Mandatory Information Disclosure Policies:

Evidence from the Electricity Industry

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Information Disclosure Policies: Evidence from the Electricity Industry

While theory suggests that information programs may correct market failures and improve welfare, the empirical impacts of these programs remain undetermined. We show that mandatory disclosure programs in the electricity industry achieve stated policy goals. We find that the proportion of fossil fuels decreases and the proportion of clean fuels increases in response to disclosure programs. However, the programs may produce unintended consequences. For example, programs may make "clean" firms cleaner while leaving "dirty" firms relatively unchanged. If the marginal benefits of pollution abatement are larger at dirty firms than at clean firms, disclosure programs may induce inefficient abatement allocations.

I. INTRODUCTION

Developed nations' environmental policies have evolved substantially in the last several decades. Early pollution control programs involved command and control approaches. Policies then frequently included pollution charges, tradable permits, and other market based instruments. Most recently, a "third wave" of environmental policy has emerged that emphasizes information provision as an integral part of the risk mitigation strategy. Here, government regulation is replaced or augmented by publicly provided information presumed to assist more cost effective private market and legal forces. Common examples include the toxics release inventory, lead paint disclosures, drinking water quality notices, and eco-labels. The empirical effects of such programs, however, remain largely undetermined. This paper examines the impact of a prominent mandatory disclosure program on the fuel mix percentages of large electric utility corporations.

The prominence of mandatory information policies is not restricted to environmental arenas. For example, OECD countries' equity markets generally require firm-level financial information provision. In many countries, agricultural goods require country of origin and other health labels. Restaurants are increasingly required to display hygiene grade cards. Domestic colleges and universities are required by law to inform current and prospective students of crime statistics, equity data, and performance metrics. Even significant medical errors must now be disclosed to the community.

There are several potential advantages of information provision policies, and theory suggests that disclosure programs may effectively achieve their goals. Healy and Palepu (2001) provided a survey of the evidence in capital markets. Brouhle and Khanna (2007) demonstrated that information provision can improve product quality. In the environmental area, Kennedy et

al. (1994), Arora and Gangopadhyay (1999), Maxwell et al. (2000), Kirchoff (2000), and Khanna (2001) showed that the provision of information about pollution may correct a market failure, improve performance, and enhance welfare.

Despite the literature's theoretical findings, the empirical effects of disclosure programs remain inconclusive. Early studies of securities regulation found mixed results. See Stigler (1964), Robbins and Werner (1964), and Benston (1973). A more recent literature suggested that disclosure programs in financial markets can achieve their desired effects; La Porta et al. (2006) and Greenstone et al. (2006) found that both market size and market returns were positively influenced by mandatory disclosure programs. In product quality settings, Chipty and Witte (1998) established that resource and referral agencies significantly influenced child care prices, but had no impact on the quality of care. In contrast, Jin and Leslie (2003) found that mandatory hygiene grade cards positively affected restaurant quality and health outcomes.

Studies of environmental performance yielded similarly mixed results. Desvousges, Smith, and Rink (1992) found that information-based programs influenced attitudes favorable to radon testing, but testing itself only increased when mass media dissemination was coupled with community-based implementation programs. Konar and Cohen (1997) and Khanna et al. (1998) found that stock movements associated with Toxic Release Inventory (TRI) announcements led to increased abatement and reduced emissions. However, Bui (2005) found that the declines in emissions after TRI reporting events may have been attributable to regulation rather than investor pressure. Bennear and Olmstead (2006) found that drinking water quality notices lowered violations for some systems, but not others.

This paper is the first empirical economic study of the impacts of mandatory information provision in the electric utility industry. The disclosure programs considered here differ

significantly from the TRI information programs examined previously. Notably, TRI information is not directly provided to stakeholders. Further, TRI information frequently requires expertise to process and interpret. These distinctions are important, as the broader literature on information policies suggests that transparency programs are most likely to achieve issuing agency goals when disseminated information is simple, understandable, standardized, actionable, and designed to directly benefit at least some of the disclosers themselves (Weil *et al.* 2006).

Environmental disclosure programs in electricity markets are a promising area of exploration for the efficacy of information policies for several reasons. First, electricity is a homogeneous commodity. From a consumption point of view, there are no differences in the characteristics of green or brown electricity. Therefore, this setting may allow us to more directly attribute program-induced changes to agent preferences. This is not true in much of the broader literature. For example, if eco- or organic- labeled products gain market share, it is difficult to establish whether consumers are expressing preferences for environmental improvement or whether consumers perceive other differences in product quality (like health, safety, and taste). Second, electric utilities are among the leading polluters in the United States. For example, about 40 percent of domestic CO_2 and 67 percent of domestic SO_2 emissions are attributable to electricity generation. Third, electric disclosure programs exhibit a number of features desirable for econometric identification. For example, the programs were adopted at the state-level and progressively introduced over time, so all firms were not impacted uniformly.

To what extent did mandatory disclosure laws affect fuel mix outcomes in the electric utility industry? We address this question by examining monthly firm-level fuel mix and program data from 145 of the largest investor-owned electric utility companies for the period 1995-2003. We first analyze how firms' fuel mix percentages respond to mandatory disclosure

programs. We prevent bias from potential statistical endogeneity using fixed effects and instrumental variables. We then explore the detected response in more detail. We use Ordinary Least Squares (OLS) and Instrument Variable (IV) interaction models to explore the effect of customer composition on disclosure responses and standard and IV quantile regressions to examine how the entire fuel mix distribution shifts.

We find three main results. First, *mandatory disclosure programs affect fuel-mix outcomes*. We find that the average proportion of fuel usage attributable to fossil fuels significantly decreases and the average proportion of fuel usage attributable to clean fuels significantly increases in response to disclosure programs in the electric utility industry. Second, *customer composition significantly impacts disclosure response.* We find that firms' clean fuel program responses become considerably stronger (more positive) as the firm proportionately serves more residential customers. Firms' fossil fuel program responses become weaker (less negative) as they proportionately serve more residential customers. In other words, as firms proportionately serve more residential consumers, any nuclear program responses become weaker (less positive). Third, *pre-existing fuel mix significantly impacts disclosure program response.* Our results suggest that firms that already use substantial amounts of clean fuels most significantly increase clean fuel percentages in response to disclosure programs. Similarly, firms that already use relatively small amounts of fossil fuels most significantly decrease fossil fuel usage in response to disclosure programs.

