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Carbon offsets in US cap and trade market:a thorough analysis of its drivers and its effects on allowance prices

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If you are reading this, it is NOT too late

Table of contents

Chapter 3

The demand for carbon offsets

Chapter 4

Carbon offsets and allowance prices

Abbreviations

Here there is a list of all the abbreviation recurrently used in this dissertation:

ADF: Augmented Dickey-Fuller
ARB: Air Resource Board
ARDL: Autoregressive Distributed Lag
AIC: Akaike Information Criterion
BAU: Business as Usual
BIC: Bayesian Information Criterion
BLIMP: Blatantly infra-marginal projects
CARB: California Air Resource Board
CC: Climate Change
CDM: Clean Development Mechanism
CER: Certified Emissions Reduction
CITSS: Compliance Instrument Tracking System Service
CO_2: Carbon Dioxide
CPI: Carbon Pricing Initiatives
ETS: emission trading system
EU: European Union
EUA: European Union Allowances
EU ETS: European Union Emissions Trading System
FEVD: Forecast Error Variance Decomposition
GHG: Greenhouse Gas
IPCC: Intergovernmental Panel on Climate Change
IRF: Impulse Response Analysis
JI: Joint Implementation
KPSS: Kwiatkowski-Phillips-Schmidt-Shin
MAC: Marginal Abatement Curve
MNPB: Marginal Net Private Benefit
NAICS: North American Industry Classification System

NGO: Non-governative organization

OECD: Organization for Economic Cooperation and Development

PP: Phillips-Perron

R&D: research and development

RGGI: Regional Greenhouse Gas Initiative

SCC: Social cost of carbon

SF_6: Sulfur Hexafluoride

SO_2: Sulfur Dioxide

UNFCCC: United Nations Framework Convention on Climate Change

VAR: Vector Autoregressive

VECM: Vector Error Correction Model

WCI: Western Climate Initiative

Figures

Here there is a list of all the figures appearing in this dissertation:

Introduction

Our planet is becoming warmer and warmer. Temperatures are hotter, glaciers are melting and ocean levels are rising to the point that humans can not look the other away anymore. Climate change is dangerous, so confronting and mitigating it has now become imperative for humanity.

The willingness to help, even just a little bit, in reducing global warming and its consequences is what inspired this research in the first place. It does so not scientifically, rather it inquires about the consequences of sustainable initiatives in a political-economy perspective.

The goal of the research is to explore a phenomenon that earned a lot of attention since the very first years of carbon pricing: carbon offsetting. This topic is considered within one of the world's major polluters, the United States, and its efforts to mitigate climate change without hurting the economic outcomes. As such, two different cap-and-trade (RGGI and California cap-and-trade) are analyzed to disentangle the various features that may (or may not) influence offsetting. Moreover, it is also considered what effects this practice has on prices of allowances.

The first chapter is an introduction that builds the framework for the following contribution. After reporting real-world data about the existence of climate change and about some future scenarios, carbon pricing is explained in detail, with an emphasis on emission trading systems (ETS). These are political initiatives that aim to cap emissions by forcing firms to buy permits to pollute. This kind of policy is analyzed both from the political and economic points of view, highlighting its strengths and weaknesses.

The last part of the first chapter, then, concentrates on carbon offset, the principal subject of the research. This controversial phenomenon is thoroughly investigated to obtain a deep knowledge of it. It is firstly considered in legal terms, then an economic model is shown to explain the consequences of allowing offsets in carbon markets. Issues and controversies that offsets have experienced are considered too.

Chapter two concentrates on the methodologies employed in this study.

First of all, it shows the fundamental question and some related subquestions that guide the whole research. Then, it reviews the data, the sources where the data come from and justifies the choice of variables and the case studies. Furthermore, it illustrates the data analysis process, explaining the approaches used and the possible pitfalls that can arise from those. At the end of the chapter, a short literature review is provided to give an idea of the previous studies upon which this research is built.

After this technical part, the analysis starts. To start, this research inquires about what features can influence the usage of offsets. It begins by determining the market features that may influence offsetting, then it narrows down the unit of analysis by examining sectoral elements. In the end, attention is given to the relationship between offsetting and allowance prices, trying to understand if offsets supply and demand have a significant influence in determining permits auction price in the California cap and trade market.

The third chapter develops this breakdown. Firstly, it illustrates the case studies main features and their respective offsets protocols. Secondly, it examines macro-drivers of offsets demand. It begins by analyzing standard market traits, such as quantitive limits, cap tightness, allowance prices and leakages. Then, it proceeds to discuss rules settled by offsets protocols, such as the type of projects allowed (qualitative limits), the geography of these projects and the risk of invalidation for credits.

Subsequently, factors at the sector level are studied. These are the most difficult ones to deal with since a lot of this information is kept private by emitters. As a consequence, the research includes only those components that can either be inferred from the data or have been previously estimated by other contributions. Those discussed are abatement costs, compliance obligation, competition and the possibility to transfer compliance costs to consumers. The final paragraph of chapter three is dedicated to the possible interactions between micro and macro drivers.

Chapter four, instead, looks at the offset from a different perspective. It does not consider what influences offsets, rather it assesses the elements that may be influenced by offsets within a cap and trade system. Specifically, it focuses on the relation between offsets and allowance prices, hoping to discover if it exists and if it is significant.

To do so, an autoregressive distributed lag model is implemented. In this model, permit price is the dependent variable that is explained by its past prices, allowances sold in every auction, supply of offset credits, and credits in general and compliance account of the CITSS database.

Standard econometric tests are run on the variables, to understand their nature, and on the model, to determine its goodness of fit. Chapter four reports the results of all of them.

In conclusion, the pitfalls of the approach employed are explored and some ideas for further studies are proposed.

Chapter 1

Climate change, cap and trade and carbon offsets

1. 1 Climate change and its solution: Carbon pricing

Climate change and global warming have become issues that can not be ignored anymore. There is no longer a debate about it: climate change has become a serious threat to humanity. This may seem ironic since, as a documented body of evidence confirms, global warming is very likely due to an increase in anthropogenic activities.[1] Indeed, the Business as usual (BAU) scenario may not be sustainable either in the short or in the long term.[2] According to the IPCC's predictions, the worst possible scenario entails an increase of the mean global temperature relative to the 1850-1900 period by more than 4°C. Moreover, not so many estimated scenarios seemed to be able to contain climate change under a reasonable threshold.[3]

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[1] IPCC (2007), *Climate Change 2007: Synthesis Report*, Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)], Geneva, IPCC

[2] See e.g. Stern, N. (2007), *The Economics of Climate Change: The Stern Review,* Cambridge, Cambridge University Press; or Nordhaus W. D. (2007), *A Review of the Stern Review on the Economics of Climate Change*, in «Journal of Economic Literature», n. 45 (3), pp 686-702

[3] IPCC (2022), *Summary for Policymakers*, in «Climate Change 2022: Mitigation of Climate Change» Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge and New York, Cambridge University Press

Fearing the concretization of this drastic future, almost all countries have recognized the necessity to act immediately to mitigate the "mother of all externalities"[4] avoiding dangerous and irreversible damages.

An externality is a cost (or a benefit) from an activity that reflects also on third parties not directly involved in that activity. An example is when a firm pollutes a river that is used also by another firm. In this case, the latter is suffering from an externality produced by the former. Within economic theory, the proposed solution to this kind of situation is to make the producer pay a cost. This is a procedure called internalization (*of the externality*), *i.e.* switching the externality's burden from the outside to the inside. Following the example above, the polluting firm should pay a cost for the garbage it is disposing of into the shared river. If the cost is high enough, the polluting firm will probably find a different way to deal with its trash disposal. It is within this framework that the world's major institutions have been trying to deal with Climate Change in the last decades.

Once carbon dioxide was recognized as an externality, authorities started to settle the rules for its internalization. As predictable, it was challenging to find a common perspective.

On one side, there are supporters of the traditional regulatory instruments, believed to be more popular and effective since there is not the necessity to commit to highly visible and unpopular price increases.[5] On the other side, there are advocates for pricing carbon, an innovative approach promising to couple low-carbon innovation with economically efficient changes.[6]

Carbon Pricing is a particularly interesting solution that has gained more and more credit in the climate policy debates. Legally, carbon pricing implies that "a

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[4] Tol R. S. J. (2009), *The Economic Effects of Climate Change*, in «The Journal of Economic Perspectives», Vol. 23 n. 2, pp 29-51, p 29

[5] Cullenward D. (2019), *For Insights into Climate Policy, Look to Practice—Not Just Theory*, in «One Earth», Volume 1, Issue 1, p 1

[6] Cullenward D. (2019), *For Insights into Climate Policy, Look to Practice—Not Just Theory*, in «One Earth», Volume 1, Issue 1, p 1

price is placed on greenhouse gas[7] emissions, which creates a financial incentive to reduce those emissions or enhance removal".[8] It aims to encourage changes in current patterns toward low-carbon growth through the incorporation into the decision-making of the cost of climate change.[9] Also, it does so with a high degree of freedom and flexibility.

