Tax incentives as carrots for solar energy adoption

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Abstract

This study explores the influence of the fiscal incentives introduced by Law 1715 of 2014 on the stock of solar panels, an indicator for solar energy adoption in Colombia. The policy provides a series of incentives, including up to a 50% income tax deduction, VAT exclusions for goods and services related to Non-Conventional Renewable Energy Sources (NCRES) projects, tariff exemptions for NCRES project inputs, and an accelerated depreciation regime for machinery, equipment, and civil works used in NCRES projects. I use a synthetic control approach to construct a credible counterfactual, allowing for a precise evaluation of the policy's impact. Furthermore, I fortify my findings by utilizing Synthetic Difference-in-Differences estimators, which corroborate the results obtained from the synthetic control method. The findings suggest that Law 1715 has led to an increase in the stock of solar panels, exceeding the growth that would have been observed in the absence of the policy. This study underscores the potential effectiveness of fiscal incentives in promoting the adoption of renewable energy.

Contents

1 Introduction

Colombia's electricity production is heavily dependent on hydraulic sources. According to the Inter-American Development Bank's 2018 data, hydraulic generation constituted 68.4% of the country's total energy production, with thermal generation accounting for 30.6%, and non-conventional renewable energy sources (NCRES) comprising only 1% (Planas Marti and Cárdenas, 2019). This imbalance represents a significant risk factor, particularly with respect to climate events such as the *El Niño* phenomenon. However, diversifying energy sources and increasing the installed capacity of NCRES could provide a robust solution to these risks.

Between 2012 and 2015, Colombia grappled with one of the most severe *El Niño* events in its history, triggering catastrophic droughts that led to the loss of countless lives, both human and animal, destruction of crops, inflation of food prices, and migration of farmers. This event precipitated a surge in energy prices, underscoring the urgent need for an energy transformation (El Espectador, 2014). In response, the Colombian government enacted Law 1715 of 2014, the first legislation to integrate NCRES into the National Energy System.

NCRES, which encompasses underutilized or non-commercialized energy sources such as nuclear energy, biomass, small-scale hydroelectric, wind, geothermal, solar, and sea-based power, offer a sustainable alternative to traditional power generation. The Ministry of Mines and Energy (MME) outlined an ambition in its 2010 *"Plan de Acción Indicativo 2010-2015"* to increase the contribution of NCRES to the National Energy System to 3.5% in 2015, and further to 6.5% in 2020. Although this goal was not met, the government revised its targets in 2018, setting an objective of 8% to 10% by 2023 (Presidencia de la República, 2019).

The enactment of Law 1715 of 2014 was a significant step towards achieving this objective. The law provided several fiscal incentives to stimulate the use of NCRES. These included an income tax deduction of up to 50% (Art. 11), VAT exemption for equipment and machinery used in NCRES investment and production (Art. 12), tariff exemption for machinery, equipment, and materials exclusively used for NCRES projects (Art. 13), and the opportunity for accelerated depreciation of machinery, equipment, and civil engineering works integral to NCRES generation (Art. 14).

Among the NCRES, solar energy is a sector in which Colombia has a significant comparative advantage due to its average solar irradiation of 4.5 kWh/m^2 per day. This figure surpasses the global average of 3.9 kWh/m^2 per day. It is significantly higher than Germany's average, which stands at 3.0 kWh/m^2 per day despite Germany being a global leader in solar PV energy use (UPME, 2015). Despite this advantage, by 2019, Colombia had only 6 GW of installed solar capacity (Twenergy, 2019), while Germany, the most extensive user of solar energy, had approximately 36 GW of installed capacity by 2013 (Urrego et al., 2018). Colombia's privilege in the availability of solar resources underscores the potential for solar energy as one of the most promising renewable energy sources in the country.

The core objective of this study is to investigate the impact of the fiscal incentives offered by Law 1715 on the adoption of solar energy in Colombia. I hypothesize that these incentives, particularly those related to income tax deductions, VAT, and tariff exemptions for machinery, equipment, materials, and inputs required for solar energy projects, may have spurred an increase in the stock of solar panels in the country. Firms that make the investment can apply to get the deduction at any stage of the investment process, from the planning to the operational stage. This design of the policy presents two complications. First, it lends itself to tax planning because the firm will apply in the tax period that maximizes the tax benefit. Second, it is not straightforward to measure the effect of the law on investment by looking at the group of firms that apply to get the tax benefit because the application does not track the time of the investment and the firms can choose the time of treatment.

As a consequence, I am not able to compare the groups of treated and non-treated firms, instead, I will compare the effect of the law on a specific product type whose importation is impacted by the policy, and a synthetic counterpart that is very similar. I test whether these fiscal benefits have acted as compelling incentives for the adoption of solar energy in Colombia, using import data related to the Harmonized System's 4-digit product code for solar panels, specifically, the HS code 8541, because this import tracks the investment better than the tax deduction itself.

The data for this research is derived from administrative import records from Colombia. In my identification strategy, I employ the synthetic difference-in-differences and synthetic control approaches, using as donor units goods that fall under the same chapter of the Harmonized System but were unaffected by the policy[1].

The results of this study have important implications for both policy and research. From a policy perspective, my findings provide valuable insights into the effectiveness of fiscal incentives in promoting the adoption of non-conventional renewable energy sources. For researchers, this study contributes to the literature on the economic impacts of fiscal policies on energy transition.

To the best of my knowledge, this is the first study that uses a synthetic difference-in-differences approach to evaluate the impact of fiscal incentives on the adoption of solar energy in Colombia. In doing so, it adds to the body of knowledge on the Colombian energy sector.

The remainder of this paper is organized as follows: Section 2 discusses the contribution and the relation of this study with existing branches of the literature. Section 3 provides a comprehensive overview of the policy background. Section 4 outlines the data and the methodology for the synthetic control and synthetic difference in differences. The results obtained from both methodological approaches are discussed in Section 5, and Section 6 concludes with a discussion on policy implications in terms of societal welfare.

2 Literature Contribution

The study of the effect of tax incentives on renewable energy investments has been relatively under-explored in the existing literature. For instance, Nicolini and Tavoni (2017) investigated the efficacy of renewable energy subsidies across five major European countries—France, Germany, Italy, the United Kingdom, and Spain. Utilizing regression analysis, they estimated the impact of the incentives on three distinct indicators of renewable energy production: incentivized production, total production, and installed capacity. They employed a difference-in-differences approach to account for unobserved heterogeneity across countries and years. They observe that the policies were effective in promoting renewable energy, both in the short run, by increasing production, and in the long run, by increasing the installed capacity.

[1] Appendix A2 provides a list of the goods that are included in the analysis.

In a parallel vein, Reuter et al. (2012) explored the impact of feed-in tariffs, a policy mechanism designed to encourage renewable investment. Their model acknowledged that large companies might influence market prices, and it explicitly encapsulated the uncertainties stemming from both markets and environmental conditions, which are perceived as potential deterrents to renewable investment. They scrutinized the policy's impact and its associated uncertainty within the German context, where they found the feed-in tariffs to be effective means of promoting renewable investment.

My research supplements the literature on the influence of tax incentives on renewable energy investments, offering a novel perspective by examining the context of a developing country. Simultaneously, it is connected with literature examining the role of tax reductions in stimulating investment. My work aligns with studies such as Atanassov and Liu (2020), who used a difference-in-differences design to evaluate how corporate income tax cuts affect corporate innovation. Their study revealed that firms benefiting from tax breaks produced more patents and garnered more citations per patent post-tax cut.

