Ex post evaluation of voluntary environmental policies on the energy intensity in Chilean firms

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Abstract

This study analyzes the impact of two voluntary environmental policies (carbon footprint and energy efficiency) on the intensity of energy expenditure in Chilean firms between 2015 and 2017. Both policies could be considered successful in environmental terms if they reduce the energy or induce a substitution from fossil fuels to electricity. The analysis is carried out with two methods, matching with differences-in-differences (assuming exogenous treatment) and instrumental variables (assuming endogenous treatment), using a panel database built from the Longitudinal Survey of Firms. The results show that the carbon footprint policy does not affect the intensity of fuel expenditure or electricity expenditure. On the other hand, the energy efficiency policy increases the intensity of electricity expenditure. Thus, it is concluded that both policies are not effective in reducing the energy intensity at the firm level. The above could be attributed to a weak implementation, monitoring, and/or commitment of these voluntary environmental policies in many Chilean firms.

Keywords Matching with differences-in-differences · Instrumental variable · Treatment endogeneity · Impact evaluation · Intensity of energy expenditure

1 Introduction

Energy intensity can be defined as the energy consumed per unit of production, while the inverse of energy intensity is traditionally considered in the literature as a measure of energy efficiency (Zhang, Li, et al., 2020; Zhang, Liu, et al., 2020). The study of energy intensity is essential since it allows characterizing and evaluating energy consumption at the firm level (Chen, Zhou, et al., 2020; Roy & Yasar, 2015; Tang, 2020), economic sectors

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(Golder, 2011; Soni et al., 2017), and countries (Bertoldi & Mosconi, 2020; Azhagaliyeva et al., 2020; Santiago et al., 2020).

The relationship between government environmental policies and energy intensity is direct since the former usually establish standards that regulate emissions, waste generation, etc. However, there is a set of voluntary environmental policies that are self-imposed by the firms and can meet multiple objectives, such as improving corporate image, obtaining environmental certifications, reducing production costs, contributing to sustainability, among others. Voluntary environmental policies can offer advantages over regulation due to their flexibility when they are introduced or updated, a greater degree of acceptance by firms, and the possibility of tailor-made solutions. However, these policies have been criticized for the lack of specific obligations, undemanding goals, and monitoring and self-reporting problems (Rezessy & Bertoldi, 2011).

Voluntary environmental policies of energy efficiency and carbon footprint are framed in Chile's National Energy Efficiency Plan and the Nationally Determined Contribution (NDC). National Energy Efficiency Plan[1] aims to reduce energy intensity by 4.5% by 2026. In this plan, the main energy efficiency measures in the productive sector point to the implementation of energy management systems, promotion of efficient solutions for thermal and motor uses, the establishment of energy efficiency standards for vehicles, promotion of electromobility, energy renewal, thermal reconditioning, energy rating of buildings, and training and certification of human capital. On the other hand, the carbon footprint policy aligns with the country's Nationally Determined Contribution,[2] focusing on replacing fossil energy with renewable energy, electrification of machinery and engines, and replacing conventional vehicles with electric vehicles.

Currently, voluntary environmental policies of energy efficiency and carbon footprint are applied in many Chilean firms and could contribute to reducing the intensity of energy use, as evidenced by international literature for other countries (Adua et al., 2021; Chen, Chen, et al., 2020; Labandeira et al., 2020). However, the voluntary nature of these policies, differences in the design or implementation among countries, high heterogeneity of firms, and multiple other factors can condition the effects on energy intensity. Therefore, this study attempts to determine the impact of two voluntary environmental policies on the intensity of fuel expenditure and electricity expenditure[3] in Chile through ex post evaluation methods. Specifically, it seeks to demonstrate whether the energy efficiency and carbon footprint policies promoted by the government through the Sustainability and Climate Change Agency[4] have reduced energy consumption and/or generated substitution from fossil fuels to cleaner energy at the firm level. It should be noted that most of the previous studies addressing the impacts of voluntary environmental policies are based on sectoral data (Goh & Ang, 2019; Horowitz, 2014; Horowitz & Bertoldi, 2015). The study's novelty lies in providing evidence for developing countries and finding a causal identification strategy between the treatment and outcome variables.

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[1] https://energia.gob.cl/sites/default/files/documentos/plan_nacional_de_eficiencia_energetica_2022-2026.pdf

[2] https://cambioclimatico.mma.gob.cl/wp-content/uploads/2020/08/NDC_2020_Espanol_PDF_web.pdf

[3] The intensity of fuel expenditure is defined as fuel expenditure divided by sales. The intensity of electricity expenditure is defined as electricity expenditure divided by sales. Although these definitions are not commonly used in the literature, they are included in this study to differentiate between the use of fossil fuels and electricity, which would allow identifying the degree of substitution of both types of energy.

[4] Former Clean Production Council.

Initially, an in-depth review of previous studies related to energy intensity, environmental policies and regulations, and the most popular methods used for ex post evaluations of environmental policies were carried out. Once the context of the study was defined, the available databases were analyzed, concluding that the best option was to use a panel database built from the Longitudinal Survey of Firms (ELE in Spanish) in its fourth (ELE-4) and fifth (ELE-5) versions. The ELE-4 and ELE-5 are the only versions of this survey that ask about the environmental policies' implementation. According to the available data and the review of statistical techniques, it was decided to use the matching with differences-in-differences (MDID) method to determine the impact of two voluntary environmental policies (carbon footprint and energy efficiency) on the intensity of the electricity expenditure and intensity of the fuel expenditure. However, the two environmental policies could be endogenous, that is, correlated with unobservable factors that also affect the outcome variable (for example, the firm's reputation). Consequently, the initial analysis is complemented with an instrumental variables method that allows identifying the effect of a treatment when the treatment is endogenous (Baltagi, 2021). The identification mechanism is through relevant and exogenous instrumental variables (reputation measured through belonging to a holding company and the lagged outcome variable). The instrumental variables method requires that reputation (measured through belonging to a holding company) and the lagged outcome variable affect energy intensity only through environmental policies that this paper investigates, which is validated with statistical tests. The results obtained with both methodologies are similar, demonstrating the ineffectiveness of voluntary environmental policies in Chile. Although, in the available survey, it is not possible to determine the specific actions[5] and goals of these policies in each firm, it is known that 33.1% of firms with a carbon footprint policy calculate indicators and report their results, while 55.9% of firms with measures of energy efficiency calculate indicators and report their results.

2 Literature review

Some studies have analyzed the determinants of energy intensity in firms using panel data. For example, Roy and Yasar (2015) examine the impact of exporting on energy efficiency in Indonesia. They use instrumental variables and the generalized method of moments with data at the firm level between 2001 and 2007. The results indicate that export reduces the use of fuels relative to electricity use; thus, the analysis suggests that promoting exports in developing countries may have unintended environmental benefits. Tang (2020) studies the relationship between energy prices, new investments, and the reduction of energy intensity in the industrial sector of China, using panel data at the firm level that include energy consumption and the energy price from 1997 to 2004. The results indicate that the current and past energy prices are critical factors in reducing energy intensity in state, private, and foreign firms. In addition, it is determined that state firms can further reduce energy intensity

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[5] Energy efficiency measures are diverse and may include minimum energy performance standards for buildings, machinery and equipment, renovation of machinery and equipment; procurement regulations; elimination of inefficient equipment; information campaigns; energy audits; among others (Bertoldi & Economidou, 2018). On the other hand, firms can reduce their carbon footprint through the aforementioned measures and also substituting fossil energy by renewable energy, purchasing supplies with a lower carbon footprint, buying tons of carbon in the international emissions market, among others.

since they respond better to the rise in energy prices through more efficient investments in energy use. However, using ex post evaluation methods to identify the impact of a program or policy on energy intensity is very scarce in the literature. For example, Chen, Chen, et al. (2020) empirically investigate the effect of energy regulations on the energy intensity of Chinese manufacturing firms between 2003 and 2009. To do so, they estimate a differences-in-differences model that allows comparing the changes in the energy intensity of firms before and after the Eleventh Five-Year Plan (11th FYP). The explanatory variables include characteristics of the firms such as equity, debt, employment, firm's age, and the decision to export. The results show that stricter energy regulations generate a decrease in energy intensity and that non-state firms are responsible for reducing energy intensity.

