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Different rays of sunlight: Understanding information disclosure and carbon transparency

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HIGHLIGHTS

- ▸ This article evaluates the Carbon Disclosure Project and state carbon reporting requirements.
- ▸ Evaluation is conducted with propensity score matching and difference-in-differences.
- ▸ State Disclosure Programs fail to lead power plants to reduce carbon dioxide emissions.
- ▸ The Carbon Disclosure Project leads to decreases in carbon emissions and electricity output.
- ▸ Information disclosure and transparency may be important part of policy mix but have limitations.

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ABSTRACT

This study assesses the effectiveness of two types information disclosure programs – state-based mandatory carbon reporting programs and the voluntary Carbon Disclosure Project, which uses investor pressure to push firms to disclose carbon emissions and carbon management strategies. I match firms in each program to control groups of firms that have not participated in each program. Using panel data methods and a difference in differences specification, I measure the impact of each program on plant-level carbon emissions, plant-level carbon intensity, and plant level output. I find that neither program has generated an impact on plant-level carbon emissions, emissions intensity, or output. Placing this study in contrast with others that demonstrate improvements from mandatory information disclosure, these results suggest that how information is reported to stakeholders has important implications for program effectiveness.

1. Introduction

The use of information disclosure programs has been increasingly prevalent in order to improve risk management and allow for more cost-effective private-market and legal forces to replace the heavy hand of government intervention. A variety of examples include lead paint disclosures, toxic emissions data, drinking water quality notices, eco-label notices, health, hygiene, and nutrition labeling, surgeon general's warnings, and financial market data provision. Agricultural products increasingly are labeled with information regarding the origin or the product and organic labeling. Colleges, universities, and hospitals must disclose a variety of statistics and performance metrics. Increasingly, information provision and product labeling has come to represent a common way of attempting to provide consumers and investors with greater choice, without directly mandating behavioral changes from regulatory targets.

As industrialized nations prepare to deal with climate change policy, it has become increasingly important that quality greenhouse gas emissions data are collected from firms. The aggregation of this information is the first step towards improved management of greenhouse gases. In addition, the transparency of firm operations and the reduction of information asymmetry between firms and their investors and consumers may provide a vehicle for free-market environmental policy and the impetus for improved management and increased efficiency of greenhouse gas operations.

A variety of information disclosure programs have arisen on the national, state, and international levels. Since 1993, Wisconsin has mandated greenhouse gas emissions disclosure from large emitters of carbon dioxide (EPA, 2009). Over time, the number of states requiring this disclosure has increased to 18 states, and as of January 1, 2010, a rule exists to require national greenhouse gas reporting from all large emitters. Additionally, the U.S. Securities and Exchange Commission requires the disclosure of

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climate change related risks, as of February 10, 2010. Voluntary initiatives have proliferated as well. The Department of Energy's 1605b program encourages firms to voluntarily report carbon emissions to the federal government. The Carbon Disclosure Project (CDP) is a private, non-profit voluntary initiative designed to improve transparency between firms and investors, and encourage improved management of greenhouse gases by firms.

Because research regarding the effectiveness of information disclosure programs has demonstrated mixed results, increased attention has turned towards determining what makes some information disclosure programs more effective than others, or what makes information disclosure programs effective in certain circumstances (Bae et al., 2010). Information disclosure programs can collect different types of information, use a variety of tools to disseminate information, and can be sponsored by government, industry groups, or non-governmental organizations (Darnall et al., 2009). As industrialized countries seek to address greenhouse gases, they are faced with an increasingly broad array of policy tools and approaches to policy that can be used to improve the governance of greenhouse gases. Evaluating policy experiments and institutional arrangements can lead to an improved understanding of institutional design and how to solve collective action problems (Ostrom, 2005).

Using a panel of plant-level data, this research seeks to evaluate a private voluntary (the CDP) and a public mandatory approach (State Reporting Requirements) to the disclosure of carbon dioxide emissions. This research will help contribute to the debate regarding the effectiveness of information disclosure programs, while helping to shed light on the possible tradeoffs between various designs of information disclosure approaches. The broader implications of this research may help policy-makers and researchers better understand the tradeoffs of voluntary and mandatory environmental policy, and an understanding of the extent to which information disclosure programs can play a role in the mix of policy tools used to address climate change.

This seeks to provide insight regarding the effectiveness of information disclosure programs on carbon dioxide and electricity generation, which may have different incentives and institutional arrangements than programs to address toxics or other environmental pollutants. In addition, this research tests two different approaches to information disclosure – a government mandated reporting mechanism, and a voluntary NGO-led reporting mechanism. The findings of this research – that the CDP seems to produce a modest decrease in plant level carbon emissions and electricity output while state reporting requirements have no impact – contributes to a range of findings in the literature that have demonstrated cases where information disclosure programs are effective and ineffective. I explore this diversity of results in the context of the structure of information disclosure program design.

2. The success and failure of information disclosure programs

Information disclosure programs can be run by government, as a mandatory or voluntary reporting program, but are increasingly designed as a form of 'civil regulation' (Murphy and Bendell, 1999), where civil society actors pressure firms to establish and adhere to environmental and social norms and standards. The institutionalization and standardization of information disclosure allows stakeholders to demand accountability and certain performance levels, rewarding strong performers and exerting pressure on poor performers or non-disclosers (Fiorino, 2006). Information disclosure programs evolved as a response to the challenges of implementing increasingly expensive command and control regulatory policy (Bae et al., 2010). Regulatory innovation, including a move to market based mechanisms, voluntary programs, and information disclosure programs have been thought of as ways to improve environmental outcomes using less costly and coercive policy tools (Konar and Cohen, 1997).

Information disclosure has been hypothesized to work via several mechanisms. Most traditionally, information disclosure programs promote increased transparency that allows markets to react to differences across firm behavior. Investors and shareholders may perceive environmental behavior as an indicator of firm risk management, or more directly as a financial liability (Hamilton, 1995; Khanna et al., 1998; Kim and Lyon, 2011b; Konar and Cohen, 1997; Patten, 2002). Improved information disclosure allows investors and shareholders to gauge risk and respond accordingly by rewarding or punishing firms in the stock market. Evidence for this is mixed. Some studies have concluded that firms with large releases experience decreases of stock prices (Hamilton, 1995, 2005; Khanna et al., 1998; Konar and Cohen, 1997; Shapiro, 2005), and subsequently reduce emissions (Grant, 1997). In contrast, others have found that information disclosure was ineffective (Grant and Jones, 2004; O'Toole et al., 1997) and that changes in emissions may be due to regulatory changes (Bui, 2005) or community characteristics (Hamilton, 2005; Shapiro, 2005).

Improved information disclosure can allow consumers to make choices based on the environmental performance of firms or the environmental labeling of products (Delmas et al., 2010; Shimshack et al., 2007). Firms may gain a marketing advantage through improved environmental performance or by participating in a voluntary environmental program. Evidence in this area is also mixed. Information provision can improve product quality (Brouhle and Khanna, 2007) and lead to "greener" fuel mixes in the electricity industry (Delmas et al., 2010). However, it has been difficult to distinguish the advantage gained by environmental performance from the advantage gained from environmental marketing, which has been demonstrated to lead to a reputational, financial, and competitive advantage for firms (Miles and Covin, 2000; Prakash, 2002).

An alternative mechanism for the success of information disclosure programs suggests that information disclosure targets internal stakeholders, such as employees, and leads firms to pursue cost-effective environmental improvements (Cerin, 2002). The process of information disclosure can allow a firm to analyze its activities, seek out means for improvements in efficiency, and improve management techniques; however, the degree to which information disclosure leads to improvements in behavior is related to the level of embeddedness of the information for both the user of the information and the discloser (Weil et al., 2005). This hypothesis suggests that the mechanism for disclosure plays an important role in the success of a disclosure program. If firm managers, investors, and consumers are unable to easily access and understand the disclosure of emissions, firm behavior is unlikely to change (Bae et al., 2010).

Significant research has been conducted in the area of information disclosure programs, yet much remains to be learned regarding the design characteristics of information disclosure programs and how these promote or hinder performance (Stephan, 2002). In particular, the comparative performance of different designs of information disclosure programs is not well understood.

