Online Appendix

Can Digitalization Improve Public Services? Evidence from Innovation in Energy Management

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A Additional Background on AMI in the U.S.

A1 Drivers of AMI Adoption in the United States

Digitization of the electricity grid initially progressed slowly in the U.S. Some of the main factors affecting initial roll-out included financial barriers, differential state support for AMI, a lack of regulatory standards, and utility learning about the technology (Guo, Bond and Narayanan 2015; Strong 2018). In the paragraphs that follow, we discuss how alleviating constraints related to each of these factors likely helped to deliver AMI adoption in the United States.

Alleviating financial constraints: Since the mid-2000s, utility AMI investments have increased, which is at least partially attributable to government efforts. At the federal level, government efforts started with the Energy Policy Act of 2005, which provided a policy framework for AMI. The Energy Independence and Security Act of 2007 was then enacted "to support the modernization of the Nation's electricity transmission and distribution system, to maintain a reliable and secure electricity infrastructure that can meet the future demand growth" (Public Utility Commission of Texas 2010). This act tasked the U.S. Department of Energy with detecting barriers to smart grid technology adoption, while also deploying funding and encouraging states to permit utilities to recover the costs of investing in AMI.

Adoption substantially increased with the introduction of federal funding for AMI, alleviating financial barriers. The American Recovery and Reinvestment Act of 2009 directed substantial amounts of federal funding towards AMI (U.S. Department of Energy 2012b). As of 2012, $3.4 billion had been invested in federal funds through the Smart Grid Investment Grant (SGIG) program. Given private sector matching funds were required, the program increased investment in AMI by nearly $8 billion as of 2012 (U.S. Department of Energy 2012b). The SGIG program, which funded a total of 99 projects across the country (U.S. Department of Energy 2012a), was intended to accelerate the installation of smart grid technologies in four areas with investments in AMI being one of the four. The program did induce greater adoption of AMI and the number of smart meters installed increased fourfold between 2007 and 2011 (Gold, Waters and York 2020). As we show in Appendix Figure D1, Panel A, installations by utilities have increased steadily since 2007.

The cost of smart meters in the market have also declined over time, which also is another channel through which the financial constraints of AMI adoption were alleviated over time (Strong 2018; Guo et al. 2015).

Increasing state support: There is considerable heterogeneity in AMI adoption rates across states. These differences are likely correlated with variation in the extent to which relevant studies, policies, and legislation were carried out in the states (EIA 2012). Strong (2018) finds state support for AMI adoption is positively correlated with adoption, but this relationship is not always statistically significant. In some states —although not all —regulatory approval is required to approve utilities' plans for AMI cost recovery (EIA 2017). The U.S. Energy Information Administration (EIA) tracked smart grid legislative regulatory policies by state through at least 2011 (see, e.g., EIA 2011).

Developing regulatory standards: Some utilities have indicated that they waited for certain industry technology standards to be developed and finalized before investing in

AMI. One main example of this is the development of an interoperability standard, which was finalized in 2012 (Strong 2018).

Learning about the technology: Evidence also suggests at least two forms of learning—learning by doing and learning from others—played a role in the steady increase of AMI deployment (Strong 2018). Such learning would affect both the deployment of AMI by the utility over time as well as the benefits the utility (and potentially the customers as well) derive from the installation of AMI.

A2 Expected Benefits of AMI Deployment

Government and industry reports cite a number of benefits from deploying AMI that accrue to the utilities and customers. Many of the expected benefits are linked to the two-way transmission of data permitted by AMI, which is claimed to help improve utility operational efficiency in multiple respects.

AMI's remote transmission of electricity consumption data can reduce the reliance on employees to manually read meters. This can remove the need to estimate or interpolate bills when meter reading is not possible and decrease overall human error in the billing process (Nangia, Oguah and Gaba 2016; Cooper and Shuster 2021). Customer complaints decrease and billing disputes resolve more quickly (U.S. Department of Energy 2016).

Utilities can use the real-time information to improve billing processes and efficiency, enhance forecasting capabilities, balance supply and demand more precisely, decrease outage response times, identify bottlenecks or other potential threats to the grid, improve safety, and improve overall grid operations including within the transmission and distribution systems (Nangia et al. 2016; Gold et al. 2020; Public Utility Commission of Texas 2010).

In terms of improving reliability, AMI meters can help in several ways. First, they assist in identifying outages faster and expediting service restoration. For example, smart meters are often enabled with a "last gasp" alarm, which informs the utility at the time when an outage occurs and then again when power is restored (U.S. Department of Energy 2014). Of the 99 projects funded through the SGIG program, 48 projects had the explicit goal of improving electric distribution reliability (U.S. Department of Energy 2012a).[1] Second, smart meters allow utilities to remotely disconnect customers—such as those who agree to allow utilities to do so when needed by enrolling in demand response programs—at times when either wholesale electricity prices are particularly high or the electrical system is stressed (Public Utility Commission of Texas 2010), which can help avoid outages and distribution system damages altogether.

Some, although not all, of these operational efficiencies—such as the faster, remote identification of outage locations—also benefit utility customers. For example, EIA documentation notes that AMI "can support demand response and distributed generation, ... [and] provide information that consumers can use to save money by managing their use of electricity" (EIA 2017). Others note the role of AMI and the additional functionalities

[1] According to the DOE, these 48 projects had one or more of the following goals: "(1) reducing the frequency of both momentary and sustained outages, (2) reducing the duration of outages, and (3) reducing the operations and maintenance costs associated with outage management" (U.S. Department of Energy 2012a).

that AMI can enable—which can help utility customers realize the many of the benefits of AMI (e.g., lower costs and improving understanding of prices and billing)—have by and large been underutilized by many utilities (Gold et al. 2020).

A3 Valuing the Returns to AMI Deployment

The benefits of AMI vary across utilities depending on a number of factors, such as the utilities' baseline infrastructure, the functions of the AMI employed, the characteristics of the territory served (such as how remote it is), and the complementary investments utilities make.

Early on, federal and state agencies underscored the need to methodologically enumerate and estimate the benefits and costs of AMI deployment projects. Considerable effort has been invested in developing methodological approaches to defining, categorizing, and estimating both benefits and costs from the ratepayers perspective (see, e.g., Electric Power Research Institute 2010 2012). In some states, electricity utilities provided testimony to their state public utilities commissions to provide assurance that the benefits of these project outweigh the costs (for early examples see, e.g., Southern California Edison 2006; Public Utility Commission of Texas 2010). To understand the expectations of AMI's benefits to individual utilities would therefore require examining, on a case-by-case base, the utility testimonies to their state public utility commissions, where they are available.