Environmental policies can be divided into three broad categories: command and control regulations, instruments based on economic incentives (market-based), and voluntary agreements (Crespi et al., 2015). Command and control instruments regulate the behavior of firms, production methods, and/or pollution control through mandatory administrative orders such as laws, regulations, and plans formulated by the government (Blackman et al., 2018). Economic instruments aim to reduce energy consumption and/or emissions by encouraging more sustainable production practices using taxes, subsidies, fiscal incentives, or soft credits (Crespi et al., 2015). Voluntary environmental policies complement the first two categories and are less strict in terms of the conduct of firms with respect to environmental protection. On the other hand, voluntary environmental policies offer firms an alternative to other types of policies since the government can provide a tax exemption or the promise of less strict environmental regulation in the future if the firm participates in a voluntary agreement (Henriksson & Söderholm, 2009). In addition, voluntary policies can be effective for small-sized firms to face barriers to competition and information, especially when there are activities to exchange knowledge and experiences among participants. Therefore, voluntary environmental policies can be an effective policy to stimulate improvements in the energy efficiency of smaller firms (Cornelis, 2019).

Some previous studies have evaluated command and control regulations, economic instruments, and/or voluntary agreements. For example, Wu et al. (2020) examine the relationship between energy consumption, environmental regulations, and CO_2 emissions. Specifically, a dynamic panel data model is estimated based on provincial data from China between 2006 and 2015. The results indicate that energy consumption significantly promotes CO_2 emissions and that environmental regulations reduce the increase in emissions. Zhang, Liu, et al. (2020) study the effect of some economic instruments on the environmental and energy efficiency of mining firms in China. The database includes 30,689 firms in the period 2008 and 2011. The results show that mining firms have poor environmental and energy efficiency, but that tax incentives improve both, especially in private firms. Also, it is concluded that there is positive feedback between taxes, energy efficiency, and the environment when the most efficient firms receive greater tax incentives. Mardones and Bienzobas (2019) evaluate the impact of clean production agreements on water, electricity, fuel consumption, and CO_2 emissions in Chile, using pseudo-panel models with data from industrial firms between 2001 and 2014. The results show that clean production agreements only diminish oil and liquefied petroleum gas consumption, reducing the intensity of energy use and CO_2 emissions. Wakabayashi and Arimura (2016) investigate voluntary agreements implemented by associations of Japanese firms between 1997 and 2012; the study's objective is to determine whether these agreements have contributed to establishing CO_2 emission goals in the firms. From a database of 1000 firms, it is determined that small- and medium-sized firms that have implemented voluntary agreements are four times more likely to establish CO_2 emission targets than firms belonging to associations that have

not implemented voluntary agreements. However, goal setting in large firms is not affected by voluntary agreements. Henriksson and Söderholm (2009) study the Swedish Energy Efficiency Program (PFE) using firm-level data. The focus of the study is to determine how the presence of asymmetric information could affect the cost-effectiveness of voluntary programs. The results indicate that the main reason for intervening with energy efficiency policies is the asymmetry of information in the firms. However, replacing energy management systems through electricity taxes or environmental taxes does not cost-effectively solve the problem of information asymmetry.

3 Material and methods

3.1 Data

The database used in this study is obtained from the Longitudinal Survey of Firms (ELE) in its fourth (ELE-4) and fifth (ELE-5) versions. Both versions were consolidated under the same format, obtaining 4,172 firms with observations for 2017 and 2015. This database includes income from sales, energy expenditures, firm size, economic sector, adoption of voluntary environmental policies, and others. It should be mentioned that the first three versions of this survey (ELE-1, ELE-2, and ELE-3) do not ask whether the firms have voluntary environmental policies, which limits the analyzed period. Furthermore, the distinction between fuel and electricity expenditures was only made from ELE-4.

When using survey data, energy efficiency or intensity is difficult to measure at the firm level. In contrast, methods based on engineering and surveys at the firm level or combined with energy statistics at the sector or national level can produce more precise estimates (Horowitz & Bertoldi, 2015). In addition, energy intensity can be calculated as energy per physical unit of product, energy per value-added, energy expenditure per value-added, or energy expenditure per gross value of production (Goh & Ang, 2019; Horowitz, 2014). In this study, the last indicator is calculated since the database only has energy expenditures but not energy use in physical units, while the absence of payment to capital prevents directly obtaining the value-added.

Figure 1 shows the intensity of fuel expenditure according to the implementation of voluntary environmental policies. It is observed that there is a greater intensity of fuel expenditure in firms that have adopted energy efficiency measures and less intensity of fuel expenditure in firms that have adopted a carbon footprint policy. It should be noted that the impact of energy efficiency measures to reduce energy consumption has been determined by previous studies such as Adua et al. (2021) and Chen, Chen, et al. (2020). However, the apparent opposite effect observed in Fig. 1 could be attributed to self-selection; that is, the firms with a higher intensity of fuel expenditure could be more inclined to adopt energy efficiency policies. Also, it could be explained by more demanding environmental regulations. For example, Tan and Lin (2020) determine that some environmental regulations cause energy-intensive firms to substitute coal with oil and gas, which are more expensive.

Figure 2 shows the intensity of electricity expenditure according to the implementation of voluntary environmental policies. On average, the intensity of electricity expenditure is lower in firms that have adopted these policies, especially in 2017. In addition, it is observed that in 2017 there was a greater intensity of electricity expenditure in firms that did not adopt these policies. The previous results agree with Bertoldi and Mosconi (2020), Adua et al. (2021), and Chen, Chen, et al. (2020), which find energy savings induced by
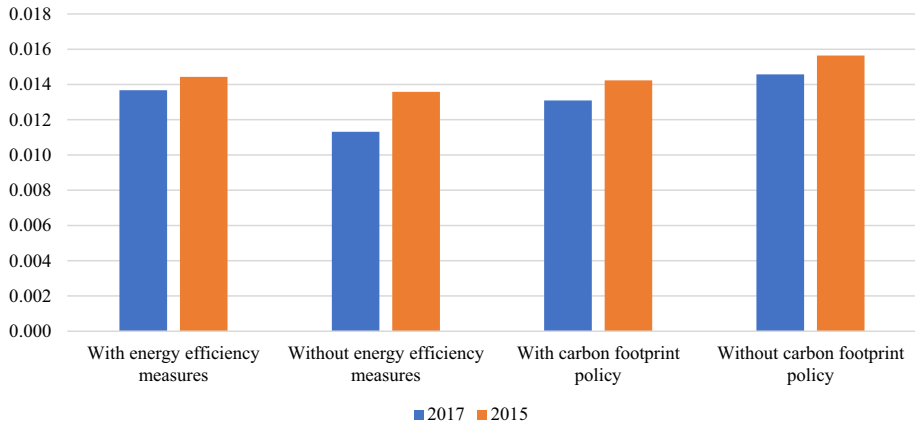
Fig. 1 The intensity of fuel expenditure according to the adoption of voluntary environmental policies. *Source*: Own elaboration based on ELE data
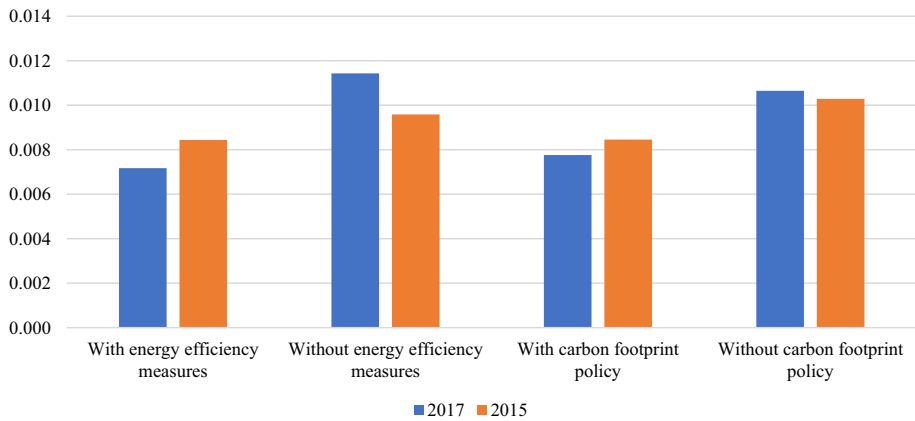
Fig. 2 The intensity of electricity expenditure according to the adoption of voluntary environmental policies. *Source*: Own elaboration based on ELE data

energy efficiency policies. However, it could also be attributed to other factors such as lower production or more stringent environmental regulations in intensive firms using fossil fuels.