3. Theory and contributions of this research

Recent research has focused on the design of information disclosure programs to understand what makes information disclosure programs more or less successful. Increasing evidence suggests that the manner in which information is provided to potential users may be the most important factor in determining whether information provision programs can be effective (Bae et al., 2010; Kolk et al., 2008; Weil et al., 2005). If data are made available to stakeholders in user-friendly manner, it may be more consequential than if raw data are simply released to the public. Information that is more detailed, accurate, and congruent to a policy goal may be more effective for achieving a policy outcome (Dranove et al., 2003).

Voluntary information disclosure programs may cater to the interests of stakeholders. Empirical findings suggest that firms pursue an open disclosure policy due to investor (Reid and Toffel, 2009) or employee (Spence, 2009) pressure, legal liabilities and securities laws (Skinner, 1994), increased growth rates and shareholder value (Blacconiere and Patten, 1994; Lev, 1992), improved terms of trade with suppliers and customers (Lev, 1992), reduced regulatory intervention (Lev, 1992; Walker and Salt, 2006), and reduced cost and increased access to capital (Blacconiere and Patten, 1994; Botosan, 1997).

Previous research has demonstrated wide variations in strategic decision-making of firms related to carbon disclosure (Kolk and Pinske, 2004, 2005), carbon management (Kolk and Pinske, 2004, 2005; Sullivan, 2009), and investment in energy efficient technologies (Hoffman, 2007). This variation can be explained by institutional, economic, and managerial determinants of information disclosure. While there is an emerging understanding of the institutional, economic, and management pressures that lead to increased reporting, much less is known about the extent to which the disclosure of environmental performance leads to or reflects changes in behavior (Chen and Bouvain, 2009; Cormier et al., 2005).

Voluntary disclosures supervised by NGOs or private organizations that cater to stakeholders have incentive to ensure that information collected and disseminated is available in an easy to use format. For example, the CDP maintains a searchable database with archived survey responses from all large corporations. In contrast, the Department of Energy's 1605b voluntary carbon reporting program participation information and data must be extracted from a series of reports and appendices that have not been updated online since 2005. State Reporting data must be obtained from state energy offices and may not be complete, up to date, or available online. NGOs and other third party organizations can make changes over time to improve the quality, detail, and accuracy of the information collected in order to satisfy stakeholder concerns, and research has demonstrated the potential for information disclosure to be most effective when made accessible to third parties, including states and NGOs for processing and dissemination (Bae et al., 2010).

The CDP, for example, has expanded/reorganized questions each year and worked to improve the quality of information being collected and disseminated; however, the CDP is increasingly restricting access to those who purchase a subscription based service, which may limit the dissemination of the information, and firms have increasingly moved to keep their disclosures private (Matisoff et al., 2012). In contrast, government-managed information disclosure programs typically pass through a legislative or a rule-making process, and may be unlikely to adapt over time to changing demands from stakeholders. While the CDP contains information regarding firm strategy, firm perceptions of risks and opportunities, and firm behavior, state and government programs tend to focus more exclusively on the raw emissions data. Government run information disclosure programs may release data in a raw format, and data releases may be delayed due to budget and time constraints and be less useful to stakeholder groups.

If private voluntary carbon disclosure programs collect detailed information and disseminate this information more effectively than government-run programs, private programs may have an impact on environmental behavior. Private programs may encourage electricity generators to discover and find inefficiencies to make efficiency improvements, and disseminated information can be employed by investors and consumers to pressure firms to make environmental improvements.

H_1: Voluntary information disclosure programs are likely to perform better than mandatory information disclosure programs.

A second motivation for this research is to understand how different pollutants may be impacted by information disclosure programs. Toxic releases, for example, represent risk due to possible litigation. Because toxics are frequently unpriced in the market, information disclosure offers an opportunity to incorporate the possible future costs of toxic emissions, or gauge the quality of management based on the response to such emissions (Hamilton, 1995). Carbon dioxide, however, represents a very different pollutant from toxics. It is generated primarily from the combustion of fossil fuels, and because fuel is costly, firms already face an incentive to reduce costs to maximize profits (Morgenstern and Pizer, 2007).

Another complicating factor, which makes carbon dioxide and electric utilities an interesting case study, is whether or not electric utilities minimize costs. Electricity markets are highly regulated and electric utilities are frequently able to pass along the costs of fuel and/or capital investments to consumers. It remains unclear whether firms have incentive to improve carbon efficiency. I test the assumption that profit-maximizing utilities will not take unilateral action to reduce total carbon dioxide emissions, carbon dioxide intensity, or electricity output.

H_2: Information disclosure programs will not reduce carbon dioxide emissions at power plants.

H_3: Information disclosure programs will not reduce carbon dioxide intensity at power plants.

H_4: Information disclosure programs will not reduce electricity output at power plants.

By examining the impact of a voluntary information disclosure program, more can be learned about the different types of voluntary programs and their effectiveness to get a better understanding of policy tools, and how they work in practice. Voluntary environmental programs can encompass many different policy tools and to date, there are few published empirical evaluations of a voluntary information provision program, and few studies compare the effectiveness of different information provision programs. Voluntary programs are particularly difficult to assess due to selection bias and difficulties of securing data both pre- and post- intervention. While there are multitudes of studies of individual voluntary programs, it is not clear which types of programs work better than others.

4. Research design

In this section I discuss my sample selection and data collection process, including the collection and coding of plant level, firm level, and state level variables. I then discuss my methodology in detail, including the discussion of a propensity score matching model and a difference-in-differences model. Table 1 below shows the specification of each variable included in each model considered.

4.1. Sample selection and approach

Two information disclosure programs were selected for this research. First, the Carbon Disclosure Project (CDP) is a private voluntary initiative designed to promote improved management

Table 1
List of variables used in Propensity Score Matching, Difference-in-differences models, and fixed effects models.

Variables	Level of observation	Included in propensity-score-matching	Included in difference-in-differences	Included in fixed effects
Number of active energy programs (2003)	State	X	X	X
Δ Number of active energy programs	State		X	
Active Energy Restructuring	State	X	X	X
Green group membership 1990	State	X		
Δ Sierra club membership per capita	State		X	
Sierra club membership per capita	State			X
Average CAA penalties (2004–2007)	State	X		
Δ Energy demand per capita	State		X	
Total energy demand per capita (2003)	State			X
Firm revenue	Firm	X		X
Average firm growth rate (1994–2003)	Firm	X		
Δ Firm revenue	Firm		X	
Log CO2 emissions	Plant			X
Δ Log CO2 emissions	Plant		X	
Year of plant construction	Plant	X		
Plant capacity	Plant	X		
Percent of electricity from coal (2003)	Plant	X		
Δ Log megawatt hours of electricity generation	Plant		X	
Log Megawatt hours of electricity generation	Plant			X

of carbon by pressuring firms to report their carbon emissions, and describe their carbon strategies and carbon related risks and opportunities. The CDP began in 2000 with a London-based coordinating secretariat for institutional investors to gain insight into climate related risk of Fortune 500 publicly traded corporations by standardizing reporting procedures for climate change related activities. The results of the first cycle of the project, released February 17th, 2003, were endorsed by approximately 35 investors controlling $4.5 trillion in assets. By the end of 2007, the CDP had grown considerably and was funded and run by over 385 institutional investors including major players such as Goldman Sachs, Merrill Lynch, and state pension funds, controlling over $40 trillion in assets. By 2007, over 2400 firms were targeted and 1300 firms responded to the survey (CDP4) reporting on various aspects of carbon management (Kolk et al., 2008). Of the Fortune Global 500 companies, CDP4 resulted in a 91% response rate and 72% answered the questionnaire in full. The CDP ranks firms based on the quality of their responses and ranks them in their Carbon Disclosure Leadership Index and their Carbon Performance Leadership Index. Firms are allowed to make their responses public, or can keep responses limited to the institutional investors that fund the program.

Second, state reporting programs are mandatory state efforts designed to help states manage and prepare for mandatory carbon regulation. Legislation enacting emissions reporting of greenhouse gases had been passed in 18 states by 2008. By 2007, state reporting mandates were in effect in Wisconsin, New Jersey, Connecticut, West Virginia, and Maine.[1] Wisconsin, the first state to require emissions reporting, required reporting since 1993 for firms that emit more than 100,000 t of carbon per year. The state's strong community right-to-know ethic makes the information readily available to the public via the Internet. New Jersey's mandatory reporting requirement began in 2003, focusing on CO_2 and methane, with a capacity threshold of 25,000 t of CO_2 equivalent, determined by criteria air pollutant emissions. West Virginia, in 2007, began requiring reporting for firms that already had reporting requirements for other air pollutants.

