FILE

PUCO EXHIBIT FILING

Date of Hearing: 5/20/13 - Volume X

Case No. 12-2400-EL-UNC; 12-2401-EL-AAM; 12-2402-EL-ATA

PUCO Case Caption:

Duke Energy Ohio

List of exhibits being filed:

OCC Exs. 11-28-29-30-31-32

FES Exs. 31-32-33-34-35-36

Reporter's Signature: Maria DiPaolo Jones

Date Submitted:

BEFORE THE PUBLIC UTILITIES COMMISSION OF OHIO

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In the Matter of the Application :
of Duke Energy Ohio, Inc., for :
the Establishment of a Charge :Case No.
Pursuant to Revised Code Section:12-2400-EL-UNC
4909.18. :

In the Matter of the Application:
of Duke Energy Ohio, Inc., for :Case No.
Approval to Change Accounting :12-2401-EL-AAM
Methods. :

In the Matter of the Application:
of Duke Energy Ohio, Inc., for :Case No.
the Approval of a Tariff for a :12-2402-EL-ATA
New Service. :

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PROCEEDINGS

before Christine M. T. Pirik, Attorney Examiner, at the Public Utilities Commission of Ohio, 180 East Broad Street, Room 11-A, Columbus, Ohio, called at 10 a.m. on Monday, May 20, 2013.

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VOLUME X-REBUTTAL

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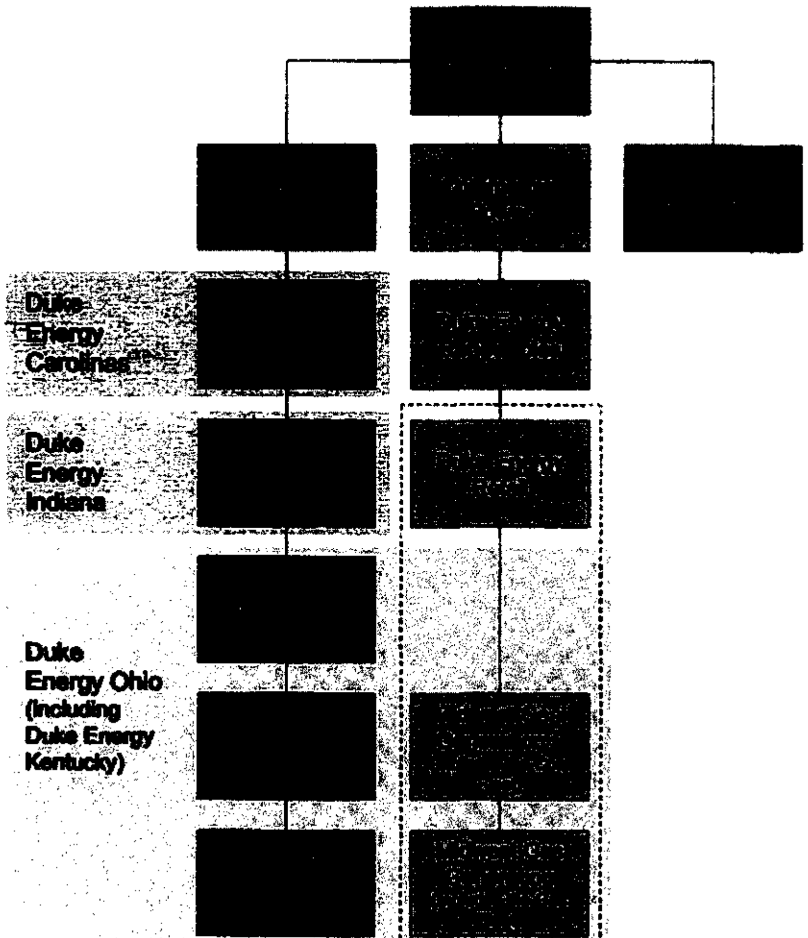
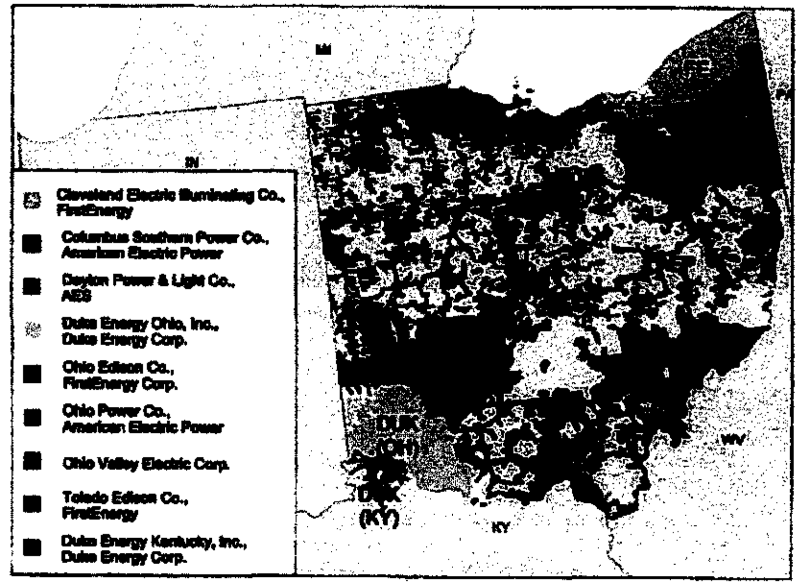
Duke Energy Ohio Overview

Duke Energy Ohio consists of both regulated and unregulated segments. The regulated segment consists of the transmission and distribution business serving Ohio, while the Generation Assets are a part of the unregulated segment.

Duke Business Segment Structure(1)



Ohio Investor Owned Electric Utilities



DEO Key Statistics(3)

[redacted]		[redacted]		[redacted]	
Area:	3,000 sq miles	MW:	6,144	Area:	DEO, OH Edison, Toledo Edison, DPL, Columbus Southern Power, OH Power
Population:	2.1mm	Fuel:	Diversified (gas / coal / oil)	Customers	
Rate Base:	$3.1bn	Type:	Baseload & mid-merit coal, CCGT and Peaker	Residential:	>[redacted]
Service Territory:	OH, KY			Commercial & Industrial:	>[redacted]
Customers				2011 Load:	[redacted] TWh
Electric:	830,000				
Gas:	500,000				

Entities covered under Transaction

(1) Represents pre-merger Duke structure.
(2) Was dedicated under ESP through December 31, 2011.
(3) T&D refers to USFE&G segment of DEO, as of YE 2011. Generation excludes Beckjord.

Overview of Gas Fleet

3,405 MWs of highly efficient 2000 vintage, mainly GE technology gas turbines.

	Hanging Rock	Washington	Fayette	Lee	Dicks Creek
Total Nominal Capacity (MW)	1,289	643	642	716	115
Total Winter / Summer Capacity (MW)	1,314 / 1,254	657 / 624	653 / 627	776 / 632	130 / 94
2015 / 2016 Committed ICAP[1]	1,240	620	620	624	136
Location	Ironton, OH	Beverly, OH	Masontown, PA	Dixon, IL	Middletown, OH
Market Zone	PJM-AEP	PJM-AEP	PJM-APS	PJM-CE	PJM-DEOK
Technology	CCGT	CCGT	CCGT	CT	CT
2011 Heat Rate (Btu / kWh)	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
COD	2003	2002	2003	2001	1965 – 1969
Fuel	Natural Gas	Natural Gas	Natural Gas	Natural Gas	Natural Gas
Turbines	GE 7FA	GE 7FA	GE 7FA	GE 7EA	GE / Westinghouse / Worthington
2011 Net Capacity Factor	[redacted]%	[redacted]%	[redacted]%	[redacted]%	[redacted]%
YTD 2012 Capacity Factor[2]	[redacted]%	[redacted]%	[redacted]%	[redacted]%	[redacted]%
Electric Interconnection	Ohio Power Co.	Ohio Power Co.	Allegheny Power System	Commonwealth Edison Co.	DEO
LTSA / Maintenance Agreement	GE	GE	GE	NA	NA
Duke Ownership	100.0%	100.0%	100.0%	100.0%	100.0%
Operator	Duke	Duke	Duke	Duke	Duke

(1) Installed capacity ("ICAP"). Committed ICAP is the capacity committed in the PJM capacity auction.
(2) YTD Capacity Factor through May 2012.

Overview of Coal Fleet

Duke Energy.

2,739 MWs of clean coal assets poised to be highly profitable given pending EPA regulations and recovery in gas prices.

	Stuart	Miami Fort	Miami Fort (CT)	Zimmer	Conesville	Killen
Owned Nominal Capacity (MW)	904	656	56	608	312	201
Total Nominal Capacity (MW)	2,317	1,025	56	1,308	780	609
Total Winter / Summer Capacity (MW)	2,317 / 2,317	1,025 / 1,025	68 / 44	1,308 / 1,308	780 / 780	609 / 609
Owned 2015 / 2016 Committed ICAP	904	653	56	605	260	204(1)
Location	Aberdeen, OH	North Bend, OH	North Bend, OH	Moscow, OH	Conesville, OH	Wrightsville, OH
Market Zone	PJM-Dayton	PJM-DEOK	PJM-DEOK	PJM-DEOK	PJM-AEP	PJM-Dayton
Technology	ST	ST	CT	ST	ST	ST
2011 Heat Rate (Btu / kWh)	9,875	10,220	38,929	9,922	10,430	10,298
COD	1970 - 1974	1975 - 1978	1971	1991	1973	1982
Fuel	Coal	Coal	Oil	Coal	Coal	Coal
Turbines	GE	GE	Westinghouse	Asea Brown Boveri / Westinghouse	Westinghouse	GE
2011 Net Capacity Factor	67.7%	69.4%	0.1%	58.9%	37.3%	73.7%
YTD 2012 Capacity Factor(2)	52.7%	80.7%	0.0%	27.1%	39.4%	54.1%
Electric Interconnection	DPL	DEO	DEO	DEO	Columbus Southern Power Co.	DPL
Coal (Primary, Secondary)	Illinois Basin, Northern Appalachia	Illinois Basin, Northern Appalachia	NA	Northern Appalachia, Illinois Basin	Northern Appalachia	Illinois Basin, Central Appalachia
Boiler Type / Manufacturer	Babcock & Wilcox	Babcock & Wilcox	NA	Babcock & Wilcox	Combustion Engineering	Babcock & Wilcox
Pollution Control Equipment	FGD / SCR	FGD / SCR	NA	FGD / SCR	FGD / SCR	FGD / SCR
Duke Ownership	39.0%	64.0%	100.0%	46.5%	40.0%	33.0%
Other Owners	AEP (26.0%) AES (35.0%)	AES (36.0%)	NA	AEP (25.4%) AES (28.1%)	AEP (43.5%) AES (16.5%)	AES (67.0%)
Operator	AES	Duke	Duke	Duke	AEP	AES

(1) Killen plant operator has filed a permit change that would allow an additional [redacted] MW owned capacity in Killen to participate in PJM capacity and energy markets (the additional MWs were included in and cleared the 2015 / 2016 capacity auction).
(2) YTD Capacity Factor through May 2012.

Key Investment Highlights

The Transaction represents a unique opportunity to acquire a sizeable growth platform of high quality assets that benefit from strong and stable cash flows with significant upside potential.

[illegible] Growth Platform

- The Portfolio is comprised of 11 electric generating assets employing steam, CCGT and peaking technologies in addition to a highly complementary retail business
- The Portfolio is well positioned to capture upside from a recovery in the currently low commodity price environment and pending environmental regulations; represents approximately 4% of PJM - RTO 2012 expected peak demand[1]
- Highly complementary assets with fuel diversity and Retail business that serves as natural hedge to generation
- Transaction represents the largest generation and retail business to come to market in recent times, providing a "turn-key" scalable platform for growth

[illegible]

- Well-positioned in the largest, most dynamic, west-to-east transmission constrained and liquid power market in the nation
  - PJM capacity payments provide long-term visibility of cash flows through May 2016
- Benefits from premium capacity, energy and ancillary revenue with significant upside potential
- The Portfolio's fuel diversity enables it to run part of its capacity as baseload in different commodity environments, thereby maximizing its gross margin

[illegible] Performance

- Assets employ highly efficient and proven technologies
- Coal Fleet has been maintained and dispatched under a utility-grade regulated framework until 2012, while the Gas Fleet has been maintained under Duke's world class operation and maintenance ("O&M") program
- Dispatching flexibility enhances Portfolio competitiveness by capitalizing on fuel diversity, environmental compliance and changes in commodity prices
  - Flexibility allows Buyer to competitively operate the Portfolio in the currently low commodity price environment and realize significant upside as commodity markets improve

[illegible]

- Coal Fleet is fully-scrubbed and compliant with EPA regulations
  - Over \$900 mm[2] invested by Duke in environmental capex over the last decade
- Portfolio stands to benefit from tightening reserve margins and expanding market heat rates due to [redacted] GW[3] of primarily coal asset retirements through the PJM Reliability Pricing Model ("RPM") 2016 / 2017 delivery year, mainly due to environmental regulations

[illegible]

- Significant EBITDA and free cash flows supported by PJM capacity payments
- The Generation Assets will be conveyed to the buyer free of legacy financing, with an option to convey hedging arrangements[4]

[illegible]

- Generation Assets have been operated and maintained by a highly experienced team of professionals and supported by a world class O&M program
- Portfolio presents several value enhancing opportunities for the Buyer's benefit

(1) Source: PA Consulting.
(2) Amount represents Duke's prorated ownership share of environmental capex.
(3) Represents summer capacity. Source: PA Consulting.
(4) The Generation Assets are partially hedged and Retail business contracts are fully hedged; hedges will be conveyed at the option of the Buyer.

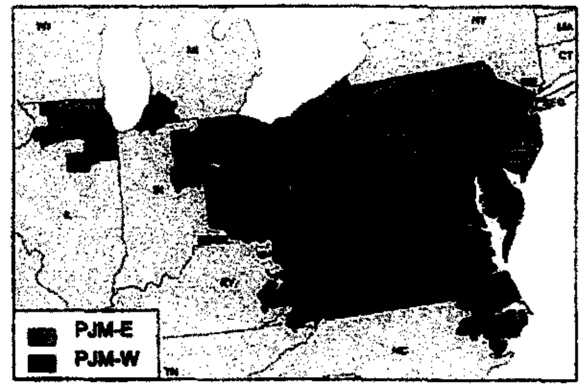
PJM Market Overview

The Generation Assets are interconnected to PJM, the nation's largest and most liquid wholesale market. PJM is a west-to-east transmission constrained market characterized by declining reserve margins, and an upward trend in energy and capacity prices.

Overview

- The PJM market has a sophisticated capacity market, as well as competitive and transparent energy and ancillary markets
- PJM administers its markets for day-ahead and real-time energy, and a capacity market administered through the RPM forward market design
- The assets are located in the PJM-W region in subzones AEP, APS, CE, Dayton and DEOK
  - While the Gas Fleet has been a part of PJM since 2004 or earlier(1), the Coal Fleet was integrated into PJM in January 2012
  - The Generation Assets receive PJM RTO capacity payments and sell into the western portion of PJM's wholesale markets

PJM Footprint



Key Characteristics of PJM-W Market

- The PJM-W market has the following key characteristics that further enhance the Portfolio's value proposition

Coal Retirements

- PJM-W has more coal capacity potentially affected by EPA regulations than the rest of PJM
- Coal retirements and retrofits are expected to increase energy and capacity pricing

Transmission

- Major transmission projects are currently being built or recently completed to export power from PJM-W to higher-priced PJM-East ("PJM-E") market

Energy Price Upside

- Energy prices are expected to escalate as forward and fundamental natural gas prices are projected to increase from today's lows and reserve margins tighten

Visible Capacity Pricing

- RPM auction and Fixed Resource Requirement ("FRR") compensation provide capacity revenue visibility through May 2016 for generators in the region

Limited New Build

- Few new thermal projects are planned in PJM given cost of new build of ~ [redacted]/ kW and associated financing difficulties, commodity price outlooks, and siting and regulatory requirements associated with new builds

 Source: PA Consulting.
(1) Except Dicks Creek, which joined PJM in 2012 along with the Coal Fleet; Lee joined PJM in 2004 while Fayette, Hanging Rock and Washington joined PJM upon commercial operation.

Strategically Located in the Attractive PJM Market

The Portfolio is interconnected to PJM, the nation's largest and most liquid wholesale market. PJM is a west-to-east transmission constrained market characterized by declining reserve margins, and an upward trend in energy and capacity prices.

Visible Capacity Pricing

- PJM is one of the most efficient power markets in the country
- Lucrative capacity payments give multi-year visibility of cash flows to the Portfolio
  - Clarity of RTO capacity payments through May 2016
  - Recent 2015 / 2016 RTO PJM auction result of $136.00 / MW-day confirms trend of increasing capacity payments
  - PA Consulting forecasts 2019 / 2020 PJM RTO capacity payments of $[redacted]/ MW-day

Premium Energy Pricing

- Tightening reserve margins and increasing heat rates, driven by environmental regulations, are expected to drive power prices upwards
  - EPA regulations are expected to increase operating costs for many unscrubbed plants, and in many cases, capital investments will be deemed uneconomic leading to retirements
- Coal Fleet is mainly on the Ohio river, which limits exposure to rail constraints and provides for more economic fuel transportation

Transmission

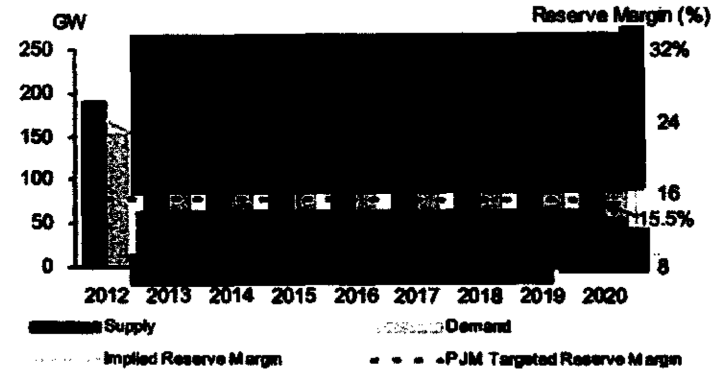
- Major transmission projects are currently being built or recently completed to export power from PJM-W to higher-priced PJM-E market

Attractive Supply & Demand Characteristics

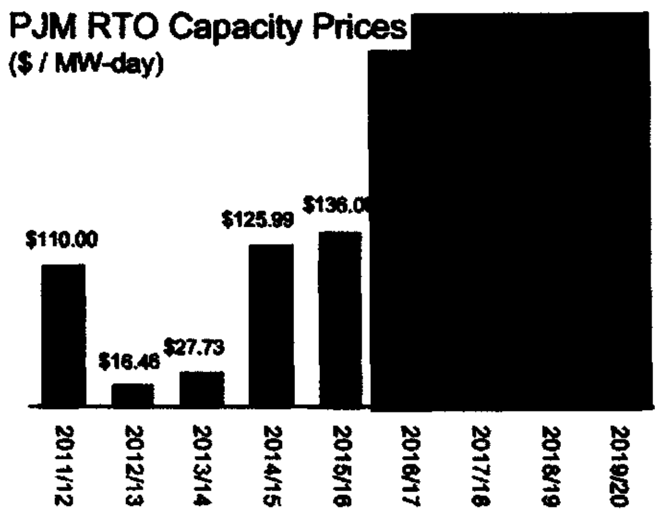
- Attractive supply demand characteristics, transmission constraints and increase in power prices as gas prices improve, are expected to potentially expand dark spreads
- New build costs estimates of approximately $[redacted]/ kW further limit capacity in the region

20 Source: PA Consulting.

Projected Supply and Demand in PJM



PJM RTO Capacity Prices
($ / MW-day)



Source: PJM actual cleared auction results through May 2016, PA Consulting projections thereafter.

Expectations and the Structure of Share Prices

John G. Cragg and
Burton G. Malkiel

The University of Chicago Press

Chicago and London

Table 2.16 Analysis of Forecasts by Industrial Category: 1963 Predictions vs. 1963-68 Actual Earnings

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

would be 4 for the most difficult industry (in years when there were four predictors compared), 3 for the next most difficult, and so on. In this case, the coefficient of concordance (Kendall's W) would be unity. The values of Kendall's W were significantly different from zero beyond the 0.05 level for most of the years, as were differences between industries for the correlation coefficients for most of the predictors.[1] These findings indicate that there were industry differences. For the long-term predictions, correlation coefficients between forecasts and realizations tended to be highest in the oil, food and stores, and "cyclical" industries. For the short-term predictions, there was really no industry that was particularly easy to predict compared with the others; that is, prediction performances were uniformly mediocre across industries.

The electric utility industry turned out to be one of the more difficult industries for which to make long-term forecasts. This would come as a distinct surprise to the participating security analysts who claimed at the outset that they had some reservations about their abilities to predict earnings for the metals and other "cyclical" companies, but had confidence that they could make accurate predictions for the utilities.[2] It turned out that the long-term predictions for the utility industry were considerably worse than for the metals and "cyclicals."

In general, we had little success in associating forecasting performance with industry or company characteristics. Forecasting differences between industries were only moderately related to the average realized

[1] The latter was tested on the basis of the asymptotic distribution of the correlation coefficient and the assumption that the data were distributed normally.

[2] This confidence was also reflected in the fact that for the electric utility industry there was high agreement among the forecasters, whereas agreement was relatively low for the [illegible].

THE ACCOUNTING REVIEW
Vol. LIII, No. 3
July 1978

An Evaluation of Security Analysts' Forecasts

Timothy Crichfield, Thomas Dyckman, and Josef Lakonishok

ABSTRACT: Recent literature in accounting, finance, and economics often assumes that information can be processed efficiently. Among the outputs of the processing activity are the presumably appropriate assessments of the underlying probability distributions for all important variables, and a good deal of the recent research assumes that observable realizations of the variables are drawn from these distributions. This paper provides evidence concerning the ability of selected individuals, namely security analysts, to provide estimates of earnings per share after presumably processing the available information. Several aspects of the quality of analyst forecasts are examined. The study indicated, as expected, that analysts' forecasts become more accurate as the reporting date is approached. Furthermore, the predictions of changes in earnings per share data contain no significant systematic bias. However, the authors do not find sufficient support for the expected decline in forecast variability among analysts as the reporting date is approached.

THE subject of forecasting financial variables for firms has received wide attention recently, particularly since the Securities and Exchange Commission (SEC) announced in February, 1973, its intention to require that certain disclosures of forecasts be made public (see Gonedes, Dopuch, and Penman, [1976]). One aspect of these proposals was to require that if company officials report forecasts to outsiders, then these forecasts would have to be made public through filings with the SEC. Although the SEC has since altered its basic position, the widespread interest in forecast disclosure remains. As Gonedes, Dopuch, and Penman (GDP) point out, the basic arguments in the debate concerning public disclosure of managements' forecasts revolve around two issues: (1) the extent to which required forecasts embody information useful for establishing equilibrium values for firms, and (2) the extent to which the proposed requirements are consistent with an optimal allocation of resources for society. GDP provide an empirical analysis of the first issue and some theoretical arguments pertaining to the second issue.

One factor which may influence the information content as well as the desirability—from a resource allocation perspective—of managements' forecasts is that security analysts also provide forecasts of company variables. If security analysts provide this service more efficiently, one could question the desirability of requiring company officials to provide forecasts. Of course, comparing

The authors wish to acknowledge the helpful comments of Kenneth J. Boudreaux and Larry L. Lookabill.

Timothy Crichfield is Assistant Professor, University of California, Berkeley; Thomas Dyckman is Professor of Accounting, Cornell University; and Josef Lakonishok is Assistant Professor, Tel-Aviv University.

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the efficiency of managements' forecasts to those of security analysts is a difficult task. Moreover, any such comparison would have to consider not only the relative costs of forecasting but also the effects upon users' decision processes as different forecasting sources are considered.

While it is difficult to assess the significance of competing information alternatives upon the decisions of market agents, it is possible to judge how well any of several information sources fulfill their stated or implied purposes. For example, an implied purpose of earnings per share forecasts provided by security analysts is to yield unbiased estimates of future earnings per share which would be useful for investors in assessing firms' equilibrium values. If such forecasts are found to contain systematic biases, then a minimum criticism of the forecasts is that users make adjustments to the forecasts that would be unnecessary in the absence of the bias.

Our study is an attempt to assess the significance of any bias in the forecasts of earnings per share by security analysts. We are concerned with the performance of security analysts over a relatively long period of time. This differs from most published studies of forecast accuracy (for example, Barefield and Comiskey, [1975]) which deal with relatively few points in time. However, by requiring extensive time series observations, we encounter data-gathering problems that did not plague other researchers. These data problems are discussed subsequently.

Forecasts of Earnings Per Share

Forecasting is one useful means for estimating the values of important variables under uncertainty. A forecast, or prediction, is simply a statement about an unknown event or events. Typically, as is true in our case, they are future events. The forecast is useful if it influences the decision makers' estimates of the parameters of the relevant probability distribution.[1]

In the present study, we are concerned with security analyst (SA) predictions of earnings per share (EPS) figures for major corporations. The SAs have no direct control over the eventual realization of the prediction and, hence, following Theil [1966], we might call these predictions anticipations.[2] The predictions made are single-valued point estimates of each firm's EPS for the current fiscal year. These estimates are based on primary accounting earnings before extraordinary items and, where necessary, these EPS figures have been adjusted for stock splits and dividends. The assumption is that SAs attempt to predict a normalized figure free from the impact of non-recurring factors and unaffected by company distributions. Cragg and Malkiel [1968, p. 68] offer supportive evidence for this assumption. We will evaluate the accuracy of these forecasts as compared with predictions from alternative statistical models.

We will consider also whether point-estimate forecasts of EPS by SAs lead to efficient parameter estimates for the underlying probability distribution when considered together with the existing set of information available to the market.

[1] The notion of usefulness here ignores the cost of the forecast. While it is simple enough to state that the forecast's cost should be less than the benefit obtained, this is not easily done. The difficulties arise not only because of measurement problems, but also because it is not easy to establish who bears the costs. Further, the costs and benefits may fall selectively across individuals creating the problem of measuring the impact of wealth transfers.

[2] The anticipations of SAs may reflect the predictions by a firm's managers. Furthermore, there may be an attempt by managers to make their own predictions come true. This could reflect on an evaluation of SAs' forecasts. Nevertheless, the lack of a direct effect still remains.

This is the second objective of a useful forecast as discussed above. We now turn to a discussion of the means by which such an evaluation can be made.

Forecasts are based on *ex ante* assessments. Recognizing the uncertainty inherent in the process, the eventual realization can be treated as an observation on a random variable. Forecasters, and in particular SAs, should not, then, be expected to predict the realizations precisely. Rather, they can be expected to predict the parameters, such as the mean, of the probability distribution governing the random variable. We would, then, expect the actual realization to differ from this mean predicted value.

This discussion implies that a relatively long time span is required to test the ability of SAs to estimate the mean of the EPS distribution. If true, studies based on a comparison of realizations with forecasts over a short time horizon are likely to be deficient. We should not expect to predict the actual observations with perfect accuracy.[3]

The discussion further implies that if we can assume the mean of the probability distribution to be stable over time, the predictions should, on average, be very close to the mean of the true probability distribution. This suggests in turn that there should not be a systematic bias in the predictions.[4] Moreover, if essentially costless information is available to the forecaster, it should already be impounded in the forecast. It should not be possible to improve on the predictions by incorporating such data as, for example, predictions based on statistical models incorporating past realization data. Our tests will reflect these ideas.

Data Base

The basic source of data for this study was selected copies of the *Earnings Forecaster* (*EF*), published by Standard and Poor's. Our data cover forecasts for the period from 1967, when the *EF* was first published, to 1976. The same publication also provides actual EPS data.[5]

The *EF* is published bi-weekly and contains annual EPS forecasts for several hundred companies. Over 50 different investment firms are responsible for these forecasts. There may be from one to ten or more forecasts for a single firm in each issue.

Due to the nature of the available data, the firms used in this study could not be selected in a truly random fashion. Instead, we were constrained to select several consecutive pages at two different starting points in the last issue of the *EF* for each month from January, 1967, through May, 1976. Thus, we obtained data for 113 consecutive months. Firms for which forecasts did not appear in every year of the *EF* were deleted from the sample. But a firm was not deleted if data were missing only for some months in a given year; hence, missing data points were a problem for some firms. We will discuss this problem in more detail subsequently.

The final sample consisted of 46 firms. Where more than one forecast was pre-

[3] See Basi, Carey, and Twark [1976] for an example. Furthermore, at any point in time, forecasts for all companies may be cross-sectionally correlated due to aggregate market events. Thus, there may be a tendency for all forecasts to be either optimistic or pessimistic.

[4] Theil [1966, p. 14], based on certain macro economic data, states that "generally speaking, forecasters tend to be between the limits of naive no-change extrapolators and perfect predictors in the sense that they underestimate changes more frequently than they overestimate them." Studies involving earnings forecasts have not been consistent with this statement by Theil. McDonald [1973, p. 509] and Barefield and Comiskey [1975, p. 244] both observed "a persistent optimistic bias." (Since, during the periods covered in these two studies, earnings and EPS tended to increase, the result is an overestimation of the change.)

[5] Actual EPS data for some firms in 1976 were obtained from *The Wall Street Journal* and Annual Reports since they were not included in copies of the *Earnings Forecaster* available to us at the time of the analysis.

sented in a single month for a given firm, the mean forecast was used. This was necessary due to the complexity of attempting to track particular analysts over long time periods. Thus, we are examining the forecasts of analysts as a group. We also calculated the standard deviation of the forecasts among analysts in each month.

The analysis for each firm in each year used 13 months of predictions rather than 12. This was done because forecasts are made in the month following the end of the firm's fiscal year but before the actual EPS figure is released. For example, a firm with a fiscal year ending June 30, 1971, would have forecast data for that same year from July, 1970, through July, 1971, inclusive.[6] In total, but subject to missing observations, we have 13 monthly predictions on each firm for each of 10 years; a total of 130 predictions for each firm.[7]

Because the firm selection process was not random, it is possible that some selection bias exists for at least two reasons. First, there may be an industry bias created by industry clustering in the alphabetical listing used by the *EF*. Table 1 provides a distribution of the 46 sample firms by industry. We also know that most firms have December 31 fiscal years. Sixty-eight percent of our sample firms also have December 31 fiscal years. Although we performed out analyses separately for calendar year firms and non-calendar-year firms, there were no pronounced differences in the separate analyses, and only the analyses for all firms regardless of fiscal year are provided here.

Second, there is likely to be some sample bias due to the limited coverage of firms by companies providing forecast data. This bias is toward a greater coverage of large and somewhat older firms that have had forecast data reported for the ten years used in this study. For this reason, any conclusions obtained from this research apply, strictly, only to those firms covered by the *EF*. Extrapolation to larger populations should be made with care.

TABLE 1
INDUSTRY CLASSIFICATION
(*2 Digit SIC Code*)

Industry	*Number of Companies*
Mining	
Metal Mining	1
Oil and Gas Extraction	1
Manufacturing	
Food and Kindred Products	1
Textile Mill Products	1
Apparel and Other Fabrics	1
Furniture and Fixtures	1
Paper and Allied Products	1
Chemicals and Allied Products	6
Stone, Clay, Glass, and Concrete Products	4
Primary Metal	6
Machinery, Except Electrical	5
Instruments: Measuring, Photographic, Optical Medical, Watches and Clocks	1
Transportation, Communication, and Other Public Utilities	
Transportation	1
Electric, Gas, and Sanitation	7
Retail Trade	
General Merchandise Stores	3
Food Stores	2
Apparel and Accessories	1
Finance, Insurance, and Real Estate	
Holding and Other Investment Companies	2
Services	
Business Services	1
Total	46

[6] Occasionally, the forecast data occur before July, 1970, and after July, 1971.

[7] If a firm changed fiscal years, all observations before the change were treated as missing observations.

The Analysis

Following Theil's approach, we use the mean-square prediction error to evaluate the goodness of any forecast.[8] Summing over all sample firms for a given point in time yields:

$$\frac{1}{n}\sum_{j=1}^{n}(P_j^* - A_j^*)^2 \qquad (1)$$

where P_j^* is the predicted level of EPS for firm j; and A_j^* is the actual level of EPS for firm j.

If these prediction errors (*i.e.*, $P_j^* - A_j^*$) can be considered random variables, then the results from (1) can be used to formulate probability statements concerning predictions. Standard statistical tools invariably require that successive elements in any summation be independent. This assumption, however, is unrealistic if the forecast errors are measured in terms of levels of EPS. As the level of EPS increases in absolute magnitude, we should expect analysts' forecast errors likewise to increase in absolute magnitude. In a cross-sectional sense, performance measures which evaluate differences between the levels of forecasted EPS and the levels of actual EPS would be biased against firms with high absolute levels of EPS and biased in favor of firms with low absolute levels of EPS. This would make empirical results based upon such measures difficult to interpret.

For these reasons, we chose to work in terms of percentage changes in EPS. In order to avoid asymmetry problems, percentage changes are measured as log relatives of EPS (*e.g.*, using log relatives, a change in EPS from $2.10 to $2.00 is the negative of the change in EPS from $2.00 to $2.10).

Specifically, we define:

$$A_t \equiv ln\,(A_t^* \div A_{t-1}^*) \qquad (2a)$$

$$P_{it} \equiv ln\,(P_{it}^* \div A_{t-1}^*) \qquad (2b)$$

$$P_{itk} \equiv ln\,(P_{itk}^* \div A_{t-1}^*) \qquad (2c)$$

where:

- A_t is the actual log relative EPS from year $t-1$ to year t;
- P_{it} is the analysts' prediction of the log relative EPS from year $t-1$ to year t for the prediction made in month i, $i = 1, 2, \cdots, 13$;
- P_{itk} is P_{it} for the kth statistical forecast model (to be specified in the next subsection);
- A_t^* is the actual EPS in year t;
- P_{it}^* is the mean of the analyst predictions of EPS for year t for the predictions made in month i; and
- P_{itk}^* is the prediction of EPS for year t using model k where the prediction is made in month i.

The quality of the analysts' forecasts can be evaluated using Theil's [1966] U^2 statistic given in the following form:

$$U_{itk}^2 = \sum_{j=1}^{n}(P_{jit} - A_{jt})^2 \div \sum_{j=1}^{n}(P_{jitk} - A_{jt})^2 \qquad (3)$$

where:

- U_{itk}^2 is computed using cross-sectional data for $j = 1, \cdots, n$ firms for every month i in year t (for which forecasts were made) with model k as a standard. If the average of the analysts' predictions for each firm in month i were to be exactly realized, then $(P_{jit} - A_{jt})$ will be zero for all firms and so will U_{itk}^2. Increasing values of U_{itk}^2 indicate increasingly poor forecasting ability.

[8] Use of the mean square error implies that the loss from an inaccurate forecast is symmetrical and that the effect is captured by the square of the error.

Comparison Models

Analysts' forecasts ought to be compared with a standard, namely with how well forecasts could be made using simple statistical models not based on the expertise of the forecaster. We have selected the following five simple statistical models for this comparison:

1. $k=1$: The naive forecast model: Last year's EPS for firm j will be repeated. $P^*_{it1}=A^*_{t-1}$ for all i. (We note that for model $k=1$, $P_{it1}=0$, for all i and t.)
2. $k=2$: A 3-year moving average: This year's EPS for firm j will equal the average EPS over the last 3 years

$$P^*_{it2}=\frac{1}{3}\left[\sum_{m=1}^{3} A^*_{t-m}\right]$$

for all i.

3. $k=3$: A quarterly model: Each quarterly reported EPS serves as an independent prediction of annual EPS.

$$P^*_{it3}=\begin{cases} A^*_{t-1} & i=1,2,3\\ 4Q_{1t} & i=4,5,6\\ 4Q_{2t} & i=7,8,9\\ 4Q_{3t} & i=10,11,12,13\end{cases}$$

where Q_{jt} is the EPS for the jth quarter of year t.

4. $k=4$: A quarterly model: Each quarterly reported EPS is averaged with previous quarters' EPS.

$$P^*_{it4}=\begin{cases} A^*_{t-1} & i=1,2,3\\ 4Q_{1t} & i=4,5,6\\ 4\left[\dfrac{Q_{1t}+Q_{2t}}{2}\right] & i=7,8,9\\ 4\left[\dfrac{Q_{1t}+Q_{2t}+Q_{3t}}{3}\right] & i=10,11,12,13\end{cases}$$

5. $k=5$: A quarterly model: Each quarterly reported EPS serves as a prediction of annual EPS after adjusting for the error in the previous year.

$$P^*_{it5}=\begin{cases} A^*_{t-1} & i=1,2,3\\ 4Q_{1t}+(A^*_{t-1}-4Q_{1t-1}) & i=4,5,6\\ 4Q_{2t}+(A^*_{t-1}-4Q_{2t-1}) & i=7,8,9\\ 4Q_{3t}+(A^*_{t-1}-4Q_{3t-1}) & i=10,11,12,13\end{cases}$$

The above models were chosen as standards due to their simplicity and acceptance in similar forms in the literature. For example, model $k=3$ was used by Green and Segall [1967].

The numerator, $\sum(P_{jit}-A_{jt})^2$, of Theil's U^2 is the critical component. The denominator is merely a means of facilitating interpretation of the measure. Values of U^2_{itk} greater than one indicate that, on the average, forecasts using model k are more accurate than those made by the analysts. By decomposing this numerator several useful insights are obtained. The following specific decomposition will prove most useful to our purpose.[9]

$$\sum_{j=1}^{n}(P_{jit}-A_{jt})^2=n(\bar{P}_{it}-\bar{A}_t)^2+n(s_p-rs_A)^2+n(1-r^2)s_A^2 \quad (4)$$

where:

$\bar{P}_{it}$ and $\bar{A}_t$ are the mean values of P_{it} and A_t
s_p and s_A are the standard deviations of P_{it} and A_t and
r is the correlation coefficient between the predicted and realized changes.

[9] See Theil [1958, pp. 33–35] and Granger and Newbold [1973, p. 46]. Granger and Newbold argue that Equation (4) is the more appropriate decomposition.

Note that:

$$r = \frac{\sum_{j=1}^{n} (P_{jit} - \bar{P}_{it})(A_{jt} - \bar{A}_t)}{n s_p S_A}.$$

The interpretation of the terms in (4) is based on a model of the forecaster's decision process. Suppose the forecaster regards any forecast as consisting of (1) a systematic and (2) a nonsystematic part of the realization. It would be reasonable for the forecaster to concentrate attention on the systematic portion. If the forecaster is able to predict the systematic portion exactly, then the realization, A_t, can be viewed as consisting of the systematic portion P_{it} and a random component which has mean zero and which is independent of P_{it}. In this situation a regression of the form:

$$A_t = \alpha + \beta P_{it} + e_{it} \qquad (5)$$

would show $\alpha = 0$ and $\beta = 1$. In other words, a regression of the actual change in EPS on the predicted change would detect no systematic bias.[10]

Now, since the residuals in (5) have zero mean, the mean values of A_t and P_{it} are identical and the first term on the right of the equal sign in (4) should tend to disappear as predictors do a better job of evaluating the systematic proportion.

Next it can be shown that:

$$\beta = \frac{r s_A}{s_p} \qquad (6)$$

and if, in addition, $\beta = 1$ then

$$r = \frac{s_p}{s_A} \quad \text{and} \quad r s_A = s_p.$$

Under these conditions the second term on the right-hand side of (4) also tends to vanish as predictors improve. If analysts predict EPS without systematic linear bias, then we should observe α near zero and β near one.

Even if analysts' predictions contain bias, the worth of the forecast is not necessarily destroyed. If the user can detect the bias and adjust for it, then the corrected forecasts will be just as useful as forecasts that contain no bias; however, the corrected forecasts may (though not necessarily) be obtained at higher cost than unbiased forecasts from analysts. If we assume that analysts' forecast bias is of a linear nature and constant over time, then users may use Equation (5) to obtain estimates of α and β. If the corrected forecasts $\hat{\alpha} + \hat{\beta} P_{it}$ are used as the predictions in Equation (4), then the right hand side would again reduce to $n(1 + r^2)s_A^2$.

