

utilities request and receive. The change is a flow variable while the total rate base is the stock of all previous rate base changes. It includes both new investment and depreciation of existing assets. We primarily focus on the effect on the *change* in the rate base, rather than the entire rate base, because the former is actively decided in each rate case and the data is more complete. However, we observe similar effect sizes when looking at the entire rate base. We consider both the requested change and the approved change, though the approved value is our preferred specification. We estimate $\hat{\beta}$ from the following, where we regress the rate base increase (RBI) on the estimated RoE gap, various controls, and fixed effects.

$$\log(RBI_{i,t}) = \beta RoE_{i,t}^{gap} + \gamma X_{i,t} + \theta_i + \lambda_t + \epsilon_{i,t} \quad (1)$$

where an observation is a utility rate case for utility i in year-of-sample t . The dependent variable, $RBI_{i,t}$, is the increase in the rate base, and we take logs.¹⁸ The ideal independent variable would be the gap between the allowed RoE and the utilities' costs of equity. Because the true value is unobservable, we use $RoE_{i,t}^{gap}$, the gap between the allowed RoE and the baseline RoE. Unlike section 4.1, for this analysis we care about differences in the gap between utilities or over time, but do not care about the overall magnitude of the gap. For ease of implementation, we begin by considering the gap as the spread between the approved rate of return and the 10-year Treasury bond yield. We do not expect the actual cost of equity to be equal to the 10-year Treasury yield, but our fixed effects account for any constant differences. We calculate $RoE_{i,t}^{gap}$ by taking the difference between the allowed RoE and the average of the time-varying baseline RoE, over the D years the rate case is in place.

$$RoE_{i,t}^{gap} = RoE_{i,t}^{allowed} - \frac{1}{D} \sum_t^{t+D} RoE_{i,t}^{benchmark} \quad (2)$$

18. Cases where the rate base shrinks are rare; we drop these cases.

4.3.1 Fixed Effects Specifications

Our goal is to make causal claims about $\hat{\beta}$, so we are concerned about omitted variables that are correlated with both the estimated RoE gap and the change in rate base. We begin with a fixed-effects version of the analysis. Our preferred version includes time fixed effects, λ_t , at the year-of-sample level and the unit fixed effects, θ_i , are at the service type, utility company and state level. Utilities that operate in multiple states still file rate cases with each state's utility regulator. Our state fixed effects account for constant differences across states, including any persistent differences in the regulator. Here, the identifying assumption is that after controlling for state and year effects, there are no omitted variables that would be correlated with both our estimate of the RoE gap and the utility's change in rate base. The identifying variation is the differences in the RoE gap within the range of rate case decisions for a given utility, relative to the annual average across all utilities.

The fixed effects handle some of the most critical threats to identification, such as macroeconomic trends, technology-driven shifts in electrical consumption, or static differences in state PUC behavior. Of course, potential threats to causal identification remain. One possibility is omitted variables – perhaps regulators in some states change their posture toward utilities over time, in a way that is correlated with both the RoE and the change in rate base. Another possibility is reverse causation – perhaps the regulator pushes for more capital investment (e.g. aiming to increase local employment) and the utility, facing increasing marginal costs of capital, needs a higher RoE.

4.3.2 Instrumental Variables Specifications

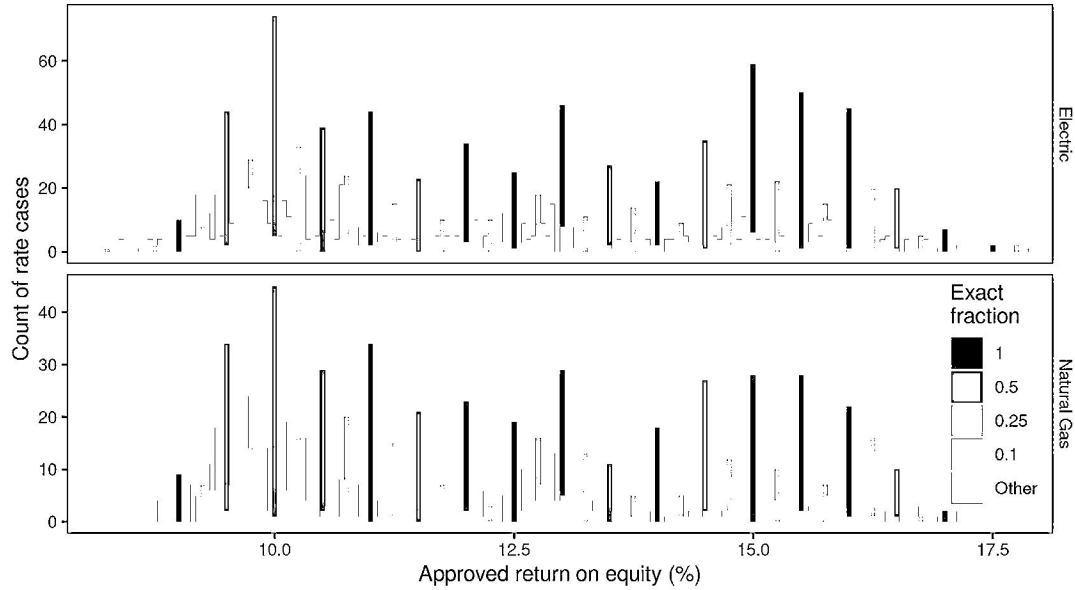
To try and further deal with concerns regarding identification, we examine an instrumental variables approach based on the timing and duration of rate cases. The average utility has ten rate cases over the course of our sample period and the

average rate case is in effect for about three years. Our IV analysis takes the idea that market measures of the cost of capital move around in ways that aren't always easy for the regulator to anticipate. For instance, if the allowed return on equity is set in year 0 and financial conditions change in year 2 such that the RoE gap increases, then we would expect the utility to increase their capital investments in ways that are unrelated to other aspects of the capital investment decision. For this instrument to work, it needs to be the case that these movements in capital markets are conditionally independent of decisions that the utility is making, except via this return on equity channel. We control for common year fixed effects, and then the variation that drives our estimate is that different utilities will come up for their rate case at different points in time.

A second IV strategy we explore is to exploit an apparent bias toward round numbers, where regulators tend to approve RoE values at integers, halves, quarters, and tenths of percentage points. Unfortunately this instrument does not produce a strong first-stage and so is not a core focus of our subsequent analysis. Even so, the existence of such an arbitrary phenomenon in our setting is still interesting, and can be seen clearly in figure 3. Small deviations created by rounding have large implications for utility revenues and customer payments. If for instance, a PUC rounds in a way that changes the allowed RoE by 10 basis points (0.1%), the allowed revenue on the existing rate base for the average electric utility in 2019 would change by \$114 million (the median is lower, at \$52 million).

We believe the actual, unknown, cost of equity is smoothly distributed. There is therefore some unobserved RoE^* that is unrounded. The regulatory process often then rounds from RoE^* to the nearest multiple of 10 or 25 basis points (bp). We argue that this introduces an exogenous source of variation into the actual approved RoE. To construct our instrument we calculate the difference between the observed RoE and the nearest rounded RoE. We take the absolute value of this difference and interact it with a dummy for the sign of the difference. When we say “rounded”, we

Figure 3: Return on equity is often approved at round numbers



Colors highlight values of the nominal approved RoE that fall exactly on round numbers. More precisely, values in red are integers. Values in dark orange are integers plus 50 basis points (bp). Lighter orange are integers plus 25 or 75 bp. Yellow are integers plus one of {10, 20, 30, 40, 60, 70, 80, 90} bp. All other values are gray. Histogram bin widths are 5 bp. Non-round values remain gray if they fall in the same histogram bin as a round value. In that case, the bars are stacked.

SOURCE: Regulatory Research Associates (2021).

don't know the rounding rule (e.g. up, down, or nearest) and it may differ across utilities and regulators. Our preferred specification uses numbers rounded up to 25 bp, but we check multiples of 10, 50 and 100 bp. For the instrument to be valid, we need to assume that the rounding is related to rate base only via assigned RoE. As noted earlier, because any rounding only accounts for a small portion of the variation in overall RoE, this instrument does not have a strong first stage.

5 Results

5.1 Return on Equity Gap Results

Beginning with the RoE gap analysis from section 4.1, we find there has been an increase in the gap between utilities' allowed return on equity and various measures of their estimated cost of capital. Our results on the RoE gap show this has increased

Table 2: RoE gap, by different benchmarks (percentage points)

A: Electric	Corp	UST	UST auto	CAPM low	CAPM high	UK
1985	0.693	0.415	1.39	1.50	-2.84	
1990	-0.238	0.459	0.412	1.36	-3.09	
1995	0.788	1.09	0.139	2.09	-2.49	
2000	0.666	1.41	0.153	2.42	-1.76	2.79
2005	2.99	2.84	0.722	3.91	-0.552	1.93
2010	3.04	3.21	0.517	4.50	-0.448	-0.585
2015	3.57	3.64	0.416	4.99	0.446	2.77
2020	4.25	4.49	0.706	5.60	0.786	1.88
B: Natural Gas						
1985	1.14	0.798	1.78	1.68	-2.35	
1990	-0.0272	0.848	0.819	1.59	-2.50	
1995	0.873	1.18	0.238	1.99	-2.27	
2000	0.757	1.35	0.0924	2.18	-1.65	
2005	2.85	2.70	0.623	3.54	-0.635	
2010	3.25	3.35	0.707	4.31	-0.516	
2015	3.98	4.01	0.850	5.04	0.646	2.43
2020	4.58	4.86	1.09	5.67	1.06	1.55

Note: Gap percentage figures are a weighted average across utilities, weighted by rate base. For cases where it's relevant the benchmark date is January 1995. See text for details of each benchmark calculation.

over time and are summarized in Table 2.

When benchmarking against changes in market measures of the cost of capital (e.g. 10-yr US Treasury bonds or Moody's corporate bonds) the RoE gap is around 4–4.5 percentage points. It seems plausible that such a large divergence should not arise over the long-term unless the utility sector were to undergo substantial changes.

It is not clear that the cost of equity should necessarily move in a one-for-one manner with these two measures of bond yields. Using the more conservative automatic update rule, which adjusts at half the rate of changes in bond yields, produces an RoE gap by 2020 of around 0.5–1 percentage points. Whether adjusting at 50% of the change in bond yields is the correct approach is unclear. For instance, Canada has used a 75% adjustment ratio in the past. What is clear is that even using this more conservative approach, we still see a divergence between allowed equity returns today and changes in the benchmark cost of capital.

Benchmarking against changes in bond yields relative to some baseline year is necessarily quite simplistic. Our two implementations of the CAPM approach allow us to see how a standard method used in the industry performs. Our “low” version of the CAPM uses assumptions for the risk-free rate, beta and market risk premium that are on the lower end of what has been historically used in the industry. This is particularly true when looking at the practices of US regulators, which appear to utilize higher values than regulators in the UK, Europe and Australia. The result is an RoE gap by 2020 of around 5.5 percentage points.¹⁹ Looking back to the 1980s and 1990s though, the RoE gap becomes much smaller, with predictions of the cost of equity from our “low” CAPM version only showing a 2 percentage point gap against allowed rates of return.

Our “high” version of the CAPM uses assumptions for the risk-free rate, beta and

19. At this point average allowed RoE for US utilities is around 10%, compared with a CAPM prediction for the cost of equity of 4–5%.

market risk premium that are on the higher end of what has been historically used in the industry. This produces an RoE gap by 2020 of around 1 percentage points. Allowed rates of return are therefore still above the predictions from our “high” CAPM case, although much more closely aligned with the current approach of US state PUCs. Notably though, projecting this same approach back in time appears to suggest that past allowed returns in the 1980s and 1990s were well below the estimated cost of equity. This seems implausible given the large capital expenditures the industry has continued to engage in over the last four decades.

Lastly, when comparing against UK utilities we see a fairly consistent premium, with an RoE gap in 2020 of around 2 percentage points. A similar premium would likely emerge when comparing to utilities in other countries in Europe which have tended to approve similar rates of return to those we find for the UK. There are good reasons to think that US state PUCs should not simply adopt UK rates of return – there are many differences between the utility sector and investor environment in the US and UK. Even so, it is striking that other countries are able to attract sufficient investment in their gas and electric utilities while guaranteeing lower regulated returns than are available in the US context.

5.2 Asymmetric Adjustment Results

One mechanism for the emergence of the RoE gap is asymmetric adjustment of allowed return on equity to underlying benchmark rates of return. Table 3 provides the results of this analysis. Here we do find some potential evidence of asymmetric adjustment. Focusing on the US Treasury Bond benchmark and proposed returns on equity (column 1), the coefficient on the positive error correction term, θ^+ , is -0.0111 . This estimate indicates that where the actual return on equity is above the long-run equilibrium (e.g. due to a negative shock to the benchmark) there will be slow convergence back toward equilibrium at a rate of 1.11% of the difference

Table 3: Asymmetric Adjustments in Return on Equity

Model:	(1)	(2)	(3)	(4)
Variables				
θ^+	-0.0111*** (0.0018)	-0.0085*** (0.0022)	-0.0120*** (0.0020)	-0.0097*** (0.0020)
θ^-	-0.0274*** (0.0075)	-0.0320*** (0.0107)	-0.0207*** (0.0057)	-0.0229*** (0.0073)
Approved RoE			Yes	Yes
Index Baa Corp		Yes		Yes
Index UST 10yr	Yes		Yes	
Time Series				
LR coef.	0.5775	0.6054	0.5173	0.5411
$\theta^+ = \theta^-$ Fstat	4.132	3.631	2.146	2.504
$\theta^+ = \theta^-$ pval	0.0421	0.0567	0.1430	0.1136
Fit statistics				
Observations	116,537	116,537	94,012	94,012
R ²	0.02	0.01	0.01	0.01
Adjusted R ²	0.02	0.01	0.01	0.01

Clustered (Year) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

NOTES: θ^+ is the coefficient on the positive error correction term (convergence when actual RoE is above long-run equilibrium). θ^- is the coefficient on the negative error correction term (convergence when actual RoE is below long-run equilibrium). "LR Coef" refers to the long-run β coefficient from the initial regression: $RoE_{i,t} = \beta Index_{i,t-1} + \varepsilon_{i,t}$.

each month. Conversely, the coefficient on the negative error correction term, θ^- , is -0.0274 . This indicates that where the actual return on equity is below the long-run equilibrium there will be more rapid convergence back toward equilibrium at a rate of 2.74% of the difference each month. To put it more clearly, a sudden increase in the benchmark cost of capital will result in a faster subsequent rise in utilities' return on equity, while a sudden decrease in the benchmark cost of capital will result in a slower subsequent fall in utilities' return on equity.

Across all specifications we consistently see this pattern repeated whereby long-run adjustments occur faster for increases in the benchmark cost of capital than for decreases ($\theta^+ < \theta^-$). Notably though, this difference is more clearly statistically significant for proposed rates of return (columns 1–2) rather than for approved rates of return (columns 3–4). This is consistent with the rates that utilities propose being more likely to exhibit this kind of asymmetric behavior. The regulatory approval process may serve to dampen the asymmetry somewhat, although given the consistent differences in the magnitudes of the coefficients it does not appear to eliminate it entirely.

5.3 Rate Base Impact Results

We next consider how the RoE gap affects capital ownership in Table 4. Across our fixed effects specifications (columns 1–3) we find broadly consistent results. A 1 percentage point increase in the approved RoE gap leads to a 5.6–8.7% higher increase in approved rate base. Our IV specification using rate case timing (column 4) has a strong first stage (Kleibergen–Paap F -stat of 69).²⁰ Using this approach we find an effect of 5.3% which broadly aligns with our fixed effects estimates. This is our preferred specification.

In addition to looking at the increase in the rate base, we also look at the total

20. Our IV specification using rounding has a weak first stage (Kleibergen–Paap F -stat of 2.1) and so is not presented here.

Table 4: Relationship Between Approved Rate of Return and Approved Rate Base Increase

Model:	Fixed effects specs.			IV
	(1)	(2)	(3)	(4)
Variables				
RoE gap (%)	0.0551*** (0.0200)	0.0752*** (0.0240)	0.0867*** (0.0225)	0.0523** (0.0252)
Fixed-effects				
Service Type	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Year		Yes	Yes	Yes
Company			Yes	Yes
Fit statistics				
Observations	2,491	2,491	2,491	2,491
R ²	0.33	0.36	0.69	0.69
Within R ²	0.01	0.004	0.01	0.009
Wald (1st stage), RoE gap (%)				69.1
Dep. var. mean	38.63	38.63	38.63	38.63

Clustered (Year & Company) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

NOTES: The table uses approved RoE. The dependent variable is log of the utility's rate base increase in millions of \$. Columns 1–3 show varying levels of fixed effects. Column 4 is the IV discussed in section 4.3. Our preferred specification is column 4 of table 4. First-stage *F*-statistic is Kleibergen–Paap robust Wald test.

Table 5: Relationship Between Approved Rate of Return and Approved Total Rate Base (both absolute and per MWh; electric utilities only)

Model:	Total, FE (1)	Total, IV (2)	per MWh, FE (3)	per MWh, IV (4)
Variables				
RoE gap (%)	0.0524*** (0.0188)	0.0779** (0.0301)	0.1202** (0.0571)	0.1204 (0.0751)
Fixed-effects				
Service Type	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Company	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,787	1,787	705	705
R ²	0.85	0.85	0.84	0.84
Within R ²	0.006	0.004	0.02	0.02
Wald (1st stage), RoE gap (%)		25.6		21.2
Prop. or Appr.	Appr.	Appr.	Appr.	Appr.
Dep. var. mean	1,516.5	1,516.5	379.5	379.5

Clustered (Year & Company) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

NOTES: The table uses approved RoE. Dependent variables are the total rate base in millions of \$ (Columns 1–2) and the rate base per quantity delivered in \$ per MWh (Columns 3–4). The FE results correspond to the specification used for column 3 in table 4 and the IV results correspond to the specification used for column 4 in table 4. First-stage *F*-statistic is Kleibergen–Paap robust Wald test.

rate base and the total rate base per MWh. These results are in Table 5. We find similar effects for the total rate base, and the effects for total rate base per MWh are potentially even larger. However, these findings are less precisely estimated, in part due to data quality challenges.²¹ Overall we take these results as providing evidence that higher equity returns do lead utilities to increase their capital holdings.²²

As a caveat, we note that an utility can increase their capital holdings in two

21. The total rate base data is less complete. Also when calculating on a per MWh basis, we are only able to merge quantity data for a subset of years for electric utilities.

22. The equivalent results from looking at the proposed changes to the rate base can be found in the appendix.

distinct ways. One option is to reshuffle capital ownership, either between subsidiaries or across firms, so that the utility ends up with more capital on its books, but the total amount of capital is unchanged. The second option is to actually buy and own more capital, increasing the total amount of capital that exists in the state’s utility sector. We do not differentiate between these two cases. Because we don’t differentiate, we consider excess payments by utility customers, but we remain agnostic about the socially optimal level of capital investment.

5.4 Excess Consumer Cost Results

Table 6: Excess costs, by different benchmarks (2019\$ billion per year)

A: Electric		Corp	UST	UST auto	CAPM low	CAPM high	UK
Fixed	2000	1.03	2.37	0.250	4.21	−2.74	4.71
	2020	8.58	9.40	1.43	11.8	1.83	3.90
Adjust	2000	1.06	2.55	0.252	4.76	−2.48	5.42
	2020	10.5	11.7	1.49	15.4	1.91	4.29
B: Natural Gas							
Fixed	2000	0.165	0.371	0.0226	0.620	−0.415	
	2020	2.44	2.76	0.624	3.24	0.655	0.886
Adjust	2000	0.171	0.398	0.0227	0.693	−0.378	
	2020	3.05	3.48	0.661	4.23	0.692	0.959

Note: Excess payments are totals for all IOUs in the US, in billions of 2019 dollars per year. Missing rate base data for utilities in our sample was interpolated based on the estimated average growth rate of the rate base over time. The “fixed” rows take the observed rate base as fixed and estimates excess payments. The “adjust” rows also account for changes in the rate base size, as estimated in table 4 column 4. For cases where it’s relevant the benchmark date is January 1995. See text for details of each benchmark calculation.

Table 6 summarizes our estimates of the excess cost for utility customers. Here we multiply the rate base by the RoE gap to come up with a measure of the additional

payments made to cover the premium in equity returns. To ensure these excess costs are calculated for all utilities in our sample, we must remedy the missing rate base data for some utilities, particularly in the earlier years of our sample.²³ To do this we interpolate using an estimate of the average growth rate for the rate base over time.²⁴

Across our five benchmark measures and using the existing rate base we find excess costs to consumers in 2020 of \$2–15 billion per year. These excess costs, like the RoE gap, depend on the choice of baseline. The economic welfare loss is likely smaller than these excess cost measures – the excess capital provides non-zero benefit, and the ultimate recipients of utility revenues place some value on the additional income.²⁵

Accounting for the way the RoE gap can affect capital ownership increases our estimate of the excess cost to consumers to \$2–20 billion per year. The majority of these costs come from the electricity sector.²⁶

6 Conclusion

Utilities invest a great deal in capital, and need to be compensated for the opportunity cost of their investments. Getting this rate of return correct, particularly the return on equity, is challenging, but is a first-order important task for utility regulators.

Our analysis shows that the RoE that utilities are allowed to earn has changed

23. Approved rate base data is available for 95% of utilities in 2020 and 65% of utilities in 2000.

24. We regress approved rate base on time, controlling for utility by state by service type fixed effects. Within each grouping of utility, state and service type, we start with the first non-missing value and linearly interpolate backwards assuming the rate base changes from period to period according to our estimated growth rate.

25. The RoE gap will ultimately affect utility rates, including the costs of buying electricity, but the ultimate impact on consumption decisions will depend on each utility's rate structure. Analyzing these is outside the scope of this paper.

26. For comparison, total 2019 electricity sales by investor owned utilities were \$204 billion, on 1.89 PWh of electricity (US Energy Information Administration 2020a). Natural gas sales to consumers are \$146 billion on 28.3 trillion cubic feet of gas US Energy Information Administration 2020b. These figures include sales to residential, commercial, industrial, and electric power, but not vehicle fuel. They also include all sales, not just those by investor owned utilities.

dramatically relative to various financial benchmarks in the economy. We estimate that the current approved average return on equity is substantially higher than various benchmarks and historical relationships would suggest. These results are necessarily uncertain, and depending on our chosen benchmark for the cost of equity the premium ranges from 0.5–5.5 percentage points. Put another way, even our most conservative benchmarks come in below the allowed rates of return on equity that regulators set today.

We link this divergence to the apparent asymmetric adjustment of rates to changes in market measures of the cost of capital. Increases to benchmark measures of the cost of capital lead to faster rises in utility returns on equity than is the case for decreases. This is the so-called “rockets and feathers” phenomenon and could be indicative of regulators being more responsive to pressures from the utilities they regulate than from consumers’ demands to keep prices down.

We then turned to the Averch–Johnson effect, and estimated the additional capital this RoE gap generates. In our preferred specification, we estimate that an additional percentage point in the RoE gap leads to 5% higher rate base increases. Depending on our chosen benchmark for the gap, the excess rates collected from consumers could amount to \$2–20 billion per year.

If utilities are earning excess equity returns, a key challenge is to identify what changes to the ratemaking process may help remedy this. Regulators have taken numerous steps over the past few decades to improve the way costs are passed through into rates. For instance, explicit benchmarking and automatic update rules were introduced for fuel costs decades ago. It seems plausible that they could also be used to help equity costs adjust more quickly to changing market conditions, and do so in ways that are less prone to the subjective negotiations of the ratemaking process.

However, the cost of equity is unlikely to perfectly track any single benchmark in the same way as the cost of fuel. Also the automatic update rules for equity returns

that have already been put in place by some PUCs have done little to prevent the trends we highlight.²⁷ As such, a significant degree of regulatory judgment is inevitable in this area.

A clear first step for improving the decisions regulators make over the cost of equity is to avoid some of the arbitrary “rules of thumb” that have been employed to date – see for instance the evidence we find of whole number rounding, or the reluctance to set rates below a nominal 10% that Rode and Fischbeck (2019) highlight.

Bolstering the financial expertise of regulators is another promising path forward.²⁸ Seemingly objective methods like the capital asset pricing model cannot provide a definitive answer on the cost of equity. As we have documented, a range of plausible input assumptions can lead to widely divergent estimates of the cost of equity. When incorporating evidence from these methods regulators need to have the expertise to understand their limitations and push back on the assumptions utilities put forward when using them.

