

Advanced Metering Infrastructure: a comparison of like utilities
Discussion Draft
Energy Conservation and Management Division
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In response to the directives outlined in the New Mexico Energy Grid Roadmap Act of 2020,¹ the Energy Conservation and Management Division (ECMD) of the Energy Minerals and Natural Resources Department (EMNRD) convened the Grid Modernization Advisory Group (GMAG) for a series of eight workshops in 2020. The workshops involved representatives from the electricity sector, national labs, academia, renewable energy developers, and consumer/environmental advocates. These meetings resulted in eleven white papers detailing background information and implications for separate grid modernization concepts and technologies. The first of these papers discussed the role of advanced metering infrastructure (AMI)² as the “foundation” of the smart grid by facilitating two-way communication between utilities and customers. AMI, when equipped with certain capabilities and functionalities, allows for enhanced reliability, increased distributed generation, and improved energy efficiency through more transparency. The GMAG highlighted Xcel Colorado as an example utility that was considering an AMI rollout across its service territory.

Four years later, the Xcel Colorado AMI rollout is nearly complete and lends itself as a natural experiment to assess AMI deployment’s impact on ratepayers across key metrics. Xcel Colorado and Public Service Company of New Mexico (PNM) exhibit comparable seasonality in pricing and electricity consumption (Figures 1 and 2). Given these parallel trends, a difference-in-differences estimation leveraging EIA Form 861 reports with PNM as the counterfactual utility can be used to demonstrate the effect of Xcel Colorado’s AMI rollout on changes in residential electricity consumption, the residential price per kWh of electricity, and distribution system reliability. Findings from this analysis can then be used to estimate how a similar deployment of grid modernization technologies might affect PNM’s system and those who rely on it. This is a preliminary analysis that will be discussed in greater length as part of a larger update on ECMD’s 2021 Baseline Report of the Electricity Sector.³

¹ NMSA 1978, § 71-11-1 (2020)

² See https://www.emnrd.nm.gov/ecmd/wp-content/uploads/sites/3/AMI_1.29.21.pdf

³ See https://www.emnrd.nm.gov/ecmd/wp-content/uploads/sites/3/Baseline_FINAL.pdf

Methodology

Difference-in-differences analysis is a statistical method designed to evaluate the causal effect of policy changes on an outcome of interest where randomized controlled trials are not feasible methods. In a randomized control trial participants are assigned to treatment and control groups to ascertain the causal effect of the treatment. Difference-in-differences takes advantage of discrepancies in policy across borders (in this case utility service territories) to compare treatment and control group impacts⁴.

Parallel trends between the control and treatment groups in the absence of the treatment is the most critical assumption for difference-in-differences analysis. This confirms that the control group is a true counterfactual and allows for the attribution of any differential changes in the outcome variable of interest to the treatment applied (in this case AMI).

The regression model below was used to calculate the causal effect on four different dependent variables in this analysis.

$$Y_{ut} = \beta_0 + \beta_1 Treatment_u + \beta_2 After_t + \beta_3 (Treatment_u \times After_t) + \epsilon_{ut}$$

Where:

Y_{ut} is the dependent variable for utility u at month t .

$Treatment_u$ is a binary indicator that equals 1 if the utility u is in the treatment group.

$After_t$ is a binary indicator that equals 1 for time periods after AMI.

$Treatment_u \times Post_t$ is the interaction term capturing that change in Y_{ut} for the treatment group relative to the control group.

ϵ_{ut} is an error term unique to the utility u in time period t accounting for unobserved influences on Y_{ut} not accounted for by the model.

⁴ See World Bank Impact Evaluation In Practice, Gertler et al 2016, <https://openknowledge.worldbank.org/server/api/core/bitstreams/4659ef23-61ff-5df7-9b4e-89fda12b074d/content>

The coefficient β_3 is the treatment effect of interest. That is the coefficient that represents any incremental change in the outcome variable between the treatment and control after AMI. ECMD also included a seasonal indicator variable in the final analysis to control for peak month changes in consumption and price.