Similarly, Ohrn (2018) assessed how changes in a firm's effective corporate income tax rate impact its investment, financing, and payout responses. Focusing on the implementation of the Domestic Production Activities Deduction (DPAD) in the United States, they discovered that a one percentage point reduction in tax rates via DPAD led to an investment increase equivalent to 4.7 percent of installed capital. Their findings suggested a one percentage point reduction in the corporate tax rate to be significantly more potent in stimulating corporate investment than a comparable reduction in investment costs via accelerated depreciation policies.

Exploring a developing country's context, Osimiri (2002) examined Nigerian legislation designed to promote natural gas as an energy source. This legislation comprised total tax and fiscal duty exemptions, as well as tax deductions, aimed at incentivizing energy production from gas. Despite political instability, they provided a descriptive analysis indicating positive outcomes from these policies.

This study also draws connections with works using synthetic control approaches to evaluate environmental policy effectiveness, such as Arcila and Baker (2022). They reassessed the effectiveness of British Columbia's carbon tax policy, implemented in 2008, aiming to reduce greenhouse gas emissions. Their findings suggested a significant long-term diminution of the carbon tax's effectiveness, with CO_2 emissions, gasoline consumption, and gasoline prices being unresponsive or even opposite to the policy's theoretical intentions. However, they did find evidence of a smaller share of the economy devoted to energy relative to the counterfactual in the post-policy change years.

Building upon this foundation, my study contributes by assessing the efficacy of similar policies within the unique context of Colombia, a developing country. I argue that understanding the effectiveness of fiscal incentives on renewable energy adoption in diverse socio-economic environments is crucial for informing future policy interventions.

3 Policy background

Colombia's Law 1715 of 2014 was enacted to promote the development and use of non-conventional energy sources (NCES), predominantly those of renewable nature, within the national energy system. The law characterizes NCES as environmentally sustainable energy sources with a global presence but not extensively utilized or traded within the country. NCES encompass nuclear energy and NCRES such as biomass, small hydroelectric, wind, geothermal, solar, and sea energy.

To achieve its objectives, the government instituted various tax, tariff, and accounting incentives detailed in Articles 11-14 of the law. These include: (i) an income tax deduction of up to 50% of the pre-deduction tax base; (ii) Value-Added Tax (VAT) exclusions on the acquisition of goods and services for NCRES project execution; (iii) tariff exemptions for imports of machinery, equipment, materials, and inputs exclusively allocated for reinvestment and investment activities of NCRES projects; and (iv) an accelerated depreciation regime for machinery, equipment, and civil works necessary for the pre-investment, investment, and operation of NCRES projects.

Despite the law's enactment in 2014, the incentives were not exercised until 2016 due to the lack of established regulations surrounding the project certification process and the tax break effectiveness as stipulated in the law. Only in 2016 were the governing regulations published, specifically, Resolution 1283 of 2016 from the Ministry of Environment and Sustainable Development and Resolution 68 of 2016 from the National Tax and Customs Office (DIAN, as per the Spanish acronym).

The application of these incentives is predicated on certifying the investments as projects of electrical energy generation from NCRES. Until 2019, the Ministry of Environment and Sustainable Development, according to Resolution 1283 of 2016, oversaw the certification process. A modification of the law in May 2019 transferred the responsibility of assessing and certifying the investments to the Mining-Energy Planning Unit (UPME, as per the Spanish acronym). This modification also extended the term of the income tax deduction benefit from 5 to 15 years, as described in the amended Article 11.

The requirements for applying for the certification are established in Resolution 203 of 2020 from UPME. According to this resolution, projects at the pre-investment, investment, or operation stages are eligible for application. However, the resolution stipulates that only a few pieces of equipment can be in the pre-investment stage, with the majority of the listed elements required to be at least in the investment stage. This flexibility in the timing of the income tax deduction post-certification allows firms to utilize the investment as a tax planning instrument, maximizing their intertemporal profits.

A distinctive aspect of this policy design allows firms to adopt tax planning behavior, given that they can apply for the certification even after making the investment. It is plausible that firms will apply for certification to minimize their tax payments over several years, including the post-investment year. This is because firms declare according to their income, and in the investment year, they might have no returns. However, in subsequent years, they should have returns that count as income in their tax returns. Thus, firms may prefer to apply for the tax deduction when their income increases due to the investment returns.

The policy's current design poses a challenge in identifying all investments in NCRES projects that can generate a tax break from the certified projects, as firms may invest today and choose to apply for the project's certification in the future. Consequently, firms investing in NCRES projects may not apply for certification in a given year if they anticipate applying for certification at a later date. Therefore, a comparison between certified and non-certified firms could lead to a non-compliance problem, as the control group might include firms that are potential candidates for treatment. To circumvent this issue, this study uses the import of machinery, a prerequisite for initiating an NCRES project, as an indicator of the commencement of the investment stage.

Colombia has significant potential in terms of renewable energy, with an average solar irradiation of 194 W/m^2 across the national territory, localized winds with average speeds of 9 m/s, and energy potentials of the order of 450,000 TJ per year in biomass residues. These are attractive conditions compared to countries located in different latitudes UPME (2015). Despite this potential, this study focuses exclusively on the impact of the law on the adoption of solar energy, as solar energy has higher growth potential in Colombia compared to other NCRES.

Each of the various NCRES outlined in the law, namely biomass, wind, geothermal, and solar energy, have unique production contexts and potentials. Biomass, a traditional source of renewable energy, is predominantly used in rural areas of developing countries for cooking and lighting (e.g., firewood). Geothermal, wind, and solar energy production are largely dependent on geographical conditions. Colombia's geothermal project development potential is relatively low due to the scarcity of volcanic zones, and the high risk and cost associated with exploration stages present significant challenges. Similarly, wind energy production in Colombia faces implementation challenges primarily because the region with the highest wind speeds, La Guajira, has communities that oppose infrastructure construction for wind energy production and distribution (Azzopardi, 2022).

4 Data

As previously noted, the policy provides various benefits for Non-Conventional Energy Resources (NCER) project investors. However, the current policy design poses a challenge when measuring its impact due to the variable timing of beneficiary identification. Under the law, investors can apply for project certification at any investment stage, encouraging potential tax planning behaviour, and complicating treatment identification. If an investor initiates an NCER project at time t without certification, they would fall within the control group. However, they may later apply for certification and still obtain tax benefits, potentially contaminating both treatment and control groups. An investor intending to obtain certification might defer their income until the year they maximize their tax deduction, thereby maximizing policy benefits and reducing their previous tax liability.

To circumvent these issues, this analysis assesses the policy's impact at the point of tangible investment, which in this case is indicated by the import of solar technology, given that Colombia does not domestically produce solar panels. I utilize administrative data on Colombian imports spanning from

2008 to 2019. This data, meticulously collected by the Tax and Customs Office (DIAN), is published monthly by the Department of Statistics (DANE).

The data includes variables such as the countries of origin of goods, product identifiers according to the Harmonized System (HS) codes, quantities imported with their respective units of measurement, Cost Insurance and Freight (CIF) value, Free On Board (FOB) value of the merchandise, importer company identification number, destination department, freight value, sales tax, tariff percentage, and others. This dataset allows us to discern variations in volumes of imported solar panels pre and post implementation of the law.

The Harmonized System (HS) is a globally recognized classification system that identifies all traded goods. The HS assigns six-digit codes to diverse product categories. Nations can append additional digits for further product specification. For instance, Andean Community countries employ the NANDINA nomenclature, extending HS codes to ten digits, thus enhancing specificity. The HS codes consist of four components: the chapter (first two digits), the heading (first four digits), the subheading (first six digits), and the additional digits. Appendix A1 presents a diagram that further explains how the HS works.

