BEFORE THE NEW MEXICO PUBLIC REGULATION COMMISSION

IN THE MATTER OF THE APPLICATION OF PUBLIC SERVICE COMPANY OF NEW MEXICO FOR REVISION OF ITS RETAIL ELECTRIC RATES PURSUANT TO ADVICE NOTICE NO. 513	)	**Case No. 15-00261-UT**
PUBLIC SERVICE COMPANY OF NEW MEXICO,	)	
Applicant	)	

DIRECT TESTIMONY AND EXHIBITS

OF

DR. AHMAD FARUQUI

August 27, 2015

NMPRC CASE NO. 15-00261-UT
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WITNESS FOR
PUBLIC SERVICE COMPANY OF NEW MEXICO

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NMPRC CASE NO. 15-00261-UT

I. INTRODUCTION AND QUALIFICATIONS

Q. PLEASE STATE YOUR NAME AND OCCUPATION.

A. My name is Ahmad Faruqui. I am a Principal with *The Brattle Group* ("Brattle"), located at Suite 2800, 201 Mission Street, San Francisco, CA 94105.

Q. ON WHOSE BEHALF ARE YOU SUBMITTING THIS TESTIMONY?

A. I am submitting this testimony on behalf of Public Service Company of New Mexico ("PNM"), which is a subsidiary of PNM Resources, Inc.

Q. WHAT IS YOUR EXPERIENCE IN ELECTRIC UTILITY MATTERS?

A. I am an economist with 35 years of research and consulting experience. During my career, I have advised several dozen utilities, private energy companies, technology providers, transmission system operators, regulatory commissions and government agencies in the United States and in Australia, Canada, Chile, Egypt, Hong Kong, Jamaica, Philippines, Saudi Arabia, South Africa, and Vietnam on a wide range of customer-side issues including sales and peak demand forecasting, demand response, energy efficiency, rate design, integrated resource planning, and the use of demand-side resources to facilitate the integration of retail and wholesale markets. I have testified or appeared before a dozen state and provincial regulatory commissions and legislative bodies. My load forecasting expertise consists of three areas: first, developing and reviewing models used to forecast energy consumption, peak demand, and hourly load shapes; second, evaluating data used in model estimation; and, third, assessing the accuracy of model-based forecasts and the usefulness of the ways in which they are communicated to internal and external users of the forecast. In my career, I have contributed to the development of new approaches to demand forecasting including econometric, time series, end-use, load shape, and hybrid econometric end-use models. Industrial sales forecasting was the focus of my doctoral dissertation at the University of California at Davis, which was developed while I worked as an analyst in the Demand Assessments office at the California Energy Commission. Later, I managed the end-use analysis and forecasting research program at the Electric Power Research Institute which saw the development of a wide range of forecasting models for residential, commercial and industrial customers. I hold a doctorate in economics from the University of California at Davis, where I was a Regents Fellow, and bachelor's and master's degrees in economics from the University of Karachi, where I was awarded the Rashid Minhas Gold Medal. A summary of my professional and educational qualifications – including my experience testifying on demand forecasting issues, publications, and presentations – is provided as PNM Exhibit AF-1.

Q. WHAT WAS YOUR ASSIGNMENT FROM PNM, AND WHAT DID YOU DO?

A. My assignment was to develop model-based sales forecasts for PNM's Residential, Small Power, General Power, Large Power (excluding some large customers), and Irrigation rate classes.[1] These classes collectively accounted for 81 percent of total billed sales in 2014.[2] I led a team of forecasting specialists at Brattle, PNM, and the Applied Energy Group ("AEG") to develop PNM's sales forecast for the future test year ("FTY"), October 1, 2015-September 30, 2016. My goal was to ensure that the forecasts would be accurate and robust and to utilize the best available data sources and econometric methodologies.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY IN THIS PROCEEDING?

A. My testimony serves two purposes: first, to present the FTY sales forecast and second, to explain how the forecast was constructed. I understand that PNM will rely on the FTY sales forecast to develop its billing determinants for its rate design proposals.

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[1] The rate classes are: Rate 1A – Residential Service ("Rate 1A"), Rate 1B - Residential Service Time-of-Use Rate ("Rate 1B"), Rate 2A – Small Power Service ("Rate 2A"), Rate 2B - Small Power Service Time-of-Use ("Rate 2B"), Rate 3B - General Power Service Time-of-Use ("Rate 3B"), Rate 3C - General Power Service (Low Load Factor) Time-of-Use ("Rate 3C"), Rate 4B - Large Power Service Time-of-Use ("Rate 4B"), Rate 10A - Irrigation Service ("Rate 10A"), and Rate 10B - Irrigation Service Time-of-Use ("Rate 10B").

Rate 4B includes some large customers that are individually forecasted rather than econometrically forecasted. In 2014, 47 percent of sales in Rate 4B were individually forecasted.

In my testimony, Rate 33B - Large Service for Station Power ("Rate 33B"), which was implemented in May 2015, is included in Rate 3B/3C.

[2] In 2014, approximately 8.6 percent of total sales were Unbilled and Economy Service. Both Unbilled and Economy Service sales are excluded from the results that I report in my testimony.

In the process of developing the forecast for this rate case, I also developed sales forecasts through December 31, 2021.

Q. HOW IS YOUR TESTIMONY ORGANIZED?

A. My testimony is organized in five sections. First, I give a high-level overview of PNM's sales forecast and my approach to developing the forecast. Second, I explain the process of model specification and estimation for the rate classes that are econometrically forecasted. Third, I describe the post-estimation adjustments for governmentally mandated Codes and Standards, PNM's Energy Efficiency ("EE") programs, and PNM's Distributed Generation ("DG") program. Fourth, I present the forecasts through 2021. Lastly, I highlight the main points of my testimony and present tables of total sales, use per customer ("UPC"), and number of customers between 2013 and 2016.

Q. CAN YOU PROVIDE A BREAKDOWN OF THE RELATIVE PERCENTAGES OF TOTAL BILLED SALES BY THE VARIOUS RATE CLASSES?

A. In 2014, Residential, Small Power, General Power, Large Power (excluding some large customers), and Irrigation rate classes made up 81.4 percent of total sales. The remaining 18.6 percent of sales consisted of large customers[3], which

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[3] Large customers include other large customers in Rate 4B - Large Power Service Time-of-Use ("Rate 4B"), Rate 5B - Large Service for Customers ≥ 8,000 kW Minimum at 115kV, 69kV and 34.5kV ("Rate 5B"), Rate 15B - Large Service for Public Universities ≥ 8,000 kW Minimum with

represented 15.4 percent, and lighting and public goods[4], which represented 3.2 percent.

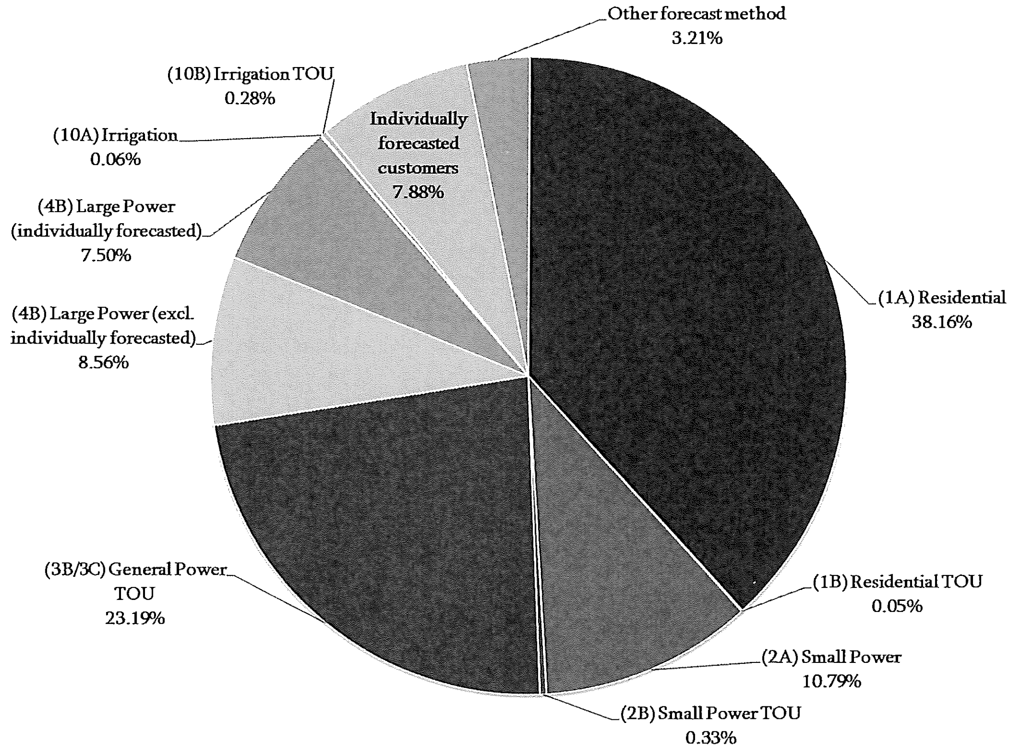
Q. HAVE YOU PREPARED A CHART THAT SHOWS THE ALLOCATION OF PNM'S BILLED SALES BY RATE CLASS?

A. Figure AF-1 shows the allocation of PNM's total billed sales in calendar year 2014 by rate class. As noted above, the subset of rate classes that are the focus of my econometric analysis comprise 81 percent of total sales. Within this subset of rate classes, Non-residential customers (Rates 2A, 2B, 3B, 3C and 4B) are 53 percent of the sales while the remaining 47 percent are almost entirely attributable to the Rates 1A and 1B. The contributions to total sales of Rates 1B, 2B, 10A, and 10B are dwarfed by that of Rates 1A, 2A, 3B & 3C, and 4B.

Customer-Owned Generation Facilities Served at 115 kV ("Rate 15B"), and Rate 30B - Large Service for Manufacturing for Service ≥ 30,000 kW Minimum at Distribution Voltage ("Rate 30B").

4 Lighting and public goods include Rate 6 - Private Area Lighting ("Rate 6"), Rate 11B - Water and Sewage Pumping Service Time-of-Use-Rate ("Rate 11B"), and Rate 20 - Integrated System Streetlighting and Floodlighting Service New Installations ("Rate 20").

Figure AF-1: Total Billed Sales in 2014, by Rate Class



Source: Public Service Company of New Mexico (July 2015)
Notes: "TOU" stands for Time-of-Use. "Individually forecasted" includes Rate 5B, Rate 15B, and Rate 30B. "Other forecast method" includes some of Rate 2A (Cable TV, Temporary Service, Traffic Signals), Rate 6, Rate 11B, and Rate 20.

Q. IS ANY OTHER PNM WITNESS PRESENTING TESTIMONY OF SALES FORECASTING ISSUES?

A. No. However, my forecast serves as the basis for the billing determinants used in the rate design testimony of PNM Witness Chan.

Q. HOW DO ELECTRIC UTILITY COMPANIES FORECAST ELECTRICITY SALES?

A. The process begins by specifying the factors that drive electricity sales. Such factors include economic growth, income, population growth, weather conditions, price of electricity, EE, DG, and governmental Codes & Standards. Sales forecasts are often made at the rate class level. For some customer classes, sales are forecasted indirectly, that is, as the product of use per customer ("UPC") and the number of customers. For other classes, sales are forecasted directly. In many cases, econometric methods are used to quantify the relationship between sales and the driving factors by rate class. This often requires the collection of monthly data on sales and the driving factors going back several years. Different model specifications are then estimated over this database using standard econometric methods. The model that fits the data best is selected. For very large customers, sales may be individually forecasted using information provided by the customers themselves.

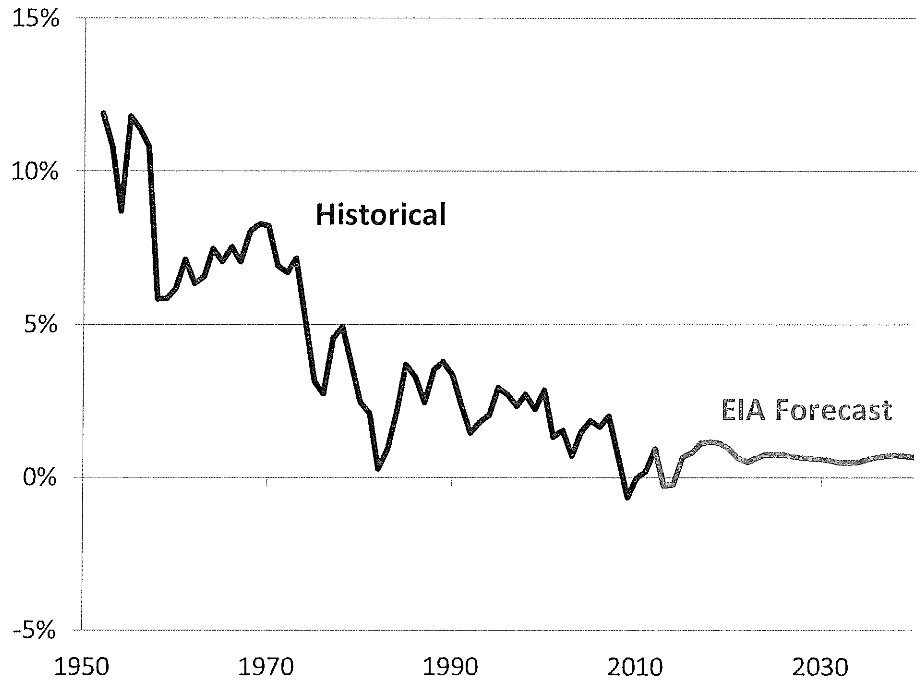
Q. DID YOU FOLLOW THIS PROCESS WHEN DEVELOPING PNM'S SALES FORECASTS?

A. Yes, I followed this process, as detailed later in my testimony.

Q. CAN YOU DESCRIBE THE NATIONAL TRENDS IN SALES FORECASTS?

A. U.S. electricity sales growth slowed during the Great Recession of 2008-09. The U.S. Energy Information Administration ("EIA") has been tracking sales growth going back several decades. This is shown in Figure AF-2 below.

Figure AF-2: U.S. Electricity Sales Growth (3 year rolling average)



Source: *EIA, 2015 Annual Energy Outlook and 2014 Annual Energy Review.*

EIA predicts that growth will remain below one percent per year in the future. Drawing upon my inquiries with two dozen forecasters at a cross-section of electric utilities, I published an article in the December 2012 edition of the *Public Utilities Fortnightly* about the issue that utility sales forecasting models are consistently over-forecasting sales. I have also presented these ideas concerning over-forecasting at conferences sponsored by Goldman Sachs, PJM Interconnection, and the Eastern Interconnect State's Planning Conference.

Q. HOW HAS "THE GREAT RECESSION OF 2008-09" AFFECTED ELECTRICITY SALES FOR PNM?

A. According to the Bureau of Business and Economic Research ("BBER") at the University of New Mexico ("UNM"), the economic recession was severe and more persistent in New Mexico than most other states. Between October 2009 and September 2014, New Mexico ranked 48th in employment growth. Even as the U.S. economy showed signs of recovery after 2009, New Mexico's economy "moved reliably sideways."[5]

New Mexico's depressed economy through 2014 and the expansion of EE initiatives put downward pressure on PNM's sales. Similar to other utilities, PNM's previous forecasts overestimated sales in the near future. For PNM and the electric utility industry as a whole, underestimating the persistence of the recession and future growth in EE were two key reasons for over-forecasting.

Q. WHAT ARE YOUR MAIN CONCLUSIONS FOR PNM'S SALES FORECAST IN 2016?

A. My conclusions are summarized in Table AF-1, which reports total sales in 2013 through 2016 and the corresponding year-on-year growth rates.[6] The results are presented for the subset of rate classes that form the core of my analysis. In Table AF-1, individually and econometrically forecasted Large Power are summed

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[5] See page 1 of "FOR-UNM: A Quarterly Economic Forecast of the New Mexico Economy, April 2015 Through 2020:4"

[6] In Table AF-1, I report actual sales in 2013 and 2014, which are the latest full calendar years at the time of writing this testimony. For 2015, annual sales are composed of actual sales from January-March and forecasted sales from April-December.

together as Rate 4B.[7] Thus, total sales for the subset of rate classes are 89 percent of the grand total in 2014.

Table AF-1: Summary of PNM Sales Forecast

	% of Total Sales in 2014	Actual, in GWh 2013	Actual, in GWh 2014	Forecast, in GWh 2015	Forecast, in GWh 2016
1A Residential	38.16%	3290.4	3161.5	3216.5	3183.7
1B Residential Time-of-Use	0.05%	4.1	3.7	3.7	3.7
2A Small Power	10.79%	916.8	893.8	902.7	879.6
2B Small Power Time-of-Use	0.33%	27.3	27.5	27.9	27.7
3B/3C General Power	23.19%	1933.9	1921.1	1941.4	1923.5
4B Large Power	16.06%	1364.1	1330.2	1232.2	1212.1
10A Irrigation	0.06%	4.8	4.8	4.7	4.7
10B Irrigation Time-of-Use	0.28%	21.2	22.8	22.0	21.6
Subtotal	88.91%	7562.8	7365.7	7351.1	7256.6
Other Rates	11.09%	1015.0	918.7	962.7	1002.3
Grand total (excluding unbilled)	100.00%	8577.7	8284.4	8313.7	8258.9

	% of Total Sales in 2014	Average YoY % change, 2013-2016	Year-on-year percent change 2013-2014	Year-on-year percent change 2014-2015	Year-on-year percent change 2015-2016
1A Residential	38.16%	-1.1%	-3.9%	1.7%	-1.0%
1B Residential Time-of-Use	0.05%	-2.9%	-8.6%	-0.6%	0.6%
2A Small Power	10.79%	-1.4%	-2.5%	1.0%	-2.6%
2B Small Power Time-of-Use	0.33%	0.5%	0.7%	1.3%	-0.7%
3B/3C General Power	23.19%	-0.2%	-0.7%	1.1%	-0.9%
4B Large Power	16.06%	-3.8%	-2.5%	-7.4%	-1.6%
10A Irrigation	0.06%	-0.8%	-0.3%	-2.3%	0.3%
10B Irrigation Time-of-Use	0.28%	0.7%	7.6%	-3.9%	-1.7%
Subtotal	88.91%	-1.4%	-2.6%	-0.2%	-1.3%
Other Rates	11.09%	-0.2%	-9.5%	4.8%	4.1%
Total	100.00%	-1.2%	-3.4%	0.4%	-0.7%

Source: Actual sales in 2013, 2014, and January-March 2015 are provided by Public Service Company of New Mexico (July 2015)

Notes: For 2015, annual sales are based on actual sales from January-March and forecasted sales from April-December. Other Rates include some of Rate 2A (Cable TV, Temporary Service, Traffic Signals) and Rates 5B, 6, 11B, 15B, 20, and 30B. Beginning in April 2015, the proposed Rate 35B is classified under "Other Rates." Unbilled and Economy Service are excluded from the grand total.

[7] I understand that a new proposed rate class, Rate 35B – Large Power Service >= 3,000kW ("Rate 35B"), will comprise of some customers from Rate 4B. After April 2015 (inclusive), I do not include sales for the proposed Rate 35B in sales for Rate 4B. Instead, the proposed Rate 35B is included in Other Rates.

