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Written Comments Regarding Recommendation on Methodology for Deriving Operating Ratio for Solid Waste Haulers

Submitted on Behalf of WRRA

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TG-131255

Inquiry into methods for setting rate for solid waste collection companies

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I. EXECUTIVE SUMMARY

A. Assignment and Summary

1. We have been asked by Washington Refuse & Recycling Association ("WRRA") to evaluate the Report to the Utilities and Transportation Commission ("WUTC") titled "Recommendation on methodology for deriving operating ratio for solid waste haulers" dated January 16, 2019, and submitted by Danny Kermode, CPA, Assistant Director for Water and Transportation ("January 2019 Staff Report").[3] Our work includes reviewing in detail the proposed methodology contained in that report and developing alternatives to that method for consideration by the WUTC and its staff.

2. Our proposal adheres to the principle of using best practices such that the proposal is logic-based and understandable, uses standard approaches, is reliable and replicable, and is well-documented so future updates can adhere to the method. Overall, the method is designed to provide margins and returns to the regulated solid waste collection companies that are fair, reasonable, and sufficient.

3. The regulated solid waste collections industry in Washington has used a model that has been in in place for several decades which provides a mechanism for the WUTC to use in determining permitted revenues, the LG Model. A growing consensus has emerged that this model is in need of updating, largely due to the fact that the underlying data upon which margins and returns are based is from the period 1968-1977. The WUTC staff has issued a proposal to update both the data and the underlying model which uses this data in determining rates, the DuPont model discussed in the January 2019 Staff Report.

4. The proposed Staff DuPont Model has several positive attributes, such as the underlying premise upon which companies are determined to be comparable, and the general manner in which the data is used for estimating revenues. The use of a regression approach and a model such as DuPont can result in margins and returns that are fair, reasonable, and sufficient. However, there are several attributes of the January 2019 Staff Report and the proposed Staff DuPont Model discussed in that report which can be substantially improved upon.

5. In these comments, we provide a proposal on behalf of WRRA which builds upon the sound and fundamental attributes of the proposed Staff DuPont Model described in the January 2019 Staff Report. We provide alternative approaches for several of the features which do not represent, in our view, a best-practices approach in the Staff DuPont Model.

6. The concept of the DuPont model is to select comparable firms which reflect the inherent underlying economics, and thus face similar risks as the regulated solid waste collection firms. The proposed Staff DuPont Model selects firms that are generally identified as transportation companies. However, the process proposed by Staff incorporates a set of

[3] We refer to the DuPont model proposed in the January 2019 Staff Report as the "Staff DuPont Model." We refer to the regression analysis proposed by staff as part of the Staff DuPont Model as the "Staff DuPont Regression". We refer to the spreadsheet that is part of the Staff DuPont Model as the "Staff DuPont Spreadsheet".

filtering techniques which adds a substantial degree of subjectivity. The Staff-proposed techniques are based on a series of statistical tests that are misapplied and logically circular. Importantly, however, if the rule for including firms is a "good" rule, then a complex set of additional rules for excluding entire groups of firms as proposed by Staff is not warranted.

7. We propose two alternative sets of comparable companies which are both consistent with the objectives expressed in the January 2019 Staff Proposal, but without unnecessary filtering processes. The first set of comparable companies we propose are those that provide transportation services using vehicles (information from which are used in our Model 1). The second set of comparable companies we propose are those that provide transportation services, whether using vehicles or not (information from these companies are used in our Model 2). In our view, both of these alternative sets of companies represent a best-practices approach for modeling purposes.

8. Using firms providing transportation services with vehicles (Model 1) has advantages because it is a definition that targets closely the sorts of firms that provide similar services as waste collection companies. The disadvantage is that because it is more targeted, there are fewer companies and data points for the analysis. Using firms providing transportation services (Model 2) has advantages because this definition adds many data points (largely natural gas and pipeline firms), and the resulting predicted margins from the regression model using this data has a similar shape to both the original LG regression and the Staff's proposed DuPont Model. Model 2 is somewhat less targeted than Model 1 in terms of the similarity of firms included in the analysis.

9. Data points from comparable firms are used in a regression analysis.[4] Here, the objective of the regression analysis is to predict a margin based on other characteristics of the data. The Staff DuPont Regression uses the asset turnover ratio as a variable for predicting margins. Then the Staff DuPont Spreadsheet essentially fixes the predicted margins based on a theoretical proposition (the Modigliani-Miller Theorem) which says that firm value (and therefore margins earned) are unrelated to capital structure (Debt/Equity ratio). This is a substantial departure from the approach used in the LG, which effectively finds a ROE following the regression analysis, and then determines the margin sufficient to ensure that ROE regardless of capital structure.

10. The problem with the approach in the Staff DuPont Model is that the Modigliani-Miller Theorem upon which the structure of the Staff DuPont Spreadsheet is based has sparse empirical support. In fact, *many studies* have failed to find support for the theory in the real-world, and many others have pointed to real-world considerations which are ignored in the theorem. Therefore, the theoretical underpinnings of the Staff DuPont Spreadsheet are not well-supported. There certainly are redeeming qualities to the Modigliani-Miller Theorem. However, the empirical shortcomings of the theory simply are too great to be ignored for the purposes of setting rates.

[4] A regression analysis is a statistical technique that estimates relationships between variables based on the underlying data in the analysis.

11. We propose a solution to this problem. Let the data show us to what extent the Modigliani-Miller Theorem is operative in this industry. This is accomplished by including Debt/Equity ratio directly into the regression analysis. If the Modigliani-Miller Theorem is at work, the data will tell us so. Our solution also has the advantage of being in line with the original DuPont formula which indicates that PM has a relationship with both asset turnover (ATO) and capital structure (Debt/Equity). We find that when including Debt/Equity in the model, the results are between the original LG (which fixes ROE) and the Staff DuPont Model (which fixes PM).

12. We also propose a standard statistical approach for identifying outliers in the raw data to avoid any one data point substantially influencing the results. This approach (Mahalanobis) takes into account underlying correlations between the variables under study. In contrast, the January 2019 Staff Proposal uses a subjective cutoff without any particular justification.

13. Finally, the Staff DuPont Spreadsheet can be modified to account for corporate income taxes, similar to the way in which the current LG spreadsheet accounts for corporate income taxes. Moreover, if the WUTC decides to continue to use the original LG model, a version of our regression model (without any provision for capital structure) can used as an input in the original LG.

B. Summary of Specific Analytical Steps

14. Based on the principles expressed above, and on the analyses included throughout these comments, a break-down of our specific proposals for the analysis are the following.

    a. Use data from Capital IQ. Capital IQ is a widely-used data source and is expected to be available on a go-forward basis.

    b. Include companies in the analysis which have SIC codes indicating that companies in those codes are principally engaged in transportation. We provide two alternative sets of companies. Model 1 includes SIC codes which describe companies that conduct transportation primarily by the use of vehicles. Model 2 does not include this restriction (and so is a broader set of companies), and is more in line with the January 2019 Staff Report.

    c. Use an outlier detection method (Mahalanobis method) which is a standard statistical approach that is widely recognized as a reliable method which takes into account relationships between multiple variables in determining outlier observations.

    d. Use ten years of data for Model 1 and seven years of data for Model 2. The difference is to ensure that Model 1 has sufficient data for estimation of profit margin.

    e. Use the following regression specification to predict margins:

$$\ln PM = \alpha + \beta_1(\ln ATO) + \beta_2\left(ln\frac{D}{E}\right) + \varepsilon ,$$

where, *PM* is profit margin defined as 100**EBIT/(Net Revenue)*,[5] *ATO* is defined as 100**(Net Revenue)/(Average PPE)*,[6] and *D/E* is defined at 100**(Total Debt)/(Total Equity)*. This regression specification is consistent with the relationships described in the DuPont model, and it allows for the relationship between the capital structure of a firm and margins to be empirically determined rather than by strict adherence to theory. The Staff DuPont Spreadsheet can be modified readily to accommodate D/E ratio as an additional variable in the regression model.

f. The Staff DuPont Spreadsheet can be modified to account for corporate income taxes, similar to the way in which the current LG spreadsheet accounts for corporate income taxes.

C. Specific Points of Differentiation from Proposed Staff DuPont Model

15. Our proposal differs from the January 2019 Staff Report in several important respects. These key differences include that:

a. We select SIC codes based upon the economic rationale for their inclusion. The proposed use of Chow tests in the January 2019 Staff Report is especially ill-suited for the SIC selection question at hand. The proposed method contains circular logic and may not lead to a unique solution. If certain observations are inappropriate for use in the analysis, these observations are excluded by the outlier method we describe in our proposal.

b. The January 2019 Staff Report has cut-offs for outliers at 400 ATO and 100 PM without any particular justification. Our proposed approach (Mahalanobis distance) is widely accepted and takes into account the particular characteristics of the data in determining outlier observations.

c. The Staff DuPont Spreadsheet imposes a strict relationship between capital structure and margins. In particular, calculated return on equity (ROE) is forced to increase mechanically with increased debt, and decline mechanically with less debt. This design is based on the Modigliani-Miller Theorem regarding firm value and capital structure. However, as we discuss below, the Modigliani-Miller Theorem lacks empirical justification. Instead, we recommend incorporating this capital

[5] *EBIT* is defined as Earnings Before Interest and Taxes.

[6] *Average PPE* is the average Property Plant and Equipment for a year. Since PPE is reported as a snapshot, the average PPE for 2018 for a company is the PPE for calendar year-end 2017 plus PPE for calendar year-end 2018, divided by 2.

structure into the model directly to empirically estimate the relationships rather than through strict adherence to theory.

d. The January 2019 Staff Report includes a range of return that intends to provide the WUTC with flexibility in setting rates. However, the metric by which this range is determined (the standard error of the intercept term of the estimated regression model) is misapplied. To the extent the WUTC would like to reward a company or lower margins for a companies, this is better accomplished by changing the allowable expenses and/or investments in the spreadsheet rather than using a range around a single coefficient point estimate from the estimated regression model.

16. Each of our recommendations and departures from the January 2019 Staff Report are discussed in detail below.

II. BACKGROUND AND EXPECTATION OF RESULTS

17. A motivating factor behind the update to the LG model has been to update data used in the modeling to reflect a more recent, lower-inflation period, with the apparent expectation that this would lower earnings for companies. The January 2019 Staff Report *begins* its description of the DuPont Formula Model Results with the statement, "[w]ith the current data in the Lurito Gallagher Model reflecting a high inflationary period, it should be no surprise that the returns provided in staff's proposed DuPont Formula Model are lower."[7] Similar sentiments are expressed in in the Solid Waste Rate Setting Methodology Final Report, dated December 19, 2014 ("2014 Bell Study"):[8]

> A brief comment regarding the impact of inflation is warranted. For the ten-year period (1968-1977) used to estimate the L-G curve, inflation, based on the CPI for urban consumers (all items), averaged 6.4%. In contrast, inflation for the 2011, 2012, and 2013 averaged just 2.2%. Holding other factors constant, this should produce lower nominal returns on equity. At a minimum, the L-G curve(s) should be updated when inflation rates change appreciably.

While the above statement is essentially true – the qualifications are important, namely that "*[h]olding other factors constant*, this *should* produce lower nominal returns on equity."[9]

[7] January 2019 Staff Report, p. 15. The January 2019 Staff Report also states that, "if inflation becomes a factor in the near future, it would be expected that earnings would start to increase to offset the effects of inflation." (January 2019 Staff Report, p. 13.)

[8] "Solid Waste Rate Setting Methodology" Report Submitted by Bell & Associates, Inc. & Sound Resource Economics, December 19, 2014, Docket No. UG 131255, p. 4.

[9] "Solid Waste Rate Setting Methodology" Report Submitted by Bell & Associates, Inc. & Sound Resource Economics, December 19, 2014, Docket No. UG 131255, p. 4. (emphasis added)

18. Contrary to the statement above, in reality, when inflation changes other factors are *not held constant*. Businesses experience inflation through increases in input prices – that is, through cost pressures. A business is unsure how much of this cost increase is due to general cost increases and how much is specific to the business (or industry). Pass-through of these cost increases likely will be incomplete and/or delayed. All of these factors put downward pressure on margins, and earnings. Moreover, inflationary periods may occur in more unstable economic environments, putting further pressure on margins and earnings.[10]

19. Reilly (1997) conducted an empirical study of the impact of inflation on ROE, using the DuPont model, the issue we are examining here.[11] As part of this analysis, Reilly (1997) studied two low-inflation periods (1956-1967 and 1982-1995) against a high-inflation period (1968-1981). Table 2.1 below replicates his comparisons across these periods.[12]

TABLE 2.1 – Replication of Table 4 in Reilly (1997)
Time Period Averages for Stock Returns ROE
Components, and Nominal and Real Earnings Growth

	S&P % Total Return	U.S. Inflation % Price Return	Inflation Adjusted S&P 500 % Total Return	TAT	PM	ROA	LEV	ROE	Annual Growth Rate Nominal Earnings	Annual Growth Rate Real Earnings
1956-1967 (12 Years)	11.28	1.97	9.18	1.18	6.12	7.20	1.59	11.45	4.40	2.46
1968-1981 (14 Years)	7.51	7.60	0.08	1.22	5.12	6.28	2.02	12.75	8.11	0.52
1982-1995 (14 Years)	17.01	3.57	13.02	1.04	4.36	4.52	2.96	13.20	5.34	1.80

20. In the above table, "TAT" is total asset turnover (what we have typically referred to as ATO, measured somewhat differently), "PM" is profit margin, "ROA" is return on assets, "LEV" is leverage defined as assets/equity, and "ROE" is return on equity. The high-inflation period shows margins that are between each of the low-inflation periods. In addition, while "Nominal Earnings" is higher in the high-inflation period, the ROE for the high-inflation period is between each of the low-inflation periods.

[10] Hazlitt, Henry, "Inflation Versus Profits," Foundation for Economic Education, November 1, 1977. https://fee.org/articles/inflation-versus-profits/

[11] Reilly, Frank K. (1997) "The Impact of Inflation on ROE, Growth and Stock Prices," Financial Services Review, 6(1): 1-17.

[12] Reilly, Frank K. (1997) "The Impact of infliction on ROE, Growth and Stock Prices," Financial Services Review, 6(1): 1-17, p. 14.

21. Reilly (1997) describes that margins and returns were lower during high-inflation periods:[13]

> …[I]t was demonstrated that the critical variable was what happened to ROE, which was determined by what happened to the DuPont components and especially the profit margin during periods of inflation…
>
> The correlation analysis confirmed prior results which showed a negative relationship between stock returns and inflation (stocks are a poor inflation hedge) and between profit margins and inflation which helps explain the stock return results. An analysis of stock returns and ROE results during periods of relatively low inflation (1956-1967 and 1982-1995) versus a period of high inflation (1968-1981) confirms these results because real stock returns were significantly higher during periods of low inflation and there was clearly a higher growth rate of real earnings during periods of low inflation. Finally, the superior returns on stocks during periods of low inflation can be explained by the direct comparison of inflation and implied growth rate of earnings. Specifically, during periods of low inflation the implied growth rate of earnings generally exceeds inflation, while during periods of high inflation, the implied growth rate of earnings is equal to *or less than* the rate of inflation.

22. Reilly found a correlation between margins and inflation of negative 0.10.[14] A review of data specific to the transportation industry also shows negative correlation between inflation and margins. For example, Figure 2.2 shows a scatterplot between inflation and PM by year from 1968 to 2018 using the companies from our proposed Model 1 (discussed in more detail below). Here we see a correlation of negative 0.32. In fact, the years with the largest margins all occur in years with low inflation. Figure 2.3 below shows a corresponding scatterplot using companies from out proposed Model 2 (again, discussed in more detail below). The correlation between inflation and margins over the period 1968 to 2018 for these companies is negative 0.076. We are not claiming that these correlations must be negative. Instead, we are demonstrating that there is little reason to assume that they must be positive.

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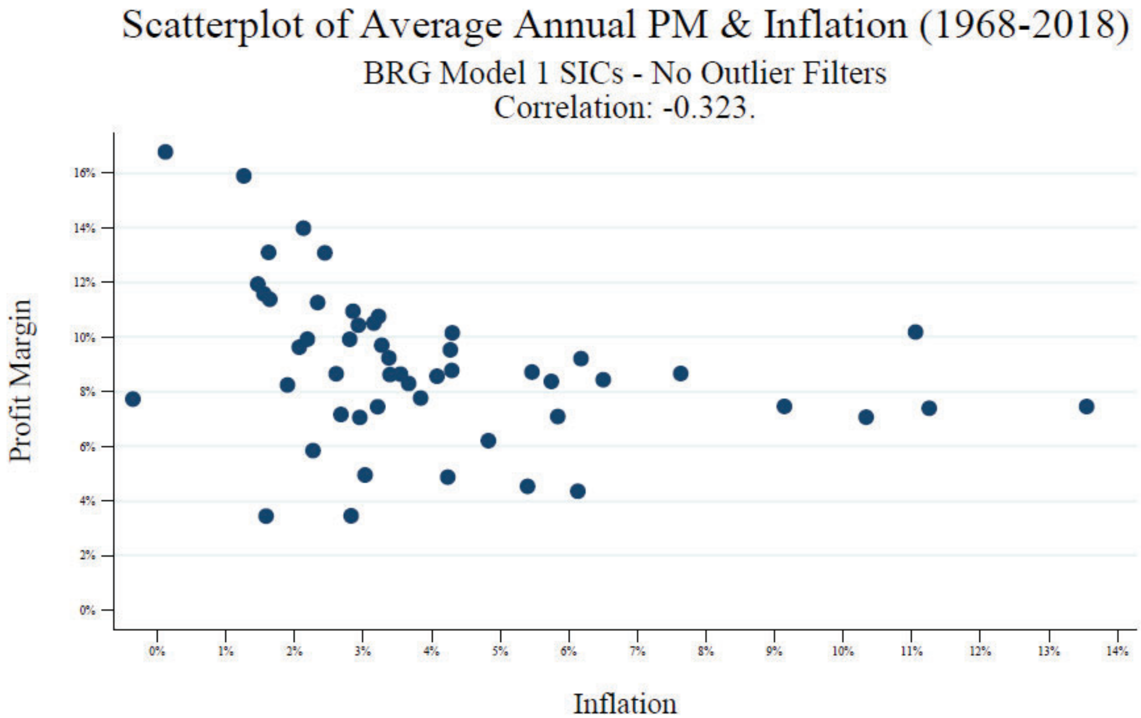
[13] Reilly, Frank K. (1997) "The Impact of inflation on ROE, Growth and Stock Prices," Financial Services Review, 6(1): 1-17, pp 15-16. (emphasis in original)

[14] Reilly, Frank K. (1997) "The Impact of infliction on ROE, Growth and Stock Prices," Financial Services Review, 6(1): 1-17, p. 13.