Lastly, process reforms may also be beneficial. In most rate case proceedings, utilities submit their planned expenditures and then regulators decide whether they are prudent. This relies on the notion that utilities are best placed to forecast their detailed needs for labor, materials and equipment (e.g. numbers of new transformers needed and where). However, it is less clear that utilities possess the same unique level of insight when it comes to the cost of equity, especially given that this is so dependent on wider market forces, the performance of peer companies and general investor sentiment. For this component of utility costs the regulator could conduct its own independent internal analysis of the cost of equity first, and then consult on their proposals. In this way it is the regulator that is anchoring the starting point of

27. For instance, regulators at the California PUC feel that the rule, called the cost of capital mechanism (CCM), performed poorly. “The backward looking characteristic of CCM might have contributed to failure of ROEs in California to adjust to changes in financial environment after the financial crisis. The stickiness of ROE in California during this period, in the face of declining trend in nationwide average, calls for reassessment of CCM.” (Ghadessi and Zafar 2017)

28. Azgad-Tromer and Talley (2017) found that providing finance training to regulatory staff did have a moderate effect on moving rates of return closer to standard asset pricing predictions.

the discussion, not the utility.

Our findings have important implications beyond just the additional cost they place on consumers. From a distributional standpoint, higher rates create a transfer from ratepayers to utility stockholders. A high rate of return for *regulated* utilities may also lead to a reshuffling of which assets are owned by regulated versus non-regulated firms. Finally, efficiently pricing energy has important implications for environmental policy, particularly with regard to encouraging electrification which is a key component of efforts to tackle climate change.

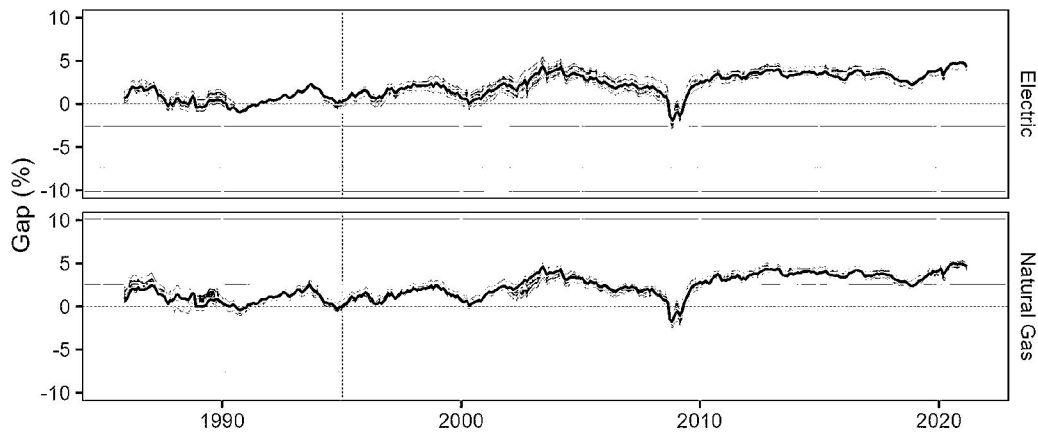
Appendix

A Detail on RoE gap benchmarks

For each of the strategies we utilize, we plot the timeseries of the RoE gap. These are plotted in figures 4, 5, 6, 7, 8, and 9.

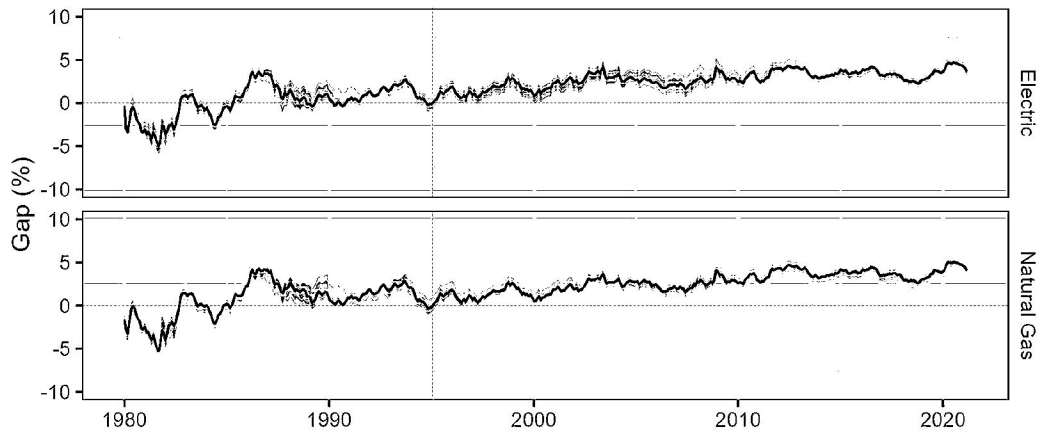
In each plot, we present the median of our RoE gap estimates, weighting by the utility's rate base (in 2019 dollars). Our goal is to show the median of rate base dollar value, rather than the median of utility companies, as the former is more relevant for understanding the impact of the RoE gap. We also show bands, in different shades of blue, that cover the 40–60 percentile, 30–70 percentile, 20–80 percentile, 10–90 percentile, and 2.5–97.5 percentile (all weighted by rate base).

Figure 4: Return on equity gap, benchmarking to same-rated corporate bonds



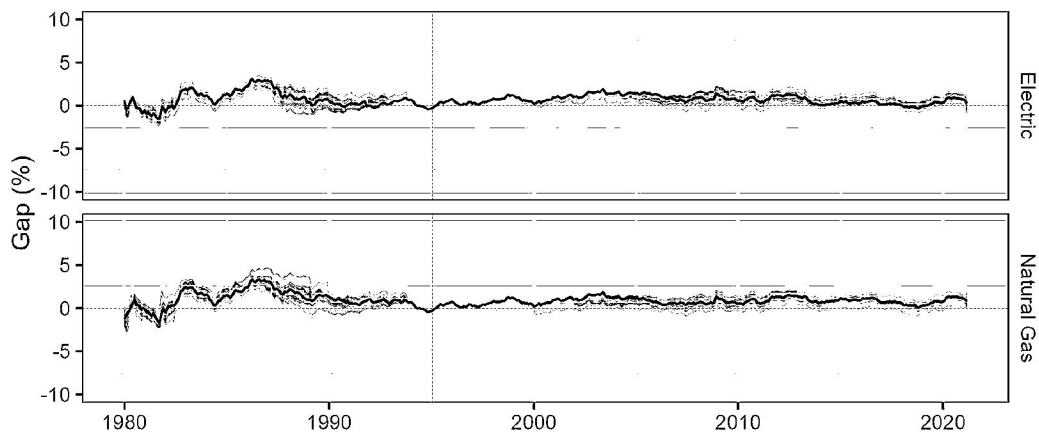
Base year is 1995. Line represents median; shading represents ranges that cover the central 20, 40, 60, 80, and 95% of total IOU rate base. See calculation details in section 4.1.

Figure 5: Return on equity gap, benchmarking to 10-year Treasuries



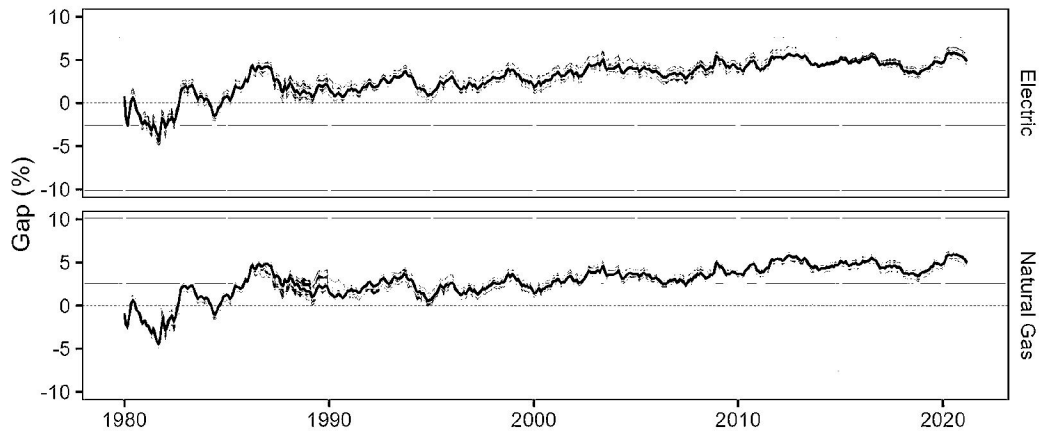
Line represents median; shading represents ranges that cover the central 20, 40, 60, 80, and 95% of total IOU rate base. See calculation details in section 4.1.

Figure 6: Return on equity gap, using automatic update rule



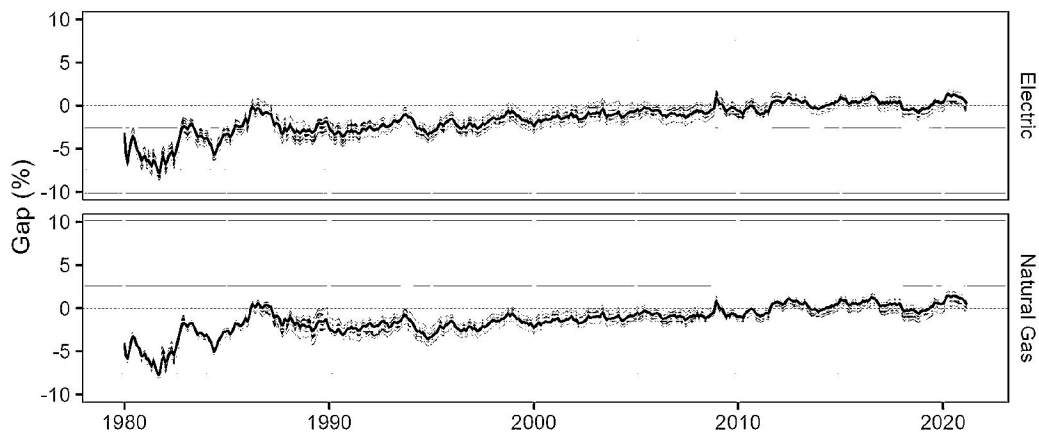
Line represents median; shading represents ranges that cover the central 20, 40, 60, 80, and 95% of total IOU rate base. See calculation details in section 4.1.

Figure 7: Return on equity gap, benchmarking to CAPM (low)



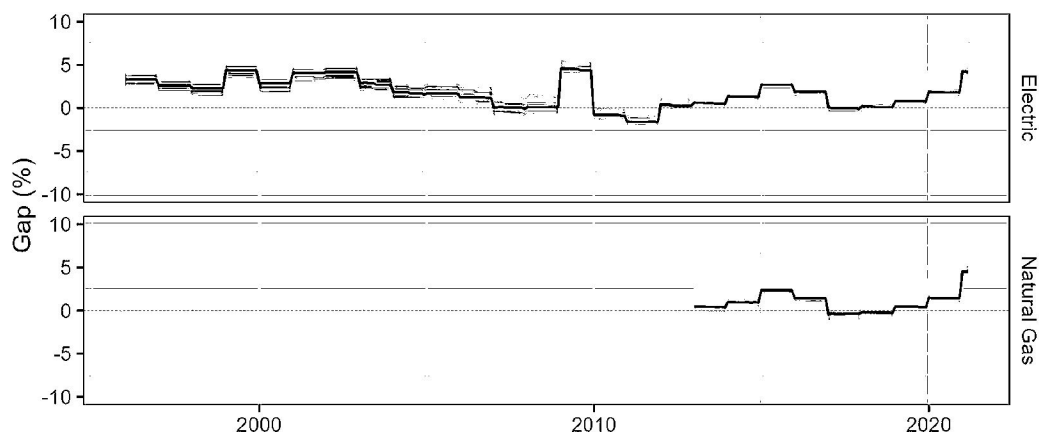
Line represents median; shading represents ranges that cover the central 20, 40, 60, 80, and 95% of total IOU rate base. See calculation details in section 4.1.

Figure 8: Return on equity gap, benchmarking to CAPM (high)



Line represents median; shading represents ranges that cover the central 20, 40, 60, 80, and 95% of total IOU rate base. See calculation details in section 4.1.

Figure 9: Return on equity gap, compared to UK utilities



Line represents median; shading represents ranges that cover the central 20, 40, 60, 80, and 95% of total IOU rate base. See calculation details in section 4.1.

B Detail on Rate Base Impacts

Here we include additional information on our analysis of rate base impacts. The results include estimates using proposed (instead of approved) rate base changes, as well as estimates using the total rate base.

Table 7: Relationship Between Proposed Rate of Return and Proposed Rate Base Increase

Model:	Fixed effects specs.			IV
	(1)	(2)	(3)	(4)
Variables				
RoE gap (%)	0.0670*** (0.0134)	0.0436* (0.0217)	0.0672*** (0.0151)	0.0353 (0.0215)
Fixed-effects				
Service Type	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Year		Yes	Yes	Yes
Company			Yes	Yes
Fit statistics				
Observations	3,210	3,210	3,210	3,210
R ²	0.37	0.39	0.73	0.73
Within R ²	0.02	0.002	0.01	0.008
Wald (1st stage), RoE gap (%)				50.9
Dep. var. mean	63.69	63.69	63.69	63.69

Clustered (Year & Company) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

NOTES: The table uses proposed RoE. The dependent variable is log of the utility's rate base increase in millions of \$. Columns 1–3 show varying levels of fixed effects. Column 4 is the IV discussed in section 4.3. First-stage *F*-statistic is Kleibergen–Paap robust Wald test.

*Table 8: Relationship Between Proposed Rate of Return and
Proposed Total Rate Base (both absolute and per MWh)*

Model:	Total, FE (1)	Total, IV (2)	per MWh, FE (3)	per MWh, IV (4)
Variables				
RoE gap (%)	0.0384 (0.0232)	0.0704** (0.0348)	0.1490** (0.0702)	0.1610** (0.0720)
Fixed-effects				
Service Type	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Company	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,140	2,140	919	919
R ²	0.83	0.83	0.83	0.83
Within R ²	0.003	0.0008	0.03	0.03
Wald (1st stage), RoE gap (%)		19.7		15.1
Prop. or Appr.	Prop.	Prop.	Prop.	Prop.
Dep. var. mean	1,583.5	1,583.5	404.4	404.4

Clustered (Year & Company) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

NOTES: The table uses proposed RoE. Dependent variables are the total rate base in millions of \$ (Columns 1–2) and the rate base per quantity delivered in \$ per MWh (Columns 3–4). The FE results correspond to the specification used for column 3 in table 4 and the IV results correspond to the specification used for column 4 in table 4. First-stage *F*-statistic is Kleibergen–Paap robust Wald test.

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How Is The S&P 500 Different From GDP?

November 4, 2014 2:36 pm by LPL Financial

S&P Is Not GDP by LPL Financial

It is important to recognize that the S&P 500 is not GDP. S&P 500 companies have different drivers for earnings than the components that drive GDP.

The backdrop of solid business spending within a slower trajectory of overall GDP growth can be a favorable one for the stock market.

Although stocks are at the low end of our target 10–15% S&P 500 return range for 2014, we see further gains between now and year end as likely, with profit growth as a primary driver.

S&P Is Not GDP

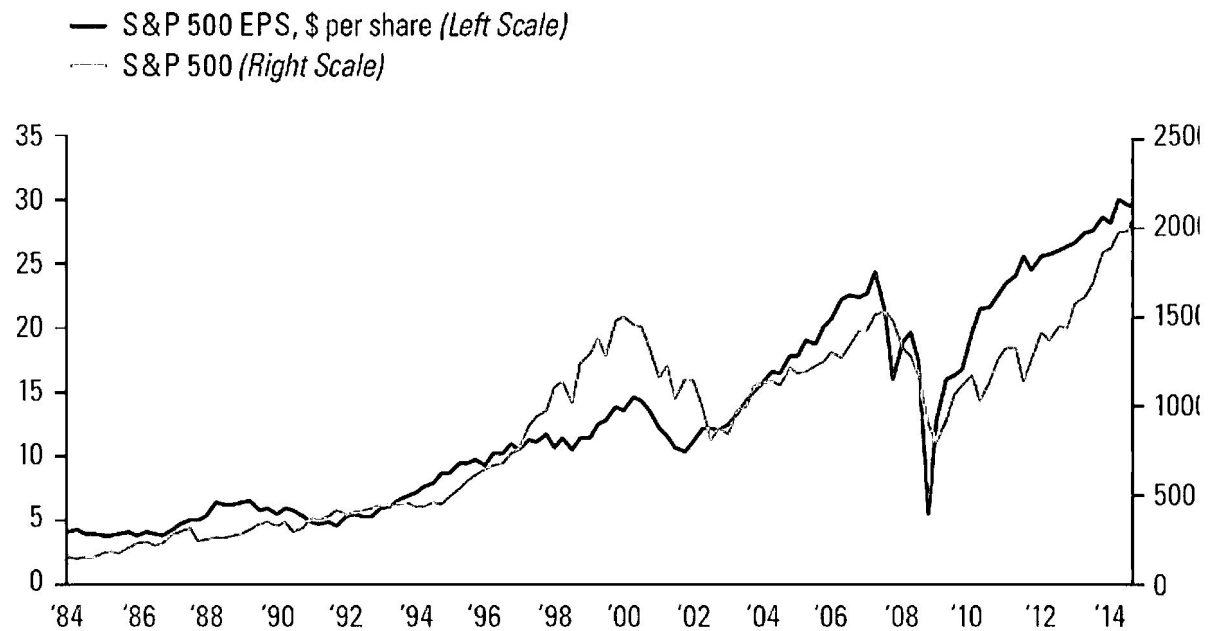
U.S. economic growth has been subpar—right around 2%—during much of the ongoing economic expansion. Yet, the S&P 500 has returned nearly 230% cumulatively since the bear market low on March 9, 2009. How did that happen and is it justified?

Before trying to answer to those questions, it is worth pointing out that this situation is not all that unusual. In fact, since 1950, the S&P 500 median return is 13% (average is 12%) when real gross domestic product (GDP) grows less than 3%, with the S&P generating a positive return 68% of the time. However, a good portion of those returns come during recessions—historically, the best time to buy stocks is at recession troughs. But even if we take those periods in and around recessions out of the equation and look at annual returns when GDP growth is between 1–3%, the median (and average) S&P 500 return is a respectable 7–8%. Stocks tend to like average (or slightly below average) growth, which is not strong enough to generate worrisome inflation.

Now back to the question of what has driven this stock market to far outperform economic growth. Some might say quantitative easing (QE), which ended at the end of October 2014 in the United States (the Bank of Japan expanded its QE program last week on Halloween). While QE has benefitted U.S. stocks (how much is up for debate) by helping keep interest rates low and encouraging investors to buy riskier assets (see this week's Weekly Economic Commentary for details), the bull market has been driven by much more than that. Increasing confidence in the economic recovery—albeit a slow one?—and greater policy clarity in Washington have also

been factors. But we think the best answer is earnings. In fact, over the past four decades, earnings have provided solid support for equity market gains [Figure 1].

1 Earnings Have Supported 40 Years of Bull Market Gains



Source: LPL Financial Research, Bloomberg, Thomson Reuters, FactSet 10/30/14

Quarterly data.

S&P GDP

But this commentary is not a deep dive into earnings (that's coming soon). Instead, this week we highlight the differences between the S&P 500 and GDP, i.e., the U.S. economy, to shed some light on how corporate profits can grow so much faster than the economy, and bring stock prices right along with them.

S&P GDP

S&P	GDP
2/3 manufacturing	2/3 consumption
20–25% business spending	70% consumer spending
15% consumer discretionary spending	20–25% discretionary consumer categories
40% overseas	10% international trade
higher commodity prices BOOST	higher commodity prices DRAG

Source: LPL Financial Research 11/03/14

How Is S&P Different from GDP?

S&P 500 companies have different drivers for earnings than the components that drive GDP. There are several key factors that differentiate the economic data from the earning power of corporate America that we think are important for investors to keep in mind:

Corporate profits are more manufacturing driven. Two-thirds of S&P 500 profits are from manufacturing, while two-thirds of U.S. consumption in GDP is services. The Institute for Supply Management (ISM) Manufacturing Survey has exceeded a solidly expansionary 55 level for five consecutive months, a positive signal for U.S. manufacturers. The recently released report on GDP for the third quarter of 2014 showed capital spending growth of 7% annualized, double the 3.5% growth rate of the overall U.S. economy. Many U.S. industrial and materials companies are benefiting from the U.S. energy renaissance that has brought greater access to

cheaper energy sources and demand for infrastructure. The strength of the U.S manufacturing economy continues to support our positive industrials sector view.

Corporate profits are less consumer driven. While 70% of GDP is consumer spending, only one-third of it is from discretionary categories, while an even lower 15% of S&P 500 profits come from consumer discretionary spending. A more significant portion of S&P 500 earnings?—?estimated 20–25%?—?comes from business spending. As we move into the latter half of the economic cycle, we expect a stronger contribution from the business spending side than consumer spending side, suggesting the S&P 500 is better positioned than GDP as 2014 comes to a close and we enter 2015. Still, we expect U.S. GDP to sustain a growth rate at or around 3% through year end and well into 2015.

Corporate profits are more international trade driven. International trade only accounts for about 10% of GDP and acts as a drag on growth for most quarters because the United States imports more than it exports. Today, we estimate that 40% of S&P 500 profits are earned overseas?—?with about half of that from rapidly emerging market economies, including China. This makes S&P 500 earnings less dependent upon U.S. growth than 15–20 years ago, when roughly 20% of S&P profits were earned overseas, and 30 years ago when only a small portion of earnings were foreign sourced.

Corporate profits are hurt much less by higher commodity prices than the S&P 500. In fact, higher commodity prices generally benefit S&P 500 companies because most of them either produce commodities (energy and materials), supply commodity producers with equipment (largely industrials), or are not heavy commodity users and are therefore not impacted much by higher commodity prices (technology, healthcare, financials, and telecommunications). U.S. corporations are increasingly benefiting from access to cheaper energy as the energy renaissance continues, although the pace of oil and gas production and the corresponding infrastructure build-out may slow and be a modest drag on S&P 500 earnings should oil prices fall much further. Our view is that oil stabilizes at or near \$80 and begins to move higher; but lower oil prices are a risk for energy producers and equipment manufacturers.

Solid Business Spending with Slower GDP Growth Trajectory

We believe the backdrop of solid business spending within a slower trajectory of overall GDP growth can be a favorable one for the stock market. The economic data, while good recently, do not accurately reflect the earning power of corporate America, which remains quite strong. The S&P is not GDP?—?S&P 500 companies have different drivers for earnings than the components that drive GDP growth. Stocks are fundamentally driven by earnings, which have supported the gains during the current bull market and left valuations still within a reasonable range. The earnings picture still looks quite good today, with the S&P 500 on track for 9% year-over-year earnings growth in the third quarter, with about three quarters of the index constituents having reported.

Although stocks are at the low end of our target 10–15% S&P 500 return range for 2014, we see further gains between now and year end may be likely, with profit growth as a primary driver—with perhaps some help from the calendar, as midterm elections have historically been positive for stock returns.

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Markets

Penalty for Being Rated Junk Drops to Lowest Level Since 2007

By [Alex Wittenberg](#)

May 4, 2021, 12:51 PM EDT

► Spread between high grade and high yield now 197 basis points

► Gap narrows amid rally in high yield as risk appetite grows

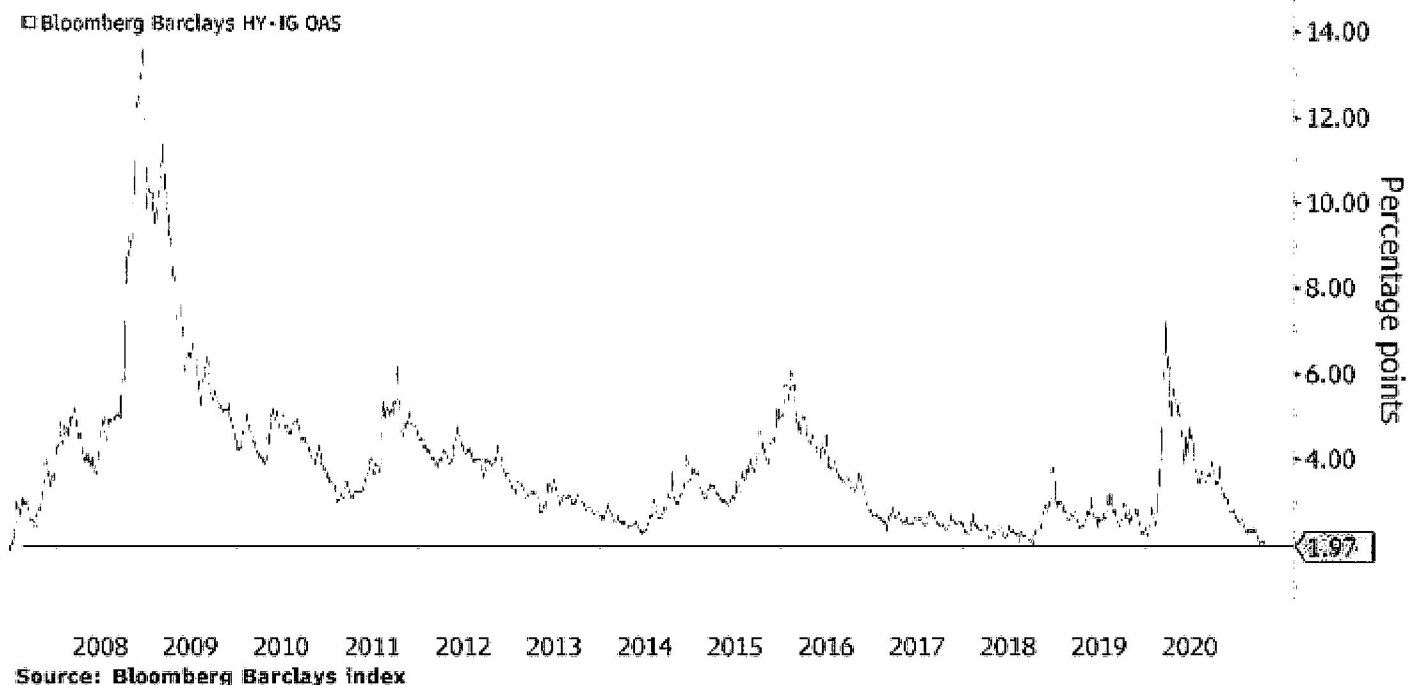
For investment-grade companies on the cusp of junk, it might not be so bad on the other side.

