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. 507	)	**Case No. 14-00332-UT**
PUBLIC SERVICE COMPANY OF NEW MEXICO,	)	
Applicant	)	

DIRECT TESTIMONY AND EXHIBITS

OF

DR. AHMAD FARUQUI

DECEMBER 11, 2014

NMPRC CASE NO. 14-00332-UT
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WITNESS FOR
PUBLIC SERVICE COMPANY OF NEW MEXICO

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AFFIDAVIT

DIRECT TESTIMONY OF
DR. AHMAD FARUQUI
NMPRC CASE NO. 14-00332-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.

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

A. 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, 2016. For planning purposes, I also provided sales forecasts through 2021. 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] that collectively accounted for 80 percent of total sales in

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[1] The rate classes are: Residential Service (1A), Residential Service Time-of-Use Rate (1B), Small Power Service (2A), Small Power Service Time-of-Use (2B), General Power Service Time-of-Use (3B), General Power Time-of-Use with low load factor (3C), Large Power Service Time-of-Use with PNM-owner or customer-owned transformer (4B), Irrigation Service (10A), and Irrigation Service Time-of-Use (10B). Large Power (4B) includes some large customers that are

2013.[2] My goal was to ensure that the forecasts would be accurate and robust and utilize the best available data sources and econometric methodologies.

The remaining 20 percent of sales consists of large customers (*i.e.*, other large customers in Large Power (4B), Industrial Power Service customers (5B), Universities (15B), and Manufacturing (30B)), which represent 17 percent, and lighting and public goods (*i.e.*, Private Area Lighting (6), Water and Sewage Pumping (11B), and Streetlighting and Floodlighting (20)), which represent 3 percent. Forecasts for large customer classes are developed based on historical actuals that are adapted using customer information obtained and relayed by the PNM account managers. The remaining rate classes are forecasted based on the assumption that, in the absence of any notable changes, historical actual sales levels will continue.

Figure 1 shows the allocation of PNM's total sales in 2013 by rate class. As noted above, the subset of rate classes that are the focus of our econometric analysis comprise 80 percent of total sales. Within this subset of rate classes, Non-residential customers (2A, 2B, 3B, 3C and 4B) are 52 percent of the sales

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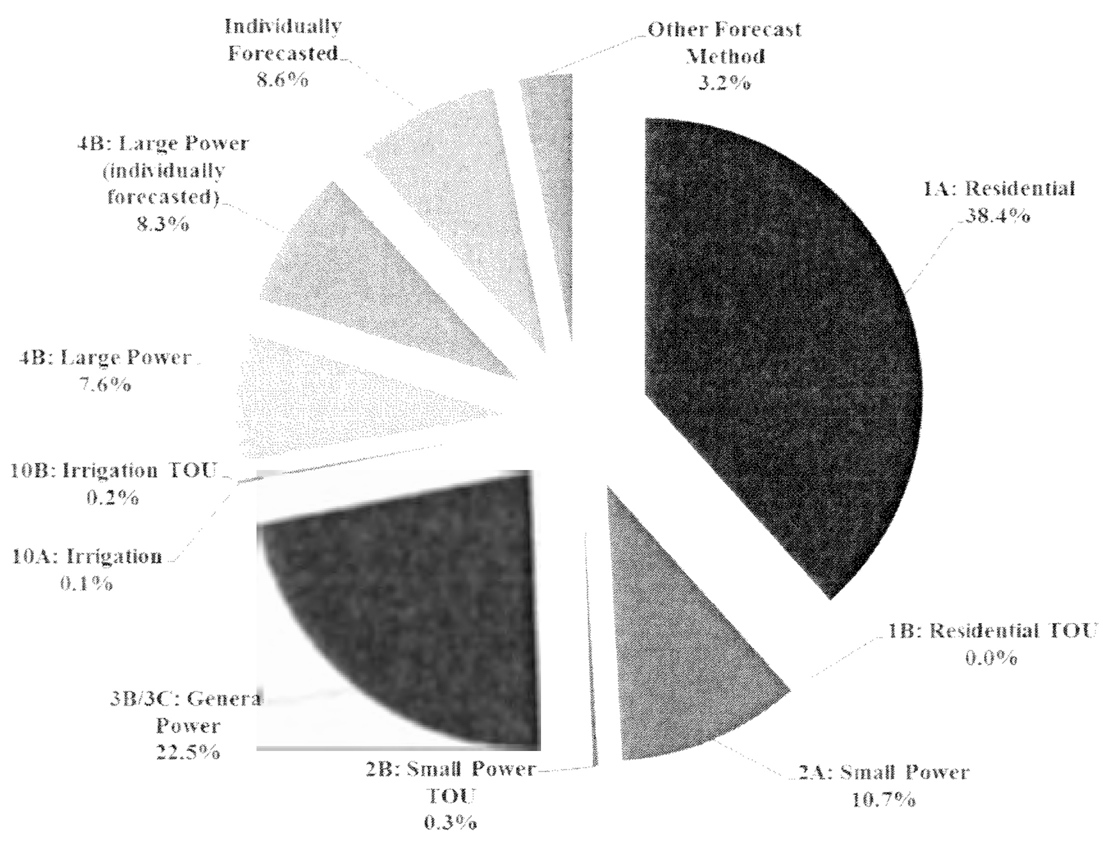
individually forecasted rather than econometrically forecasted. In 2013, 52 percent of sales in Large Power were individually forecasted.

[2] In 2013, approximately 0.2 percent of total sales were unbilled, and unbilled sales are excluded from the results that I report in my testimony.

while the remaining 48 percent are almost entirely attributable to the Residential rate classes (1A and 1B). The contributions to total sales of Residential Time-of-Use (1B), Small Power Time-of-Use (2B), Irrigation (10A), and Irrigation Time-of-Use (10B) are dwarfed by that of Residential (1A), Small Power (2A), General Power Time-of-Use (3B & 3C), and Large Power Time-of-Use (4B).[3]

Figure 1: Total Sales in 2013, by Rate Class



[3] For simplicity of notation, I will drop "Time-of-Use" for General Power and Large Power, and I will refer to Rate Classes 3B and 3C as "Rate Class 3" and Rate Class 4B (either with a PNM-owned transformer or with a customer-owned transformer) as "Rate Class 4."

Source: Public Service Company of New Mexico (November 2014)
Notes: "TOU" stands for Time-of-Use.
"Individually forecasted" includes Industrial Power Service (5B), Universities (15), and Manufacturing (30B).
"Other forecast method" includes Small Power (Cable TV, Temporary Service, Traffic Signals; 2A), Private Area Lighting (6), Water and Sewage Pumping (11), and Streetlights (20).

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

A. My testimony serves two purposes: first, to present the future test year ("FTY") sales forecast for 2016 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.

In the process of developing the forecast for the FTY, I also developed sales forecasts through 2021. I understand that PNM will use the five-year forecast for planning purposes.

Q. WHAT IS YOUR EXPERIENCE IN ELECTRIC UTILITY FORECASTING?

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, 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. 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 Ms. Stella 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, population growth, weather conditions, the price of electricity, Energy Efficiency ("EE"), and governmental Codes & Standards. Sales forecasts are often made at the rate class level. For some customer classes, sales are forecasted indirectly, *i.e.*, 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.

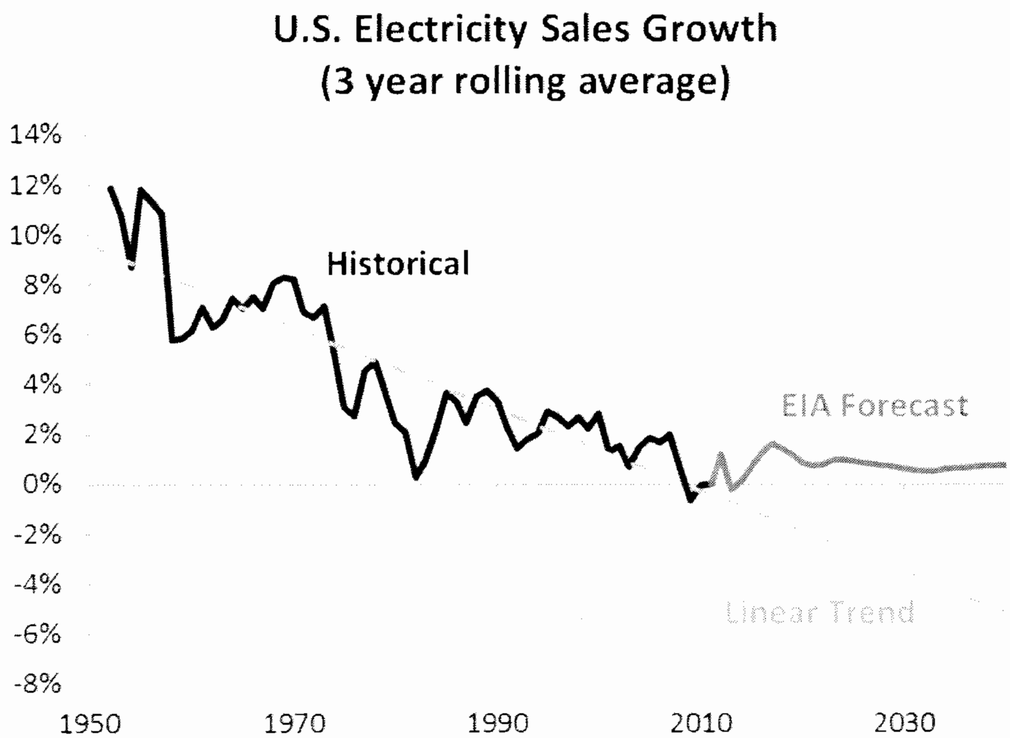
Q. DID YOU FOLLOW THIS PROCESS WHEN DEVELOPING PNM'S SALES FORECASTS?

