Clean Technology, Regulation and Government Intervention: The Australian Experience

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Abstract

This study assesses the impact of an Australian government clean energy plan and a related grant program on the manufacturing industry by using a production function approach to decompose a facility's change in emission into components corresponding to change in energy usage, a sector-wide technological change, and the additional impact of the program. The study also tests whether exposure to facilities that receive the grant encourages the adoption of clean technologies elsewhere. The results point to about 10% emission reduction as part of a sector-wide shift to cleaner technologies which is fully associated with the introduction of a carbon pricing scheme in Australia. The grant program has had mixed effects and mostly small recipient facilities manage to reduce emission intensity beyond the average. The estimates also reveal that exposure to the program mostly affects firms where production is geographically concentrated.

Keywords: Carbon Emission, Carbon Pricing, Clean Technology, Technology Adoption, Climate Change, Public Policy.

JEL Codes: D22, H23, L6, Q54.

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1 Introduction

Urging reduction in carbon emission while counting the economic impact of switching to cleaner technology has been part of a long standing policy debate (See Nordhaus & Boyer, 1999; Stern, 2008; Tol, 2009, for instance). Governments in different countries have adopted a combination of regulation and taxation together with subsidies and assistance programs to accelerate the move to cleaner technologies while reducing the cost to private companies of compliance (Andrews, 1994). Whether such package of measures is effective lays with the understanding of how firms are responding to those regulations and how the response from firms receiving assitance differs from the average.

In 2011, the Australian government followed a similar path by the introduction of Clean Energy Future Plan (Clean Energy Act, 2011). The centerpiece of this policy was a carbon pricing scheme that came into effect in July 2012 and was later terminated in 2014 by the succeeding administration. Under this scheme, emission producers had to pay a set price for each tonne of carbon emission or the equivalent (Jotzo, 2012).

The other elements of the plan constituted initiatives to finance research in green technology and to facilitate switching to cleaner technology or renewable energy sources among Australian businesses. These programs were intended to allow businesses to switch to cleaner technologies while retaining their competitiveness relative to international competitors that might not be burdened by similar regulations. One of these programs that is the focus of this study is the Clean Energy Investment Program (codenamed CleanTech). The program provides financial incentives to manufacturing activities in order to encourage investment in cleaner and more efficient technologies and capital equipment. The incentives are in the form of grants that pay up to half the value of the proposed undertakings. The projects take place in designated facilities (i.e. locations) that could be part of a larger parent firm.

In this paper, I investigate whether the introduction of the carbon pricing scheme led to any significant reduction in emission intensity – i.e. the volume of emission per unit of energy consumed. I also examine whether the change in emission intensity among facilities receiving CleanTech is any different from that in other facilities, either within the same parent firm or in general. On one hand, one expects that the availability of government funding to these facilities prompts larger emission reductions than a similar facility but without CleanTech.

On the other hand, these facilities could be representing a selected group of businesses not competitive enough to carry out emission reduction without government's assistance, and their ability to reduce emission is likely to be marked down as a result of this selection. I use a dataset of CleanTech projects matched to a national database of facilities' report on energy consumption and emission to test these hypotheses.

The quantitative approach entails decomposing the change in a facility's emission into components that pertain to the change in energy usage, change in the sector-wide emission technology and the impact of CleanTech above and beyond the sector-wide technological shift. For this purpose, I model the emission technology as a production function with time-varying parameters, where the function takes energy consumption as input and generates emission as output. The change in emission between two time points can then be decomposed into the change in energy consumption keeping production function fixed plus the change in production function while keeping energy consumption fixed. A log-linear specification develops that can be estimated by Ordinary Least Squares (OLS). I then use the estimated coefficients to predict the contribution of each factor in reducing emissions within a facility with a special focus on the role of sector-wide technology and CleanTech.

I apply the decomposition technique to the change in emissions from 2011 (before the policies are introduced), to 2014 (the last year of carbon pricing scheme). The findings point to a remarkable 9.7 per cent drop in emissions among manufacturing facilities over this period caused by a sector-wide shift to cleaner and less emission intensive technology. In absolute terms, the change corresponds to more than 11.2 megatonnes of savings in carbon emission or the equivalent per year in the manufacturing sector. A 0.8 per cent technology-related increase in emission can be detected for the period 2009 to 2011, suggesting that the more recent trend is fully associated with the enactment of the carbon pricing scheme as the most important climate-related regulation during this period. In fact, assuming that the latter trend would have continued in the absence of carbon pricing scheme, the full contribution of the scheme is estimated at 10.5 per cent reduction in emissions. This evidence especially resonates with the finding of (O'Gorman & Jotzo, 2014) where they estimate an 8.2 per cent reduction in the emissions generated by electricity sector over a similar period.

The effectiveness of CleanTech in reducing emission intensity, however, is ambiguous in the results. Some CleanTech facilities deliver larger than average reductions in emission intensity. There are also facilities that deliver smaller than average reduction in emission intensity by carrying out CleanTech projects. A more detailed study shows that small facilities with CleanTech projects are in fact the ones that achieve better than average results. Large facilities with CleanTech projects are a mix of those that realize greater than average reduction in emission intensity and those that realize less than average or no reduction in emission intensity. Given that reduction in energy intensity – i.e. energy consumed per unit of business activity – is not captured in the methodology, it is possible that some large facilities are focusing in that area rather than switching to cleaner technology.[1] According to the evidence, small CleanTech facilities conform to the first hypothesis stated earlier: they manage to utilize the government funding to augment their own capabilities. Those large CleanTech facilities that do not realize much reduction in emission intensity conform to the second hypothesis insofar as they fail to realize any reduction in energy intensity as well.

Initial indications are that the impact of CleanTech has been very localized and lacks any diffusive nature even across facilities belonging to the same parent firm. I do more detailed tests by introducing a few exposure measures and checking whether exposure to CleanTech projects has had any impact on other facilities, belonging to the same parent or to other parent firms, in adopting cleaner technologies. I find that the geographic concentration of firm activity matters and the reaction of firms to CleanTech projects diminishes for firms that are segmented and where the distance between segments is far. One can argue that proximity between headquarter and production facility – more broadly, the strength of the feedback line from facility to its headquarter – is a potent force in making the firm adopt a new technology when one of its facilities is exposed to one.

2 Data

This study is based on a matched dataset that uses National Greenhouse and Emission Reporting Scheme (NGERS) from the Australian Clean Energy Regulator in conjunction with the CleanTech program data from the Australian Department of Industry. In what

[1] In fact, some CleanTech projects are about switching to LED lighting or using controls to automatically shut down electrical devices during periods of inactivity.

follows, I will separately introduce these databases and then describe the matching process.

2.1 NGERS

The National Greenhouse and Emission Reporting Scheme Act of 2007 (coming into effect in 2008) was introduced by the Australian Government in part to fulfill Australia's international obligations but also as an initiative to collect data that would help in the design of policies targeting emission reduction and climate change (See NGER Act, 2007, for details). The thresholds for obligatory reporting have been gradually lowered since the inception of the act. As of 2010, firms or entities meeting either of the following annual thresholds are obligated under the legislation to report into NGERS (NGER Act, 2007, Part 2 Section 13):

(a) total amount of greenhouse gases emitted from the operations of facilities under the operational control of entity is 50 kilotonnes or more; or

(b) total amount of energy produced from the operations of facilities under the operational control of entity is 200 terajoules or more; or

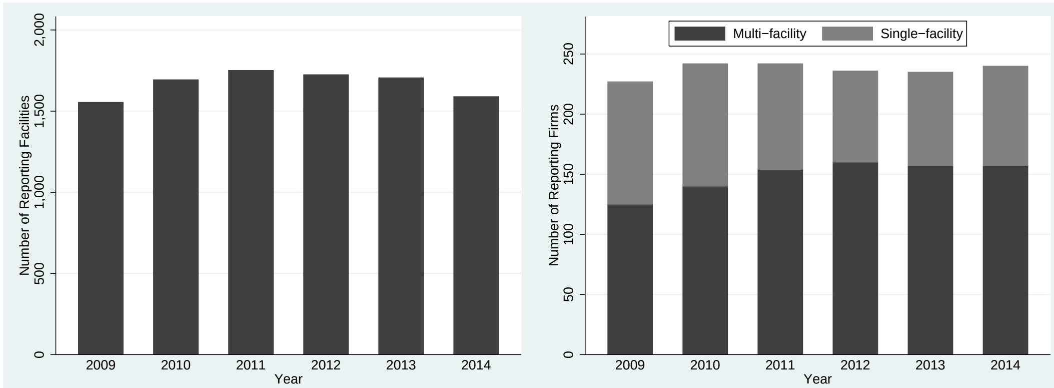
(c) total amount of energy consumed from the operations of facilities under the operational control of entity is 200 terajoules or more.