Although the DANE import dataset provides ten-digit codes, I aggregate the data at the four-digit level corresponding to product categories. The HS4 level, albeit less detailed, provides a sufficiently granular view of the trade landscape. This level of aggregation ensures that the treatment unit, solar panels (HS4 category 8541), and the control units are defined broadly enough to capture significant heterogeneity, thus increasing the robustness of the analysis. The HS4 level provides data stability and reliability. With fewer categories, there are fewer opportunities for data misclassification or errors, which often arise when dealing with highly detailed trade data.

The control group is established by selecting other four-digit categories within chapter 85, encompassing machinery and electrical equipment products. I exclude categories potentially affected by the law, as outlined in Appendix 1 of the UPME's Resolution 203 of 2020. This selection process yields a total of 17 four-digit categories for the donor pool. I designate 2014 as the treatment period since, despite the certification regulations being introduced two years later, investors could have initiated their NCRES projects in 2014 and applied for certifications in 2016. Thus, the sample includes 6 years of pre-intervention and 6 years of post-intervention data, ending in 2019 to avoid potential bias due to the COVID-19 pandemic.

To characterize the HS4 categories, I establish several covariates: the proportion of imports from China, the United States, Hong Kong, Mexico, and Vietnam (which collectively account for 74.4% of the total import value in USD, making them the top five trade partners); the proportion of imports destined for Cundinamarca, Bogota, and Antioquia (the top three destination regions, accounting for 83.8% of the total import value in USD); the proportion of imports transported by sea, land, and air; the proportion of imports from North America and Asia; the number of trade partners; the number of importers engaged with the HS4 category; the number of HS10 products traded within this category; the median net weight of merchandise in this category; and the mean and median freight, sales tax, customs value, and VAT. The mean of other insurance costs and tariff percentages are also included.

5 Methodology

This study aims to quantify the impact of Law 1715 on the accumulation of solar panels in Colombia, defined as the cumulative sum of imported quantities. This is an appropriate definition considering Colombia's dependence on imports for solar panels and the long lifespan of these durable goods—typically several decades. Consequently, the annual demand for solar panels is not a reset event but is influenced by the running total of solar panels in the country. Given the time window for this study, 12 years, it is reasonable to assume a zero depreciation rate, as the average lifespan of a solar panel ranges from 30 to 35 years (Solar Energy Technologies Office, nd).

The decision to focus on the cumulative total of imported panels rather than the annual count is underpinned by two crucial methodological considerations that bolster the robustness of the analysis and align with the nature of the policy. First, it helps mitigate the influence of year-to-year fluctuations in the import quantities, which could be affected by various factors such as exchange rates, shifts in global supply chains, or economic cycles. By concentrating on the cumulative total, I am able to dampen these short-term fluctuations and present a clearer picture of the overarching trend. Second, it enables the inclusion of improvements in solar panel efficiency over time. As technological advancements reduce the number of panels needed for equivalent energy output, import quantities might decline even as the actual usage of solar energy increases. By focusing on the cumulative total, I incorporate both quantity and technological progress, thus providing a more accurate assessment of the policy's impact. Appendix Figure A2 presents the results of the statistical analysis using the imported quantities as the dependent variable. It reveals that the high volatility of the imported quantities impedes obtaining a robust estimate of the synthetic controls and therefore, the effect of the law. The stock of solar panels removes this volatility and allows me to have more reliable estimates.

The dependent variable is defined for $t \in \{2008, 2009, ..., 2019\}$ and corresponds to the difference between the stock of solar panels in a given year t, $Stock_t$, and the stock in 2008, $Stock_{2008}$. As previously mentioned, $Stock_t$ is defined as $\sum_{t=2008}^{T} q_t$, where T is the specific year of the stock and q_t are the imported quantities. From here on, I'm going to refer to the dependent variable as $\Delta_{2008}Stock_t$ which is $Stock_t - Stock_{2008}$. Note that $Stock_t$ can also be defined iteratively as $Stock_{t-1} + q_t$. Therefore, for the baseline year 2008, the stock equals the imported quantities, therefore, the change in stock, $\Delta_{2008}Stock_{2008}$, would be zero. By construction, $\Delta_{2008}Stock_{2009} = q_{2009}$, and this would incrementally increase year by year. Standardizing the dependent variable to a baseline year (2008) allows me to scrutinize the relative impact of the policy over time. This approach may yield more insightful results than absolute numbers, which could be skewed by uncontrolled, extraneous factors.

This approach to defining the dependent variable facilitates a more nuanced understanding of the policy's effects over time, with the metric adjusted for baseline stock levels. This strategy helps isolate the policy's impact, considering the growth from the baseline year, thus yielding a more insightful and accurate understanding of the policy's efficacy.

5.1 Synthetic Control

The initial inclination was to implement a comparative analysis between certified and non-certified firms. However, due to the design of the policy, such a direct comparison is unfeasible. An alternative approach is to focus on a specific product type whose importation is impacted by the policy, rather than on the group of firms directly benefiting from it. Given the circumstances, the study is restricted to one treatment unit. In this scenario, traditional impact evaluation methods, which leverage the law of large numbers, are unsuitable. Thus, an alternate methodology, valid for a single treatment unit case, is necessitated.

In this study, instead of comparing groups that are statistically similar, I will attempt to compare units that are statistically similar: the import of HS4 product category 8541- encompassing solar panels and other photosensitive semiconductor devices- and the import of a synthetic product category that is very similar to the 8541. This is accomplished through the use of synthetic control methodology, which enables causal inference on small samples and is especially apt for cases with a single treated unit, as in this study. This approach involves constructing a synthetic counterfactual—a weighted average of the unaffected units, also referred to as the donor pool. Initially proposed by Abadie and Gardeazabal (2003), this technique has seen extensive application in empirical research in recent years.

The synthetic control method is predicated on the idea that a linear combination of unaffected units often provides a more accurate comparison point than any single control unit, particularly when the number of aggregate unit observations is limited. The synthetic control approach offers a data-driven method for constructing a counterfactual unit—in this case, a "synthetic solar panels" (i.e., synthetic HS4 8541)—that emulates the key characteristics of the treated unit in the pre-treatment period. It employs pre-policy observations to discern the optimal weights for units within the donor pool. As a result, the synthetic control aligns closely with the pre-policy trend of the treatment unit. It's worth noting that this process involves more than just identifying similar units in terms of the outcome variable's pre-treatment values. The synthetic control is sensitive to the selection of the predictors (X), as it considers the potential influence of these predictors on the outcome variable.