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

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

A. The Great Recession of 2008-09 caused a slowdown in sales growth that has not abated because of the weak economic recovery. The U.S. Energy Information Administration ("EIA") has been tracking sales growth going back several decades. This is shown in Figure 2 below.

Figure 2



Source: *EIA, 2014 Annual Energy Outlook and 2012 Annual Energy Review.*

EIA predicts that growth will remain below one percent per year in the years to come. My informal conversations with two dozen forecasters at a cross-section of electric utilities revealed that utility sales forecasting models are consistently over-forecasting sales. I published a paper containing these findings in the December 2012 edition of the *Public Utilities Fortnightly.* 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" IMPACTED ELECTRICITY SALES FOR PNM?

As stated by the Bureau of Business and Economic Research ("BBER") at the University of New Mexico ("UNM"), the recovery of the U.S. economy since 2009 has "failed to take hold in New Mexico." Population growth has fallen to nearly zero, and from 2010-2013, New Mexico ranked 50th in job creation.[4]

New Mexico's depressed economy and the expansion of EE initiatives have put downward pressure on PNM's sales since 2010. Similar to other utilities, PNM has seen that its 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 have been two key reasons for over-forecasting.

[4] See UNM BBER, "A Quarterly Economic Forecast of the New Mexico Economy – October 2014 Through 2019:4" [report] and "A Quarterly Economic Forecast of the New Mexico Economy – August 2014 Through 2019:4" [PowerPoint presentation slides]

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

A. Our conclusions are summarized in Table 1, which reports total sales in the last full calendar year, 2013, through the forecasted FTY used in this case, 2016.[5] The results are presented for the subset of rate classes that form the core of our analysis.[6] In the far right column, I calculate the average year-on-year growth rate from 2013 through 2016. In Table 1, individually and econometrically forecasted Large Power customers are summed together as Rate Class 4B, either with a PNM-owned transformer or a customer-owned transformer.[7] Thus, total sales for the subset of rate classes is 88 percent of the grand total because individually forecasted Large Power customers comprise around 8 percent of total sales.

Across all rate classes, PNM's sales are expected to fall by approximately 3.1 percent from 2013 to 2016. On average, sales fell by 1.0 percent from year to

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[5] In Table 1, I report actual sales in 2013, which is the latest full calendar year at the time of writing this testimony. For 2014, annual sales are composed of actual sales from January-June and forecasted sales from July-December.

[6] In Table 1, Rate Classes 3 and 4 are broken down into 3B & 3C or PNM-owned & customer-owned transformers. In our analysis, we aggregate Rate Classes 3B & 3C to form one class for General Power and aggregate customers in Rate Class 4B with PNM-owned or their own transformer to form Large Power (excluding individually forecasted Large Customers).

[7] The reason why we summed individually and econometrically forecasted Large Power customers together is because adjustments for energy savings from EE and Distributed Generation programs are made over the entire rate class.

year, but the year-to-year growth rates can range from -3.8 percent from 2013-2014 to -1.0 percent from 2014-2015. For the subset of rate classes that we analyzed, total sales declined by 1.8 percent over the same period. Sales decrease in most rate classes. The exceptions – General Power with low load factor, Large Power in which customers own their transformers, and Irrigation Time-of-Use – are small in terms of shares of total sales (11 percent), and among the rate classes comprising a larger share of total sales (77 percent), the net changes in sales from 2013 to 2016 are negative or nearly flat.

Table 1: Summary of FTY Sales Forecast

			Annual Sales, in GWh				
		% of Total	Actual		Forecasted		
Rate Class	Description	Sales in 2013	2013	2014	2015	2016	Average % Change
1A	Residential	38.4%	3,290	3,166	3,218	3,205	-0.9%
1B	Residential Time-of-Use	0.05%	4	4	4	4	-1.0%
2A	Small Power	10.7%	917	882	871	865	-1.9%
2B	Small Power Time-of-Use	0.3%	27	25	24	24	-3.9%
3B	General Power	20.2%	1,736	1,726	1,731	1,728	-0.2%
3C	General Power (low load factor)	2.3%	198	203	204	206	1.3%
4B	Large Power (PNM-owned transformer)	7.3%	628	566	565	547	-4.4%
4B	Large Power (customer-owned transformer)	8.6%	736	741	802	820	3.7%
10A	Irrigation	0.06%	5	5	4	4	-6.1%
10B	Irrigation Time-of-Use	0.2%	21	22	23	22	1.0%
	Subtotal	88.2%	7,563	7,340	7,446	7,425	-0.6%
	Other Rate Classes, e.g. Universities, Lighting	11.8%	1,015	916	898	888	-4.3%
	Grand Total (excluding unbilled)	100%	8,578	8,256	8,344	8,313	-1.0%

Source: Actual sales in 2013 and January-June 2014 are provided by Public Service Company of New Mexico (November 2014)

Notes: Average percent change is taken over year-on-year changes from 2013-2016.
For 2014, annual sales are based on actual sales from January-June and forecasted sales from July-December.
Other Rate Classes include Industrial Power Service (5B), Private Area Lighting Service (6), Water and Sewage Pumping Service Time-of-Use (11B), Large Service for Universities (15B),

Integrated System Streetlighting and Floodlighting Service (20), and Large Service for Manufacturing (30B).

In most customer classes, the sales forecast can be characterized as the product of the number of customers and use per customer (UPC). Thus, the decline in sales can be driven by fewer customers or lower UPC. Our forecast indicates that the number of customers will remain flat or increase for most rate classes except Irrigation and Large Power. On the other hand, UPC dips for most rate classes, ranging from a drop of 1.4 percent for General Power to a drop of 13.6 percent for Irrigation between 2013 and 2016. For Residential and Non-residential (excluding Irrigation) 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]

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 and new governmental Codes & Standards that do not exist in the historical period and whose impact would not be captured by the econometric model.

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

II. MODEL SPECIFICATION AND ESTIMATION

Q. PLEASE PROVIDE A BROAD OVERVIEW OF PNM'S FORECASTING PROCEDURE.

A. I will first summarize the components of the sales forecast and then explain our 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 Distributed Generation programs that have not yet been rolled out. The magnitude of the adjustments can be expressed as a proportion of unadjusted sales, *i.e.*, a fraction of 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), in conjunction with my team of experts, I developed an econometric model for UPC. For the same rate classes, we 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

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

account for the effects of savings from governmentally mandated Codes & Standards for Residential customers and PNM's EE and Distributed Generation programs for both Residential and Non-Residential (excluding Irrigation) customers.

Sales to large customers – manufacturers, universities, Industrial Power (mining), and some Large Power customers – are individually forecasted rather than economically forecasted.[10] 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.

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

A. An econometric model consists of an equation or set of equations that describe how the variable of interest varies as a function of several "explanatory" variables. In the context of PNM's sales forecast, the variables of interest are the UPC, the number of customers, or total sales for customers that are individually forecasted. When developing a model,

[10] The forecasting procedure for lighting is assumed to perpetuate at the actual level of sales as of June 2014.

we first decide on the form of the equation, e.g., a linear or a logarithmic equation, and the explanatory variables, such as income or weather. This step is called "model specification" because we are specifying or defining what the model structure should look like. Second, we estimate the model, meaning that we fit the specified equation to data. After we have specified and estimated the model, we can then apply projected values of the inputs to generate a prediction for the output.

For UPC, we chose to use a logarithmic functional form. This implies that changes in the inputs affect UPC (or total sales) as a proportional amount that scales UPC up or down rather than a fixed amount that is either subtracted or added. The assumption of proportional rather than fixed changes in UPC 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.

The set of potential inputs in the model were selected based on the availability of data and my experience with sales forecasting. We 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, 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.

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, we 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, we 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 we 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.

A detailed description of our model selection criteria and process of model testing can be found in PNM Exhibit AF-2. In short, we 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 2016 plausible given historical usage patterns and those that I have seen from comparable utility companies?
5. Is the model specification transparent, *i.e.*, do we know the drivers of the forecasted values?
6. What is the overall credibility of the results?

In Table 2, I present a summary of the model specifications, *i.e.*, the inputs into model, for each rate class that we developed for PNM. The estimated parameters of the UPC models are also included in PNM Exhibit AF-3.

Table 2: Summary of Econometric Models for UPC

			Inputs				
Rate Class	Description	Output	Income	Price	Weather	South	Time Trend
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
1A	Residential	UPC	Yes	Yes	Yes	No	No
1B	Residential Time-of-Use	UPC	Yes	No	Yes	No	No
2A	Small Power	UPC	Yes	Yes	Yes	No	Yes
2B	Small Power Time-of-Use	UPC	Yes	No	Yes	Yes	No
3B, 3C	General Power	UPC	No	No	Yes	Yes	No
4B*	Large Power	Total Sales	No	No	No	Yes	Yes
10A	Irrigation	UPC	No	No	Yes	Yes	No
10B	Irrigation Time-of-Use	UPC	Yes	No	Yes	No	Yes

Notes: "UPC" stands for use per customer.
"Income" is measured by real personal income for Rate Classes 1A, 1B, 2A, and 2B and by real Gross State Product for Rate Class 10B.
"Weather" is measured by heating degree days and cooling degree days.
"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 Class 4B (which is demarcated by *), large customers are excluded from the econometric model and, instead, are individually forecasted.

