Mandatory Information Disclosure and Environmental Performance in the Electricity Industry

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Abstract

This paper examines empirically the impact of mandatory environmental disclosure programs on fuel mix percentages in the United States’ electric utility industry. Our findings show that mandatory disclosure programs can improve environmental performance. 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. We also find that customer composition and pre-existing fuel mix significantly impact disclosure program response.

Keywords: disclosure, information, pollution, fuel mix, electric utilities

D83 – Search, Learning, and Information;  
D21 – Firm Behavior;  
K32 – Environmental, Health, and Safety Law

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1. 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, (further) 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, food nutrition labels, drinking water quality notices, and eco-labels. The empirical effectiveness of such programs, however, remains 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 products like beef require country of origin and other health labels. Even domestic colleges and universities are required by law to inform current and prospective students of crime statistics, equity information, and performance metrics.

There are several potential advantages of information provision policies. For example, such policies flexibly allow different outcomes for agents with varying risk exposure, risk susceptibility, and risk preferences. Information provision may also be particularly useful for persistent problems and problems that are difficult to enforce in a regulatory context.

Indeed, theory suggests that disclosure programs may effectively achieve their goals. See Healy and Palepu (2001) for a survey of the evidence in capital markets. In the environmental area, Kennedy et al. (1994) showed that the provision of information about pollution can correct a market failure and be welfare improving. Further, disclosure programs can lead to improved environmental performance by: 1. increasing consumer demand for a reporting firm’s environmental performance, 2. increasing a reporting firm’s susceptibility to liability under legal statutes, 3. increasing investor and/or employee pressure for reporting firm’s pollution
abatement, and 4. increasing community coercion. Arora and Gangopadhyay (1999), Maxwell et al. (2000), Kirchhoff (2000), and Khanna (2001) provide a more complete discussion of these issues.

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 suggests 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. Studies of environmental performance yielded similarly mixed results. 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 are more likely attributable to regulation than investor pressure.

This paper is the first empirical economic study of the effectiveness of information provision in the electric utility industry. Electricity disclosure programs are a promising area of exploration for the efficacy of environmental information policies for several reasons. First, electric utilities are among the leading polluters in the United States. For example, about 40.5 percent of domestic CO₂ emissions are attributable to electricity generation, and utilities are the largest source of anthropogenic mercury emissions. Second, 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 affected equally. Third, electricity is a homogeneous commodity. From a consumption point of view, there are no differences in the characteristics of green or brown electricity. Therefore, program-induced changes are attributable to preferences for environmental performance rather than changes in product quality. 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).

To what extent did mandatory disclosure laws affect the environmental performance of the electric utility industry? We address the 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. Panel data techniques allow us to identify disclosure program effects separately from the effects of other state and local programs like Renewable Portfolio Standards. We also correct for the potential statistical endogeneity of the program variable. We then explore the detected response in more detail. We use interaction models to explore the effect of customer composition on disclosure responses and conditional quantile regressions to examine how the entire fuel mix distribution shifts.

We find three main results. First, mandatory disclosure programs can improve environmental performance. We find that the average proportion of fuel usage attributable to fossil fuels substantially 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, nuclear program responses become weaker (less positive). Third, pre-existing fuel mix significantly impacts disclosure program response. We find 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.

The paper proceeds as follows. Section 2 provides background information on the electric utility industry and its disclosure programs. Section 3 discusses economic theories explaining why information disclosure programs may alter environmental performance. Section 4 describes our Energy Information Administration and Interstate Renewable Energy Council data. Section 5 presents an empirical foundation. In Section 6, we first analyze how firm-level fuel mix percentages respond to mandatory disclosure programs. We then explore the detected response in more detail. Section 7 concludes.
2. **Background**

2.1 **Fuel Mix in the Electric Utility Industry**

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 was attributable to oil. Nuclear sources generated nearly 20 percent of electricity. Cleaner energy sources, like hydropower, biomass, geothermal, solar and wind, generated approximately 9 percent (Edison Electric Institute 2005).