A facility within this context is basically a plant, location or establishment with the possibility of being part of a larger multi-facility parent firm.

The NGERS requires that the reporting firms record their energy consumptions and CO_2 equivalent emissions by activity in each facility that they control. The general class of activities reported in NGERS are those releasing emission as a result of (a) energy production, (b) fuel combustion, (c) fugitive emissions, (d) industrial processes, (e) scope 2 energy consumption (see below), or (f) waste handling. Facilities in practice undertake multiple activities internally, each reported separately, and each firm has the potential to own and control multiple facilities in various locations.

The NGERS, in particular, is detailed about the type of emissions produced by reporting them in two components:

Scope 1: emission and energy usage as a result of on-site energy conversion; and



(a) Facilities

(b) Firms

Figure 1: The count of facilities and firms reporting into NGERS over the years.

Scope 2: purchased energy (such as electricity) and the associated indirect emissions.

Total energy usage and emission by a facility is the sum of the two components. Firms also report the number of operation days for which emission and energy is recorded. The majority of facilities report for 365 days. To make the reports uniform, I use this information to proportionally inflate the remaining values to a 365-day operation, assuming that the operation is uniformly distributed across every day. Most facilities in the data are geocoded and come with their longitude and latitude coordinates that makes exact positioning possible. Finally, each facility is reported with the industry classification code pertaining to its activities regardless of the industry of the parent firm. The data is confidential and is available by authorization from the Australian Clean Energy Regulator.[2]

For my study, I am using the Section 19 activity report of the NGERS. Since CleanTech investment grants are offered to manufacturing activities only, I also restrict my data to manufacturing facilities. The data encompasses about 1,700 manufacturing facilities per year being controlled by close to 250 parent companies (Figure 1). The firms reporting into NGERS are split between single-facility firms and multi-facility parents, and since 2010 about two-thirds of all firms reporting into NGERS have been multi-facility.

[2]See `http://www.cleanenergyregulator.gov.au/` .

2.2 CleanTech

In 2012, the Australian government introduced the Clean Technology Investment Program (or CleanTech) as part of Clean Energy Act (2011) to assist Australian manufacturing businesses to maintain competitiveness in domestic and international markets while reducing their carbon emissions by switching to more efficient and cleaner capital equipment and technologies.[3] The program offered grants of up to half the estimated cost of the proposed projects. The last applications for this grant were accepted in 2014. The program had three components:

Innovation Program: Grants for research and innovation in the field of clean energy (about $28 million for 28 projects).

Investment Program: Grants to facilitate switching to cleaner technology (about $250 million for 232 projects).

Food and Foundries Investment Program: Almost half of the overall budget for the investment grants was dedicated to food manufacturing and foundries due to special demand (about $250 million for 315 projects).

The last two types of grants were only offered to manufacturing activities.

The Australian government keeps an administrative database of the CleanTech projects which is regularly updated by registrant reports to keep the government abreast of the progress in each project and for post-project evaluations. Some details of the database, such as business contacts, are confidential whereas the rest of the information is posted publicly.[4] For this study, I am given access to the confidential database.

In this study, I am focusing on the role of this program in reducing emission intensity, therefore, I will restrict myself to Investment and Food and Foundry projects. By 2015, 391 investment projects have finished, while 156 are still in progress but expected to conclude soon (Figure 2).

In the CleanTech database each applicant describes the project and the facilities (and their locations) where the project is to take place and the estimated cost of the project. A

[3] See `http://www.business.gov.au/grants-and-assistance/closed-programs/CleanTechnology/` for details.

[4] The data can be accessed at `http://www.business.gov.au/grants-and-assistance/closed-programs/CleanTechnology/CleanTechnologyInvestment/Pages/CTIP-Grantee.aspx`.

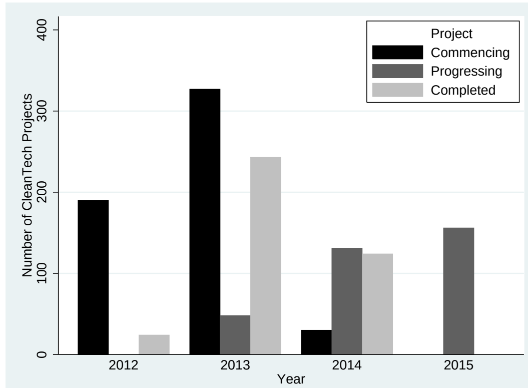


Figure 2: The count of CleanTech projects by year.

percentage of up to half the project cost is then offered to the firm. Once the offer is taken, the project goes ahead and actual cost reports are regularly produced. The government pays the agreed percentage of actual costs up to a pre-determined ceiling in installments as the project proceeds. The progress of projects is monitored by the government to ensure that the grant is spent on the designated project and at the designated facility described in the initial submission. A facility might apply for more than one CleanTech grant to carry out multiple projects. Alternatively, a grant can be requested to treat multiple facilities.

2.3 Matched Data

The NGERS is an activity-level data, reporting emission and energy consumption for each activity at each facility. For the matching, I aggregate emission and energy consumption to facility level. On the other hand, CleanTech is a project level data. Through careful examination of the projects, I manage to link each project to the facility or facilities the project is intended for.

The matches are not necessarily one-to-one. Some projects indicate that the grant will be used to treat multiple facilities. In such cases, I am assuming that the total cost of project and the offered grant are equally divided between the facilities in the absence of any detailed information on the distribution of funds. The value of projects does not play any key role in the empirical modeling, therefore, the simplifying assumption is inconsequential to the main findings.

There are also facilities that conduct multiple projects and receive separate grants for each project. These projects do not necessarily start and finish at the same time but mostly take place over the period 2012 to 2014. In case a facility is associated with multiple projects, I aggregate the cost of projects and the offered grants to a total per facility.

At this point, it is worth mentioning that not all projects from CleanTech database can be matched to a facility in the NGERS. That is because several of the registered firms in the CleanTech database fall below the thresholds in the NGERS for mandatory reporting. Still, several of the facilities in the NGERS matched to the CleanTech projects are small but part of a larger parent firm.

The objective is to look at the reduction in emission intensity as a result of the carbon pricing scheme being introduced and also to investigate whether there is any reduction above and beyond the sector-wide shift among facilities that carried out CleanTech projects. I will approach the issue by defining and comparing the emission production technology in 2011 (which I call period 1) versus that in 2014 (which I call period 2). Both the carbon pricing scheme and the CleanTech program commenced in 2012, hence, the year 2011 depicts the manufacturing sector prior to the enforcement of emission related policies due to the clean energy act. Year 2014 is the year carbon pricing scheme was curtailed and most CleanTech projects have already concluded by then with no new applications being processed. In case, for any reason, a facility is not reporting in 2011 or 2014, I will use the facility's report in 2010 or 2013, respectively, to fill the gap where possible (142 facilities fall into this category).

The size and composition of the matched dataset is illustrated in Table 1, where each row lists the number of facilities in periods 1 and 2 by industry or by the state of operation. The table also lists the number of facilities with CleanTech projects. Some facilities reporting in period 1 are not reporting in period 2 or vice versa for one reason or the other. Those facilities will be dropped from the analysis as facilities must report in both periods for a proper assessment of changes that took place. This requirement limits the number of facilities that are used in the empirical exercises to 1,061.