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 our econometric models for the number of customers, we 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 include 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 electricity regardless of the outdoor temperature. The model specifications of the customer forecast are summarized in Table 3. The model parameters are provided in PNM Exhibit AF-4.

Table 3: Summary of Econometric Models for Number of Customers

			Inputs				
Rate Class	Description	Output	Population	Income	Post-2008	South	Time Trend
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
1A	Residential	Number of customers	Yes*	No	No	No	No
1B	Residential Time-of-Use	Number of customers	Yes	No	No	No	No
2A	Small Power	Number of customers	Yes	No	No	Yes	No
2B	Small Power Time-of-Use	Number of customers	No	No	No	No	Yes
3B, 3C	General Power	Number of customers	No	Yes	Yes	No	No
4B	Large Power	N/A					
10A	Irrigation	Number of customers	No	No	No	Yes	No
10B	Irrigation Time-of-Use	Number of customers	No	No	No	Yes	No

Notes: "Population" is the total population of New Mexico.
"Income" is measured as the real Gross State Product.
"Post-2008" is a binary variable that equals 1 in all time periods including and after 2008.
"South" is a binary variable that equals 1 in March 2007.
"Time Trend" is a constructed variable that increases by 1 unit each month.
Customer forecasts for Rate Class 4B (Large Power) are not made with an econometric model because growth for Large Power customers does not substantially vary over time. Instead, PNM uses a qualitative approach that allows for increases every few years.

*The model allows for the effect of population on the number of customers for Rate Class 1A to differ between the pre-2008 and post-2008 periods.

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

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

PNM provided data on sales, number of customers, and average price by rate class on a monthly basis from January 2002 through May 2014.[11]

The economic variables for New Mexico – namely personal income, Gross State Product ("GSP"), Consumer Price Index ("CPI"), and population – are provided by BBER. These variables are reported on a quarterly basis, and to convert them to monthly values, we interpolated between quarters using a third-degree polynomial function.[12]

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

[11] June 2014 data was not available at the time of developing the UPC models, and thus, the UPC forecasts are estimated using data up to May 2014. The customer forecasts are estimated using data up to August 2014.

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

70° F for HDD and CDD respectively among residential customers and 60° F for both HDD and CDD among commercial customers.

Q. HOW DID YOU PROJECT THE EXPLANATORY VARIABLES?

A. Since weather and income beyond 2014 have not yet been observed, we need to rely on forecasted values of these inputs to construct PNM's sales forecast. For weather, we assume that the 10-year average of HDD or CDD by month serves as a reasonable approximation of future weather patterns.[13] For real personal income, we rely on BBER's forecasted values.

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

A. We use BBER's pessimistic personal income forecast.

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

A. After studying the trend in quarter-on-quarter percentage changes in personal income after 2010, we chose to use BBER's most recent (July 2014) pessimistic personal income forecast at the time of our analysis. As shown in Figure 3, BBER's forecasts of the growth rate for personal income have consistently overestimated actual growth rates

[13] The 10-year average is taken over January 2004 through December 2013.

in the post-recession era. In the first quarter of 2014, the difference between the July 2013 baseline forecast and actual growth rate was two percentage points. Since BBER's baseline forecasts have historically been high relative to the realized growth rate, the pessimistic income forecast is a reasonable choice.

Moreover, the trend in the pessimistic income forecast more closely aligns with recent history than the baseline income forecast. Personal income for New Mexico grew at a compound annual growth rate[14] of 3.4 percent per year from 2010 to 2013. BBER's baseline income forecast increases at 4.1 percent per year from 2012 to 2019 whereas the pessimistic income forecast rises at 3.7 percent per year over the same period.[15]

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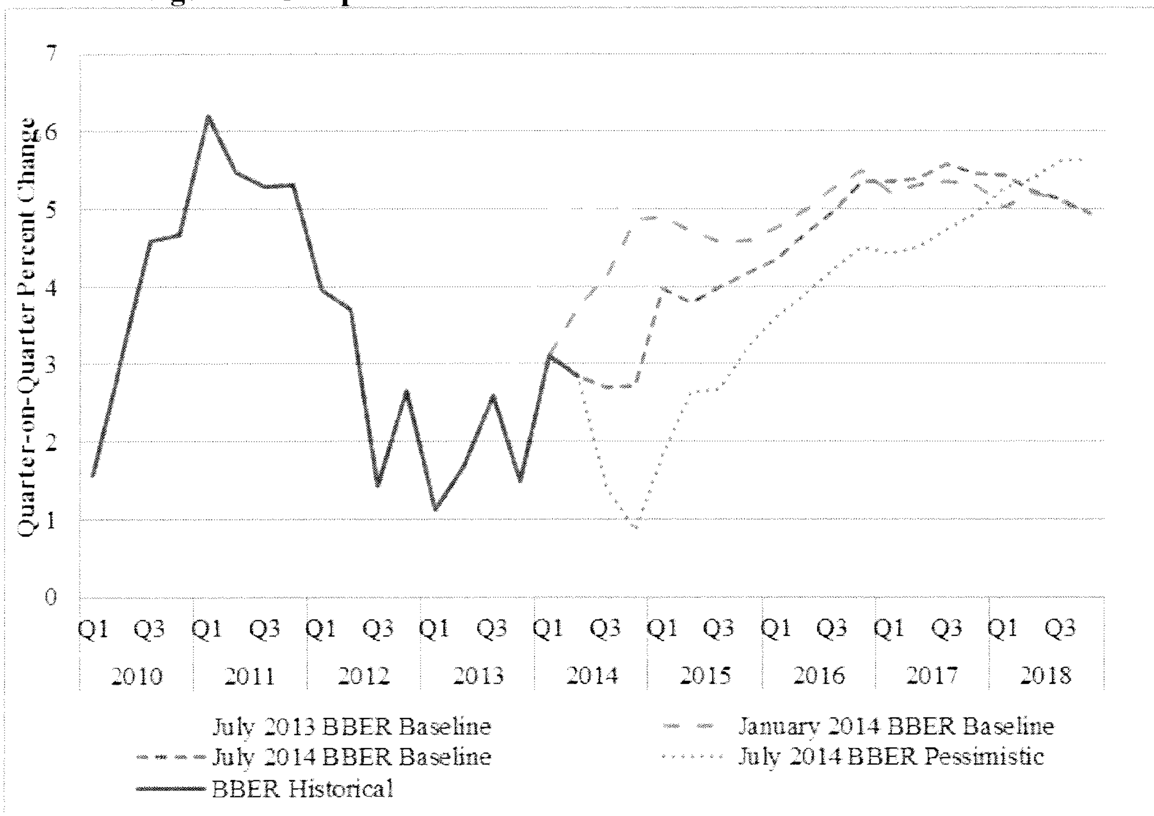
[14] Compound annual growth rate is essentially the average growth rate over a designated period of time when the percentage increase from year to year is assumed to be the same.

[15] The compound annual growth rates are calculated based on nominal personal income.

Figure 3: Comparison of BBER's Forecasts for Personal Income



Source: Bureau of Business and Economic Research, University of New Mexico (November 2014)

III. POST-ESTIMATION ADJUSTMENTS

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

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

The adjustments are necessary because energy savings from expanded or new utility EE and Distributed Generation 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 sales, we 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 (*e.g.* 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"[16] 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.

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

A. The Codes & Standards adjustment is deducted off of total sales as a share rather than a fixed amount. The percentage deducted in each year is shown in Table 4, and the deductions are made relative to 2014 as the baseline. For example, because of Codes & Standards, Residential sales in 2016 are expected to be 96.3 percent of 2014 Residential sales. In the far-right column of Table 4, I report the increase in the Codes & Standards deduction from the preceding year. In other words, the numbers in the far-right column reflect the additional savings from Codes & Standards on top of the savings from the previous year.

A key assumption behind the Codes & Standards adjustment is the speed at which incandescent lamps will be phased out. We take a conservative approach since PNM has a higher fraction of low-income customers than other utility companies. Further, because low-income customers favor the lowest-cost lamps, retailers may

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

keep an inventory of incandescent lamps for at least a few years, and consumers would continue to access cheap incandescent lamps in that time frame.

Table 4: Summary of Codes and Standards Adjustment

Year	Codes & Standards adjustment as a share of the unadjusted forecast	Codes & Standards deduction as a percentage of total kWh	Increase in deduction from preceding year
2014	98.8%	1.2%	1.2%
2015	97.8%	2.2%	1.0%
2016	96.3%	3.7%	1.5%
2017	96.1%	3.9%	0.2%
2018	96.0%	4.0%	0.1%
2019	95.8%	4.2%	0.2%
2020	93.3%	6.7%	2.4%
2021	93.3%	6.7%	0.0%

Source: Applied Energy Group
Notes: Codes and Standards adjustment for 2021 is held constant at 2020 level.

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

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. 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. The existing programs will eventually be replaced by new programs. Savings from new programs is based on expected EE spending, which must meet EUEA's threshold of three percent of sales revenues.