[1] While state reporting requirements had been passed by many states, there is generally a delay between the passage of the legislation and the implementation of the reporting requirements.

To measure the effectiveness of the two information disclosure programs, focus on power plant emissions, intensity, and output and calculate estimated CO_2 emissions by the type and amount of fuel use. There are a variety of practical reasons for limiting the sample to power plants and calculating estimated CO_2 emissions in this manner. First, power plants are the largest generators of CO_2 and are the most likely targets of any efforts to control greenhouse gas emissions. Second, emissions data from specific programs varies greatly in the method of accounting used and the accuracy and quality of the data (Lyon and Kim, 2011). Third, data sources such as EPA's Continuous Emissions Monitoring System are incomplete and have produced highly variable and potentially inaccurate estimates of CO_2 emissions (Lyon and Kim, 2011). Fourth, emissions data for manufacturing plants and firms not participating in voluntary or mandatory information disclosure programs is not publicly available, making it impossible to establish a control group. And finally, emissions monitoring in the states, in Europe, and in future U.S. federal regulation is likely to be based on engineering based estimates, derived from fuel use data, making this approach consistent with state, national, and international standards, as well as other approaches in the literature (Lyon and Kim, 2011; Morgenstern et al., 2007).

4.1.1. Data collection

Three types of data were collected to analyze the effectiveness of these programs. First, plant level data, including CO_2 emissions, electricity output, and emissions intensity (emissions/output) were collected as dependent variables. Electricity generation, type of fuel use, and plant construction year were also collected at the plant level. Second, because participation in voluntary programs is determined at the firm level, firm level data were collected, including firm size (measured as revenue), firm growth rate, and whether or not a firm is publicly traded. Finally, state characteristics relating to the regulatory climate of each state were coded and collected to control for varying levels of regulations and incentives that might impact regionally situated electricity producers. In addition, environmental interest group membership was collected in order to proxy for environmental attitudes of each state (Ringquist, 1993).

4.1.1.1. Plant level data. Fuel use data were used to estimate carbon emissions. To calculate carbon dioxide emissions, the amount of each type of fuel used in each power plant was multiplied by the heat rate, and the DOE regulations were used for the 1605b voluntary program in order to determine carbon dioxide emissions for each power plant reporting fuel use to the Energy Information Administration.[2] Data also included electricity generation by power plant. Plant level data were collected from 1994–2007 for approximately 5000 prime movers[3] (engines or turbines), which was then compiled, based on locational attributes, to generate fuel use data for 960 fossil fuel power plants in the United States. Plant level data were compiled with the assistance of Indianapolis Power and Light from the Velocity data suite, which relies primarily on data collected from EIA forms 861, 412, 906, 920, 923, and FERC form 1.[4] In addition, variables were collected to control for plant characteristics. These variables include plant capacity, electricity generation, year of construction, and the percentage of electricity generated from coal.[5]

4.1.1.2. Firm level data. Firms were coded as public or private using Compustat, Google Finance, and other search engine methods. Firm revenue data were collected from the Compustat database.[6] Firm growth rate was calculated as the growth in revenue between 1994 and 2003.

4.1.1.3. State level data. Several state-level variables were collected in order to control for regulatory differences across states. The average penalty assessed to Clean Air Act violators was derived from the EPA ECHO state data in order to proxy for state regulatory pressure (Lyon and Kim, 2011). Membership in environmental interest groups, represents citizen pressure to enact greenhouse gas regulation (Ringquist, 1993).

State regulatory data and information regarding renewable energy and energy efficiency programs were compiled from the Database for State Incentives for Renewable Energy (DSIRE) and individual state energy offices, as well as the Environmental Protection Agency website (DSIRE, 2009). The changing regulatory environment in each state may have a relationship with the electricity generation decisions made by individual power plants. Previous research has demonstrated the number of energy programs active in a state to be the product of political ideology, geographic resources, economic resources, and carbon-intensive industry present in a state (Matisoff, 2008).

Similarly to Hall and Kerr (1991) and Gray and Shadbegian (2003), who employ a count of laws regulating toxic waste in the states in order to construct a TOXIC index, measuring the regulatory stringency of each state, I count the total number of renewable energy and energy efficiency programs active in a particular state, for each year, as an indicator of regulatory activity in each state (Gray and Shadbegian, 2003; Hall and Kerr, 1991). This was compiled through the DSIRE website, as well as via e-mails and phone calls to individual state energy offices. While this measurement is an imperfect measurement of the regulatory stringency of each state, it is a good time-variant indicator available of the changing energy regulatory environment at the state level, which is likely to be correlated with mandatory transparency rules by the state as well as pressure on a firm to join a voluntary program.[7] The EPA website and state energy offices were used to determine whether or not states had active restructuring in each year. As of 2010, 22 states had active or suspended electricity restructuring (Energy Information Administration, 2010). State level energy demand per capita was collected from the EIA.

4.1.2. Obstacles and challenges

Due to the nature of this work, a variety of tradeoffs had to be made to secure such a complete and detailed dataset. First, plant data is only available for power plants that have greater than 25 MW capacity. Second, unregulated electricity generators did not have to report plant data beginning in 2003. I was able to determine which plants had closed after 2002, and which had ceased to report data based on whether the plant had reported fuel use, which was still required after 2002. If plants had no reported fuel use and fuel use (and thereby emissions) were inputted as 0s. If firms had reported fuel use, then emissions could still be calculated and plant characteristics were carried down from pre-2003 years. Third, plants that do not have reported fuel use do not appear in the dataset, eliminating many renewable energy plants. Fourth, deregulated plants that began operation in 2003 or later may not have appeared in the dataset, due to changes in reporting requirements. Finally, nuclear plants and plants held by universities were also eliminated from the dataset to achieve greater unit homogeneity. For the CDP, plants owned by non-publicly traded firms were eliminated from the dataset, since the CDP only targets publicly traded firms. For the state reporting requirements, one sample was created that includes plants owned by all firms, including cooperatives and municipal utilities, and another sample which drops plants owned by non-publicly traded firms serves as a better comparison to the CDP sample.

4.2. Methodology and identification strategy

This study employs propensity score matching, to control for static observable differences between the treatment group and control group, and a difference-in-differences model to control for unobservable static differences between the treatment group and the control group. I check for robustness by estimating effects with a fixed effects model as well. These results are included in the appendix. Below, I review the methodology in further detail.

Non-experimental methods of assessing program effectiveness are susceptible to a variety of biases (LaLonde, 1986). These include selection biases based on the propensity to join a program, the distributions of propensity to join a program, and "pure" self-selection, when individuals' self selection behavior is based on information that researchers cannot observe, or is caused by inter-temporal dependence of an outcome variable (Heckman et al., 1997; Heckman et al., 1999; Jung and Pirog, 2011). Selection bias based on the observable propensity to join a program can be controlled for using propensity score matching (Dehejia and Wahba, 2002; Heckman et al., 1997; Jung and Pirog, 2011).

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[2] Because the 1605b regulations only have carbon dioxide emissions information for major types of fuel, I used the closest match for rare types of fuel.

[3] Prime movers are the engines or turbines in a power plant. Each power plant may be composed of multiple prime movers. Fuel use is reported to the EIA at the prime mover level.

[4] Because fuel use data, data containing plant characteristics, and firm level and state level data were contained in separate datasets, data were merged into one large dataset using plant ID. numbers, and operator ID numbers.

[5] Missing plant construction year data and capacity data were periodically encountered. In these cases data were carried down from previous years.

[6] Following Berry and Fording (1997), I imputed missing data for firms missing a year to several years of revenue data using Stata's ****linear trending missing data function Berry, W., Fording, R.C., 1997. Measuring State Tax Capacity and Effort. Social Science Quarterly 78.. These observations were less than 2% of the total observations.

[7] For more information about the types of energy policies included in this measure, see the DSIRE database and Matisoff (2008). For more information about the reliability of this measurement, see Matisoff (2008).