Across all rate classes, PNM's sales are expected to fall by approximately 3.7 percent between 2013 and 2016. On average, sales fell by 1.2 percent from year to year. The average masks that most of the decline occurred between 2013 and 2014, which are the last two full years of actual data. The year-to-year growth rate between 2013 and 2014 was -3.4 percent. From 2014 through 2016, total sales are expected to hover around 8,300 GWh. For the subset of rate classes that I analyzed, total sales declined by 4.0 percent over the same period, and again, much of the decline occurred between 2013 and 2014. Sales decreased in most rate classes. The exceptions – Rates 2B and 10B – are small in terms of shares of total sales (less than 1 percent).

In most customer classes, the sales forecast is the product of the number of customers forecasted and forecasted UPC. Thus, the decline in sales can be driven by fewer customers or lower UPC. The forecast indicates that, with the exception of Rates 1B and 4B, the number of customers will remain flat or modestly increase. Between 2013 and 2016, UPC dips for most rate classes except Rates 2B and 10B. For Residential and Non-residential customers, increasing savings from new EE initiatives and governmental Codes & Standards are the primary drivers of the decline. The fact that EE is a key driver behind the slowdown in electricity sales has been noted in other contexts across the United States.[8]

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[8] See Nadel, Steven and Rachel Young (2014). "Why is Electricity Use No Longer Growing?" *Public Utilities Fortnightly*, September 2014, pages 42-48.

Q. HOW DID YOU ARRIVE AT YOUR CONCLUSIONS?

A. The sales forecast is based on econometric modeling and on adjustments to the projections made outside of the econometric model. The adjustments account for the projected expansion in PNM's EE programs, additional DG interconnects, and new governmental Codes & Standards that did not exist in the historical period and whose impact would not be captured by the econometric model.

II. MODEL SPECIFICATION AND ESTIMATION

Q. PLEASE PROVIDE A SUMMARY OF THE PROCESS FOR DEVELOPING PNM'S SALES FORECAST.

A. I will first summarize the components of the sales forecast and then explain my method for calculating each component.

The sales forecast is the sum of total sales across all rate classes. For a given rate class, total sales is the product of UPC and the number of customers minus adjustments.[9] The adjustments include governmentally mandated Codes & Standards, EE programs, and DG programs that have not yet been rolled out. The magnitude of the adjustments can be expressed as a proportion of unadjusted sales

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9 Throughout my testimony, I will refer to the product of UPC and the number of customers without adjustments as "unadjusted sales."

or as a fixed amount. In the form of an equation, the sales forecast [with a fixed adjustment] at a point in time (t) can be written as:

$$Sales_t = \sum_r \left[\left(UPC_{rt} \times Customers_{rt} \right) - Adjustments_{rt} \right].$$

For each rate class (r), I developed an econometric model for UPC. For the same rate classes, I developed a separate econometric model for the number of customers. The UPC and number of customers were multiplied to yield the forecast. Further adjustments were made to this forecast to account for the effects of savings from governmentally mandated Codes & Standards, PNM's EE programs, and PNM's DG program for applicable Residential and Non-Residential customers.

Sales to some large power customers, manufacturers, universities, and Industrial Power (mining) are individually forecasted rather than econometrically forecasted. These customers have unique and sizeable energy needs, and account managers at PNM work closely with them on an individual basis. To form a sales forecast, PNM's account managers solicit information on projected changes to the customers' future electricity usage. In combination with data on the customer's historical usage levels, PNM constructs the forecasts on a case-by-case basis. For lighting, the actual level of sales as of the latest historical date is assumed to perpetuate into the future.

Q. HOW DO YOU DEFINE AN ECONOMETRIC MODEL?

A. An econometric model consists of an equation or set of equations that describe how the outcome variable varies as a function of several "explanatory" variables. In the context of PNM's sales forecast, the outcome variables may be UPC, the number of customers, or kWh sales. Explanatory variables could be income, price, or weather.

Broadly speaking, there are two categories of models used in sales forecasting – time series models and least squares regression models. Time series models use past values of the outcome to predict its future and may also include other explanatory variables. Least squares regression models use other observable variables, which typically have some theoretical basis, to predict future values of the outcome. An Autoregressive Moving Average ("ARMA") model is an example of a time series model; the autoregressive ("AR") component consists of lagged values of the outcome, and the moving average ("MA") component consists of lagged values of the error term. Ordinary Least Squares ("OLS") and Generalized Least Squares ("GLS") are examples of least squares regression models.[10]

[10] Please refer to PNM Exhibit AF-2 for a more detailed explanation about these model structures.

Q. WHAT STEPS DID YOU TAKE TO DEVELOP THE ECONOMETRIC MODELS?

A. When developing a model, I first decide on the model's specification. Things to consider for model specification are: whether to use a time series or least squares regression model (such as ARMA or OLS); what is the appropriate form of the equation (such as a linear or a logarithmic equation); and what explanatory variables should be included (such as income and/or weather). This step is called "model specification" because I am specifying or defining what the model structure should look like. Second, I estimate the model, meaning that I fit the specified equation to data. After I have specified and estimated the model, I can then apply projected values of the inputs to generate a prediction for the output.

Q. HOW DID YOU CHOOSE THE FUNCTIONAL FORM OF THE ECONOMETRIC MODELS?

A. For most of the UPC and Customer models, I chose to use a logarithmic functional form. This implies that changes in the inputs affect UPC or number of customers by a proportional amount rather than a fixed amount. The assumption of proportional rather than fixed changes is reasonable. For example, a drop in income would not cause the same decline in UPC regardless of the level of UPC since customers at low UPC levels are unlikely to decrease usage by the same amount as customers at high UPC levels.

Q. HOW DID YOU CHOOSE WHICH EXPLANATORY VARIABLES SHOULD BE INCLUDED IN THE ECONOMETRIC MODELS?

A. The set of potential inputs in the model were selected based on the availability of data, my experience with sales forecasting, and tests to validate the forecasts with actual sales. I considered the following explanatory variables: real personal income (or real Gross State Product) as a proxy for New Mexico's economic environment, real price per kilowatt-hour ("kwh"), weather, the addition of PNM South (formerly Texas-New Mexico Power or "TNMP") to PNM in January 2007, and a time trend, which serves as a proxy for unobserved factors that are increasing or decreasing from 2002 to 2021. In rare occasions, I also considered a structural shift in the parameters if the data indicate that a change in the composition of the rate class may have occurred. A shift in May 2013 is included for the UPC model of Rate 3B/3C and kWh model of Rate 4B.

Not every explanatory variable is applicable to each rate class. The decision to include some factors as opposed to others is rooted in economic theory and testing with data. From a theoretical perspective, I ask, "Does this factor have a direct influence on the customer's decision of electricity use?" If the answer is yes, then the factor is included as an input. Sometimes, the answer is ambiguous, and in these cases, I can test the hypothesis in the data by asking whether a robust relationship exists between the explanatory variable and the outcome of interest. That is, even after I control for sensible alternative explanations, the statistical relationship between the explanatory variable and the outcome of interest still holds. If so, then the empirical evidence is consistent with the hypothesis that the explanatory variable is a valid input.

Q. WHAT CRITERIA DID YOU USE TO EVALUATE THE ECONOMETRIC MODELS?

A. A detailed description of my model selection criteria and process of model testing can be found in PNM Exhibit AF-2. In short, I evaluated various model specifications based on six criteria:

1. How closely does the model's forecast align with the historical data on which it was developed? This process is called in-sample testing.
2. How accurately does the model predict UPC or the number of customers relative to historical data that was withheld in the process of developing the model? This process is called out-of-sample testing.
3. Are the model parameters plausible relative to the economic literature on demand for electricity?
4. Are the forecasted values in 2015-16 plausible given historical usage patterns and those that I have seen from comparable utility companies?
5. Is the model specification transparent, that is, do I know the drivers of the forecasted values?
6. What is the overall credibility of the results?

Q. FOR EACH RATE CLASS, WHAT IS YOUR RECOMMENDED ECONOMETRIC MODEL FOR "USAGE PER CUSTOMER," AND HOW DID YOU ARRIVE AT IT?

A. In Table AF-2, I present a summary of the UPC model specifications (that is, the inputs into model) that I developed for PNM. The estimated parameters of the UPC (or kWh) models are also included in PNM Exhibit AF-3 and, for Rate 4B, in PNM Exhibit AF-4.[11]

Table AF-2: Summary of Econometric Models for UPC and kWh

			Inputs					
Rates [1]	**Description** [2]	**Output** [3]	**Income** [4]	**Price** [5]	**Weather** [6]	**South** [7]	**Time Trend** [8]	**Shift in May 2013** [9]
1A	Residential	UPC	**Yes**	**Yes**	**Yes**	No	No	No
1B	Residential TOU	UPC	**Yes**	No	**Yes**	No	No	No
2A	Small Power	UPC	No	**Yes**	**Yes**	No	No	No
2B	Small Power TOU	UPC	No	No	**Yes**	**Yes**	**Yes**	No
3B/3C	General Power	UPC	No	No	**Yes**	No	No	**Yes**
4B*	Large Power	kWh	No	No	**Yes**	**Yes**	**Yes**	**Yes**
10A	Irrigation	UPC	No	No	**Yes**	**Yes**	No	No
10B	Irrigation TOU	UPC	**Yes**	No	**Yes**	**Yes**	No	No

Notes: "UPC" stands for Usage per Customer. "TOU" stands for Time-of-Use. "Income" is measured by real personal income for Rates 1A and 1B and by real Gross State Product for Rate 10B. "Weather" is measured by Cooling Degree Days and Heating Degree Days. For Rates 1A and 1B, the temperature threshold is 70 for CDD and 58 for HDD. For Rates 2A, 2B, 3B/3C, 4B, 10A, and 10B, the temperature threshold is 60 for both CDD and HDD. For Rates 2B, 10A, and 10B, only CDD is included in the models; for other Rates, both CDD and HDD are included in the models. "South" is a binary variable that equals 1 for time periods after March 2007 (inclusive) and 0 otherwise. "Time Trend" is a constructed variable that increases by 1 unit each month. For Rate 4B (which is demarcated by *), large customers are excluded from the econometric model and, instead, are individually forecasted. For Rate 1A, the model structure is AR(1) MA(6,12). For Rate 4B, the model structure is OLS. For the remaining rate classes, the models are estimated using GLS. Rates 1A and 3B/3C have seasonal models in which the parameter estimates for all explanatory variables are allowed to vary between summer (June-October) and winter (November-May).

[11] Given the high degree of heterogeneity in usage patterns across customers in Rate 4B (even after excluding individually forecasted large customers), I chose to directly forecast kWh rather than UPC and number of customers separately.

Except for Rates 1A and 4B, the models in Table AF-2 are estimated using GLS. GLS corrects for serial correlation. Serial correlation means that an unobserved component of the outcome variable is time dependent. If serial correlation is not accounted for, then the precision of the estimated coefficients in the model may be overstated.[12]

For Rate 1A, the model differs into two respects: (1) I use an ARMA model instead of GLS or OLS; and (2) I estimate the model on data through May 2015 rather than ending in March 2015. I considered three model structures (ARMA, GLS, and OLS) and two sample periods (ending in March 2015 and ending in May 2015). The decision to use an ARMA model estimated on data through May 2015 for Rate 1A is based on forecasting accuracy.[13]

Q. PLEASE EXPAND ON WHY THE ECONOMETRIC MODEL FOR USAGE PER CUSTOMER OF RATE 1A HAS A DIFFERENT STRUCTURE THAN THE OTHER RATE CLASSES.

A. I compared the forecasting accuracy of three models structures (ARMA, GLS, and OLS), and I found that ARMA performed the best.

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[12] Serial correlation is a problem with measuring uncertainty in the estimated coefficients. The forecast itself may still be accurate (that is, unbiased), but the researcher may incorrectly infer that the observed explanatory variables are statistically significantly correlated with the outcome when, in fact, there is no systematic relationship.

[13] I measure "forecasting accuracy" using Mean Absolute Percentage Error ("MAPE"). A low MAPE indicates that the model's predictions are closely aligned with actual data. In other words, a smaller MAPE means a more accurate forecast.

ARMA is a time series model in which the outcome (such as UPC) can depend on its past values and on "shocks" from earlier periods. In this context, a shock refers to an unexpected event that changes UPC. One reason why shocks would be persistent is that the consumer may adjust his or her behavior in a subsequent period to compensate for the shock. These two effects are not necessarily mutually exclusive, and the forecaster has some discretion over how to model the lag structure. For Rate 1A, I chose to model UPC as an AR(1) MA(6,12), which means that current UPC depends on UPC in the previous month and on unanticipated events that occurred 6 and 12 months ago. My decision is based on the patterns of correlation in the unexplained portion, that is, the residual, of UPC between time periods. Ideally, there would be no systematic correlations between periods in the residual. I test different combinations of lags to get as close to this ideal as possible while maintaining a model that does not contradict with my knowledge of consumer behavior for electricity.

To compare the forecasting accuracy across model structures, I use MAPE. The results are shown in Table AF-3. The MAPEs indicate that ARMA is most accurate among the three candidates, and the differences are more pronounced in the summer months.

Table AF-3: MAPE of UPC for Rate 1A by Model Structure

	ARMA	GLS	OLS
MAPE: All months	2.60%	2.76%	3.12%
MAPE: Summer months	2.88%	3.08%	3.35%
MAPE: Winter months	2.41%	2.53%	2.96%

Notes: Summer months include June through October. MAPE stands for "Mean Absolute Percentage Error." MAPEs are calculated over the period January 2002-May 2015.

Q. PLEASE EXPAND ON WHY YOU CHOSE TO USE A DIFFERENT SAMPLE PERIOD FOR THE UPC MODEL OF RATE 1A.

A. I compared the forecasting accuracy of the ARMA model using the sample period January 2002-March 2015 and sample period January 2002-May 2015. I find that the model estimated on data through May 2015 performs better in terms of a lower MAPE.

In Table AF-4 below, I report the MAPE from the model estimated on data through March 2015 (middle column) and MAPE for the model estimated on data through May 2015 (right column). Each row corresponds to a different period over which the MAPE is calculated; for example, the first row shows the MAPE calculated over January 2002-March 2015. The second row shows the MAPE calculated for April 2015 only. The table demonstrates that the model estimated on data through May 2015 performs equally well as the model estimated on data through March 2015 when the MAPE is being calculated only for the period ending in March 2015. However, the May 2015 model performs substantially better for the period ending in May 2015.

Table AF-4: MAPE of UPC models for Rate 1A by Sample Period

	Model: March 2015	Model: May 2015
MAPE: Jan 2002-Mar 2015	2.57%	2.57%
MAPE: Apr 2015	8.86%	7.57%
MAPE: May 2015	7.16%	2.46%

Notes: "Model: March 2015" refers to the ARMA model estimated using data from January 2002-March 2015. "Model: May 2015" refers to the ARMA model estimated using data from January 2002-May 2015. "MAPE" stands for Mean Absolute Percentage Error.

Q. DID YOU ESTIMATE ALL MODELS USING DATA THROUGH MAY 2015?

A. No. The UPC model for Rate 1A is estimated using data through May 2015. The UPC models for other rate classes are estimated using data through March 2015.

Q. WHY DID YOU USE DATA THROUGH MARCH 2015 FOR OTHER RATE CLASSES ?

A. To be consistent with PNM's financial reporting practices, I chose to estimate the econometric models using data through March 2015, which is the end of the first quarter of 2015. I find that estimating all other models on data through May 2015 rather March 2015 makes little difference in terms of forecasting accuracy of total sales. The UPC model of Rate 1A is the exception in which the model is estimated on data through May 2015.

Q. FOR EACH RATE CLASS, WHAT IS YOUR RECOMMENDED ECONOMETRIC MODEL FOR "NUMBER OF CUSTOMERS," AND HOW DID YOU ARRIVE AT IT?

A. To develop the econometric models for the number of customers, I focused on the same subset of rate classes that was used for modeling UPC. Since UPC and the number of customers are inherently different outcomes, the econometric models for UPC and customers also differ. Importantly, for the customer models, the set of inputs includes the total population of New Mexico but does not include weather. While the number of customers depends on the total number of people living in New Mexico, weather has no direct effect since the majority of people need access to the grid regardless of the outdoor temperature. The model specifications of the customer forecast are summarized in Table AF-5. The model parameters are provided in PNM Exhibit AF-5.

Table AF-5: Summary of Econometric Models for Number of Customers

			Inputs				
Rates [1]	**Description** [2]	**Output** [3]	**Population** [4]	**Income** [5]	**South** [6]	**Time Trend** [7]	**Shift in Jan 2009** [8]
1A	Residential	Customers	No	No	No	**Yes**	**Yes**
1B	Residential TOU	N/A					
2A	Small Power	Customers	**Yes**	No	**Yes**	No	No
2B	Small Power TOU	N/A					
3B/3C	General Power	Customers	No	**Yes**	**Yes**	**Yes**	No
10A	Irrigation	N/A					
10B	Irrigation TOU	N/A					

Notes: "TOU" stands for Time-of-Use. "Population" includes residents of PNM's service territory only. "Income" is measured by real Gross State Product. "South" is a binary variable that equals 1 for time periods after March 2007 (inclusive) and 0 otherwise. "Time Trend" is a constructed variable that increases by 1 unit each month. For Rates 1A and 3B/3C, the time trend is interacted with the shifts in January 2009 or March

2007, which are represented by indicator variables. For Rates 1B, 2B, 10A, and 10B, customer forecasts are based on the average across the last 12 months (April 2014-March 2015).

My approach to estimating the customer models differs across rate classes:

- The customer models for Rates 2A and 3B/3C are estimated using GLS for the same reasons that I estimate the UPC models using GLS.
- The customer model for Rate 1A is estimated using OLS. OLS is used to summarize the average growth rates in number of customers between January 2002 and December 2008 and between January 2009 and March 2015. In other words, the customer model for Rate 1A assumes that the average monthly growth rate after January 2009 will continue into the future. For Rate 1A, the forecast based on growth rates had a lower MAPE than the forecast based on population.
- For Rates 1B, 2B, 10A, and 10B, the forecasts are the average number of customers over the last 12 months of actuals. This decision was based on the facts that these rate classes comprise less than one percent of PNM's total sales and, for this set of small rate classes, changes in the number of customers beyond a few months are highly uncertain.
- For Rate 4B (excluding individually forecasted customers), changes greater than five are rare. While there may be small fluctuations across months, the change in number of customers has been on average zero since 2004. Thus, the last actual level is used as the forecast.

Q. WHAT DATA DID YOU USE TO ESTIMATE THESE MODELS?

A. To estimate the UPC and customer econometric models, I relied on data from PNM, BBER, and the National Oceanic and Atmospheric Administration ("NOAA").

PNM provided data on electricity sales, number of customers, and average price by rate class on a monthly basis from January 2002 through March 2015.[14]

The economic variables for New Mexico – namely personal income, Gross State Product, Consumer Price Index, and population – are provided by BBER. These variables are reported on a quarterly basis, and to convert them to monthly values, I interpolated between quarters using a third-degree polynomial function.[15]

Heating Degree Days ("HDD") and Cooling Degree Days ("CDD") by month are calculated based on weather data from NOAA. The temperature cutoffs are 58° F and 70° F for HDD and CDD respectively among residential customers and 60° F for both HDD and CDD among commercial customers. The weather variables are weighted to be representative of the billing cycle month rather than the calendar month.