Prior to the 2013 amendment to EUEA, PNM spent $8.0 million (less than 1 percent of applicable revenue[17]) on EE programs in 2008 and $18.1 million (approximately 2 percent of applicable revenue) in 2013. Thus, the requirement to spend 3 percent of sales revenues on EE programs represents a 50 percent increase [of EE spending as a share of applicable revenue] for PNM that will occur after 2014, and historical data would not capture the sharp rise in PNM's investment in EE. Thus, it is important to adjust the sales forecast for the expanded scale of the PNM's EE programs.

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

A. The annual savings from EE programs are shown in Table 5. The table reports the forecasted EE savings, total unadjusted sales, and the reduction in sales from EE as a percentage of total unadjusted sales.

[17] Applicable revenue includes sales for Residential, Commercial, Industrial, and Public authority classes in New Mexico only.

Table 5: Summary of Energy Efficiency Savings (GWh)

	Forecasted EE	Unadjusted Sales	% of Unadjusted Sales
2015	432	8,574	5.0%
2016	474	8,653	5.5%
2017	518	8,731	5.9%
2018	558	8,791	6.3%
2019	586	8,892	6.6%
2020	611	8,977	6.8%
2021	646	9,062	7.1%

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

The adjustment for PNM's Distributed Generation program is constructed by multiplying the capacity of the system across photovoltaic customers with total solar insolation during the month. Solar resource information is provided by the National Renewable Energy Laboratory ("NREL"). Forecasted capacity is based on the trends in number of applications and megawatts installations over the past few years.

Q. ARE THESE ADJUSTMENTS IN LINE WITH YOUR EXPECTATIONS?

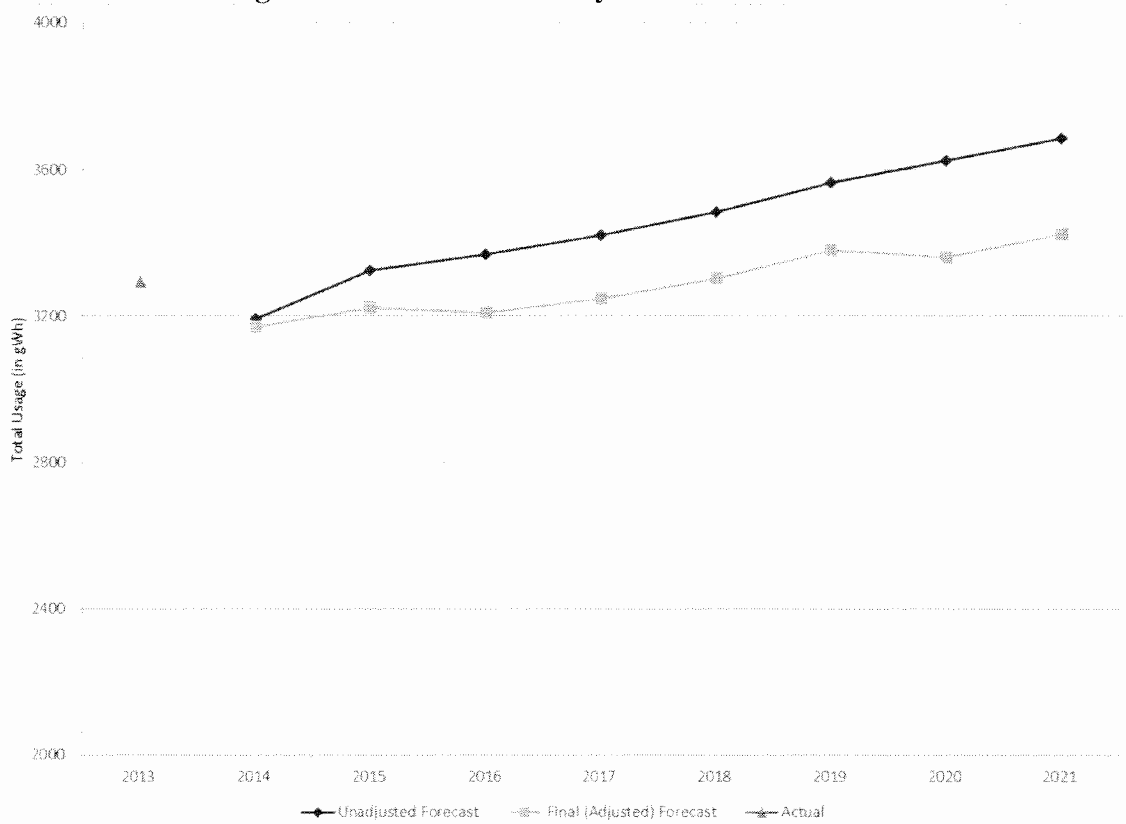
A. Yes, the adjustments align with my expectations.

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 4 through Figure 8. 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 Distributed Generation program. The gap between the unadjusted and adjusted forecasts is the magnitude of savings. The data point in 2013 is the actual usage level.

Figure 4: Annual Electricity Sales for Residential



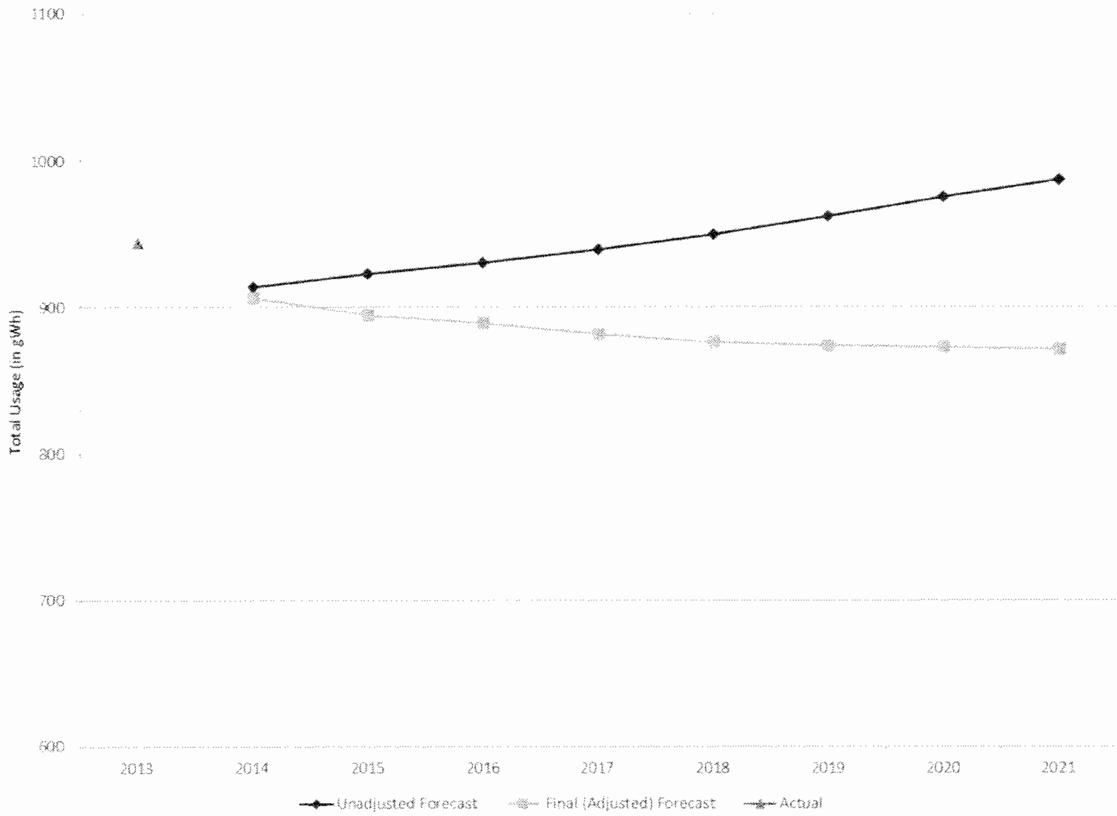
Notes: 2014 values are actual sales from January-June and forecasted sales from July-December
Residential customers include Rate Classes 1A and 1B.

Figure 4 shows the annual sales among Residential customers from 2013 to 2021. Among Residential customers, the final adjusted forecast indicates a rise in total sales from 2013 through 2021 by 3.9 percent. From year to year, Residential sales may fall by as much as -3.8 percent (2013-2014) or rise by as much as 2.3 percent (2018-2019).

Over the period from 2014 to 2021, post-model forecast adjustments from Codes & Standards, EE programs, and Distributed Generation program are expected to grow from at 1.4 percent of total unadjusted sales in 2014 to 7.1 percent of total unadjusted sales in 2021. More than 70 percent of the post-estimation adjustment is attributable to tightening Codes & Standards. In 2016, post-estimation adjustments are 4.8 percent of the unadjusted sales forecast for the Residential class; 78 percent of the post-estimation adjustment comes from Codes & Standards, and EE and Distributed Generation programs make up the remaining 14 percent and 8 percent, respectively.

Overall, because growth in savings outpaces growth in sales between 2014 and 2016, total sales in the Residential class are expected to show a slight decline in 2016. After 2016, sales grow modestly as both UPC and the number of customers are expected to increasing with rising income and population.