This approach, of course, is not free of pitfalls. Firstly, it leaves a wide maneuvering space for governments that are implementing it. Just to cite one, entities need to decide whether or not revenues from pricing should go directly to the government (instead of other designated agencies, for example) and their decisions will strongly affect the outcomes.[10] Secondly, once decided who gets the revenues, there are different options in determining how to spend them. If not continuously evaluated and improved, this "green spending"[11] can become a waste of resources.[12]

Nonetheless, the weakness of carbon pricing is at the same time its strength: since the perfect formula does not exist, it can be tailored to every specific context. This means that carbon pricing initiatives can differ greatly from one another, but they will always be within two extreme cases: direct vs indirect carbon pricing.

The latter refers to "instruments that change the price of products associated with carbon emissions in ways that are not directly proportional to those emissions".[13] Fuel or commodity taxes/subsidies lay within this category.

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[7] Greenhouse gases include (but are not limited to): Carbon Dioxide; Methane; Nitrous Oxide; Chlorofluorocarbon-12; Hydrofluorocarbon-23; Sulfur Hexafluoride; Nitrogen Trifluoride.

[8] The World Bank (2022), *State and Trends of Carbon Pricing 2022*, Washington D.C, World Bank

[9] High-Level Commission on Carbon Prices (2017), *Report of the High-Level Commission on Carbon Prices*, Washington, DC, World Bank

[10] Cullenward D. (2019), *For Insights into Climate Policy, Look to Practice—Not Just Theory*, in ≪One Earth≫, Volume 1, Issue 1, p 1

[11] Carl J., Fedor D. (2016), Tracking global carbon revenues: a survey of carbon taxes versus cap-and-trade in the real world, in ≪Energy Policy≫, n. 96 (2016), p. 51

[12] D. Cullenward (2019), *For Insights into Climate Policy, Look to Practice—Not Just Theory*, in ≪One Earth≫, Volume 1, Issue 1, p 1

[13] The World Bank (2022), *State and Trends of Carbon Pricing 2022*, Washington D.C, World Bank, p 1

Direct carbon pricing, instead, consists in applying “price incentives directly proportional to the GHG emissions generated by a given product or activity”.[14] These are the hardest to implement and may not be enough on their own. Therefore, some sort of complementary initiative might be needed to reach the targets. Despite that, direct carbon pricing initiatives (CPIs) have mushroomed across the globe, peaking in 2022 with sixty-eight operating CPIs (and three more scheduled to be implemented) covering about 23% of total GHG emissions. Amongst those, 37 are carbon taxes and 34 are Emissions Trading systems (ETSs).[15]

A carbon tax consists of charging a price to companies for (usually) every ton of GHG emitted by burning fossil fuels. In turn, fossil fuel prices will increase and this will (in theory) lead to the switch to low-carbon energies. Following a Pigouvian approach, a carbon tax main purpose should not be to raise revenues but to adjust market failures (as climate change is). Thus, it should reflect the cost of the externality,[16] technically called the “Social cost of carbon (SCC)”.[17]

The crystal clear cost of emitting GHG (the tax rate) and the absence of too many administrative burdens have made this policy so appreciated. Particularly, there are information benefits associated with it: the regulators do not need to know the abatement cost curves of firms, an information that they will not be able to obtain. Nevertheless, it has received some critiques. Politically speaking, taxes are not welcomed by electors (such as citizens or managers). It could be a political suicide to propose a tax during election time, therefore politicians tend to avoid it. Rebates are often seen as the solutions to this,[18] yet it is not clear if

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[14] The World Bank (2022), *State and Trends of Carbon Pricing 2022*, Washington D.C, World Bank, p 13

[15] The World Bank (2022), *State and Trends of Carbon Pricing 2022*, Washington D.C, World Bank, p 15

[16] For further discussion, look at Golosov et al (2011) and Stern (2006)

[17] The Social Cost of Carbon is “an estimate, in dollars, of the economic damages that would result from emitting one additional ton of carbon dioxide into the atmosphere”, definition from Rennert K., Kingdon C. (2019), Social cost of Carbon 101: A review of the social cost of carbon, from a basic definition to the history of its use in policy analysis, in «Resources for the Future», pp 1-4

[18] Examples of Countries with such policies are Canada and Switzerland

they help or not in increasing political support.[19] Economically speaking, the determination of the optimal tax to apply heavily depends on the SCC, which, in turn, depends on the discount rate. That is the predominance of current generation interests over future ones.[20] The problem is that it is a modeling choice on which there is not a common agreement on the basis (*i.e.* normative or positive) to make the decision and, once the basis is determined, on the actual discount rate ought to be. Depending on these choices, the final price of carbon can vary widely, making it difficult to choose the right carbon tax.[21]

Ultimately, the major critique that carbon taxes attract is that they provide no certainty on the degree of emission abatement.. This is a natural consequence of the tradeoff that policymakers are doomed to face every time they implement green policies: cost uncertainty *vs* emissions uncertainty.

While assigning a price to GHG, a carbon tax is imposing a cost on emitters. A tax involves certainty over abatement cost: entities know how much they pay for every ton of CO_2. It is the emitter's task to reduce emissions to minimize this burden to an acceptable grade. Hence, the market must deal with emissions on its own. In these circumstances, it is impossible to know *ex-ante* the magnitude of GHG reductions. If policymakers want to be certain about the cost imposed on firms and do not care to know *ex-ante* the amount of emissions reductions, a carbon tax is what they are looking for. If, instead, knowing the amount of emissions reductions is the main concern for authorities, an emissions trading system (ETS) is their best bet.

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[19] See e.g.: Mildenberger M., Lachapelle E., Harrison K. et al. (2022), Limited impacts of carbon tax rebate programmes on public support for carbon pricing, in « Nature Climate Change» no. 12, pp 141–147

[20] For broader discussion about discounting, look at Revesz, R. L. (1999), *Environmental Regulation, Cost-Benefit Analysis, and the Discounting of Human Lives*, in «Columbia Law Review», no. 99(4), pp 941–1017; and Polasky S., Dampha N. K. (2021), *Discounting and Global Environmental Change*, in «Annual Review of Environmental Resources», no. 46, pp 691-717

[21] Although a discussion about discount rates and carbon taxes is not in the interest of this study, it may be useful to give a general idea of how wide the difference in carbon taxes could be. For example, with a near-zero discount rate (0.1%, as was suggested by Stern 2006) the SCC is 917 2018$ per ton of CO2 in 2050, while considering a discount rate of 4% (usually estimations tend to use a discount rate in the range between 3.0% and 5.0%) leads the SCC to 93 2018$ per CO2 ton in 2050, according to Nordhaus W. D. (2018), *Climate Change: The ultimate challenge for economics*, Prize Lectur

1.2 Cap and trade: reducing emissions at the lowest cost

Proposed by Dales in 1968,[22] cap and trade (or emission trading systems) policies have gained prominence among major countries. For example, China, the host of the largest ETS by emissions,[23] the European Union, that shows the highest trading volume of allowances,[24] and the US opt for cap and trade systems to tackle emissions.

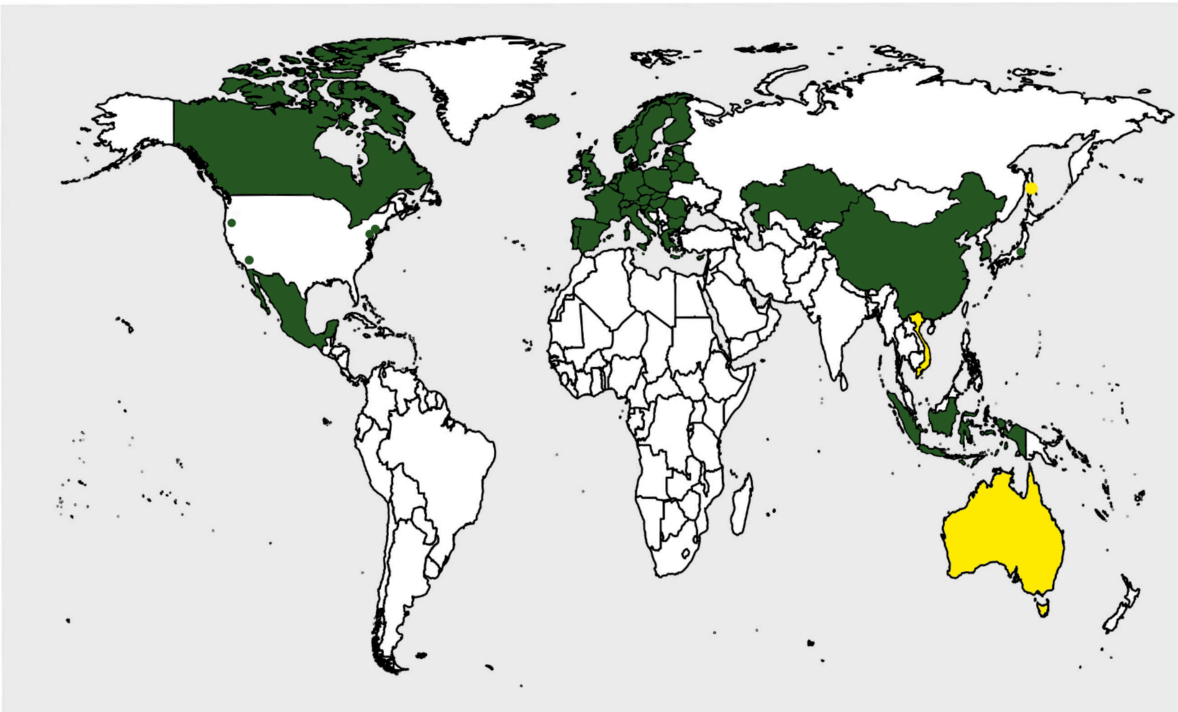

Figure 1. Implemented and Scheduled ETS systems in the world (2023). Green: systems implemented; Yellow: systems scheduled to be implemented. Dots represent local ETS. Data Source: World Bank, Carbon Pricing Dashboard, available at: https://carbonpricingdashboard.worldbank.org/map_data. Chart by the author.

