Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

The Judgment of Garbage: End-of-Pipe Treatment and Waste Reduction

Nilanjana Dutt, Andrew A. King

MANAGEMENT SCIENCE
Vol. 60, No. 7, July 2014, pp. 1812–1828
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)
http://dx.doi.org/10.1287/mnsc.2013.1827

The Judgment of Garbage: End-of-Pipe Treatment and Waste Reduction

Nilanjana Dutt
Department of Management and Technology, Bocconi University, 20136 Milan, Italy,
nilanjana.dutt@unibocconi.it

Andrew A. King
Tuck School of Business at Dartmouth, Hanover, New Hampshire 03755,
andrew.a.king@dartmouth.edu

Many scholars have argued that systems for treating waste impede organizations from preventing waste in the first place. They theorize that end-of-pipe (EOP) treatment diminishes the incentive to avoid creating waste in the production process and obscures the information necessary to devise prevention techniques. This prediction has been widely accepted, influencing both policy and practice, despite both a lack of supporting empirical evidence and the existence of a counterprediction. In this paper, we use data describing U.S. manufacturing establishments from 1991 to 2005 to test the connection between EOP treatment and waste reduction. Our findings show that EOP treatment is associated with an initial jump in reported waste, followed by ongoing reduction. We analyze these results by exploring mechanisms that may drive this relationship. For practitioners, our paper provides critical guidance about strategies for reducing waste. For scholars of environmental management, our paper provides new insight on when facilities accomplish "source reduction" of process waste. For broader management theories of operations and organizational design, our analysis provides new insight on boundary conditions for extrapolation from existing theories. Finally, our paper provides new guidance for the formulation of effective regulatory policy.

Keywords: waste treatment; environmental management; operations design
History: Received November 20, 2010; accepted June 10, 2013, by Christian Terwiesch, operations management. Published online in *Articles in Advance* January 27, 2014.

1. Introduction

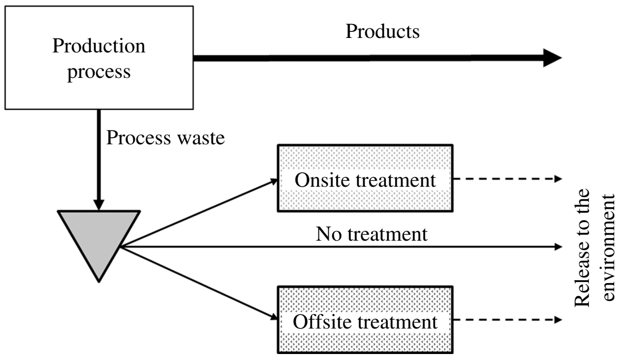
For more than 20 years, authorities have predicted that waste treatment is antithetical to waste prevention. Evidence of this sentiment can be found in the statements of chemical executives (Avila and Whitehead 1993), government reports (U.S. Government Accountability Office 1997, Office of Technology Assessment 1994), and influential articles on the negative impact of regulations that require waste treatment (Porter and van der Linde 1995). Among scholars, Clelland et al. (2000, p. 118) provide a pointed summary of the prediction: "Firms heavily dependent on nonproductive, end-of-pipe means of reducing pollution ... are likely to be foregoing the indirect operational-efficiency benefits provided by WMPs [waste-minimization practices]."

End-of-pipe (EOP) treatment refers to any waste management system that processes, before discharging to the environment, waste produced by a production process (Office of Technology Assessment 1986). The visual image is of waste processing equipment in a manufacturing facility that is sited literally at the end of a pipe containing waste material (Figure 1). EOP treatment typically is accomplished with one or a combination of three methods: burning, recycling, and chemical treatment. In many cases, some value is recovered in the form of energy or useful materials, but in all cases the total recovered value is less than the total cost of processing.[1] Firms often adopt EOP treatment systems because they can be implemented relatively easily, without disrupting ongoing production processes (Cebon 1992, King 1995b).

Scholars have drawn from ideas in the context of lean production to advance two predictions that cast EOP treatment in a negative light. The first prediction suggests that EOP treatment diminishes both workers' awareness of waste and their ability to identify wastes' root causes. Because of its location at the end of the production system, EOP treatment separates the observation of waste from its creation and thereby reduces workers' ability to eliminate waste (MacDuffie 1997, Rothenberg et al. 2001, King and Lenox 2001). The second prediction is that by giving

[1] The U.S. Environmental Protection Agency separates secondary products from waste by means of this distinction.

Figure 1 **A Stylized Operation**



Notes. The production process produces both products and process waste. The process waste may be treated onsite, offsite, or (most commonly) not at all before being released into the environment. In our analysis, we measure yearly changes in the creation of *process waste* as our dependent variable. We measure *onsite* and *offsite* treatment as key independent variables, and we measure the amount of chemical *products* output as a control variable.

operations personnel the opportunity to treat waste and fix mistakes ex post, EOP treatment reduces incentives to eliminate waste ex ante (Rothenberg et al. 2001, Sharma 2001). Both critiques of EOP treatment suggest that facilities that continue to use EOP treatment will be less likely to reduce waste at the source and should experience lower waste reductions over time (Hart 1995, Rondinelli and Berry 2000).

However, nascent evidence across several fields suggests a counterprediction for the effect of EOP systems on waste reduction. We combine research on quality management (Flynn et al. 1994) that suggests data collection, measurement, and analysis could enable waste reduction, with empirical case studies on EOP systems that highlight EOP treatment's ability to provide the necessary data and analytical context (Pil and Rothenberg 2003). Building on these ideas, we argue EOP treatment systems allow facilities to uncover "sticky information" useful to understanding the causal links between production systems and waste creation (Rothenberg 2003). In doing so, we build on a few case studies that have found evidence that EOP treatment can be associated with process improvements that reduce waste (King 1995a, 1999; Pil and Rothenberg 2003).

In this paper, we test these two contrasting predictions by using data from the U.S. Environmental Protection Agency (EPA). Empirical difficulties inherent in this research have prevented prior studies from systematically testing the association between EOP treatment and process waste reduction (Sarkis and Cordeiro 2001). We overcome many problems of measurement and identification by using detailed, chemical-level production data and a differences-in-differences analysis. We reduce the effect of bias from endogenous choice by using a matched-pairs analysis and numerous fixed effects.

Our results show that the use of EOP treatment is associated with a dramatic initial increase in reported process waste followed by a substantial and prolonged reduction of waste. We infer that EOP treatment causes facilities both to measure waste more accurately and to identify ways to reduce waste. We test our findings by conducting robustness checks and by exploring mechanisms that could link EOP use and waste reduction.

2. Theory and Hypotheses

2.1. EOP Treatment and Detrimental Impacts on Waste Reduction

Rothenberg et al. (2001, p. 230) cogently summarize the prevailing perspective on EOP treatment systems: "pollution control technologies and management practices, which treat or dispose of pollutants or harmful by-products at the end of the manufacturing process ... are not 'value-added' and as such have been associated with worse manufacturing performance." Klassen and Whybark (1999, p. 601) argue that there are two "dominant approaches to environmental management ... proactive pollution prevention, which relies on strategic resources and thereby can deliver sustainable competitive advantage, and reactive pollution control, which cannot impart competitive advantage." The argument is made even more starkly in Sharma (2001, p. 10): "Significant change, it just won't happen ... for an existing process in which waste is managed as an end-of-pipe fact."

If EOP treatment systems are detrimental to waste reduction and other process improvements, why do firms adopt them in the first place? Scholars have arrived at an explanation by drawing on organizational theory that predicts managers will tend to pick the least disruptive response to new requirements (Galbraith 1974, Thompson 1967). According to this logic, EOP treatment is an attractive solution for managers, because although such systems can be financially costly to install and operate, they do not usually require disturbance of existing operations (Ashford and Heaton 1983, Cebon 1992). Indeed, to prevent firms from taking this easy way out, some scholars have suggested that government regulation should be stringent enough to discourage the use of EOP systems (Kemp 2000). Porter and van der Linde (1995, p. 100), for example, criticize "relatively lax regulation [which] can be dealt with incrementally and without innovation, and often with 'end-of-pipe' or secondary treatment solutions."

Criticisms of EOP systems have also drawn inspiration from ideas of lean production (Corbett and Klassen 2006, Kleindorfer et al. 2005), which argue that slack resources can reduce the accuracy and timeliness of information about process problems (MacDuffie and Helper 1997). Noting the functional similarity between EOP systems and rework operations, scholars have extrapolated central ideas from lean production to develop a set of ideas that describe effective "green" management (Theyel 2000, King and Lenox 2001). The main logic of the resulting argument is illustrated by a diagram familiar to many MBA students: a cutaway image of a lake showing high water (representing slack resources such as excess inventory) hiding sharp rocks (representing process problems). The message of the illustration is that inventory and rework systems (and by extension, EOP systems) are like the high water, keeping boats on the lake from running into jagged rocks but also allowing hidden problems to go uncorrected. More precisely, the logic is that EOP treatment is analogous to using a rework station to correct defects in production. Using these systems impedes operational improvement by separating, in time and space, the result of a problem (waste or product defect) from its origin (MacDuffie and Helper 1997, Staats et al. 2011). Inspired by the analogy between lean and green management, scholars have explored an empirical connection between the adoption of lean production and green management practices (King and Lenox 2001, Florida 1996).