3.2 Ex post evaluation techniques

The ex post evaluation aims to find the "causal effect" of a treatment (intervention, program, or policy) on a set of participating units (individuals, firms, regions, countries, etc.) based on statistical evidence (Abadie & Cattaneo, 2018). In a non-experimental context, a counterfactual scenario is constructed with the data from the non-treated individuals to infer the outcome variable that would have been observed if a treated individual had not participated in the treatment (Cerulli, 2015). There are different ex post evaluation methods

to consistently estimate the treatment effect under the hypothesis of "selection on observables" or "selection on unobservables."[6] Also, the possibility that the treatment is endogenous should be considered for the correct choice of method.

Following the formulation of Angrist and Pischke (2009), the effect of a treatment in period t can be defined as:

$$\tau = y_{ist}^1 - y_{ist}^0 \tag{1}$$

where y_{ist}^1 is the outcome variable of individual i belonging to group s in period t conditional on the presence of the treatment and y_{ist}^0 is the outcome variable of individual i belonging to group s in the period t conditional on the absence of treatment. For each individual, it is only possible to observe y_{ist}^1 or y_{ist}^0, so it is not possible to calculate τ at the individual level. Furthermore, s is equal to 1 for the group of individuals who are affected by the treatment, s is equal to 0 for a group of individuals not affected by the treatment, and X_{ist} is a vector of individual characteristics observed by the researcher. Thus, the average effect of treatment on the treated (ATT) can be defined as follows:

$$ATT = E\big(\tau|s=1, X_{ist}\big) = E\big(y_{ist}^1 - y_{ist}^0|s=1, X_{ist}\big) = E\big(y_{ist}^1|s=1, X_{ist}\big) - E\big(y_{ist}^0|s=1, X_{ist}\big) \tag{2}$$

Equation (2) estimates the average treatment effect among the treated individuals. However, in observational studies, there is no direct way to calculate the counterfactual mean of $E\big(y_{ist}^1|s=1, X_{ist}\big)$, that is, $E\big(y_{ist}^0|s=1, X_{ist}\big)$. Therefore, non-treated individuals are used as an approximation to obtain the counterfactual mean. ATT estimation can be based on statistical methods that assume "selection on observables" (for example, matching) or "selection on unobservables" (for example, differences-in-differences or instrumental variables).

The matching method tries to find in the control group an individual (or group of individuals) not chosen for the treatment that possesses characteristics very similar to an individual who participated in the treatment, which allows the difference in the outcome variable to be interpreted as the treatment effect. This estimator works under the assumption that the result variable is independent of the state of participation (defined as D_{ist}) subject to a group of observable characteristics V_{ist} that can be a subset of X_{ist} ("selection on observables"). Furthermore, it is assumed that there is a positive probability of participating or not participating in the treatment given the set of characteristics V_{ist}, which ensures that a match can always be found for the treated individuals. If these two assumptions are met, the ATT can be obtained. In some cases, it might be challenging to find an individual in the artificial control group similar in all V_{ist} characteristics to another individual in the treatment group. To face this problem, the propensity score matching takes all the observable characteristics to a score or propensity score $P(V_{ist})$ that serves as a criterion to find a match between the individuals of the treatment group and the control group (Imbens & Rubin, 2015). The empirical estimator of propensity score matching is as follows:

$$\widehat{ATT}_M = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} \left[y_{ist}^1 - \sum_{j \in I_0} W(i,j) y_{ist}^0 \right] \tag{3}$$

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[6] Unobservable factors are not part of the characteristics available in the database, so they are unknown to the researcher.

where I_1 is the set of individuals that belong to the treatment group, n_1 is the number of individuals in I_1, I_0 is the set of individuals that belong to the control group, S_P is the common support region that is a subset of V_{ist} where consistent matchings can be found. The match for each individual of I_1 is constructed from the weighted average on the outcome variables of the non-treated individuals, where the weights $W(i,j)$ depend on the distance between the propensity score of individual i (P_{ist}) and the propensity score of individual j (P_{jst}). Furthermore, a neighborhood $C(P_{ist})$ for each individual i must be defined in the treatment group, determining which individuals in the control group will be matched to individual i.

Differences-in-differences (DID) is a method that assumes "selection on unobservables." This method is useful when data exist for treated and non-treated individuals before and after treatment. The first difference makes it possible to eliminate unobservable factors that remain constant over time for individuals belonging to the treatment group. The second difference makes it possible to eliminate unobservable factors that vary over time and simultaneously affect the treatment and control groups, generating a better estimate of the treatment effect. The DID method can be represented through a regression. For the above, let us remember that y_{ist}^1 is the outcome variable for individual i belonging to group s in period t in the presence of the treatment, while y_{ist}^0 is the outcome variable for individual i belonging to group s in period t in the absence of treatment. Thus, y_{ist} can be defined as:

$$y_{ist} = D_{ist}\tau + \delta_s + \mu_t + \varepsilon_{ist} \tag{4}$$

where D_{ist} is a dichotomous variable that indicates participation or non-participation in the treatment (1 or 0), τ is a parameter to be estimated that represents the treatment effect (ATT), δ_s is a time-invariant effect, μ_t is an invariant group effect, and ε_{ist} is the random error whose expectation is assumed to be zero. Another popular way to apply the DID method is through regression with constant (α) and explanatory variables that include participation (D_{ist}), a dichotomous variable indicating that the post-treatment period (t_1), and the interaction of both variables ($D_{ist}t_1$).

$$y_{ist} = \alpha + \delta D_{ist} + \mu t_1 + \tau(D_{ist}t_1) + \varepsilon_{ist} \tag{5}$$

The advantage of using Eq. (5) is that new explanatory variables can be easily added (X_{ist}), which allows these observable factors to be controlled through a vector of parameters (γ):

$$y_{ist} = \alpha + \delta D_{ist} + \mu t_1 + \tau(D_{ist}t_1) + X'_{ist}\gamma + \varepsilon_{ist} \tag{6}$$

Serial correlation is a common problem when applying the DID method, but it can be easily solved using cluster–robust standard errors at the group level (Bertrand et al., 2004). Another critical aspect of the DID method is that it assumes parallel tendencies, implying that individuals in the control and treatment groups should have the same behavior without treatment. To test this assumption, Abadie & Cattaneo (2018) mention two alternatives, which require having multiple periods before applying the treatment or groups of individuals who are not at risk of being exposed to the treatment.[7]

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[7] In this study, the database only has two periods, and firms that are not at risk of being exposed to treatment cannot be identified. So, there are clear limitations to validating the assumptions if this method was chosen.

A hybrid method such as matching with differences-in-differences (MDID) could generate more robust estimates than both methods independently (Cerulli, 2015). The above is explained because the traditional matching estimators assume that after conditioning for a set of observable characteristics, the means of the outcome variables are conditionally independent of the treatment status. However, there might be differences between the outcome variables of treated and non-treated individuals, even after conditioning for observable variables. Therefore, Heckman et al. (1997) developed the MDID method, allowing unobservable individual differences invariant over time in the treatment and control groups. The MDID or propensity score MDID estimator assumes that there is no difference in the mean change observed in the outcome variable between the periods before (t_0) and after treatment (t_1) for the control group and treatment group if the treatment is not implemented, conditional on the propensity score P_{ist}. This estimator requires that the conditions of traditional matching are met in both periods. Thus, the MDID estimator is given by:

$$\widehat{ATT}_{MDID} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} \left\{ (y_{ist_1}^1 - y_{ist_0}^0) - \sum_{j \in I_0 \cap S_P} W(i,j)(y_{jst_1}^0 - y_{jst_0}^0) \right\} \tag{7}$$

In this case, $W(i,j)$ depends on the chosen matching method, such as the nearest-neighbor matching, caliper matching, kernel matching, among others. It should be noted that the MDID technique depends on the condition of independence, which is why it is helpful to carry out a sensitivity analysis of the results (Cerulli, 2019). For example, Waibel et al. (2018) use different matching types, add new variables, and separate the matching estimators by subsets of the total sample.