For reporting the empirical results of our work, we divide each term on the right-hand side of (4) by the total to obtain:

$$\frac{n(\bar{P}_{it} - \bar{A}_t)^2}{\sum_{j=1}^{n} (P_{jit} - A_{jt})^2} = U^M \qquad (7a)$$

$$\frac{n(s_p - r s_A)^2}{\sum_{j=1}^{n} (P_{jit} - A_{jt})^2} = U^R \qquad (7b)$$

$$\frac{n(1 - r^2)s_A^2}{\sum_{j=1}^{n} (P_{jit} - A_{jt})^2} = U^D. \qquad (7c)$$

Hence $U^M + U^R + U^D = 1$.

It is our contention that Theil's development of a forecast evaluation technique provides superior measures to those typically found in the accounting literature.

Hypotheses

1. Analysts' forecasts of EPS in any

[10] It should be noted that our tests result from cross-sectional regressions. This was necessary in order to have enough observations for efficient parameter estimates. The interpretation of the parameters is very similar to that which would result from time series regressions.

year are more accurate as the end of that year is approached.

2. Analysts predict changes in EPS without systematic bias. In terms of equation (5), α should be close to zero and β should be close to one; furthermore U^D should be large relative to U^M and U^R.
3. The standard deviations of the forecasts among analysts for any year's EPS will decline as the end of the year is approached.

Results

Tables 2–6 give Theil's U^2 statistic for the five comparison models. In each table, the values given are $1-U^2$. Thus, unity represents a perfect forecast in these tables. The values of $1-U^2$ are given for each year from 12 months prior to one month following the end of the fiscal year. The bottom row provides an average across the ten years used in the study.

Applying the Cox-Stuart [1955] Trend Test yields a significant upward trend at the 0.016 probability level for the years 1967, 1968, 1970–1973, and 1975 in both Tables 2 and 3. The level of significance is greater for the other years. The pooled observations in the last rows of the tables are significant at the 0.001 probability level. These results are consistent with improved analyst forecast accuracy over the year.

When the statistical models incorporate quarterly EPS, however, the upward trend is less pronounced. This can be observed in Tables 4–6, particularly Table 5. In Tables 4 and 6, the upward trend in forecast accuracy is fairly significant, though the significance does not appear to be as strong as in Tables 2 and 3. These results imply that, as the end of the year approaches, the analysts' predictions become increasingly better than the predictions given by models $k=3$ and $k=5$ but do not become increasingly better than the predictions given by quarterly model $k=4$. By noting that Table 6 contains more negative values than any other table, we conclude that model $k=5$ was the most difficult of the five standards for the analysts to match. The large number of positive values in Table 2–6 provides evidence that the analysts performed well in terms of forecast accuracy when compared to the performance of the five statistical models.

One explanation for the low values of $1-U^2$ (and consequent upward trend for the year) in the early months in Tables 2 through 6 is that the statistical models used as standards assume that analysts have knowledge of the previous year's EPS in the first month of the current year. An examination of announcement dates for EPS in *The Wall Street Journal Index* revealed that less than 50 percent of our firms had announced the year's EPS by the end of the month immediately following the close of the fiscal year.[11] Nearly all firms had announced annual EPS by the second month of the subsequent year. In contrast, nearly all firms reported quarterly EPS within one month of the statement date. Thus the statistical models used for measuring analysts' forecast accuracy are somewhat biased against the analysts. In other words, that analysts do somewhat better than our tests suggest. On the other hand, we have not examined all possible alternative models. There may well be simple statistical models that do better than the ones we selected for comparison. Further, the appropriate statistical model may change over time and from firm to firm. Such ideas await further study.

[11] It is, of course, possible that for some firms in some years, the EPS data may reach the market sooner than indicated by *The Wall Street Journal Index*.

TABLE 2

THEIL'S U^2: NAIVE ANNUAL MODEL:* ($k = 1$)

Year	Month 1	2	3	4	5	6	7	8	9	10	11	12	13	Significance Level of Trend Cox-Stuart Test
1967	−0.017	0.197	0.054	0.067	0.088	0.097	0.175	0.234	0.345	0.415	0.459	0.605	0.659	0.016
1968	0.462	0.494	0.481	0.534	0.539	0.630	0.590	0.608	0.668	0.604	0.749	0.751	0.681	0.016
1969	0.575	0.581	0.583	0.473	0.483	0.504	0.512	0.558	0.663	0.659	0.666	0.719	0.778	0.109
1970	−0.292	−0.040	0.078	0.014	0.100	0.190	0.097	0.220	0.014	0.347	0.447	0.552	0.714	0.016
1971	0.219	0.055	0.113	0.119	0.243	0.320	0.451	0.698	0.795	0.799	0.827	0.871	0.902	0.016
1972	0.719	0.749	0.390	0.373	0.434	0.453	0.458	0.871	0.870	0.845	0.832	0.941	0.961	0.016
1973	0.236	0.237	0.271	0.266	0.281	0.334	0.348	0.402	0.497	0.510	0.607	0.702	0.709	0.016
1974	0.121	0.152	0.195	−0.622	−0.362	−0.298	−0.406	−0.024	0.293	0.326	0.539	0.589	0.586	0.109
1975	0.106	0.295	0.302	0.324	0.266	0.387	0.320	0.614	0.791	0.788	0.772	0.813	0.859	0.016
1976	0.759	0.756	0.212	0.138	0.176	0.174	0.284	0.319	0.397	0.592	0.795	0.806	0.890	0.344
10-Year Average	0.2888	0.3472	0.2679	0.1686	0.2248	0.2791	0.2829	0.4500	0.5333	0.5885	0.6693	0.7349	0.7739	<0.001

* Unity represents a perfect forecast. $1 - U^2$ is tabulated.

TABLE 3
THEIL'S U^2: MOVING AVERAGE ANNUAL MODEL* ($k=2$)

Year	Month													Significance Level of Trend Cox-Stuart Test
	1	2	3	4	5	6	7	8	9	10	11	12	13	
1967	0.290	0.045	0.211	0.173	0.207	0.222	0.266	0.352	0.428	0.504	0.550	0.729	0.762	0.016
1968	0.075	0.161	0.171	0.283	0.265	0.464	0.378	0.421	0.511	0.477	0.600	0.602	0.589	0.016
1969	0.732	0.372	0.498	0.392	0.384	0.371	0.417	0.459	0.564	0.582	0.624	0.689	0.727	0.109
1970	−0.274	0.031	0.171	0.109	0.182	0.283	0.223	0.323	0.111	0.422	0.504	0.599	0.748	0.016
1971	0.351	0.331	0.343	0.355	0.437	0.496	0.601	0.781	0.850	0.850	0.872	0.900	0.923	0.016
1972	0.559	0.610	0.340	0.326	0.337	0.356	0.347	0.770	0.843	0.813	0.803	0.895	0.934	0.016
1973	0.356	0.309	0.360	0.349	0.379	0.416	0.426	0.470	0.560	0.578	0.669	0.741	0.751	0.016
1974	0.423	0.440	0.479	−0.012	0.163	0.195	0.130	0.341	0.549	0.573	0.706	0.736	0.738	0.109
1975	0.196	0.293	0.327	0.349	0.293	0.390	0.323	0.616	0.684	0.679	0.656	0.719	0.791	0.016
1976	0.648	0.644	0.187	0.111	0.150	0.148	0.262	0.257	0.342	0.555	0.777	0.774	0.880	0.344
10-Year Average	0.3356	0.3236	0.3087	0.2435	0.2797	0.3341	0.3373	0.4790	0.5442	0.6033	0.6761	0.7384	0.7843	< 0.001

* Unity represents a perfect forecast. $1-U^2$ is tabulated.

TABLE 4
THEIL'S U^2: QUARTERLY MODEL* ($k = 3$)

Year	Month**										Significance Level of Trend Cox-Stuart Test
	4	5	6	7	8	9	10	11	12	13	
1967	0.533	0.611	0.580	0.354	0.395	0.481	0.783	0.815	0.861	0.880	0.016
1968	0.733	0.711	0.779	0.771	0.779	0.813	0.697	0.784	0.803	0.760	0.109
1969	0.928	0.932	0.934	0.812	0.828	0.795	0.811	0.789	0.848	0.875	0.344
1970	0.271	0.335	0.393	−0.069	−0.003	−0.399	0.546	0.583	0.660	0.732	0.109
1971	0.665	0.712	0.759	0.489	0.764	0.793	0.789	0.820	0.856	0.921	0.016
1972	0.955	0.954	0.956	0.909	0.938	0.940	0.927	0.916	0.962	0.975	0.109
1973	0.340	0.293	0.348	−0.107	0.377	0.478	0.232	0.378	0.438	0.442	0.109
1974	−0.120	0.099	0.124	0.622	0.758	0.768	0.044	0.307	0.387	0.412	0.109
1975	0.464	0.539	0.562	0.396	0.582	0.670	0.833	0.861	0.836	0.840	0.016
1976	0.489	0.511	0.510	0.738	0.728	0.759	0.217	0.607	0.548	0.788	0.109
10-Year Average	0.5258	0.5697	0.5945	0.4915	0.6146	0.6098	0.5879	0.6860	0.7199	0.7625	<0.001

* Unity represents a perfect forecast $1 - U^2$ is tabulated.
** Months 1–3 are identical to the numbers in Table 2.

TABLE 5
THEIL'S U^2: QUARTERLY MODEL* ($k=4$)

Year	Month**							Significance Level of Trend Cox-Stuart Test
	7	8	9	10	11	12	13	
1967	0.314	0.353	0.510	−0.499	−0.272	0.577	0.640	>0.500
1968	0.715	0.723	0.766	0.482	0.570	0.575	0.595	>0.500
1969	0.804	0.815	0.563	0.695	−0.073	0.755	0.798	>0.500
1970	−0.422	−0.321	−0.970	−2.413	−1.886	−1.347	−0.477	>0.500
1971	0.445	0.635	0.680	−0.268	−0.0045	0.151	0.351	>0.500
1972	0.930	0.949	0.951	0.831	0.801	0.912	0.941	>0.500
1973	−0.608	0.019	0.167	−0.454	−0.189	0.119	0.124	>0.500
1974	−0.606	−0.269	0.129	−0.234	0.042	0.132	0.240	>0.500
1975	0.414	0.594	0.679	0.082	0.187	0.372	0.406	>0.500
1976	0.520	0.562	0.612	0.555	0.777	0.771	0.880	0.344
10-Year Average	0.2506	0.4060	0.4087	−0.1223	−0.0088	0.3017	0.4498	>0.500

* Unity represents a perfect forecast. $1-U^2$ is tabulated.
** Months 1–3 are identical to the numbers in Table 2, and Months 4–6 are identical to the numbers in Table 4.

Table 7 provides several additional measures of the ability of analysts to forecast EPS. Column 1 gives the mean absolute deviation (MAD) of the forecasts computed as:

$$\text{MAD}_{it} = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{P_{jit} - A_{jt}}{A_{jt}}\right| \qquad (8)$$

where the symbols are as defined followlowing Equation (2). Decreasing values of MAD indicate increasing forecast accuracy. Commencing with month 6, the values of MAD decline monotonically, providing further evidence that analysts show increasing forecast accuracy with time.

Still further information on forecasters' ability is provided in columns 5 through 9 of Table 7. Cross-sectional data for each month $i=1$ to 13 are used to fit equation (5) to the predicted values. Unbiased forecasts would be reflected by α's insignificantly different from zero and β's close to one. Columns 7, 8 and 9 provide the t statistics for the null hypotheses that $\alpha=0$, $\beta=1$ and $\beta=0$ respectively.[12]

Due simply to the number of t statistics computed some are bound to be significant. However, on the average, α is not significantly different from zero ($t=\pm 1.68$ at the 0.10 probability level for a two-tail test given d.f.$=40$), although there is a tendency for α to be negative on the average. We are also not able to reject the null hypothesis that $\beta=1$. The fact that the null hypothesis

[12] Column 10 gives the degrees of freedom for the t statistics. The low value is due to the single year 1976 when observations were available only up to May.

TABLE 6

THEIL'S U^2: QUARTERLY MODEL* ($k = 5$)

Year	Month** 4	5	6	7	8	9	10	11	12	13	Significance Level of Trend Cox-Stuart Test
1967	0.409	0.505	0.494	0.069	0.122	0.286	0.780	0.813	0.858	0.877	0.016
1968	−0.192	−0.093	0.083	−0.170	−0.115	0.058	0.505	0.560	0.563	0.579	0.344
1969	0.474	0.521	0.536	0.559	0.605	0.694	0.615	0.624	0.689	0.746	0.016
1970	−0.425	−0.505	−0.366	−0.101	−0.218	−0.887	−0.184	−0.006	0.200	0.488	0.344
1971	−0.291	−0.342	−0.147	0.625	0.827	0.849	0.444	0.525	0.624	0.707	0.016
1972	0.572	0.586	0.610	0.766	0.745	0.759	0.595	0.516	0.798	0.865	0.016
1973	−0.499	−0.454	−0.350	−0.001	0.058	0.207	0.278	0.449	0.794	0.817	0.344
1974	−0.310	−0.116	−0.085	−3.095	−1.951	−0.954	0.407	0.595	0.640	0.636	0.344
1975	0.455	0.440	0.509	0.693	0.757	0.793	0.803	0.836	0.806	0.784	0.016
1976	3.973	−3.758	−3.764	−0.873	−1.022	−0.791	−2.001	−0.506	−0.447	0.189	>0.500
10-Year Average	−0.3780	−0.3216	−0.2480	−0.1528	−0.1920	0.1014	0.2242	0.4406	0.5525	0.6688	<0.010

* Unity represents a perfect forecast. $1 - U^2$ is tabulated.
** Months 1–3 are identical to the numbers in Table 2.

TABLE 7

MAD; DECOMPOSITION OF U^2; AND REGRESSION STATISTICS

Month		1 MAD	2 U^M	3 U^R	4 U^D	5 α	6 β	7 $t_{\alpha=0}$	8 $t_{\beta=1}$	9 $t_{\beta=0}$	10 d.f.
1	10-Year Ave. Range	1.2313 0.874–1.684	0.1307 0.001–0.619	0.0462 0.001–0.280	0.8230 0.375–0.997	−0.0739 −0.360–0.076	1.0837 0.584–1.446	−0.8676 −3.709–1.089	−0.471 −2.289–0.832	2.9572 1.617–6.597	21.2 2.29
2	10-Year Ave. Range	1.4118 0.795–3.764	0.1181 0.000–0.414	0.0536 0.000–0.200	0.8281 0.527–0.992	−0.1098 −0.305–0.022	1.3560 0.805–2.053	−1.7086 −4.612–0.236	0.7069 −0.686–2.532	4.2710 1.826–8.736	26.6 3.38
3	10-Year Ave. Range	1.3716 0.693–2.568	0.1360 0.002–0.459	0.0494 0.000–0.132	0.8145 0.501–0.993	−0.0787 −0.318–0.239	1.2305 −0.127–2.259	−1.6263 −4.506–1.331	0.6589 −0.514–3.111	3.9001 −0.098–7.622	29.8 4.38
4	10-Year Ave. Range	1.5344 0.707–2.603	0.1326 0.000–0.427	0.1075 0.000–0.411	0.7600 0.539–0.966	−0.0693 −0.252–0.289	1.0395 −0.762–2.044	−1.5977 −5.038–1.640	0.2147 −5.166–2.867	3.4035 −2.235–6.527	32.8 4.41
5	10-Year Ave. Range	1.5344 0.612–4.010	0.1390 0.000–0.412	0.0537 0.000–0.246	0.8074 0.565–0.983	−0.0779 −0.209–0.201	1.0810 −0.277–2.166	−1.5412 −4.508–0.317	0.2116 −3.596–1.972	3.5511 −0.779–6.607	31.6 4.40
6	10-Year Ave. Range	1.5394 0.554–3.203	0.1403 0.000–0.412	0.0554 0.001–0.196	0.8044 0.578–0.985	−0.0710 −0.180–0.197	1.1272 −0.012–1.753	−1.6255 −4.447–1.453	0.5201 −3.188–2.436	4.2333 −0.037–6.985	33.2 4.41
7	10-Year Ave. Range	1.3270 0.526–3.189	0.1218 0.000–0.379	0.0734 0.002–0.248	0.8046 0.619–0.982	−0.0697 −0.178–0.168	1.0637 −0.041–1.757	−1.5538 −3.652–1.326	0.1660 −3.783–3.069	4.2193 −0.150–7.800	32.6 4.42
8	10-Year Ave. Range	1.1542 0.581–2.452	0.1325 0.000–0.449	0.0919 0.001–0.251	0.7756 0.550–0.906	−0.0657 −0.123–0.180	1.1805 0.555–1.799	−1.6836 −3.424–1.764	1.0605 −1.672–3.528	6.7416 1.228–13.510	33.6 5.54
9	10-Year Ave. Range	1.0856 0.553–2.215	0.1901 0.000–0.485	0.1229 0.002–0.285	0.7682 0.505–0.928	−0.0597 −0.138–0.166	1.1455 0.457–1.699	−1.6055 −3.170–1.822	1.1823 −3.196–3.846	8.4434 1.731–16.878	34.4 5.42
10	10-Year Ave. Range	1.0199 0.481–2.162	0.1253 0.006–0.640	0.1102 0.000–0.364	0.7644 0.284–0.936	−0.0600 −0.122–0.142	1.2197 0.533–1.942	−1.5370 −3.071–2.542	1.4183 −0.932–4.242	8.5668 3.998–16.038	33.5 5.43
11	10-Year Ave. Range	0.6862 0.466–1.519	0.1057 0.004–0.446	0.0855 0.002–0.236	0.8090 0.551–0.896	−0.0575 −0.127–0.094	1.1502 0.853–1.444	−1.4976 −2.709–1.544	1.3079 −0.889–3.431	9.2539 4.074–15.081	34.2 5.42
12	10-Year Ave. Range	0.8203 0.540–1.397	0.0859 0.000–0.427	0.0601 0.000–0.195	0.8538 0.569–0.961	−0.0323 −0.100–0.095	1.0980 0.876–1.405	−0.9958 −2.198–1.308	0.9662 −0.941–2.912	10.9169 3.700–22.591	34.2 4.41
13	10-Year Ave. Range	0.7026 0.405–1.382	0.0801 0.003–0.372	0.1180 0.000–0.497	0.8019 0.131–0.957	−0.0391 −0.078–0.003	1.1650 0.940–1.599	−1.1174 −2.048–0.234	1.5649 −0.499–4.359	13.4861 7.866–31.398	33.8 5.43

that $\beta=0$ can be rejected ($t=\pm 2.08$ at the 0.05 probability level for a two-tail test given d.f.$=21$) indicates that, on average, analysts can predict the direction of earnings changes. These tests provide information which supports the hypothesis that analysts predict EPS changes without significant systematic bias.[13] This evidence supports the second hypothesis.

Columns 2 through 4 of Table 7 provide the decomposition of U^2 as given by equations (7a), (7b), (7c). As expected, and hypothesized, U^D constitutes a large fraction (between 76 to 85 percent) of U^2 in every year. Hence, we conclude that most of the error in the forecasters' predictions is due to factors that could not be eliminated simply by applying a linear correction to the forecasts. This is again consistent with the second hypothesis.

The third hypothesis concerns forecast variability. Specifically, we hypothesized that the variability among analysts' forecasts declines as the end of the year is approached.

In Table 8 we provide specific information on the variability of earnings forecasts among analysts in any given month. The mean standard deviation is given for each year and each month. The data are inconclusive. While there is a tendency for the variation to decline, the decline is uneven and often shows some increase in the middle months. The years 1969, 1971, 1973, and 1974 (4 of 10 years in the study) either do not show the anticipated decline or it is not significant.

The Cox-Stuart Trend Test support the hypothesized downward trend at the 0.02 probability level for 1967, 1972, 1975 and 1976; and at the 0.11 probability level for 1968 and 1970. The information is not, in our opinion, sufficient to support the third hypothesis, and we can find no convincing explanation for the result.

Table 8 also suggests that the standard deviation of the forecasts has tended to be higher over the last three years of the study, a result whose cause is unclear. Further observations and further analysis of these issues constitute part of our continuing research interest in analysts' forecasts.

LIMITATIONS

Data-gathering difficulties are probably the most serious obstacle to undertaking studies which evaluate analysts' predictions over long periods of time. Although we were successful in gathering ten years of data, as can be seen in Table 9, we were faced with missing forecasts for some firms in several months. While most of the cell values in Table 9 are of comparable size, this is not the case for 1976. However, the analysis in 1976 is confined to non-December firms. Although our separate analysis of December and non-December firms did not yield pronounced differences, there was a slight tendency for non-December firms to pose more difficulty for analysts (at least in our limited sample of non-December firms). Therefore, the 1976 data should bias our results against the analysts. Since our overall conclusions support the quality of analysts' predictions, we can conclude that missing data problems probably did not seriously affect our results.

It would also be useful to investigate forecast-accuracy by industry. It may be the case that different industries pose different forecasting problems for ana-

[13] The tendency for α to be negative and for β to exceed one are not statistically significant. The results are inconsistent with the conclusion reached by Barefield and Comiskey [1976, p. 244] and McDonald [1973, p. 509]. Both of these studies report a persistent optimistic bias in the analysts' forecasts observed. We note that their methodology of examining the percent of forecasts made which exceeded actual is quite different from ours.

TABLE 8

AVERAGE STANDARD DEVIATION AMONG ANALYSTS' FORECASTS

Year		Month 1	2	3	4	5	6	7	8	9	10	11	12	13
1967	Average Standard Deviation	0.1458	0.1802	0.1480	0.1723	0.2023	0.1542	0.1249	0.1399	0.1639	0.1380	0.1288	0.1316	0.1181
	Number of Observations	11	18	18	27	22	24	27	28	30	31	27	33	30
1968	Average Standard Deviation	0.2307	0.2603	0.2265	0.2080	0.1801	0.1766	0.1775	0.1806	0.1624	0.1866	0.1716	0.1748	0.2411
	Number of Observations	20	26	30	33	31	35	35	37	36	31	31	33	29
1969	Average Standard Deviation	0.2410	0.2417	0.1454	0.1449	0.1436	0.1421	0.1668	0.1913	0.1530	0.1537	0.1543	0.1640	0.1642
	Number of Observations	9	14	29	29	26	28	30	30	28	31	31	32	32
1970	Average Standard Deviation	0.1858	0.1789	0.2104	0.1712	0.1800	0.1669	0.1462	0.1284	0.0988	0.1189	0.1740	0.1523	0.1513
	Number of Observations	11	19	26	29	22	28	28	28	31	30	25	21	20
1971	Average Standard Deviation	0.1932	0.2141	0.1540	0.1627	0.1947	0.1744	0.1684	0.1898	0.1510	0.1795	0.1783	0.0975	0.1085
	Number of Observations	12	20	21	24	24	24	26	26	26	21	20	25	20
1972	Average Standard Deviation	0.1786	0.1765	0.1999	0.1587	0.2047	0.2285	0.2040	0.1771	0.1604	0.1175	0.1342	0.1563	0.1259
	Number of Observations	7	12	16	21	25	22	17	20	22	25	24	20	19
1973	Average Standard Deviation	0.1708	0.1475	0.1650	0.1588	0.1594	0.2284	0.2134	0.2032	0.2018	0.1940	0.1874	0.1513	0.1642
	Number of Observations	13	15	18	17	20	26	26	26	27	23	30	24	28
1974	Average Standard Deviation	0.2663	0.2045	0.2233	0.2138	0.3309	0.3109	0.3158	0.4457	0.4492	0.4710	0.4986	0.4355	0.3930
	Number of Observations	14	11	18	22	26	26	25	23	29	29	27	22	26
1975	Average Standard Deviation	0.7552	0.4435	0.5939	0.5040	0.4217	0.4239	0.3917	0.3878	0.4183	0.3683	0.3299	0.3247	0.2770
	Number of Observations	15	21	23	26	28	28	28	27	27	28	28	27	24
1976	Average Standard Deviation	0.4262	0.4735	0.3881	0.3730	0.3368	0.2789	0.3494	0.3654	0.4317	0.2202	0.2393	0.1580	0.1830
	Number of Observations	14	17	22	26	30	7	8	8	5	4	2	2	4

TABLE 9
NUMBER OF AVAILABLE OBSERVATIONS

	Month												
Year	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
1967	23	23	23	33	29	30	34	35	37	38	32	38	37
1968	30	31	35	38	36	37	36	38	38	33	34	35	32
1969	15	25	35	38	34	32	33	36	33	36	41	41	38
1970	18	37	40	40	35	42	38	43	42	41	38	43	37
1971	31	40	40	43	38	43	44	45	44	39	39	43	39
1972	26	36	36	40	42	39	35	35	36	36	40	36	39
1973	25	27	31	33	36	40	36	35	41	38	44	37	43
1974	30	27	33	37	40	42	43	41	44	45	44	40	45
1975	30	35	39	40	40	41	41	41	42	42	43	43	41
1976	4	5	6	6	6	6	6	7	7	7	7	6	7

lysts. Unfortunately, our data base was insufficient to perform a meaningful analysis by industry. Such an analysis was conducted by Richards [1976] who concluded "that there are significant differences in forecast errors for different industries and even for different firms within industries; however, the differences among analysts are not significant."

CONCLUSIONS

If security analysts' forecasts are to be useful, they should influence users' estimates of parameters of appropriate probability distributions. While we cannot provide direct evidence for this usefulness criterion, we are able to provide evidence that analysts' predictions are accurate in the sense that we have described. This provides indirect evidence concerning the usefulness of analysts' forecasts.

Some specific results include the fact that analysts' forecasts become more accurate as the end of the forecast year approaches. Moreover, these forecasts do not exhibit any significant systematic bias. We also find, using an approach developed by Theil, that the accuracy in the analysts' forecasts cannot be substantially reduced by linear correction models. Without addressing cost issues, however, we can make no statements concerning the efficiency of this activity.

On the other hand, the expected decline in the variability of analysts' forecasts as the end of the forecast year approaches is not supported by our data. In fact, there is some suggestion that the variability near the end of the year has increased in recent years.

Finally, our results are consistent with a large body of empirical research which finds that the market reflects an efficient processing of publicly available information.[14]

[14] It should, perhaps, be mentioned that our work does not speak to the question of the relative accuracy of management versus analyst forecasts. We do not present any management forecast data in this study.

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Professional Expectations: Accuracy and Diagnosis of Errors

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Abstract

The purpose of this paper is to analyze the errors made by professional forecasters (analysts) in estimating earnings per share for a large number of firms over a number of years. We have demonstrated in a previous paper that consensus (average) estimates of earnings per share play a key role in share price determination. In this paper, we examine consensus estimates with respect to the following questions: (1) What is the size and pattern of analysts' errors? (2) What is the source of errors? (3) Are some firms more difficult to predict than others? (4) Is there an association between errors in forecasts and divergence of analysts' estimates?

I. Introduction

Expectations play an important role in the theoretical literature of financial economics as well as in the day-to-day world of the investment community. Expectations as to the future dividend-paying capacity of the firm are often held to be a key variable in the determination of share price. Almost every model of share valuation that has been proposed, whether part of a theoretical system or invented by a practicing analyst, requires estimates of earnings or cash flow. The perceived importance of forecasts of next year's earnings to the valuation process can be seen from the fact that almost without exception, analysts at major brokerage firms and financial institutions produce estimates of next year's earnings. Firms often (and, in fact, should) forecast earnings into the future as well as a myriad of other variables. The potpourri of other forecasted variables differs from firm to firm, but forecasts of the next fiscal year's earnings per share are almost always produced.

The purpose of this paper is to analyze the errors made by professional forecasters (analysts) in estimating earnings per share for a large number of firms over a number of years.[1] We have demonstrated in a previous paper that con-

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[1] See [2], [3], [5], and [8]. Crichfield, Dyckman, and Lakonishok [4] use data on a larger number of forecasts over a long period of time for a relatively small (46) sample of firms. This last article comes closest to the analysis in this paper. See [1] for additional discussion of related work.

sensus (average) estimates of earnings per share play a key role in share price determination. In this paper, we examine consensus estimates with respect to the following questions: 1. What is the size and pattern of analysts' errors? 2. What is the source of errors? 3. Are some firms more difficult to predict than others? 4. Is there an association between errors in forecasts and divergence of analysts' estimates?

The first of these topics involves an examination of the average size and the time pattern of analysts' errors. The second topic involves an examination of the type of errors that analysts make. For example, what percent of the error in forecasting is due to an inability to forecast correctly the average growth rate in earnings in the economy; what percent is due to the inability to forecast how well individual industries will perform; and what percent is due to an inability to forecast how well individual companies will do? The second topic also examines other forecast characteristics. The third topic involves an examination of the persistence of errors over time. Are there particular industries or companies for which it is particularly hard or easy to forecast earnings?[2] The final topic involves an examination of disagreement among analysts concerning forecasts and the relationship of this disagreement to the error in the consensus forecast.

II. Sample

Our data source was the I/B/E/S database put together by Lynch, Jones and Ryan, a New York brokerage firm. Lynch, Jones and Ryan collect, on a monthly basis, earnings estimates from all major brokerage firms on over 2,000 corporations. The earnings estimates are for each of the next two years. Lynch, Jones and Ryan publish a number of characteristics of these earnings estimates for each corporation followed. These include among others the arithmetic mean, median, range, and standard deviation of the estimates of earnings per share for each corporation.

For part of this study, we wanted to have earnings estimates prepared a given number of months before the end of the fiscal year to be at a common calendar time. This restriction means that all analysts would have access to the same macroeconomic information at the time these forecasts were prepared (N months before the end of the fiscal year). Because the majority of firms have fiscal years ending in December, only these firms were selected.

Our second restriction was to include only firms followed by three or more analysts. We studied properties of consensus estimates of earnings. Requiring three analysts was a trade-off between a desire for a large sample and a desire to have the forecasts reflective of a consensus rather than of the idiosyncrasies of

[2] Crichfield, Dyckman, and Lakonishok [4] examine the size and convergent rate of errors as well as present one partitioning of sources of errors. Our study differs from theirs in several ways. Our sample of firms is much larger (over 400 versus 46). We present more analysis of pattern of errors within years and the partitioning of errors. We analyze predictability of errors for individual firms and the relationship of difficulty of prediction to error size. Their sample of years was larger than ours and they placed more emphasis on pattern of errors between succeeding years.

one or two analysts. Our final sample consisted of 414 firms for each of the years 1976, 1977, and 1978.[3]

III. Size of Analysts' Errors and Their Time Series Properties

Our first set of tests involved looking at the accuracy of analysts' estimates of earnings (and growth in earnings) and the change in the error with successive forecasts over the fiscal year. We used several different measures of analysts' errors. The first measure was the dollar error, defined as the absolute value of the difference between actual earnings and forecasted earnings. If F_t is the earnings forecast made t months before the end of the fiscal year and A is the actual earnings, then dollar error is

$$(1) \qquad |A - F_t| .$$

The second measure of analysts' accuracy was the error in estimated growth. This is the metric that will be emphasized in the latter section of this paper. There is ambiguity in this metric if actual earnings were negative or zero. In addition, if firms with extremely small earnings were included in the sample, the average results would be dominated by these few observations. To avoid these problems, we excluded firms with earnings less than 20¢.[4] Eliminating firms with negative earnings resulted in deletion of 21 observations and eliminating firms with very small earnings resulted in deletion of an additional nine observations out of a total of 1,242 observations. With last year's actual earnings denoted by A_L, the second error measure can be expressed as the difference between the actual growth and forecasted growth, or

$$(2) \qquad \left|(A/A_L) - (F_t/A_L)\right| \quad \text{for} \quad A, A_L > 0 .$$

Our final measure was Theil's [10] inequality coefficient. Define the subscript i as referring to firm i and define[5]

	For Change in Earnings	For Growth in Earnings
Realized change	$R_i = A_i - A_{iL}$	$R_i = (A_i - A_{iL})/A_{iL}$
Predicted change	$P_i = F_{it} - A_{iL}$	$P_i = (F_{it} - A_{iL})/A_{iL}$

[3] A large amount of data checking was performed. We ran all the normal screens. We cross-checked all stock splits and stock dividends with CRSP and COMPUSTAT. As a further check on splits and dividends we used Moody's. In almost all cases, we were able to resolve inconsistencies. Lynch, Jones and Ryan were very helpful in this process and we thank them. In total, we deleted 11 firms in which an inconsistency existed, but we were unable to check its accuracy. An example would be the appearance of a $16 forecast when all other analysts were forecasting about 16¢. We eliminated only firms with this type of extreme divergence in estimates. In practice, we either found this type of extreme estimate or an estimate such as 36¢ that could be legitimate and, hence, was retained.

[4] At several points in the analysis, the impact of including firms with earnings of less than 20¢ is discussed. The large impact of deleting firms with earnings of less than 20¢ can be seen by the fact that while only 30 out of 1242 observations were deleted, the mean square error in the analysts' estimates of growth was cut by more than one-half when these few observations were excluded.

[5] See [9] and [10]. Once again, firms with earnings less than 20¢ were deleted when growth was examined.

Theil's inequality coefficient is

$$(3) \qquad U = \sum_{i=1}^{N}\left(R_i - P_i\right)^2 / \sum_{i=1}^{N} R_i^2 .$$

One advantage of this measure is that it is scaled. A value of zero is associated with a perfect forecast. A value of one is associated with a forecast that on average has the same error as a ''naive'' no change forecast.

All the analysis in this article was done for alternative measures of error. Alternative formulations were employed because without knowledge of a potential user's loss function, one measure could not be singled out as best. Because the results of the analysis were sufficiently similar under alternative measures, in most cases the analysis is reported in terms of error in growth, and differences that arise from other measures are briefly noted.

To analyze the time-series properties of errors in forecasts, we regressed each of our measures on time. The results are presented in Table 1. Month 1 is the month in which analysts prepared their last forecast of earnings per share for a fiscal year and month 12 is 12 months earlier. Thus, the positive regression slope indicates a decrease in errors in forecasts over time. The most striking feature of Table 1 is the regularity of the decline in errors over successive forecasts. The reader might well anticipate a decline in error size over time, given that additional information is made available throughout the year. The high degree of association between error and time (over 99 percent in some cases) shows that the decline in error is about the same size from month to month over the year.

TABLE 1

Regressions of Mean Consensus Error on Time

$P = a + bT + \varepsilon$

	Dollar Error			Error in Growth			Theil's U in Change			Theil's U in Growth		
	a	b	R^2	a	b	R^2	a	b	R^2	a	b	R^2
Overall	.146	.036	.997	.043	.013	.998	.083	.054	.990	−.061	.061	.947
1976	.144	.035	.996	.048	.015	.998	.038	.045	.988	−.049	.048	.944
1977	.159	.036	.991	.045	.013	.991	.164	.079	.985	−.077	.081	.891
1978	.136	.037	.994	.036	.013	.993	.062	.042	.949	−.068	.064	.980

The second striking feature of Table 1 is the similarity between years for most of our error measures. For example, the change in the error for different years between months was 3.5 cents, 3.6 cents, and 3.7 cents for dollar error. Using the Chow test, we cannot reject the hypothesis that the equations are the same at the 5 percent level of significance. Thus, one cannot reject the appropriateness of pooling the observations across years.

For error in growth, the decline per month was .015, .013, and .013 in the three years. Once again, one could not reject the hypothesis that the regressions were the same in each year.[6] Similar results held for other measures.

Before leaving this section, some comments on the Theil inequality coefficient are in order. Theil's measure for growth ranged from .801 in month 12 down to .055 in month 1. This pattern implied that analysts forecasted better than the naive model of no change and that their forecasts became more accurate as the fiscal year progressed.

IV. Error Diagnosis

While the size and time pattern of analysts' error is interesting in itself, more can be learned about analysts' performance by diagnosing the source of analysts' errors. In this section, we examine two sets of error partitions:

1. Level of aggregation—how significant are errors that are unique to each company in comparison with a more general level of aggregation?
2. Forecast characteristics—are there recognizable patterns in errors?

The partition results are for the mean squared error of analysts' estimates of the growth in earnings per share. The analysis also was performed in terms of the dollar change in earnings; when differences or similarities in the alternative metrics are sufficiently interesting, we comment upon them.

The formula for the average mean squared forecast error in growth is

$$\text{MSFE} = 1/N\sum_{i=1}^{N}\left(P_i - R_i\right)^2 \tag{4}$$

where

P_i is the consensus prediction of growth for firm i
R_i is the actual of growth for firm i
N is the number of observations.

Note that MSFE can be calculated for each month in which forecasts are prepared. Thus, we have twelve values of MSFE for each year. We now examine the partitioning of the MSFE.

A. Partitioning by Level of Aggregation

Institutions differ in the way their analysts prepare forecasts for individual firms. Some institutions start with forecasts for the economy as a whole, then prepare industry studies, and finally prepare forecasts for individual firms (top-down approach). Other institutions start with the forecasts for individual firms

[6] Before eliminating firms with earnings less than 20¢, we did not observe this consistency from year to year in measures using growth, although the error declined from month to month. This inconsistency was caused primarily by a firm with earnings of 1¢ in one year causing an error in the thousands. For such a skewed sample, it is worthwhile examining the median as a measure of central tendency. We did so, and the results similar to those shown in Table 1 were obtained.

and only after such forecasts are prepared, check with the economists' forecasts for macroeconomic consistency (bottom-up approach). Thus, it is useful to examine the level of aggregation at which serious errors are being made: are they made at the economy level, the industry level, or the individual firm level?

The mean squared error of the forecasts can be partitioned as follows

$$\text{MSFE} = 1/N\sum_{i=1}^{N}\left(P_i - R_i\right)^2 = \left(\bar{P} - \bar{R}\right)^2 + 1/N\sum_{j=1}^{J}N_j\left[\left(\bar{P}_j - \bar{P}\right) - \left(\bar{R}_j - \bar{R}\right)\right]^2 \tag{5}$$
$$+ 1/N\sum_{j=1}^{J}\sum_{i=1}^{Nj}\left[\left(P_i - \bar{P}_j\right) - \left(R_i - \bar{R}_j\right)\right]^2$$

where

- $\bar{P}$ is the mean value for P across all companies
- $\bar{R}$ is the mean value for R across all companies
- $\bar{P}_j$ is the mean value for P across all companies in industry j
- $\bar{R}_j$ is the mean value for R across all companies in industry j
- J is the number of industries in our sample
- N_j is the number of firms in industry j.

The first term measures how much of the forecast error is due to the inability of analysts to predict what earnings per share will be for the economy (actually for the total of firms in our sample). The second term is a measure of how much of the total error is due to the analysts' misestimating the differential performance of individual industries. The final term measures how much of the error is due to the inability to predict how each firm will differ from its industry average.

By dividing both sides of equation (5) by MSFE and multiplying by 100, we express each source of error as a percentage of the total mean squared forecasting error. To perform this analysis, modification of our sample was necessary. In our earlier analysis, several industries were represented by very few firms. Because we are interested in errors in forecasting for industries as well as firms, for this part of our study we limited the sample to all industries containing seven or more firms. This restriction reduced our sample size to 225 firms.

B. Partitioning by Forecast Characteristics

The decomposition discussed above was designed to aid management in finding the level of aggregation at which mistakes were made. This section presents a partitioning that looks for systematic errors in analysts' forecasts to improve (either mechanically or through discussions with analysts) their forecasts. Error is partitioned into bias, inefficiency, and a random component. The partition is given by[7]

$$\text{MSFE} = \left(\bar{P} - \bar{R}\right)^2 + (1 - \beta)^2 S_P^2 + \left(1 - \rho^2\right)S_R^2 \tag{6}$$

[7] This method of partitioning was derived by Mincer and Zarnovitz [7]. It is the same method of

where

β is the slope coefficient of the regression of R on P.

ρ is the correlation of P and R.

S_p is the standard deviation of P.

S_R is the standard deviation of R.