An ETS's main principle is to set a cap on GHG and let the capped entities trade the permits to emit. Every single permit allows the owner to emit a determined quantity of pollutants.

[22] Note that J. H. Dales spoke about river pollution, not directly about emissions. To know more: Dales J. H.(1968), *Pollution, Property & Prices: an Essay in Policymaking and Economics*, Toronto, University of Toronto Press, Digitalized by The Internet Archive, https://archive.org/details/pollutionpropert0000dale/page/n5/mode/2up

[23] The World Bank (2022), *State and Trends of Carbon Pricing 2022*, Washington D.C, World Bank, p 18

[24] The World Bank (2022), *State and Trends of Carbon Pricing 2022*, Washington D.C, World Bank, p 18

Two different stages compose the functioning of cap-and-trade policy: the first one is the authorities' duty, and the other is left to the market.

Authorities[25] have two main tasks to complete: decide the cap coverage (*i.e* what kind of businesses and emissions are included), level of emissions (*i.e* how many tons can be emitted) and its rate of decrease; and to create, assign and distribute a number of permits equals to the cap. Also, the amount of GHG units that a single permit allows must be specified. Once distributed, businesses can trade the permits they hold. Entities with a surplus of permits will sell them, while those who do not have enough to cover the total emissions will become buyers. Thanks to a demand-and-supply mechanism, the market will determine the market-clearing price of the permits. This mechanism makes the ETS emissions certain (it is not possible to exceed the cap) and cost uncertain (*ex-ante* the price of permits is not clear).

As evident, the good functioning of an ETS system lies in the rules settled by the authority and in the capacity of the market to play accordingly. Thus, the decision-making phase is fundamental. Here, different aspects must be considered.

The first one is the cap: it must be settled at the right level to effectively decrease emissions. If it is too high, maybe as a consequence of adverse political forces, it would fail in its purpose. For example, a cap higher than real emissions is useless. Although this is a situation that seems unlikely, it happened in the first years of The Regional Greenhouse Gasses Initiative (RGGI).[26] On the other hand, a too-low cap can become a large burden on the economy. Considering that the cap determines the permit quantity, indirectly it determines their price too. If there are too few permits (*i.e.* the cap is too tight), the cost of buying one will increase to the point of breaching the acceptability threshold. This would probably lead to political turmoil and strong opposition. To ensure that the price moves within a reasonable and politically acceptable range, projected emissions

[25] Authorities can be governments, interstate organizations, or a committee built with exactly this purpose

[26] Ramseur J. L. (2013), The Regional Greenhouse Gas Initiative: Lessons Learned and Issues for Policymakers, Washington, D.C., Congressional Research Service, CRS Report

are re-estimated, and the cap is adjusted accordingly. Moreover, the cap is settled to be declining over time. The result is a constant reduction at a fair price.

Choosing what kind of emissions are capped is another important consideration. Even though it may seem reasonable to cover every type of GHG, some ETSs cover just some specific kinds of emissions (such as just CO_2 or SO_X). For example, RGGI covers just CO_2 emissions.

Along with that, it must be decided which entities should comply with the rules. It is not rare to see some specific sectors (financial, forestry, agriculture and so on) excluded from this obligation. Still, they can join the program voluntarily (but are not forced to do so).

Lastly, authorities have to rule how to distribute allowances. There are two ways to do so: grandfathering and auctioning. Grandfathering consists in giving allowances for free to selected entities. Then, the trading starts. The discriminants here are the criteria based on which allowances are distributed. Among the most used there are past emissions, share of the market and relevance of the firm/ sector.[27] The EU ETS used grandfathering in its first pilot phase. In the case of allowance auctions, permits are distributed based on the winning bids of periodic auctions. Their features, however, can vary quite broadly. There could be differences among types, presence of price floors and ceilings, frequency and so on. Of course, the choices on these issues reflect on prices too.[28] RGGI is an ETS that relies on auctioning. Finally, authorities can opt for a mixed approach: assigning a pre-determined amount of allowances through grandfathering and auctioning the others. In this case, it must be determined how many allowances each method should allocate. The strength of this approach is that it allows even the smallest businesses to get some allowances at a lower price (and/or gain a profit from their sale). An example where this approach is utilized is California.

The mix of all these design decisions constitutes the foundation of the policy. As such, permit exchange will take place within that framework. Based on economic

[27] See e.g. Böhringer and Lange (2003), Woerdman et al (2008), Knight (2012).

[28] See e.g. Holt et al. (2007), Busch et al. (2018), Löfgren et al. (2018)

theory, models from Economides et al (2018)[29] and Pearce and Turner (1990),[30] illustrate clearly a cap and trade trading mechanisms.

The starting point is a situation of perfect market competition with just two firms (say firm A and firm B) polluting the environment. To decrease their emissions, each firm should engage in abatement activities. Of course, abatement has a cost. Thus, each firm has its own (different) marginal cost of abatement curve (MAC). The MAC could be constructed as a Marginal Net Private Benefit (MNPB) function if the only way to decrease emissions is to reduce output.[31] Let's assume that firm A decreases emissions more efficiently than firm B. Note that the abatement curve increases as the level of emissions reduction gets higher:

$$\frac{\partial MAC_i(E_i)}{\partial E_i} < 0 \qquad \text{With } i = A,B \tag{1}$$

If no regulation exists, both firms will not engage in any kind of abatement. The emission levels will be, respectively, E_A and E_B, since no one is willing to sustain an unnecessary cost if not forced to.

To limit GHGs, the authority can decide to create a number of permits A* equal to the emissions cap E_C, settled to be:

$$E_C < E_A + E_B \tag{2}$$

To effectively reduce emissions. E_C is the fixed supply of available permits.

Supposing that permits are auctioned, each firm has two options for complying with regulations: reducing its emissions (for example, with new technologies) or

[29] Economides G., Papandreou A., Sartzetakis E. and Xepapadeas A. (2018), *The Economics of Climate Change*, Athens, Climate Change Impacts Study Committee, Bank of Greece

[30] Pearce D. W. and Turner R. K. (1990), Economics of Natural Resources and The Environment, Baltimore, The Johns Hopkins University Press

[31] Pearce D. W. and Turner R. K. (1990), Economics of Natural Resources and The Environment, Baltimore, The Johns Hopkins University Press

buying permits. The MAC curve shows exactly this tradeoff, so it is the demand curve for permits. With two firms, there will be two different demand curves: MAC_A and MAC_B . The aggregate demand MAC_{AGG} will be their sum.

Since the permit market follows a supply-demand mechanism, the optimal price (P*) will be the result of the intersection between the demand and the fixed supply. Each firm will behave in the same way: it will abate up to the point where the last unit of abatement has the same cost as purchasing a permit. The logic is that the most efficient producer (*i.e.* the ones with lower abatement costs, firm A in this case) will find it more profitable to abate emissions on its own and sell permits rather than buy them to emit more. Instead, the firm with high-abatement cost (*i.e.* firm B) will be in the opposite condition. As a consequence, firm A will sell permits while firm B will buy them. A market for permits is created. In the example, firm A will emit E_{CA} units of emissions and will purchase an A_A number of permits. firm B will do the same. The equilibrium will be reached when:

$$MAC_A(E_{CA}) = MAC_B(E_{CB}) = P^* \tag{3}$$

Since this situation ensures the efficient allocation of permits.

If the authority decides to opt for grandfathering, instead of allowances auctioning, the result will be the same (Economides et al, 2019). Consider an initial allocation where the government split equally A* between two firms A and B. Both firms will have A*/2 permits. However, firm A has a higher MAC, leading to the situation where:

$$MAC_A(A^*/2) > MAC_B(A^*/2) \tag{4}$$

In this case, firm B has an incentive to further decrease its emission and sell its permits in excess to gain a profit. For firm A, instead, it is more convenient to buy permits from firm B to increase their emissions and reduce its abatement cost. This process will stop only when firm A MAC equates to firm B MAC.