The additional cost for firms to borrow in the U.S. high-yield market versus high grade narrowed to 197 basis points Monday, the tightest since before the global financial crisis, according to Bloomberg Barclays index data. The spread last dipped below 200 basis points in 2007, the data show.

A relentless rally in junk-rated debt is narrowing the gap, as high-yield spreads also hit a pre-crisis tight _____ Monday. Yields dropped to an all-time low as investors pile into riskier assets for higher returns, betting _____ a recovery will boost particularly the most speculative names.

Tighter and Tighter

Spread between HY and IG bonds hits lowest since 2007



Cheap borrowing costs are encouraging a barrage of high-yield issuance, which has broken records in every month this year after setting a new high mark in 2020. It's especially helping the lowest-rated companies tap the market, with CCC yields dropping 34 basis points to a new low of 5.72%.

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JUN 20 2006

UTILITY STOCKS AND THE SIZE EFFECT: AN EMPIRICAL ANALYSIS

Annie Wong*

I. Introduction

The objective of this study is to examine whether the firm size effect exists in the public utility industry. Public utilities are regulated by federal, municipal, and state authorities. Every state has a public service commission with board and varying powers. Often their task is to estimate a fair rate of return to a utility's stockholders in order to determine the rates charged by the utility. The legal principles underlying rate regulation are that "the return to the equity owner should be commensurate with returns on investments in other enterprises having corresponding risks," and that the return to a utility should be sufficient to "attract capital and maintain credit worthiness." However, difficulties arise from the ambiguous interpretation of the legal definition of *fair and reasonable rate of return* to an equity owner.

Some finance researchers have suggested that the Capital Asset Pricing Model (CAPM) should be used in rate regulation because the CAPM beta can serve as a risk measure, thus making risk comparisons possible. This approach is consistent with the spirit of a Supreme Court ruling that equity owners sharing similar level of risk should be compensated by similar rate of return.

The empirical studies of Banz (1981) and Reinganum (1981) showed that small firms tend to earn higher returns than large firms after adjusting for beta. This phenomenon leads to the proposition that firm size is a proxy for omitted risk factors in determining stock returns. Barry and Brown (1984) and Brauer (1986) suggested that the omitted risk factor could be the differential information environment between small and large firms. Their argument is based on the fact that investors often have less publicly available information to assess the future cash flows of small firms than that of large

firms. Therefore, an additional risk premium should be included to determine the appropriate rate of return to shareholders of small firms.

The samples used in prior studies are dominated by industrial firms, no one has examined the size effect in public utilities. The objective of this study is to extend the empirical findings of the existing studies by investigating whether the size effect is also present in the utility industry. The findings of this study have important implications for investors, public utility firms, and state regulatory agencies. If the size effect does exist in the utility industry, this would suggest that the size factor should be considered when the CAPM is being used to determine the fair rate of return for public utilities in regulatory proceedings.

II. Information Environment of Public Utilities

In general, utilities differ from industrials in that utilities are heavily regulated and they follow similar accounting procedures. A public utility's financial reporting is mainly regulated by the Securities and Exchange Commission (SEC) and the Federal Energy Regulatory Commission (FERC). Under the Public Utility Holding Company Act of 1935, the SEC is empowered to regulate the holding company systems of electric and gas utilities. The Act requires registration of public utility holding companies with the SEC. Only under strict conditions would the purchase, sale or issuance of securities by these holding companies be permitted. The purpose of the Act is to keep the SEC and investors informed of the financial conditions of these firms. Moreover, the FERC is in charge of the interstate operations of electric and gas companies. It requires utilities to follow the accounting procedures set forth in its Uniform Systems of Accounts. In particular, electric and gas utilities must request their Certified Public Accountants to certify that certain schedules in the financial reports are in conformity with the Commission's accounting requirements. These detailed reports are submitted annually and are open to the public.

*Western Connecticut State University. The author thanks Philip Perry, Robert Hagerman, Eric Press, the anonymous referee, and Clay Singleton for their helpful comments.

The FERC requires public utilities to keep accurate records of revenues, operating costs, depreciation expenses, and investment in plant and equipment. Specific financial accounting standards for these purposes are also issued by the Financial Accounting Standards Board (FASB). Uniformity is required so that utilities are not subject to different accounting regulations in each of the states in which they operate. The ultimate objective is to achieve comparability in financial reporting so that factual matters are not hidden from the public view by accounting flexibility.

Other regulatory reports tend to provide additional financial information about utilities. For example, utilities are required to file the FERC Form No. 1 with the state commission. This form is designed for state commissions to collect financial and operational information about utilities, and serves as a source for statistical reports published by state commissions.

Unlike industrials, a utility's earnings are predetermined to a certain extent. Before allowed earnings requests are approved, a utility's performance is analyzed in depth by the state commission, interest groups, and other witnesses. This process leads to the disclosure of substantial amount of information.

III. Hypothesis and Objective

Due to the Act of 1935, the Uniform Systems of Accounts, the uniform disclosure requirements, and the predetermined earnings, all utilities are reasonably homogeneous with respect to the information available to the public. Barry and Brown (1984) and Brauer (1986) suggested that the difference of risk-adjusted returns between small and large firms is due to their differential information environment. Assuming that the differential information hypothesis is true, then uniformity of information availability among utility firms would suggest that the size effect should not be observed in the public utility industry. The objective of this paper is to provide a test of the size effect in public utilities.

IV. Methodology

1. Sample and Data

To test for the size effect, a sample of public utilities and a sample of industrials matched by equity value are formed so that their results can be compared. Companies in both samples are listed on the Center for Research in Security Prices (CRSP)

Daily and Monthly Returns files. The utility sample includes 152 electric and gas companies. For each utility in the sample, two industrial firms with similar firm size (one is slightly larger and the other is slightly smaller than the utility) are selected. Thus, the industrial sample includes 304 non-regulated firms.

The size variable is defined as the natural logarithm of market value of equity at the beginning of each year. Both the equally-weighted and value-weighted CRSP indices are employed as proxies for the market returns. Daily, weekly and monthly returns are used. The Fama-MacBeth (1973) procedure is utilized to examine the relation between risk-adjusted returns and firm size.

2. Research Design

All utilities in the sample are ranked according to the equity size at the beginning of the year, and the distribution is broken down into deciles. Decile one contains the stocks with the lowest market values while decile ten contains those with the highest market values. These portfolios are denoted by MV_1 , MV_2 , ..., and MV_{10} , respectively.

The combinations of the ten portfolios are updated annually. In the year after a portfolio is formed, equally-weighted portfolio returns are computed by combining the returns of the component stocks within the portfolio. The betas for each portfolio at year t , $\hat{\beta}_{pt}$'s, are estimated by regressing the previous five years of portfolio returns on market returns:

$$\tilde{R}_{pt} = \alpha_p + \hat{\beta}_{pt}\tilde{R}_{mt} + \tilde{U}_{pt} \quad (1)$$

where

R_{pt} = periodic return in year t on portfolio p

R_{mt} = periodic market return in year t

U_{pt} = disturbance term.

Banz (1981) applied both the ordinary and generalized least squares regressions to estimate β ; and concluded that the results are essentially identical (p.8). Since adjusting for heteroscedasticity does not necessarily lead to more efficient estimators, the ordinary least squares procedures are used in this study to estimate β in equation (1).

The following cross-sectional regression is then run for the portfolios to estimate γ_i , $i = 0, 1$, and 2:

$$R_{pt} = \gamma_0 + \gamma_1 \hat{\beta}_{pt} + \gamma_2 \hat{S}_{pt} + U_{pt} \quad (2)$$

where

$\hat{\beta}_{pt}$ = estimated beta for portfolio p at year t ,
 $t=1968, \dots, 1987$

$\hat{S}_{pt}$ = mean of the logarithm of firm size in
portfolio p at the beginning of year t

U_{pt} = disturbance term.

Depending on whether daily, weekly or monthly returns are used, a portfolio's average return changes periodically while its beta and size only change once a year. The γ_1 and γ_2 coefficients are estimated over the following four subperiods: 1968-72, 1973-77, 1978-82 and 1983-1987. If portfolio betas can fully account for the differences in returns, one would expect the average coefficient for the beta variable to be positive and for the size variable to be zero. A t -statistic will be used to test the hypothesis. The coefficients of a matched sample are also examined so that the results between industrial and utility firms can be compared.

V. Analysis of Results

1. Equity Value of the Utility Portfolios

The mean equity values of the ten size-based utility portfolios are reported in Table 1. Panels A and B present the average firm size of these portfolios at the beginning and end of the test period, 1968-1987. The first interesting observation from Table 1 is that the difference in magnitude between the smallest and the largest market value utility portfolios is tremendous. In Panel A, the average size of MV_1 is about \$31 million while that of MV_{10} is over \$1.4 billion. In Panel B, that is twenty years later, they are \$62 million and \$5.2 billion, respectively. Another interesting finding is that there is a substantial increase in average firm size from MV_9 to MV_{10} . Since these two findings are consistent over the entire test period, the average portfolio market values for interim years are not reported. These results are similar to the empirical evidence provided by Reinganum (1981).

The utility sample in this study contains 152 firms whereas Reinganum's sample contains 535 firms that are mainly industrial companies. Two conclusions may be drawn from the results of the Reinganum study and this one. First, utilities and industrials are similar in the sense that their market

values vary over a wide spectrum. Second, the fact that there is a huge jump in firm size from MV_9 to MV_{10} indicates that the distribution of firm size is positively skewed. To correct for the skewness problem, the natural logarithm of the mean equity value of each portfolio is calculated. This variable is then used in later regressions instead of the actual mean equity value.

2. Betas of the Utility and Industrial Samples

The betas based on monthly, weekly and daily returns are reported for the utility and industrial samples. For simplicity, they will be referred to as monthly, weekly, and daily betas. In all cases, five years of returns are used to estimate the systematic risk. The betas estimated over the 1963-67 time period are used to proxy for the betas in 1968, which is the beginning of the test period. By the same token, the betas obtained from the time period 1982-86 are used as proxies for the betas in 1987, which is the end of the test period.

The betas from using the equally-weighted and value-weighted indices are calculated in order to check whether the results are affected by the choice of market index. Since the results are similar, only those obtained from the equally-weighted index are reported and analyzed.

Table 2 reports the monthly, weekly and daily betas of the two samples at the beginning and end of the test period. Panel A shows the various betas of the industrial portfolios. Two conclusions may be drawn. First, in the 1960's, smaller market value portfolios tend to have relatively larger betas. This is consistent with the empirical findings by Banz (1981) and Reinganum (1981). Second, this trend seems to vanish in the 1980's, especially when weekly and daily returns are used.

The betas of the utility portfolios are presented in Panel B. The table shows that none of the utility betas are greater than 0.71. A comparison between Panels A and B reveals that utility portfolios are relatively less risky than industrial portfolios after controlling for firm size. The comparison also reveals that, unlike industrial stocks, betas of the utility portfolios are not related to the market values of equity.

The negative correlation between firm size and beta in the industrial sample may introduce a multicollinearity problem in estimating equation (2). Banz (p.11) had addressed this issue and concluded that the test results are not sensitive to the

multicollinearity problem. For the utility sample, this problem does not exist.

3. Tests on the Coefficients of Beta and Size

The beta and firm size are used to estimate γ_1 and γ_2 in equation (2). A t-statistic is used to test if the mean values of the gammas are significantly different from zero. The tests were performed for four 5-year periods which are reported in Table 3. The mean of the gammas and their t-statistic are presented in Panel A for the utilities and in Panel B for the industrial firms.

The empirical results for the utility sample are reported in Panel A of Table 3. When monthly returns are used, 60 regressions were run to obtain 60 pairs of gammas for each of the 5-year periods. When daily returns are used, over 1200 regressions were run for each period to obtain the gammas. The results are similar: in all of the time periods tested, none of the average coefficients for beta and size are significantly different from zero. When weekly returns are used, 260 pairs of gammas were obtained. The average coefficients for beta are not significant in any test period, and the average coefficients for size are not significant in three of the test periods. For the test period of 1978-82, the average coefficient for size is significantly negative at a 5% level.

The test results for the industrial sample are reported in Panel B of Table 3. When monthly returns are used, the average coefficient estimates for size and beta are significant and have the expected sign only in the 1983-87 test period. When weekly returns are used, only the size variable is significantly negative in the 1978-82 period. When daily returns are used, the coefficient estimates for betas and size are not significant at any conventional level.

According to the CAPM, beta is the sole determinant of stock returns. It is expected that the coefficient for beta is significantly positive. However, the empirical findings reported in this study and in Fama and French (1992) only provide weak support for beta in explaining stock returns. The empirical findings in this study also suggest that the size effect varies over time. It is not unusual to document the firm size effect at certain time periods but not at others. Banz (1981) found that the size effect is not stable over time with substantial differences in the magnitude of the coefficient of the size factor (p.9, Table 1). Brown, Kleidon and Marsh (1983) not only have shown that size effect is not constant over time but also have reported a reversal of the size anomaly for certain years.

The research design of this study allows us to keep the sample, test period, and methodology the same with the holding-period being the only variable. The size effect is documented for the industrial sample in one of the four test periods when monthly returns are used and in another when weekly returns are used. When daily returns are used, no size effect is observed. For the utility sample, the size effect is significant in only one test period when weekly returns are used. When monthly and daily returns are used, no size effect is found. Therefore, this study concludes that the size effect is not only time-period specific but also holding-period specific.

VI. Concluding Remarks

The fact that the two samples show different, though weak, results indicates that utility and industrial stocks do not share the same characteristics. First, given firm size, utility stocks are consistently less risky than industrial stocks. Second, industrial betas tend to decrease with firm size but utility betas do not. These findings may be attributed to the fact that all public utilities operate in an environment with regional monopolistic power and regulated financial structure. As a result, the business and financial risks are very similar among the utilities regardless of their sizes. Therefore, utility betas would not necessarily be expected to be related to firm size.

The objective of this study is to examine if the size effect exists in the utility industry. After controlling for equity values, there is some weak evidence that firm size is a missing factor from the CAPM for the industrial but not for the utility stocks. This implies that although the size phenomenon has been strongly documented for the industrials, the findings suggest that there is no need to adjust for the firm size in utility rate regulations.

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Table 1

Average Equity Size of the Utility Portfolios at the
Beginning and End of the Test Period
(Dollar figures in millions)

	A: Beginning (1968)	B: End (1987)
MV ₁	\$31	\$62
MV ₂	\$77	\$177
MV ₃	\$113	\$334
MV ₄	\$161	\$475
MV ₅	\$220	\$715
MV ₆	\$334	\$957
MV ₇	\$437	\$1,279
MV ₈	\$505	\$1,805
MV ₉	\$791	\$2,665
MV ₁₀	\$1,447	\$5,399

Table 2

Betas of the Two Samples at the Beginning and End of the Test Period

	<u>Monthly Betas</u>		<u>Weekly Betas</u>		<u>Daily Betas</u>	
	1963-67	1982-86	1963-67	1982-86	1963-67	1982-86
Panel A: Industrial Firms						
MV ₁	0.89	1.00	1.15	0.95	1.11	0.92
MV ₂	0.94	0.87	1.07	1.01	1.14	1.01
MV ₃	0.88	0.82	1.12	0.86	1.14	1.04
MV ₄	0.69	0.74	1.00	0.83	1.03	0.86
MV ₅	0.73	0.80	1.05	0.96	1.13	1.01
MV ₆	0.66	0.82	1.03	1.01	1.05	1.04
MV ₇	0.64	0.81	0.97	1.04	0.98	1.09
MV ₈	0.62	0.75	0.97	1.11	1.00	1.20
MV ₉	0.52	0.78	0.84	1.06	0.94	1.16
MV ₁₀	0.43	0.65	0.78	1.01	0.86	1.22
Panel B: Public Utilities						
MV ₁	0.30	0.37	0.31	0.43	0.30	0.40
MV ₂	0.28	0.38	0.37	0.47	0.36	0.44
MV ₃	0.22	0.42	0.33	0.42	0.31	0.49
MV ₄	0.27	0.35	0.36	0.52	0.34	0.54
MV ₅	0.25	0.45	0.37	0.61	0.35	0.62
MV ₆	0.25	0.41	0.39	0.54	0.40	0.65
MV ₇	0.20	0.35	0.34	0.54	0.37	0.63
MV ₈	0.17	0.38	0.34	0.65	0.33	0.68
MV ₉	0.19	0.34	0.35	0.60	0.34	0.71
MV ₁₀	0.18	0.29	0.38	0.59	0.39	0.71

Table 3

Tests on the Mean Coefficients of Beta (γ_1) and Size (γ_2)

$$R_{pt} = \gamma_{\alpha} + \gamma_{1t}\hat{\beta}_{pt} + \gamma_{2t}\hat{S}_{pt} + U_{pt}$$

Returns Used:		Monthly (t-value)	Weekly (t-value)	Daily (t-value)
Panel A: Utility Sample				
1968-72	γ_1	-0.46% (-0.26)	-0.32% (-0.42)	-0.02% (-0.18)
	γ_2	-0.07% (-0.78)	-0.01% (-0.51)	-0.00% (-0.46)
1973-77	γ_1	-0.28% (-0.13)	0.14% (0.14)	-0.03% (-0.21)
	γ_2	-0.11% (-0.70)	-0.03% (-0.67)	-0.00% (-0.53)
1978-82	γ_1	0.55% (0.36)	0.54% (1.00)	0.05% (0.43)
	γ_2	-0.10% (-0.75)	-0.05% (-1.71)*	-0.01% (-1.60)
1983-87	γ_1	1.74% (1.28)	-0.24% (-0.51)	-0.02% (-0.18)
	γ_2	-0.16% (-1.54)	-0.03% (-0.86)	-0.01% (-0.63)
Panel B: Industrial Sample				
1968-72	γ_1	-0.36% (-0.27)	-0.28% (-0.55)	-0.02% (-0.32)
	γ_2	0.07% (0.43)	-0.01% (-0.19)	0.00% (0.51)
1973-77	γ_1	1.34% (0.64)	-0.23% (-0.31)	0.14% (1.45)
	γ_2	-0.01% (-0.06)	-0.04% (-0.85)	-0.00% (-0.64)
1978-82	γ_1	-0.84% (-0.28)	-0.56% (-0.91)	-0.09% (-0.81)
	γ_2	-0.29% (-0.75)	-0.01% (-1.72)*	-0.00% (-1.33)
1983-87	γ_1	2.51% (1.83)*	0.34% (0.64)	0.11% (1.40)
	γ_2	-0.25% (-1.90)*	-0.01% (-0.43)	0.00% (0.14)

* Significant at the 5% level based on a one-tailed test.

The Accuracy of Analysts' Long-Term Earnings Per Share Growth Rate Forecasts

January 24, 2008

Patrick Cusatis, CFA and J.Randall Woolridge
The Pennsylvania State University

ABSTRACT: In this study we examine the accuracy of analyst long-term and one-year earnings per share growth rate forecasts over the last 20 years. We find that analysts' earnings growth rate estimates are consistently overly-optimistic and are about two times the level of GDP growth. Analyst predictions of earnings are better for one-year projections than for long-term projections, but are still overly-optimistic. We find that analyst coverage does not have a significant impact on the optimistic bias in analysts' EPS growth rate forecasts. We do find that a contributing factor for the bias in analysts' earnings estimates is the resistance of analysts to project negative earnings growth. Furthermore, we find that earnings estimates have a continued bias after the 2003 Global Analyst Research Settlements.

Introduction

The expected growth rate of long-term earnings plays a critical role in investment management and corporate finance. An essential element in valuation modeling and cost of capital estimation, long-term earnings growth is periodically forecasted by Wall Street analysts to provide investors with a better understanding of the current and future cash flows likely to be generated by a firm's operations. Periods of high earnings growth rates are usually accompanied with bull markets, and periods of low or negative earnings growth rates tend to produce bear markets. In addition, companies with high earnings growth rates usually sell at high price-to-earnings (P/E) ratios, and stocks with low earnings growth rates trade at low P/E ratios.

A number of studies have indicated that analysts' forecasts of earnings are upwardly biased. For example, Barefield and Comiskey (1975), DeBondt and Thaler (1990), Butler and Lang (1991), Abarbanall (1991), and Brown (1997) find an overall optimism in analysts' earnings forecasts. Becchetti, Hasan, Santoro, and Anandarajan (2007) find evidence that an over-optimism bias is highest during bull markets. Hong and Kubik (2003) find that brokerage houses reward optimistic analysts who promote stocks. In addition, the popular press occasionally highlights evidence of analysts forecast bias.¹

However, these studies assessing the accuracy of analysts' earnings estimates are based on forecasts of quarterly earnings. That is, these studies evaluate the accuracy of analysts' earnings forecasts for periods up to one quarter before a quarterly EPS figure is released. Our study examines analysts' long-term (three- to five- year) and one-year

¹ See for example, Brown (2003) and Smith (2003).

ahead EPS growth rate forecasts. According to financial theory, long-term expected earnings growth drives the valuation of the overall stock market and individual common stocks. As such, long-term EPS growth rate forecasts are an essential component of cash flow valuation models for firms and the market and are used in estimating the cost of capital.

We begin by evaluating historic EPS growth. Many have argued that there is an upward limit on EPS growth as determined by sustainable GDP growth. Bernstein and Arnott (2003) and Arnott (2004) indicate that EPS growth must be below sustainable growth in economic productivity. We show that the historic growth rate in EPS and GDP in the U. S. is in the 7.0% range. As an initial indication of accuracy of analysts' forecasts, we find that analysts' estimates of long-term EPS growth are substantially above this level.

We examine the accuracy of analysts' long-term earnings and one-year ahead EPS growth rate estimates over the last 20 years. We find that analysts' earnings growth rate estimates are consistently overly-optimistic. Analyst predictions of earnings growth are better for one-year growth rate projections than for long-term growth rate projections, but are still significantly overly-optimistic. Analysts only underestimate EPS growth following periods of economic recession which are associated with EPS recovery after large declines in earnings. We also evaluate whether the number of analysts covering a company is associated with the overly-optimistic bias in projected EPS growth rates. We find that analyst coverage does not have a significant impact on the bias in projected EPS growth rates. We do find that a contributing reason for the bias in analysts' long-term and one-year EPS growth rate estimates is the resistance of analysts to project negative earnings growth. We find that analysts rarely project negative EPS growth, despite the fact that companies commonly experience negative earning growth over three- to –five-

year time periods. Based on the research of others, we suggest three explanations for the upward bias in analysts' earnings estimates. The first explanation is based on career concerns or conflicts of interest. Analysts are rewarded for biased forecasts by their employers (brokerage houses) who want them to hype stocks so that the brokerage house can garner trading commissions and win underwriting deals. The second explanation is based on selection bias. Analysts only follow stocks that they recommend and do not issue forecasts on those that they do not like. The third explanation is a cognitive or behavioral bias. Analysts become attached to the companies that they cover and lose objectivity. This would imply that analysts are systematically biased. Since they are only projecting the companies they follow, and not the market, the end result is a strong upward bias on earnings projections.

Finally, we assess the optimistic bias in analysts' EPS growth rate estimates for the period after the Global Analyst Research Settlements in 2003. Presumably, any bias in the research of Wall Street investment firms should have been impacted by New York Attorney General (now Governor) Elliot Spitzer's investigation and the \$1.5B payment made by nine major brokerage firms. Nonetheless, we find a continued optimistic bias in long-term earnings growth rate estimates after the Settlements.

This study is organized as follows. Initially, the historic growth of earnings on S&P 500 companies is compared to the growth in GDP to establish the historic relationship between corporate earnings growth and economic growth. Then, analysts' forecasts of earnings growth for long-term and one-year time horizons are compared to actual earnings growth. We also evaluate analyst coverage as a possible contributing factor in earnings forecast bias. Next, negative earnings growth projections are examined as a possible explanation for the earnings estimate bias. Finally we investigate analysts'

earnings estimates following the Global Research Regulatory Settlement to see if analysts have adjusted their bias.