II. THE ELECTRIC UTILITY INDUSTRY

<u>Fuel Mix</u>

In 2004, domestic electricity generation totaled 3,953,407 gigawatt hours. Of total generation, 50 percent was attributable to coal, 18 percent was attributable to gas, and 3 percent

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was attributable to oil. Nuclear sources generated nearly 20 percent of electricity. Other energy sources, like hydropower, biomass, geothermal, solar and wind, generated approximately 9 percent (Edison Electric Institute 2005). Cleaner energy sources such as photovoltaic and wind plants represent higher operating expenses than nuclear or fossil fuel, but they are growing rapidly. For example, wind power usage increased 27 percent in 2004.

Mandatory Information Disclosure Programs

In the U.S. electricity industry, information disclosure refers to the mandatory provision of fuel mix percentages and pollution discharge statistics to utility consumers. For example, Minnesota's Public Utilities Commission decreed:

> *"The Commission recognizes that there is a need for the consumer to be informed*
>
> *and educated on environmental issues and that all Minnesota utilities' customers*
>
> *... should have similar access to information." (Minnesota PUC, 2002)*

The state issued an order requiring regulated utilities to disclose information on fuel mix and air emissions to customers. Twice annually, utilities must include a bill insert that contains a pie chart depicting the mix of fuel sources, a bar chart of air pollutant emissions, a chart of costs associated with different generating sources, and a discussion of energy efficiency measures. Further, the utility must list a phone number and web address on all bills so that consumers can access environmental information. Other states' disclosure programs are similarly motivated and implemented, although specific details may vary. For example, several states' disclosure programs require quarterly (rather than biannual) inserts.

Figure 1 indicates which states had disclosure programs in 2005. By that year, 25 states had adopted generation disclosure rules, and these states represented over 65 percent of the United States population. Since consumer preferences may factor into disclosure impacts,

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programs may be particularly meaningful in deregulated states. Indeed, 23 of the 25 state-level

disclosure programs were enacted in deregulated states, including NY, IL, TX, MI, AZ, NM, and

much of the mid-Atlantic and northeastern regions. Colorado and Florida instituted mandatory

disclosure programs without deregulating their industries.

Figure 1. State Generation Disclosure Rules – September 2005

■ **State has a Disclosure Rule**
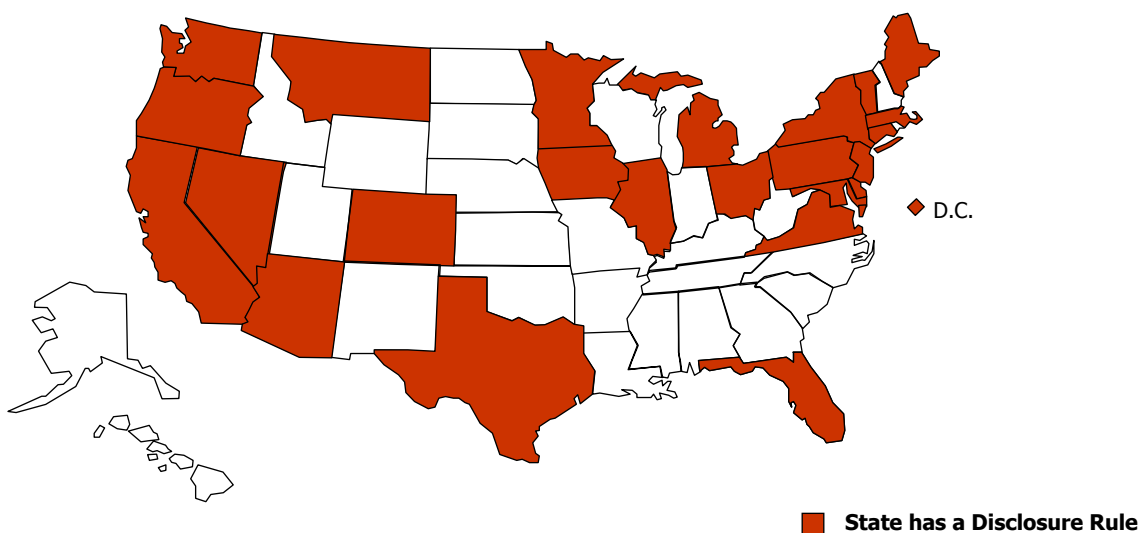
Source: Database of State Incentives for Renewable Energy (DSIRE).
Accessible online at http://www.dsireusa.org/.

Other Programs in the Electric Utility Industry

In addition to the mandatory state-level disclosure programs that are the focus of this

study, many electric utilities must comply with other information requirements. Most notably,

"major" firms are required to file Federal Energy Regulatory Commission Form Number 1, the

Annual Report for Major Electric Utilities, each and every year.[1] These reports average 140

pages and contain general corporate information, financial statements, supporting schedules, and

information on environmental investments. In addition, electric utilities are required to provide

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[1] Major electric utilities are classified as those with annual sales or transmission service that exceeds one of the following: (1) one million megawatt hours of total annual sales, (2) 100 megawatt hours of annual sales for resale, (3) 500 megawatt hours of gross interchange out, or (4) 500 megawatt hours of wheeling for others (deliveries plus losses).

information about their environmental performance to the U.S. Environmental Protection Agency (EPA) and the Energy Information Administration (EIA). Although all of the aforementioned data is publicly accessible through government databases, users typically must have environmental and database expertise to interpret the information. In marked contrast, disclosure programs are designed explicitly to produce easily accessible and readily interpretable information.

Several other policies may also impact firms' fuel mix percentages. Examples include Renewable Portfolio Standards, mandatory Green Power Initiatives, and tax incentives. Renewable Portfolio Standards (RPS) typically mandate tradable credit programs with fixed quotas for renewable generation. Mandatory green power policies require utilities operating in the state to offer and publicize green power options to consumers. State and local sales and corporate tax credits and exemptions provide financial incentives for green energy generation.

III. THEORIES LINKING DISCLOSURE AND FUEL MIX OUTCOMES

Several theories allow for a link between mandatory information disclosure programs and fuel mix outcomes.[2] Perhaps the simplest theoretical explanations entail increased community coercion or investor or employee pressure. In the presence of information on the relative environmental performance of a given firm, community activists may lobby for future regulation or attempt to harm the firm's reputation with the consuming public (indirectly reducing demand). Employee turnover and dissatisfaction may result from disclosed poor environmental performance (Tietenberg (1998)). Investors may express environmental preferences or concerns over future environmental regulation by decreasing demand for shares (Khanna *et al.* (1998)). However, the information provided by disclosure programs in the electricity industry is typically

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[2] See Khanna (2001) for an excellent overview of the literature on non-mandatory environmental policies, including information disclosure programs.

already available to highly motivated and trained experts like lawyers, investors, and community activists.