The counts show that food and beverage together are by far the largest group in the NGERS; about one third of facilities listed in the NGERS are food or beverage manufacturers. This disproportionate presence of food industry in the Australian manufacturing can explain the CleanTech's focus on food facilities. Accordingly, more than 40 per cent of the matched

	Number of Facilities			
	Period 1		Period 2	
Industry	Total	CleanTech	Total	CleanTech
Food Products	420	43	469	51
Beverage and Tobacco	94	6	105	6
Textile, Leather, Clothing and Footwear	12	1	9	1
Wood Products	108	2	77	4
Pulp and Paper Products	83	0	78	9
Printing	26	5	25	5
Petroleum and Coal Products	66	4	47	3
Basic Chemicals	182	11	191	10
Polymer and Rubber Products	85	3	62	4
Non-metallic Minerals	170	10	156	12
Primary Metal Products	106	3	81	3
Fabricated Metal Products	107	5	131	10
Transport Equipment	70	3	64	3
Machinery and Equipment	35	2	27	2
Furniture and Other Manufacturing	34	2	30	0
State	Total	CleanTech	Total	CleanTech
Australian Capital Territory	12	1	13	1
New South Wales	404	34	422	42
Northern Territory	22	0	22	0
Queensland	347	15	327	19
Southe Australia	157	9	154	11
Tasmania	98	3	73	3
Victory	386	30	360	36
Western Australia	172	8	181	11
Total number of facilities	1598	100	1552	123

Table 1: The count of facilities in the matched data by industry and state of operation.

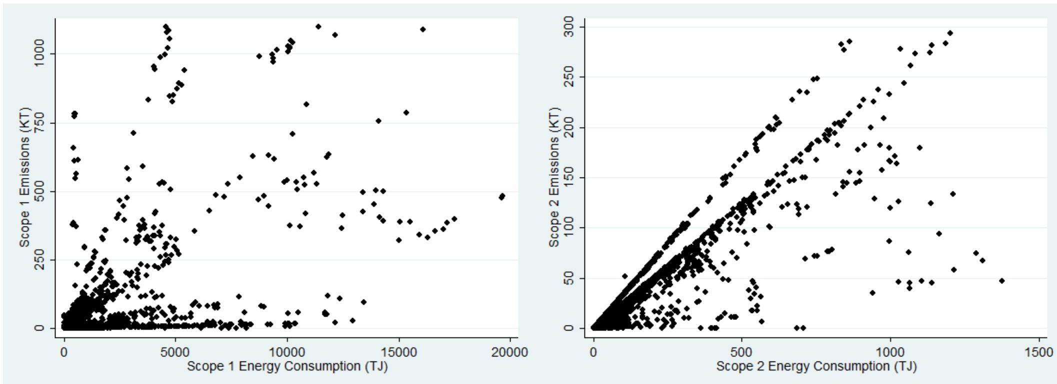
Variable	Mean	Std.Dev.	Qrtl. 1	Median	Qrtl. 3
Scope 1					
ENERGY (TJ)	1674.4	16084.5	0.4	10.9	115.7
EMISSION (KT)	53.1	840.6	0.0	0.5	4.8
Scope 2					
ENERGY (TJ)	135.3	1237.6	0.6	8.0	36.0
EMISSION (KT)	28.8	300.9	0.1	1.8	8.6
Total					
ENERGY (TJ)	1809.7	16264.2	2.1	26.3	171.8
EMISSION (KT)	81.9	921.5	0.3	3.2	16.4
					$N = 3150$

Table 2: Descriptive statistics for the emission (in kilotonnes) and energy consumption (in terajoules) by scope.

facilities with CleanTech projects are food or beverage manufacturers. The counts also exhibit a concentration of facilities and CleanTech projects within the three most populated states in Australia, namely, New South Wales, Victoria, and Queensland. One also observes a small drop in the total number of reporting facilities from period 1 to period 2 which reduces the overlap to some extent. In the analysis that will follow a facility has to be observed in both periods.

Each facility in the dataset reports scope 1 and 2 emissions and energy consumption. Table 2 lists the descriptive statistics for each of these variables across all facilities and years. The quartiles especially show that facilities are quite dispersed in size, measured in either energy consumption or emissions, and that there is a substantial presence of small facilities as well as large ones. The contrast between the quartiles and mean values, however, demonstrates that the size distributions are very skewed; the mean value is practically driven by a small number of very large facilities, whereas the quartiles establish that the data is mostly populated by smaller facilities. This distribution as a whole is very typical of size distribution of firms and establishments in Australia.

To better understand the relationship between energy consumption and emission in support of a production function modeling, I present Figure 3 where the energy consumption and emission of each observation in the data are plotted against each other for scope 1 (panel



(a) Scope 1

(b) Scope 2

Figure 3: The plot of facility-level energy consumption and emission by scope and using the pooled NGERS data. The plots exclude extreme observations.

(a)) and scope 2 (panel (b)) reports. A notable feature of the plots is that they exhibit multiple *rays*. This pattern seems to be driven by the mix of technology – e.g. gas, coal, oil , or petroleum based – used by each manufacturing sub-sector present in the data. For instance, in Figure 3(a) the upper ray is mostly populated by Non-metallic Mineral production facilities, whereas most chemical and metal production facilities are located around the middle ray.

3 A Structural Approach

Let emission in manufacturing facility j controlled by parent firm f be produced according to the general production technology

$$EMISSION_{jf,t} = e^{c_t + i_{jft} + \epsilon_{jft}} ENERGY_{jf,t}^{a_t}, \quad t = 1, 2. \tag{1}$$

In this function, a represents the returns to scale and c represents the level of efficiency in manufacturing. These parameters are allowed to vary from period one to period two in response to a sector-wide trend in the adoption of newer technology. Such change is expected as the period in question coincides with the implementation of a range of emission-related policies in Australia – most prominently the carbon pricing scheme – which could have made businesses seek ways to curb their emissions even in the absence of government grants or incentives. Also note that, given the undesired nature of output, higher efficiency is implied by a lower value of c.

In view of Figure 3, efficiency in a facility can also depend on its manufacturing subsector, which is included in the production function in the form of a set of industry effects, i_{jft}. The disturbance term, ϵ_{jft}, accounts for any idiosyncratic difference in the efficiency of facilities not captured by the prevailing mode of technology or industry effects.

Putting production function (1) in logs and taking differences yields

$$\begin{aligned} \Delta emission_{jf} &= \Delta c + a_2 energy_{jf,2} - a_1 energy_{jf,1} + \iota_{jf} + \varepsilon_{jf} \\ &= \Delta c + a_2 \Delta energy_{jf} + \Delta a\ energy_{jf,1} + \iota_{jf} + \varepsilon_{jf}, \end{aligned} \tag{2}$$

where lower case names denote variables in logs, and Δ operator indicates the change from period 1 to period 2. In equation (2), $\iota_{jf} = \Delta i_{jft}$ accounts for industry-specific change in efficiency and $\varepsilon_{jf} = \Delta \epsilon_{jft}$.

To study the impact of CleanTech, the production function (1) is extended to include additional changes in period 2 resulting from the implementation of the program. This production function only applies to those facilities with CleanTech projects and is written as

$$EMISSION_{jf,2} = e^{c_2 + \delta_c + i_{jft} + \epsilon_{jf2}} ENERGY_{jf,2}^{a_2 + \delta_a},$$

where δ_a and δ_c are the parameters associated with the impact of CleanTech above and beyond the sector-wide trend. Again, putting in logs and taking differences yields

$$\begin{aligned} \Delta emission_{jf} &= \Delta c + \delta_c + (a_2 + \delta_a) energy_{jf,2} - a_1 energy_{jf,1} + \iota_{jf} + \varepsilon_{jf} \\ &= \underbrace{a_2 \Delta energy_{jf}}_{\text{Change in Scale}} + \underbrace{\Delta c + \Delta a\ energy_{jf,1}}_{\text{Sector Technology Shift}} + \underbrace{\delta_c + \delta_a energy_{jf,2}}_{\text{CleanTech}} + \iota_{jf} + \varepsilon_{jf}. \end{aligned} \tag{3}$$

The first term above describes the change in emission production as a result of change in energy consumption, keeping the emission technology fixed. A large part of reduction (or increase) in emission is in fact not caused by a change in technology but simply due to a change in the scale of energy consumption. For a more accurate measurement of policy effect, this component needs to be factored out.