Data and Methodology

One of the most common approaches to estimating the long-term earnings growth rates for companies is to use the mean estimates of the forecasts of Wall Street securities' analysts as published by such services as Zack's Investment Research, Thomson First Call Research, or the Institutional Brokers' Estimate System (I/B/E/S). I/B/E/S has a more comprehensive coverage of brokerage firms and financial analysts than the other databases. It includes many more analysts from smaller brokerage firms, and also includes important brokerage firms such as Merrill Lynch, Goldman Sachs, and Donaldson, Lufkin & Jenrette that are not included in Zack's Investment Research.

Using the I/B/E/S database, we collect long-term and one-year ahead annual growth rate estimates for all firms from 1984 to 2006, inclusive. We require that companies not only have projected EPS growth rate estimates, but also have EPS figures for the four-year ahead period (for the long-term forecasts) and the one-year ahead period (for the one-year forecasts) so that forecasted and actual EPS growth rates can be compared. Based on projected and actual earnings per share, we calculate implied geometric growth rates. We compare analysts' projected and actual EPS growth rates for long-term EPS growth rate forecasts and one-year EPS growth rate estimates. The data result in an average of 1,383 firms and 1,275 firms per year, for one-year and long-term growth rates, respectively. The descriptive statistics for the data are reported by year in Table 1.

Table 1
Number of Companies and Average Number of Analysts:
One-Year and Long-Term Analyst Forecast Data

	One-Year Forecasts		Long-Term Forecasts	
Year	Number of Companies	Average Number of Analysts	Number of Companies	Average Number of Analysts
1984	1,245	8.61	--	--
1985	1,154	10.30	--	--
1986	1,140	10.44	--	--
1987	1,047	11.02	--	--
1988	1,095	10.70	808	6.09
1989	1,245	10.64	899	6.29
1990	1,260	10.78	892	6.49
1991	1,138	10.01	921	6.34
1992	1,192	9.60	1,003	5.49
1993	1,314	9.55	1,125	5.90
1994	1,475	9.71	1,175	5.69
1995	1,557	9.11	1,148	5.86
1996	1,652	8.74	1,158	5.68
1997	1,489	8.33	1,218	5.51
1998	1,375	7.75	1,466	4.99
1999	1,258	8.54	1,490	4.95
2000	1,176	8.26	1,503	5.08
2001	1,469	7.68	1,467	5.26
2002	1,367	7.13	1,518	5.39
2003	1,464	7.78	1,577	5.56
2004	1,565	8.60	1,663	5.24
2005	1,620	8.73	1,578	5.07
2006	2,502	6.92	1,628	5.59
Mean	1,383	9.08	1,275	5.61
Median	1,314	8.74	1,218	5.56

Source: I/B/E/S. Long-term numbers are based on the average of quarterly numbers for each year.

Analysts Long-Term EPS Growth Rate Forecasts

For the analysts' long-term growth rate estimates, I/B/E/S reports the number of analysts as well as the mean and median EPS growth rate estimates for a 'three-to-five' year period. Given that I/B/E/S projected EPS growth rate is for a 'three-to-five' year period, the projected EPS growth rate is assumed to be four years. For each company in the I/B/E/S database with long-term analysts' EPS growth rate forecasts, as of the end of

each quarter we obtain the annual EPS, EPS_t , as the sum of the trailing four quarters' EPS and the mean projected three-to-five year projected EPS growth rate, g . As an example, assume that EPS_t for a particular company as of the end of the fourth quarter of 2000 is \$1.00 and g is 10%, as shown in Table 2. The projected EPS in four years, EPS_{t+4} , for this company is calculated as:

$$EPS_{t+4} = (EPS_t)(1 + g)^4$$

Table 2
Example: EPS and Projected Growth for a Hypothetical Company

Actual Quarterly EPS					
First Quarter 2000	Second Quarter 2000	Third Quarter 2000	Fourth Quarter 2000	Actual Annual EPS	I/B/E/S Projected EPS Growth
0.25	0.35	0.25	0.15	1.00	10.0%

In this example, the company's projected EPS is calculated as:

$$EPS_{t+4} = (1.00)(1.10)^4 = \$1.46.$$

This figure is compared to the company's actual annual EPS growth rate from the end of 2000 to the end of 2004. The actual EPS growth rate is calculated as the compound annual growth rate in earnings over the time period, g_a , as shown below:

$$g_a = 1 - \left(\frac{EPS_{t+4}}{EPS_t} \right)^{.25}$$

As an example, if the company's actual annual EPS as of the fourth quarter of 2004 is \$1.25; the company's actual four-year EPS growth rate is calculated as 5.74%. This is shown in Table 3. In this example, analysts projected this company to grow EPS at 10% over the four-year time period, and the company had an actual EPS growth rate of 5.74%. This procedure is repeated on a quarterly basis for each company in the I/B/E/S database.

Table 3
Example: Actual Long-Term EPS
Growth Rate Calculation for a Hypothetical Company

Actual Quarterly EPS					
First Quarter 2004	Second Quarter 2004	Third Quarter 2004	Fourth Quarter 2004	Actual Annual EPS	Actual EPS Growth (2000 – 2004)
0.30	0.35	0.25	0.35	1.25	5.74%

Analysts' One-Year EPS Growth Rate Estimates

For one-year EPS estimates, I/B/E/S reports the number of analysts as well as the mean and median one-year EPS estimates. We compare the growth rates associated with the one-year projected EPS estimates with the actual EPS as of the end of the calendar year. For this reason, we limit this analysis to firms with December 31st fiscal year-ends.

As an example, using the hypothetical company in Table 4, of the end of the fourth quarter of 2004, the company's EPS_t is \$1.00. If the analysts' projected one-year growth in EPS, EPS_{t+1} , is \$1.15, the company's projected one-year EPS growth rate is calculated as 15.0%. This figure is compared to the company's actual EPS growth rate based on quarterly earnings in 2005. In the example in Table 4, the company's actual one-year EPS growth rate is 10.0%. This procedure is then repeated on an annual basis for each company in the I/B/E/S database

Table 4
Example: Actual Annual EPS Growth
Rate Calculation for a Hypothetical Company

Actual EPS						
First Quarter 2004	Second Quarter 2004	Third Quarter 2004	Fourth Quarter 2004	2004 Actual Annual EPS	2005 Actual Annual EPS	Projected One-Year EPS Growth (2004 – 2005)
0.30	0.30	0.20	0.20	1.00	1.10	15.0%

We calculate forecast errors, FE , based on the ratio of the forecasted and actual estimated growth rates, as follows:

$$FE = \frac{g}{g_a} - 1$$

Based on this calculation, a positive forecast error indicates an upward bias in forecasted earnings and a negative forecast error indicates a downward bias in forecasted earnings.

The tabulated growth rates are based only on firms who survive for the following one or four years, for one-year and long-term growth rates, respectively. The survivorship bias may induce an upward bias in actual earnings growth rates. Moreover, we do not calculate growth rates when the base-year value is negative.

Historic Growth Rate in Earnings

The historic record for EPS and GDP growth provides a benchmark for long term growth estimates. Ibbotson and Cheng (2003) show that growth in earnings is in line with overall growth in economic productivity. Bernstein and Arnott (2003) and Arnott (2004) make the point that corporate earnings growth rates cannot exceed sustainable GDP growth, even though analysts consistently forecast growth rates that indicate the opposite.

We begin by examining the actual five-year earning per share (EPS) growth for the S&P 500 and five-year Gross Domestic Product (GDP) growth from 1960 to 2006. EPS for the S&P 500 has averaged 7.02% with a median of 7.08%. GDP has averaged 7.42% with median of 7.40%. The results are presented in Figure 1.

Historically, EPS growth has been is more volatile than GDP growth. EPS growth rates range from -2.71% to 16.89% with a standard deviation of 4.51%. Growth rates for GDP range from 4.62% to 11.38% with a standard deviation of 2.03%. In addition, average GDP growth has exceeded EPS growth. This result corresponds with

previous research.

Figure 1
Five-Year S&P 500 EPS Growth Versus Five-Year GDP Growth

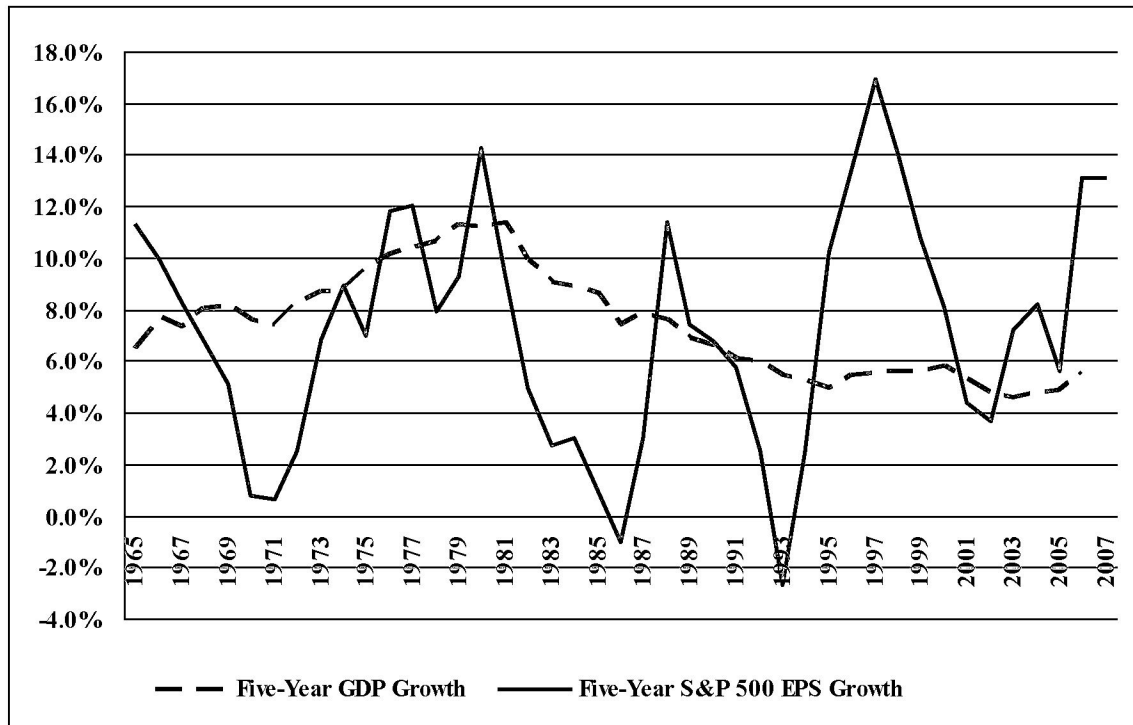


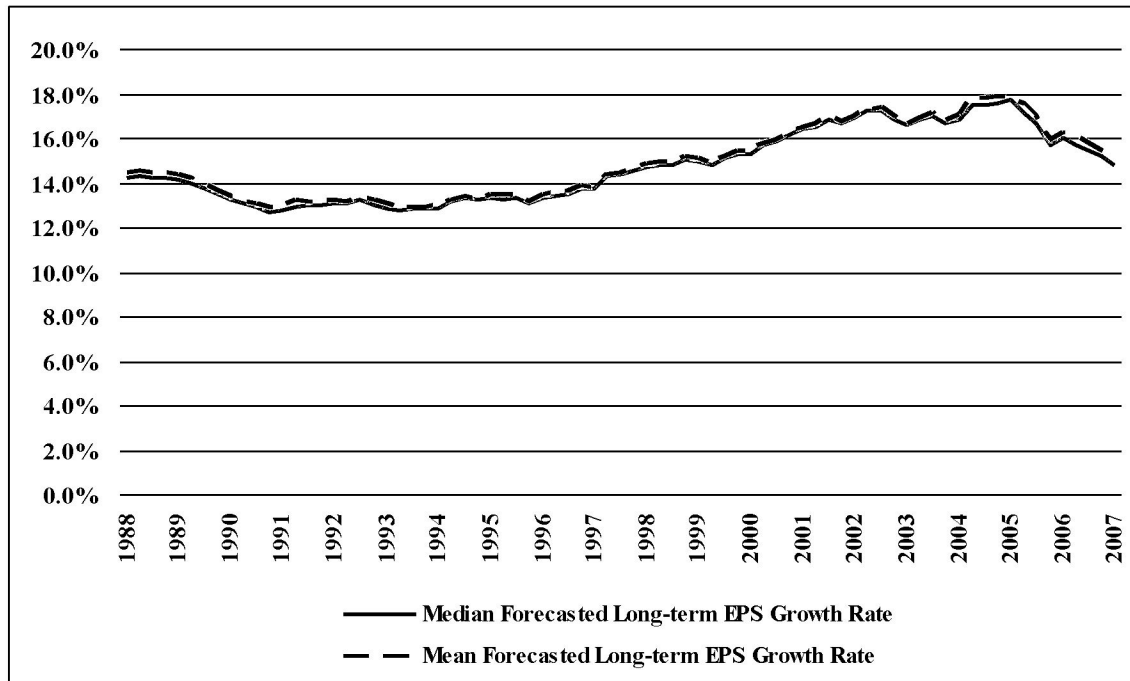
Figure 2 shows the mean and median long-term analysts EPS forecasts from 1988 through the first quarter of 2007. Although GDP growth has averaged 7.42% with median of 7.40% over the last 40 years, analysts over our sample period project long-term growth at an average rate of 14.71%. This suggests that analysts consistently forecast long-term EPS growth at a level that is two times that of historic GDP growth.

Several observations can be made from Figure 2. First, analysts consistently project long-term growth rates in a range of 13% to 18%. Second, mean and median observations are practically identical suggesting that these results are not driven by outliers. Finally, analysts' forecasts have increased over time, even though GDP growth has decreased over time.

In the sections that follow, we examine analysts' long-term and one-year ahead

forecasts relative to actual EPS growth rates.

Figure 2
Long-Term IBES Forecasted EPS Growth Rates
1988-2006



Analysts IBES Forecast Versus Actual EPS Growth Rates: Long-Term Projections

We examine forecasted long-term EPS growth versus actual three-to-five-year EPS growth based on IBES data from 1984 to 2006. The results are presented by quarter in Table 5 and Figure 3.

Over the entire time period, analysts continually forecast long-term EPS growth for the sample between 13% and 18%. Actual EPS growth for the sample ranges between 1.23% and 19.93%. Firm's meet or exceed analysts' expectations in periods around 1996 and 2006, both of which followed a large decline in corporate earnings. This is the most likely scenario for corporations to attain the lofty growth rates projected by analysts. This pattern is seen clearly in Figure 3.

Over the entire period analysts' long-term forecasted EPS growth averaged

14.71% per year, but companies only averaged long-term EPS growth of 9.10%. The analyst bias is obvious and clearly significant. A test for a difference in means--the null hypothesis is the difference in the mean actual EPS growth is equal to the mean projected EPS growth--has a t-stat of -10.68 which is significant at the .005 level (n=77).

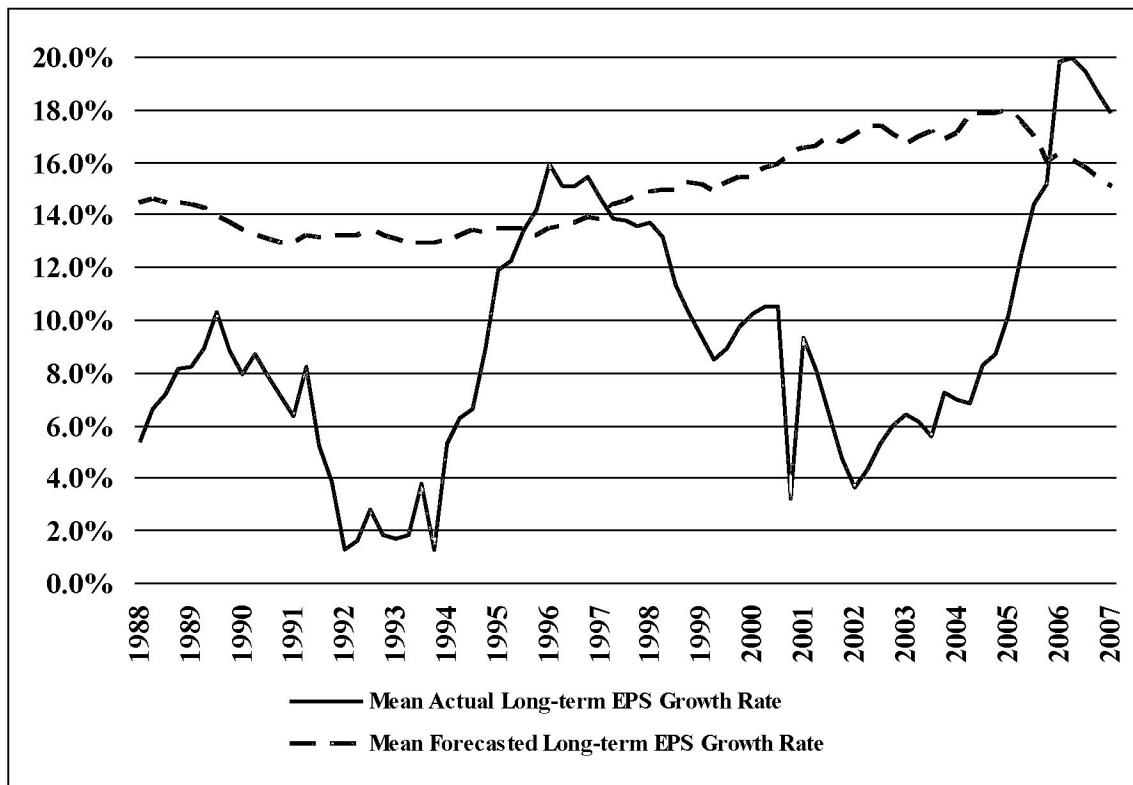
Table 5
Summary of Forecasted and Actual Long-Term EPS Growth Rates by Quarter

Year	Quarter Ended	Mean Actual Long-term EPS Growth Rate	Mean Forecasted Long-term EPS Growth Rate	Forecast Error for Mean (%)	Number of Companies	Average Number of Analyst Estimates
1988	Mar-88	5.36%	14.47%	170.07%	768	6.24
	Jun-88	6.61%	14.55%	120.32%	797	6.26
	Sep-88	7.12%	14.45%	102.96%	817	5.96
	Dec-88	8.12%	14.46%	78.13%	850	5.88
1989	Mar-89	8.20%	14.35%	75.08%	910	6.09
	Jun-89	8.92%	14.21%	59.34%	892	6.36
	Sep-89	10.28%	13.88%	35.03%	889	6.57
	Dec-89	8.81%	13.65%	55.00%	905	6.15
1990	Mar-90	7.94%	13.41%	68.98%	907	6.42
	Jun-90	8.66%	13.23%	52.76%	863	6.46
	Sep-90	7.84%	13.05%	66.44%	880	6.48
	Dec-90	7.10%	12.89%	81.48%	916	6.62
1991	Mar-91	6.35%	12.89%	103.13%	939	6.70
	Jun-91	8.21%	13.19%	60.63%	914	6.68
	Sep-91	5.20%	13.14%	152.80%	897	6.07
	Dec-91	3.84%	13.18%	243.60%	932	5.90
1992	Mar-92	1.25%	13.22%	955.21%	950	5.58
	Jun-92	1.57%	13.18%	737.49%	986	5.41
	Sep-92	2.75%	13.40%	387.75%	1008	5.47
	Dec-92	1.83%	13.22%	621.01%	1068	5.52
1993	Mar-93	1.64%	13.04%	697.33%	1062	5.79
	Jun-93	1.81%	12.90%	612.01%	1183	5.93
	Sep-93	3.76%	12.89%	243.17%	1115	5.98
	Dec-93	1.23%	12.92%	951.11%	1140	5.90
1994	Mar-94	5.31%	12.98%	144.61%	1143	5.66
	Jun-94	6.27%	13.21%	110.79%	1158	5.56
	Sep-94	6.61%	13.42%	103.17%	1207	5.75
	Dec-94	8.89%	13.34%	49.99%	1192	5.81
1995	Mar-95	11.88%	13.47%	13.39%	1166	5.88
	Jun-95	12.20%	13.44%	10.21%	1144	5.84
	Sep-95	13.37%	13.45%	0.61%	1147	5.87

	Dec-95	14.14%	13.18%	-6.78%	1134	5.87
1996	Mar-96	15.88%	13.47%	-15.20%	1115	5.76
	Jun-96	15.05%	13.59%	-9.74%	1154	5.62
	Sep-96	15.07%	13.65%	-9.38%	1177	5.70
	Dec-96	15.42%	13.87%	-10.04%	1185	5.63
1997	Mar-97	14.62%	13.83%	-5.37%	1213	5.55
	Jun-97	13.82%	14.36%	3.92%	1223	5.55
	Sep-97	13.72%	14.49%	5.61%	1260	5.48
	Dec-97	13.52%	14.69%	8.67%	1174	5.45
1998	Mar-98	13.67%	14.88%	8.85%	1477	5.14
	Jun-98	13.13%	14.95%	13.85%	1448	4.92
	Sep-98	11.33%	14.91%	31.68%	1475	4.98
	Dec-98	10.27%	15.22%	48.16%	1462	4.93
1999	Mar-99	9.37%	15.13%	61.49%	1510	4.88
	Jun-99	8.50%	14.90%	75.28%	1480	4.96
	Sep-99	8.89%	15.20%	70.90%	1490	4.89
	Dec-99	9.70%	15.39%	58.64%	1481	5.06
2000	Mar-00	10.21%	15.45%	51.25%	1491	5.00
	Jun-00	10.48%	15.78%	50.53%	1515	4.94
	Sep-00	10.48%	15.93%	51.96%	1503	5.12
	Dec-00	3.19%	16.31%	412.19%	1502	5.25
2001	Mar-01	9.30%	16.53%	77.61%	1502	5.26
	Jun-01	8.09%	16.63%	105.58%	1485	5.26
	Sep-01	6.36%	16.97%	166.79%	1465	5.33
	Dec-01	4.72%	16.76%	255.42%	1414	5.18
2002	Mar-02	3.63%	17.02%	369.17%	1461	5.37
	Jun-02	4.28%	17.35%	305.30%	1517	5.26
	Sep-02	5.27%	17.38%	229.93%	1541	5.45
	Dec-02	5.98%	16.98%	183.88%	1553	5.50
2003	Mar-03	6.37%	16.68%	161.92%	1537	5.55
	Jun-03	6.11%	16.92%	177.12%	1566	5.46
	Sep-03	5.52%	17.15%	210.57%	1598	5.58
	Dec-03	7.25%	16.85%	132.37%	1605	5.65
2004	Mar-04	6.93%	17.08%	146.39%	1629	5.70
	Jun-04	6.80%	17.76%	161.30%	1664	5.18
	Sep-04	8.28%	17.81%	115.12%	1687	5.23
	Dec-04	8.70%	17.84%	104.95%	1670	4.87
2005	Mar-05	10.11%	17.92%	77.23%	1616	4.93
	Jun-05	12.45%	17.53%	40.74%	1578	4.87
	Sep-05	14.39%	16.96%	17.82%	1599	5.16
	Dec-05	15.15%	15.95%	5.32%	1517	5.33
2006	Mar-06	19.82%	16.22%	-18.18%	1563	5.33
	Jun-06	19.93%	16.07%	-19.40%	1580	5.65
	Sep-06	19.45%	15.75%	-19.05%	1644	5.83
	Dec-06	18.60%	15.41%	-17.14%	1723	5.57
2007	Mar-07	17.81%	15.07%	-15.39%	1734	5.25
	Mean	9.10%	14.89%	143.06%	1,281	5.60
	Median	8.50%	14.55%	75.08%	1,223	5.56

Also presented in Table 5 are forecast errors. Previous studies based on quarterly estimates (see, for example, Kwag and Shrieves (2006)) find that forecast errors are mixed. Our findings indicate that forecast errors for long-term estimates are predominantly positive, which indicates an upward bias in growth estimates. The mean and median forecast errors over the observation period are 143.06% and 75.08%, respectively. They are only negative for 11 time periods: five consecutive quarters starting at the end of 1995 and six consecutive quarters starting in 2006. As can be seen in Figure 3, the negative forecast errors clearly follow periods of declined earnings growth when higher growth rates can be attained. Overall, there is evidence of a persistent upward bias in long-term EPS growth forecasts.

Figure 3
Long-Term Forecasted Versus Actual EPS Growth Rates
1988-2006



Long-Term EPS Forecasts: Breakdown by Number of Analysts

It is possible that the results from the previous section are affected by the level of analyst coverage. Smaller and newly-traded companies tend to have less analyst coverage. It is possible that companies with fewer analysts would bias the results. Earnings for small or newly-traded companies are more difficult to forecast and would be expected to lead to higher forecasted earnings growth rates. For this reason we divide the sample into two groups: companies with three or fewer analysts and companies with more than three analysts.

While our data averages 5.61 analysts per company, many companies have three or fewer analysts. The two groups evenly divide the data. On average, of 1,273 companies, 628 have three or fewer analysts and 645 have more than three analysts. The data is described in Table 6 and displayed in Figure 4.