A synthetic control can be characterized as a vector of weights $W_{1\times NC}$, with the weighted average of these units closely aligning with the treated unit regarding observable pre-treatment characteristics (X_1 for the treated unit and X_0 for the untreated units). The weighting process is formalized by minimizing a distance metric, specifically, the mean squared prediction error (MSPE). These weights are non-negative and sum to one, ensuring a convex combination of potential control units. The problem solved by the algorithm can be formally represented as follows:

$$\min_{W} \sum_{m=1}^{k} v_m \left(X_{1m} - X_{0m}W\right)^2$$
$$\text{subject to} \quad \sum_{r} w_r = 1, \quad W \geq 0$$

In the above minimization problem, k is the number of covariates included in the model, v_m is a scalar that measures the relative importance of the m-th predictor. At the same time, X_1 and X_0 denote the pre-treatment characteristics of the treated and untreated units, respectively[2]. The quality of the synthetic control is typically assessed by how well it tracks the treated unit's pre-treatment outcome trajectory. If the synthetic control and the treated unit follow a similar trend before the treatment, it strengthens the confidence in the synthetic control as a reliable counterfactual. Given the optimal weights vector, $\hat{W}$, the policy's impact in period t can be computed as the difference in outcomes between the treated unit and its synthetic control in the post-treatment period as:

$$\hat{\tau}_{1t}^{Synth} = Y_{1t} - \sum_{r=2}^{N} \hat{w}_r Y_{rt} \tag{1}$$

Note that N corresponds to the number of units of the study. The synthetic control method allows for the computation of a time-specific treatment effect, thereby facilitating the detection of the law's differential impact depending on the post-treatment year under assessment. Some researchers further consider the average treatment effect over the post-intervention period as an auxiliary estimator (see Isaksen 2020). It should be noted that, like any other method, the synthetic control approach relies on some key assumptions. Primarily, it assumes that in the absence of treatment, the treated unit would have continued to follow the trend established by the synthetic control. While this assumption is untestable, the credibility of the synthetic control results can be bolstered by robustness checks and placebo tests.

[2] The optimization problem is solved using the statistical software R with the package `'Synth'` developed by Abadie et al. (2011).

5.2 Synthetic Difference in Differences

This study also applies the Synthetic Difference in Differences (Synthetic DiD) estimator, a recent methodology introduced by Arkhangelsky et al. (2021), which synthesizes the synthetic control and difference in differences (DiD) methodologies. This combination has been shown to possess greater robustness compared to each of the individual methods. The Synthetic DiD method aims to improve causal inference in observational studies, especially when the parallel trends assumption is violated. In order to tackle this challenge, Arkhangelsky et al. (2021) advocate for the integration of synthetic control methods into the DiD framework, enabling the comparison unit to closely mirror the pre-treatment characteristics and outcomes of the treated unit. This ensures the procurement of a more appropriate counterfactual.

Distinctive to the Synthetic Diff-in-Diff from the synthetic control estimator is the incorporation of time weights for the pre-treatment periods and the inclusion of unit fixed effects. The former can mitigate bias and enhance precision by eliminating the influence of time periods that are significantly divergent from the post-treatment periods. Concurrently, including unit fixed effects can elevate precision given their propensity to account for a substantial fraction of the variation in outcomes. Consequently, the average causal treatment effect (denoted by τ) is estimated by:

$$\underset{\tau,\mu,(\alpha_i)_N,(\beta_t)_T}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - \tau S_{it})^2 \hat{w}_i^{sdid} \hat{\lambda_t^{sdid}} \right\} \tag{2}$$

where N corresponds to the number of units in the study, T is the number of periods, μ denotes the intercept, α_i corresponds to the unit fixed effects, β_t are the year fixed effects, S_{it} is a binary treatment variable, and $\hat{w}_i^{sdid}$ $\hat{\lambda_t^{sdid}}$ are the unit and time weights, respectively.

The Synthetic DiD method encompasses a two-step estimation procedure. The initial step is dedicated to estimating the weights for the synthetic control unit. These optimal weights are ascertained by minimizing the disparity between the pre-treatment outcomes and covariates of the treated unit and a weighted average of the control units. The subsequent step calculates the treatment effect as the weighted difference in outcomes between the treated unit and the synthetic control unit, during and after the treatment period.

Two subtle distinctions exist between the unit weights generated by the Synthetic DiD algorithm and those of the synthetic control algorithm: First, the objective function incorporates an intercept term. This suggests that the synthetic control need not perfectly mimic the trajectory; rather, the weights should align with the trends. Second, a regularization penalty is introduced into the function to increase dispersion and ensure the uniqueness of the weights. Therefore, the optimal unit weights solve the following optimization problem:

$$\min_{W} \sum_{t=1}^{T_{pre}} \left(w_0 + \sum_{i=1}^{N_{co}} w_i Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it} \right)^2 + \zeta^2 T_{pre} \|w\|_2^2 \tag{3}$$

Here, w_0 denotes the intercept, w_i represents the unit weights, N_{co} and N_{tr} are the number of control and treated units, which sum N, ζ is the regularization parameter and T_{pre} are the number of pretreatment periods.

Conversely, the optimal time weights resolve the following optimization problem:

$$\min_{\lambda} \sum_{i=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} \right)^2 \tag{4}$$

It is crucial to note that only the unit weights problem incorporates the regularization parameter. The reason is that the Synthetic DiD allows for correlated observations within time periods for the same unit but not across units within a time period.

5.3 Inference

To evaluate the significance of these estimates, I follow Arkhangelsky et al. (2021). The authors propose an inference approach based on the estimation of placebo variance, which is the variance of the treatment effects computed for a set of placebo units. This technique is closely related to permutation tests. The main rationale behind the placebo tests is to examine the behavior of the synthetic control estimation when the treated unit is substituted by different units that were not exposed to the treatment. Since the HS4 products in the control group were not influenced by Law 1715, the placebo effects estimates offer a means of assessing the noise level.

Specifically, the algorithm randomly selects a treated unit from the control group. It repeats this process multiple times[3] while excluding the originally treated unit from the test. In each iteration, a synthetic control is estimated, resulting in a distribution of the average treatment effects of the placebos by the end of the procedure. The variance of this distribution, denoted as $\hat{V}_\tau$, is utilized to construct the confidence intervals as:

$$\hat{\tau} \pm z_{\alpha/2}\sqrt{\hat{V}_\tau} \tag{5}$$

This methodological approach provides a robust avenue for evaluating the significance and reliability of the estimated treatment effects.

6 Results

In this section, I justify the choice of the previously outlined methodologies as they apply to this specific case. Subsequently, I present the estimated effects of the enactment of Law 1715 in 2014 on the change in the stock of solar panels, using 2008 as the benchmark year. The findings from both the synthetic control and the synthetic difference-in-differences analyses will be presented concurrently, providing a holistic view of the policy's impact. The dual-perspective approach allows for robust conclusions, reinforcing the credibility of my findings. Finally, I elaborate on a cost-benefit analysis to complement the understanding of the results.

Figure 1 depicts the trajectories of the change in stock relative to 2008 for both solar panels and the average of the control HS4 product-categories. Although both exhibit an increasing trend, the treated unit consistently demonstrates a larger slope throughout the analysis period. It is evident from the figure that the average of the control units does not provide a credible counterfactual for evaluating the impact of Law 1715 on solar panels, as the pretreatment trajectories are dissimilar and do not exhibit parallel trends.