Renewable fuel use has trended upward since the fuels’ widespread debut in 1993. More than 300 electric utilities currently offer green power options to their customers (U.S. Dept. of Energy (2004)). Renewable capacity is quite variable across both space and time. For example, in 2003, many states, including CA, NY, ME, and VT, had green energy generation proportions in excess of 20 percent (U.S. Dept. of Energy (2003)). In 2004, although it remained a small portion of total electricity generation, wind power usage increased 27 percent.

Green power generation is driven by both supply-side and demand-side factors. On the consumption side, Lamarre (1997) and Delmas et al. (2006) find a distinct market niche for renewable energy even at a price premium. The number of customers participating in green pricing programs increased nearly five-fold between 1999 and 2003, to nearly 900,000 (Bird et al. (2004), US Dept of Energy (2004)).

2.2 **Mandatory Information Disclosure Programs in the Electric Utility Industry**

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 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. State Generation Disclosure Rules – September 2005

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 factor into disclosure effectiveness, programs are most 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. Additionally, Colorado and Florida instituted mandatory disclosure programs despite failing to deregulate their industries.
2.3 Other Information 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” facilities are required to file Federal Energy Regulatory Commission Form Number 1, the Annual Report for Major Electric Utilities, each and every year. 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 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 environmental information. Further, they are designed to provide such information directly to consumers.

3. Theories Linking Disclosure and Environmental Performance

We will present evidence that information disclosure programs alter fuel mix outcomes in the electricity industry. Indeed, this improved environmental performance was the declared intention of the state agencies that issued the policies. Several theories allow for a link between mandatory information disclosure programs and environmental performance.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 firms, 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

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

Perhaps the most 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 and that shifts in awareness can translate in behavioral changes. Loureiro and Lotade (2005), Leire and Thidell (2005), Loureiro (2003), and Blamey et al. (2000) all demonstrate shifts in consumer awareness after exposure to environmental information or eco-labels. 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. Teisl, Roe, and Hicks (2002) and Shimshack, Ward, and Beatty (2006) establish that changes in environmental awareness can be translated into new consumption patterns. More broadly, Stigler and Becker (1977) provide a general framework for information to enter a consumer demand framework.
Here, information is viewed as an input in the household production function of Lancaster (66) and Michael & Becker (73).

Consumers increasingly have the option to purchase greener energy at a price premium, and therefore increasingly have choice among consumer products. Thirty-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 alternative 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. Note also that the direct demand mechanism does not require customer choice across electricity providers, i.e. if information provision shifts consumers’ relative marginal willingness to pay curve for different energy products, firms’ marginal revenue calculations change and a new equilibrium will result. Since existing and future green pricing and certificate programs allow firms to differentiate their products and price discriminate, many electricity sellers were very interested in mandatory disclosure programs when they were being considered (National Council on Competition and the Electric Industry (2002)).

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 shifts are easily obtainable. First, utilities can alter their capacity utilization. Second, major electric utilities can buy and sell power in response to changing market conditions. In particular, nearly all large utilities solicit proposals from smaller firms to supply electricity on the margin. Many of these solicitations stipulate renewable or other clean energy sources. Georgia Power, the Tennessee Valley Authority, Duke Power, Oklahoma Gas and Electric, PacifiCorp, and

Portland General Electric are just a few of the major firms recently requesting proposals or signing new contracts for green power supply.4

Thus, several theories can explain the link between information disclosure and environmental performance. Empirically, we will follow the literature and estimate the reduced-form impact of mandatory information programs. Such a reduced-form regression of quantity on information variables (and other covariates) is 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.

4. Data

4.1 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, utilities are among the nation’s leading sources of pollution. Second, fuel mix is the most readily identifiable and interpretable measure of environmental performance on disclosure program bill inserts and web postings.

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. Fuel mix data come from forms EIA-906 (and its predecessor EIA-759), the monthly utility electric power plant reports. We focus on production-based fuel mix rather than sales-based fuel mix to identify actual changes in environmental quality.5 Facility characteristics are obtained from forms EIA-861, the annual electric power industry reports. 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.