A more compelling theory, then, for the link between information and environmental performance in the electricity industry might involve the threat of future regulation or legal action. In a dynamic political economy context, disclosure programs may simply signal the state's willingness to impose future regulations on the industry unless firms self-regulate. Similarly, disclosure programs may increase a reporting firm's susceptibility to liability under legal statutes. Segerson and Miceli (1998) and Maxwell, Lyon, and Hackett (2000) explore firms' incentives to preempt future regulation or legal liability.

Another persuasive theory for the link between disclosure and environmental performance is a direct demand effect. In the presence of simple, easily interpretable, and directly provided information, consumers may increase demand for fuels perceived as environmentally favorable and decrease demand for fuels perceived as environmentally unfavorable. Of course, this mechanism requires: (1) that information affects consumer awareness, (2) that consumer awareness can translate to changes in demand, and (3) current or future consumer choice among electricity products. However, the mechanism does not require choice among electricity *providers*.

An emerging literature suggests that consumer awareness changes in response to environmental information [Desvousges, Smith, and Rink (1992), Blamey et al. (2000), Loureiro (2003), Loureiro and Lotade (2005), and Leire and Thidell (2005)]. In our context, disclosed information may remind consumers of the consequences of their own actions, notify customers that alternative fuels exist and are widely used, and demonstrate the variability in utilities' fuel

mix percentages and emissions. Further, shifts in awareness can translate into new consumption outcomes [Teisl, Roe, and Hicks (2002) and Shimshack, Ward, and Beatty (2006)].

Consumers increasingly have the option to purchase greener energy at a price premium, and therefore increasingly have choice among consumer products. Lamarre (1997) and Delmas et al. (2007) found a distinct market niche for renewable energy even at a price premium. Thiry-six states and over 600 utilities currently offer green power pricing programs where consumers can support cleaner energy usage in exchange for an electricity price increase.[3] Further, there are dozens of certificate programs (many at the national level) that allow consumers to purchase green certificates or green tags that require the replacement of traditional types of energy with greener alternatives. These certificates are available whether or not the consumer has direct access to green power options from their own provider. Many utilities were very interested in disclosure programs when they were being considered since such policies allowed firms to "distinguish their price structure, fuel mix, or environmental profile in the eyes of the consumer and found mandatory standard labels to be a credible way to do that." (NCCEI 2002) In other words, disclosure programs were perceived as an effective and particularly convincing way to price discriminate immediately or in the future.

Of course, all theories linking disclosure programs and fuel mix percentages in the electric utility industry require that supply of a given fuel type category is not completely inelastic. In other words, firms must be able to realistically alter their fuel mix portfolios in the short- to medium- run. On the margin, at least, they can. While purchasing or building new facilities may be required to dramatically alter fuel mix portfolios, relatively small portfolio

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[3] U.S. Department of Energy, Energy Efficiency and Renewable Energy pages. Retrieved October 2006 from http://www.eere.energy.gov/greenpower/markets/.

shifts are easily obtainable. First, utilities can alter their capacity utilization. Second, major electric utilities can buy and sell power generation in response to changing market conditions.

Several theories can explain the link between information disclosure and environmental performance. Empirically, we will follow the broader information literature and estimate the general impact of mandatory information programs. Regressions of quantity on information variables (and other covariates) are identified under any of the mechanisms discussed above, and an identified response represents the impact of disclosure programs on the equilibrium quantity of electricity generated from the specifically analyzed fuel source.

IV. DATA

Data sources and content

Our research assesses the impact of environmental disclosure programs on the fuel mix percentages of major electric utility firms. We focus on fuel mix indicators from the electric power industry for two reasons. First, fuel mix is the most readily identifiable and interpretable measure of environmental performance on disclosure program bill inserts and web postings. Second, information disclosure programs are heterogeneous, yet all require generation mix information.

We analyze data from the Energy Information Administrations (EIA)'s Annual Electric Power Industry Database and the Interstate Renewable Energy Council (IREC)'s Database of State Incentives for Renewable Energy. Monthly fuel mix data come from forms EIA-906 (and its predecessor EIA-759). We focus on production-based fuel mix rather than sales-based fuel mix to minimize program induced sales shifts across states. Disclosure program information comes directly from IREC's Database. Since it is possible that other state-level programs like

Renewable Portfolio Standards and Green Power initiatives may impact utilities' fuel mix percentages, we also analyze other program data from the IREC database.

The Sample

Our sample includes monthly information from 145 major investor-owned electric utility companies. We focus on large investor-owned firms because these companies represent the majority of industry electricity and pollution generation. Further, EIA data (EIA-906 and EIA-759) is imputed for smaller companies based upon information from these larger firms. All firms with at least one plant with a capacity of 50 megawatts or more (25 megawatts or more prior to 1999), all firms with nuclear generation, and all firms with significant renewable capacity file reports with the EIA for each and every month of operation. Since our data represent the big incumbents in the electric utility industry, the results of our analysis should be extrapolated to smaller firms with a degree of caution.

Our sample data are observed at the firm level. Management decisions are centralized and disclosure program requirements operate at the firm/product level. Disclosure program requirements and generation product definitions cross plant boundaries, but not firm boundaries. We observe fuel mix percentages for our 145 firms for the 108 months spanning 1995-2003. Our sample begins in 1995 in order to obtain pre-program information for all impacted states; the first disclosure program was enacted in mid-1997. The sample concludes in 2003 due to data availability.

Summary Statistics

Conditional on positive generation, aggregate fossil fuels represent approximately 74 percent of generation for all sample firms over all sample periods. We define fossil fuels as coal, oil, and gas. Aggregate clean fuels represent approximately 9 percent of generation. We define

"clean" fuels as renewables and hydroelectric.[4] Nuclear represents approximately 17 percent of generation. Nuclear is categorized as neither fossil fuel nor clean fuel, and it is analyzed separately in all analyses. Note that our generation sample statistics closely correspond to total national proportions for the sample period.

Additional summary statistics, broken down by disclosure status, are presented in Table 1. Standard errors appear in parentheses. The summary statistics in Table 1 indicate that firms never subject to disclosure decreased clean fuel usage and increased fossil fuel usage over the sample period. In contrast, firms subject to disclosure increased clean fuel usage and decreased fossil fuel usage over the sample period.