Following Heckman et al. (1997), and similarly to Pizer et al. (2011), this study employs propensity score matching and a difference-in-differences approach, which has been demonstrated effective at eliminating bias, especially when it is due to temporally invariant omitted variables – that is, static differences between the treatment group and control group (Heckman et al., 1997). It is an extremely effective way of measuring average program effects under much weaker assumptions than matching alone (Heckman et al., 1997). The effects of the treatment on the treated can be identified under the relatively weak mean independence assumption, formulated in terms of $P(X)$, where X represents the observable conditions that lead to program participation and D represents whether or not plants participate in a specific program.

$$E(Y_0|P(X),D=1)=E(Y_0|P(X),D=0) \tag{1}$$

In order to fulfill this assumption and identify the causal effects in the difference-in-differences approach, at least one of the matching variables (X) must be uncorrelated with the outcome variable Y (in this case, the annual change in plant-level carbon dioxide emissions, carbon dioxide intensity, and electricity output) (Caliendo and Kopeinig, 2008). For more information on this identification strategy, or alternative identification strategies, see Heckman et al. (1997), or Heckman and Robb (1986). A more thorough discussion of the consequences of this approach follows below.

4.2.1. Matching

Because plants participating in a voluntary program may be systematically different than plants not participating in a voluntary program, it is necessary to establish a control group of plants for each of the treatment groups. Creating a matched control group can serve as a method to form a quasi-experimental contrast between a treatment and control (Morgan and Winship, 2007), and can serve as a form of nonparametric preprocessing that can improve the reliability of parametric estimates (Ho et al., 2007a). I matched samples using 1–1 nearest neighbor approach, with replacement, which has been demonstrated to reduce selection bias (Heckman et al., 1996).[8]

Plants are matched based on the probability that plants are participants in the CDP or State Reporting Requirements programs, given plant, firm, and state characteristics. The nearest neighbor method matches plants, with replacement, to the non-participating plant that has the closest probability of joining each program.

Plants from each program were matched with a sample of non-participating plants, based on participation status in 2007, which represents the widest net for program participation.[9] A one to one nearest neighbor match, with replacement, was conducted using the Stata user generated program psmatch2, using a probit regression (Leuven and Sianesi, 2003).

$$\Pr\left[\text{joining}=1=1|\sum x\right]=\frac{e^{(a+b_1x_1+b_2x_2+b_nx_n)}}{1+e^{(a+b_1x_1+b_2x_2+b_nx_n)}} \tag{2}$$

For each program – as indicated in Eq. (2) above, plants were matched by psmatch2 using the likelihood of participation in each program (joining=1), where $\sum x$ represents the year of plant construction, the capacity of the plant (in megawatts), the percentage of electricity at the plant generated from coal in 2003, the average amount of penalties assessed to polluting firms in each state for Clean Air Act violations between 2004 and 2007, the average growth rate in the holding company from 1994–2003, the per-capita membership in environmental organizations in 1990, the parent company size (measured as the natural log of millions of dollars in revenue), the number of active state energy programs in 2003, and whether or not utility restructuring was active in a state in 2003 (1=yes).

To identify the causal effects in the difference-in-differences approach below, it is important to have at least one predictor in the propensity score matching equation that is correlated with the decision to participate, but is uncorrelated with plant level carbon dioxide emissions or plant output. Several variables in the matching model ought to be uncorrelated with plant-level carbon dioxide emissions or output. First, state-level green group membership from 1990 is temporally antecedent to program participation and is unlikely directly correlated with annual changes in plant-level emissions between 1994 and 2007. States with strong environmental group membership are also more likely to mandate carbon disclosure. Second, the regulatory threat provided by the Clean Air Act may be correlated to the decision to join a voluntary environmental program or correlated to a state's decision to require carbon disclosures, but should not be correlated to carbon dioxide emissions, because the Clean Air Act does not regulate carbon dioxide emissions. Third, the long-term *parent* company growth rate and holding company size ought to be uncorrelated with *plant* level annual change of carbon dioxide emissions. Because each holding company owns multiple plants – and in many cases operates in multiple industries – there is little reason to believe that the size of the corporate parent is correlated with plant-year observations of changes in carbon dioxide emissions. However, the size of the corporate parent, the growth rate of the firm, the membership in green groups, and the average penalties assessed to firms violating the Clean Air Act are strong predictors of whether or not a firm joins a voluntary or state mandated environmental program, making them good instrumental variables for this purpose.

Participation decisions in voluntary environmental agreements are made by corporate parents, rather than individual plants, and larger firms have consistently participated in voluntary environmental agreements more regularly than smaller firms (Khanna, 2001). Logged revenues for the holding company in 2003 measure firm size. Finally, because of varied state regulatory activity, plants that operate in states with more regulatory activity related to energy may be more likely to participate in voluntary initiatives and are also more likely to exist in a state that mandates carbon disclosure. This method does not control for unobserved heterogeneity within each plant, nor does it control for changes in conditions over time. These issues are addressed in the difference-in-differences approach discussed next.

4.2.2. Difference in differences approach

To control for unobserved heterogeneity or omitted variables in matching process as well as changes in conditions at each plant over the study period, I take the first difference of my outcome variable y (carbon emissions, megawatt hours of electricity production, and carbon intensity) and each of my control variables λ over time period s (1994–2007), where x (program participation) is not differenced and is a dummy variable that denotes program participation in year t (Allison, 1990; Moffit, 1991; Morgenstern et al., 2007). Thus, I estimate the change in the dependent variable as a function of program participation and

[8] Alternative matching specifications, including a Gaussian Kernel approach did not result in different results. 1–1 matching without replacement was unable to generate sufficiently good matches for the CDP project.

[9] Once firms chose to join the CDP, they rarely, if ever, left. Matching based on 2007 data ought to reduce selection bias, as it accounts for firm future expectations regarding the regulatory environment, firm growth, and expected plant openings and closings when deciding to join the CDP during program years 2004–2006.

changes in conditions.

$$\Delta_s y_{it} = \alpha + \sum \mathrm{B}_{it} X_{it} + \sum \Delta_s \lambda_{it} + \varepsilon_{it} \quad (3)$$

where $\Delta y_{it} = y_{it} - y_{i(t-1)}$ and $\Delta \lambda_{it} = \lambda_{it} - \lambda_{i(t-1)}$

This equation is estimated using Stata 10, using weighted least squares (linear regression) where frequency weights are applied based on the matching results. Robust standard errors are clustered on the panel variable *i*.

The difference in differences approach controls for static heterogeneity between the treatment group and the control group, assuming that participants and controls have the same distributions of unobserved attributes; that they have the same distributions of the observed attributes; and that they are in a common economic environment (Heckman et al., 1997). The time-variant control variables control for observable conditions that change over time including changes in the state regulatory environment (measured as the number of energy programs in a state each year, and whether or not a state has active electricity restructuring) and firm growth rate. Thus, the difference in differences approach does not control for any time-variant unobserved heterogeneity, such as a change in firm philosophy over time, or a change in firm management over time, and assumes constant program effects over time (or alternatively calculates an average program effect over time). Because the panel consists of 14 years of data, for time-variant unobserved heterogeneity to impact the measurement of program effects, it must occur simultaneously with the program participation. That is, the difference-in-differences approach only fails to control for unobserved heterogeneity when it is time-variant and occurs simultaneously to the decision to participate in the voluntary program. This time-variant unobserved heterogeneity is particularly problematic in an assessment of a voluntary environmental program, as firms may pursue a variety of management-oriented changes simultaneously to choosing to participate in a voluntary program. This weakness is discussed further below.

The matching method is used for both the State Reporting Requirements and the Carbon Disclosure Project. The difference in difference method is repeated for each program for plant level CO_2 emissions (in metric tons), electricity output (in megawatt hours), and carbon intensity (in metric tons/megawatt hours). A fixed effects specification for each model is included in the appendix.

Table 2
Generating a matched sample for the Carbon Disclosure Project: predicting participation in the Carbon Disclosure Project, or State Reporting Requirements in 2007.