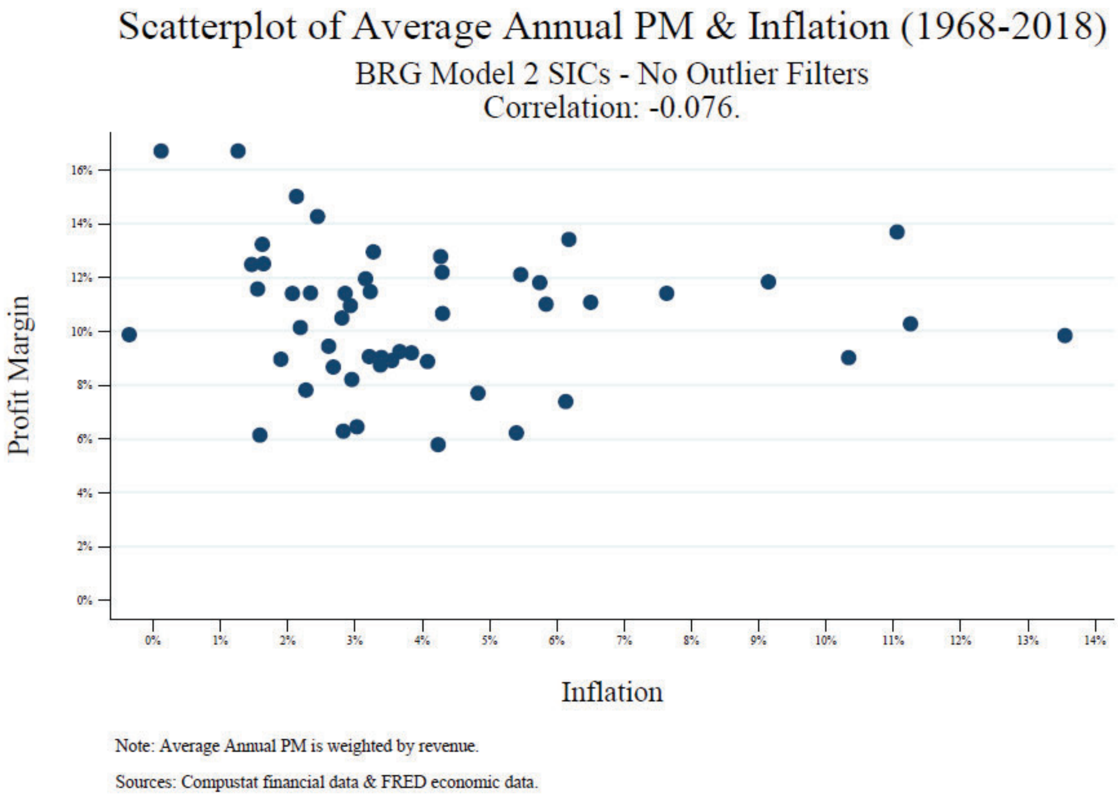
FIGURE 2.2



Note: Average Annual PM is weighted by revenue.

Sources: Compustat financial data & FRED economic data.

FIGURE 2.3



23. The averages that Reilly reports in his paper can be computed using data from the transportation industry. Tables 2.4 and 2.5 below shows ATO, PM, and ROE for the high-inflation period from 1968-1981 (same as Reilly) and during low-inflation periods from 1982-2008 and from 2009-2018, for Models 1 and 2 respectively.

TABLE 2.4
High-Inflation and Low-Inflation Averages of
PM, ATO, and ROE for Transportation Companies
BRG Model 1 SICs – No Outlier Filters

	Avg Annual Inflation Rate	ATO	PM	ROE
1968-1981 (14 Years)	7.47	1.00	8.20	8.46
1982-2008 (27 Years)	3.25	1.10	8.23	7.11
2009-2018 (10 Years)	1.56	1.04	12.63	15.50

Note: Asset Turnover Ratio (ATO) is calculated as 100 * total revenue / average PPE. Profit Margin (PM) is calculated as 100 * EBIT / total revenue. Return on Equity (ROE) is calculated as 100 * net income / equity.

Sources: Compustat financial data & FRED economic data.

TABLE 2.5
High-Inflation and Low-Inflation Averages of
PM, ATO, and ROE for Transportation Companies
BRG Model 2 SICs – No Outlier Filters

	Avg Annual Inflation Rate	ATO	PM	ROE
1968-1981 (14 Years)	7.47	1.01	10.93	10.90
1982-2008 (27 Years)	3.25	1.03	9.18	7.62
2009-2018 (10 Years)	1.56	0.82	13.57	10.94

Note: Asset Turnover Ratio (ATO) is calculated as 100 * total revenue / average PPE. Profit Margin (PM) is calculated as 100 * EBIT / total revenue. Return on Equity (ROE) is calculated as 100 * net income / equity.

Sources: Compustat financial data & FRED economic data.

24. In the high-inflation period from 1968 to 1981, the annual inflation rate was nearly 7.5 percent, margins were between 8 and 11 percent, and the measured ROE was also between 8 and 11 percent. In the next 27-year period, inflation was much lower at 3.25 percent on average. Both margins and measured ROE also fell to some extent for Model 2, but rose for Model 1. Additionally, in the most recent 10 years (the period of time recommended

for Model 1), annual inflation was still lower at about 1.5 percent per year, yet margins exceeded 12.5 percent for both models and ROE exceeded 10 percent for both models.

25. Macroeconomic conditions and industry-specific changes have occurred over the last 40-50 years. These all can impact the observed financial performance of an industry and of firms in an industry. In essence, relationships between inflation, margins, and earnings are complex and one cannot easily surmise *a priori* that higher inflation necessarily leads to higher margins and/or earnings, or that lower inflation necessarily lowers margins and/or earnings.

26. This is not to say that the model should never be updated. Our view is that using recent data will capture the risks inherent to the industry better than outdated information. However, given the myriad factors that can influence margins and returns, one cannot reliably expect to predict how results will change based on the change in just one factor (like inflation) over time.

III. DATA SOURCE AND COMPARABLE COMPANIES SELECTION

A. Data Source

27. The January 2019 Staff Proposal uses Compustat data from S&P as its data source. Compustat's coverage of financial data is limited in comparison to Capital IQ's data. While Compustat only covers financial data from public companies, Capital IQ provides coverage for both public and private companies. Additionally, Compustat financial data is prioritized based on market capitalization and index constituency, while Capital IQ is able to cover companies that trade on lower exchanges such as the Over the Counter (OTC) markets.[15] S&P does provide sufficient information in its Capital IQ data to perform the analyses discussed in these comments. We recommend using Capital IQ from S&P for the analysis.

28. Appendix C to these comments provides a detailed description of the process used to download and clean the data used in our analysis.[16] We would anticipate that any policy or rule would include detailed instructions for downloading data for use in future updates.

B. Definition of Companies to Include

29. The January 2019 Staff Proposal focuses on developing a "portfolio of comparable companies that arguably all face similar risks inherent to the transportation industry,

[15] Correspondence with S&P Global. For more information, please see: https://www.capitaliq.com/help/sp-capital-iq-help/website-disclosures/quality-program.aspx.

[16] This includes, for instance, a description for how to remove (what we found to be a small number of) duplicate entries.

including solid waste collection companies."[17] In particular, "[t]he selection criteria limits the proxy portfolio to companies that load, transport, and deliver, without changing or converting that which is transported."[18]

30. We agree that developing a portfolio of comparable companies with risks similar to those faced by solid waste collection companies will provide for meaningful analysis for setting rates for solid waste collection companies. Companies are selected by choosing SIC codes rather than assessing inclusion on a company-by-company basis.[19] Any attempt to consider companies individually would invariably lead to subjectivity in the selection process. However, while there can be some "grey areas" in selecting SIC codes, we have found that the alternatives below lead to relatively few "grey areas" in selecting SIC codes for inclusion.[20]

31. We offer two alternative definitions for identifying the relevant sets of comparable companies.

    a. Model 1: SIC codes describing companies primarily engaged in transportation with the use of vehicles. *See* Attachment 1 for a list of companies.

    b. Model 2: SIC codes describing companies primarily engaged in transportation. See Attachment 2 for a list of companies.

    Our definitions are quite similar to the definition offered in the January 2019 Staff Proposal, except without the limitations that companies must "load, transport, and deliver" and "without changing or converting that which is transported."[21] Attachment 3 compares the SIC codes available from Capital IQ selected for Model 1 (transportation using vehicles), Model 2 (transportation companies), and for those proposed by staff (taking into account the SIC codes excluded under the January 2019 Staff Proposal, discussed below).

[17] January 2019 Staff Proposal, p. 10.

[18] January 2019 Staff Proposal, p. 10.

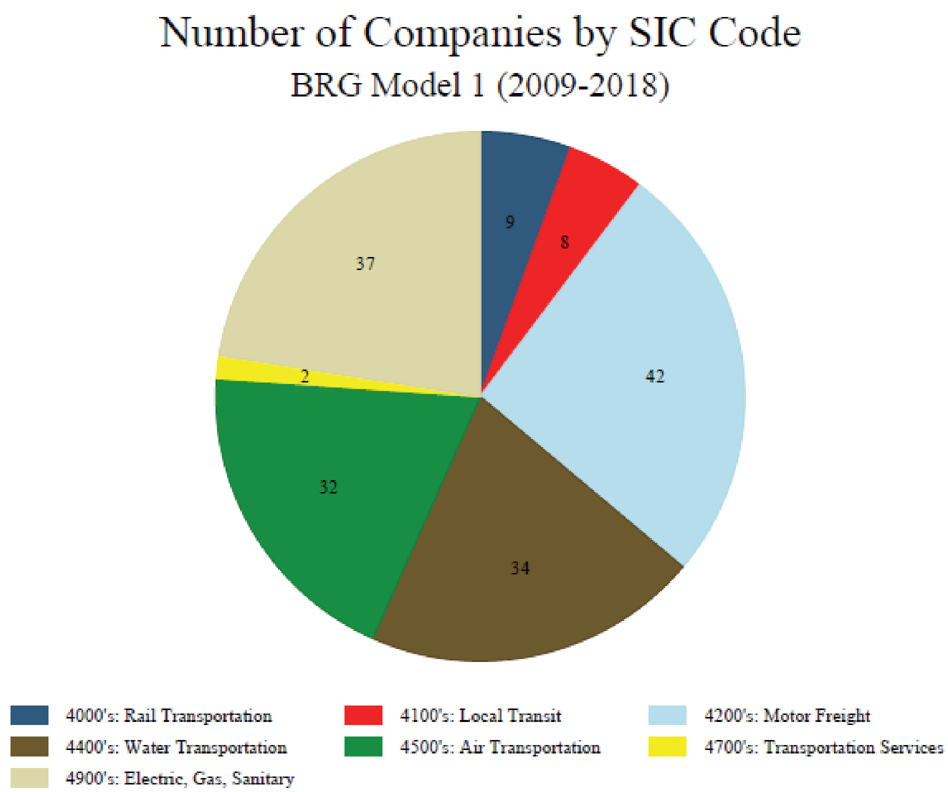
[19] The Standard Industrial Classification (SIC) is a system that classifies industries by a four digit code. The first two digits of the code identify the major industry group, while the third digit identifies the industry group and the fourth identifies the industry.

[20] Note that we use SIC codes for this definition, however, the same process can be used for NAICS codes (or some alternative grouping of companies). We focus on SIC codes because the Capital IQ data includes SIC codes by company, but does not provide information on NAICS codes.

[21] Solid waste collection companies actually convert what is delivered by compacting waste, so we found this limitation not particularly meaningful. In addition, an economic conversion of a product can occur just by moving the product. That is, food delivered to my doorstep is "different" than food at the store simply because it is at my doorstep, though it is not physically converted.

32. The differences in the companies included in Model 1 and Model 2, based on 2-digit SIC codes, are shown in Figures 3.1 and 3.2 below, respectively.

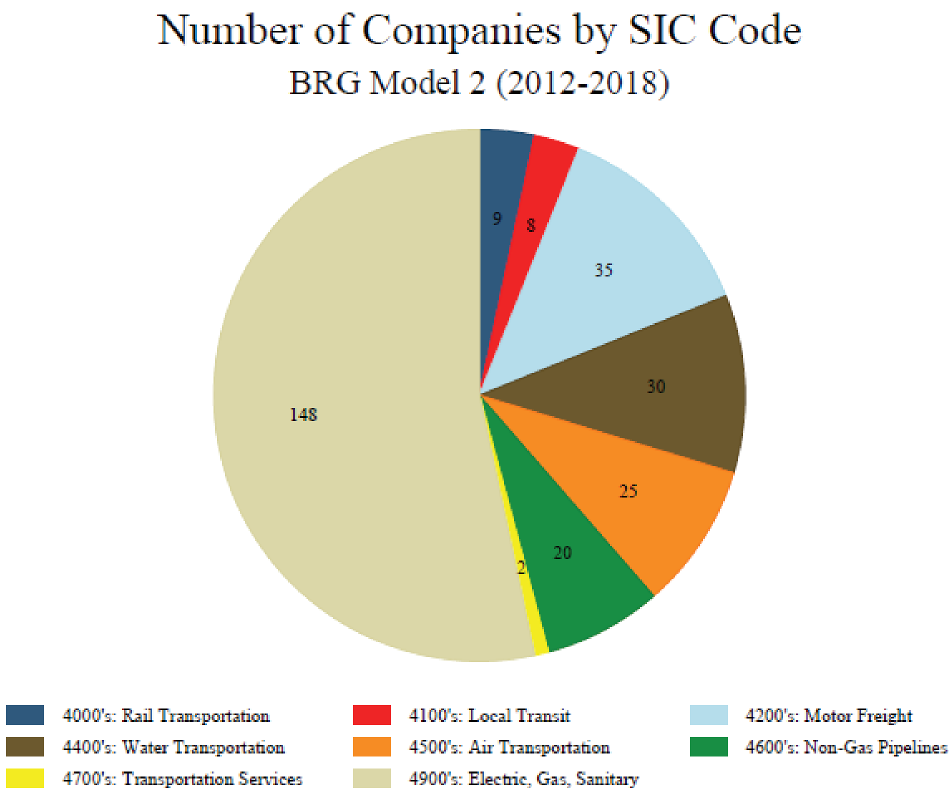
FIGURE 3.1



Note: Companies tallied prior to any outlier filtering.

Source: Capital IQ financial data.

FIGURE 3.2

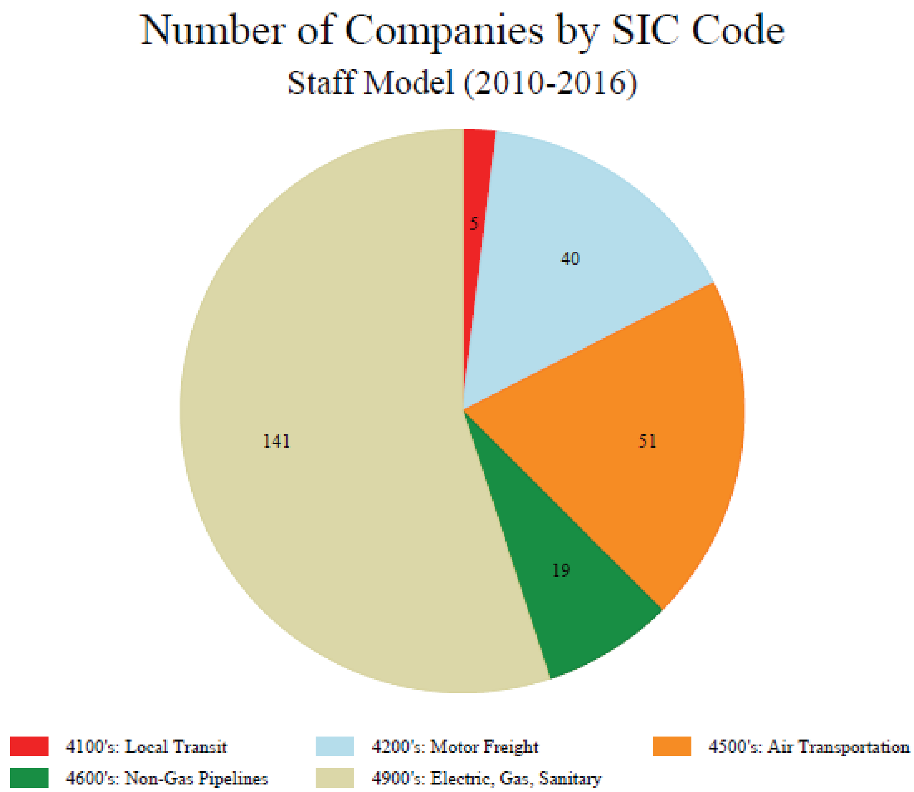


Note: Companies tallied prior to any outlier filtering.

Source: Capital IQ financial data.

33. The primary differences between the companies in Model 1 and Model 2 is that Model 2 includes pipeline and natural gas companies. Figure 3.3 below shows the breakdown of the companies in the SICs included in the January 2019 Staff Proposal.

FIGURE 3.3



Note: Companies tallied prior to any outlier filtering.

Source: Capital IQ financial data.

34. Staff's proposal does not include companies involved in transportation by water or rail, but does include natural gas and pipeline companies and water treatment companies.

35. Model 1 includes all SIC codes involving transportation by vehicle (primarily, transportation by land, air, water, and rail, and waste companies), but not natural gas, pipeline, or water treatment companies. Model 2 includes all companies from Model 1, but also includes pipeline and natural gas companies.