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[14] When estimating the forecasting models, I use data through the end of the first quarter, March 2015, with the exception of the UPC model for Rate 1A, for which I use data through May 2015. See PNM Exhibit AF-2. For Rate 4B, I use data from March 2004-March 2015.

[15] The results are similar when I assume that each month takes on the average value for the quarter.

Q. HOW DID YOU PROJECT THE EXPLANATORY VARIABLES?

A. I rely on forecasted values of weather and income to construct PNM's sales forecast. For weather, I assume that the 10-year average of HDD or CDD by month serves as a reasonable approximation of future weather patterns. The 10-year average is taken over January 2005 through December 2014. For real personal income, I rely on BBER's forecasted values.

Q. WHICH SCENARIO OF BBER'S INCOME FORECAST DID YOU CHOOSE TO USE?

A. I use BBER's pessimistic personal income forecast.[16]

Q. WHY DID YOU CHOOSE TO USE BBER'S PESSIMISTIC INCOME FORECAST?

A. I chose to use BBER's pessimistic income forecast because, prior to 2014, BBER's forecasts were consistently higher than actuals, and although the growth rate of income exceeded its forecast in late 2014, the high growth rate is unlikely to be sustained. In Figure AF-3 below, I plot the historical and forecasted growth rates of personal income from 2010 to 2018. I show the forecasted growth rates from BBER's July 2013, January 2014, and July 2014 releases.

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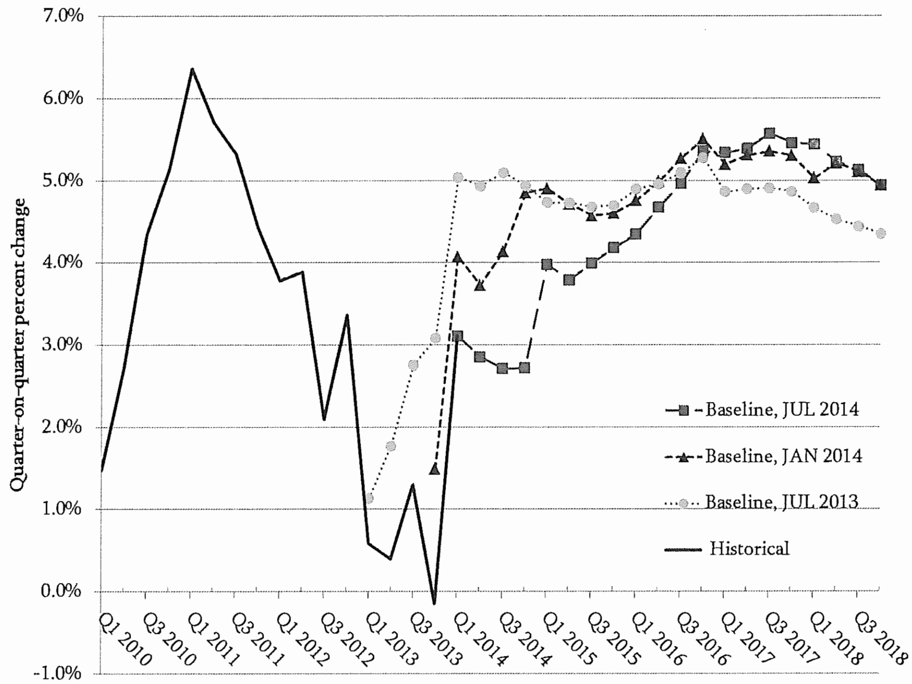
[16] A comparison of the assumptions behind BBER's baseline scenario, pessimistic scenario, and optimistic scenario can be found on page 14 of "FOR-UNM: A Quarterly Economic Forecast of the New Mexico Economy, April 2015 Through 2020:4."

Figure AF-3: Comparison of BBER Personal Income Forecasts



Three times in a row, BBER lowered the growth rate in its baseline forecast because in every instance, the forecast exceeded actuals in recent history.[17] Figure AF-3 above shows these patterns. The forecasts were high in part because forecasters around the country underestimated the persistence of the economic recession.

In late 2014, New Mexico's economy began to improve, and in contrast to past releases, BBER's forecasts came in lower than the actual growth rates. Much of the improvement is attributed to growth in Medicaid transfer payments, which contributed to job creation in the healthcare sector and the acceleration in personal

[17] Please refer to BBER's July 2013, January 2014, and July 2014 forecasts.

income growth.[18] The impact of gains in personal income on PNM's future sales will depend on whether the recent spurt of growth can be sustained.

There are several reasons why I think that the growth rate for real personal income will not continue through the end of the decade. First, Medicaid's contribution to the growth in income is expected to decrease as the expansion of Centennial Care nears completion.[19] Second, while other areas of income (such as wage and salary disbursements) are expected to continue trending upwards, growth in the national economy may be slowing, which could dampen New Mexico's recovery. Third, the assumptions for the pessimistic forecast more closely align with four events that have transpired thus far in 2015: the Greek debt crisis, volatility in China's stock market, slow U.S. GDP growth in the first quarter, and weak gains in labor productivity in the first two quarters.[20]

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[18] See pages 2, 16, and 18 of "FOR-UNM: A Quarterly Economic Forecast of the New Mexico Economy, April 2015 Through 2020:4."

[19] See page 21 of "FOR-UNM: A Quarterly Economic Forecast of the New Mexico Economy, April 2015 Through 2020:4." Centennial Care is New Mexico's Medicaid program. It was implemented in January 2014.

[20] See "Sputtering Worker Productivity Vexes Economy," *The Wall Street Journal*, 11 August 2015 (accessed online at http://www.wsj.com/articles/u-s-productivity-increases-at-1-3-pace-in-second-quarter-1439296327 on August 11, 2015).

III. POST-ESTIMATION ADJUSTMENTS

Q. WERE ANY POST-ESTIMATION ADJUSTMENTS MADE TO THE FORECAST?

A. Yes, I made adjustments to the forecasted sales generated by the econometric models for UPC and number of customers.

Q. WHAT ADJUSTMENTS WERE MADE AND WHY?

A. I made three post-estimation adjustments to account for savings from (1) governmentally mandated Codes & Standards, (2) PNM's EE programs, and (3) PNM's DG program.

The adjustments are necessary because energy savings from expanded or new utility EE and DG programs and new governmental Codes & Standards will not be counted in the econometric models. The econometric models are estimated using historical data. Thus, the models' predictions of the future are extrapolations based upon historical information, and the impact of future programs and standards cannot be predicted if there is no information about them from the past.

Q. HOW DID YOU MAKE THE ADJUSTMENT FOR CODES AND STANDARDS?

A. To estimate the effects of Codes & Standards on Residential and Commercial sales, I used AEG's Load Analysis and Planning Model ("LoadMAP™"). LoadMAP™ is an end-use model that calculates sales based on utilization of technologies requiring electricity (such as electric appliances and lighting) across customer segments. In other words, an end-use model calculates sales by summing utilization across consumers from a "bottom up" approach. Specifically, the impacts of the Energy Independence and Security Act ("EISA") Lighting Standard and next wave of "white goods"[21] appliance standards are computed by taking the difference in total sales between a scenario in which all appliance-choice options are available to consumers and a scenario in which only appliances that conform to the standards are available. Exhibit AF-6 provides a detailed discussion the Codes and Standards adjustment for Residential and Commercial sales.

Q. WHAT IS THE MAGNITUDE OF THE ADJUSTMENT FOR CODES AND STANDARDS?

A. The adjustment for Codes & Standards is shown in Table AF-6. The table reports the Codes & Standards adjustment in levels and as a percentage of unadjusted sales for Residential and Commercial sectors.

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[21] "White goods" refer to major household appliances such as refrigerators and stoves.

Table AF-6: Summary of Codes and Standards Adjustment

	Residential		Commercial	
	C&S Adjustment (in GWh)	C&S Adjustment as % of unadjusted sales	C&S Adjustment (in GWh)	C&S Adjustment as % of unadjusted sales
2015	53.4	2.18%	0.7	0.11%
2016	124.7	3.70%	14.7	1.63%
2017	134.8	3.94%	13.4	1.46%
2018	139.6	4.04%	17.6	1.92%
2019	149.7	4.25%	20.3	2.18%
2020	240.6	6.66%	25.7	2.72%
2021	244.5	6.66%	26.0	2.72%

Source: Applied Energy Group

Notes: Codes and Standards adjustment for 2021 is held constant at 2020 level as a percent of unadjusted sales. Codes and Standards adjustment in 2015 reflects a partial year (April-December).

Q. WHAT PROGRAMS DRIVE ENERGY EFFICIENCY MEASURES FOR PNM?

A. I understand that New Mexico's Efficient Use of Energy Act ("EUEA") was amended in 2013 such that utilities in the state are required to invest three percent of retail sales revenues on EE and load management (or demand response) programs starting in 2015.

Q. HOW DID YOU MAKE THE ADJUSTMENT FOR ENERGY EFFICIENCY PROGRAMS?

A. In its forecasts, PNM assumes that the EUEA threshold is met in all future periods. Savings associated with an existing program can be calculated as the product of customer participation and savings per participant, which is measured and verified by an independent third party. Total savings is the sum across these programs.[22]

The existing programs will eventually be replaced by new programs. It is important to adjust the sales forecast for the expanded scale of the PNM's EE programs since historical data would not capture the rise in PNM's investment in EE. Forecasted savings from new programs are based on two assumptions: first, EE spending is fixed at three percent of retail sales revenues in accordance with New Mexico's EUEA, and second, the average cost per kWh of savings is $0.02/kWh in 2015 and rises to $0.025/kWh in 2021. The increase in the cost of acquiring new EE savings is based on PNM's experience during the last several years and on input from public participants in PNM's Integrated Resource Planning process.

Q. WHAT IS THE MAGNITUDE OF THE ADJUSTMENT FOR ENERGY EFFICIENCY PROGRAMS?

A. The adjustment for EE programs is shown in Table AF-7. The table reports the aggregate EE adjustment in levels and as a percentage of total unadjusted sales.

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22 For a description of existing EE programs and new EE programs for PNM's 2014 EE Plan, please see PNM Exhibit SMB-1 filed with the Commission on October 6, 2014 in NMPRC Case No. 14-00310-UT. All documents filed in that docket are public and can be found at the NMPRC's website (http://164.64.85.108/) by logging in with username "webguest" and password "webguest1" and clicking on the "Quick Case Lookup" link on the upper left hand corner of the screen then typing in the above referenced case number. The 2014 EE Plan went into effect on May 27, 2015, and PNM will file its 2015 EE Plan in April 2016.

Table AF-7: Summary of Energy Efficiency Adjustment

	EE Adjustment (in GWh)	EE Adjustment as % of unadjusted sales
2015	39.0	0.61%
2016	108.6	1.27%
2017	176.1	2.04%
2018	253.2	2.92%
2019	330.6	3.77%
2020	403.6	4.54%
2021	473.2	5.27%

Notes: EE adjustment in 2015 reflects a partial year (April-December).

Q. HOW DID YOU MAKE THE ADJUSTMENT FOR DISTRIBUTED GENERATION?

A. The adjustment for PNM's DG program is constructed by multiplying the capacity of the system across photovoltaic customers with total sun hours for a fixed tilt, south facing solar panel in Albuquerque during the month. Solar resource information is provided by the National Renewable Energy Laboratory ("NREL").[23] Capacity of the system is determined by total kWAC across interconnected customers, kWAC across customers who applied but had not interconnected, and after 2016, the average historical growth rate of kWAC installed per month.

[23] For the NREL data, please refer to: http://rredc.nrel.gov/solar/pubs/redbook/PDFs/NM.PDF

Q. WHAT IS THE MAGNITUDE OF THE ADJUSTMENT FOR DISTRIBUTED GENERATION?

A. The adjustment for DG is shown in Table AF-8. The table reports the aggregate DG savings in levels as a percentage of total unadjusted sales.

Table AF-8: Summary of Distributed Generation Adjustment

	DG Adjustment (in GWh)	DG Adjustment as % of unadjusted sales
2015	10.2	0.16%
2016	26.1	0.31%
2017	34.7	0.40%
2018	44.2	0.51%
2019	51.9	0.59%
2020	49.5	0.56%
2021	50.4	0.56%

Notes: DG adjustment in 2015 reflects a partial year (April-December).

Q. ARE THESE ADJUSTMENTS IN LINE WITH YOUR EXPECTATIONS?

A. Yes, the adjustments align with my expectations.

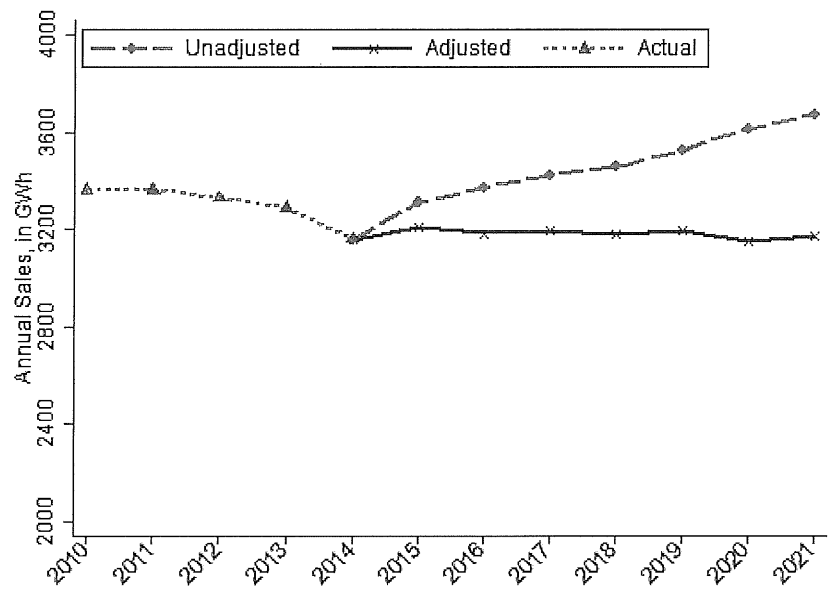
IV. FINAL FORECAST NET OF ADJUSTMENTS

Q. PLEASE DESCRIBE THE FINAL FORECAST WITH AND WITHOUT THE POST-FORECASTING ADJUSTMENTS BY RATE CLASS.

A. The final forecasts net of post-estimation adjustments are presented in Figure AF-4 through Figure AF-11. Each figure shows the unadjusted forecast from the econometric model and the final forecast after accounting for energy savings from Codes & Standards, EE programs, and the DG program. The gap between the unadjusted and adjusted forecasts is the magnitude of savings. The historical trends from 2010-2014 are depicted in dashed lines with triangles. Electricity sales in 2015 are constructed as a hybrid of three months of actuals (January-March) and nine months of forecasted values (April-December).

Figure AF-4 shows the annual sales for Rate 1A from 2010 to 2021. The final adjusted forecast indicates a decline in total sales from 2010 through 2021 by 5.6 percent. Between 2014 and 2021, total sales remain flat around 3,170 GWh. From year to year, Residential sales may fall by as much as -3.9 percent (2013-2014) or rise by as much as 1.7 percent (2014-2015).

Figure AF-4: Annual Electricity Sales for Rate 1A

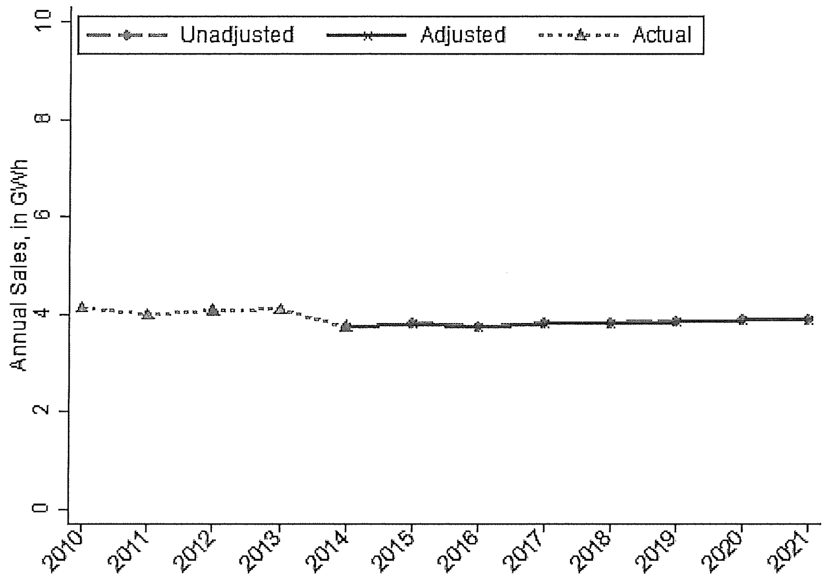


The unadjusted sales forecast (long-dashed line with circles) shows an increasing trend after 2014. The key driver behind the growth in total sales is the number of customers, which has been increasing at 0.04 percent per month on average (0.5 percent per year) since 2008. Unadjusted UPC shows modest growth in the summer months as income rises.

The difference between the adjusted and unadjusted sales is the post-estimation adjustment from Codes & Standards, PNM's EE programs, and PNM's DG program. Between 2015 and 2021, post-estimation adjustments are expected to grow from 3.2 percent of total unadjusted sales in 2015 to 13.5 percent of total unadjusted sales in 2021. More than 50 percent of the post-estimation adjustment is attributable to tightening Codes & Standards. In 2016, post-estimation adjustments are 5.6 percent of the unadjusted sales forecast for the Residential class; 66.5 percent of the post-estimation adjustment comes from Codes & Standards, EE programs, and DG program make up the remaining 28.1 percent and 5.4 percent, respectively.

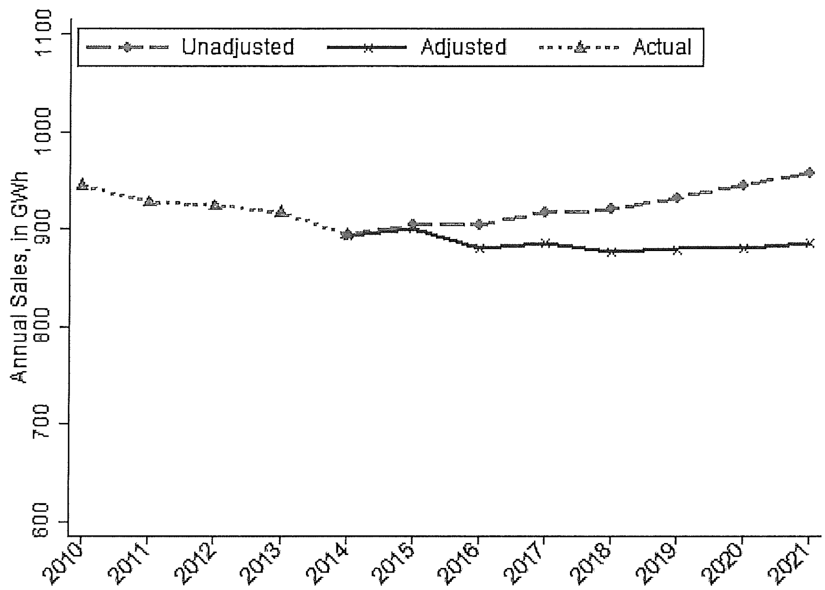
Figure AF-5 below depicts the forecast for Rate 1B. Rate 1B is 0.05 percent of PNM's total sales in 2014 and 0.1 percent of the size of Rate 1A in terms of sales. The number of customers declined since 2010 and, given the high degree of uncertainty and low numbers, the forecasted number of customers is held constant at the level observed in March 2015. UPC also shows little change from its level in 2014. Thus, forecasted sales are nearly flat through 2021.