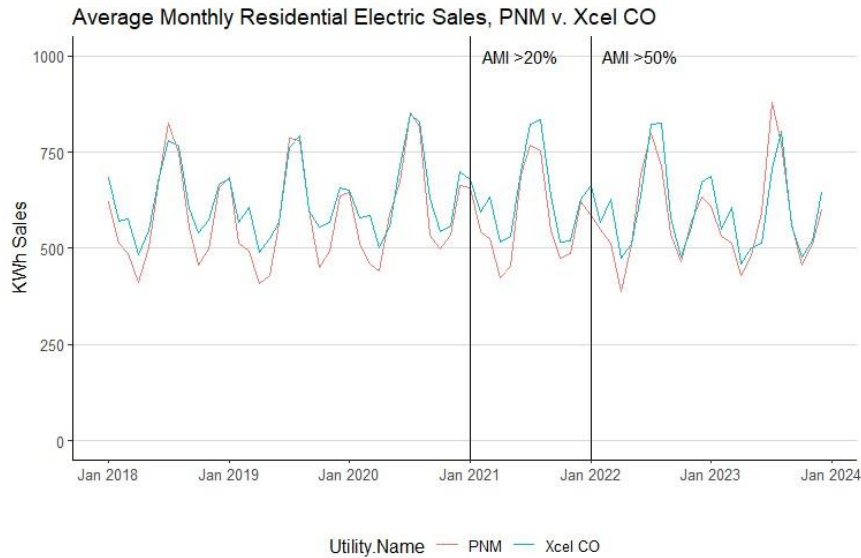


Figure 1: Average Monthly Residential Electricity Consumption

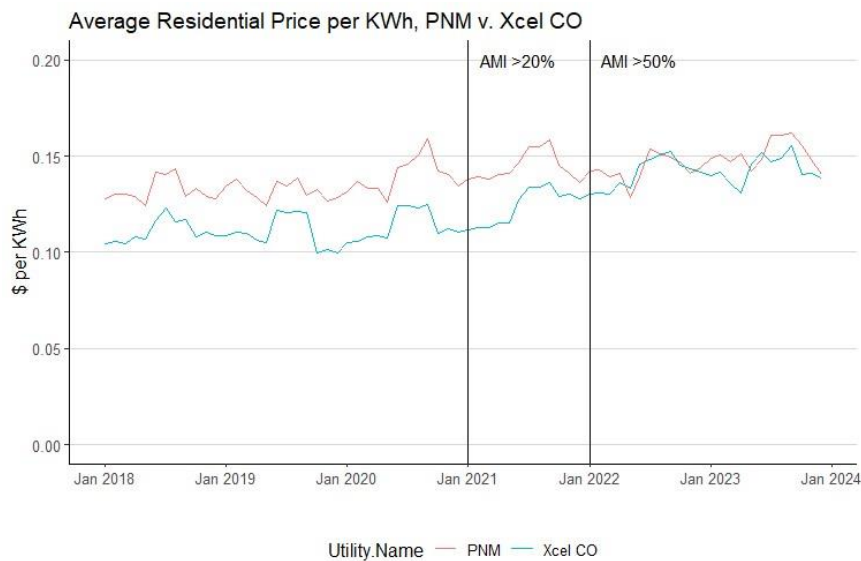


Figure 2: Average Monthly Residential Price of Electricity per kWh

Figures 1 and 2 above indicate that Xcel CO and PNM satisfy the parallel trends condition in addition to similarities in climate and regulatory frameworks that govern utility operations and pricing.

Demand and Pricing Impacts

ECMD estimates average monthly residential electricity consumption at Xcel Colorado is 23.1 kWh lower than it otherwise would have been had the utility not deployed AMI and associated technologies. Notably, much of the reduced load is represented by a decline in summer peak demand likely spurred by AMI-induced, time variable pricing (Figure 3). ECMD estimates that average monthly pricing is 1.7 cents per kWh higher than it otherwise would have been at Xcel Colorado following AMI deployment.

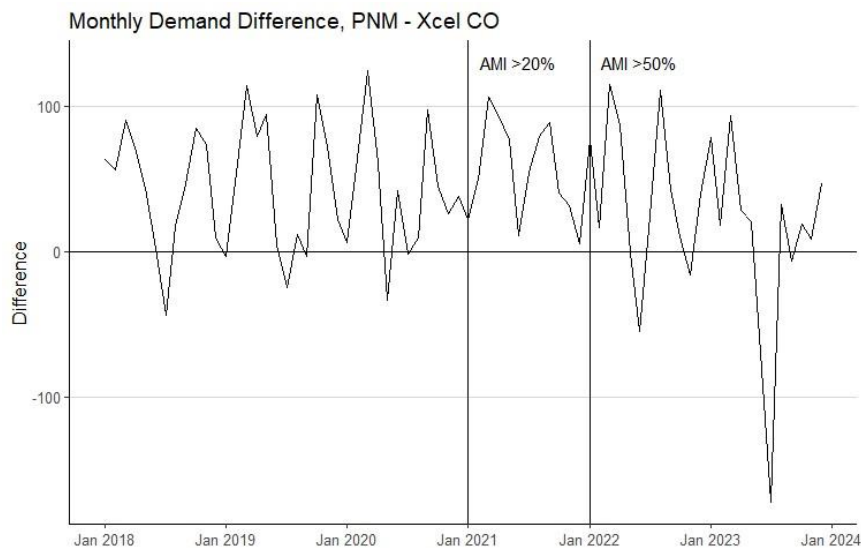


Figure 3: Difference in Average Monthly Residential Demand (Xcel Co – PNM)



