				
SIZE	0.4795 <.0001	0.0841 <.0001	0.1606 <.0001	1			
LEV	-0.0290 0.0617	-0.0176 0.257	-0.0336 0.0304	-0.0563 0.0003	1		
SIZE * RD	-0.0533 0.0006	-0.0349 0.0247	-0.0724 <.0001	-0.2395 <.0001	-0.0086 0.5807	1	
(GDW/TA) * (RE/TA)	0.0299 0.0539	-0.1224 <.0001	0.0484 0.0018	0.0893 <.0001	0.0054 0.7302	-0.0246 0.1133	1

TEN_{it} = the dependent variable, an indicator variable, equal to 1 if the firm is in the top 10% of operating earnings after depreciation expense for all firms during year t, otherwise equals 0;
$INTANG_{i(t-1)}$ / $TA_{i(t-1)}$= the firm's intangible assets scaled by total assets at time t-1;
$PE_{i(t-1)}$/ $TA_{i(t-1)}$= the firm's plant and equipment assets scaled by total assets at time t-1;
$SIZE_{i(t-1)}$ = the natural log of the firm's total assets at time t-1;
$LEV_{i(t-1)}$ = the firm's total liabilities scaled by total assets at time t-1;
$RD_{i(t-1)}$ = the firm's research and development costs scaled by total assets at time t-1;
$GDW_{i(t-1)}$ / $TA_{i(t-1)}$ = the firm's goodwill scaled by total assets at time t-1; and
$RE_{i(t-1)}$ / $TA_{i(t-1)}$ = the firm's retained earnings scaled by total assets at time t-1.

TABLE 4 (CONTINUED)
PEARSON CORRELATION COEFFICIENTS

Panel C -- Pearson Correlation Coefficients (1998, N = 2762)

	TEN	INTANG/ TA	PE/TA	SIZE	LEV	SIZE * RD	(GDW/TA) * (RE/TA)
TEN	1						
INTANG/TA	0.0141 0.458	1					
PE/TA	0.0957 <.0001	-0.1081 <.0001	1				
SIZE	0.5208 <.0001	0.0294 0.1223	0.1714 <.0001	1			
LEV	-0.0199 0.2959	-0.0220 0.2487	-0.0399 0.0362	-0.0364 0.0556	1		
SIZE * RD	-0.0535 0.0049	-0.0469 0.0137	-0.1135 <.0001	-0.2833 <.0001	-0.0013 0.9453	1	
(GDW/TA) * (RE/TA)	0.0415 0.0291	-0.0836 <.0001	0.0187 0.3258	0.1267 <.0001	-0.0018 0.9266	-0.0147 0.4387	1

TEN_{it} = the dependent variable, an indicator variable, equal to 1 if the firm is in the top 10% of operating earnings after depreciation expense for all firms during year t, otherwise equals 0;
$INTANG_{i(t-1)}$ / $TA_{i(t-1)}$= the firm's intangible assets scaled by total assets at time t-1;
$PE_{i(t-1)}$/ $TA_{i(t-1)}$= the firm's plant and equipment assets scaled by total assets at time t-1;
$SIZE_{i(t-1)}$ = the natural log of the firm's total assets at time t-1;
$LEV_{i(t-1)}$ = the firm's total liabilities scaled by total assets at time t-1;
$RD_{i(t-1)}$ = the firm's research and development costs scaled by total assets at time t-1;
$GDW_{i(t-1)}$ / $TA_{i(t-1)}$ = the firm's goodwill scaled by total assets at time t-1; and
$RE_{i(t-1)}$ / $TA_{i(t-1)}$ = the firm's retained earnings scaled by total assets at time t-1.

TABLE 5
LOGISTIC REGRESSION RESULTS

$TEN_{it} = a + \beta_1 (INTANG_{i(t-1)}/ TA_{i(t-1)}) + \beta_2 (PE_{i(t-1)}/ TA_{i(t-1)}) + \beta_3 (SIZE_{i(t-1)}) + \beta_4 (LEV_{i(t-1)}) + \beta_5 (SIZE_{i(t-1)} * RD_{i(t-1)}) + B_6 (GDW_{i(t-1)} / TA_{i(t-1)}) * (RE_{i(t-1)} / TA_{i(t-1)}) + \varepsilon_{it}$

Panel A -- Logistic Regression Results for 2016 (N = 5,757)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-50.5787	2.1601	548.2748	<.0001	NA
INTANG/TA	2.8914	0.3724	60.2906	<.0001	18.0185
PE/TA	1.2097	0.287	17.7721	<.0001	3.3525
SIZE	2.0843	0.0905	530.971	<.0001	8.0390
SIZE*RD	0.00571	0.00203	7.954	0.0048	1.0057
(GDW/TA) * (RE/TA)	6.0297	0.8919	45.7076	<.0001	415.5903

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	2564.5311	<.0001
Score	1250.4111	<.0001
Wald	535.9646	<.0001

Panel B -- Logistic Regression Results for 2006 (N=4,153)

Parmaeters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-60.0511	3.2502	341.3689	<.0001	NA
INTANG/TA	1.3957	0.6111	5.2159	0.0224	4.0378
PE/TA	2.1254	0.3906	29.6032	<.0001	8.3762
SIZE	2.5101	0.1372	334.5215	<.0001	12.3062
LEV	0.0146	0.00469	9.7403	0.0018	1.0147
SIZE*RD	0.1756	0.0232	57.4475	<.0001	1.1920
(GDW/TA) * (RE/TA)	6.8399	2.071	10.908	0.001	934.3957

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1989.3639	<.0001
Score	975.2642	<.0001
Wald	336.077	<.0001

See Panel C for Variable Definitions

TABLE 5 (CONTINUED)
LOGISTIC REGRESSION RESULTS

$TEN_{it} = a + \beta_1 (INTANG_{i(t-1)}/ TA_{i(t-1)}) + \beta_2 (PE_{i(t-1)}/ TA_{i(t-1)}) + \beta_3 (SIZE_{i(t-1)}) + \beta_4 (LEV_{i(t-1)}) + \beta_5 (SIZE_{i(t-1)} * RD_{i(t-1)}) + B_6 (GDW_{i(t-1)} / TA_{i(t-1)}) * (RE_{i(t-1)} / TA_{i(t-1)}) + \varepsilon_{it}$

Panel C -- Logistic Regression Results for 1998 (N=2,762)