Then, the market equilibrium is the same as the auctioning case:

$$MAC_A(E_{CA}) = MAC_B(E_{CB}) = P^* \qquad (5)$$

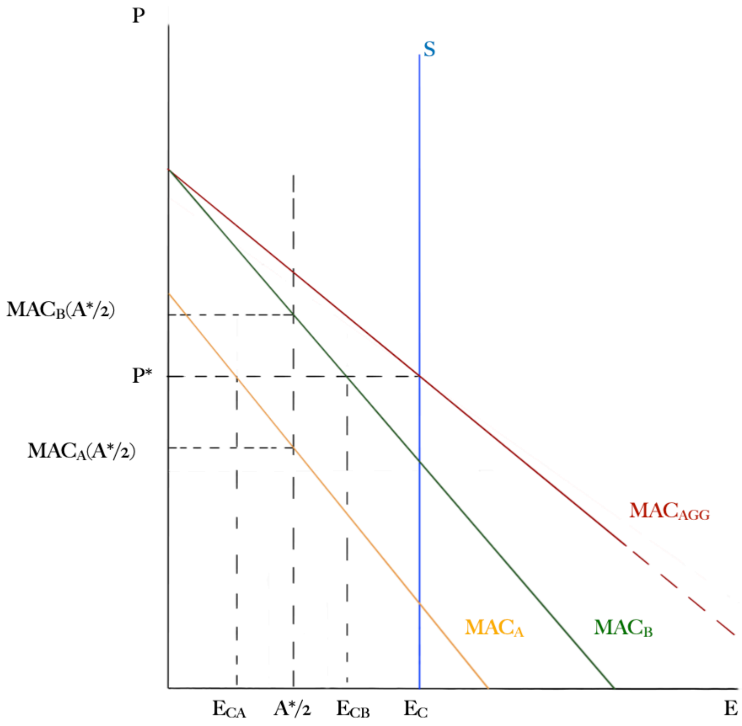

Figure 2. ETS with allowances auctioning *vs* ETS with grandfathering.

This means that the initial allocation does not change the final equilibrium. Therefore, the decision about how to allocate permits can be employed to serve goals of political feasibility or ethical concerns. (Economides et al, 2019).

The possibility of trading permits reduces also the costs of achieving the environmental target (Economides et al, 2019). Back to the situation previously analyzed:

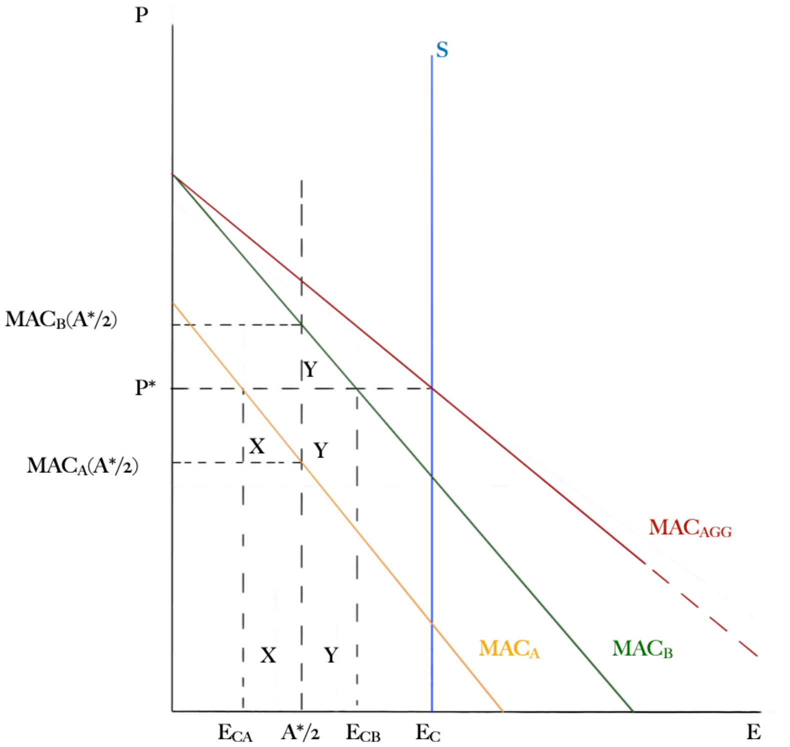

Figure 3. Tradable permits and costs of achieving the pollution target.

While reducing the necessity for permits by A*/2-E_{CA}, firm A is reducing its abatement cost by area X. On the other hand, the purchase of an equal amount of permits allows firm B to decrease its abatement cost by the area Y. Since Y > X, trading reduces the cost of achieving the target. The logic is that, if the market is perfectly competitive, permits will flow to the firm that has the higher MAC (or the higher demand for permits). Plus, tradable permits help in dealing with new entrants, inflation and adjustment costs, and technological lock-in. (Pearce and Turner, 1990).

One more feature will guarantee the correct functioning of the system: monitoring. Coupled with penalties for noncompliance, it can help in effectively reaching an ETS target.[32] Periodical checking of emissions, compliance reports, behaviors, auctions, presence of leakages and offsets use will help in ensuring a high level of compliance and minimize each kind of controversies. Additionally, it is necessary to "complement the national monitoring system with

[32] Schmalensee R., Stavins R.N. (2017), *Lessons Learned from Three Decades of Experience with Cap and Trade*, in «Review of Environmental Economics and Policy», pp 59-79

internationally accredited institutions"[33] to clinch effective controllability. Concretely, ETSs with continuous monitoring are the ones that have obtained the most successful results. The problem with that is its cost. The more surveillance is in place, the higher the price to maintain this high standard. An ETS, also, may need an international accredited institution to properly assure monitoring. If not constantly surveilled, this institution can become a "rent-seeking oriented bureaucracy"[34] more interested in making profits than effectively ensuring that everything abides to the rule.

Unfortunately, monitoring costs are not the only issue that a cap and trade system encounters in its life.

Leakage is a major concern for every carbon policy. Defined as "a reduction in emissions of greenhouse gases within a state that is offset by an increase in emissions of greenhouse gases outside the state", carbon leakage occurs when a firm that is subject to a cap and trade system moves its business to other states (or countries) that have no such rules in place.[35] Coupled with it is resource shuffling. It happens when "utilities and power traders […] face an incentive to swap their high-emitting imports for cleaner replacement".[36] If this happens, emissions reported within an ETS system are not reflected by a real reduction of GHG into the atmosphere: firms are just changing the place that they are polluting. In this way, the emissions' total amount is not reduced. This is a consequence of different policies in different countries: not all have carbon pricing systems and even amongst ETSs the coverage is often not the same. A border carbon tax is often proposed as the ideal solution to rebalance these differences, yet there is not a shared agreement on this point.[37]

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[33] Yeldan A. E. (2019), *Chapter 9 - Economic instruments of greening*, in: Editor(s): Sevil Acar S. and , Erinç Yeldan A. E. (eds), *Handbook of Green Economics*, London, Elsevier Academic Press, pp 158

[34] Yeldan A. E. (2019), *Chapter 9 - Economic instruments of greening*, in: Editor(s): Sevil Acar S. and , Erinç Yeldan A. E. (eds), *Handbook of Green Economics*, London, Elsevier Academic Press, pp 158

[35] See Legislative Counsel of California (2014: § 38505(j))

[36] Cullenward D. (2014), *How California's carbon market actually works*, in «Bulletin of the Atomic Scientists», n. 70(5), pp. 38

[37] to know more about border carbon taxes, take a look at Moore (2010), Wooders and Cosbey (2010), Antimiani et al (2013)

The absence of a global carbon market makes room also for the possibility of linkages between different systems. Again, there is not a unique view of the costs and benefits of linking different carbon markets.[38] Among the economic benefits often are cited the gains from trade, the increased liquidity and the decreased volatility; while the political ones are the signaling of multilateral commitment and the enhancing domestic policy acceptance.[39] Instead, the biggest risks are: loss due to pre-existing distortions, loss of co-benefits, exposure to other regions' shocks, the possibility of increasing the cap to boost gains from the sale of permits, less regulatory ability and the possibility of reductions targets that are not consistent with a fair global burden sharing.[40]

Finally, fragmented carbon markets clear the way for a more controversial phenomenon: offsetting carbon emissions.

1. 3 Cap and trade and the outside: Carbon offsets

Along with market links, carbon offsets are one of the main elements thanks to which ETSs create relations with other countries.

From the legal point of view, offsets "refers to a reduction in GHG emissions – or an increase in carbon storage (*e.g.* through land restoration or the planting of trees) – that is used to compensate for emissions that occur elsewhere".[41] If a firm

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[38] to know more about carbon linking, take a look at Doda and Taschini (2017), Helm (2003), Holtsmark and Midttømme (2021), Pizer and Yates (2015), Holtsmark and Weitzman (2020), Wilson (2019), Green (2017)

[39] Flachsland C., Marschinski R. and Edenhofer O. (2009), To link or not to link: benefits and disadvantages of linking cap-and-trade systems, in «Climate Policy», vol. 9:4, pp 13

[40] Flachsland C., Marschinski R. and Edenhofer O. (2009), To link or not to link: benefits and disadvantages of linking cap-and-trade systems, in «Climate Policy», vol. 9:4, pp 13

[41] Broekhoff D., Gillenwater M., Colbert-Sangree T., Cage, P. (2019) *Securing Climate Benefit: A Guide to Using Carbon Offsets*, Stockholm Environment Institute & Greenhouse Gas Management Institute

engages in offsetting activities, it will receive some offset credits[42] (equal to the mitigated ton of GHG) that can use to comply with ETS rules. For example, a capped firm that is polluting can engage elsewhere in activities that decrease emissions, such as planting trees. In this way, it will earn some credits that it can utilize when it's time to report emissions.