36. In our view, Model 1 provides for a set of companies that approximates the economics and risks inherent to the solid waste collection industry. However, Model 2 also resides within the scope of best practices and represents a viable alternative for conducting the regression analysis. The advantage of Model 2 is that a greater number of observations are available for any particular timeframe (allowing the use of seven years of data instead of ten), and that the slope of the relationships observed using Model 2 are closer to slope of the relationships found in the LG an also the Staff Proposed Regression.

IV. DATA FILTERS

A. Removal of Data and Staff-Proposed Chow Tests

37. The January 2019 Staff Proposal states that, "[t]o safeguard the integrity of the data, groups with incomplete data or obviously incorrect data were removed during initial review…"[22] However, the January 2019 Staff Proposal does not specifically identify the groups removed or those that have "obviously incorrect data." There is no indication what criteria were used to determine that something was incomplete or incorrect.

38. In our view, additional steps for removing companies – or entire SIC codes - completed "during initial review" add an element of subjectivity into what is meant to be an objective process. Additional steps are unnecessary if the rules for SIC code inclusion discussed in the prior section are based on sound economic reasoning. Rather, we propose that any "obviously incorrect data" would be removed during the outlier removal process, discussed below.

39. In addition, the January 2019 Staff Proposal states that, "[e]ach grouping was also tested statistically using the Chow test to confirm its fitness as a subset in the representative sample."[23] A Chow test is an "F-test" which assesses statistically whether there has been a structural break in the data. That is, are there statistically significant differences in the parameters across the two subsets of the data when compared.[24]

40. Here, we cannot know what datasets to test against each other. The January 2019 Staff Proposal appears to test companies for each SIC code against companies from every other SIC code grouped together. However, when conducting the experiment this way, if anything is removed subsequently, then all other tests conducted were performed against a comparison group that included a removed subset of data.

41. An example is instructive. Assume there are 4 SIC codes named A, B, C, and D. The Chow test method performed in the January 2019 Staff Proposal would test A against the combination of B, C, and D; test B against the combination of A, C, and D; test C against the combination of A, B, and D; and test D against the combination A, B, and C. Assume that the first test showed that A was statistically different compared with B, C, and D. Now all of the other tests are not particularly meaningful, because they each assume A is a valid set of data to be compared against. This suggests an iterative process.

42. However, removing A from each of the other tests might demonstrate additional differences (perhaps now B is different from C and D). Moreover, if additional sets of data

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[22] January 2019 Staff Proposal, pp. 10-11.

[23] January 2019 Staff Proposal, p. 11. We understand that the initial Chow tests conducted prior to the January 2019 Staff Proposal are no longer available. We were provided subsequent analysis by staff performed in support of the January 2019 Proposal consisting of Chow tests for each of the 16 SIC codes (and groupings). Those results indicate that 8 SIC codes were statistically different from the remainder (p-value 1%). However, it appears that only 1 SIC was eliminated from the subsequent regression analysis in the proposed Staff DuPont Model.

[24] Wooldridge, Jeffrey M., <u>Introductory Econometrics: A Modern Approach</u>, Nelson Education, 2016, pp. 223, 406.

are removed, data subset A may no longer be statistically different from the remaining group of SIC codes, if retested. In short, we don't know what to test against what, leading to a circular process that is not guaranteed to result in a unique or stable outcome.

43. There are additional issues. The results depend on the definition of the codes considered in the analysis. Some SIC codes for companies are at the 2-digit level, some at the 3-digit level, and some are at the 4-digit level, depending on what information is recorded by S&P. In fact, the Capital IQ dataset has a more granular set of SIC codes for companies than does Compustat. This suggests an entirely different set of information included in an analysis based on Chow tests that would be driven mostly by the granularity of the data available from the data provider.

44. Overall, the use of a Chow test here does not make sense conceptually. We would expect different SIC codes to have some differences between them. In fact, we *want* to include those differences so long as they are capturing different elements of the economic circumstances faced by solid waste collection companies – such that rejecting a group of SIC codes might be eliminating a certain type of risk that is partially applicable to waste collection.

45. This is not to say that we want to keep all data points in all circumstances. Any data points that are sufficiently distinct as to potentially impact the relationships estimated in the regression analysis can be identified through the detection of outliers, discussed in the following section.

B. Outlier Methodology – Mahalanobis Method

46. The January 2019 Staff Proposal states that it removes "companies that constituted extreme outliers."[25] The workpapers subsequently provided show that these "extreme outliers" constitute any companies with an ATO of greater than 400 and/or a PM of greater than 100. Companies with a negative ATO or negative PM are also removed in the January 2019 Staff Proposal (as these observations cannot be transformed to log form).

47. Extreme data, atypical observations in the model calibrating data, can have a profound influence on the regression model describing the relationship between the variables under consideration. However, simply because a given data point appears extreme, that does not mean that it is actually extreme in terms of the statistical relationship between the variables involved. Accordingly, it is important to distinguish those data which are atypical of the data distribution in a rigorous statistical manner.[26]

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[25] January 2019 Staff Proposal, p. 11.

[26] Note that this is not to say that data should not be visually inspected, as visual inspection can provide important information to a researcher about data characteristics. However, a best practices approach for outlier determination is not to select outlier based on visual inspection, which can lead to error, especially when well-established statistical methods are available that are not subjective in nature.

48. In a multivariate setting, one in which there are multiple variables under consideration, each observation is made up of one value for each variable. For example, a single observation for a company has an ATO value, a D/E value, and a PM value. In determining whether an observation is an outlier, a best-practices approach considers not only the values of each individual variable, but also the joint relationship between the variables:[27]

> Multivariate outliers can occur in ... subtle ways. For instance, … a case may be an outlier because the subject is somewhat deviant on several of the variables, although not markedly deviant on any of them…[A] subject may be a multivariate outlier because he(she) is very deviant on one of the variables, or on a few of the variables.

49. Consideration of this joint relationship in determining outliers is accomplished through the use of a statistical method based on the calculation of the *Mahalanobis distance* for each observation in the data:[28]

> The *Mahalanobis* distance is a well-known criterion which depends on estimated parameters of the multivariate distribution…observations with a large *Mahalanobis* distance are indicated as outliers.

The Mahalanobis distance-based approach is straightforward to implement, yet is quite powerful at incorporating complex relationships between variables under consideration:[29]

> Although the Mahalanobis method seems simplistic at first sight, it is easy to overlook the fact that the Mahalanobis method accounts for the inter-attribute dependences in a graceful way, which become particularly important in high-dimensional data sets. This simple approach turns out to have several surprising advantages over more complex distance-based methods in terms of accuracy, computational complexity, and parameterization[.]

50. This approach contrasts with any approach that strictly sets thresholds on possible values any single variable can take. As noted, considering variables one at a time fails to incorporate the complex relationships that can occur between variables into the outlier analysis. Taking those relationships into account can have the effect of identifying

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[27] Stevens, James, Applied Multivariate Statistics for the Social Sciences, Lawrence Erlbaum Associates, Publishers, 1986, p. 14.

[28] Ben-Gal, Irad, "Outlier Detection," in Maimon O. and Rockach L., Data Mining and Knowledge Discovery Handbook: A Complete Guide for Practitioners and Researchers, Kluwer Academic Publishers, 2005, § 4.1.

[29] Aggarwal, Charu C., Outlier Analysis, Second Edition, Springer, 2017, p. 53. The formula for calculating Mahalanobis distances for each observation can be expressed as $MD_i^2 = (x_i - \bar{x})'S^{-1}(x_i - \bar{x})$, where MD_i^2 is the Mahalanobis distance for observation i, x_i is the vector of variable values for observation i, $\bar{x}$ is the vector of variable mean values for the observations, and S is the covariance matrix of the variables. Frequently, the Mahalanobis distance is also referred to by name and written in its root form as: $MD_i = \sqrt{(x_i - \bar{x})'S^{-1}(x_i - \bar{x})}$.

observations as outliers when they might not initially appear to be, and conversely considering a data point as typical of the data distribution despite a large value for a single variable:[30]

> In classical statistics, a univariate outlier is an observation that is far from the sample mean. (Modern statistics use robust statistics to determine outliers; the mean is not a robust statistic.) You might assume that an observation that is extreme in every coordinate is also a multivariate outliers, and that is often true. However, the converse is not true: when variables are correlated, you can have a multivariate outlier that is not extreme in any coordinate!

51. Observations with a large Mahalanobis distance can be identified as outliers and are eliminated from the data.[31,32] Figure 4.1 below demonstrates the concept of the Mahalanobis distance in a bivariate setting.

[30] Wicklin, Rick. "The geometry of multivariate versus univariate outliers." https://blogs.sas.com/content/iml/2019/03/25/geometry-multivariate-univariate-outliers.html

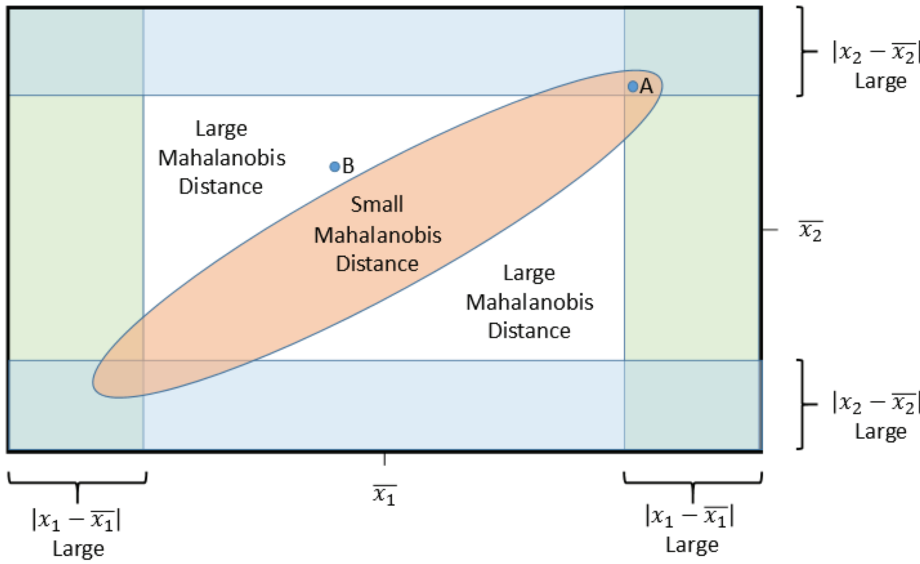
[31] The method for identifying outliers makes use of distributional properties of the Mahalanobis distance statistic. With a large number of observations, the Mahalanobis distance statistic approximately follows a χ^2 distribution with p degrees of freedom where p is the number of variables considered (*see* Stevens, James, Applied Multivariate Statistics for the Social Sciences, Lawrence Erlbaum Associates, Publishers, 1986, p. 14) which is indeed a skewed distribution.

In the Technical Workshop on October 8th, 2019, we discussed using a two-stage process for the identification of outliers: 1) calculate a Mahalanobis distance for each observation, then 2) apply the Hubert-Vandervieren approach to identify outliers in the resulting skewed distribution of distances. The Hubert-Vandervieren approach accounts for skewness in distributions, and was developed to account for generalized skewness when the distribution itself was unknown. However, the Mahalanobis distance is of a known skewness (χ^2 distribution), so the Hubert-Vandervieren approach with the Mahalanobis distance, while not "wrong", adds an unnecessary step.

Given that ATO, D/E, and PM are log transformed in the regression model, any observation which contains a negative value for any of these three variables is also excluded from the data.

[32] A Mahalanobis distance for an observation is considered large enough to be identified as an outlier if it is above the 95th percentile value (less than a 5% probability of occurring by chance alone) of a χ^2 distribution with p degrees of freedom where p is the number of variables considered. In the present scenario, ATO, D/E, and PM are being considered, so $p = 3$. Stricter cutoffs requiring the probability of a Mahalanobis distance occurring by chance alone to be lower, for example a 1% or a 0.1% probability of occurring, would result in a larger Mahalanobis distance cut-off value and fewer observations being identified as outliers.

FIGURE 4.1



Taking into consideration the relationship between the two variables identifies a circular or oval shaped region of pairs of variable values which would not be considered outliers. In our regression model recommendations, we use three variables, ATO, D/E, and PM.[33] In the context of three variables (rather than two variables as contemplated above in Figure 4.1), the typical data distribution region would be three-dimensional – in an egg-like shape, or ovoid – rather than a two-dimensional oval.

52. This data driven approach is also not fixed; it is flexible to adapt as the underlying company data changes in future years. With each data update, though the method to determine the Mahalanobis distance values for each observation and the method for determining which observations are outliers will stay that same, the threshold (the boundary of the ovoid or shell of the egg) will naturally adapt to correspond with the calibrating data. This is a distinct flexibility and robustness advantage over any method which sets any fixed single or set of thresholds to determine observation outliers.

V. CAPITAL STRUCTURE

A. Capital Structure in the Staff's DuPont Model

53. The January 2019 Staff Proposal seeks to update the manner in which capital structure is handled compared with the LG model. The LG model, in essence, based on a regression model which predicts PM based on ATO of a company, finds a calculated ROE. This calculated ROE is invariant to the actual capital structure of the company of the solid waste collection company itself, though the PM changes based on the capital structure of the

[33] Note that the addition of D/E to the regression model is discussed in detail below.

company.[34] The January 2019 Staff Proposal's DuPont model instead estimates the PM of a firm (from a regression of PM on ATO). By doing so, the calculated ROE does change when the capital structure of a firm changes.[35]

54. The Staff Proposal describes that the basis for this structure of the DuPont Model is the Modigliani and Miller Theorem. The Staff Proposal elaborates on this theorem:[36]

> The commonly-called Modigliani and Miller Theorem holds that the weighted average cost of capital does not change as capital structure changes. The pair showed the value of a company is in its operations, not in the method used to finance those operations. For example, Modigliani and Miller showed that as debt increased, equity shareholders perceive higher risk and expect a higher return, thereby increasing the cost of equity. But, because the equity component would make up a smaller portion of the total capital structure due to the higher debt load, the weighted cost of equity may actually decrease. Therefore, in spite of increased costs for both debt and equity, the overall average weighted cost of capital would remain close to the pre-leverage structure.
>
> In addition, the DuPont Formula Model assumes the proxy companies will, as a group, reflect the optimal cost of capital. The model assumes the specific capital structures financial the operations of the proxy companies are not relevant to the computation of revenue requirement because the average weighted cost of capital reflected in the data should be optimal and consistent with the Modigliani and Miller theorem. Simply put, the weighed cost of capital is not materially affected by capital structure.

55. The January 2019 Staff Proposal relies entirely on the Modigliani-Miller Theorem for its treatment of (and decision to not adjust for) capital structure in the DuPont model.

B. Assumptions and Empirical Assessment of the Modigliani-Miller Theorem

56. Economic theories are meant to be tested, both in terms of the underlying assumptions and with empirical testing. Jean Tirole, also a Nobel-prizing winning economist for his work in industrial organization, describes the Modigliani-Miller Theorem in his book The Theory of Corporate Finance:[37]

> As a matter of fact, economists were stunned when, in two articles in 1958 and 1961, Modigliani and Miller came up with the following rather striking and somewhat counterintuitive result. Under some conditions, the total

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[34] *See*, January 2019 Staff Proposal, p. 15, Chart 2.

[35] *See*, January 2019 Staff Proposal, p. 17, Chart 4.

[36] January 2019 Staff Proposal, p. 12.

[37] Tirole, Jean, The Theory of Corporate Finance, Princeton University Press, 2006, pp. 77-78.

> value of the firm – that is, the value of all claims over the firm's incomes – is independent of the financial structure. That is, the level of debt, the split of debt into claims with different levels of collateral and different seniorities in the case of bankruptcy, dividend distributions, and many other characteristics or policies relative to the financial structure have no impacts on total value. In other words, decisions concerning the financial structure affect only how the "corporate pie" (the statistical distribution of income that the firm generates) is shared, but has not effect on the total size of the pie. Thus, an increase in debt or a dividend distribution dilutes the debt-holders' claim and benefits the shareholders, but the latter's gain exactly offsets the former's loss.

57. However, Tirole also underscores the disconnect between the real world and what is predicted by the Modigliani-Miller Theorem, and the research by economists into the factors that may influence these disconnects:[38]

> It is only recently that economists have started developing a better understanding of the role of the financial structure. And, although the theory of corporate finance is still evolving, it is fair to say that considerable progress has been made. To examine whether the business community's close attention to the financial structure is warranted, economists have questioned the idea that the size of the pie is exogenously determined. At an abstract level, one can analyze the matter in the following terms. *Whenever managerial decisions cannot be perfectly specified contractually*, the incentives given to those who pick those decisions affect the firm's income (the size of the pie) and therefore *the split of the pie matters*.

58. Tirole spends the next 24 pages or so of his book discussing details of debt and equity financing, addressing issues such as tax considerations ("debt usually enjoys tax advantages relative to equity"[39]), clientele effects ("financial intermediaries…have for regulatory reasons higher demands for certain classes of claims"[40]), and the enforcement of financial contracts ("[b]ankruptcy laws can therefore have an impact on the financial structure of firms."[41]). Thus, there are numerous avenues of research which question the underling propositions of the Modigliani-Miller Theorem and its implications.

59. Merton H. Miller (the "Miller" in the Modigliani-Miller Theorem) has acknowledged the difficulty that has been encountered in empirically demonstrating the operation of the Modigliani-Miller Theorem. In an article addressing the theorem 30 years after its introduction, Dr. Miller described that:

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[38] Tirole, Jean, The Theory of Corporate Finance, Princeton University Press, 2006, pp. 78-79. (emphasis added)

[39] Tirole, Jean, The Theory of Corporate Finance, Princeton University Press, 2006, p. 79.

[40] Tirole, Jean, The Theory of Corporate Finance, Princeton University Press, 2006, p. 79.

[41] Tirole, Jean, The Theory of Corporate Finance, Princeton University Press, 2006, pp. 80.