A second criticism of the use of EOP treatment systems is that they reduce workers' incentives to prevent waste at the source (Clelland et al. 2000, Rothenberg et al. 2001). One logic for this argument is that acquiring waste treatment equipment onsite (or through an ongoing contract with a waste handler) reduces the marginal cost of producing waste and discourages efforts to keep waste in check. Policy makers in particular are concerned with the potential for such a "rebound effect."[2] A second logic for the incentives argument is that EOP treatment impedes the *administration* of efficient incentives. Efforts toward waste prevention are usually unobservable, and this can make it difficult to either reward workers for engaging in "source reduction" or penalize them for not doing so. EOP systems can exacerbate this problem because they provide an alternative to preventing waste at the source. The logic of the argument closely follows a model developed by Alles et al. (2000) for "yield improvement." In their model, actors have incentives both to meet production requirements and to improve yield or reduce waste. Because improvement efforts are relatively less observable, there is a tendency for workers to shirk such work unless strict limits are set for yield or waste. Alles et al. (2000, p. 1529) observe that because "tight constraints ... make it impossible for output targets to be attained using standard production techniques ... workers are forced to work *smarter*." Following this logic, Sharma (2001) argues that by removing constraints and allowing ex post correction of waste, EOP systems reduce incentives to decrease process waste. Knowing that EOP treatment is available, workers tend to focus on hitting their production targets and have little incentive to reduce waste.

Hypothesis 1 (H1). *End-of-pipe treatment of waste will be associated with lower rates of waste reduction.*

2.2. EOP Treatment and Information Benefits for Waste Reduction

Although a negative perception of EOP treatment has dominated thinking among scholars and practitioners, a minority perspective has emerged to explain both case study evidence of EOP personnel initiating waste reduction and related research focusing on benefits of data collection, measurement, and analysis. This counterperspective again has an analogy in the operations literature, in this case to theories of quality management. Quality management, defined as "an approach to achieving and sustaining high quality output" (Flynn et al. 1994, p. 339), refers to a broad set of practices focused on the use of information and analysis to engender process improvements (Fine 1986, Samson and Terziovski 1999). According to Benson et al. (1991), better measurement of important quality indicators allows for more refined identification and rectification of process problems. Their research integrates organizational elements with operations management to demonstrate that access to better information through data collection, measurement, and analysis is an essential component of operational improvement. If EOP treatment causes more careful analysis of waste material, it could potentially reduce waste, especially when compared with a counterfactual case where waste is released to the environment without examination. Consistent with this perspective, a number of different studies of waste management suggest that EOP treatment may actually increase attention to waste, speed identification of the root cause of waste, and hasten waste reduction.

A handful of empirical case studies illustrate some possible benefits from EOP treatment. In an example of one of these case studies, King (1995a) reports that personnel running EOP systems initiated more than a third of the identified process improvements. In a separate study of automobile assembly plants, Rothenberg (2003) finds that specialist environmental personnel contributed to more than 35% of the process changes leading to waste reduction. This evidence lends support to a contrasting perspective on EOP treatment systems: EOP systems operate not like "slack resources" or "buffers" but more like process

[2] An example of the rebound effect among consumer goods is when regulation causes consumers to buy more fuel-efficient cars, but the same consumers then drive more miles (Binswanger 2001).

quality sensors, revealing information about waste that would otherwise go unnoticed.

How does EOP treatment provide operations personnel with relevant data on process quality? Although typical quality monitoring methods such as statistical tracking and measurement can reveal changing waste levels and provide valuable information about process changes (Corbett and Klassen 2006), such data are inherently delayed by the need for aggregation and statistical comparison. EOP systems, evidence suggests, can provide faster feedback in some cases. For example, Pil and Rothenberg (2003, p. 414) report that, in auto assembly facilities, "employees in the water treatment facility discussed how changes in the chemistry of the water treatment system reveal when and how the paint process is not operating optimally ... [and] because of their access to this data, environmental staff could catch paint process problems before paint shop staff." Similarly, King (1995b, p. 275) reports that managers in electronics fabrication facilities report using waste treatment operations "to diagnose problems in the upstream process ... personnel told me that if the water in the treatment process turned blue, it meant that chelate copper was leaking from one of the pumps in production."

Extending the argument, King (1995b, 1999) and Rothenberg (2003) argue that EOP operations may also reduce the cost of obtaining process health information. Drawing on ideas of sticky information, they argue that waste treatment operations may actually provide advantageous locations for uncovering information about process health. Sticky information, according to von Hippel and Tyre (1996), is costly to obtain, and its cost varies by location and context. King (1995b) proposes that waste treatment systems can reduce the cost of detecting changes in process health and thus become, as Spear (2002, p. 754) suggests, an "embedded diagnostic test" of production health. As a result, waste treatment operators can become, according to process engineers, "a second pair of eyes and ears" (King 1995b, p. 273). If feedback from EOP systems indeed provides operators with relevant information that would otherwise be overlooked, learning theories predict there will be an association between EOP use and process improvement. Scholars in the learning literature have observed, for example, that experience-based learning works better when operators observe the defects immediately following their creation (Jaber and Guiffrida 2008, Li and Rajagopalan 1998).

Rothenberg (2003) argues further that the rich information available to operators of EOP systems supplies valuable contextual knowledge necessary for process improvement. She concurs with previous research on lean production that emphasized the knowledge of line workers because they "know their jobs better than anyone else," but she argues that such knowledge is insufficient for some types of process improvement (p. 1792). For such improvement, she argues, "contextual knowledge is a critical aspect of the learning process" (p. 1792). Environmental personnel, she contends, are particularly likely to acquire such contextual and "interorganizational" knowledge through the course of their work because the problems they face involve multiple locations and operations.

In summary, consistent with core principles of quality management, the above studies of waste production highlight three benefits of using EOP treatment: improved observation, quicker access to data, and expedited problem diagnosis. The need for a direct test of the effect of EOP treatment is further reinforced by evidence from two related studies. First, based on a study of cross-sectional data, Sarkis and Cordeiro (2009, p. 1167) find that "Plants with scrubber technology in place seem to be significantly and positively correlated with technical efficiency." Second, Lee et al. (2011, p. 1251) find that command and control regulation requiring EOP emissions in the auto industry led to important technological innovations; they conclude that concerns about such regulation are "based on a particular premise that may not be general" and call for more empirical research on the topic.

Thus, case studies and initial research across several fields suggests that EOP systems might support waste reduction by providing an embedded diagnostic test that uncovers data that had previously gone unexamined—either through a lack of attention or because it was too "sticky" to extract. Principles of quality management suggest that such diagnostic information would then lead to more rapid identification of and correction of the causes of waste.

Hypothesis 2 (H2). *End-of-pipe waste treatment will be associated with higher rates of waste reduction.*

3. Data and Methods

3.1. Data and Sample

Our sample consists of manufacturing facilities drawn from the population of U.S.-based producers operating during 1991–2005. We collected data from the EPA's Toxics Release Inventory (TRI) database (King and Lenox 2001, 2002; Terlaak and King 2006). Published annually by the EPA since 1987, the TRI includes 612 chemicals routinely used by production facilities. There are limitations to the TRI data: only facilities that manufacture, store, or use more than a threshold level of these chemicals (from less than 1 pound to 25,000 pounds, depending on the chemical) and employ 10 or more full-time people during the year are required to complete TRI reports. This censored sample may limit the generality of our

Table 1 Descriptive Statistics for Total Sample

Variable	Mean	Std. dev.	1	2	3	4	5	6	7
1 *Change in waste*	−2.996	107.020	1.000						
2 *Onsite processing*	0.383	0.486	−0.049	1.000					
3 *Off processing*	0.536	0.499	−0.057	−0.025	1.000				
4 *Recent EMS activity*	0.218	0.413	−0.008	0.078	0.122	1.000			
5 *ISO 14000*	0.020	0.138	0.000	−0.001	0.003	−0.007	1.000		
6 *Tenure tech*	3.351	3.468	0.003	−0.008	0.003	−0.023	0.026	1.000	
7 *Tenure cert*	2.308	2.557	0.001	−0.017	−0.011	−0.024	0.033	0.317	1.000
8 *Change in production*	−1.137	45.036	0.144	0.003	−0.005	0.008	0.004	−0.005	−0.005
Demeaned coefficients $\Delta X_{ict} = X_{ict} - \bar{X}_{ic}$									
1 *Change in waste*	−1.732	102.940	1.000						
2 *Onsite processing*	0.010	0.204	−0.042	1.000					
3 *Off processing*	0.013	0.238	−0.048	−0.025	1.000				
4 *Recent EMS activity*	0.011	0.241	−0.009	0.078	0.122	1.000			
5 *ISO 14000*	−0.002	0.096	−0.002	−0.001	0.003	−0.007	1.000		
6 *Tenure tech*	0.056	2.386	−0.002	−0.008	0.003	−0.023	0.026	1.000	
7 *Tenure cert*	0.076	1.934	−0.003	−0.018	−0.011	−0.023	0.032	0.317	1.000
8 *Change in production*	−1.333	39.049	0.170	0.004	−0.006	0.008	0.005	−0.004	−0.004

Note. The number of observations is 677,809.

findings, but our analytical methods should reduce the propensity for biased coefficients. We chose not to include years after 2005 because in 2006 the EPA switched to reporting based on the North American Industry Classification System (NAICS) instead of Standard Industrial Classification (SIC) codes. From the TRI database, we created an unbalanced longitudinal panel data set covering 31,221 manufacturing facilities operating during the years from 1991 to 2005. These facilities reported a median of four chemicals, yielding 126,673 facility–chemical and 677,809 facility–chemical–year observations. Table 1 reports descriptive statistics for the sample.