	Information disclosure – all plants	Information disclosure – publicly traded	CDP
Publicly traded (1=yes)	1.325***		
	(0.278)		
Firm level revenue (ln$000,000)	−0.114	0.00553	0.243***
	(0.0723)	(0.100)	(0.0613)
Plant capacity (MW)	−0.000218	−0.000215	6.99e−05
	(0.000133)	(0.000142)	(9.43e−05)
Year of construction	0.00136	0.00730*	−0.00321
	(0.00340)	(0.00423)	(0.00304)
Firm growth rate	−0.522***	−0.723***	−0.106
	(0.133)	(0.160)	(0.0669)
Active state restructuring (1=yes)	−0.830***	−1.209***	0.0243
	(0.182)	(0.222)	(0.148)
Average regulatory penalties	0.0515***	0.0271	−0.0590***
	(0.0198)	(0.0227)	(0.0215)
Coal % of electricity generation	0.354**	0.308	0.0861
	(0.173)	(0.197)	(0.138)
Green Group Membership (1990)	0.0948***	0.155***	0.0791***
	(0.0251)	(0.0309)	(0.0239)
Total state energy programs	0.0717***	0.0921***	0.0150
	(0.0113)	(0.0143)	(0.0128)
Constant	−5.272	−16.98**	4.555
	(6.749)	(8.524)	(6.049)
Observations	904	642	638
Pseudo R^2	0.276	0.306	0.0547
LR Chi^2	149.2***	134.1***	34.04***

* Represents significance at the α=.10 level.
** Represents significance at the α=.05 level.
*** Represents significance at the α=.01 level.

5. Results

As demonstrated above in Table 2, firm, state, and plant characteristics provide significant explanatory power to help predict which plants participate in state reporting requirements or the Carbon Disclosure Project, allowing a matched sample to be created for each program. I predict 5.5% of the variation in CDP participation after limiting the sample to publicly traded plants, and 31% of the variation in state reporting requirement participation. While parameter estimates are unbiased and consistent, the standard errors are incorrect due to correlation across observations on the independent variables. This heteroskedasticity means that the parameter estimates cannot be used for hypothesis testing on the independent variables, but can be used for predictive purposes. However, these results seem to support previous findings demonstrating that larger firms and plants located in areas with stronger citizen and regulatory pressures are more likely to participate in a voluntary information disclosure programs. Plants participating in state reporting requirements are more likely to belong to smaller publicly traded firms in areas with stronger regulatory regimes. After eliminating unmatched observations, and calculating the first difference of observations, two matched samples are left totaling 1873 plant-year observations for the state reporting programs, and 12,467 plant-year observations for the Carbon Disclosure Project (see Table 4 below).

Recent literature suggests that because poorly matched samples may create bias in estimated program effects, the matched samples should be examined to ensure that the matching process sufficiently controls observable differences between the treatment and control group (Smith and Todd, 2005a, 2005b; Smith and Zhang, 2009). Following the recommendations of Ho et al., (2007b), I provide the pre and post-matched samples as well as the propensity scores of those samples (see Table 3). In addition, I provide descriptive statistics of dependent variables in Table 3.

The matching exercise had dramatic effects on the sample characteristics (see Table 3). For state reporting requirements, participants had slightly smaller and older plants, more likely to be owned by publicly traded firms, owned by firms with slower growth rates, larger environmental group membership, in states with much greater environmental enforcement, and in states much more likely to have active electricity restructuring and many more state energy programs. As demonstrated in Table 3, the matched sample has much more similar observable characteristics and provided a much closer propensity score match. Prior to matching, non-participants were 21–24% less likely to have participated in state reporting requirements. After matching there is no difference between the samples' likelihood of participation.

For the CDP, prior to matching, participants were slightly larger, grew faster, had a greater presence of environmental organizations, less stringent environmental enforcement, more energy programs, and have a greater percentage of coal generation. Prior to matching non-participants were 5% less likely to have participated in the CDP (given that all plants owned by

Table 3
Means and standard deviations of matched samples.

	All plants	Publicly traded	State req- all - pre		State req - all -post		State req – pub - pre		State req – pub – post		CDP - pre		CDP - post	
	Full Sample	Full Sample	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Number of plants	935	660	855	80	80	80	591	69	69	69	123	533	516	516
Publicly traded	0.70	1	0.69	0.86	0.77	0.86	1	1	1	1	1	1	1	1
	(0.46)	(0.00)	(0.46)	(0.35)	(0.42)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm level revenue	7.80	8.77	7.79	7.87	7.46	7.86	8.82	8.34	8.37	8.34	8.44	8.85	8.69	8.85
(ln$000,000)	(1.85)	(0.98)	(1.87)	(1.56)	(1.79)	(1.56)	(0.96)	(1.00)	(0.72)	(1.00)	(1.37)	(0.85)	(1.29)	(0.85)
Plant capacity	624	740	634	517	388	517	759	572	641	572	685	755	755	773
(MW)	(651)	(703)	(658)	(554)	(421)	(554)	(714)	(574)	(638)	(574)	(666)	(713)	(606)	(716)
Year of	1967	1965	1967	1962	0.49	1962	1965	1963	1955	1963	1968	1964	1963	1964
construction	(21.2)	(20.4)	(21.0)	(22.78)	(0.50)	(22.78)	(20.4)	(20.9)	(24.8)	(20.9)	(19.2)	(20.6)	(18.9)	(20.6)
Average growth	0.80	0.93	0.83	0.56	0.57	0.56	0.98	0.57	0.65	0.57	0.88	0.95	0.54	0.48
rate	(0.85)	(0.96)	(0.87)	(0.53)	(0.48)	(0.53)	(0.99)	(0.57)	(0.69)	(0.57)	(0.84)	(0.99)	(0.50)	(0.50)
Green group	7.79	7.85	7.61	9.62	9.52	9.62	7.63	9.76	10.49	9.76	7.32	7.95	7.17	7.98
membership	(3.01)	(2.96)	(2.89)	(3.60)	(2.40)	(3.60)	(2.81)	(3.50)	(2.15)	(3.50)	(3.00)	(2.94)	(2.71)	(2.92)
Average penalties	3.56	3.65	3.28	6.49	5.46	6.49	3.33	6.45	5.82	6.45	4.04	3.55	3.68	3.55
$000	(3.37)	(3.56)	(2.67)	(6.85)	(4.86)	(6.85)	(2.79)	(6.83)	(4.03)	(6.83)	(4.31)	(3.36)	(2.55)	(3.38)
Active state	0.44	0.47	0.43	0.51	0.48	0.51	0.47	0.51	0.46	0.51	0.45	0.47	0.87	0.95
restructuring	(0.50)	(0.50)	(0.48)	(0.50)	(0.51)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.95)	(1.00)
(1=yes)														
Number of state	9.19	9.14	8.61	15.3	15.42	15.3	8.47	14.90	14.51	14.90	8.94	9.19	10.44	9.17
energy program	(6.71)	(6.51)	(6.24)	(8.3)	(8.61)	(8.33)	(5.87)	(8.56)	(8.32)	(8.56)	(6.16)	(6.62)	(6.07)	(6.54)
% of Coal	0.43	0.46	0.43	0.42	0.57	0.42	0.47	0.41	0.48	0.41	0.40	0.48	0.53	0.48
	(0.48)	(0.49)	(0.48)	(0.48)	(0.48)	(0.48)	(0.49)	(0.48)	(0.49)	(0.48)	(0.49)	(0.49)	(0.50)	(0.49)
Propensity scores	0.19	0.25	0.07	0.28	0.28	0.28	0.07	0.31	0.31	0.31	0.77	0.82	0.82	0.82
	(0.13)	(0.13)	(0.11)	(0.19)	(0.19)	(0.19)	(0.14)	(0.18)	(0.18)	(0.18)	(0.10)	(0.06)	(0.06)	(0.06)

Table 4
Descriptive statistics: dependent variables.