The first term represents bias, the tendency of the average forecast to overestimate or underestimate the true average. The second term represents inefficiency or the tendency for forecasts to be underestimated at high values of P and overestimated at low values, or vice versa. If the beta of actual growth regressed on forecasted growth is greater than one, forecasts are underestimates at high values and overestimates at low values. If beta is less than one, the forecasts are overestimates at high values and underestimates at low values. The final component is the random disturbance term, a measure of error not related to the value of the prediction P or the realization R.

C. Results

The results of both decompositions are presented in Table 2.

1. Partition by Level of Aggregation

Table 2 presents the partition of MSFE, in percentage terms, by level of aggregation. Note that the error in forecasting the average level of growth in earnings per share for the economy is quite small and is below 3 percent of the total error. Analysts on average make very little error in estimating the average growth rate in earnings per share for the economy.

TABLE 2
Partitioning of Percentage Error in Growth

	Economy	Industry	Company	Bias	Inefficiency	Random Error
January	2.0	37.3	60.7	1.0	27.4	71.6
February	2.2	36.8	61.0	1.1	26.3	72.6
March	2.4	36.2	61.5	1.7	14.2	84.1
April	2.1	33.1	64.8	1.8	8.6	89.6
May	2.5	32.6	64.9	2.2	7.8	90.0
June	2.7	29.4	67.9	2.5	9.5	88.0
July	2.8	30.2	67.0	2.6	6.7	90.7
August	2.7	30.6	66.8	2.4	7.7	89.9
September	2.7	26.5	70.8	2.4	8.5	89.1
October	2.3	26.3	71.5	2.2	6.4	91.4
November	1.3	23.0	75.7	1.6	3.4	95.0
December	0.8	15.5	83.7	0.9	3.0	96.1

partitioning used by Crichfield, Dyckman, and Lakonishok [4]. Our results differ from theirs in that they examine the log of growth and used a much smaller sample size.

The vast majority of error in forecasting arises from misestimates of industry performance and company performance. The percentage of error due to industry misestimates starts as 37.3 percent in January and declines over time to 15.5 percent. Similarly, the percentage of error due to misestimating individual companies starts at 60.7 percent in January and increases to 83.7 percent by December.[8] We already know (from Section III) that analysts become more accurate as the fiscal year progresses. Now we see that while analysts become more accurate in forecasting both industry performance and company performance, their ability to forecast industry performance grows relative to their ability to forecast company performance over the year.

2. Partitioning by Forecast Characteristics

Table 2 also presents the results of partitioning analysts' mean square error by forecast characteristics. *It is apparent that bias is an extremely small source of* error and in all months is below 3 percent.[9] Note that inefficiency starts as a fairly important component of the error but its importance diminishes as successive forecasts are made. The percentage of error accounted for by inefficiency begins at about 27 percent for early forecasts and shrinks to 3 percent as successive forecasts are made during the year. The percent of error due to random error grows from 71.6 percent to 96.1 percent over the year. This initial importance of inefficiency is due primarily to the tendency of analysts to systematically overestimate the growth for high growth companies and to overestimate shrinkage in earnings for very low growth companies. This can be seen from the fact that the beta from equation (6) was below one for all three years examined.[10] This indicates that a linear correction applied to analysts' forecasts of growth could improve these forecasts.

V. Relationship of Errors in Adjacent Periods

Are the firms for which analysts make large errors in forecasting in one year the same as those for which they make large errors in the adjacent year? The answer to this question is clearly *yes*. For both errors in change and errors in growth, we divided firms into five equal groups by size of error in each month for each year. We then examined whether a firm that fell into one quintile in a par-

[8] This analysis was repeated for the entire industry sample, including firms with earnings less than 20¢. This increased the sample size from 216 to 225 in 1976 but resulted in an entirely different breakdown of error in growth. These firms had gigantic analysts' errors in terms of growth rate and because they were not concentrated in one industry, the importance of industry error dropped markedly. The analysis also was repeated in terms of error in earnings change per share. The partitioning is indistinguishable from that presented in Table 2.

[9] Note that the measure of bias used here is the same as the first term in the partitioning by level of aggregation. The numerical value is different because the sample is different. The analysis by level of aggregation used a subsample with heavy representation from a few industries. In this section, we use the full sample. However, note that with either sample the misestimate of average earnings is very small.

[10] When the error in forecasting earnings change was examined, beta was much closer to one and the percentage error due to inefficiency was much smaller.

ticular month in one year ended up in the same or adjacent quintiles that month in the next year.

The tendency for firms to remain in the same quintile is statistically significant in all cases (by a chi-squared test) at the 1 percent level. This is true whether the analysis is performed in terms of change in earnings or growth rates in earnings. These results support the proposition that firms for which analysts prepare poor forecasts in any year tend to be the same firms for which they prepare poor forecasts in the subsequent year.

VI. Dispersion of Analysts' Estimates

Up to this point, we have examined properties of estimates by consensus. The forecasts by consensus are an average of the forecasts produced by all analysts following that company. In this section, we examine some characteristics of the differences of opinion among analysts about a company's growth rate in earnings per share. We use the standard deviations computed across different analysts' estimates of the same company's growth rate at a point in time as our measure of difference of opinion. We examine three topics in this section. First, does the standard deviation of analysts' estimates decrease over time? Second, do the analysts consistently make more diverse forecasts for companies in some industries than they do for others? Finally, is the divergence of opinion between analysts associated with the size of forecast error in the average (consensus) forecast? When analysts disagree about the level of future earnings for any firm, a plausible reason is that earnings for that firm are difficult to forecast. If this is true, then a high standard deviation of forecasts by different analysts should be associated with a high error in the forecast by consensus.

TABLE 3

Average Standard Deviation of Analysts' Estimates of Growth

Number of Months before December	Overall	1976	1977	1978
11	.104	.134	.096	.081
10	.102	.126	.099	.080
9	.093	.105	.098	.077
8	.086	.100	.083	.074
7	.080	.092	.081	.067
6	.080	.096	.077	.066
5	.079	.094	.079	.065
4	.080	.094	.079	.068
3	.076	.087	.074	.068
2	.073	.082	.071	.066
1	.074	.086	.072	.065
0	.067	.073	.065	.062

We now examine the first of these issues, the time pattern of the divergence of analysts' estimates. Table 3 presents the average standard deviation of analysts' estimates of growth for each month from January to December. Note that, although there is some decline in the average dispersion as the estimates get closer to the end of the year, the dispersion is not uniform. Most of the decrease in dispersion across analysts occurs in the first four months of the year. From May on, there is only a slight decline and this decline does not occur in every month in either the combined three year analysis or in any individual year.[11] The only other month of major decline occurs from November to December. Note that, while the standard deviation of the analysts' estimates is fairly stable over the last eight months of the year, the accuracy of the analysts' estimate by consensus is markedly improving. Analysts are producing more accurate forecasts, but the disagreement between analysts is not shrinking.

TABLE 4

SIC	Industry Name
451	Air Transportation
331	Steel
401	Railroads
260	Paper and Paper Containers
280	Chemical
371	Automobile, Automobile Parts and Trucks
291	Integrated Oil
208	Beverages
353	Machinery Construction and Oil Well
602	Banks
492	Pipelines and Natural Gas Distribution
491	Electric Companies
271	Newspaper and Magazines
284	Soaps and Cosmetics
631	Life Insurance
357	Office and Business Equipment
283	Drug

Three digit industries ranked from (top) those industries for which analysts had most disagreement about future earnings to those for which they had least (bottom).

The second question we examined was whether the disagreement among analysts differed across industries. To test this effect, we first calculated the average standard deviation in analysts' estimates of growth for firms in each industry. This result gave us a *measure of divergence of opinion of analysts' forecasts for* each industry. We then calculated the Spearman rank correlation between the dispersion (standard deviation) of analysts' estimates for each industry in one year with the same measures in other years. When we compared the standard deviations for June estimates across the 17 industries for 1976 and 1977, the rank correlation was .63 and for 1977 and 1978 it was .79. The rank correlation between forecasts' dispersions for other months was similar. In all cases, the results were statistically significant at the 1 percent level. The industries we examined

[11] Crichfield, Dyckman, and Lakonishok [4] found no significant pattern when they examined the same question. They found some tendency for a decrease but not in all years. The number of analysts following the firm is fairly constant over the year.

are listed in Table 4 in order (from top to bottom) of those with the greatest disagreement on average over the three years to those with the least.

The final question we examined was whether the error in the forecast by consensus of earnings growth was related to analysts' uncertainty about earnings growth. To study this, we used the absolute error in the forecast of growth for each company as our measure of error. We used the standard deviation of analysts' estimates in growth rates as our measure of analysts' uncertainty. For each month, we regressed the absolute error in the forecasts of growth against our measure of uncertainty of analysts' forecasts. This gave us a total of 36 regressions.[12]

The results of those regressions for every other month in each year are displayed in Table 5. From the full results, we see that the t value associated with the regression coefficient was statistically significant in each of the 36 regressions. There is a strong and significant relationship between error and uncertainty. The median R-square was .40 with a range from .13 to .77. Although there was no clear time pattern to the parameters of the regression relationship, the coefficient on analysts' uncertainty appeared to be smaller in the last two months of the year.

VII. Summary

In this paper, we have explored the characteristics of analysts' estimates of the growth rate in earnings per share. We have shown that, on average, over a wide variety of error measures, analysts' errors decline monotonically as the end of the fiscal year approaches. When we partitioned analysts' error we found that analysts were accurate in estimating the average level of growth in earnings for all stocks in our sample. The error in estimating company growth (with industry error removed) was larger (and in some months much larger) than the size of the error due to misestimating the level of industry earnings. When partitioning by source of error we saw that early in the forecasted year, analysts had a marked tendency to overestimate the growth rates of securities they believed would perform well and to underestimate the growth rate of companies they believed would perform poorly. We next showed that there is persistent difficulty in forecasting growth rates for some companies. If analysts on average have large errors when forecasting the growth of a company in one year, they are likely to have difficulty in the next year.

Finally, we examined some characteristics of the divergence across analysts in their estimates of growth rates in earnings per share. Analysts tend to have greater divergence of opinion for the first four months of a year. However, there is no systematic decrease in divergence of opinion over the rest of the year. Analysts have greater disagreement about the growth of certain industries. They tend

[12] Regressions were also run between the absolute dollar error in forecast and the standard deviation of analysts' dollar forecasts. In addition, squared errors were examined. The results were consistent with the results described in the text and reported in Table 5. The relationships were not quite so strong though still statistically significant and were more unstable. For example, when the relationship was formulated in dollar values rather than growth, the median R-square was .29 instead of .40.

TABLE 5

Absolute Error in Growth = $a + b$ (Divergence of Analysts' Opinion) + ε

	January			March			May			July			September			November		
	76	77	78	76	77	78	76	77	78	76	77	78	76	77	78	76	77	78
a	.134	015	.068	.051	.007	.097	.060	.023	.068	.061	047	.053	051	.015	.048	.014	.021	.046
b	.769	2 030	1.585	1.565	1.891	1.107	1.401	1.701	1 296	.972	1 195	1.233	1.295	1.334	.772	1.051	.853	402
R^2	.42	.72	.28	34	69	.19	.25	65	25	24	.50	.29	44	.42	30	.50	.46	.16

Median R-Square .40
Range of R-Square .13-.77

to disagree more about the earnings of the same industries in different years. Finally, disagreement is related to analysts' errors.

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PROPERTIES OF ANALYSTS' FORECASTS OF EARNINGS: A REVIEW AND ANALYSIS OF THE RESEARCH*

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ABSTRACT

The paper provides an overview of the evidence that has accumulated on the properties of financial analysts' forecasts of earnings. Among the properties examined are accuracy, rationality, and usefulness for investors. The paper evaluates the evidence and its implications for investors and researchers and suggests avenues for further research in the area.

1. INTRODUCTION

No better proof exists for the important role that earnings play in financial markets than the handsome livelihood derived by many professionals from the production, analysis, and forecasting of earnings numbers. Investors have a keen interest in predicting future earnings: Stock valuation models commonly employ some measure of earnings as their major parameter. Earnings-per-share emerges from various studies as the single most important accounting variable in the eyes of investors. Gonedes [1974] provides evidence showing that the earnings-per-share number (EPS) has the greatest information content of an array of accounting variables. He concludes (p. 49) that "our results seem to ascribe special importance to the information reflected in the EPS variable, relative to other variables examined." In an extensive survey of hundreds of individual investors, institutional investors, and financial analysts [Chang and Most, 1980], earnings forecasts were considered by respondents in the United States to be the most important expectational data, more important than dividends and sales forecasts. Similar results are reported in that survey for the United Kingdom and New Zealand.

The information content of earnings to investors was directly tested by numerous studies originating with the seminal work of Ball and Brown [1968]. These studies found that the message contained in the earnings report is correlated with factors that determine stock prices. Since then, many other studies have confirmed the key role that earnings play in investment decisions.

* We would like to thank Robert Kaplan and two anonymous referees for their helpful comments.

The investigation of the properties of FAF is of special interest if FAF adequately represent market expectations of earnings; in such a case, the examination of the process by which analysts form their earnings expectations adds to our understanding of investor behavior, the operation of capital markets, and the relationship between accounting information and stock prices.

Several recent studies explore the relationship between earnings forecasts made by financial analysts and stock price behavior. The results show that revisions in FAF and price changes are correlated and that, moreover, investors behave as if their earnings expectations coincide with those of financial analysts. Detail and evaluation of these findings are provided in Section 7.

Section 8 discusses yet another, perhaps the least studied, property of FAF: their cross-sectional dispersion. Almost all research on FAF uses the mean, or "consensus," forecast, without giving any recognition to the dispersion around that mean. The divergence of beliefs about future earnings may convey important information about the uncertainty surrounding future earnings and, thus, the perceived importance of the respective mean forecast. The cross-sectional dispersion of analysts' forecasts may represent a surrogate for the risk associated with the firm. Such a surrogate is of unique value to empirical researchers because, unlike most other risk surrogate estimated from past-series (e.g., the standard deviation of the return or the security beta), this one presents an *ex-ante* measure of risk. The measure and its theoretical support, as well as some preliminary results, are discussed in Section 8. The last section contains concluding remarks and suggestions for further research.

Before turning to the main issues, the data sources on earnings expectations used by previous research, their limitations, and their problems are described in Section 3.

3. EXPECTATIONAL DATA: AVAILABLE SOURCES AND SOME MEASUREMENT ISSUES

3.1 DATA SOURCES

The use of expectational data in accounting is fairly new, and, as a result, many researchers may not be familiar with the main sources of these data.

There are three publicly available (although not free) sources of earnings forecasts that have been used by researchers: the *Earnings Forecaster* of Standard and Poor's (S&P), the *Value Line's Investment Survey*, and Lynch, Jones, and Ryan's *IBES Service*. The *Value Line's Survey* is apparently the most widely circulated among the three. Other sources, mostly private (forecasts made by individual brokerage houses, pension funds, etc.), have occasionally been used by researchers.

The *Earnings Forecaster* is a weekly publication by S&P that first appeared in 1967. The publication lists forecasts of annual EPS of the current year and (if available) of the following year for about 1,500 companies. The forecasts are those made by S&P itself and by about 70 other security analysts and brokerage houses who agreed to submit their forecasts, upon release, for publication. The number of contemporaneous forecasts available for each company depends on the prominence of the company and the time of the year (more forecasts become available as the year progresses); typically, however, two to four forecasts of the current year's earnings are available around April, for most companies. The *Earnings Forecaster* has been used by Barefield and Comiskey [1975], Basi, Carey and Twark [1976], Gonedes, Dopuch, and Penman [1976], Crichfield, Dyckman, and Lakonishok [1978], Ruland [1978], Givoly and Lakonishok [1979, 1980, 1982], Fried and Givoly [1982], and Givoly [1982] among others.

The *Value Line's Survey* lists one- to five-quarter-ahead forecasts for about 1,600 firms. The survey has been published weekly since 1971 and provides quarterly earnings predictions by Value Line's analysts four times a year for each firm included. The Value Line forecasts have been employed by Brown and Rozeff [1978], Collins and Hopwood [1980], and Jaggi [1980], among others.

Lynch, Jones, and Ryan, a New York based brokerage firm, has available in both manual and computer-readable form, consensus (average) earnings estimates for the current and the next fiscal year for about 1,500 firms. This service is designated by Lynch, Jones, and Ryan as IBES (Institutional Brokers Estimate System). In its monthly issues, the service includes, besides average forecasts (which are typically based on 10 to 20 different forecasts), the lowest and the highest forecast as well as the standard deviation of the estimate across forecasters, and other statistics. *IBES Service* is a relatively new research source. It was used by Elton, Gruber, and Gultekin [1981] and is currently being used in several research projects.

Another source of FAF, which has only recently become available to researchers, is the *Icarus Services* by Zacks Investment Research, Inc. This data base contains EPS estimates for some 1,500 companies, with an average of 12 forecasters per company. The estimates, made by over 50 brokerage firms, are available for the current fiscal year, the next fiscal year, and the next five years.

3.2 SELECTING A REPRESENTATIVE FORECAST

Almost all studies relying on data that consist of more than one forecaster used mean-forecast rather than individual forecasts. The use of the mean forecast is, of course, necessary when individual forecasts are not provided (as in the IBES case). However, there are certain advantages and drawbacks of the use of the mean forecast that should be considered in interpreting the results.

Averaging individual forecasts has the effect of reducing the measurement error that is inherent in each individual forecast. This effect is achieved whenever the measurement errors across forecasters are less than perfectly correlated. In addition, the use of individual forecasts may not be very meaningful for the examination of time-series properties when the identity of the individual forecaster changes over time (as is the case of forecasts made by brokerage firms).

Some aggregate measure of FAF is likely to be superior to most individual forecasters, particularly if the weight of each forecast(er) is based on past performance and its correlation with errors of other forecasts (for a discussion of this weighting scheme and an application of the technique, see Granger and

Newbold, 1977, and Figlewski, 1980). Even a simple average may outperform each of the individual forecasts when the forecast errors are not highly correlated cross-sectionally. In fact, much of the concept of efficient markets composed of unsophisticated and less than perfectly knowledgeable investors relies on the notion of the "aggregate wisdom" of the market — that is, the superiority of the consensus over individual assessments. The fact that a consensus can reflect "greater than average" knowledge is illustrated by Beaver [1981] in a seemingly unrelated context—the prediction of outcomes of football games. Beaver provides results that suggest that the consensus of game-score predictions made by staff members of a daily newspaper (the *Chicago Daily News*) consistently outperformed predictions made by each of the individual staff members. This conclusion is shared by Zarnowitz [1979], who, after investigating forecasts of economic indicators, commented, "while published forecasts by ranking practitioners are often developed with particular skill and care, group average forecasts benefit greatly from cancellations of individual errors of opposite sign" [p. 8].

Some pitfalls in using the mean forecasts should also be recognized. First, when aggregating forecasts cross-sectionally, the assumption is made that each represents an updated, contemporaneous prediction; yet, due to problems of data collection and preparation, some of the forecasts are less updated than others, thus rendering the average forecast less meaningful. A second problem arises from the change over time in the composition of the group of forecasters who participate in forecasting the earnings of a given firm. This change makes it difficult to conduct a time-series analysis of earnings forecasts.

Finally, even if all these measurement problems did not exist, the reliance on the mean forecast might obscure patterns that are present among individual forecasters. For instance, adaptive behavior by individual forecasters may not be revealed by examining the series of the mean forecast. Bierwag and Grove [1966] showed that the mean expectation does not follow necessarily an adaptive process even when individuals form their expectations adaptively. Similar difficulties lie in identifying other time-series patterns from data on the means.

4. ACCURACY OF FAF

4.1 ERROR MEASURES AND EVALUATION BENCHMARKS

The two error measures that are most widely used in assessing the accuracy of FAF are the relative (absolute) error of the form $|P-A|/A$, and the relative square error, $(P-A)^2/A$, where P and A are the predicted and realized earnings variables, respectively. The second measure is more appealing because of its mathematical and statistical tractability. Furthermore, this measure gives more than proportional weight to large errors, a property consistent with a quadratic loss (and utility) function.

Which of the error measures is selected may not be important because of the very high correlation between the measures. However, in light of the evidence that FAF produce fewer "outliers," or extreme error cases, than (at least some of) the naive models [see Collins and Hopwood, 1980], one may suspect that the use of the square error as an accuracy measure favors FAF over naive models.

In evaluating analysts' forecasts, different benchmarks have been used; one, common to many studies, is the "no-change" naive model which is usually employed in conjunction with Theil's U statistic. This measure, proposed by Theil [1966] for the evaluation of economic forecasts, is defined as

$$U = \frac{\sum_i (P_i - A_i)^2}{\sum_i A_i^2}$$

where P_i and A_i are, respectively, predicted and actual growth in earnings of firm i. When predictions are perfect, $U = 0$; when predictions are "no-change," U becomes 1. The value 1, thus, serves as a benchmark for the performance of FAF. A smaller-than-1 U-value for FAF means that FAF outperform a naive no-change prediction model. Some studies relied exclusively on Theil's U for evaluating FAF; others used more sophisticated models that generally belong to four groups:

(1) Submartingale (random walk plus drift);
(2) Box-Jenkins models (models that exploit the serial correlation of the time-series);
(3) Index Model (a model that relates the earnings of the individual company to a market-wide index of earnings); and
(4) Management forecasts.

The first two models were found by recent studies to represent quite adequately the time-series behavior of annual earnings [see Albrecht, Lookabill, and McKeown, 1977; and Watts and Leftwich, 1977].[8] Quarterly earnings, however, appear to follow an autoregressive process with seasonal and quarter-to-quarter components; this process can be formulated as a Box-Jenkins model [see Brown and Rozeff, 1977; Foster, 1977; and Griffin, 1977].

The use of the Index Model is supported by the relationship that was found between the first differences in individual company earnings and the average of the first differences in earnings across all firms [see Ball and Brown, 1968; and Gonedes, 1973].

The studies that examined the accuracy of analysts vis-à-vis management forecasts were interested primarily in the incremental value of the latter to investors. These studies provided, however, additional evidence on the performance of analysts. Our concern in this context is whether the forecasting power of analysts can compensate for the better knowledge that management is presumed to possess about its own company.

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[8] In fact, as a general representative firm-model, the submartingale was found to perform as well as the firm specific Box-Jenkins models in describing the time-series characteristics of annual earnings [see Albrecht, Lookabill, and McKeown, 1976].

4.2 EMPIRICAL RESULTS

Research on the accuracy of FAF has been surprisingly inconclusive. While several studies conclude, perhaps counterintuitively, that analysts' performance is only as good as naive models, others claim that analysts' predictions are significantly more accurate than naive models. Of course, the diversity of the naive models might be the cause of this discord; yet a closer look reveals that agreement or disagreement between the conclusions of individual studies do not appear to be correlated with the particular models tested. Moreover, as pointed out earlier, it is unlikely that the conflicting conclusions are due to the use of different error measures by different studies. Before commenting further on possible causes for this inconclusiveness, a short review of the results is presented below. Some of the studies cited contain work that relates to other properties of FAF. However, only the findings concerning accuracy are discussed in this section.

The first comprehensive study on the accuracy of FAF is that by Cragg and Malkiel [1968]. Forecasts of five-year growth rate in earnings, made by five investment houses for 185 companies in the two years 1962-63, were confronted with two sets of naive models, one predicting no change and the other a change equal to past change. The tests led to the conclusion that "forecasts based on perceived past growth rates . . . do not perform much differently from the [FAF] predictions" [p. 77]. This conclusion does not square well with the notion of rational investors, since it suggests that the costly analysts' product is not superior to a practically costless product. Indeed, Cragg and Malkiel were not apparently at ease with their own findings, so they recommended that caution should be exercised in interpreting the results because the period might be "atypical" and "only a few firms were able to participate in the study" [p. 83].

Cragg and Malkiel's conclusion was reaffirmed, nonetheless, a few years later by Elton and Gruber [1972], who evaluated annual earnings forecasts made by analysts in a large pension fund, in an investment advisory service, and in a large brokerage house. In the three years examined (1962-64), they found no significant difference in accuracy between the best naive model (an exponential smoothing model) and each of the three groups of analysts.

Later studies reported somewhat different results. Barefield and Comiskey [1975] examined mean forecasts for 100 companies in the years 1967-72 and showed (using Theil's U) that FAF outperformed the no-change model. Furthermore, FAF's superiority was more pronounced in years characterized by a turning point in the earnings trend. Using a more elaborate research design, Brown and Rozeff [1978] tested the performance of Value Line forecasts for one to five quarters ahead for 50 randomly selected firms during the period 1972-75. These forecasts showed a lower relative absolute error than a company-specific Box-Jenkins model and seasonal martingale and submartingale models (Brown and Rozeff used nonparametric tests in their design). The superiority of FAF, however, declined as the forecast horizon was shortened.

Collins and Hopwood [1980] designed a multivariate analysis of variance which corrected for the apparent dependence in repeated samples of the same companies over time and for the possibility of a random rejection of the null hypothesis in separate individual samples. The authors evaluated the performance of Value Line earnings forecasts, one, two, three, and four quarters ahead, made for 50 companies at the beginning of each of the 20 quarters in 1970-74. They compared the accuracy of FAF with that of several Box-Jenkins models.[3]

Value Line predictions were more accurate than the competing models. The mean relative absolute error of Value Line one-quarter-ahead forecasts was 10 percent, while the error produced by the best mechanical model was 15 percent. The longer the forecast horizon, the more marked was the difference in accuracy in favor of the analysts. Collins and Hopwood also found that Value Line predictions produced fewer and smaller extreme errors, pointing to the ability of analysts to incorporate evidence on changing economic situations.

In a more recent paper, Fried an Givoly [1982] reported on the accuracy of annual EPS estimates of analysts relative to that of two naive models: a modified version of the submartingale process and the index model for first differences in earnings.[4] The results, which were based on about 100 mean forecasts in each of the 11 years 1969-79, showed FAF to be, on average, more accurate than the two competing models: The mean relative absolute error over the tested period was 16.4 percent for FAF, significantly lower than the mean error for the modified submartingale and the index model (19.3 percent and 20.3 percent, respectively).

These results, like those of other recent studies, are in conflict with the findings of the earlier studies by Cragg and Malkiel [1968] and Elton and Gruber [1972]. Several explanations for the conflicting findings might be suggested. First, Cragg and Malkiel's study used predictions of five-year growth rates rather than the more common forecasts published by analysts which are made for one year. It is possible that analysts are more trained and capable in predicting short-term changes in earnings. Factors such as new contracts, acquisitions, labor disputes, and personnel shuffles, to which naive models are "blind," are properly incorporated in FAF while long-term trends are quite adequately captured by past patterns.

Second, Cragg and Malkiel's results are subject to serious measurement errors. The definition of the earnings variable was not uniform across forecasters sampled by their study: some used reported earnings; others used their own estimate for "normalized" earnings. As a result, it is difficult to interpret and analyze the forecast errors.

Like most of the studies on FAF, Cragg and Malkiel [1968] and Elton and Gruber [1972] used forecasts relating to a few years only. Cragg and Malkiel

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[3] The Box-Jenkins models considered were (1) a consecutively and seasonally differenced first-order moving average and seasonal moving average and (2) a seasonally differenced first-order autoregressive and seasonal moving average model. The selection of these models was guided by the findings of the research on the time-series behavior of quarterly earnings. In particular, the first model was found to be well specified by Griffin [1977], while the second and the third models were advocated by Foster [1977], and Brown and Rozeff [1978], respectively.

[4] The first model was the submartingale for most years. however, in years following large fluctuations in earnings, an exponential smoothing process was employed as the predictor; this was done in light of the findings by Brooks and Buckmaster [1976] of a mean-reverting behavior of earnings in the period immediately following large deviations of the earnings from their "norm."

examined forecasts made in 1962 and 1963, while Elton and Gruber used forecasts made in the three years 1964-66. It is conceivable that both the relative and absolute accuracy of FAF vary over time. Conclusions drawn from only two or three years of forecasts are subject to a considerable amount of noise. There are some indications that the performance of FAF relative to naive models is indeed time-dependent.[8]

A relatively long time series of FAF, 11 years, was used by Fried and Givoly [1982]. Although the accuracy of FAF was found in that study to be, on average, greater than that of two widely used naive models, FAF were outperformed (although not significantly) by the naive models, in two of the 11 years, and in three other years their superiority was not statistically significant. This pattern suggests that the reliance on short time series may lead to unwarranted conclusions. Considering the fact that all recent and methodologically more careful studies reached basically the same result, it is safe to conclude that, at least during the 1970s, analysts appear to outperform naive models that are based only on past history of the earnings series.

Most of the research on FAF accuracy suffers from several methodological flaws, which might explain, in part, the inconclusive nature of the early research on the topic. First, when an array of naive models is pitted against FAF, there is always a possibility that, even if the naive models are inferior, one of them would outperform FAF by a mere chance, particularly when the time period examined is short. Second, the null hypothesis in all studies was that FAF performed no better than naive models. Had the null been that FAF performed better than naive models, most tests would likely have been unable to reject that null hypothesis. In addition, the data base used by these studies, particularly the later ones, was susceptible to measurement errors, such as inconsistent definitions of the earnings variable in the expectational data and the actual earnings data (fully diluted vs. primary earnings-per-share, inclusion vs. exclusion of extraordinary items, etc.).

With respect to the comparison of FAF with management forecasts, all studies point to a slight and mostly insignificantly edge to management forecasts. Basi, Carey, and Twark [1976] reported that the mean absolute percentage forecast error during the years 1970 and 1971 was 10.1 percent for management forecasts compared to 13.8 percent for FAF (the data source for analysts' estimates was the Earnings Forecaster). In a follow-up study based on the years 1970-73, Ruland [1978] reached the same conclusion concerning the parity between the two types of forecasts. Similar results were also derived by Jaggi, Imhoff and Paré [1980] who examined the accuracy of management forecasts vs. FAF for the periods of 1971-74 and 1971-77, respectively.

The finding of a parity between the forecasting performance of analysts and managers is not surprising considering the similar information set and the contin-

[8] Brown and Rozeff [1978], for instance, concluded that Value Line predictions are better than Box-Jenkins forecasts. Yet, as was pointed out by Abdel-khalik and Thompson [1977], the pattern of Value Line superiority over Box-Jenkins is strongly temporal with only two out of the four years examined by Brown and Rozeff exhibiting significant results.

uous dissemination of "inside" information from managers to analysts (the forces behind this transfer of information were documented and analyzed by Lees, 1983).

The generalizability of the studies on the performance of management forecasts is questionable since all management forecasts used by these studies were voluntary. Presumably, management is not likely to reveal publicly its own earnings estimates unless it assigns them a high degree of certainty. As a result, the comparison between FAF and voluntary management forecasts is likely to be biased in favor of the latter.

Another problem that has not been solved satisfactorily by any of these studies is the timing of analysts' forecasts. While the exact date of the disclosure of management forecasts is a matter of public record (the forecasts are usually made as part of a press release), the determination of the timing of FAF is less precise. At least three pertinent forecast dates may exist: the date on which the forecast was finalized and released to preferred clients; the date on which the forecast was released to all clients; and the date on which the forecast is first published in the S&P or Value-Line publications. The times between these three dates are not trivial and in fact might be exploited by privileged clients [see, for example, Abdel-khalik and Ajinkya, 1982]. While the first date is the most relevant for evaluating the performance of FAF vis-à-vis competing prediction models, only the latter was available to, and therefore used by, the above studies. The performance of FAF was, therefore, underestimated by these studies, since in many instances, there existed other, more updated, yet still unpublished forecasts which were likely to be better than those available to the studies.

If a proper allowance were made for the gap in timing between management and analyst forecasts, the slight edge found for management forecasts might have been completely erased.

5. RATIONALITY OF FAF

Muth's [1961] criterion for rationality states that expectations should be generated by the same stochastic process that generates the variables to be forecasted. Most tests for the Muthian hypothesis, however, have employed a somewhat weaker condition, namely, that expectations fully reflect all the information in the past history of the forecast variable. This implies that the rational forecast cannot be improved by studying past forecasts and realizations.

The issue of rationality of earnings expectations is important since it is directly related to the efficiency of the stock market. Evidence of rational earnings forecasts would be consistent with both the finding of stock market efficiency and the important role of earnings in stock valuation. Findings of irrational forecasting by analysts would be inconsistent with stock market efficiency unless either FAF do not represent the true market expectations or earnings expectations do not play the role envisioned for them by the various valuation models.

Several testable implications of the rationality assumption exist: rational expectations should be *unbiased* and the *most accurate*, and the time-series of forecast errors should be *serially uncorrelated*. In general, all possible extrapolations of the time-series of the variable, and utilization of the cross-sectional relationship between realized earnings across companies, should be embedded in the forecast. All these implications mean, in essence, that no systematic improvement of the forecasts can be made by studying the past series of forecasts and realizations.

The concept of rational expectations has recently become the underpinning of many economic models. It is therefore not surprising to find major research efforts in the empirical evaluation of the degree of rationality in the expectations of economic variables. In particular, the manner by which inflationary expectations are formed has been examined by various studies through the use of Livingston survey data [see for example, Gibson, 1972; Pyle, 1972; Cargill, 1976; Lahiri, 1976; Figlewski and Wachtel, 1981; and Ahlers and Lakonishok, 1983]. The main conclusion that emerges from this research is that economists' expectations are not formed in a fully rational manner.

The increased availability of earnings expectation data has stimulated research on the rationality of earnings expectations. This research is discussed below.

5.1 SYSTEMATIC ERROR OF FAF

Various tests have been employed for assessing the degree of systematic error (bias) of earnings forecasts. A common procedure involves estimating a regression* of the form

$$A = \alpha + \beta P + u \qquad (1)$$

where A is the realized earnings (or earnings growth), P is the predicted earnings (or earnings growth), and u is a random error with a zero expectation. Then, the null hypothesis $\alpha = 0$ and $\beta = 1$ is tested. Failure to reject the null hypothesis is consistent with an unbiased predictor. This test has been employed for assessing the rationality of inflationary expectations [see, for example, Fama, 1975; Frenkel, 1975; Friedman, 1979; Figlewski and Wachtel, 1981; and Ahlers and Lakonishok, 1983] exchange rate expectations [see Fama, 1976; and Agmon and Amihud, 1981], and stock market expectations [see Lakonishok, 1980]. Another approach for assessing bias and inaccuracy is the decomposition procedure, developed by Theil [1966], and Mincer and Zarnowitz [1969], whereby the accuracy of the forecasts, measured by the mean square error, is decomposed into the following structure:

$$\frac{1}{n}\sum_i (P_i - A_i)^2 = (\overline{P} - \overline{A})^2 + (s_P - rs_A)^2 + (1 - r^2)s_A^2 \qquad (2)$$

where i denotes the observation index, $\overline{P}$ and $\overline{A}$ are the means of P and A, s denotes standard deviation, and r the correlation coefficient between A and P.

In expression (2) the error is decomposed into three components so that the relative magnitude of the systematic error, the first two terms in the righthand

* The regression can be estimated from a time series of company earnings or from contemporaneous cross-sectional data.

side of the expression, can be assessed. When (in equation (1) above) $\alpha = 0$ and $\beta = 1$, these two terms disappear.

The bias element has been evaluated in the literature also through other related measures such as the average error, i.e., $\overline{P} - \overline{A}$, or the relative frequency of cases of underestimation or overestimation.

The studies by Crichfield, Dyckman, and Lakonishok [1978], Givoly [1982], and Malkiel and Cragg [1980] used the regression in (1) to assess the bias of FAF. Using mean forecasts (of earnings growth) from the *Earnings Forecaster*, Crichfield, Dyckman, and Lakonishok estimated the coefficients over a cross section of FAF made for 46 companies for each of 10 years 1967-76. The coefficients averaged over the years were, in general insignificantly different from their hypothesized values (H_0: $\alpha = 0, \beta = 1$). However, the values of α were mostly negative and the values of β mostly above 1. These values suggest that FAF are "smoother" than actual trends: they exhibit an upward bias in predicting rate of growth in earnings in years with below-average growth rate and downward bias in predicting years with above-average growth rate, but overall the average forecast was not significantly different from the average realization. A similar finding is also reported by Malkiel and Cragg [1980] for five-year earnings growth predictions made by several investment firms in the years 1961-69.[7]

Testing the unbiasedness hypothesis through a cross-sectional test raises two problems. First, conceptually, earnings expectations are formed for each individual company. An unbiasedness in a cross section of companies does not necessarily suggest rational (unbiased) expectations with respect to all or even most companies: It is conceivable that earnings expectations of individual companies are biased in different directions so as to produce an unbiased *average*. Second, statistically, in a cross-sectional test the forecasts made for different companies are viewed as a random sample of forecasts. However, realizations of earnings growth are known to be correlated with marketwide factors so as to induce a cross-sectional dependence of the contemporaneous forecast errors. One way to circumvent the statistical problem of a cross-sectional dependence of the errors is to derive the coefficients' estimate as an average of the estimates produced by the yearly cross-sectional regressions.

A study by Givoly [1982] estimated the coefficients α and β from a time series of mean earnings forecasts made for individual companies (the mean of different contemporaneous forecasts was used as the basic observation) and from individual forecasts for the same company made by each individual forecaster over time. Although the typical time series was short (8-11 years over the period 1969-79), the results for the (about) 50 companies examined showed that FAF were unbiased. The joint hypothesis $\alpha = 0, \beta = 1$ could not be rejected for the vast majority of companies and for all the forecasters that were examined.

Crichfield, Dyckman, and Lakonishok [1978] assessed the bias through Theil's decomposition. They found that, on average, only 18 percent of the mean squared error in the prediction of earnings growth could be attributed to the

[7] The number of participating firms was not disclosed, but they represent a subsample from a sample of 178 companies.

systematic error. Out of this proportion, 13 percent stems from level bias and 5 percent from regression bias.

Despite its statistical insignificance and the fact that its direction may change over time, there is an accumulation of evidence that some upward bias is present in FAF. Barefield and Comiskey [1975] reported the results for analyst forecasts made in the years 1967-72. Out of the 600 forecasts examined, 382 exceeded actual, 207 were below actual, and 11 were equal to the actual earnings. A similar tendency to overestimate earnings was also found, not surprisingly, among managers by McDonald [1975]. Fried and Givoly [1982] reported the average relative error (considering sign) of about 1,200 mean forecasts made in the years 1969-79. The average error (realized value less prediction) over time was significantly negative (indicating an upward bias), although in five of the eleven years the error was positive.

It is interesting to compare these findings with the performance of forecasts of other economic variables. Mincer and Zarnowitz [1969] presented accuracy statistics for several sets of business forecasts of levels of GNP, consumption, plant and equipment outlays, and industrial production. In most cases, the statistical tests led to the rejection of the joint hypothesis $\alpha = 0, \beta = 1$. This result was accounted for largely by level bias, and the preponderant bias was an underestimation of consumption and of GNP. Theil's decomposition revealed that the residual variance component accounted for most of the error.

Ahlers and Lakonishok [1983] investigated the performance of economists' forecasts of ten important macroeconomic variables over the 32 years 1947-78. Two forecasting horizons were examined, six months and twelve months. The joint hypothesis $\alpha = 0, \beta = 1$ for change predictions was rejected in 17 of the 20 (10 x 2) cases. Ahlers and Lakonishok's results concerning inflation forecasts are in accord with several earlier studies [see Turnovsky, 1970; Pesando, 1975; Gibson, 1977; and Figlewski and Wachtel, 1981].

It is instructive to note that while there is a downward bias in forecasting general economic variables, no significant bias could be detected among FAF. This might be a result of the degree of specialization of analysts in the history of the companies whose earnings they predict, in contrast to the wider scope of the economists' task. To be sure, this is merely a conjecture.