TRI data is self-reported, but the EPA can assess a civil penalty of up to $25,000 per violation of TRI reporting requirements. Some scholars have found that, in spite of this penalty, TRI reports include errors caused by the use of formulas, estimates, and partial measurements (Marchi and Hamilton 2006). The EPA conducted its own assessments of sectors and found that 95% of facilities interpreted the threshold requirements properly and that facilities "correctly identified release and other waste management activities that were occurring" (EPA 1996, p. 13).

Whereas other researchers have used TRI waste data aggregated to the facility level, we are the first to analyze waste levels separately for each chemical reported by a facility. Our approach provides important empirical advantages, including more precise controls for changes in production output and a more precise estimate of waste reduction. Analysis at the chemical level also enables us to use both facility plus year fixed effects to control for facility-level changes such as new management and chemical plus year fixed effects to control for changing cost of chemicals, disposal, and so on.

Some cleaning was required to make the TRI data more suitable for use. Most problematic was the "production ratio" intended to capture year-to-year changes in unit outputs. Respondents are supposed to report the decimal ratio of production levels, in units, for the current year relative to the previous year. For example, for an output of 110 units in year t relative to 100 units in year $t-1$, respondents should report 1.1 (110/100). A few users report these numbers improperly as, for example, 10 (for a 10% increase) or 110 (1.1 in percentage form). Many such errors can be captured by looking for negative numbers (which are not possible if the reporting is done correctly) or missing decimal points (1.1 has a decimal point, but 10 and 110 do not) or by comparing reporting patterns across multiple reports filed by the same individual. (For example, if a report contains a 13 and three instances of 1.3, a reporting error has likely occurred.) The large amount of data to be checked required us to create a computer program that inspected each data point for a decimal, looked for similarities among the chemicals reported by the same person in the same facility in the same year, and examined historical reporting patterns. We corrected observations we inferred to be misreported.

To identify the reports made by individual technical and certifying officers, we wrote another computer program to match last and first names, and hand checked for spelling mistakes by inspecting all reports in which names were different but had a large number of overlapping letters.

To gauge facility size, which we employ to identify comparable facilities, we used the National Establishment Time Series (NETS) database to acquire information on the number of employees at each facility. These data, originally gathered by Dun &

Bradstreet (D&B), are distributed under contract by NETS to research scholars at a discounted rate. Under contract from several researchers, NETS matched its data to the EPA's TRI for the years from 1991 to 2005 and then checked the matches using both computer programs and human matching.

3.2. Measures

3.2.1. Dependent Variables. *Change in waste*. Our main dependent variable is the degree to which a facility reduces the volume of each waste chemical generated by the production process (see "process waste" in Figure 1). We measure change in waste as year-to-year changes in waste levels before a facility receives the EOP treatment.[3] *Change in waste* is measured as the log of the ratio of the pounds of waste generated in the next year (year $t+1$) divided by the waste generated in the current year (year t). The log form is commonly used in analysis of production changes because it diminishes the effect of extreme values while maintaining approximate linearity around the mode (Kesavan et al. 2010). For moderate changes in the sample, our measure can be interpreted as approximating the percentage change in waste (e.g., $\ln(1.1/1.0) = 0.095 \cong 10\%$). To allow interpretation of our coefficients as an approximation of percentage changes in the dependent variable, we multiply the ratio by 100, calculated as follows:

$$\textit{Change in waste} = \Delta Y_{cit} = 100 * \left\{ \ln\left(\frac{W_{cit}}{W_{cit-1}}\right)\right\}, \quad (1)$$

where ΔY_{cit} is the change in waste in pounds for a particular chemical c, for a particular facility i, for year t relative to year $t-1$.

Source reduction activities and sources. For our analysis of the mechanism of process change, we used the source reduction activity fields from the TRI. The source reduction activity fields record the methods that facilities use to reduce waste at its "source." We divided the changes into three types: "management modifications," "technology modifications," and "input modifications."[4] We also collected the reports for whether or not these modifications were suggested by a regulator, a vendor, or an employee. We dichotomized each of these to indicate that in this year, for this chemical, an activity of this type occurred. For example, if the report for facility j in year t for chemical i disclosed an activity we categorize as a management modification, our binary variable received the value of 1; otherwise it would be 0.

In total, we calculated three types of changes (management modifications, technology modifications, input modifications) and three types of sources (employee, regulator, or vendor). The variable *suggestion from employees* takes a value of 1 if the change is attributed to "participative team management" or "employee recommendation (independent of a formal company program)"; *suggestion from a vendor* takes a value of 1 if the change is attributed to "vendor assistance."

Predicted change in waste. In further analysis, we evaluated whether managers anticipate future changes in waste levels. As part of normal TRI reporting, managers are asked to forecast each chemical's waste generation for the following year; we created a similar ratio to assess predictions:

$$\textit{Predicted waste change} = P\Delta Y_{cit} = 100 * \ln\left(\frac{PY_{cit}}{Y_{cit-1}}\right), \quad (2)$$

where PY_{cit} is the prediction for waste in pounds (Y) for a particular chemical c, for a particular facility i, for year t. The prediction is made in year $t-1$.

3.2.2. Independent Variables. To capture the effect of different sorts of EOP treatment, we coded multiple dummy variables for each treatment and its timing relative to its first reported use. Waste is typically released to the environment (the most common fate), treated onsite by the generating facility, or treated offsite by a contractor. We coded different dummies for onsite and offsite treatment.

Onsite treatment. We estimated onsite EOP treatment for each chemical at each facility with a dummy variable (0 for no onsite treatment and 1 for some onsite treatment). We also created time dummies to mark years relative to this change. For a facility that first reported processing a chemical in 1995, for instance, 1994 is marked as the year before the change, and 1996 as the year after it. These dummies enable us to estimate trends in the years before and after EOP treatments are adopted. For facility–chemical combinations where EOP treatment was used, discontinued, and then used again, we marked the time dummies relative to the most proximate case.

Offsite treatment. We measured facilities that use offsite EOP treatment similarly with a dummy variable (0 for no offsite treatment and 1 for some offsite treatment) and time dummies to mark years relative to this change.

[3] To correct for changes in waste caused by output changes, we included a measure of production changes as a right-hand-side variable in our empirical analysis.

[4] Specifically, we used the following codes for management modifications: W13, W14, W19, W21, W22, W23, W24, W25, W29, W31, W32, W36, W39, W54, W55, W63, W64; technology modifications: W33, W35, W51, W52, W53, W59, W60, W65, W66, W67, W68, W71, W72, W73, W74, W75, W78, W81, W82, W83, W89; and input modifications: W41, W42, W49, W58, W61. For details, see EPA (2006, p. 59).

Placebo treatments. To facilitate comparison of each treated chemical in a facility with its matched control chemical and facility, we created a set of "placebo" treatments for the control pair that parallels actual events at the paired treated facility (e.g., if a treated facility added onsite waste treatment of a particular chemical in 1995, we created a placebo treatment in that year for the same chemical at the matched facility). We used this placebo treatment to make time dummies in the same manner as for actual treatments.

3.2.3. Control Variables. We used facility–chemical fixed effects (discussed further in the analysis section) to reduce the potential for unobserved facility or chemical attributes to bias our results, and we created a series of control variables to capture other possible and important changes in a facility or for a chemical in a facility that could affect waste reduction.

Production output change. To account for changes in waste occasioned by changes in output, we created a variable that captures, for each line of operation (as reported for each chemical in a facility), the log ratio of production output in years t and $t-1$. Reporting the ratio of units in production (p_t/p_{t-1}) for the production line that produced or used each chemical is required by the TRI. Reporting 1.1 indicates a 10% increase, and reporting 0.9 indicates a 10% decrease, in the units of production in year t relative to year $t-1$. As previously discussed, we cleaned the data to remove mistakes in reporting:

$$\textit{Production output change} = 100 * \ln\left(\frac{P_{cit}}{P_{cit-1}}\right). \quad (3)$$

ISO 14000. The International Organization for Standardization (ISO) grants ISO 14000 certification to organizations that "identify and control environmental impact, improve environmental performance continually and in accordance with ISO auditors, [and] implement goals and objectives with respect to achieving better environmental performance" (ISO 2011). Because facilities with ISO 14000 certification might be predisposed to waste reduction, this variable is coded 1 if a facility was ISO 14000 certified in a given year, and 0 otherwise. Facilities certified once are assumed to maintain that certification in future years.