Even though the mechanism may seem straightforward, it is not. First of all, a firm that wants to earn offset credits should identify a project that effectively reduces emissions. Then, the developer of the project must estimate the number of credits that can be received for it and complete an application to the administration to obtain credits. Often, it is not important which country the project is in. Moreover, it is fundamental that the cap and trade program includes offset credits within the options to comply with obligations. Otherwise, they will be worthless. The pledged reduction is monitored by some third-party agencies with the duty of reporting if something is not functioning.

Of course, every ETS that accepts offsets has some sort of protocol to define the guidelines of their acceptability. Nevertheless, some characteristics are normally required for all offsets. Those are:

- Additionality: "emissions reductions or removals from the atmosphere above and beyond what would occur in the absence of carbon offsets incentives".[43]
- Permanence: credited reductions must last for a long-term period and not be reversed.
- Absence of leakage: leakages are "net change of greenhouse gas emissions or removals that are attributable to the mitigation activity but occur outside the boundary of that activity. These include, for example, indirect

[42] An offsets credit is a "transferable instrument certified by governments or independent certification bodies to represent an emission reduction of one metric tonne of CO_2, or an equivalent amount of other GHGs", Broekhoff, D., Gillenwater, M., Colbert-Sangree, T., Cage, P. (2019) *Securing Climate Benefit: A Guide to Using Carbon Offsets*, Stockholm Environment Institute & Greenhouse Gas Management Institute

[43] Van Kooten G.C. and De Vries F.P. (2013), Carbon Offsets, in: Shogren J. F. (eds), Encyclopedia of Energy, Natural Resource and Environmental Economics, London, Waltham and San Diego, Elsevier, p. 6

emission changes upstream or downstream of the mitigation activity or rebound effects”.[44]

- Verification: an independent authority has verified the offsets qualities.

Due to this complexity, the majority of theoretical studies tend to favor direct market links despite offset programs. Linkages are less resource intensive, do not require a project-by-project evaluation and are wider in scope. Offsets, instead, come with high transaction costs and a narrow application. As a result, linking markets should be the most widespread means of cooperation.[45]

Nonetheless, in the real world, the situation is quite the opposite: offsets have mushroomed across the globe, while linked ETSs have remained very thin.

Probably, the first (and most famous) examples of an offsets program are the Joint Implementation (JI) and the Clean Development Mechanism (CDM). Both part of the Kyoto Protocol (December 1997), they were, respectively, "flexible compliance mechanisms involving carbon offsets generated either in economies in transitions[46] or in the developing world[47]”.[48]

Thanks to the broad diversity of projects participating in the CDM,[49] it has become one of the largest markets for offsets. Since its beginning, more than 8000 projects have been registered, peaking between 2011 and 2013.[50] This led to the issuances of more than 2 billion Certified Emissions Reductions (CERs), mostly to projects hosted by China, India, Brazil and Mexico.

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[44] WWF & EDF (2020), What makes a high quality carbon credit? Phase 1 of the “Carbon Credit Guidance for Buyers” project: Definition of criteria for assessing the quality of carbon credits, https://files.worldwildlife.org/wwfcmsprod/files/Publication/file/54su0gjupo_What_Makes_a_High_quality_Carbon_Credit.pdf?_ga=2.248097281.724092613.1631902150-1745645757.1631041263

[45] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, p. 137

[46] Economies in transitions include states such as Russia or Ukraine

[47] Developing countries include (but are not limited to) China, India, Brazil, Mexico, Chile.

[48] Wara M. and Victor D. G. (2008), *A Realistic Policy on International Carbon Offsets*, in «Program on Energy and Sustainable Development Working Paper», n. 74, p. 9

[49] Wara M. and Victor D. G. (2008), *A Realistic Policy on International Carbon Offsets*, in «Program on Energy and Sustainable Development Working Paper», n. 74, p. 9

[50] Data from the UNFCCC, accessible from: https://cdm.unfccc.int/sunsetcms/Statistics/Public/CDMinsights/index.html#val

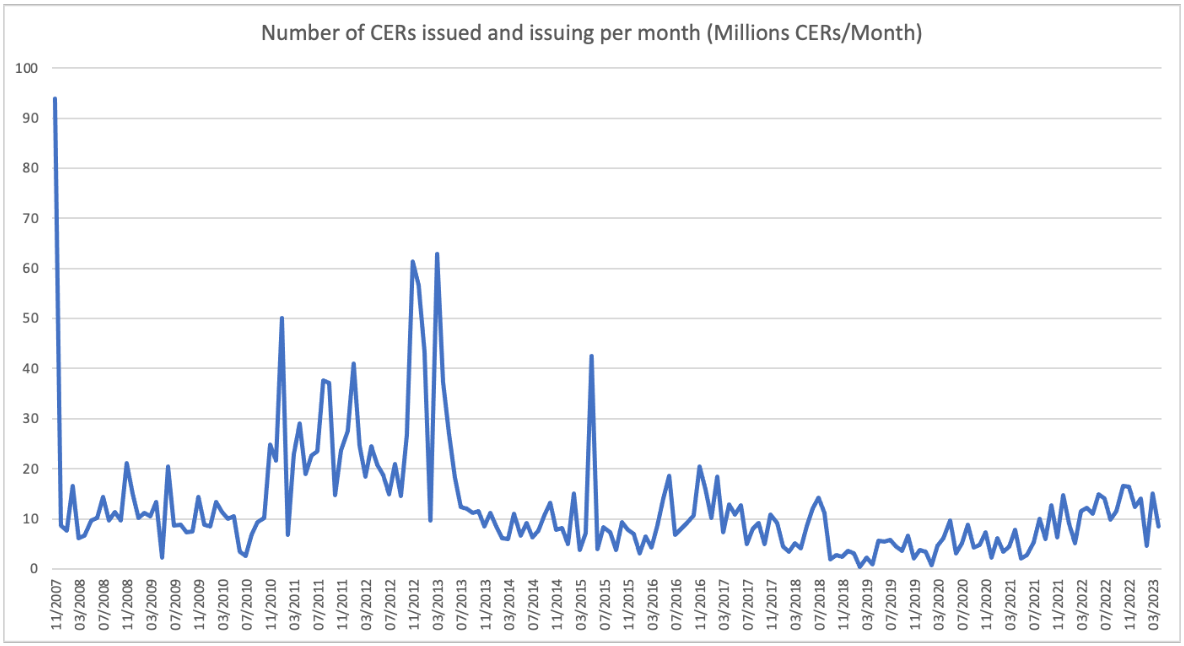

Figure 4. Number of CERs issued and issuing per month (Millions CERs/Month). Data Source: UNFCCC, CERs issued and issuing per month, available at: https://cdm.unfccc.int/sunsetcms/Statistics/Public/CDMinsights/index.html#val. Chart by the author.

CERs quantify the emissions avoided by an offset project. They are the carbon credits coming from the CDM. Notably, their peculiarity is the possibility for EU ETS countries to employ CERs to comply with their obligations. One of the main problems, however, is that abating emissions with CERs is less expensive than concretely abating emissions within a country border or buying allowances.[51] This is the reason why the CDM has become the target of many critiques claiming the necessity to reform it.[52]

The EU ETS is not the only scheme which issues credits for offsets projects. The Regional Greenhouse Gas Initiative (RGGI), the Western Climate Initiative (WCI) and China's national ETS have similar mechanisms in place.

China National cap and trade system confirmed the possibility of offsets use in a notice from 2021[53], as long as they follow two rules: they can count up only to

[51] Wara M. and Victor D. G. (2008), *A Realistic Policy on International Carbon Offsets*, in «Program on Energy and Sustainable Development Working Paper», n. 74, p. 9

[52] For more information about this point take a look at: Wara and Victor (2008).

[53] Ministry of the Ecology and Environment of the People's Republic of China (2012), Notice on the liquidation of carbon emission quotas in the first performance cycle of the national carbon emission trading market, Environmental Office Climate Letter, n. 492

5% of the obligation; and they should not come from projects already included in the national carbon market. Yet, there are no restrictions on the type of projects accepted.[54]

The RGGI is a "cooperative effort among twelve eastern states to reduce carbon dioxide (CO_2) from power plants within each participating State".[55] Inside its regulation, it considers the possibility to give offset credits for projects as long as these initiatives are located within RGGI states and within some categories. Furthermore, no more than 3.3% of total compliance can be fulfilled by offsets.[56]

The WCI is "the largest carbon market in America"[57] and it consists of a shared ETS between some US states (California and Washington) and some Canadian provinces (Québec and Nova Scotia). This means that allowances from the US are recognized in Canada, and *vice versa*. Offset credits, both from national and linked jurisdictions, are accepted too. It is up to every single jurisdiction to design a protocol to settle the quantity and the type of offset credits that will be accepted. The only exception is Nova Scotia, which has not shown any commitment in developing offsets projects and protocols.