The second component models the part of change in emission that is driven by a sector-wide trend in the adoption of cleaner technologies, keeping energy consumption fixed. This term particularly represents any change that could have resulted, for instance, from the sector's general reaction to the introduction of carbon pricing scheme.

The last component specifically models the premium that carrying out a CleanTech project within the facility could offer compared to unassisted facilities. This last component will be absent for all facilities that do not receive any CleanTech grant.

Putting (2) and (3) together leads to the complete specification below:

$$\begin{aligned}\Delta emission_{jf} = a_2 \Delta energy_{jf} + \Delta c + \Delta a \ energy_{jf,1} \\ + \left(\delta_c + \delta_a energy_{jf,2}\right) \times CleanTech_{jf} + \iota_{jf} + \varepsilon_{jf}.\end{aligned} \tag{4}$$

In this equation, $CleanTech$ is a dummy variable that indicates whether facility j of firm f received CleanTech grant(s). ι_{jf} is modeled by a set of industry dummies for each manufacturing sub-sector.

Equation 4 is a linear form that can be simply estimated using OLS. However, the estimation of production functions is often beset by endogeneity issues insofar as firms can promptly react to idiosyncratic shocks by adjusting input factors. In this case, it is possible that positive(negative) shocks force firms to react by reducing(increasing) energy consumption in a facility, generating some correlation between ε_{jf} and $energy_{jf,2}$ (in turn, $\Delta energy_{jf}$). Olley & Pakes (1996) and Blundell & Bond (2000) each propose a fix by using capital investment or lags of variables as instruments in the estimation of Total Factor Productivity. Due to limitations in the number of variables and the available years, these approaches are infeasible in the current setting. Instead, I explore the potential for biases by focusing on a subset of observations where the endogeneity is minimized.

The premise is that endogeneity has to be the strongest within multi-facility firms. These firms have the flexibility to quickly redistribute business activity among their facilities when some of those facilities are hit by worse shocks than the others; thus, the firm can quickly mitigate shocks without incurring any major cost. Single-facility firms, on the other hand, lack this flexibility, and energy consumption in these firms has to do more with demand than shocks. Estimating (4) by restricting the sample to single-facility firms or firms with very

Dependent:	$\Delta emission$					
	Total	Total	Scope 1	Scope 2	Total	Total
Variable	(1)	(2)	(3)	(4)	(5)	(6)
a_2	0.710***	0.712***	0.802***	0.851***	0.718***	0.641***
	(0.057)	(0.057)	(0.067)	(0.048)	(0.055)	(0.082)
Δc	-0.125***	-0.129***	-0.081**	-0.091***	-0.128***	-0.200**
	(0.031)	(0.030)	(0.039)	(0.034)	(0.031)	(0.090)
Δa	0.006	0.007	0.005	0.020***	0.008	0.020*
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.011)
δ_c (CleanTech)		0.436**	0.404**	0.285	0.371**	0.572*
		(0.201)	(0.178)	(0.200)	(0.176)	(0.301)
δ_a (CleanTech)		-0.084**	-0.069*	-0.065	-0.080**	-0.097**
		(0.037)	(0.036)	(0.045)	(0.037)	(0.041)
Sample	All	All	All	All	Completed Projects	#Facility≤ 3
Adj. R^2	0.729	0.731	0.693	0.835	0.737	0.628
F	16.27	30.68	31.10	65.44	29.14	14.08
Log Likelihood	-643.7	-640.1	-842.7	-299.0	-623.5	-46.2
N	1,061	1,061	931	1,025	1,037	151

Table 3: OLS estimates of model (4). In column (5) sample excludes CleanTech facilities with no completed projects and in column (6) only firms with at most three facilities are included. Numbers in parentheses are standard errors clustered by parent firms. ***, **, and * denote 1%, 5% and 10% significances, respectively. A set of industry dummies are also included but not reported.

few facilities can provide guidance on whether there is a bias and on how the bias might be affecting the results.

4 Empirical Findings

4.1 General Results

The OLS estimates of (4) are reported in Table 3 in a nested order to test for the importance of CleanTech as a program in the first place. Column (1) in the table reports the estimated coefficients without the CleanTech components. Those components are added in column (2), where the full model is estimated.

Since the scope of energy consumption and emission is also reported in the data, it is instructive to check whether CleanTech program is focused on a certain scope of emission. I estimate specification (4) separately first using scope 1 quantities with the results reported in column (3) and then using scope 2 quantities with the result reported in column (4). It is likely that strategic decisions are made at headquarters and affect all facilities belonging to the same parent firm to some degree. For this reason, the standard errors in every column are clustered by parent firms.

In the last two columns I conduct two robustness tests. In column (5), I estimate model (4) by leaving out those facilities where no CleanTech project is completed by 2014. This is a test to make sure that including facilities with progressing CleanTech projects is not distorting the results. In Column (6), I estimate the model using only firms with three or fewer facilities to mitigate endogeneity and explore whether the potential of a bias jeopardizes the findings.[5]

First of all, using the log likelihoods reported in columns (1) and (2), one finds that the likelihood ratio statistic between the two models is 7.2 with a a p-value of 0.027 (using a χ^2_2), hence, CleanTech appears to have a significant impact on the estimates.

The first coefficient in the table, a_2, accounts for change in emission caused by a change in the level of energy consumption keeping the emission production technology fixed. The estimated values are all statistically significant and point to the fact that a substantial part of the change in the log of emission can in fact be accounted for by a change in the log of energy consumption alone.

The next two coefficients are associated with a sector-wide change in the emission production technology. Per these findings, the emission technology seems to have become more efficient over the period. All estimates for Δc are negative and statistically very significant. Not much change seems to have taken place in returns to scale: estimates for Δa are very small and statistically insignificant. The only exception is that of scope 2 emissions, where the estimated value points to some increase in the value of a from period 1 to period 2.

The rest of the coefficients represent the effect of CleanTech grants above and beyond the sector-wide trend. The estimates for both δ_c and δ_a, again, corroborate that CleanTech had a statistically significant effect on the operation of those facilities that utilized the grants. However, the direction of the effect is such that it moves the technology in the opposite

[5]Restricting the sample to single-facility firms generates similar results, but the statistical significance gets weaker owing to the small number of observations. Note that the median number of facilities in the matched dataset is 15.

direction to that of the general technological trend. More specifically, the effect of CleanTech projects has been to reduce the returns to scale in the production function of emission at the expense of making production more inefficient (i.e. increasing c). This pattern is present across all models in the table regardless of the scope of energy and emission reports. Considering this pattern, it seems that large facilities must have benefited from CleanTech in a very peculiar way. The drop in returns to scale effectively introduces a cap on emissions among large facilities without making the technology any more efficient. This issue is studied in more details in Section 4.3.

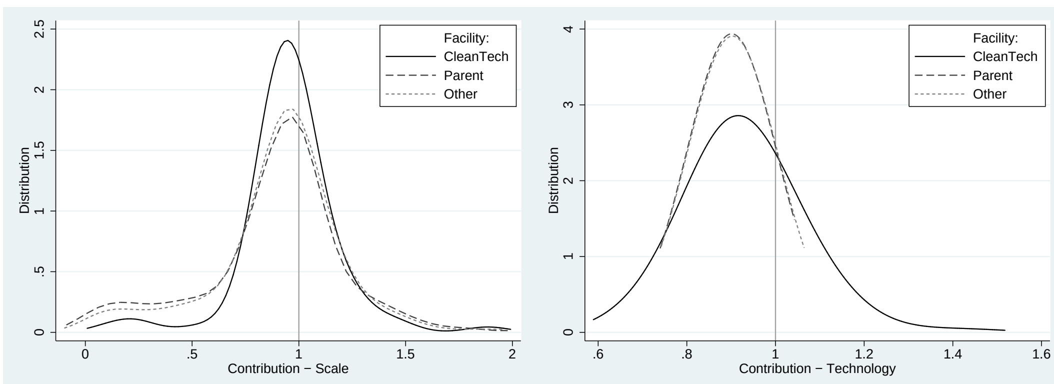
Results in column (5) confirm that dropping CleanTech facilities with no completed projects does not have any substantial effect on the implications, therefore, the results are robust to this type of sample restriction. In column (6), one observes that after restricting the sample to firms with three or fewer facilities there is no change in the qualitative implications; as a matter of fact, the results get stronger.