> Our Proposition I, holding the value of a firm to be independent of its capital structure (that is, its debt/equity ratio) is accepted as an implication of equilibrium in perfect capital markets. The validity of our then-novel arbitrage proof of that proposition is also no longer disputed, and essentially similar arbitrage proofs are not common throughout finance…[42]
>
> …[I]t may be worth emphasizing at this point…that our proposition that value was independent of capital structure at the individual firm level was never intended to suggest that the debt/equity ratio was *indeterminate*. At the firm level, there were clearly other costs of the various financial alternatives to be taken into account…[43]
>
> Indeed, we devoted more than a third of the original paper…to empirical estimates of how closely real world markets values approached those predicted by our model. Our hopes of settling the empirical issues by that route, however, have largely been disappointed. Direct statistical calibration of the goodness of fit of the MM value-invariance propositions has not so far been achieved by us or others for a variety of reasons…[44]

60. Levati et al (2012) provide an overview of the sorts of empirical studies described by Miller (and more) that do not find support for the Modigliani-Miller Theorem:[45]

> The opposition to the MM theorem comes from many angles. Weston (1963) tests the theorem using the same sample of electricity utility industries as used by Modigliani and Miller (1958), but for the year 1959 rather than for the years 1947 and 1948. His multiple regression analysis indicates that leverage does have an influence on a firm's cost of capital when earnings growth is taken into account. Robichek et al. (1967) extend the analysis of Miller and Modigliani (1966) to the years 1955 and 1958–1964. They conclude that MM's results are a consequence of circumstances prevailing at the time of their study. Davenport (1971) uses data on three industry groups (chemicals, food, and metal manufacturing), and his results are indicative of a U-shaped cost of capital with respect to leverage. Other empirical studies suggesting that a firm's value changes significantly in response to changes in the capital structure include Masulis (1980), Dann (1981), Masulis and Korwar (1986), Pinegar and Lease (1986), Graham and Harvey (2001), and Arzac and Glosten (2005). These studies and, generally,

[42] Miller, Merton H. (1988), "The Modigliani-Miller Propositions After Thirty Years," Journal of Economic Perspectives, 2(4): 99-120, at p. 99.

[43] Miller, Merton H. (1988), "The Modigliani-Miller Propositions After Thirty Years," Journal of Economic Perspectives, 2(4): 99-120, at p. 102. (emphasis in original)

[44] Miller, Merton H. (1988), "The Modigliani-Miller Propositions After Thirty Years," Journal of Economic Perspectives, 2(4): 99-120, at p. 103.

[45] Levati et al (2012), "Testing the Modigliani-Miller theorem directly in the lab," Experimental Economics, 15(4), pp. 693-716, p. 694.

most of the works rejecting the propositions of the MM theorem rely on some kind of market imperfections.

61. The difficulties in demonstrating that the theory operates in the real-world stem from the rather strict assumptions adopted in the theory – in particular, the assumption of perfect capital markets and the ability to arbitrage (that is, the absence of market imperfections described by Levati et al (2012) above). Charness and Neugegauer (2019) describe the restrictiveness of these assumptions in the Modigliani-Miller Theorem:[46]

> The core of the theorem is an arbitrage proof, whereby if two assets, one leveraged and one unleveraged, represent claims on the same cash flow, any market discrepancies that arise are arbitraged away. But due to its assumptions of perfect capital markets and the no-limits-to-arbitrage condition (which requires the perfect positive correlation of asset returns, no fees on the use of leverage, etc.), the MM theorem has not been satisfactorily tested on real-world market data. Its empirical significance has thus been unclear.
>
> [fn1] The assumption of perfect capital markets requires, among other things, that no taxes and transaction fees be levied and that the same interest rate applies to everyone. Lamont and Thaler (2003) present several real-world examples where the law of one price is violated. They argue that these violations result from limits to arbitrage. An early objection concerned the applicability of value-invariance in relation to the variation of payout policy. Modigliani and Miller (1959) replied to this objection by stating that a firm's dividend policy is irrelevant for the value of the company. However, it is now widely accepted that dividends impact empirical valuations (for a recent discussion of the dividend puzzle, see DeAngelo and DeAngelo (2006)). With the dividend irrelevance theorem thus empirically rejected, it is considered as of theoretical interest only. The value-invariance theorem and its proof, however, have remained widely accepted in the profession even without empirical evidence to support it.

62. In sum, the Modigliani-Miller Theorem has not performed well under empirical testing over the last 60 years. So, while certain elements of the theorem have theoretical appeal, the real-world operates quite differently than what is assumed in the proposed DuPont model. In our view, the empirical shortcomings of the Modigliani-Miller Theorem mean that the assumptions underlying the proposed DuPont model also include those shortcomings. As such, we assume that the Modigliani-Miller Theorem strictly applied is not a best-practices approach for determining rates here. We present an alternative below

[46] Charness, Gary and Tibor Neubegauer (2019), "A Test of the Modigliani-Miller Invariance Theorem and Arbitrage in Experimental Asset Markets," The Journal of Finance, 74(1): 493-529, at pp. 493-494. Charness and Neubegauer (2019) experiment provides some support for the Modigliani-Miller Theorem in a laboratory setting, based on study of the behavior of 174 students at the University of California, Santa Barbara, where arbitrage opportunities were permitted.

that allows for the theoretical proposition described in the Modigliani-Miller Theorem, but also allows for real-world divergences from the strict assumptions of the theory.

C. Alternative Proposal for Capital Structure in the DuPont Model

63. As described above, given the lack of empirical evidence for the strict application of the Modigliani-Miller Theorem in the real world, the inclusion of this theorem in the rate-setting process here would be to rest on a proposition without widespread empirical support.

64. There is a better alternative. Instead, we propose that capital structure of transportation firms be included in the regression model itself. This approach allows for the experiences of the transportation industry itself to dictate to what extent the Modigliani-Miller Theorem applies in the real world. We submit that this approach is superior to imposing a relationship between capital structure and returns that does not exist in reality.

65. Another advantage of this approach is that it brings the proposal closer to the original concept of the DuPont formula approach. The DuPont formula essentially has 3 elements: profit margin (PM), asset turnover (ATO), and the capital structure (D/E). The January 2019 Staff Proposal analyzes two of these (profit margin and asset turnover), but ignores the third (capital structure). Incorporating capital structure into the regression model itself once again would capture all elements of the DuPont formula, but in an empirical manner (as opposed to any rigid tautological relationship).

66. Table 5.1 below shows empirical results from potential ways of modeling capital structure (D/E) using the firms for Models 1 and 2. Specification (1) shows regression results for Model 1 without any allowance for capital structure, but with the natural log of ATO. Specification (2) shows results when the natural log of D/E is included for Model 1. Specification (3) shows the regression results for Model 2 without any allowance for capital structure. Specification (4) shows the regression results when the natural log of D/E is included for Model 2.

TABLE 5.1
Regression Specifications Incorporating Debt/Equity[47]

	Model 1		Model 2	
Specification:	1	2	3	4
(Intercept)	3.723***	4.149***	4.858***	5.385***
	[0.124]	[0.203]	[0.082]	[0.135]
Ln(ATO)	-0.302***	-0.303***	-0.503***	-0.482***
	[0.023]	[0.023]	[0.018]	[0.018]
Ln(Debt/Equity Ratio)		-0.077**		-0.121***
		[0.033]		[0.023]
N	801	741	1,241	1,184
R2	0.174	0.196	0.382	0.395
Adjusted R2	0.173	0.193	0.381	0.394
AIC	1,999.649	1,776.430	2,847.708	2,580.379

Standard errors are reported in brackets. *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

67. Table 5.1 demonstrates that capital structure is empirically related to the PM for firms in the transportation industry in a non-linear manner. That is, each of the non-linear coefficients for D/E are statistically significant. In our view, the second and fourth specifications in Table 5.1 are most appropriate for use in estimating profit margins here.

68. Figures 5.2 and 5.3, below, show the PM and calculated ROE for a hypothetical firm (with ATO of 142.86) with varying levels of debt. As these figures demonstrate, the empirical relationship we estimate is consistent with the Modigliani-Miller Theorem directionally, in that as D/E increases, the ROE also increases – though not to the full extent predicted by the Modigliani-Miller Theorem. We view our proposal as both allowing for the theoretical proposition of the Modigliani-Miller Theorem, while also recognizing the empirical realities regarding capital structure and value.[48]

[47] R-squared measures the proportion of the total sample variation in the dependent variable that is explained by the independent variable(s). The adjusted r-squared adjusts the r-squared by taking into account the number of independent variables used in the model. The Akaike Information Criterion (AIC) is an estimator of statistical model quality where a lower AIC value is generally considered to demonstrate better "fit" for a model.

[48] The non-linear relationship between D/E and PM is captured through use of natural log (for both variables). Given this non-linear relationship, as the D/E gets closer to a value of 0, the predicted PMs increase proportionately with a proportionate reduction in D/E. Therefore, we have incorporated an adjustment such that the D/E is not permitted to fall below a value of 9, which would indicate 10 percent debt.

FIGURE 5.2
Profit Margin and ROE Predicted for Different Debt Percentages, Model 1

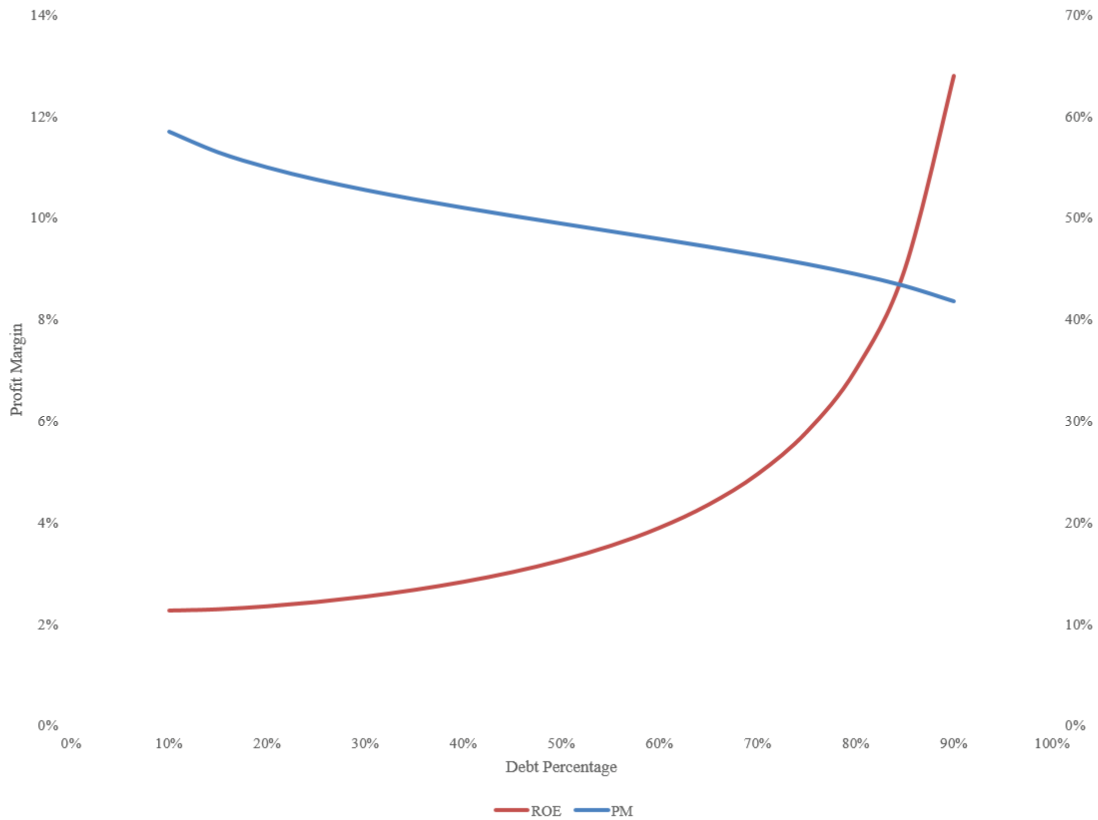
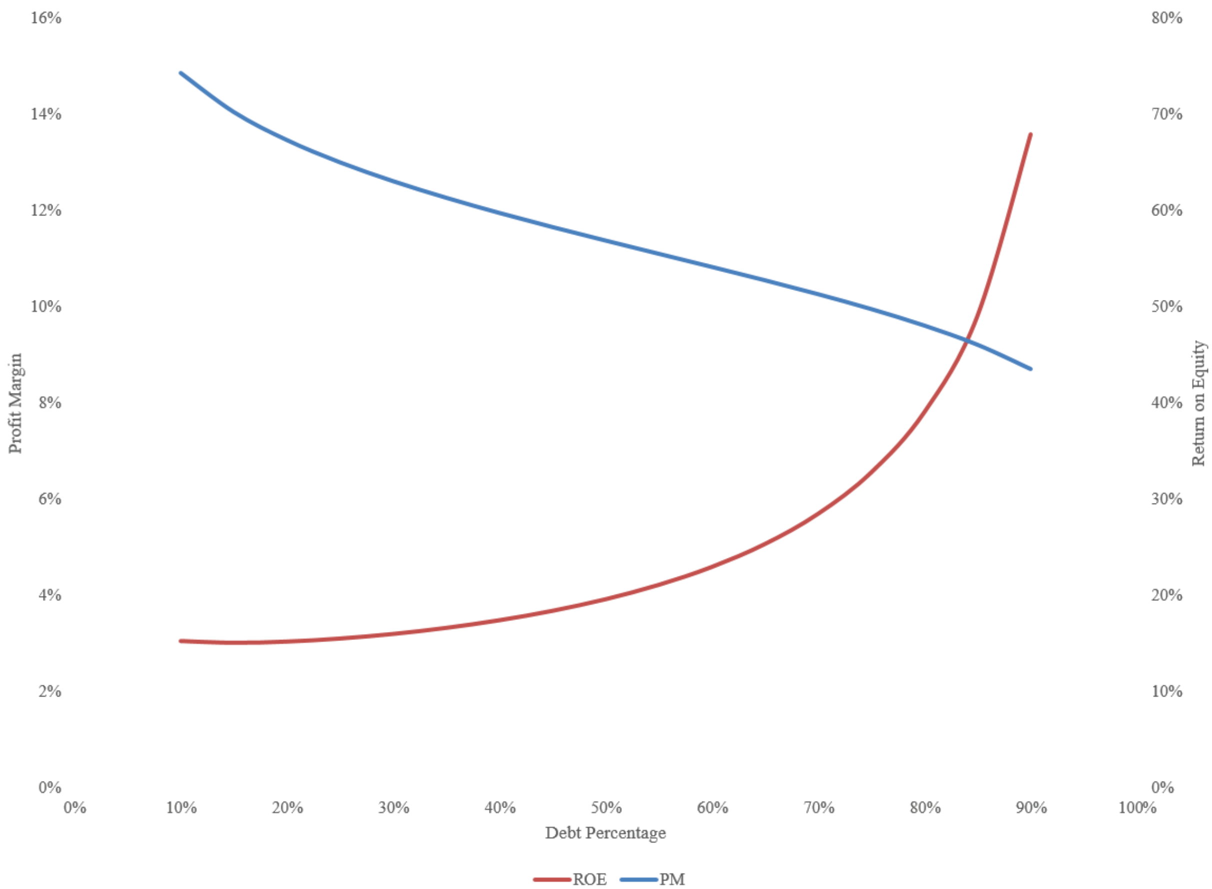


FIGURE 5.3
Profit Margin and ROE Predicted for Different Debt Percentages, Model 2



VI. REGRESSION ANALYSIS

A. Regression Model Specification

69. Based on our discussions above, we propose using the following regression model for estimating PM for given values of ATO and D/E for a solid waste collection company:[49]

$$\ln PM = \alpha + \beta_1(\ln ATO) + \beta_2\left(ln\frac{D}{E}\right) + \varepsilon\ ,$$

where, *PM* is profit margin defined as *100*EBIT*/(*Net Revenue*), *ATO* is defined as *100**(*Net Revenue*)/(*Average PPE*), and *D/E* is defined at *100**(*Total Debt*)/(*Total Equity*).[50] This model is to be used in conjunction with the datasets described in Section

[49] Note that this regression estimates statistical correlations and is not intended to represent a causal model.

[50] Each of these variables is multiplied by 100 prior to running the regression. This is consistent with the proposed Staff DuPont Model and the original LG regression.

III.A., above. The coefficient β_1 indicates the empirical relationship between ln(PM) and ln(ATO), all else equal. The coefficient β_2 indicates the empirical relationship between ln(D/E) and ln(ATO), all else equal.

70. The January 2019 Staff Proposal estimates its regression model using log10 as opposed to natural log (ln).[51] We recommend using natural log (ln), as this transformation of data is far more typical than the use of log 10. Given that we are seeking to build a model that will be used for years (and perhaps decades) into the future, using a recognized, standard approach for data transformation is more likely in our view to be accepted on a go-forward basis than using a non-conventional approach.

71. We propose using ten years of data for Model 1 and seven years of data for Model 2. The January 2019 Staff Proposal describes a trade-off between rapid updates to the model to reflect current economic conditions (especially with regard to inflation) and instability in results. Since we are proposing two models – Model 1 which is more precise with regard to the types of companies included, and Model 2 which is broader – this highlights another trade-off to consider. Using a longer time period provides more data for estimation of the regression. Since Model 1 is more selective in terms of the companies it includes, it also includes fewer companies, and thus, fewer observations to use in estimating empirical relationships through the regression analysis. Therefore, we propose a longer timeframe for Model 1 (10 years) compared with Model 2 (7 years). The evaluation of different timeframes is presented in our sensitivity analyses below.