Table 1. Mean Fuel Mix Percentage Statistics:
Firms subject to disclosure vs. Firms not subject to disclosure

Group	First Period (Month1)	Last Period (Month 108)	Difference
Clean Fuels			
Firms Not Subject to Disclosure	.121	.113	-.008
During the Sample Period	(.049)	(.050)	(.004)
Firms Subject to Disclosure During	.104	.109	+.005
the Sample Period	(.029)	(.031)	(.022)
Fossil Fuels			
Firms Not Subject to Disclosure	.754	.774	+.020
During the Sample Period	(.052)	(.053)	(.018)
Firms Subject to Disclosure During	.701	.698	-.003
the Sample Period	(.035)	(.042)	(.034)

Results in Table 1 are suggestive of disclosure program effects on fuel mix outcomes, but the differences between the last period and the first period are only statistically significant at the five percent level for the clean fuel response of firms never subject to disclosure. These simple summary statistics also do not control for confounding factors that may impact changes in fuel mix over time. Consequently, a more complete empirical analysis is necessary.

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[4] Here and throughout the paper, we refer to fuels as "clean" if they generate low levels of common air pollutants relative to fossil fuels and are not nuclear. This definition is debatable but consistent with issuing agencies' goals that emphasize air quality over other environmental or social objectives.

V. PRIMARY METHODS

Our overall empirical strategy is to use panel data techniques to exploit within-firm temporal variation in program status to analyze the effect of mandatory disclosure programs on fuel mix percentages. We first use OLS and IV regression methods to demonstrate that disclosure programs significantly reduce the proportion of fossil fuel usage and significantly increase the percentage of clean fuel usage. Second, we examine the disclosure response in more detail.

The basic regression model is $y_{it} = D_{it}\delta + \mathbf{X_{it}}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$, where i indexes the unit of observation (a firm) and t indexes time (months). y_{it} represents the percentage of firm i's generation in period t attributable to the fuel source being analyzed. D_{it} represents the proportion of firm i's sales that are subject to an effective disclosure program in period t. The elements of the vector $\mathbf{X_{it}}$ include all of the non-program explanatory variables discussed below. α_i is an unobserved time invariant individual effect and ε_{it} is the usual time variant idiosyncratic shock.

Primary Variables

Our key dependent variables represent fuel mix percentages. These include the percentage of firm i's generation in period t attributable to fossil fuels (including coal, oil, and natural gas), to clean fuels (including hydroelectricity and renewables like wind, solar, and biomass), or to nuclear power. Our key explanatory measure is a continuous variable representing the proportion of firm i's sales that are subject to an operational or effective mandatory disclosure program in period t. If all of a firm's sales are subject to disclosure requirements in a given month, this explanatory variable takes a value of 1. If only 80 percent of a firm's electricity sales are subject to disclosure in a given month (such that 20 percent of

company sales go to states without operational disclosure programs), this variable takes a value of 0.80.

Joskow (1998) noted that restructuring of electricity supply has the potential to significantly impact industry fuel mix outcomes. On one hand, competitive retail power markets may provide market incentives for electric utilities to offer green power to consumers (Delmas et al (2007). On the other hand, competition in restructuring markets might favor low-cost power and induce utilities to minimize generation costs and prices to consumers by focusing on low cost fuel. As noted in the background section, the vast majority of disclosure programs were enacted in deregulated states at some point after restructuring. Consequently, we include a variable representing the percent of firm's sales in deregulated states.[5]

We use firm-specific fixed effects to capture unobservable fuel mix determinants and several nearly constant fuel mix determinants that have been identified in the previous literature. These latter covariates include firm size, age, community political and environmental attributes (as often proxied by League of Conservation Voter (LCV) scores), management profiles, average regulatory stringency, and ownership type. The literature indicates that fossil fuel generation percentages decrease with higher LCV scores, decrease with size, increase with merger processes, and increase with private ownership.[6] Fixed effects also capture differences in input and output prices due to factors like distance to fossil fuel markets and state-level variation in taxation.

Since plant production varies seasonally, we include quarterly dummy variables. A priori,

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[5] Ideally, one might also interact disclosure program variables with deregulation indicators to see if program responses become stronger in restructured markets. However, since only 2 states implemented disclosure without restructuring, such results are quite sensitive to model specification and are not reported.

[6] These factors are not literally fixed over the sample period, but practical empirical measures vary little over our sample. For example, data on LCV, ownership, and size exhibit no statistically meaningful variation. Reassuringly, the inclusion or omission of these variables with fixed effects does not affect the signs, significance, or approximate magnitudes of any estimated coefficient.

the impact of seasonality on fuel mix is ambiguous. One might expect that fossil fuel percentages are higher and clean fuel percentages are lower in the late summer months as generation of hydro and wind is lower during these time periods. Finally, we include annual dummies to account for broad trends in prices, technological change, and other factors.

Consistency Considerations

A potential concern with our key program D_{it} variable is that it may be statistically endogenous. For example, consider the possibility that the likelihood of program adoption is a function of the average environmental performance of the large electric utilities operating within the state. In terms of the basic regression model, the concern is that the time invariant individual effect α_i is correlated with the program variable D_{it}. However, fixed effects prevent bias from this type of correlation. In our context, the inclusion of fixed effects prohibits the possibility of bias introduced when program adoption is a function of the *temporal average* fuel mix of the firm.

It is also possible that the program variable D_{it} is correlated with the time variant error term ε_{it}. For example, consider the possibility that states choose to adopt disclosure programs in periods in which large electric utilities operating within that state are utilizing more fossil fuels *than usual*. A standard correction for this type of statistical endogeneity is instrumental variables. Our chosen instrument is the weighted average of program status in states near those states in which the particular firm operates. However, since it is possible that emissions from upwind states influence program adoption in the state of interest, our instrument conservatively eliminates states directly upwind and directly downwind from the states in which the particular

firm operates.[7]

The validity of this instrument requires that: (*A1*) state policymakers' disclosure program decisions are influenced by disclosure program status in nearby states, and (*A2*) policy choices in states where firm i does not operate do not depend directly on the environmental performance of firm i in period t. *A1* is supported by empirical evidence that consistently reveals important spillover effects of policy choices in one state for decisions in neighboring states.[8] *A1* is also testable. The coefficient on the instrument in the first stage regressions is significant in both an economic and a statistical sense (t-statistics above 7). Requirement *A2* is simply a maintained assumption, but it seems unlikely firms make production choices based upon laws that have no influence on them or that states where firm i does not operate decide to adopt a program based upon the environmental performance of firm i in period t. We later examine the sensitivity of our instrumental variable.