[3] Arkhangelsky et al. (2021) suggest 200 repetitions

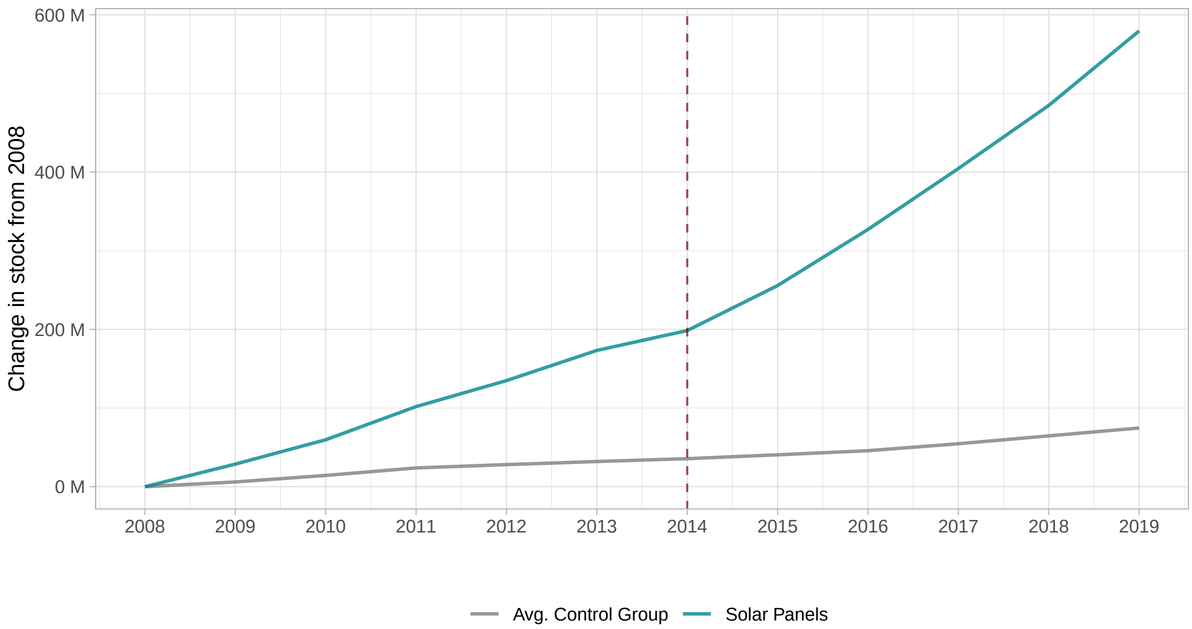


Figure 1: Trajectories of the treated unit vs. the average of the sample control units

To establish an appropriate counterfactual, I employed synthetic control and synthetic difference-in-differences (DiD) methods. As previously discussed, these methods estimate a suitable comparison unit as a convex combination of units within the donor pool. The synthetic control seeks to replicate the pretreatment trajectory of the treated unit, whereas the synthetic DiD aims to reproduce the treated unit's trends, thus satisfying the parallel trends assumption. Table 1 demonstrates the similarity in pretreatment characteristics between the synthetic control and solar panels, corroborating that the synthetic control offers a more reliable comparison than the average of the donor pool. The table includes only a subset of covariates, specifically those with positive weights exceeding 0.01. These covariates are crucial for the synthetic control, as they possess considerable predictive power for the change in solar panel stock.

Table 2 displays the non-zero weights assigned by both algorithms to units in the control group. The synthetic control assigns positive weights solely to two HS4 product-categories within the donor pool, while the synthetic DiD distributes the weights among seven of the control units. The algorithms concur that the trajectory of the change in solar panel stock prior to Law 1715 is best replicated by a combination of electrical carbon products and telecommunications devices. These two HS4 product-categories can serve as good comparison and provide relevant information about the behavior of solar panels because

Table 1: Comparison of pre-treatment predictor means on the synthetic control methodology

	Solar Panels		Avg. Control Units
	Real	Synthetic	
Prop. imports from Hong Kong	0.06	0.06	0.03
Prop. imports by seaway	0.23	0.23	0.46
Prop. imports by land	0.02	0.02	0.01
Prop. imports by airway	0.75	0.75	0.51
Prop. imports from Asia	0.51	0.52	0.65
Median net weight	5.12	23.92	103.48
Number of HS10 products	9	8.85	7.26
Mean tariff percentage	2.02	3.45	6.87

their demand is directly affected by the growth and development of electrical infrastructure and energy projects as the demand for solar panels. They also share with the treated unit the fact that they have been subject to technological advancements during the analysis period which makes them likely to experience similar shifts in demand and market trends. Moreover, the synthetic DiD also allocates minor but positive weights to the HS4 product-categories of: audio devices and equipment, automotive electrical components, electric heating appliances and accessories, communication and broadcasting equipment components, and transportation infrastructure safety and control equipment.

Table 2: Product weights in the synthetic solar panel

HS4	Description	SC Weight	SDID Weight
8545	Electrical carbon products	0.392	0.434
8517	Telecommunications devices	0.608	0.315
8518	Audio devices and equipment	0.000	0.107
8512	Automotive electrical component	0.000	0.061
8516	Electric Heating Appliances and Accessories	0.000	0.060
8529	Communication and Broadcasting Equipment Components	0.000	0.022
8530	Transportation Infrastructure Safety and Control Equipment	0.000	0.001

Figure 2 illustrates the trajectories estimated by both the synthetic control and synthetic DiD methods. In both graphs, the blue line represents the trajectory of the change in the stock of solar panels relative to 2008, while the gray line represents the estimated counterfactual. The black arrow denotes the magnitude and direction of the impact, and the light gray arrows flanking it represent the lower and upper limits of the 95% confidence intervals. During the pre-treatment period, both estimates closely align with the actual trajectory of changes in solar panels stock relative to 2008, as expected. Post-treatment, the real solar panels display a sharper upward trend from 2014, while the synthetic solar panels maintain a more consistent pattern throughout the period. Thus, the estimated average treatment effect is positive for both methods, indicating that Law 1715 had a substantial and escalating impact on the stock of solar panels relative to 2008 levels.

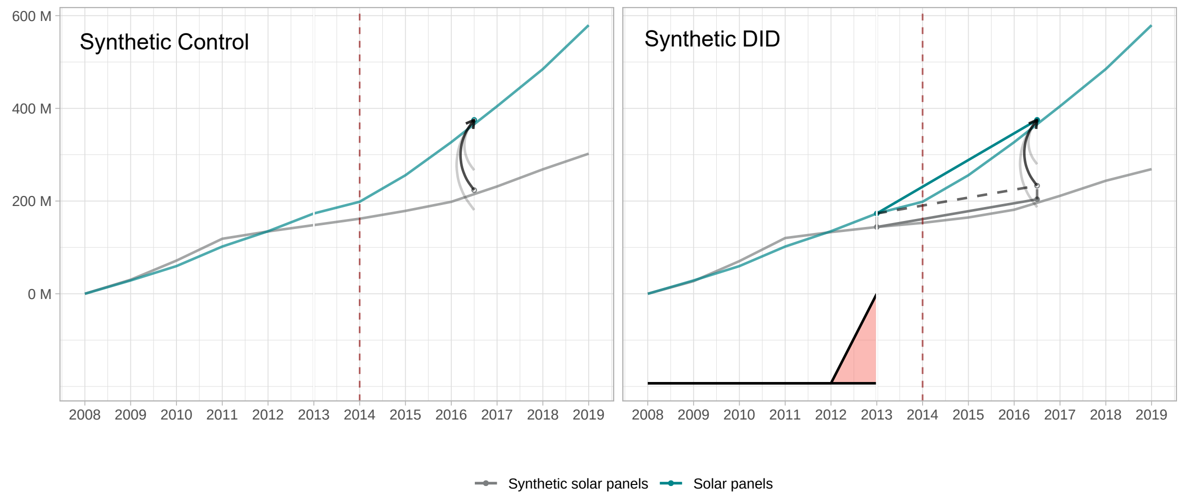


Figure 2: Synthetic Control and Synthetic Diff-in-Diff

Table 6 presents the estimated average treatment effects obtained from both algorithms and their corresponding 95% confidence intervals. The two methods yield to similar results: the synthetic control suggests that the average post-treatment change in solar panel stock from 2008 is approximately 151.4 million units greater than if the policy had not been implemented, while the synthetic DiD estimates an increase of 141.9 million units. Both effects are statistically significant at the 1% level. Regarding the confidence intervals, the effect from the synthetic control is estimated to range from an increase of 117.6 million to as high as 185.3 million additional solar panels compared to 2008 levels. For the synthetic DiD, the estimates are marginally lower, ranging from an additional 104.8 million to 179 million solar panels.