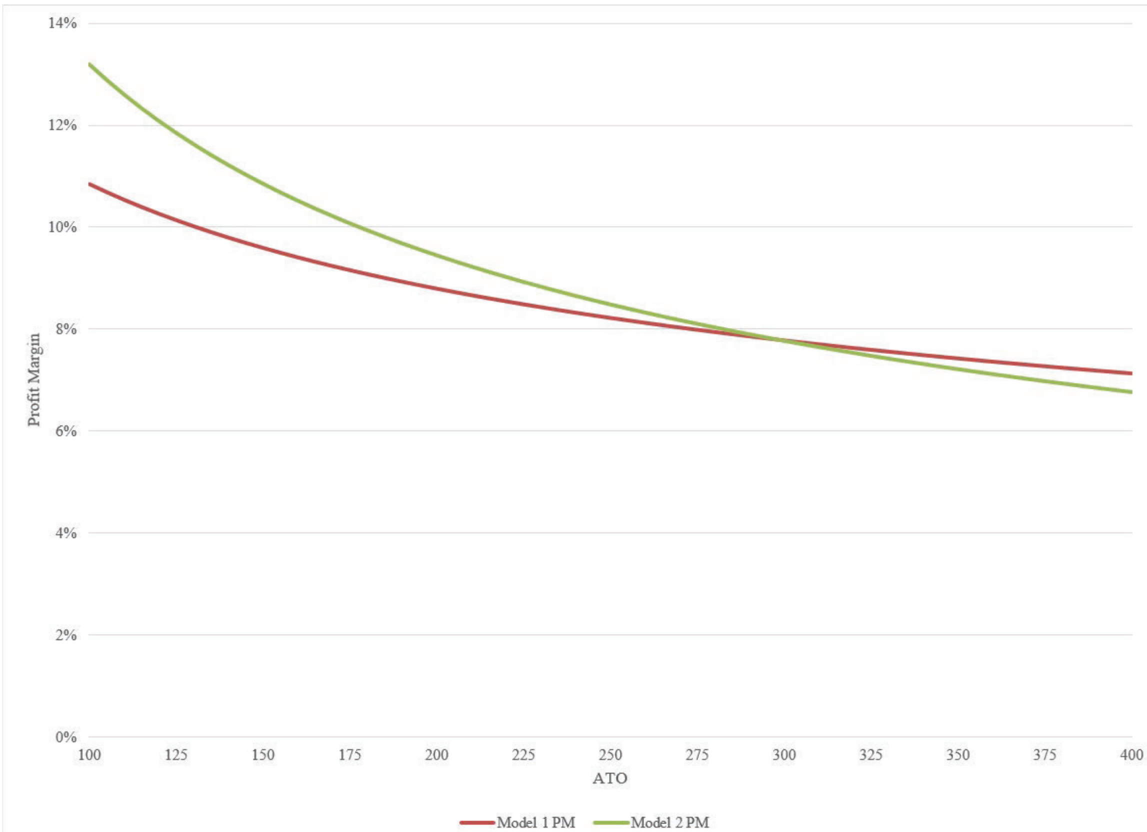
B. Results

72. The results for Model 1 are shown above in Table 5.1 (specification 2); the results for Model 2 are shown above in Table 5.1 (specification 4). Figure 6, below, graphically shows PM for various ATO from 100 to 400 for both models.[52] As a reminder, Model 1 uses the more targeted set of SIC codes for companies that transport with the use of vehicles. Model 1 shows declining PM with greater ATO, though has a "flatter" relationship and is generally lower (for ATOs less than about 300) than Model 2.

[51] In our testing, we have found similar results when using either natural log (ln) or log 10. The January 2019 Staff Proposal indicates that it also found the results similar between the two models.

[52] Assumes debt percentage of 55% and weighted cost of debt of 3.85%.

FIGURE 6
Predicted PM for Model 1, Staff Proposed Model, and LG



C. Sensitivity Testing

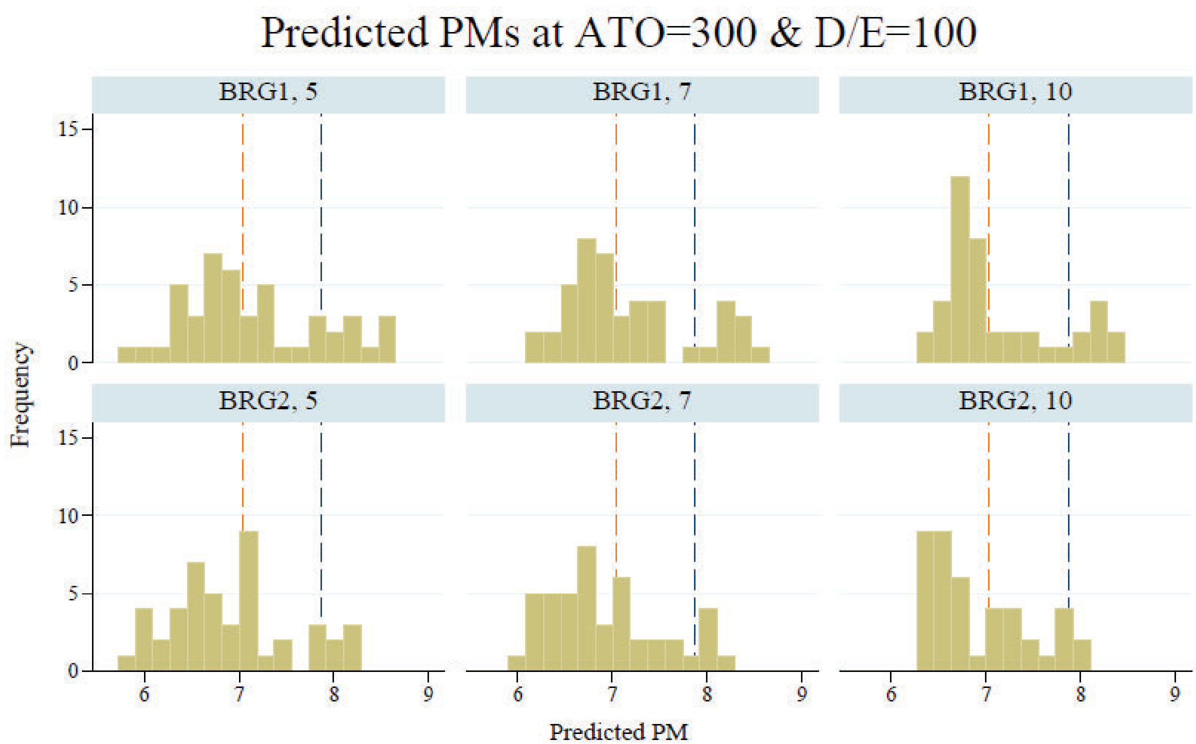
1. Timeframe Used in Regression Analyses (5, 7, or 10 years)

73. As described above, we propose the use of 10 years of data for Model 1 and the use of 7 years of data for Model 2. These proposed timeframes are based the tradeoffs between incorporated information captured recent macroeconomic conditions and having sufficient data for a reliable estimate of the relationships between ATO, D/E, and PM.

74. Here, we use Compustat data (since it is available going back many decades) to evaluate the use of 5, 7, or 10 years. We do this by running Model 1 and Model 2 repeatedly through time beginning in year 1968 all the way through 2018. For example, for Model 1 (including selecting companies in the SIC codes back in 1968) we run Model 1 for the period 1968-1977, but also for every 10-year period to the present (*i.e.*, 1969-1978, 1970-1979, …, 2009-2018). This approach gives us many time-periods over which we can calculate predicted margins (PM) for each model (*e.g.* 42 for the 10-year timeframe).

75. Figure 6.3 shows the predicted PMs for both Model 1 and Model 2 assuming an ATO of 300 and a D/E of 100.[53] The top row of charts shows the frequency distribution of PM for Model 1, using 5 years of data, 7 years of data, and 10 years of data (reading left to right). The lower row of charts shows the frequency distribution of PM for Model 2. The blue dotted lines show the results for Model 1 from the most recent time-frames available (and thus is comparable to our proposal for Model 1). The orange dotted lines show the results for Model 2 from the most recent time-frames available (and thus is comparable to our proposal for Model 2).

FIGURE 6.3
Frequency Distribution of PM for Model 1 and Model 2



Notes:
[1] PMs predicted for models ranging from 1968 through 2018.
[2] Navy dashed vertical bar represents predicted PM using the BRG Model #1 over 2009-2018 at ATO=300 & D/E=100.
[3] Orange dashed vertical bar represents predicted PM using the BRG Model #2 over 2012-2018 at ATO=300 & D/E=100.

Source: Compustat financial data.

76. Figure 6.3 shows that the frequency distribution getting "tighter" (*i.e.*, less spread out) if longer time-frames are used. This makes sense in that as we add more data, we would expect to see less variation in the predictions. We also see that Model 2 is somewhat "tighter" (*i.e.*, less spread out) than Model 1 for the same number of years used. This again makes sense since we have more observations for Model 2. Finally, these numbers show that historically speaking we are towards the top of the distribution (especially for Model 1). However, we have observed that margins have increased for the transportation industry

[53] Both the ATO and D/E are indexed (multiplied by 100) to stay consistent with the methods used in the original LG and the proposed Staff DuPont Model.

in recent years (see, Table 2.4 for instance). So, we do not know if the higher margins predicted today represent a "high-water mark" with reversions to the mean to be expected, or represent a new normal of higher margins compared with what has been historically observed.

2. Outlier

77. Observations are identified as outliers if their calculated Mahalanobis distance exceeds the 95th percentile for a chi-square distribution with three degrees of freedom (5% of the theoretical chi-square distribution exceeds this threshold). Tables 6.1 and 6.2 show that adjusting this threshold to the 90th or 99th percentile has little impact on the results for six company comparables.

TABLE 6.1
Outlier Threshold Sensitivity Testing in Model 1

Company	5% Chi-Squared Trimming			10% Chi-Squared Trimming			1% Chi-Squared Trimming		
	Revenue Increase	Operating Ratio	ROE	Revenue Increase	Operating Ratio	ROE	Revenue Increase	Operating Ratio	ROE
Waste Management	2,271,824	92%	26%	2,271,824	92%	26%	2,267,160	92%	26%
Peninsula Sanitation Services, Inc.	-5,317	91%	19%	-5,317	91%	19%	-4,803	91%	19%
Rabanco	305,447	92%	29%	305,447	92%	29%	306,140	92%	29%
Stanley's Sanitary Service	64,809	90%	14%	64,809	90%	14%	64,767	90%	14%
Yakima Waste Systems, Inc.	431,816	92%	30%	431,816	92%	30%	431,710	92%	30%
Methow Valley Sanitation Service	118,228	92%	20%	118,228	92%	20%	118,295	92%	20%

TABLE 6.2
Outlier Threshold Sensitivity Testing in Model 2

Company	5% Chi-Squared Trimming			10% Chi-Squared Trimming			1% Chi-Squared Trimming		
	Revenue Increase	Operating Ratio	ROE	Revenue Increase	Operating Ratio	ROE	Revenue Increase	Operating Ratio	ROE
Waste Management	2,470,045	91%	27%	2,470,045	91%	27%	2,470,045	91%	27%
Peninsula Sanitation Services, Inc.	18,995	90%	21%	18,995	90%	21%	18,995	90%	21%
Rabanco	308,418	92%	29%	308,418	92%	29%	308,418	92%	29%
Stanley's Sanitary Service	73,357	88%	17%	73,357	88%	17%	73,357	88%	17%
Yakima Waste Systems, Inc.	442,489	92%	30%	442,489	92%	30%	442,489	92%	30%
Methow Valley Sanitation Service	122,552	91%	22%	122,552	91%	22%	122,552	91%	22%

VII. FINAL ISSUES AND CONCLUDING REMARKS

78. Several additional issues were raised in the January 2019 Staff Proposal that are addressed here.

Range of Return

79. First, the January 2019 Staff Proposal introduces a "Range of Return" whereby "[s]taff proposes in its model a range of +/- one standard deviation associated with the regression's y-intercept coefficient…"[54] This range is based on one robust standard error of the intercept in the regression model.[55]

80. A standard error is a measure of the precision of a regression model's estimate, here, for the intercept term. This error provides information about the range in which the true value of the estimated coefficient is likely to reside. For rate-setting purposes, we think there is insufficient justification to use estimates incorporating the variability of a single coefficient from the regression model rather than the "best estimate" provided by the regression. This is, after all, the best estimate. We see insufficient justification for suggesting a range of results rather than use of the best estimate.

81. If the WUTC seeks a range of return, we recommend changing other inputs that feed into to Staff Proposed Spreadsheet such as the allowable expenses, or investments. Our understanding is that differences in allowed rates are likely to be related to these inputs in the rate-setting process.

Frequency of Updates

82. The regression analysis that we conduct is based on annual data. From a modeling perspective, the regression analysis could be updated as frequently as each year. However, we recognize that every regression update can impose costs on both the regulators and the regulated. In our view, these regulation update costs are the appropriate driver of this decision. There are benefits from rapid updates, but also believe most of those benefits would be achieved even with updates that occur every 5 years.

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[54] January 2019 Staff Proposal, p. 17.

[55] January 2019 Staff Proposal, p. 17, footnote 35.

X

Cleve B. Tyler

X

Paul Diver

Appendix A: Cleve B. Tyler CV

Curriculum Vitae

Cleve B. Tyler, Ph.D.

BERKELEY RESEARCH GROUP, LLC
1800 M Street, NW, 2nd Floor | Washington, DC 20036
Direct: 202.480.2727
ctyler@thinkbrg.com

SUMMARY:

Cleve B. Tyler is a managing director at Berkeley Research Group. For more than 20 years, he has applied economic analyses to competition, intellectual property, and damages issues in matters before federal and state courts, administrative law judges, and regulatory commissions, and in merger investigations as a consulting expert. He has developed or analyzed damages models in a range of industries pertaining to various allegations including patent infringement, antitrust, breach of contract, and fraud. Dr. Tyler has testified at deposition and trial in federal court and at arbitration. Dr. Tyler is an adjunct professor of economics in Johns Hopkins University's applied economics program, teaching graduate-level courses in industrial organization and microeconomics for nearly a decade.

Dr. Tyler's antitrust work includes evaluation of market definition and competitive effects using regression analysis and economic modeling. He has evaluated horizontal (e.g., merger as well as price fixing) and vertical (e.g., monopolization and foreclosure) competition issues in many industries, including waste collection and disposal, semiconductors, pharmaceuticals, insurance, avionics, medical devices, video games, automobile components, home appliances, software, cable services, and food and beverages. Dr. Tyler has evaluated the antitrust implications of reverse payment settlements between branded and generic pharmaceutical companies. He also has analyzed competition and regulation in the electric industry, including issues related to electric power sales, derivative trading, entry conditions, and capacity payments.

Dr. Tyler holds a Ph.D. in economics specializing in industrial organization, finance, and the economics of the public sector. He previously taught economics at Clemson University and has published papers on competition issues including in *Antitrust*, *Antitrust Bulletin*, and *The Global Competition Review* and has published a chapter on expert admissibility in the book *Calculating Intellectual Property Damages* yearly since 2010. Dr. Tyler is the managing editor of *BRG Review* and a member of the American Economic Association and American Bar Association.

EDUCATION

Ph.D., Economics	Clemson University
B.A., Economics	University of Virginia

PROFESSIONAL EXPERIENCE:

Berkeley Research Group
Managing Director (January 2018 to present)
Director (December 2014-17)
Principal (December 2010–14)

Johns Hopkins University
Adjunct Professor of Economics, graduate-level classes in microeconomics and industrial organization (2010 to present)

LECG
Senior Managing Economist (2006–10)
Managing Economist (2003–05)
Senior Economist (2001–02)

Economic Analysis LLC
Economist (1998–2000)

Clemson University
Instructor, Microeconomics and Macroeconomics (1996–98)
Teaching Assistant, Microecnomics and Macroeconomics (1995–96)
Research Assistant for Robert E. McCormick and Michael T. Maloney (Fall 1996)

Electric Lite
Economic Consultant and Director of Business Development (1997)

General Accounting Office: Resources, Community, and Economic Development Division
Intern (Summer 1995)

Strategic Analysis Inc.
Analyst (Summer, 1990–93)

TESTIMONY and EXPERT REPORTS:

- *ChanBond, LLC. v. Atlantic Broadband Group, LLC.*, U.S. District Court, Delaware, C.A. No. 1:15-cv-00842-RGA. Provided opinions regarding the number of purchased and/or deployed cable modems, number of monthly subscriptions of high-speed data services, and the relationship between price and speed (Mbps) using regression analyses. (Expert Reports and Deposition Testimony) Related matters with same plaintiff (ChanBond, LLC.), same scope, and the following defendants:
    - *Bright House Networks, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00843-RGA. (Expert Reports and Deposition Testimony)

- *Cable ONE, Inc.*, District Court, Delaware, C.A. No. 1:15-cv-00844-RGA. (Expert Reports and Deposition Testimony)

- *Cablevision Systems Corporation and CSC Holdings, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00845-RGA. (Expert Reports and Deposition Testimony)

- *Cequel Communications Holdings I, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00846-RGA. (Expert Reports and Deposition Testimony)

- *Charter Communications, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00847-RGA. (Expert Reports and Deposition Testimony)

- *Comcast Corporation and Comcast Communications, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00848-RGA. (Expert Reports and Deposition Testimony)

- *Cox Communications, Inc.*, District Court, Delaware, C.A. No. 1:15-cv-00849-RGA. (Expert Reports and Deposition Testimony)

- *Mediacom Communications Corporation*, District Court, Delaware, C.A. No. 1:15-cv-00850-RGA. (Expert Reports and Deposition Testimony)

- *RCN Telecom Services, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00851-RGA. (Expert Reports and Deposition Testimony)

- *Time Warner Cable, Inc.*, District Court, Delaware, C.A. No. 1:15-cv-00852-RGA. (Expert Reports and Deposition Testimony)

- *WaveDivision Holdings, LLC.*, District Court, Delaware, C.A. No. 1:15-cv-00853-RGA. (Expert Reports and Deposition Testimony)

- *WideOpen West Finance*, LLC., District Court, Delaware, C.A. No. 1:15-cv-00854-RGA. (Expert Reports and Deposition Testimony)

- *Signature Pharmaceuticals, LLC. v. Ranbaxy Pharmaceuticals, Inc.*, American Arbitration Association, Case No. 01 16 004 6534. Estimated damages related to alleged breaches of contract and breach of fiduciary duty with regard to sales of liquid metformin and solid metformin pursuant to joint venture agreement. (Expert Report and Arbitration Testimony)

- *MobilizeGreen, Inc. v. The Community Foundation for the National Capital Region, et al.*, Superior Court of the District of Columbia, C.A. No. 14-005764. Evaluated damages related to alleged lost business opportunities for nonprofit organization allegedly due to breach of contract and breach of fiduciary duty, and provided opinions related to reliability of damages estimate. (Expert Reports and Declarations)