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[54] International Carbon Action Partnership, China releases instructions for the first compliance cycle of the national ETS and procedures for offset use, ETS-news, Nov 23 2021, https://icapcarbonaction.com/en/news/china-releases-instructions-first-compliance-cycle-national-ets-and-procedures-offset-use

[55] RGGI, The RGGI 101 Fact Sheet, January 2023, p1, available at: https://www.rggi.org/sites/default/files/Uploads/Fact Sheets/RGGI_101_Factsheet.pdf

[56] RGGI, The RGGI 101 Fact Sheet, January 2023, p.1 available at: https://www.rggi.org/sites/default/files/Uploads/Fact Sheets/RGGI_101_Factsheet.pdf

[57] WCI, participating Jurisdiction Overview, May 2023

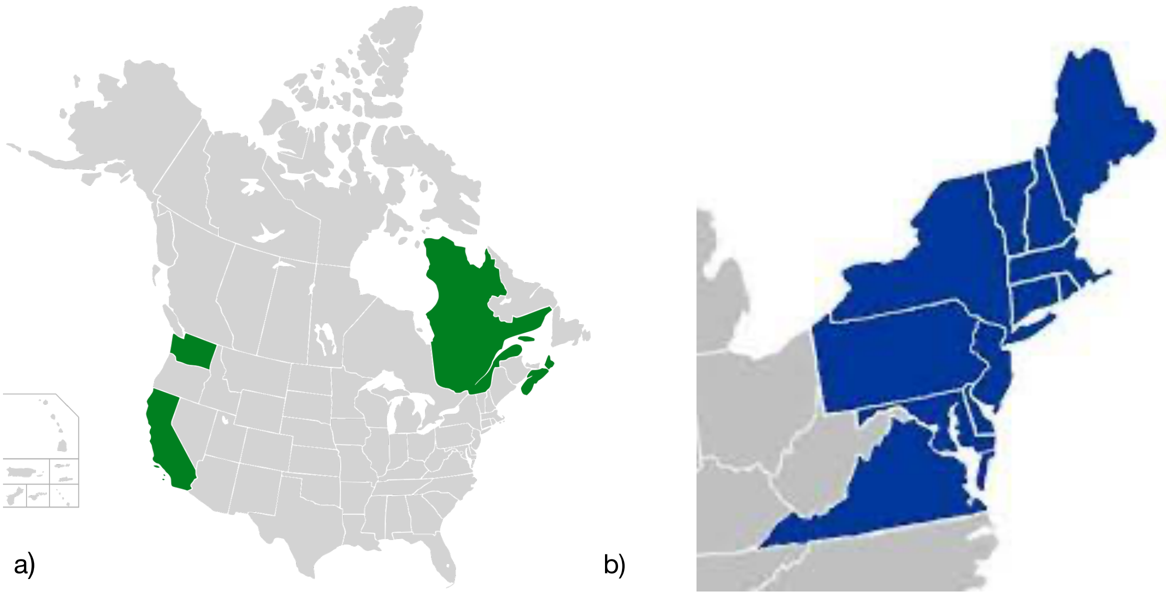

Figure 5. US States and Canadian Provinces member of the Western Climate Initiative (a) and States Members of the Regional Greenhouse Gasses Initiative (b). Sources: a) Wikipedia, https://en.wikipedia.org/wiki/Western_Climate_Initiative, b) RGGI, The RGGI 101 Fact Sheet, January 2023, p1.

1.3.1 Carbon Offsets Economic Model

In theory, there are two benefits behind the necessity of offsets in every ETS.

In the first place, offsets reduce compliance costs for capped entities. This, in turn, increases the political acceptability of climate policies (Cullenward and Victor (2020); Wara and Victor (2008)).

Secondly, offsets help in broadening the scope of a policy outside its border, favoring the engagement of countries that have no such standards in place (Cullenward and Victor (2020); Wara and Victor (2008)).

Economic theory explains why offsets are the most cost-effective measure to reduce emissions.

Consider just one firm, say firm A, that is engaged in abating emissions. As seen before, firm A has its own marginal abatement cost curve (MAC_A) that increases as the levels of emissions reductions get higher. Again, if no regulation is in place, firm A will probably not abate at all, since it is costly. In this case, it emits as much as it needs (E_{MAX}). If some regulations are in place, firm A will be constrained to emit E_R and will pay the cost of abatement to reach that level (area C).

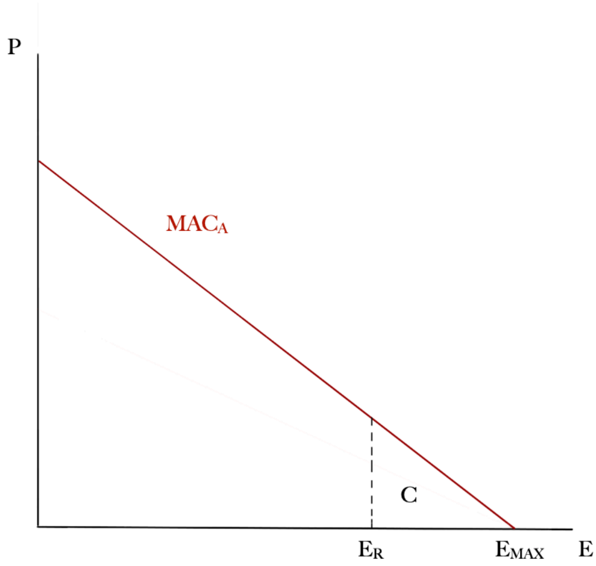

Figure 6. firm A Marginal Abatement Curve and Abatement costs with and without restrictions.

In this situation, firm A has only two ways to reduce emissions: buy permits or effectively decrease GHG.

Yet, if a jurisdiction allows offsetting a third possibility is added: invest in offset projects, obtain some carbon credits, and use those for compliance purposes. The widespread view is that offset credits are less expensive than allowances. Hence, firm A now is more efficient than before since it has a cheaper way to deal with GHG (even though some quantitative limits may exist). That is, firm A has lower abatement costs compared to the no-offsets case, *i.e.* offsets are a cost-effective measure to achieve emissions targets.

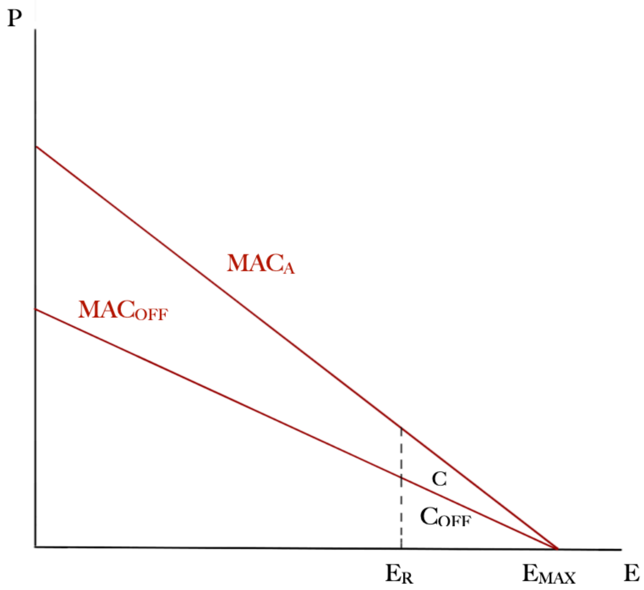

Figure 7. Offsets effects on marginal abatement costs. If offsets are not allowed, the marginal abatement cost for $firm_A$ is MAC_A. In this case, the cost of abatement is $C + C_{OFF}$. The possibility of offsets will reduce the marginal abatement costs, therefore the MAC will shift from MAC_A to MAC_{OFF}. Now, the cost of abatement is C_{OFF}. Since $C_{OFF} < C + C_{OFF}$, offsets reduce abatement costs.

This intuition is confirmed also by considering the aggregate MAC (MAC_{AGG}). MAC_{AGG} is the sum of all capped entities MACs and it is the aggregate (or total) demand for permits. The price of permits will be determined by the intersection of the demand (MAC_{AGG}) and the supply (the Cap) of permits. Now, the possibility for capped entities to employ offset credits for compliance instead of allowances will decrease the demand for allowances. Firms will opt for the cheapest way to decrease emissions, and, since $P_{OFF} < P_{ALL}$, the most effective strategy is to buy offset credits. Of course, this will not have any effect on the permits supply, which will remain the chosen cap. Yet, following a decrease in demand, the price of allowances will decrease too, reducing the abatement costs. Even in this case, offsets have helped in reducing the abatement costs.