Table 3: Results of Synthetic Control and Synthetic DID

	Dependent Variable: Change in Stock from 2008 (In millions)	
	Synthetic Control	Synthetic DID
Average Effect ($\hat{\tau}$)	151.4***	141.9***
95% Confidence Interval	(117.6, 185.3)	(104.8, 179.0)

This table reports the average estimated effects of the Law 1715 on the change in solar panels stock from 2008 (in millions) using the Synthetic Control and the Synthetic DID estimators. The 95% confidence intervals are constructed using the placebo variance estimation approach outlined in section 4.2. Significance levels are reported as. *p<0.1; **p<0.05; ***p<0.01.

In conclusion, both the synthetic control and synthetic DiD methods provide evidence that Law 1715 significantly boosted the change in solar panel stock relative to 2008 levels. This finding underscores the importance of implementing renewable energy policies to foster the adoption of clean energy technologies.

6.1 Cost-effectiveness analysis

In this section, I undertake a cost-effectiveness analysis to further elucidate the impact of the policy. The purpose of this analysis is to measure how much it cost the government, under this specific design, to reduce 1 million tons of CO2. Therefore, the cost of this policy is seen as the potential government revenue foregone due to the tax exemptions provided by Law 1715, while the benefits are the potential reduction in CO_2 emissions through the energy generated by NCRES. However, as my analysis primarily traces the investment in solar panels, due to the policy design, these estimations are limited to this aspect alone. Hence, the calculations in this section should be interpreted as a lower-bound estimation of the policy's total impact.

It is possible to estimate quantities that might have been imported in the absence of the policy using the synthetic control estimates. My estimates correspond to the difference in stock from the 2008 levels, and the stock in a given year corresponds to the previous year's stock plus quantities imported during that year. Hence, I can calculate synthetic quantities in the absence of the policy using the following equation (refer to Appendix 2 for the mathematical derivation):

$$\hat{q}_t = \Delta_{2008}St\hat{o}ck_t - \Delta_{2008}St\hat{o}ck_{t-1} \tag{6}$$

Where $\Delta_{2008}St\hat{o}ck_t$ and $\Delta_{2008}St\hat{o}ck_{t-1}$ correspond to the estimates of the synthetic control in periods t and $t-1$, while $Stock_{2008}$ is a fixed quantity representing the actual imported quantities in 2008 (i.e. approximately 16.8 million solar panels) because both the synthetic versions estimate $\Delta_{2008}S\hat{t}ock_{2008}$ as zero, just as its real value. An equation for the cost of the policy would be:

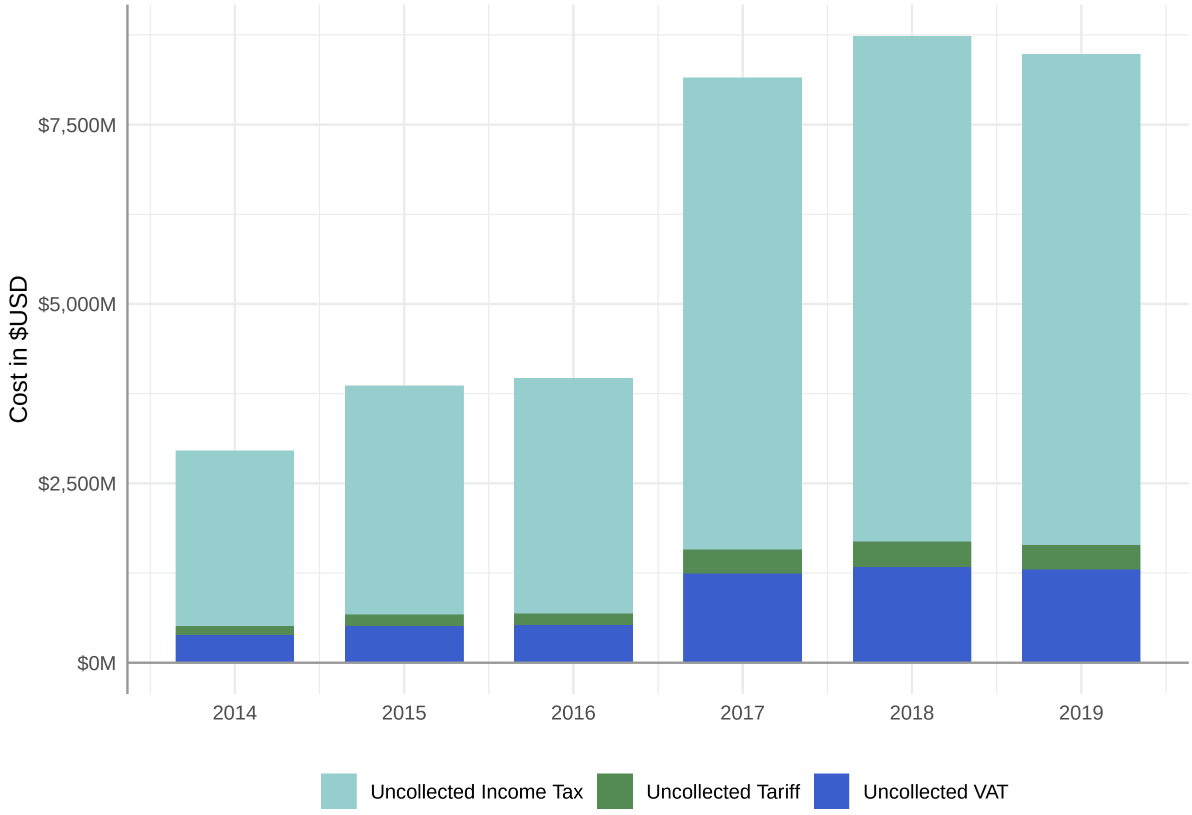
$$Cost = \sum_{t=2014}^{2019} (\hat{q}_t \cdot \bar{p_t}) \cdot (\text{VAT}_t + \text{Tariff}_{pre} + 1) \tag{7}$$

In this equation, $\bar{p}_t$ denotes the average unit value of solar panels in a given year, obtained by dividing the FOB value in USD among the import quantities, and it oscillates around 200 USD. VAT_t corresponds to the VAT percentage at time t, specifically, it is 16% before 2017 and 19% from there on. $Tariff_{pre}$ is the percentage of tariffs associated with solar panels before the law, corresponding to a 5%. Here it is important to highlight that the effect of the policy is not driven by one single incentive but by the full set of incentives. I found in the data that from 2012 the mean tariff percentage of the HS4 8541 was zero, indicating that before the law the solar panels were already exempted from tariffs. Hence, contrary to a presumption that the changes in imports might be driven predominantly by alterations in the tariff policy, the evidence shows that, at least for solar panels, the least significant incentive of Law 1715 was the tariff exemption. Indeed, the other tax deductions have been instrumental in promoting investment in solar energy projects. The usage of synthetic, rather than actual, imported quantities in this analysis represents a prudent and conservative approach. This decision is grounded in the premise that, without Law 1715, the government would have collected taxes solely from the quantities imported under that specific counterfactual. Using synthetic quantities derived from the synthetic control method allows a more realistic and unbiased estimation of the government's foregone revenue, thereby enhancing the robustness of the present cost-benefit analysis.