Ex ante studies on the adoption of smart grids (and associated dynamic pricing policies) find benefit-cost ratios greater than 1, however some have indicated that not all of the benefits included in those calculations actually came to fruition (Guo et al. 2015). This could be the result of utilities not employing all the potential functions permitted by the AMI.

The magnitude of AMI benefits relative to the costs depends on the specific utility's needs and use of the technology. There are some states and smaller jurisdictions that have not approved their utility's proposal to install AMI, with the common opposition to AMI being the magnitude of their costs relative to their expected benefits (or uncertainty in those expected benefits) (Gold et al. 2020). In contrast, however, documentation on the SGIG program reports large O&M cost savings for some AMI projects, including one project that saved $174 million alone (U.S. Department of Energy 2016).

B Data and Sample Construction

B1 Utility-Level Data

We assemble utility-level information on basic characteristics, operations, sales, and meter adoption for the period 2007–2018 from the Energy Information Administration (EIA) forms and S&P Global. We restrict our sample to the contiguous U.S. (not including Alaska, Hawaii, or other offshore territories).

Basic Characteristics. We use S&P Global, EIA Forms 860 and 861 to construct detailed data on utility-level basic characteristics, including location, county-level service territory, ISO, FERC region, regulation status, ownership type (i.e., cooperative, investor-owned, government agencies, etc.), and electric activities (i.e., generation, transmission, and distribution).

Advanced Metering. Advanced metering information is derived from Schedule 6 of EIA-861. Since 2007, the data reports the number of electric meters by state, customer category, and meter type, including automated meter reading (AMR) and advanced metering infrastructure (AMI). In addition to smart meter adoption, these data also include the number of customers with the following advanced technology features enabled by the AMI since 2013: (1) digital access to daily energy usage; (2) home area network (HAN) gateway that allows the meter to communicate with customer's devices; (3) direct load control (LC) that permits remote shutdown or cycle a customer's electrical equipment on short notice. We aggregate the data to the utility level and calculate the total number of AMR and AMI per utility in each year. For any missing values in the number of AMI for certain years, we impute them using the value from the nearest available year prior to the missing year.

Operations. Operational data comes from EIA-861. We collect utility-level total electricity losses, which measure the amount of electricity lost from transmission and distribution. We drop the records with negative loss values as these are likely mistakes in EIA's data collection and reporting process. We then calculate the electricity loss rate as the share of total electricity losses relative to total electricity disposition. EIA-861 also reports detailed sales and revenue information, which is decomposed into different parts, including retail sales to ultimate customers (i.e., electricity sold to customers purchasing electricity for their own use and not for resale), sales for resale (i.e., electricity sold for resale purposes), delivery customers (i.e., unbundled customers who purchase electricity from a supplier other than the electric utility that distributes power to their premises), transmission of electricity, and other electric activities. For the retail sales to ultimate customers, EIA-861 has information on sales, revenues, and customer counts by four customer categories, including residential, commercial, industrial, and transportation.

Dynamic Pricing and Demand Response. EIA-861 contains the number of customers enrolled in demand response programs (e.g., energy savings or actual peak savings) or dynamic pricing programs (e.g., time-of-use pricing or real-time pricing) by utility, state, customer category, and balancing authority. The information on aggregate customer counts for all demand response or dynamic pricing programs is available after 2007, but Specific customer count on a single program is only available after 2013. We therefore calculate the total number of customers enrolled in any demand response programs or any dynamic pricing programs for each utility in a year. For any missing values in the number of enrolled customers, we impute them using the value from the nearest available year prior to the missing year. There are also data entry errors in the raw data where the number of enrolled customers is reported to be zero but the values in adjacent years are positive. For these cases, we replace the zeros with the non-zero values from the previous year.

Population and Building Construction. We supplement the utility data with measures on local population and building construction. The population data comes from the Survey of Epidemiology and End Results (SEER). It has annual population size for each county by age, race, and sex since 1969. For each year, we create two population measures based on this data: total population in a county and the size of the population older than 18. The second measure aims to capture the number of adults but excludes infants or teenagers who are unlikely to be homeowners. Data on new building units comes from the Building Permits Survey (BPS) administrated by the U.S. census. It provides annual statistics on the number and valuation of new privately owned residential housing units authorized by building permits for each county. From this data, we calculate the new and cumulative building units for the period 2007–2018. We merge these county-level population and housing data with electric utility data through their service territory information. Specifically, we sum up all the population or housing measures for the counties that a utility serves.

Sample Construction. We merge the utility-level annual data sets based on EIA-assigned unique utility ID and year. We implement a few additional cleaning steps. First, we exclude utilities that do not operate in the distribution segment of electricity delivery. Second, we omit observations that likely represent data entry errors, such as negative losses or customer counts. Third, for each utility, we calculate the ratio of year-specific disposition of electricity to its mean disposition and then drop the observations with such ratio larger than 2. These observations exhibit a sudden jump in total disposition of electricity and could be mistakes in data reporting. Fourth, we restrict to utilities that have at least 11 years of non-missing electricity losses data to maintain a high degree of panel balance. Finally, we omit utilities that adopted AMI prior to 2010 and after 2016 such that the sample includes all utilities that never adopt and those that do adopt between 2010 and 2016. This allows us to include at least three years of pre-treatment data and one year of post-treatment data for all adopters. We also exclude extreme outliers with respect to loss rates and number of customers. We omit utilities with average pre-treatment loss rates in the top 1% or bottom 1% of the distribution of utilities' average loss rates when they have not adopted AMI as well as utilities with fewer than 20 customers. The final data set used throughout our primary analyses contains 14,252 observations of 1,304 utilities.

B2 Feeder-Level Reliability in Texas

Feeder line data on service quality comes from the Public Utility Commission of Texas (PUCT), a state agency regulating electric, water, and telecommunication utilities. Each year, PUCT requires electric utilities to submit an annual service quality report in accordance with Substantive Rule §25.81. These reports contain detailed information on service quality and the total number of customers for each feeder line.

We focus on two international standards for measuring service reliability within an electricity distribution system: the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI). These measures provide standardized methods of electricity service reliability such that services are comparable across utilities and over time.[2] Both of these address interruptions, which are defined as losses of power delivery to one or more customer. According to the IEEE Guide for Electric Power Distribution Reliability Indices, SAIFI is a measure as to how often the utility's average customer experienced a sustained interruption in service (more than 5 minutes) within a given year. SAIDI measures the number of minutes of sustained interruptions that the utility's average customer experiences, with interruption duration being the length of time between the start of service being interrupted and the time when service delivery is restored.