Figure AF-5: Annual Electricity Sales Forecast for Rate 1B



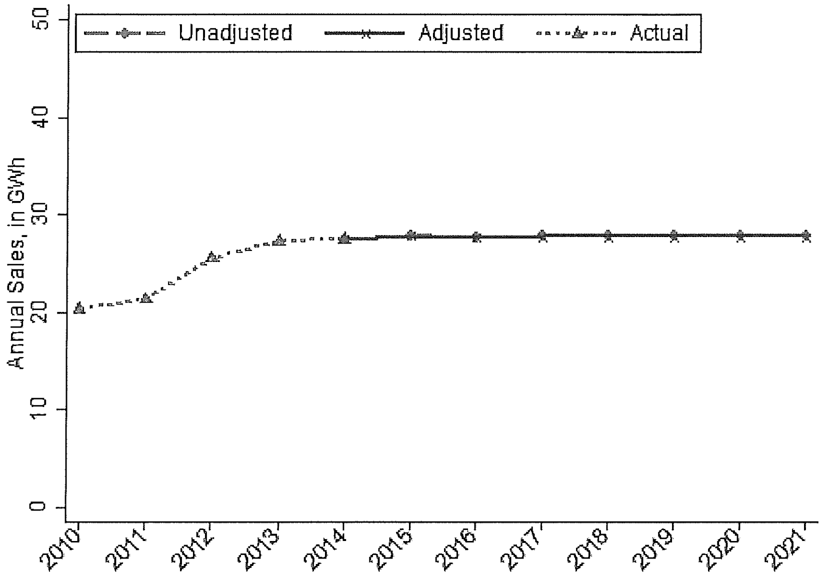
As shown in Figure AF-6 below for Rate 2A, sales will decline until 2016 and remains constant around 880 GWh through 2021. Similar to Rate 1A, the growth in unadjusted sales for Rate 2A is driven by additional customers from a larger population; unadjusted UPC is fairly flat in the range of 18.1 to 18.7 GWh per year. Post-estimation adjustments for Commercial Codes and Standards, PNM's EE programs, and PNM's DG program are expected to lower total sales by as much as 7.5 percent of the unadjusted forecast value in 2021. In 2016, savings are mostly coming from Codes and Standards (58.6 percent of the post-estimation adjustment). By 2017, EE is the primary source of savings (48.4 percent of the post-estimation adjustment). Savings attributed to DG are highest as a percent of the post-estimation adjustment in 2017 at 8.8 percent.

Figure AF-6: Annual Electricity Sales Forecast for Rate 2A



As displayed in Figure AF-7 below, total sales for Rate 2B (Small Power customers on time of use rates) jumped up in 2012 when the number of customer and UPC increased. Since then, both customers and UPC have been fairly flat, and the forecast of total sales assumes that the stagnant trend continues through 2021.

Figure AF-7: Annual Electricity Sales Forecast for Rate 2B



For Rate 3B/3C, Figure AF-8 shows that total sales have fallen since 2012, and the [adjusted] final forecast modestly increases through 2017. Between 2017 and 2021, forecasted sales are constant at just under 1,930 GWh per year; 1,930 GWh is a 0.5 percent increase over total sales in 2014. The increase in sales leading up to 2012 is driven by more customers and higher UPC. The decrease from 2012 to 2013 is caused by a drop in number of customers, and although the number of customers recovers in 2014, lower UPC pushes sales down between 2013 and 2014.

Post-estimation adjustments, which are captured in Figure AF-8 as the gap between the unadjusted and adjusted forecasts, grow over time. For Rates 3B and

3C, post-estimation adjustments are either EE or DG, and over three-quarters of savings are attributed to EE.

Figure AF-8: Annual Electricity Sales Forecast for Rate 3B/3C

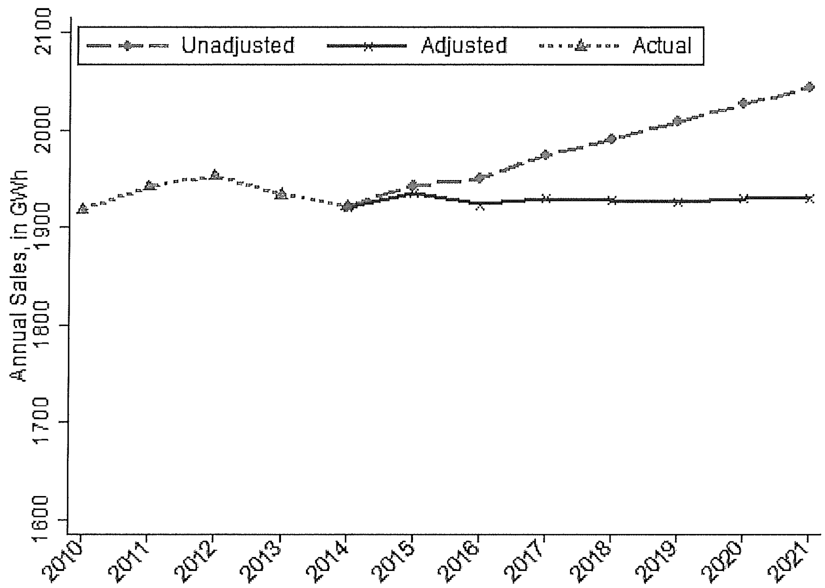
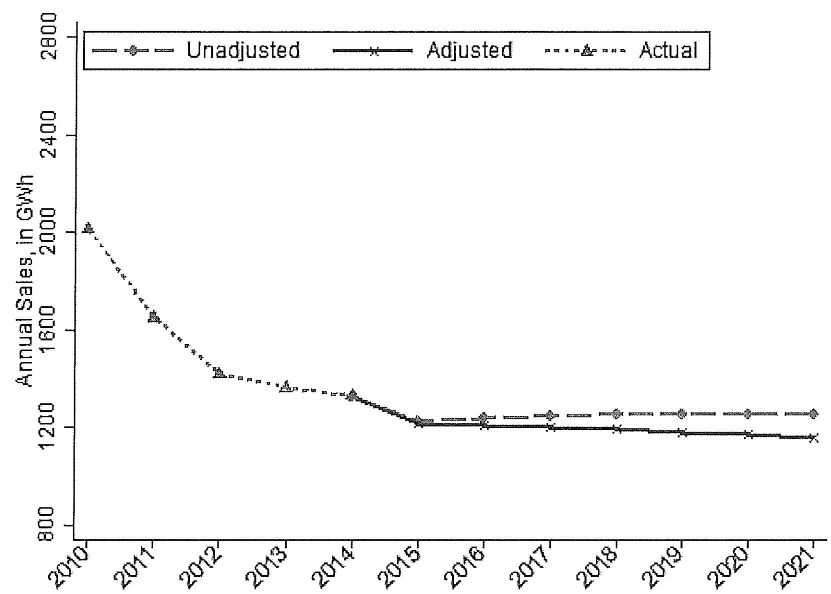


Figure AF-9 plots the trend in sales for Rate 4B, which includes customers whose sales are individually forecasted. Total class usage declined by 34 percent between 2010 and 2014, and over the same period, the average number of customers per month fell from 251 to 223. After 2015, unadjusted forecasted sales are steady around 1,255 GWh, and adjusted forecasted sales show a modest decrease through 2021.[24] Like Rate 3B/3C, adjustments for Rate 4B come from either EE or DG, and more than half of the savings is attributed to EE.

[24] The drop between 2014 and 2015 is the movement of some customers from Rate 4B to the proposed Rate 35B. Sales in Rate 4B appear to be lower in 2015 than 2014, but if the proposed Rate 35B is included, then forecasted unadjusted sales would remain around 1,330 GWh from 2014 to 2015.

Figure AF-9: Annual Electricity Sales Forecast for Rate 4B



Notes: Individually forecasted Large Power customers are included.

Rates 10A and 10B are Irrigation customers on standard and TOU rates, respectively, and the forecasts are shown in Figure AF-10 and Figure AF-11. In terms of sales and number of customers, Rate 10B is larger than Rate 10A. There are no EE or DG programs for Irrigation, and thus, the unadjusted and adjusted forecasts are the same. For both rate classes, the sales forecasts are constant at or near the levels in 2014 and 2015. Changes in the number of customers and, to some extent, UPC are highly irregular. Thus, the most recent data often serve as the best predictors in the near term.

Figure AF-10: Annual Electricity Sales Forecast for Rate 10A

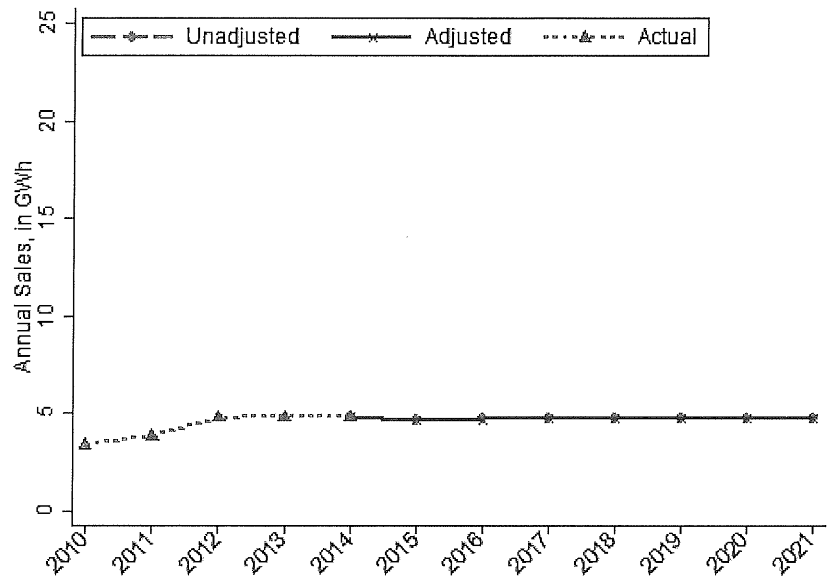
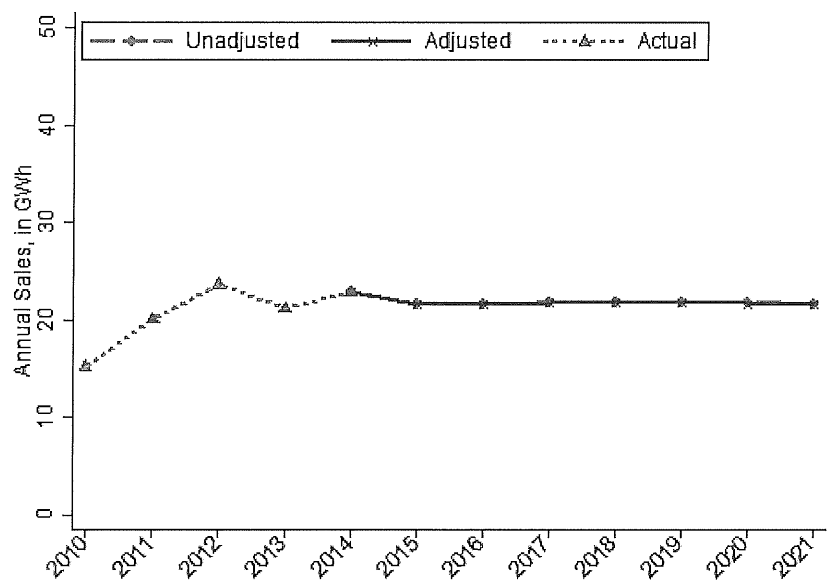


Figure AF-11: Annual Electricity Sales Forecast for Rate 10B



Q. WHAT ARE THE MOST IMPORTANT DRIVERS BEHIND THE FORECASTS?

A. In the first step of generating the unadjusted forecast, the key drivers of UPC and number of customer are income, price, weather, and population.[25] For UPC, income is a statistically and economically significant driver for the Rate 1A. Demand for electricity among Rates 1A and 2A are also sensitive to changes in price per unit. Across Rates 1A, 2A, and 3B/3C, extreme temperatures on the low or high end raise UPC. For the number of customers, population is a key determinant, and a growing population is expected to grow the customer base for Rate 2A.

In the second step of making post-estimation adjustments, decrements for governmentally mandated Codes & Standards and EE programs are critical. Codes & Standards depend on the rate at which incandescent light bulbs are phased out, and the impact of EE programs depends on customers' responsiveness to energy-saving incentives.

Q. HOW DOES THE SALES FORECAST THROUGH THE FTY COMPARE WITH PNM'S HISTORICAL TREND IN SALES?

A. In Figure AF-12, I plot the actual and forecasted trend in sales from 2010-2021. The line with circles corresponds to total sales, and the line with crosses

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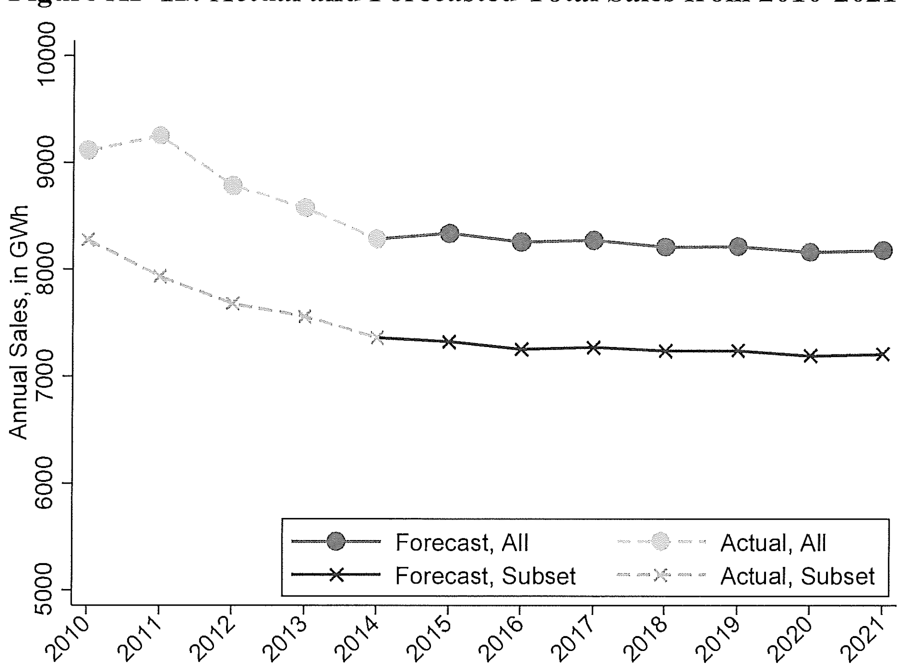
[25] Please refer to PNM Exhibit AF-3, PNM Exhibit AF-4, and PNM Exhibit AF-5 for the regression output tables for UPC, kWh, and number of customers, respectively.

corresponds to total sales among the subset of rate classes that are econometrically forecasted (plus individually forecasted large customers in Rate 4B). The solid lines represent forecasts, and the dashed lines represent actuals.

Since 2011, PNM has experienced declining sales. Total sales have dropped by 10.4 percent from 2011 to 2014, and among the subset of rate classes comprising 89 percent of total sales, sales have fallen by 11.0 percent since 2010. The forecast for 2015-16 represents a conservative yet reasonable estimate of total sales. A sluggish recovery in New Mexico's economy beyond 2015 or acceleration in take-up of EE programs would further lower the sales forecast relative to the results that I have presented in my testimony.

Figure AF-12: Actual and Forecasted Total Sales from 2010-2021



Source: Actual sales (2010-2014, January-March 2015) are provided by Public Service Company of New Mexico (July 2015). Unbilled and Economy Service sales are excluded. "Subset" includes Rates 1A, 1B, 2A, 2B, 3B/3C, 4B, 10A, and 10B.

Q. HOW DO THE FINAL FORECASTS COMPARE WITH OTHERS THAT YOU HAVE SEEN IN THE INDUSTRY?

A. They are in line with what I have seen elsewhere in the industry. As noted earlier, sales growth has slowed down since the beginning of the Great Recession of 2008-09. It is recovering slowly from weak economic growth, the expansion of utility EE programs, and the introduction of new governmental Codes & Standards that raise the energy efficiency requirements of appliances, light bulbs and buildings.

V. CONCLUSION

Q. PLEASE SUMMARIZE PNM'S SALES FORECAST.

A. As shown in Table AF-1, which has been reproduced below for convenience, PNM's aggregate sales are projected to decline by 3.7 percent between 2013 and 2016. Among the rate classes that have been the focus of my testimony, total sales are expected to fall by 4.0 percent through 2016.

Table AF-1: Summary of PNM Sales Forecast

	% of Total	Actual, in GWh		Forecast, in GWh	
	Sales in 2014	2013	2014	2015	2016
1A Residential	38.16%	3290.4	3161.5	3216.5	3183.7
1B Residential Time-of-Use	0.05%	4.1	3.7	3.7	3.7
2A Small Power	10.79%	916.8	893.8	902.7	879.6
2B Small Power Time-of-Use	0.33%	27.3	27.5	27.9	27.7
3B/3C General Power	23.19%	1933.9	1921.1	1941.4	1923.5
4B Large Power	16.06%	1364.1	1330.2	1232.2	1212.1
10A Irrigation	0.06%	4.8	4.8	4.7	4.7
10B Irrigation Time-of-Use	0.28%	21.2	22.8	22.0	21.6
Subtotal	88.91%	7562.8	7365.7	7351.1	7256.6
Other Rates	11.09%	1015.0	918.7	962.7	1002.3
Grand total (excluding unbilled)	100.00%	8577.7	8284.4	8313.7	8258.9

Source: Actual sales in 2013, 2014, and January-March 2015 are provided by Public Service Company of New Mexico (July 2015)

Notes: For 2015, annual sales are based on actual sales from January-March and forecasted sales from April-December. Other Rates include some of Rate 2A (Cable TV, Temporary Service, Traffic Signals) and Rates 5B, 6, 11B, 15B, 20, and 30B. Beginning in April 2015, the proposed Rate 35B is classified under "Other Rates." Unbilled and Economy Service are excluded from the grand total.

The forecasted trends vary by rate class. Net of future savings from Codes & Standards, PNM's EE programs, and PNM's DG program, total sales for Residential, Small Power, and Large Power customers are forecasted to decline while total sales for General Power and Irrigation remain close to historical levels. The drop in sales for Residential and Small Power comes from lower UPC because of higher savings from Codes & Standards, EE programs, and DG program. Falling number of customers underlie lower sales for the Large Power class. The relatively flat levels of sales for General Power are attributed to an offsetting effect of changes in UPC and customer counts. Summary tables for UPC (with adjustments for energy savings), and number of customers by rate class are shown in Table AF-9 and Table AF-10.

Table AF-9: Summary of Final UPC Forecast

	Actual, in MWh		Forecast, in MWh	
	2013	2014	2015	2016
1A Residential	7.29	6.96	7.03	6.93
1B Residential Time-of-Use	31.7	29.3	29.6	29.8
2A Small Power	19.2	18.6	18.7	18.1
2B Small Power Time-of-Use	39.8	40.1	40.3	40.0
3B/3C General Power	764.2	738.8	743.5	730.9
4B Large Power	NA	NA	NA	NA
10A Irrigation	42.1	42.5	41.0	41.1
10B Irrigation Time-of-Use	98.1	105.5	100.3	98.1

Notes: Annual sales in MWh are reported. For 2015, annual sales are based on actual sales from January-March and forecasted sales from April-December. For Rate 4B, UPC is not forecasted; instead, kWh sales is directly forecasted.