Finally, the last term in the equation represents the government's cost in terms of foregone income tax revenue. Given the policy's design allowing investors to select the year they claim the deduction, they will naturally opt for a year when their incomes are sufficiently large to deduct the total amount of the investment. The law says that the deduction cannot overpass the 50% of the total income tax, hence the investors will choose to deduct in a year when their incomes are sufficiently large so that the 50% is at least as big as the investment they made. Think about company A whose taxable income in 2014 was \$100, and assume that in that year the firm makes an investment of \$30 in solar panels. For that year its income tax would be \$25[4], and the deduction would be 12.5% if the company applies for the certification in that year. However, the company could decide to apply later when its income has increased enough so that the deduction could be as large as the investment made in 2014. Let's say company A decided to get the certification in 2016 when its taxable income was about \$300, therefore its income tax would be \$75 and the corresponding potential deduction would be up to \$37.5, but since

[4]The percentage of the income tax for legal entities was 25% from 2014 until 2016, and increased to 33% from 2017 onwards.

Figure 3: Computed costs from uncollected taxes

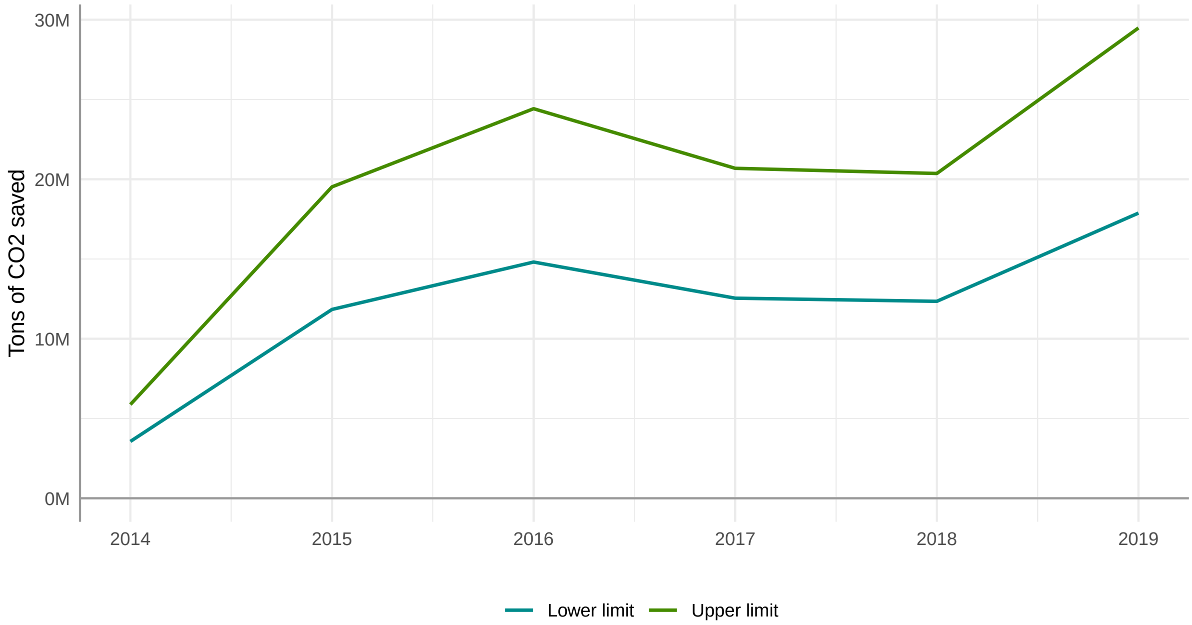


the deduction cannot be larger than the investment it would be $30. Thus, the investors' behavior is integral to the cost calculation.

Figure 3 presents the computed cost per year obtained from Equation 7, showing the highest cost being related to income tax deductions and the smallest to tariff exemptions. The total calculated cost has risen over the years alongside the increasing adoption of solar panels. I estimate a potential loss of government revenue of around 6,025.7 million USD per year, representing an average of 1.8% of GDP from 2014 to 2019.

Moving on to benefits, they are quantified in terms of potential savings in coal tonnage thanks to energy produced by the additional solar panels. Most common solar panels in Colombia have a power rating between 200W and 330W (Celsia, nd), implying their potential energy generation per hour. Assuming an average of 5 hours of sufficient solar irradiation per day, an average solar panel could generate between 1kW to 1.65kW daily and between 365kW to 602kW annually. Avoiding the production of this energy through non-renewable sources translates into averting 0.285 to 0.47 tons of CO2 emissions per year, based on the US Environmental Protection Agency's Greenhouse Gas Equivalency Calculator.

Figure 4: Benefits as tons of CO_2 saved from the additional solar panels



Following these computations, I estimate an additional solar energy production of 15,578 GW per year with the less efficient panels, or of 25,693 GW per year with the more efficient ones. This translates into an average annual saving of 11.04 (18.2) million tons of CO2 emissions, which is equivalent to the greenhouse gas emission of more than 2.5 (4.05) million gasoline vehicles driven for one year (EPA, 2021) in the scenario with the less (more) efficient panels. As a reference, as of the end of 2022, Colombia has approximately 18 million vehicles, based on data from RUNT. This means that these estimates correspond to a reduction in CO_2 emissions equivalent to removing between 13.9% and 22.5% of the country's vehicles from the roads. Figure 4 illustrates the estimated benefits of the policy per year under both scenarios.

7 Conclusion

According to data from the International Energy Agency, in 2014 the energy generation sector was responsible for about 20% of the total CO_2 emissions in the country. This sector's significant contribution to greenhouse gas emissions underscores its critical role in climate change mitigation efforts and in achieving the country's commitment to net-zero emissions by 2050. In 2014, Law 1715 was introduced to catalyze the energy transition in Colombia, addressing challenges such as the sector's high vulnerability to hydrometeorological events and the effects of climate change. Consequently, evaluating the policy's implementation success is crucial for the country's sustainable development.

The previous analysis, employing synthetic control and synthetic difference-in-differences (DiD) methods, suggests that Law 1715 has effectively spurred the growth in the adoption of solar energy above the levels that it could have increased in the absence of the policy. In particular, the average effect of Law 1715 on the solar panel stock change estimated by the synthetic control (synthetic diff-in-diff) was of 151.4 (141.9) million units more in the presence of Law 1715. These findings highlight the importance of policies like Law 1715 in fostering the growth and development of renewable energy sectors like solar power.