In the PUCT reports, both SAIDI and SAIFI are calculated by taking the mean of outage duration and frequency over all customers served by a feeder line in a year. Specifically, for feeder line i in year t,

$$I_{it} = \frac{\sum_{c \in i} X_{cit}}{N_{it}}. \tag{B1}$$

In the above equation, X_{cit} is the number (for SAIFI) or duration (for SAIDI) of outage events experienced by customer c served by feeder line i in year t, and N_{it} is the total number of customers. A lower SAIDI or SAIFI value means a higher level of service reliability.

Sample Construction. The raw feeder line data contains 104,610 observations of 11,470 feeder lines from 12 utilities during 2007-2020. We implement a few additional processing steps to construct the final data. First, we restrict the sample to 2007 – 2016. After 2016, there are mergers and acquisitions among these utilities, since which the identifiers of feeder lines owned by those utilities have completely changed. Consequently, we are not able to match those feeder lines with the pre-2016 data. We also exclude two utilities —Cap Rock and Sharyland —that experienced mergers or acquisitions before 2016. Second, we restrict to feeder lines that have at least 6 years of non-missing reliability data. Then, we match this feeder-line-level data with utility-level AMI deployment based on EIA-assigned utility ID and name. The final data set for analysis contains 61,234 observations of 7,294 feeder lines from 10 utilities in Texas.

B3 Regional Employment Data

We assemble a dataset on occupation-level employment in each Metropolitan (MSA) and nonmetropolitan (non-MSA) area using the information from the Occupational Employment and Wage Statistics (OEWS) provided by the U.S. Bureau of Labor Statistics (BLS). It provides annual information on the number of total employment for each occupation category in each area, dating back to 1997. This area-level data, however, does not pro-

[2] The measures are limited to an extent, as they capture interruptions but not other power quality measures, such as drops and surges in voltage.

vide industry decomposition, and hence the employment represents all industries in an area. We retrieve the area-level employment data for the 2007-2018 period and restrict to the contiguous U.S.

We define an occupation as bill-collection-related labor if it belongs to the following category (with the corresponding occupation code in parenthesis): Meter Readers, Utilities (43-5041). We then drop other occupations in the same 2-digit category as those bill-collection-related ones (i.e., 43 - Office and Administrative Support Occupations). This is to mitigate the concern on spillover effects or occupation substitutions between those bill collection jobs and other office- or administration-related jobs. Then, the six-digit-level occupation data is aggregated to the two-digit level. We define jobs related to quantitative and computation if they belong to the following 2-digit occupation category: Computer and Mathematical Occupations (15-0000).

Sample Construction. To match this area-level employment data with AMI information, we first create county-level AMI adoption by aggregating the utility-level advanced metering data based on each utility's service territory. Specifically, for each county and year, we sum up the number of AMI meters over all the utilities serving that county. Then, we aggregate the county-level data to the area-level using the MSA and non-MSA area definitions provided by BLS.[3] For the counties that are matched with more than one area, we evenly divide the number of AMI meters in those counties before doing the aggregation. The combined data set contains 140,760 observations of 22 two-digit occupation categories in 642 MSA or non-MSA areas. We made two additional steps for the data cleaning. First, we omit the observations with a positive average wage but zero number of employment, which are likely to be data reporting errors. Second, we exclude areas that never had any bill-collection-related labor throughout the sample period. The final data set contains 100,848 observations of 22 two-digit occupation categories in 434 areas.

[3]BLS provides a mapping between each county and the corresponding MSA or non-MSA area. The data is available here: https://www.bls.gov/oes/2020/may/msa_def.htm.

C Additional Tables

Table C1: Falsification Test - No Effect on Loss Rate for Utilities with Initially Low Loss Rates in Pre-Treatment Period

Dependent Variable:	Loss Rate	Loss Rate
	(1)	(2)
PostAMI	0.001	-0.000
	(0.002)	(0.005)
Observations	3,417	2,907
Mean Pre-Treat Dep. Var.	0.029	0.029
Utility FEs	x	x
State-Year FEs	x	x
Local Market Controls	x	x

Notes: Table presents coefficients from estimating effect of smart meter deployment on the loss rate when restricting the sample to only include utilities with low pre-treatment loss rates (i.e., initially high performers). Provides a falsification test, as no effect is expected. All specifications are estimated using our 2SLS procedure. Local market controls are new construction build and (log) population, and a one-year treatment variable lead is used as the excluded instrument for (log) population. Standard errors are clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table C2: Effect of Smart Meters on Loss Rate Using OLS Instead of 2SLS

Dependent Variable:	Loss Rate (1)	Loss Rate (2)	Loss Rate (3)	Loss Rate (4)
Panel A: Binary Treatment				
PostAMI	-0.001*	-0.002***	-0.002*	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	15,556	11,754	13,455	10,172
Panel B: Continuous Treatment				
Prop. AMI	-0.003***	-0.003***	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	15,556	11,754	13,455	10,172
Sample Restrictions:				
Omit Initially High Performers		x		x
Include 3+ Years Post-Adoption Only			x	x
Utility FEs	x	x	x	x
State-Year FEs	x	x	x	x
Local Market Controls	x	x	x	x

Notes: Table presents estimates from running the same regressions as in the main results table (Table 2) but using OLS rather than 2SLS. The dependent variable is the loss rate in all cases. Panel A uses our primary (binary) treatment variable to estimate the effect of AMI, and in Panel B, we replace this with a continuous treatment variable measured as the proportion of a utility's customers that have AMI. Local market controls are new construction build and (log) population. Standard errors are clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table C3: Doubly-Robust Stacked Diff-in-Diff Estimates

Dep. Var.:	Loss Rate (1)	Loss Rate (2)	Loss Rate (3)	Loss Rate (4)
PostAMI	-0.002** (0.001)	-0.003*** (0.001)	-0.002** (0.001)	-0.003*** (0.001)
Observations	14,259	10,786	14,259	10,786
Control Group	Never Treated	Never Treated	All	All
Sample	Full	Omit High Perf.	Full	Omit High Perf.
Utility FEs	x	x	x	x
Year FEs	x	x	x	x
Controls	x	x	x	x

Notes: Regression results from implementing the"stacked" doubly robust DiD method of Sant'Anna and Zhao (2020) based on stabilized inverse probability weighting and OLS. In Columns 1 and 2, only utilities that are never treated are included in the control group and untreated observations are included in the control group in Columns 3 and 4. In Columns 2 and 4, we omit the bottom quartile of the pre-treatment loss rate distribution (i.e., high pre-treatment performers). The dependent variable is the loss rate in all cases. Local market controls are new construction build and (log) population. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C4: SUTVA - Investigating Whether Spillovers Bias the Results