Figure 4: Comparison of Demand Means (0 – before AMI at Xcel CO, 1 – after AMI at Xcel CO)

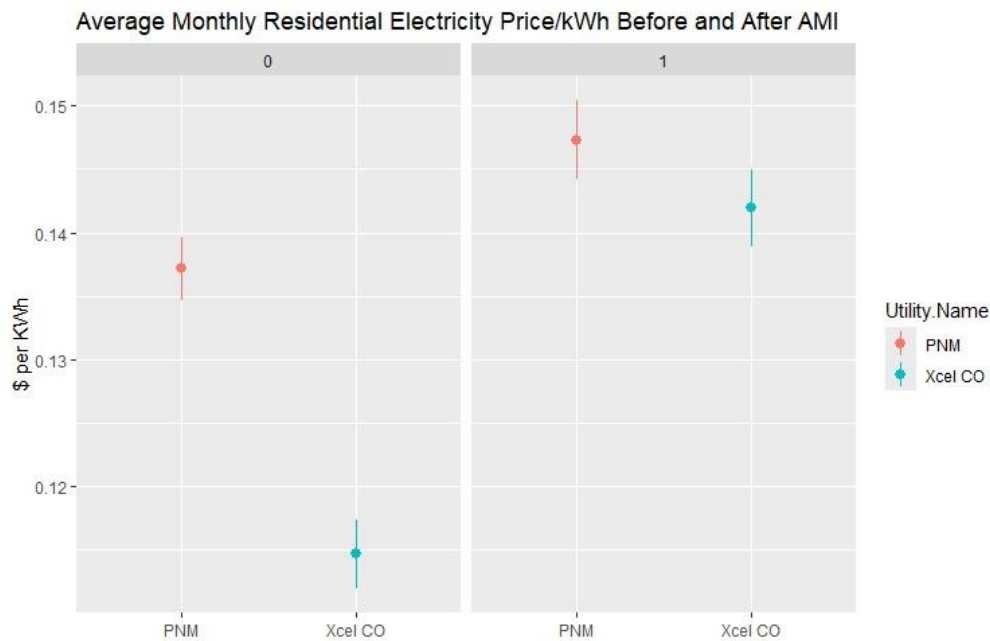


Figure 5: Comparison of Price Means (0 – before AMI at Xcel CO, 1 – after AMI at Xcel CO)

The resulting analysis suggests that the pricing effect outweighed the reduction in demand for electricity and the average monthly residential electricity bill at Xcel CO likely grew by \$7.74 more than it otherwise would have had AMI not been deployed (Figure 4, Figure 5). The implications

of this finding confirm that consumers will respond to price signals achieving the desired effect of reducing electricity demand during peak periods. Utilities can amplify this demand response impact by educating ratepayers about and promoting AMI-enabled home area networks that link meters to electrical appliances, EV chargers, and other load contributors. This action would further empower customers to take advantage of dynamic pricing by programming these devices to operate at the lowest electricity rate (during off-peak hours).

Distributed Resources Impact

The GMAG also identified DER integration as a benefit of AMI. Using AMI-enabled distributed energy management systems (DERMS), utilities can increase the hosting capacity of the distribution grid by communicating with DERs to better manage the dispatch of generation and charge of distributed energy storage.