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Appendices

A1 Diagram of the Harmonized System

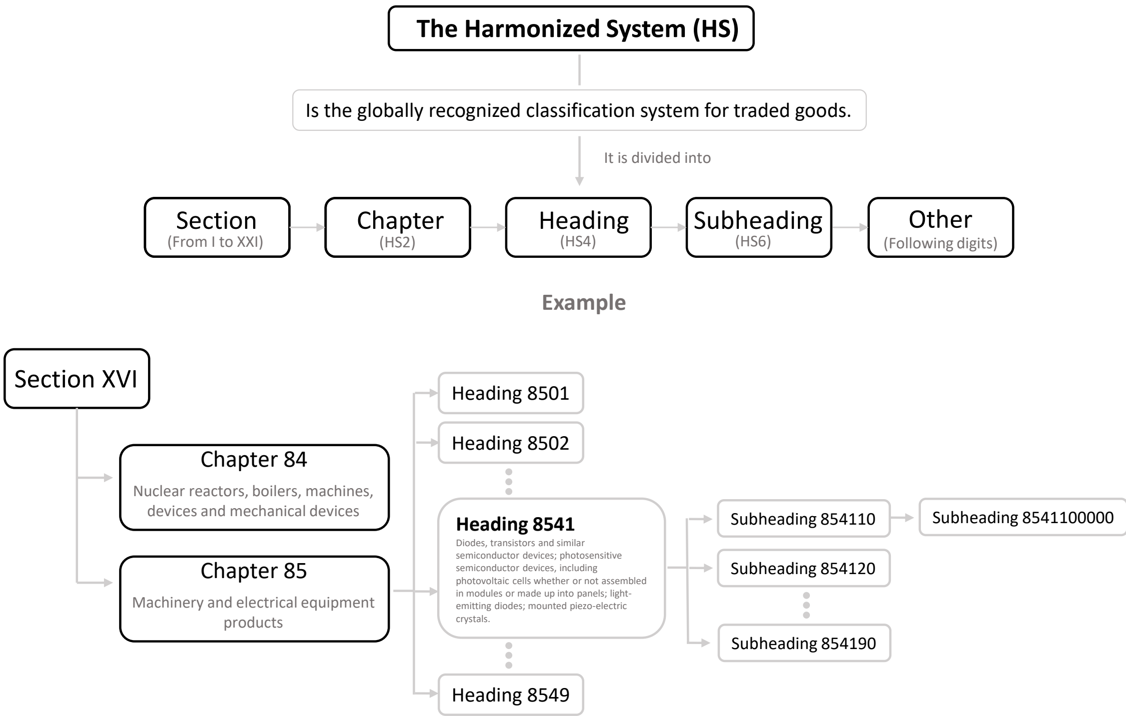

Figure A1: Diagram of the Harmonized System

A2 HS4 products in the donor pool

Table A1: List of the HS4 product categories in the control group.

HS4	Description
8508	Electromechanical tools for working in the hand, with self-contained electric motor; vacuum cleaners; other vacuum cleaners.
8509	Electro-mechanical domestic appliances, with self-contained electric motor (e.g., food grinders and mixers, fruit or vegetable juice extractors).
8510	Shavers, hair clippers and hair-removing appliances, with self-contained electric motor.
8512	Electrical lighting or signalling equipment (excluding articles of heading 8539), windscreen wipers, defrosters and demisters, of a kind used for cycles or motor vehicles.
8516	Electric instantaneous or storage water heaters and immersion heaters; electric space heating apparatus and soil heating apparatus; electro-thermic hair-dressing apparatus (for example, hair dryers, hair curlers, curling tong heaters) and hand dryers; electric smoothing irons; other electro-thermic appliances of a kind used for domestic purposes; electric heating resistors, other than those of heading 8545.
8517	Telephone sets, including telephones for cellular networks or for other wireless networks; other apparatus for the transmission or reception of voice, images or other data, including apparatus for communication in a wired or wireless network (such as a local or wide area network).
8518	Microphones and stands therefor; loudspeakers, whether or not mounted in their enclosures; headphones and earphones, whether or not combined with a microphone, and sets consisting of a microphone and one or more loudspeakers; audio-frequency electric amplifiers; electric sound amplifier sets.
8519	Sound recording or reproducing apparatus.
8521	Video recording or reproducing apparatus, whether or not incorporating a video tuner.
8522	Parts and accessories suitable for use solely or principally with the apparatus of headings 8519 or 8521.
8524	Flat screen display modules, even those incorporating touch screens.
8525	Transmission apparatus for radio broadcasting or television, whether or not incorporating reception apparatus or sound recording or reproducing apparatus; television cameras, digital cameras and video camera recorders.
8526	Radar apparatus, radio navigational aid apparatus and radio remote control apparatus.
8527	Reception apparatus for radio broadcasting, whether or not combined, in the same housing, with sound recording or reproducing apparatus or a clock.
8528	Monitors and projectors, not incorporating television reception apparatus; reception apparatus for television, whether or not incorporating radio-broadcast receivers or sound or video recording or reproducing apparatus.
8529	Parts suitable for use solely or principally with the apparatus of headings 8525 to 8528.
8530	Electrical signaling, safety or traffic control equipment for railways, tramways, roads, inland waterways, parking facilities, port installations or airfields (other than those of heading 8608)
8545	Carbon electrodes, carbon brushes, lamp carbons, battery carbons and other articles of graphite or other carbon, with or without metal, of a kind used for electrical purposes.

A3 Derivation of estimated quantities from the estimated outcome

By construction, the outcome variable of the change on the stock from 2008 is:

$$\Delta_{2008}\hat{Stock}_t = Stock_t - Stock_{2008} \tag{A.1}$$

From A.1, we can get $Stock_t$:

$$Stock_t = \Delta_{2008}\hat{Stock}_t + Stock_{2008} \tag{A.2}$$

And we can expand A.1 as:

$$\Delta_{2008}\hat{Stock_t} = q_t + Stock_{t-1} - Stock_{2008}$$

We can use A.2 to re-write the second term, hence:

$$\Delta_{2008}\hat{Stock_t} = q_t + \Delta_{2008}\hat{Stock}_{t-1} + Stock_{2008} - Stock_{2008}$$

$$\Delta_{2008}\hat{Stock_t} = q_t + \Delta_{2008}\hat{Stock}_{t-1}$$

Solving for q_t, we get:

$$q_t = \Delta_{2008}\hat{Stock_t} - \Delta_{2008}\hat{Stock}_{t-1}$$

A4 Synthetic controls using the imported quantities

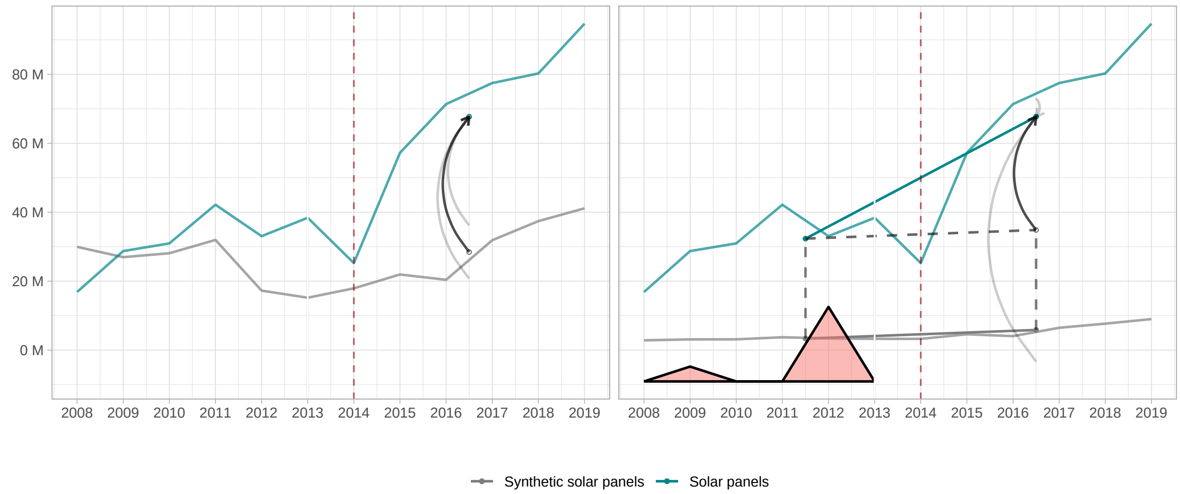

Figure A2: Synthetic Control and Synthetic Difference-in-Differences using imported quantities as the outcome variable