5 Sales-based fuel mix data could result in a “shell game” type outcome, where cleaner energy is simply reported in states with disclosure programs without real shifts in fuel mix or environmental performance.
4.2 The Sample

Our final sample includes monthly information from the 145 major investor-owned electric utility companies with relatively complete data in EIA databases.\textsuperscript{6} 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 firms 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. We focus on the firm level (as opposed to the plant-level) since management decisions are centralized and disclosure program requirements operate at the company-level.

We observe fuel mix percentages and program variables 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 because we were unable to obtain reliable data for 2004.

4.3 Summary Statistics

Fuel mix summary statistics are presented in Table 1. Fossil fuels represent approximately 70 percent and clean fuels represent nearly 9 percent of generation over our entire sample. For aggregated fuel mix categories, the table indicates that the percentage of generation attributable to fossil fuels is lower after the introduction of disclosure programs and the percentage of generation attributable to clean fuels is higher after the introduction of disclosure programs. This is true despite increasing fossil fuel usage, across all firms, in the later years of the sample. Disaggregated fuel mix summary statistics generally parallel the aggregated results.

\textsuperscript{6} In terms of identifiable characteristics like age, size, and generation, the 145 sample firms do not differ significantly from the 112 investor owned utilities without relatively complete EIA records.
Table 1. Fuel Mix Percentage Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Entire Sample (145 firms)</th>
<th>Firms Subject to Disclosure During Sample Period (98 firms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Periods</td>
<td>Pre-Disclosure</td>
</tr>
<tr>
<td>Aggregated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fossil Fuels</td>
<td>.701</td>
<td>.704</td>
</tr>
<tr>
<td>“Clean” Fuels</td>
<td>.089</td>
<td>.091</td>
</tr>
<tr>
<td>Nuclear</td>
<td>.159</td>
<td>.161</td>
</tr>
<tr>
<td>Disaggregated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydroelectric</td>
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<td>.076</td>
</tr>
<tr>
<td>Renewables</td>
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<td>.015</td>
</tr>
<tr>
<td>Nuclear</td>
<td>.159</td>
<td>.161</td>
</tr>
<tr>
<td>Oil</td>
<td>.060</td>
<td>.063</td>
</tr>
<tr>
<td>Coal</td>
<td>.540</td>
<td>.543</td>
</tr>
<tr>
<td>Gas</td>
<td>.101</td>
<td>.098</td>
</tr>
</tbody>
</table>

None of the differences between pre-disclosure and post-disclosure fuel mix proportions, however, are statistically significant. Further, fuel mix changes may be attributable to a variety of factors other than disclosure programs. Consequently, we must conduct a more careful analysis in order to understand the impact of information disclosure programs on the environmental performance of the electric utility sector.

5. Primary Methods

Our overall empirical strategy is to use panel data techniques to analyze the effect of mandatory disclosure programs on fuel mix percentages. First, using ordinary least squares and instrumental variables regression methods, we 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. We use OLS and IV regressions with interactions to demonstrate that the impact of information programs on the proportion of clean fuel usage is significantly greater when facilities have proportionately greater
sales to residential customers. We then use standard and IV conditional quantile regressions to explore the impact of disclosure programs on the entire range of the fuel mix distribution. We establish that firms that already use substantial amounts of clean fuels most significantly increase clean fuel percentages in response to mandatory programs.

5.1 Primary Variables

Our key dependent variables represent fuel mix percentages. For example, the dependent variable may signify the percentage of the firm’s generation in a given month attributable to fossil fuels, including coal, oil, and natural gas. The dependent variable may also frequently denote the percentage of the firm’s generation in a given month attributable to the clean fuels, including hydroelectricity and renewable fuels like wind, solar, and biomass. In other cases, the dependent variable represents disaggregated fuel mix percentages, including the percentage of the firm’s electricity generation attributable to coal, oil, gas, renewables, hydroelectricity, or nuclear.

Our key explanatory variable represents the proportion of the firm’s sales that are subject to an operational or effective mandatory disclosure program. 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.