If there are reasons to believe that unobservable factors affect the allocation of treatment and the outcome variable, another type of method should be chosen (Cerulli, 2015). For example, the firm's reputation could induce the adoption of voluntary environmental policies and affect the intensity of energy expenditure (fuel or electricity). The instrumental variables (IV) method is an excellent alternative to deal with endogenous treatment produced by "selection on unobservables." However, this method can have consistency and efficiency problems in the presence of "weak" instruments that are not sufficiently correlated with the endogenous explanatory variable or are not entirely exogenous (Baltagi, 2021). Therefore, the relevance and exogeneity of the chosen instruments must be demonstrated through statistical tests. The instrumental variables method with panel data assumes that the treatment variable (D_{ist}) is endogenous and allows it to be correlated with the error (ε_{ist}). Also, a vector of strictly exogenous instrumental variables (Z_{ist}) is required, $E(Z'_{ist}\varepsilon_{ist}) = 0$. In this context, the model of interest can be specified as:

$$y_{ist} = \alpha + \tau D_{ist} + X'_{ist}\gamma + c_{is} + \varepsilon_{ist} \tag{8}$$

Equation (8) recognizes that the application of the treatment may be correlated with the individual characteristics (c_{is}) that affect the outcome variable. Furthermore, D_{ist} could be correlated with ε_{ist}, which also affects the outcome variable. Therefore, Eq. (8) must be modified to estimate τ. The fixed effects estimator uses deviate variables from time averages ($\ddot{y}_{ist} = y_{ist} - \bar{y}_{is}; \ddot{D}_{ist} = D_{ist} - \bar{D}_{is}; \ddot{X}_{ist} = X_{ist} - \bar{X}_{is}; \ddot{\varepsilon}_{ist} = \varepsilon_{ist} - \bar{\varepsilon}_{is}$) to remove c_{is} in Eq. (8) and then to apply an IV method to Eq. (9) such as pooled two-stage least squares (2SLS) (Wooldridge, 2010):

$$\ddot{y}_{ist} = \tau \ddot{D}_{ist} + \ddot{X}'_{ist}\gamma + \ddot{\varepsilon}_{ist} \tag{9}$$

To apply an IV method to Eq. (9) requires at least one valid instrument for $\ddot{D}_{ist}$. Therefore, the relevance of the instrumental variables (Z_{ist}) must be tested through an F test that yields a value greater than 10, and the (strict) exogeneity through a Sargan–Hansen overidentification test with a significance level greater than 5%.

4 Results and discussion

This section presents the different estimators that analyze the impact of voluntary environmental policies on the intensity of fuel expenditure and the intensity of electricity expenditure in Chilean firms. In the MDID method, different bandwidths (0.02, 0.06, and 0.10), kernel types (Epanechnikov, Gaussian, uniform, biweight, and tricube), and subsets of firms grouped according to size are used. In the instrumental variables method, the intensity of fuel/electricity expenditure[8] in the previous period (years 2014 or 2016) and belonging to a holding company[9] are used as instrumental variables. In both methods, the control variables include the firm's age, percentages of capital according to the type of property (national private, foreign private, and/or state), sales, marketing margin, firm size, and/or economic sector.

4.1 The intensity of fuel expenditure

The effects of the energy efficiency policy on the intensity of fuel expenditure are presented in Table 1 and Table 2. The results obtained with MDID show no significant impact of this voluntary environmental policy on the intensity of fuel expenditure when all firms or firms disaggregated according to size are analyzed. This finding is robust to different bandwidths and kernel types (see Table 1). The instrumental variables method also does not show an impact of this policy on the outcome variable. Statistical inference with this method is valid since the F test does not reject that the instruments are relevant, and the Sargan–Hansen test shows that the instruments are exogenous (see Table 2). The previous results contrast with Adua et al. (2021) and Chen, Chen, et al. (2020), which determine that energy efficiency measures significantly reduce energy consumption at the firm level.

The effects of the carbon footprint policy on the intensity of fuel expenditure are presented in Tables 3 and 4. The results obtained with MDID only show positive impacts that are statistically significant for small firms. Still, these impacts have a sign opposite to the expected and are not robust as they are sensitive to different bandwidths and/or kernel types (see Table 3). On the other hand, the instrumental variables method does not show an impact of this policy on the intensity of fuel expenditure. Statistical inference with this method is valid since the F test does not reject that the instruments are relevant, and the Sargan–Hansen test shows that the instruments are exogenous (see Table 4). Thus,

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[8] Firms with higher intensity of fuel/electricity expenditure in the previous period should have more incentives to implement carbon footprint or energy efficiency policies, and in addition, they are unlikely to be influenced by current shocks affecting the outcome variable.

[9] Firms that belong to a holding company have a greater reputation to uphold, which is why they could have more incentives to implement carbon footprint or energy efficiency policies.

Table 1 Effect of energy efficiency measures on the intensity of fuel expenditure using matching with differences-in-differences. Source: Own elaboration

(bw = 0.02)

Type of kernel	Treated t=0	Treated t=1	Controls t=0	Controls t=1	Coef	SE
All firms						
Epanechnikov	518	805	3644	3072	−0.001	0.002
Gaussian	518	805	3644	3072	−0.001	0.002
Biweight	518	805	3644	3072	−0.001	0.002
Uniform	518	805	3644	3072	−0.001	0.002
Tricube	518	805	3644	3072	−0.001	0.002
Large-sized firms						
Epanechnikov	404	561	1883	1308	−0.001	0.003
Gaussian	404	561	1886	1309	−0.001	0.003
Biweight	404	561	1883	1308	−0.001	0.003
Uniform	404	561	1883	1308	−0.001	0.003
Tricube	404	561	1883	1308	−0.001	0.003
Medium-sized firms						
Epanechnikov	56	118	524	319	0.002	0.005
Gaussian	56	118	530	322	0.004	0.005
Biweight	56	118	524	319	0.000	0.005
Uniform	56	118	524	319	0.004	0.005
Tricube	56	118	524	319	0.003	0.005
Small-sized firms						
Epanechnikov	51	102	858	666	0.011	0.007
Gaussian	51	102	865	670	0.005	0.007
Biweight	51	102	858	666	0.012	0.007
Uniform	51	102	858	666	0.009	0.007
Tricube	51	102	858	666	0.010	0.007

(bw = 0.06)

Type of kernel	Treated t=0	Treated t=1	Controls t=0	Controls t=1	Coef	SE
All firms						
Epanechnikov	518	805	3644	3072	−0.001	0.002
Gaussian	518	805	3644	3072	−0.001	0.002
Biweight	518	805	3644	3072	−0.001	0.002
Uniform	518	805	3644	3072	−0.001	0.002
Tricube	518	805	3644	3072	−0.001	0.002
Large-sized firms						
Epanechnikov	404	561	1886	1309	0.000	0.003
Gaussian	404	561	1886	1309	−0.001	0.003
Biweight	404	561	1886	1309	−0.001	0.003
Uniform	404	561	1886	1309	0.000	0.003
Tricube	404	561	1886	1309	0.000	0.003
Medium-sized firms						
Epanechnikov	56	118	530	322	0.004	0.005
Gaussian	56	118	530	322	0.005	0.005
Biweight	56	118	530	322	0.004	0.005
Uniform	56	118	530	322	0.004	0.005
Tricube	56	118	530	322	0.004	0.005
Small-sized firms						
Epanechnikov	51	102	864	669	0.005	0.007
Gaussian	51	102	865	670	0.002	0.007
Biweight	51	102	864	669	0.005	0.007
Uniform	51	102	864	669	0.005	0.007
Tricube	51	102	864	669	0.005	0.007

(bw = 0.10)

Type of kernel	Treated t=0	Treated t=1	Controls t=0	Controls t=1	Coef	SE
All firms						
Epanechnikov	518	805	3644	3072	−0.002	0.002
Gaussian	518	805	3644	3072	−0.002	0.002
Biweight	518	805	3644	3072	−0.002	0.002
Uniform	518	805	3644	3072	−0.002	0.002
Tricube	518	805	3644	3072	−0.002	0.002
Large-sized firms						
Epanechnikov	404	561	1886	1309	−0.000	0.003
Gaussian	404	561	1886	1309	−0.001	0.003
Biweight	404	561	1886	1309	−0.000	0.003
Uniform	404	561	1886	1309	−0.001	0.003
Tricube	404	561	1886	1309	−0.001	0.003
Medium-sized firms						
Epanechnikov	56	118	530	322	0.004	0.005
Gaussian	56	118	530	322	0.005	0.005
Biweight	56	118	530	322	0.004	0.005
Uniform	56	118	530	322	0.005	0.005
Tricube	56	118	530	322	0.005	0.005
Small-sized firms						
Epanechnikov	51	102	865	670	0.003	0.007
Gaussian	51	102	865	670	0.002	0.007
Biweight	51	102	865	670	0.004	0.007
Uniform	51	102	865	670	0.002	0.007
Tricube	51	102	865	670	0.003	0.007