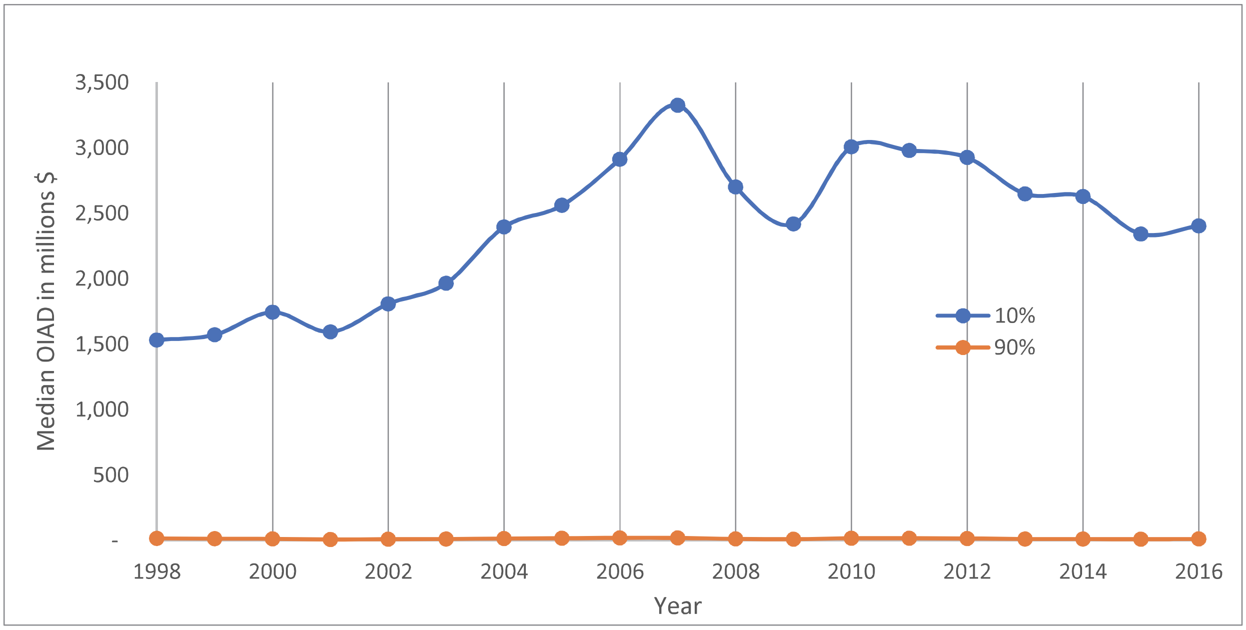
Parmaeters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-55.7263	3.6302	235.6474	<.0001	NA
INTANG/TA	2.2779	1.0873	4.3892	0.0362	9.7562
PE/TA	1.8751	0.4388	18.259	<.0001	6.5215
SIZE	2.3758	0.1564	230.7751	<.0001	10.7596
SIZE*RD	0.4724	0.0579	66.5724	<.0001	1.6038
(GDW/TA) * (RE/TA)	13.8434	5.0263	7.5856	0.0059	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1287.1072	<.0001
Score	778.0561	<.0001
Wald	231.1568	<.0001

$INTANG_{i,t-1}$ / $TA_{i,t-1}$ = the firm's intangible assets scaled by total assets at time t-1;
$PE_{i,t-1}$ / $TA_{i,t-1}$ = the firm's plant and equipment assets scaled by total assets at time t-1;
$SIZE_{i,t-1}$ = the natural log of the firm's total assets at time t-1;
$LEV_{i,t-1}$ = the firm's total liabilities scaled by total assets at time t-1;
$RD_{i,t-1}$ = the firm's research and development costs scaled by total assets at time t-1;
$GDW_{i,t-1}$ / $TA_{i,t-1}$ = the firm's goodwill scaled by total assets at time t-1; and
$RE_{i,t-1}$ / $TA_{i,t-1}$ = the firm's retained earnings scaled by total assets at time t-1.

FIGURE 6
FIRMS' MEDIAN OIAD BETWEEN TOP 10% AND BOTTOM 90%, 1998 TO 2016



Industry Effects

The effects of selected industries were tested by including indicator variables in model (1). None of these indicator variables are significant and none are positively associated with the top OIAD firms (results not shown). Thus, supporters that contend specific industries likely produce the top corporate earners, their comments cannot be substantiated (e.g., McAfee and Brynjolfsson (2008)). However, some industries display a greater propensity to slot in the top 10% of OIAD each year, although not statistically significant. Table 6 shows the top three industries with the most number of firms in the top 10% of OIAD for each year of the study period. Industry codes 6020 (commercial banks) and 4911 (electric services) are consistently in the top 10%.

Merger and Acquisition Activity

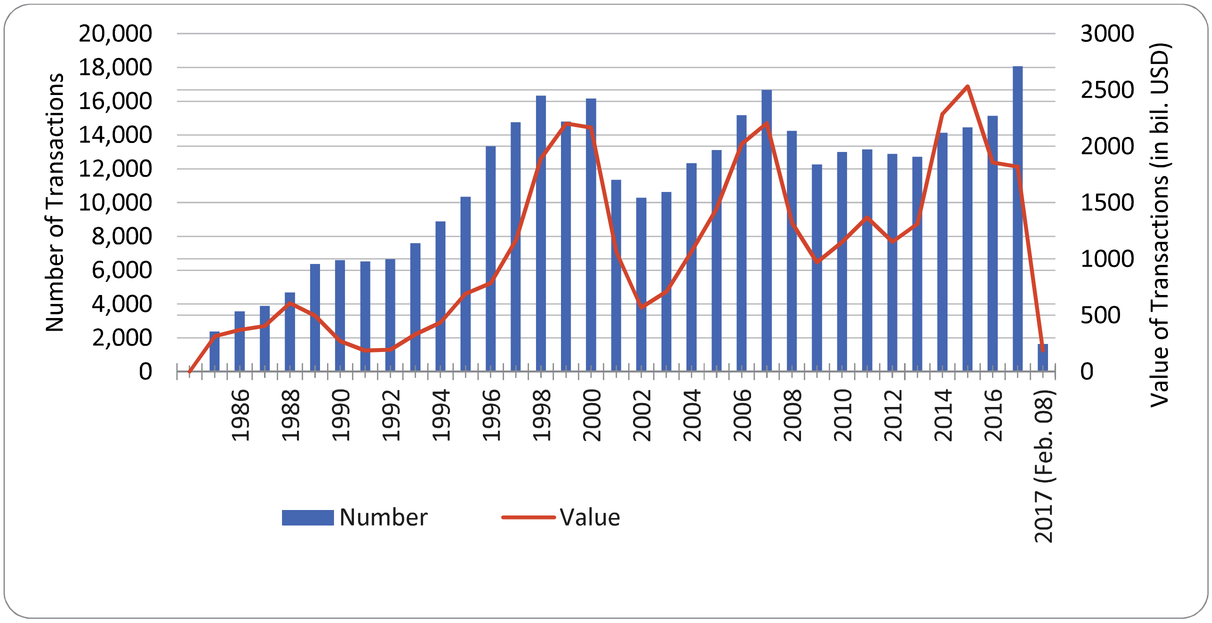
Figure 7 shows the merger and acquisition activities in North America from 1985 to 2017. Since the mid-1990s the volume of merger and acquisition activities have increased substantially in both the number of transactions and dollar value. In fact, during the 1995 to 2017 period, the year with the fewest transactions and dollar value (1995), exceeds the number of transactions and dollar value for each year of the prior decade (1985 to 1994). Further, from 1996 to 2017 the number of mergers and acquisitions increased from 13,336 to 18,070 (IMAA 2018). The increase in merger and acquisition activities over the past 20 years provides evidence that firms seek to grow in size by acquiring other businesses. Growth in this manner provides a springboard for firms to maximize its OIAD.