Table AF-10: Summary of Final Customer Forecast

	Actual		Forecast	
	2013	2014	2015	2016
1A Residential	451,651	454,268	457,255	459,256
1B Residential Time-of-Use	129	128	126	126
2A Small Power	47,748	48,062	48,319	48,681
2B Small Power Time-of-Use	686	686	691	691
3B/3C General Power	4,236	4,275	4,296	4,341
4B Large Power	229	223	220	220
10A Irrigation	115	114	115	115
10B Irrigation Time-of-Use	216	215	218	220

Notes: Average number of customer per month is reported. For 2015, the averages are based on actual number of customers from January-March and forecasted number of customers from April-December.

PNM's sales forecasting model incorporates both sound econometric techniques and the available information about impending regulations and energy-saving programs to construct a reasonable estimate of total sales in the future. While weather and economic conditions are important drivers of the sales forecast, expected savings from Codes & Standards, expanded EE programs, and the DG program are projected to significantly impact the outlook for total sales.

Q. DOES THIS CONCLUDE YOUR TESTIMONY?

A. Yes, it does.

GCG#520339

Resume of Dr. Ahmad Faruqui

PNM Exhibit AF-1

Is contained in the following 17 pages.

Ahmad Faruqui, Ph.D.

Dr. Faruqui is an internationally recognized expert on demand forecasting, including peak demand, energy sales, and hourly load forecasting. He was one of the first analysts in the US to recognize that the slowdown in sales growth that began with the Great Recession of 2008-09 was likely to persist during the weak economic recovery that followed the recession. He was asked to speak twice on the topic at Goldman Sachs Annual Power and Utility Conference and spoke recently on the topic at PJM's Grid 20/20 Conference and at the annual meeting of the Eastern Interstate State's Interconnection Council. His article in the December 2012 issue of the *Public Utilities Fortnightly*, "Demand Growth and the New Normal," has been widely cited.

He has also pioneered the use of quantile regression on forecasting peak demands. He has co-authored a paper on this topic with Charlie Gibbons and presented it at California's Demand Analysis Working Group, the National Regulatory Research Institute and the National Association of Regulatory Utility Commissioners.

He has advised more than two dozen clients on demand forecasting issues. These have included utilities, government agencies and transmission system operators in the United States, Canada, the Middle East, Asia-Pacific and South Africa. He has provided three types of expert services: first, reviewing the methods being used to forecast energy consumption, peak demand, and hourly load shapes; second, evaluating the data being used in model estimation; and, third, assessing the accuracy and usefulness of the resulting forecasts. To enhance the efficacy and credibility of the forecasts, he has suggested improvements in model structure, data sources, and the way in which results are communicated to internal and external users of the forecast.

In addition, he has developed models for forecasting monthly and hourly loads for clients using a variety of econometric and time series methods. He helped develop an hourly load forecasting model to assist a competitive wholesaler in bidding for default service. For a utility, he diagnosed why energy sales were below forecasts even after adjusting for the effects of the economy. He assisted a transmission system operator understand why peak demand was being under-forecast by a large amount. And he assisted a regulated provider of steam analyze the customer's decision to switch from purchasing steam to self-generating of steam and also to analyze the response of steam usage to rising steam prices. The analysis was carried out on a customer-by-customer basis and involved the use of discrete choice methods and conventional regression analysis.

More recently, Dr. Faruqui has been involved in the estimation of hourly, daily and monthly demand models in the context of dynamic pricing pilots. Dr. Faruqui has managed the design and evaluation of large-scale dynamic pricing experiments in California, Connecticut, Florida, Illinois, Maryland and Michigan. This work involved the estimation of a variety of econometric models for estimating customer response to prices that varied by time of day. These models also involved the analysis of hourly load data and the normalization of loads for the effect of weather and it also involved the assessment of new technologies such as web portals, in-home displays, and smart thermostats on load forecasts.

He began his career as a demand forecasting analyst at the California Energy Commission and wrote his dissertation on forecasting the industrial demand for energy. This analysis was carried out at the industry-by-industry level and involved the use of innovative econometric methods to estimate the dynamics of energy substitution. Subsequently, he managed the development of EPRI's suite of forecasting models. This included a Regional Load Curve Model (RLCM) that was designed to predict hourly loads including peak demand for 32 regions in the continental United States. This project worked with system load data and employed a methodology that later came to be known as conditional demand analysis to infer the load contribution of individual classes and end uses. For example, the project also demonstrated for the first time in the utility industry how ex ante and ex post measures of forecast accuracy could be conducted by using out-of-sample forecasting experiments. RLCM ultimately morphed into the Hourly Electric Load Model (HELM) that used a bottom-up approach to aggregate system loads by working up from end-use and class loads. HELM used a weather response function that was econometrically estimated and was of great use to utilities and agencies in the evaluation of demand-side programs, given its end-use model architecture.

Dr. Faruqui also managed the Weather Normalization of Sales (WENS) project, where the innovative time-varying parametric estimation algorithm was used to quantify the movement in weather sensitivity parameters caused by unobserved changes in consumer attitudes toward energy conservation. This technique later found its way into the FORECAST MASTER project that focused on short-term forecasting. This project used both econometric and time series methods to help utilities forecast energy sales, peak demands and hourly loads over the short term.

Later in his EPRI tenure, he managed the entire portfolio of demand forecasting models, including end-use and econometric models for forecasting energy consumption, peak demand and load shapes the residential, commercial and industrial sectors. The portfolio included the widely used REEPS, COMMEND, and INDEPTH models. In a second tour of duty at EPRI, he developed innovative ways to developing dynamic pricing rate designs and to predict their impact on utility loads. Later, he managed the power markets and risk management program which involved among other things the integration of demand forecasts with resource planning models.

Dr. Faruqui is the author, co-author or editor of four books and more than 150 articles, papers, and reports on efficient energy use, some of which are featured on the websites of the Harvard Electricity Policy Group and the Social Science Research Network. He has taught economics at San Jose State University, the University of California at Davis and the University of Karachi. He holds a an M.A. in agricultural economics and a Ph. D. in economics from The University of California at Davis, where he was a Regents Fellow, and B.A. and M.A. degrees in economics from The University of Karachi, where he was awarded the Gold Medal in economics.

AREAS OF EXPERTISE

- *Demand forecasting and weather normalization.* He has pioneered the use of a wide variety of models for forecasting product demand in the near-, medium-, and long-term, using econometric, time series, and engineering methods. These models have been used to bid into energy procurement auctions, plan capacity additions, design customer-side programs, and weather normalize sales.
- *Innovative pricing.* He has identified, designed and analyzed the efficiency and equity benefits of introducing innovative pricing designs such as dynamic pricing, time-of-use pricing and inclining block rates.
- *Regulatory strategy.* He has helped design forward-looking programs and services that exploit recent advances in rate design and digital technologies in order to lower customer bills and improve utility earnings while lowering the carbon footprint and preserving system reliability.
- *Cost-benefit analysis of advanced metering infrastructure.* He has assessed the feasibility of introducing smart meters and other devices, such as programmable communicating thermostats that promote demand response, into the energy marketplace, in addition to new appliances, buildings, and industrial processes that improve energy efficiency.
- *Customer choice.* He has developed methods for surveying customers in order to elicit their preferences for alternative energy products and alternative energy suppliers. These methods have been used to predict the market size of these products and to estimate the market share of specific suppliers.
- *Hedging, risk management, and market design.* He has helped design a wide range of financial products that help customers and utilities cope with the unique opportunities and challenges posed by a competitive market for electricity. He conducted a widely-cited market simulation to show that real-time pricing of electricity could have saved Californians millions of dollars during the Energy Crisis by lowering peak demands and prices in the wholesale market.
- *Competitive strategy.* He has helped clients develop and implement competitive marketing strategies by drawing on his knowledge of the energy needs of end-use customers, their values and decision-making practices, and their competitive options.

He has helped companies reshape and transform their marketing organization and reposition themselves for a competitive marketplace. He has also helped government-owned entities in the developing world prepare for privatization by benchmarking their planning, retailing, and distribution processes against industry best practices, and suggesting improvements by specifying quantitative metrics and follow-up procedures.

- *Design and evaluation of marketing programs.* He has helped generate ideas for new products and services, identified successful design characteristics through customer surveys and focus groups, and test marketed new concepts through pilots and experiments.
- *Expert witness.* He has testified or appeared before state commissions in Arizona, Arkansas, California, Colorado, Connecticut, Delaware, the District of Columbia, Illinois, Indiana, Iowa, Kansas, Michigan, Maryland, Ontario (Canada), Pennsylvania and Texas. He has assisted clients in developing and submitting testimony in Georgia and Minnesota. He has made presentations to the California Energy Commission, the California Senate, the Congressional Office of Technology Assessment, the Kentucky Commission, the Minnesota Department of Commerce, the Minnesota Senate, the Missouri Public Service Commission, and the Electricity Pricing Collaborative in the state of Washington. In addition, he has led a variety of professional seminars and workshops on public utility economics around the world and taught economics at the university level.

EXPERIENCE

Demand Forecasting

- **Comprehensive Review of Load Forecasting Methodology: PJM Interconnection.** Conducted a comprehensive review of models for forecasting peak demand and re-estimated new models to validate recommendations. Individual models were developed for 18 transmission zones as well as a model for the RTO system.
- **Analyzed Downward Trend: Western Utility.** We conducted a strategic review of why sales had been lower than forecast in a year when economic activity had been brisk. We developed a forecasting model for identifying what had caused the drop in sales and its results were used in an executive presentation to the utility's

board of directors. We also developed a time series model for more accurately forecasting sales in the near term and this model is now being used for revenue forecasting and budgetary planning.

- **Analyzed Why Models are Under-Forecasting: Southwestern Utility**. Reviewed the entire suite of load forecasting models, including models for forecasting aggregate system peak demand, electricity consumption per customer by sector and the number of customers by sector. We ran a variety of forecasting experiments to assess both the ex-ante and ex-post accuracy of the models and made several recommendations to senior management.

- **U.S. Demand Forecast: Edison Electric Institute.** For the U.S. as a whole, we developed a base case forecast and several alternative case forecasts of electric energy consumption by end use and sector. We subsequently developed forecasts that were based on EPRI's system of end-use forecasting models. The project was done in close coordination with several utilities and some of the results were published in book form.

- **Developed Models for Forecasting Hourly Loads: Merchant Generation and Trading Company.** Using primary data on customer loads, weather conditions, and economic activity, developed models for forecasting hourly loads for residential, commercial, and industrial customers for three utilities in a Midwestern state. The information was used to develop bids into an auction for supplying basic generation services.

- **Gas Demand Forecasting System - Client: A Leading Gas Marketing and Trading Company, Texas.** Developed a system for gas nominations for a leading gas marketing company that operated in 23 local distribution company service areas. The system made week-ahead and month-ahead forecasts using advanced forecasting methods. Its objective was to improve the marketing company's profitability by minimizing penalties associated with forecasting errors.

TESTIMONY

California

Prepared testimony before the Public Utilities Commission of the State of California on behalf of Pacific Gas and Electric Company on rate relief, Docket No. A.10-03-014, summer 2010.

Qualifications and prepared testimony before the Public Utilities Commission of the State of California, on behalf of Southern California Edison, Edison SmartConnect™ Deployment Funding and Cost Recovery, exhibit SCE-4, July 31, 2007.

Testimony on behalf of the Pacific Gas & Electric Company, in its application for Automated Metering Infrastructure with the California Public Utilities Commission. Docket No. 05-06-028, 2006.

Colorado

Rebuttal testimony before the Public Utilities Commission of the State of Colorado in the Matter of Advice Letter No. 1535 by Public Service Company of Colorado to Revise its Colorado PUC No.7 Electric Tariff to Reflect Revised Rates and Rate Schedules to be Effective on June 5, 2009. Docket No. 09al-299e, November 25, 2009.

Direct testimony before the Public Utilities Commission of the State of Colorado, on behalf of Public Service Company of Colorado, on the tariff sheets filed by Public Service Company of Colorado with advice letter No. 1535 – Electric. Docket No. 09S-__E, May 1, 2009.

Connecticut

Testimony before the Department of Public Utility Control, on behalf of the Connecticut Light and Power Company, in its application to implement Time-of-Use , Interruptible Load Response, and Seasonal Rates- Submittal of Metering and Rate Pilot Results- Compliance Order No. 4, Docket no. 05-10-03RE01, 2007.

District of Columbia

Direct testimony before the Public Service Commission of the District of Columbia on behalf of Potomac Electric Power Company in the matter of the Application of Potomac Electric Power Company for Authorization to Establish a Demand Side Management Surcharge and an Advance Metering Infrastructure Surcharge and to Establish a DSM Collaborative and an AMI Advisory Group, case no. 1056, May 2009.

Illinois

Direct testimony on rehearing before the Illinois Commerce Commission on behalf of Ameren Illinois Company, on the Smart Grid Advanced Metering Infrastructure Deployment Plan, Docket No. 12-0244, June 28, 2012.

Testimony before the State of Illinois – Illinois Commerce Commission on behalf of Commonwealth Edison Company regarding the evaluation of experimental residential real-time pricing program, 11-0546, April 2012.

Prepared rebuttal testimony before the Illinois Commerce Commission on behalf of Commonwealth Edison, on the Advanced Metering Infrastructure Pilot Program, ICC Docket No. 06-0617, October 30, 2006.

Indiana

Direct testimony before the State of Indiana, Indiana Utility Regulatory Commission, on behalf of Vectren South, on the smart grid. Cause no. 43810, 2009.

Maryland

Direct testimony before the Public Service Commission of Maryland, on behalf of Potomac Electric Power Company and Delmarva Power and Light Company, on the deployment of Advanced Meter Infrastructure. Case no. 9207, September 2009.

Prepared direct testimony before the Maryland Public Service Commission, on behalf of Baltimore Gas and Electric Company, on the findings of BGE's Smart Energy Pricing ("SEP") Pilot program. Case No. 9208, July 10, 2009.

Minnesota

Rebuttal testimony before the Minnesota Public Utilities Commission State of Minnesota on behalf of Northern States Power Company, doing business as Xcel Energy, in the matter of the Application of Northern States Power Company for Authority to Increase Rates for Electric Service in Minnesota, Docket No. E002/GR-12-961, March 25, 2013.

Direct testimony before the Minnesota Public Utilities Commission State of Minnesota on behalf of Northern States Power Company, doing business as Xcel Energy, in the matter of the Application of Northern States Power Company for Authority to Increase Rates for Electric Service in Minnesota, Docket No. E002/GR-12-961, November 2, 2012.

Pennsylvania

Direct testimony before the Pennsylvania Public Utility Commission, on behalf of PECO on the Methodology Used to Derive Dynamic Pricing Rate Designs, Case no. M-2009-2123944, October 28, 2010.

REGULATORY APPEARANCES

Arizona

Presented before the Arizona Commerce Commission, " Strategies and Tactics for Dealing with Changing Customer Energy Use Patterns," ACC Workshop, March 20, 2014.

Arkansas

Presented before the Arkansas Public Service Commission, "The Emergence of Dynamic Pricing" at the workshop on the Smart Grid, Demand Response, and Automated Metering Infrastructure, Little Rock, Arkansas, September 30, 2009.

Delaware

Presented before the Delaware Public Service Commission, "The Demand Response Impacts of PHI's Dynamic Pricing Program" Delaware, September 5, 2007.

Kansas

Presented before the State Corporation Commission of the State of Kansas, "The Impact of Dynamic Pricing on Westar Energy" at the Smart Grid and Energy Storage Roundtable, Topeka, Kansas, September 18, 2009.

Ohio

Presented before the Ohio Public Utilities Commission, "Dynamic Pricing for Residential and Small C&I Customers" at the Technical Workshop, Columbus, Ohio March 28, 2012.

PUBLICATIONS

Books

Electricity Pricing in Transition. Co-editor with Kelly Eakin. Kluwer Academic Publishing, 2002.

Pricing in Competitive Electricity Markets. Co-editor with Kelly Eakin. Kluwer Academic Publishing, 2000.

Customer Choice: Finding Value in Retail Electricity Markets. Co-editor with J. Robert Malko. Public Utilities Inc. Vienna. Virginia: 1999.

The Changing Structure of American Industry and Energy Use Patterns. Co-editor with John Broehl. Battelle Press, 1987.

Customer Response to Time of Use Rates: Topic Paper I, with Dennis Aigner and Robert T. Howard, Electric Utility Rate Design Study, EPRI, 1981.

Technical Reports

Impact Evaluation of Ontario's Time-of-Use Rates: First Year Analysis, with Sanem Sergici, Neil Lessem, Dean Mountain, Frank Denton, Byron Spencer, and Chris King, prepared for Ontario Power Authority, November 2013.

Time-Varying and Dynamic Rate Design, with Ryan Hledik and Jennifer Palmer, prepared for RAP, July 2012. http://www.raponline.org/document/download/id/5131

The Costs and Benefits of Smart Meters for Residential Customers, with Adam Cooper, Doug Mitarotonda, Judith Schwartz, and Lisa Wood, prepared for Institute for Electric Efficiency, July 2011.
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Measurement and Verification Principles for Behavior-Based Efficiency Programs, with Sanem Sergici, prepared for Opower, May 2011. http://opower.com/uploads/library/file/10/brattle_mv_principles.pdf

Methodological Approach for Estimating the Benefits and Costs of Smart Grid Demonstration Projects. With R. Lee, S. Bossart, R. Hledik, C. Lamontagne, B. Renz, F. Small, D. Violette, and D. Walls. Pre-publication draft, prepared for the U. S. Department of Energy, Office of Electricity Delivery and Energy Reliability, the National Energy Technology Laboratory, and the Electric Power Research Institute. Oak Ridge, TN: Oak Ridge National Laboratory, November 28, 2009.

Moving Toward Utility-Scale Deployment of Dynamic Pricing in Mass Markets. With Sanem Sergici and Lisa Wood. Institute for Electric Efficiency, June 2009.

Demand-Side Bidding in Wholesale Electricity Markets. With Robert Earle. Australian Energy Market Commission, 2008. http://www.aemc.gov.au/electricity.php?r=20071025.174223

Assessment of Achievable Potential for Energy Efficiency and Demand Response in the U.S. (2010-2030). With Ingrid Rohmund, Greg Wikler, Omar Siddiqui, and Rick Tempchin. American Council for an Energy-Efficient Economy, 2008.

Quantifying the Benefits of Dynamic Pricing in the Mass Market. With Lisa Wood. Edison Electric Institute, January 2008.

California Energy Commission. *2007 Integrated Energy Policy Report,* CEC-100-2007-008-CMF.

Applications of Dynamic Pricing in Developing and Emerging Economies. Prepared for The World Bank, Washington, DC. May 2005.

Preventing Electrical Shocks: What Ontario—And Other Provinces—Should Learn About Smart Metering. With Stephen S. George. C. D. Howe Institute Commentary, No. 210, April 2005.