Environmental management system (EMS). Waste reduction might be greater at facilities with an EMS, defined by the EPA as "a framework that helps a company achieve its environmental goals through consistent control of its operations" (EPA 2011, p. 1). We followed the standard practice of inferring the existence of an EMS when a facility reports a waste management modification attributable to such a framework. Because an EMS sometimes falls into disuse, we created a dummy variable that measures whether or not a firm has reported in the last three years source-reduction activities attributable to an EMS. This variable is coded 1 in the presence of such a report, and 0 otherwise.

Tenure of technical personnel. The tenure of the personnel responsible for waste monitoring and reduction might influence the rate of waste reduction. To estimate this, we created a variable that measures how long (in years) a technical officer has been completing the TRI form for a particular chemical at a particular facility.

Tenure of certifying personnel. Because waste reduction might be influenced by the tenure of the managers responsible for it, we created a variable that codes the tenure (in years) of the manager who signs and certifies the accuracy of the TRI form for a particular chemical at a particular facility.

3.3. Empirical Strategy

This paper tests two theories of the effect of EOP treatment on waste reduction in production processes. Identifying the effect of EOP treatment is made more difficult by the fact that the choice to treat a particular chemical is neither random nor exogenous. Managers *choose* how to handle waste material, and some unobserved attribute might jointly explain the choice to use an EOP system and to incur future waste reduction. For example, new management in a facility might embark on a program to jointly reduce pollution by adopting EOP systems and by rewarding waste reduction. Alternatively, a change in chemical prices might cause more EOP recycling and less waste. To identify the independent effect of EOP treatment on waste reduction, we must disentangle it from the effect of the endogenous choice. We employ three strategies to meet this challenge.

3.3.1. Reducing Bias from Fixed Facility or Chemical Attributes. First, to reduce potential bias from unobserved facility attributes that might jointly influence both the choice to use EOP treatment and reduce waste, we employ differencing and fixed effects at the chemical and facility levels. We use first-difference estimates to remove the effect of unobserved constant attributes for each chemical in each facility. More formally, we specify models where the change in waste levels (ΔY_{cit}) is a function of the use of EOP (EOP_{cit-1}), the change in production (ΔP_{cit}), and a set of changing attributes (Z_{cit-1}) (e.g., a change in the individual reporting the chemical) for each chemical c, facility i, and year t. To remove the effect of fixed facility and chemical attributes on waste trends, we also specify a set of constant fixed effects for each chemical in each facility (μ_{ci}):

$$\Delta Y_{cit} = \beta EOP_{cit-1} + \beta \Delta P_{cit} + \beta Z_{cit-1} + \mu_{ci} + e_{cit}. \quad (4)$$

3.3.2. Using Matched Controls to Reduce Bias. Differencing and fixed effects reduces the potential for bias from fixed facility attributes that might jointly explain the choice to use EOP and waste reduction. However, changing facility attributes could still cause bias. To help reduce bias from these attributes, we used coarsened exact matching (CEM) to find a control (or placebo) case comparable in attributes and trends to each "treated" case where EOP processing was added. The goal of matching is to try to find control observations that so closely match the treated ones it is as if a real randomized experiment had been run (Simcoe and Toffel 2013). According to Iacus et al. (2012), CEM better corrects for endogenous treatments than do other methods, such as propensity score matching, because CEM matches on all sample moments of the treated and placebo groups does not require a separate procedure to restrict data to common support and does not affect the imbalance of other variables not used in matching. CEM also meets the congruence principle because it uses only observed data (not imputed or extrapolated data) in forming matches.

CEM either creates categories based on exact values or it coarsens each variable into categories into which each observation is then placed. If the measured categories for a treated case match all of those for a nontreated case, a potential match has been found (Iacus et al. 2012). For our study, we required matches to have *exactly* the same regulatory region, industry, and chemical, and we required at least a *coarsened* match for levels and trends for waste, waste reduction, and facility size. Each match m links a particular chemical–facility combination to its matched pair. Our matching enables us to estimate either the coefficients on placebo changes or to estimate differences across the matched pair:

$$\Delta Y_{mt} - \overline{\Delta Y}_m = \beta(EOP_{mt-1} - \overline{EOP}_m) + \beta(\Delta P_{mt} - \overline{\Delta P}_m) + \beta(Z_{mt-1} - \bar{Z}_m) + \varepsilon_{mt}. \quad (5)$$

3.3.3. Using Nonparametric Facility and Chemical Trends to Reduce Bias. Unfortunately, matching techniques, no matter how sophisticated, are only as good as the matches they identify. To test the robustness of our results to an alternative method of correcting bias, we also specified models saturated with temporal fixed effects designed to capture individual facility and chemical trends. In these analyses, we specified fixed effects for each chemical–year combination, facility–year combination, and both together. These specifications should remove the effect of unobserved facility-level or chemical-level shocks that might influence both EOP use and waste reduction. For example, these dummies will capture the effect of a change in management or a change in chemical prices, which might cause both more EOP use and less waste. Unfortunately, although powerful, this method is prone to type II error because all coefficient estimates must be based on differences in EOP use among chemicals within a facility. If EOP use is added to all chemicals in the same year, this method will fail to find any effect, even if a true one were to exist.

3.4. Procedure for Matching Treated and Control Groups

We used CEM (described above) to disentangle the effects of endogenous facility attributes that could influence both adoption choice and waste reduction. We matched each instance of EOP adoption for a particular chemical at a facility to a case where EOP was not adopted for that same chemical at a similar facility. We first identified eight covariates that characterize important attributes of chemicals and facilities. For a feasible match, we required exact correspondence for three of these variables (chemical, industry (SIC 4), and EPA region). For the remaining five variables, we required approximate matches. These "coarsened" variables were the number of employees at a facility, the waste (log pounds) for the chemical, an exponentially smoothed measure ($\alpha = 0.5$) of waste in previous years, the changes in the waste relative to the previous year, and an exponentially smoothed measure ($\alpha = 0.5$) of waste reduction (or increase) in previous years.

We created separate matched pairs for cases of EOP onsite treatment and EOP offsite treatment. This process yielded matched groups of 8,861 data points for onsite EOP treatment and 6,295 for offsite EOP treatment. Missing data in our measure of the number of employees led to matched groups with employment figures for 7,336 and 4,774 matches for onsite and offsite treatment, respectively. Table 2 reveals that using CEM dramatically reduces differences between the treated and control groups; after matching, the means of the treated and control groups are not significantly different.

4. Results

4.1. Pretreatment/Posttreatment Analysis

Table 3 reports coefficient estimates for six models specified as in Equation (4). For these analyses, we use not just the matched pairs but the entire sample of TRI facilities available for matching. Model 1 shows the results for a model that includes only the control variables. The coefficients appear to make intuitive sense. EMS systems and ISO 14000 certifications are associated with meaningful reductions in waste. Production increases are associated with increases in waste (a 1% increase in units of product output leads to an approximately 0.45% increase in waste). We also find greater

Table 2 Descriptive Statistics for Effect of Matching Treatment and Control Groups

	All not treated onsite	Treated onsite	Control onsite	All not treated offsite	Treated offsite	Control offsite
Change in waste (smoothed)	0.036	−0.126	−0.111	0.034	−0.070	−0.067
	(0.910)	(0.907)	(0.871)	(0.915)	(0.536)	(0.524)
Change in waste (t)	0.021	−0.139	−0.105	0.020	−0.068	−0.063
	(0.991)	(1.037)	(0.928)	(0.996)	(0.559)	(0.541)
Waste level (smoothed)	0.106	−0.104	−0.095	0.108	−0.333	−0.318
	(0.966)	(0.859)	(0.876)	(0.964)	(0.863)	(0.872)
Waste (t)	0.108	−0.135	−0.118	0.110	−0.342	−0.325
	(0.968)	(0.877)	(0.884)	(0.966)	(0.854)	(0.861)
Employment	0.103	−0.130	−0.114	0.107	−0.493	−0.488
	(1.010)	(0.957)	(0.903)	(1.009)	(0.823)	(0.804)
Production change	−0.017	−0.054	−0.061	−0.017	−0.067	−0.063
	(0.798)	(0.774)	(0.829)	(0.798)	(0.796)	(0.787)
N	700,986	8,861	8,861	705,837	6,295	−0.070
N (with employees)	600,387	7,336	7,336	605,257	4,774	−0.493

Notes. "Smoothed" indicates that the value was created using exponential smoothing ($\alpha = 0.5$). Matching on both level and smoothed values was used to ensure that values and trends were similar for control and treated group. Employment is the log number of FTEs. Because levels and changes are chemical dependent, all values were normalized by chemical year before matching. All variables used in matching are not statistically different ($p < 0.1$) for treated and control groups. The "all" sample is larger than the one used in the main regressions because matches were not limited by presence of other variables.

experience with TRI oversight tasks (*Tenure cert*) to be associated with future waste reduction.