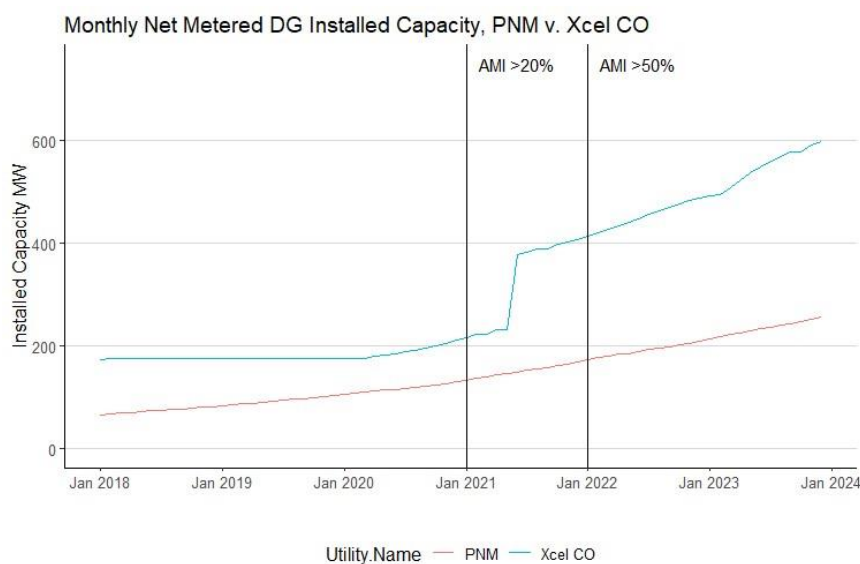


Figure 6: Net Metered DG Solar Installed Capacity, Monthly

Customers may also be incentivized to adopt rooftop solar in light of higher monthly bills they face on average due to dynamic pricing. In the Xcel Colorado example, net metered DG solar capacity experienced a stepwise increase in the summer of 2021 when AMI penetration on the distribution system was between 20% and 50% (Figure 6). The effect is estimated to be 180 MW of additional distributed solar capacity added so far due to the AMI roll-out at Xcel Colorado. EMNRD suspects this behavior to be an anticipatory pull-forward in demand for rooftop solar ahead of 2022's time-of-use pricing, aided by expanded hosting capacity available on certain feeders.

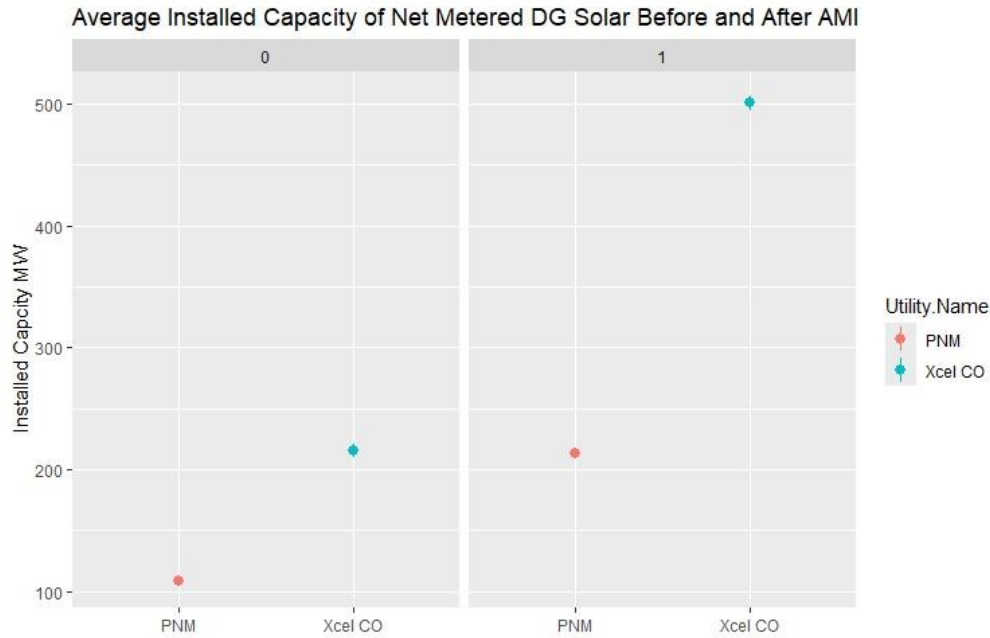


Figure 7: Utility Mean Comparison Installed DG Capacity (0 – before AMI at Xcel CO, 1 – after AMI at Xcel CO)

Reliability Impacts

This analysis next looks at the impact of AMI on reliability, a key objective of a modern grid and suggested benefit of AMI. A similar analysis studying reliability is complicated by differing reporting cadences between electricity sales data and reliability metrics at the EIA. Given a two-year lag, there is only visibility into the early years of the AMI rollout at Xcel CO as it relates to reliability. The chart below demonstrates that the as the deployment of AMI accelerated across Xcel’s system, the customer average interruption duration index (CAIDI) increased at a slower pace versus that of PNM, suggesting an enhanced reliability impact following the rollout. An average reduction of CAIDI of 11 minutes (which has been observed thus far across Xcel CO’s system) would save those reliant on PNM’s distribution roughly 45 million dollars over the 20-year AMI lifecycle according to the Interruption Cost Estimator developed by Berkeley National Laboratory⁵.