	Full sample	Info disc – full	Info disc – public	CDP
mtons CO_2	2,620,011 (38,39,564)	1,517,936 (2,687,279)	2,972,146 (3,862,400)	2,972,146 (3,862,400)
Δmtons CO_2	26,057.24 (571,324)	12,147.72 (459,423.8)	29,932.83 (677,466.1)	29,932.83 (677,466.1)
Log(mtons CO_2)	12.61281 (3.716165)	12.17451 (3.313123)	13.207 (3.181676)	13.207 (3.181676)
ΔLog(mtons CO_2)	0.0216811 (1.520729)	0.0611164 (1.395417)	0.0245452 (1.371718)	0.0245452 (1.371718)
mtons CO_2/MWh	0.9133231 (0.6367144)	0.9727636 (0.4723918)	0.9164988 (0.892954)	0.9164988 (0.892954)
Δ(CO_2/MWh)	−0.0036663 (0.8017527)	−0.0065189 (0.3979274)	−0.0056177 (1.220779)	−0.0056177 (1.220779)
MWh	2,916,743 (4,037,082)	1,632,770 (2,800,107)	3,238,667 (3,978,911)	3,238,667 (3,978,911)
ΔMWh	35,906.5 (629,225.8)	16,964.53 (490,231.5)	33,593.65 (680,768)	33,593.65 (680,768)
Log(MWh)	12.90875 (3.575979)	12.32976 (3.256617)	13.52854 (2.898621)	13.52854 (2.898621)
ΔLog(MWh)	0.0366739 1.365307	0.06476 (1.321161)	0.0217253 (1.04781)	0.0217253 (1.04781)

Table 5
Observations in dataset and for CDP and state reporting programs.

Program	State reporting programs – full sample	State reporting programs – publicly traded	CDP
Number of initial plants	935	642	642
Initial plant-year observations	12,406	8863	8892
Unique treated plants	80	69	516
Unique control plants	56	42	95
Matched pairs (including weights)	80	69	516
Total plant-year observations after matching, weighting, and first differencing	1873	1660	12,467

non-publicly traded firms were dropped from the sample). After matching, both the treatment and control were equally likely to have participated in the CDP. Characteristics of the dependent variable are described in Table 5.

Results from the differences-in-differences model (see Tables 6–8 below) demonstrate little statistically significant evidence of emissions reductions or emissions intensity reductions attributable to state reporting requirements. The CDP seems to demonstrate a decrease in carbon dioxide emissions plant level electricity output with increasing plant level carbon dioxide intensity.

State reporting requirements demonstrate negative parameter estimates for the impact of the program on the change in carbon dioxide emissions (2%) and the change in electricity production (2%). It exhibits a slightly positive change in carbon dioxide intensity.

Table 6
State reporting mandates versus the Carbon Disclosure Project: difference in differences model, effect of participation on ΔLn(CO_2 emissions) (metric tons), WLS parameter estimates shown, clustered standard errors in parentheses.

	State reporting-all	State reporting-all	State reporting-pub	State reporting-pub	CDP	CDP
Program participation	−0.0225	−0.000396	0.0536	0.00109	−0.0603*	−0.0261
	(0.0531)	(0.0214)	(0.0547)	(0.0262)	(0.0340)	(0.0267)
Prog*Δcoal		−0.966)		2.060***		0.233 (0.954)
		(1.280		(0.596)		
Prog*Δng		0.575		0.464		1.267
		(0.516)		(0.506)		(0.925)
Δcoal		3.002**		−0.253		−0.00681
		(1.201)		(0.469)		(0.568)
Δng		−0.165		−0.281		−0.146
		(0.360)		(0.452)		(0.550)
Publicly traded	0.0176	0.0388				
	(0.106)	(0.0259)				
Active electricity restructuring	−0.0423	−0.0735*	−0.105*	−0.0596 (0.0367)	−0.137***	−0.104***
	(0.0911)	(0.0382)	(0.0580)		(0.0351)	(0.0310)
ΔRevenue (ln)	0.0225	0.0539	0.0554	0.172**	0.0744*	0.114***
	(0.0989)	(0.0547)	(0.0870)	(0.0721)	(0.0413)	(0.0387)
ΔState energy programs	−0.0215*	−0.00127	0.00164	0.00373	−0.0159	−0.0162
	(0.0120)	(0.00600)	(0.00893)	(0.00670)	(0.0137)	(0.0129)
ΔSierra club membership	−0.000355	0.000809	−3.59e−05	−0.000580	−0.000590	−0.000769
	(0.00160)	(0.000705)	(0.00105)	(0.000607)	(0.00116)	(0.00105)
ΔEnergy consumption per capita	0.0113	0.00822	0.0117	0.0203*	0.0145**	0.0134**
	(0.0317)	(0.00830)	(0.0288)	(0.0106)	(0.00623)	(0.00597)
Constant	0.0837	−0.0115	0.00721	−0.00576	0.0821***	0.0439**
	(0.0967)	(0.0246)	(0.0468)	(0.0257)	(0.0232)	(0.0208)
Observations	1873	1803	1660	1617	12,467	12,204
R-squared	0.002	0.078	0.003	0.032	0.005	0.010

* Represents significance at the α=.10 level.
** Represents significance at the α=.05 level.
*** Represents significance at the α=.01 level.

Table 7
State reporting mandates versus the Carbon Disclosure Project: difference-in-differences model, matched sample, effect of participation on Δ(CO_2/MWh), WLS parameter estimates shown, clustered standard errors in parentheses.

	State reporting-all	State reporting -all	State reporting-pub	State reporting-pub	CDP	CDP
Program participation	0.0109	0.0134	0.0137	0.0170	0.0245**	0.0252***
	(0.0133)	(0.0127)	(0.0141)	(0.0138)	(0.0100)	(0.00958)
Prog*Δcoal		0.268		0.614***		0.0866
		(0.185)		(0.173)		(0.259)
Prog*Δng		0.00200		−0.0226		0.000833
		(0.107)		(0.0966)		(0.478)
Δcoal		0.252**		−0.0162		0.187**
		(0.106)		(0.0983)		(0.0897)
Δng		−0.419***		−0.331***		−0.330**
		(0.0752)		(0.0760)		(0.137)
Publicly traded	0.00586	−0.00117				
	(0.0146)	(0.0122)				
Active electricity restructuring	0.0157	0.0156	0.0255*	0.0202	0.0278***	0.0265**
	(0.0137)	(0.0128)	(0.0140)	(0.0140)	(0.0107)	(0.0105)
ΔRevenue (ln)	0.0142	0.0124	0.0123	0.0134	0.0877	0.0878
	(0.0145)	(0.0143)	(0.0153)	(0.0151)	(0.0954)	(0.0955)
ΔState energy programs	−0.000906	0.000559	−0.000453	0.000248	0.000248	0.000811
	(0.00291)	(0.00248)	(0.00316)	(0.00296)	(0.00638)	(0.00646)
ΔSierra club membership	3.93e−05	6.84e−05	0.000139	0.000192	−0.000995	−0.00105
	(0.000182)	(0.000168)	(0.000223)	(0.000218)	(0.000895)	(0.000913)
ΔEnergy consumption per capita	0.000739	0.00147	0.000420	0.000531	0.00184	0.00193
	(0.00225)	(0.00225)	(0.00202)	(0.00202)	(0.00176)	(0.00179)
Constant	−0.0219*	−0.0159	−0.0210	−0.0188	−0.0230	−0.0220
	(0.0128)	(0.0112)	(0.0211)	(0.0210)	(0.0174)	(0.0171)
Observations	1772	1772	1595	1595	11,958	11,958
R-squared	0.001	0.025	0.001	0.016	0.001	0.002

* Represents significance at the α=.1 level.
** Represents significance at the α=.05 level.
*** Represents significance at the α=.01 level.

However, none of these parameter estimates are statistically significantly different from zero, and alternative specifications that examine only publicly traded firms suggest an increase in emissions and output of about 5%. A fixed-effects specification, included in the appendix, shows more statistically significant results for CO_2 decreases and electricity generation decreases.

Table 8
State reporting mandates versus the Carbon Disclosure Project: difference-in-differences model, matched sample, effect of participation on ΔLn(MWh) (electricity output), OLS parameter estimates shown, clustered standard errors in parentheses.