TABLE 6
INDUSTRY FREQUENCY OF FIRMS IN THE TOP 10% OF OIAD

Year	Top Three Industries in Top 10% OIAD (No. of firms)	Total Number of Firms in Top 10% of OIAD
1998	1:6020(27) 2:4911(24) 3:2834(10)	276
1999	1:6020(31) 2:4911(27) 3:4813(11)	302
2000	1:6020(31) 2:4911(23) 3:2911(12)	330
2001	1:6020(38) 2:4911(31) 3:2911(13)	348
2002	1:6020(45) 2:4911(29) 3:4813(14)	366
2003	1:6020(47) 2:4911(30) 3:4813(16)	377
2004	1:6020(45) 2:4911(28) 3:4813(15)	390
2005	1:6020(46) 2:4911(24) 3:4812(15)	402
2006	1:6020(45) 2:4911(26) 3:2911(16)	415
2007	1:6020(43) 2:4911(24) 3:4812(14)	422
2008	1:6020(39) 2:4911(27) 3:2911(16)	432
2009	1:6020(37) 2:4911(34) 3:4812(16)	447
2010	1:6020(46) 2:4911(30) 3:2911(16)	461
2011	1:6020(48) 2:4911(28) 3:2911(17)	483
2012	1:6020(51) 2:4911(28) 3:2911(18)	507
2013	1:6020(53) 2:4911(29) 3:2911(18)	552
2014	1:6020(57) 2:4911(31) 3:2834(17)	576
2015	1:6020(60) 2:4911(27) 3:2834(19)	582
2016	1:6020(58) 2:4911(29) 3:2834(19)	575

Standard Industrial Classification (SIC) Codes:
6020: Commercial Banks
4911: Electric Services
4813: Telephone Communications
4812: Radiotelephone Communications
2911: Petroleum Refining
2834: Pharmaceutical Preparations

FIGURE 7
MERGER AND ACQUISITION ACTIVITIES IN NORTH AMERICA



Source: Institute for Mergers, Acquisitions, and Alliances (IMAA), Retrieved on March 12, 2018: https://imaa-institute.org/mergers-and-acquisitions-statistics/

How Can Corporate Income Inequality Influence Individual Income Inequality?

Historically, larger firms have been shown to systemize the wage-setting process through job evaluation. In a prototypical job evaluation system, jobs in larger firms are evaluated in terms of required skills, responsibilities, and working conditions (Boxall and Purcell (2011)). Jobs are then assigned wages based on their value to the firm, and to ensure consistency or avoid conflicts, pay increases are restricted within modest ranges (Beer et al. (1984)). One consequence of prototypical job evaluation systems for larger firms is that there often is a phenomenon called wage compression (Cappelli (2001)), which refers to the reducing of wage dispersion in firms compared to a hypothesized marginal product schedule (Sanchez and Levine (2012)). Historically, larger firms have also consistently used incentive compensation schemes. Most large firms base their incentives on performance measure systems (Jansen, Merchant, and Van der Stede (2009)). Some of these larger firms also use smaller second and third formula bonuses to rebalance multitask incentives (Jansen, Merchant, and Van der Stede (2009)). An important consequence of incentive-based systems used by large firms is that the incentive is conditional on performance which tends to *lower* the overall wage outcome for all employees.

Cobb and Stevens (2017) use insights from research on the effect of firm size on wages (Oi and Idson (1999)), social comparisons within firm boundaries (Nickerson and Zenger (2008)), and organizational wage setting (Granovetter (1981)), to develop a theory about how changes in corporate earnings affect individual income inequality. Cobb and Stevens (2017) argue that rates of income inequality are affected by the extent to which workers are employed by larger firms versus smaller firms. In an analysis of employment data in 48 States from 1978 to 2008, Cobb and Stevens (2017) explore the way the size of a firm affects this inequality of outcome in the U.S. Their study provides several important findings. Larger firms' employees are more susceptible to do social comparisons about wages than smaller firms' employees, and as a consequence larger firms are more prone to undertake strategies to control social comparison through wage compression. In terms of wage compression, internal pay equity requires that employers compress pay along two dimensions. Horizontal compression occurs when those in the same job receive relatively equal pay even if their contribution varies. Vertical compression occurs when pay differentials across jobs are flattened, despite the varying contributions to organizational output. This may be the most crucial wage compression process in place for larger firms. Flattening differentials between jobs means that larger firms pay: (i) above marginal product for lower-skilled or lower-wage workers, and/or (ii) pay near or below the marginal product for higher-skilled or higher-wage employees (i.e., excluding executive pay schemes). Other prior research has found that: (i) otherwise identical workers earn more when working for larger firms than smaller firms; and (ii) firm-size wage effects are greater for low-skilled workers than for high-skilled workers (Hollister (2004)). By paying lower-skilled workers a greater wage premium than higher-skilled ones, larger firms vertically compress wages (i.e., excluding executive pay schemes). Larger firms may do so to reduce the costs of social comparisons, as workers are prone to compare their rewards with those received by others (Festinger (1954); Adams (1963)) and employees' responses to perceived inequity has a cost for larger firms (Cohn et al. (2014)). Overall, this systemic process of wage compression results in lower wages for all workers in larger firms with the exception of the top managers.

The Role of Regulation

Regulation plays an important role in income inequality at both the individual and corporate levels. At the individual level, entitlements such as welfare and unemployment insurance are designed to assist those individuals who are at the low end of the income scale or who have lost their employment income through job loss. In addition, U.S. tax policy is based on marginal tax rates that increase with levels of income (i.e., progressive rate of taxation). These policy choices made by legislators are designed to reduce the extent of extreme income inequality either by raising the income of low income individuals (e.g. unemployment insurance) or by reducing the after-tax income of high income individuals (e.g. progressive marginal tax rates).

Piketty (2014, p. 497) believes current policies do not go far enough to address the individual income inequality problem as evidenced by the growing inequality over the past few decades. For example, Piketty believes the progressive tax system cannot work effectively because extreme high-income earners have the ability to avoid or evade taxes by sheltering their incomes in tax havens (Piketty (2014), pp. 525-526). Rather, Piketty proposes a progressive tax on an individual's capital (Piketty (2014), pp. 515-534). Essentially, Piketty recommends a wealth tax that is implemented across jurisdictions by sharing financial information and transparency. Piketty's plan has been attacked by various economists for a variety of reasons (Del Sol et al. (2017)). For example, a progressive wealth tax could do more harm than good by creating disincentives to work harder (Del Sol et al. (2017), pp. 234 and 239-240).