Analyses also include several other explanatory variables. Fixed effects allow us to capture systematic firm differences due to factors such as size, age, geographic location, community characteristics, management profiles, and ownership type. Plant production varies seasonally, so we include quarterly dummy variables. Technological change and other policy interventions may be an issue given our relatively long data series. Thus we include flexible annual dummies to account for broad trends in technology and other factors.
5.2 Basic Regression Model

The basic regression model is \( y_{it} = D_{it} \delta + X_{it} \beta + \alpha_i + \epsilon_{it} \), 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 \( X_{it} \) include all of the non-program explanatory variables discussed above. \( \alpha_i \) is an unobserved time invariant individual effect and \( \epsilon_{it} \) is the usual time variant idiosyncratic shock.

5.3 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 \( \alpha_i \) is correlated with the program variable \( D_{it} \). However, fixed effects are robust to such a 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.

Fixed effects do not, however, account for the possibility that the program variable \( D_{it} \) is correlated with the time variant error term \( \epsilon_{it} \). 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. The traditional correction for this type of statistical endogeneity is instrumental variables.

An effective instrument must be correlated with the state's choice of disclosure but not with the error term in our primary fuel mix decision equation. Therefore, our chosen instrument is the weighted average of the program status of states near to, but not upwind from, those states in which the particular firm operates. Since state policymakers pay attention to policy choices made in nearby states, it is likely that adjacent states’ disclosure choices are correlated with the given state’s likelihood of disclosure adoption. However, it seems unlikely that a state decides to adopt a program based upon the environmental performance of firms in non-upwind states, since the state is unable to regulate firms in other states and the emissions from firms in non-upwind
states do not impact the environmental quality of the state in question. Upwind states are determined by following prevailing westerly, southwesterly, and southerly winds. Pollution transport follows these winds fairly closely.

6. Empirical Analysis

6.1 Ordinary Least Squares and Instrumental Variables Regressions

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. We first ran fixed effects linear regressions. Fixed effects control for systematic firm differences and account for any potential time-invariant statistical endogeneity of the disclosure program variable. Since it is possible that the program variable remained correlated with the error term in a time variant fashion, we also ran instrumental variables regressions. Results are presented in Table 2.

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7 In order to avoid making the instrument itself statistically endogeneous, constructed instruments do not contain any information from any state in which the particular firm operates.

8 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/. We also experimented with an instrument that contains program information from all states adjacent to those in which the firm operates (not just non-upwind states). For all regression analyses, this instrument generated coefficients and standard errors that are quite similar to those reported.
Table 2. Firm-Level Regression Results: Aggregate

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Dependent Variable: Percentage of Fuel Mix Attributable to Fossil Fuels</th>
<th></th>
<th>Dependent Variable: Percentage of Fuel Mix Attributable to Clean Fuels</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Linear Regression</td>
<td>Instrumental Variables Regression</td>
<td>Linear Regression</td>
<td>Instrumental Variables Regression</td>
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<td>Disclosure Program</td>
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<td>-.311**</td>
<td>.020**</td>
<td>.174**</td>
</tr>
<tr>
<td>Season 2 Dummy</td>
<td>.004</td>
<td>.006</td>
<td>.002</td>
<td>-.001</td>
</tr>
<tr>
<td>Season3 Dummy</td>
<td>.017**</td>
<td>.020**</td>
<td>-.013**</td>
<td>-.017**</td>
</tr>
<tr>
<td>Season4 Dummy</td>
<td>-.001</td>
<td>.007</td>
<td>-.003</td>
<td>-.008**</td>
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<td>Year2 Dummy</td>
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<td>-.009</td>
<td>-.037**</td>
<td>-.038**</td>
</tr>
<tr>
<td>Year3 Dummy</td>
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<td>.013*</td>
<td>-.036**</td>
<td>-.035**</td>
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<tr>
<td>Year4 Dummy</td>
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<td>.041**</td>
<td>-.051**</td>
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<tr>
<td>Year5 Dummy</td>
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<td>.032**</td>
<td>-.064**</td>
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<tr>
<td>Year6 Dummy</td>
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<td>.032*</td>
<td>-.065**</td>
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<td>Year8 Dummy</td>
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<td>.143**</td>
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<td>-.082**</td>
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<tr>
<td>Year9 Dummy</td>
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<td>.154**</td>
<td>-.007</td>
<td>-.092**</td>
</tr>
</tbody>
</table>

- Fixed Effects 144Firm-Level FEs 144Firm-Level FEs 144Firm-Level Fes 144Firm-Level Fes

\* 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.