Figure 5: Annual Electricity Sales Forecast for Small Power

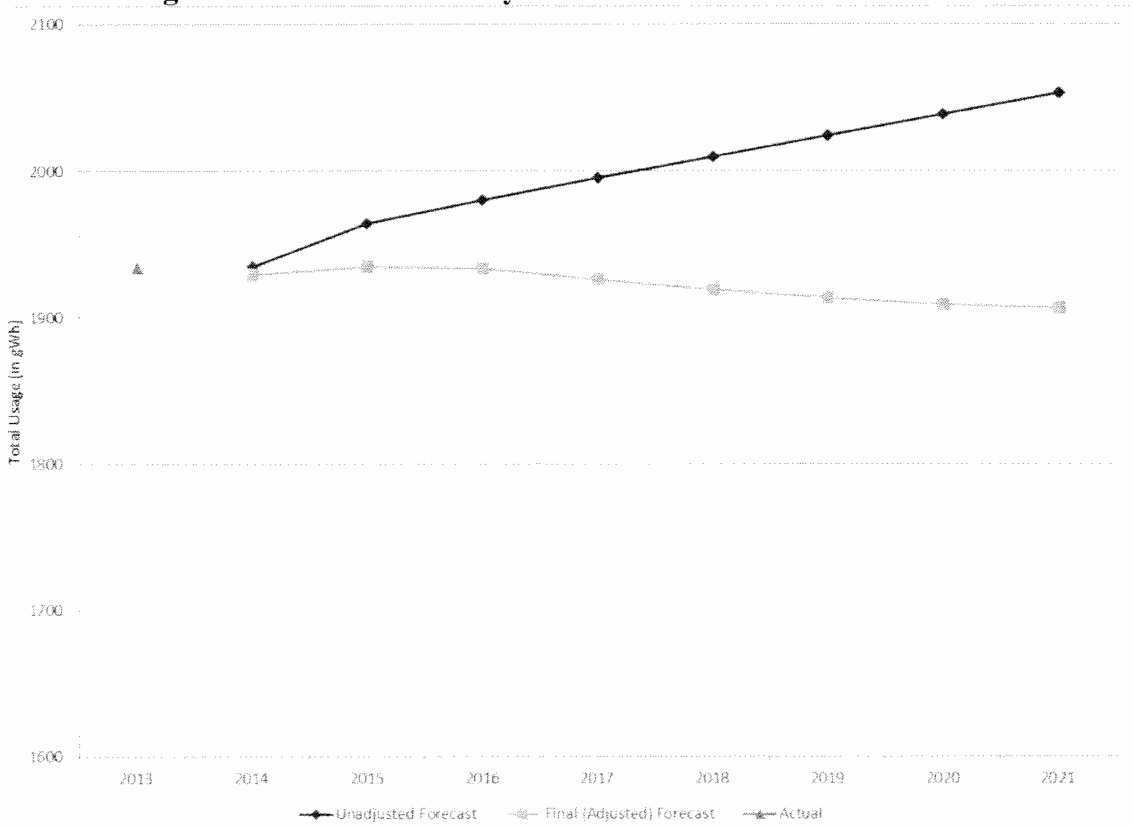


Notes: 2014 values are actual sales from January-June and forecasted sales from July-December.

As shown in Figure 5 for Small Power customers, EE and Distributed Generation programs are expected to lower total sales by as much as 11.7 percent of the unadjusted forecast value (in 2021) such that sales will decline by 7.7 percent from 2013 to 2021 in the final forecast. Savings are primarily coming from EE programs, which account for 89 percent to 98 percent of savings.

The trend in unadjusted sales is increasing because of growth in the number of customers. A larger population and secular upward trend in the number of customers push up the customer count for Small Power.

Figure 6: Annual Electricity Sales Forecast for General Power

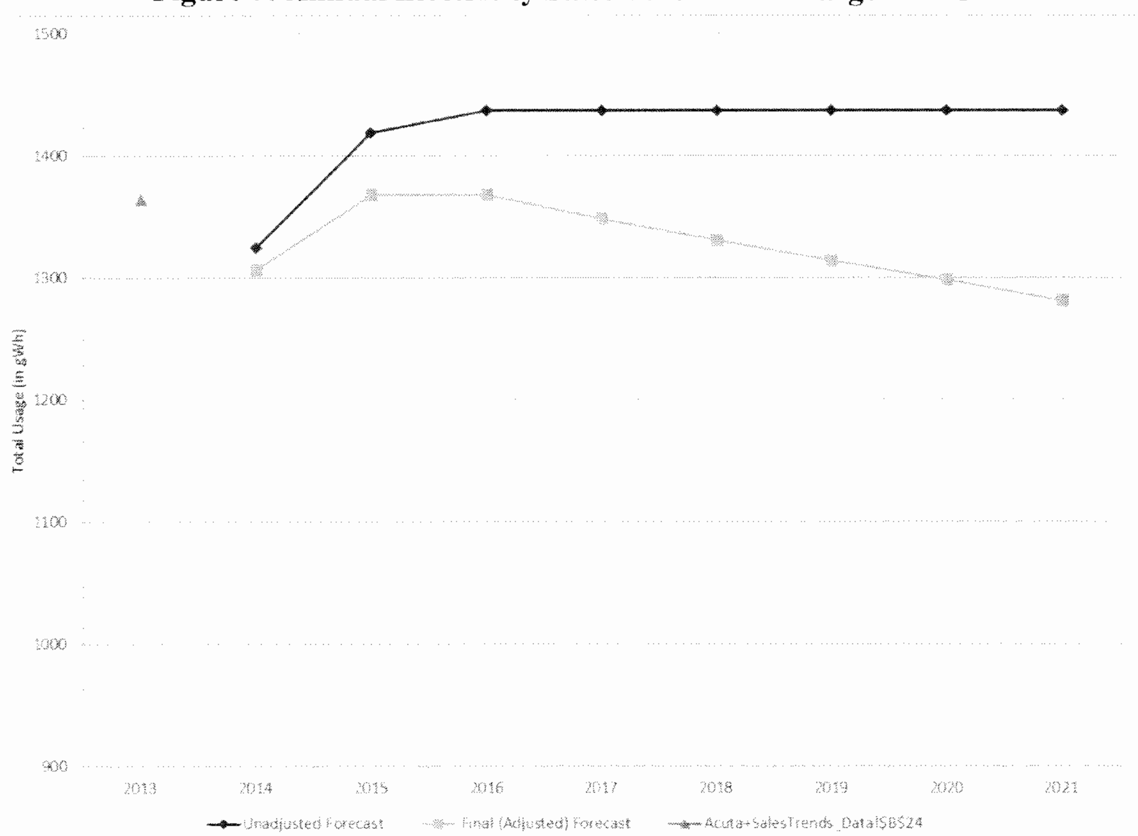


Notes: 2014 values are actual sales from January-June and forecasted sales from July-December.

Figure 6 depicts the annual sales forecast for General Power. Like the final forecast for Small Power, large energy savings by as much as 7.2 percent of the unadjusted forecasts (in 2021) are expected to lower the trend in sales for General Power through 2021. Again, EE programs account for more than 80 percent of savings. Net of adjustments, total class usage will fall by 1.4 percent from 2013 to 2021.

Growth in the unadjusted sales forecast is driven by an increase in the number of customers as the economic environment of New Mexico begins to recover from 2014 to 2016, as measured by the real Gross State Product. Assuming "normal" weather patterns, UPC stays fairly flat between 2015 and 2021.

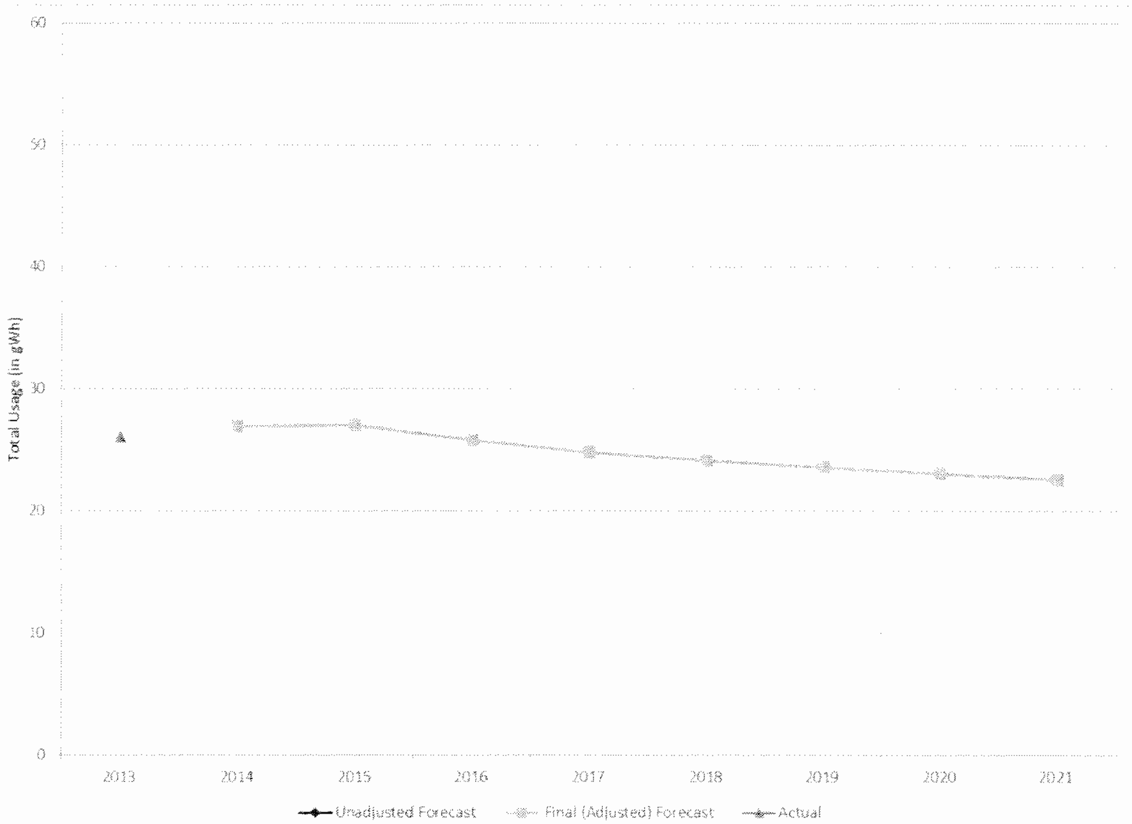
Figure 7: Annual Electricity Sales Forecast for Large Power



Notes: 2014 values are actual sales from January-June and forecasted sales from July-December. In 2013, individually forecasted customers constitute about 52% of Rate Class 4B; the remaining customers are econometrically forecasted

Figure 7 plots the trend in sales for the entire Large Power class, which includes customers whose sales are individually forecasted. These individually forecasted customers comprise 52 percent of the total sales for Large Power in 2013. Total class usage initially rises from 2014 to 2015 by 4.6 percent and subsequently declines by 6.3 percent from 2015 through 2021. Total sales decreases as savings from EE and Distributed Generation programs grow, largely from EE programs that make up 84 percent to 92 percent of savings.