Dependent Variable:	Loss Rate (1)	Imports (2)	Exports (3)
PostAMI	-0.002**	-0.022	-0.082
	(0.001)	(0.067)	(0.068)
Post Neighbor Deploying	0.000		
	(0.001)		
Observations	14,252	14,252	14,252
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

Notes: Table provides results from tests exploring whether SUTVA might be violated. The dependent variable in Column 1 is the loss rate. In Columns 2 and 3, it is (ihs) imported and exported electricity, respectively. Neighboring utilities are defined as those serving the same county. All specifications are estimated using our baseline 2SLS procedure. Local market controls are new construction build and (log) population, and a one-year treatment variable lead is used as the excluded instrument for (log) population. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C5: OLS Results for Provision of Complementary Products

Dependent Variable:	Dyn. Pricing (1)	Dem. Resp. (2)	Sales/ Cust. (3)	Sales/ Cust. (4)	Loss Rate (5)	Loss Rate (6)
PostAMI	0.071***	0.065***	0.011*	0.014***	-0.001	-0.001
	(0.014)	(0.012)	(0.006)	(0.005)	(0.001)	(0.001)
PostAMI x DP			-0.026*		0.000	
			(0.015)		(0.001)	
DP			0.007		-0.000	
			(0.011)		(0.001)	
PostAMI x DR				-0.052***		-0.001
				(0.018)		(0.001)
DR				0.024*		-0.001
				(0.012)		(0.001)
Observations	15,556	15,556	15,556	15,556	15,556	15,556
Utility FEs	x	x	x	x	x	x
State-Year FEs	x	x	x	x	x	x
Local Mkt. Controls	x	x	x	x	x	x

Notes: Table presents OLS results related to products that could enhance the benefits of AMI (dynamic pricing and demand response programs) for comparison to the 2SLS results of Table 3. In Columns 1-2, dependent variables are indicators for whether utilities offer dynamic pricing or demand response programs, respectively. In Columns 3-4, the dependent variable is (logged) sales per customer, and in Columns 5-6, it is the loss rate. In all regressions, the year prior to initial AMI adoption ("-1") is the omitted year. Standard errors are clustered at the utility level. Asterisks denote *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table C6: Robustness Checks for Reorganization of Workers Results

Dep. Var. (log):	Number of Employment			
	(1)	(2)	(3)	(4)
Panel A: Exclude MSAs with AMI Deployment before 2008 or after 2017				
PostAMI × Billing	-0.186***	-0.182***		
	(0.041)	(0.041)		
PostAMI × Quant			0.070***	0.065***
			(0.019)	(0.019)
Observations	56,763	54,102	56,763	55,162
Panel B: Exclude MSAs with AMI Deployment before 2009 or after 2017				
PostAMI × Billing	-0.189***	-0.187***		
	(0.058)	(0.058)		
PostAMI × Quant			0.043*	0.037
			(0.025)	(0.025)
Observations	32,951	31,410	32,951	31,986
MSA-Occupation FEs	x	x	x	x
MSA-Year FEs	x	x	x	x
Drop Quants		x		
Drop Meter Readers				x

Notes: Table provides results from estimating effects on the number of employment when restricting the sample in different ways that align with the restrictions imposed in our main analyses using utility-level data. In Panel A, we exclude MSAs with any AMI deployment before 2008 or after 2017. In Panel B, we exclude MSAs with any AMI deployment before 2009 or after 2017. Dependent variable is the logarithm of employment by MSA-occupation-year. Standard errors are clustered by MSA area. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C7: Summary Statistics of Key Variables by Utility Ownership

	All Utilities			Adopters Pre-AMI			Non-Adopters		
	Gov	Coop	IOU	Gov	Coop	IOU	Gov	Coop	IOU
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loss Rate (%)	0.048	0.058	0.054	0.045	0.058	0.051	0.050	0.061	0.057
	(0.027)	(0.023)	(0.028)	(0.024)	(0.022)	(0.024)	(0.028)	(0.026)	(0.033)
Total Losses (000s MWh)	22.59	28.46	668.86	28.78	30.20	1051.20	13.00	26.77	343.97
	(90.10)	(35.86)	(857.39)	(94.45)	(33.70)	(1069.21)	(21.99)	(43.97)	(402.10)
Total Sales (000s MWh)	477	530	10948	623	564	16578	273	442	6063
	(1414)	(732)	(12950)	(1635)	(837)	(14951)	(472)	(563)	(8086)
Total Revenue (million)	45.9	52.4	1169.3	56.2	52.7	1674.6	25.1	44.2	620.7
	(169.7)	(65.0)	(1574.6)	(177.3)	(64.5)	(1840.3)	(42.9)	(57.2)	(740.1)
No. of Customers (000s)	17.88	23.87	599.19	22.11	24.10	770.93	10.32	21.36	331.53
	(60.70)	(28.02)	(838.84)	(65.39)	(25.16)	(912.61)	(21.35)	(29.28)	(389.93)
Sales per Cust. (MWh)	36.71	24.49	22.90	29.90	24.18	26.63	42.23	25.24	21.14
	(190.01)	(20.31)	(14.83)	(13.13)	(20.44)	(11.05)	(251.15)	(22.50)	(16.94)
Rev. per Cust. (000s)	3.31	2.38	2.32	2.63	2.24	2.41	3.79	2.42	2.25
	(16.18)	(1.38)	(1.16)	(0.94)	(1.27)	(0.77)	(21.39)	(1.56)	(1.35)
Avg. Prices ($/kWh)	0.097	0.107	0.119	0.093	0.101	0.101	0.097	0.108	0.131
	(0.028)	(0.036)	(0.058)	(0.022)	(0.031)	(0.040)	(0.031)	(0.046)	(0.067)
Observations	7,709	5,642	901	2,002	2,015	222	4,399	1,730	417
No. of Utilities	707	515	82	303	357	44	404	158	38

Notes: Table provides summary statistics of key variables by utility ownership separately for government-owned utilities, co-operatives, and investor-owned utilities (IOUs). Standard errors are in parentheses. Data are from the Energy Information Administration for the years 2007 through 2017.