\* A superscript * indicates statistical significance at the 5% level. ** indicates statistical significance at the 1% level.

\* All analyses consist of 14,168 observations from 145 plants 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 0.05 percent (OLS point estimate) and 0.31 percent (IV point estimate).

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 percent (OLS point estimate) and 0.17 percent (IV point estimate).

These results can perhaps be reasonably extrapolated. As the proportion of the average firm’s sales subject to disclosure increases 10 percent, the average proportion of generation attributable to clean fuels increases between 0.2 percent (OLS point estimate) and 1.7 percent (IV point estimate). As always, however, care should be exercised interpreting the coefficients in Table 2 for non-marginal changes. Large-scale fuel mix changes may require considerable investments over long time horizons. However, results seem plausible for modest changes, as large investor owned utilities have the ability to buy and sell generation of any sort, on the margin, to meet customer, investor, or community demands.

Results in Table 2 also demonstrate the potential statistical endogeneity of the program variable. In the ordinary least squares regressions, clean fuel coefficients were negatively biased and fossil fuel coefficients were positively biased. Results suggest the presence of time variant correlation between the program variable and the error term. Specifically, disclosure program adoption may have been most likely when fossil fuel usage was particularly high and clean fuel usage was particularly low.

As expected, seasonality appears to play a strong 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. We also find that fuel mix decisions appear to trend over time, although non-linearly. Systematic differences across firms also exist, as firm specific intercepts differ substantially.
Table 3 presents instrumental variables results disaggregated to the specific fuel source. Results are consistent with the aggregate results presented in Table 2. There is a statistically significant negative relationship between disclosure programs and the proportional use of all fossil fuels. For example, as the proportion of the average firm’s sales subject to disclosure increases 1 percent, the average proportion of generation attributable to coal decreases approximately 0.22 percent (IV point estimate). There is a statistically significant positive relationship between disclosure programs and the proportional use of clean fuels. For example, as the proportion of the average firm’s sales subject to disclosure increases 1 percent, the average proportion of generation attributable to renewable sources increases approximately 0.04 percent (IV point estimate). There is also a significant positive relationship between disclosure programs and the proportional use of nuclear electricity generation (categorized as neither fossil fuel nor clean fuel and therefore unanalyzed in Table 2).

Table 3. Firm-Level Instrumental Variable Regression Results: Disaggregated

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Disclosure Program</th>
<th>Season2 Dummy</th>
<th>Season3 Dummy</th>
<th>Season4 Dummy</th>
<th>Year Dummies</th>
<th>9 Year Dummies</th>
<th>Fixed Effects</th>
<th>144 Firm-Level Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Sales Attributable to Coal</td>
<td>-.227**</td>
<td>-.009*</td>
<td>-.012**</td>
<td>.011**</td>
<td></td>
<td></td>
<td></td>
<td>9 Year Dummies</td>
</tr>
<tr>
<td>% of Sales Attributable to Oil</td>
<td>-.041*</td>
<td>-.006**</td>
<td>.022**</td>
<td>-.005*</td>
<td></td>
<td></td>
<td></td>
<td>144 Firm-Level Fixed Effects</td>
</tr>
<tr>
<td>% of Sales Attributable to Gas</td>
<td>-.043*</td>
<td>.022**</td>
<td>.037**</td>
<td>.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Sales Attributable to Renewables</td>
<td>.037**</td>
<td>-.001</td>
<td>-.001</td>
<td>-.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Sales Attributable to Hydroelectric</td>
<td>.137**</td>
<td>.001</td>
<td>-.017**</td>
<td>-.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Sales Attributable to Nuclear</td>
<td>.091**</td>
<td>-.008**</td>
<td>-.010**</td>
<td>-.004</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 5% level. ** indicates statistical significance at the 1% level.

All analyses consist of 14,168 observations from 145 plants over the 108 sample months.
6.2 Sensitivity Analysis

The results of the preceding sections are consistent across multiple specifications and different levels of aggregation. Below, we provide evidence that these results are robust to consideration of other important government policies, the choice of variable definitions, model structure, and the precise nature of the ‘event’.