The importance of the unbiasedness property to the overall quality of FAF should be put in a proper perspective. Given the research on the time-series behavior of earnings, even a very naive model, whereby the expected change in earnings is equal to some deterministic growth element based on past growth, may produce unbiased predictions. However, there are good reasons to believe that FAF are based on more than mere extrapolation of past realizations: as mentioned in Section 4, FAF were found to be more accurate than naive models at turning points, suggesting the employment of exogeneous information. Indeed, Fried and Givoly [1982] showed that FAF contain autonomous information not captured by both the time-series submartingale model and the cross-sectional index model of earnings. In another study, Abdel-khalik and Ajinkya [1982] provided evidence suggesting that analysts possess inside information. The finding of bias and 5

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5.1 INCORPORATION OF AVAILABLE INFORMATION

A simple way to test whether forecasts fully incorporate available information is to regress the forecast errors on specific data that were available to the forecasters. One easily available piece of information that a rational forecaster should consider is his previous forecast error. To test whether FAF fully exploit information on past errors, current errors could be regressed on past errors. Givoly [1982] estimated a regression of the form

$$P_t - A_t = a + b(P_{t-1} - A_{t-1}) + e_t$$

using both time series (of individual companies and individual forecasters) and cross-sectional versions, for a sample of about 6,000 annual earnings forecasts made over 11 years (1969-79). The hypothesis $a = 0$ and $b = 0$ could not be rejected: In most regressions the coefficients were very small and insignificant. This result suggests that the information contained in past forecast errors is fully utilized in forming predictions of future earnings.

A broader test of expectations rationality is whether the forecasters effectively incorporate *all* historical information available. Apparently, it is unfeasible to test whether a particular set of earnings expectations incorporate all the information that can be deduced from the earnings time series. However, more limited tests were conducted by Malkiel and Cragg [1980] and Fried and Givoly [1982].

Malkiel and Cragg found no consistent combination between information on historical growth rates and analysts' forecasts that could be used to make better one- or five-year-ahead earnings predictions. These results led to the conclusion that "there is no systematic relationship between historical and realized growth that is not directly incorporated into the forecasts."

Fried and Givoly conducted a test on the degree to which analysts' forecasts exploit the time-series properties and the cross-sectional relationship of earnings as captured by following two naive prediction models:

$$\text{(a)} \quad P_t = A_{t-1} + c_t$$

and

$$\text{(b)} \quad P_t = A_{t-1} + \alpha_t + \beta_t \Delta A_{mt}$$

where c_t is the arithmetic average past growth in EPS, α and β regression parameters, and ΔA_{mt} is the change in the market earnings (represented by S&P's Composite 500). The models, the submartingale[6] and the index model, were found to represent the behavior of the individual firm's earnings (see, for example, Gonedes, 1973; and Albrecht, Lookabill, and McKeown, 1977).

[6] The submartingale model was replaced by a mean reverting model (exponential smoothing) in years that follow a large fluctuation in earnings. According to the findings of Brooks and Buckmaster [1976], those years' earnings behave differently. The parameters of the exponential smoothing model used here were those selected by Brooks and Buckmaster.

The partial correlation between actual earnings and the naive model's prediction, given FAF, measures the extent to which FAF exploit the information contained in the past earnings series. The reported conditional correlation coefficients were very small and not significantly different from zero. This finding suggests that analysts fully exploit at least those time-series and cross-sectional properties of the earnings series that are captured by the two frequently used prediction models.

The results so far are consistent with FAF being formed in a rational manner. This finding is of interest since earnings expectations, including FAF, play an important role in stock valuation. The result would be even more relevant if it were established also that FAF serve as a good proxy for the unobservable "market" expectation of earnings; indeed, there is some supportive evidence for this effect, which will be described in Section 7.

6. THE TIME-SERIES BEHAVIOR OF FAF

Understanding how information is put together to form an estimate of future earnings is important because market processes are typically very sensitive to the way expectations are influenced by the actual course of events. Furthermore, it is often necessary to make predictions about the way expectations would change when either the amount of available information or the structure of the system is changed.

The study on the time-series behavior of FAF is related also to the time-series properties of quarterly and annual earnings: The behavior of FAF may or may not be consistent with the observed time-series pattern of earnings with implications for both the validity of the time-series studies and the degree of rationality of FAF.

The empirical evidence on the time-series behavior of FAF is scant, due apparently to the unavailability of long enough time series of earnings estimates. The model that has been almost exclusively examined in this context uses the adaptive expectations. Under the adaptive specification, expectations are revised so as to incorporate that portion of the most recent forecast error that is considered permanent. The adaptive model has been used extensively in the economic literature to describe the formation of expectations concerning future behavior of variables such as the inflation rate [see, for example, Solow, 1969; Mussa, 1975; and Nerlove, 1958] or permanent income [see Friedman, 1957]. There is empirical support for the notion that inflation expectations, for example, are formed in an adaptive way [see the evidence provided by Turnovsky, 1970; Lahiri, 1976; and Figlewski and Wachtel, 1981]. Depending on the underlying generating process of the predicted variable, adaptive expectations represent rational expectations in the Muthian sense.*

The adaptive model can be formulated as

$$P_t - P_{t-1} = \theta_0 + \theta_1(A_{t-1} - P_{t-1}) + u_t.$$

* Muth [1960] has shown that expectations formed adaptively are also minimum-error variance forecasts, i.e., rational, if the underlying process is a random walk with noise.

Under the null hypothesis of adaptive behavior, the constant term is zero and the slope coefficient falls between zero and one.

Brown and Rozeff [1979] tested the behavior of revisions in FAF of quarterly earnings. Their sample consisted of 50 Value Line firms and five years of quarterly forecast data [1972-76]. They examined the revision made in the EPS forecast for the remainder of the year following the release of, separately, the first, second, and third quarters earnings reports. For each quarter, the above regression was estimated for the cross section of companies. In all three cases, a significant portion of the analysts' forecast revision was explained by the most recent one-quarter-ahead forecast. Consistent with the adaptive expectation model, the estimated regression intercepts were small and largely insignificant, while the slope coefficients were significant and fell within the range zero to one.

Interestingly, the slope coefficients for the three quarters were not the same: 0.70, 0.28, and 0.57 were observed for quarters one, two and three, respectively. It is difficult to draw conclusions from this finding about the relative degree of content of the three quarters. First, as the authors pointed out, differing coefficients could occur if the quarters are not equally difficult to predict; that is, the adaptive coefficient is a function not only of the important assigned to the recent error but also of the unpredictability of the next quarter. Second, the sample covered only five years. If the adaptive behavior varies over time, a sample that covered only five years might not be representative. If the adaptive coefficient is also firm unique, the cross-sectional tests that were conducted by Brown and Rozeff are not very meaningful. These limitations may also explain the small portion of the total variance that could be explained by the adaptive model.

Abdel-khalik and Espejo [1978] examined the manner by which forecasts of annual EPS are revised in the wake of the release of each of the quarterly reports. They expressed the relationship between the revision in the estimate of EPS and the prediction error in forecasting the last quarter through the following model:

$$F_{q,y} - F_{q-1,y} = \lambda_q D^q_y + u_{q,y}$$

where q is the quarter (q = 1, ..., 4), y is the fiscal year for which the forecasts are made, $F_{q,y}$ is the forecasted annual earnings per share made at the end of quarter q for fiscal year y, D^q_y is the forecast error for quarter q of year y, λ is the adaptation coefficient, and u is a random error.

Three alternative hypotheses concerning the way the quarterly prediction error, D, is preceived by investors were examined:

(1) D^q_y is judged as temporary with no effect on the forecasts of the remaining quarters. In this case, the revision will be in the magnitude of D^q_y, and λ is hypothesized to be equal to one.

(2) The same pattern set by D^q_y is expected to continue: In this case, the revision will be larger than D^q_y, and λ_q is, therefore, hypothesized to be greater than one, reflecting an adaptive behavior.

(3) D^q_y is expected to be compensated for in other quarters so that the entire year will be "normal." In this case, there will be a revision in a direction opposite to that of D^q_y, and λ_q is hypothesized to be smaller than one.

The empirical test was based on a random sample of 100 industrial firms from those appearing in Value Line Investment Survey in the four quarters of 1976. The results showed a clear adaptive behavior of FAF: The coefficients of D_y^q were significantly above one in all three quarters. [10] This conclusion is consistent with that of Brown and Rozeff [1979] who examined the behavior of quarterly forecasts: both studies found that the error in one quarter is perceived to contain a permanent component, thus inducing analysts to revise their forecasts for the new quarter, or for the remainder of the year, in the same direction. This pattern in FAF revisions is consistent with the time-series properties of quarterly earnings, indicating the utilization by analysts of information on past behavior of quarterly earnings.

The findings by Brown and Rozeff [1979] and by Abdel-khalik and Espejo [1978] relied on cross-sectional tests. However, the time series of earnings may vary across companies, and therefore earnings forecasts of different companies are likely to (and, in the case of rational forecasts, must) be formed according to different processes.[11] Furthermore, even if the process of expectation formation for all firms is adaptive, the coefficient of adaptation may vary across firms. Givoly [1982] tested the relationship between the formation by analysts of annual earnings forecasts and the last annual prediction error, through a time series over the years 1969-79. The tests were conducted for individual companies (with the mean forecast, computed over different contemporaneous forecasts, serving as the basic observation) as well as for individual forecasters.

The results suggest that in the vast majority of the companies the adaptive expectation model adequately represents the process by which forecasts of annual earnings are formed: The R^2 values were high (an average of 0.622), and the adaptation coefficients significant, between 0 and 1 in most cases. It is instructive to note, however, that the hypothesis of equality of the adaptation coefficients

[10] The following multivariate model was used by Abdel-khalik and Espejo [1978] to test their hypotheses:

$$F_y - A_y = \lambda_1 D_y^1 + \lambda_2 D_y^2 + \lambda_3 D_y^3 + e_y$$

where F_y is the forecasted annual EPS at the beginning of the year, A_y the realized annual EPS, and D_i the prediction error in forecasting the EPS of quarter i. This model was derived recursively from the univariate model described in the text of this paper. Abdel-khalik and Espejo tested each of the λ's against the null hypothesis $\lambda = 0$ rather than against Ho: $\lambda = 1$; this point was correctly made by Brown, Hughs, Rozeff, and Vanderweide [1980], who also contended that for econometric reasons, the univariate rather than the multivariate model should be tested. Nonetheless, the validity of Abdel-khalik and Espejo's findings was not impaired by this critique. This point is convincingly made in Abdel-khalik's comments [1980].

[11] In a recent methodological paper, Abdel-khalik [1982] examined the econometric properties of the univariate and the multivariate model discussed in Abdel-khalik and Espejo [1978] and in Brown et al. [1980]. He showed that both formulations had model specification and estimation problems that resulted in overfitting the models. Furthermore, he demonstrated that the R^2 of both models had considerably overstated the effect of the quarterly prediction errors on the revision of annual earnings forecasts. Despite the apparent model overfitting, the correct effect of quarterly prediction error was still significant.

among different companies was rejected. Similar results were reported for the adaptive coefficients of individual forecasters.

The study of the formation of analysts' forecasts is in its infant stages. The consistency that FAF revisions show with a simple adaptive model does not mean the model is the most appropriate to describe the formation of analysts' forecasts of earnings. More elaborate models may be examined. Furthermore, in the study of the time-series properties of FAF, there is a need for a theoretical framework, similar to that developed for the formation of inflationary expectations [see, for example, Cukierman and Wachtel, 1979; and Brunner, Cukierman, and Meltzer, 1980]. Such a framework would consider elements such as the loss function of the individual analysts, the time-series behavior of earnings, and the extent and reliability of exogeneous information available to analysts.

7. FAF AND STOCK PRICE BEHAVIOR

The relevance of the research on FAF and its most interesting implications stem, to a large extent, from the assumption that earnings forecasts by analysts are actually used by market participants. There is a considerable body of "circumstantial" evidence to suggest that this is indeed the case: Earnings forecasts, annual and sometimes quarterly, are disclosed by all major brokerage houses; many clients are ready to pay for forecasting services; and at least three organizations, S&P, Lynch Jones and Ryan, and Zacks and Co., issue a periodical summary of contemporaneous forecasts made by different analysts for a large number of companies.

Whether investors utilize the information conveyed by FAF is an empirical question. Several studies have examined the association between earnings forecasts and stock price behavior. The focus of these studies has varied, yet their conclusions seem to have the same tenor: Stock price movements are correlated with earnings forecasts and their revision thereof, issued by analysts. This section presents and discusses these findings.

7.1 THE INFORMATION CONTENT OF FAF

An early study by Niederhoffer and Regan [1972] analyzed the relationship between the error of analysts in predicting the earnings for 1970 and the performance of the respective stocks. Two groups of 50 stocks each were selected, one consisting of those with the worst stock market performance (lowest return) and the other of those with the best performance during 1970. The analysts consistently underestimated (in 89 percent of the cases) the earnings of the top firms and overestimated the earnings of *all* the firms at the bottom; in other words, earnings predictions formed by analysts seem to be a useful signal to investors. Neiderhoffer and Regan concluded by saying that "these results present both challenge and opportunity for financial analysts. If their estimates are more accurate than the conventional published forecasts of large institutions, there is ample opportunity for differentiating between the best and worst-performing companies" (p. 71). The methodology and the design of Regan and Neiderhoffer study were rather crude: Only the extreme 100 cases (out of 1,253 common stock) in a single year were examined.[18]

Gonedes, Dopuch, and Penman [1976], in a study on the value of mandatory disclosure of management forecasts, conducted an empirical analysis of the information content of FAF which they used as a proxy for management forecasts. They used a sample of 148 firms, each represented by 24 biweekly earnings forecasts in each of the years 1967 and 1968 (the forecasts were collected from the *Earnings Forecaster*). Each firm was reassigned, every two weeks, to one of four portfolios, depending on the ratio of its earnings forecast to its price (observed ten days earlier). The return of each portfolio in the ten days surrounding the forecast disclosure was measured and compared to that of a control portfolio of equal risk. The results showed that the portfolio of the firms with the highest E/P ratio had an average return somewhat above that of an equally risky portfolio and that, in particular, the portfolio of the firms with the lowest E/P ratio had an average return significantly below that of the control portfolio. They concluded that "forecasted earnings per share seem to reflect information pertinent to valuing firm. It seems that this information content can be almost entirely ascribed to the unfavorable implications of an extremely low (scaled) forecast" [p. 127].

While their test of information content is not very powerful (the portfolio affiliation of a particular stock might not constitute new information; there is also a publication lag of the source document), Gonedes, Dopuch, and Penman's findings are in accord with other studies in suggesting that FAF have information content.

In a more direct test on the information content of FAF, Givoly and Lakonishok [1979] examined the response of the market to revisions in FAF. Using a sample of 49 firms from the *Earnings Forecaster*, Givoly and Lakonishok observed the stock price response to 1,420 revisions in FAF during the years 1967-74. The results revealed significant abnormal returns in the expected direction (i.e., positive or negative abnormal return associated with upward and downward revisions, respectively) in the month of the forecast revision, as well as in the month preceding it and the two months following it. The abnormal returns were quite substantial and positively related to the size of the revision: In the revision month and the two following months the abnormal return was 2.2 percent for all revisions and 4.5 percent for revisions over 10 percent [see ibid, Table 7]. Refinements to the basic design (exclusion of revisions made concurrent with earnings releases; different procedures for computing abnormal returns) left the results intact. These results strongly suggest that FAF do have information content. Furthermore, the slow response of the market to analyst's revision is inconsistent with the semistrong efficiency of the market.

In a followup work, Givoly and Lakonishok [1980] directly tested the extent to which investment strategies could be designed to exploit the publicly available

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[18] Due to the exclusive attention to the 100 extreme cases, the same results could be produced by a variety of models; that is, if extreme price fluctuations are indeed correlated with extreme changes in earnings (i.e., earnings have information content), then the forecast error, in such cases, of other prediction models beside FAF would very likely yield a similar correlation with price changes.

information on revisions of analysts' forecasts. Portfolios consisting of stocks whose earnings have recently been revised upward systematically outperformed an equally risky random portfolio. Depending on the particular strategy selected, such a portfolio was shown to yield over 15 percent annual abnormal return, net of transaction cost [see ibid, Table 4].

In a more recent paper, Elton, Gruber, and Gultekin [1981] evaluated the degree of excess return that could be generated by utilizing information on, separately, consensus mean earnings forecasts, prediction errors of earnings forecasts, and revisions in earnings forecasts. The expectational data consisted of a monthly file of one- and two-year earnings forecasts prepared by analysts in the years 1973, 1974, and 1975, which was compiled by Lynch, Jones and Ryan (the Institutional brokers Estimate System). The final sample consisted of 913 and 696 one- and two-year forecasts, respectively, made at two forecast dates, March and September. The results showed that

> (1) No excess return could be made by the knowledge of the existing forecast; firms for which a high earnings growth was forecasted performed as well as firms with a low forecasted earnings growth. This finding is consistent with the stock market being efficient with respect to the publicly available earnings forecasts.
> (2) Significant excess returns were associated with the earnings prediction error. Furthermore, the amount of excess returns that could be earned varied with the magnitude of the forecast error. These results suggest that FAF have information content.
> (3) Significant excess returns were associated with changes in the analysts estimates. In fact, the return from forecasting accurately future forecasts themselves were somewhat higher than the return from being able to forecast actual earnings. The result is consistent with other evidence showing that it is consensus forecasts that determine security prices.

Abdel-khalik and Ajinkya [1982] examined whether both early knowledge of FAF revisions (possessed by select clients and analysts themselves) and published FAF revisions are reflected in security prices. The sample consisted of estimates revisions made by Merrill, Lynch, Pierce, Fenner and Smith, Inc., for optionable stocks during the period August 1977 to December 1978. These revisions were first announced internally (and to select clients) and made public in the first weekly *Options Alert* issued by that firm. The research was designed so as to enable testing of both the strong form and the semistrong form of the efficient market hypothesis. Specifically, the existence of a significant association between the content of the revision and stock price movements during the few days between its internal distribution and public disclosure would lead to a rejection of the "strong-form" hypothesis while the existence of such association well after the public disclosure of the revision would lead to a rejection of the "semistrong" hypothesis. The results showed that while the "strong-form" hypothesis was rejected, no abnormal return could be earned after the week of publication, a finding consistent with the "semi-strong-form" hypothesis.[12]

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[12] The results concerning the semistrong hypothesis conflict with those reported by Givoly and Lakonishok [1979]. The following points should, however, be borne in mind. (1) Abdel-khalik and

7.2 FAF AS A SURROGATE FOR MARKET EXPECTATION OF EARNINGS

The findings of the studies on the association between the content of FAF and stock price movements lead basically to the same conclusion, namely, that FAF do have information content. The fact that the content of analysts' forecasts of earnings is associated with stock returns does not necessarily mean that FAF are the preferred surrogate for the unobservable market expectation of earnings. Other expectation models might better explain stock price behavior and, hence, more properly be viewed as the true representative of market expectation.

Considering the fact that FAF are, on average, more accurate than other tested models, and assuming that investors are rational, it is reasonable to assume that FAF represents better than other models the earnings expectation of the market.

The question whether FAF are a better expectational surrogate is important for several reasons. First, many studies, particularly those dealing with the information content of earnings, used some naive, or mechanical, models to generate the expected earnings and to measure "unexpected earnings." These studies could become more powerful if a better surrogate for earnings is identified. Second, stock valuation models as well as P/E studies often rely on expected earnings as a basic parameter. Better identification of market expectation would improve these models. Finally, establishing that FAF provide a satisfactory surrogate for market expectation would underscore the importance of studies on various properties of FAF (accuracy; rationality; time-series behavior) and provides motivation for further research in the area.

Two of the first studies to examine the adequacy of FAF as a surrogate for market expectations of earnings, relative to predictions based on past accounting data, were by Malkiel [1970] and Malkiel and Cragg [1970]. These studies attempted to explain the P/E ratio by a regression is which the growth rate, dividend yield, and risk measures were the independent variables. The future growth rate was estimated, once from historical long-term growth rates and once from an average predicted future long-term growth rate, of earnings-per-share. The first study used a sample of 178 companies from a cross section of industries in the years 1961-65; the second study concentrated on public utilities of which 33 were included in the sample covering the years 1961-67. The design of the two studies was similar.

To select the representative of the historically based growth estimates, 40 alternative predictors of growth were examined to find those that showed the closest correlation with market price-earnings multiples over each of the years covered by the studies. These growth rates differed with respect to the period of calculation, the method of calculation, and the financial data upon which the

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Ajinkya's work relates to one forecaster only. (1) Previous evidence by Givoly and Lakonishok [1979] indicates clustering or "waves" of revisions, all of which are positively correlated. Thus, Merrill and Lynch's forecasts might not necessarily constitute new information to which the stock market is expected to respond. (3) As was pointed out by Abdel-khalik and Ajinkya, "companies with optionable stocks are large and the generalizability of the results to other companies will need further testing."

calculation was made. The ten-year growth rate of cash earnings per share was either clearly superior to, or at least no worse than, any of the others in each of the years and was therefore used in the yearly regressions. Needless to say, this procedure introduced a selection bias in the results in favor of finding a greater explanatory power of the historically based estimates. The analysts' were gathered from nine security firms, and their average was calculated to produce a single predictor.

Despite the aforementioned bias, the results in both studies showed that the regression fits were much better using the expectational variables than the historical ones. The average R^2 in Malkiel and Cragg's study [1970] was 0.75 and .49 (across five years) for the FAF-based and historically based growth estimates, respectively. The corresponding values reported in Malkiel's [1970] study (and averaged over four years) were 0.83 and 0.59. Based on these findings, Malkiel concluded that "a reasonable proxy has been obtained for what might be considered the expectations of the 'representative investor'" [p. 152].

In a recent study, Fried and Givoly [1982] evaluated FAF against naive models as a surrogate for market expectation of earnings. The comparison was based on the relationship between stock price movements and the signals (both the sign and the magnitude of the prediction error) produced by alternative expectation models. The model whose signals were the most strongly associated with stock price behavior was considered the best surrogate.

Analysts' forecasts for the 11 years 1969-79 were collected from the *Earnings Forecaster*. Considered each year were the FAF of that year's earnings outstanding at the beginning of April. Almost all forecasts were first issued to the public between the release of the annual report for the previous year and the first quarterly report. Sampled each year were companies for which at least four FAF were available (so that a meaningful average could be computed). Two naive expectation models were chosen: the submartingale (with drift) and the index model (for a description of the models, see Section 5.2).

The results showed that abnormal returns were more strongly correlated with the prediction errors of FAF than with the prediction errors of the two naive models. For instance, an investment strategy under which stocks were added to the portfolio on the basis of a foreknowledge of the direction and magnitude of FAF error was superior to that based on a foreknowledge of the prediction errors of each of the naive models (the first strategy yielded an average annual abnormal return of over 14 percent, and the strategies based on the naive models achieved less than 9 percent).

Analysts' forecasts appear to represent the earnings expectations of market participants more adequately than naive models. Still, few studies so far have used FAF to surrogate for market expections (among the few are Ajinkya and Gift [1983] and Givoly and Palmon [1982]). The superiority of FAF as an expectation surrogate does not invalidate the results of studies which used time-series (naive) models to find the association between unexpected earnings and unexpected share price movements (the information content of earnings). Rather, it reinforces these results by indicating that the association might even be stronger. The results provide added motivation for studying other important properties of FAF such as time-series behavior and cross-section dispersion.

7.3 CAUSES OF FAF SUPERIORITY

Fried and Givoly [1982] also analyzed the causes for the superiority of FAF over the naive models. Two such causes were hypothesized. (1) FAF use a broader information set which includes nonaccounting information on the firm, its industry, and the general economy, while naive models (and particularly those examined) rely exclusively on accounting information. (2) FAF have a timing advantage in that they are issued some time within the year being forecasted. Thus, they can use more recent information about the firm's earnings which becomes available only after the end of the fiscal year.

To test the effect of broadness of information on the relative performance of FAF, Fried and Givoly used the partial correlation $r_{AP \cdot X}$ where A is the realized earnings, P is FAF and X is the earnings predicted by the naive model. Values of $r_{AP \cdot X} > 0$ suggest that FAF contain predictive power based not only on extrapolation but also on an autonomous component.

The results showed relatively high positive partial correlation coefficients: The average coefficient of the correlation between realization and FAF, given the naive prediction, was 0.55 and 0.56 for the comparison with the submartingale and the index model, respectively. The values remain high, 0.51 on average, when the correlation was conditioned on the predictions of both naive models. These values, which are significantly greater than zero, suggest that FAF utilize a considerable amount of information that is independent of the time-series and cross-sectional properties of the earning series that are captured by the two naive models.

To test the effect of the timing of the forecast, the performance of different subsamples of forecasts, each initially released in a different month, was compared and analyzed. As expected, forecasts released earlier showed a stronger association with price movements during the forecast year. However, the improvement between "early" forecasts (defined in the study as those released in January and February) and "late" forecasts (those released in March and early April) was not significant.

The idea that the timing advantage of a few weeks possessed by FAF is inconsequential to their overall performance is echoed also in the results obtained by Brown and Rozeff [1978]. They correlated Value Line forecasting error with the time interval since the most recent quarterly earnings announcement. The correlation was essentially zero, leading them to conclude that "Value Line superiority can be attributed to its use of the information set available to it on a quarterly earnings announcement date, and not to the acquisition of information arriving after the quarterly earnings announcement date" [p. 73].

The insignificance of the difference in the performance of analysts' forecasts made several weeks apart should not be confused with a lack of improved forecasting as the year's end approaches. To the contrary, the evidence shows that as the year progresses, the accuracy of FAF improves [see, for example, Crichfield, Dyckman, and Lakonishok, 1978; Collins and Hopwood, 1980; and Elton, Gruber, and Gultekin, 1981].

8. DISPERSION OF FAF

Most of the research on FAF has centered around the properties of the consensus, or the mean, forecast. Recently, attempts have been made to explore the information content of financial analysts' divergence of beliefs about future earnings. This attention to dispersion parallels that observed in the research on the expectations of economic variables. In particular, the dispersion of economists' forecasts of the inflation rate was examined and found to be an important determinant of the interest rate [see, for example, Barnea, Dotan, and Lakonishok, 1979; Levi and Makin, 1979; and Bomberger and Williams, 1981].

8.1 DISPERSION OF FAF AS A MEASURE OF RISK

Dispersion of earnings expectations, as measured by the cross-sectional variance (or standard deviation) of FAF, can be interpreted as an earnings uncertainty measure. Another uncertainty measure that has long been employed by academicians and practitioners in their attempts to model investor's behavior and evaluate stocks is earnings variability [see, for example, the use of this measure by Litzenberger and Rao, 1971; and Ahlers, 1972].

The idea that past volatility is only partially related to uncertainty surrounding future expectations has been recently developed by Cukierman and Wachtel [1982a, 1982b] (for the inflation variable) and Cukierman and Givoly [1982]. Cukierman and Givoly developed a model for the formation of earnings expectations whereby each forecaster, in making a prediction, employs both information common to all other forecasters (e.g., past earnings) and specific information. They showed that under fairly general conditions (pertaining primarily to the stability of the variances of the series), the cross-sectional error in earnings forecasts is the correct empirical counterpart of uncertainty, that is, of the dispersion of the distribution of expected earnings. Their model also implies (and this implication is confirmed by empirical tests) that the cross-sectional error is positively associated with the dispersion of forecasts across forecasters.

The alternative risk measures seem to be correlated. Givoly and Lakonishok [1983] found that the dispersion of earnings forecasts, as well as the predictability of earnings forecasts, is related to traditional risk measures such as systematic risk (beta), total risk (standard deviation of returns), and earnings growth variability. Cukierman and Givoly [1982] and Elton, Gruber, and Gultekin [1982] found that dispersion of FAF is positively related to the error in the consensus forecast of earnings.

Dispersion of earnings forecasts and earnings unpredictability are apparently perceived by investors as valuable information and as proxies for risk. Value Line publishes regularly the unpredictability rating of companies earnings; Standard and Poor's provides in its *Earnings Forecaster* a number of earnings forecasts for each of the approximately 1,500 companies listed in the publication, and the firm of Lynch, Jones, and Ryan, supplies investors with such measures as range and standard deviation of a multitude of contemporaneous earnings forecasts made by different financial analysts.

Friend, Westerfield, and Granito [1978] and Malkiel and Cragg [1980] used dispersion of expectations as an additional measure of risk. Friend, Westerfield, and Granito tried to explain a consensus expected return by several risk measures. The expected return was computed as the mean forecast of seven financial institutions. Three independent risk variables were tested. The first two were the traditional risk variables, beta and the residual standard deviation of returns. The interesting variable was the third one, a measure of heterogeneity of expectations derived from expected stock returns from various institutions. The empirical results revealed that the measure of heterogeneity of expectations was the most consistent variable in explaining expected returns. When actual returns instead of expected returns were used as the dependent variable, the results remained qualitatively the same. The measure used by Friend, Westerfield, and Granito is conceptually similar to the dispersion measure based on earnings expectations. Malkiel [1981], in a test similar to the one performed by Friend, Westerfield, and Granito, used dispersion of earnings expectation as one of his explanatory variables. Additional explanatory variables were beta, economy risk, inflation risk, and interest rate risk. The last three variables measure the sensitivities of given stock to movements in National Income, CPI, and market interest rates. The dependent variable was defined as the expected rate of return and derived from the dividend valuation model. Malkiel concluded that

> The best single risk proxy is not the traditional beta calculation but rather the dispersion of analysts' forecasts. . . Companies for which there is a broad consensus with respect to future earnings and dividends seem to be less risky (and hence have lower expected returns) than companies for which there is little agreement among security analysts.

Givoly and Lakonishok [1983] examined the effect of earnings uncertainty, as measured by dispersion of earnings expectations and earnings unpredictability, on the information content of earnings. Their sample consisted of over 1,200 cases (company-years), each represented by at least four forecasts. The data source for FAF was the *Earnings Forecaster* in the years 1969-79. The methodology involved the testing of a regression in which the abnormal return in the period surrounding the earnings release was the dependent variable and the prediction error and the cross-sectional dispersion and forecast error of FAF the independent variables.

The results showed that the response to unexpected earnings depends on the dispersion (uncertainty) of the earnings forecasts. In general, when uncertainty concerning future earnings is great, the stock price movement triggered by a given prediction error (unexpected earnings) is relatively small.

8.2 THE PATTERN OF FAF DISPERSION OVER TIME

The pattern of the FAF dispersion during the forecast year was examined by Crichfield, Dyckman, and Lakonishok [1978] and by Elton, Gruber, and

Gultekin [1982]. The former reported a slight tendency of the cross-sectional standard deviation of FAF to decline as the end of the year is approached (though this tendency was in most years insignificant at 5 percent significance level). This finding is quite interesting since the accuracy of these estimates increased continuously as the year's end approached. They found no convincing explanation for this puzzling result. Collins and Hopwood [1980] suggested that the stability over time in the divergence of analysts' estimates is due to the very small number of outliers among FAF, which reflects analysts' ability to incorporate exogenous information in their forecasts.

Elton, Gruber, and Gultekin [1982] found a decline in FAF's dispersion over the first four months of the forecast year, but no further reduction in the remaining eight months. The apparent conflict with respect to FAF behavior over the first four months between Crichfield, Dyckman, and Lakonishok and by Elton, Gruber and Gultekin might be due to the different data sources. While the latter used processed data (the standard deviations) available from Lynch, Jones, and Ryan (the *IBES* Service), the former used raw data on individual forecasts (from S&P's *Earnings Forecaster*). Corrections to the data due to illogical values, etc., which would and probably have been done by the latter, could not be performed by Elton, Gruber, and Gultekin who used the ready statistics. On the other hand, they used a more comprehensive sample—over 400 companies—each represented by 3 to 20 concurrent forecasts each year, while Crichfield, Dyckman, and Lakonishok sampled only 46 companies with few concurrent forecasts for each company-year. Additional research in the area is necessary to resolve the conflicting findings.

9. CONCLUDING REMARKS

The last two decades have witnessed a growing interest in the formation and characteristics of expectations of economists and investors. Given the important role that earnings numbers should theoretically play in stock valuation, and the overwhelming empirical evidence that earnings do indeed possess an information content, it is clear why earnings forecasts have attracted much research effort.

The research on FAF in recent years has been stimulating with rich implications for the behavior of investors, the usefulness of earnings numbers, and the competence of analysts. The findings show that FAF performance is, in general, superior to that of naive models. This result is consistent with a rational market for forecasting services, where the higher cost of FAF is compensated by a better performance.

An important property of FAF is their rationality: FAF were found to incorporate the past history of realizations and predictions in an unbiased manner. It is interesting to note that this property is not exhibited by economists in their prediction of variables such as inflation, GNP, or unemployment.

Various studies provide evidence that investors use FAF and, in fact, behave as if they form their own expectations on the basis of FAF. The finding that FAF can serve as a reasonable surrogate for the (unobservable) market expectation of earnings may help future studies that rely on knowledge of earnings expectation.

The finding also underscores the importance of the research on FAF to our understanding of the operation of the market.

The study of the dispersion of FAF provides an interesting, yet not fully modeled, result: that divergence of earnings expectations is an important measure of risk, shadowing the traditional risk variables such as security beta or the variability of the return.

There are many questions important to our understanding of the way FAF are formed and used that have not yet been addressed. We do not have a good enough knowledge of the forecasting process. We know something about the revision process that takes place whenever new quarterly reports are published, but we do not know how extrapolative data are synthesized with other information nor how marketwide factors (inflation, interest rate, GNP, etc.) are incorporated in the earnings predictions. Little is also known about the degree of uniqueness of the information used by the individual analyst. Do analysts truly possess inside information or do they rely basically on a common body of knowledge? Do they use each other's forecast as an important input? An interesting work in this respect is that by Lees [1981], in which certain aspects of the symbiosis of analysts and corporate managers were analyzed.

An important dimension of the forecaster's behavior is his loss function. This function must relate to the way forecasts are evaluated. Do brokerage houses measure the performance of their forecasters? Given the complexity of this task (e.g., how to control for uncontrollable states of nature or how to compare performance of forecasts made for different firms), it is possible that many institutions do not even attempt to carry it out. The knowledge of the forecaster's loss function can provide us with an understanding of the nature of the point estimate provided by him—is it likely to be the mean, the median, or some other measure of the expected earnings distribution?

The analysis of the accuracy of FAF relied, in most studies on the performance of the mean forecast. No attempt has been made to explore quality differentials among analysts. Is there a superior forecaster? Such a finding might be inconsistent with rational behavior of investors. Another important question is whether brokerage houses specialize in certain industries or firms and, if so, does the specialization result in a better performance?

Another interesting issue is the degree by which the market index of earning and, indirectly, stock market movements could be accurately predicted from individual companies' forecasts of earnings. It was found, for example, that investors could benefit from the knowledge of revisions in FAF made for individual companies. Could they similarly benefit from the knowledge on the aggregate (cross-sectional) behavior of FAF?

These unresolved questions make this research area lively and rewarding for both theoreticians and empiricists interested in the operation of the financial analysts' industry, the formation of investors' expectations and the interaction between accounting numbers and stock behavior.

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Analyst Forecasting Errors: Additional Evidence

Lawrence D. Brown

Analyst forecasting errors are approximately as large as Dreman and Berry (1995) documented, and an optimistic bias is evident for all years from 1985 through 1996. In contrast to their findings, I show that analyst forecasting errors and bias have decreased over time. Moreover, the optimistic bias in quarterly forecasts was absent for S&P 500 firms from 1993 through 1996. Analyst forecasting errors are smaller for (1) S&P 500 firms than for other firms; (2) firms with comparatively large amounts of market capitalization, absolute value of earnings forecast, and analyst following; and (3) firms in certain industries.

In recent issues of this journal, David Dreman, Michael Berry, and I have presented alternative views of analysts' earnings forecast errors and their implications for security analysis (Dreman and Berry 1995, Brown 1996, Dreman 1996). The first two papers provided alternative views concerning several issues, including whether (1) analysts' earnings forecast errors are "too large," (2) analysts' earnings forecast errors have increased over time, and (3) analysts' earnings forecasts are optimistically biased.

In the opinion of Dreman and Berry, analysts' earnings forecast errors are too large, and using the deflators the authors suggested (e.g., actual or predicted earnings), analyst forecasting errors do appear large. If analysts' earnings forecast errors are deflated by stock price, however, or compared with forecasts based on extrapolative techniques, they do not appear too large. Dreman–Berry also maintained that analysts' earnings forecasting errors have increased over time. My analysis of their findings, however, suggested that the accuracy of analysts' earnings forecasts has actually improved over time. In addition, Dreman–Berry provided evidence that analysts' earnings forecasts are biased toward optimism. Relying on information provided by I/B/E/S International, I showed that an optimistic bias was absent for S&P 500 firms for the 11 quarters from first-quarter 1993 through third-quarter 1995.

In his letter to the editor, Dreman (1996) responded to the views I expressed in my article, disagreeing with most of them. He correctly observed that much of my analysis was based on the Abel–Noser database, which Dreman–Berry had used but which was inaccessible to me; my analysis relied on summary information provided in the Dreman–Berry article. Moreover, although not stated by Dreman, neither did I examine the I/B/E/S data that I had relied on in my 1996 article. Instead, I relied on summary information provided to me by I/B/E/S.

This article is based on I/B/E/S data for fourth-quarter 1983 through second-quarter 1996. It presents evidence regarding the following issues:

- Is the Dreman–Berry result that analyst forecasting errors are "too large" robust to using a different data source than the Abel–Noser database?
- Is the Dreman–Berry conclusion that analysts' forecasting errors have increased over time robust to using I/B/E/S data? Does it pertain equally to S&P 500 firms and other firms?
- Is the optimistic bias documented by Dreman–Berry robust to using I/B/E/S data? Does this optimism pertain equally to S&P 500 and other firms? Has it been mitigated over time? Is the extent of mitigation similar for both S&P 500 firms and other firms?
- Do analyst forecasting errors and bias differ depending on such firm-specific factors as market capitalization, absolute value of predicted EPS, analyst following, and industry classification?

PRELIMINARY RESULTS

Dreman and Berry relied on the Abel–Noser database, which uses information from Value Line, Zacks Investment Research, I/B/E/S, and First Call. Because different vendors of analyst forecasts define both forecasted and actual earnings numbers differently, mixing data from different vendors introduces error (Philbrick and Ricks 1991), potentially making analysts' earnings forecast errors appear larger than they actually are. For this study, I used the data of a single vendor, I/B/E/S, for the

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time period from fourth-quarter 1983 through second-quarter 1996. The sample consists of all U.S. firms for which analyst earnings forecast errors could be calculated.

Figure 1 provides frequency distributions using the SURPE and SURPF definitions of analyst forecasting errors (earnings surprise), defined as

SURPE = (Actual quarterly earnings – Predicted quarterly earnings)/|Actual quarterly earnings|

SURPF = (Actual quarterly earnings – Predicted quarterly earnings)/ | Predicted quarterly earnings |.

Predicted quarterly earnings were obtained from the I/B/E/S summary tape using the last consensus (mean) estimate prior to the firm's quarterly earnings announcement.[1]

SURPE and SURPF are two of the four definitions of earnings surprise Dreman–Berry and I used in our research.[2] My Figure 1 corresponds to their Figure 1 pertaining to SURPE and SURPF, and my results are very similar to theirs. More specifically, the modal and median values of earnings surprise are zero; *small* positive errors are more frequent than negative errors; and *large* negative errors outnumber positive errors. These findings suggest that whereas analysts are more likely to be on target than anywhere else, managers manipulate earnings in a way to generate a considerable number of small positive (relative to small negative) surprises and large negative (relative to large positive) surprises ("big baths").[3]

I/B/E/S VERSUS ABEL–NOSER DATA

Table 1 provides summary statistics on the I/B/E/S and Abel–Noser data. The I/B/E/S results are based on my analysis of these data; the Abel–Noser results are reproduced from Dreman–Berry's Table 1. The average error (mean absolute surprise) using the I/B/E/S data is substantially larger than that using the Abel–Noser data. The I/B/E/S SURPE of 0.590 is approximately one-third greater than the Abel–Noser SURPE of 0.438, and the I/B/E/S SURPF of 0.916 is more than twice as large as the Abel–Noser SURPF of 0.415. Moreover, the mean surprise (bias) using the I/B/E/S data is also substantially larger in absolute value than that documented by Dreman–Berry using the Abel–Noser data. More particularly, the I/B/E/S SURPE and SURPF are –0.316 and –0.414, respectively, compared with the Abel–Noser SURPE and SURPF of –0.250 and –0.111.