From the corporate income inequality viewpoint, federal anti-trust laws ameliorate the effect of corporate income inequality. The primary federal anti-trust laws are the Sherman Act and the Clayton Act. The Sherman Act was passed by Congress in 1890 primarily as an act to protect consumers' welfare (Hazlett (1992)). Similarly, the Clayton Act of 1914 supplements the Sherman Act by prohibiting firms' behavior that conflicts with a competitive market (i.e., section 7 of the Clayton Act prohibits the acquisition of another firm in an attempt to lessen competition). Thus, the anti-trust laws are designed to prevent firms from becoming too large in size. Since a larger firm's size is positively associated with its presence in the top 10% of OIAD, then restricting size will have a positive effect on reducing corporate income inequality. However, Baker (2003) notes that the enforcement of anti-trust laws does not involve a detailed review of all merger and acquisition cases. For example, only six monopolization cases were investigated during the 1990s (Baker (2003), p.33). This finding suggests increasing enforcement under the anti-trust laws by reviewing and rejecting a greater number of large-firm acquisitions would reduce corporate income inequality. However, if policymakers followed such a plan, firms would be unable to take advantage of the efficiencies due to economies of scale.

Limitations

This study does not take into account the changes in tax laws and accounting standards that affect reported incomes. For example, the Tax Reform Act of 1986 resulted in a shift of income from the corporate unit to a pass-through entity (e.g. S Corp) which results in higher individual incomes (Guvenen and Kaplan (2017)). The authors state, "Such income is not 'new' income earned by top earners but simply income that was previously labeled as corporate income rather than household income," (Guvenen and Kaplan (2017), p. 14). Researchers should review and interpret the sources of corporate and individual income data with caution, understanding the assumptions and limitations of the data employed in their studies.

CONCLUSION

Overall, the results provided from this study support the existence of corporate income inequality over the past twenty years mirroring the increasing individual income inequality over a similar period. The firms' size factor is positively associated with the firms in the top 10% of OIAD. This result suggests an economies of scale effect that firms utilize to increase their operating profits. Further, the positive association of intangible assets and R&D costs with the top 10% of OIAD firms parallels the association of education/skills-based knowledge with the top individual income earners in the individual income inequality literature stream.

When examining the effect of corporate income inequality on individual income inequality, prior research shows larger firms tend to compress employees' wages internally resulting in higher individual income inequality. Also, government policies address individual and corporate income inequality. On the one hand, government policies such as welfare and the progressivity of personal income taxation attempt to mitigate the degree of individual income inequality. On the other hand, federal anti-trust laws restrict firms' size, thus indirectly addressing corporate income inequality. Despite these efforts, both individual and corporate income inequality are on the rise leading some researchers to suggest governments need to do more to reduce income inequality, especially individual income inequality (e.g. Piketty suggests a wealth tax). However, increasing taxation and regulation to reduce either corporate or individual income inequality could result in harmful consequences such as negating the benefits of economies of scale for growth-oriented companies and providing disincentives for individuals to work harder and invest.

REFERENCES

Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, 113(4), 1055-1089.

Acemoglu, D., & Autor. D. (June 2010). Skills, tasks and technologies: Implications for employment and earnings. *National Bureau of Economic Research, Working Paper No. 16082*. Retrieved on August 31, 2017: http://www.nber.org/papers/w16082.pdf

Adams, J. S. (1963). Towards an understanding of inequity. *The Journal of Abnormal and Social Psychology*, 67(5), 422.

AFLCIO. (2015, May 13). *Blog — Executive PayWatch 2015: CEO Pay Continues to Skyrocket*. Retrieved on April 10, 2018. https://aflcio.org/2015/5/13/executive-paywatch-2015-ceo-pay-continues-skyrocket

Autor, D. H. (2014, May 23). Skills, education, and the rise of earnings inequality among the other 99 percent. *Science*, 344(6186), 843–851.

Baker, J. B. (2003). The case for antitrust enforcement. *Journal of Economic perspectives*, 17(4), 27-50.

Baumol, W. (1959). *Business Behavior, Value, and Growth*. MacMillan, New York.

Beer, M., Spector B., Lawrence P., Mills, D.Q., & Walton, R., (1984). *Managing Human Assets*. New York: Free Press.

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, 69(5), 1923-1960.

Bentele, K., & Kenworthy, L. (2013). Globalization and earnings inequality in the United States. In R. Rycroft (ed.), *The Economics of Inequality, Poverty and Discrimination in the 21st Century*, Praeger, Santa Barbara, CA, pp. 343-358.

Boxall P., & Purcell J. (2011). *Strategy and Human Resource Management*. 3rd ed. New York: Palgrave Macmillan.
Breen, R., & García-Peñalosa, C. (2005, August). Income inequality and macroeconomic volatility: An empirical investigation. *Review of Development Economics*, 9(3), pp. 380-398.
Buzzell, R. D., Gale, B. T., & Sultan, R. G. (1975). Market share-a key to profitability. *Harvard business review*, 53(1), 97-106.
Cappelli, P. H. (2001). Assessing the decline of internal labor markets. In Berg I., Kalleberg A. L. (eds.), *Sourcebook of Labor Markets: Evolving Structures and Processes*, New York: Kluwer Academic/Plenum, pp. 207-245.
Coady, D., & Dizioli, A. (2018). Income inequality and education revisited: persistence, endogeneity and heterogeneity. *Applied Economics*, 50(25), 2747-2761.
Cobb, J. A., & Stevens, F. G. (2017). These Unequal States: Corporate Organization and Income Inequality in the United States. *Administrative Science Quarterly*, 62(2), 304-340.
Coburn, D. (2000). Income inequality, social cohesion and the health status of populations: the role of neo-liberalism. *Social science & medicine*, 51(1), 135-146.
Cohn, A., Fehr, E., Herrmann, B., & Schneider, F. (2014). Social comparison and effort provision: Evidence from a field experiment. *Journal of the European Economic Association*, 12(4), 877-898.
Corbae, D., & D'Erasmo, P. (2011). A quantitative model of banking industry dynamics. *Federal Reserve Bank of Atlanta*, Retrieved on August 31, 2017. https://www.frbatlanta.org/-/media/documents/research/seminars/2011/seminarderasmo100611.pdf
Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015, June). Causes and consequences of income inequality: a global perspective. *International Monetary Fund Staff Discussion Note*, Retrieved on August 31, 2017. https://www.imf.org/external/pubs/ft/sdn/2015/sdn1513.pdf
De Gregorio, J. D., & Lee, J. W. (2002). Education and income inequality: new evidence from cross‐country data. *Review of Income and Wealth*, 48(3), 395-416.
Delsol, J-P., Lecaussin, N., & Martin, E. (2017). Anti-Piketty ─ Capital for the 21st Century. *Cato Institute*, Washington, D.C.
Festinger, L. (1954). A theory of social comparison processes. *Human relations*, 7(2), 117-140.
Frick, W. (May 11, 2016). Corporate Inequality Is the Defining Fact of Business Today. *Harvard Business Review Digital Articles*, 2-9.
Fuglie, K., Heisey, P., King, J., & Schimmelpfennig, D. (December 3, 2012). Rising concentration in agricultural input industries influences new farm technologies. *U.S. Department of Agriculture*, Retrieved on August 31, 2017. https://www.ers.usda.gov/amber-waves/2012/december/rising-concentration-in-agricultural-input-industries-influences-new-technologies/
Furman, J., & Orszag, P. (2015). A firm-level perspective on the role of rents in the rise in inequality. October 16, 2015, presentation at "A Just Society," Centennial Event in Honor of Joseph Stigliz Columbia University. Retrieved on August 31, 2017. http://gabriel-zucman.eu/files/teaching/FurmanOrszag15.pdf
Galor, O., & Moav, O. (2000). Ability-biased technological transition, wage inequality, and economic growth. *The Quarterly Journal of Economics*, 115(2), 469-497.
Granovetter M. (1981). Toward a sociological theory of income differences. In Berg I. (ed.), *Sociological Perspectives on Labor Markets*, New York: Academic Press, pp. 11-47.
Gujarati, D., (2003). *Basic Econometrics*. 4th Edition, McGraw-Hill, New York.
Guvenen, F., & Kaplan, G. (2017, October). Top income inequality in the 21st century: some cautionary notes. *Federal Reserve Bank of Minneapolis Quarterly Review*, 38(1), 2-15.
Hall, M., & Weiss, L. (1967). Firm size and profitability. *The Review of Economics and Statistics*, 319-331.
Hazlett, T. W. (1992). The legislative history of the Sherman act re‐examined. *Economic Inquiry*, 30(2), 263-276.