Other Programs Impacting Fuel Mix Percentages

There are other state and local regulations and financial incentives that impact firms’ fuel mix percentages. However, disclosure programs were adopted by different states at considerably different times. Further, our data reflect a diverse set of firms observed over a relatively long time series. Panel data techniques allow us to separately identify the effect of disclosure programs from all other programs unless those programs are systematically adopted at the state-level and their introduction is highly correlated with the launch of the disclosure programs.

As a sensitivity analysis, however, we tested whether other prominent state-level programs targeting utilities’ fuel mixes impacted our results. The most notable other programs are Renewable Portfolio Standards (RPS), which frequently mandate tradeable credit programs with fixed quotas for renewable generation. First, we simply examined whether the inclusion of a variable for the introduction of RPS changed our disclosure results. Instrumental variable coefficients for the disclosure program variable were virtually identical (signs, significance, and magnitudes) to the results presented in Tables 2 and 3. Second, we ran the experiment that replicates the regression analyses in Tables 2 and 3 only for observations in which RPS program variables take a value of 0. Again, we find results that are extremely similar in terms of signs, magnitude, and significance as those presented in Tables 2 and 3. Since disclosure programs impact fuel mix percentages even when RPS programs have not yet been enacted, it seems unlikely that correlated RPS introductions are driving our disclosure results.

We also repeated these sensitivity experiments for mandatory green power programs. Green power policies require utilities operating in the state to offer and publicize green power

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9 The only changes of significance were for the disaggregated hydroelectricity and oil sources.
options to consumers. In both experiments, all coefficients are extremely similar in magnitude, sign, and significance to the coefficients reported in Tables 2 and 3.

**Sensitivity to Other Assumptions**

One 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 (including the preceding sensitivity experiments) 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 key program variable is constructed by weighting each firm’s state-level disclosure program status by the percentage of sales that occur in each state. A possible concern 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.

### 6.3 The Impacts of Disclosure: Further Exploratory Analysis

The regressions in Tables 2 and 3 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. 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 the policy variable with the residential variable, fixed effects, and other covariates. More formally, we consider the basic regression model

\[ y_{it} = D_{it}\delta + R_{it}\gamma + D_{it}R_{it}\eta + X_{it}\beta + \alpha_i + \epsilon_{it}. \]

\(D_{it}\) 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 \(X_{it}\) 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, i.e. the weighted average of the program status of non-upwind states near to those in which the particular firm operates. 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 4.\(^{10}\)

\(^{10}\) Disaggregated results are similar and are omitted to conserve space.
Table 4. Disclosure & Customer Composition Instrumental Variable Regression Results

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Percent Fossil Fuels</th>
<th>Percent Clean Fuels</th>
<th>Percent Nuclear</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of Sales to Residential</td>
<td>-.022</td>
<td>-.619**</td>
<td>.639**</td>
</tr>
<tr>
<td>Disclosure Program</td>
<td>-.709**</td>
<td>-.045</td>
<td>.519**</td>
</tr>
<tr>
<td>Disclosure/Residential Interaction</td>
<td>1.151**</td>
<td>.722**</td>
<td>-1.290**</td>
</tr>
<tr>
<td>Season2 Dummy</td>
<td>.006</td>
<td>-.002</td>
<td>-.008*</td>
</tr>
<tr>
<td>Season3 Dummy</td>
<td>.021**</td>
<td>-.018**</td>
<td>-.009**</td>
</tr>
<tr>
<td>Season4 Dummy</td>
<td>.008</td>
<td>-.009*</td>
<td>-.005</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>9 Year Dummies</td>
<td>144 Firm-Level Fixed Effects</td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* 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.

** A superscript * indicates statistical significance at the 5% level. ** indicates statistical significance at the 1% level.

* All analyses consist of 14,168 observations from 145 plants over the 108 sample months.

The Table 4 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 program variable indicate that, when firms sell to no residential customers, disclosure programs reduce the proportion of usage attributable to fossil fuels and increase the proportion of usage attributable to nuclear energy.