My results could differ from Dreman–Berry's because of different sample-selection procedures. Dreman–Berry's sample is confined to firms with fiscal years ending in March, June, September, or December that are followed (after 1981) by at least four analysts. When the I/B/E/S sample is similarly restricted, the results are nearly identical to Dreman–Berry's.[4] More particularly, for the 46,859 I/B/E/S observations that satisfy these criteria, the average absolute surprise of 0.416 (SURPE definition) is similar to Dreman–Berry's 0.438, and the mean SURPE of –0.218 using the I/B/E/S sample closely approximates Dreman–Berry's –0.250.

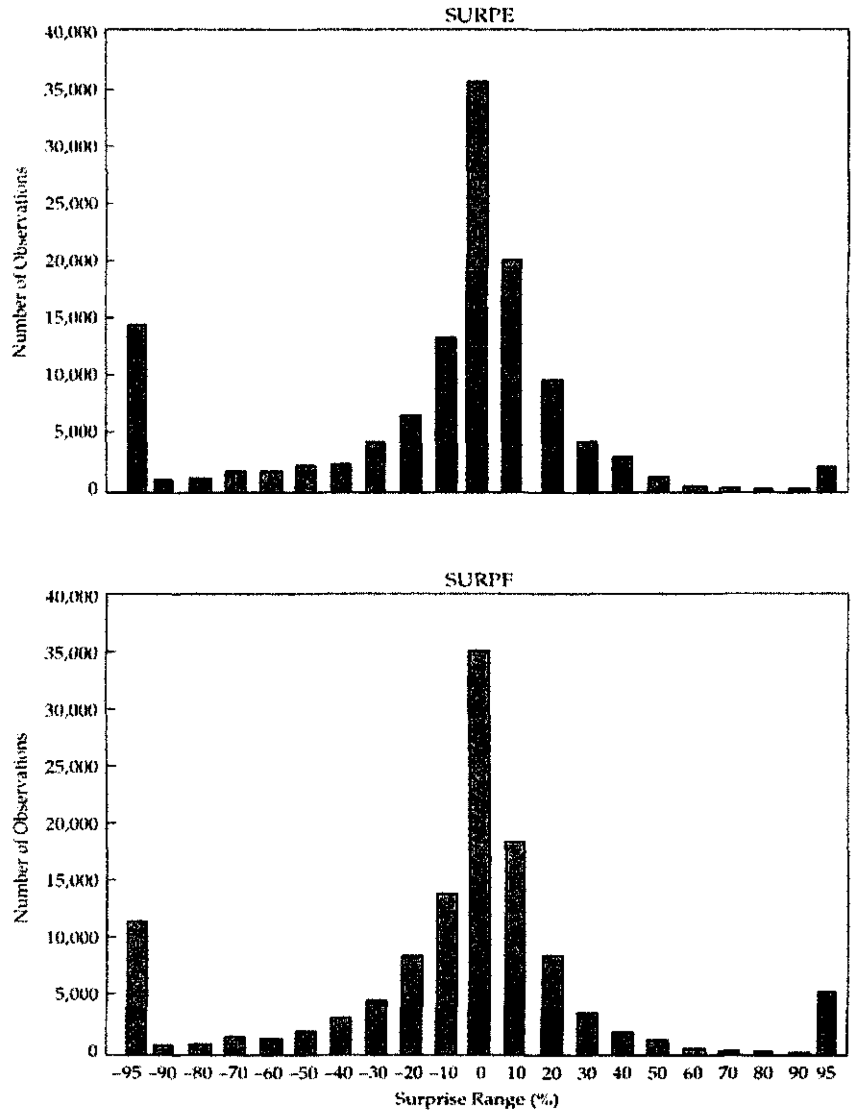
From these results, I conclude that the Dreman–Berry finding of large analyst forecasting errors is robust to using a different data source. Dreman–Berry used Abel–Noser data and examined the first-quarter 1974 through fourth-quarter 1991 time period; I obtained similar results using the I/B/E/S data for fourth-quarter 1983 through second-quarter 1996.

HAVE FORECASTING ERRORS CHANGED?

Evidence regarding five definitions of error—mean absolute surprise, mean surprise (bias), and the proportion of errors outside the +/–10 percent, +10 percent, and –10 percent bandwidths—is presented in Table 2 for all firms, S&P 500 firms, and non-S&P 500 firms.[5] All five error metrics use the SURPF definition of earnings surprise, which has predicted quarterly earnings as its deflator. Dreman–Berry provided evidence pertaining to three +/– bandwidths: 5 percent, 10 percent, and 15 percent. I focused on the second of these bandwidths, +/–10 percent, and considered its plus and minus sides separately.[6]

Dreman–Berry concluded that analyst forecasting errors increase over time. In contrast, Table 2 reveals that both mean absolute surprise and mean surprise (bias) have *decreased* significantly over time. This result is borne out by the rank correlations of analyst forecasting error with year, which are –0.973 and 0.489 for mean absolute surprise and mean surprise, respectively.[7] Nevertheless, the mean surprise is negative and significant in every year from 1985 through 1996, suggesting that, although the optimistic bias has been mitigated, it remains significant. The rank correlations of time with the proportion of errors outside the +/–10 percent, +10 percent, and –10 percent bandwidths are –0.995, –0.038, and –0.945, respectively. The –10 percent bandwidth result is significant, but the +10 percent bandwidth result is not. Thus, the temporal reduction of error results from mitigation of the optimistic bias. Indeed, no temporal reduction in the percentage of large positive errors (i.e., earnings *underestimates*) has occurred.

Figure 1. Histograms of SURPE and SURPF



Comparison of S&P 500 firms with other firms is important because many investors invest exclusively in S&P 500 firms and/or use the S&P 500 Index as a benchmark. Analyst forecasting errors are much smaller for S&P 500 firms than for other firms. More specifically, in *every* year, the mean absolute surprise and the proportion of forecasts outside the +/−10 percent, +10 percent, and −10 percent bandwidths is smaller for the S&P 500 firms than it is for the other firms. Clearly, the earnings of S&P 500 firms are easier to forecast than are those of non-S&P 500 firms.

Although forecasts for S&P 500 firms exhibit a significant optimistic bias for the 1984–96 period as a whole, the optimistic bias in forecasting quarterly earnings of S&P 500 firms disappeared as of 1993. More specifically, for S&P 500 firms, a significant optimistic bias is evident in every year in the 1985–92 period but not in the four most recent years, 1993 through 1996. In contrast, the bottom panel of Table 2 reveals that the optimistic bias in forecasting quarterly earnings of other (non-S&P 500) firms exists in all 12 years, 1985 through 1996. Perhaps the disappearance of the optimistic bias for S&P 500 firms is attributable to mitigation of the big-bath phenomenon or a lessening of the tendency of these firms' managers to manipulate earnings in a way to generate a large number of small positive (relative to small negative) surprises.[8]

Table 1. Descriptive Statistics for Earnings Forecast Errors

	I/B/E/S (4Q 1983–2Q 1996)		Abel–Noser (1Q 1974–4Q 1991)	
Statistic	SURPE	SURPF	SURPE	SURPF
Number of forecasts	129,436		66,100	
Mean absolute surprise	0.590	0.916	0.438	0.415
Mean surprise (bias)	–0.316*	–0.414*	–0.250*	–0.111*
Median	0.000	0.000	0.000	0.000
Maximum	314.000	863.000	49.000	48.000
Minimum	–186.259	–819.000	–216.000	–282.600

Note: SURPE (SURPF) is consensus EPS surprise as a percent of absolute value of actual (forecast) EPS.
*Significant at the 5 percent level, two-tailed test.

DO FORECASTING ERRORS DIFFER BY FIRM-SPECIFIC FACTORS?

Table 3 shows whether errors differ by market capitalization, absolute value of earnings forecast, or analyst following. Such comparisons are relevant because many investors invest primarily in large firms, firms with comparatively large earnings forecasts, or firms with relatively heavy analyst following. For these investors, the average analyst earnings forecast error per se is less relevant than the average forecasting error for these firm-specific subsamples.

The market capitalization results are monotonic for four of the five error measures: mean absolute surprise, mean surprise, and proportion of errors outside the +/–10 percent and –10 percent bandwidths. The highest capitalization group (i.e., firms with market caps in excess of $3 billion) has a smaller proportion of errors outside the +10 percent bandwidth than do any of the other market cap groups. Regarding bias, a significant optimistic bias (negative mean surprise) is evident for all market caps except the largest one.

The absolute value of earnings forecast results is not monotonic for any of the five definitions of error. Nevertheless, the mean absolute surprise and the mean surprise (bias) results are nearly monotonic; the exception occurs when forecasted earnings are at least $1. For this group, the mean absolute surprise and the mean surprise (bias) are approximately halfway between what they are for the [$0.10, $0.25) and [$0.25, $0.50) groups. The bandwidth results are similar to the mean absolute surprise and bias results in that the largest absolute value of earnings forecast group (i.e., ≥ $1) does not have the smallest proportion of errors outside the +/–10 percent, +10 percent, or –10 percent bandwidths.[9]

Similar to the absolute value of earnings forecast results, the analyst-following results are not monotonic for any of the five definitions of error. Nevertheless, the results are monotonic for all five error measures as the number of analysts increases from 1 to 5, and the smallest errors are obtained for the largest analyst following (10 or more) for four of the error measures.[10] Moreover, the rank correlations for the five error measures range from an absolute value of 0.782 to 0.988, and they all are statistically significant. Thus, error generally decreases when analyst following increases.

DO FORECASTING ERRORS DIFFER BY SECTOR?

The five error metrics are provided in Table 4 for each of the 14 industries in the I/B/E/S sample with data pertaining to at least 50 firms. The mean absolute surprise ranges from a low of 0.255 to a high of 1.663. Two industries have a mean absolute surprise below 0.400: food and kindred products (0.255) and holding companies and other investment offices (0.392). At the other extreme, two industries have mean absolute surprises in excess of 1.0: oil and gas extraction (1.663) and primary metal industries (1.267).

Eleven of the 14 industries evidence a significant optimistic bias. Optimistic bias for the other three—transportation equipment, communications, and insurance carriers—is not significant. The mean surprises range from a low of –0.068 to a high of –0.721. Three industries have an optimistic bias below 0.080 in absolute value: food and kindred products (–0.068), transportation equipment (–0.070), and communications (–0.076). At the other extreme, two industries have an optimistic bias above 0.500 in absolute value: oil and gas extraction (–0.721) and primary metal industries (–0.532).

The proportion of analyst forecasting errors outside the +/–10 percent bandwidth ranges from a low of 0.361 to a high of 0.780. Two industries have less than 40 percent of their observations outside the +/–10 percent bandwidth: food and kindred products (0.361) and depository institutions (0.369). At the other extreme, two industries have more than two-thirds of their observations outside the +/–10 percent bandwidth: oil and gas extraction (0.780) and primary metal industries (0.683). Twelve of the 14 industries have more errors outside the –10 percent than outside the +10 percent

Table 2. Forecast Errors by Year: All Firms, S&P 500 Firms, and Other Firms

Year/Statistic	Number of Firms	Number of Forecasts	Mean Absolute Surprise	Mean Surprise	+/−10 Percent[a]	+10 Percent[a]	−10 Percent[a]
All firms							
1984	2,109	2,246	2.525	0.795	0.697	0.311	0.386
1985	2,525	8,608	1.593	−0.667*	0.651	0.226	0.426
1986	2,580	8,506	1.773	−1.007*	0.656	0.245	0.412
1987	2,829	8,856	1.362	−0.700*	0.650	0.264	0.386
1988	2,804	9,041	1.067	−0.468*	0.620	0.269	0.351
1989	2,874	9,461	0.959	−0.537*	0.615	0.240	0.374
1990	2,890	9,627	1.034	−0.685*	0.600	0.215	0.384
1991	2,875	9,583	0.802	−0.444*	0.598	0.242	0.356
1992	3,195	10,702	0.688	−0.330*	0.557	0.261	0.296
1993	3,630	12,563	0.583	−0.230*	0.544	0.258	0.286
1994	4,193	14,213	0.494	−0.189*	0.514	0.258	0.256
1995	4,476	15,013	0.541	−0.244*	0.510	0.256	0.255
1996	4,593	11,008	0.527	−0.173*	0.501	0.260	0.241
Mean			0.916	−0.414*	0.577	0.252	0.326
Rank Correlation			−0.973*	0.489*	−0.995*	−0.038	−0.945*
S&P 500 firms							
1984	431	452	0.701	0.237	0.593	0.305	0.288
1985	443	1,743	0.748	−0.474*	0.503	0.186	0.317
1986	453	1,714	0.620	−0.250*	0.496	0.225	0.271
1987	463	1,791	0.487	−0.137*	0.487	0.245	0.243
1988	466	1,852	0.382	−0.143*	0.470	0.259	0.211
1989	473	1,842	0.427	−0.166*	0.447	0.203	0.245
1990	476	1,896	0.331	−0.113*	0.441	0.191	0.249
1991	481	1,892	0.442	−0.267*	0.467	0.189	0.277
1992	485	1,887	0.467	−0.148*	0.420	0.205	0.215
1993	486	1,983	0.345	0.027	0.409	0.220	0.189
1994	492	1,993	0.233	0.027	0.335	0.208	0.126
1995	492	1,936	0.190	−0.008	0.335	0.196	0.139
1996	494	1,314	0.310	0.002	0.318	0.177	0.141
Mean			0.418	−0.129*	0.431	0.211	0.220
Rank Correlation			−0.868*	0.357	−0.978*	−0.462	−0.819*
Other firms							
1984	1,678	1,794	2.985	0.935	0.724	0.312	0.411
1985	2,082	6,865	1.807	−0.716*	0.689	0.236	0.453
1986	2,127	6,792	2.064	−1.198*	0.697	0.250	0.447
1987	2,366	7,074	1.583	−0.843*	0.692	0.269	0.422
1988	2,338	7,189	1.244	−0.552*	0.659	0.272	0.387
1989	2,401	7,619	1.087	−0.626*	0.655	0.250	0.406
1990	2,414	7,731	1.206	−0.825*	0.639	0.221	0.417
1991	2,394	7,691	0.890	−0.488*	0.630	0.255	0.376
1992	2,710	8,815	0.735	−0.369*	0.586	0.274	0.313
1993	3,144	10,580	0.628	−0.278*	0.569	0.265	0.305
1994	3,701	12,220	0.537	−0.225*	0.543	0.266	0.277
1995	3,984	13,077	0.593	−0.279*	0.536	0.264	0.272
1996	4,099	9,694	0.557	−0.197*	0.526	0.272	0.254
Mean			1.019	−0.473*	0.608	0.260	0.348
Rank Correlation			−0.973*	0.489*	−0.984*	0.088	−0.912*

Note: Mean absolute surprise, mean surprise, and the percentage of surprises outside the three bandwidths use absolute value of earnings forecast as the deflator.

[a]Proportion of surprises outside bandwidth.

*Significant at the 5 percent level, two-tailed test.

Table 3. Forecast Errors Classified by Market Capitalization, Absolute Value of Earnings Forecast, and Analyst Following

	Number of Firms	Number of Forecasts	Mean Absolute Surprise	Mean Surprise	+/−10 Percent[d]	+10 Percent[d]	−10 Percent[d]
Market capitalization ($ millions)[a]							
<50	3,137	18,247	2.198	−1.445*	0.774	0.242	0.532
[50–100)	3,316	17,572	1.228	−0.616*	0.679	0.266	0.412
[100–500)	4,529	46,349	0.749	−0.271*	0.585	0.267	0.318
[500–3,000)	2,350	33,777	0.511	−0.096*	0.481	0.246	0.234
≥3,000	652	12,445	0.278	−0.019	0.370	0.203	0.167
Rank correlation			−1.000*	1.000*	−1.000*	−0.300	−1.000*
Absolute value of earnings forecast (cents)[b]							
<5	2,731	8,588	5.407	−2.564*	0.819	0.348	0.471
[5–10)	3,750	13,796	1.528	−0.681*	0.827	0.363	0.464
[10–25)	5,863	40,552	0.644	−0.300*	0.598	0.258	0.340
[25–50)	5,210	37,857	0.380	−0.159*	0.499	0.218	0.282
[50–100)	2,957	22,100	0.297	−0.105*	0.444	0.199	0.245
≥100	1,094	6,544	0.607	−0.250*	0.507	0.277	0.281
Rank correlation			−0.829*	0.829*	−0.771	−0.771	−0.943*
Analyst following (number of analysts)[c]							
1	6,189	35,979	1.421	−0.593*	0.707	0.293	0.414
2	5,011	22,983	1.035	−0.578*	0.629	0.272	0.358
3	3,913	15,728	0.790	−0.364*	0.581	0.251	0.330
4	3,077	11,411	0.674	−0.294*	0.544	0.246	0.298
5	2,384	8,532	0.581	−0.225*	0.519	0.241	0.278
6	1,898	6,775	0.762	−0.460*	0.482	0.217	0.266
7	1,555	5,354	0.553	−0.285*	0.465	0.207	0.258
8	1,296	4,356	0.795	−0.135	0.449	0.191	0.258
9	1,090	3,664	0.486	−0.233*	0.452	0.208	0.244
≥10	1,023	14,654	0.354	−0.126*	0.387	0.192	0.195
Rank correlation			−0.782*	0.842*	−0.988*	−0.939*	−0.988*

Note: Mean absolute surprise, mean surprise, and the percentage of surprises outside the three bandwidths use absolute value of earnings forecast as the deflator.

[a]Stock price multiplied by number of common stocks outstanding.

[b]Earnings forecast is the I/B/E/S mean forecast.

[c]Number of analysts whose forecast is included in the calculation of the I/B/E/S mean forecast.

[d]Proportion of surprises outside bandwidth.

*Significant at the 5 percent level, two-tailed test.

bandwidth, indicating that when large errors occur, analysts are more likely to overestimate earnings (optimistic bias) than to underestimate them (pessimistic bias). The two exceptions are depository institutions and insurance carriers. Perhaps these two industries are less likely than the other 12 to take big baths, which induce large negative errors and give the appearance of analyst optimism.

CONCLUSION

Using the Abel-Noser database for 1974 through 1991, Dreman and Berry argued that analyst forecasting errors are too large. Based on the I/B/E/S database for 1983 through 1996, I show that analysts' earnings forecast errors are approximately as large as Dreman–Berry documented. Thus, their results appear to have external validity.

Dreman–Berry maintained that analyst forecasting errors have increased over time. In a 1996 article, I argued that the Abel-Noser data, as summarized by Dreman–Berry, suggest precisely the opposite. In his critique of my analysis, David Dreman correctly pointed out that I did not access the data Dreman–Berry used to reach their conclusions. In this study, I used I/B/E/S data to examine five error metrics to determine whether analyst forecasting accuracy has deteriorated over time. I found that analyst forecasting errors have *decreased* significantly over time, especially for mean absolute surprise and the proportion of errors outside the +/−10 percent and −10 percent bandwidths.[11] My finding that analysts' earnings forecast errors have decreased over time is robust to firms included in as opposed to those excluded from the S&P 500.

I examined whether analyst forecasting errors differ according to certain firm-specific factors:

Table 4. Forecast Errors by Industry

SIC Code	Industry Name	Number of Firms	Number of Forecasts	Mean Absolute Surprise	Mean Surprise	+/−10 Percent[a]	+10 Percent[a]	−10 Percent[a]
13	Oil and gas extraction	73	1,681	1.663	−0.721*	0.780	0.338	0.442
20	Food and kindred products	55	1,644	0.255	−0.068*	0.361	0.166	0.195
28	Chemicals and allied products	128	3,910	0.454	−0.159*	0.422	0.189	0.233
33	Primary metal industries	63	1,619	1.267	−0.532*	0.683	0.298	0.385
35	Industrial, commercial machinery and computer equipment	128	3,958	0.794	−0.243*	0.596	0.274	0.322
36	Electronics and other equipment companies	104	2,824	0.856	−0.370*	0.556	0.237	0.319
37	Transportation equipment	66	2,096	0.820	−0.070	0.553	0.249	0.305
38	Measurement instruments; photo goods; watches	76	1,991	0.445	−0.186*	0.425	0.186	0.239
48	Communications	56	1,292	0.455	−0.076	0.429	0.202	0.227
49	Electric, gas, and sanitary services	190	6,766	0.436	−0.130*	0.560	0.261	0.299
60	Depository institutions	421	7,298	0.543	−0.336*	0.369	0.197	0.171
63	Insurance carriers	189	4,453	0.512	−0.142	0.517	0.285	0.232
67	Holding; other investment offices	82	777	0.392	−0.151*	0.539	0.175	0.364
73	Business services	78	2,111	0.540	−0.263*	0.448	0.182	0.266

Notes: Mean absolute surprise, mean surprise, and the percentage of surprises outside the three bandwidths use absolute value of earnings forecast as the deflator. To be included in Table 4, an industry must have more than 50 firms in the sample.

[a]Proportion of forecast errors (using absolute value of earnings forecast as a deflator) outside bandwidth.

*Significant at the 5 percent level, two-tailed test.

inclusion in the S&P 500, market capitalization, absolute value of earnings forecast, analyst following, and industry membership. I showed that: (1) analyst forecasting errors for S&P 500 firms are smaller than for other firms; (2) analyst forecasting errors are relatively small for firms with comparatively large market cap, absolute value of earnings forecast, and analyst following; and (3) analyst forecasting errors for firms in certain industries are substantially larger than those in other industries. Thus, depending on the nature of the firms followed by investors, analysts' earnings forecast errors may be considerably larger or smaller than average.

Dreman and Berry showed that analysts' earnings forecasts exhibit an optimistic bias. I had argued in my 1996 paper that the optimistic bias was not evident for S&P 500 firms for the period from first-quarter 1993 through third-quarter 1995. Moreover, according to I/B/E/S, the optimistic bias has not been evident for S&P 500 firms for the subsequent period, fourth-quarter 1995 through second-quarter 1997.[12]

Based on the I/B/E/S data, which include both S&P 500 and other firms, I documented an optimistic bias in analysts' quarterly earnings forecasts for all years, 1985 through 1996, and in 11 of 14 industries. I also showed that the optimistic bias in quarterly forecasts has diminished significantly over time for both S&P 500 and other firms and that it was absent for S&P 500 firms for each year from 1993 through 1996. The optimistic bias in quarterly forecasts for non-S&P 500 firms remains.[13]

NOTES

1. Because earnings forecast errors cannot be calculated when the actual or quarterly earnings forecast equals zero, these observations were omitted from the analysis. To be consistent with Dreman–Berry, I did not adjust outliers in any manner.
2. The other two definitions of earnings surprise are SURP8 and SURPC7, which respectively use the standard deviation of trailing eight-quarter actual earnings per share and the standard deviation of trailing seven-quarter changes in earnings per share.
3. Other studies have documented that managers manipulate earnings in order to report positive earnings, positive earnings growth, and/or earnings that exceed analyst expectations. When managers cannot succeed in these goals, they are likely to take a "big bath." See Lowenstein (1997).
4. For simplicity, I do not provide these results in a table.
5. These results and those that follow are based on the full I/B/E/S sample of 129,436 observations described in Table 1.
6. This suggestion was made when I presented an earlier version of this article at the 1997 Prudential Securities Quantitative Research Seminar for Institutional Investors.
7. The positive rank correlation for mean surprise indicates that the bias has become less negative (i.e., there has been a temporal reduction in the optimistic bias).
8. Such an analysis is beyond the scope of this study but is on the author's research agenda.
9. When I presented results at the 1997 Prudential Securities

Quantitative Research Seminar for Institutional Investors, I used the actual EPS as a deflator. It was suggested to me that the aberrant results for the largest EPS group may be attributable to large random shocks in the actuals. When I substituted forecasted EPS for actual EPS (as in this article), the tenor of my results was unchanged.

10. The exception is the proportion of errors outside the +10 percent bandwidth, for which the proportion of 19.2 percent for the analyst following of ≥10 slightly exceeds the proportion of 19.1 percent for the analyst following of 8.

11. The exception is that the percentage of errors outside the +10 percent bandwidth has not decreased significantly for either the entire I/B/E/S sample or the non-S&P 500 subsample.

12. According to information provided to me by I/B/E/S, the mean surprises for S&P 500 firms for these seven quarters (sample sizes are in parentheses) are 1.7 percent (488), 2.4 percent (492), 2.6 percent (490), 2.4 percent (490), 1.9 percent (481), 3.3 percent (492), and 2.2 percent (491). The optimistic bias is still present for S&P 500 firms for annual forecasts.

13. I am grateful to Deres Tegenaw for providing me with excellent research assistance.

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EXHIBIT
31
FES

2014/2015 RPM Base Residual Auction Results

Table 5 – Generation, Demand Resources, and Energy Efficiency Resources Offered and Cleared Represented in Unforced Capacity MW

	RTO*						
Auction Results (all values in UCAP)**	**2008/2009**	**2009/2010**	**2010/2011**	**2011/2012**	**2012/2013**	**2013/2014**	**2014/2015**
Generation Offered	131,164.8	132,614.2	132,124.8	136,067.9	134,873.0	147,188.6	144,108.8
DR Offered	715.8	936.8	967.9	1,652.4	9,847.6	12,952.7	15,545.6
EE Offered	-	-	-	-	652.7	756.8	831.9
Total Offered	131,880.6	133,551.0	133,092.7	137,720.3	145,373.3	160,898.1	160,486.3
Generation Cleared	129,061.4	131,338.9	131,251.5	130,856.6	128,527.4	142,782.0	135,034.2
DR Cleared	536.2	892.9	939.0	1,364.9	7,047.2	9,281.9	14,118.4
EE Cleared	0.0	0.0	0.0	0.0	568.9	679.4	822.1
Total Cleared	129,597.6	132,231.8	132,190.5	132,221.5	136,143.5	152,743.3	149,974.7
Uncleared	2,283.0	1,319.2	902.2	5,498.8	9,229.8	8,154.8	10,511.6

* RTO numbers include all LDAs

** UCAP calculated using sell offer EFORd for Generation Resources. DR and EE UCAP values include appropriate FPR and DR Factor.

Table 6 contains a summary of capacity additions and reductions from the 2007/2008 Base Residual Auction to the 2014/2015 Base Residual Auction. A total of 4,170.3 MW of incrementally new capacity in PJM was available for the 2014/2015 Base Residual Auction. This incrementally new capacity includes new generation capacity resources, capacity upgrades to existing generation capacity resources, new demand resources, upgrades to existing demand resources, and new energy efficiency resources. The increase is partially offset by generation capacity derations to existing generation capacity resources to yield a net increase of 2,620.2 MW of installed capacity.

Table 6 also illustrates the total amount of resource additions and reductions over eight Delivery Years since the implementation of the RPM construct. Over the period covering the first seven RPM Base Residual Auctions, 13,164.8 MW of new generation capacity was added which was partially offset by 8,894.8 MW of capacity de-ratings or retirements over the same period. Additionally, 15,480.9 MW of new demand resources and 733.4 MW of new energy efficiency resources were offered in the 2014/2015 auction. The total net increase in installed capacity in PJM over the period of the last seven RPM auctions was 20,557.4 MW.

2011/2012 RPM Third Incremental Auction Results

Introduction

This document provides information for PJM stakeholders regarding the results of the 2011/2012 Reliability Pricing Model (RPM) Third Incremental Auction. The 2011/2012 Third Incremental Auction was held from February 28, 2011 to March 4, 2011.

The Third Incremental Auction

RPM Third Incremental Auctions provide capacity suppliers with a final opportunity to sell or purchase capacity for the Delivery Year through a PJM-administered auction process. Resource-specific sell offers are submitted into this auction by suppliers with excess capacity beyond what is needed to satisfy their commitments from previous auctions for the Delivery Year. All resource-specific sell offers into a Third Incremental Auction are subject to market power mitigation through the application of the Three-Pivotal Supplier Test.

Any party that desires to purchase LDA-specific replacement capacity for the Delivery Year may do so by submitting a buy bid into the Third Incremental Auction. Cleared Buy Bids purchased in a Third Incremental Auction may be used as replacement capacity to cover Delivery Year commitment and compliance shortfalls. Those parties that do not clear buy bids in a Third Incremental Auction but still desire to purchase capacity for the Delivery Year may do so bilaterally.

A Third Incremental Auction is cleared in a similar fashion to that of a Base Residual Auction with the exception that no Variable Resource Requirement curve is utilized. The demand in a Third Incremental Auction is composed of the LDA-specific buy bids submitted by participants who wish to purchase replacement capacity. The relative positions of supply and demand in each region will determine the resulting cleared MW and price quantities.

Since the purpose of the Third Incremental Auction is to allow resource owners to purchase replacement capacity, PJM does not procure additional capacity on behalf of load and the 2011/2012 Zonal UCAP obligations posted on February 1, 2011 and zonal capacity prices that LSEs in PJM pay for capacity are not affected by the results of this auction. Zonal capacity prices are only affected by the Base Residual and Second Incremental Auctions and the amount of certified ILR. Those prices are then finalized after the ILR Certification Period and Withdraw Period.

2011/2012 RPM Third Incremental Auction Results

Table 1 - 2011/2012 Third Incremental Auction Results

LDA	Total Sell Offers (MW ICAP)	Total Sell Offers (MW UCAP***)	Total Buy Bids (MW UCAP)	Cleared Buy Bids (MW UCAP)	Cleared Sell Offers (MW UCAP)	Clearing Price ($/MW-Day)
RTO	6512.9	6537.8	8865.2	1557.0	1557.0	$5.00

***Resource offers converted to UCAP using Delivery Year EFORd for generation resources or applicable FPR and DR Factor for Demand Resources

Table 1 contains a summary of the offer, bid and clearing data for 2011/2012 Third Incremental Auction. Only the RTO was modeled as an LDA in the 2011/2012 Delivery Year, therefore the summary illustrates all resources as being located in the RTO. Each column in this table is explained in more detail in the upcoming sections of this report.

Supply in the 2011/2012 Third Incremental Auction

The 6512.9 MW of sell offers (supply) offered into the Third Incremental Auction is composed of uncleared capacity from the 2011/2012 Base Residual Auction and 2011/2012 First Incremental Auction, new capacity in the form of uprates or resources that were not previously capacity resources in PJM, and additional capacity that resulted from an improvement in resource forced outage rates (EFORd) between the Base Residual and Third Incremental Auctions. All supply offers provided by sellers are quoted in Installed Capacity (ICAP) terms.

Each generation resource sell offer was converted to UCAP using the Delivery Year EFORd and each demand resource and energy efficiency sell offer was converted to UCAP using the Delivery Year Forecast Pool Requirement (FPR) and Demand Resource (DR) Factor. As a result, 6537.8 MW of UCAP was offered into this auction.

2011/2012 RPM Third Incremental Auction Results

Demand in the 2011/2012 Third Incremental Auction

The demand in a Third Incremental Auction is composed of LDA-specific buy bids submitted by participants. The buy bids are specified in UCAP terms and, if cleared, are binding commitments to purchase capacity for the entire Delivery Year. There was a total of 8865.2 MW of buy bids submitted into this auction.

Mitigation in the 2011/2012 Third Incremental Auction

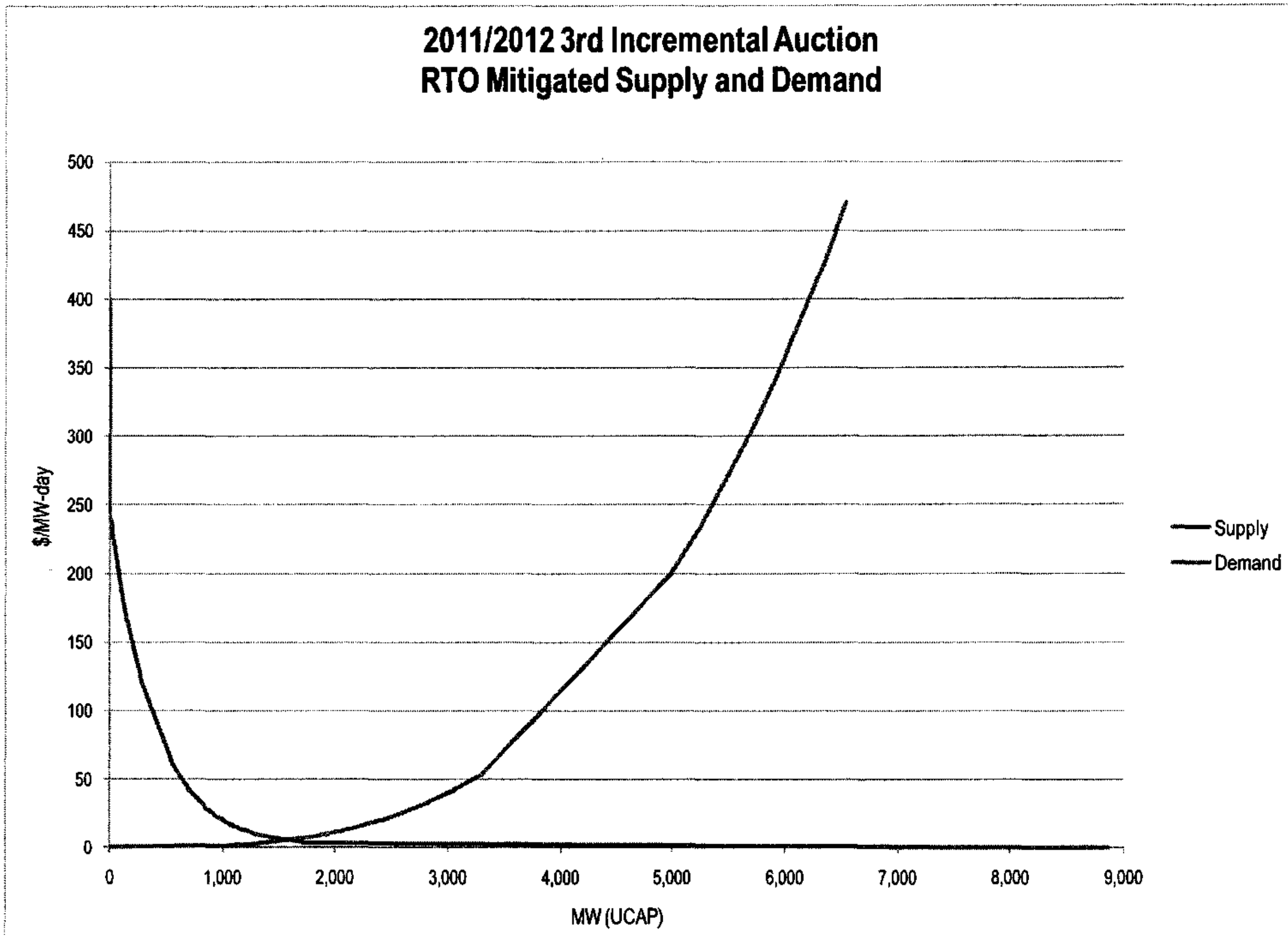
The RTO as a whole, failed the Market Structure Test. As a result, mitigation was applied to all existing generation resources in the execution of the RPM auction clearing. Therefore, in the event a generator's price-based offer exceeded the calculated offer cap, cost-based offers were utilized in the RPM auction clearing. Demand Resources or Energy Efficiency Resources are not subject to market mitigation as a result of the recent FERC Order issued on October 29, 2009.

2011/2012 Third Incremental Auction Clearing Results

In the 2011/2012 Third Incremental Auction, a total of 1557 MW of UCAP was cleared at a single clearing price of $5.00.

Figure 1 shows the intersection of the RTO mitigated supply and demand curves. The plot below is truncated to show the intersection at $5.00/MW-Day. The full RTO supply and demand curves are shown in Figure 2. On January 20, 2011, FERC approved the PJM filing of docket number ER09-1063-003. This order instructs PJM to utilize formulaic approach to smooth the supply curves using a statistical technique that fits a smooth curve to the underlying supply curve data while ensuring that the point of intersection between supply and demand curves is at the market clearing price. The resulting smoothed curve is displayed below.

Figure 1 - RTO Mitigated Supply and Demand Curve



Duke Integration Assumptions

In the following document, "**Duke**" is referring to the Duke Energy affiliates that are integrating into PJM on January 1, 2012, namely, Duke Energy—Ohio, Inc. and Duke Energy—Kentucky, Inc. and associated regulated and unregulated generation assets, unless otherwise specifically identified.

General Assumptions -

The industry will request additional information surrounding the potential impacts of this integration. Such request will generate the need to conduct the following studies:

i. Impacts on flowgates
ii. Administrative Cost Analysis to all PJM members
iii. MMU Assessment/Study
[Planning will verify that there are no significant differences in IRM due to Duke integration]

Transmission Service

OASIS

1. Transition

- There will be one OASIS node, the PJM OASIS.
- Transmission customers will submit and receive transmission reservations to the PJM single node OASIS. It will be available to transmission customers one month prior to integration to allow reservation of monthly transmission service.

2. Reservation Conversion

- Reservations purchased on the MISO OASIS node prior to one month ahead of integration will be converted to the appropriate PJM RTO product and subject to the PJM RTO rates as filed in the PJM OATT. Customers who have reservations that need to be converted will be contacted directly by PJM. Converted reservations and long term firm contracts will be converted to PJM equivalent products.

3. Transmission Provider

- PJM becomes the Transmission Provider and approver for **Duke** transmission customers under the PJM tariff, using PJM rates including a single RTOR (Regional Through and Out Rate).

4. Path Selection

- PORs/PODs and Sources/Sinks will be redefined to reflect the inclusion of **Duke** within PJM. Based on the POR and POD selected on the OASIS, only one path will be allowed. PJM will determine the allowable path based on a load-flow analysis.

5. **AFC/ATC**
   - There will be one AFC/ATC engine, to be run by PJM.
   - Additional flow gates will be introduced to the AFC/ATC engine and calculation.
   - Decrementing of ATC will be based on reservations, IDC schedule data, EES, and Super Regional Congestion Management (SRCM) flow gate limits.

6. **Losses**
   - Losses on transmission reservations for block schedules will be financial and marginal.
   - Exceptions to marginal losses for any grandfathered transactions will be handled on a case by case basis and recorded in "special case" documentation.

7. **Long Term Reservation**
   - PJM will manage the granting of Long-Term Firm transmission service requests for **Duke**.

Tagging & Scheduling

1. **Tagging**
   - E-Tag 1.8.1 will be used; however, PJM will not support vertical stacking of OASIS reservations on schedules sinking, leaving, or going through PJM. PJM will provide for horizontal stacking of OASIS reservations on schedules in all situations.
   - Conversion of existing NERC Tags must be evaluated.

2. **Tagging Service**

   PJM will use OATI for tagging services (agent, authority, and approval) for the **Duke** Control Zone. Transmission customers will be required to specify the full contract path on their tags, including all Scheduling Entities on the path. PJM must appear as the Transmission Provider on the tag.

3. **External Energy Scheduling**
   - Generators will submit External Energy Schedules using the PJM Enhanced Energy Scheduling (EES) application for scheduling outside the PJM RTO.
   - Scheduling of imports, exports, or wheels through multiple interfaces of the new PJM footprint will be managed through EES.
   - There will be additional valid contract paths in EES for external schedules that include **Duke** in PJM footprint.
   - There will be one ramp limit for the PJM RTO. Because ramp is limited, PJM allows for scheduling on 15-minute increments.

System Operations

1. **Energy Management**

Duke Integration Assumptions

- PJM will be responsible for the operation of the **Duke** transmission system under the current system operating policies and procedures. PJM is registered and as the BA and TOP for this additional footprint.
- **Duke**'s network model will be incorporated into the current PJM EMS model down to at least 100 kV. The model building will occur incrementally in the succeeding model builds leading up to the January 1, 2012 integration date.
- There will be one State Estimator solution for the PJM footprint.
- PJM will receive **Duke**'s operational data through ICCP links from the **Duke** control room in Cincinnati.
- **Duke**'s EMS will be the backup for generation dispatch in the event of communication problems with the PJM EMS via PJMnet.
- **Duke** will receive a GT (generation transfer) signal for backup AGC purposes.
- The PJM-calculated **Duke** control zone ACE will provide separate fleet regulation signals to the generators' EMS systems and any directly connected SCADA plant that participates in the regulation market.
- A Reactive Interface Analysis may need to be done to determine if any additional Reactive Interfaces are necessary.