	State reporting-all	State reporting-all	State reporting-pub	State reporting–pub	CDP	CDP
Program participation	−0.0268	−0.00243	0.0502	−0.00873	−0.0730***	−0.0358**
	(0.0530)	(0.0205)	(0.0542)	(0.0262)	(0.0280)	(0.0180)
Prog*Δcoal		−1.507		−0.247		−1.616***
		(1.200)		(0.624)		(0.577)
Prog*Δng		0.590		0.147		−0.301
		(0.559)		(0.365)		(0.594)
Δcoal		2.825***		1.269***		0.824*
		(1.056)		(0.369)		(0.432)
Δng		0.237		0.401*		0.486*
		(0.352)		(0.234)		(0.253)
Publicly traded	−0.0398	0.0162				
	(0.101)	(0.0242)				
Active electricity restructuring	−0.0317	−0.0865***	−0.112**	−0.0688*	−0.0966***	−0.0637***
	(0.0872)	(0.0278)	(0.0555)	(0.0360)	(0.0296)	(0.0234)
ΔRevenue (ln)	−0.0186	0.00353	0.00391	0.120**	−0.0116	0.0249
	(0.0931)	(0.0238)	(0.0748)	(0.0547)	(0.0297)	(0.0233)
ΔState energy programs	−0.0204*	0.000658	0.00282	0.00450	0.00677	0.00686
	(0.0108)	(0.00513)	(0.0101)	(0.00671)	(0.00724)	(0.00479)
ΔSierra club membership	−0.00111	0.000384	0.000125	−0.000670	−7.64e−06	5.93e−06
	(0.00158)	(0.000542)	(0.00100)	(0.000640)	(0.000699)	(0.000431)
ΔEnergy consumption per capita	0.0159	0.00709	0.0126	0.0221*	0.00710*	0.00545**
	(0.0325)	(0.00697)	(0.0298)	(0.0115)	(0.00393)	(0.00236)
Constant	0.138	0.00933	0.0165	0.00174	0.0563***	0.0134**
	(0.0944)	(0.0245)	(0.0453)	(0.0238)	(0.0143)	(0.00667)
Observations	1849	1780	1632	1595	12,248	12,005
R-squared	0.003	0.096	0.003	0.029	0.003	0.012

* Represents significance at the $\alpha=.1$ level.
** Represents significance at the $\alpha=.05$ level.
*** Represents significance at the $\alpha=.01$ level.

Specifications that include interaction terms with fuel use show that facilities that increased use of coal and are required to report emissions increased total emissions for plants owned by publicly traded firms. Interacting program participation and coal use generates positive parameter estimates for carbon intensity, but is only significant for plants participating in the Carbon Disclosure Project. The relationship between program participation and an increase in coal use, and electricity output is negative, but again is only statistically significant for the Carbon Disclosure Project.

The Carbon Disclosure Project produces a negative, statistically significant parameter estimate for a change in plant-level carbon dioxide emissions and electricity output, equivalent to 6% per year for CO_2 emissions, and 7% per year for electricity generation. Parameter estimates suggest that the carbon intensity of electricity production increased, as a result of electricity generation being reduced by a greater amount than CO_2 emissions. This is consistent with efficiency characteristics of power plants. Fixed effects specifications, included in the appendices, suggest similar results.

Comparing the results between state reporting requirements and the Carbon Disclosure Project suggest potentially large differences between the effectiveness of these approaches. In the sample of publicly traded firms, the CDP decreased plant level emissions by 6% and output by 7%, while state reporting requirements increased emissions and output by 5%. However, there were minimal differences in the emissions intensity of these two approaches, with emissions intensity of CDP participants.

6. Discussion

There is some evidence to suggest that firms will voluntarily undertake emissions reductions due to voluntary transparency programs. However, this research suggests that mandatory carbon reporting requirements were ineffective at reducing CO_2 emissions, electricity output, or carbon intensity. While results from Delmas et al. (2010) suggest that information disclosure can allow consumers to drive fuel use changes in power plants, the results presented in this manuscript highlight some potential important differences in evaluation methodology and program design that lead to these disparate conclusions.

First, data aggregation choices may drive some differences between the two studies. In order to achieve greater unit homogeneity, I examined plant level changes in carbon dioxide emissions. In contrast, Delmas et al. (2010) use holding company level data and include nuclear and renewable energy while calculating fuel mix as a percentage of electricity production. While the specification in this paper attempts to isolate plant level changes, Delmas et al. (2010), allow for greater flexibility in shifting electricity generation across plants.

Second, Delmas et al. (2010) examine information disclosure programs that require disclosure of fuel mix directly to consumers. In contrast, the dataset that is used in this study measures whether utilities must report carbon dioxide emissions to a state authority, or voluntarily to institutional investors. In fact, there are large differences between the states that require fuel mix disclosure and states that require carbon emissions reporting. Delmas et al. (2010) report that 25 states had enacted fuel mix disclosure rules and most of these programs were in deregulated states. In contrast, by 2007, five states had implemented state reporting rules (an additional 13 states were preparing to implement disclosure rules) and just 3 of these states overlap with fuel mix reporting states and state with electricity restructuring.

Providing fuel choice or retail options to consumers will have a different impact than providing emissions data to regulatory authorities. This difference in program design and outcomes emphasizes the importance of empowering consumers directly with useful information that enables them to drive production decisions through green consumerism.

These findings contribute to mixed findings in the information disclosure literature related to carbon emissions. Recent research has found the DOE 1605b program to be similarly ineffective (Kim and Lyon, 2011a). This program also does a poor job disseminating results – where participation and data are contained in appendices of annual reports, and as of January 2011, have not been updated more recently than 2004. And a study with an alternative specification of the CDP found the CDP to be ineffective at producing reductions in carbon emissions (Matisoff, 2012), suggesting that CDP impacts may be driven by emissions and output reductions from small plants.

These findings highlight limitations and opportunities for information disclosure. While research suggests that product labeling and providing information to consumers can make a difference, it appears some types of mandatory disclosure programs do not disseminate information closely enough to the ultimate consumers of electric power. Nor is it clear that these types of programs internally motivate changes in the behavior by firms. Propensity score matching and difference in differences cannot differentiate between observed changes in behavior, such as participation in the CDP, and simultaneously occurring unobservable changes in behavior, such as firm managers deciding to pay increased attention to carbon dioxide emissions. Participation in the CDP may not cause firms to change environmental behavior, but may be a mechanism to signal investors of changes in environmental management. It is statistically indistinguishable whether information disclosure is the first step towards improved environmental management, or simply a mechanism to signal investors of planned improvements in environmental management.

The models estimated in this manuscript provide insight into two possible pathways for improved environmental management. First, participating firms in the CDP reduced electricity output from power plants, suggesting that they replaced electricity production from dirty fossil fuel plants with production from alternative forms of electricity production. Second, there is evidence to suggest that firms did not switch between natural gas production and coal production. Emissions intensity from existing plants actually increased, and plants that participated in the CDP and increased their percentage of coal use did not reduce emissions more.

One possibility driving the ineffectiveness of mandatory information disclosure programs relates to the type of information provided and the manner in which it is disseminated. It seems increasingly important to design information disclosure programs that are transparent, that adapt information collection efforts to more effectively convey relevant and important information to stakeholders, and that disseminate those results to stakeholders. It is likely that the CDP – with downloadable and searchable records - performs this role better than state government agencies, which may not disseminate collected data.

These results bolster findings by Bae et al. (2010) who found that the manner in which information disclosure data are disseminated matters greatly. Some types of voluntary programs have been found to improve environmental outcomes. ISO 14001 certification, for example, requires that firm managers develop environmental management systems, which seems to translate into improved environmental compliance and performance. In contrast, CDP surveys or carbon reporting data may be handled by public relations, public affairs, or stakeholder relations units, rather than being handled by those who make decisions regarding capital investments for efficiency upgrades, fuel use, or other strategic initiatives. It seems unlikely that filling out a CDP survey leads to improvements in environmental performance; however, participating in the CDP may be a mechanism of signaling investors that attention is being paid to environmental performance, and participation may be part of a broader effort to improve environmental behavior.

7. Conclusions and directions for future research

This research, when placed in the context of the information disclosure literature, highlights the importance of not just collecting data from firms, but that the dissemination efforts and types of information collected may be highly important as well.

This research also emphasizes the limitations of information disclosure. The state reporting requirements had no impact on either carbon intensity or total carbon emissions. Results from the Carbon Disclosure Project suggest that voluntary environmental disclosure programs may help a firm signal the market of improved environmental behavior. However, plants owned by CDP participants increased their carbon intensity in comparison to plants owned by non-participating firms, suggesting that there may be efficiency losses associated with overall decreases in CO_2 emissions.