Hollister, M. N. (2004). Does firm size matter anymore? The new economy and firm size wage effects. *American Sociological Review*, 69(5), 659-679.
Institute for Mergers, Acquisitions, and Alliances (IMAA). Retrieved on March 12, 2018. https://imaa-institute.org/mergers-and-acquisitions-statistics/
Ip, G. (November 5, 2015). Inequality ─ a Company thing. *The Wall Street Journal*, p. A2.
Jansen, E. P., Merchant, K. A., & Van der Stede, W. A. (2009). National differences in incentive compensation practices: The differing roles of financial performance measurement in the United States and the Netherlands. *Accounting, Organizations and Society*, 34(1), 58-84.
Jenkins, C. L., & Jozefowicz, J. J. (2006). How things have changed: income inequality in Pennsylvania in the 1990s. *Pennsylvania Economic Review*, 14.
Johnson, G. E. (1997). Changes in earnings inequality: the role of demand shifts. *Journal of Economic Perspectives*, 11(2), 41-54.
Kumbhakar, S. C., Amundsveen, R., Kvile, H. M., & Lien, G. (2015). Scale economies, technical change and efficiency in Norwegian electricity distribution, 1998–2010. *Journal of Productivity Analysis*, 43(3), 295-305.
Lerman, R. I., & Yitzhaki, S. (1985). Income inequality effects by income source: a new approach and applications to the United States. *The Review of Economics and Statistics*, 151-156.
Manyika, J., Pinkus, G., & Ramaswamy, S., (January 21, 2016). The Most digital companies are leaving all the rest behind. *Harvard Business Review Digital Articles*, pp. 2-4.
McAfee, A., & Brynjolfsson, E. (2008). Investing in the IT that makes a competitive difference. *Harvard Business Review*, 86(7/8), 98.
Mincer, J. (1975). Education, experience, and the distribution of earnings and employment: an overview. From the volume titled: Education, Income, and Human Behavior, Ed. F. T. Juster, *National Bureau of Economic Research*, 71-93.
Mishel, L., & Kroeger, T. (October 27, 2016). Strong across-the-board wage growth in 2015 for both bottom 90 percent and top 1.0 percent. *Economic Policy Institute*. Retrieved on August 31, 2017. http://www.epi.org/blog/strong-across-the-board-wage-growth-in-2015-for-both-bottom-90-percent-and-top-1-0-percent/
Muller, A. (2002). Education, income inequality, and mortality: a multiple regression analysis. *Bmj*, 324(7328), 23.
Nickerson, J. A., & Zenger, T. R. (2008). Envy, comparison costs, and the economic theory of the firm. *Strategic Management Journal*, 29(13), 1429-1449.
Oi, W. & Idson, T., (1999). Firm Size and Wages. in Orley Ashenfelter and David Card, eds. *Handbook of Labor Economics*, 3rd Ed., Amsterdam: North-Holland.
Orszag, P. (October 16, 2015). People are not unequal; companies are. *Brookings Institution Press*. Retrieved on August 31, 2017. https://www.brookings.edu/opinions/people-are-not-unequal-companies-are/
Piketty, T. (2014). *Capital in the Twenty-First Century*. The Belknap Press of Harvard University, Cambridge, MA.
Porter, M. (1985). *Competitive Advantage: Creating and Sustaining Superior Performance*. New York Press.
Saez, E. (2016, June 30). *Striking it richer: the evolution of top incomes in the United States* (Updated with 2015 Preliminary Estimates). UC Berkeley. Retrieved on August 31, 2017. https://eml.berkeley.edu/~saez/saez-UStopincomes-2015.pdf
Sanchez, J. I., & Levine, E. L. (2012). The rise and fall of job analysis and the future of work analysis. *Annual Review of Psychology*, 63, 397-425.
Shields, D. (2010). Consolidation and Concentration in the US Dairy Industry. *Congressional Research Office*.
Strauss, S. (November 2, 2011). The Blog ─ the connection between education, income inequality and unemployment. *HuffPost*, Retrieved on August 31, 2017. http://www.huffingtonpost.com/steven-strauss/the-connection-between-ed_b_1066401.html

The United State Census Bureau. (2010). *Statistical abstracts of the United States: 2010*. 129th Edition, https://www.census.gov/library/publications/2009/compendia/statab/129ed.html

The United States Census Bureau. (2017). Income and poverty in the United States: 2016. *Report Number: P60-259*. Retrieved on September12, 2017. https://www.census.gov/library/publications/2017/demo/p60-259.html

U.S. Federal Communications Commission. (2014, December 18). Seventeenth mobile wireless competition report. Retrieved on August 31, 2017. https://www.fcc.gov/17th-annual-mobile-wireless-competition-report

Vogt, W., & Town, R. (2006). How has hospital consolidation affected the price and quality of hospital care. *Robert Wood Johnson Foundation: The Synthesis Project*, No. 9.

Western, B., & Rosenfeld, J. (2011). Unions, norms, and the rise in U.S. wage inequality. *American Sociological Review*, 76, 513-537.