Table 1 (continued)

Type of kernel	(bw=0.02)						(bw=0.06)						(bw=0.10)					
	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE
	t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1		
Micro-sized firms																		
Epanechnikov	7	24	225	165	−0.010	0.007	7	24	227	172	0.000	0.008	7	24	227	172	0.003	0.009
Gaussian	7	24	227	172	−0.004	0.007	7	24	227	172	0.005	0.009	7	24	227	172	0.006	0.010
Biweight	7	24	225	165	−0.011	0.007	7	24	227	172	−0.002	0.008	7	24	227	172	0.001	0.009
Uniform	7	24	225	165	−0.009	0.007	7	24	227	172	0.002	0.009	7	24	227	172	0.006	0.010
Tricube	7	24	225	165	−0.009	0.007	7	24	227	172	0.001	0.009	7	24	227	172	0.005	0.010

(*) Significant at 5% and (**) Significant at 1%

Table 2 Effect of energy efficiency measures on the intensity of fuel expenditure using instrumental variables. Source: Own elaboration

Variable	Model 6	Model 5	Model 4	Model 3	Model 2	Model 1
Energy efficiency measures	2.519	2.394	2.383	2.383	2.383	2.414
	[2.322]	[2.159]	[2.141]	[2.141]	[2.141]	[2.173]
Large-sized	−0.0793	−0.0763	−0.076	−0.076	−0.076	−0.0771
	[0.136]	[0.129]	[0.128]	[0.128]	[0.128]	[0.130]
Medium-sized	−0.157	−0.149	−0.149	−0.149	−0.149	−0.151
	[0.174]	[0.163]	[0.162]	[0.162]	[0.162]	[0.164]
Small-sized	−0.117	−0.11	−0.11	−0.11	−0.11	−0.112
	[0.123]	[0.115]	[0.114]	[0.115]	[0.115]	[0.116]
Mining sector	−0.0378	−0.0428	−0.0436	−0.0435	−0.0435	−0.043
	[0.257]	[0.246]	[0.245]	[0.245]	[0.245]	[0.248]
Professional services sector	0.122	0.118	0.115	0.115	0.115	0.116
	[0.230]	[0.217]	[0.215]	[0.215]	[0.215]	[0.218]
Industrial sector	−0.0922	−0.0853	−0.0877	−0.0877	−0.0877	−0.0897
	[0.207]	[0.195]	[0.195]	[0.195]	[0.195]	[0.198]
Agricultural sector	−0.0538	−0.0538	−0.0553	−0.0553	−0.0553	−0.0536
	[0.256]	[0.243]	[0.242]	[0.242]	[0.242]	[0.246]
Transport and storage sector	−0.277	−0.265	−0.265	−0.265	−0.265	−0.266
	[0.317]	[0.298]	[0.297]	[0.297]	[0.297]	[0.301]
Telecommunication sector	0.0494	0.0439	0.0344	0.0344	0.0344	0.0343
	[0.207]	[0.196]	[0.196]	[0.196]	[0.196]	[0.198]
Commerce sector	0.12	0.116	0.113	0.113	0.113	0.112
	[0.211]	[0.200]	[0.198]	[0.198]	[0.198]	[0.200]
Services sector	−0.0857	−0.0807	−0.0821	−0.0821	−0.0821	−0.0824
	[0.164]	[0.155]	[0.155]	[0.155]	[0.155]	[0.156]
% of capital national private		−0.00132	−0.00345	−0.00345	−0.00345	−0.00349
		[0.00155]	[0.00540]	[0.00540]	[0.00540]	[0.00547]
% of capital foreign private			−0.00233	−0.00233	−0.00233	−0.00234
			[0.00502]	[0.00502]	[0.00502]	[0.00508]
Sales				−5.67E−14	−5.67E−14	−5.79E−14
				[9.25e−14]	[9.25e−14]	[9.43e−14]
Marketing margin					7.82E−10	7.64E−10
					[2.85e−09]	[2.88e−09]
Firm's age						−0.000905
						[0.00219]
Constant	−0.302	−0.167	0.0508	0.0508	0.0508	1.858
	[0.333]	[0.239]	[0.473]	[0.473]	[0.473]	[4.391]
Observations	8292	8292	8292	8292	8292	8292
R^2	0.0019	0.0021	0.002	0.002	0.002	0.002
Sargan–Hansen test	1.556	1.799	1.814	1.814	1.814	1.743
F test	54.98**	41.87**	41.74**	41.33**	41.32**	39.61**

(*) Significant at 5% and (**) Significant at 1%. Cluster–robust standard errors in brackets

Table 3 Effect of the carbon footprint policy on the intensity of fuel expenditure using matching with differences-in-differences. Source: Own elaboration

Type of kernel	(bw=0.02)						(bw=0.06)						(bw=0.10)					
	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE
	t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1		
All firms																		
Epanechnikov	284	346	3859	3599	0.001	0.002	284	346	3860	3600	0.000	0.002	284	346	3862	3601	0.000	0.002
Gaussian	284	346	3861	3601	0.000	0.002	284	346	3861	3601	0.001	0.002	284	346	3862	3601	0.000	0.002
Biweight	284	346	3859	3599	0.001	0.002	284	346	3860	3600	0.000	0.002	284	346	3862	3601	0.000	0.002
Uniform	284	346	3859	3599	0.000	0.002	284	346	3860	3600	0.001	0.002	284	346	3862	3601	0.000	0.002
Tricube	284	346	3859	3599	0.001	0.002	284	346	3860	3600	0.001	0.002	284	346	3862	3601	0.000	0.002
Large-sized firms																		
Epanechnikov	220	258	2056	1648	0.000	0.003	220	258	2057	1649	0.000	0.003	220	258	2057	1649	-0.000	0.003
Gaussian	220	258	2058	1649	0.001	0.003	220	258	2058	1649	0.000	0.003	220	258	2058	1649	-0.000	0.003
Biweight	220	258	2056	1648	0.000	0.003	220	258	2057	1649	0.000	0.003	220	258	2057	1649	-0.000	0.003
Uniform	220	258	2056	1648	0.000	0.003	220	258	2057	1649	0.000	0.003	220	258	2057	1649	-0.001	0.003
Tricube	220	258	2056	1648	0.000	0.003	220	258	2057	1649	0.000	0.003	220	258	2057	1649	-0.001	0.003
Medium-sized firms																		
Epanechnikov	32	48	501	347	0.002	0.006	32	48	523	355	-0.005	0.006	32	48	524	356	-0.001	0.005
Gaussian	32	48	525	357	-0.002	0.006	32	48	525	357	-0.003	0.005	32	48	525	357	-0.004	0.005
Biweight	32	48	501	347	0.003	0.006	32	48	523	355	-0.005	0.006	32	48	524	356	-0.001	0.006
Uniform	32	48	501	347	0.001	0.005	32	48	523	355	-0.004	0.006	32	48	524	356	-0.002	0.005
Tricube	32	48	501	347	0.002	0.006	32	48	523	355	-0.004	0.006	32	48	524	356	-0.002	0.005
Small-sized firms																		
Epanechnikov	26	30	886	737	0.001	0.009	26	30	889	740	0.021	0.008**	26	30	890	740	0.021	0.008***
Gaussian	26	30	890	740	0.021	0.008**	26	30	890	740	0.021	0.008*	26	30	890	740	0.021	0.008*
Biweight	26	30	886	737	-0.006	0.009	26	30	889	740	0.021	0.008**	26	30	890	740	0.021	0.008***
Uniform	26	30	886	737	0.010	0.009	26	30	889	740	0.021	0.008**	26	30	890	740	0.021	0.008***
Tricube	26	30	886	737	0.007	0.009	26	30	889	740	0.021	0.008**	26	30	890	740	0.021	0.008***

Table 3 (continued)