2. **Reliability Coordination**
   - PJM will take over responsibility for reliability coordination ("RC") for **Duke** as of the integration date of January 1, 2012. As the Reliability Coordinator for **Duke**, PJM has the authority to direct **Duke** operations, in accordance with the PJM Reliability Plan, NERC Standards, and good utility practice in order to preserve the reliability on the interconnection.

3. **Emergency Coordination**
   - As the RC/TOP/BA, PJM will direct/coordinate emergencies (i.e. emergency conditions, TLR 5 events, restoration).

4. **Congestion Management**
   - PJM will provide congestion management in accordance with the PJM Market, CM2 processes, and the NERC Transmission Loading Relief (TLR) Standard as per the JOAs.
   - AFC coordination will be addressed through PJM's CM2 application as well as any other existing AFC processes adhered to by PJM.
   - **Duke** and PJM must perform Flow gate studies to determine the updated flow gate list.
   - Flowgate data will be exchanged per the processes defined between PJM and MISO

5. **Dispatch**
   - PJM will economically dispatch the PJM RTO as a single, security constrained solution.
   - PJM will direct all generation owners to redispatch, for most internal constraints.
   - PJM Dispatch will include effective marginal losses.

- Individual Generator Dispatch (IGD) signals will be sent to all generators within the Duke footprint upon integration into PJM.
- PJM Dispatch will have to consider flow gates outside of the PJM footprint as they do today.
- Transmission and generation operators will be PJM Certified before integration.

6. Checkout

- PJM will handle checkout for **Duke** footprint transactions.

7. eDART

1. Generator Outage Ticket
   a. Generators will need to comply with the rules set out for the following ticket types Forecasted Planned, Maintenance and Unplanned.
      i. Forecasted Planned tickets will need to be submitted at least thirty days before the start of the outage to be considered Forecasted Planned. Forecasted Planned tickets are approved based on the amount of Available Reserve, Blackstart Scenario checkout, and are approved when not within the time period for Peak Period Maintenance season (for non- Hydro-Run of River units).
      ii. Maintenance tickets are postpone-able to after the following Monday.
      iii. Unplanned tickets are those that must happen at the time stated such as in the case of a unit trip.
2. Transmission Outage Ticket
   a. **Duke** will submit the tentative dates of all planned transmission outages of Reportable Transmission Facilities to PJM via eDART as far in advance as possible and update PJM at least monthly. For transmission outages exceeding five days, **Duke** shall use reasonable efforts to submit the planned outage schedule via eDART one year in advance but no later than the first of the month six months in advance of the requested start date along with a minimum of monthly updates.
   b. **Duke** is required to submit all outage requests in excess of 5 days in duration by the 1st of the month six months in advance of the start of the outage.
   c. **Duke** is required to submit all other outage requests by the 1st of the month prior to the month of the requested start date of the outage.
   d. Outages scheduled for the following Planning year (i.e. June 1 – May 31) exceeding 30 days in duration are to be submitted via eDART by February 1 for use in the annual FTR auction.
   e. As the Reliability Coordinator, PJM has the ultimate approval of transmission outage requests in order to maintain system reliability.
   f. **Duke** will designate an engineer responsible for support of PJM peak seasonal (OATF) and interregional assessments to ensure an accurate model reflective of expected upcoming system topology including both generator and transmission outages and upgrades.
3. Transmission Equipment Ratings Monitor (TERM)
   a. **Duke** will now be responsible for the semi-annual review of all equipment ratings (i.e. May and November)

4. Overload Reporting
    a. Reports will be adjusted to include overloads for **Duke**.
5. Instantaneous Reserve Check (IRC)
    a. One new column for the control zone **Duke** will be added to the reports.
    b. **Duke** generator owners will now be included as part of the IRC and will need to submit data for the IRC whenever one is called.
6. Minimum Generation Report (MinGen)
    a. **Duke** generator owners will now be included as part of the MinGen and will need to submit data for the MinGen whenever a MinGen Event or Alert is called.
7. Status Reports (SR)
    a. Current Status Report
        i. The Interchange will be adjusted to no longer include **Duke**.
        ii. All of the other values for the report will be adjusted to include **Duke**
    b. Peak Status Report
        i. The Interchange will be adjusted to no longer include **Duke**.
        ii. All of the other values for the report will be adjusted to include **Duke**
    c. Supplemental Status Report (SSR)
        i. One new column for the control zones **Duke** will be added to the reports.
        ii. **Duke** footprint generator and transmission owners will now be included as part of the SSR and will need to submit data for the SSR whenever one is called.
8. NERC Data
    Duke will supply NERC SDX data as they progress through the levels of submission below, with level 1 being the initial level and level 3 being the ultimate result. There will be a period where they are in between levels 2 and 3. They will advance through these levels independent of each other.
        i. Level 1 – **Duke** will continue to send their own pre-constructed SDX file to be appended to the PJM file
        ii. Level 2 – They will be entering load forecast data into the Load Forecast form. This data will be merged with the MW Outage Generator Tickets and the Transmission Outage Tickets when sent to NERC.
        iii. Level 3 - They will no longer need to enter Load Forecast data as it will be derived from other means (i.e. GDB, eMKT, eDART – Generator Tickets, and EES).
9. Restoration Data
    a. Restoration plans in the event of an outage must be updated and coordinated by **Duke** and delivered to PJM.
    b. **Duke** generator and transmission owners will now be included as part of the Restoration Drill and will need to submit data for the Restoration Drill whenever a Restoration Drill is called.

Billing and Settlement

1. **Internal Energy Schedules**
   - Load serving entities will submit internal schedules using the PJM eSchedules application. Internal Schedules includes any schedules within the **Duke** and PJM boundaries.

2. **MSET**
   - PJM will perform the Billing and Settlements functions for the **Duke** zone through the current PJM MSET application.
   - The weekly and monthly billing cycles will be consistent with that of the remainder of the PJM membership
   - Settlements and billing data will expand to include additional customers, eMTR accounts, energy schedules, and LMP nodes for the new buses, aggregates, and zones.
   - There may be municipal entities that may choose to serve their load via point-to-point transmission service. (need to identify if there are any entities that currently serve their load in this manner)
   - **Duke** zone settlements will reconcile Load Responsibility energy schedules on a two calendar month lag to be consistent with that of the remainder of the PJM membership
   - PJM will distribute Market Settlements Reports via the MSRS application.
   - PJM will calculate and distribute invoices for Transmission, Energy, Capacity, and Ancillary Services billing line items.
   - Special Schedules (Joint-owned units, Dynamic Schedules, etc.) will be handled on a case by case basis and recorded via special case documentation.
   - Market to Market allocation methodology remains the same.

3. **Ancillary Services**
   - The **Duke** zone will be included in the RTO Regulation Market and will not be included in any reserve sub-zones (i.e., Mid-Atlantic).
   - Generators will need to qualify units for the Regulation Market by providing past data to prove the generator can support regulation approximately 60 days before integration.
   - Generators will need to qualify units for Black Start approximately 90 days before integration.
   - PJM will select resources hourly to provide regulation and certain resources to provide synchronized reserve based on a co-optimization between energy, regulation and synchronized reserve. These hourly assignments may be updated in real-time via PJM. Hourly assignments will be communicated to owners/operators through the eMKT user interface. Intra-hour Regulation assignments will be communicated to owners/operators by the PJM generation dispatcher. Intra-hour synchronized reserve assignments will be communicated via dispatch signals.

Market Operations

1. **Capacity - RPM**
   - **Duke** will submit Capacity Transactions and Load Contributions using the eRPM application. There will be a transition period following integration during which **Duke** will participate in RPM via an FRR plan. The FERC-filed integration agreement will document whether **Duke** participates in the RPM Base Residual Auctions following integration as opposed to waiting the minimum 5 years otherwise applicable to FRR entities.
   - **Duke** will contract bi-laterally with capacity resource providers for capacity needed to meet their capacity obligations for the remainder of the 2011/12 delivery year and the entirety of the 2012/13 and 2013/14 delivery years.
   - A new LDA will be established for the Duke transmission zone.
   - The Reliability Assurance Agreement (RAA) will be updated to reflect changes due to **Duke** Market Integration.

2. **ARR/FTR Allocations and FTR Auctions**
   - **Duke** footprint Network and Firm Point-to-Point transmission customers will participate in the annual allocation for ARRs effective on June 1, 2012. This allocation will be conducted approximately 3 months prior to when the ARRs become effective. ARRs allocated in this allocation may be directly converted into FTRs prior to the annual FTR Auction.
   - A Special FTR Allocation will be conducted for the **Duke** zone since the integration date is not on the first of June. This special allocation of FTRs will cover the period of time between the implementation of the **Duke** zone on January 1, 2012 and the next Annual ARR Allocation in which the **Duke** zone actually integrates into PJM (ARRs effective for June 1, 2012).
   - **Duke** pricing points will be available in the Annual, Long-Term and Monthly Balance of Planning Period FTR Auctions through eFTR beginning with the first auction after integration.

3. **Markets**
   - **Duke** and generators in the **Duke** footprint will submit Generation / Demand Bids using the PJM eMKT application.
   - There will be a single Energy Market.
   - The inclusion of generators in the **Duke** footprint in the PJM wholesale energy markets will be based on PJM's current market rules.
   - The timeline for clearing the market and posting the results for day ahead and real-time markets will remain the same based on Eastern Prevailing Time. All PJM Market applications assume EPT unless otherwise specified.
   - Market trials will be conducted approximately two months prior to Market Integration.
   - **Duke** and generators in the **Duke** footprint will join the PJM Balancing Authority as a separate Control Zone; PJM will assume BA Operations.

- There will be one Area Control Error (ACE) for the PJM BA, any adjustments to the definition of PJM interface pricing points post-**Duke** integration will need to be determined based on the distribution factor analysis.
- There will be a single Duke transmission zone

4. Revenue Quality Metering
- The **Duke** utilities and the generators in the **Duke** footprint will submit Meter Data (Internal / External Ties to PJM and Generators) using the PJM eMTR application. If generator metering is only available on a plant basis, this limits the eMKT offer data for those generators to also be only on a plant basis.
- **Duke** will be incorporated into the single PJM Inadvertent calculation.

5. Locational Marginal Price
- **Duke** and the generators in the **Duke** footprint will be included in the single PJM energy market; and will have LMP.
- LMPs will include the effective marginal losses.

6. eData
- The contour map will be updated to include the **Duke** control zone within the PJM Control Area.

7. Market Monitoring
- Monitoring Analytics will perform the Market Monitoring functions for **Duke** and generators in the **Duke** footprint.

8. Demand Response
- PJM will administer economic and emergency demand response for market participants in the **Duke** zone according to the PJM rules.

Business Support

1. Control Documents
- PJM's tariff will require a compliance filing to include **Duke**'s rates.
- PJM Tariff (OATT) and Operating Agreement will need to be modified to accommodate the **Duke** integration.

2. PJMnet
- PJM will continue to use PJMnet for retrieving telemetry and SCADA data for **Duke**. Cincinnati control center links will be used to transmit EMS data to PJM.

3. Participant Readiness/Training Development
- PJM has developed a comprehensive approach to assist new PJM market customers with the integration of **Duke** into the PJM footprint. This approach consists of two parallel and complimentary efforts: Participant Readiness and Training Delivery.

- Participant Readiness includes distribution of relevant information, references to whitepaper and other PJM resources to provide details and requirements, and a customized checklist for each customer which highlights the major topics that need to be covered to prepare for integration.
- To facilitate the Participant Readiness process, PJM will establish client manager teams that will work with the various customer groups (i.e. Generation Owners, Load Servers, etc.) to conduct meetings, recommend training, and monitor progress.
- Training should continue with the objective of increasing customer comfort with PJM systems, processes, and markets. A comprehensive training schedule of in person classroom training will be developed for delivery within the **Duke** footprint. The schedule will include the following courses and programs. PJM 101, Load Serving Entity (LSE) Program (LSE 201, 202, 203, 204, 205), Market Operations Center Program (Generation 101, 201 and 301 and Operations 101), Local Control Center (LCC) Program (Transmission 101, 201, and Operations 101), System Restoration Workshop, and Market Settlements 301, Additional topics may be developed as needs are identified and delivered in person or via synchronous on-line training (WebEx). Additionally, asynchronous training, or on-line on-demand training, covering many of the above topics will be available on the PJM website or through the PJM LMS 24/7.
- Transmission and generation operational personnel who will be communicating with and carrying out directives from the PJM control center will need to be identified along with a company designated Training Liaison (role of the Training Liaison is outlined in Manual M-40). Information and assistance will be provided regarding PJM Certification for this audience. It will be necessary for this group to individually earn their PJM Certification credential (Transmission or Generation) prior to the integration date.
- **Duke** operators will need to maintain or acquire a NERC Certification (Transmission Operator, RC, or TO/BI) prior to integration in PJM.
- If necessary, an additional course will be developed for existing PJM members to provide an overview of changes and highlight specific business rule and application changes (if any) related to the **Duke** integration.
- The Dispatch Training system at PJM will be used to train dispatchers on the new systems. **Duke** will need to assist in training PJM System Operators on the nuances of the Duke system.

NERC and Regional Compliance

1. NERC Certification
   - PJM will request from RFC and NERC that a certification team be constituted to certify PJM as the RC, TOP, and BA for the Duke footprint.
   - Certification process will likely involve field visits to PJM and Duke as part of the process.
   - The certification process will likely occur in late 2011, just ahead of the integration date.

- PJM will need to demonstrate that it has the processes, tools, and properly trained personnel to execute the integration.

2. NERC Registration
   - Duke will drop its registration as a TOP and re-register as a TO as most of the existing transmission owning member of PJM have done.

Outage Planning

1. **Transmission Outage**
   - Prior to integration, transmission outages must be entered directly into eDART in accordance with the timing in the current PJM Transmission ticket outage rules highlighted in "System Operations" section 7.2 "eDART Transmission Outage Ticket" above.
   - As the Reliability Coordinator, PJM has the ultimate approval of transmission outage requests in order to maintain system reliability.
2. **Generation Outage**
   - Generators within the **Duke** control zone will enter generation outages directly into eDART 30 days prior to integration.

Membership & Credit

1. **Membership**
   - **Duke** and any entities operating within the Duke area must register as PJM transmission customer (point to point), member or affiliate 60 days prior to integration.

Stakeholder Process

- PJM will schedule Stakeholder meetings in the **Duke** service territory to discuss market integration timing and issues.
- PJM will utilize regularly scheduled Committee meetings to discuss and recommend or approve any necessary changes for **Duke** market integration. For example:
  - PJM Members Committee (MC) meeting to review OA and OATT changes
  - Markets and Reliability Committee (MRC) meeting to review and endorse Manual changes prior to MC review
  - Tariff Advisory meeting to review tariff changes
  - TOA-AC meeting to review any changes to transmission rates.
  - NERC OC approval of PJM Reliability Plan

Risks

- Need to coordinate with **Duke** to ensure they are able to use their EMS systems as backup for generation dispatch in the event of communication problems with the PJM EMS via PJMnet.

EXHIBIT 34 FES

PENGAD 800-631-6989

Transmission Expansion Advisory Committee

March 7, 2013

Issues Tracking

Issues Tracking

- Open Issues
  - None
- New Issues

Stage 1A ARR Transmission Project Update

Stage 1A ARR Transmission Project

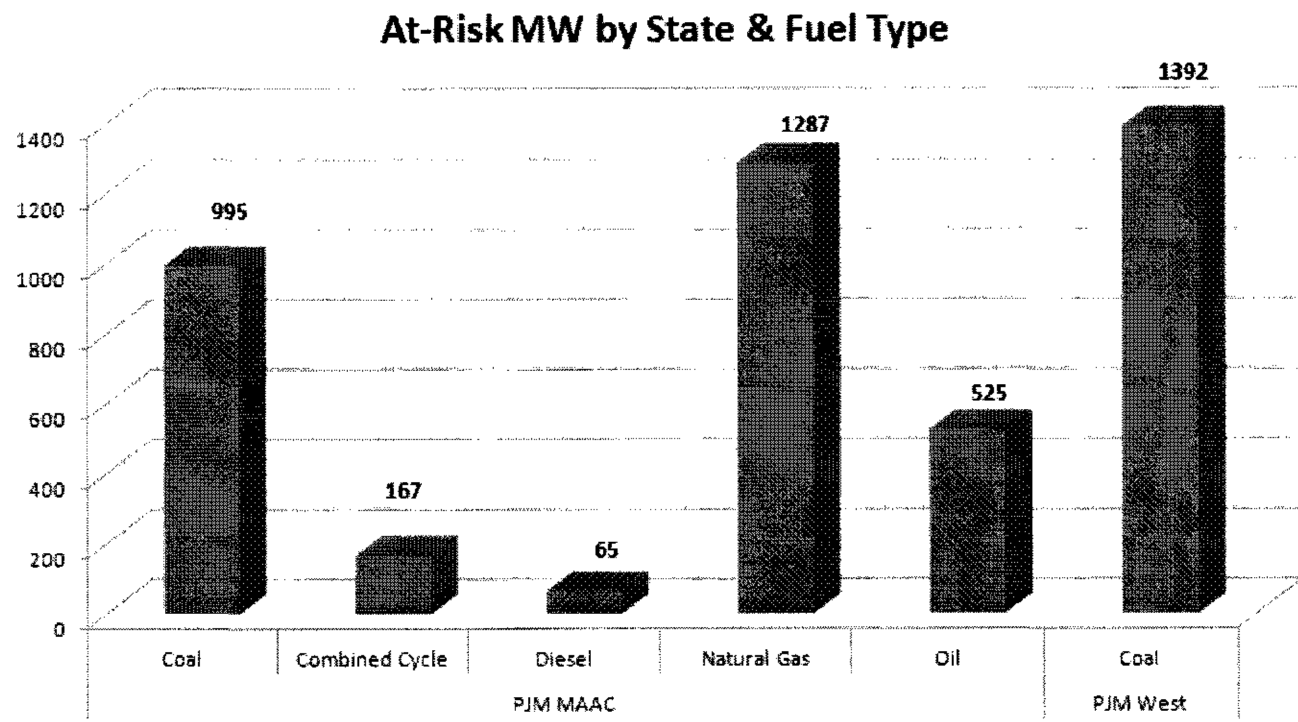
Byron to Wayne 345 kV Transmission Line

- Eliminates COMED Area Stage 1A 10 year infeasibilities
- Approved by PJM Board for inclusion into Regional Transmission Expansion Plan (RTEP) in October 2012
- Operating Agreement requires an analysis of the benefits of the project given that this project is not subject to a market efficiency cost/benefit analysis
- Estimated 15-year Congestion Cost Savings: $200-250 million
- Estimated 15-year Production Cost Savings: $75-125 million

PJM Scenario Analysis Update

At-Risk Generation

- Approximately 4,500 MW of At-Risk generation remains
- Known deactivation notifications not included



2013 RTEP Scenario - At-Risk Generation

- Proposed Scenario:
  - Develop 2018 At-Risk generation case
    - Perform load flow analysis
  - Determine potential transmission enhancements to accommodate current At-Risk Generation
  - Incorporate all recent deactivation notification upgrades and RTEP upgrades
  - Perform sensitivity study on the potential violations to queued FSA generation

2013 RTEP Scenario – DR Sensitivity

- Proposed Scenario
  - Develop Load Deliverability cases for each LDA to account for Demand Response sensitivity
    - Reduce each LDAs DR by amount of generation in LDA that did not clear in RPM auction (load deliverability test only)
  - Perform Load Deliverability analysis
  - Identify locational supply concerns before they actually occur

2013 RTEP - RPS Scenario

- Update state requirements as required
- Finalize RPS1 2GW scenario
- "Optimize" transmission overlay
  - 2013 RTEP will investigate what parts of overlay develop in 2012 RTEP may not be required for a given scenario
- Generation commitment
  - Sensitivity study around unit commitment assumptions used in production cost simulations – check impact on wind curtailment
- Refine Offshore HVDC Modeling (i.e. apply limits)
- State reporting of production cost simulation results

Next Steps - 2013 RTEP Scenarios

- Proposed scenarios reviewed with ISAC in February
- Incorporate state feedback
- Initiate analysis

High Voltage in PJM Operations Analysis Update

Progress Update

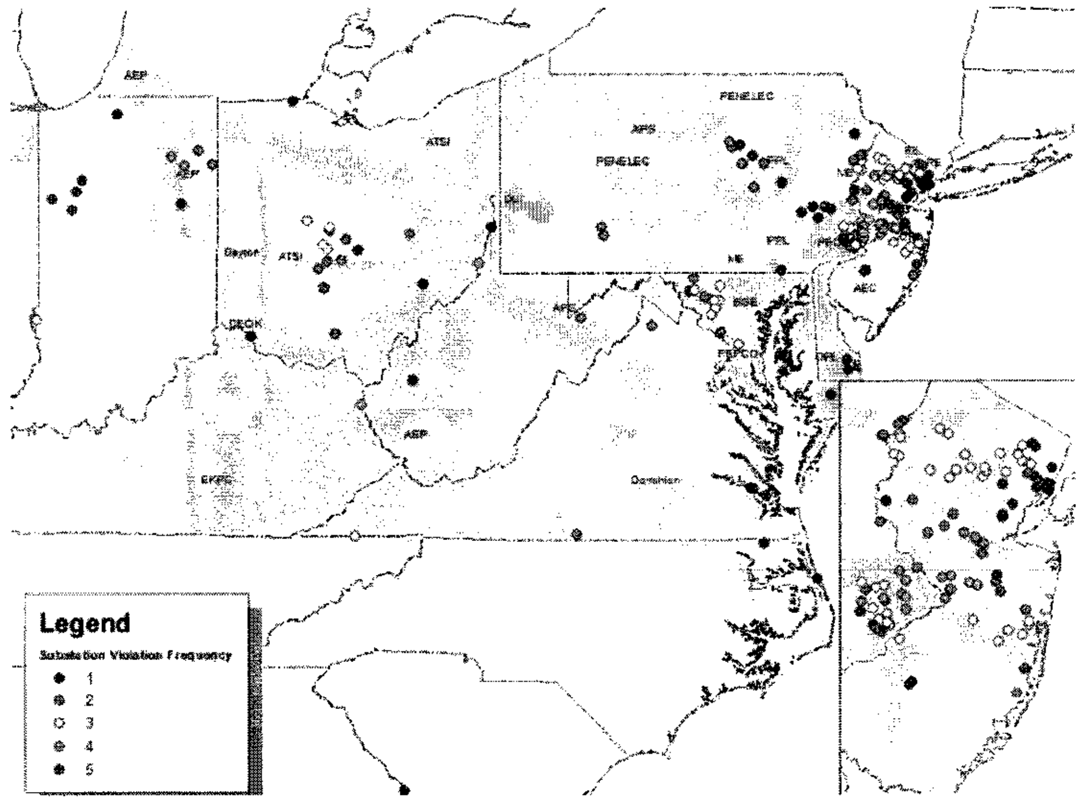
- Determined potential reactor locations
  - from historical PI data and high voltage alarm data

- Modeled and simulated reactors in several operational cases to determine the potential magnitude that is necessary to control high voltage

- Also simulated high voltage conditions and reactors in a planning case to determine system needs beyond the operational cases

High Voltage Locations from PJM Operations Cases

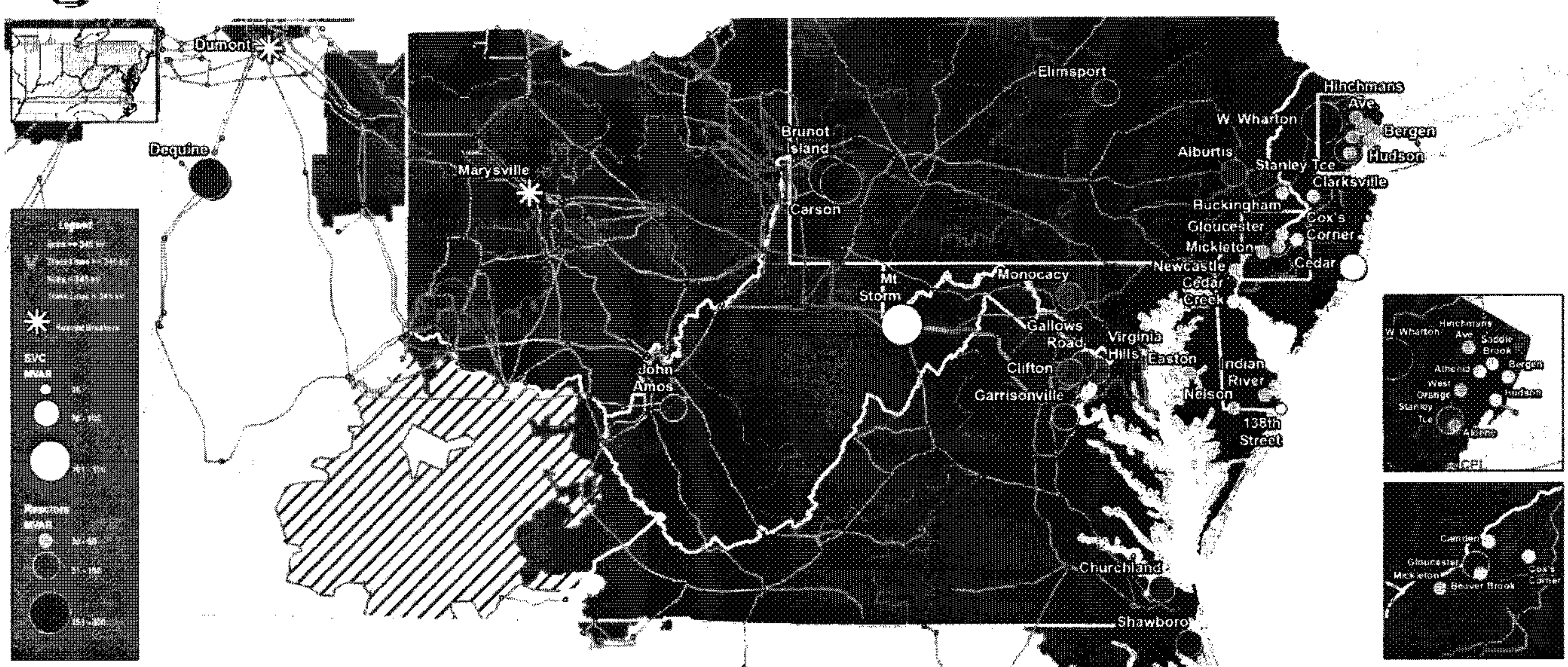
- 5 snapshot cases from PJM Operations evaluated



Progress Update

- Provided TOs with historic high voltage alarm data and voltage analysis performed on five historic EMS cases
- Received feedback from TOs
- Potential solutions received to date include
  - Shunt reactors
  - SVCs
  - Modifications to / optimization of existing facilities
    - Generator voltage schedules
    - Transformer tap settings
    - Switched shunt settings

Preliminary Solutions and Locations



Preliminary Solutions

- AEC
  - 50 MVAR shunt reactor at Mickleton 230 kV
  - +150/-100 MVAR SVC at Cedar 230 kV
- AEP
  - Install a 300 MVAR reactor at Dequine 345 kV
  - Replace existing 150 MVAR reactor on Amos – N. Proctorville Hanging Rock 765 kV with 300 MVAR reactor
  - Install 765 kV reactor breaker at Dumon and Marysville 765 kV substations
- ComEd
  - Optimization of existing facilities at Twin Grove and Kincaid
- DLCO
  - 200 MVAR shunt reactor at Brunot Island 345 kV
  - 200 MVAR shunt reactor on future Brunot Island – Carson 345 kV circuit

Preliminary Solutions

- Dominion
  - Previously approved RTEP upgrades b1805, b2125 and b2126
- DPL
  - Previously approved RTEP upgrades b0876 and b1899.1-b1899.3
- FE
  - 260 MVAR reactor at West Wharton 230 kV (JCPL, this solution is still under review by PJM and FirstEnergy)
  - 130 MVAR reactor at Monocacy 230 kV (APS , this solution is still under review by PJM and FirstEnergy)
  - Optimization of existing facilities (JCPL, ME, PN, APS)
- PECO
  - 50 MVAR reactor at Buckingham 230 kV
- PPL
  - 150 MVAR reactor at Alburtis 500 kV
  - 100 MVAR reactor at Elimsport 230 kV
  - Change generator voltage schedule at Montour

Preliminary Solutions

- PSEG
  - Near Term: Optimization of existing facilities
  - Longer Term: Shunt reactors

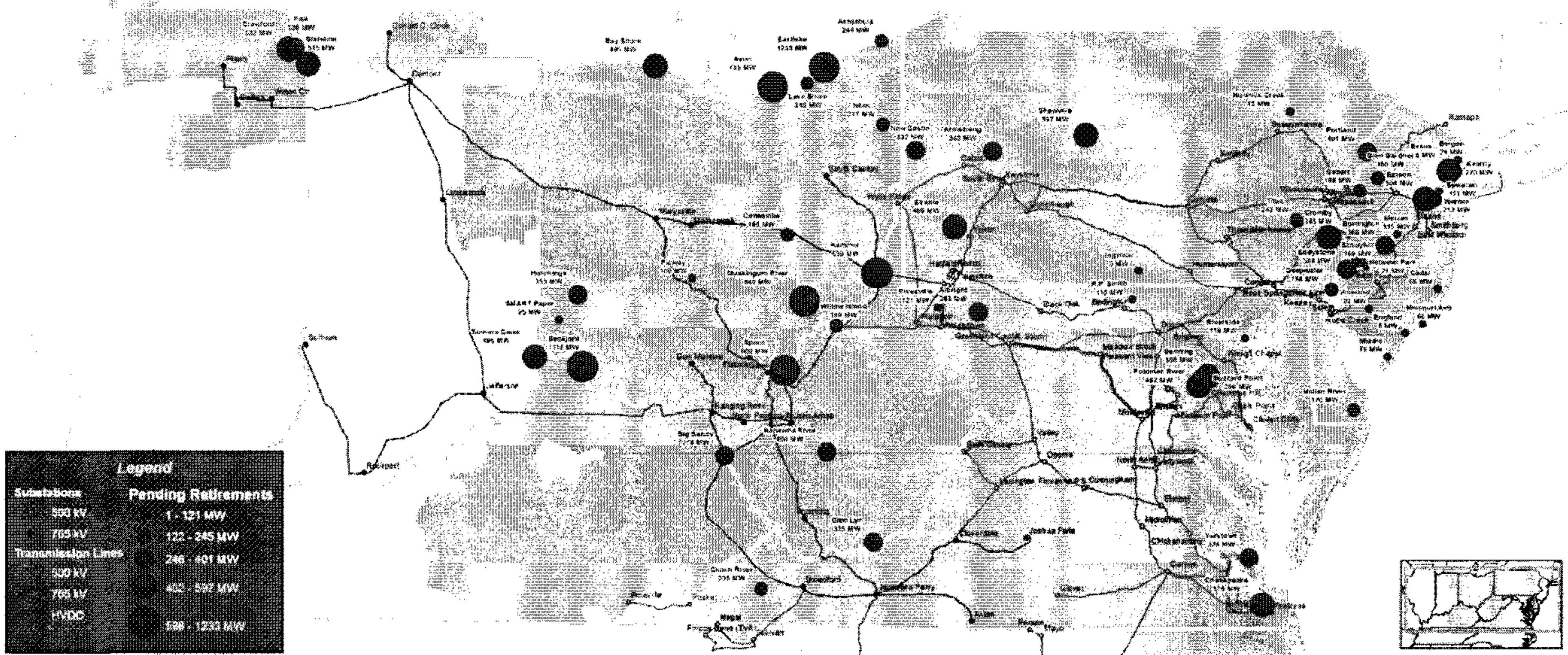
Location	Number	Size (MVAR)
Saddlebrook	1	50
Athenia	1	50
Bergen	1	50
Hudson	1	50
Stanley Tce	2	50
West Orange	1	50
Aldene	1	50
Camden	1	150
Gloucester	1	100
Clarksville	1	50
Hawthorne/Hinchmans /Jackson Rd	1	50
Beaverbrook	1	50
Cox's Corner	1	50
Total	**14**	**850**

Next Steps

- Analysis of the locations proposed by transmission owners
- Confirm proposed locations address the issues
- Evaluate the effectiveness of proposed locations for those that are electrically close to each other

Generation Deactivation Notification (Retirements) Update

Generation Retirements

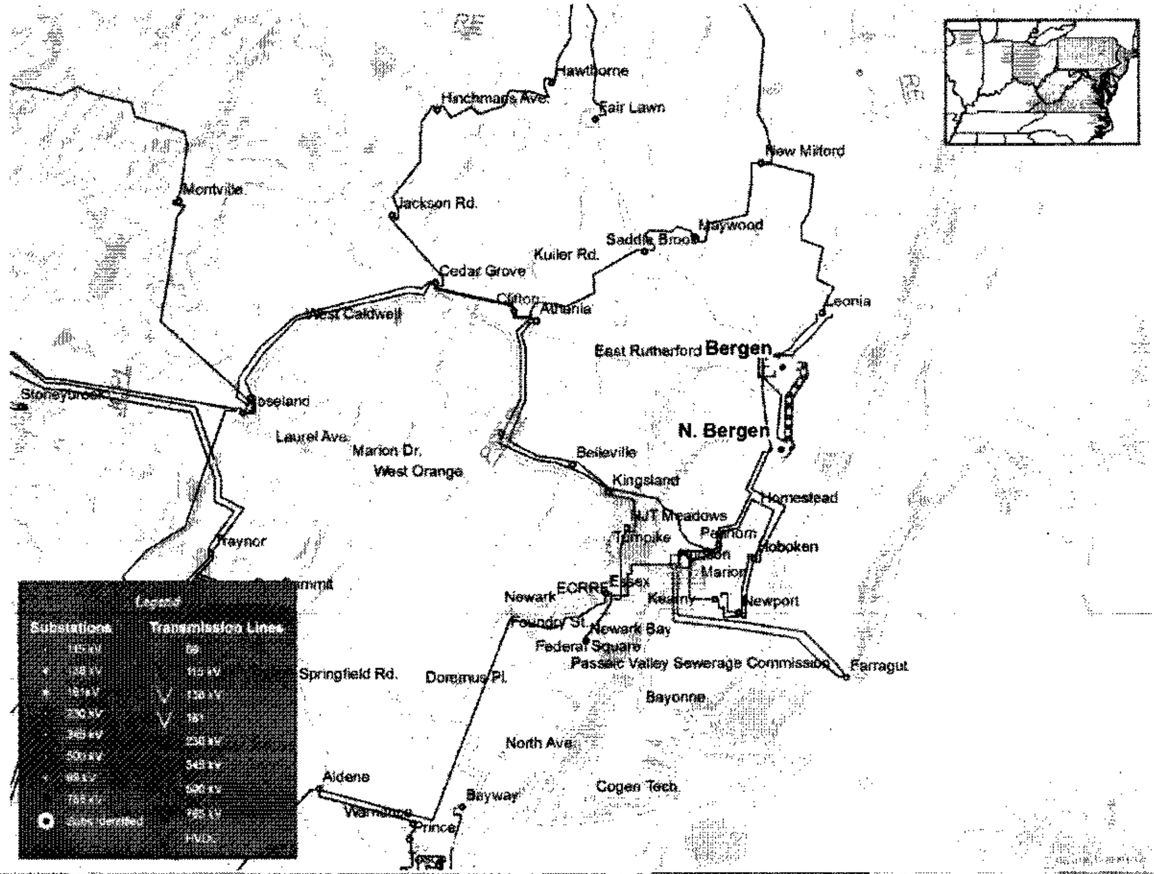


Deactivation Status

- No additional generation deactivation requests received since 2/7/2013 TEAC update
- Completed analysis related to deactivation requests received in January 2013
- Continue to retool previous deactivation studies to refine required upgrades

PS Transmission Zone

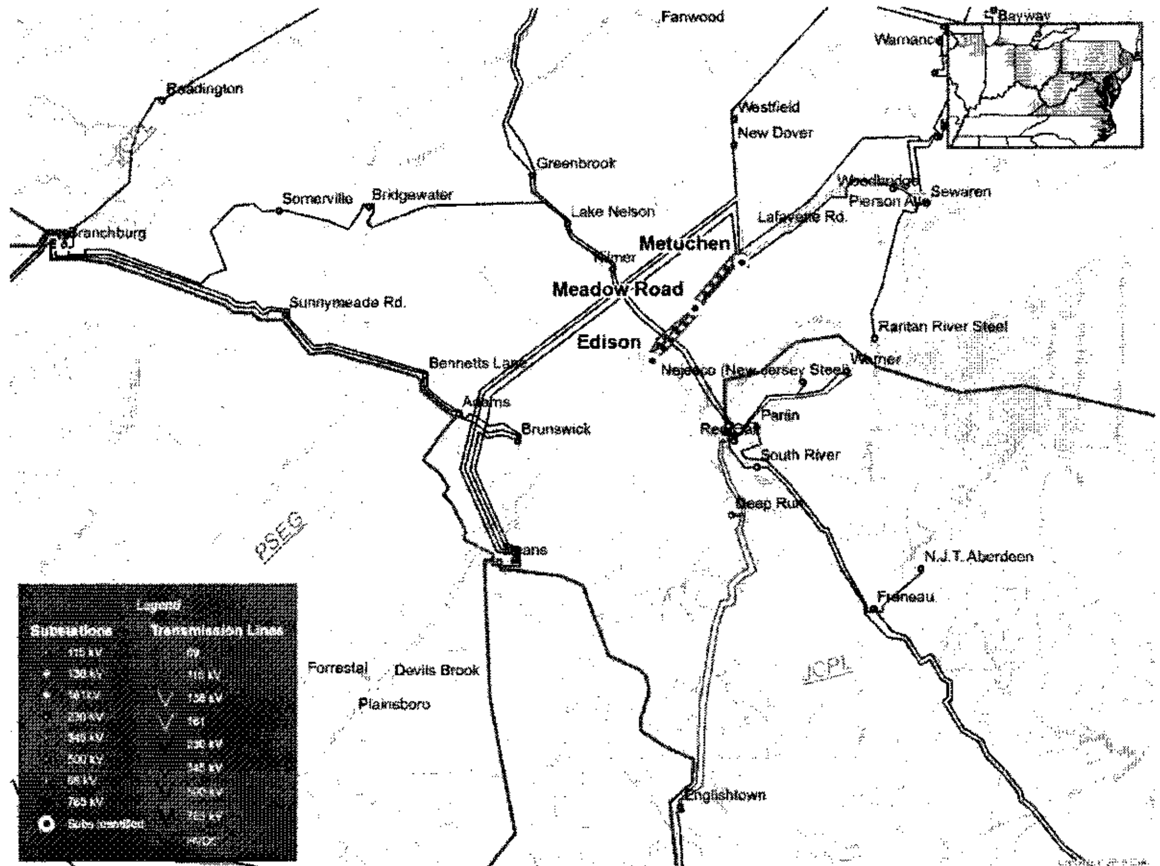
- The Bergen – North Bergen 138 kV line is overloaded for loss of the Bergen 138 kV bus section #3.
- Proposed Solution: Rebuild 2.19 miles of overhead line E-1305-5 (Bergen - North Bergen). (b2217).
- Cost Estimate: $38 M
- Required IS Date: 6/1/2015.