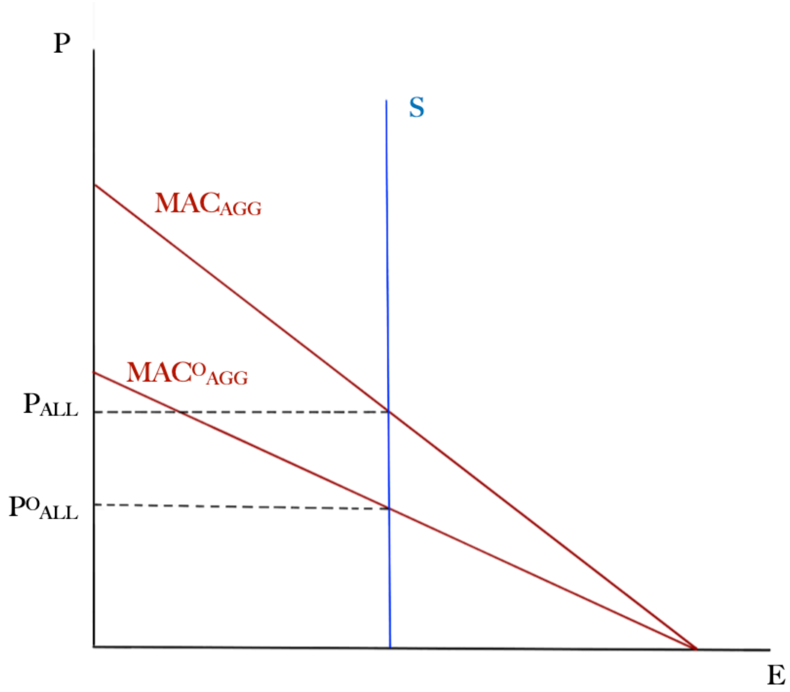

Figure 8. Carbon permits price as a result of supply and demand mechanism. The price of permits is obtained from the intersection between supply and demand. If offsets are not allowed, the aggregate demand is MAC_{AGG}, and the permits price will be P_{ALL}. If capped entities can use offsets, the marginal abatement curve will be MAC^{O}_{AGG} , and the permits price will become P^{O}_{ALL}. Since $P^{O}_{ALL} < P_{ALL}$, offsets decrease permits' prices.

In political terms, the cost-efficiency that offsets bring to an ETS will be translated into a warmer political welcome (or a softer opposition) since businesses, citizens and politicians are hostile to policies that bear high costs.

At the same time, offsets can widen the scope of climate policies. This derives from a characteristic of offsetting projects: they can be implemented outside the geographical and sectorial coverage of an ETS system. That is, an entity capped in country A could obtain offsets credits by financing a climate-friendly project in country B. In this way, offsets should encourage firms to browse across the globe to find the cheapest projects. Usually, the biggest opportunities are in those places where poor administration leads to inefficient behavior and causes emissions.[58] In turn, host countries will see a decrease in their emissions, even if no strategy is in place. In its most ambitious projection, the idea is that if a country experiences voluntary climate markets, it will be encouraged to engage in binding climate efforts as policymakers get to know new sectors and sectors become aware of

[58] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, p. 138

market-based regulation.[59] It is a "win-win situation": benefits will be both at home and abroad.

1. 3. 2 Controversies with Carbon Offsets

Even though carbon offsets theoretically do a great job in tackling climate change, in real life they have seen plenty of controversies that makes unclear their effects on prices and emissions.

Additionality is the most controversial requirement. Offset credits are assigned based on estimated emission reductions. By definition, additionality should be measured thanks to the difference between the case where a project has been built and the situation where it has not. The point is that the first is an observable situation while the second one can only be estimated. Furthermore, to obtain a proper estimation, knowledge about competing projects and market conditions is needed. The natural consequence is that it leaves a lot of freedom when it comes to assessing whether a reduction is an addition or not.[60] Leakages and permanence are other difficult conditions to estimate and foresee in advance (they can be a consequence of a tragedy, such as a fire that destroys a forest).[61] Adding regulated industries that care more about lowering costs than reducing emissions and a political class lacking in-depth knowledge and that can be easily influenced by major stakeholders, it is not a surprise that plenty of low-quality (*i.e.* non-additional or leakage-inducing) offsets are approved.[62]

Strictly correlated with additionality is infeasibility. A project should receive credits just if it could not be developed on its own. If it is not the case, then it could be financed without any help from offsets. However, since projects are

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[59] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, p. 138

[60] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, pp 141-142

[61] Van Kooten G.C. and De Vries F.P. (2013), *Carbon Offsets*, in: Shogren J. F. (eds), *Encyclopedia of Energy, Natural Resource and Environmental Economics,* London, Waltham and San Diego, Elsevier, p. 6

[62] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, pp 142-143

often low-cost, they just claim to be "barely infeasible"[63]: on their own they make sense, yet they do not on purpose to obtain credits.[64] Calel et al. (2021) proposed an innovative approach to evaluate infeasibility, trying to identify Blatantly Infra-marginal Projects (BLIMPs). BLIMPs provide a lower bound on the degree of subsidy allocation since their blatantly infra-marginal characteristic means that there are other projects that are less profitable but were built without subsidies (*i.e.* offsets credits). Their study shows that offsets misallocation is a real issue.[65] Probably, this is a consequence of the conflict of interests that permeates offsets allocation. NGOs, non-profit organizations, firms and even institutions have become closer and closer in developing offsets projects and assigning credits that their interests have almost blended (Culleneward and Victor (2020)). More dangerously, entities that carry project verifications are often paid by projects developers,[66] and the same entities help in writing offset regulations. In this context, it is not hard to figure out why poor-quality low-cost projects are approved: they bring money into all involved actors' pockets.

Another critique is that offsets are not as global as they were intended to be. The issue here is the struggle between the global approach (seek offsets wherever a firm wants) and the national political interest (keep the benefits inside your border). Each kind of project creates economic benefits (jobs, economic development, environmental benefits) that increase support for those politicians that propose it. If it produces local benefits, the political support will be more significant. Hence, it is logical for politicians to seek inside rather than outside-of-the-country projects.[67]

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[63] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, pp 144

[64] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, pp 143-144

[65] The study analyzes CDM wind-related projects developed in India. The results were not encouraging: 52% of approved carbon offsets have been assigned to projects that would be built anyway and the offsets' sale to regulated polluted has increased CO2 emissions

[66] Harvey H., Robbie Orvis R., Jeffrey Rissman J. (2018), *Designing Climate Solutions: A Policy Guide for Low-Carbon Energy*, Island Press, Washington D.C, p. 268

[67] Cullenward D. and Victor D. G. (2020), *Making Climate Policy Work*, Medford, Polity Press, pp 148-149

Moreover, offsets have failed in boosting the use of market-based policies. Considering that offsets beneficiaries receive income that would be lost if emissions reductions become mandatory, it is in their interest to avoid so. Thus, it is not rare to see the interests of different jurisdictions differ when it comes to implementing carbon policies.[68] In the worst-case scenario, offsets may even prevent regulation (Cullenward and Victor (2020)).

Altogether these issues have led offsets to be permeated with two traditional regulatory problems: moral hazard[69] and adverse selection[70].[71]

1. 4 Scope of the Study

Due to their complexity, offsets have become an interesting phenomenon to study. It is fascinating how many different analyses, assessments, and opinions they have received from citizens, businesses, politicians, and experts. It is no wonder that they enjoy a wide academic literature.

Broadening the contribution of this literature is one of the goals of this dissertation. In particular, this work investigates carbon offsets political economy within different US carbon markets and inside different sectors. Starting from an analysis of offset surrendered for compliance, it discusses different variables that lead to greater usage of carbon offsets by capped firms. In addition, thanks to easy econometric estimations, it disentangles the relation between offsets supply and allowance prices in the California cap and trade.

[68] Bushnell J. B. (2010), *The economics of Carbon Offsets*, in «NBER working paper series», n.16305, p. 4

[69] In this case, moral hazard means making upward estimation when it comes to estimate a firm's baseline, Bushnell (2010).

[70] In this context, adverse selection entails paying too much firms with already low-emissions, Bushnell (2010).

[71] Bushnell J. B. (2010), *The economics of Carbon Offsets*, in «NBER working paper series», n.16305, p. 5

Chapter 2

Methodology

2. 1 Fundamental and related questions

Analyzing offset demand from a political economy perspective is the purpose of this paper. It does so by a quantitative and qualitative mixed approach.

Particularly, the goal is to assess offset effects in both directions: what has an influence on them and on what they have an influence. This work is twofold: it wants to examine the main factors that affect offset use by capped entities in US carbon markets; and if, in a market where offsets are heavily used, the use of offsets has an impact on allowance price.

As a consequence, I start by breaking down the aggregated use of offsets in two different cap and trade systems. Here, market features (economic, political, legal) that may lead to higher offsets are studied. This is done by spotting differences among carbon markets in their implementation and compliance rules. The result is a study about market-level variables that affect offsetting.

Then, I narrow down the focus by considering offset inside a specific carbon market. In this case, differences are demarcated by the sector to which a specific firm belongs. This helps in nullifying the incidence of variables at the market level (*i.e.* cap, allowance prices, and so on) since the firms are all in the same market; and focus on fundamental firms and sectors features. That is, the goal is to understand which micro-variables drive firms toward the choice of employing offsets to comply.

Up to this moment, my focus is on the features that may (and may not) influence the number of offset credits used for compliance by capped entities. However, the goal of this thesis is to have a comprehensive view of the offseting phenomenon.

As a consequence, it is worth considering even if offsets may have a role in influencing some other elements of a cap and trade system. In the literature, it is acknowledged that offsets help in decreasing both compliance costs and allowance prices.