The interaction results in Table 4 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 firms proportionately serve more residential customers, clean fuel program responses become stronger (more positive). Alternatively, as firms proportionately serve more residential customers, fossil fuel program responses become weaker (less negative).
These results are not inconsistent. Examining the last column of Table 4, we see that the interaction coefficient for nuclear energy is negative and statistically significant. As firms proportionately serve more residential customers, nuclear program responses become weaker (less positive). In other words, disclosure programs induce considerably smaller increases in nuclear fuel usage when firms’ residential customer proportions are high (relative to the average program response).

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. Therefore, we use Koenker and Bassett (1978)’s conditional quantile regressions. In our context, quantile regressions decompose the mean response revealed by the linear regression results in Tables 2 and 3 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 estimates the effect of disclosure on the sample median of the dependent variable in question.

More formally, we consider the linear model for the conditional quantile function,

\[ Q_{yi}(\tau \mid D_{it}, \mathbf{X}_{it}) = \alpha(\tau) + D_{it}\delta(\tau) + \mathbf{X}_{it}\beta(\tau) \quad \text{for } \tau \text{ between 0 and 1.} \]

\( D_{it} \) 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 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, a 75th percentile coefficient would be the disclosure response when firms are using a particularly large proportion of fuel from source Y, relative to their own typical levels of fuel Y. In contrast, our purpose is to investigate what happens to the overall emissions distribution. In other words, we wish to examine if the fuel mix distribution shifts more strongly for firms that typically use high proportions of fuel Y.
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. In these instances, the instrument remains the weighted average of the program status of non-upwind states near to those in which the particular firm operates. For basic quantile regressions, estimation and inference follows Koenker and Bassett (1982) and Rogers (1993). For instrumental variable quantile regression, we use the implementation by Chernozhukov and Hansen (2004a) for estimation and inference.\textsuperscript{11}

Results for aggregate categories are presented in Tables 5 and 6. Table 5 presents results of the disclosure program on proportional clean fuel usage. We conduct quantile regressions at the 70\textsuperscript{th}, 75\textsuperscript{th}, 80\textsuperscript{th}, 85\textsuperscript{th}, and 90\textsuperscript{th} percentiles because these represent the relevant range for the clean fuel distribution. There is little variation below the 70\textsuperscript{th} percentile, as 70 percent of observations reflect proportional clean fuel usage at or near 0. Table 6 presents results of the disclosure program on proportional fossil fuel usage. Here, we conduct quantile regressions at the 20\textsuperscript{th}, 30\textsuperscript{th}, 40\textsuperscript{th}, 50\textsuperscript{th}, and 60\textsuperscript{th} percentiles because these represent the relevant range for this distribution. There is little variation below the 20\textsuperscript{th} percentile, as 20 percent of observations reflect proportional fossil fuel usage at or near 0. Similarly, there is little variation above the 60\textsuperscript{th} percentile, as 60 percent of observations reflect fossil fuel usage at or near 1 (100%).

\textsuperscript{11} Empirical examples of this technique can be found in Chernozhukov and Hansen (2004b) and Hausman and Sidak (2004).
Table 5. Conditional Quantile Regressions: Clean Fuels

<table>
<thead>
<tr>
<th></th>
<th>Std. Quantile Regression</th>
<th>Instrumental Var. Quantile Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q70</td>
<td>Q75</td>
</tr>
<tr>
<td>Disclosure Program</td>
<td>-.002*</td>
<td>.003</td>
</tr>
<tr>
<td>Season2 Dummy</td>
<td>-.001</td>
<td>-.002</td>
</tr>
<tr>
<td>Season3 Dummy</td>
<td>-.007*</td>
<td>-.012*</td>
</tr>
<tr>
<td>Season4 Dummy</td>
<td>-.004*</td>
<td>-.008*</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>9 Year Dummies</td>
<td>9 Year Dummies</td>
</tr>
</tbody>
</table>

* 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 5% level.
c All analyses consist of 14,168 observations from 145 plants over the 108 sample months.