- *Waste Management of Louisiana, LLC. v. River Birch, Inc. et al.,* U.S. District Court, Eastern District of Louisiana, Case No. 11-2405. Provided rebuttal testimony regarding damages related to RICO allegations and closure of construction and demolition (C&D) landfill used in the clean-up of debris in the aftermath of Hurricane Katrina. Provided rebuttal testimony regarding damages related to RICO allegations and claimed diverted waste from municipal solid waste (MSW) landfill. (Expert Report, Written Testimony, and Deposition Testimony)

- *Digital Recognition Network, Inc. v. Accurate Adjustments, Inc. et al.*, U.S. District Court, Northern District of Texas, C.A. No. 4:14-CV-00903-A. Opined on relevant antitrust market, monopoly power, competitive effects, and damages issues regarding vertical restraints in sale of Automated License Plate Recognition (ALPR) solutions in case involving trade secret misappropriation. (Expert Report)

- *Apotex, Inc. and Apotex Corp. v. UCB, Inc. and Kremers Urban Pharmaceuticals, Inc.*, U.S. District Court, Southern District of Florida, C.A. No. 12-60706 (DMM). Analyzed and opined on a reasonable royalty for a manufacturing process for pharmaceutical products based on trade secrets. (Expert Report and Deposition Testimony)

- *William Brody v. Village of Port Chester, et al.*, U.S. District Court, Southern District of New York, Case No. 00 CIV 7481 (HB). Estimated damages related to the loss of right to appeal the taking of property pursuant to New York's eminent domain law. (Expert Report, Written Testimony, Deposition Testimony, and Trial Testimony)

SELECTED EXPERT CONSULTING EXPERIENCE:

Intellectual Property and Damages

- Reasonable royalty for patent infringement involving technology related to network architecture and operation of video games

- Reasonable royalty and base for patent infringement involving technogies related to the manufacture and operation of semiconductors

- Reasonable royalty and base for patent infringement involving technology related to digital rights management

- Reasonable royalty and base for patent infringement invovling technology used in medical devices

- Reasonable royalty and base for patent infringement for a technology related to international cell phone roaming

- Economic implications of allowing discontinuance of patents of insolvent firm in the semi-conductor industry

- Lost profits, reasonable royalty, and base associated with patents related to golf ball technology

- Reasonable royalty and base for alleged infringement of patents related to liquid crystal display (LCD) monitors

- Damages for trademark infringement related to online search engine

Antitrust - Competition

- Analysis of damages from alleged anticompetitive exercise of market power in data integration servies related to provision of software applications to automobile dealerships

- Evaluation of class certification and damages issues related to alleged conspiracy by automakers to limit competition in quality of vehicles, and to mislead consumers regarding quality of vehicles

- Evaluation of class certification, merits, and damages issues related to proposed class of au pair alleging antitrust claims and unfair labor practices regarding payment of weekly stipend

- Claims of patent misuse in provision of version control for business intelligence software – market definition, monopolization, and competitive effects

- Claims of patent misuse, exclusive contracts, and tying in markets related to pulse oximetry – market definition, market power, vertical restraints and competitive effects

- Class certification in markets for small container commercial waste collection – market definition and common impact

- Competitive effects from provision of security standard compliance for merchants in the payment card industry – market definition, market power, and competitive effects

- Claims related to contracts between preferred broker and carriers in the provision of professional liability insurance – market definition, market power, competitive effects from vertical restraints, efficiencies, and damages

- Claims related to contracts between steel producers and steel service centers – market definition, market power, and competitive effects from vertical restraints

- Claims related to exclusive contracting in the provision of fitness benefits to

Medicare Advantage plans – market definition, monopoly power, and competitive effects related to vertical restraints

- Claims of monopolization and abuse of a dominant position in the provision of specialized search advertising during investigations by the Federal Trade Commission and EU Commission – use of big data in econometric models to investigate competitive effects, survey design, and remedies

- Reverse payment settlements between branded pharmaceutical companies and potential generics under Hatch-Waxman regulations (multiple engagements) – market definition, market power, competitive effects, and valuation of ancillary deals

- Claims related to contractual provisions related to billboard leases – market definition, market power, raising rivals' costs, and damages

- Vertical restrictions related to sales of fountain beverages by retail outlets – market definition, market power, competitive effects, and damages

- Claims related to single-entity structure of sports league including - evaluation of financial structure of organization

- Claims involving flight control systems and flight management systems for regional and corporate aircraft – Evaluation of damages from alleged tying behavior

Antitrust – Mergers

- Merger of companies involved in the provision of customer relations management software and data used in CRM software – market definition, monopolization, and competitive effects including impacts on innovation

- Merger of companies selling gasoline at wholesale and retail – market definition and potential unilateral and coordinated competitive effects in 14 alleged markets

- Merger in the avionics industry (DOJ investigation) – market definition, horizontal and vertical effects, and evaluation of potential for raising rivals' costs

- Merger in the hazardous waste industry in British Columbia (Canadian Bureau of Competition litigation) – market definition, monopoly power, competitive effects using econometric analyses, and efficiencies

- Merger in the coffee industry (FTC investigation) – market definition (including econometric analysis), market power, vertical competitive effects, and efficiencies

- Consummated merger and monopolization in the battery separator industry (FTC investigation and litigation) – market definition, competitive effects, efficiencies, and remedies

- Merger in the waste collection and disposal industries (DOJ investigation) – market definition, competitive effects (horizontal and vertical), efficiencies, and remedies

- Merger in the video game industry – market definition and competitive effects

- Merger involving financial management and human resource management enterprise software products (DOJ litigation) – market definition and competitive effects

- Joint venture between oil refiners - evaluation of appropriate competition authority oversight

Damages and Finance

- Prediction of municipal solid waste and waste recovery volumes based on demographic variables and trends

- Evaluation of host fees paid to municipalities by waste industry companies with disposal assets

- Syndicated loan availability and cost for company operating on certain relevant sectors, including transportation (aviation, rail, shipping), energy, commercial real estate, and wholesale financial services

- Evaluated claims of unfair competition, false advertising, and unfair trade practices in provision of confirmatory urine drug testing for pain management health care practitioners

- Recoverable profit resulting from insider trading pursuant to Section 16(b) of the SEC Act

- Damages model using event study analyses related to misrepresentation claims in banking industry

- Analyzed claim that the bankruptcy of a regional drug store was caused by a major supplier’s change in payment terms

- Alleged breach of contract and alleged fraud associated with an agreement to sell fuel injectors for use in diesel engines – estimation of damages (including econometric analysis)

- Damages involving marketing programs in selling genetically modified soybeans and herbicides

- Value of a right of first refusal for season ticket holders following relocation of sports team

- Analysis of matched and manipulative stock trading

Energy and Regulation

- Evaluated regulated rate methodology in the waste collection industry

- Claimed manipulative trading of energy derivative products – econometric evaluation of electricity prices

- Wholesale electricity prices – evaluation of competitive reasonableness of 2006 Illinois auction

- Claims that an artificial price in electricity forward markets was created through spot market actions and information dissemination

- Claims realted to sale of electricity in California and the western U.S. during California electricity crisis – market definition and competitive effects

- Regulatory proposal for a locational installed capacity market (LICAP) in New England – market power, generator availability, shape of the demand curve, and role of historical capacity levels

- Analyses of California electricity crisis (transmission constraints, calculation of rebates under various scenarios, and trading practices of electric power generators during 2000 and 2001)

PUBLICATIONS:

"United States Overview," The Handbook of Competition Economics 2020, Global Competition Review, 2020, forthcoming with Henry J. Kahwaty. (also prior editions, 2016, 2017, 2018, and 2019)

"Intellectual Property Expert Damages Admissbility," in Assets and Finances: Calculating Intellectual Property Damages, 2019-2020 Edition, forthcoming by Kerr, William O. and Gregory Smith, West Publishing, Thomson-Reuters, with Deepa Sundararaman. (also prior edition, 2018)

"Intellectual Property Expert Damages Admissbility," in Assets and Finances: Calculating Intellectual Property Damages, 2017 Edition, by Troxel, Richard B. and William O. Kerr, West Publishing, Thomson-Reuters, with Deepa Sundararaman.

“Admissibility of Expert Damages Testimony in IP Cases,” in Assets and Finances: Calculating Intellectual Property Damages, 2016 Edition, by Troxel, Richard B. and William O. Kerr, West Publishing, Thomson-Reuters. (also prior editions, 2010, 2011, 2012, 2013, 2014, and 2015)

“Canada High Court Breathes New Life Into M&A Efficiences,” *Law360*, February 6, 2015, with Henry J. Kahwaty.

“Market Definition – Achieving an Integrated Analysis,” *The Antitrust Bulletin*, 59 (3): 667-685, Fall 2014, with Henry J. Kahwaty.

“Measuring Reverse Payments in the Wake of *Actavis*,” *Antitrust*, 28 (1): 29-35, Fall 2013, with William O. Kerr.

“Shifting Regulatory Oversight of Utility Mergers” in Innovating for Transformation: The Energy and Utilities Project, Montgomery Research, Inc., 2006, with Cliff W. Hamal.

“Market Power Mitigation or Obviation, That is the Question: FERC’s Pending Decision on New England’s Installed Capacity Market Design,” *The Energy Antitrust News*, Winter 2005.

“Renewed Interest in Coordinated Effects in Merger Analysis: The *UPM* Case,” *Trade Practices Law Journal*, Summer 2004, with David A. Weiskopf.

“Issues in the Deregulation of the Electric Industry,” Ph.D. Dissertation, Clemson University, 1998.

“The Wires Charge: Risk and Rates for the Regulated Distributor,” *Public Utilities Fortnightly*, September 1997, with Michael T. Maloney and Robert E. McCormick.

PAPERS, COMMENTARY, and CONTRIBUTIONS:

Contributor to Section of Antitrust Law, Antitrust Law Developments (Eighth), American Bar Association, 2017.

“What Drives Physician Testing for Pain Medication Compliance – Risk or Reward?”, Working Paper, December 2014, with Robin Cantor, Shireen Meer, Daniel Boada, and Sandra Wetzel, presented by Robin Cantor at Society for Risk Analysis Annual Meeting, Complex Challenges in Health Policy.

Contributor to Selected Readings in Antitrust Economics: Game Theory (VI. Vertical Restraints), American Bar Association, Section of Antitrust Law Economics Committee, May 2014.

“Reasonable Royalty Damages: Expert Testimony and Admissibility,” 2014.

“An Economic Evaluation of the Competitive Nature of Reverse Payment Settlements,” 2013.

“Analysis of Horizontal Market Power in Transactions Under the Federal Power Act: Comments” with Carl Danner, Henry J. Hahwaty, and Keith Reuter, FERC Docket No. RM11-14-000, May 23, 2011.

Comments for Hoizontal Merger Guidelines Review Project, “Comments on Questions 2, 4, and 13,” November 9, 2009.

“An Agreement in the Rough: A Modified Cournot Approach to Distribution Agreements,” with Ecer, Kahwaty, Nieberding, and Weiskopf. Winter 2006.

“A Plan for Restructuring the Electric Industry in South Carolina,” Citizens for a Sound Economy. June 30, 1997, with Michael T. Maloney and Robert E. McCormick.

“Redistribution and Retribution: A Positive Theory of Transfers and Police Expenditures,” Public Finance Workshop Paper, Clemson University. December 1996.

“Amtrack: Information on Subsidies in Thruway Bus Operations,” General Accounting Office. Resources, Community, and Economic Development Division. May 9, 1995. (major contributor)

PRESENTATIONS

Presentation at Washington Utilities and Transportation Commission Technical Conference, “Inquiry into methods for setting rates for solid waste collection companies”, Docket TG-131255, on behalf of Washington Recycling & Refuse Association, with Paul Diver, PhD, October 8, 2019.

“Section 337 Exclusion Orders for New Technology (Mock Hearing on Public Interest for Infringing Biologic Product),” Practicioners’ Think-Tank on ITC Litigation & Enforcement, American Conference Institute, June 27, 2019.

“2019 Antitrust Trends, Developments and Legal Issues,” The Knowledge Group, April 24, 2019.

“Reverse Payment Settlements: Economic Issues Arising in Antitrust Litigation,” The Knowledge Group, August 30, 2018.

Patent Infringement Mock Trial Damages Testimony - Japanese Intellectual Property Association; Washington, DC; November 3, 2017 (and previously on November 6, 2015, November 7, 2013, November 11, 2011, November 13, 2009, and November 9, 2007).

"Antitrust Enforcement for Pay-For-Delay Settlements: U.S. and E.U. Perspective," The Knowledge Group, October 20, 2016.

"Merger Analysis: The CCS Case," Clemson University; Clemson, South Carolina; October 18, 2012.

"Quantitative Analysis in Consulting Engagements," University of Virginia; Charlottesville, VA; September 7, 2012; with Anthony D'Andrea.

"A Discussion of the Rolls Royce Decision and Expert Testimony," BRG – Washington, DC, July 2011 with Keith Reutter.

"Capacity Market Design Fundamentals," EUCI conference workshop, Baltimore, MD; October 27, 2010, with Cliff Hamal and Julie Carey.

"Merger Analysis in the Waste Industry – Republic and Allied," University of Virginia; Charlottesville, VA, October 21, 2010, with Paul Diver.

"Critical Elements of Ancillary Services Market Design," EUCI conference workshop, Minneapolis, MN; June 18, 2010, with Scott M. Harvey.

"An Analysis of Reverse Payments in the Pharmaceutical Industry – An Antitrust Topic," Charlottesville, VA; September 25, 2008.

"Market Design Choices for Ancillary for Ancillary Services Products," workshop at EUCI conference, Minneapolis, MN; September 12, 2007, with Cliff Hamal.

"Reliability, Ancillary Service Markets and Scarcity Pricing," presented at EUCI conference, Minneapolis, MN; September 11, 2007; authored by Scott M. Harvey.

"Daubert and Economic Experts," Mock Daubert Hearing, LECG Summer Seminar Series, July 9, 2003.

Presentation before the Public Service Commission of South Carolina on behalf of Citizens for a Sound Economy, Hearings on Electricty Deregulation, August 1997.

ACTIVITIES, HONORS, and AWARDS:

- Signatory of Panmure House Declaration, at The New Enlightenment: Reshaping Capitalism and the Global Order in a Neo-Mercantilist World (2019)
- American Economic Association (2001 to present)
- American Bar Association (2004 to present)
- Managing Editor, *BRG Review* (2015 to present)

- Co-Office Director for BRG’s Washington DC office (2015-17)
- United States Association for Energy Economics (2009 to 2017)
- International Association for Energy Economics (2009 to 2017)
- American Health Lawyers Association (2014-15)
- WCEE (2009-10)
- Close Fellowship (1994–96)
- Macaulay Award for Outstanding Performance by a Graduate Student in Economics (1993–94)
- Earhart Fellowship (1993–94)

Appendix B: Paul G. Diver CV

Curriculum Vitae

PAUL G. DIVER, PH.D.
BERKELEY RESEARCH GROUP, LLC
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Washington, D.C. 20036

Direct: 202.846.9393
pdiver@thinkbrg.com

SUMMARY

Paul Diver, Ph.D., is an associate director in BRG's Washington, D.C., office. He has provided statistical and economic analysis pertaining to horizontal and vertical competition, intellectual property, and damages matters heard before federal and state courts, administrative law judges, and regulatory commissions. Dr. Diver has been engaged and submitted expert reports as a statistical expert, and he has been deposed in a matter heard before federal court.

Dr. Diver has applied statistical and econometric techniques in solving complex problems, including regression analysis, cluster and classification analysis, matching, synthetic control method analysis, difference in differences analysis, and nonparametric methods. He has developed complex sampling designs, drawn samples, and evaluated the statistical validity of samples and their associated extrapolations for clients. Further, he has experience working with Big Data and parallel processing.

Dr. Diver's work extends across a range of industries including automotive, telecommunications, luxury goods, waste collection and disposal, and battery separators. He has also provided consulting services to healthcare clients and their counsel, including the evaluation of Centers for Medicare & Medicaid Services (CMS) RADV audit sampling and extrapolation methodologies, the evaluation of potential bias in the CMS-Hierarchical Condition Category (CMS-HCC) risk adjustment model and the application of the associated Fee for Service Adjuster, and guidance for internal quality-control practices and outlier detection. Additionally, Dr. Diver has provided strategic and evaluative advisory services to Division I collegiate athletic programs.