Type of kernel	(bw = 0.02)						(bw = 0.06)						(bw = 0.10)					
	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE
	t = 0	t = 1	t = 0	t = 1			t = 0	t = 1	t = 0	t = 1			t = 0	t = 1	t = 0	t = 1		
Micro-sized firms																		
Epanechnikov	6	10	192	150	0.005	0.007	6	10	196	154	0.007	0.007	6	10	196	154	0.006	0.007
Gaussian	6	10	196	154	0.006	0.007	6	10	196	154	0.006	0.007	6	10	196	154	0.006	0.007
Biweight	6	10	192	150	0.005	0.007	6	10	196	154	0.006	0.007	6	10	196	154	0.006	0.007
Uniform	6	10	192	150	0.005	0.006	6	10	196	154	0.007	0.007	6	10	196	154	0.006	0.007
Tricube	6	10	192	150	0.004	0.006	6	10	196	154	0.007	0.007	6	10	196	154	0.006	0.007

(*) Significant at 5% and (**) Significant at 1%

Table 4 Effect of the carbon footprint policy on the intensity of fuel expenditure using instrumental variables. Source: Own elaboration

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Carbon footprint policy	2.882	2.821	2.806	2.794	2.794	2.869
	[2.642]	[2.557]	[2.530]	[2.516]	[2.517]	[2.603]
Large-sized	−0.0101	−0.0103	−0.0103	−0.0102	−0.0102	−0.0106
	[0.103]	[0.101]	[0.100]	[0.0999]	[0.0999]	[0.103]
Medium-sized	−0.0511	−0.05	−0.05	−0.0498	−0.0498	−0.0512
	[0.0947]	[0.0926]	[0.0921]	[0.0918]	[0.0918]	[0.0943]
Small-sized	−0.00959	−0.00918	−0.0095	−0.00948	−0.00948	−0.00992
	[0.0555]	[0.0543]	[0.0540]	[0.0538]	[0.0538]	[0.0552]
Mining sector	0.219	0.212	0.209	0.208	0.208	0.215
	[0.281]	[0.269]	[0.267]	[0.266]	[0.266]	[0.275]
Professional services sector	0.121	0.119	0.116	0.115	0.115	0.118
	[0.175]	[0.171]	[0.168]	[0.168]	[0.168]	[0.172]
Industrial sector	0.0522	0.052	0.0484	0.0483	0.0483	0.048
	[0.145]	[0.141]	[0.140]	[0.139]	[0.139]	[0.143]
Agricultural sector	0.00939	0.00817	0.006	0.00592	0.00592	0.0105
	[0.207]	[0.203]	[0.202]	[0.201]	[0.201]	[0.207]
Transport and storage sector	0.219	0.213	0.21	0.209	0.209	0.218
	[0.302]	[0.294]	[0.290]	[0.289]	[0.289]	[0.300]
Telecommunications sector	0.0141	0.0126	0.00145	0.00143	0.00143	0.000494
	[0.212]	[0.207]	[0.208]	[0.208]	[0.208]	[0.213]
Commerce sector	0.00342	0.00412	0.000269	0.000222	0.000222	−0.00281
	[0.127]	[0.124]	[0.124]	[0.123]	[0.123]	[0.127]
Services sector	−0.197	−0.192	−0.193	−0.193	−0.193	−0.196
	[0.237]	[0.230]	[0.229]	[0.228]	[0.228]	[0.234]
% of capital national private		−0.000501	−0.00306	−0.00304	−0.00304	−0.00311
		[0.00104]	[0.00547]	[0.00545]	[0.00545]	[0.00559]
% of capital foreign private			−0.00279	−0.00278	−0.00278	−0.00282
			[0.00544]	[0.00541]	[0.00542]	[0.00555]
Sales				6.16E−12	6.16E−12	6.32E−12
				[5.55e−12]	[5.55e−12]	[5.74e−12]
Marketing margin					3.44E−09	3.48E−09
					[5.28e−09]	[5.35e−09]
Firm's age						−0.00161
						[0.00278]
Constant	−0.215	−0.165	0.0957	0.0948	0.0948	3.319
	[0.250]	[0.224]	[0.497]	[0.495]	[0.495]	[5.608]
Observations	8292	8292	8292	8292	8292	8292
R^2	0.002	0.0019	0.002	0.002	0.002	0.002
Sargan–Hansen test	2.563	2.701	2.726	2.755	2.755	2.57
F test	56.5**	40.08**	39.94**	39.92**	39.92**	38.99**

(*) Significant at 5% and (**) Significant at 1%. Cluster–robust standard errors in brackets

Table 5 Effect of energy efficiency measures on the intensity of electricity expenditure using matching with differences-in-differences. Source: Own elaboration

Type of kernel	(bw=0.02)						(bw=0.06)						(bw=0.10)					
	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE
	t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1		
All firms																		
Epanechnikov	518	805	3644	3072	0.004	0.002*	518	805	3644	3072	0.005	0.002*	518	805	3644	3072	0.002	0.001
Gaussian	518	805	3644	3072	0.005	0.002*	518	805	3644	3072	0.004	0.002*	518	805	3644	3072	0.002	0.001
Biweight	518	805	3644	3072	0.004	0.002*	518	805	3644	3072	0.005	0.002*	518	805	3644	3072	0.002	0.001
Uniform	518	805	3644	3072	0.004	0.002*	518	805	3644	3072	0.005	0.002**	518	805	3644	3072	0.002	0.001
Tricube	518	805	3644	3072	0.004	0.002*	518	805	3644	3072	0.005	0.002**	518	805	3644	3072	0.002	0.001
Large-sized firms																		
Epanechnikov	404	561	1883	1308	0.003	0.002	404	561	1886	1309	0.003	0.002	404	561	1886	1309	0.003	0.002
Gaussian	404	561	1886	1309	0.003	0.002	404	561	1886	1309	0.003	0.002	404	561	1886	1309	0.003	0.002
Biweight	404	561	1883	1308	0.003	0.002	404	561	1886	1309	0.003	0.002	404	561	1886	1309	0.003	0.002
Uniform	404	561	1883	1308	0.003	0.002	404	561	1886	1309	0.003	0.002	404	561	1886	1309	0.003	0.002
Tricube	404	561	1883	1308	0.003	0.002	404	561	1886	1309	0.003	0.002	404	561	1886	1309	0.003	0.002
Medium-sized firms																		
Epanechnikov	56	118	524	319	0.003	0.004	56	118	530	322	0.001	0.004	56	118	530	322	0.001	0.004
Gaussian	56	118	530	322	0.002	0.004	56	118	530	322	0.001	0.004	56	118	530	322	0.001	0.004
Biweight	56	118	524	319	0.004	0.004	56	118	530	322	0.001	0.004	56	118	530	322	0.001	0.004
Uniform	56	118	524	319	0.002	0.004	56	118	530	322	0.001	0.004	56	118	530	322	0.001	0.004
Tricube	56	118	524	319	0.002	0.004	56	118	530	322	0.001	0.004	56	118	530	322	0.001	0.004
Small-sized firms																		
Epanechnikov	51	102	858	666	0.000	0.002	51	102	864	669	0.000	0.011	51	102	865	670	0.000	0.003
Gaussian	51	102	865	670	0.000	0.002	51	102	865	670	0.001	0.011	51	102	865	670	0.001	0.003
Biweight	51	102	858	666	0.000	0.002	51	102	864	669	0.002	0.011	51	102	865	670	0.000	0.003
Uniform	51	102	858	666	0.000	0.002	51	102	864	669	0.000	0.011	51	102	865	670	0.001	0.003
Tricube	51	102	858	666	0.000	0.002	51	102	864	669	0.000	0.011	51	102	865	670	0.001	0.003

Table 5 (continued)

Type of kernel	(bw=0.02)						(bw=0.06)						(bw=0.10)					
	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE
	t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1		
Micro-sized firms																		
Epanechnikov	7	24	220	165	−0.011	0.010	7	24	227	172	−0.006	0.011	7	24	227	172	−0.008	0.011
Gaussian	7	24	227	172	−0.007	0.010	7	24	227	172	−0.008	0.011	7	24	227	172	−0.007	0.011
Biweight	7	24	220	165	−0.011	0.011	7	24	227	172	−0.006	0.011	7	24	227	172	−0.007	0.011
Uniform	7	24	220	165	−0.010	0.010	7	24	227	172	−0.006	0.011	7	24	227	172	−0.008	0.010
Tricube	7	24	220	165	−0.011	0.010	7	24	227	172	−0.006	0.011	7	24	227	172	−0.008	0.011