While information disclosure programs, product labeling, and improving transparency have been hailed as market-friendly ways to improve environmental behavior without imposing costly regulations, it seems unlikely that lessons from toxics can be applied to carbon. While toxic emissions are an unpriced liability risk, carbon emissions do not share these similar traits, and carbon emissions are directly linked to electricity output. The failure of state reporting requirements to produce changes in carbon dioxide emissions suggests that consumers may not be responsive to carbon disclosure. If carbon dioxide emissions are to be reduced, the design of programs must link information disclosure to consumer decision-making.

An important role for information disclosure and mandatory reporting requirements may be in conjunction with other policy tools, or to prepare for eventual mandatory carbon regulation. By collecting carbon emissions data, it is easier to project costs and benefits associated with cap-and-trade or with a carbon tax system. Further, this type of information is useful if permits are to be allocated in an eventual cap-and-trade program.

Finally, future research can go beyond binary participation data and seek to correlate environmental behavior with outcomes. Both of the information disclosure programs studied in this manuscript and in much of the other cited literature are studied with dichotomous variables indicating program participation. Future research should seek to link internal firm behavior and more detailed disclosure information to environmental performance.

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Appendix A

See Table A1

Appendix B

See Table B1

Table A1
State reporting mandates versus the Carbon Disclosure Project: fixed effects model, effect of participation on Log(CO_2 emissions) (metric tons).

	State reporting-all	State reporting-all	State reporting-pub	State reporting-pub	CDP	CDP
Program participation	−0.625**	−0.457**	−0.120	−0.378**	−0.253**	−0.947***
	(0.253)	(0.176)	(0.265)	(0.181)	(0.0997)	(0.213)
Program participation* coal		0.175		0.723***		1.085***
		(0.274)		(0.199)		(0.204)
Program participation * NG		0.421		0.187		0.376
		(0.349)		(0.306)		(0.239)
Coal Pct		2.858***		0.940***		1.810***
		(0.936)		(0.288)		(0.387)
NG Pct		0.0126		0.654**		1.234***
		(0.339)		(0.276)		(0.300)
Publicly traded	0.318	0.0367				
	(0.306)	(0.130)				
State electricity restructuring	0.0838	−0.0666	0.109	0.0327		
	(0.304)	(0.145)	(0.260)	(0.129)		
Sierra club membership per 10,000 capita	0.0427	0.0271	0.0313	0.0588	−0.351**	−0.322***
	(0.117)	(0.0512)	(0.162)	(0.110)	(0.144)	(0.108)
Total state energy programs	0.0234	0.00436	−0.0189	−0.0123	0.443***	0.385**
	(0.0142)	(0.00462)	(0.0178)	(0.00931)	(0.170)	(0.169)
Energy consumption per capita	0.00158	0.000535	0.00187	−0.000436	−0.00661	−0.00573
	(0.00176)	(0.000927)	(0.00184)	(0.000833)	(0.00879)	(0.00647)
Firm revenue	−0.0334	0.00182	−0.00964	0.0311**	−0.00220	−0.00173
	(0.0492)	(0.0110)	(0.0409)	(0.0147)	(0.00164)	(0.00132)
Constant	11.50***	10.84***	12.33***	11.65***	0.0227**	0.0227**
	(0.847)	(0.608)	(1.317)	(1.013)	(0.00932)	(0.00888)
Observations	2033	1969	1798	1763	13,487	13,246
R-squared	0.010	0.081	0.008	0.057	0.027	0.059

* Represents significance at the α=.1 level.
** Represents significance at the α=.05 level.
*** Represents significance at the α=.01 level.

Table B1
State reporting mandates versus the Carbon Disclosure Project: fixed effects model, effect of participation on CO_2 intensity (MWh/CO_2).

	State reporting-all	State reporting-all	State reporting-pub	State reporting-pub	CDP	CDP
Program participation	0.0122	−0.0757	−0.00389	−0.126	0.0732**	0.110
	(0.0442)	(0.149)	(0.0498)	(0.172)	(0.0337)	(0.121)
Program participation* coal		0.113		0.173		−0.0633
		(0.176)		(0.198)		(0.118)
Program participation * NG		0.100		0.165		0.0196
		(0.203)		(0.235)		(0.161)
Coal Pct		0.212**		0.0788		−0.209
		(0.105)		(0.162)		(0.349)
NG Pct		−0.506***		−0.588***		−1.020**
		(0.0858)		(0.136)		(0.494)
Publicly traded	−0.0489	−0.0295				
	(0.0418)	(0.0385)				
State electricity restructuring	−0.0109	−0.0242	−0.0138	−0.0265	0.0558**	0.0445**
	(0.0332)	(0.0311)	(0.0318)	(0.0286)	(0.0242)	(0.0200)
Sierra club membership per 10,000 capita	−0.0311	−0.0301	−0.0245	−0.0212	−0.0547	−0.0500
	(0.0257)	(0.0253)	(0.0237)	(0.0238)	(0.0438)	(0.0363)
Total state energy programs	−0.00225	−0.000382	−0.00185	−0.000184	−0.00538	−0.00381
	(0.00140)	(0.000973)	(0.00210)	(0.00176)	(0.00493)	(0.00522)
Energy consumption per capita	0.000126	0.000267	−5.68e−05	0.000156	−0.000299	−0.000432
	(0.000273)	(0.000236)	(0.000287)	(0.000250)	(0.000683)	(0.000813)
Firm revenue	−0.00187	−0.00224	−0.00112	−0.00210	−0.000757	−0.00103
	(0.00521)	(0.00521)	(0.00511)	(0.00516)	(0.00172)	(0.00171)
Constant	1.272***	1.254***	1.161***	1.276***	1.412***	1.838***
	(0.242)	(0.277)	(0.218)	(0.260)	(0.379)	(0.665)
Observations	1944	1944	1745	1745	13,055	13,055
R-squared	0.005	0.036	0.004	0.040	0.003	0.016

* Represents significance at the α=.10 level.
** Represents significance at the α=.05 level.
*** Represents significance at the α=.01 level.

Table C1
State reporting mandates versus the Carbon Disclosure Project: fixed effects model, effect of participation on log (electricity output) (MWh).

	State reporting-all	State reporting-all	State reporting-pub	State reporting-pub	CDP	CDP
Program participation	−0.688***	−0.634***	−0.143	−0.473**	−0.184*	−0.702***
	(0.249)	(0.159)	(0.240)	(0.189)	(0.0958)	(0.159)
Program participation* coal		0.378		0.409		0.824***
		(0.253)		(0.247)		(0.150)
Program participation * NG		0.744**		0.524*		0.325*
		(0.306)		(0.296)		(0.193)
Coal Pct		2.561***		2.370***		1.813***
		(0.926)		(0.754)		(0.484)
NG Pct		0.561*		1.123***		1.341***
		(0.336)		(0.342)		(0.251)
Publicly traded	0.300	−0.0157				
	(0.303)	(0.102)				
State electricity restructuring	−0.0251	−0.159	0.0627	−0.0631	−0.335**	−0.257**
	(0.298)	(0.112)	(0.241)	(0.105)	(0.157)	(0.116)
Sierra club membership per 10,000 capita	−0.00299	−0.0208	0.0311	0.0852	0.203***	0.117***
	(0.116)	(0.0406)	(0.152)	(0.0980)	(0.0566)	(0.0328)
Total state energy programs	0.0301**	0.00698	−0.0149	−0.00780	−0.00109	−0.000604
	(0.0144)	(0.00425)	(0.0158)	(0.00627)	(0.00852)	(0.00588)
Energy consumption per capita	0.00109	7.41e−05	0.00197	−0.00104	−0.00247*	−0.00153**
	(0.00179)	(0.000904)	(0.00202)	(0.000916)	(0.00130)	(0.000704)
Firm revenue	−0.0277	0.00863	−0.0139	0.0309**	0.0175**	0.0151***
	(0.0513)	(0.0100)	(0.0427)	(0.0141)	(0.00717)	(0.00451)
Constant	12.00***	11.40***	12.51***	10.84***	11.96***	11.44***
	(0.833)	(0.568)	(1.225)	(0.976)	(0.438)	(0.404)
Observations	2015	1951	1780	1745	13,354	13,113
R-squared	0.012	0.114	0.007	0.076	0.014	0.093

* Represents significance at the α=.10 level.
** Represents significance at the α=.05 level.
*** Represents significance at the α=.01 level.

Appendix C

See Table C1

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