VI. EMPIRICAL ANALYSIS

<u>Fixed Effects and Instrumental Variables Regressions</u>

Do disclosure programs affect fuel mix percentages on average? Our goal here is to investigate the relationship between disclosure programs and firm's fossil fuel and clean fuel usage. Thus, we regressed fuel mix proportion measures on the percent of a firm's sales subject to disclosure requirements and other covariates. Simultaneous estimation of the multiple fuel mix equations through a SUR regression would yield no efficiency gain, since the covariates in each

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[7] Upwind and downwind states are determined by following prevailing westerly, southwesterly, and southerly winds. Pollution transport follows these winds fairly closely. See, for example, the Ozone Transport Assessment Group (OTAG)'s Map of Ozone Pollution Transport, available online as the Air Quality Analysis Workgroup Results Summary at http://capita.wustl.edu/OTAG/ .

[8] For example, Fredriksson and Millimet (2002) find a positive association between states' environmental policies, and that association is strongest among neighboring states. Baicker (2005) finds strong spillover effects for neighboring states' public spending as well. Busch and Jorgens (2005) even find a number of policy convergence mechanisms operating across international political boundaries.

equation are identical. We ran both fixed effects linear regressions and fixed effects instrumental variables regressions. Results are presented in Table 2. All computed standard errors are heteroskedastic-consistent. T-statistics appear in parentheses.[9]

Table 2. Firm-Level Regression Results: Aggregate

Variable Description	Dependent Variable: Percentage of Fuel Mix Attributable to Fossil Fuels		Dependent Variable: Percentage of Fuel Mix Attributable to Clean Fuels	
	Linear Regression	Instrumental Variables Regression	Linear Regression	Instrumental Variables Regression
Disclosure Program	-.057***	-.227**	.022***	.268***
	(-8.39)	(-2.45)	(4.86)	(3.43)
Deregulation	.016***	.077**	-.005	-.094***
	(3.14)	(2.33)	(-1.09)	(-3.21)
Season 2 Dummy	.004	.005	.002	.001
	(1.15)	(1.25)	(0.51)	(0.24)
Season3 Dummy	.016***	.017***	-.013***	-.014***
	(4.49)	(4.48)	(-4.10)	(-3.99)
Season4 Dummy	-.001	.002	-.002	-.006
	(-0.23)	(0.38)	(-0.72)	(-1.56)
Year Dummies	8 Year FEs	8 Year FEs	8 Year FEs	8 Year Fes
Fixed Effects	144Firm-Level FEs	144Firm-Level Fes	144Firm-Level FEs	144Firm-Level Fes

[a] The dependent variables are the percentage of fuel mix attributable to the source indicated in the column heading. The key independent variable, the disclosure program variable, ranges from 0 to 1. It indicates the percentage of firm sales subject to operational disclosure programs.
[b] Superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.
[c] All analyses consist of 14,168 observations from 145 firms over the 108 sample months.

Results in Table 2 indicate that the estimated impact of an operational disclosure program is negative and significant at the 1 percent level for fossil fuel production. The results are also economically significant. As the proportion of the average firm's sales subject to disclosure increases 1 percent, the average proportion of generation attributable to fossil fuels drops between 0.06 percentage points (OLS point estimate) and 0.23 percentage points (IV point estimate).

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[9] Later quantile regressions suggest that slope parameters are sensitive the distribution of the dependent variables, suggesting the presence of heteroskedasticity.

Similarly, results in Table 2 indicate that the estimated impact of an operational disclosure program is positive and significant at the 1 percent level for clean sources like hydroelectric and renewables. As the proportion of the average firm's sales subject to disclosure increases 1 percent, the average proportion of generation attributable to clean fuels increases between 0.02 percentage points (OLS point estimate) and 0.27 percentage points (IV point estimate).

We find that deregulation negatively affected the proportion of fuel mix attributable to clean fuels like renewable and hydro and positively affected the proportion of fuel mix attributable to fossil fuels. Results are consistent with the hypothesis that deregulation could potentially trigger investments in lower cost fuel. Seasonality also appears to play a role in fuel mix percentages. The proportion of fossil fuel usage is higher and the proportion of clean fuel usage is lower in the late summer and fall months. This may reflect the fact that generation of hydro and wind is lower during these time periods. We also find that fuel mix decisions appear to trend over time, although non-linearly.

Disaggregated results for specific fuel sources mimic these aggregate results.[10] There is a statistically significant negative relationship between disclosure programs and the proportional use of coal. Program effects on oil and gas are economically small and statistically insignificant. There is a statistically significant positive relationship between disclosure programs and the proportional use of both renewable and hydroelectric generation. Results also suggest no statistically significant relationship between disclosure programs and the proportional use of nuclear electricity generation (categorized as neither fossil fuel nor clean fuel and therefore omitted from Table 2).

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[10] Disaggregated results are available from the authors.

Sensitivity Analysis: Renewable Portfolio Standards and Other Programs

One concern with the preceding results is omitted variables. Other state and local regulations like Renewable Portfolio Standards, mandatory Green Power Initiatives, and tax incentives may also impact firms' fuel mix percentages. Of course, the instrumental variable approach should prevent bias unless the instrument is itself correlated with the omitted variable. Further, the adoption of RPS, green power, and tax incentive programs does not generally closely coincide with the adoption of disclosure across time and omitted time variant factors only bias results if they are correlated with disclosure program introductions across both time and space. To be complete, however, we tested whether other prominent state-level programs targeting utilities' fuel mixes impacted our key results. Including variables indicating the percent of the firm's sales subject to RPS, mandatory green power, and state and local tax incentives, either individually or simultaneously, yields regression results (signs, significance, and point estimates) that are extremely similar to the results presented in Table 2.