(*) Significant at 5% and (**) Significant at 1%

Table 6 Effect of energy efficiency measures on the intensity of electricity expenditure using instrumental variables. Source: Own elaboration

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Energy efficiency measures	1.305	1.284	1.283	1.283	1.283	1.293
	[0.638]	[0.635]	[0.636]	[0.636]	[0.636]	[0.642]
Large-sized	−0.0452	−0.045	−0.0449	−0.0449	−0.0449	−0.0453
	[0.0627]	[0.0619]	[0.0618]	[0.0618]	[0.0618]	[0.0623]
Medium-sized	−0.0826	−0.0811	−0.0811	−0.0811	−0.0811	−0.0818
	[0.0651]	[0.0644]	[0.0644]	[0.0644]	[0.0644]	[0.0649]
Small-sized	−0.0617	−0.0604	−0.0605	−0.0605	−0.0605	−0.0611
	[0.0465]	[0.0459]	[0.0459]	[0.0459]	[0.0459]	[0.0463]
Mining sector	−0.043	−0.0463	−0.0468	−0.0468	−0.0468	−0.0464
	[0.126]	[0.125]	[0.125]	[0.125]	[0.125]	[0.126]
Professional services sector	0.0721	0.0719	0.0705	0.0705	0.0705	0.0708
	[0.107]	[0.105]	[0.105]	[0.105]	[0.105]	[0.106]
Industrial sector	−0.0399	−0.038	−0.0394	−0.0394	−0.0394	−0.0402
	[0.100]	[0.0986]	[0.0988]	[0.0988]	[0.0988]	[0.0997]
Agricultural sector	−0.0129	−0.0137	−0.0145	−0.0145	−0.0145	−0.0134
	[0.132]	[0.130]	[0.130]	[0.130]	[0.130]	[0.132]
Transport and storage sector	−0.126	−0.124	−0.125	−0.125	−0.125	−0.125
	[0.131]	[0.129]	[0.129]	[0.129]	[0.129]	[0.130]
Telecommunications sector	0.0312	0.0292	0.0245	0.0245	0.0245	0.0243
	[0.105]	[0.104]	[0.104]	[0.104]	[0.104]	[0.105]
Commerce sector	0.0664	0.0665	0.0648	0.0648	0.0648	0.0643
	[0.0966]	[0.0952]	[0.0950]	[0.0950]	[0.0950]	[0.0957]
Services sector	−0.0335	−0.0324	−0.0332	−0.0332	−0.0332	−0.0331
	[0.0778]	[0.0766]	[0.0767]	[0.0767]	[0.0767]	[0.0772]
% of capital national private		−0.000673	−0.00176	−0.00176	−0.00176	−0.00177
		[0.000639]	[0.00257]	[0.00257]	[0.00257]	[0.00259]
% of capital foreign private			−0.00118	−0.00118	−0.00118	−0.00118
			[0.00254]	[0.00255]	[0.00255]	[0.00257]
Sales				−3.79E−14	−3.79E−14	−3.84E−14
				[4.61e−14]	[4.61e−14]	[4.66e−14]
Marketing margin					−3.87E−10	−3.98E−10
					[1.57e−09]	[1.58e−09]
Firm's age						−0.000503
						[0.00111]
Constant	−0.158	−0.0952	0.0149	0.0149	0.0149	1.018
	[0.111]	[0.101]	[0.254]	[0.254]	[0.254]	[2.233]
Observations	8292	8292	8292	8292	8292	8292
R^2	0.0014	0.0013	0.0014	0.0014	0.0014	0.0015
Sargan-Hansen test	0.647	0.743	0.753	0.753	0.753	0.732
F test	58.6**	45.53**	45.48**	45.09**	46.08**	43.06**

(*) Significant at 5% and (**) Significant at 1%. Cluster–robust standard errors in brackets

it is concluded that there is no evidence to affirm that the carbon footprint policy generates reductions in the intensity of fuel expenditure. The previous contradicts the results of Ratanakuakangwan and Morita (2021), which determine that environmental regulations drastically reduce energy intensity in firms that use fossil fuels.

4.2 The intensity of electricity expenditure

The effects of the energy efficiency policy on the intensity of electricity expenditure are presented in Table 5 and Table 6. The results obtained with MDID show positive impacts that are statistically significant for all firms, but these impacts disappear when firms are disaggregated by size. In addition, these impacts are not robust as they are sensitive to different bandwidths (see Table 5). The results obtained with the instrumental variables method show that energy efficiency measures increase the intensity of electricity expenditure. The previous is statistically significant at 5%, but the sign is contrary to the expected. This finding cannot be justified in the substitution of fossil fuels with electricity according to the evidence previously reported in Table 1 and Table 2. Statistical inference with the instrumental variables method is valid because the F test shows that the instruments are relevant, and the Sargan–Hansen test does not reject that the instruments are exogenous (see Table 6). The results contrast with previous studies that determine energy savings in firms induced by energy efficiency policies (Bertoldi & Mosconi, 2020; Labandeira et al., 2020).

The effects of the carbon footprint policy on the intensity of electricity expenditure are presented in Table 7 and Table 8. The results obtained with MDID show some significant impact on medium-sized and micro-sized firms when using some bandwidths and kernel types, but these impacts are not robust and even change the sign in the case of micro-sized firms (see Table 7). The instrumental variables method does not show an effect of this policy on the intensity of electricity expenditure. However, statistical inference with this method is not valid since the Sargan–Hansen test rejects that the instruments are exogenous (see Table 8). Based on this partially valid evidence, it could be stated that the carbon footprint policy is unlikely to induce a reduction in the intensity of electricity expenditure. The previous results contrast with Martin et al. (2014), which show that environmental regulations negatively impact energy intensity.

All the results obtained in this study show that energy efficiency and carbon footprint policies have not had a relevant impact on reducing the energy intensity in Chilean firms. There is even evidence of an increase in the intensity of electricity expenditure when firms adopt energy efficiency measures. On the other hand, it is not observed that these voluntary environmental policies generate a substitution from fossil energy to electrical energy. For the above, it would be necessary to obtain a negative impact on the intensity of fuel expenditure and a positive impact on the intensity of electricity expenditure for the same policy.

5 Conclusions

The decrease in energy intensity is critical to contributing to sustainability. One option to reduce the energy intensity is implementing governmental regulations or voluntary environmental policies. However, many factors can affect the effectiveness of these policies.

Table 7 Effect of the carbon footprint policy on the intensity of electricity expenditure using matching with differences-in-differences. Source: Own elaboration

Type of kernel	(bw = 0.02) Treated t=0	t=1	Controls t=0	t=1	Coef	SE	(bw = 0.06) Treated t=0	t=1	Controls t=0	t=1	Coef	SE	(bw = 0.10) Treated t=0	t=1	Controls t=0	t=1	Coef	SE
All firms																		
Epanechnikov	284	346	3858	3598	0.003	0.002	284	346	3858	3598	0.002	0.002	284	346	3858	3598	0.000	0.002
Gaussian	284	346	3861	3601	0.003	0.002	284	346	3861	3601	0.002	0.002	284	346	3861	3601	0.000	0.002
Biweight	284	346	3858	3598	0.003	0.002	284	346	3858	3598	0.002	0.002	284	346	3858	3598	0.000	0.002
Uniform	284	346	3858	3598	0.003	0.002	284	346	3858	3598	0.003	0.002	284	346	3858	3598	0.000	0.002
Tricube	284	346	3858	3598	0.003	0.002	284	346	3858	3598	0.002	0.002	284	346	3858	3598	0.000	0.002
Large-sized firms																		
Epanechnikov	220	258	2056	1649	0.001	0.002	220	258	2057	1649	0.002	0.002	220	258	2057	1649	0.002	0.002
Gaussian	220	258	2058	1649	0.002	0.002	220	258	2058	1649	0.002	0.002	220	258	2058	1649	0.002	0.002
Biweight	220	258	2056	1649	0.002	0.002	220	258	2057	1649	0.002	0.002	220	258	2057	1649	0.002	0.002
Uniform	220	258	2056	1649	0.002	0.002	220	258	2057	1649	0.002	0.002	220	258	2057	1649	0.002	0.002
Tricube	220	258	2056	1649	0.002	0.002	220	258	2057	1649	0.002	0.002	220	258	2057	1649	0.002	0.002
Medium-sized firms																		
Epanechnikov	32	48	519	353	-0.007	0.003**	32	48	524	356	-0.005	0.003	32	48	524	356	-0.004	0.003
Gaussian	32	48	525	357	-0.006	0.003*	32	48	525	357	-0.003	0.003	32	48	525	357	-0.003	0.004
Biweight	32	48	519	353	-0.008	0.003**	32	48	524	356	-0.005	0.003	32	48	524	356	-0.004	0.003
Uniform	32	48	519	353	-0.007	0.002**	32	48	524	356	-0.004	0.003	32	48	524	356	-0.003	0.004
Tricube	32	48	519	353	-0.007	0.002**	32	48	524	356	-0.004	0.003	32	48	524	356	-0.004	0.004
Small-sized firms																		
Epanechnikov	26	30	886	737	0.000	0.003	26	30	889	740	0.000	0.003	26	30	890	740	0.000	0.003
Gaussian	26	30	890	740	0.000	0.003	26	30	890	740	0.000	0.003	26	30	890	740	0.000	0.003
Biweight	26	30	886	737	0.000	0.003	26	30	889	740	0.000	0.003	26	30	890	740	0.000	0.003
Uniform	26	30	886	737	0.000	0.002	26	30	889	740	0.000	0.003	26	30	890	740	0.001	0.003
Tricube	26	30	886	737	0.000	0.003	26	30	889	740	0.000	0.003	26	30	890	740	0.001	0.003