APPENDIX 1

Descriptive Statistics: 1998 to 2016			
Fiscal Year = 1998			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	2,762	0.100	0.300
INTANG/TA	2,762	0.058	0.118
PE/TA	2,762	0.276	0.258
SIZE	2,762	19.349	2.813
LEV	2,762	5.464	63.182
SIZE * RD	2,762	0.836	2.414
(GDW/TA) * (RE/TA)	2,762	-0.002	0.095
Fiscal Year = 1999			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	3,022	0.100	0.300
INTANG/TA	3,022	0.070	0.137
PE/TA	3,022	0.270	0.254
SIZE	3,022	19.342	2.913
LEV	3,022	3.919	26.755
SIZE * RD	3,022	1.246	5.282
(GDW/TA) * (RE/TA)	3,022	-0.009	0.260
Fiscal Year = 2000			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	3,304	0.100	0.300
INTANG/TA	3,304	0.076	0.144
PE/TA	3,304	0.257	0.254
SIZE	3,304	19.383	3.079
LEV	3,304	3.771	15.148
SIZE * RD	3,304	1.060	4.393
(GDW/TA) * (RE/TA)	3,304	-0.012	0.328
Fiscal Year = 2001			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	3,487	0.100	0.300
INTANG/TA	3,487	0.086	0.155
PE/TA	3,487	0.253	0.252
SIZE	3,487	19.443	3.194
LEV	3,487	4.197	22.609
SIZE * RD	3,487	0.911	3.928
(GDW/TA) * (RE/TA)	3,487	-0.013	0.199

APPENDIX 1 (CONTINUED)

Descriptive Statistics: 1998 to 2016			
Fiscal Year = 2002			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	3,661	0.100	0.300
INTANG/TA	3,661	0.096	0.164
PE/TA	3,661	0.254	0.255
SIZE	3,661	19.378	3.349
LEV	3,661	3.369	10.969
SIZE * RD	3,661	1.054	4.858
(GDW/TA) * (RE/TA)	3,661	-0.014	0.201
Fiscal Year = 2003			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	3,774	0.100	0.300
INTANG/TA	3,774	0.103	0.170
PE/TA	3,774	0.252	0.257
SIZE	3,774	19.287	3.608
LEV	3,774	3.357	13.423
SIZE * RD	3,774	1.634	19.231
(GDW/TA) * (RE/TA)	3774	-0.032	0.571
Fiscal Year = 2004			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	3,905	0.100	0.300
INTANG/TA	3,905	0.104	0.170
PE/TA	3,905	0.240	0.256
SIZE	3,905	19.372	3.535
LEV	3,905	3.492	15.907
SIZE * RD	3,905	1.132	7.315
(GDW/TA) * (RE/TA)	3,905	-0.109	4.096
Fiscal Year = 2005			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	4,025	0.100	0.300
INTANG/TA	4,025	0.108	0.172
PE/TA	4,025	0.231	0.252
SIZE	4,025	19.528	3.377
LEV	4,025	3.847	33.820
SIZE * RD	4,025	1.318	13.847
(GDW/TA) * (RE/TA)	4,025	-0.058	0.884

APPENDIX 1 (CONTINUED)

Descriptive Statistics: 1998 to 2016			
Fiscal Year = 2006			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	4,153	0.100	0.300
INTANG/TA	4,153	0.116	0.181
PE/TA	4,153	0.222	0.247
SIZE	4,153	19.640	3.338
LEV	4,153	3.792	23.489
SIZE * RD	4,153	1.101	4.937
(GDW/TA) * (RE/TA)	4,153	-0.055	0.808
Fiscal Year = 2007			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	4,227	0.100	0.300
INTANG/TA	4,227	0.121	0.183
PE/TA	4,227	0.222	0.250
SIZE	4,227	19.796	3.168
LEV	4,227	3.599	15.908
SIZE * RD	4,227	1.358	7.709
(GDW/TA) * (RE/TA)	4,227	-0.061	0.936
Fiscal Year = 2008			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	4,321	0.100	0.300
INTANG/TA	4,321	0.129	0.189
PE/TA	4,321	0.223	0.254
SIZE	4,321	19.897	3.207
LEV	4,321	4.118	26.830
SIZE * RD	4,321	1.568	22.393
(GDW/TA) * (RE/TA)	4,321	-0.213	10.406
Fiscal Year = 2009			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	4,471	0.100	0.300
INTANG/TA	4,471	0.128	0.192
PE/TA	4,471	0.233	0.257
SIZE	4,471	19.837	3.305
LEV	4,471	3.884	33.445
SIZE * RD	4,471	1.813	12.166
(GDW/TA) * (RE/TA)	4,471	-0.191	9.054

APPENDIX 1 (CONTINUED)

Descriptive Statistics: 1998 to 2016			
Fiscal Year = 2010			
Variable	**N**	**Mean**	**Std Dev**
TEN	4,613	0.100	0.300
INTANG/TA	4,613	0.127	0.193
PE/TA	4,613	0.231	0.259
SIZE	4,613	19.763	3.444
LEV	4,613	8.543	363.438
SIZE * RD	4,613	1.650	18.467
(GDW/TA) * (RE/TA)	4,613	-0.052	0.960
Fiscal Year = 2011			
Variable	**N**	**Mean**	**Std Dev**
TEN	4,830	0.100	0.300
INTANG/TA	4,830	0.129	0.195
PE/TA	4,830	0.223	0.259
SIZE	4,830	19.727	3.561
LEV	4,830	4.603	73.069
SIZE * RD	4,830	2.514	53.640
(GDW/TA) * (RE/TA)	4,830	-0.061	0.929
Fiscal Year = 2012			
Variable	**N**	**Mean**	**Std Dev**
TEN	5,072	0.100	0.300
INTANG/TA	5,072	0.132	0.198
PE/TA	5,072	0.222	0.259
SIZE	5,072	19.745	3.500
LEV	5,072	5.532	85.258
SIZE * RD	5,072	2.264	48.014
(GDW/TA) * (RE/TA)	5,072	-0.052	0.763
Fiscal Year = 2013			
Variable	**N**	**Mean**	**Std Dev**
TEN	5,523	0.100	0.300
INTANG/TA	5,523	0.134	0.203
PE/TA	5,523	0.220	0.263
SIZE	5,523	19.527	3.712
LEV	5,523	3.678	22.429
SIZE * RD	5,523	4.295	169.321
(GDW/TA) * (RE/TA)	5,523	-0.059	0.893

APPENDIX 1 (CONTINUED)

Descriptive Statistics: 1998 to 2016			
Fiscal Year = 2014			
Variable	**N**	**Mean**	**Std Dev**
TEN	5,763	0.100	0.300
INTANG/TA	5,763	0.135	0.203
PE/TA	5,763	0.213	0.263
SIZE	5,763	19.551	3.690
LEV	5,763	4.313	40.548
SIZE * RD	5,763	4.523	199.071
(GDW/TA) * (RE/TA)	5,763	-0.059	0.995
Fiscal Year = 2015			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	5,827	0.100	0.300
INTANG/TA	5,827	0.140	0.207
PE/TA	5,827	0.206	0.259
SIZE	5,827	19.790	3.399
LEV	5,827	4.771	98.506
SIZE * RD	5,827	3.711	100.893
(GDW/TA) * (RE/TA)	5,827	-0.072	1.409
Fiscal Year = 2016			
Variable	**N**	**Mean**	**Std. Dev.**
TEN	5,757	0.100	0.300
INTANG/TA	5,757	0.146	0.211
PE/TA	5,757	0.204	0.260
SIZE	5,757	19.980	3.271
LEV	5,757	6.878	193.351
SIZE * RD	5,757	3.602	93.659
(GDW/TA) * (RE/TA)	5,757	-0.049	0.839

See “Hypotheses and Research Model” section for a description of the variables.