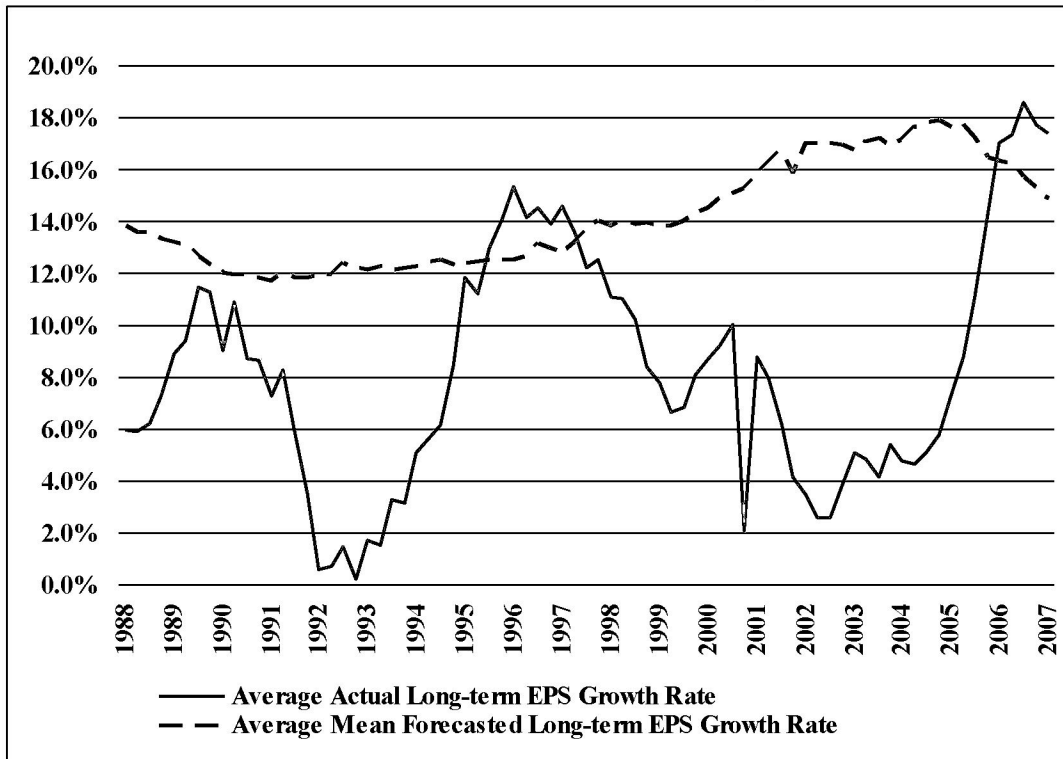
The results indicate that the group of companies with more than three analysts has lower long-term earnings growth rate forecasts. However, that group also has significantly lower actual growth in earnings, as indicated by a difference in means test ($t\text{-stat} = -5.77$, $n = 77$). Furthermore, while there is no significant difference between the forecasted growth rates by group since 2002, actual earnings continue to be lower for the group with more than three analysts. Overall, the forecast errors by group are very close. The median forecast error for the group with fewer than three analysts is 48.65%. For the group with more than three analysts the median forecast error is 48.68%.

Table 6
Number of Companies by
Analyst Coverage for Long-Term IBES Data

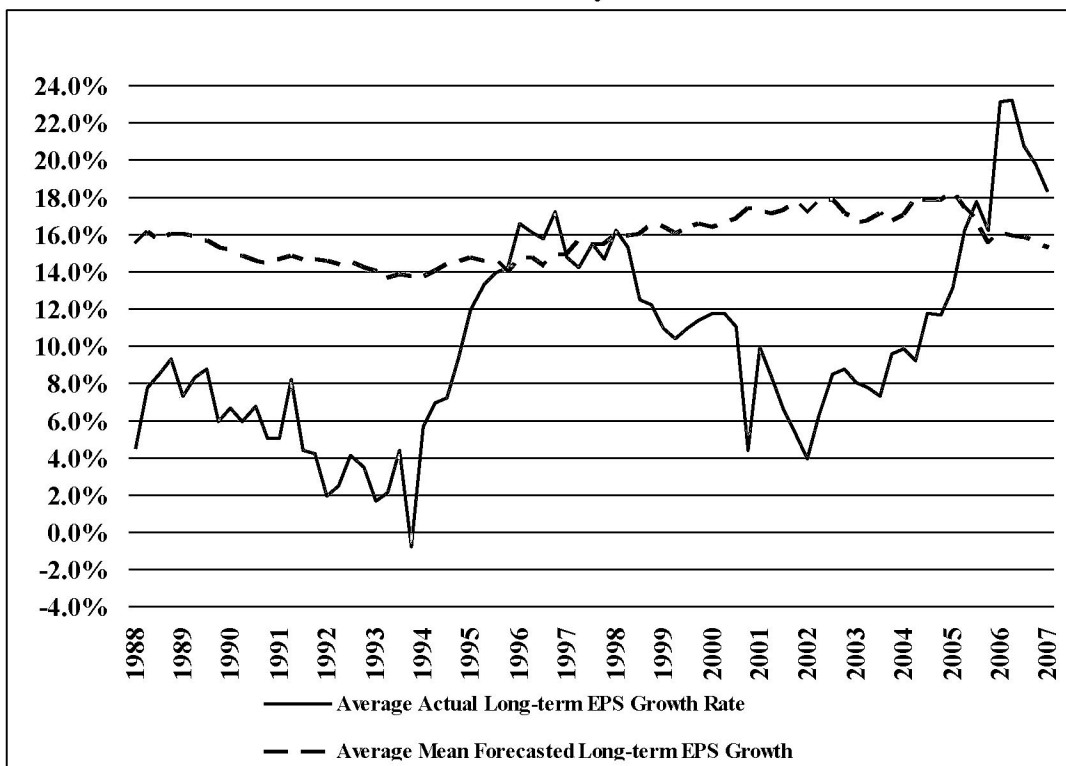
Year	Total Number of Companies	Companies with 3 and fewer Analysts	Companies with more than 3 Analysts
1988	808	325	485
1989	899	379	522
1990	892	389	508
1991	921	410	511
1992	1,003	502	505
1993	1,125	535	577
1994	1,175	561	615
1995	1,148	533	616
1996	1,158	530	633
1997	1,218	576	646
1998	1,466	731	735
1999	1,490	735	756
2000	1,503	747	756
2001	1,467	759	707
2002	1,518	825	693
2003	1,577	871	705
2004	1,663	875	788
2005	1,578	809	769
2006	1,628	898	730
Mean	1,273	628	645
Median	1,218	576	646

Source: I/B/E/S. Based on the average of quarterly numbers for each year.

Figure 4
Long-Term IBES Forecasted EPS Growth Rates by Analysts Coverage
Panel A: Greater Than Three Analysts



Panel B: Three Analysts or Fewer



Analysts IBES Forecast Versus Actual EPS Growth Rates: One-Year Projections

Although we have shown a significant bias in growth rate forecasts, we realize that long-term growth is difficult to forecast. Over longer forecast periods, analysts face a greater probability of unexpected events that will lead to inaccurate estimates. One possible explanation for the persistent bias is that analysts consistently project long-term growth estimates higher than short-term estimates to allow for the possibility of unforeseen events. For this reason, we extend the analysis to one-year EPS growth rate forecasts, expecting that analysts' estimates will be more accurate over a shorter period of time with less event risk.

We collect forecasted and actual one-year EPS growth rate data for firms from 1984 to 2006. We compare the analysts' forecasted EPS growth rates to the actual annual growth rates over the year. The results are presented by year in Table 7.

Analysts consistently project upwardly biased growth rates, even for shorter time horizons. Analysts forecasted one-year EPS growth at an average rate of 13.80% while the actual EPS growth rate over the time period averaged 9.77%. These growth rates are significantly different as indicated by a difference in means test ($t\text{-stat} = -4.91$, $n=23$).

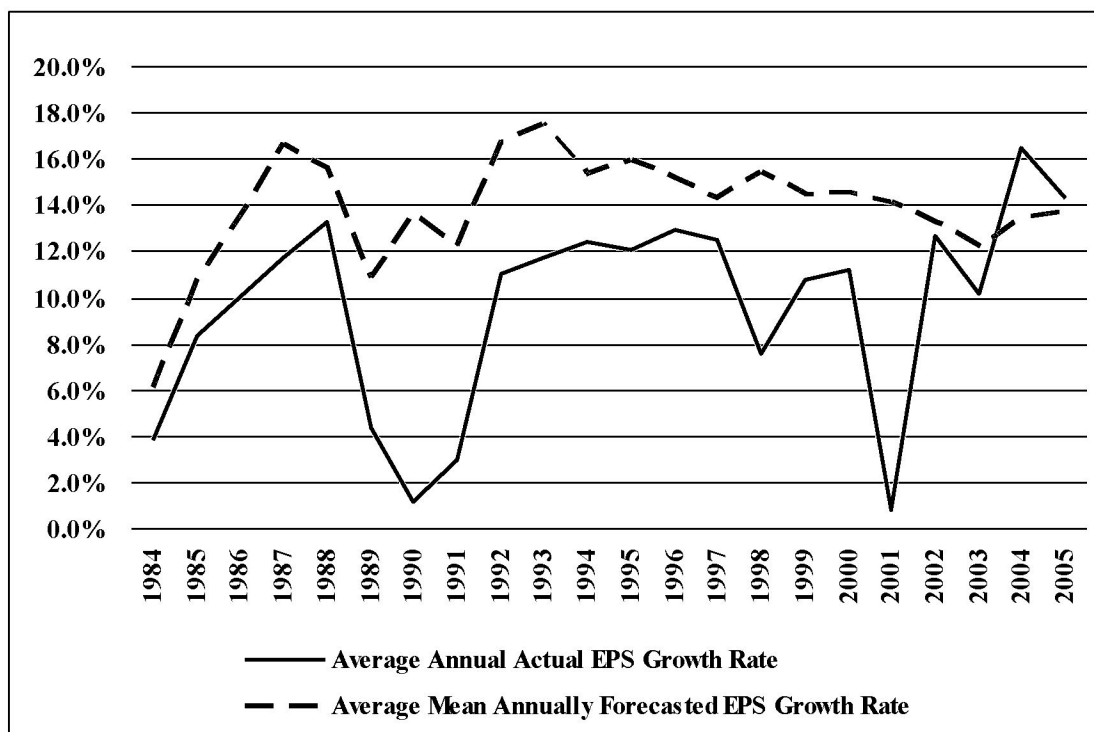
Although the one-year forecast errors are lower, they are still large and predominantly positive. The mean and median forecast errors over the observation period are 165.94% and 32.51%, respectively. Forecast errors are only negative for the last three years, indicating an overall negative bias to earnings estimates.

Table 7
Summary of IBES Forecasted and Actual One-Year Growth Rates by Year

Year	Mean Annual Actual EPS Growth Rate	Mean Annual Forecasted EPS Growth Rate	Forecast Error for Mean Growth Rate	Number of Companies	Average Number of Analyst Estimates
1984	3.79%	6.10%	61.24%	1245	8.61
1985	8.33%	10.77%	29.40%	1154	10.30
1986	9.96%	13.43%	34.84%	1140	10.44
1987	11.68%	16.67%	42.71%	1047	11.02
1988	13.22%	15.62%	18.16%	1095	10.70
1989	4.32%	10.81%	150.19%	1245	10.64
1990	1.15%	13.60%	1082.97%	1260	10.78
1991	2.97%	12.20%	311.26%	1138	10.01
1992	10.98%	16.72%	52.24%	1192	9.60
1993	11.66%	17.49%	50.09%	1314	9.55
1994	12.42%	15.31%	23.34%	1475	9.71
1995	12.05%	15.97%	32.51%	1557	9.11
1996	12.88%	15.15%	17.63%	1652	8.74
1997	12.50%	14.26%	14.11%	1489	8.33
1998	7.52%	15.38%	104.62%	1375	7.75
1999	10.76%	14.46%	34.32%	1258	8.54
2000	11.20%	14.51%	29.55%	1176	8.26
2001	0.77%	14.08%	1730.98%	1469	7.68
2002	12.64%	13.27%	5.04%	1367	7.13
2003	10.16%	12.23%	20.37%	1464	7.78
2004	16.46%	13.40%	-18.62%	1565	8.60
2005	14.25%	13.79%	-3.20%	1620	8.73
2006	13.10%	12.17%	-7.09%	2502	6.92
Mean	9.77%	13.80%	165.94%	1383	9.08
Median	11.20%	14.08%	32.51%	1314	8.74

The one-year analysts' forecasts and actual EPS growth rates are presented in Figure 5. The persistent upward bias is evident from the graph. As with long-term analyst forecasts, the only negative forecast errors follow a period of lower actual EPS growth. Higher growth is most likely to be attained after such a period.

Figure 5
One-Year Forecasted versus Actual EPS Growth Rates



Negative Earnings Growth Rate Forecasts

One explanation of the persistent bias of analysts' projections is a resistance to report negative earnings growth rates. A resistance to report negative earnings growth could be linked to the investment banking influences addressed by the Global Analyst Research Settlements. It could also be caused by a cognitive bias often called familiarity. Familiarity is a behavioral flaw common to investors. Investors have a tendency to favor investments they know, such as the common stock of their employer. Similarly, analysts

may become attached to companies they follow and lose objectivity.

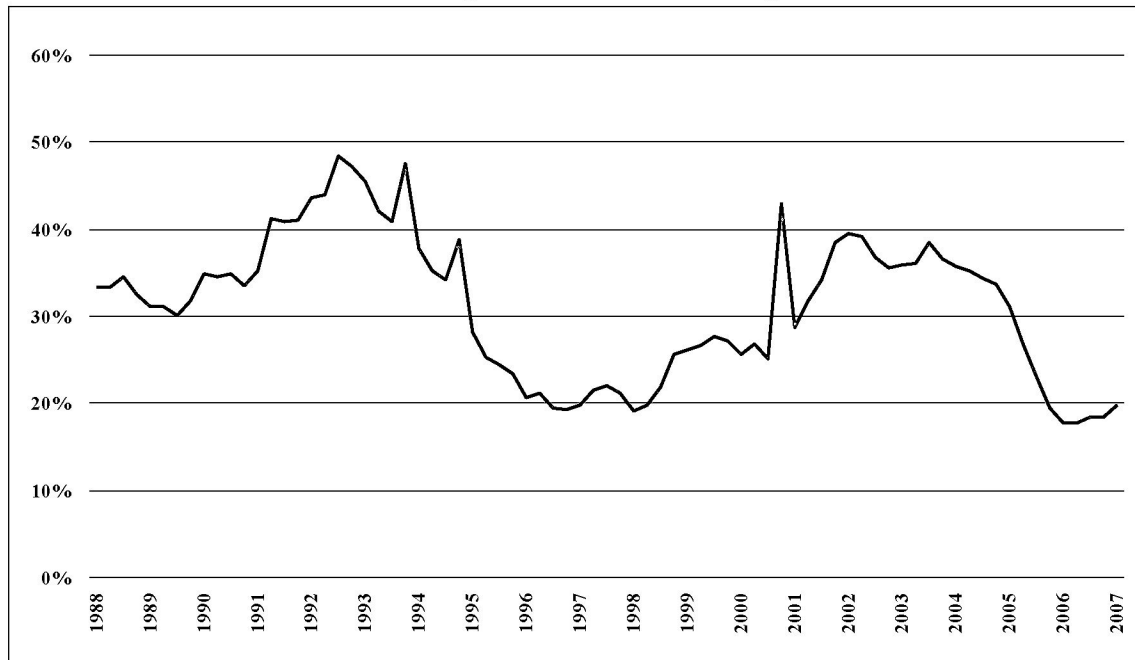
Using long-term growth projections, we begin by comparing the number of companies with projected negative EPS growth rates to those with actual negative EPS growth rates in each time period. The differences are striking. The results are summarized in Panel A and Panel B of Figure 6.

Panel A shows the percent of companies with actual negative EPS growth. The average number of companies with actual negative EPS growth is 391 with a minimum of 227 and a maximum of 644. An average of 31.12% of all companies had negative earnings growth in each quarter.

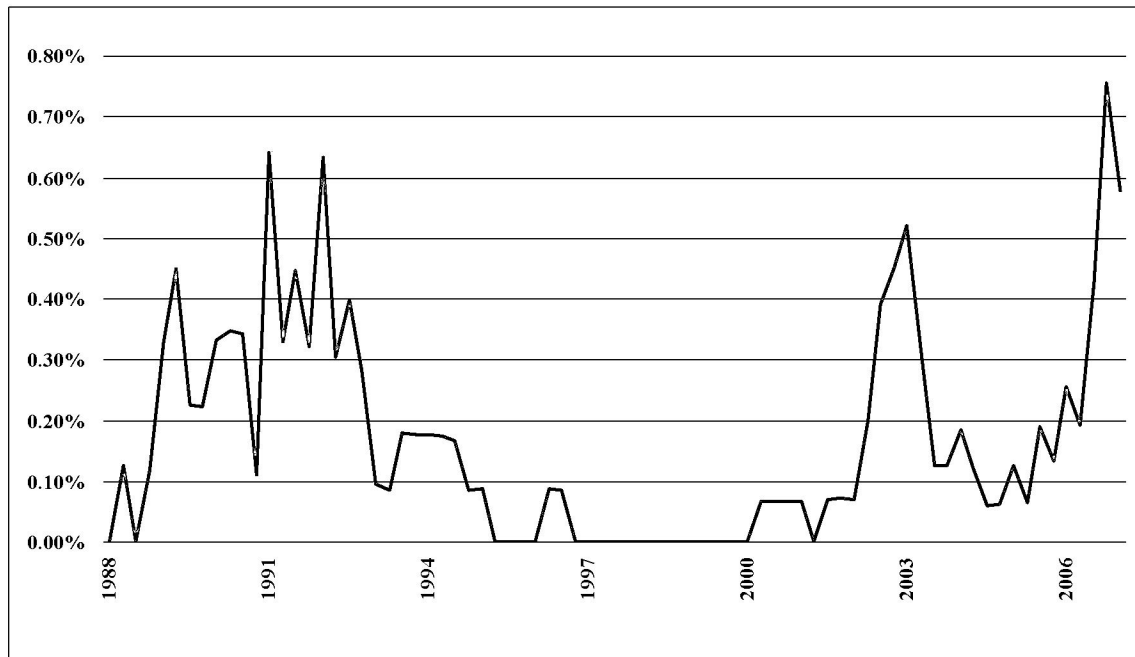
Shown in Panel B is the percent of companies with forecasted negative EPS growth. The average number of companies with forecasted negative EPS growth by quarter is only 2.10 with a minimum of 0 and a maximum of 13. Only 0.17% of all companies were projected to have negative earnings growth.²

² We also examine the percentage of negative earnings growth that is captured by analysts' projections. We begin by collecting all companies that experienced negative long-term growth in each time period. Then we calculate the percentage of those companies that were project to have long-term negative EPS growth. An average of 0.55% of companies that reported negative EPS growth was captured by analysts' estimates. The average number of companies with negative earnings growth that were missed by analysts was 389 out of an average 391 companies that reported an actual decline in earnings. There is clear resistance by analysts to project negative growth.

Figure 6
Comparison of Companies with
Actual and Forecasted Negative EPS Growth
Panel A: Percent of Companies with Actual Negative EPS Growth



Panel B: Percent of Companies with Forecasted Negative EPS Growth



Results after the Global Analyst Research Settlements

The Global Analysts Research Settlements (GARS) is a set of agreements reached on April 23, 2003 between the SEC, NASD, NYSE and ten of the largest U.S. investment firms. GARS, as outlined by the Securities and Exchange Commission (2003), addresses conflicts of interest within firms that have investment banking and analysts operations. A conflict of interest can exist between the investment banking and analysis departments of the large investment firms. The investment firms involved in the settlement had engaged in practices involving the influence by investment bankers seeking favorable analysts' projections within their firm.

As part of the settlement decision several regulations were introduced to prevent investment bankers from pressuring analysts to provide favorable projections. These regulations include (1) firms must separate their investment banking and analysis departments with firewalls; (2) budget allocation to management in research departments must be independent of investment departments; (3) research analysts are prohibited from attending pitches with investment bankers during advertising and promotion of IPOs; and (4) historical analysts' ratings must be made available to investors.

One possible explanation for the upward bias in analysts' forecasts is the conflict of interest that exists between analysts and investment bankers. This presumably would have been removed by the GARS. For this reason, we compare long-term actual and forecasted growth rates for the periods prior to and following the GARS. The persistence of a bias following the GARS would indicate another explanation for the bias.

Table 8 shows descriptive statistics for long-term analysts' earnings growth rates

estimates before and after the GARS. Actual and forecasted growth rate estimates are higher since the GARS and forecast errors have decreased. While forecast errors have decreased, they are still significantly positive.

It is evident that analysts' growth rate forecasts have remained around their historic levels of about 15%. Growth rates remain at levels that are unattainable given historic and expected GDP growth. Hence, there is no evidence that analyst behavior has changed since the GARS.

Table 8
Comparison of Long-Term Analysts' EPS
Growth Rate Forecasts Before and After GARS

1988 – 2002(1)			
	Actual	Forecasted	FE
Mean	8.25%	14.40%	141.65%
Median	8.20%	13.88%	65.29%
SD	4.06%	1.36%	197.57%
n	61	61	61
2003 – 2007(2)			
Mean	12.33%	16.77%	66.94%
Median	11.28%	16.94%	51.60%
SD	5.49%	0.92%	61.70%
n	16	16	16

(1) Based on data beginning in 1984. (2) From April 2003 to and including the first quarter of 2007.

Possible Explanations for the Upward Bias

There are three suggested explanations for the upward bias. The first, as suggested by previous research, is based on career concerns or conflicts of interest. Analysts are rewarded for biased forecasts by their employers who want them to hype stocks so that the brokerage house can garner trading commissions and win underwriting deals. However, the scrutiny of the GARS should have removed this influence. We find little evidence of a change in forecast bias following the GARS. Therefore another

explanation is likely.

A second explanation is based on selection bias. Analysts only follow stocks that they recommend and do not issue forecasts on those that they do not like. A third explanation is a cognitive or behavioral bias commonly called familiarity. Analysts become attached to the companies that they follow and lose objectivity.

The second and third explanations imply that analysts are systematically biased. If analysts systematically believe that they follow companies that are superior to others, they will be reluctant to issue negative earnings forecasts. Since they are only projecting the companies they follow, and not the market, the end result is a strong upward bias on earnings projections.

Summary

In this study we examine the accuracy of analysts' long-term and one-year ahead EPS growth rate forecasts over the last 20 years. Unlike previous studies, we examine long-term and one-year analysts' earnings growth rate forecasts and not quarterly EPS forecasts. Long-term EPS growth rate projections are consistently overly-optimistic. Analysts' growth rate forecasts of earnings are better for one-year than for three- to five-years, but are still over-optimistic. We discover that analysts only underestimate EPS growth rates for periods of earnings recoveries after economic recession. We find that analyst coverage does not have an impact on the overly-optimistic bias in projected EPS growth rates. We do discover that a contributing factor in the bias in analysts' long-term and one-year EPS growth rate estimates is the resistance of analysts to project negative earnings growth rates. We show that analysts' projections fail to capture the majority of negative earnings growth realized by corporations they follow. Finally, we examine the

level of long-term analysts' EPS growth rate forecasts following the GARS. We find that analysts' forecasts have not significantly changed and continue to be overly-optimistic. Analysts' long-term EPS growth rate forecasts before and after the GARS, are about two times the level of historic GDP growth.

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THE WALL STREET JOURNAL.

By

Anna Hirtenstein

June 14, 2020 7:00 am ET

Safe Utilities Have Been More Volatile Than Broader Stock Market

Shares of utilities have been fluctuating more than the S&P 500 as investors fret about impact of coronavirus



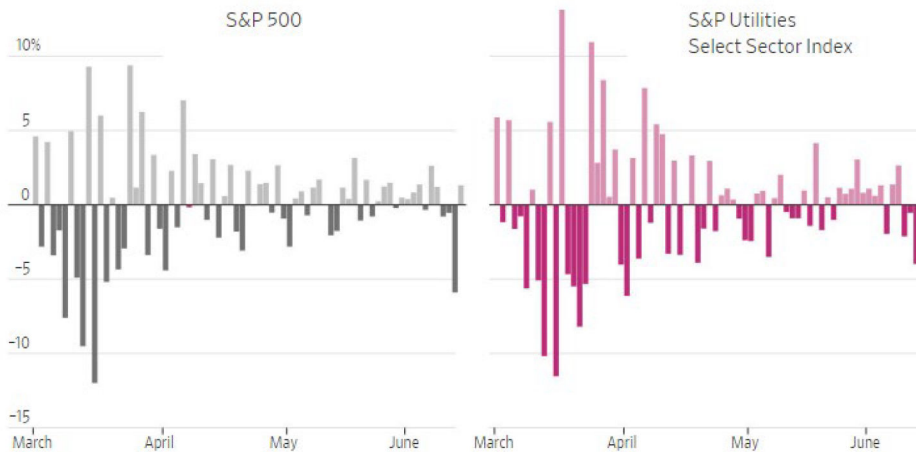
Con Edison workers in New York City. The utility cut its 2020 earnings guidance last month.