The estimated coefficients discussed above point to interesting shifts in the emission technology. However, the fact that the production function is driven by two parameters, namely, efficiency and returns to scale, makes it non-trivial to answer the fundamental question as to whether technological changes – and CleanTech in particular – resulted in a drop or an increase in emissions. In this part of the analysis, I use the estimated figures from column (3) of Table 3 to separately predict the share of contributions associated with change in the scale of energy usage, sector-wide technology, or CleanTech and compare the distribution of these contributions across facilities. I compute the contribution for each observation as the exponential of the change predicted for each undersigned component in (3) keeping all else fixed. In this context, a value less than one indicates a proportional drop and a value larger than one indicates a proportional increase in the emission of a facility due to a specific factor.

Table 4 reports the mean values for the predicted contributions, where the full distributions are illustrated in Figure 4. I am making a distinction between facilities that directly receive CleanTech grants versus facilities with no CleanTech projects that, nevertheless, are controlled by a parent with other CleanTech facilities. Watching for differences among these two types of facilities has the potential to further highlight the direct and indirect impacts of CleanTech. Facilities belonging to parents with no CleanTech projects are listed separately.

	Contributions				
Type of Facility	Scale	Sector-wide Technology	CleanTech	Full Technology	N
CleanTech	0.983	0.913	1.019	0.929	90
Parent	1.082	0.901		0.901	395
Other	1.060	0.903		0.903	576
Total	1.061	0.903	1.019	0.904	1061

Table 4: The average contributions from change in energy scale, sector-wide technology and CleanTech program. Full technology accounts for contributions from both sector-wide and CleanTech technological changes. Contributions smaller than one represent emission reductions and those larger than one represent emission increases.



(a) Scale (b) Full Technology

Figure 4: Kernel density estimates of contributions from (a) change in the scale of energy consumption and (b) full technological change. A Gaussian kernel with a bandwidth of 0.1 is used for density estimates.

For each type of facility, the mean value of contributions is reported in the three categories of change in scale, change in sector-wide technology, and the additional change associated with CleanTech where available. An extra column lists the full contribution of technological change by putting CleanTech and sector-wide technological changes together for easier cross-group comparisons.

The first interesting observation is that neither the table of means nor the distributions show any major difference between non-CleanTech facilities with CleanTech parents and other non-CleanTech facilities, whereas there is a substantial gap between CleanTech facilities and every other facility. This pattern suggests a lack of intra-firm diffusion and much less interfirm spill-overs. I will look at this issue in more details in Section 5 where I define a few indexes of exposure to CleanTech program and test them for any implied effects.

The mean values in Table 4 indicate some contraction in the scale of energy consumption among CleanTech facilities, whereas energy consumption appears to have increased among other facilities. However, Figure 4(a) shows substantial dispersion among facilities. In this figure, a larger proportion of facilities in each group falls to the left of one, that is, the scale of energy consumption dropped among most facilities regardless of their nomination. Energy consumption expanded for a small fraction of facilities. The drop in energy consumption could be driven by a contraction in business activity as well as switching to less energy-intensive technologies. Stanwix et al. (2015) show that about 2.5 per cent drop in the energy consumption of manufacturing during the period can directly be related to a fall in energy intensity. Given the scale of contributions in Figure 4(a), adjusting for this shift would not make a substantial difference in the inferences.

On the emission technology, the mean values for sector-wide changes point to significant drop of about 9.7 per cent in emission as a result of the manufacturing sector as a whole shifting to cleaner technologies.[6] The total emission in 2011 among firms reporting in the NGERS is about 115.27 megatonnes, therefore, the change translates to about 11.2 megatonnes reduction in carbon emission or the equivalent among these firms over the period. Estimating a similar model for the period 2009 to 2011 shows a 0.8 per cent increase in emission specific to technological factors. Assuming that the same trend would have prevailed in the absence of carbon pricing scheme, one estimates the full contribution of the carbon pricing scheme to be a 10.5 per cent reduction in emission generation.

Facilities with CleanTech projects on average experienced smaller reductions in emission intensity: using the mean value of full technological change among CleanTech facilities shows that these facilities on average had only about seven per cent reduction in emission compared to 10 per cent average reduction in similar facilities without CleanTech as a result of technological shift. The distributions in Figure 4(b) further make the point that almost all facilities without CleanTech projects experienced some improvement in their emission technology. CleanTech facilities are much more dispersed than other facilities in this picture and

[6] Clean technology in this context refers to those technologies with lower emission intensity, where emission intensity is defined as emission to energy ratio.

Panel A: Scope 1 Contributions

Type of Facility	Contributions: Scale	Sector-wide Technology	CleanTech	Full Technology	N
CleanTech	1.061	0.943	1.115	1.050	87
Parent	1.470	0.936		0.936	333
Other	1.072	0.937		0.937	511
Total	1.214	0.938	1.115	0.948	931

Panel B: Scope 2 Contributions

Type of Facility	Contributions: Scale	Sector-wide Technology	CleanTech	Full Technology	N
CleanTech	4.913	0.980	1.063	1.040	88
Parent	1.075	0.954		0.954	384
Other	1.423	0.954		0.954	553
Total	1.592	0.956	1.063	0.961	1025

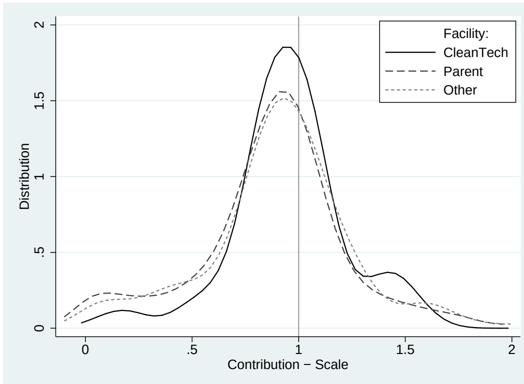
Table 5: The average scope 1 and 2 contributions from change in energy scale, technology and CleanTech program. Full technology accounts for contributions from both sector-wide and CleanTech technological changes. Contributions smaller than one represent emission reductions and those larger than one represent emission increases.

a fraction of those facilities appear to have had their emission intensity increase over the period in discussion. Having said that, the lower tail of the distribution for CleanTech facilities shows that a fraction of CleanTech facilities managed to improve their emission technology beyond that of any other facility. At this point, it looks as if a fraction of recipient firms conform to the first hypothesis stated earlier, whereas a fraction of facilities are more in line with the second hypothesis.

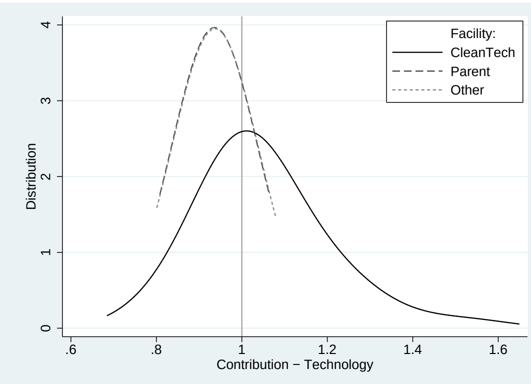
4.2 Scope 1 versus Scope 2 Technology

Table 5 and Figure 5 report the same contributions but computed for scope 1 and scope 2 emissions using the estimated models in columns (3) and (4) of Table 3, respectively.