Primer on Demand-Side Management. Prepared for The World Bank, Washington, DC. March 21, 2005.

Electricity Pricing: Lessons from the Front. With Dan Violette. White Paper based on the May 2003 AESP/EPRI Pricing Conference, Chicago, Illinois, EPRI Technical Update 1002223, December 2003.

Electric Technologies for Gas Compression. Electric Power Research Institute, 1997.

Electrotechnologies for Multifamily Housing. With Omar Siddiqui. EPRI TR-106442, Volumes 1 and 2. Electric Power Research Institute, September 1996.

Opportunities for Energy Efficiency in the Texas Industrial Sector. Texas Sustainable Energy Development Council. With J. W. Zarnikau et al. June 1995.

Principles and Practice of Demand-Side Management. With John H. Chamberlin. EPRI TR-102556. Palo Alto: Electric Power Research Institute, August 1993.

EPRI Urban Initiative: 1992 Workshop Proceedings (Part I). The EPRI Community Initiative. With G.A. Wikler and R.H. Manson. TR-102394. Palo Alto: Electric Power Research Institute, May 1993.

Practical Applications of Forecasting Under Uncertainty. With K.P. Seiden and C.A. Sabo.TR-102394. Palo Alto: Electric Power Research Institute, December 1992.

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"Demand Growth and the New Normal," with Eric Shultz, *Public Utilities Fortnightly*, December 2012.

"Impact Measurement of Tariff Changes When Experimentation is Not an Option – a Case Study of Ontario, Canada," with Sanem Sergici, Neil Lessem, and Dean Mountain, SSRN, March 2014.

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"Dynamic Pricing in a Moderate Climate: The Evidence from Connecticut," with Sanem Sergici and Lamine Akaba, *Energy Journal*, 35:1, pp. 137-160, January 2014.

"Charting the DSM Sales Slump," with Eric Schultz, *Spark*, September 2013.
http://spark.fortnightly.com/fortnightly/charting-dsm-sales-slump

"Arcturus: International Evidence on Dynamic Pricing," with Sanem Sergici, *The Electricity Journal*, 26:7, August/September 2013, pp. 55-65.

"Benchmarking your Rate Case," with Ryan Hledik, *Public Utility Fortnightly*, July 2013.
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"Surviving Sub-One-Percent Growth," *Electricity Policy*, June 2013.
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"Dynamic Pricing of Electricity for Residential Customers: The Evidence from Michigan," with Sanem Sergici and Lamine Akaba, *Energy Efficiency*, 6:3, August 2013, pp. 571–584.

"Energy Efficiency and Demand Response in 2020 – A Survey of Expert Opinion," with Doug Mitarotonda, March 2012.

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http://www.electricenergyonline.com/?page=show_article&mag=76&article=618

"Dynamic Pricing of Electricity and its Discontents" with Jennifer Palmer, *Regulation*, Volume 34, Number 3, Fall 2011, pp. 16-22.
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"The Energy Efficiency Imperative" with Ryan Hledik, *Middle East Economic Survey*, Vol LIV: No. 38,
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"Are LDCs and customers ready for dynamic prices?" with Jürgen Weiss, *Fortnightly's Spark*, August 25, 2011.
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"Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment," with Dan Harris and Ryan Hledik, *Energy Policy*, Volume 38, Issue 10, October 2010, pp. 6222-6231.
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"The Power of Dynamic Pricing," with Ryan Hledik and John Tsoukalis, *The Electricity Journal*, April 2009, pp. 42-56.
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"Ethanol 2.0," with Robert Earle, *Regulation*, Winter 2009.
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"Inclining Toward Efficiency," *Public Utilities Fortnightly*, August 2008, pp. 22-27.
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"California: Mandating Demand Response," with Jackalyne Pfannenstiel, *Public Utilities Fortnightly*, January 2008, pp. 48-53.
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Model Specification and Testing for PNM Sales Forecast

PNM Exhibit AF-2

Is contained in the following 21 pages.

Model Specification and Testing for PNM Sales Forecast

I. Introduction

PNM Exhibit AF-2 provides a detailed description of how I derived the recommended models for Usage per Customer ("UPC," measured in kWh sales per customer), sales (measured in kWh), and the number of customers. First, I discuss the metrics by which I evaluated alternative models for forecasting. Second, I explain how I determined the model specifications that would be most appropriate for PNM. Tables AF-2 and AF-5 in my testimony summarize the recommended models specifications by rate class, and I have reproduced them below for convenience. The estimated parameters of the models are provided in PNM Exhibit AF-3, PNM Exhibit AF-4, and PNM Exhibit AF-5.

Table AF-2: Summary of Econometric Models for Usage per Customer and kWh sales

			Inputs					
Rates [1]	**Description** [2]	**Output** [3]	**Income** [4]	**Price** [5]	**Weather** [6]	**South** [7]	**Time Trend** [8]	**Shift in May 2013** [9]
1A	Residential	UPC	**Yes**	**Yes**	**Yes**	No	No	No
1B	Residential TOU	UPC	**Yes**	No	**Yes**	No	No	No
2A	Small Power	UPC	No	**Yes**	**Yes**	No	No	No
2B	Small Power TOU	UPC	No	No	**Yes**	**Yes**	**Yes**	No
3B/3C	General Power	UPC	No	No	**Yes**	No	No	**Yes**
4B*	Large Power	kWh	No	No	**Yes**	**Yes**	**Yes**	**Yes**
10A	Irrigation	UPC	No	No	**Yes**	**Yes**	No	No
10B	Irrigation TOU	UPC	**Yes**	No	**Yes**	**Yes**	No	No

Notes: "UPC" stands for Usage per Customer. "TOU" stands for Time-of-use. "Income" is measured by real personal income for Rates 1A and 1B and by real Gross State Product for Rate 10B. "Weather" is measured by Cooling Degree Days and Heating Degree Days. For Rates 1A and 1B, the temperature threshold is 70 for CDD and 58 for HDD. For Rates 2A, 2B, 3B/3C, 4B, 10A, and 10B, the temperature threshold is 60 for both CDD and HDD.

For Rates 2B, 10A, and 10B, only CDD is included in the models; for other Rates, both CDD and HDD are included in the models. "South" is a binary variable that equals 1 for time periods after March 2007 (inclusive) and 0 otherwise. "Time Trend" is a constructed variable that increases by 1 unit each month. For Rate 4B (which is demarcated by *), large customers are excluded from the econometric model and, instead, are individually forecasted. For Rate 1A, the model structure is AR(1) MA(6,12). For Rate 4B, the model structure is OLS. For the remaining rate classes, the models are estimated using GLS. Rates 1A and 3B/3C have seasonal models in which the parameter estimates for all explanatory variables are allowed to vary between summer (June-October) and winter (November-May).

Table AF-5: Summary of Econometric Models for Number of Customers

			Inputs				
Rates [1]	**Description** [2]	**Output** [3]	**Population** [4]	**Income** [5]	**South** [6]	**Time Trend** [7]	**Shift in Jan 2009** [8]
1A	Residential	Customers	No	No	No	**Yes**	**Yes**
1B	Residential TOU	N/A					
2A	Small Power	Customers	**Yes**	No	**Yes**	No	No
2B	Small Power TOU	N/A					
3B/3C	General Power	Customers	No	**Yes**	**Yes**	**Yes**	No
10A	Irrigation	N/A					
10B	Irrigation TOU	N/A					

Notes: "TOU" stands for Time of Use. "Population" includes residents of PNM's service territory only. "Income" is measured by real Gross State Product. "South" is a binary variable that equals 1 for time periods after March 2007 (inclusive) and 0 otherwise. "Time Trend" is a constructed variable that increases by 1 unit each month. For Rates 1A and 3B/3C, the time trend is interacted with the shifts in January 2009 or March 2007, which are represented by indicator variables. For Rates 1B, 2B, 10A, and 10B, customer forecasts are based on the average across the last 12 months (April 2014-March 2015).

II. Criteria for Evaluating Forecasting Models

My recommendations are based on six criteria: (1) historical goodness-of-fit or in-sample performance; (2) out-of-sample performance; (3) model parameter plausibility; (4) plausibility of forecasted values in 2015-2016, which includes the Future Test Year ("FTY"); (5) model specification transparency ; and (6) overall credibility of results. Each criterion addresses the accuracy, theoretical soundness, or robustness of the model's forecast.

A. Accuracy

How well do the model predictions fit the in-sample data, that is, the data that were used to estimate the model's parameters? To measure model fit, I calculated the mean absolute percentage error ("MAPE"). In the context of PNM's sales forecast, MAPE is the average difference between predicted electricity sales and actual sales as a percentage of the latter. Other measures of model fit include root mean square error ("RMSE") and mean absolute deviation ("MAD"). I estimated the model for each rate class using PNM's historical data and calculated the in-sample MAPE on this data.

Since the model parameters are chosen to minimize the difference between predicted and actual values (that is, prediction error[1]) in some form, one would expect that the in-sample prediction errors are small across all models. A more challenging test would be to evaluate how well the model predictions fit out-of-sample data, or the data that were not used to estimate the model's parameters. To perform this test, I trained the model using data from January 2002 through May 2014 (the "in-sample period"), and I treated June 2014 through May 2015 as the "out-of-sample period." I then calculated and compared the MAPE for the out-of-sample period across models.

B. Theoretical Soundness

The in-sample and out-of-sample fits measure the accuracy of the model given existing information, but past performance does not guarantee reliable forecasts. Thus, I also evaluated

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1 The "prediction error" would be the difference between electricity sales and actual sales.

whether the model parameters are consistent with economic theory of demand for electricity. I have studied and published papers about demand for electricity by residential and commercial customers, and there are a few well-established properties of electricity demand: first, as income rises, usage increases; second, as the price per kWh rises, usage decreases; and with more extreme weather conditions such as hotter summers or colder winters, usage increases. If the model parameters show otherwise, then that would suggest the model may be missing an important piece of information or input that is correlated with sales.

Not only should the model parameters be defensible from a theoretical standpoint, but I also considered whether the model specification allows us to identify which factors are driving the long-run trends in UPC, number of customers, or kWh sales. Some complex models perform well, that is, forecasting with fairly high accuracy (on the basis of in-sample and out-of-sample MAPEs). However, the models can be opaque, a sort of "black box." Purely statistical models heavily rely on the quality and representativeness of the data. In the event of a significant shift by customers from their past behavior, the past is no longer relevant, and a model estimated on past data may become obsolete. Thus, I generally preferred models that can be clearly traced back to economic theory as opposed to being a purely statistical construct.

C. Robustness

In addition to accuracy and theoretical soundness, I evaluated the robustness of the model by comparing the 2015-16 forecasts of electricity usage with the observed usage patterns in recent history, especially after the economic recession in 2008-09, and with the 2015-16 forecasts from other candidate models that are based on different assumptions. If small alterations in the assumptions can drastically change the forecast, then the model is not robust.

Overall, my criteria – accuracy, theoretical soundness, and robustness – are accepted as desirable forecasting model properties. An additional general principle is to aim for simplicity when possible.[2]

III. Model Specification: Structure, Functional Form, and Inputs

An econometric model is an equation, or set of equations, that describes how a variable of interest, such as electricity usage per customer, changes as other factors vary over time and/or across individuals. The variable of interest is sometimes called an "outcome variable" or "dependent variable" and the other factors are called "explanatory variables" or "independent variables" because they explain how (or why) the outcome variable may differ when the explanatory variables change, but their behavior does not depend on the outcome variable.[3] When deciding on a model, one must choose the functional form of the equation, that is, linear, nonlinear, or linear logarithms, and given the functional form, the explanatory variables to be included.

In addition to functional form and the explanatory variables, it is important to consider how the variables evolve over time. If the evolution of one or more variables is (are) time dependent – meaning that even after accounting for changes in the other factors, the variable's current value

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[2] Allen, P. Geoffrey and Robert Fildes (2001). "Econometric Forecasting." Principles of Forecasting: A Handbook for Researchers and Practitioners, edited by J. Scott Armstrong. Norwell, MA: Kluwer Academic Publishers.

[3] Another name for the "outcome variable" is the "left-hand side variable." Other names for the "explanatory variables" include "right-hand side variables," "control variables," and "covariates." Here, I will use the terms "outcome variable" and "explanatory variables."

depends on its past value – then the model needs to be designed such that it captures those relationships. Different model structures allow for different ways in which variables can interact and change over time.

In the sections below, I first describe standard sales forecasting models that are used in the electric utility industry and how I chose among them. In short, I tested three classes of models – Ordinary Least Squares ("OLS"), Generalized Least Squares ("GLS"), and Autoregressive Integrated Moving Average ("ARIMA"). While OLS may be the simplest and most transparent of the models, certain forms of the GLS specification address time dependency and are recommended where appropriate. Second, I detail my functional form choice, the explanatory variables to include in each model for each rate class for UPC as well as the number of customers. In practice, I considered the model's structure, form, and inputs simultaneously.

A. MODEL STRUCTURE: OLS, GLS, AND ARIMA

There are two broad categories of sales forecasting models that are widely used in the utility industry: econometric (or causal) models and time series models.[4] Econometric models are based on causal relationships derived from economic theory and seek to measure the relationship between electricity sales and explanatory factors such as income, price, or weather. For example: an econometric model may be designed to characterize a consumer's decision of

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[4] For an introduction to forecasting methods and time series models, see Kennedy, Peter (2003). A Guide to Econometrics, 5th edition. Cambridge, MA: The MIT Press.

Note that, in the Economics discipline, time series is also included in the study of econometrics. For the purpose of explaining the development of the forecast, a less confusing nomenclature might be "least squares regressions" instead of "econometric (or causal) models." Another reason to use "least squares regressions" is that causality is often based on the postulates of economic theory.

how much electricity to use during a month. Time series models are based on the premise that historical changes in the outcome variable of interest are a good predictor of future changes. For example: past values of, say electricity usage, may serve as good predictors of future usage levels. These models are designed to best fit the observed data rather than explain an underlying process. The advantages and disadvantages of both methods have long been discussed and debated.

I considered three classes of forecasting models that are widely used: OLS, GLS, and ARIMA. OLS and GLS are common causal models and ARIMA is a typical time series model.

OLS fits a line to the data by minimizing the sum of the prediction errors squared, which is why it is called least squares. Although OLS is appealing for its intuitive simplicity, it works best when observations in the data are jointly independent of one another. In other words, each observation provides new information about the relationship between the outcome and explanatory variables regardless of the other observations included in the sample.

The assumption of independently distributed errors would be violated if observations in the sample were related to one another in a systematic way that cannot be directly controlled for in the model. This can arise when past and present prediction components are linked, that is, serial correlation in the forecasting errors. In the context of electricity usage, the fact that household demand for electricity is closely tied to ownership of durable appliances, which may not change over time and may not be directly observed, could be one reason why there is serial correlation.

In the presence of serial correlation, GLS may be more suitable than OLS because GLS can directly address the co-dependencies in the estimated model's in-sample prediction errors.[5] While the observations may be correlated over time, the partial difference[6] between observations may be independently distributed. GLS transforms the data by estimating the coefficient to be used in the partial difference of in-sample prediction errors, then transforms the outcome and explanatory variables based on that coefficient, and applies OLS to the transformed observations. To check for the appropriate use and robustness of implementing GLS, I test for serial correlation.

ARIMA is an example of a time series model, that is, non-causal model, and the model predicts future values of the outcome, say UPC, using solely past values of UPC and a moving average of unexpected events (also known as "shocks") over a specified time period. More precisely, the ARIMA(p,d,q) model allows the outcome to depend on 'p' lags of itself, 'd' differences to remove any trend, and 'q' periods of persistence in the error term. [7]

In numerous applications, especially forecasting in the short-term, ARIMA performs well according to statistical measures such as MAPE. However, choosing the number of lags and difference can be a challenge, and many researchers rely the pattern of the autocorrelation and

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5 Specifically, the Prais-Winsten procedure addresses serial correlation when errors follow an autoregressive process with a one-period lag. Prais-Winsten can be estimated as GLS. See Prais, S.J. and C.B. Winsten (1954) "Trend Estimators and Serial Correlation." *Cowles Commission Discussion Paper No. 383*.

6 A partial difference means that I subtract a fraction of the lagged value from the current value rather than taking the simple difference between observations.

7 If the series is not differenced, *i.e.*, d equals 0, then ARIMA may be called Autoregressive Moving Average ("ARMA") instead.

autocorrelation functions of the model to choose the length of the p's and q's. [8] Thus, a common critique of ARIMA is that the model is statistically rather than theoretically based, and the underlying drivers of the forecast are not always well understood.

Since transparency in the model's specification is one of my criteria for model selection, I have chosen to recommend OLS and GLS models over ARIMA, even when the in-sample and out-of-sample MAPEs for ARIMA are lower.[9] For Rate 1A, I make an exception for the UPC model; as I will explain below, I find that ARMA performs substantially better than OLS and GLS models in terms of forecasting accuracy (as measured by MAPE), especially for summer months.

B. Choosing the Model's Functional Form and Explanatory Variables

Functional form refers to the algebraic form of the model. Examples include a line, a quadratic polynomial, and an exponential. Implicit in the functional form are assumptions about the relationship between the outcome variable and the explanatory variable. A linear function assumes a proportional relationship between the outcome and explanatory variables. A one unit increase in the explanatory variable has the same effect on the outcome variable regardless of the value of the explanatory variable. A logarithmic function in which both the outcome and explanatory variables are in logarithms assumes a constant proportional relationship between the outcome and explanatory variables in logarithms. A one percentage point increase in the

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8 See Enders, Walter (1995). Applied Econometric Time Series 2nd edition. Hoboken, NJ: Wiley.

9 The forecast from ARIMA can serve as a robustness check.

explanatory variable has the same percentage impact on the outcome variable. This version of a model is useful because it can be transformed to an elasticity model.

The decision to include or exclude certain explanatory variables depends on statistical fit, guided by economic theory principles. For UPC, economic theory attempts to characterize how an individual in each rate class makes decisions about their electricity usage. According to demand theory, income, prices, and demand shifters, such as climate and weather, are important factors. The number of customers is typically driven by forces different to UPC. Since PNM is the only electric utility in its service territory, understanding (and/or measuring) the movement of customers in and out of PNM's service territory is essential.[10]

When deciding which variables should be included in the model, the first need is to understand the customer base in each rate class. After understanding the customer base, I can then identify factors that likely influence the customer's electricity usage or the customer's propensity to move. While some factors may affect all rate classes, others factors may be pertinent only to a subset of rate classes. For example, personal income of residents in New Mexico affects usage for residential customers and small businesses; however, personal income of New Mexico residents may have little to no influence on usage among large manufacturers whose products are sold in part outside PNM's service territory.

In brief, the customer composition of each rate classes that I econometrically forecast is:[11]

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10 A map of PNM's service territory is available online at https://www.pnm.com/about-pnm (accessed on November 24, 2014).