Utilities' stocks have long been seen as a safe place to park cash and collect steady dividends. But as [the coronavirus](#) spread around the world this year, they have been more volatile than the broader market.

In March and April, shares of companies that sell electricity, water and gas posted bigger daily moves than the S&P 500 on a majority of days. The only other time this has happened in the past two years is during a bout of market volatility in February 2018. So far in June, it is a tie, with utilities moving more on five days.

The utilities sector within the S&P 500 is down almost 10% this year, even as the benchmark index rebounded to erase most of its losses.

Daily index moves



Source: FactSet

That is because of concerns about [falling power demand](#) and [the spike in unemployment](#) following the lockdowns put in place to curb the outbreak, analysts said. Millions of people have lost their jobs in recent months, prompting concerns that they [may stop paying their bills](#). As dozens of companies cut or [suspended their dividends](#) to preserve their cash piles, some investors wondered if the major utilities could be next.

“Utility investors are not used to uncertainty,” said Jeremy Tonet, an equity research analyst at [JPMorgan Chase & Co.](#) “There were a lot of concerns with regard to Covid-19 and how much it could impact the space.”

Largest utilities stocks and the S&P 500, change year to date



Source: FactSet

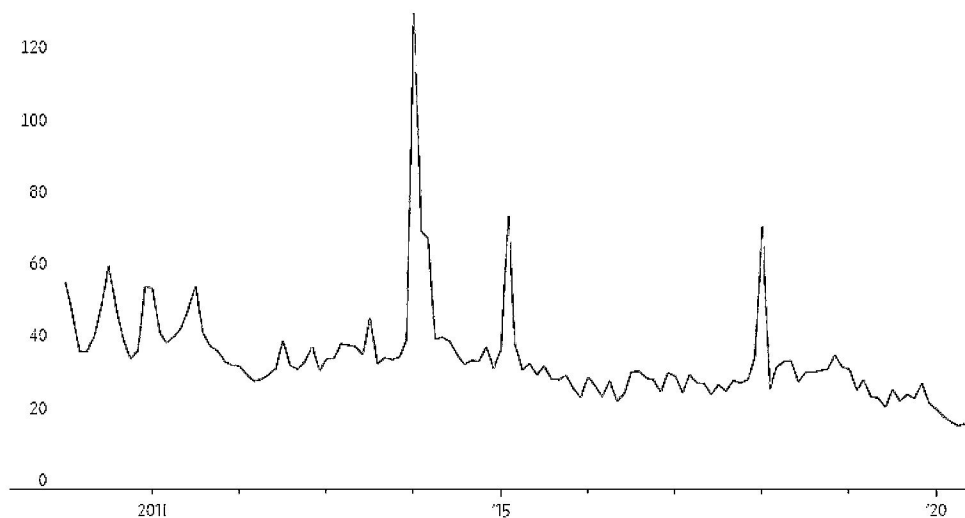
As of June 12, 5:38 p.m. ET

Utility stocks are normally popular with pension funds and insurers, who buy them for their stability and reliable dividend yields. Those expectations came into question during the peak of the market turmoil that ensued in March.

The lockdowns have resulted in a significant drop in energy use as commercial and industrial activity ground to a halt. A benchmark for wholesale power prices in the U.S. fell 20% in April, compared with the beginning of the year, and is still down nearly 15%, according to data from Bloomberg New Energy Finance. The Energy Information Administration said on June 9 that it expects electricity consumption in the U.S. to decline 5.7% in 2020.

Power price at a U.S. benchmark hub^a

\$140 a megawatt-hour

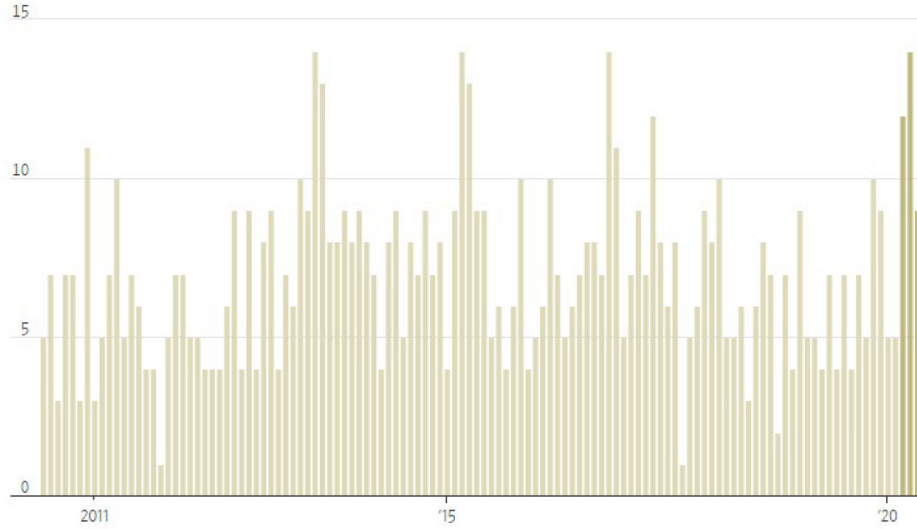


^a Monthly average price at PJM West Hub ATC (Pennsylvania, Jersey, Maryland Power Pool), the most liquidly-traded U.S.

Despite this, nearly all major U.S. utilities have reaffirmed their full-year guidance, according to JPMorgan. One of the few exceptions is Consolidated Edison Inc., ED 0.95% which operates primarily in New York, the U.S. city that has been hardest-hit by the coronavirus. Con Ed last month cut its 2020 earnings guidance. Meanwhile, CenterPoint Energy Inc. CNP 1.29% in Texas has been one of the few utilities to trim its quarterly dividend so far.

The regulated nature of the industry means that the revenue holds steady even if power prices fluctuate or sales fall, according to Noah Barrett, head of energy and utilities research at Janus Henderson. There are rules in place in many states that decouple energy demand from the companies' cash flows and fix a rate of return on their investments to ensure that the businesses supplying the population with essential services remain in good health, he said.

Trading days each month where the S&P 500 Utilities Select Sector index moved more than the broader index



Note: June figure is through June 12.

Source: FactSet

“The dynamic we saw this year with Covid-19 is something that no one knew how to model,” given the uncertainty around electricity or natural-gas demand, Mr. Barrett said. “If you look at the stability of the earnings, it hasn’t really changed.”

The utility companies’ very stability may now be working against them, he said. Some investors are seeking out stocks that have been hard-hit amid the economic downturn and could rebound sharply, or sectors such as technology that could benefit during lockdowns.

Another reason that utilities’ stocks are currently unloved is because of the sharp moves seen in March, said JPMorgan’s Mr. Tonet. Passively managed funds and asset managers that use algorithmic or quantitative strategies may not continue to view these stocks as predictable, low-volatility investments.

But in the long run, the companies still have strong fundamentals and “there’s room for utilities to regain their stance as a defensive stock,” he said.



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FEATURE ARTICLE

The effect of the SEC's regulation fair disclosure on analyst forecast attributes

Rong Yang

*Department of Business Administration, SUNY-College
at Brockport, Brockport, New York, USA, and*

Yaw M. Mensah

Rutgers Business School, Rutgers University, Piscataway, New Jersey, USA

Abstract

Purpose – This study aims to examine the effect of the Securities and Exchange Commission's regulation fair disclosure (Reg. FD) on analyst forecast performance for pre-Reg. FD closed-call (CLC) and open-call (OPC) firms compared with the non-conference-call (NCC) firms in the post-Reg. FD period.

Design/methodology/approach – Specifically, it examines whether Reg. FD influenced the earnings forecast accuracy and forecast dispersion of financial analysts for the previous-CLC firms in the post-Reg. FD period compared with the previous-OPC firms, and both sets of conference call firms relative to the NCC firms in the same period.

Findings – The main findings indicate that forecast accuracy improved for both OPC and CLC firms compared with the NCC firms in the post-Reg. FD period. More importantly, the differences in earnings forecast performance between the pre-Reg. FD OPC and CLC firms had disappeared in the post-Reg. FD period.

Originality/value – These results offer further confirmation of previous findings that Reg. FD has contributed to leveling the playing field for financial analysts and investors.

Keywords Financial institutions, Earnings, Forecasting, Disclosure, Conferencing

Paper type Viewpoint

1. Introduction

On October 23, 2000, the US Securities and Exchange Commission (SEC) issued regulation fair disclosure (hereafter Reg. FD) which prohibits selective disclosure of material nonpublic information to certain financial analysts, institutional investors and others prior to making it available to the general public. Information is considered material if it is important enough to persuade an investor to buy or sell a stock. Before the implementation of Reg. FD, most conference calls were accessible only to certain analysts and institutional investors. It has been argued that conference calls, because they were predominantly closed, may have contributed to an information gap between analysts privy to the call and analysts and other investors excluded from the call. The intent of Reg. FD was to prevent this selective disclosure of information.

A number of published studies have already examined the impact of Reg. FD on various aspects of the capital markets and investment climate, including the effect on



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analyst forecast accuracy and dispersion, although the findings have been contradictory. Using data from the first three quarters after the release of Reg. FD, Agarwal and Chadha (2003) report that sell-side analysts' forecasts were less accurate and more dispersed than before its adoption, where Heflin *et al.* (2003) report no change in analysts' earnings forecast bias, accuracy or dispersion compared to the pre-Reg. FD period. Furthermore, Shane *et al.* (2001), also using data from the same period, find that analysts gathered more information between earnings announcements so that their forecasts are ultimately as accurate as those made in the period before Reg. FD was adopted.

This study has two main objectives. The first is to examine if there were changes in analyst earnings forecast errors (FE) and forecast dispersion (FD) in the pre- and post-Reg. FD period between the "closed-call" (henceforth referred to as CLC) firms and "open-call" (OPC) firms. The second objective is to determine if there were any changes in analyst earnings forecast attributes between the CLC and OPC firms as a group (labeled CC – conference call firms), and the non-conference-call (NCC) firms in the post-Reg. FD environment.

Thus, this study contributes to the existing literature by differentiating between firms in the pre-Reg. FD period that held closed conference calls, firms that held open conference calls, and other firms which held NCCs. By limiting the study only to OPC and NCC firms in the post-Reg. FD period, we are able to control for extraneous factors such as changing group membership in our analyses. Second, because the study covers the period from October 1998 to September 2002, more quarterly observations are available to conduct the tests than in previous research.

The remainder of this study is organized as follows. Section 2 presents a brief summary of previous studies focused on only the main sources, and an outline of the hypotheses examined in the paper. Section 3 describes the sample selection and a brief outline of our research methodology. Section 4 presents the major results of the study. Section 5 presents the conclusions and suggestions for future research. In the Appendix, we provide details on the research methodology and the regression equations used to analyze the data.

2. Literature review and hypothesis development

2.1 Brief review

Economic theory suggests that expanded disclosures can reduce information asymmetry arising between the firm and its shareholders or among potential buyers and sellers of firm shares and benefit firms by correcting any firm mis-valuation and increasing institutional interest and liquidity for the firm's stock. For example, Diamond and Verrecchia (1991) find that credible commitments by managers to improve disclosure increasing the precision of public information about firm value results in higher current stock prices due to reduced information asymmetry and increased liquidity. Frankel *et al.* (1999) provide evidence that firms holding conference calls as a voluntary disclosure medium tend to be relatively larger, more profitable, more heavily followed by analysts, and access the capital markets more often than other firms.

In other related findings, Bowen *et al.* (2002) provide evidence that regular use of earnings-related conference calls could present a selective disclosure problem if the public is not privy to these calls, even if conference calls tend to reduce both FE and FD. Bushee and Noe (2000) find that firms with greater analyst following and greater

institutional ownership are less likely to have conference calls that provide open access to all investors. Core (2001) presents evidence consistent with the intuition that informed investors prefer less disclosure, and that analysts and institutions produce information that reduces information asymmetry and the need for conference calls.

As cited previously, some of the research focused on the effect of Reg. FD on financial analyst behavior have yielded mixed results. In general, however, the majority of these studies conclude that Reg. FD has had the intended benefit of diminishing the information advantage of analysts with previously exclusive access to management, although some anecdotal stories in the press still hint at the continued exclusive disclosure of material non-public information (*Wall Street Journal*, 2004). Interested readers can contact the lead author for a more detailed reference list.

2.2 Expected effects of Reg. FD on analysts forecast performance and related stock market

The arguments surrounding Reg. FD revolve around two major themes:

- (1) its potential to level the playing field for all investors; and
- (2) its potential to increase the cost of capital by restricting the availability of information to investors.

The first of these themes relies on the rationale that, by providing equal access to firm information, Reg. FD can reduce the level of information asymmetry, leading stock prices to be less dependent on private information. This logic implies that any loss of accuracy in earnings forecasts by analysts would be offset by the wider dissemination of information and hence, a more informed general investor population. In addition, Reg. FD may enhance the accuracy and precision of analysts' earnings forecasts, if it succeeded in opening up new sources of information to analysts, or if analysts could substitute the information obtained directly from companies with the information gathered from customers, suppliers, competitor's industry observers, and other sources of information. That is consistent with Mohanram and Sunder's (2006) finding, analysts may substitute privately acquired information for public-disclosed information for firms after the enactment of Reg. FD.

The counter-argument relies on the possibility that Reg. FD could have an adverse effect on certain analysts' forecast accuracy through denying them the sometimes-exclusive access to management that they previously enjoyed. Given the important role of financial analysts as intermediaries who provide professional investment to the capital markets, the decreased accuracy may have deleterious capital market consequences. In addition, it has been argued that Reg. FD induce firms to reduce the level of information and guidance that they may have provided originally in the closed conference calls, but which they may be unwilling to impart in open conference calls.

Recently, Bushee *et al.* (2004) find that Reg. FD had a significantly negative impact on managers' decisions to continue hosting conference calls even though this impact was not large. Hence, the level of specialty guidance may have decreased in the post-Reg. FD period. At the same time, Gintschel and Markov (2004) report that the informativeness of analysts output has dropped in the post-FD environment.

Specifically, they found that the absolute price impact of information disseminated by financial analysts dropped by 28 percent in this period. Eleswarapu *et al.* (2004) also report that the return volatility around mandatory announcements had decreased, and the impact was more pronounced for smaller and less liquid stocks. Taken together, these results suggest a strong impact of Reg. FD on the functioning of capital markets.

2.3 Hypothesis development

Extant studies assume that public information is common across all analysts and private information is idiosyncratic and uncorrelated across analysts. They have used FE and FD as proxies for analyst forecast attributes. Both FE and FD capture the extent to which private information differs across analysts, which also represents the level of actual past selective disclosure. For instance, Barron *et al.* (1998) present a model that expresses two properties of their forecasts, proxied by both dispersion in individual forecasts and the squared error in the mean forecast, as functions of the amount or "precision" of analysts' public and private information in forecasting firms' earnings. Sunder (2001) further find that "restricted-call" firms faced higher information asymmetry compared to "open-call" firms in the pre-Reg. FD period, while in the post-Reg. FD period, the differences in information asymmetry between two groups do not persist.

In summary, analysts should make more FE for OPC firms than for CLC firms if open conference calls do not provide as much information as closed conference calls. The first objective of Reg. FD was to level the playing field among all investors and analysts with respect to access to corporate information. If this objective were achieved with the implementation of Reg. FD, then one observable effect should be no difference in analysts' earnings forecast attributes between the previous-OPC and previous-CLC firms. This line of reasoning leads to the following set of hypotheses (stated in null form):

- $H_{01.1}$. Analysts' quarterly earnings FE for the previous-CLC firms are not significantly different from those for the previous-OPC firms in the post-Reg. FD period (i.e. $FE_{POST}^{CLC} \approx FE_{POST}^{OPC}$).
- $H_{01.2}$. Analysts' quarterly earnings FD for the previous-CLC firms is not significantly different from that for the previous-OPC firms in the post-Reg. FD period (i.e. $FD_{POST}^{CLC} \approx FD_{POST}^{OPC}$).

Using the same line of reasoning, it can be argued that the earnings FE and FD of NCC firms should be greater than those of both CLC and OPC firms (if they remained conference call firms) in the post-Reg. FD period. In other words, Reg. FD's exclusive effect should be on closing the information gap between the OPC and CLC firms, but should have no effect on the greater informativeness of conference calls as a means of communicating more information to investors (as demonstrated by prior research). This leads to the following set of hypotheses (in alternative form):

- $H_{a1.3}$. Analysts' quarterly earnings FE for NCC firms are significantly greater than those for both previous-CLC and OPC firms in the post-Reg. FD period (i.e. $FE_{POST}^{NCC} > (FE_{POST}^{CLC}, FE_{POST}^{OPC})$).

H_a 1.4. Analysts' quarterly earnings FD for NCC firms is significantly greater than that for both previous-CLC and OPC firms in the post-Reg. FD period (i.e. $FD_{POST}^{NCC} > (FD_{POST}^{CLC}, FD_{POST}^{OPC})$).

In addition to the effects hypothesized above, the effectiveness of Reg. FD can be further evaluated by its effect on changes in the forecast attributes. That is, if the equality of the earnings forecast attributes between the CLC and OPC firms in the post-Reg. FD period is to be attributed to the adoption of Reg. FD, then the change in the forecast attributes from the pre- to the post-FD period should reflect this. So the absolute change in both FE and FD for the previous-CLC firms should be bigger than those for the OPC firms. These hypotheses can be stated in alternative form as follows:

H_a 2.1. The absolute change in analysts' quarterly earnings FE for the previous-CLC firms is significantly higher than that for the previous-OPC firms in the post-Reg. FD period (i.e. $|\Delta FE^{CLC}| > |\Delta FE^{OPC}|$).

H_a 2.2. The absolute change in analysts' quarterly earnings FD for the previous-CLC firms is significantly higher than that for the previous-OPC firms in the post-Reg. FD period (i.e. $|\Delta FD^{CLC}| > |\Delta FD^{OPC}|$).

3. Brief description of research methodology

3.1 Sample selection

Following the Bushee *et al.* (2003) approach, firms on the Bestcalls.com list are considered to be "open-call" firms (i.e. calls that allow unlimited real time access), while the firms provided by First Call Corporation but not included on the Bestcalls.com list are considered to be "closed-call" firms (i.e. calls that restrict access to invited professionals) in the pre-Reg. FD period. According to Bowen *et al.* (2002, p. 286, footnote 1), Bestcalls.com launched a web site in March 1999 publicizing the dates and times of conference calls open to individual investors. However, some firms did not allow individuals access to their calls. Meanwhile, other firms began live broadcasts of their conference calls using internet web casts. So it is reasonable to assume that after March 1999, all firms on the Bestcalls.com list had OPCs. Therefore, we divide the samples into three groups, OPC, CLC and NCC (where no disclosures are made via conference calls) firms in the pre-Reg. FD period. More specifically, the firms listed by the Bestcalls.com are regarded as OPC firms, while the firms listed by First Call Corporation but not included in the Bestcalls.com list are regarded as CLC firms. Firms listed in CRSP and the I/B/E/S databases but not included in either Bestcalls.com or First Call Corporation lists are regarded as pre-NCC firms.

To obtain better control of extraneous factors, the sample is restricted to firms which retained their status in both pre- and post-Reg. FD environments. We exclude firms that Bestcalls.com lists as NCC firms, as well as NCC firms now listed as CC firms. The analyst forecast data used are obtained from I/B/E/S database, and earnings announcement dates and other control variables from quarterly Compustat data sets. To ensure the meaningful computation of dispersion, the minimum number of analysts following a firm is set to four. All firms are required to have non-missing quarterly I/B/E/S forecast data during the period of October 1998 through September 2002 and non-missing quarterly Compustat data. After applying this screening process, the surviving sample consists of 1,697 firms (521 OPC, 990 CLC, and 186 NCC firms).

The total final sample consists of 12,806 firm-quarter observations in the pre-Reg. FD period, and 13,104 firm-quarter observations in the post-Reg. FD period.

The effect of the
SEC's Reg. FD

3.2 Research methodology

Empirical accounting research frequently utilizes the properties of analyst forecasts, such as accuracy, dispersion, bias, etc. to construct proxies for variables of interest. For instance, FD and errors in the mean forecast are used to proxy for the uncertainty or the degree of consensus among analysts or market expectations. Based on prior research, we estimated the effect of Reg. FD on analysts' forecast attributes by running a series of regression equations. Technical details on the regressions estimated are provided in Appendix. The description below is a brief summary of the approach used in the paper.

To control for factors that have been shown in prior research to be highly related to the levels of analyst FE and FD, we include in our regressions proxies measures for firm size, industry effect, earnings predictability, earnings surprise, and age of the forecast. Firm size and the level of FE or the level of FD are proxies for the richness of the firm's information environment. The ability of analysts to forecast the current quarter's earnings depends on both earnings surprise in the prior quarter and any information disclosed during the conference call. Forecast age is also an important determinant of forecast accuracy.

We estimate two regression equations, with the dependent variable in the first equation the absolute FE, and in the second equation, the FD. The independent variables in both equations include the dummy variables to represent the CLC and OPC firms, interaction terms to control for the presence of high-technology firms in the sample, forecast age (AGE), the number of analysts which follow a given firm (ANA), the size of earnings surprise in the previously released quarterly earnings (SURP), and firm size (SIZE).

The interaction terms for high-technology firms are designed to evaluate whether forecast attributes are consistently different for firms in the high technology sector. Barron *et al.* (2002) find that lower levels of analyst consensus are associated with high-tech firms because of their relatively high R&D expenditures. Therefore, a significantly positive coefficient on HighTech is consistent with the belief that analysts make more FE and dispersion for high-technology firms due to a higher information asymmetry as compared to non-high-technology firms.

4. Empirical results

4.1 Descriptive statistics

Tables I-III present some descriptive statistics on the post-Reg. FD period variables. Panel A reveals that both the mean and the median of analyst FE for NCC firms are greater than those for CLC and OPC firms in the post-Reg. FD period. Also the median of FD for NCC firms is greater than the median for both OPC and CLC firms in the post-Reg. FD period. Panel B presents the significant difference in means of FE and FD using statistical tests for the differences (specifically, Scheffe's tests and *t*-tests) in the post-Reg. FD period.

The first part of panel B shows that the means of OPC and CLC firms are not statistically different (at the 0.05 probability level), whereas the means for the other two groups, NCC and OPC, NCC and CLC are significantly different in the post-Reg. FD period. On the other hand, the second part of panel B shows the means between

	CLC firms	OPC firms	NCC firms
<i>Descriptive statistics^a</i>			
<i>FE</i>			
Mean	0.0109	0.0202	0.0254
Median	0.0019	0.0021	0.0024
Std. deviation	0.0561	0.3335	0.1513
<i>FD</i>			
Mean	0.0032	0.0085	0.0065
Median	0.0008	0.0008	0.0009
Std. deviation	0.0183	0.2166	0.0412
<i>AGE</i>			
Mean	60.8104	61.9091	59.6318
Median	61.0000	63.0000	59.0000
Std. deviation	32.2772	31.7771	32.3843
<i>ANA</i>			
Mean	8.1587	9.7380	8.2127
Median	7.0000	8.0000	7.0000
Std. deviation	4.7847	6.1128	4.3793
<i>SURP</i>			
Mean	-0.0029	-0.0055	-0.0041
Median	-0.0007	-0.0016	-0.0009
Std. deviation	0.0396	0.0454	0.1156
<i>SIZE</i>			
Mean	7.3864	7.6700	7.2287
Median	7.2105	7.5224	7.3333
Std. deviation	1.6543	1.6927	1.5248

Notes: ^aVariables definitions: FE_{it} = absolute difference between actual earnings per share for quarter t less the mean forecast as provided by IBES summary file at the end of the quarter t deflated by the stock price at the beginning of quarter t . FD_{it} = standard deviation of all analyst forecasts made at the end of the quarter t from the "consensus" (mean) of analysts' forecasts deflated by the stock price at the beginning of quarter t . AGE_{it} = the number of calendar days between the analyst's forecast date and the date of the actual earnings announcement at quarter t . ANA_{it} = the total number of analysts releasing an earnings forecast for the firm i at quarter t . $SURP_{it} = \{EPS_t - EPS_{t-4}\} / P_{t-4}$, where EPS_t is the primary earnings share (excluding extraordinary items) for quarter t and P_{t-4} is the ending price per share at quarter $t - 4$. $SIZE_{it}$ = the log of market value of equity at the beginning of quarter t .

^bAll correlations are significant at the 0.001 level or better except for the correlation between $SURP$ and ANA , and ANA and AGE , which are not significant at conventional levels.

^cAbove of the table is the Pearson correlation coefficients and the below is the Spearman correlation coefficients.

¹NCC – non-conference call firms; ²CLC – closed-call firms; ³OPC – open-call firms.

& = Statistically significant at a probability of less than 0.10;

* = Statistically significant at a probability of less than 0.05;

** = Statistically significant at a probability of less than 0.01;

*** = Statistically significant at a probability of less than 0.001

Table I.
Univariate tests on
analysts forecast
attributes and other
variables after Reg.
FD: Panel A

NCC and CC, and between CLC and OPC in the post-Reg. FD period are statistically different. All the t -values are significant for each comparison except for the comparison of FD between NCC and CC in the post-Reg. FD period. These preliminary results are generally consistent with H1.1-H1.4.