APPENDIX 2

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2016 (N=5,757)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-50.5787	2.1601	548.2748	<.0001	NA
INTANG/TA	2.8914	0.3724	60.2906	<.0001	18.0185
PE/TA	1.2097	0.287	17.7721	<.0001	3.3525
SIZE	2.0843	0.0905	530.971	<.0001	8.0390
SIZE*RD	0.00571	0.00203	7.954	0.0048	1.0057
(GDW/TA) * (RE/TA)	6.0297	0.8919	45.7076	<.0001	415.5903

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi2$	*P*
Likelihood Ratio	2564.5311	<.0001
Score	1250.4111	<.0001
Wald	535.9646	<.0001

Logistic Regression Results for 2015 (N=5,827)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-49.2675	2.0931	554.0205	<.0001	NA
INTANG/TA	2.9609	0.3792	60.9652	<.0001	19.3153
PE/TA	1.0108	0.2853	12.5486	0.0004	2.7478
SIZE	2.0352	0.0879	536.6252	<.0001	7.6538
SIZE*RD	0.00438	0.00212	4.2786	0.0386	1.0044
(GDW/TA) * (RE/TA)	4.9141	0.9202	28.5179	<.0001	136.1967

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi2$	*P*
Likelihood Ratio	2576.5997	<.0001
Score	1259.7467	<.0001
Wald	540.1595	<.000

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2014 (N=5,763)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-53.0563	2.3401	514.063	<.0001	NA
INTANG/TA	2.4696	0.4171	35.0547	<.0001	11.8177
PE/TA	1.5858	0.2998	27.9815	<.0001	4.8832
SIZE	2.1973	0.0983	499.5938	<.0001	9.0007
SIZE*RD	0.00191	0.00131	2.1218	0.1452	1.0019
(GDW/TA) * (RE/TA)	6.1946	1.0202	36.8674	<.0001	490.0954

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi 2$	*P*
Likelihood Ratio	2655.5934	<.0001
Score	1176.1905	<.0001
Wald	503.45	<.0001

Logistic Regression Results for 2013 (N=5,523)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-53.2799	2.4234	483.3624	<.0001	NA
INTANG/TA	2.4436	0.4254	32.9931	<.0001	11.5144
PE/TA	1.4037	0.3096	20.56	<.0001	4.0702
SIZE	2.2088	0.1019	469.8781	<.0001	9.1048
SIZE*RD	0.00223	0.00154	2.1137	0.146	1.0022
(GDW/TA) * (RE/TA)	6.8131	1.0482	42.2468	<.0001	909.6865

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi 2$	*P*
Likelihood Ratio	2553.4416	<.0001
Score	1127.5232	<.0001
Wald	474.2853	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2012 (N=5,072)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-51.007	2.3618	466.4104	<.0001	NA
INTANG/TA	2.3539	0.4437	28.1474	<.0001	10.5265
PE/TA	1.3229	0.3188	17.2253	<.0001	3.7543
SIZE	2.1076	0.0991	452.7357	<.0001	8.2285
SIZE*RD	0.00766	0.00323	5.6168	0.0178	1.0077
(GDW/TA) * (RE/TA)	7.4167	1.1217	43.7221	<.0001	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi2$	*P*
Likelihood Ratio	2293.87	<.0001
Score	1072.7373	<.0001
Wald	457.4814	<.0001

Logistic Regression Results for 2011 (N=4,830)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-50.9612	2.4093	447.4176	<.0001	NA
INTANG/TA	2.2854	0.4577	24.9373	<.0001	9.8296
PE/TA	1.5888	0.3297	23.218	<.0001	4.8979
SIZE	2.1049	0.101	434.252	<.0001	8.2063
LEV	0.00219	0.00201	1.1922	0.2749	1.0022
SIZE*RD	0.011	0.0035	9.9715	0.0016	1.0111
(GDW/TA) * (RE/TA)	7.3907	1.1723	39.7471	<.0001	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi2$	*P*
Likelihood Ratio	2184.0841	<.0001
Score	988.6906	<.0001
Wald	438.9499	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2010 (N=4,613)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-55.5907	2.7752	401.2384	<.0001	NA
INTANG/TA	2.2449	0.4998	20.1753	<.0001	9.4395
PE/TA	2.2347	0.3587	38.8182	<.0001	9.3437
SIZE	2.2958	0.116	391.3734	<.0001	9.9324
SIZE*RD	0.0239	0.00536	19.9434	<.0001	1.0242
(GDW/TA) * (RE/TA)	6.8352	1.2242	31.1766	<.0001	930.0143

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	2152.9167	<.0001
Score	1005.4427	<.0001
Wald	393.9741	<.0001

Logistic Regression Results for 2009 (N=4,471)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-43.7351	2.0274	465.3342	<.0001	NA
INTANG/TA	3.2544	0.4456	53.3478	<.0001	25.9041
PE/TA	2.2635	0.3341	45.8954	<.0001	9.6167
SIZE	1.7806	0.0841	448.6599	<.0001	5.9334
SIZE*RD	0.0364	0.0104	12.1948	0.0005	1.0371
(GDW/TA) * (RE/TA)	5.8627	1.1359	26.64	<.0001	351.6724

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1874.518	<.0001
Score	976.29	<.0001
Wald	451.8379	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2008 (N=4,321)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-39.7166	1.8192	476.655	<.0001	NA
INTANG/TA	2.5457	0.4571	31.0119	<.0001	12.7522
PE/TA	2.4415	0.3218	57.5711	<.0001	11.4903
SIZE	1.6082	0.0753	456.3861	<.0001	4.9938
LEV	0.00741	0.00432	2.9363	0.0866	1.0074
SIZE*RD	0.0517	0.0115	20.1852	<.0001	1.0531
(GDW/TA) * (RE/TA)	6.3831	1.2847	24.6853	<.0001	591.7593

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1721.0787	<.0001
Score	953.0099	<.0001
Wald	460.1701	<.0001

Logistic Regression Results for 2007 (N=4,227)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-61.7724	3.3664	336.7087	<.0001	NA
INTANG/TA	1.5212	0.5422	7.8703	0.005	4.5777
PE/TA	2.1867	0.3888	31.6313	<.0001	8.9058
SIZE	2.5743	0.1418	329.582	<.0001	13.1221
LEV	0.0342	0.00758	20.4143	<.0001	1.0348
SIZE*RD	0.1339	0.0163	67.3375	<.0001	1.1433
(GDW/TA) * (RE/TA)	4.0886	0.6541	39.0708	<.0001	59.6563