PSEG Deactivations – Burlington 11; Edison 1, 2, & 3; Essex 10 & 11

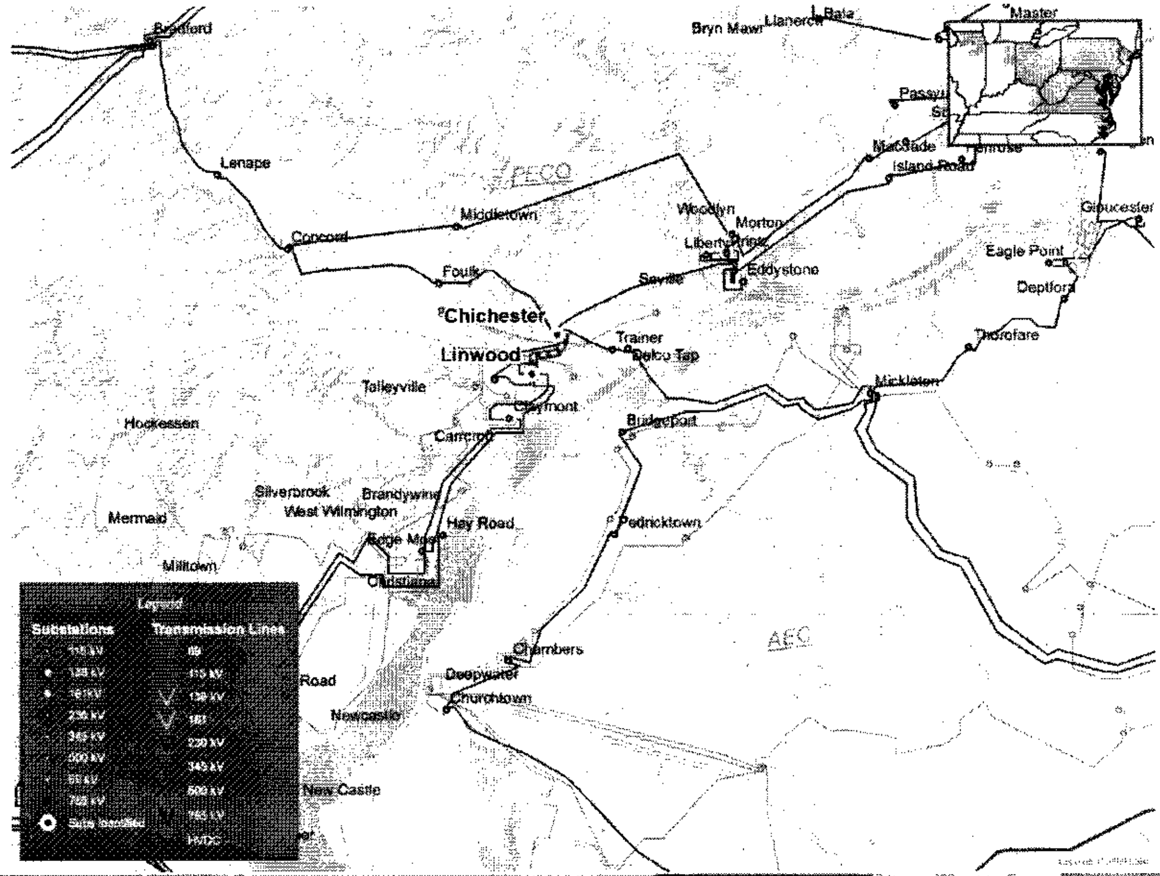
PS Transmission Zone

- The Edison – Meadow Road Q138 kV line is overloaded for various contingencies.
- The Meadow Road Q – Metuchen 138 kV line is overloaded for various contingencies.
- Proposed Solution: Rebuild 4 miles of overhead line from Edison - Meadow Rd - Metuchen (Q-1317) (b2218).
- Cost Estimate: $46 M
- Required IS Date: 6/1/2015.



PECO Transmission Zone

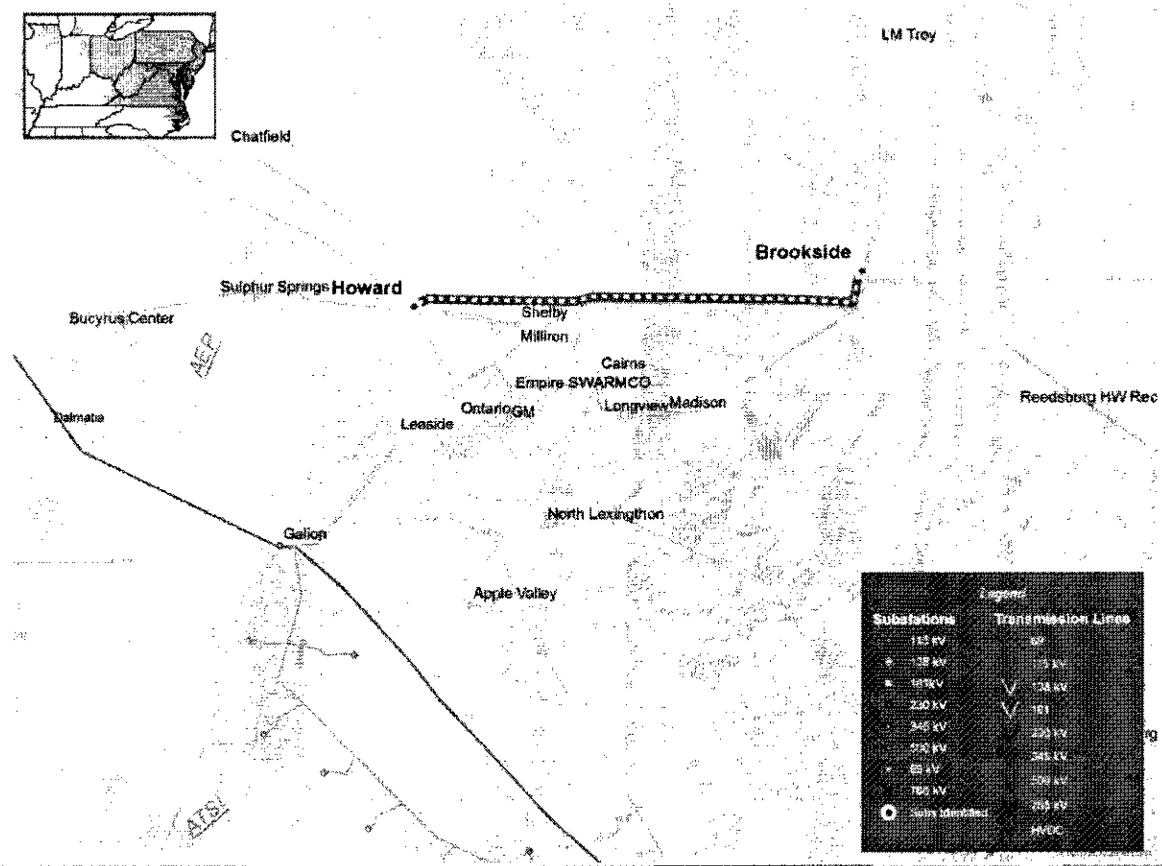
- Revised Required In-Service Date for previously approved baseline upgrade b1900:
- The Linwood – Chichester 230 kV line #1 is overloaded for the single contingency loss of the Linwood – Chichester 230 kV line #2 and loss of Philips Island generating units CT2, CT3, and ST1.
- The Linwood – Chichester 230 kV line #2 is overloaded for the single contingency ('220-43') loss of the Linwood – Chichester 230 kV line #1 and loss of Philips Island generating units CT2, CT3, and ST1.
- Proposed Solution: Add a 3rd 230 kV transmission line between Chichester and Linwood substations and remove the Linwood SPS (b1900).
- Original Required IS Date: 6/1/2018.
- Revised Required IS Date: 6/1/2015.



FirstEnergy Deactivations – Armstrong 1 & 2; Ashtabula 5; Bayshore 2-4; Eastlake 1-5; Lake Shore 18; R Paul Smith 3 & 4

ATSI Transmission Zone

- Change in scope of upgrade addressing the Howard – Brookside 138 kV overload:
- The Howard – Brookside 138 kV tie line (AEP/ATSI) is overloaded for the tower contingency loss of the Galion - Leaside 138kV line and the Galion - GM Mansfield 138kV line.
- Original Proposed Solution to be cancelled: Build a new ATSI/AEP 138 kV Substation (Brubaker) near the territory border and a new 138 kV line from the new substation to Longview (B1935).
- Estimated Project Cost (B1935): $18M
- Required IS Date (B1935): 6/1/2015
- Recommend the cancellation of B1935
- New Proposed Solution: see next 2 slides.



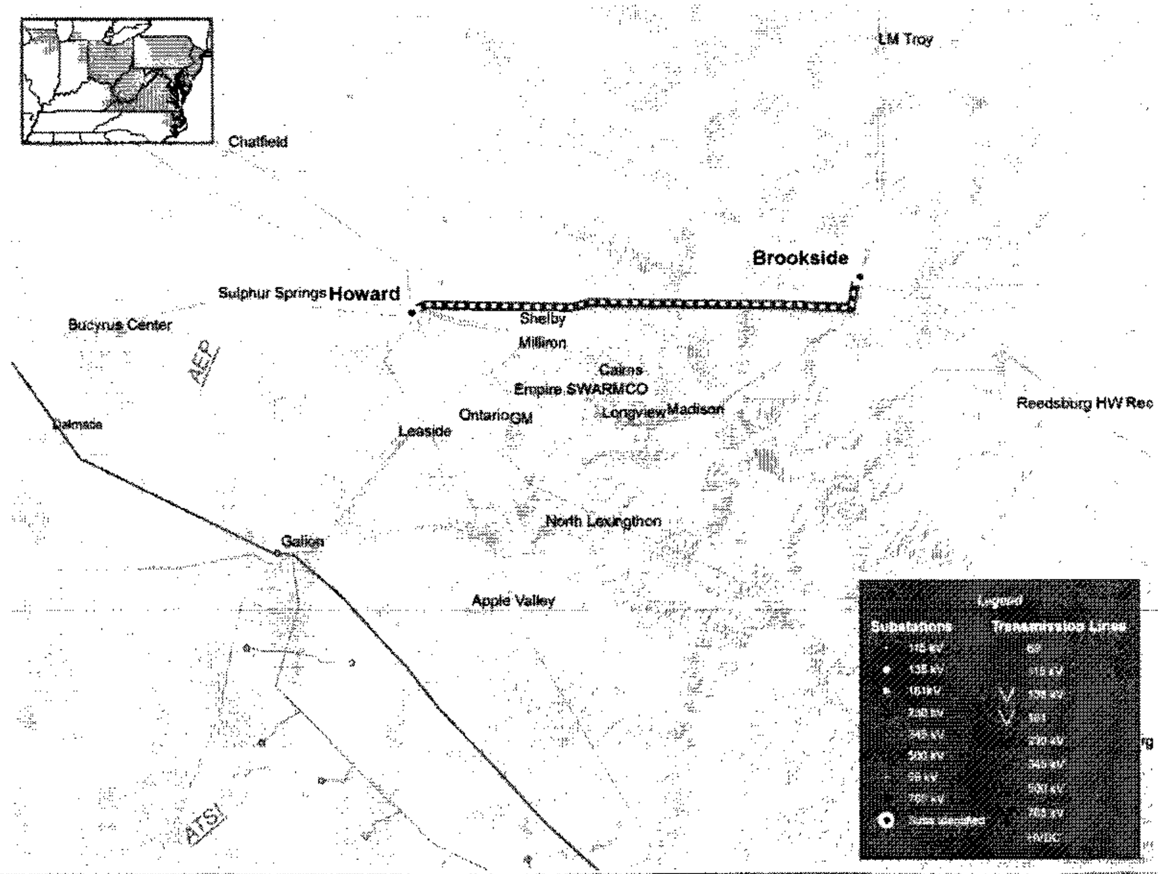
ATSI Transmission Zone

FirstEnergy Deactivations – Armstrong 1 & 2; Ashtabula 5; Bayshore 2-4; Eastlake 1-5; Lake Shore 18; R Paul Smith 3 & 4

- Continued from previous slide…
- Change in scope of upgrade addressing the Howard – Brookside 138 kV overload:

- The Howard – Brookside 138 kV tie line (AEP/ATSI) is overloaded for the tower contingency loss of the Galion - Leaside 138kV line and the Galion - GM Mansfield 138kV line.
- New Proposed Solution: Reconductor the ATSI portion of the Howard - Brookside 138 kV line (b2122.1).
- Cost Estimate: $7.75 M

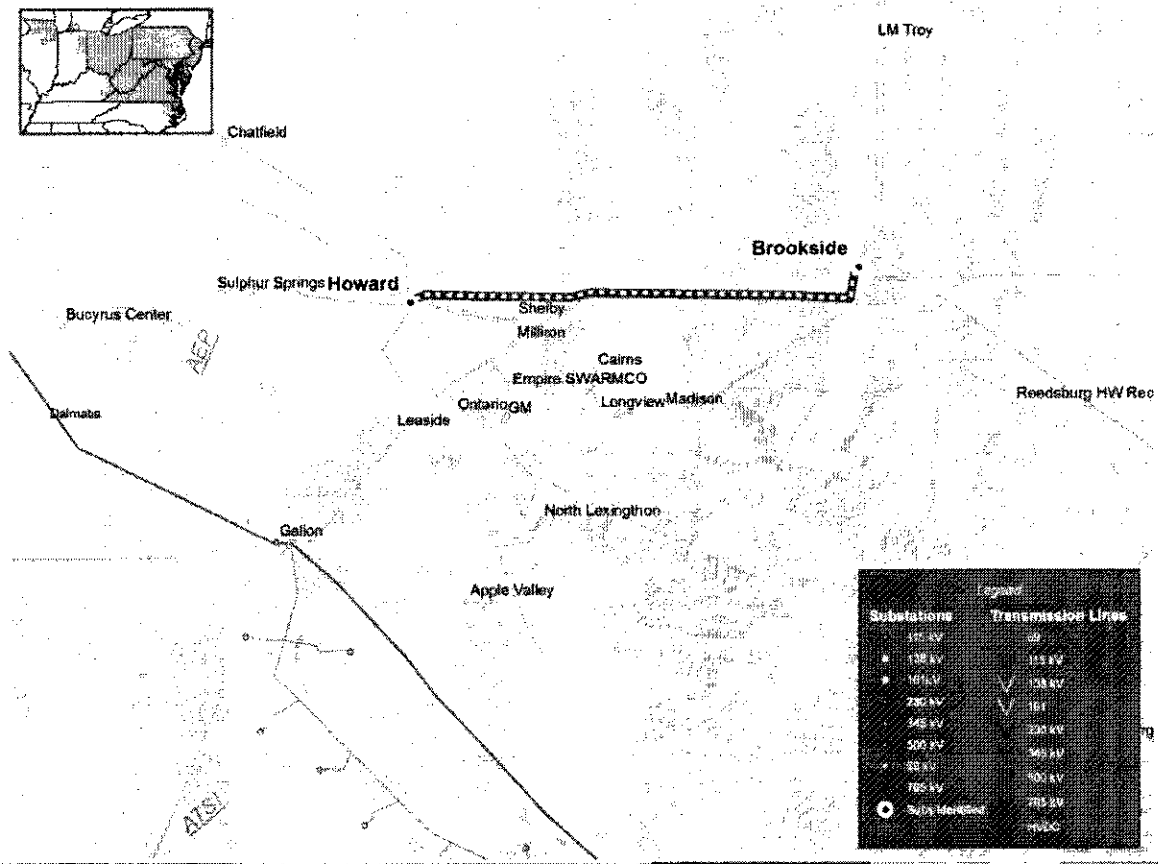
- New Proposed Solution: Upgrade terminal equipment at Brookside on the Howard - Brookside 138 kV line (b2122.2).
- Cost Estimate: $63 K
- Required IS Date: 6/1/2015.



FirstEnergy Deactivations – Armstrong 1 & 2; Ashtabula 5; Bayshore 2-4; Eastlake 1-5; Lake Shore 18; R Paul Smith 3 & 4

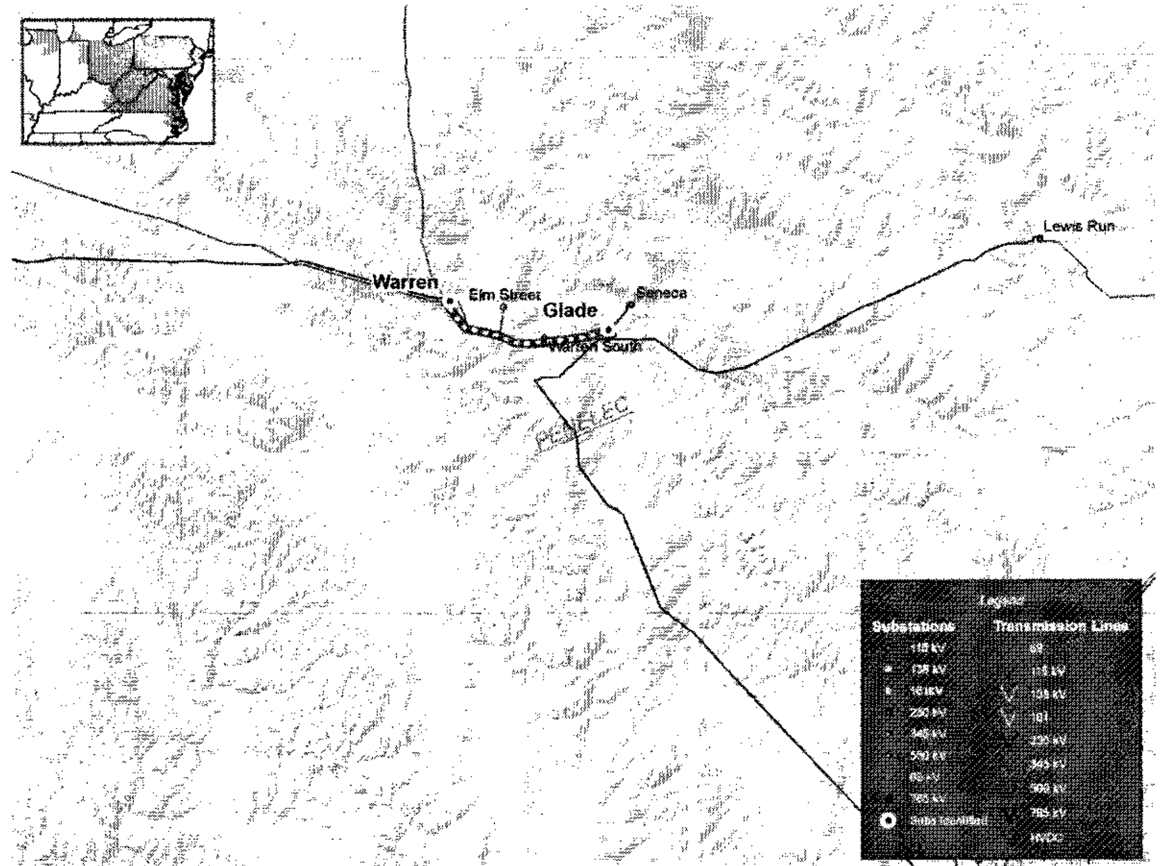
AEP Transmission Zone

- Continued from previous slide…
- Change in scope of upgrade addressing the Howard – Brookside overload:
- The Howard – Brookside 138 kV tie line (AEP/ATSI) is overloaded for the tower contingency loss of the Galion -Leaside 138kV line and the Galion - GM Mansfield 138kV line.
- New Proposed Solution: Upgrade terminal equipment at Howard on the Howard - Brookside 138 kV line (b2122.3).
- Cost Estimate: $600 K
- New Proposed Solution: Perform a sag study on the Howard - Brookside 138 kV line(b2122.4).
- Cost Estimate: $32 K
- Required IS Date: 6/1/2015.



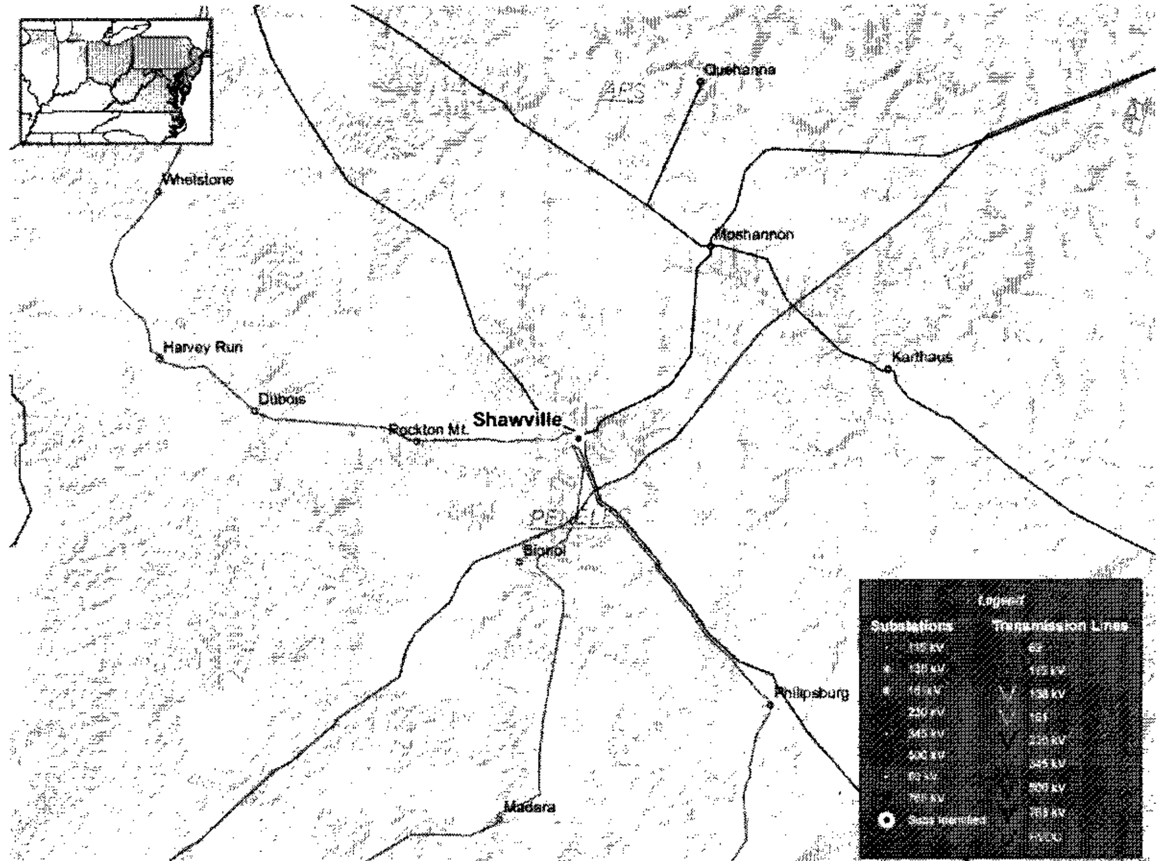
PN Transmission Zone

- Seneca pumping low voltages
- There are various low voltage magnitude and voltage drop violations in the Seneca area for various contingencies.
- Proposed Solution: Build a 2nd Glade - Warren 230 kV line (b2180).
- Cost Estimate:
  $29.6 M
- Required IS Date: 6/1/2015.



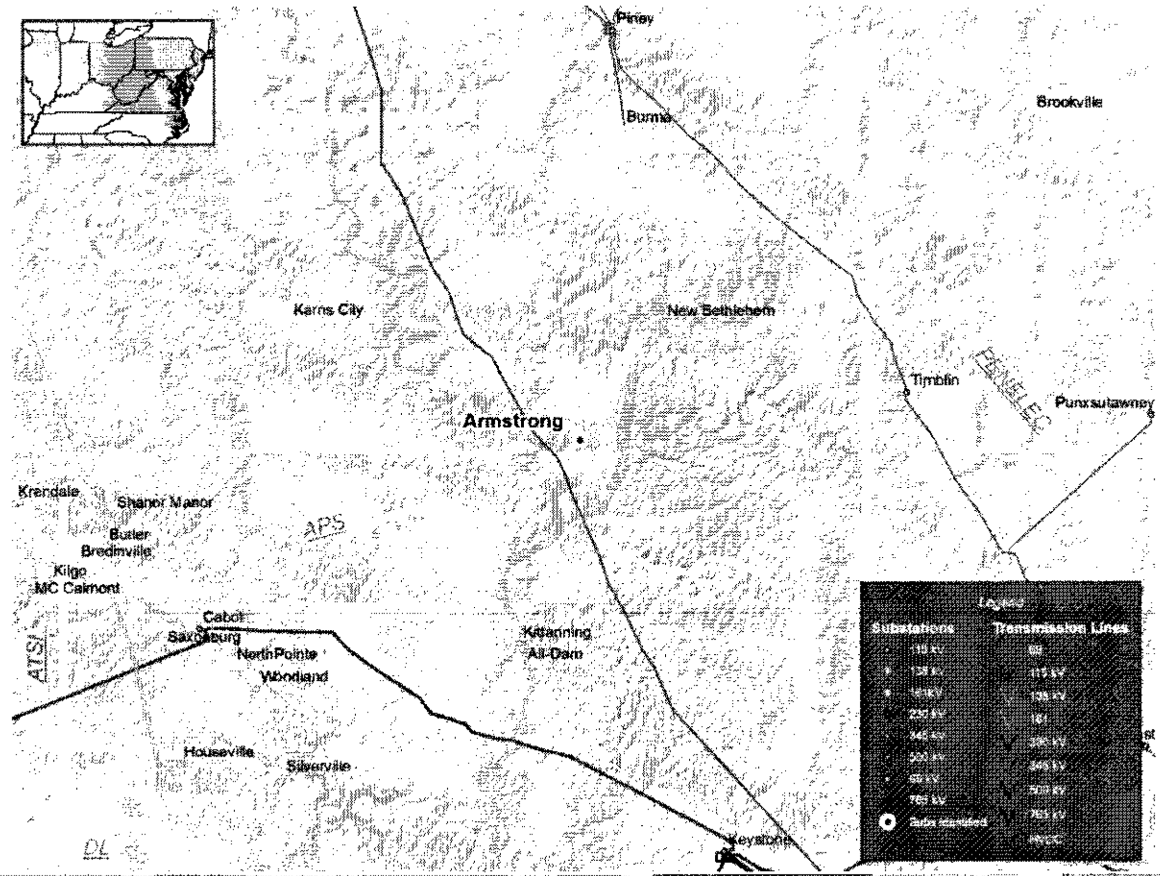
PN Transmission Zone

- Need to relocate substation control equipment due to the generation deactivations at Shawville.
- Proposed Solution: Shawville Substation: Relocate 230 kV and 115 kV controls from the generating station building to a new control building (b2212).
- Cost Estimate: $6.7 M
- Required IS Date: 12/1/2014.



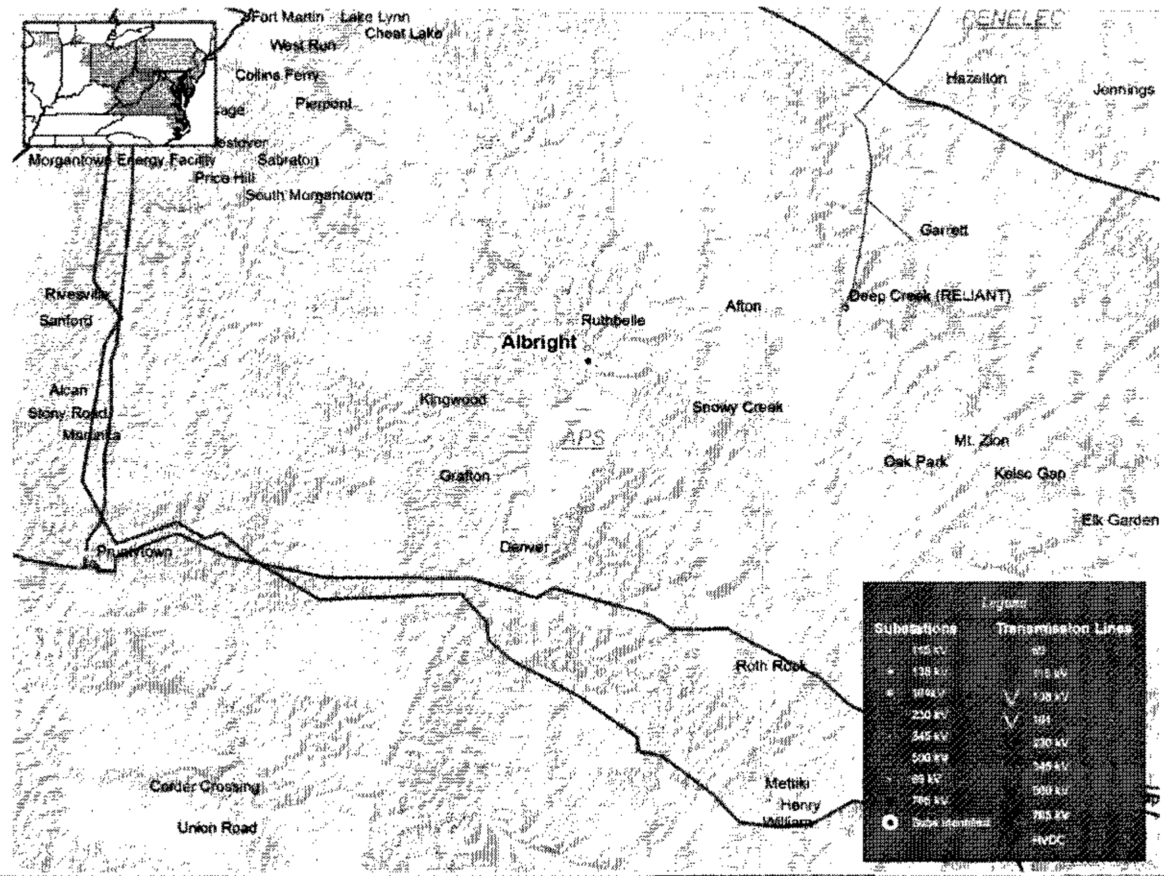
AP Transmission Zone

- Need to relocate substation control equipment due to the generation deactivations at Armstrong.
- Proposed Solution: Armstrong Substation: Relocate 138 kV controls from the generating station building to a new control building (b2213).
- Cost Estimate: $2.7 M
- Required IS Date: 12/1/2013.



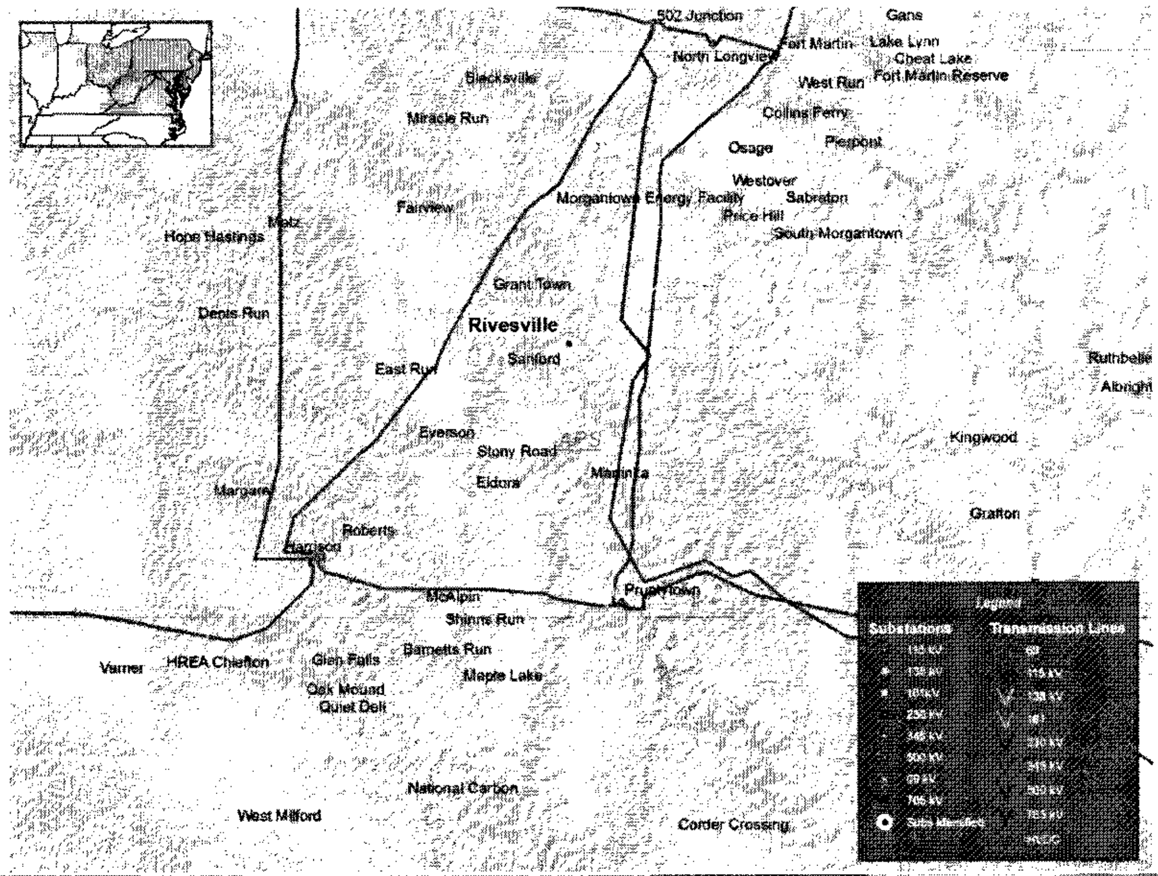
AP Transmission Zone

- Need to relocate substation control equipment due to generation deactivations at Albright.
- Proposed Solution: Albright Substation: Install a new control building in the switchyard and relocate controls and SCADA equipment from the generating station building to the new building (b2214).
- Cost Estimate: $3.4 M
- Required IS Date: 6/30/2014.



AP Transmission Zone

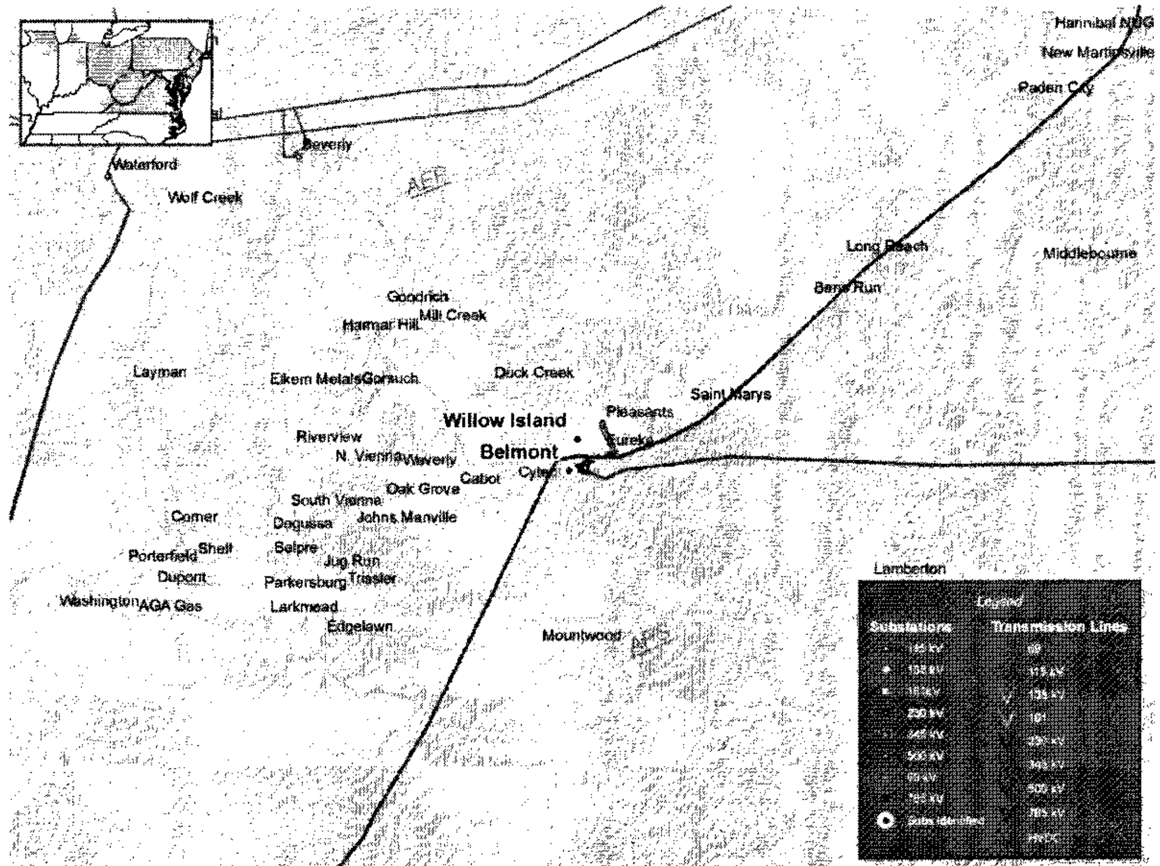
- Need to relocate substation control equipment due to generation deactivations at Rivesville.
- Proposed Solution: Rivesville Switching Station: Relocate controls and SCADA equipment from the generating station building to a new control building (b2215).
- Cost Estimate: $800 K
- Required IS Date: 12/31/2013.



FirstEnergy/Monongahela Power Deactivations – Willow Island 1 & 2

AP Transmission Zone

- Need to relocate substation control equipment due to generation deactivation at Willow Island.
- Proposed Solution: Willow Island: Install a new 138 kV cross bus at Belmont Substation and reconnect and reconfigure the 138 kV lines to facilitate removal of the equipment at Willow Island switching station (b2216).
- Cost Estimate: $2.0 M
- Required IS Date: 12/31/2014.