Sensitivity Analysis: Other Assumptions

One possible worry is the robustness of our results to the chosen instrument. If program implementation is more likely when other states' firms use more fossil fuels and less clean fuels than normal, our results understate program. If program implementation is more likely when other states' firms use less fossil fuels and more clean fuels than normal, our results overstate program impacts. Consequently, we experimented with an instrument that contains program information from all states adjacent to those in which the firm operates (not just states that are neither upwind nor downwind). Further, while we cannot come up with a convincing reason that a state where firm i does not operate (or influence due to drifting pollution) might decide to adopt disclosure based upon firm i's period t environmental performance, we supposed this was

possible. Under this supposition, the state where firm i does not operate (or influence due to drifting pollution) should at least not decide to adopt a program based upon firm i's past environmental performance. We therefore considered additional possible instruments that include lagged program status in neighboring states. All tested instruments yield similar (signs, significance, and magnitude) coefficient estimates in the first stage and a consistent economic story (signs, statistical significance, and economic importance) in the second stage. Our presented instrument yields consistently conservative empirical magnitudes.

Another possible concern is the sharpness of our study's program variables. Perhaps utilities were broadly aware of the disclosure programs prior to their effective date and changed their behavior ahead of time. Of course, if utilities had already completely responded to disclosure programs before the effective dates, it would be difficult to reconcile the observed responses in our analyses. However, as a sensitivity test, we repeated all analyses with program variables that reflect the dates the programs were enacted. In general, we find qualitatively similar results (in signs and significance) to those reported here, but magnitudes are frequently smaller.

Our program variable is constructed by weighting each firm's state-level disclosure status by the percentage of sales that occur in each state. A possible apprehension is that the percentage of a firm's sales attributable to each state may change in response to the program itself. This would introduce bias. However, if we replace our program variable with a 0/1 dummy indicating whether *any* of a firm's sales are subject to disclosure, we find qualitatively similar results.

Finally, in our analysis we control for the possibility of persistence with fixed effects and the possibility of systematic changes in technology with time dummies. However, as a sensitivity check, we include an auto-regressive term lagged one year to help control for unobserved

technology shifts. Including this lagged discharge variable did not substantively change the results; signs, significance, and approximate magnitude are similar to those reported.

VII. FURTHER EXPLORATION

The regressions in Table 2 demonstrate that disclosure programs reduce fossil fuel usage and increase clean fuel usage on average. However, it may be informative to explore these effects in more detail. Consequently, in this section, we first use regressions with interactions to explore whether the impact of information programs on fuel mix depends upon customer composition. We then explore the impact of disclosure policies beyond the mean; we utilize conditional quantile regressions to investigate program effects on the entire range of the fuel mix distribution.

Regression Models with Interactions

Are disclosure program impacts conditional on customer composition? Our goal here is to examine whether the effect of disclosure programs depends upon a firm's proportion of sales to residential consumers. Residential consumers may be more likely to respond to disclosure programs since the simplified, easily interpretable information may be more novel to them. Commercial organizations may simply have sufficient incentives and resources to obtain fuel mix information without disclosure programs. Further, groups with different preferences may simply respond differently to disclosed information.[11]

Consequently, we regress fuel mix proportion measures on the percent of the firm's sales subject to disclosure, the proportion of the firm's sales to residential consumers, an interaction of

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[11] Indeed, one might expect residential and commercial customers to have different preferences even in the absence of disclosure programs. For example, residential customers may be more likely to express green preferences or commercial customers may have greater incentives to keep costs down and therefore demand more fossil fuels than residential consumers. Alternatively, commercial consumers may be more willing to purchase green power products to appease employees, investors, or their own customers.

the policy variable with the residential variable, fixed effects, and other covariates. More

formally, we consider the regression model $y_{it} = D_{it}\delta + R_{it}\gamma + D_{it}R_{it}\eta + \mathbf{X_{it}\beta} + \alpha_i + \varepsilon_{it}$. D_{it} still

represents the proportion of firm i's sales that are subject to an effective disclosure program in

period t, R_{it} represents the proportion of firm i's sales going to residential customers, and the

elements of the row vector $\mathbf{X_{it}}$ include all of the non-program explanatory variables.

Since both the program variable D_{it} and its interaction $D_{it}R_{it}$ may be statistically

endogenous, we again employ instrumental variables regressions. One instrument remains the

same. Our second instrument is the interaction of the first with the residential variable. Since this

interaction in not a linear combination of the first instrument, it is as valid as the primary

instrument itself. Results for aggregate categories are presented in Table 3. Computed standard

errors are heteroskedastic-consistent. T-statistics appear in parentheses.

Table 3. Disclosure & Customer Composition Instrumental Variable Regression Results

	Percent Fossil Fuels	Dependent variables Percent Clean Fuels	Percent Nuclear
Percent of Sales to	-.009	-.672***	.430**
Residential	(-0.05)	(-3.85)	(2.53)
Disclosure Program	-.788***	-.285	.907***
	(-3.15)	(-1.27)	(3.58)
Disclosure/Residential	1.07***	1.23***	-1.60***
Interaction	(3.16)	(2.90)	(-4.34)
Deregulation	.156***	-.027	-.150***
	(2.78)	(-0.65)	(-2.76)
Season Dummies		3 Season Dummies	
Year Dummies		8 Year Dummies	
Fixed Effects		144 Firm-Level Fixed Effects	

[a] The dependent variables are the percentage of fuel mix attributable to the source indicated in the column heading. The key independent variable, the disclosure program variable, ranges from 0 to 1. It indicates the percentage of firm sales subject to operational disclosure programs.
[b] Superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.
[c] Analyses use 13,957 observations from 143 firms over the 108 sample months. 2 firms are missing residential data.

Table 3 coefficients on the un-interacted residential variable indicate that, in the absence

of any disclosure program, an increase in sales to residential customers increases the proportion

of fuel mix attributable to nuclear energy and decreases the proportion attributable to clean fuels.

Coefficients on the un-interacted disclosure program variable indicate that when firms sell to no residential customers, programs reduce the proportion of usage attributable to fossil fuels and increase the proportion of usage attributable to nuclear energy. As always, however, some care should be exercised interpreting coefficients conditioned on zeroed variables.

The interaction results in Table 3 indicate that the impact of disclosure programs on both clean fuel usage and fossil fuel usage becomes more positive as the percentage of residential customers rises. In other words, as a firm proportionately serves more residential customers, clean fuel program responses become stronger (more positive). Alternatively, as a firm proportionately serves more residential customers, fossil fuel program responses become weaker (less negative). These results are not inconsistent. Examining the last column of Table 3, we see that the interaction coefficient for nuclear energy is negative and statistically significant. As a firm proportionately serves more residential customers, any nuclear program responses become weaker (less positive).