Models 2–4 include our independent variables that capture the effect of adding onsite or offsite EOP treatment. Waste falls by approximately 16% per year after onsite treatment is added (Model 2) and by approximately 13% per year after offsite treatment is added (Model 3). Model 4 confirms these results considering

Table 3 Analysis of Full Sample

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE
Onsite treatment		−15.923***		−15.667***	−14.827***	−15.525***
		(0.338)		(0.336)	(0.380)	(0.341)
Offsite treatment			−12.978***	−12.726***	−12.528***	−12.461***
			(0.298)	(0.295)	(0.298)	(0.316)
Onsite × Offsite already					−3.445***	
					(0.726)	
Offsite × Onsite already						−1.679*
						(0.721)
Onsite added (t)		102.497***		100.307***	100.269***	100.712***
		(0.871)		(0.864)	(0.864)	(0.881)
Offsite added (t)			68.820***	67.041***	67.598***	67.023***
			(0.656)	(0.649)	(0.660)	(0.649)
Active EMS	−2.483***	−1.874***	−1.992***	−1.405**	−1.412**	−1.405**
	(0.514)	(0.508)	(0.509)	(0.503)	(0.503)	(0.503)
ISO 14000	−4.096***	−3.713***	−3.451***	−3.092**	−3.116**	−3.094**
	(1.295)	(1.280)	(1.282)	(1.267)	(1.267)	(1.267)
Tenure tech	−0.081	−0.040	−0.070	−0.030	−0.030	−0.030
	(0.055)	(0.054)	(0.054)	(0.053)	(0.053)	(0.053)
Tenure cert	−0.294***	−0.267***	−0.272***	−0.246***	−0.247***	−0.246***
	(0.068)	(0.068)	(0.068)	(0.067)	(0.067)	(0.067)
Production output change	0.451***	0.448***	0.449***	0.446***	0.446***	0.446***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
F	1,244.138	2,024.800	1,870.552	2,515.678	2,402.429	2,401.591
R^2	0.030	0.054	0.050	0.072	0.072	0.072

$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

both changes simultaneously. Models 5 and 6 show the estimated marginal effect when one type of treatment (onsite/offsite) is added to a chemical already undergoing the other type of EOP treatment (offsite/onsite). Model 5 shows that adding onsite treatment for a chemical already being treated offsite affords a facility an additional 3.5% reduction in waste each subsequent year. Adding offsite treatment for a chemical already being treated onsite yields an additional improvement of 1.5% reduction in waste in each subsequent year. Our models also show that EOP treatment provides meaningful explanatory power to the model. The "within" R^2 changes by 2% when one treatment is added and by 4% when both are added. This increase in explanatory power is remarkable given that only 24% of chemicals in the sample experience a change in EOP status during the sample, and thus only about 15% of the observations follow the addition of EOP. In summary, the results in Table 3 provide support for H2: EOP treatment is associated with greater reductions in waste generated by production processes.

Models 2–6 in Table 3 all reveal a dramatic increase in reported waste in the year treatment is first used. To confirm that only this one year was anomalous, we estimated coefficients for every year before and after EOP processing was applied to a given chemical. As Figures 2(a) and 2(b) demonstrate, waste reduction is small before EOP use (the 95% confidence interval often includes zero). Then, in the first year of EOP processing, there is a dramatic increase in reported waste. Thereafter, waste reductions are substantial and stable for many years.

We did not anticipate the dramatic jump in reported waste when a facility initially applied EOP processing to a given waste chemical. This jump might occur because facilities are generally unaware of the amounts of waste they generate and tend to optimistically assume their facilities are cleaner than reality. Or facilities may generally be aware of how much waste they generate but do not feel the need to reveal the true amount to regulators under the assumption that they are not held accountable for knowing these exact amounts in the absence of an EOP system. To find out which of these two explanations may be true and why facilities experience this jump in reported waste, we contacted practitioners with extensive experience with both onsite and offsite processing. Their common interpretation was that plants had not previously understood how much waste they generated. Vicor Corporation Environmental Health and Safety manager Ed Gomes explained: "I think that after the fact [use of onsite treatment] they are getting better numbers.... Tanks and chemistry all have to be calibrated, so you have to know what you start with if you are going to do the treatment. It is not a guess.

Figure 2(a) Effect of Onsite Treatment on Change in Waste

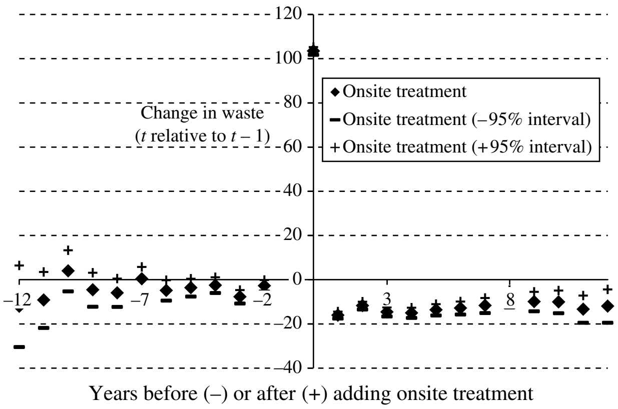
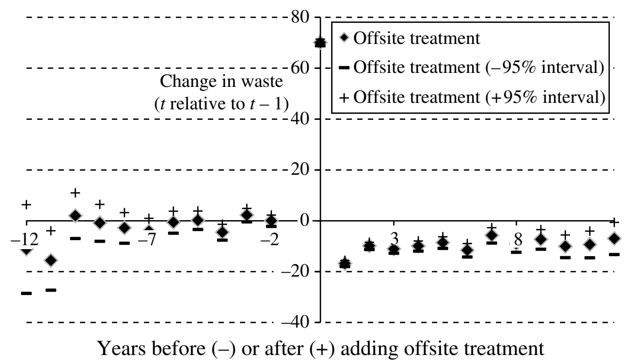


Figure 2(b) Effect of Offsite Treatment on Change in Waste



It is 'this is a 100 gallon tank and I did it seven times a week, so I know exactly how much I treated' " (Gomes 2012). With respect to offsite processing, Paul Ligon, vice president of development at Casella, concurred: "You don't know what you don't know if you haven't been carefully tracking volumes. That's part of what we help them [manufacturers] with" (Ligon 2012). These interpretations are consistent with predictions from the information theory of waste treatment, which forms the basis for H2: Waste that is not treated is not well measured nor is its composition and cause well understood.

Given the possibility that reports prior to the adoption of EOP processing are based on faulty numbers, we conducted a number of tests to ensure that our results were not simply driven by reporting errors. For example, we limited the sample to just those cases where adding an onsite or offsite system resulted in only a small (nonstatistically significant) increase in reported waste. Even for these cases, process waste decreased by 5% for onsite (and 4% for offsite) per year following use of EOP. We infer from this that EOP use is associated with greater waste reduction even when previous accounting of waste was accurate.

4.2. Accounting for Endogenous Choice

The decision to use EOP processing for a particular chemical is endogenously chosen, and this choice process might bias our results. For example, new management in a facility might choose to increase the use of EOP processing and simultaneously reward workers for waste reduction. If so, our coefficient estimates might incorrectly attribute the effect of this management initiative to the use of EOP processing. We addressed this concern by (1) identifying a control group and (2) saturating our models with additional time-varying fixed effects.

After we found a matched control for each case in which EOP processing was initiated, we marked these control observations with a placebo treatment and then conducted additional empirical tests. We first performed a simple analysis of pretreatment/posttreatment waste reduction for the treated and control groups. Models 1 and 2 in Table 4 report the coefficient estimates for this specification and both reveal strong waste reduction for the real treated group, and the control group actually experiences waste gains. Models 3 and 4 in Table 4 show the results of analyses directly comparing the treated and control groups (see Equation (5)). Results shown in Model 3 suggest that a treated facility experiences an 18%-per-year reduction in waste relative to the control facility after onsite treatment is added. Model 4 suggests that the treated facility experiences a 15%-per-year

Table 4 **Comparison of Treated and Control Groups**

	Parallel comparison		Cross-match comparison	
	Model 1	Model 2	Model 3	Model 4
	Onsite	Offsite	Onsite	Offsite
	Coef./SE	Coef./SE	Coef./SE	Coef./SE
Onsite treatment	−14.680*** (0.677)	−13.599*** (0.880)	−18.371*** (0.789)	−16.164*** (1.165)
Onsite (*matched placebo*)	2.252** (0.770)			
Offsite treatment	−10.617*** (0.675)	−12.182*** (0.744)	−12.583*** (0.920)	−14.970*** (0.956)
Offsite (*matched placebo*)		4.985*** (0.845)		
Onsite added (*t*)	91.397*** (1.214)	96.226*** (1.813)	91.557*** (1.258)	97.130*** (1.982)
Onsite added (*t*) (*placebo*)	6.479*** (1.294)		6.636*** (1.342)	
Offsite added (*t*)	58.110*** (1.471)	54.370*** (1.266)	59.504*** (1.628)	54.415*** (1.376)
Offsite added (*t*) (*placebo*)		0.373 (1.375)		0.847 (1.470)
Active EMS	−0.456 (1.085)	−0.385 (1.303)	−0.17 (1.133)	0.056 (1.375)
ISO 14000	0.203 (3.121)	−2.344 (4.128)	0.033 (3.253)	−3.291 (4.346)
Tenure tech	0.036 (0.123)	0.045 (0.143)	0.023 (0.128)	0.074 (0.151)
Tenure cert	−0.306* (0.155)	−0.304 (0.176)	−0.276 (0.163)	−0.271 (0.187)
Production output change	0.439*** (0.008)	0.399*** (0.009)	0.438*** (0.008)	0.400*** (0.009)
N	131,299	82,232	131,299	82,232
N_g	9,336	6,647	9,336	6,647
F	571.987	366.790	569.294	362.710
R^2	0.091	0.093	0.093	0.096