Table C8: Smart Meter Deployment Intensity Effects on Loss Rates by Utility Ownership

Dependent Variable:	Loss Rate (1)	Loss Rate (2)	Loss Rate (3)
	Gov-Owned	**Cooperatives**	**IOUs**
Prop. AMI	-0.005***	-0.002***	-0.000
	(0.002)	(0.001)	(0.005)
Observations	9,845	10,458	7,019
Estimate as % Change	11.1%	3.4%	0%
Mean Pre-Treat DV	0.045	0.058	0.051
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

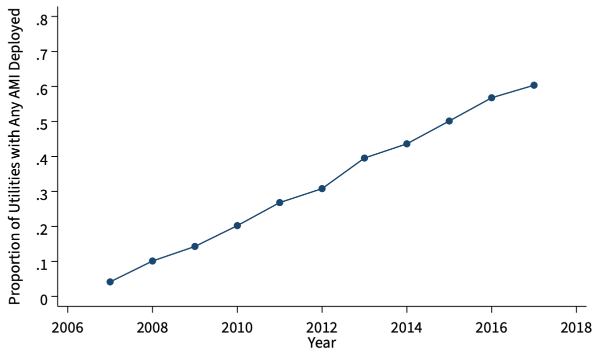
Notes: Table presents results for change in loss rate following AMI deployment by ownership when using a continuous treatment (proportion of customers with AMI). Results for government-owned utilities, cooperatives, and IOUs are presented separately in Columns 1-3, respectively. The control groups include all utilities without AMI despite ownership type whereas the treatment groups in each case only include utilities with AMI within a specific ownership group. In all regressions, we estimate the model of Equation 2 following our 2SLS approach, using a one-year lead of the binary AMI treatment variable as the excluded instrument for log(population) and the year prior to initial AMI adoption ("-1") as the omitted year. Local market controls include population and new building construction within counties that the utility serves. Mean values of dependent variable are calculated using pre-treatment observations for AMI adopters. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C9: Cost-Benefit Analysis on Payback Period

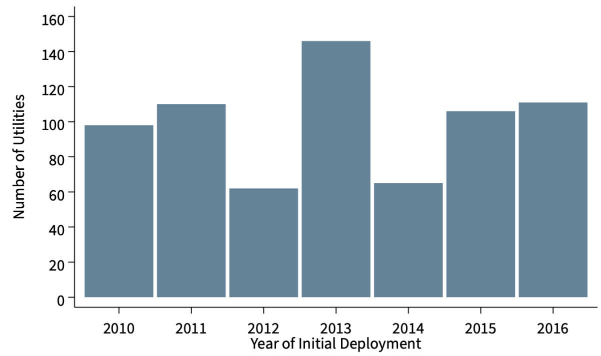
Sample	Full Sample	Omit Initially High Performers	Include 3+ Years Post-Adoption	Omit Initially High Performers and Include 3+ Years Post-Adoption
	(1)	(2)	(3)	(4)
A. Benefit: Revenue Increase				
Estimated Avg Effect on Revenue	0.009	0.014	0.017	0.022
Avg Pre-AMI Revenue ($ million)	139.30	141.60	139.30	141.60
Revenue Increase ($ million)	1.25	1.98	2.37	3.12
B. Cost: Meter Installation				
Average Customer Numbers	62,273	66,515	62,273	66,515
Assumed Cost per Meter Installation ($)	200	200	200	200
Total Cost ($ million)	12.45	13.30	12.45	13.30
C. Payback Period (years)				
Discounting at 3%	12	8	6	5
Discounting at 5%	15	9	7	5
Discounting at 7%	18	10	7	6

Notes: Table presents the key components of the cost-benefit analysis used to calculate the payback period for AMI deployment. Panel A reports the estimated benefits from increased revenue due to AMI adoption, calculated by multiplying the estimated average effect of AMI on revenue (from Table 6) by the average pre-AMI revenue for AMI adopters. Panel B reports the installation costs of AMI, assuming a per-meter installation cost of $200 based on Greenough (2015)'s 2015 estimate. Total installation costs are calculated by multiplying this unit cost by the average number of customers. Panel C reports the payback period in years, calculated using discount rates of 3%, 5%, and 7%. We assume that installation costs are incurred upfront, and the revenue gains from Panel A materialize as fixed annual cash flows received at the end of each year. Columns (1) through (4) correspond to different sample restrictions, aligned with the subsamples reported in Table 6.

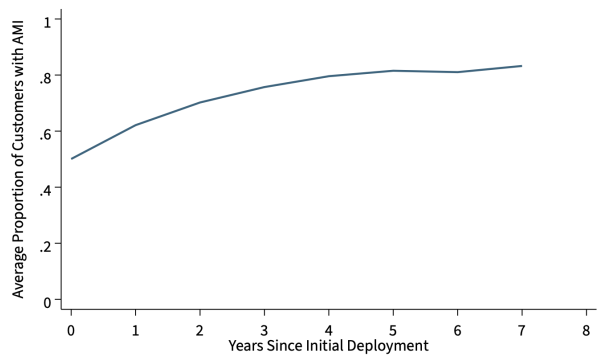
D Additional Figures



(a) Cumulative Proportion of Utilities with AMI



(b) Number of Utilities by Initial Deployment Year



(c) Avg. Proportion of Customers with AMI

Figure D1: Utilities' AMI Deployment Timing and Diffusion Rates

Notes: Figure illustrates utilities' deployment and customers' adoption of AMI over time. Panel A plots the cumulative proportion of utilities with any AMI deployed each year from 2007 through 2017. Panel B plots the number of utilities that start to deploy AMI each year for the treated utilities included in our main estimation sample (i.e., utilities that first deploy between 2010 and 2016). Panel C plots the average proportion of utilities' customers that have AMI by the number of years following a utility's initial deployment year for the treated utilities included in our main estimation sample.