Marginal disclosure program impacts clarify the interpretation of the results in Table 3. At the first quartile of the residential customer variable, the marginal impact of disclosure on clean fuel usage is +0.061.[12] At the median of this variable, the marginal impact of disclosure is +0.121, at the third quartile, the marginal impact of disclosure is +0.175, and at the 90th percentile, the marginal impact of disclosure is +0.244. Thus, clean fuel program response becomes stronger (more positive) as a firm proportionately serves more residential customers. The marginal impact of disclosure on fossil fuel usage is -0.487 at the first quartile of the residential variable, -0.435 at the median, -0.388 at the third quartile, and -0.328 at the 90th

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[12] For the percent of firm's sales subject to residential consumers, Q25=0.281, Q50=.330, Q75=.374, and Q90=.430. The marginal impacts for the program variable can be calculated as: $\partial y/\partial D = \delta + R \eta$. For the clean fuel regressions in Table 3, $\delta = -.285$ and $\eta = 1.23$. Therefore, the marginal program effect for the clean fuel regression, evaluated at the first quartile of the residential customer variable, is $-.285 + 1.23(.281) = 0.061$.

percentile. Therefore, fossil fuel program response becomes weaker (less negative) as a firm proportionately serves more residential customers. Finally, the marginal impact of disclosure on nuclear fuel usage is +0.457 at the first quartile of the residential variable, +0.379 at the median, +0.309 at the third quartile, and +0.220 at the 90th percentile. Nuclear fuel program response becomes weaker (less positive) as a firm proportionately serves more residential customers.

Conditional Quantile Regressions

Do disclosure program impacts vary across the fuel-mix distribution? Our goal here is to examine whether the effect of disclosure programs depends upon firms' pre-existing fuel mix portfolios. For example, do disclosure programs impact high fossil fuel firms the same way they impact low fossil fuel firms? To answer this question, we use Koenker and Bassett (1978)'s conditional quantile regressions.

Quantile regressions estimate functional relationships between variables for various points on the probability distribution of the dependent variable. Estimated parameters are interpreted as they would be in any ordinary regression model, but the parameter estimates are allowed to vary with the quantile of the distribution. Typically, linear models estimate the response of the mean or expected value of some dependent variable to one or more independent variables. Quantile models estimate the response of the median (or the 90th percentile or the 20th percentile, etc.) to independent variables. In contexts with heterogeneous responses across the distribution of the dependent variable, focusing on the mean may overstate, understate, or fail to reveal true changes in distributions (Cade and Noon 2003).[13]

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[13] Quantile regressions are increasingly used in economics, especially in areas such as labor, education, health, and environment, where heterogeneous responses to covariates have important implications (Cade et al. 1999, Koenker 2005). An especially common econometric application is censoring (Koenker 2005). Methodologically, quantile regression estimates are obtained by minimizing least absolute deviations (errors) with conventional linear

In our context, quantile regressions decompose the mean response revealed by the linear regression results in Table 2 into changes across the entire probability distribution of fuel mix levels. In particular, conditional quantile regressions allow us to estimate different slope coefficients for different fuel mix quantiles. For example, a regression on the 50th percentile of the fossil fuel distribution estimates the effect of disclosure on the sample median of the fossil fuel distribution. A regression on the 20th percentile of the fossil fuel distribution estimates the effect of disclosure on the 20th percentile of the distribution. If the disclosure program coefficient is larger for the 20th percentile than the 50th percentile of the fossil fuel distribution, results suggest that firms that already use relatively limited amounts of fossil fuels reduce fossil fuels the most in response to disclosure programs.

An additional advantage of conditional quantile regressions in our context relates to censoring. In our data, some observations have proportional clean fuel usage at or near 0 and proportional fossil fuel usage at or near 1. Less commonly, some observations have proportional clean fuel usage at or near 1 and proportional fossil fuel usage at or near 0. Such censoring may bias least squares regressions, but the weighted least absolute deviation estimation underlying the quantile regression method minimizes or eliminates the impact of censoring on the uncensored quantiles.

More formally, we consider the linear model for the conditional quantile function, $Q_{y_{it}}(\tau \mid D_{it}, \mathbf{X}_{it}) = \alpha(\tau) + D_{it}\delta(\tau) + \mathbf{X}_{it}\boldsymbol{\beta}(\tau)$ for τ between 0 and 1. D_{it} still represents the proportion of firm i's sales that are subject to an effective disclosure program in period t and the elements of the row vector $\mathbf{X_{it}}$ include all of the non-program explanatory variables. Note that we omit firm-level fixed effects. Including firm-level fixed effects in quantile regressions would

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programming models. Neat, closed-form solutions are not obtained, but the intuition is very similar to OLS models that minimize the sum of squared deviations.

yield coefficients that indicate an average firm's program responses across the distribution of *departures* from that individual firm's typical fuel mix levels. So, the 75th percentile coefficient in the fossil fuel quantile regression would represent the disclosure response when firms are using a particularly large amount of fossil fuels, relative to their own typical fossil fuel levels. In contrast, our purpose is to investigate what happens to the overall fuel mix distribution. In other words, we wish to examine if the fuel mix distribution shifts more strongly for firms that typically use high proportions of fossil fuels.

Of course, it is still possible that the program variable D_{it} is statistically endogenous. Therefore, in addition to standard conditional quantile regressions, we perform instrumental variable quantile regression. For basic quantile regressions, estimation, variance estimation, and inference follows Koenker and Bassett (1982) and Rogers (1993). For instrumental variable quantile regression, we use the implementation by Chernozhukov and Hansen (2004) for estimation and inference.

Table 4 presents quantile regression results for the impact of disclosure programs on proportional fossil fuel usage. Here, we conduct quantile regressions at the 20th, 30th, 40th, 50th, and 60th percentiles because these represent the relevant range for this distribution. There is little variation below the 20th percentile, as 15 percent of observations reflect proportional fossil fuel usage at or near 0. Similarly, there is little variation above the 60th percentile, as nearly 40 percent of observations reflect fossil fuel usage at or near 1 (100%).