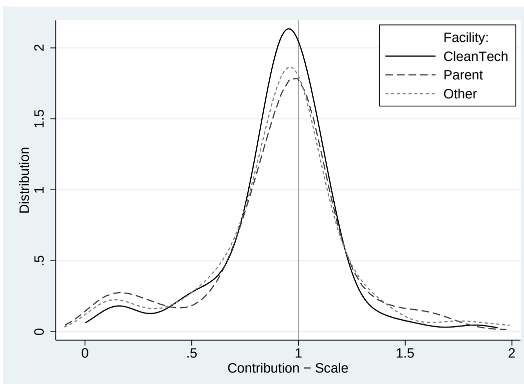
The mean values for the contributions caused by change in the scale of energy consumption in Table 5 point to substantial expansions. However, the distributions in Figure 5(a,c) still demonstrate that more than half the facilities reduced emission by consuming less energy.



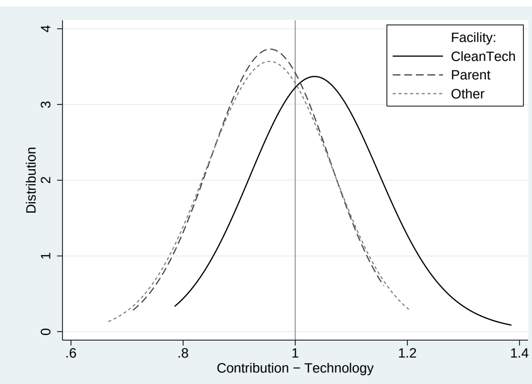
(a) Scope 1 Scale



(b) Scope 1 Full Technology



(c) Scope 2 Scale



(d) Scope 2 Full Technology

Figure 5: Kernel density estimates of scope 1 and 2 contributions from change in the scale of energy consumption and full technological change. A Gaussian kernel with a bandwidth of 0.1 is used for density estimates.

One concludes that the mean values for this component are mainly driven by a few outliers.

The mean values for sector-wide technological change show improvements in both scope 1 and scope 2 technologies. Specifically, the numbers show about six per cent improvement in scope 1 technology and about four per cent improvement in scope 2 technology across the industry. These numbers actually add up to the 10 per cent technological shift observed in Table 4 and show that the shift was distributed rather unevenly between scope 1 and 2 technologies with a larger share associated with scope 1 emission reduction.

The average contributions from CleanTech again do not show any additional reduction within facilities that carried out those projects. The same conclusion is on display in the distributions of Figure 5(b,d). In those figures, a substantial mass of CleanTech facilities lies to the right of the distribution for other facilities. In the case of scope 1 emissions, however, the lower tail of CleanTech facility in panel (b) of Figure 5 shows that some CleanTech facilities still went beyond the average reduction. The same conclusion cannot be made in the case of scope 2 emissions shown in panel (d).

4.3 Small versus Large Facilities

Following the earlier suggestion that the impact of CleanTech could be size-dependent, I additionally estimate (4) by size to investigate any size-related differences. For this purpose, I use the median rule and assign every facility with total period-one energy consumption larger than the median – which is about 47 terajoules – as large facility and any facility with lower consumption as small. Note that in this case size is referring to facility's size and not to the parent firm's size that is generally large owing to the composition of the data. Nonetheless, the correlation between the energy consumption of facilities and their parent firms is 0.587 in the data, therefore, there is a fair bit of overlap and smaller facilities tend to belong to smaller firms. the estimated coefficients by size class are reported in Table 6.

The numbers in Table 6 demonstrate that small and large facilities are indeed affected differently by CleanTech projects. Among small facilities, CleanTech projects have mostly improved the efficiency of the emission technology – at least the efficiency of scope 1 emission technology – at the cost of increasing the returns to scale parameter. For large facilities with CleanTech projects, the emission generation process is getting less efficient and the only improvement is a drop in the returns to scale of the production function that puts a cap on emission in the same way as explained in Section 4.1. It might also be noteworthy that the models fit very well to the data when using the small facilities subsample; the adjusted R^2 and F statistics show a close fit. In the case of large facilities, the quality of fit statistics show larger noise.

To fully quantify and compare the level of emission reduction in small and large facilities, I recompute the mean values for the predicted contributions using models (1) and (4) in Table 6 and report them in Table 7 separately for each size class. Figure 6 illustrates the corresponding distributions.

As the mean values show, both small and large facilities saw improvements in their tech-

Dependent:	log of emission					
	Total	Scope 1	Scope 2	Total	Scope 1	Scope 2
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Subsample	Small Facilities			Large Facilities		
a_2	0.796***	0.929***	0.992***	0.650***	0.726***	0.719***
	(0.045)	(0.034)	(0.009)	(0.087)	(0.096)	(0.090)
Δc	-0.099***	0.036	-0.095***	-0.100	-0.205*	-0.132
	(0.028)	(0.023)	(0.015)	(0.123)	(0.105)	(0.084)
Δa	0.008	-0.018*	0.000	-0.000	0.026	0.031
	(0.011)	(0.010)	(0.003)	(0.023)	(0.021)	(0.019)
δ_c (CleanTech)	-0.140**	-0.059**	0.009	1.148**	1.271***	0.422
	(0.061)	(0.023)	(0.026)	(0.574)	(0.487)	(0.280)
δ_a (CleanTech)	0.039	0.036**	0.006	-0.204**	-0.226***	-0.093
	(0.025)	(0.015)	(0.012)	(0.099)	(0.084)	(0.063)
Adj. R^2	0.850	0.918	0.982	0.640	0.565	0.699
F	47.84	231.94	1618.58	7.65	7.91	13.75
Log Likelihood	-166.9	-85.0	384.8	-386.6	-564.0	-261.8
N	528	415	506	533	516	519

Table 6: OLS estimates of model (4) by size classification. Numbers in parentheses are standard errors clustered by parent firms. ***, **, and * denote 1%, 5% and 10% significances, respectively. A set of industry dummies are also included but not reported.

nologies, however, large facilities experienced a much larger improvement: about 10 per cent drop in emission among large facilities is due to sector-wide technological improvement, whereas about eight per cent drop in emission among small facilities can be attributed to the same cause.

Regarding CleanTech program, small facilities with CleanTech are reducing emissions by an extra 2.5 per cent compared to small facilities without such projects due to technology improvement. This was expected from the results in Table 6. Large facilities with CleanTech are not experiencing any additional technology-related emission reductions; on the contrary, technology in those facilities with CleanTech projects is actually pushing emission up by five per cent compared to a typical large facility but without CleanTech.

Figure 6(b) and (d) further show that the impact of the program across small and large facilities is rather dispersed. In panel (b), one again observes that the CleanTech projects did well among small facilities and the distribution of the CleanTech facilities in this category is

Panel A: Small Facilities ($ENERGY_1 \leq$ median)

Type of Facility	Contributions: Scale	Sector-wide Technology	CleanTech	Full Technology	N
CleanTech	0.990	0.928	0.975	0.905	17
Parent	1.231	0.918		0.918	218
Other	1.224	0.914		0.914	293
Total	1.219	0.916	0.975	0.916	528

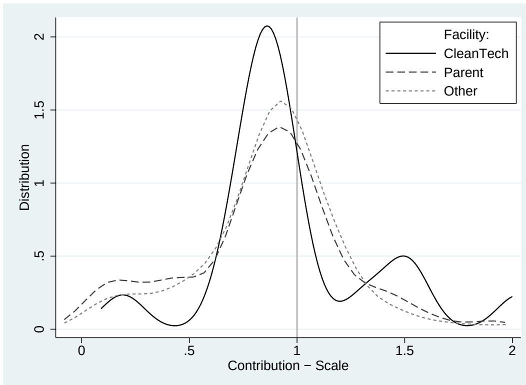
Panel B: Large Facilities ($ENERGY_1 >$ median)

Type of Facility	Contributions: Scale	Sector-wide Technology	CleanTech	Full Technology	N
CleanTech	0.981	0.903	1.041	0.940	73
Parent	0.987	0.903		0.903	177
Other	0.975	0.902		0.902	283
Total	0.980	0.903	1.041	0.908	533

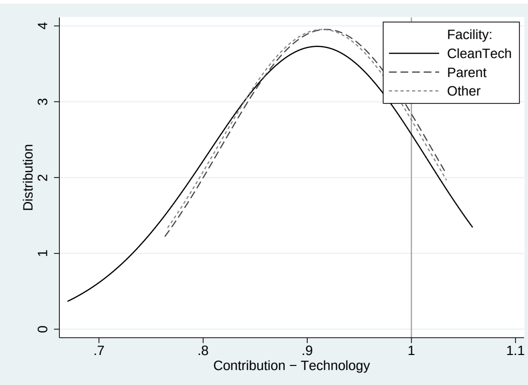
Table 7: The average contributions from change in energy scale, technology and CleanTech program for small and large facilities. Full technology accounts for contributions from both sector-wide and CleanTech technological changes. Contributions smaller than one represent emission reductions and those larger than one represent emission increases.

slightly to the left of those without it. The dispersion of small facilities with CleanTech is, however, larger than that of small facilities without CleanTech, with quite a number of small facilities falling on the lower tail of the distribution, meaning that these CleanTech facilities experienced much larger emission reductions than any other small facility.