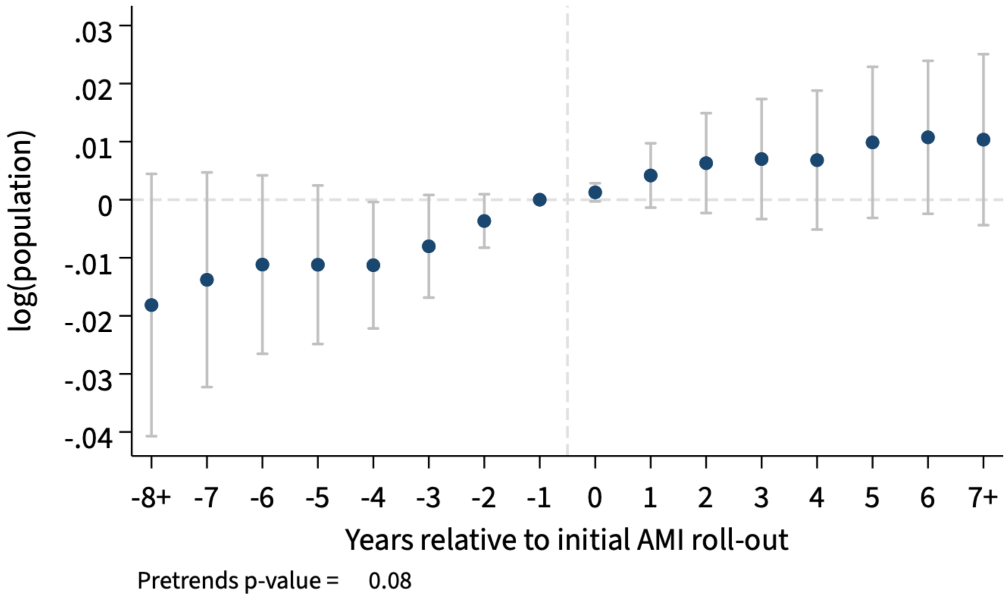
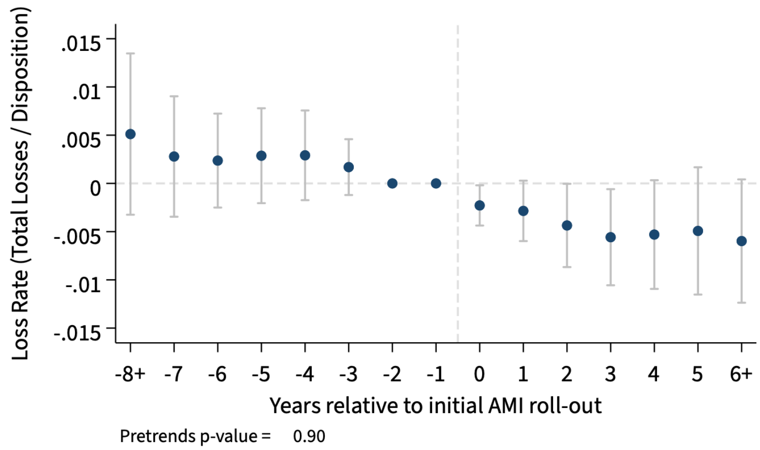
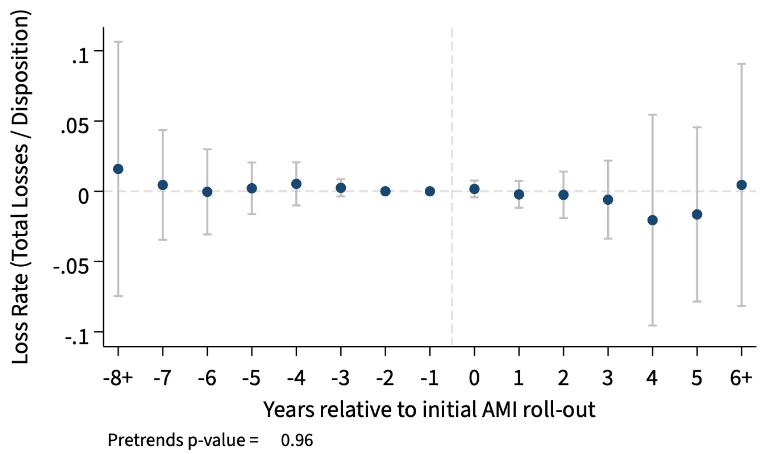


Figure D2: Dynamics of (Log) Population Around the First Year of Smart Meter Deployment

Notes: Figure plots estimates of coefficients β_j from Equation 1 using (log) population as the dependent variable with the year prior to initial AMI adoption ("-1") as the omitted year. Baseline fixed effects and controls included (besides population). Standard errors are clustered at the utility level.



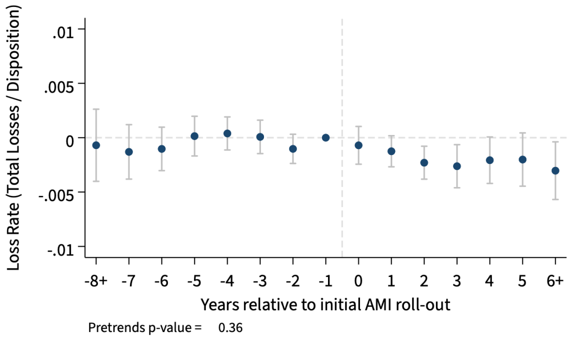
(a) High Pre-Treatment Loss Rate



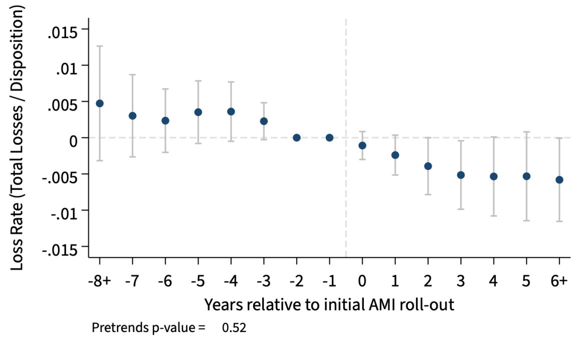
(b) Low Pre-Treatment Loss Rate

Figure D3: Heterogeneous Effects of Smart Meter Deployment on Loss Rate by Pre-Treatment Performance

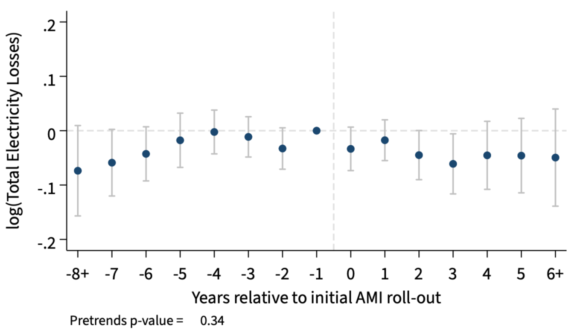
Notes: Figure illustrates heterogeneous effects of AMI deployment on loss rates by pre-treatment performance. Panel A includes utilities that were above the bottom quartile of the pre-treatment loss rate distribution (i.e., initially poor performers) and Panel B includes utilities that were in the bottom quartile (i.e., initially high performers). Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



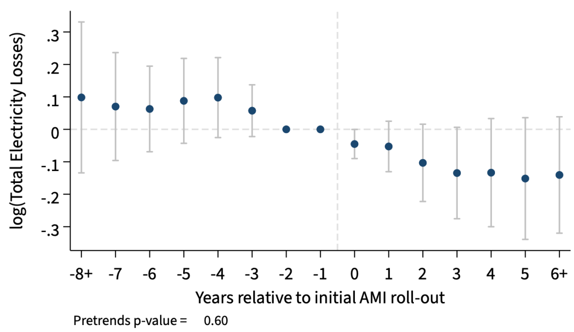
(a) Loss Rate, OLS



(b) Loss Rate, 2SLS (Main Results)