11 Detailed descriptions can be found on PNM's website at https://www.pnm.com/rates.

- Rates 1A and 1B consist of individuals and households in "single-family houses, individuals farm units, individual apartments, or separate living quarters ordinarily designated and recognized as single-family living quarters for primarily domestic or home use." Customers may pay either a fixed rate per kWh (Schedule 1A) or a rate that depends on time of use (Schedule 1B).
- Rates 2A and 2B are "Small Power" commercial classes, and "small" is defined as either on-peak load below 50 kilowatts ("kW") or monthly usage less than 15,000 kWh for at least 3 out of 12 months in a year. As for the residential class, customers may pay a fixed rate (Schedule 2A) or a rate that depends on time of use (Schedule 2B).
- Rates 3B are 3C are the "General Power [Time-of-Use]" commercial classes, and commercial entities using more than 50 kW during on-peak hours or more than 15,000 kWh for at least 3 out of 12 months in a year.
- Rate 4B is the "Large Power" commercial class (excluding some large customers, which are each forecasted separately). To qualify, the customer minimum demand must be above 500 kW. I do not econometrically forecast the number of customers for Large Power; instead, the number of customers is assumed to hold constant unless additional information indicate an impending incremental change.
- Customers in Rates 10A and 10B require electricity for irrigation pumping installations with at least 5 horsepower and 3 acres of land primarily for agricultural use. Customers may pay a fixed rate (Schedule 10A) or a rate that varies by time of use (Schedule 10B).

To choose the set of explanatory variables, I considered each variable's theoretical relevance and its statistical and economic significance when I estimate the model,[12] and whether the estimated coefficient is consistent with theory. For example: a positive price elasticity would mean that raising prices promotes higher levels of energy usage, which does not make sense from a theoretical or common sense perspective.[13] Instead, the result suggests that the model may be subject to omitted variable bias; in other words, price is capturing the effect of another factor which is both correlated with UPC and missing from the model.

In light of these principles underlying the choice of a functional form and the explanatory variables, I decided to model both UPC and number of customers as logarithmic functions. The implication of the logarithmic form is that changes in the explanatory variables have a proportional, as opposed to a level, effect on UPC (or customer counts). My choices are based upon the models' fits to observed data – namely in-sample and out-of-sample MAPEs – and standard forecasting practices that I have seen in the electric utility industry.

Rate-class specific comments about my choices for the explanatory variables for the UPC models are as follows:

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12 The term "explanatory power" can refer to the variable's statistical and economic significance. If I cannot reject that the variable is statistically different from zero and the exclusion of the variable from the model does not alter the coefficient estimates of other control variables, then I might say that the variable has "low explanatory power." Intuitively, the variable does not contribute to the understanding of how or why the outcome changes.

13 There are some rare cases in which the price elasticity may be positive. If electricity was a Giffen good, then higher prices might increase energy usage. However, a Giffen good must be an inferior good, that is, consumption falls when incomes rise, and there is no evidence that electricity falls into that category.

- **Rate 1A**[14]
    - Although I usually select GLS or OLS models instead of time series models, I chose to use an ARMA model for Rate 1A. I find that ARMA better fits historical UPC, especially in summer months (June-October) and in recent months.
    - I chose a one-month lag for the autoregressive component and six-month and twelve-month lags for the moving average component, that is, AR(1) and MA(6,12). These lags were selected based on the correlations in the residuals conditional on the logarithm of income, logarithms of price, weather terms, and month indicators.
    - Whereas other models were estimated on data through the end of the first quarter of 2015, I use data through May 2015. The reason is that the inclusion of April and May 2015 substantially improved the model fit for the last few months.
    - I use a seasonal model in the sense that the parameters are allowed to differ between the summer (June-October) and winter (November-May) months. The seasonal definitions are based on average temperature. When the parameters are constrained to be the same across seasons, I find that the forecasts over-forecast usage in the winter and under-forecast usage in the summer.
- For **Rate 1B**, I include real personal income, but not price[15] as an explanatory variable, because price has low explanatory power (that is, not statistically significant, minimally affects the other parameter estimates, and AIC is less favorable).

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[14] Refer to pages 20-23 in my direct testimony.

- For **Rate 2A**, I include real price but not real personal income because I find that the income elasticity is large and negative. Moreover, the out-of-sample MAPE is lower without income than with income.
- For **Rate 2B**, I do not include price[16] or income and, instead, include a linear time trend. The price elasticity is positive and statistically significant, and based on the out-of-sample MAPE, I find that the forecast based on a model with a linear time trend performs nearly as well as the forecast from a model with price and income. The difference in MAPE is approximately 0.005 percentage points. When forecasting, I hold the time trend constant after the last historical date. The reason is that, if the time trend is largely capturing Energy Efficiency and Codes & Standards savings, the post-estimation adjustments will better capture the effects.
- For **Rate 3B/3C**, I use a seasonal model with the same definition of summer and winter as that for Rate 1A. The seasonal model allows the marginal effect of a change in weather on UPC to differ between summer and winter months. Thus, the month indicators are average UPC levels conditional on season-specific weather. The month indicators trace out the seasonal pattern of UPC.

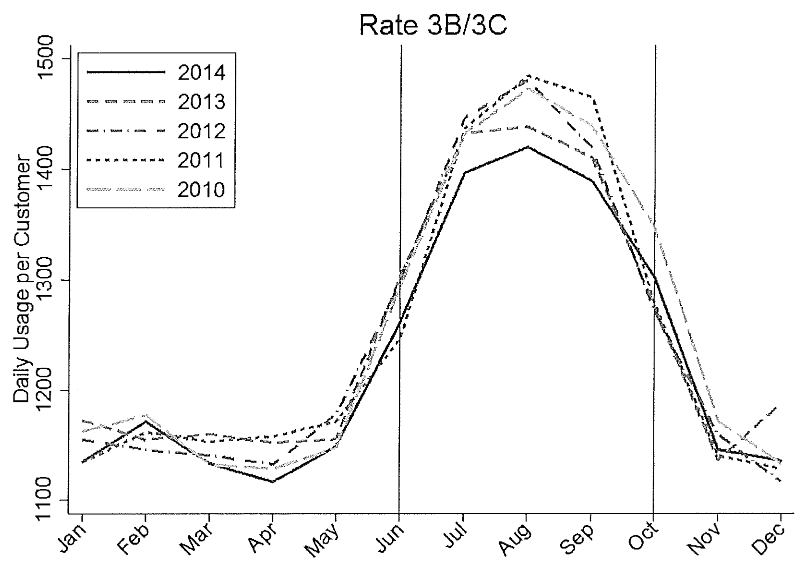
Continued from previous page

15 Price is defined as average price per kWh, that is, revenues divided by kWh sales. This is commonly used in electricity utility forecasting models and has support in the academic literature (for example, see Berndt, Ernst R. (1991). The Practice of Econometrics. Reading, MA: Addison-Wesley Publishing Company).

16 See footnote 15.

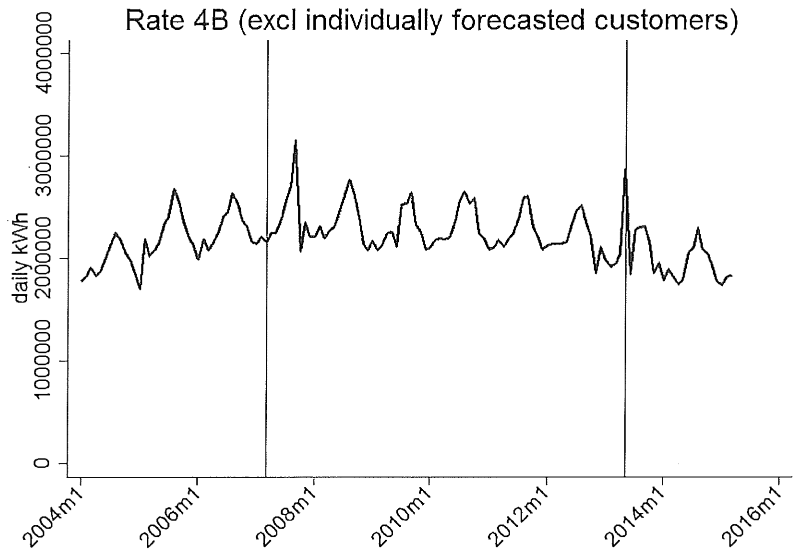
- I allow for a break in the seasonal pattern of UPC after the summer of 2013. As shown in Figure AF-2-1, UPC in the summer months is lower in 2013 and 2014. I find that including break after May 2013 reduces the out-of-sample MAPE by more than 50 percent.

Figure AF-2-1: Usage per Customer – Rate 3B/3C



- For **Rate 4B** (excluding individually forecasted Large Customers), I include an indicator for May 2013 and periods after May 2013. As evident in Figure AF-2-2, the spike in kWh in May 2013 is related to a billing issue for Bell Group. A model with a linear time trend rather than New Mexico real Gross State Product ("GSP") yielded a lower out-of-sample MAPE.

Figure AF-2-2: Kilowatt-hours – Rate 4B excluding individually forecasted customers

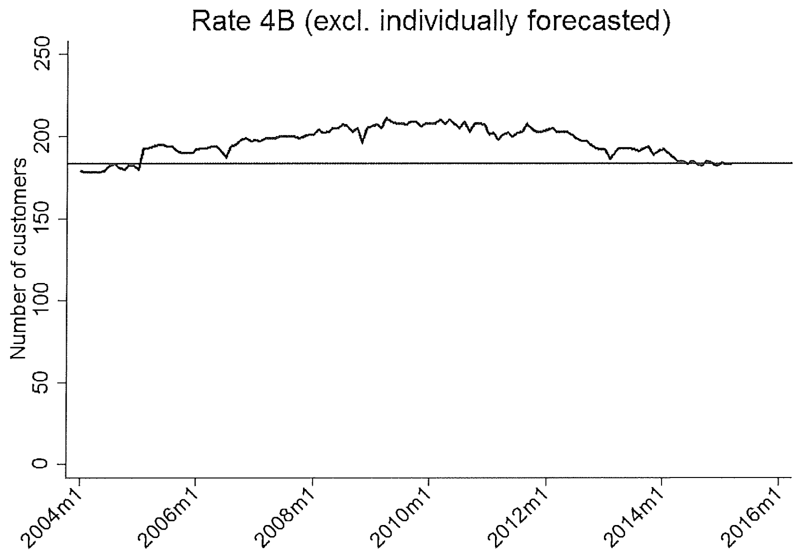


- For **Rates 10A and 10B**, the models include controls for weather (CDD 60), the addition of PNM South after March 2007, and month indicators. Warmer weather tends to increase UPC. I include GSP for Rate 10B but not for Rate 10A. For both rate classes, the inclusion of GSP makes little difference in the out-of-sample MAPE; that said, for Rate 10A, the point estimate of the income elasticity is negative. Thus, I decided to leave GSP out for Rate 10A and to keep it in the model for Rate 10B.

My choices for the explanatory variables for the customer models are as follows:

- For **Rate 4B (excluding individually forecasted Large Customers)**, the number of customers is held constant at the last historical level, which is 183 as of March 2015. The blue line in Figure AF-2-3 is the historical time trend and the red line is 183.

Figure AF-2-3: Number of Customers – Rate 4B



- For **Rates 1B, 2B, 10A, and 10B**, the average number of customers over the last 12 months (April 2014-March 2015) is used as the forecast. The reason for using the average of the last 12 months rather than an econometric model estimated over several years is that, based on discussions with PNM, there is a great deal of uncertainty over the trends in customers for these relatively small classes, particularly after the economic recession. Thus, the average over recent periods serves as a more realistic predictor than the forecast from a model estimated over a longer time span. The historical trends and averages over the last 12 months are shown in Figure AF-2-4 through Figure AF-2-7.

Figure AF-2-4: Number of Customers – Rate 1B

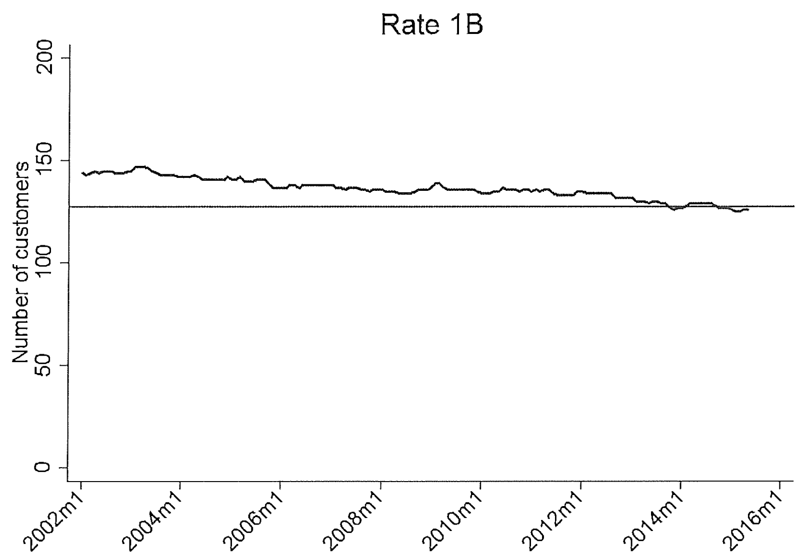


Figure AF-2-5: Number of Customers – Rate 2B

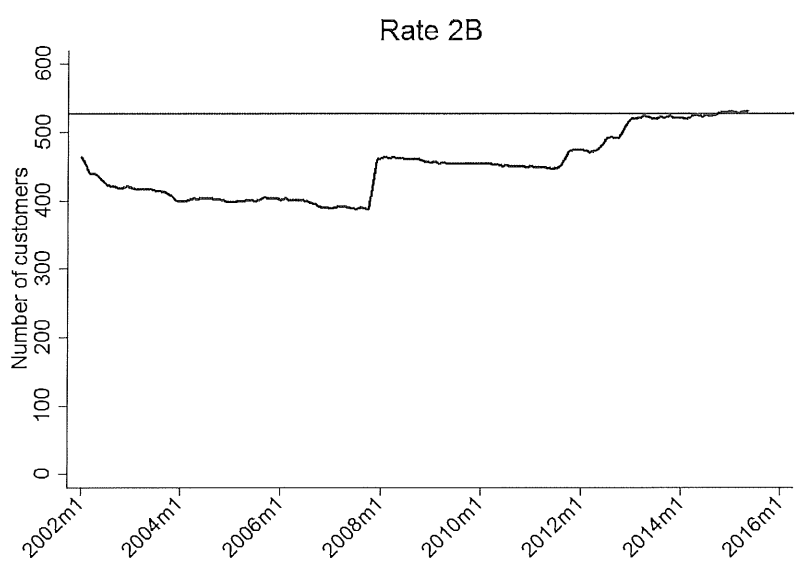


Figure AF-2-6: Number of Customers – Rate 10A

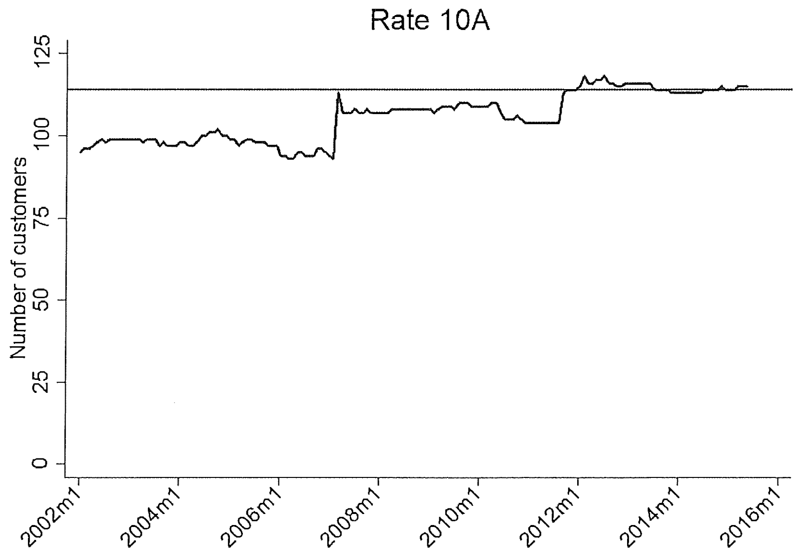
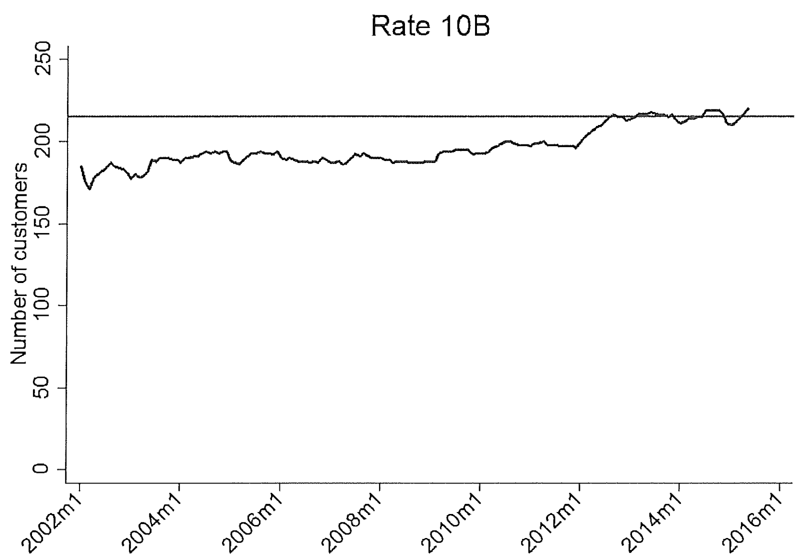
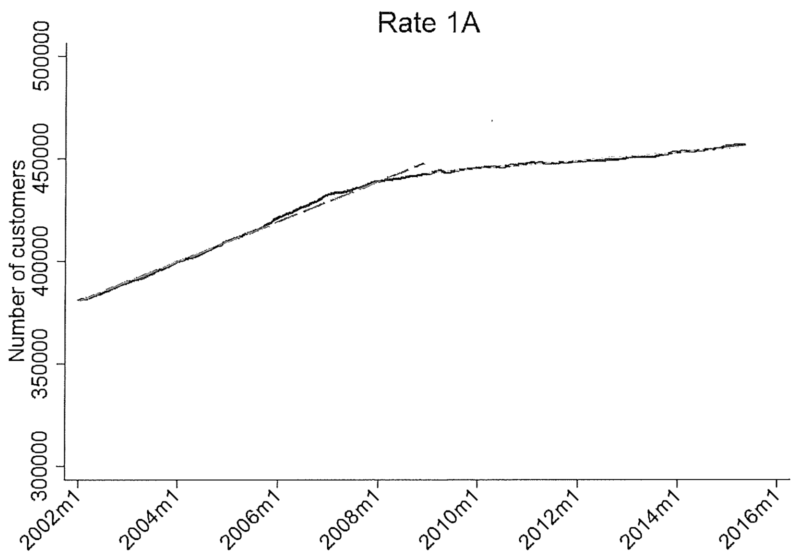


Figure AF-2-7: Number of Customers – Rate 10B



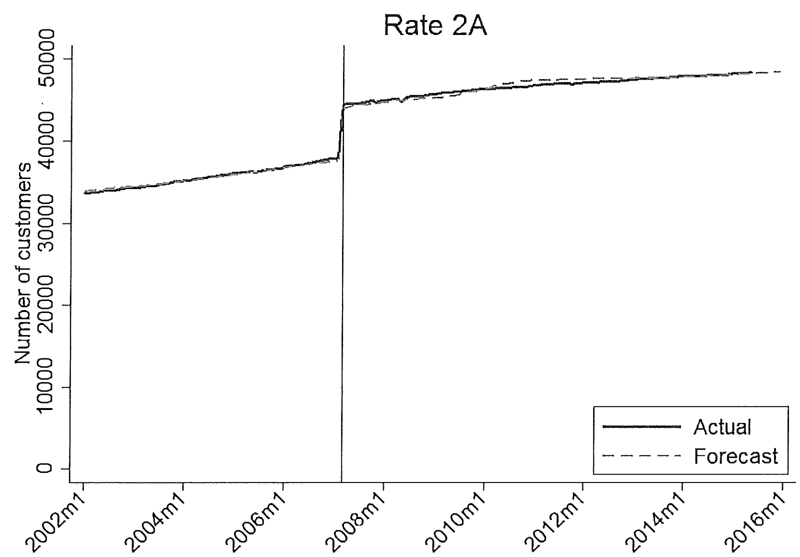
- For **Rate 1A**, which is shown in Figure AF-2-8 below, the model essentially estimates pre- (long-dashed line) and post-January 2009 (short-dashed line) growth rates. The forecast assumes that the post-January 2009 growth rate will persist. I found that the model assuming a constant growth rate had a lower MAPE than the model with population.