Notes. Models 1 and 2 include fixed effects for each facility plus chemical. Models 3 and 4 include fixed effects for each facility plus chemical pair (treated and placebo). All models include fixed effects for years.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 5 Models with Year Fixed Effects at Facility and Chemical Level

	Facility plus year fixed effects			Chemical plus year fixed effects			Facility plus year and chemical plus year		
	All	Onsite	Offsite	All	Onsite	Offsite	All	Onsite	Offsite
	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE
Onsite treatment	−14.971***	−15.515***	−12.956***	−15.709***	−14.844***	−13.548***	−12.700***	−12.500***	−10.200***
	(0.656)	(1.552)	(2.825)	(0.485)	(0.671)	(0.912)	(0.540)	(0.842)	(1.241)
Onsite (matched placebo)		1.670			2.294***			−2.500***	
		(1.316)			(0.584)			(0.685)	
Offsite treatment	−11.312***	−9.421***	−11.198***	−13.059***	−10.884***	−12.357***	−9.08***	−8.700***	−9.000***
	(0.523)	(1.438)	(2.273)	(0.379)	(0.674)	(0.731)	(0.432)	(0.835)	(0.909)
Offsite (matched placebo)			4.190**			4.888***		0.541	0.541
			(1.597)			(0.595)		(0.719)	(0.719)
Onsite added (t)	104.814***	103.397***	98.794***	100.177***	90.863***	95.826***	105.270***	92.490***	91.400***
	(3.712)	(6.547)	(11.231)	(2.387)	(2.652)	(4.326)	(2.988)	(3.344)	(5.365)
Onsite added (t) (placebo)		7.407*			6.864***		3.600***	3.600***	
		(2.940)			(1.260)		(1.419)	1.419)	
Offsite added (t)	58.491***	58.427***	47.210***	67.100***	58.490***	54.092***		58.602	51.615
	(2.350)	(6.041)	(6.283)	(1.821)	(3.044)	(2.329)		(3.329)	(2.644)
Offsite added (t) (placebo)			1.949			0.580		−1.903	−1.903
			(3.445)			(1.316)		(1.416)	(1.416)
Active EMS				−1.242*	−0.077	−0.510			
				(0.624)	(1.212)	(1.545)			
ISO 14000				−2.812	1.193	−2.088			
				(1.440)	(3.204)	(4.516)			
Tenure tech	−0.524**	0.262	0.398	−0.007	0.057	0.070	−0.600***	0.044	−0.092
	(0.192)	(0.721)	(1.266)	(0.068)	(0.135)	(0.161)	(0.148)	(0.335)	(0.388)
Tenure cert	−0.366	−0.054	−0.174	−0.201*	−0.272	−0.233	−0.574**	−0.805	−0.756
	(0.246)	(1.121)	(1.460)	(0.085)	(0.175)	(0.183)	(0.185)	(0.452)	(0.500)
Production output change	0.451***	0.484***	0.381***	0.443***	0.436***	0.402***	0.400***	0.400***	0.440***
	(0.015)	(0.040)	(0.051)	(0.010)	(0.020)	(0.019)	(0.012)	(0.021)	(0.020)
N	677,809	131,299	82,232	677,809	131,299	82,232	677,809	131,299	82,232
F	394.797	65.833	26.175	645.371	201.411	147.833	578.207	188.389	134.641
R^2	0.470	0.562	0.701	0.082	0.125	0.133	0.068	0.108	0.113

Notes. R^2 include "absorbed" fixed effects. For the first three models, this is facility plus year. For all other models, it is chemical plus year.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

reduction in waste relative to the control after offsite treatment is added.[5]

Our matched-pair analysis further confirms support for H2 by reducing the potential for endogenous choice to bias our coefficient estimates. Yet, the accuracy of this method depends on the precision of the matching process. To further check for bias from endogenous choice, we specified models with time-varying chemical and facility effects that directly capture both observed and unobserved attributes that might influence the choice to use an EOP system and waste reduction. For example, new management in a facility might simultaneously increase the use of EOP treatment and waste reduction, or a change in chemical costs might encourage a contemporaneous increase in recycling and waste reduction. Our addition of fixed effects for each facility–year and chemical–year combination allow each facility and chemical to have a nonparametric waste trend, thereby removing bias from unobserved facility-level actions or chemical-level changes. As shown in Table 5, models using these specifications are consistent with our earlier results. These results show that whether or not we use facility–year fixed effects, chemical–year fixed effects, or both sets of fixed effects, we find evidence that both onsite and offsite EOP treatment experience is associated with less waste being generated in the course of production.

[5] Although we consider the two matches separately, we need to include onsite and offsite treatment effects in both models to account for the fact that the other type of EOP system might be added. Also note that when we limited the sample to the treated and control groups (all models in Table 4), the within R^2 increases to 9% despite the fact that half of the remaining observations still have no treatment (i.e., they are from the control group).

4.3. Analyzing the Mechanism of Action

The logic behind our two hypotheses (H1 and H2) differs diametrically on the effect of EOP use on information, awareness, and the generation of process improvement ideas. The prediction of the current dominant perspective expects EOP systems to reduce information about root causes of problems and decrease the incentive of employees to suggest or make changes. In contrast, the counterperspective predicts that EOP systems actually uncover important information about root causes.

To directly test these mechanisms underlying the predicted hypotheses, we conducted empirical analyses of additional data from the TRI. Respondents are asked to classify modifications to the production process that result in reduced process waste and the source(s) of the ideas that led to these changes. Table 6 shows the results of a logistic regression analysis predicting the existence of two sources for improvement and three types of modifications. As shown in Model 1, EOP treatment is associated with more frequent suggestions from employees, a finding that is consistent with our inference that EOP processing increases awareness of waste and information about its root causes. Note that vendor suggestions increased only when EOP was added onsite (Model 2). Based on our discussions with industry experts, we infer that these additional suggestions came from the vendor of the treatment equipment or chemistry. Coefficient estimates in Models 3–5 show that source reduction modifications generally increased after EOP treatment was added, further indicating that EOP treatment complements rather than substitutes for source reduction. We do not find a significant relationship between onsite treatment and input modifications. Here too industry experts offered an explanation; a treatment system's processing requirements sometimes restricts which chemicals can be used in the production process (Gomes 2012). Finally, across several models in the table we estimate negative and significant coefficients ($p < 0.05$) for the placebo control group for onsite EOP. The contrasting sign of these results reinforces and amplifies the effect of onsite EOP treatment.

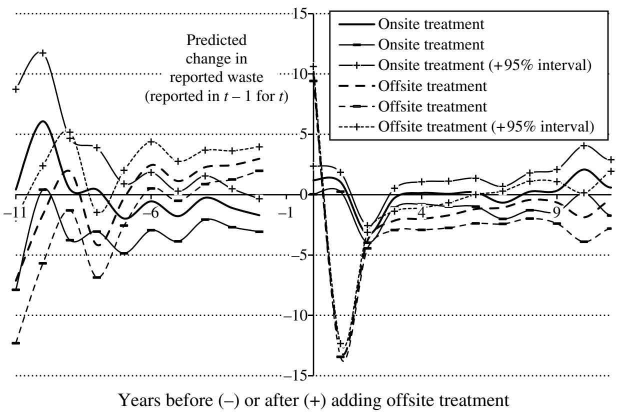
To better understand the mechanism of action and investigate a remaining concern about unobserved endogenous change, we also performed an empirical test to evaluate whether managers expected waste reductions following an EOP system's installation.

Table 6 Analysis of Mechanisms of Waste Reduction

	Model 1	Model 2	Model 3	Model 4	Model 5
	Suggestions from employees	Suggestions from vendors	Management modifications	Technology modifications	Input modifications
Onsite treatment	0.302***	0.195***	0.203***	0.461***	−0.037
	(0.029)	(0.044)	(0.028)	(0.029)	(0.046)
Offsite treatment	0.247***	0.034	0.185***	0.291***	0.326***
	(0.027)	(0.042)	(0.026)	(0.027)	(0.045)
Onsite (placebo)	−0.109*	−0.083	−0.105*	−0.092*	−0.137
	(0.045)	(0.071)	(0.043)	(0.046)	(0.072)
Offsite (placebo)	0.035	0.175	−0.074	−0.012	0.019
	(0.060)	(0.090)	(0.058)	(0.060)	(0.097)
Onsite added (t)	−0.020	−0.053	−0.041	0.111*	−0.163*
	(0.044)	(0.069)	(0.043)	(0.045)	(0.074)
Offsite added (t)	0.021	−0.063	−0.044	0.160***	0.052
	(0.038)	(0.059)	(0.037)	(0.038)	(0.063)
Onsite added (t) placebo	0.015	−0.038	0.004	0.045	0.022
	(0.064)	(0.103)	(0.061)	(0.064)	(0.098)
Offsite added (t) placebo	0.010	0.202	0.003	0.094	0.025
	(0.077)	(0.116)	(0.074)	(0.075)	(0.126)
ISO 14000	0.345***	−0.396***	−0.080	0.406***	0.403***
	(0.061)	(0.122)	(0.064)	(0.063)	(0.098)
Tenure tech	0.024***	0.033***	0.011***	0.018***	0.029***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Tenure cert	0.017***	0.027***	0.010***	0.030***	0.008
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
Production change	0.000	0.001	0.002	0.003	0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log-likelihood	−58,486.582	−25,194.582	−60,789.543	−57,976.235	−23,224.08
N	158,251	71,520	163,947	161,518	66,999
Facility plus chemical groups	19,008	8,901	19,539	19,137	8,433

Note. Includes fixed effects for each facility plus chemical and each year.
*$p < 0.05$; ***$p < 0.001$.