Table 7 (continued)

Type of kernel	(bw=0.02)						(bw=0.06)						(bw=0.10)					
	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE	Treated		Controls		Coef	SE
	t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1			t=0	t=1	t=0	t=1		
Micro-sized firms																		
Epanechnikov	6	10	191	149	0.059	0.030	6	10	196	154	−0.012	0.014	6	10	196	154	−0.021	0.009*
Gaussian	6	10	196	154	0.002	0.018	6	10	196	154	−0.023	0.008	6	10	196	154	−0.024	0.007**
Biweight	6	10	191	149	0.059	0.030	6	10	196	154	−0.006	0.016	6	10	196	154	−0.019	0.010
Uniform	6	10	191	149	0.060	0.030*	6	10	196	154	−0.019	0.011	6	10	196	154	−0.023	0.008**
Tricube	6	10	191	149	0.060	0.030*	6	10	196	154	−0.017	0.012	6	10	196	154	−0.023	0.008**

(*) Significant at 5% and (**) Significant at 1%

Table 8 Effect of the carbon footprint policy on the intensity of electricity expenditure using instrumental variables. Source: Own elaboration

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Carbon footprint policy	1.077	1.022	1.002	0.988	0.988	0.989
	[1.244]	[1.169]	[1.143]	[1.126]	[1.126]	[1.152]
Large-sized	−0.00854	−0.00851	−0.00848	−0.00843	−0.00843	−0.00852
	[0.0382]	[0.0363]	[0.0356]	[0.0351]	[0.0351]	[0.0351]
Medium-sized	−0.0212	−0.0203	−0.02	−0.0198	′0.0198	−0.0199
	[0.0366]	[0.0347]	[0.0341]	[0.0336]	[0.0336]	[0.0338]
Small-sized	−0.00528	−0.00507	−0.00515	−0.00511	−0.00511	−0.0052
	[0.0214]	[0.0204]	[0.0200]	[0.0198]	[0.0198]	[0.0198]
Mining sector	0.0599	0.0551	0.0533	0.052	0.052	0.0528
	[0.119]	[0.111]	[0.108]	[0.107]	[0.107]	[0.109]
Professional services sector	0.0538	0.0516	0.0497	0.0491	0.0491	0.0489
	[0.0726]	[0.0688]	[0.0666]	[0.0656]	[0.0656]	[0.0662]
Industrial sector	0.0277	0.027	0.0255	0.0253	0.0253	0.0248
	[0.0556]	[0.0528]	[0.0514]	[0.0507]	[0.0507]	[0.0507]
Agricultural sector	0.0177	0.0172	0.0164	0.0163	0.0163	0.0178
	[0.0783]	[0.0744]	[0.0729]	[0.0719]	[0.0719]	[0.0722]
Transport and storage sector	0.0952	0.0906	0.0883	0.0871	0.0871	0.0882
	[0.130]	[0.123]	[0.120]	[0.118]	[0.118]	[0.121]
Telecommunications sector	0.0108	0.0102	0.00637	0.00636	0.00636	0.00601
	[0.0791]	[0.0751]	[0.0745]	[0.0735]	[0.0735]	[0.0735]
Commerce sector	0.00552	0.0057	0.00439	0.00437	0.00437	0.00332
	[0.0476]	[0.0452]	[0.0445]	[0.0439]	[0.0439]	[0.0441]
Services sector	−0.0629	−0.0591	−0.0585	−0.0576	−0.0576	−0.0571
	[0.104]	[0.0980]	[0.0967]	[0.0953]	[0.0953]	[0.0965]
% of capital national private		−0.000146	−0.001	−0.000987	−0.000987	−0.000982
		[0.000400]	[0.00207]	[0.00204]	[0.00204]	[0.00206]
% of capital foreign private			−0.000936	−0.000924	−0.000924	−0.000912
			[0.00204]	[0.00201]	[0.00201]	[0.00201]
Sales				2.17E−12	2.17E−12	2.17E−12
				[2.48e−12]	[2.48e−12]	[2.54e−12]
Marketing margin					4.48E−10	4.33E−10
					[1.77e−09]	[1.77e−09]
Firm's age						−0.000564
						[0.00106]
Constant	−0.0797	−0.0621	0.0265	0.0259	0.0259	1.151
	[0.112]	[0.0935]	[0.177]	[0.174]	[0.174]	[2.142]
Observations	8292	8292	8292	8292	8292	8292
R^2	0.0009	0.0009	0.001	0.001	0.001	0.0011
Sargan–Hansen test	10.77**	11.443**	11.713**	11.896**	11.896**	12.015**
F test	39.94**	39.02**	39.87**	39.85**	39.84**	38.87**

(*) Significant at 5% and (**) Significant at 1%. Cluster–robust standard errors in brackets

For this reason, this study analyzes the impact of two voluntary environmental policies on the intensity of fuel expenditure and the intensity of electricity expenditure in Chilean firms using two ex post evaluation methods. The method of matching with differences-in-differences that assumes exogenous treatment is complemented by instrumental variables method that allows identifying the effect of a treatment endogenous. The results obtained with both methods are similar regarding the ineffectiveness of voluntary environmental policies in Chile.

From the results obtained, it is clear that the Chilean government must maintain or increase environmental regulations since voluntary environmental policies by firms are not reducing energy consumption and/or producing a substitution from fossil energy to electricity. Also, progress could be made in public/private partnerships to improve the establishment of more demanding goals, monitoring, and evaluation of the impact of voluntary policies. The possible complementarity of voluntary environmental policies with market-based instruments is an open question. The environmental taxes introduced in 2017 in Chile were only applied to thermoelectric plants and large industrial sources with thermal power greater than 50 MegaWatts. However, it is impossible to identify the firms that meet this condition in the available database. The results of this study and the low effectiveness of the tax rates currently applied in Chile (Mardones & García, 2020) suggest that any possible complementarity should be pretty limited.

It should be noted that the database used in this study corresponds to a random sample of Chilean firms, so the results obtained can be extrapolated to all firms in the same period. However, these findings cannot be extrapolated to other periods, policies, or countries. Despite the above, this study is helpful since it provides a different perspective to the traditional vision held by policymakers and business managers, showing that these voluntary environmental policies may not produce the expected benefits.

The preceding contrasts considerably with previous studies that show a negative and significant impact of these voluntary environmental policies on energy intensity (Adua et al., 2021; Bertoldi & Mosconi, 2020; Chen, Chen, et al., 2020; Labandeira et al., 2020). One possible explanation is the difference in the design, implementation, and/or monitoring of energy efficiency and carbon footprint policies in Chile compared to other countries. It should be noted that most developed countries have stricter commitments to reduce carbon emissions while developing countries have less stringent obligations. Also, it could be attributed to that the effects of these policies are perceived over a more extended period. Consequently, it is suggested that future research uses a panel database that includes more periods to determine the impact of these voluntary environmental policies in the long term. Alternatively, collecting primary information is suggested to evaluate the effectiveness of voluntary policies in specific productive sectors.

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