Figure 8: Annual Electricity Sales Forecast for Irrigation



Notes: 2014 values are actual sales from January-June and forecasted sales from July-December.

Customers engaged in irrigation for agricultural purposes are expected to use less electricity through 2021, as shown in Figure 8. Sales are predicted to fall by 13.6 percent between 2013 and 2021. Both the number of customers and UPC are falling over the forecasted period. There are no EE or Distributed Generation programs for Irrigation, and thus, the unadjusted and adjusted rate forecasts are equivalent.

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 customer counts are income, price, weather, and population.[18] For UPC, income is a statistically and economically significant driver for the Residential class. Demand for electricity among the Residential and Small Power classes are also sensitive to changes in price per unit. Across Residential, Small Power, and General Power classes, 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 the Residential and Small Power classes.

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

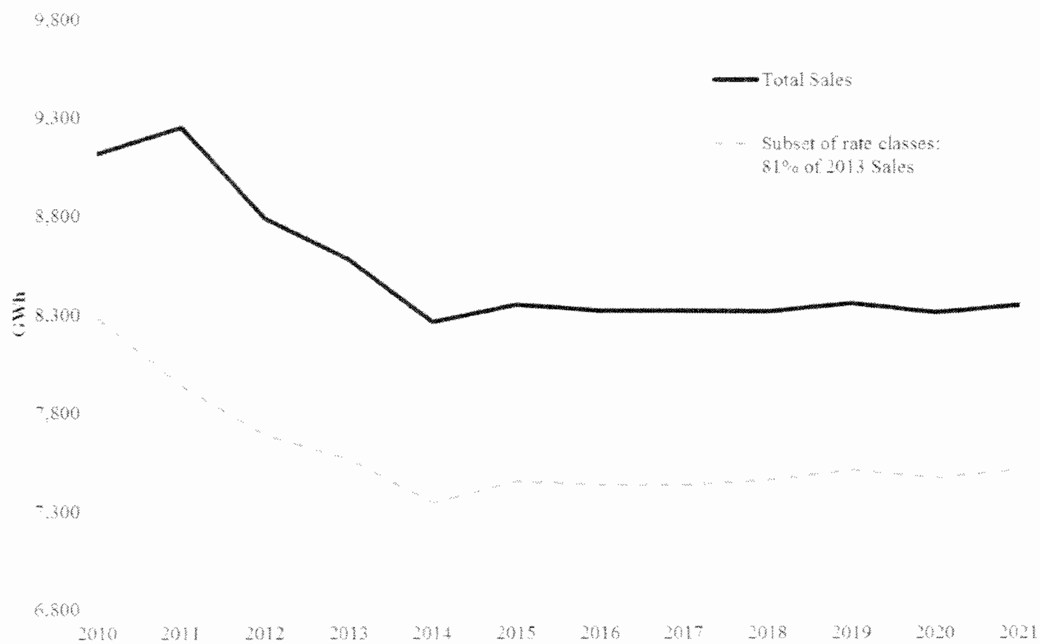
In the second step of making post-estimation adjustments, decrements for governmentally mandated Codes & Standards and EE programs are critical. Codes & Standards depend on the rate at which the government decides to eliminate incandescent light bulbs, and the impact of EE programs depends on customers'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

Q. HOW DOES THE SALES FORECAST THROUGH THE FTY 2016 COMPARE WITH PNM'S HISTORICAL TREND IN SALES?

In Figure 9, I plot the actual and forecasted trend in sales from 2010-2021. The solid line corresponds to total sales, and the dashed line corresponds to total sales among the subset of rate classes that are econometrically forecasted (plus individually forecasted large customers in Large Power).

Since 2011, PNM has experienced declining sales. Total sales have dropped by 7.3 percent from 2011 to 2013, and among the subset of rate classes comprising 88 percent of total sales, sales have fallen by 8.7 percent since 2010. Thus, our forecast for 2016 represents a conservative yet reasonable estimate of total sales. Continued stagnation 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 9: Actual and Forecasted Total Sales from 2010-2021



Source: Actual sales (2010-2013, January-June 2014) are provided by Public Service Company of New Mexico (November 2014)

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 1, which has been reproduced below for convenience, PNM's aggregate sales are projected to decline by 3.1 percent between 2013 and 2016. Among the rate classes that have been the focus of my testimony, total sales are expected to fall by 1.8 percent through 2016.

Table 1: Summary of FTY Sales Forecast

			Annual Sales, in GWh				
		% of Total	Actual		Forecasted		
Rate Class	Description	Sales in 2013	2013	2014	2015	2016	Average % Change
1A	Residential	38.4%	3,290	3,166	3,218	3,205	-0.9%
1B	Residential Time-of-Use	0.05%	4	4	4	4	-1.0%
2A	Small Power	10.7%	917	882	871	865	-1.9%
2B	Small Power Time-of-Use	0.3%	27	25	24	24	-3.9%
3B	General Power	20.2%	1,736	1,726	1,731	1,728	-0.2%
3C	General Power (low load factor)	2.3%	198	203	204	206	1.3%
4B	Large Power (PNM-owned transformer)	7.3%	628	566	565	547	-4.4%
4B	Large Power (customer-owned transformer)	8.6%	736	741	802	820	3.7%
10A	Irrigation	0.06%	5	5	4	4	-6.1%
10B	Irrigation Time-of-Use	0.2%	21	22	23	22	1.0%
	Subtotal	88.2%	7,563	7,340	7,446	7,425	-0.6%
	Other Rate Classes, e.g. Universities, Lighting	11.8%	1,015	916	898	888	-4.3%
	Grand Total (excluding unbilled)	100%	8,578	8,256	8,344	8,313	-1.0%

Source: Actual sales in 2013 and January-June 2014 are provided by Public Service Company of New Mexico (November 2014)

Notes: Average percent change is taken over year-on-year changes from 2013-2016.

For 2014, annual sales are based on actual sales from January-June and forecasted sales from July-December.
Other Rate Classes include Industrial Power Service (5B), Private Area Lighting Service (6), Water and Sewage Pumping Service Time-of-Use (11B), Large Service for Universities (15B), Integrated System Streetlighting and Floodlighting Service (20), and Large Service for Manufacturing (30B).

The forecasted trends vary by rate class. Net of future savings from Codes & Standards and EE and Distributed Generation programs, the model predicts a decline in total sales among Residential, Small Power, and Irrigation customers while total sales for General Power and Large Power remain close to their 2013 levels. The drop in sales for Residential and Small Power comes from lower UPC because of higher savings from Codes & Standards and EE and Distributed Generation programs. Falling UPC and number of customers underlie lower sales for the Irrigation 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 6 and Table 7.

Table 6: Summary of Final UPC Forecast from 2014-2016

			Annual Usage per Customer, in KWh				
		% of Total	Actual		Forecasted, with energy savings		
Rate Class	Description	Sales in 2013	2013	2014	2015	2016	Average % Change
1A	Residential	38.4%	7,286	6,972	7,059	7,000	-1.3%
1B	Residential Time-of-Use	0.05%	31,733	29,978	30,332	30,493	-1.3%
2A	Small Power	10.7%	19,201	18,353	17,976	17,662	-2.7%
2B	Small Power Time-of-Use	0.3%	39,818	36,925	35,155	35,429	-3.8%
3B	General Power	20.2%	496,253	497,276	495,642	490,992	-0.4%
3C	General Power (low load factor)	2.3%	267,919	253,160	253,102	252,974	-1.9%
4B	Large Power (PNM-owned transformer)	7.3%	5,675,596	5,420,531	5,455,538	5,280,856	-2.4%
4B	Large Power (customer-owned transformer)	8.6%	6,232,149	6,311,874	6,880,822	7,037,019	4.2%
10A	Irrigation	0.06%	42,131	39,912	36,465	36,465	-4.6%
10B	Irrigation Time-of-Use	0.2%	98,080	104,371	108,466	105,832	2.6%
	Subtotal	88.2%					
	Other Rate Classes, e.g. Universities, Lighting	11.8%					
	Grand Total (excluding unbilled)	100%					

Notes: Average percentage change is taken over year-on-year changes from 2013-2016.
"KWh" stands for "kilowatt hours."
For 2014, annual sales are based on actual sales from January-June and forecasted sales from July-December.