Figure 3 Managerial Predictions of Change in Waste



Research on goal setting and incentives clearly shows that new goals influence expectations of future performance (Heath et al. 1999). Thus, if managers anticipate future changes, one might surmise that new goals are partially responsible. In contrast, insight from new information is hard to predict; thus a failure to predict waste reductions is consistent with hypotheses that EOP systems increase information about process problems. To explore these two alternatives, we examined whether managers anticipated the effect of EOP systems by evaluating the predictions they made for waste reductions in the years subsequent to EOP adoption. Other than the substitution of predicted waste reduction for real reduction, the specification of the regression was the same as in Equation (4) using the same controls, fixed effects, and matching processes. We found no evidence that managers predicted sustained waste reductions following the adoption of onsite EOP treatment. As shown in Figure 3, the 95% confidence interval for the effect of added onsite treatment generally includes zero. In the case of offsite EOP treatment, however, managers did expect some waste reduction (4.5% for the first five years after adoption), but they predicted an amount that was less than half of the waste reduction that actually occurred (13%). According to a manager with more than a decade of experience in waste services, it is common practice for firms providing offsite EOP services to tell clients to expect some waste reduction (Ligon 2011).

In total, our analysis of the mechanism through which waste reduction occurs supports the logic for H2: EOP treatment (particularly if conducted onsite) leads to changes in the production process. These changes are often suggested by employees. Managers do not anticipate these improvements, suggesting that they result from new information or new insight rather than from a change in managerial goals.

4.4. Further Robustness Tests

Because our findings contradict the predictions of a commonly held theory, readers of our draft manuscript suggested numerous additional trials to fully validate our results. First, they suggested that financial strength might jointly explain both EOP-system use and waste reduction. To test this, we specified models including the D&B Paydex™ measure for each facility; this measure captures the degree to which the facility pays its bills on time. We also split the sample based on the mean of this measure. All tests confirmed the reported results.

The sudden increase in reported waste on first use of an EOP system raises issues that also required investigation. For example, our matched pairs are based on the reported waste levels before EOP use. Perhaps a better match would be based on the reported levels *after* first use. We created additional matched pairs and confirmed the sign and significance of the reported results.

We conjectured that it might be solely the jump in measured waste that explained subsequent waste reduction and that, shocked by the realization of the real level of waste, managers might work harder to reduce waste. To test this, we limited the sample to just those cases where adding an onsite or offsite system resulted in an insignificant increase in reported waste. Even in these facilities, EOP use was associated with waste reduction of 5% and 4% per year (onsite and offsite, respectively).

Finally, one might wonder whether our results are contingent on facility, chemical, or regulatory differences. To test this, we split the sample into (1) facilities with and without emissions permits,[6] (2) toxic versus less-toxic chemicals, and (3) regulated versus less-regulated chemicals. The sign and significance of our reported results were confirmed in all cases. That the coefficient estimates are, in fact, slightly *stronger* for less-regulated facilities and lower-toxicity chemicals suggests that regulation may cause awareness and attention to process waste, which substitutes for that occasioned by EOP treatment.

4.5. Limitations

There are a number of limitations to this study. First, we must not forget that using EOP treatment is an endogenous choice and that some unobserved variable might cause both EOP use and waste reduction. Despite all of our efforts, it remains possible that an unobserved change for a particular chemical in a given facility could influence both the use of EOP processing and the subsequent waste reduction, thereby biasing our results. Because of the endogenous choices made by managers, in spite of our best efforts, it is impossible to entirely remove all sources of bias.

[6] Even if otherwise regulated, many facilities still need to file a TRI report.

Second, TRI reports are required only from facilities that use more than a threshold amount of a listed chemical and employ 10 or more full-time people during the calendar year. This sample selection skews the data set toward facilities of a certain size and restricts the TRI to about 50% of the U.S. manufacturing base.

Finally, because all of these data are self-reported, it is possible that reporting errors could bias our results. Indeed, we suspect that, for some facilities, waste levels prior to the first use of EOP systems were reported inaccurately. Although our robustness tests reduce our concern in this regard, we hope in future research to develop a means of evaluating the accuracy of the reports.

5. Discussion and Conclusions

Drawing on theories of organizational design and operations management, scholars have posited that the use of EOP treatment will be associated with a decreased ability to identify waste-producing process problems and reduced incentives to correct these problems (Clelland et al. 2000, Ghassemi 2002, Hart 1995). This perspective has greatly influenced the literature on environmental management and prompted calls for more stringent government regulation to reduce the use of EOP treatment (Ashford and Heaton 1983, Porter and van der Linde 1995). Yet, despite this prediction's importance to both research and practice, it has not been well tested empirically. Our research explores the underlying logic of this theory and also synthesizes a rival perspective based on principles of quality management and evidence from empirical case studies on the effect of EOP. Viewed from this rival perspective, EOP systems help managers collect, measure, and analyze data about process; these new data then initiate process improvements that reduce waste at its source.

Empirically, we addressed previous measurement difficulties by using more refined data and by incorporating methods that limit the effect of unobserved attributes and endogenous choice. Specifically, we measured waste changes separately for each waste chemical (or compound) produced in a facility. Analyzing changes at the chemical level allowed us to incorporate several types of fixed effects to reduce the influence of unobserved variables. We also accounted for endogenous choice by saturating the models with fixed effects and by conducting a differences-in-differences analysis employing a set of matched pairs identified through coarsened exact matching.

Our results show that the addition of EOP treatment to a particular chemical stream in a factory is associated with an initial increase in reported waste, followed by a dramatic and sustained reduction. We infer that the use of EOP treatment increases information about waste and that this increase in information leads personnel to, first, recognize the full extent of the waste a facility generates and, second, undertake ongoing waste reduction. To verify this conjecture, we explored mechanisms that mediate the effect of using EOP systems on process improvement. We find that when EOP treatment is added for a particular chemical, suggestions from employees and vendors increase and more technology and management modifications are made. We show that managers do not anticipate waste reductions associated with the use of onsite EOP treatment and only partially anticipate those for offsite EOP treatment. All of these results are consistent with the prognosis that using EOP treatment increases information about process problems leads to better identification of the root cause of process waste and the correction of these problems.

For the literature on environmental management, our paper provides a startling refutation of one of its central predictions. It also suggests the need for renewed evaluation of a counterperspective—that EOP systems allow for the retrieval of sticky information and thereby facilitate problem identification and process improvement. Our results also raise fundamental challenges to existing theories of how firms develop effective environmental management practices. Previous studies have tended to view EOP systems as part of a reactive stage that must be supplanted by the development of source reduction (waste reduction) activities. Our data suggests that the use of EOP systems in fact *predicts* waste reduction. Previous studies have emphasized the role of planned, top-down development of environmental orientation. Our results suggest that important source reductions may also be an unanticipated outcome of EOP treatment systems.

For researchers seeking to apply ideas and frameworks from organization design and operations management, our research suggests the need for great care in extrapolating predictions from one area to another. Systems that seem functionally similar may not influence outcomes in the same way. Unobserved differences in processes, in initial conditions, and in alternatives can all diminish the predictive power of the transferred analogy. Specifically, our results suggest a need for caution when extending concepts from lean production to new domains. Among the many areas that have borrowed ideas from lean production, environmental management has been one of the most active. Many scholars have imported predictions from lean production by making an analogy between inventory and rework systems in lean production and EOP systems in environmental management. Yet our research suggests that in one important respect, this type of reasoning by analogy leads to inaccurate conclusions. First, the analogy may be wrong; for example rework and EOP systems, although superficially analogous, may not be sufficiently similar. Second, the starting point (or the base case) might be different. For example, systems at the end of a process may impede and delay existing sources of feedback, or they might actually provide a means of measuring process problems where none had previously existed. In hindsight, it appears that a more correct analogy may have been between EOP systems and inspection systems proposed by quality management theories. The difficulty of knowing which analogy is correct ex ante suggests both the need for care when drawing analogies and the need for deeper empirical analysis to understand exactly how the analogy should be applied.

Identifying how firms respond to changing environmental demands is an important issue for management scholars, practitioners, policy makers, and society as a whole. Evaluating how firms respond to new challenges also allows testing of the specific predictions and general applicability of theories of organizational design and operations management. In this paper, we clarify and test two important predictions about the effect of EOP treatment on waste reduction and reveal how firms adapt to growing demands to reduce their impact on the natural environment. For policy makers and managers, our paper identifies potential benefits of policies designed to encourage careful monitoring of process waste, including a higher level of involvement from vendors selling products to manufacturing facilities and the facilities' own employees. Most importantly, our research suggests that policy makers should be cautious in designing regulation that prevents or discourages EOP treatment.