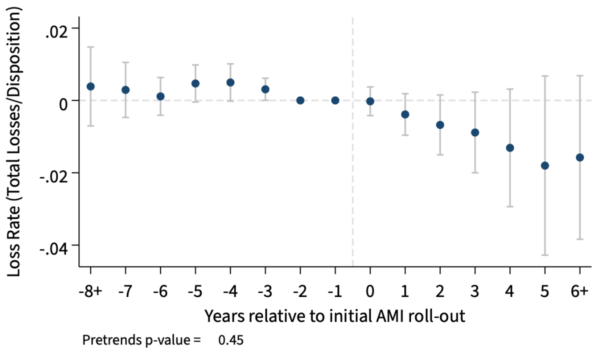
(c) Total Losses, OLS



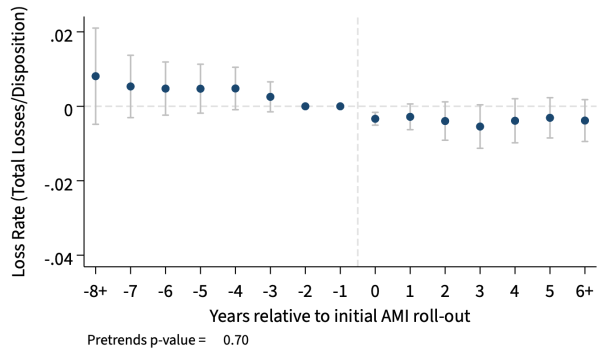
(d) Total Losses, 2SLS

Figure D4: Comparison of Results When Using OLS versus 2SLS Augmentation

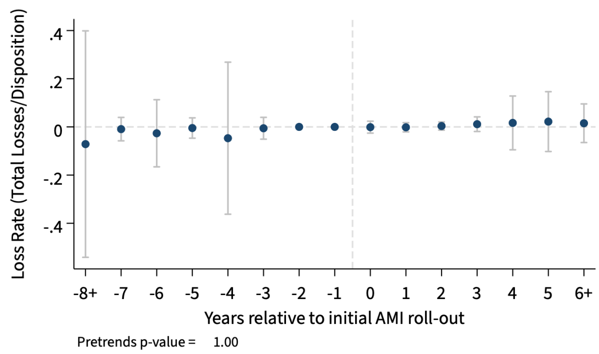
Notes: Figure illustrates the importance of implementing our 2SLS estimator to examine the effects of AMI deployment by comparing the effects on losses when just using OLS (Panels A and C) relative to when using the 2SLS approach (Panels B and D). Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1, omitting the year prior to initial AMI adoption ("-1"). In Panels B and D, we use a one year lead of the AMI treatment variable as the excluded instrument for log(population). In Panel A, there is a slight pre-trend in loss rates, and since this could be dampened by an opposing pre-trend in total disposition, we also look at total losses and find a stronger pre-trend (Panel C). These pre-trends disappear when using the 2SLS approach. Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered at the utility level.



(a) Government-Owned



(b) Cooperatives



(c) Investor-Owned

Figure D5: Heterogeneous Effects of Smart Meter Deployment on Loss Rate for Comparably-Sized "Smaller" Utilities

Notes: Figure plots heterogeneous effects of smart meter deployment on loss rates by utility ownership when omitting "large" investor-owned utilities, defining large as those with a pre-treatment average size exceeding the maximum pre-treatment average size of non-IOUs. The sub-samples for government-owned utilities and cooperatives are thus the same as they are in the main heterogeneity by ownership analysis but the IOU sub-sample omits large IOUs. This provides a sample of comparably-sized utilities. Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered at the utility level.

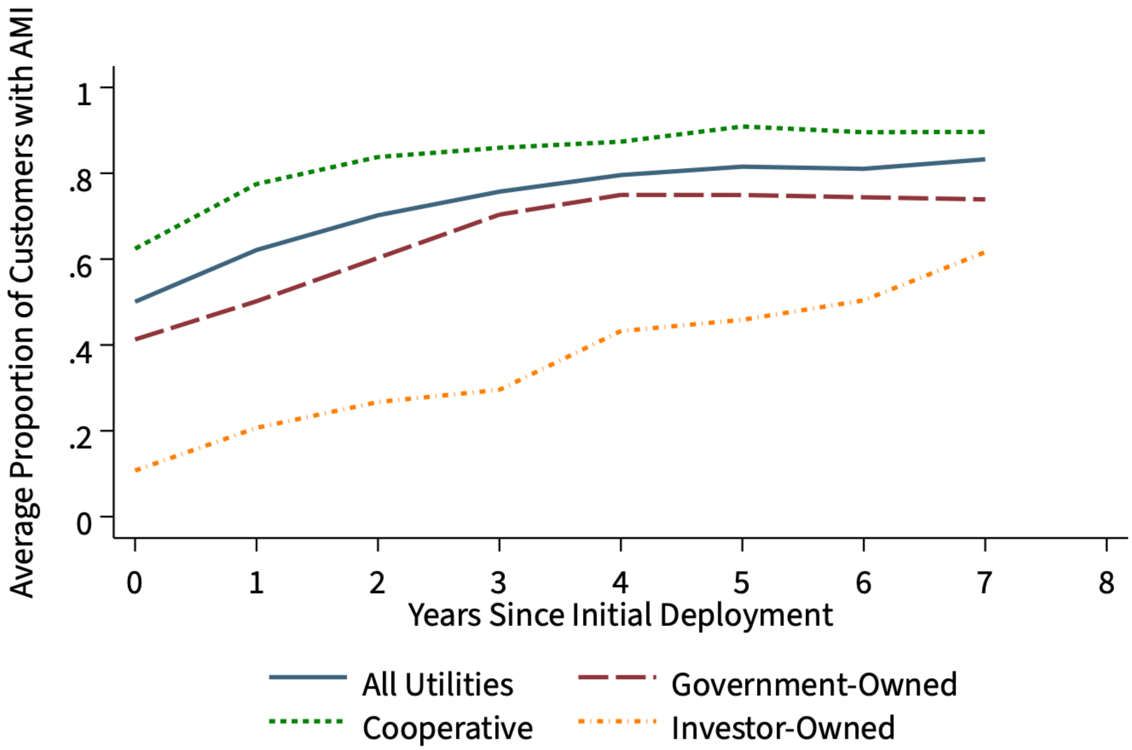
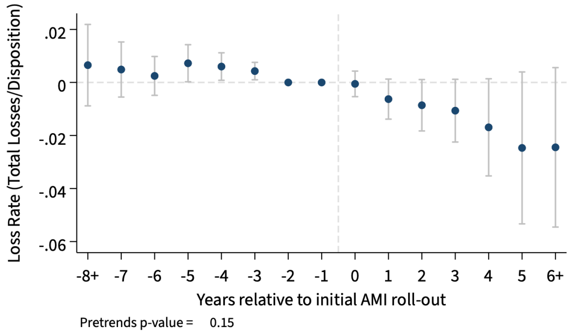
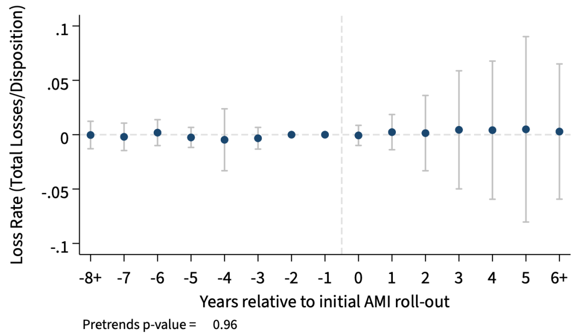