Table 7: Summary of Final Customer Forecast from 2014-2016

			Average No. of Customers per Month				
		% of Total	Actual		Forecasted		
Rate Class	Description	Sales in 2013	2013	2014	2015	2016	Average % Change
1A	Residential	38.4%	451,651	454,135	455,933	457,824	0.5%
1B	Residential Time-of-Use	0.05%	129	129	131	130	0.3%
2A	Small Power	10.7%	47,748	48,032	48,424	48,961	0.8%
2B	Small Power Time-of-Use	0.3%	686	683	682	683	-0.1%
3B	General Power	20.2%	3,498	3,469	3,489	3,516	0.2%
3C	General Power (low load factor)	2.3%	738	807	812	819	3.6%
4B	Large Power (PNM-owned transformer)	7.3%	111	105	104	104	-2.1%
4B	Large Power (customer-owned transformer)	8.6%	118	117	117	117	-0.4%
10A	Irrigation	0.06%	115	113	112	110	-1.5%
10B	Irrigation Time-of-Use	0.2%	216	215	211	206	-1.5%
	Subtotal	88.2%					
	Other Rate Classes, e.g. Universities, Lighting	11.8%					
	Grand Total (excluding unbilled)	100%					

Notes: Average percentage change is taken over year-on-year changes from 2013-2016.
For 2014, annual sales are based on actual sales from January-June and forecasted sales from July-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 Distributed Generation program are projected to significantly impact the outlook for total sales.

Q. DOES THIS CONCLUDE YOUR TESTIMONY?

A. Yes, it does.

GCG#518977

Résumé 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.

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Model Specification and Testing for PNM Sales Forecast

PNM Exhibit AF-2

Is contained in the following 14 pages.

Model Specification and Testing for PNM Sales Forecast

The purpose of PNM Exhibit AF-2 is to provide a detailed description of how we arrived at the recommended models for use per customer ("UPC") and the number of customers. First, I will discuss the metrics by which we evaluate alternative models for forecasting. Second, I explain how we decided on the model specifications that would be most appropriate for PNM. Tables 2 and 3 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 and PNM Exhibit AF-4.

Table 2: Summary of Econometric Models for Usage per Customer

			Inputs				
Rate Class	**Description**	**Output**	**Income**	**Price**	**Weather**	**South**	**Time Trend**
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
1A	Residential	UPC	Yes	Yes	Yes	No	No
1B	Residential Time-of-Use	UPC	Yes	No	Yes	No	No
2A	Small Power	UPC	Yes	Yes	Yes	No	Yes
2B	Small Power Time-of-Use	UPC	Yes	No	Yes	Yes	No
3B, 3C	General Power	UPC	No	No	Yes	Yes	No
4B*	Large Power	Total Sales	No	No	No	Yes	Yes
10A	Irrigation	UPC	No	No	Yes	Yes	No
10B	Irrigation Time-of-Use	UPC	Yes	No	Yes	No	Yes

Notes: "UPC" stands for use per customer. "Income" is measured by real personal income for Rate Classes 1A, 1B, 2A, and 2B and by real Gross State Product for Rate Class 10B. "Weather" is measured by heating degree days and cooling degree days. "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 Class 4B (which is demarcated by *), the largest industrial customers are excluded from the econometric model and, instead, are individually forecasted.

Table 3: Summary of Econometric Models for Number of Customers

			Inputs				
Rate Class	**Description**	**Output**	**Population**	**Income**	**Post-2008**	**South**	**Time Trend**
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
1A	Residential	Number of customers	Yes*	No	No	No	No
1B	Residential Time-of-Use	Number of customers	Yes	No	No	No	No
2A	Small Power	Number of customers	Yes	No	No	Yes	No
2B	Small Power Time-of-Use	Number of customers	No	No	No	No	Yes
3B, 3C	General Power	Number of customers	No	Yes	Yes	No	No
4B	Large Power	N/A					
10A	Irrigation	Number of customers	No	No	No	Yes	No
10B	Irrigation Time-of-Use	Number of customers	No	No	No	Yes	No

Notes: "Population" is the total population of New Mexico. "Income" is measured as the real Gross State Product. "Post-2008" is a binary variable that equals 1 in all time periods including and after 2008. "South" is a binary variable that equals 1 in March 2007. "Time Trend" is a constructed variable that increases by 1 unit each month.
Customer forecasts for Rate Class 4B (Large Power) are not made with an econometric model because growth for Large Power customers does not substantially vary over time. Instead, PNM uses a qualitative approach that allows for increases every few years.
*The model allows for the effect of population on the number of customers for Rate Class 1A to differ between the pre-2008 and post-2008 periods.

I. Criteria for Evaluating Forecasting Models

Our recommendations are based on six criteria: (1) historical goodness-of-fit or in-sample performance, (2) out-of-sample performance, (3) plausibility of model parameters, (4) plausibility of forecast values in 2016, which is the Future Test Year ("FTY"), (5) transparency of model specification, 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, *i.e.*, the data that was used to estimate the model's parameters? To measure model fit, we 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"). RMSE and MAD put more weight on prediction errors[1] that are large in magnitude whereas MAPE places more weight on prediction errors that are large relative to the magnitude of the actual value. We 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 (*i.e.*, prediction error) 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 was not used to estimate the model's parameters. To perform this test, we fitted the model to data from January 2002 through December 2012 (the "in-sample period"), and we treated January 2013 through May 2014 as the "out-of-sample period." We then calculated and compared the MAPE for the out-of-sample period across models.

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

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, we also evaluated 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 demand: first, as income rises, usage increases; second, as the price per kilowatt hour ("kWh") rises, usage decreases; and with more extreme weather conditions such as hotter summers or colder winters, usage increases. If the model parameters suggest otherwise, then I would suspect that the model is missing an important piece of information or input; for example, an omitted variable may be driving the unexpected result.

Not only should the model parameters be defensible from a theoretical standpoint, but we also considered whether the model specification allows us to identify which factors are driving the long-run trends in UPC or number of customers. Some complex models perform well in terms of forecasting with fairly high accuracy (on the basis of, perhaps, in-sample and out-of-sample MAPEs as previously discussed). However, the way in which the models are specified can be a "black box." Moreover, purely statistical models heavily rely on the quality and representativeness of the data. In the event of a paradigm shift and past data is no longer relevant, the model may become obsolete. To ensure that we understand how the outputs from the forecast model are generated, we opted for models that can be traced back to economic theory as opposed to being a purely statistical construct.

C. Robustness

In addition to accuracy and theoretical soundness, we evaluated the robustness of the model by comparing the 2016 forecasts of electricity usage with the observed usage patterns in recent history, especially after the economic recession in 2008-09 and with the 2016 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, our criteria – accuracy, theoretical soundness, and robustness – are accepted desirable properties of a forecasting model, and a general principle is to aim for simplicity when possible.[2]

II. 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 use per customer, can change as other factors vary over time and/or across individuals. The variable of interest is sometimes called an "outcome variable," the other factors can be called "explanatory variables" because they serve to explain how (or why) the outcome variable may differ when the explanatory variables change.[3] When deciding on a model, one must choose the functional form of the equation, *e.g.* linear or logarithmic, and the given the functional form, the set of explanatory variables to be included.

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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] Other names for the "outcome variable" include "dependent variable" and "left-hand side variable." Other names for the "explanatory variables" include "independent variables," "right-hand side variables," "control variables," and "covariates." In this Exhibit, we use the terms "outcome variable" and "explanatory variables."

In addition to functional form and the set of explanatory variables, one should 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 depends on its past value – then our model needs to be designed such that we are able to capture 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 we chose among them. In short, we 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, GLS directly addresses time dependency and is recommended where appropriate. Second, I detail our decision of functional form and the set of explanatory variables to include in each model by rate class for UPC and then for the number of customers. In practice, we 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.

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

For example: an econometric model may be designed to characterize a consumer's decision of how much electricity to use during a month. Time series models are based on the premise that changes in the past are a good predictor of future changes. 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.

We considered three classes of forecasting models that are widely used: Ordinary Least Squares ("OLS"), Generalized Least Squares ("GLS"), and Autoregressive Integrated Moving Average ("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 unpredictable components are linked, *i.e.*, 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, would be one reason why electricity usage can be serially correlated and not suited for OLS.

In the presence of serial correlation, GLS may be more suitable than OLS because GLS can directly address the co-dependencies in the residuals.[5] While the observations may be correlated over time, the difference or partial difference[6] between observations may be independently distributed. GLS transforms the data by taking partial differences and applies OLS to the transformed observations. To check for the appropriate use and robustness of implementing GLS, we test for serial correlation and compare the forecasts from OLS and GLS.

ARIMA is an example of a time series model, and the model predicts future values of the outcome, say UPC, using past values of UPC and a moving average of unexpected 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 the serial correlation,[7] and 'q' periods of persistence in the error term. For example: suppose that the outcome is UPC per month, and we model UPC with an ARIMA(1,0,1) model. The model predicts UPC today based on UPC in the previous month, unexpected shocks to electricity demand today, and unexpected shocks that occurred last month.[8]

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

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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 we subtract a fraction of the lagged value from the current value rather than taking the straight difference between observations.

[7] As with GLS, the idea behind differencing is that changes in the outcome may be independent across time.

[8] In equation form, the ARIMA(1,0,1) can be written as $UPC_t = \varphi UPC_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1}$.

difference, *i.e.* {p,d,q}, can be a challenge, and many researchers rely on measures of goodness-of-fit such as the Aikake Information Criterion ("AIC") to make these decisions. Thus, a common critique of ARIMA is that the model is statistically rather than theoretically based, and therefore, the underlying drivers of the forecast are not well understood.