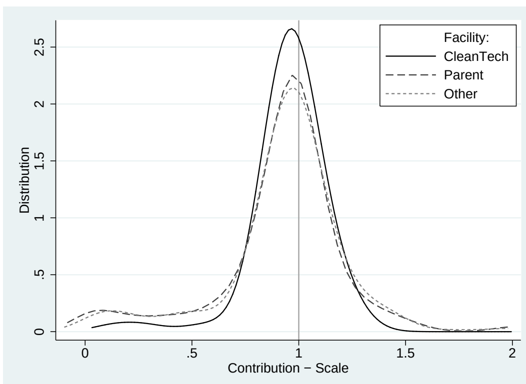
Panel (d), on the other hand, shows a picture in which the distribution of large facilities with CleanTech is slightly to the right of that of large facilities without it. This observation is in line with the conclusion from Panel B in Table 7. However, large facilities with CleanTech projects are very much dispersed and the distribution tails stretch very far on both ends. In other words, the technology response of large facilities to CleanTech projects has been very mixed with some achieving substantial reduction in emission through improving the emission technology and some others having seen their emission technology becoming less efficient. As a note of caution, the methodology is unable to separate the effect of change in business activity from that of change in energy intensity, and both are presented as change in scale.



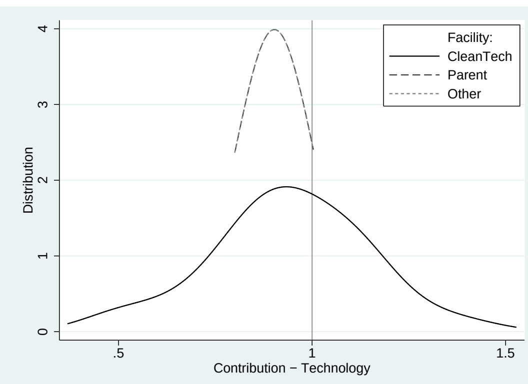
(a) Small



(b) Small



(c) Large



(d) Large

Figure 6: Kernel density estimates of contributions from change in the scale of energy consumption and full technological change for small and large facilities. A Gaussian kernel with a bandwidth of 0.1 is used for density estimates.

One can conjecture that the focus of CleanTech project among a group of large facilities might have been reducing energy intensity and not directed towards reducing emission intensity.

5 Exposure Impact of CleanTech

Apart from affecting the facilities that received grants, CleanTech can also have a broader impact by intensifying competition or providing lessons that urge other facilities to react by implementing their own emission reduction strategies on top of the general trend. In what follows, I will look at this issue by introducing a few measures of *exposure* to CleanTech.

5.1 Facilities exposed to CleanTech

I consider two types of exposure for exacter results. The first type of exposure affects those facilities that did not receive CleanTech grants, nevertheless, got exposed to CleanTech through their parent or holding company controlling facility or facilities with CleanTech projects. In case the decision to switch to a cleaner technology is made at the top levels of management, the parent firm could use the lessons learned from the implementation of a CleanTech project in one or more of its facilities to improve operation in the other facilities it controls. To test this hypothesis, I introduce the dummy variable, $Parent$, that is equal to one if a facility did not receive CleanTech funding directly but belongs to a parent company with one or more CleanTech facilities. $Parent$ is set to zero otherwise.

The second type of exposure pertains to facilities with parent firms that have no CleanTech grants across any of their facilities. One can hypothesize that being geographically co-located with another facility that does carry out CleanTech projects might have some influence on the facility's or its parent's decision to double their effort in switching to cleaner technology. To account for this type of *geographic* exposure, I define the following measure

$$Exposed_{jf}^{Num} = \sum_{j',j'\neq j,f'\neq f} \frac{CleanTech_{j'f'}}{d_{j,j'}^2}. \tag{5}$$

This measure of exposure basically finds the weighted number of projects in the geographic vicinity of facility j where the weights are the inverse of squared distances between facility j and the other CleanTech facilities. I set the measure equal to zero if a facility or its parent has any CleanTech projects, so that this measure, $Parent$, and $CleanTech$ are mutually exclusive. Using this measure, one can test whether the mere introduction of a CleanTech project in an area had any influence on how other facilities behaved. In Australia, firms can be thousands of kilometers apart, therefore, I use the Haversine formula to compute the physical distance between every pair of facilities.[7]

I also define a second measure of exposure that also accounts for the size of projects,

[7]Specifically, let the coordinates of firms j and j' be (x_j, y_j) and $(x_{j'}, y_{j'})$, then

$$d_{j,j'} = 2R\arcsin\left(\sqrt{\sin^2\left(\frac{y_j - y_{j'}}{2}\right) + \cos(y_j)\cos(y_{j'})\sin^2\left(\frac{x_j - x_{j'}}{2}\right)}\right),$$

in which $R = 6371.009km$ is the average radius of the earth.

in case larger projects received more publicity, hence, had larger influence. This measure is defined as

$$Exposed_{jf}^{Cost} = \log\left(1 + \sum_{j', j' \neq j, f' \neq f} \frac{\text{Total Project Cost}_{j'f'}}{d_{j,j'}^2}\right). \tag{6}$$

The term inside the parentheses is one plus the accumulated cost of all CleanTech projects in the vicinity of facility j. The log is taken to control for extreme values. As in (5), the measure is set equal to zero if a facility or its parent has any CleanTech projects.

The implementation of these exposure effects in the production function is identical to that of the CleanTech in (3). Therefore, following the same procedure, one can write an extended version of (4), which gives:

$$\begin{aligned}
\Delta emission_{jf} = {} & a_2 \Delta energy_{jf} + \Delta c + \Delta a \ energy_{jf1} \\
& + \left(\delta_c^{CleanTech} + \delta_a^{CleanTech} energy_{jf2}\right) \times CleanTech_{jf} \\
& + \left(\delta_c^{Parent} + \delta_a^{Parent} energy_{jf2}\right) \times Parent_{jf} \\
& + \left(\delta_c^{exposed} + \delta_a^{exposed} energy_{jf2}\right) \times Exposed_{jf} \\
& + \iota_f + \epsilon_{jf},
\end{aligned} \tag{7}$$

In this specification, *Exposed* is either of the measures define in (5) or (6).

The estimated coefficients are listed in Table 8. Columns (1) to (3) in the table use (5) as the measure of exposure. The estimates for parent or geographic exposure in these columns do not point to any significant effect. The only significant effect suggests some efficiency gain in Scope 2 emissions. However, likelihood ratio tests between any of these columns and the corresponding restricted models in Table 3 rejects the hypothesis that exposure matters in any of these cases.