Table 4. Conditional Quantile Regressions: Fossil Fuels

	Std. Quantile Regression					Instrumental Var. Quantile Regression				
	Q20	Q30	Q40	Q50	Q60	Q20	Q30	Q40	Q50	Q60
Disclosure Program	-.323*	-.294*	-.201*	-.149*	-.017*	-.525*	-.985	-.467*	-.326*	.094
	(-19.9)	(-19.2)	(-13.5)	(-21.1)	(-19.2)	(-9.18)	(-0.04)	(-9.34)	(-4.35)	(0.24)
Season2 Dummy	-.001	.024	.023	.015	.001	.003	.001	.018	.002	-.001
	(-0.02)	(1.60)	(1.61)	(2.16)	(0.01)	(0.18)	(0.01)	(1.64)	(0.20)	(-0.02)
Season3 Dummy	.056*	.049*	.041*	.019*	.001	.040	.025	.033*	.002	.001
	(3.51)	(3.33)	(2.89)	(2.79)	(0.01)	(2.40)	(0.30)	(3.22)	(0.21)	(0.02)
Season4 Dummy	.001	-.001	.012	-.010	.001	.026	.003	.017	.002	-.001
	(0.04)	(-0.01)	(0.86)	(-1.47)	(0.01)	(1.58)	(0.03)	(1.60)	(0.20)	(-0.02)
Year Dummies	8 Year Dummies					8 Year Dummies				

[a] The dependent variables are the percentage of fuel mix attributable to the source indicated in the column heading. The key independent variable, the disclosure program variable, ranges from 0 to 1. It indicates the percentage of firm sales subject to operational disclosure programs.
[b] A superscript * indicates statistical significance at the 1% level.
[c] All analyses consist of 14,168 observations from 145 firms over the 108 sample months.
[d] Quantile regressions omit the deregulation variable due to the limited sampling variability near the tails.

Results in Table 4 demonstrate that the disclosure program point estimates tend to decrease as one moves up the distribution of fossil fuel usage. These differences are frequently both statistically and economically significant. For example, all matched pair differences except (Q20, Q30) are statistically significant for the standard quantile regressions. Further, the fossil fuel program response at the 20th percentile is 1.6 (IV QREG point estimates) to 2.2 (standard QREG point estimates) times greater than the response at the 50th percentile. Results in Table 2 indicated that disclosure programs induce reductions in fossil fuel usage on average. The quantile regression results in Table 4 suggest that it is firms that already use relatively limited amounts of fossil fuels that reduce these fuels the most in response to disclosure programs.

Results for clean fuel responses to disclosure programs mirror the fossil fuel results previously presented in Table 4. Point estimates generally increase as one moves up the distribution of clean fuel usage, suggesting that disclosure programs induce firms that already use substantial amounts of clean fuel to increase clean fuel usage the most. For both fossil fuel and clean fuel responses, care should be taken interpreting these results. Technically, the quantile regressions compare differences in the absent-disclosure and present-disclosure *distributions*.

Rank preservation is not guaranteed. While it is practically quite likely that firms that are at high quantiles of the absent-disclosure distribution also appear at similarly high quantiles of the corresponding present-disclosure distribution, this is not required. Thus, quantile regression results strongly suggest, but do not prove, that firms that already use substantial amounts of clean fuels increase clean fuel usage the most in response to disclosure programs.

VIII. DISCUSSION & CONCLUSION

On the margin, we find a statistically and economically significant impact of information disclosure programs in the electricity industry. We find that mandatory disclosure programs decrease firms' percentage of generation attributable to fossil fuels and increase firms' percentage of generation attributable to clean fuels like hydroelectric and renewables. As the proportion of the average firm's sales subject to disclosure requirements increases 1 percent, the average proportion of generation attributable to fossil fuels drops between 0.06 percentage points and 0.23 percentage points. Further, as the proportion of the average firm's sales subject to disclosure increases 1 percent, the average proportion of generation attributable to clean fuels rises between 0.02 percentage points and 0.27 percentage points.

We also find that disclosure program responses are sensitive to customer composition and pre-exiting fuel mix levels. Firms' clean fuel program responses become considerably stronger (more positive) as the firm sells to more residential consumers. Fossil fuel program responses become considerably weaker (less negative) as the proportion of sales to residential consumers increases. Further, disclosure program responses differ across the fuel mix distribution. Results suggest that firms that already use relatively low levels of fossil fuels decrease their fossil fuel percentages the most in response to information disclosure policies. For example, the program-induced decrease in fossil fuel usage is approximately 2 times greater for firms generating

approximately 38 percent of their energy from fossil fuels than for firms generating approximately 83 percent of their energy usage from fossil fuels.

The key implication arising from our results is that information disclosure programs that regularly provide easily interpretable information can achieve policy goals. This result holds even when the provided information already exists in the public domain. Other significant policy implications follow from our results. Most notably, information policies may generate unintended consequences. For example, attention should be paid to customer composition when introducing disclosure programs in the electricity industry. When utilities serve high proportions of residential consumers, mandatory information programs may spur particularly significant increases in clean fuel usage. However, in these circumstances, these increases come at the relative expense of nuclear fuel usage and not fossil fuel usage. This may be consistent with stakeholder preferences, but it is unlikely to be consistent with air pollution-oriented policy goals. Second, the pre-existing fuel mix results suggest that disclosure programs induce firms that use significant amounts of clean fuels to use more clean fuels. In contrast, firms that predominantly use fossil fuels respond relatively weakly to disclosure programs. If the marginal benefits of pollution abatement are larger at high fossil fuel firms than at low fossil fuel firms, disclosure programs may induce inefficient abatement allocations.[14]

This paper suggests promising avenues for future research that are beyond the present scope. First, our results indicate that mandatory information disclosure programs affect the economic incentives and the behavior of utilities. However, assessing the full welfare effects of information-based policies requires a differentiation between new generation and ownership

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[14] In a recent meta-analysis of the air pollution epidemiology literature, Dominici et al. (2003) found consistent support for upward sloping dose-response curves. Ceteris paribus, marginal air pollution damages are greater in the neighborhood of higher polluting facilities than in the neighborhood of lower polluting facilities. Emissions per KWh are known to increase with fossil fuel usage, ceteris paribus.

changes. Second, our results and anecdotal evidence suggest that the direct demand theory provides a credible link between mandatory information disclosure programs and fuel mix outcomes. For example, sensitivity of program response to customer composition supports direct demand effects. However, a full understanding of the implications of these information-based policies requires precise identification of the underlying mechanism or mechanisms. Third, we demonstrate that information programs affect fuel mix outcomes. While fuel mix is correlated with emissions, gauging the social value of the policies involves an empirical evaluation of program-induced impacts on environmental quality. Finally, our results are suggestive for other settings. While mandatory provision programs are becoming increasingly common in other countries, the extent of policy induced changes may be sensitive to cross-country institutions.

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