⁵ See Sullivan et al (2015) <https://eta-publications.lbl.gov/sites/default/files/lbnl-6941e.pdf>

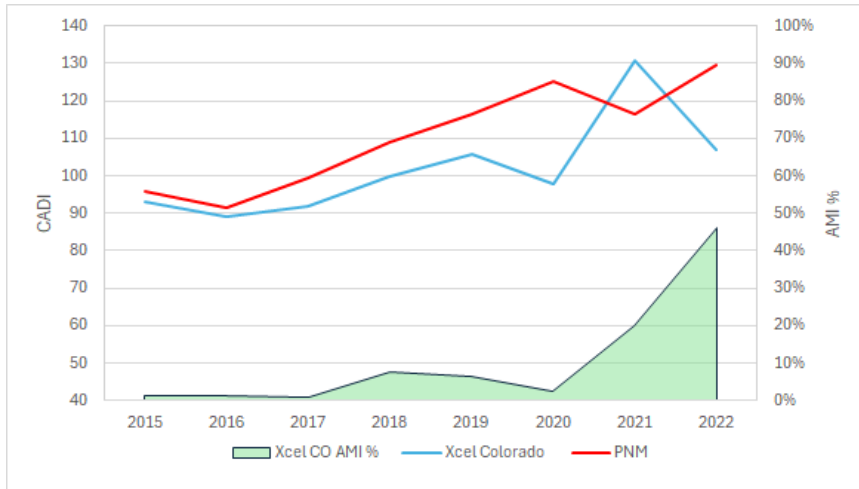


Figure 6: Reliability Comparison Yearly; AMI roll-out

Yearly Cost Savings from Reliability Improvement (2024 Dollars)	
Sector	Δ Total Cost
Residential	\$ 115,810.33
Small C&I	\$ 1,341,810.35
Medium and Large C&I	\$ 939,333.79
Total	\$ 2,396,954.48

Figure 7: Reliability Improvement Cost Savings for PNM customers derived from avoided outage minutes)

Conclusion

The full impact of Xcel Colorado’s AMI deployment has not yet been realized. As consumers are trained to respond to price signals from time-of-use pricing, and utilities learn to maximize the reliability improvement capabilities of newly installed technology, ratepayer and societal benefits are likely to be greater than shown above. This preliminary analysis suggests that the increase in price per kWh will be roughly 1.7 cents higher due to AMI and resulting pricing changes in the initial years of adoption. Households are likely to respond to these prices by reducing electricity consumption but this change in behavior will not be enough to offset price increases and will, subsequently, result in higher bills. The utility can also expect to improve reliability by reducing the average time to restore service by 11 minutes per year. This results in operations and maintenance cost savings for the utility and avoided outage savings for customers.

Appendix:

Table 1: Monthly Bill Model Output

Regression Results

Dependent variable:
Average Monthly Bill

Treatment	-7.850*** (2.334)
After	5.408* (2.858)
Seasonal Control	32.737*** (2.200)
Interaction	7.741* (4.042)
Constant	72.099*** (1.739)

Observations	144
R2	0.646
Adjusted R2	0.636
Residual Std. Error	11.433 (df = 139)
F Statistic	63.443*** (df = 4; 139)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: Monthly Price Model Output

Regression Results

Dependent variable:
Average Monthly Residential Price

Treatment	-0.022*** (0.002)
After	0.010*** (0.002)
Seasonal Control	0.010*** (0.001)
Interaction	0.017*** (0.003)
Constant	0.135*** (0.001)

Observations	144
R2	0.767
Adjusted R2	0.760
Residual Std. Error	0.008 (df = 139)
F Statistic	114.478*** (df = 4; 139)
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Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3: Monthly Demand Model Output

Regression Results	
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Dependent variable:	
Average Monthly Residential Demand	

Treatment	45.519*** (15.412)
After	-3.304 (18.876)
Seasonal control	192.822*** (14.531)
Interaction	-23.102 (26.694)
Constant	534.192*** (11.487)

Observations	144
R2	0.574
Adjusted R2	0.562
Residual Std. Error	75.503 (df = 139)
F Statistic	46.779*** (df = 4; 139)
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Note:	*p<0.1; **p<0.05; ***p<0.01