Figure AF-2-8: Number of Customers – Rate 1A



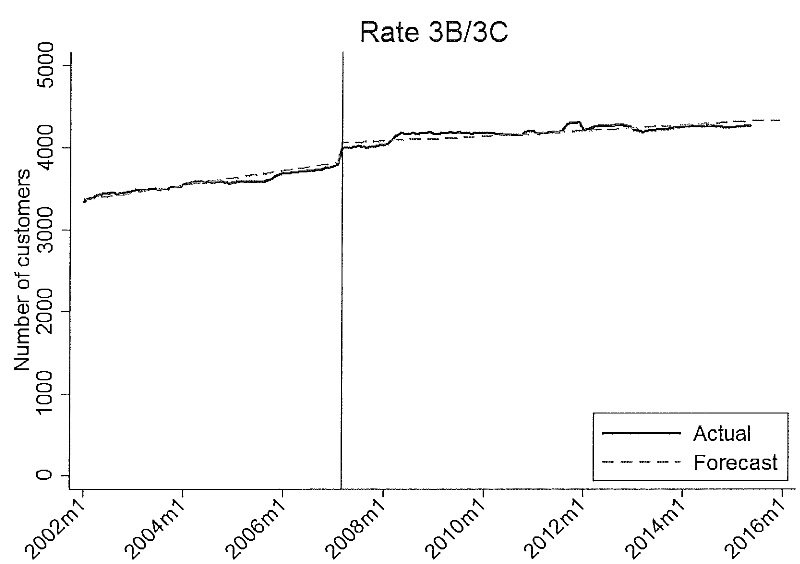
- For **Rate 2A**, the key explanatory variables are population and a dummy for the inclusion of PNM South beginning in March 2007. The black vertical line in Figure AF-2-9 marks March 2007, and there is a visible jump in the number of Small Power customers. I chose to include population rather than a time trend (which was allowed to change after March 2007) because population yielded a lower out-of-sample MAPE.

Figure AF-2-9: Number of Customers – Rate 2A



- For **Rate 3B/3C**, the model assumes that, conditional on economic conditions in the service area, there is a constant growth rate before and after the inclusion of PNM South, which is demarcated in Figure AF-2-10 by the vertical black line.

Figure AF-2-10: Number of Customers – Rate 3B/3C



Econometric Models for Usage per Customer

PNM Exhibit AF-3

Is contained in the following 1 page.

PNM Exhibit AF-3

Econometric Models for Usage Per Customer

	Outcome variable: Log of Usage Per Customer						
Rate Class:	1A	1B	2A	2B	3B/3C	10A	10B
Log of Real Price	-0.071		-0.165				
(if Seasonal model: Summer only)	(0.074)		(0.035)*				
Log of Real Personal Income	0.640	0.156					-0.042
(if Seasonal model: Summer only)	(0.104)*	(0.108)					(1.097)
If Seasonal model: Log of Real Price in	-0.223						
Winter only	(0.066)*						
If Seasonal model: Log of Real Personal	0.340						
Income in Winter only	(0.090)*						
Cooling Degree Days	19.58	2.655	4.772	14.030	11.834	39.578	12.484
(if Seasonal model: Summer only)	(11.825)	(28.170)	(5.600)	(12.538)	(6.126)	(107.051)	(74.458)
Heating Degree Days	3.964	33.230	-2.876		-1.204		
(if Seasonal model: Winter only)	(9.594)	(20.691)	(6.876)		(7.504)		
Time Trend				0.00062			
				(0.00060)			
South				0.039		0.272	0.383
				(0.041)		(0.122)*	(0.147)*
Indicator for periods after May 2013					-0.014		
					(0.018)		
Month indicators	Yes	Yes	Yes	Yes	Yes^	Yes	Yes
Seasonal model	Yes	No	No	No	Yes	No	No
Model	ARMA	GLS	GLS	GLS	GLS	GLS	GLS
AR(1)	0.431						
	(0.081)*						
MA(6)	-0.315						
	(0.089)*						
MA(12)	0.029						
	(0.092)						

Notes:

Standard errors are shown in parentheses. Unit of observation is a "rate class + month + year." Estimating period spans January 2002 through March 2015 with the exception of Rate 1A, which spans January 2002 through May 2015. For Rate 10B, "Log of Real Personal Income" is replaced by "Log of Real Gross State Product." Cooling Degree Days and Heating Degree Days have been divided by 10,000. Temperature cutoffs for Rates 1A and 1B are 58 degrees Fahrenheit for HDD and 70 degrees for CDD; for Rates 2A, 2B, 3B/3C, 10A, and 10B, both CDD and HDD use 60 degrees Fahrenheit. CDD and HDD have been weighted to match the billing cycle. South is an indicator that equals 1 for all month-years after March 2007 (inclusive). Summer season is defined as June-October, and Winter season is November-May. Seasonal model means that all explanatory variables have been interacted with both a Summer indicator and a Winter indicator except for weather, which is only CDD for Summer and HDD for Winter. ARMA stands for Autoregressive Moving Average, and GLS stands for Generalized Least Squares.

^Month indicators are interacted with indicator for time periods after May 2013

*p<0.05

Econometric Models for kWh Sales

PNM Exhibit AF-4

Is contained in the following 1 page.

PNM Exhibit AF-4

Econometric Models for kWh Sales (Rate 4B and Rate 11B)

	Outcome variable: Log of Kilowatt Hours	
Rate Class:	4B	11B
Time Trend	-0.0008 (0.0003)*	-0.0012 (0.0002)*
South	0.084 (0.020)*	
Indicator for Bell Group (May 2013)	0.296 (0.063)*	
Indicator for periods after June 2013	-0.113 (0.021)*	
Cooling Degree Days	2.999 (1.761)	12.021 (2.994)*
Heating Degree Days	1.378 (1.390)	-5.043 (2.431)*
Month indicators	Yes	Yes
Model	OLS	OLS

Notes:

Standard errors are shown in parentheses. Unit of observation is a "rate class + month + year." Rate 4B excludes customers that are individually forecasted. Estimating period spans March 2004 through March 2015. Cooling Degree Days and Heating Degree Days have been divided by 10,000. The temperature cutoff for both CDD and HDD is 60 degrees Fahrenheit. CDD and HDD have been weighted to match the billing cycle. South is an indicator that equals 1 for all month-years after March 2007 (inclusive). OLS stands for Ordinary Least Squares.

*$p<0.05$

Econometric Models for Numbers of Customers

PNM Exhibit AF-5

Is contained in the following 1 page.

PNM Exhibit AF-5

Econometric Models for Number of Customers

	Outcome variable: Log of Number of Customers		
Rate Class:	1A	2A	3B/3C
Time Trend	0.00196 (0.00002)*		0.0019 (0.0002)*
Time Trend x Periods after January 2009	-0.00159 (0.00002)*		
Time Trend x South			-0.0013 (0.0002)*
Indicator for periods after January 2009	0.139 (0.003)*		
South		0.156 (0.002)*	0.155 (0.017)*
Log of Population		1.126 (0.041)*	
Log of Real Gross State Product			0.057 (0.052)
Model	OLS	GLS	GLS

Notes:

Standard errors are shown in parentheses. Unit of observation is a "rate class + month + year." Estimating period spans January 2002 through March 2015. South is an indicator that equals 1 for periods after March 2007 (inclusive). Population has been adjusted to represent PNM's geographic coverage. Econometric models are not used for forecasting the number of customers in Rates 1B, 2B, 10A, and 10B. OLS stands for Ordinary Least Squares, and GLS stands for Generalized Least Squares.

*$p<0.05$

Codes and Standards Adjustment

PNM Exhibit AF-6

Is contained in the following 6 pages.

Codes and Standards Adjustment

RESIDENTIAL CUSTOMERS

There are several standards in effect during the forecast horizon. Some of the standards were in place in 2014, and the effects of those standards continue to produce energy savings as appliances are replaced on failure in each year of the forecast period. The standards are described below, and a timeline that summarizes the appliance standards can be found in Figure AF-6-1 on page 3.

- **Lighting Standards.** The Energy Independence and Security Act of 2007 ("EISA") was signed into law in December 2007 and established the energy efficiency standards for light bulbs and other consumer products. The law was phased-in over three years, starting in January 2012 and ending on January 2014. The Department of Energy ("DOE") codified these standards in the Code of Federal Regulations, 10 Part 430.32 and the Electronic Code of Federal Regulations.

  The energy conservation standards for standard-spectrum general service incandescent lamps are summarized below:

Rated Lumen Ranges	*Maximum Rated Wattage*	*Effective Date*
1490-2600	72	1/1/2012
1050-1489	53	1/1/2013
750-1049	43	1/1/2014
310-749	29	1/1/2014

  - The consequence of this standard is to essentially eliminate general service incandescent lamps from the marketplace. As these lamps burn out during the forecast period, consumers must replace them with more efficient lamps.

- **Central Air Conditioners and Heat Pumps**. On June 27, 2011, amended standards were issued for central air conditioners and heat pumps. The energy conservation standards are specified in the Code of Federal Regulations, 10 CFR 430.32 and the Electronic Code of Federal Regulations. The minimum standard for single package air conditioners was raised from SEER 13 to SEER 14. The minimum standard for single package heat pumps was raised from SEER 13, HSP 7.7 to SEER 14, HSPF 8. The standards apply to equipment manufactured on or after January 1, 2015.

- **Room Air Conditioners**. In August 2011, DOE issued amended standards for room air conditioners that took effect on June 1, 2014. The energy conservation standards are specified in the Code of Federal Regulations and the Electronic Code of Federal Regulations, 10 CFR 430.32. The minimum standard for an 8,000 to 13,999 Btu/h room air conditioners was raised from EER of 9.8 to EER 10.9. For room air conditioners less than 8,000 Bth/h, the EER of 9.7 was raised to EER 11.0.

- **Refrigerators and Freezers.** On September 15, 2011, amended standards were issued for residential refrigerators and freezers. The energy conservation standards are specified in the Code of Federal Regulations, 10 CFR 430.32 and the Electronic Code of Federal Regulations. The standards and apply to equipment manufactured on or after September 15, 2014. The standards are expressed as the maximum annual energy consumption based on its adjusted volume. The energy savings are in the range of 20-30% depending on the product class.

- **Clothes Washers.** In May 2012, DOE issued amended standards for clothes washers. The energy conservation standards are specified in the Code of Federal Regulations, 10 CFR 430.32 and the Electronic Code of Federal Regulations. Clothes washers have a two-phase standard effective March 2015 and January 2018. The energy savings for clothes washers are expressed in IMEF (integrated modified energy factor) and IWF (integrated water factor). (Previously the metrics were expressed in MEF and WF.) In March 2015, the MEF for top load clothes washer changed from 1.26 to 1.72. In January 2018, the MEF will be 2.0.

- **Clothes Dryers.** In August 2011, DOE adopted standards for clothes dryers that took effect on January 1, 2015. The energy conservation standards are specified in the Code of Federal Regulations, 10 CFR 430.32 and the Electronic Code of Federal Regulations. The efficiency of clothes dryer is measured by the energy factor (EF) in lbs/kWh. The current EF standards are 3.01 for electric dryers. The new standard is EF 3.73.

- **Dishwashers**. In May 2012, DOE issued amended standards for dishwashers that took effect in mid-2013. The energy conservation standards are specified in the Code of Federal Regulations, 10 CFR 430.32 and the Electronic Code of Federal Regulations. The standard-size dishwasher is required to use no more than 307 kWh/year and 5.0 gallons/cycle.

The Codes and Standards listed above continue to affect new appliance purchases through 2021 as old units are replaced on failures. Codes and Standards in 2016 and 2017 were already in place in 2015.

In 2020, the Codes and Standards adjustment increases by 61 percent, which is higher than the growth rate in previous years. This jump is attributable to the EISA legislation, which calls for a second-tier improvement in efficiency beginning in 2020. It requires a minimum lamp efficiency of 45 lumens per Watt for general service lamps. The additional savings in 2020 are a result of this standard.

Figure AF-6-1

2013's Efficiency or Standard Assumption

1st Standard (relative to 2013's standard)

2nd Standard (relative to 2013's standard)

End Use	Technology	2013	2014	2015	2016	2017	2018	2019	2020	2021
Cooling	Central AC	SEER 13		SEER 14						
	Room AC	EER 9.8	EER 11.0							
Cooling/Heating	Heat Pump	SEER 13.0/HSPF 7.7		SEER 14.0/HSPF 8.0						
Water Heating	Water Heater (<=55 gallons)	EF 0.90		EF 0.95						
	Water Heater (>55 gallons)	EF 0.90		Heat Pump Water Heater						
Lighting	Screw-in/Pin Lamps	Incandescent	Advanced Incandescent - tier 1 (20 lumens/watt)						Adv Incand. - tier 2 (45 lumens/watt)	
Appliances	Refrigerator/2nd Refrigerator	NAECA Standard	25% more efficient							
	Freezer	NAECA Standard	25% more efficient							
	Dishwasher	14% more efficient than 2010 standard (307 kWh/yr)								
	Clothes Washer	Conventional (MEF 1.26 for top loader)		MEF 1.72 for top loader			MEF 2.0 for top loader			
	Clothes Dryer	EF 3.01		EF 3.73						

COMMERCIAL CUSTOMERS

The timeline and description of how Codes & Standards for Commercial customers were implemented in the modeling are summarized in Figure AF-6-2 on page 6.

- **General Service Lamps.** The Energy Independence and Security Act of 2007 (EISA) was signed into law December 2007 and established the energy efficiency standards for light bulbs and other consumer products. The law was phased-in over three years, starting in January 2012 and ending on January 2014. The Department of Energy codified these standards in the Code of Federal Regulations, 10 Part 430.32 and the Electronic Code of Federal Regulations.

  The energy conservation standards for standard-spectrum general service incandescent lamps are summarized below:

Rated Lumen Ranges	*Maximum Rated Wattage*	*Effective Date*
1490-2600	72	1/1/2012
1050-1489	53	1/1/2013
750-1049	43	1/1/2014
310-749	29	1/1/2014

- **Linear Fluorescent Lamps.** Standards for linear fluorescent lamps that were initially established by the Energy Policy Act (EPACT) of 1992 were updated in June 2009. The updated standards went into effect on July 14, 2012 (10 CFR Part 430). The efficiency standards vary by type of lamp, but the standard for the most common lamp type (4 foot medium bipin, ≤ 4500 K) is 89 lumens per watt which can be met by T8 lamps. The consequence of this standard is to essentially replace T12 lamps from the market place. As these lamps burn out during the forecast period, consumers must replace them with the more efficient T8 lamps.

  The energy conservation standards for general fluorescent lamps effective July 14, 2012 are summarized below. (Since then DOE has published a final rule for updated standards in January 2015.)

Lamp type	*Correlated color temperature*	*Energy conservation standard (lm/W)*
4-Foot Medium Bipin	≤ 4500 K	89
	>4,500 K and ≤7,000K	88
2-Foot U-Shaped	≤ 4500	84
	>4,500 K and ≤7,000K	81
8-Foot Slimline	≤ 4500	97
	>4,500 K and ≤7,000K	93
8-Foot High Output	≤ 4500 K	92
	>4,500 K and ≤7,000K	88
4-Foot Miniature Bipin Standard Output	≤ 4500	86
	>4,500 K and ≤7,000K	81

4-Foot Miniature Bipin High Output	≤ 4500	76
	>4,500 K and ≤7,000K	72

- **Small Electric Motors.** The Department of Energy published a final rule in March 2010 to establish energy conservation standards for small electric motors (1/4 to 3 horsepower), effective March 2015. The small motors must have an average full load efficiency as specified in the Code of Federal Regulations, 10 CFR 431.446 and the Electronic Code of Federal Regulations. The minimum efficiency standards depend on the horsepower and the number of poles.

Figure AF-6-2

2013's Efficiency or Standard Assumption

1st Standard (relative to 2013's standard)

2nd Standard (relative to 2013's standard)

End Use	Technology	2013	2014	2015	2016	2017	2018	2019	2020	2021
Lighting	Screw-in/Pin Lamps	Incandescent	Advanced Incandescent - tier 1 (20 lumens/watt)						Adv incand. - tier 2 (45 lumens/watt)	
	Linear Fluorescent	T8								
Miscellaneous	Small Motors	62.3% Efficiency		70% Efficiency						

BEFORE THE NEW MEXICO PUBLIC REGULATION COMMISSION

IN THE MATTER OF THE APPLICATION OF	)	
OF PUBLIC SERVICE COMPANY OF NEW	)	
MEXICO FOR REVISION OF ITS RETAIL	)	**Case No. 15-00261-UT**
ELECTRIC RATES PURSUANT TO ADVICE	)	
NOTICE NO. 513,	)	
	)	
PUBLIC SERVICE COMPANY OF NEW MEXICO,	)	
Applicant.	)	
	)	

AFFIDAVIT

STATE OF CALIFORNIA)
) ss
COUNTY OF SAN FRANCISCO)

DR. AHMAD FARUQUI, Principal with the Brattle Group, upon being duly sworn according to law, under oath, deposes and states: I have read the foregoing **Direct Testimony of and Exhibits of Dr. Ahmad Faruqui** and it is true and accurate based on my own personal knowledge and belief.

SIGNED this 4th day of August, 2015.

DR. AHMAD FARUQUI

SUBSCRIBED AND SWORN to before me this _________ day of August, 2015.

NOTARY PUBLIC IN AND FOR
THE STATE OF CALIFORNIA

My Commission Expires: See attached

____

GCG # 520236

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☐ See Statement Below (Lines 1–6 to be completed only by document signer[s], *not* Notary)

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5 ______
6 ______

Signature of Document Signer No. 1 *Signature of Document Signer No. 2 (if any)*

A notary public or other officer completing this certificate verifies only the identity of the individual who signed the document to which this certificate is attached, and not the truthfulness, accuracy, or validity of that document.

State of California
County of San Francisco

Subscribed and sworn to (or affirmed) before me on this 4 (*Date*) day of August (*Month*), 2015 (*Year*), by

(1) AHMAD Faruqui

(and (2) ______),
Name(s) of Signer(s)

proved to me on the basis of satisfactory evidence to be the person(s) who appeared before me.

Signature ______
Signature of Notary Public

SHERRY VALDEZ
Commission # 2102903
Notary Public - California
San Francisco County
My Comm. Expires Mar 13, 2019

Seal
Place Notary Seal Above

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