Figure D6: Average Proportion of Customers with AMI by Utility Ownership

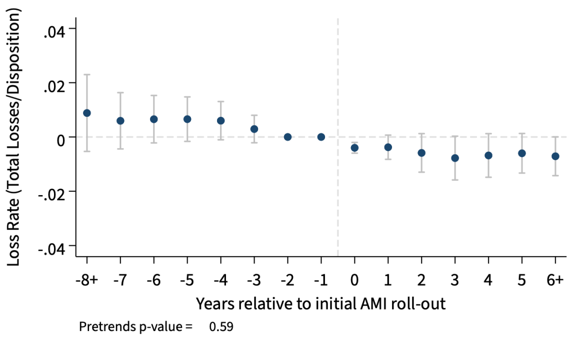
Notes: Figure plots the average proportion of customers with AMI (measured as the number of AMI meters over number of customers within utility) by utility ownership.



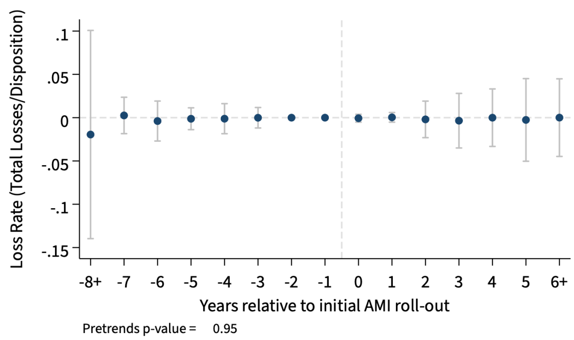
(a) Not Deregulated, Gov-Owned



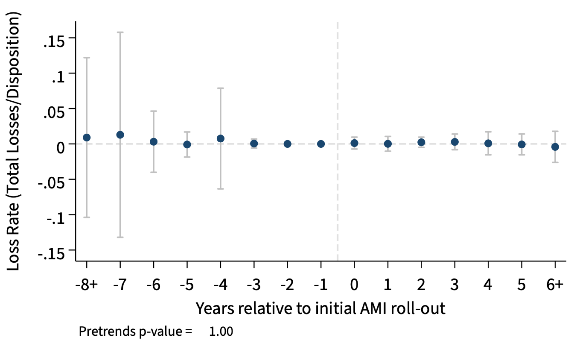
(b) Deregulated, Gov-Owned



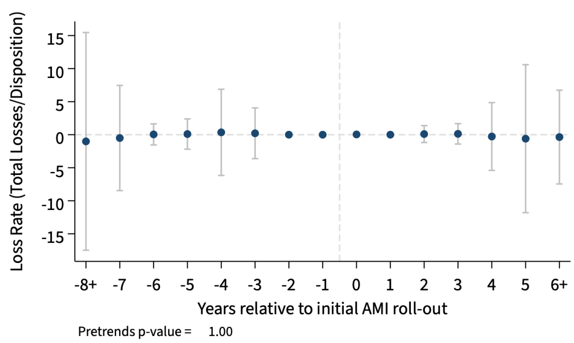
(c) Not Deregulated, Cooperatives



(d) Deregulated, Cooperatives



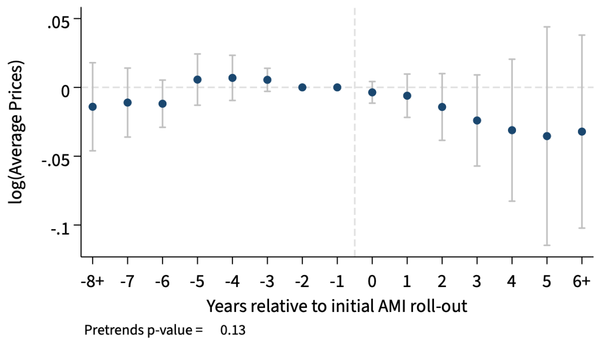
(e) Not Deregulated, IOUs



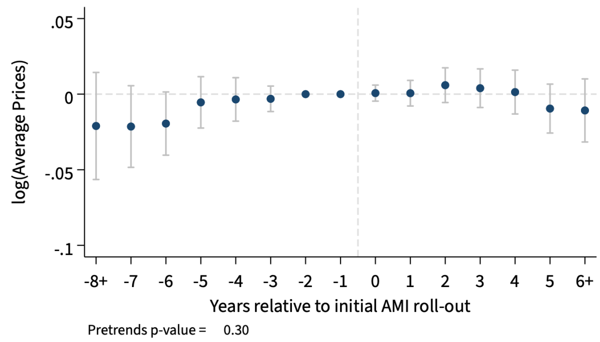
(f) Deregulated, IOUs

Figure D7: Effects on Loss Rates by Ownership and Electricity Market Deregulation

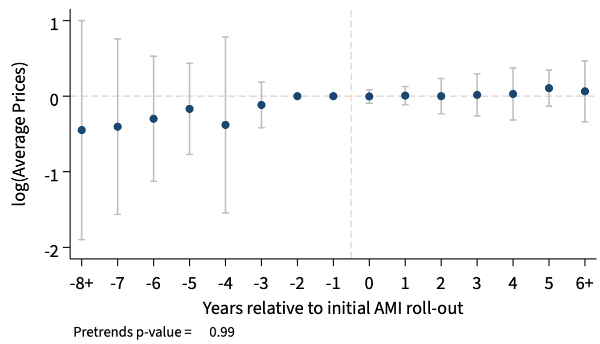
Notes: Figure plots results for the effect of AMI on loss rates when splitting the sample by utility ownership and whether the utility is located in a state with any electricity market deregulation. Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered by utility.



(a) Government-Owned



(b) Cooperatives



(c) Investor-Owned Utilities (IOUs)

Figure D8: Effects on Average Prices by Ownership

Notes: Figure plots results for the effect of AMI on (log) average prices by ownership. Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered by utility.

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