Columns (4) to (5), alternatively, look at the exposure using measure (6). Likelihood ratio tests still reveal that exposure is not a significant force in columns (4) and (5). However, in column (6), where the estimation is focused on Scope 2 emissions, the likelihood ratio statistic is significant at 2.5%. Accordingly, facilities exposed to CleanTech projects through their parents do show some efficiency improvement in Scope 2 emissions. No such impact can be detected for geographic exposure as those coefficients are all statistically insignificant. This last result particularly suggests that the size of projects matters and larger projects,

Dependent: log of emissions Variable	Total (1)	Scope 1 (2)	Scope 2 (3)	Total (4)	Scope 1 (5)	Scope 2 (6)
Exposure	Number of CleanTechprojects			Cost of CleanTechprojects		
a_2	0.712***	0.801***	0.845***	0.723***	0.799***	0.835***
	(0.055)	(0.063)	(0.050)	(0.054)	(0.064)	(0.053)
Δc	-0.139***	-0.052	-0.057	-0.238***	-0.060	0.015
	(0.039)	(0.041)	(0.039)	(0.072)	(0.074)	(0.062)
Δa	0.007	0.004	0.015**	0.019	-0.000	0.005
	(0.011)	(0.014)	(0.006)	(0.015)	(0.017)	(0.010)
δ_c (CleanTech)	0.446**	0.378**	0.253	0.547**	0.391**	0.180
	(0.213)	(0.186)	(0.202)	(0.223)	(0.193)	(0.211)
δ_a (CleanTech)	-0.084**	-0.068*	-0.061	-0.097**	-0.065	-0.051
	(0.041)	(0.040)	(0.044)	(0.043)	(0.041)	(0.045)
δ_c (Parent)	0.006	-0.011	-0.074*	0.106	0.001	-0.148**
	(0.064)	(0.063)	(0.038)	(0.088)	(0.082)	(0.072)
δ_a (Parent)	0.002	-0.008	0.012	-0.010	-0.005	0.022
	(0.019)	(0.025)	(0.009)	(0.022)	(0.027)	(0.014)
δ_c (Exposed)	0.033	-0.094*	-0.018	0.023**	-0.004	-0.016
	(0.036)	(0.050)	(0.039)	(0.011)	(0.012)	(0.010)
δ_a (Exposed)	-0.002	0.017	0.004	-0.003	0.002	0.002
	(0.009)	(0.013)	(0.011)	(0.002)	(0.003)	(0.002)
Adj. R^2	0.730	0.693	0.835	0.731	0.692	0.836
F	31.88	34.06	72.13	29.91	31.15	76.42
Log Likelihood	-639.8	-841.2	-296.3	-637.4	-842.0	-293.1
N	1,061	931	1,025	1,061	931	1,025

Table 8: OLS estimates of model (7). Numbers in parenthesis are standard errors clustered by parent firms. ***, **, and * denote 1%, 5% and 10% significances, respectively. A set of industry dummies are also included but not reported.

measured in their total cost, tend to generate some ripple effect where a number of small projects would have failed to make an impression.

5.2 Geographic segmentation and CleanTech exposure

In view of the results of the last section, I also hypothesize that the exposure effect of CleanTech program might have to do with geographic segmentation of production. Firms that are highly segmented – e.g. operate a lot of facilities in various and possibly remote locations – could experience some detachment between their headquarters where the decisions are made and the facility floors where observations are made. The more the detachment, the weaker the reaction to exposure to CleanTech program. To test whether this is the case, I re-estimate the coefficients in (7) but by weighting each facility by the inverse of number of manufacturing facilities that the parent controls. In this way, I am putting more emphasis on firms with lower number of facilities and less operational segmentation.

Alternatively, and to test for geographic remoteness, I define another weighting variable which is the following Herfindahl index:

$$H_{jf} = \sum_{s} h^2_{jfs}, \tag{8}$$

where h is the share of facilities belonging to firm f located in state s. If all facilities belonging to a firm are located within the same state, then $H = 1$; otherwise, $H < 1$ depending on how facilities are distributed between different states. I will then do an OLS estimation using H as observation weights. Again, this weighting puts more emphasis on firms whose operation is mostly concentrated within the same state.

Each of the weighted OLS estimates are reported in Table 9. For these estimations, I am using the exposure measure in (6) since it is the only measure that has been shown to have statistical significance.

Comparing coefficients in this table to those from Table 8 demonstrates that, again, scope 2 technology is the only area that is being impacted by exposure to large CleanTech projects. More importantly, the estimated coefficients in this case are larger in magnitude and statistically more significant, that is, geographic segmentation matters and facilities tend to react more strongly to CleanTech projects when the parent firm is less segmented and more concentrated geographically.

6 Conclusion

The advantages and disadvantages of government emission-related regulations and intervention in the clean technology market are still a matter of research. In this paper, I look at the impact of a carbon pricing scheme on the Australian manufacturing and the implications of a related assistance program by the Australian government through the lens of a time-varying production function for emission. I manage to decouple the effect of change in the scale of operation from that of the technological change and scrutinize the trend in the emission technology among the Australian manufacturing firms and facilities keeping size fixed. Comparing the change in manufacturing from 2011 to 2014 consistently shows that emission technology spontaneously became cleaner to the extent that consuming the same amount of energy now generates about 10 per cent lower emissions. This trend can be mostly credited to the enactment of the carbon pricing scheme that was in full force during this period. The effect of CleanTech program has a more selected nature, and small manufacturing facilities apparently managed to surpass other facilities in reducing their emission intensities as the result of the grants. Large manufacturing facilities show a mixed response and a number of them seem to have focused on reducing energy intensity or to use these grants merely not to fall behind.

The study also detects a broader impact of the program on facilities that did not receive CleanTech grants but were exposed to other facilities that did. However, this exposure effect is mostly manifested as a change in scope 2 emission technology. Not every facility responded to being exposed either. The findings show that segmented firms, with many facilities across different states, had harder time assimilating the exposure effects, whereas firms with more concentrated operations responded more effectively. One can conjecture that the proximity between the operations and the headquarter or having a strong feedback line from operations to headquarter is a crucial factor in assimilating field observations, such as the implementation of a CleanTech project, into the decision making process.

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Dependent: log of emissions Variable	Total (1)	Scope 1 (2)	Scope 2 (3)	Total (4)	Scope 1 (5)	Scope 2 (6)
Weights	1/# Facilities			Herfindahl Index		
a_2	0.701***	0.709***	0.636***	0.726***	0.770***	0.732***
	(0.058)	(0.085)	(0.131)	(0.050)	(0.066)	(0.079)
Δc	-0.288**	-0.026	0.501**	-0.256***	-0.063	0.200*
	(0.116)	(0.131)	(0.219)	(0.074)	(0.085)	(0.110)
Δa	0.024	-0.003	-0.083*	0.019	-0.001	-0.020
	(0.018)	(0.019)	(0.045)	(0.013)	(0.015)	(0.022)
δ_c (CleanTech)	0.728***	0.673*	-0.052	0.609***	0.530**	0.434
	(0.235)	(0.407)	(0.461)	(0.217)	(0.237)	(0.410)
δ_a (CleanTech)	-0.121***	-0.104*	-0.008	-0.108**	-0.093**	-0.111
	(0.038)	(0.063)	(0.100)	(0.042)	(0.045)	(0.089)
δ_c (Parent)	0.104	-0.055	-0.698**	0.073	-0.022	-0.325**
	(0.140)	(0.153)	(0.300)	(0.090)	(0.096)	(0.140)
δ_a (Parent)	-0.002	0.005	0.141**	0.000	0.004	0.061**
	(0.026)	(0.029)	(0.063)	(0.019)	(0.023)	(0.028)
δ_c (Exposed)	0.031	-0.028	-0.107**	0.027**	-0.005	-0.045**
	(0.019)	(0.025)	(0.046)	(0.011)	(0.014)	(0.021)
δ_a (Exposed)	-0.002	0.007**	0.020**	-0.002	0.004	0.008*
	(0.003)	(0.004)	(0.008)	(0.002)	(0.003)	(0.004)
Adj. R^2	0.679	0.551	0.795	0.729	0.640	0.786
F	17.31	10.91	19.29	20.28	19.26	26.63
N	1,061	931	1,025	1,061	931	1,025

Table 9: Weighted OLS estimates of model (7) using the inverse of number of facilities or Herfindahl index as observation weights. Numbers in parenthesis are standard errors clustered by parent firms. ***, **, and * denote 1%, 5%, and 10% significances, respectively. A set of industry dummies are also included but not reported.