EDUCATION

Ph.D. (Statistics),	University of Virginia, 2017
M.A. (Economics),	University of Virginia, 2010
M.S. (Mathematics and Statistics),	Georgetown University, 2007
B.S. (Mathematics),	Georgetown University, 2006

PROFESSIONAL EXPERIENCE:

Berkeley Research Group, LLC

Associate Director	2019 – present
Senior Managing Consultant	2017 – 2019
Independent Contractor	2011 – 2017

PROFESSIONAL EXPERIENCE *(continued)*:

LECG, LLC

Independent Contractor	2009 – 2011
Senior Associate	2009
Associate	2007 – 2009

U.S. Census Bureau

Mathematical Statistician 2006 – 2007

Analyzed the imputation methodology of several national surveys and their supplements (Current Population Survey, Annual Social Economic Supplement, and American Community Survey)

NPR, Inc. (National Public Radio)

Sponsorship Coordinator 2005 – 2006

TEACHING EXPERIENCE:

Georgetown University

Adjunct Associate Professor 2018 – present

Graduate-level class in nonparametric statistical methods

University of Virginia

Instructor 2012, 2015 – 2016

Undergraduate-level classes in nonparametric statistical methods and regression analysis

Teaching Assistant 2009 – 2014

Undergraduate-level classes in theoretical and applied statistical analysis

SELECTED CONSULTING EXPERIENCE

Damages Analysis

- Damages estimation in the automotive industry – econometric modeling to evaluate damages related to undisclosed vehicle defects
- Evaluation of theories of injury and damages related to the fiscal sponsorship of a 501(c)(3) public charity

Antitrust – Mergers and Competition

- Analysis of claims of monopolization and abuse of a dominant position in the provision of specialized search advertising during investigations by the EU Commission – statistical modeling to investigate competitive effects, experimental design, and remedies

SELECTED CONSULTING EXPERIENCE *(continued)*

- Analysis of claims of monopolization in a consummated merger in the battery separator industry (FTC investigation and litigation) – market definition, competitive effects, efficiencies, and remedies

- Analysis for merger in the waste collection and disposal industries (DOJ investigation) – market definition, competitive effects (horizontal and vertical), efficiencies, and remedies

Investigations and Strategic Advisory Services

- Analysis of Medicare Risk Adjustment data, development of statistical sampling designs, and procurement of samples in support of a health services internal investigation into the detection of fraudulent diagnosis code submissions - robust statistical methods of outlier detection, sampling design, and probability distribution assessment

- Development of statistical sampling designs and procurement of samples in support of a health services internal investigation into the medical necessity of provided procedures – sampling design

PUBLICATIONS, REFERENCES, AND ACKNOWLEDGMENTS

"MOOCs as a massive research laboratory: opportunities and challenges," Distance Education, 36:1, 5-25, 2015, DOI:10.1080/01587919.2015.1019968 (with Ignacio Martinez)

"Website Volume Prediction," *Twelfth Industrial Mathematical and Statistical Modeling Workshop for Graduate Students*. North Carolina State University, pgs. 1 – 22, (with Richard Barnard, Roxana Hritcu, Asuman Turkmen, Joe Zhang, and Gang Zhao), *available at*: http://www.ncsu.edu/crsc/reports/ftp/pdf/crsc-tr06-23.pdf

"What are the Chances," *Virginia*, 22 July 2014, *(referenced), available at*: http://uvamagazine.org/articles/uva_baseball_chances

Automated Trading with R: Quantitative Research and Platform Development, Chris Conlan, Apress, 2016 (*acknowledged*)

PRESENTATIONS

"Statistical Analysis in the Assessment of Disparate Impact and Treatment," Presentation to the Washington Lawyers' Committee for Civil Rights and Urban Affairs, Washington, D.C., April 19, 2019

"Statistical Sampling in Litigation," Presentation to the Bureau of Consumer Financial Protection, Washington, D.C., with David Campbell, August 15, 2018

PRESENTATIONS *(continued)*

"Inquiry into methods for setting rates for solid waste collection companies," Docket TG-131255, on behalf of Washington Recycling & Refuse Association, Presentation at Washington Utilities and Transportation Commission Technical Conference, with Cleve Tyler, Ph.D., October 8, 2019.

HONORS AND AWARDS

The Jefferson Trust "Developing Students for Leadership in Data-intensive Research and Innovation" Award (Big Data Initiative Award sponsored by the Jefferson Trust and the VP for Research), University of Virginia, 2013

Huskey Research Exhibition, 1st Prize, "A Proposed Methodology for Two-Level Cluster Analysis," Physical Science and Math Posters, University of Virginia, 2016

Appendix C: Data Download and Processing

I. CAPITAL IQ DATA DOWNLOAD

A. Summary

1. The regression models rely on data sourced from Capital IQ. This section outlines the process for downloading these data. The following screening criteria are applied to the data system:

   i. SIC Codes: Division E: Transportation, Communications, Electric, Gas, And Sanitary Services (Primary)

   ii. Geographic Locations: United States of America (Primary)

   iii. Total Revenue (Max - 51 Years) [CY 2018] ($USDmm, Historical rate): is greater than 0

2. After applying these filters, the following additional fields are selected:

   i. Excel Company ID

   ii. SIC Codes (Primary Code Only)

   iii. SIC Codes (Primary)

   iv. Company Type

   v. Company Status

   vi. Total Revenue

   vii. EBIT

   viii. Net Property, Plant and Equipment

   ix. Cost of Goods Sold

   x. Net Income

   xi. Total Liabilities

   xii. Total Equity

   xiii. Total Assets

3. This process is discussed in more detail in the following sections.

B. Accessing Capital IQ Company Screening

4. Log into the S&P Capital IQ Platform Log In page.

5. Once logged in, hover over the "Screening" panel on the top bar. Next, click on "Companies" under the "Screening" tab located on the upper left of the pop-up.

6. This will lead to the “Company Screening” page.

C. Criterion 1 – Industry Classification

7. The first step is to filter the full Capital IQ database by industry. Find the “Company Details” box on the left side of the screen. Next, click on “Industry Classifications” which is found in the “Company Details” box.

8. This will load the “Screening Criteria: Industry Classifications” section at the top of the page. Click on the “Use SIC Code tree” hyperlink located to the right of the “Clear” button in order to access the Standard Industrial Classification (SIC) Codes.

9. This will load all SIC Codes segmented by Division. There will be 10 divisions starting from “Division A: Agriculture, Forestry, and Fishing” to “Division J: Public Administration.”

10. Select “Division E: Transportation, Communications, Electric Gas, and Sanitary Services.” In Capital IQ, “Division E: Transportation, Communications, Electric Gas, and Sanitary Services” will have all industry SIC codes that start with the “4.”

11. In the lower right corner of the “Company Screening” box, click “Add Criteria.”

12. The first query will appear at the top of the page, returning the number of companies that are in Division E industries.

D. Criterion 2 – Geographic Locations

13. To further filter companies, select companies headquartered in the United States. To do this, go back to the “Company Details” box on the left side of the page, which is where “Industry Classifications” were found. Click on “Geographic Locations.”

14. This will load the box “Screening Criteria: Geographic Locations.” Click the plus-sign next to the “United States and Canada” box, then check the “United States of America” box.

15. Click “Add Criteria” at the lower right corner of the box. This will now have 2 criteria for SIC Codes and Geographic Locations which will return a smaller set of companies.

E. Criterion 3 – Financial Information

16. To filter this list of companies further, companies whose revenues were greater than 0 at least once in the chosen time period will be selected. Locate the “Financial Information” box on the left side of the screen.

17. Click on “Financial Statements” which will be the first option available in the box. This will load all different financial data items that Capital IQ provides. Capital IQ provides data from both Capital IQ and Compustat. Data sourced from both Capital IQ and Compustat will be pulled separately through this process.

18. Expand the “CIQ Financial Statements” option using the “+” button next to it. This will pull up different financial statements options such as the Income Statement, Balance Sheet, and Statement of Cash Flows. To separately pull Compustat data, repeat this step and select “Compustat Financials” instead.

19. Expand the “Income Statement” option by clicking the “+” button. This will bring up all income statement line items available such as Total Revenue, R&D Expense, Operating Income, and other fields.

20. As mentioned above**,** the next step will be to filter this list of companies by revenue data availability. Revenue is chosen as it is the top line item in the income statement; if revenue data is unavailable, it is highly likely that other financial data items will be unavailable as well for a company. Click on “Total Revenue” under the “Income Statement” section.

21. To only select companies whose revenue is greater than 0, click on the “Aggregates” button on the upper panel of the right box.

22. In the “Metric” drop down, click on “Maximum”. Next, go to the “Time Frame” option by selecting the drop down for the number of years of data to be pulled. Select “Enter Value” in the dropdown, and type “51” for the number of years that will be pulled for this search. In the “As of” option, click on the bubble next to “CY” (Calendar Year) and set it to 2018. Lastly, go to the “Value ($mm)” option and type in 0 in the box to the right of the “Greater than” box.

23. Click “Add Criteria” at the lower right corner of the box**.** There will now be 3 criteria for SIC Codes, Geographic Locations, and Total Revenue Data Availability which will return a smaller set of companies.

F. Selecting the Data Fields – Accessing “Customize Display Columns”

24. Above the “SIC Codes” query at the top of page will be a bar that currently highlights the “View Criteria.” To the right of it, click on the option to “Customize Display Columns.”

25. This will lead to a new page with different boxes to choose from. These are all the options available in Capital IQ to display data fields for your query.

G. Data Fields 1 – Codes and Identifiers

26. Locate the “Company Details” box on the left side of the “Customize Display Columns” page.

27. Click on “Codes/Identifiers” in the “Company Details” box which will return Capital IQ’s complete set of company identifiers in the in the “Available Items” box. For this search, “SIC Codes (Primary Code Only),” “SIC Codes (Primary),” and “Excel Company ID” will be selected, as these fields will give us the 4 digit SIC code, SIC description for the SIC code, and a unique company identification provided by Capital IQ respectively.

28. Click on each one of these fields one by one and press the single right arrow button (">"). The items will have moved from the "Available Items" box to the "Selected Items" box on the right. Click on the "Add Columns" button in the lower right corner.

29. There will now be 6 items in the Company Screening.

H. Data Fields 2 – Company Type and Company Status

30. Go back to the Company Details box and **c**lick on "General Business Details."

31. For this search, "Company Type" and "Company Status" will be selected. "Company Type" tells us whether a company is private or public, while "Company Status" can tell us whether a company is a subsidiary.

32. Click on each one of these fields one by one and press the single right arrow button (">"). The items will have moved from the "Available Items" box to the "Selected Items" box on the right. Click on the "Add Columns" button in the lower right corner.
33. There will now be 8 items in the Company Screening.

I. Data Fields 3 – Financials

34. Locate the "Financial Information" box in the center of the screen of the "Customize Display Columns" page.

35. Click on "Financial Statements" which will be the first option in the box. This will show both Capital IQ ("CIQ") and Compustat data**.**

36. Expand the "CIQ Financial Statements" option using the "+" button next to it. This will pull up different financial statements options such as the Income Statement, Balance Sheet, and Statement of Cash Flows.

37. Expand the "Income Statement" option by clicking the "+" button. This will bring up all income statement line items available such as Total Revenue, R&D Expense, Operating Income, and other fields. For this search, "Total Revenue," "Cost of Goods Sold," "EBIT," and "Net Income" fields will be pulled from the Income Statement.

38. Click on "Total Revenue" and the "Display" options box will be populated with multiple options and toggles.

39. Go to the "Display Range" option and click the drop down for number of years, which will be set to 1 as the default. Click on "Enter Value" and type in 51, for the number of years, in the box next to it.

40. Next, click on the bubble below Last 51 years, and select the second drop down in this option which will already be preset to 2019. Select "Enter Value" and set it to 1968. Next, select the third drop down in this option which will be preset to 2019.

Set this to 2018. As a result, this will display Total Revenue from Calendar Years 1968 to 2018.

41. Click on the "Add Columns" button in the lower right corner. As a result, there will now be "Total Revenue" data fields from Calendar Years 1968 to 2018.

42. Repeat S**teps 34-41** for "Cost of Goods Sold, ", "EBIT," and "Net Income."

43. From the Balance Sheet, "Net Property Plant and Equipment," "Total Liabilities,", "Total Equity," and "Total Assets," will be selected. As a result, expand the "Balance Sheet" option in the "Financial Statements" box by clicking the "+" button.

44. Find "Net Property, Plant, & Equipment" item, and click on this. Repeat **Steps 34-41.**

45. Repeat **Steps 34-41** for "Total Liabilities," "Total Equity," and "Total Assets."

46. To separately pull Compustat data, repeat the steps in this section, selecting "Compustat Financials" instead.

J. Export

47. Once all the financials are selected, click on the "View Results >>" box in the lower right corner.

48. This will lead to the "Company Screening Results Screen" page.

49. Next to the "Screening Settings" icon, in the top left part of the screen, click on the Excel icon that exports this dataset to Excel. This will take some time to generate the workbook. A pop up will come up with the loading screen.

50. Once the dataset has finished downloading at 100%, click on the download button, and your Excel workbook will appear.

II. DATA PROCESSING

A. Transformation

51. The CIQ data is presented in a "wide" format such that there is a different variable for each year-financial variable combination. Thus, the level of observation is the company level. Transform the data to "long" format such that there is a single variable for the year and the level of observation is the company-year level.

B. Filtering and Calculation of Fields

52. The following steps are taken, in order, after transforming the raw data in preparation of the regression model.

53. Remove any observation that has a missing value in any of the following fields: EBIT, PPE, revenue, debt, or equity.

54. Remove any duplicate companies from the data by manually reviewing company names. When duplicates are identified, only one entry for each company-year is be kept. The following process is used:

    i. If one duplicate has more years of data than the other(s), only that duplicate is kept.

    ii. If there are N duplicates and N-1 of the companies are subsidiaries of the non-subsidiary, only the non-subsidiary is kept.

    iii. When it is not clear which duplicate company should be kept, keep the company with the highest total revenue.

55. The IDs for the companies that have been removed from the Capital IQ data used in these analyses are listed below.

    i. IQ1236048
    ii. IQ1579389
    iii. IQ4935625
    iv. IQ273513334
    v. IQ298968
    vi. IQ3053303
    vii. IQ2908516
    viii. IQ1035237
    ix. IQ22183895
    x. IQ28448
    xi. IQ428613487
    xii. IQ30547
    xiii. IQ179862
    xiv. IQ2203069
    xv. IQ4027729
    xvi. IQ4233224
    xvii. IQ555725368
    xviii. IQ328874
    xix. IQ243169350
    xx. IQ3040966
    xxi. IQ413909753
    xxii. IQ610501
    xxiii. IQ3114038
    xxiv. IQ4176500
    xxv. IQ285932557
    xxvi. IQ409424
    xxvii. IQ30232680
    xxviii. IQ862497
    xxix. IQ169142
    xxx. IQ650516
    xxxi. IQ26

56. Limit to only public and private companies.

57. Limit to only companies with headquarters in the United States.

58. Limit to the appropriate range of years (ten years for Model 1 or seven years for Model 2).

59. Limit to the appropriate set of SIC codes (vehicle transportation companies for Model 1 or all transportation companies for Model 2).

60. Calculate each company-year's PPE as the average of PPE_t and PPE_{t-1}. If the period t-1 does not exist for a given company-year, simply use PPE_t for that observation.

61. Calculate profit margin as EBIT divided by revenue, multiplied by 100.

62. Calculate asset turnover as revenue divided by PPE, multiplied by 100.

63. Calculate debt-equity ratio as debt divided by equity, multiplied by 100.

64. Calculate the Mahalanobis distance as defined in footnote 29 for each observation on the basis of profit margin, asset turnover, and debt-equity ratio. Filter out any observation with a Mahalanobis distance greater than the 95th percentile value of a chi-squared distribution with three degrees of freedom (approx. 7.815).

65. The data is now ready to run through the regression model, which transforms the profit margin, asset turnover, and debt-equity ratio to the natural log form.

Attachment 1: Companies Included in Model 1

Companies Included in Model 1

Advanced Disposal Services, Inc. (NYSE:ADSW)
Air Methods Corporation
Air T, Inc. (NasdaqGM:AIRT)
Air Transport Services Group, Inc. (NasdaqGS:ATSG)
AirTran Holdings, LLC
Alaska Air Group, Inc. (NYSE:ALK)
Allegiant Travel Company (NasdaqGS:ALGT)
Alpine Air Express Inc.
American Airlines Group Inc. (NasdaqGS:AAL)
Andes Gold Corporation (OTCPK:AGCZ)
ArcBest Corporation (NasdaqGS:ARCB)
Atlas Air Worldwide Holdings, Inc. (NasdaqGS:AAWW)
Avalon Holdings Corporation (AMEX:AWX)
Baltic Trading Limited
BNSF Railway Company
Bristow Group Inc. (OTCPK:BRSW.Q)
Burlington Northern Santa Fe, LLC
C.H. Robinson Worldwide, Inc. (NasdaqGS:CHRW)
Carnival Corporation & Plc (NYSE:CCL)
Casella Waste Systems, Inc. (NasdaqGS:CWST)
Celadon Group, Inc. (OTCPK:CGIP)
Choice Environmental Services, Inc.
CitiWaste, LLC
Clean Harbors, Inc. (NYSE:CLH)
Commercial Barge Line Company
Covenant Transportation Group, Inc. (NasdaqGS:CVTI)
CSX Corporation (NasdaqGS:CSX)
Daseke, Inc. (NasdaqCM:DSKE)
Delta Air Lines, Inc. (NYSE:DAL)
Diamond S Shipping Group, Inc.
Dorian LPG Ltd. (NYSE:LPG)
Eagle Bulk Shipping Inc. (NasdaqGS:EGLE)
EnergySolutions, Inc.
Envision Healthcare Corporation
Era Group Inc. (NYSE:ERA)
FedEx Corporation (NYSE:FDX)
Forward Air Corporation (NasdaqGS:FWRD)
Frontier Group Holdings, Inc.
Genco Shipping & Trading Limited (NYSE:GNK)
Genesee & Wyoming Inc. (NYSE:GWR)
Glenrose Instruments Inc.
Global Aviation Holdings Inc.
Gordon Trucking, Inc.
Great Lakes Aviation, Ltd. (OTCPK:GLUX)
Gulfmark Offshore, Inc.
Hawaiian Holdings, Inc. (NasdaqGS:HA)
Heartland Express, Inc. (NasdaqGS:HTLD)
Heritage-Crystal Clean, Inc (NasdaqGS:HCCI)
Hornbeck Offshore Services, Inc. (NYSE:HOS)
Hudson Technologies Inc. (NasdaqCM:HDSN)
Industrial Services of America, Inc. (NasdaqCM:IDSA)
International Seaways, Inc. (NYSE:INSW)
International Shipholding Corp.
J.B. Hunt Transport Services, Inc. (NasdaqGS:JBHT)
JanOne Inc. (NasdaqCM:JAN)
JetBlue Airways Corporation (NasdaqGS:JBLU)
Kansas City Southern (NYSE:KSU)
Kirby Corporation (NYSE:KEX)
Knight-Swift Transportation Holdings Inc. (NYSE:KNX)
Landstar System, Inc. (NasdaqGS:LSTR)
Marten Transport, Ltd. (NasdaqGS:MRTN)
Matson, Inc. (NYSE:MATX)
Mesa Air Group, Inc. (NasdaqGS:MESA)
Mouser Electronics, Inc.
Norfolk Southern Corporation (NYSE:NSC)
Norwegian Cruise Line Holdings Ltd. (NYSE:NCLH)
NRC Group Holdings Corp. (AMEX:NRCG)
Old Dominion Freight Line, Inc. (NasdaqGS:ODFL)
Op-Tech Environmental Services Inc.
Overseas Shipholding Group, Inc. (NYSE:OSG)
P.A.M. Transportation Services, Inc. (NasdaqGM:PTSI)
Pangaea Logistics Solutions, Ltd. (NasdaqCM:PANL)
Patriot Transportation Holding, Inc. (NasdaqGS:PATI)
Perma-Fix Environmental Services, Inc. (NasdaqCM:PESI)
PHI, Inc.
Pinnacle Airlines Corp.
Precicion Trim, Inc. (OTCPK:PRTR)
Principal Maritime Tankers Corporation
Providence and Worcester Railroad Company
R3 Treatment Inc.
Rand Logistics, Inc.
Republic Airways Holdings Inc.
Republic Services, Inc. (NYSE:RSG)
Ridgebury Crude Tankers LLC
Royal Caribbean Cruises Ltd. (NYSE:RCL)
Rural/Metro Corporation
Safety-Kleen, Inc.
Saia, Inc. (NasdaqGS:SAIA)
Schneider National, Inc. (NYSE:SNDR)
SCI Engineered Materials, Inc. (OTCPK:SCIA)
SEACOR Holdings Inc. (NYSE:CKH)
SEACOR Marine Holdings Inc. (NYSE:SMHI)
Seven Seas Cruises S. DE R.L.
Sharps Compliance Corp. (NasdaqCM:SMED)
SkyWest, Inc. (NasdaqGS:SKYW)
Southwest Airlines Co. (NYSE:LUV)
Spirit Airlines, Inc. (NYSE:SAVE)
Stericycle, Inc. (NasdaqGS:SRCL)
Swift Transportation Company
TexCom, Inc. (OTCPK:TEXC)
TForce Final Mile, LLC
The Providence Service Corporation (NasdaqGS:PRSC)
Tidewater Inc. (NYSE:TDW)
Transport America, Inc.
U.S. United Ocean Services, LLC
U.S. Xpress Enterprises, Inc. (NYSE:USX)
Union Pacific Corporation (NYSE:UNP)
United Airlines Holdings, Inc. (NasdaqGS:UAL)
United Maritime Group LLC
United Parcel Service, Inc. (NYSE:UPS)
Universal Logistics Holdings, Inc. (NasdaqGS:ULH)
US 1 Industries Inc.
US Airways Inc.
US Ecology, Inc. (NasdaqGS:ECOL)
USA Truck, Inc. (NasdaqGS:USAK)
Virgin America Inc.
Waste Connections, Inc. (NYSE:WCN)
Waste Management, Inc. (NYSE:WM)
WCA Waste Corporation
Werner Enterprises, Inc. (NasdaqGS:WERN)
XPO CNW, Inc.