Results in Table 5 demonstrate that the disclosure response point estimates generally increase as one moves up the distribution of clean fuel usage. Further, while often not statistically significant, the differences across quantiles are economically significant.¹² For example, the clean fuel usage program response at the 85th percentile is approximately 3-4 times greater than the response at the 80th percentile. Results in Tables 2 and 3 indicated that disclosure programs induce increases in clean fuel usage on average. The quantile regression results in Table 6 indicate it is firms that already use substantial amounts of clean fuels that increase clean fuels the most in response to disclosure programs.

¹² Several matched pair differences are statistically different from one another. For example, the standard quantile coefficient at Q80 statistically differs from coefficients at Q85 and Q90. Care should be exercised when making statistical comparisons with non-statistically significant coefficients. This is especially true for the IV quantile estimates, since statistically insignificant point estimates and standard errors were sensitive to estimation parameters like the grid search size and region.
Table 6. Conditional Quantile Regressions: Fossil Fuels

<table>
<thead>
<tr>
<th></th>
<th>Std. Quantile Regression</th>
<th>Instrumental Var. Quantile Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q20</td>
<td>Q30</td>
</tr>
<tr>
<td>Disclosure Program</td>
<td>-.323*</td>
<td>-.294*</td>
</tr>
<tr>
<td>Season2 Dummy</td>
<td>-.000</td>
<td>.024</td>
</tr>
<tr>
<td>Season3 Dummy</td>
<td>.056*</td>
<td>.049*</td>
</tr>
<tr>
<td>Season4 Dummy</td>
<td>.001</td>
<td>.001</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>9 Year Dummies</td>
<td>9 Year Dummies</td>
</tr>
</tbody>
</table>

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 5% level. ** indicates statistical significance at the 1% level.

c All analyses consist of 14,168 observations from 145 plants over the 108 sample months.

Results in table 6 largely mirror the results in Table 5. Here, point estimates of the disclosure program response tend to decrease as one moves up the distribution of fossil fuel emissions. Further, while often not statistically significant, the differences across quantiles are economically significant. For example, the fossil fuel usage program response at the 30th percentile is nearly 2-3 times greater than the response at the 50th percentile. Results in Tables 2 and 3 indicated that disclosure programs induce reductions in fossil fuel usage on average. The quantile regression results in table 6 indicate that it is firms that already use limited amounts of fossil fuels that reduce fossil fuels the most in response to disclosure programs.

13 Several matched pair differences are statistically different from one another. For example, the standard quantile coefficient at Q20 statistically differs from coefficients at Q40, Q50, and Q60 and the Q40 IV quantile coefficient differs statistically from the Q50 coefficient. As before, care should be exercised when making statistical comparisons with non-statistically significant coefficients. This is especially true for the IV quantile estimates, since statistically insignificant point estimates and standard errors were sensitive to estimation parameters like the grid search size and region.
7. Discussion and conclusion

On the margin, we find a 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. Impacts are practically significant. As the proportion of the average firm’s sales subject to disclosure requirements increases 10 percent, the average proportion of generation attributable to fossil fuels drops between 0.5 and 3.1 percent. Further, as the proportion of the average firm’s sales subject to disclosure increases 10 percent, the average proportion of generation attributable to clean fuels rises between 0.2 and 1.7 percent.

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. Firms that already use substantial amounts of clean fuels increase their clean fuel percentages the most in response to information disclosure policies. For example, the program-induced increase in clean fuel usage is nearly 5 times greater for firms generating approximately 28 percent of their energy from clean fuels than for firms generating approximately 3.5 percent of their energy usage from clean fuels.

Significant policy implications arise from these key results. First, information disclosure programs that regularly provide easily interpretable environmental information to customers can be an effective and low cost means of achieving policy goals. This result holds even when the provided information already exists in the public domain. Second, particular attention must 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 not be consistent with the issuing agency’s policy goals. Third, the pre-existing fuel mix results indicate that disclosure programs make “clean” firms cleaner while leaving “dirty” firms
relatively unchanged. If the marginal benefits of pollution abatement are larger at dirty facilities than at clean facilities, disclosure programs may induce inefficient abatement allocations.

**Acknowledgements**

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References