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	2038.4347	<.0001
Score	1082.3618	<.0001
Wald	332.5588	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2006 (N=4,153)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-60.0511	3.2502	341.3689	<.0001	NA
INTANG/TA	1.3957	0.6111	5.2159	0.0224	4.0378
PE/TA	2.1254	0.3906	29.6032	<.0001	8.3762
SIZE	2.5101	0.1372	334.5215	<.0001	12.3062
LEV	0.0146	0.00469	9.7403	0.0018	1.0147
SIZE*RD	0.1756	0.0232	57.4475	<.0001	1.1920
(GDW/TA) * (RE/TA)	6.8399	2.071	10.908	0.001	934.3957

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1989.3639	<.0001
Score	975.2642	<.0001
Wald	336.077	<.0001

Logistic Regression Results for 2005 (N=4,025)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-56.1122	3.0265	343.7399	<.0001	NA
INTANG/TA	1.6856	0.679	6.1628	0.013	5.3957
PE/TA	1.688	0.3757	20.1828	<.0001	5.4087
SIZE	2.3511	0.1281	336.9574	<.0001	10.4971
LEV	0.00658	0.00415	2.5157	0.1127	1.0066
SIZE*RD	0.0462	0.00956	23.3722	<.0001	1.0473
(GDW/TA) * (RE/TA)	6.8741	2.2196	9.5919	0.002	966.9048

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1892.2818	<.0001
Score	940.095	<.0001
Wald	337.8957	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2004 (N=3,905)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-55.1223	2.9941	338.9466	<.0001	NA
INTANG/TA	1.2257	0.7027	3.0428	0.0811	3.4065
PE/TA	2.0468	0.3832	28.5239	<.0001	7.7431
SIZE	2.3081	0.1266	332.1845	<.0001	10.0553
LEV	0.0234	0.00789	8.7754	0.0031	1.0237
SIZE*RD	0.1156	0.0193	36.034	<.0001	1.1225
(GDW/TA) * (RE/TA)	8.2967	2.2736	13.3165	0.0003	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi2$	*P*
Likelihood Ratio	1829.656	<.0001
Score	861.3514	<.0001
Wald	333.3255	<.0001

Logistic Regression Results for 2003 (N=3,774)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-54.9258	3.0252	329.6346	<.0001	NA
INTANG/TA	1.2197	0.7188	2.8794	0.0897	3.3862
PE/TA	2.0099	0.3947	25.9258	<.0001	7.4626
SIZE	2.309	0.1283	323.7568	<.0001	10.0644
LEV	0.0361	0.0124	8.4913	0.0036	1.0368
SIZE*RD	0.0332	0.00842	15.5458	<.0001	1.0338
(GDW/TA) * (RE/TA)	6.2455	2.4891	6.296	0.0121	515.6870

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	$\chi2$	*P*
Likelihood Ratio	1770.019	<.0001
Score	800.7879	<.0001
Wald	325.0087	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2002 (N=3,661)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-48.2769	2.5862	348.4646	<.0001	NA
INTANG/TA	0.8956	0.69	1.6849	0.1943	2.4488
PE/TA	2.0735	0.3765	30.3278	<.0001	7.9526
SIZE	2.0275	0.1098	340.704	<.0001	7.5951
SIZE*RD	0.0928	0.0198	21.8974	<.0001	1.0972
(GDW/TA) * (RE/TA)	3.6872	2.9744	1.5367	0.2151	39.9329

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1630.0265	<.0001
Score	837.0739	<.0001
Wald	340.8907	<.0001

Logistic Regression Results for 2001 (N=3,487)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-42.9718	2.2574	362.3736	<.0001	NA
PE/TA	1.9297	0.3578	29.0839	<.0001	6.8874
SIZE	1.8045	0.0964	350.3086	<.0001	6.0769
SIZE*RD	0.1339	0.0679	3.886	0.0487	1.1433
(GDW/TA) * (RE/TA)	9.7115	2.6331	13.6034	0.0002	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1468.5188	<.0001
Score	802.7448	<.0001
Wald	351.274	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 2000 (N=3,304)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-50.9636	2.9215	304.3027	<.0001	NA
PE/TA	1.8403	0.3896	22.3106	<.0001	6.2984
SIZE	2.1611	0.1253	297.3449	<.0001	8.6807
LEV	0.0293	0.0163	3.2283	0.0724	1.0297
SIZE*RD	0.1658	0.0191	75.294	<.0001	1.1803
(GDW/TA) * (RE/TA)	12.117	3.2579	13.8328	0.0002	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1496.1152	<.0001
Score	823.7268	<.0001
Wald	298.6698	<.0001

Logistic Regression Results for 1999 (N=3,022)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-59.1277	3.7505	248.5398	<.0001	NA
PE/TA	2.1496	0.4383	24.0566	<.0001	8.58143
SIZE	2.5219	0.1613	244.4312	<.0001	12.45223
LEV	0.00728	0.00196	13.7226	0.0002	1.00731
SIZE*RD	0.1844	0.0208	78.2748	<.0001	1.20250
(GDW/TA) * (RE/TA)	16.464	3.5911	21.0194	<.0001	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1435.8058	<.0001
Score	830.2534	<.0001
Wald	244.7853	<.0001

APPENDIX 2 (CONTINUED)

LOGISTIC REGRESSION RESULTS: 1998 TO 2016

Logistic Regression Results for 1998 (N=2,762)

Parameters	β	*SE* β	Wald's χ^2	*P*	*Odds Ratio* e^{β}
Intercept	-55.7263	3.6302	235.6474	<.0001	NA
INTANG/TA	2.2779	1.0873	4.3892	0.0362	9.7562
PE/TA	1.8751	0.4388	18.259	<.0001	6.5215
SIZE	2.3758	0.1564	230.7751	<.0001	10.7596
SIZE*RD	0.4724	0.0579	66.5724	<.0001	1.6038
(GDW/TA) * (RE/TA)	13.8434	5.0263	7.5856	0.0059	>999.999

Overall Model Evaluation -- Testing Global Null Hypothesis of **β** =0

Test	χ2	*P*
Likelihood Ratio	1287.1072	<.0001
Score	778.0561	<.0001
Wald	231.1568	<.0001

$INTANG_{i,t-1}$ / $TA_{i,t-1}$ = the firm's intangible assets scaled by total assets at time t-1;
$PE_{i,t-1}$ / $TA_{i,t-1}$ = the firm's plant and equipment assets scaled by total assets at time t-1;
$SIZE_{i,t-1}$ = the natural log of the firm's total assets at time t-1;
$LEV_{i,t-1}$ = the firm's total liabilities scaled by total assets at time t-1;
$RD_{i,t-1}$ = the firm's research and development costs scaled by total assets at time t-1;
$GDW_{i,t-1}$ / $TA_{i,t-1}$ = the firm's goodwill scaled by total assets at time t-1; and
$RE_{i,t-1}$ / $TA_{i,t-1}$ = the firm's retained earnings scaled by total assets at time t-1.