Attachment 2: Companies Included in Model 2

Companies Included in Model 2

Advanced Disposal Services, Inc. (NYSE:ADSW)
Aerex Industries Inc.
Air Methods Corporation
Air T, Inc. (NasdaqGM:AIRT)
Air Transport Services Group, Inc. (NasdaqGS:ATSG)
Alaska Air Group, Inc. (NYSE:ALK)
Allegiant Travel Company (NasdaqGS:ALGT)
American Airlines Group Inc. (NasdaqGS:AAL)
American Midstream Partners, LP
American States Water Company (NYSE:AWR)
American Water Works Company, Inc. (NYSE:AWK)
Andeavor Logistics LP
Aqua America, Inc. (NYSE:WTR)
ArcBest Corporation (NasdaqGS:ARCB)
Artesian Resources Corporation (NasdaqGS:ARTN.A)
Atlas Air Worldwide Holdings, Inc. (NasdaqGS:AAWW)
Atmos Energy Corporation (NYSE:ATO)
Avalon Holdings Corporation (AMEX:AWX)
Azure Midstream Holdings LLC
Azure Midstream Partners, LP
Black Hills Gas Holdings, LLC
Blue Dolphin Energy Company (OTCPK:BDCO)
Blueknight Energy Partners, L.P. (NasdaqGM:BKEP)
BNSF Railway Company
Boardwalk Pipeline Partners, LP
BP Midstream Partners LP (NYSE:BPMP)
Bristow Group Inc. (OTCPK:BRSW.Q)
Buckeye Partners, L.P. (NYSE:BPL)
Burlington Northern Santa Fe, LLC
C.H. Robinson Worldwide, Inc. (NasdaqGS:CHRW)
California Water Service Group (NYSE:CWT)
Carnival Corporation & Plc (NYSE:CCL)
Casella Waste Systems, Inc. (NasdaqGS:CWST)
Celadon Group, Inc. (OTCPK:CGIP)
Centerpoint Energy Resources Corp.
Charah Solutions, Inc. (NYSE:CHRA)
Chesapeake Utilities Corporation (NYSE:CPK)
CitiWaste, LLC
Clean Harbors, Inc. (NYSE:CLH)
CNX Midstream Partners LP (NYSE:CNXM)
Colorado Interstate Gas Company, L.L.C.
Columbia Pipeline Partners LP
Commercial Barge Line Company
Connecticut Natural Gas Corporation
Connecticut Water Service, Inc. (NasdaqGS:CTWS)
Copano Energy, L.L.C.
Corning Natural Gas Holding Corporation (OTCPK:CNIG)
Covanta Holding Corporation (NYSE:CVA)
Covenant Transportation Group, Inc. (NasdaqGS:CVTI)
Crestwood Midstream Partners LP
CSX Corporation (NasdaqGS:CSX)
Daseke, Inc. (NasdaqCM:DSKE)
Delta Air Lines, Inc. (NYSE:DAL)
Delta Natural Gas Company, Inc.
Diamond S Shipping Group, Inc.
Dominion Energy Midstream Partners, LP
Dorian LPG Ltd. (NYSE:LPG)
DTE Gas Company
Eagle Bulk Shipping Inc. (NasdaqGS:EGLE)
El Paso Natural Gas Company, L.L.C
El Paso Pipeline Partners, L.P.
Enable Midstream Partners, LP (NYSE:ENBL)
Enable Oklahoma Intrastate Transmission, LLC
Enbridge Energy Partners, L.P.
Energen Corporation
Energy Transfer LP (NYSE:ET)
EnergySolutions, Inc.
EnLink Midstream, LLC (NYSE:ENLC)
Enterprise Products Operating LLC
Envision Healthcare Corporation
EQGP Holdings, LP
EQM Midstream Partners, LP (NYSE:EQM)
EQT Corporation (NYSE:EQT)
Equitrans Midstream Corporation (NYSE:ETRN)
Era Group Inc. (NYSE:ERA)
FedEx Corporation (NYSE:FDX)
Forward Air Corporation (NasdaqGS:FWRD)
Frontier Group Holdings, Inc.
Genco Shipping & Trading Limited (NYSE:GNK)
Genesee & Wyoming Inc. (NYSE:GWR)
Global Water Resources, Inc. (NasdaqGM:GWRS)
Golden State Water Company
Gordon Trucking, Inc.
Great Lakes Aviation, Ltd. (OTCPK:GLUX)
Great Lakes Gas Transmission Limited Partnership
Green Plains Partners LP (NasdaqGM:GPP)
Gulf South Pipeline Company, LP
Gulfmark Offshore, Inc.
Gulfstream Natural Gas System, L.L.C.
Hawaiian Holdings, Inc. (NasdaqGS:HA)
Hearthstone Utilities Inc.
Heartland Express, Inc. (NasdaqGS:HTLD)
Heritage-Crystal Clean, Inc (NasdaqGS:HCCI)
Holly Energy Partners, L.P. (NYSE:HEP)
Hornbeck Offshore Services, Inc. (NYSE:HOS)
Hudson Technologies Inc. (NasdaqCM:HDSN)
Independent Delivery Services, Inc.
Indiana Gas Company, Inc.
Industrial Services of America, Inc. (NasdaqCM:IDSA)
Inergy Midstream, L.P.
International Seaways, Inc. (NYSE:INSW)
International Shipholding Corp.
Iroquois Gas Transmission System, L.P.
J.B. Hunt Transport Services, Inc. (NasdaqGS:JBHT)
JanOne Inc. (NasdaqCM:JAN)
JetBlue Airways Corporation (NasdaqGS:JBLU)
Kansas City Southern (NYSE:KSU)
Kern River Gas Transmission Company
Kinder Morgan, Inc. (NYSE:KMI)
Kirby Corporation (NYSE:KEX)
Knight-Swift Transportation Holdings Inc. (NYSE:KNX)
Landstar System, Inc. (NasdaqGS:LSTR)
Magellan Midstream Partners, L.P. (NYSE:MMP)
Marlin Midstream Partners, LP
Marten Transport, Ltd. (NasdaqGS:MRTN)
Matson, Inc. (NYSE:MATX)
Mesa Air Group, Inc. (NasdaqGS:MESA)
Midcoast Energy Partners, L.P.
Midcontinent Express Pipeline LLC
Middlesex Water Company (NasdaqGS:MSEX)
Mouser Electronics, Inc.
MPLX LP (NYSE:MPLX)
National Fuel Gas Company (NYSE:NFG)
National Grid Generation LLC
New England Service Company, Inc. (OTCPK:NESW)
New Jersey Resources Corporation (NYSE:NJR)
Niska Gas Storage Partners LLC
Noble Midstream Partners LP (NYSE:NBLX)
Norfolk Southern Corporation (NYSE:NSC)
North Shore Gas Company
Northern Border Pipeline Company
Northern Natural Gas Company
Northwest Natural Holding Company (NYSE:NWN)
Northwest Pipeline LLC
Norwegian Cruise Line Holdings Ltd. (NYSE:NCLH)
NRC Group Holdings Corp. (AMEX:NRCG)
NSTAR Gas Company
Oasis Midstream Partners LP (NYSE:OMP)
Old Dominion Freight Line, Inc. (NasdaqGS:ODFL)
ONE Gas, Inc. (NYSE:OGS)
ONEOK, Inc. (NYSE:OKE)
Overseas Shipholding Group, Inc. (NYSE:OSG)
P.A.M. Transportation Services, Inc. (NasdaqGM:PTSI)
PAA Natural Gas Storage, L.P.
Pangaea Logistics Solutions, Ltd. (NasdaqCM:PANL)
Panhandle Eastern Pipe Line Company, LP
Patriot Transportation Holding, Inc. (NasdaqGS:PATI)
PBF Logistics LP (NYSE:PBFX)
PennTex Midstream Partners, LP
Perma-Fix Environmental Services, Inc. (NasdaqCM:PESI)
PHI, Inc.
Phillips 66 Partners LP (NYSE:PSXP)
Piedmont Natural Gas Company, Inc.
Principal Maritime Tankers Corporation
Providence and Worcester Railroad Company
Public Service Company of North Carolina, Incorporated
Pure Cycle Corporation (NasdaqCM:PCYO)
QEP Midstream Partners, LP
Questar Gas Company
Rand Logistics, Inc.
Rattler Midstream LP (NasdaqGS:RTLR)
Republic Airways Holdings Inc.
Republic Services, Inc. (NYSE:RSG)
RGC Resources, Inc. (NasdaqGM:RGCO)
Ridgebury Crude Tankers LLC
Royal Caribbean Cruises Ltd. (NYSE:RCL)
Rural/Metro Corporation
Sabal Trail Transmission, LLC
Sabine Pass Liquefaction, LLC
Saia, Inc. (NasdaqGS:SAIA)
Sanchez Midstream Partners LP (AMEX:SNMP)
Schneider National, Inc. (NYSE:SNDR)
SCI Engineered Materials, Inc. (OTCPK:SCIA)
SEACOR Holdings Inc. (NYSE:CKH)
SEACOR Marine Holdings Inc. (NYSE:SMHI)
Seven Seas Cruises S. DE R.L.
Sharps Compliance Corp. (NasdaqCM:SMED)
Shell Midstream Partners, L.P. (NYSE:SHLX)
SJW Group (NYSE:SJW)
SkyWest, Inc. (NasdaqGS:SKYW)
South Jersey Industries, Inc. (NYSE:SJI)
Southcross Energy Partners, L.P. (OTCPK:SXEE.Q)
Southern California Gas Company
Southern Company Gas
Southern Natural Gas Company, L.L.C.
Southern Star Central Corp.
Southern Union Co.
Southwest Airlines Co. (NYSE:LUV)
Southwest Gas Holdings, Inc. (NYSE:SWX)
Southwestern Energy Company (NYSE:SWN)
Spectra Energy Partners, LP
Spire Inc. (NYSE:SR)
Spirit Airlines, Inc. (NYSE:SAVE)
Stericycle, Inc. (NasdaqGS:SRCL)
Sunoco Logistics Partners L.P.
Swift Transportation Company
Tallgrass Energy Partners, LP
Targa Resources Corp. (NYSE:TRGP)
Texas Eastern Transmission, LP
TexCom, Inc. (OTCPK:TEXC)
The Berkshire Gas Company
The Peoples Gas Light and Coke Company
The Providence Service Corporation (NasdaqGS:PRSC)
The Southern Connecticut Gas Company
The Torrington Water Company (OTCPK:TORW)
The Williams Companies, Inc. (NYSE:WMB)
The York Water Company (NasdaqGS:YORW)
Tidewater Inc. (NYSE:TDW)
Transcontinental Gas Pipe Line Company, LLC
TransMontaigne Partners LLC
Transport America, Inc.
U.S. Xpress Enterprises, Inc. (NYSE:USX)
Union Pacific Corporation (NYSE:UNP)
United Airlines Holdings, Inc. (NasdaqGS:UAL)
United Parcel Service, Inc. (NYSE:UPS)
Universal Logistics Holdings, Inc. (NasdaqGS:ULH)
US Airways Inc.
US Ecology, Inc. (NasdaqGS:ECOL)
USA Truck, Inc. (NasdaqGS:USAK)
USD Partners LP (NYSE:USDP)
Valero Energy Partners LP
Vectren Corporation
Virgin America Inc.
Washington Gas Light Company
Waste Connections, Inc. (NYSE:WCN)
Waste Management, Inc. (NYSE:WM)
Werner Enterprises, Inc. (NasdaqGS:WERN)
Western Midstream Partners, LP (NYSE:WES)
WGL Holdings, Inc.
Wisconsin Gas LLC
XPO CNW, Inc.
Yankee Gas Services Company

Attachment 3: SIC Codes Included in Model 1, Model 2, and Staff DuPont Model

SIC Codes Included in Model 1, Model 2, and Staff DuPont Model

SIC Code	Description	Model 1	Staff Used SICs	Model 2
4011	Railroads, line-haul operating	Yes	No	Yes
4013	Switching and terminal services	No	No	No
4100	Local and suburban transit and interurban highway passenger transportation	Yes	Yes	Yes
4111	Local and suburban transit	Yes	Implicitly	Yes
4119	Local passenger transportation	Yes	Implicitly	Yes
4121	Taxicabs	Yes	Implicitly	Yes
4131	Intercity and rural bus transportation	Yes	Implicitly	Yes
4141	Local bus charter service	Yes	Implicitly	Yes
4142	Bus charter service, except local	Yes	Implicitly	Yes
4151	School buses	Yes	Implicitly	Yes
4210	Trucking and courier services, except air	Yes	Yes	Yes
4212	Local trucking, without storage	Yes	Implicitly	Yes
4213	Trucking, except local	Yes	Yes	Yes
4214	Local trucking with storage	Yes	Implicitly	Yes
4215	Courier services, except by air	Yes	Implicitly	Yes
4220	Public warehousing and storage	No	No	No
4221	Farm product warehousing and storage	No	No	No
4222	Refrigerated warehousing and storage	No	No	No
4225	General warehousing and storage	No	No	No
4226	Special warehousing and storage	No	No	No
4231	Trucking terminal facilities	No	No	No
4400	Water transportation	Yes	No	Yes
4412	Deep sea foreign transportation of freight	Yes	No	Yes
4424	Deep sea domestic transportation of freight	Yes	No	Yes
4432	Freight transportation on the Great Lakes	Yes	No	Yes
4449	Water transportation of freight	Yes	No	Yes
4481	Deep sea passenger transportation, except ferry	Yes	No	Yes
4482	Ferries	Yes	No	Yes
4489	Water passenger transportation	Yes	No	Yes
4491	Marine cargo handling	No	No	No
4492	Towing and tugboat service	Yes	No	Yes
4493	Marinas	No	No	No
4499	Water transportation services	No	No	No
4512	Air transportation, scheduled	Yes	Yes	Yes
4513	Air courier services	Yes	Yes	Yes
4522	Air transportation, nonscheduled	Yes	Yes	Yes
4581	Airports, flying fields, and services	No	No	No
4610	Pipelines, except natural gas	No	Yes	Yes
4612	Crude petroleum pipelines	No	No	No
4613	Refined petroleum pipelines	No	No	No
4619	Pipelines	No	No	No
4700	Transportation services	No	No	No
4724	Travel agencies	No	No	No
4725	Tour operators	No	No	No
4731	Freight transportation arrangement	No	No	No
4741	Rental of railroad cars	No	No	No
4783	Packing and crating	No	No	No
4785	Inspection and fixed facilities	No	No	No
4789	Transportation services	Yes	No	Yes
4812	Radiotelephone communications	No	No	No
4813	Telephone communications, except radio	No	No	No
4822	Telegraph and other communications	No	No	No
4830	Radio and television broadcasting stations	No	No	No
4832	Radio broadcasting stations	No	No	No
4833	Television broadcasting stations	No	No	No
4841	Cable and other pay Television services	No	No	No
4888	Cable and other pay Television services	No	No	No
4888	Diversified Multi-Media	No	No	No
4899	Communication services	No	No	No
4911	Electric services	No	No	No
4922	Natural gas transmission	No	Yes	Yes
4923	Gas transmission and distribution	No	Yes	Yes
4924	Natural gas distribution	No	Yes	Yes
4925	Gas production and/or distribution	No	No	No
4931	Electric and other services combined	No	No	No
4932	Gas and other services combined	No	No	No
4939	Combination utilities	No	No	No
4941	Water supply	No	Yes	Yes
4950	Sanitary services	No	Yes	Yes
4952	Sewerage systems	No	No	No
4953	Refuse systems	Yes	Yes	Yes
4955	Hazardous waste management	Yes	Yes	Yes
4959	Sanitary services	No	No	No
4961	Steam and air-conditioning supply	No	No	No
4971	Irrigation systems	No	No	No
4991	Cogeneration services and small power producers	No	No	No

Source : United States Department of Labor; www.osha.gov, Capital IQ.