Since transparency in the model's specification is one of our criteria for model selection, we have chosen to recommend OLS and GLS models over ARIMA, even when the in-sample and out-of-sample MAPEs for ARIMA are lower. However, the forecast from ARIMA can serve as a robustness check.

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 constant 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 logs assumes a constant proportional relationship between the outcome and explanatory variables. A one percentage point increase in the explanatory variable has the same percentage impact on the outcome variable.

The decision to include or exclude certain explanatory variables depends on statistical fit and guiding principles of economic theory. For UPC, economic theory aims to characterize how an individual in each rate class makes decisions about electricity usage. According to demand theory, income, prices, and demand shifters, such as climate and weather, are important factors.

The number of customers can be driven by different forces from UPC. Since PNM is the only electric utility in its service territory, understanding (and/or measuring) the movement of people in and out of PNM's service territory is essential.[9]

When deciding which variables should be included in the model, we first need to understand the customer base in each rate class. After understanding the customer base, we can then identify factors that 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 across the country.

In brief, the customer composition of each rate classes that we econometrically forecast is:[10]

- Rate Classes 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).

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

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

- Rate Classes 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).
- Rate Class 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 Class 4B is the "Large Power" commercial class (excluding the largest customers, which are each forecasted separately). To qualify, the customer minimum demand must be above 500 kW. We 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 Rate Classes 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, we considered each variable's theoretical relevance, its statistical and economic significance when we estimate the model,[11] and whether the estimated coefficient matches with theory. For example: a positive price elasticity would mean

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[11] The term "explanatory power" can refer to the variable's statistical and economic significance. If we 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 we might say that the variable has "low explanatory power." Intuitively, the variable does not contribute to our understanding of how or why the outcome changes.

that raising prices promotes higher levels of energy usage, which does not make sense from a theoretical or common sense perspective.[12] Instead, the result suggests that the model may be subject to omitted variable bias, *i.e.*, that price is capturing the effect of another factor that is missing in the model.

In light of these principles behind choosing a functional form and set of explanatory variables, we decided to model UPC as a logarithmic function and the number of customers as a linear function. The implication of the logarithmic form is that changes in the explanatory variables scale UPC up or down, and the magnitudes of these effects depend on the level of UPC. Our choices are based upon the models' fits to observed data and standard forecasting practices that I have seen in the electric utility industry.

Our choices for the explanatory variables for the UPC models are as follows:

- We have included real price as an explanatory variable for Rate Classes 1A and 2A.
- Real personal income is included for Rate Classes 1A, 1B, 2A, and 2B for reasons mentioned earlier.[13] Wealthier households can afford to use more electricity, to buy more appliances that use electricity, or to own or rent larger housing units.
- Nearly all rate classes include weather controls except for Rate Class 4B. Customers wish to regulate temperature and comfort levels, and thus, more extreme temperatures are likely to increase electricity usage. Residential customers will turn on heating or cooling

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[12] 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, *i.e.* consumption falls when incomes rise, and there is no evidence that electricity falls into that category.

[13] For Rate Class 10B, we use real Gross State Product to control for the economic environment.

systems for very cold or very warm days whereas commercial customers will be more inclined to maintain a stable temperature throughout the year. The agricultural sector will need more water in a hot year, and thus, we would expect usage to be higher for those years.

- The inclusion of a time trend can capture unobserved factors that influence UPC and are either increasing (or decreasing) throughout the sample period. For most rate classes, we avoided including a time trend because one could argue that it is not informative about the underlying drivers of usage. Often, its inclusion does not substantially improve the forecast given that our models account for fluctuations in income, price, and weather. However, we include a time trend for three rate classes: 2A, 4B, and 10B. For Rate Class 4B, the omission of the time trend substantially reduces the model's accuracy. For Rate Class 2A, a model without the time trend yields a negative income elasticity, and with the time trend, the income elasticity is positive. These results suggest that the time trend is capturing the effect of an unobserved factor motivating the long-run decline in UPC. Given the information available, we are unable to further explore this hypothesis, and we allow the time trend to serve as the proxy.

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

- For obvious reasons, the population size of New Mexico is an essential explanatory variable to explain the number of Residential (1A and 1B) and Small Power (2A) customers. For Rate Class 1A, we allow the relationship between population size and number of customers to differ between the pre- and post-recession periods. We find that the recession weakened the relationship in the sense that, after 2008, changes in population size had little impact on the number of Residential customers.

- The addition of PNM South (formerly known as Texas-New Mexico Power) in March 2007 increased the number of Small Power (2A) and Irrigation (10A and 10B) customers but had no discernible impact on Residential customers.[14]
- For General Power (3B/3C), we control for real Gross State Product. Businesses are more likely to move into PNM's service territory if the local economy is growing. One might also think that this reasoning should apply to Residential and Small Power customers as well, but we find that having controlled for population size, GSP has low explanatory power.
- As previously explained for the UPC models, we generally avoided using a time trend in modeling because the time trend is not informative about the fundamental drivers behind the forecast. However, for Small Power Time-of-Use, we find that a linear trend is a strong predictor of the number of customers.

[14] Given that we were already controlling for population, we were unable to reject that South is statistically different from zero for the Residential customer model, and we also found that the inclusion of South did not alter the coefficient estimates on population.

Econometric Models for Usage per Customer

PNM Exhibit AF-3

Is contained in the following 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	4B	10A	10B
Intercept	0.525 (0.255)**	3.417 (0.309)***	3.175 (0.458)***	3.671 (0.855)***	7.079 (0.033)***	14.593 (0.031)***	2.086 (0.156)***	6.561 (6.480)
Log of Real Price	-0.164 (0.041)***		-0.197 (0.043)***					
Log of Real Personal Income	0.526 (0.056)***	0.219 (0.087)**	0.054 (0.174)	0.295 (0.256)				-0.792 (1.514)
Cooling Degree Days	9.918 (1.105)***	5.245 (2.429)**	5.592 (0.603)***	10.202 (2.887)***	5.187 (0.663)***		24.989 (15.337)	22.773 (10.628)**
Heating Degree Days	4.493 (0.655)***	10.897 (1.591)***	1.898 (0.473)***		0.343 (0.449)			
Time Trend			-0.00112 (0.00032)***			-0.0026 (0.0003)***		0.00484 (0.00225)**
South				0.134 (0.037)***	-0.059 (0.009)***	0.133 (0.023)***	0.261 (0.123)**	
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	GLS, AR(1)	GLS, AR(1)	OLS	OLS	GLS, AR(1)	OLS	GLS, AR(1)	GLS, AR(1)

Notes: Standard errors are shown in parentheses. Unit of observation is a "rate class + month + year," and estimating period spans January 2002 through May 2014. For Rate Class 4B, estimating period begins in January 2004, and individually forecasted large customers are excluded. For Rate Class 10B, "log of real personal income" is replaced by "log of real Gross State Product." Cooling Degree Days and Heating Degree Days have been scaled down by 10,000. Temperature cutoffs for Rate Classes 1A/1B are 58 degrees Fahrenheit for HDD and 70 degrees for CDD; for Rate Classes 2A/2B/3B/3C/10A/10B, both CDD and HDD use 60 degrees. South is an indicator that equals 1 for all month-years after March 2007 (inclusive). GLS stands for Generalized Least Squares, and OLS stands for Ordinary Least Squares. ** $p<0.05$, *** $p<0.01$

Econometric Models for Number of Customers

PNM Exhibit AF-4

Is contained in the following page.

PNM Exhibit AF-4

Econometric Models for Number of Customers

Outcome variable: Number of Customers							
Rate Class:	1A	1B	2A	2B	3B/3C	10A	10B
Intercept	130.628 (42.766)**	215.046 (8.330)***	27.439 (10.830)**	402.159 (14.346)***	9.196 (7.520)	105.506 (2.382)***	197.087 (2.740)***
NM population	0.395 (0.032)***	-0.00007 (0.00001)***	0.017 (0.007)**				
NM population X Post-2008	-0.363 (0.030)***						
Post-2008					-21.348 (11.371)		
NM real Gross State Product					14.539 (13.696)		
South			6424 (67.48)***			12.491 (1.542)***	0.968 (2.243)
Time Trend				0.595 (0.139)***			
Model	First differences	GLS, AR(1)	First differences	GLS, AR(2)	First differences	GLS, AR(2)	GLS, AR(2)

Notes: Standard errors are shown in parentheses. Unit of observation is a "rate class + year + month," and estimating period spans January 2002 through August 2014. Post-2008 is an indicator that equals 1 for periods after January 2008 (inclusive). South is an indicator that equals 1 on March 2007. GLS stands for Generalized Least Squares. ** $p<0.05$, *** $p<0.01$

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. 507	)	**Case No. 14-00332-UT**
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 Dr. Ahmad Faruqui** and it is true and accurate based on my own personal knowledge and belief.

SIGNED this 2nd day of December, 2014.

DR. AHMAD FARUQUI

SUBSCRIBED AND SWORN to before me this 2 day of December, 2014.

NOTARY PUBLIC IN AND FOR
THE STATE OF CALIFORNIA

My Commission Expires:

2/12/15

SHERRY VALDEZ
Commission # 1925338
Notary Public - California
San Mateo County
My Comm. Expires Feb 12, 2015