Panel C presents correlation coefficients (both the Pearson product-moment and Spearman rank-order correlations) between analyst forecast attributes and their determinants in the post-Reg. FD period. All the correlation coefficients have signs consistent with those expected for the regression coefficients and all are significant except for the correlation coefficient between the number of analysts following (ANA) and forecast age (AGE), and between ANA and earnings surprise (SURP). The correlation coefficients between the number of analysts following (ANA) and the firm size (SIZE) is the highest among all coefficients, which is consistent with the previous research findings that large firms usually have a large group of analysts following regardless of the implementation of Reg. FD.

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4.2 Regression results

Table IV presents the results of regressing analyst FE and FD in the pre- and post-Reg. FD periods by using equations (1) and (2). As expected, the coefficients of two dummy variables, CLC and OPC, are significantly negative. Moreover, the coefficients of CLC are greater than the coefficients of OPC for both regressions of FE and FD in both pre- and post-Reg. FD periods. Also as expected, forecast age (AGE), the number of forecasts (ANA) and high-tech firms (HighTech) are positively associated with FE and FD, while earnings surprise (SURP) and firm size (SIZE) are negatively associated with FE and FD.

Focusing on the tests of *H1-H4*, the results in Table IV (PRE period) indicate that conference calls did provide additional information to financial analysts, with both OPC and CLC firms having fewer earnings FE than NCC firms prior to the

Tests	Group/Variables ^a	FE	FD
<i>Scheffe's tests and Satterthwaite unequal variance t-tests for OPC³, CLC² and NCC¹ firms</i>			
Scheffe's test – Difference in means	NCC ¹ – CLC ²	0.0224*	0.0057*
	NCC ¹ – OPC ³	0.0224*	0.0062*
	CLC ² – OPC ³	–0.0001	0.0005
T-test among 3 groups: <i>t</i> value	NCC ¹ – (CLC ² + OPC ³)	4.43***	1.47
	CLC ² – OPC ³	4.18***	3.71***

Note: See Table I for key

Table II.
Univariate tests on
analysts forecast
attributes and other
variables after Reg. FD:
Panel B

Variables ^a	FE	FD	AGE	ANA	SURP	SIZE
<i>Correlations between forecast attributes and other variables^{bc}</i>						
FE	1	0.7646	0.0620	–0.0329	–0.1510	–0.1749
FD	0.6123	1	0.0253	–0.0405	0.0415	–0.1706
Age	0.1422	0.0151	1	0.0108	–0.0191	0.0228
ANA	–0.1604	–0.1827	0.0526	1	–0.0196	0.5160
SURP	–0.3063	–0.1450	–0.0170	–0.0012	1	–0.0020
Size	–0.3806	–0.4391	0.0233	0.5003	0.0381	1

Note: See Table I for key

Table III.
Univariate tests on
analysts forecast
attributes and other
variables after Reg.
FD: Panel C

Table IV.
Regression of analyst FE
and dispersion on both
pre- and post-Reg. FD
variables

Regression of FE and FD	Variables ^a	Expected sign	Among NCC, CLC and OPC firms			
			Before Reg. FD (PRE)		After Reg. FD (POST)	
			FE	FD	FE	FD
			Coefficient	t-value	Coefficient	t-value
	Intercept		0.0169	56.49***	0.0877	31.26***
	CLC	-	-0.0006	-2.34*	-0.0225	-12.09***
	OPC	-	-0.0011	-4.09***	-0.0232	-11.72***
	HighTech × CLC	+	-0.0004	-2.71**	0.0121	6.43***
	HighTech × OPC	+	0.0016	11.9***	0.0127	7***
	HighTech × NCC	+	0.0019	3.31***	-0.0077	-2.39*
	AGE	+	0.0001	29.38***	0.0001	9.89***
	ANA	+	0.0001	5.82***	0.0010	8.95***
	SURP	-	-0.0366	-35.5***	-0.2127	-24.14***
	SIZE	-	-0.0018	-74.74***	-0.0097	-28.82***
	Adjusted R ²		0.1294		0.0697	
	F-statistic		1,038.41***		213.36***	
	F-test ($\alpha_1 =$		31.73***		129.65***	
	$\alpha_2, \beta_1 = \beta_2$)				0.11	

Notes: ^aVariables definitions: FE_{*t*}, absolute difference between actual earnings per share for quarter *t* less the mean forecast as provided by IBES summary file at the end of the quarter *t* deflated by the stock price at the beginning of quarter *t*; FD_{*t*}, standard deviation of all analyst forecasts made at the end of the quarter *t* from the "consensus" (mean) of analysts' forecasts deflated by the stock price at the beginning of quarter *t*; AGE_{*t*}, the number of calendar days between the analyst's forecast date and the date of the actual earnings announcement at quarter *t*; ANA_{*t*}, the total number of analysts releasing an earnings forecast for the firm *i* at quarter *t*; SURP_{*t*} = {EPS_{*t*} - EPS_{*t-4*}/P_{*t-4*}, where EPS_{*t*} is the primary earnings share (excluding extraordinary items) for quarter *t* and P_{*t-4*} is the ending price per share at quarter *t* - 4; SIZE_{*t*}, the log of market value of equity at the beginning of quarter *t*; ^ball correlations are significant at the 0.001 level or better except for the correlation between SURP and ANA which is not significant at conventional levels; ^cabove of the table is the Pearson correlation coefficients and the below is the Spearman correlation coefficients; ^dNCC - non-conference call firms; ^eCLC - closed-call firms; ^fOPC - open-call firms; ^gstatistically significant at a probability of <0.10; ^hstatistically significant at a probability of <0.05; ⁱstatistically significant at a probability of <0.01; ^jstatistically significant at a probability of <0.001.

implementation of Reg. FD. This conclusion can be drawn from the differences in the values of the intercepts terms for the NCC and CLC dummy variables. The intercept of the regression of FE in the pre-Reg. FD period is 0.0169 for NCC firms, 0.0163 (i.e. $0.0169 - 0.0006$) for CLC firms, and 0.0158 (i.e. $0.0169 - 0.0011$) for OPC firms. The intercept of the regression of FD in the pre-Reg. FD period is 0.0049 for NCC firms, 0.0045 (i.e. $0.0049 - 0.0004$) for CLC firms, and 0.0044 (i.e. $0.0049 - 0.0005$) for OPC firms.

Further examination of the regressions results in Table IV (POST period) supports the inference that analysts still made more FE and had higher FD for the NCC firms as compared to the OPC and CLC firms after the release of Reg. FD. In the post-Reg. FD period, the intercept of the regression of FE is 0.0877 for NCC firms, 0.0652 (i.e. $0.0877 - 0.0225$) for CLC firms, and 0.0645 (i.e. $0.0877 - 0.0232$) for OPC firms. The intercept of the regression of FD in the post-Reg. FD period is 0.0203 for NCC firms, 0.0158 (i.e. $0.0203 - 0.0045$) for CLC firms, and 0.0157 (i.e. $0.0203 - 0.0046$) for OPC firms.

To determine if Reg. FD has any impact on analysts FE, it is necessary to compare the coefficients across CLC and OPC firms within each period which can be done using the standard *F*-test. The *F*-tests performed show that the observed differences between the coefficients of interest (α_1 and α_2 in equation (1) and β_1 and β_2 in equation (2) in the Appendix) support the hypotheses presented earlier. In the pre-Reg. FD period, the *F*-value for FE (FD) is 31.73 (11.28), and the *p*-value is significant at the 0.001 level. Thus, these two null hypotheses that $\alpha_1 = \alpha_2$, and $\beta_1 = \beta_2$ can both be rejected. However, in the post-Reg. FD period, the *F*-value for FE (FD) is 0.37 (0.11) with an insignificant probability level. Thus, the null hypotheses that $\alpha_1 = \alpha_2$ in equation (1) and $\beta_1 = \beta_2$ in equation (2) cannot be rejected.

In summary, there are observable differences in the regression coefficients between CLC and OPC firms in the PRE period, and these statistically significant differences in coefficients disappear in the POST period. These results thus support both *H1.1* and *H1.2*, and provide evidence that differences in analyst forecast performance between the previous-CLC and previous-OPC firms do not persist after Reg. FD went into effect[1].

4.3 Univariate analyses of change in analyst forecast attributes

Tables V-VII present some descriptive statistics on the absolute change in analyst FE ($|\Delta FE|$) and FD ($|\Delta FD|$). From panel A, it can be observed that the means of $|\Delta FE|$ and $|\Delta FD|$ for CLC firms are smaller than those for OPC firms. Panel B presents the significant difference in means of the absolute change in FE and FD using both Scheffe's tests and the pairwise *t*-tests.

The results from Scheffe's tests show the comparisons in means are significantly different at the 0.05 level among three groups except for one comparison, $|\Delta FE|$ between CLC and OPC firms. At the same time, the results from the *t*-tests show that there is no significant difference in mean levels of $|\Delta FE|$ or $|\Delta FD|$ for the comparison between NCC and CC (including CLC and OPC firms) firms and the comparison between CLC and OPC firms. Panel C presents the Pearson and Spearman correlation coefficients between the absolute change in analyst forecast attributes and their determinants.

Statistics	CLC firms	OPC firms	NCC firms
<i>Descriptive statistics^a</i>			
$ \Delta FE $			
Mean	0.0113	0.0199	0.0318
Median	0.0021	0.0023	0.0024
Std. deviation	0.0477	0.4281	0.2186
$ \Delta FD $			
Mean	0.0027	0.0069	0.0087
Median	0.0005	0.0005	0.0007
Std. deviation	0.0129	0.2061	0.0744
ΔAGE			
Mean	1.1795	1.3668	8.0495
Median	-1.0000	-1.0000	-1.0000
Std. deviation	46.5676	45.8835	53.9615
ΔANA			
Mean	1.5168	2.0406	1.1011
Median	1.0000	1.0000	0.0000
Std. deviation	4.8651	5.4807	4.6420
$\Delta SURP$			
Mean	-0.0062	-0.0134	-0.0048
Median	-0.0031	-0.0029	-0.0018
Std. deviation	0.0596	0.0909	0.1276
$lagSIZE$			
Mean	7.3170	7.6682	7.1224
Median	7.1327	7.5000	7.1416
Std. deviation	1.6198	1.7113	1.4797
$lagFE$			
Mean	0.0086	0.0083	0.0132
Median	0.0016	0.0017	0.0020
Std. deviation	0.0451	0.0349	0.0474
$lagFD$			
Mean	0.0021	0.0020	0.0035
Median	0.0007	0.0006	0.0009
Std. deviation	0.0093	0.0098	0.0167

Notes: ^aVariable definition: CLC = a dummy variable equal to 1 if the firm is a CLC firm and 0 if the firm is a NCC or OPC firm. $|\Delta FE_t|$ = the absolute value of the difference between forecast errors in the post- and the pre-Reg. FD period deflated by the price at the beginning of the pre-Reg. FD period. $|\Delta FD_t|$ = the absolute value of the difference between forecast dispersion in the post- and the pre-Reg. FD period deflated by the price at the beginning of the pre-Reg. FD period. ΔAGE_t = the difference in forecast age between the post- and pre-Reg. FD period. ΔANA_t = the difference in the number of followed analysts between the post- and pre-Reg. FD period. $\Delta SURP_t$ = the difference in earnings surprise between the post- and pre-Reg. FD period. $lagSIZE$ = the log of market value of equity in the pre-Reg. FD period. $lagFE$, $lagFD$ = the level of forecast error or forecast dispersion in the pre-Reg. FD period.

^bAbove the table is the Pearson correlation coefficients and the below is the Spearman correlation coefficients. All correlations are significant at the 0.001 level or better except for the correlations between $\Delta SURP$ and ΔANA , $\Delta SURP$ and ΔAGE , ΔAGE and $lagFE$, and $\Delta SURP$ and $lagSIZE$, which are not significant at conventional levels.

¹NCC – non-conference call firms;

²CLC – closed-call firms;

³OPC – open-call firms.

& = Statistically significant at a probability of less than 0.10;

* = Statistically significant at a probability of less than 0.05;

** = Statistically significant at a probability of less than 0.01;

*** = Statistically significant at a probability of less than 0.001

Table V.
Univariate tests on the
change in analysts
forecast attributes:
Panel A

4.4 Regression results for change in analyst forecast attributes

Table VIII presents the regression results obtained when the absolute changes in analyst quarterly FE ($|\Delta FE|$) and FD ($|\Delta FD|$) are regressed on the hypothesized independent variables (as presented in equations (3) and (4) in Appendix). The sign of coefficients on the dummy variable, OPC, for both regressions of $|\Delta FE|$ and $|\Delta FD|$ is not significant, a result which contradicts *H2.1* and *H2.2*. In addition, the sign of coefficients on the dummy variable, NCC, is significantly positive for both regressions of $|\Delta FE|$ and $|\Delta FD|$.

Because we adopt October 23, 2000 as the boundary between the pre-Reg. FD period and the post-period, it is possible that the failure to support *H2.1* and *H2.2* may be due to the choice of the cut-off date. Previous research by Mac (2003) finds that firms had already changed their voluntary disclosure policy in the pre-enactment period (December 20, 1999-October 22, 2000), before Reg. FD became effective on October 23, 2000. Thus, if some firms in the sample have already changed their voluntary disclosure policy prior to the release of Reg. FD because they anticipate the passage of Reg. FD, the tests may not be sufficiently powerful.

Figures 1 and 2 show the graph of the means of FE and FD among three groups, CLC, OPC and NCC firms, from the third quarter of 1998 to the third quarter of 2002. Both Figures 1 and 2 show that FE and FD for NCC firms are higher than those for both OPC and CLC firms in both pre- and post-Reg. FD periods. However, the means of FE (FD) for CLC firms are greater than those for OPC firms in the pre-Reg. FD period

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Tests ^a	Group/Variables ^a	$ \Delta FE $	$ \Delta FD $
<i>Test of difference in means of ΔFE and ΔFD – Scheffe's tests and Satterthwaite unequal variance T-tests</i>			
1. Scheffe's Tests – Difference between Means	NCC ¹ – CLC ²	0.158 *	0.0046 *
	NCC ¹ – OPC ³	0.0163 *	0.005 *
	CLC ² – OPC ³	0.0005	0.0004
	NCC ¹ – (CLC ² + OPC ³)	1.62	1.18
2. T tests – t value	CLC ² – OPC ³	1.02	1.03

Note: See Table V for key

Table VI.
Univariate tests on the
change in analysts
forecast attributes:
Panel B

	$ \Delta FE $	$ \Delta FD $	ΔAge	ΔANA	$\Delta SURP$	lagSIZE	lagFE	lagFD
<i>Correlations^{ab}</i>								
$ \Delta FE $	1	0.5810	0.1128	-0.0467	-0.1486	-0.1476	0.6277	0.5205
$ \Delta FD $	0.5004	1	0.0806	-0.0322	0.0634	-0.1171	0.4934	0.5922
ΔAge	0.0741	0.0556	1	-0.0493	-0.0375	-0.1274	0.0402	0.0073
ΔANA	-0.0649	-0.0663	-0.0121	1	-0.0090	0.1034	-0.0306	-0.0211
$\Delta SURP$	-0.1501	-0.0723	0.0035	0.0023	1	0.0060	0.0006	-0.0746
lagSIZE	-0.2966	-0.3287	-0.0728	0.1086	-0.0038	1	-0.1846	-0.1692
lagFE	0.5398	0.4751	0.0465	-0.0540	0.0159	-0.3826	1	0.7908
lagFD	0.4242	0.5425	0.0352	-0.0858	-0.0189	-0.3673	0.5494	1

Note: See Table V for key

Table VII.
Univariate tests on the
change in analysts
forecast attributes:
Panel C

Variables ^a	Expected sign	ΔFE		ΔFD	
		Coefficient	t-value	Coefficient	t-value
Intercept		0.0075	2.61 **	0.0005	0.68
OPC	—	−0.0013	−0.88	−0.0003	−0.87
NCC	—	0.0188	7.26 ***	0.0029	4.11 ***
HighTech × CLC	+	0.0018	0.71	0.0014	2.05 *
HighTech × OPC	+	0.0069	2.98 **	0.0012	1.93 &
HighTech × NCC	+	−0.0175	−3.27 **	−0.0021	−1.42
ΔAGE	+	0.0001	4.13 ***	0.0000	3.57 ***
ΔANA	+	−0.0004	−1.7 &	−0.0001	−1.29
ΔSURP	—	−0.0900	−11.69 ***	0.0039	1.84 &
lagSIZE	—	−0.0005	−1.25	0.0000	−0.11
lagFE	—	0.8006	42.55 ***		
lagFD	—			0.8514	40.01 ***
Adjusted R ²		0.4435		0.3831	
F-statistic		222.35 ***		173.53 ***	

Notes: ^aVariable definition: CLC, a dummy variable equal to 1 if the firm is a CLC firm and 0 if the firm is a NCC or OPC firm; OPC, a dummy variable equal to 1 if the firm is a OPC firm and 0 if the firm is a NCC or CLC firm; HighTech, a dummy variable equal to 1 if the firm is a high-technology firm and 0 if the firm is not a high-technology firm; |ΔFE_{*t*}|, the absolute value of the difference between FE in the post- and the pre-Reg. FD period deflated by the price at the beginning of the pre-Reg. FD period; |ΔFD_{*t*}|, the absolute value of the difference between FD in the post- and the pre-Reg. FD period deflated by the price at the beginning of the pre-Reg. FD period; ΔAGE_{*t*}, the difference in forecast age between the post- and pre-Reg. FD period; ΔANA_{*t*}, the difference in the number of followed analysts between the post- and pre-Reg. FD period; ΔSURP_{*t*}, the difference in earnings surprise between the post- and pre-Reg. FD period; lagSIZE, the log of market value of equity in the pre-Reg. FD period; lagFE, lagFD, the level of FE or FD in the pre-Reg. FD period; ¹NCC – non-conference call firms; ²CLC – closed-call firms; ³OPC – open-call firms; & statistically significant at a probability of less than 0.10; * statistically significant at a probability of < 0.05; ** statistically significant at a probability of < 0.01; *** statistically significant at a probability of < 0.001

Table VIII.
Regression of the change
in analyst forecast
attributes

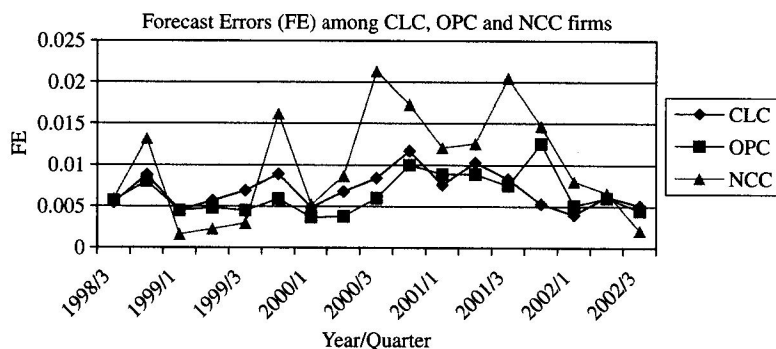


Figure 1.

(before the third quarter of 2000), but generally indistinguishable in the post-Reg. FD period.

The statistical tests performed earlier show that the difference in OPC and CLC means for FE and FD are not statistically significant (when the control variables are

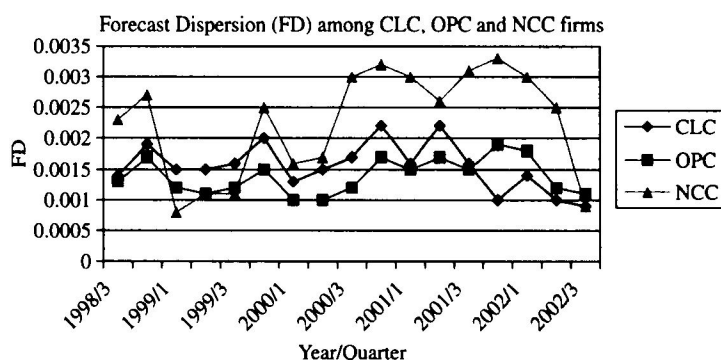


Figure 2.

accounted for) in the post-Reg. FD period. However, CLC firms have statistically significant (and positive) intercepts compared to NCC firms in both pre- and post-Reg. FD periods. This finding indicates that both FE and FD for NCC firms increase relative to those of OPC and CLC firms (both of which held conference calls). Thus, the overall view conveyed is that conference calls continue to be useful in helping analysts to produce accurate forecasts during a period when NCC firms experience a huge jump in earnings FE and FD.

4.5 Additional analysis and robustness tests

It can be argued that FE is another factor which affects FD. To evaluate this possibility, we use a recursive two-stage regression approach by allowing FE to be included as an explanatory variable for the FD equation. The regression results of FE and FD are qualitatively consistent with the previous results without adding FE in the regression of FD.

To evaluate the robustness of these results to possible outliers, we apply four diagnostic tests recommended by Belsley *et al.* (1980):

- (1) the diagonal of the projection matrix (Hat matrix);
- (2) the studentized residuals (RSYUDENT);
- (3) the change in the determinants of the covariance matrix of the estimates (CovRatio); and
- (4) the change in the predicted value (DFFITS).

The filters are applied by setting observations exceeding the cutoffs recommended by Belsley *et al.* (1980) to missing values. Qualitatively, the results are the same regardless of whether the outliers are eliminated or not.

5. Conclusion

Prior to the release of Reg. FD, CLC firms were accustomed to disclosing material nonpublic information to certain analysts and institutional investors while not concurrently releasing the information to the general public. There is considerable anecdotal evidence indicating that managers penalize analysts based on the content of their forecasts by limiting or cutting off analysts' future contact with management. Since, voluntary disclosures (e.g. conference calls) put individual investors at a larger

informational disadvantage, it has been of concern to the SEC that the effect of selective disclosure is similar to insider trading. The primary purpose of Reg. FD is to curtail analysts' private channels to companies that they had previously enjoyed.

The results of this study are somewhat mixed. On one hand, there is support for the inference that, at least with respect to closing the information gap between analysts privy to the closed conference calls and those not privy to these calls, Reg. FD succeeded in that no statistical difference in earnings FE and FD between the previous-CLC and previous-OPC firms remained in the post-Reg. FD period. Moreover, in the post-Reg. FD period, conference calls continue to lead to lower FE and FD for both previous-OPC and previous-CLC firms, despite a huge jump in the earnings forecast attributes for firms which do not hold conference calls.

Against these favorable findings may be offset the contrary finding that no change in the earnings forecast attributes centered on the actual date of adoption of Reg. FD could be detected. Moreover, the findings reported by Gintschel and Markov (2004) that the informativeness of analysts' information output have declined in the post-Reg. FD period suggests that analysts' forecast attributes may no longer play as vital a role in the capital markets as in the pre-Reg. FD period. To the extent that this was the intent of the SEC in adopting Reg. FD, then the policy may be deemed to be a success[2].

Notes

1. These results are consistent with the findings reported by Shane *et al.* (2001). They provide evidence that analysts gather relatively more uncertainty-relieving information between earnings announcements and by the end of the quarter, their forecasts are as accurate as they were in the prior year. That is to say, the previous-CLC firms may have changed their selective disclosure policy, and Reg. FD may have contributed to the leveling of such information asymmetry.
2. It is not clear what the implication of the findings of Clement and Tse (2003) that investors respond more strongly to the earlier forecasts than to the later forecasts (despite the greater accuracy of the later forecasts) are to the findings reported by Gintschel and Markov (2004). Presumably, analysts forecasts may be more useful when released early than later. The effect of Reg. FD on analyst behavior in terms of earlier or later revisions of forecasts have yet to be examined.