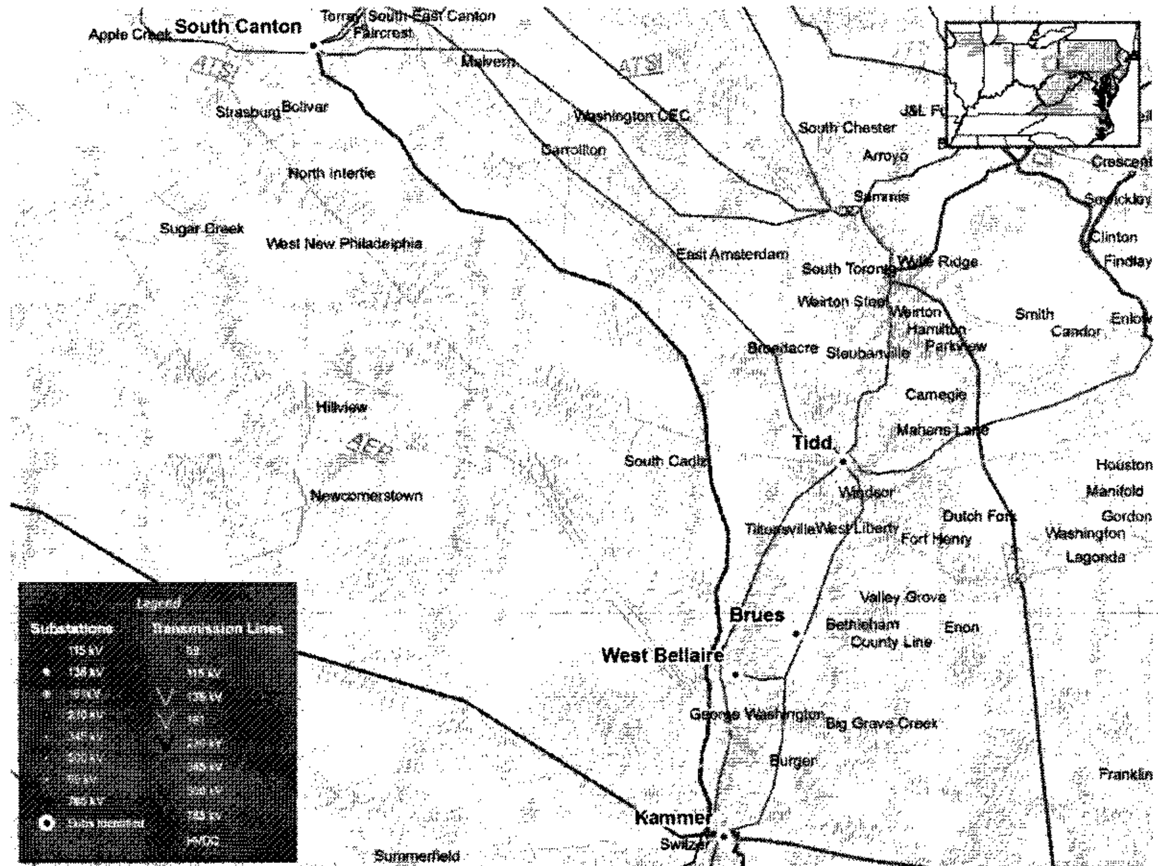


AEP Transmission Zone

- The Brues 138 kV bus section 1-2 is overloaded for the N-1-1 loss of the Kammer – South Canton 765 kV line and South Canton 765/345 kV transformer and South Canton 345/138 kV transformer #4 followed by the loss of the Tidd – West Bellaire 345 kV line.
- Proposed Solution: Upgrade relay at the Brues station (b2055).
- Cost Estimate:

$100 K

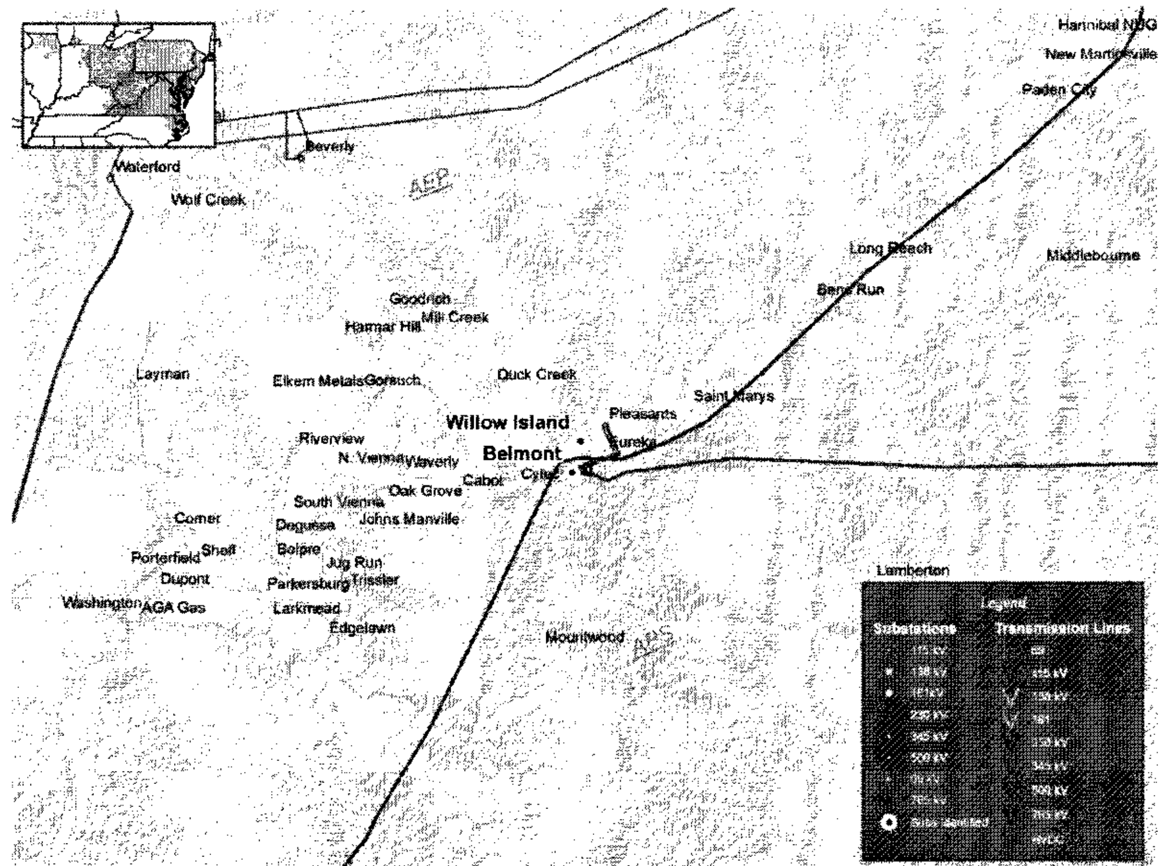
- Required IS Date: 6/1/2015.



AP Transmission Zone

AEP Deactivations - Conesville 3; Big Sandy 1; Clinch River 3; Glen Lyn 5 & 6; Kammer 1-3; Kanawha River 1 & 2; Muskingum River 1-4; Pickway 5; Sporn 1-4; Tanner Creek 1-3

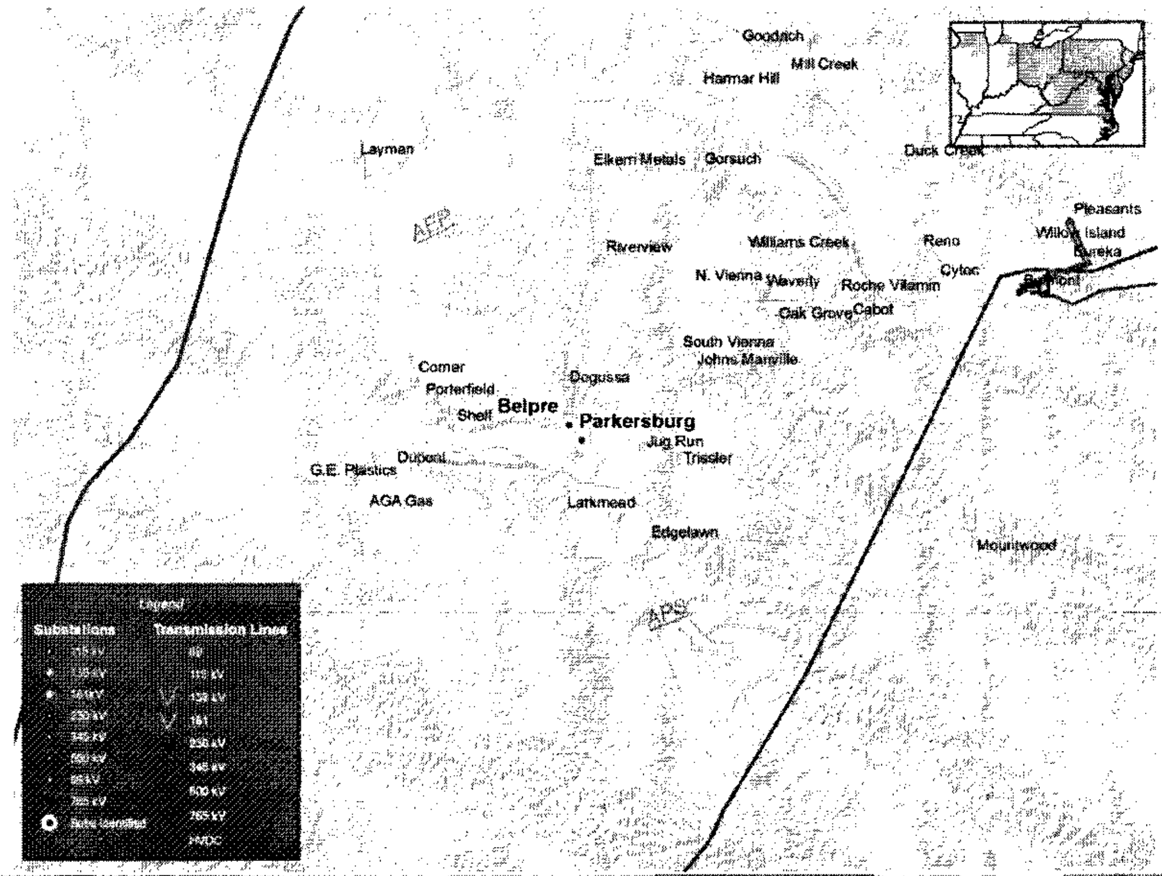
- The Willow Island – Belmont 138 kV line is overloaded for the N-1-1 loss of the Belmont – Kammer 765 kV line followed by the loss of the Belmont - Roche Vitamin 138 kV line.
- The Willow Island – Roche Vitamin - Belmont 138 kV line is overloaded for the N-1-1 loss of the Belmont – Kammer 765 kV line followed by the loss of the Willow Island – Belmont 138 kV line.
- Proposed Solution: Replace wave traps at Willow Island and Belmont to improve both Willow Island - Belmont 138 kV lines (b2116).
- Cost Estimate:
  $150 K
- Required IS Date: 6/1/2015.



AP Transmission Zone

AEP Deactivations - Conesville 3; Big Sandy 1; Clinch River 3; Glen Lyn 5 & 6; Kammer 1-3; Kanawha River 1 & 2; Muskingum River 1-4; Pickway 5; Sporn 1-4; Tanner Creek 1-3

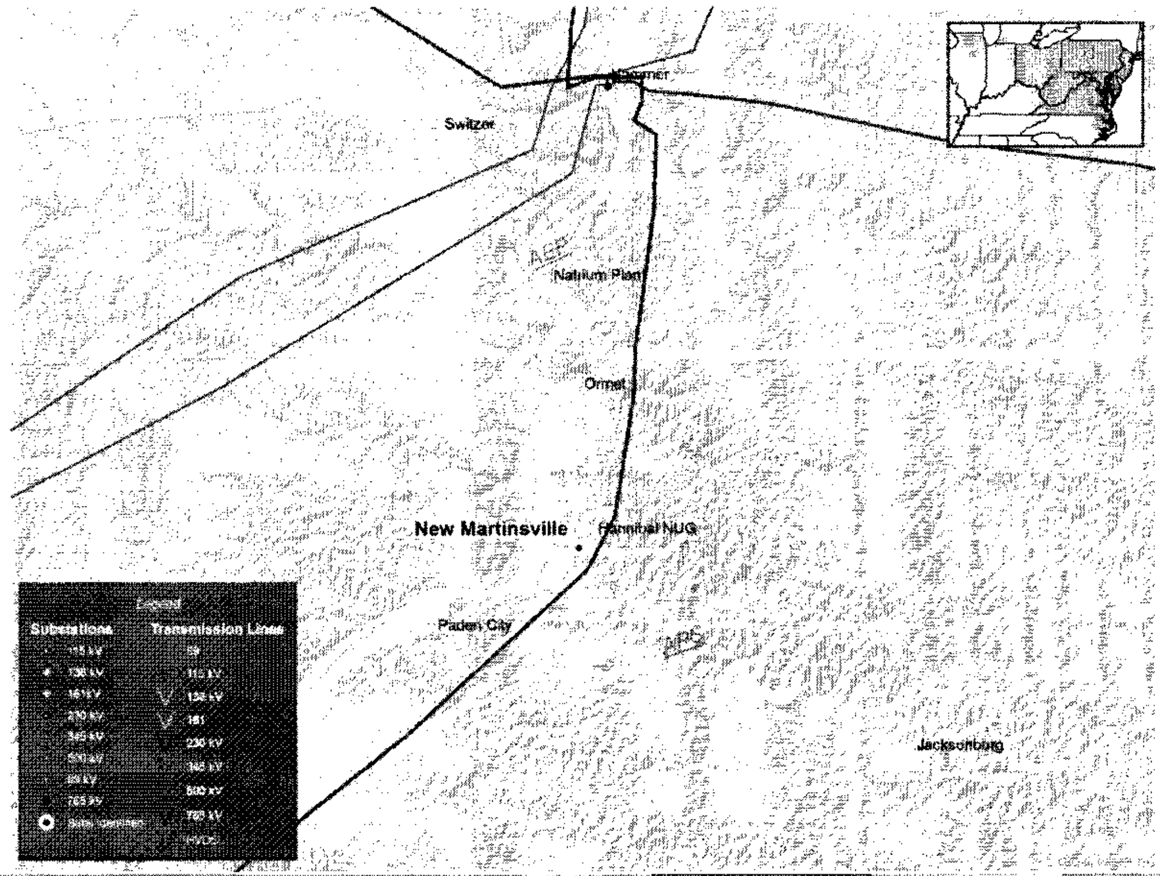
- The Parkersburg – Belpre 138 kV line is overloaded for the N-1-1 loss of the Waverly – Williamstown 138 kV line followed by the loss of the Muskingham River 345/138 kV transformer banks A & B.
- Proposed Solution: Reconductor 1.5 miles of the Parkersburg - Belpre line and upgrade Parkersburg terminal equipment (b2117).
- Cost Estimate:
  $250 K
- Required IS Date: 6/1/2015.



AP Transmission Zone

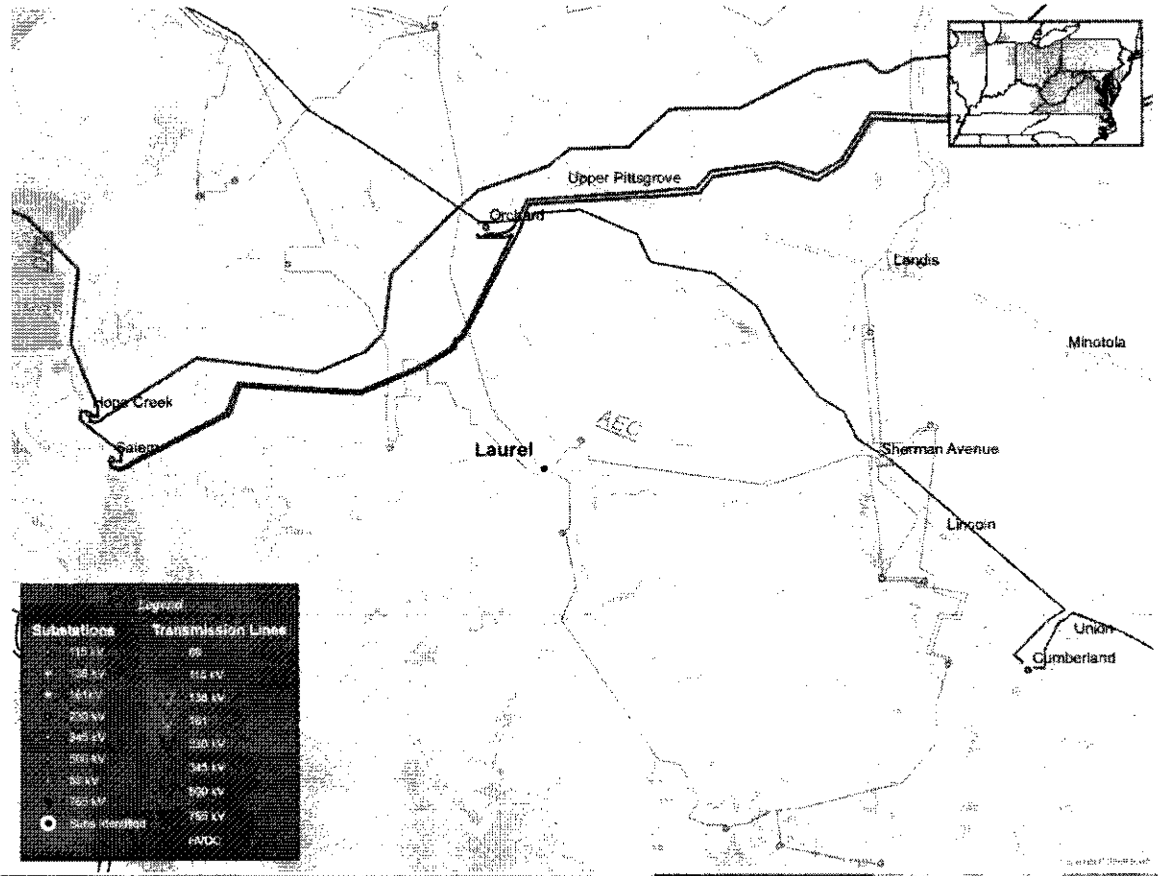
AEP Deactivations - Conesville 3; Big Sandy 1; Clinch River 3; Glen Lyn 5 & 6; Kammer 1-3; Kanawha River 1 & 2; Muskingum River 1-4; Pickway 5; Sporn 1-4; Tanner Creek 1-3

- Low voltage magnitude at the Paden City and New Martinsville 138 kV buses for the N-1-1 loss of the Kammer – Natrium 138 kV line followed by the loss of the Kammer – Ormet 138 kV line.
- Proposed Solution: Add a 44 MVAR Capacitor at New Martinsville (b2118).
- Cost Estimate:
  $1.10 M
- Required IS Date: 6/1/2015.



AE Transmission Zone

- The Carlls Corner - Laurel 69 kV line is overloaded for the tower contingency loss of the BL England – Scull – Mill 138 kV lines #1 and #2.
- Proposed Solution: Upgrade the 69 kV bus at Laurel (b2123).
- Cost Estimate: $175 K
- Required IS Date: 6/1/2015.



Brattle Recommendation – 2017 CETO/CETL Values

Brattle Recommendation

- 2012 RTEP Assumptions
  - Include transmission approved by the PJM Board through December 2012
- 2017 CETO & CETL values from 2012 RTEP
- Limiting facilities identified

Year 2017 RTEP Base Case

2017 RTEP Base Case CETO & CETL Values

Area	MW CETO	MW CETL	CETL/CETO %	Limiting Facility	Violation Type	Limiting Element
AE	1000	> 1500	>150%			
AEP	1470	> 2205	>150%			
APS	1740	> 2610	>150%			
ATSI	5460	7861	144%	Butler - Shanor Manor 138 kV for loss of Cabot - Cranberry 500 kV	Thermal	Terminal Equipment Limited
BGE	4080	5673	139%	Howard - Pumphrey 230 kV Base Case	Thermal	Conductor Limited (cable)
Cleveland	3850	5647	147%	Hanna - Juniper 345 kV for loss of Hanna - Chambers 345 kV	Thermal	Terminal Equipment Limited
ComEd	2610	> 3915	>150%			
Dayton	610	> 915	>150%			
DLCO	1470	> 2205	>150%			
DPL	980	> 1470	>150%			
DPL SOUTH	1550	1832	118%	Wye Mill - Longwood 69 kV for loss of Easton - Steele 138 kV	Thermal	Terminal Equipment Limited
DEOK	3930	4008	102%	Pierce - Beckjord 138 kV for loss of Pierce - Foster 345 kV	Thermal	Terminal Equipment Limited
EKPC	990	> 1485	>150%			
EMAAC	5010	7506	149%	Peach Bottom - Limerick 500 kV for loss of Keeney - Rock Springs 500 kV	Thermal	Terminal Equipment Limited
JCPL	3190	> 4785	>150%			
MAAC	1100	> 1650	>150%			
METED	1310	> 1965	>150%			
PECO	2840	> 4260	>150%			
PENELEC	1210	> 1815	>150%			
PEPCO	2880	> 4320	>150%			
PJM WEST	7010	> 10515	>150%			
PLGRP	1640	> 2460	>150%			
PSEG	4830	6275	130%	Roseland - Cedar Grove "F" 230 kV for loss of Roseland - Cedar Grove "B" 230 kV	Thermal	Conductor Limited
PSEG NORTH	2430	2817	116%	Roseland - Cedar Grove "F" 230 kV for loss of Roseland - Cedar Grove "B" 230 kV	Thermal	Conductor Limited
SWMAAC	4640	> 6960	>150%			
VAP	220	> 330	>150%			
WMAAC	-4010	> -2005	>150%			

Artificial Island

Artificial Island Stability Background

Max generation power output for stable operation is expressed as:

$$P_{max} = (V_t \times E_i) / X_d$$

- V_t is system voltage
  - More is theoretically better, but has operational limits
- E_i is internal machine voltage
- X_d is system impedance
  - Smaller is better

Artificial Island Stability

- Stability Requirements
  - Artificial Island Operating Guide (AIOG)
  - Minimum MVAR output requirements from Hope Creek, Salem 1&2

- Reliability Issues
  - High voltage

Artificial Island Proposal Window

- Goals
  1. System Performance
     - Outage conditions - improve system performance and AI stability margin under N-1 (forced or unforced)
     - Normal conditions - Improve system performance and stability margin under normal system conditions
  2. AIOG
     - Eliminate the AIOG

Pre-Qualification & Timeline

- See Today's Planning Committee Presentations
  - Pre-Qualification Submittal
  - CEII & NDA Requirements
  - Possible window timeline

Artificial Island Proposal Requirements

- Sponsoring entity information
  - Company name, contact information etc.
- Project Description
  - Include scope, interconnection points, configurtion (e.g. overhead, underground, AC/DC etc>), ROW, high level project schedule including CPCN, engineering, construction start, and in-service date
  - Project cost estimate

Artificial Island Proposal Requirements

- Technical Report
  - Include assumptions and calculations demonstrating the efficacy of the project
    - Report should include information about the origin of power flow case and any modifications, station single line drawings and results of any sensitivity studies
    - Modeling information such as conductor type, calculated impedances, contingency files, *.idev files and dynamic files

Artificial Island Case Development

- PJM coordinating development and benchmark of critical system condition cases to the current case
  - Cases will be available in PSS/E v32.1.1 (*.sav format)
  - Power flow case and dynamics data file
  - Other environment files (.snp, .dll and .rsp)

Artificial Island Proposal Window Timeline

Announcement
Today (3/7/2013)
- Announce window and potential timeline
- Request CEII/NDA submittals from anticipated participants
- Request Designated Entity Pre-Qualification

→

Case Development
Estimated 3/8/2013 through 4/5/2013
- Develop and benchmark critical system condition cases

→

Open Window
(60 Day Duration)
- Open the "Artificial Island" RTEP Proposal Window
- Analytical files available

→

Coordinate with Window Participants and Receive Solution Proposals
- Coordination VIA www.pjm.com
- Data, Information
- Questions & Answers

→

Close Proposal Window
(Estimated 6/7/2013)

→

PJM Evaluates Solution Proposals

Next Steps

- Update Artificial Island Proposal window progress
- Finalize 2013 RTEP base case development (2018)
- Finalize 2013 RTEP scenario scope
- Recommend solution package for High Voltage in PJM Operations

Questions?

Email: RTEP@pjm.com

EXHIBIT
35
FES

PENGAD 800-631-6989

2016-2017 RPM Base Residual Auction Planning Parameters — **4/30/2013** — **734653-v6**

Updated on 4/30/2013

	RTO	Notes:
Installed Reserve Margin (IRM)	15.6%	1. Load data: from 2013 Load Report.
Pool-Wide Average EFORd	5.69%	2. Adjustments were made in the Zonal Peak Load Forecast of AEP, DEOK, and EKPC to account for EKPC integration.
Forecast Pool Requirement (FPR)	1.0902	3. See "Net CONE" worksheet for Net CONE calculations.
Demand Resource (DR) Factor	0.955	Planning Parameters were updated on 4/16/2013 to reflect: (1) FRR Elections for which FRR Obligations were satisfied by the 4/13/2013 deadline; (2) increased CETL for SWMAAC, PEPCO and DPL SOUTH LDAs associated with customer-funded upgrades for which ICTR certifications were made by the 3/29/2013 deadline; and (3) 13 MW decrease in EKPC forecast load due to correction of historical load data used in original EKPC load forecast.
Preliminary Forecast Peak Load	165,412.0	
Short-Term Resource Procurement Target	2.5%	
Pre-Clearing BRA Credit Rate, $/MW	**$36,193.04**	Limited DR Reliability Targets revised based on FERC approved alternate methodology (Filing 20121130-er13-486-000).

		LOCATIONAL DELIVERABILITY AREA (LDA)								
	RTO	**MAAC**	**EMAAC**	**SWMAAC**	**PS**	**PS NORTH**	**DPL SOUTH**	**PEPCO**	**ATSI**	**ATSI-Cleveland**
CETO	NA	5,220.0	6,140.0	5,840.0	6,450.0	2,450.0	1,580.0	2,730.0	5,390.0	3,800.0
CETL	NA	6,495.0	8,916.0	8,786.0	6,581.0	2,936.0	1,901.0	6,846.0	7,881.0	5,245.0
Reliability Requirement	180,332.2	72,299.0	39,694.0	17,316.0	12,870.0	6,440.0	3,160.0	9,012.0	16,255.0	6,164.0
Total Peak Load of FRR Entities	13,029.4	0	0	0	0	0	0	0	0	0
Preliminary FRR Obligation	14,204.7	0	0	0	0	0	0	0	0	0
Reliability Requirement adjusted for FRR	**166,127.5**	**72,299.0**	**39,694.0**	**17,316.0**	**12,870.0**	**6,440.0**	**3,160.0**	**9,012.0**	**16,255.0**	**6,164.0**
Short-Term Resource Procurement Target	4,153.2	1,664.7	907.6	384.0	288.9	140.1	66.5	185.3	362.4	124.3
Net CONE, $/MW-Day (UCAP Price)	**$330.53**	**$276.90**	**$329.94**	**$276.90**	**$329.94**	**$329.94**	**$329.94**	**$276.90**	**$362.64**	**$362.64**
Variable Resource Requirement Curve:										
Point (a) UCAP Price, $/MW-Day	$495.80	$415.35	$494.91	$415.35	$494.91	$494.91	$494.91	$415.35	$543.96	$543.96
Point (b) UCAP Price, $/MW-Day	$330.53	$276.90	$329.94	$276.90	$329.94	$329.94	$329.94	$276.90	$362.64	$362.64
Point (c) UCAP Price, $/MW-Day	$66.11	$55.38	$65.99	$55.38	$65.99	$65.99	$65.99	$55.38	$72.53	$72.53
Point (a) UCAP Level, MW	157,663.0	68,758.0	37,756.3	16,482.7	12,247.1	6,132.8	3,011.5	8,592.8	15,470.8	5,879.7
Point (b) UCAP Level, MW	163,411.4	71,259.7	39,129.8	17,081.8	12,692.4	6,355.6	3,120.9	8,904.6	16,033.3	6,093.0
Point (c) UCAP Level, MW	169,159.7	73,761.4	40,503.3	17,681.0	13,137.8	6,578.4	3,230.2	9,216.5	16,595.7	6,306.3
Customer-Funded ICTRs Awarded	NA	159.0	NA	444.0	NA	NA	37.0	191.0	NA	NA
Min Ext Summer Resource Req'ment, MW	158,512.2	62,179.2	28,559.2	7,503.3	5,483.4	3,113.3	1,114.3	1,712.9	7,668.1	676.8
Min Annual Resource Req'ment, MW	149,469.1	58,109.3	24,606.9	6,183.2	4,214.2	2,503.1	903.5	750.0	6,200.8	0.0
FRR Load Requirements:										
Min % Internal Resource Req'ment	NA	98.8%	84.8%	55.5%	54.4%	62.5%	47.4%	29.2%	57.8%	18.5%
Min % Ext Summer Resource Req'ment	95.0%	86.0%	71.9%	43.3%	42.6%	48.3%	35.3%	19.0%	47.2%	11.0%
Min % Annual Resource Req'ment	89.1%	80.4%	62.0%	35.7%	32.7%	38.9%	28.6%	8.3%	38.1%	0.0%

LDA CETO/CETL Data; Zonal Peak Loads, Base Zonal FRR Scaling Factors, and Zonal Short-Term Resource Procurement Target.

*** (Asterisk) – LDA has adequate internal resources to meet the reliability criterion.**

ATSI, DPL and PS Zonal peak loads and Short-Term Resource Procurement Targets include the corresponding sub-zonal values.

LDA/Zone	CETO	CETL (Changes shown in red)	CETL to CETO Ratio	2012 Zonal W/N Coincident Peak Loads	Preliminary Zonal Peak Load Forecast	Base Zonal FRR Scaling Factor	Short-Term Resource Procurement Target	FRR Portion of the Preliminary Peak Load Forecast	Preliminary Zonal Peak Load Forecast less FRR load**
RTO	*NA*	*NA*	*NA*	***154,501.8***	***165,412.0***	*NA*	***4,153.2***	***13,029.4***	***152,382.6***
AE	1,030	> 1185	> 115%	2,600.0	2,782.0	1.07000	75.8	0	2,782.0
AEP	2,110	> 2427	> 115%	22,663.9	24,007.6	1.05929	324.5	12,102.3	11,905.3
APS	1,970	> 2266	> 115%	8,210.0	8,786.0	1.07016	239.5	0	8,786.0
ATSI	5,390	7,881	146%	12,660.0	13,295.0	1.05016	362.4	0	13,295.0
ATSI-CLEVELAND	3,800	5,245	138%	NA	4,562.3	NA	124.3	0	4,562.3
BGE	5,130	> 5900	> 115%	6,870.0	7,288.0	1.06084	198.6	0	7,288.0
COMED	1,330	> 1530	> 115%	21,650.0	23,504.0	1.08564	640.6	0	23,504.0
DAYTON	960	> 1104	> 115%	3,230.0	3,556.0	1.10093	96.9	0	3,556.0
DEOK	3,800	> 4370	> 115%	5,246.5	5,572.2	1.06208	127.5	894.4	4,677.8
DLCO	1,350	> 1553	> 115%	2,800.0	2,996.0	1.07000	81.7	0	2,996.0
DOM	-70	*	*	18,570.0	20,415.0	1.09935	556.4	0	20,415.0
DPL	1,000	> 1150	> 115%	3,950.0	4,212.0	1.06633	114.8	0	4,212.0
DPL SOUTH	1,580	1,901	120%	NA	2,438.7	NA	66.5	0	2,438.7
EKPC	580	> 667	> 115%	2,096.4	2,200.2	1.04951	59.1	32.7	2,167.5
JCPL	3,300	> 3795	> 115%	5,960.0	6,381.0	1.07064	173.9	0	6,381.0
METED	1,170	> 1346	> 115%	2,820.0	3,068.0	1.08794	83.6	0	3,068.0
PECO	2,860	> 3289	> 115%	8,320.0	8,908.0	1.07067	242.8	0	8,908.0
PENLC	1,300	> 1495	> 115%	2,740.0	3,044.0	1.11095	83.0	0	3,044.0
PEPCO	2,730	6,846	251%	6,540.0	6,800.0	1.03976	185.3	0	6,800.0
PL (incl. UGI)	1,360	> 1564	> 115%	7,075.0	7,581.0	1.07152	206.6	0	7,581.0
PS	6,450	6,581	102%	10,100.0	10,600.0	1.04950	288.9	0	10,600.0
PS NORTH	2,450	2,936	120%	NA	5,141.0	NA	140.1	0	5,141.0
RECO	NA	NA	NA	400.0	416.0	1.04000	11.3	0	416.0
EMAAC	6,140	8,916	145%	NA	33,299.0	NA	907.6	0	** Used to allocate Short-Term Resource Procurement Target to Zones.
SWMAAC	5,840	8,786	150%	NA	14,088.0	NA	384.0	0	
Western MAAC	-3,840	*	*	NA	13,693.0	NA	373.2	0	
MAAC	5,220	6,495	124%	NA	61,080.0	NA	1,664.7	0	
Western PJM	5,940	> 6831	> 115%	NA	83,917.0	NA	1,932.0	13,029.4	

Limiting conditions at the CETL for modeled LDAs:

LDA	Violation/Limiting Facility
MAAC	Thermal/Sandy Springs-High Ridge 230 kV
EMAAC	Voltage/Loss of Keeney - Rock Springs 500 kV
SWMAAC	Thermal/Graceton - Bagley 230 kV
PS	Thermal/Roseland - Cedar Grove 230 kV F
PSNORTH	Thermal/Cedar Grove F - Clifton K 230 kV line
DPLSOUTH	Thermal/Easton - Trappe Tap 69 kV
PEPCO	Thermal/Conastone - Northwest 230 kV
ATSI	Thermal/*Ashtabula* 345/138 kV *transformer*
ATSI-CLEVELAND	Thermal/Ashtabula 345/138 kV transformer

EXHIBIT 36 FES

PENGAD 800-631-6989

2014-2015 RPM Base Residual Auction Planning Parameters with FRR Adjustments						5/11/2011	626190v9	
See notes below for summary of updates made to parameters originally posted on 2/1/11.								

	RTO	Notes:
Installed Reserve Margin (IRM)	15.3%	1. Load data: from 2011 Load Report, adjusted for Non-Zone Load.
Pool-Wide Average EFORd	6.25%	2. See "Net CONE" worksheet for Net CONE calculations.
Forecast Pool Requirement (FPR)	1.0809	3. New Fixed Resource Requrement (FRR) elections were made in DEOK Zone on 3/2/11.
Demand Resource (DR) Factor	0.956	4. Reliability Requirement and Short-Term Resource Procurement Target are reduced due to FRR elections.
Preliminary Forecast Peak Load	164,757.6	
Short-Term Resource Procurement Target	2.5%	
Pre-Clearing BRA Credit Rate, $/MW	$37,474	

		LOCATIONAL DELIVERABILITY AREA (LDA)						
	RTO	MAAC	EMAAC	SWMAAC	PS	PS NORTH	DPL SOUTH	PEPCO
CETO	NA	2,020.0	5,790.0	5,420.0	4,880.0	2,110.0	1,410.0	3,500.0
CETL	NA	5,694.0	8,189.0	7,718.5	5,720.7	2,372.0	1,925.0	5,606.3
Reliability Requirement	178,086.5	72,187.0	39,995.0	17,358.0	13,099.0	6,211.0	3,018.0	8,951.0
Total Peak Load of FRR Entities	27,535.8	0	0	0	0	0	0	0
Preliminary FRR Obligation	**29,763.4**	0	0	0	0	0	0	0
Reliability Requirement adjusted for FRR	**148,323.1**	**72,187.0**	**39,995.0**	**17,358.0**	**13,099.0**	**6,211.0**	**3,018.0**	**8,951.0**
Short-Term Resource Procurement Target	3,708.1	1,667.3	910.1	389.2	294.6	134.0	64.0	189.1
Net CONE, $/MW-Day (UCAP Price)	**$342.23**	**$241.91**	**$275.02**	**$241.91**	**$275.02**	**$275.02**	**$275.02**	**$241.91**
Variable Resource Requirement Curve:								
Point (a) UCAP Price, $/MW-Day	$513.35	$362.87	$412.53	$362.87	$412.53	$412.53	$412.53	$362.87
Point (b) UCAP Price, $/MW-Day	$342.23	$241.91	$275.02	$241.91	$275.02	$275.02	$275.02	$241.91
Point (c) UCAP Price, $/MW-Day	$68.45	$48.38	$55.00	$48.38	$55.00	$55.00	$55.00	$48.38
Point (a) UCAP Level, MW	140,755.8	68,641.5	38,044.3	16,517.2	12,463.6	5,915.4	2,875.5	8,529.1
Point (b) UCAP Level, MW	145,901.4	71,145.8	39,431.8	17,119.4	12,918.0	6,130.8	2,980.2	8,839.6
Point (c) UCAP Level, MW	151,047.1	73,650.1	40,819.3	17,721.6	13,372.5	6,346.3	3,084.9	9,150.1
Participant-Funded ICTRs Awarded	NA	159.0	NA	NA	NA	NA	NA	NA
Post-Clearing BRA Credit Rate (LMT), $/MW	$ 9,159.31	$ 9,159.31	$ 9,159.31	$ 9,159.31	$ 9,159.31	$ 15,619.81	$ 9,159.31	$ 9,159.31
Post-Clearing BRA Credit Rate (ES), $/MW	$ 9,197.27	$ 9,964.50	$ 9,964.50	$ 9,964.50	$ 9,964.50	$ 16,425.00	$ 9,964.50	$ 9,964.50
Post-Clearing BRA Credit Rate (ANL), $/MW	$ 9,197.27	$ 9,964.50	$ 9,964.50	$ 9,964.50	$ 9,964.50	$ 16,425.00	$ 9,964.50	$ 9,964.50
Min Ext Summer Resource Req'ment, MW	137,808.8	61,255.3	28,773.1	8,402.1	6,374.1	3,382.1	887.0	2,729.1
Min Annual Resource Req'ment, MW	128,450.2	57,748.7	25,397.4	7,152.1	4,977.3	2,813.2	654.4	1,897.8
FRR Load Requirements:								
Min % Internal Resource Req'ment	NA	99.7%	87.4%	61.9%	62.6%	71.6%	42.7%	44.2%
Min % Ext Summer Resource Req'ment	95.4%	NA	NA	NA	NA	NA	NA	NA
Min % Annual Resource Req'ment	89.1%	NA	NA	NA	NA	NA	NA	NA

LDA CETO/CETL Data; Zonal Peak Loads, Base Zonal FRR Scaling Factors, and Zonal Short-Term Resource Procurement Target.

*** (Asterisk) – LDA has adequate internal resources to meet the reliability criterion.**

DPL and PS Zonal peak loads and Short-Term Resource Procurement Targets include the corresponding DPL SOUTH and PS NORTH values.

LDA/Zone	CETO	CETL	*CETL to* CETO Ratio	2010 Zonal W/N *Coincident* Peak Loads	Preliminary *Zonal Peak* Load Forecast	Base Zonal *FRR Scaling* Factor	Short-Term Resource *Procurement* Target	FRR Portion of the Preliminary Peak Load Forecast	Zonal Peak Load Forecast less FRR load **
RTO	NA	NA	NA	**152,947.0**	**164,757.6**	NA	**3,708.1**	**27,535.8**	**137,221.8**
AE	1,440	> 1656	> 115%	2,550.0	2,773.0	1.08745	74.9	0.0	2,773.0
AEP	*	*	NA	22,460.0	24,273.0	1.08072	62.2	21,972.8	2,300.2
APS	270	> 311	> 115%	8,280.0	8,639.0	1.04336	233.4	0.0	8,639.0
ATSI	3,670	> 4221	> 115%	12,600.0	13,542.0	1.07476	365.9	0.0	13,542.0
BGE	4,190	> 4819	> 115%	7,080.0	7,405.0	1.04590	200.1	0.0	7,405.0
COMED	1,980	> 2277	> 115%	21,580.0	23,649.0	1.09588	639.1	0.0	23,649.0
DAYTON	730	> 840	> 115%	3,340.0	3,564.0	1.06707	96.3	0.0	3,564.0
DEOK (adjusted for Non-Zone Load)	2,630	> 3025	> 115%	5,267.0	5,811.6	1.10340	6.7	5,563.0	248.6
DLCO	1,030	> 1185	> 115%	2,800.0	2,961.0	1.05750	80.0	0.0	2,961.0
DOM	690	> 794	> 115%	18,960.0	20,618.0	1.08745	557.2	0.0	20,618.0
DPL	1,260	> 1449	> 115%	3,900.0	4,121.0	1.05667	111.4	0.0	4,121.0
DPL SOUTH	1,410	**1,925.0**	137%	NA	2,369.2	NA	64.0	0.0	2,369.2
JCPL	3,890	> 4474	> 115%	6,080.0	6,539.0	1.07549	176.7	0.0	6,539.0
METED	510	> 587	> 115%	2,720.0	3,051.0	1.12169	82.4	0.0	3,051.0
PECO	2,680	> 3082	> 115%	8,270.0	8,911.0	1.07751	240.8	0.0	8,911.0
PENLC	730	> 840	> 115%	2,630.0	2,986.0	1.13536	80.7	0.0	2,986.0
PEPCO	3,500	**5,606.3**	160%	6,730.0	6,996.0	1.03952	189.1	0.0	6,996.0
PL (incl. UGI)	390	> 449	> 115%	6,950.0	7,584.0	1.09122	204.9	0.0	7,584.0
PS	4,880	**5,720.7**	117%	10,340.0	10,901.0	1.05426	294.6	0.0	10,901.0
PS NORTH	2,110	**2,372.0**	112%	NA	4,960.0	NA	134.0	0.0	4,960.0
RECO	NA	NA	NA	410.0	433.0	1.05610	11.7	0.0	433.0
EMAAC	5,790	**8,189.0**	141%	NA	33,678.0	NA	910.1	0.0	** Used to allocate Short-Term Resource Procurement Target to Zones.
SWMAAC	5,420	**7,718.5**	142%	NA	14,401.0	NA	389.2	0.0	
Western MAAC	*	*	NA	NA	13,621.0	NA	368.1	0.0	
MAAC	2,020	**5,694.0**	282%	NA	61,700.0	NA	1,667.3	0.0	
Western PJM	*	*	NA	NA	82,439.6	NA	1,483.6	27,535.8	

Limiting conditions at the CETL for modeled LDAs

LDA	Limiting Facility
MAAC	Meadow Brook 500 kV
EMAAC	Rock Springs - Keeney 500 kV line
SWMAAC	Pleasant View - Edwards Ferry 230 kV line
PS, PSNORTH	Cedar Grove F - Clifton K 230 kV line
DPLSOUTH	Easton - Trappe 69 kV line
PEPCO	Pleasant View - Edwards Ferry 230 kV line