Acknowledgments
The authors thank department editor Christian Terwiesch, one anonymous associate editor, and three anonymous reviewers for their valuable guidance. Adam Kleinbaum, Daniel Feiler, Jordan Tong, Ashish Arora, Brian Tomlin, Rob Shumsky, Ken Baker, and Bill Simpson provided the authors with additional feedback and guidance. The authors also received useful comments during seminars at the London Business School in 2010, the Academy of Management Meeting in 2010, the Strategic Management Society Meeting in 2010, and the Alliance for Research on Corporate Sustainability Conference in 2011.

References
Alles M, Amershi A, Datar S, Sarkar R (2000) Information and incentive effects of inventory in JIT production. *Management Sci.* 46:1528–1544.

Ashford NA, Heaton GR Jr (1983) Regulation and technological innovation in the chemical industry. *Law and Contemporary Problems* 46:109–157.

Avila JA, Whitehead BW (1993) What is environmental strategy? *McKinsey Quart.* 4:53–68.

Benson PG, Saraph JV, Schroeder RG (1991) The effects of organizational context on quality management: An empirical investigation. *Management Sci.* 37:1107–1124.

Binswanger M (2001) Technological progress and sustainable development: What about the rebound effect? *Ecological Econom.* 36:119–132.

Cebon PB (1992) 'Twixt cup and lip organizational behaviour, technical prediction and conservation practice. *Energy Policy* 20:802–814.

Clelland IJ, Dean TJ, Douglas TJ (2000) Stepping towards sustainable business: An evaluation of waste minimization practices in US manufacturing. *Interfaces* 30(3):107–124.

Corbett CJ, Klassen RD (2006) Extending the horizons: Environmental environmental excellence as key to improving operations. *Manufacturing Service Oper. Management* 8:5–22.

Fine CH (1986) Quality improvement and learning in productive systems. *Management Sci.* 32:1301–1315.

Florida RL (1996) Lean and green: The move to environmentally conscious manufacturing. *Calif. Management Rev.* 39: 80–105.

Flynn BB, Schroeder RG, Sakakibara S (1994) A framework for quality management research and an associated measurement instrument. *J. Oper. Management* 11:339–366.

Galbraith JR (1974) Organization design: An information processing view. *Interfaces* 4(3):28–36.

Ghassemi A (2002) *Handbook of Pollution Control and Waste Minimization* (Marcel Dekker, New York).

Gomes E (2012) Personal correspondence with authors, March 30.

Hart SL (1995) A natural-resource-based view of the firm. *Acad. Management Rev.* 20:986–1014.

Heath C, Larrick RP, Wu G (1999) Goals as reference points. *Cognitive Psych.* 38:79–109.

Iacus SM, King G, Porro G (2012) Causal inference without balance checking: Coarsened exact matching. *Political Anal.* 20:1–24.

International Organization for Standardization (ISO) (2011) ISO 14000—Environmental management. Accessed January 9, 2014, http://www.iso.org/iso/home/standards/management-standards/iso14000.htm.

Jaber MY, Guiffrida AL (2008) Learning curves for imperfect production processes with reworks and process restoration interruptions. *Eur. J. Oper. Res.* 189:93–104.

Kemp R (2000) Technology and environmental policy: Innovation effects of past policies and suggestions for improvement. *Innovation and the Environment* (OECD, Paris), 35–61.

Kesavan S, Gaur V, Raman A (2010) Do inventory and gross margin data improve sales forecasts for U.S. public retailers? *Management Sci.* 56:1519–1533.

King A (1995a) Avoiding ecological surprise: Lessons from long-standing communities. *Acad. Management Rev.* 20:961–985.

King A (1995b) Innovation from differentiation: Pollution control departments and innovation in the printed circuit industry. *IEEE Trans. Engrg. Management* 42:270–277.

King A (1999) Retrieving and transferring embodied data: Implications for the management of interdependence within organizations. *Management Sci.* 45:918–935.

King A, Lenox MJ (2001) Lean and green? An empirical examination of the relationship between lean production and environmental performance. *Production Oper. Management* 10:244–256.

King A, Lenox MJ (2002) Exploring the locus of profitable pollution reduction. *Management Sci.* 48:289–299.

Klassen RD, Whybark DC (1999) The impact of environmental technologies on manufacturing performance. *Acad. Management J.* 42:599–615.

Kleindorfer PR, Singhal K, Van Wassenhove LN (2005) Sustainable operations management. *Production Oper. Management* 14:482–492.

Lee J, Veloso FM, Hounshell DA (2011) Linking induced technological change, and environmental regulation: Evidence from patenting in the U.S. auto industry. *Res. Policy* 40:1240–1252.

Li G, Rajagopalan S (1998) Process improvement, quality, and learning effects. *Management Sci.* 44:1517.

Ligon P (2011) Personal correspondence with authors, November 11.

Ligon P (2012) Personal correspondence with authors, October 16.

MacDuffie JP (1997) The road to "root cause": Shop-floor problem-solving at three auto assembly plants. *Management Sci.* 43:479–502.

MacDuffie JP, Helper S (1997) Creating lean suppliers: Diffusing lean production through the supply chain. *Calif. Management Rev.* 39:118–151.

Marchi SD, Hamilton JT (2006) Assessing the accuracy of self-reported data: An evaluation of the toxics release inventory. *J. Risk Uncertainty* 32:57–76.

Office of Technology Assessment (1986) *Technology, Public Policy, and the Changing Structure of American Agriculture*, Vol. NTIS PB86-184637 (U.S. Government Printing Office, Washington, DC).

Office of Technology Assessment (1994) *Industry, Technology and the Environment: Competitive Challenges and Business Opportunities*, Vol. OTA-ITE-586 (U.S. Government Printing Office, Washington, DC).

Pil FK, Rothenberg S (2003) Environmental performance as a driver of superior quality. *Production Oper. Management* 12:404–415.

Porter ME, van der Linde C (1995) Toward a new conception of the environment-competitiveness relationship. *J. Econom. Perspect.* 9:97–118.

Rondinelli DA, Berry MA (2000) Corporate environmental management and public policy—Bridging the gap. *Amer. Behavioral Scientist* 44:168–187.

Rothenberg S (2003) Knowledge content and worker participation in environmental management at NUMMI. *J. Management Stud.* 40:1783–1802.

Rothenberg S, Pil FK, Maxwell J (2001) Lean, green, and the quest for superior environmetal performance. *Production Oper. Management* 10:228–243.

Samson D, Terziovski M (1999) The relationship between total quality management practices and operational performance. *J. Oper. Management* 17:393–409.

Sarkis J, Cordeiro JJ (2001) An empirical evaluation of environmental efficiencies and firm performance: Pollution prevention versus end-of-pipe practice. *Eur. J. Oper. Res.* 135:102–113.

Sarkis J, Cordeiro JJ (2009) Investigating technical and ecological efficiencies in the electricity generation industry: Are there win-win opportunities? *J. Oper. Res. Soc.* 60:1160–1172.

Sharma HC (2001) Role of pollution prevention in waste management/environmental restoration. Ghassemi A, ed. *Handbook of Pollution Control and Waste Minimization*, Vol. 8 (CRC Press, Boca Raton, FL), 9–30.

Simcoe T, Toffel MW (2013) Government green procurement spillovers: Evidence from municipal building policies in California. Working paper, Harvard Business School, Boston.

Spear SJ (2002) The essence of just-in-time: Embedding diagnostic tests in work-systems to achieve operational excellence. *Production Planning and Control* 13:754–767.

Staats BR, Brunner DJ, Upton DM (2011) Lean principles, learning, and knowledge work: Evidence from a software services provider. *J. Oper. Management* 29:376–390.

Terlaak A, King A (2006) The effect of certification with the ISO 9000 Quality Management Standard: A signaling approach. *J. Econom. Behav. Organ.* 60:579–602.

Theyel G (2000) Management practices for environmental innovation and performance. *Internat. J. Oper. Production Management* 20:249–266.

Thompson JD (1967) *Organizations in Action* (McGraw-Hill, New York).

U.S. Environmental Protection Agency (EPA) (1996) *1996 Toxic Release Inventory: Data Quality Report* (EPA Office of Pollution Prevention and Toxics, Washington, DC).

U.S. Environmental Protection Agency (EPA) (2006) *Toxic Chemical Release Inventory Reporting Forms and Instructions—Revised 2005 Version* (EPA Office of Pollution Prevention and Toxics, Washington, DC). http://www2.epa.gov/sites/production/files/documents/ry2005rfi.pdf.

U.S. Environmental Protection Agency (EPA) (2011) *2012 Environmental Management Systems (EMS)* (EPA Office of Pollution Prevention and Toxics, Washington, DC).

U.S. Government Accountability Office (GAO) (1997) Environmental protection: Challenges facing EPA's efforts to reinvent environmental regulation. Office GA, ed., Vol. GAO/RCED-97-155 (U.S. Government Printing Office, Washington, DC).

von Hippel E, Tyre MJ (1996) The mechanics of learning by doing: Problem discovery during process machine use. *Tech. Culture* 37:312–329.