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Appendix. Description of regression equations estimated

Test of first set of hypotheses (H1.1-H1.4)

We use the following two regression models in the cross-sectional tests to test H1.1-H1.4, using data for the pre- and the post-Reg. FD period, respectively:

$$FE_{it} = \alpha_0 + \alpha_1 CLC_{it} + \alpha_2 OPC_{it} + \alpha_3 (HighTech \times CLC) + \alpha_4 (HighTech \times OPC) + \alpha_5 (HighTech \times NCC) + \alpha_6 AGE_{i,t} + \alpha_7 ANA_{i,t} + \alpha_8 SURP_{i,t} + \alpha_9 SIZE_{it} + \epsilon_{it} \quad (1)$$

$$FD_{it} = \beta_0 + \beta_1 CLC_{it} + \beta_2 OPC_{it} + \beta_3 (HighTech \times CLC) + \beta_4 (HighTech \times OPC) + \beta_5 (HighTech \times NCC) + \beta_6 AGE_{i,t} + \beta_7 ANA_{i,t} + \beta_8 SURP_{i,t} + \beta_9 SIZE_{it} + \epsilon_{it} \quad (2)$$

where, CLC, a dummy variable equal to 1 if the firm is a CLC firm and 0 if the firm is a NCC or OPC firm; OPC, a dummy variable equal to 1 if the firm is an OPC firm and 0 if the firm is a NCC

or CLC firm; NCC, a dummy variable equal to 1 if the firm is a NCC firm and 0 if the firm is an OPC or CLC firm; HighTech, a dummy variable equal to 1 if the firm is a high-technology firm and 0 if the firm is not a high-technology firm; FE_{it} , the absolute difference between actual earnings per share for quarter t less the mean forecast as provided by IBES summary file at the end of the quarter t deflated by the stock price at the beginning of quarter t ; FD_{it} , the standard deviation of all analyst forecasts made at the end of the quarter t from the "consensus" (mean) of analysts' forecasts deflated by the stock price at the beginning of quarter t . The consensus forecast used is the last one on the IBES summary tape prior to earnings being reported; AGE_{it} , the number of calendar days between the analyst's forecast date and the date of the actual earnings announcement at quarter t ; ANA_{it} , total number of analysts releasing an earnings forecast for the firm i at quarter t ; $SURP_{it} = \{EPS_t - EPS_{t-4}\} / P_{t-4}$, a proxy for the difficulty in forecasting earnings, where EPS_t is the primary earnings share (excluding extraordinary items) for quarter t and P_{t-4} is the ending price per share at quarter $t - 4$; $SIZE_{it}$, the log of market value of equity at the beginning of quarter t .

To evaluate *H1.1*, an F -test of whether $\alpha_1 = \alpha_2$ in equation (1) is performed. Similarly, to evaluate *H1.2*, an F -test of whether $\beta_1 = \beta_2$ in equation (2) is performed. Rejection of the equalities and the relative magnitude of the two parameters would permit us to infer that analyst earnings forecast attributes are different for the previous-CLC firms versus the previous-OPC firms in the post-Reg. FD period. The test of *H1.3* is an F -test of whether $\alpha_1 + \alpha_2 = 0$. Rejection of that equality would provide support for *H1.3*. Similarly, a test of *H1.4* is whether $\beta_1 + \beta_2 = 0$, with its rejection an indication that *H1.4* is supported by the data.

Test of second set of hypotheses (H2.1-H2.4)

To test *H2.1* and *H2.4*, the dependent variables for testing the attributes of analyst earnings forecast are the change in FE and the change in FD. Using changes rather than levels of FE and dispersion mitigates the effect of cross-sectional differences in information environments. The general form of each dependent variable is:

$$\frac{\text{Post-Reg. FD event measure} - \text{Pre-Reg. FD event measure}}{\text{Stock price at Pre-Reg. FD event date}}$$

The pre-Reg. FD event measure component of the dependent variable is the quarterly FE or quarterly FD measured at quarter t before Reg. FD, and the post-Reg. FD event measure component of the dependent variable is the quarterly FE or quarterly FD measured at quarter t after Reg. FD:

$$|\Delta FE| = \left| \frac{FE_{\text{post},it} - FE_{\text{pre},it}}{P_{\text{pre},it}} \right|$$

$$|\Delta FD| = \left| \frac{FD_{\text{post},it} - FD_{\text{pre},it}}{P_{\text{pre},it}} \right|$$

The regressions estimated to evaluate *H2.1* and *H2.4* can be written as follows:

$$\begin{aligned} |\Delta FE_{it}| = & \lambda_0 + \lambda_1 \text{OPC}_{it} + \lambda_2 \text{NCC}_{it} + \lambda_3 (\text{HighTech} \times \text{CLC}) \\ & + \lambda_4 (\text{HighTech} \times \text{OPC}) + \lambda_5 (\text{HighTech} \times \text{NCC}) + \lambda_6 \Delta \text{AGE}_{it} + \lambda_7 \Delta \text{ANA}_{it} \\ & + \lambda_8 \Delta \text{SURP}_{it} + \lambda_9 \text{lagSIZE}_{i,\text{pre}} + \lambda_{10} \text{lagFE}_{i,\text{pre}} + \delta_{it} \end{aligned} \quad (3)$$

$$\begin{aligned} |\Delta FD_{it}| = & \gamma_0 + \gamma_1 \text{OPC}_{it} + \gamma_2 \text{NCC}_{it} + \gamma_3 (\text{HighTech} \times \text{CLC}) \\ & + \gamma_4 (\text{HighTech} \times \text{OPC}) + \gamma_5 (\text{HighTech} \times \text{NCC}) + \gamma_6 \Delta \text{AGE}_{it} + \gamma_7 \Delta \text{ANA}_{it} \\ & + \gamma_8 \Delta \text{SURP}_{it} + \gamma_9 \text{lagSIZE}_{i,\text{pre}} + \gamma_{10} \text{lagFD}_{i,\text{pre}} + \delta_{it} \end{aligned} \quad (4)$$

where $\text{lagSIZE}_{i,\text{pre}}$, the log of market value of equity in the pre-Reg. FD period; $\text{lagFE}_{i,\text{pre}}$, the level of FE in the pre-Reg. FD period; $\text{lagFD}_{i,\text{pre}}$, the level of FD in the pre-Reg. FD period, and all terms are as defined earlier.

As presented in equations (3) and (4), the CLC effect is captured in the intercept. Thus, to evaluate *H2.1*, the test is whether $\lambda_1 < 0$ in equation (3). This essentially examines whether the change in FE is higher for the firms classified as CLC in the pre-Reg. FD period than that for the OPC firms. If so, then Reg. FD had a more pronounced effect on the firms which previously held closed conference calls. This is exactly the effect that should be expected if Reg. FD had the desired effect.

Similarly, to evaluate *H2.2*, the test is whether $\gamma_1 < 0$ in equation (4). Rejection of the equality with positive coefficients would permit an inference that the absolute change in analyst earnings forecast attributes for the previous-CLC firms was greater than the absolute change for the previous-OPC firms.

Corresponding author

Rong Yang can be contacted at: ryang@brockport.edu

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The Most Important Number in Finance

The Quest for the Market Risk Premium



Marc Zenner
marc.p.zenner@jpmorgan.com
(212) 834-4330

Scott Hill
scott.d.hill@jpmorgan.com
(415) 315-8842

John Clark
john.hs.clark@jpmorgan.com
(212) 834-2156

Nishant Mago
nishant.x.mago@jpmorgan.com
(212) 834-2172

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1. The most important number in finance

You will not find it in section C of *The Wall Street Journal*. *CNBC* will not mention it in its morning market recap. *The Economist* will not provide it in its back pages with other financial data. Yet it is one of the most critical metrics in finance, a figure implicit in the evaluation of financing and investment opportunities: the market risk premium. What is it? How and where should it be used? What is the right number to use? Does it change over time?

In this report, we (1) estimate a current range of risk premiums; (2) explain how the risk premium has increased since the beginning of the subprime crisis; (3) discuss how, thanks to Federal Reserve intervention, a higher risk premium does not necessarily lead to a higher cost of capital; and (4) debate how possible divergence between equity and credit markets since last summer may affect strategic and financial decision-making. In addition, we review some common methods used to estimate the market risk premium.

What is the market risk premium?

The *market risk premium* (MRP) reflects the incremental premium required by investors, relative to a risk-free asset like U.S. Treasury bonds, to invest in a globally diversified market portfolio. Below is a simple and generally accepted equation:

$$\text{Expected return on the market portfolio} = \text{Risk-free rate of return} + \text{market risk premium}$$

Should the market risk premium be higher for some assets and lower for others? Most likely yes, but how should the adjustment be made? The Capital Asset Pricing Model (CAPM) proposes one such adjustment. CAPM states that the expected return on an asset is the risk-free rate plus an MRP that is adjusted, through beta, to reflect the market risk of the asset:

$$\text{Expected return on an asset} = \text{Risk-free rate of return} + \text{beta} * \text{market risk premium}$$

The beta is a calibration factor that is higher (lower) than one if the asset has a systematic, or non-diversifiable, risk that is higher (lower) than the market's risk. In the CAPM framework, the MRP should apply to all assets, including bonds, real estate, art, etc. In practice, however, the risk premium is mostly used to estimate the expected return on equity (also referred to as the cost of equity). Bond markets rely on their own risk premium concept, the credit spread, which is the difference between the yield on a bond and the maturity-matched Treasury rate.

From a macroeconomic perspective, the MRP reflects the broader outlook on the whole economy. Factors influencing investors' views on market risk include outlooks for economic growth, consumer demand, inflation, interest rates, and geopolitical risks. As such, the MRP is a single metric that reflects these inputs in the expected returns of various asset classes.

Why is the market risk premium so important?

While many finance professionals and executives actively manage their debt and debate the incremental basis points their firm may have to pay on new bonds, they do not tend to focus much on the cost of equity. Is it that debt financing is so much more prevalent than equity financing? Not really. Even with a tax system that favors debt financing, equity financing constitutes over 80% of the total market capitalization for a typical non-financial S&P 500 firm today.

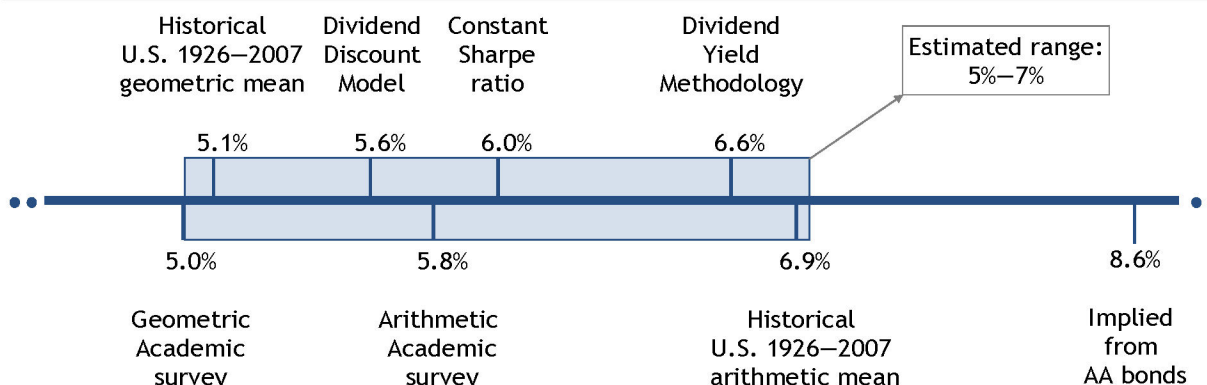
Why then is there less focus on the cost of equity? Maybe because most firms manage debt actively and equity only passively; or because an economic cost of equity of 12% does not translate into an actual cash outlay of 12%; or perhaps because there is no consensus on how to estimate the market risk premium.

Practical Application: Understanding and quantifying the MRP is critical to the value-creation process. With most of their capitalization in the form of equity, decision-makers require an estimate of the MRP to determine their cost of capital, identify projects that create shareholder value, decide how much to pay for acquisition targets, evaluate their capital structure, and compare the costs of various sources of financing. Not adjusting the cost of equity to new market realities may lead firms to (1) over or under-invest or (2) forgo capital-structure opportunities.

What is the market risk premium today?

No single method to estimate the MRP is used universally. Our review of various methods (detailed in Section 2) suggests that they each have strengths and weaknesses. They also generate a wide range of results as summarized in the figure below. We therefore recommend thinking about the MRP in terms of a range rather than a unique number. Based on our results, the MRP probably falls within a range of 5% - 7% today.

Figure 1: Summary of risk premium estimates



Source: JPMorgan

If I do not use CAPM, should I still focus on the market risk premium?

Most practitioners use CAPM as their method of choice to estimate the cost of capital. Interestingly, while academics often emphasize the limitations of CAPM, they still tend to focus on it when teaching about the cost of capital. Two of the risk premium estimation methods we used rely on CAPM (the Dividend Yield and the bond-based methods). The Dividend Discount and Sharpe ratio methods, as well as the historical analysis, do not rely on CAPM. Practitioners who do not use CAPM can still use the risk premium range we suggest by using the low (high) end of the range for projects they perceive to be at the low (high) end of their risk spectrum.

My firm is global, so should I focus on a risk premium based on U.S. data?

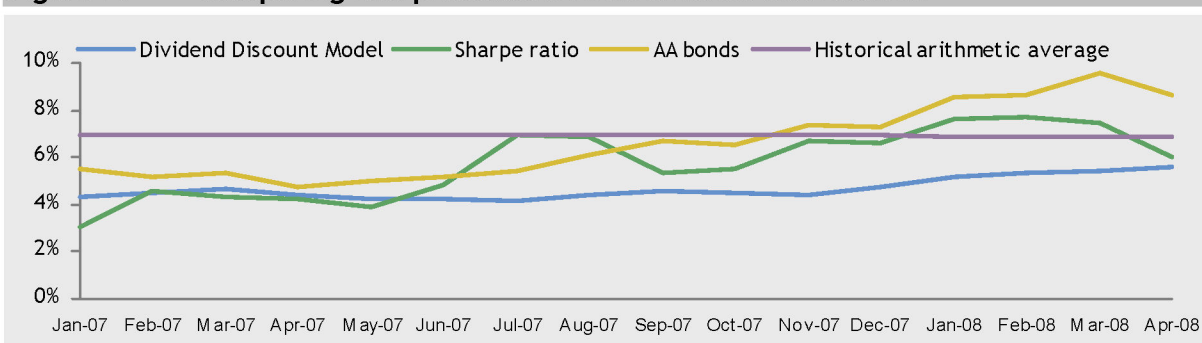
The results we present are based on U.S. market data. Can you use these risk premium estimates for investments in other countries? We believe that the U.S.-based MRP is a reasonable estimate for developed economies for a couple of reasons. First, an unconstrained investor would not freely invest in a market in which he/she would earn a lower risk-adjusted return. Hence risk premiums should gravitate to each other across open developed markets, and the U.S.-based risk premium should serve as a good estimate for this. The situation may be different in emerging markets, however, where non-market risks may exist (e.g., political risk) or where investor segmentation and constraints limit the free flow of capital into and out of the country. Second, the U.S. market has some data advantages, namely very broad markets with long data histories. Many other markets tend to be over-weighted in some sectors (e.g., banking, shipping, energy, telecommunications) or have data series that have been interrupted by political events in the 20th century.

Has the risk premium changed since last summer?

Are we in a new risk premium environment? The figure below shows that the answer depends on the methodology. The historical method, as expected, suggests no change in the risk premium. On the other hand, methods that rely on current market information (which we discuss in detail later)

signal that the risk premium has increased since the credit crisis began last summer, but that it has declined from its peak in February/March.

Figure 2: Comparing risk premium estimates since last summer



Source: JPMorgan, SBBI Market Report-Morningstar, Bloomberg

Should executives change their hurdle rates for capital allocation?

Boards of Directors and senior executives implicitly use the MRP when determining hurdle rates for new projects and acquisitions. There is a preference for hurdle rates that do not change often, possibly because stable hurdle rates facilitate communication with regional and divisional management. In some cases, however, it is critical to understand whether changing market conditions affect how the market prices risk. Financial decision-makers examine day-to-day data when they look at debt financing, so why not also for equity, often the biggest component of the capital structure? We believe that today's environment warrants re-estimating the cost of capital using new market information, in particular when considering large capital projects or acquisitions.

Practical Application: The cost of capital for many S&P 500 firms has not increased since last summer. Why? While risk premiums increased in both credit and equity markets, the Fed's policy of lowering interest rates has succeeded in offsetting this increase for the largest firms in the economy. It is worth noting that, even in today's environment, many firms tend to use a hurdle rate that is a few percentage points higher than their true cost of capital, which may lead them to forgo valuable investment opportunities.

Which is right—equity or credit markets?

Many market observers have focused on how the equity and credit markets have behaved differently since last summer. While credit markets lost significant liquidity and experienced dramatic pricing changes, the non-financial component of equity markets remained relatively unaffected until the beginning of this year. Have credit markets overreacted, and should they revert to more normalized pricing? Have the equity markets failed to completely absorb the effects of the financial crisis, and should we expect a further decline in equity values, along with an increase in the MRP? Or do credit markets reflect a higher overall premium combining both a heightened risk premium and an increased liquidity premium? In many segments of the credit markets, liquidity diminished significantly over the last few months, but not so in the equity markets. We believe that both effects have taken place; i.e., the equity risk premium has increased, but the credit markets have been affected even more because they are also pricing in an additional premium for liquidity.

Practical Application: Executives should consider this debt vs. equity market premium dynamic when making funding decisions. For example, the after-tax cost of hybrids should be compared to an updated after-tax cost of equity. Furthermore, as discussed above, given that low Treasury rates have offset rising risk premia for the largest firms, executives should consider locking in a low long-term cost of capital, especially if they have near-term refinancing, capital or liquidity needs, or if they expect rates to increase because of inflationary pressures.

2. Different methods to estimate the MRP

A. Historical average realized returns

A common way to estimate the MRP has been to compare realized annual equity returns to average returns of U.S. Treasury bonds over some historical time period.

$$MRP = \text{average annual equity index return} - \text{average return on Treasury bonds}$$

This method is widely used in practice but has a few weaknesses which diminish its usefulness.

Choice of averaging method: The choice of arithmetic vs. geometric averaging methods can lead to significant differences in MRP estimates. For example, if \$100 grows to \$110 in one year and then drops back to \$100 the next, the arithmetic average annual return is $[(+10.0\% - 9.1\%)/2]$, or 0.5%. The arithmetic average represents the best estimate of annual expected return. The geometric mean, however, will be 0%, which is the compounded annual return the investor actually earned. Many academics prefer the arithmetic average because it represents an investor's expected return at any given point in time. But the geometric mean better reflects asset returns investors should expect over long horizons.

Time horizon: As evidenced in Figure 3 below, different time horizons also yield different MRP estimates. For example, an observer examining the U.S. data since 1978 using the geometric mean would determine that the MRP is 4.9%, whereas an observer viewing the data since 1946 would instead conclude it is 5.7%.

Figure 3: Historical risk premium estimates across various time periods

Large company stocks - Intermediate T bonds	Arithmetic	Geometric
1926-2007	6.9%	5.1%
1946-2007	6.8%	5.7%
1978-2007	5.7%	4.9%

Source: Morningstar, JPMorgan

Reaction to changing risk premium: In a changing risk-premium environment, this method can produce counterintuitive results. For example, if the risk premium increases and cash-flow projections remain unchanged, equity prices will drop. This drop in equity prices reflects investors' demand for higher *future* expected returns in the riskier environment. But the drop would cause lower realized returns, which in turn would lower the average *historical* returns, thereby suggesting a lower instead of higher risk premium. Though this backward-looking method may not capture the direction of the change in risk premium well, it may still be a viable long-term estimate of the risk premium investors expect to earn by investing in equity.

Figure 4: Pros and cons of using the historical method

Pros	Cons
■ Easy to compute ■ Has been a standard in business schools ■ Does not change often and rapidly ■ Can be sourced by a third-party provider such as Ibbotson Associates	■ Estimate depends on historical window ■ Estimate depends on averaging method ■ Does not change often and rapidly; i.e., does not incorporate new market realities ■ Responds in a counterintuitive way to changes in actual risk premium

Source: JPMorgan

B. Dividend Discount Model

Another means of estimating the MRP is through the Dividend Discount Model (DDM), which can be used to calculate the current market cost of equity. The model solves for an internal rate of return (cost of equity) based on the price level and expected dividend stream of an index (often the S&P 500 as a proxy for the broad market). Dividends are projected by applying an expected payout ratio to forecasted earnings. Earnings are forecasted, in turn, by combining near-term (i.e., 5 years) market estimates with a perpetuity growth rate equivalent to long-term nominal GDP growth. The dividend payout ratio is initially assumed to be the average of recent historical payout ratios, but increases over the long-term towards 80% in the terminal period as reinvestment opportunities are assumed to subside. Simplistically, the formula for the market cost of equity is:

$$Price_0 = \sum_{t=1}^{\infty} \frac{Dividend_t}{(1 + Cost\ of\ Equity)^t}$$

where t is time from now to infinity. Subtracting the 10-year government bond yield from the market cost of equity then provides the market risk premium. Thus, the MRP formula is as follows:

$$MRP = Cost\ of\ equity\ implied\ by\ DDM - 10\text{-}year\ government\ bond\ yield$$

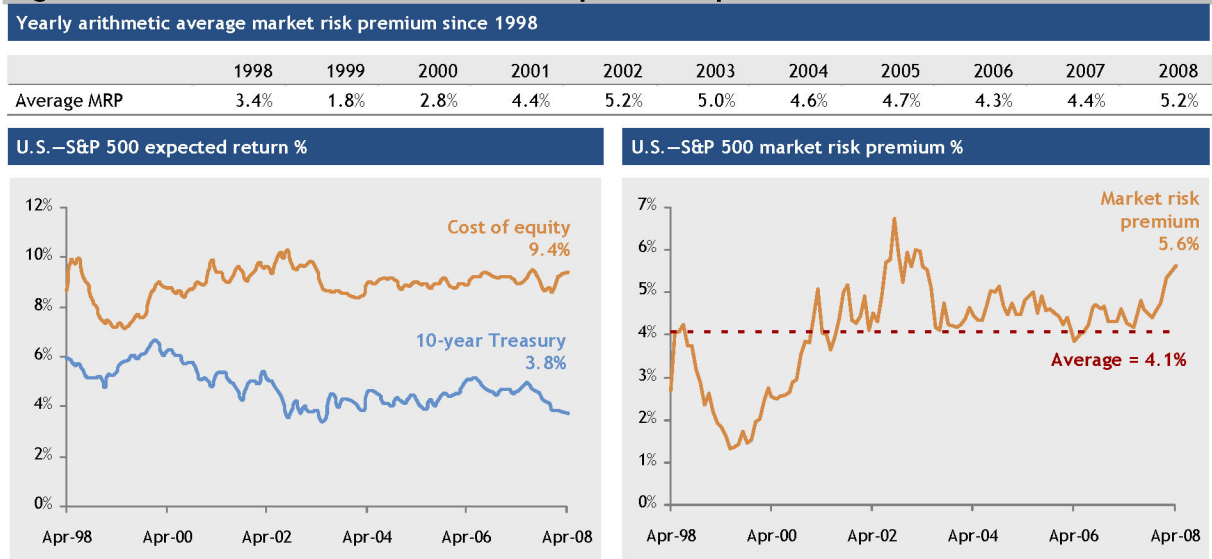
Figure 5: Pros and cons of risk premium implied from Dividend Discount Model

Pros	Cons
- Implied from equity market values - Changes and responds to current market environment - Forward-looking; not heavily reliant on historical data	- Price variable changes daily - Highly dependent on future dividend/cash flow estimates - Dividend forecasts not updated frequently; may not take market cycles into account

Source: JPMorgan

Changes over time: The market cost of equity varies primarily with movements in the level of the index, but also with changes in expectations for future dividends. The chart below shows the market cost of equity based on the S&P 500, as well as the 10-year Treasury yield, over the last 10 years. The resulting MRP, shown to the right, varies from a low of 1.3% at the peak of the market to a high of over 6% in the post-9/11 era. After 2003, the MRP stabilized in the 4% range until the recent credit crisis, which has led to a re-pricing of risk and a higher MRP.

Figure 6: Dividend Discount Model implied risk premium over time



Source: JPMorgan, Bloomberg

C. Constant Sharpe ratio method

Another useful metric to estimate the risk premium, the Sharpe ratio, has been inherited from portfolio management theory. The Sharpe ratio measures a portfolio's excess return per unit of risk and can be used to estimate the MRP:

$$\text{Market Sharpe ratio} = S_M = \frac{\text{Portfolio MRP}}{\text{Volatility of MRP}}$$

We estimate that, over the last 50 years, the Sharpe ratio for the broad market (using the S&P 500 index as a proxy) has been about 0.3, which is consistent with academic research. Assuming that this ratio is constant going forward, we can then solve for the forward-looking MRP by multiplying the S&P 500 Sharpe ratio by a measure of future market volatility. We estimate future market volatility via the VIX index, which measures the volatility implied from options on the S&P 500 index. Thus, the Sharpe ratio-implied MRP is:

$$\text{MRP} = \text{Market (S\&P 500) Sharpe ratio} * \text{Market (S\&P 500) implied volatility}$$

Figure 7: Pros and cons of the Sharpe ratio method

Pros	Cons
■ Estimate of Sharpe ratio based on more than 50 years of historical data; consistent with academic research ■ VIX component is forward-looking; captures shifts in investor sentiment very quickly	■ Some evidence that Sharpe ratio may change over time instead of remaining constant ■ VIX measures short-term volatility (<1 year), whereas risk premium is generally viewed long-term (10+ years)

Source: JPMorgan

Changes over time: Figure 8 displays the Sharpe ratio-implied MRP over the last 10 years. By definition, the Sharpe ratio-implied MRP moves proportionally with the VIX volatility index. At times of greater uncertainty and market panic, including the Long-Term Capital Management fallout in 1998, the 2000-2002 recession/tech bubble burst, and the current credit crisis, investors have fled to safer securities and demanded a greater MRP to keep their investments in riskier assets. Such shifts in risk preferences have been accompanied by spikes in volatility.

Figure 8: Historical risk premiums computed from the Sharpe ratio method