Confirming or disproving that idea is out of the scope of this study. However, what I aim to do is to examine it, understand if a relation between offsets supply and demand and allowance price exists, and propose some hypothesis about the sense of this relation (is it negative? Is it positive?).

Summarizing, this study tries to contribute to enlarging offsets literature by tackling these specific questions:

Main question 1: *What are the main factors that influence the demand for offsets within the US carbon market?*

Sub-question 1: *What are a carbon market's main features that push for higher offsets use?*

Sub-question 2: *Which are the main sectors that use offsets?*

Sub-question 3: *What are the variables at the firm level that influence offset use*?

Main question 2: *What are the effects of available offsets and those used for compliance on allowance prices?*

2. 2 Data, sources and choice of variables

The data used in this research are publicly available. In this situation, the main thing to verify is the reliability of the data. Bad-quality data can lead to bias and incorrect results. Hence, it is important to get more information about the organization that owns the dataset, if it has been recently updated, and whether or not it is complete in all its components.

I have chosen to consider data from highly reliable sources. Environmental and economic data were both extracted from publicly available databases gathered by governmental agencies and made available on their websites. Data were either collected by official agencies designed to deal with climate change or self-reported by capped entities in emissions reports. Even for the second option, data are always verified by designated agencies before being officially published. Moreover, authorities periodically, with different frequencies[72], accomplish these tasks to maintain information as recent as possible.

As a result, it is reasonable to consider the data used in this paper as trustworthy. They give complete and unbiased information, are original, comprehensive, up-to-date, and are cited (quite often) by other researchers. Altogether, these characteristics reduce the risk that my results are incorrect due to the use of poor-quality data.

2. 2. 1 Sources

Both primary and secondary sources were consulted to perform this research.

The latter refers to a situation in which "another had direct access to the data on which the source rests and the researcher reads that person's analysis".[73] In this specific case, secondary sources were mainly academic papers, journals, and newspapers. They consist mainly of theories and models developed starting from raw data to assess the efficiency of a policy or to forecast its future development. At the same time, they also included opinions and considerations about the ongoing situation in different carbon markets. In this way, secondary sources proved themselves to be a fundamental way to get to know different aspects and opinions about the topics, helping in giving a more exhaustive picture of the problem.

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[72] For example, Auctioning reports are published quarterly, just after the auctioning took place; while compliance reports are posted on an annual basis, when capped entities surrender the instruments to comply.

[73] Lombard E. (2010), *Primary and Secondary Sources*, in ≪The Journal of Academic Librarianship≫, n. 36, pp 250-253, p 253

Primary sources, instead, are documents to which the "researcher has direct access without report or analysis".[74] In this dissertation, what was mainly used were official government reports, role models, and legal documents. These were employed to understand the general framework (*i.e.* the main rules) and the achievements of US carbon markets. Examples of official documents that have been consulted are (but are not limited to): World Bank's official reports, Congressional Research Server Reports, RGGI Inc. reports and California Air Resource Boards (CARB) reports.

Primary sources played a fundamental role also in quantitative data analysis. These data was employed to have a 360-degree viewpoint of offsets demand and supply in the US carbon markets. Major sources of these data are: the programs official websites,[75] the North American Industrial Classification System (NAICS),[76] the Bureau of Economic Analysis by the US Department of Commerce,[77] The National Center for Environmental Services,[78] the OECD website,[79] and the Federal Reserve of St. Louis.[80]

2. 2. 2 Choice of variables

This study employs several variables for different targets. As a consequence, it is crucial to distinguish among the various questions that distinct variables try to answer.

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[74] Lombard E. (2010), *Primary and Secondary Sources*, in ≪The Journal of Academic Librarianship≫, n. 36, pp 250-253, p 253

[75] Available at: RGGI: https://www.rggi.org/; California cap and trade: https://ww2.arb.ca.gov/resources

[76] Available at: https://www.census.gov/naics/

[77] Available at: https://www.bea.gov

[78] Available at: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series/4/tavg/3/8/2011-2022?base_prd=true&begbaseyear=1901&endbaseyear=2000

[79] Available at: https://data.oecd.org/

[80] Available at: https://fred.stlouisfed.org/

To inspect the offset usage at the market level, compliance and emissions reports were consulted. The time range considered goes from 2013 to 2020, the first three periods of the California cap and trade program. Data frequency is based on these periods (that last from 2 to 3 years). The choice of considering periods up to 2020 was a mandatory choice due to the lack of period four reports.

The main idea is to consider the for offset credits use. The necessity to employ a proxy is a consequence of the difficulty in estimating the demand for offsets. The logic behind this choice is that a firm can surrender offset credits only if it has purchased them before. Transactions in carbon offset credits are a consequence of both demand and supply. As such, it is necessary to be careful while considering the number of surrendered offset credits as only the demand for them. Moreover, some other factors influence offset demand, such as permit prices and abatement costs. What offsets surrendered can provide is an indication of offset demand by capped entities based on their usage. As such, it is important to be cautious when it comes to draw conclusions about this demand since many other variables should be taken into account.

Along with offsets surrendered for compliance, six other variables have been considered: Period, Entity ID, legal name, ARB GHG ID, full compliance obligation, and total allowances surrendered. Note that the variable "full compliance obligation" is the sum between "total allowances surrendered" and "offsets surrendered".

To investigate firm and sectoral offset appetite, each firm needed to be assigned to the proper NAICS sector.

For this purpose, four variables have been added to the previously mentioned. Those are: NAICS code, NAICS description, EPA and Sector. The frequency and time range are the same, nevertheless, they were considered just for California. Figure 9 summarizes all the variables, displaying their nature and a brief description.

Name of the Data	Data Type	Description
Period	Discrete	Period (1,2,3) of the compliance report
Entity ID	Nominal	The unique identification number for each entity in the Compliance Instrument Tracking System Service (CITSS).
Legal Name	Nominal	The entity's legal name as entered by the registrant in CITSS.
ARB GHG ID	Nominal	The ARB facility or entity identification code(s) associated with the entity. An entity with multiple covered facilities may consolidate these facilities under a single CITSS Entity ID. The ARB facility or entity identification code(s) are unique identifiers used to report annual emissions pursuant to the Mandatory Greenhouse Gas Reporting Regulation.
Full Compliance Obligation	Discrete	Entity's full compliance obligation.
Total Allowances Surrendered	Discrete	Number of allowances surrendered for compliance.
Total Offsets Surrendered	Discrete	Number of offsets surrendered for compliance.
NAICS code	Discrete	North American Industry Classification System
NAICS description	Nominal	NAICS code description as reported
EPA/CARB Subparts	Nominal	Displays the emissions categories, or subparts, that were reported. The names for the individual subparts are available in the U.S. EPA GHG Mandatory Reporting Regulation (40 CFR Part 98), which is available here: http://www.ecfr.gov/cgi-bin/text-idx?c=ecfr&tpl=/ecfrbrowse/Title40/40cfr98 main 02.tpl. The Subpart "EPE" categorization refers to Electric Power Entities, which is specific to California reporting.
Sector	Nominal	NAICS code description as reported

Figure 9. List of Variables considered for sectoral analysis. Sources of definitions and data: 2018-2020 compliance report; 2015-2017 Compliance Report; 2013-2014 Compliance Reports; 2020 GHG Facility and Entity Emissions; 2017 GHG Facility and Entity Emissions; 2013 GHG Facility and Entity Emissions. All are available at: https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/cap-and-trade-program-data; https://ww2.arb.ca.gov/mrr-data.

Finally, the relationship between offsets and allowance prices was scrutinized. Again, the focus is on the California market. Since auctions are held on a quarterly basis, now quarterly data are considered. Furthermore, these data go from the second quarter of 2014 (Q2 2014) to the last quarter of 2022 (Q4 2022). It was not possible to start from period one's first year (2013) due to the lack of information about offsets and CITSS accounts. Here, five brand-new variables were assessed: current auction settlement price, total current allowances sold, offsets issued, number of offsets in the CITSS general account and number of offsets credits in the CITSS compliance account.

Some explanation of the choice of these variables is necessary. Allowance prices and quantity sold are both self-explanatory. Offsets issued are the supply of offsets. They are the credits recognized by CARB for every project on which capped entities can invest. In this sense, their sum is the total amount of credits available for compliance. CITSS general and compliance accounts, instead, are useful to have an idea of how many offsets capped entities hold (general account) and how many will be probably used for compliance (compliance account) at the end of the year. It is possible to submits credits for compliance only when they are inside the compliance account. Therefore, it is reasonable to assume that credits inside compliance accounts are intended to be surrendered at the end of the year. Figure 10 lists the variables along with data types, units of measure and brief descriptions.

Name of the Data	Data Type	Unit of Measure	Description
Current Auction Settlement Price	Continuou s	USD	Allowances settlement price for that specific auction
Total Current Auction Sold	Discrete	Allowance	Number of allowances sold in a specific auction
Offsets Issued	Discrete	Offset credit	Number of offsets issued up to the end of a specific quarter
Offsets in General Accounts	Discrete	Offset credit	Sum of all the offsets in all general account of CITSS database.
Offsets in Compliance Accounts	Discrete	Offset credit	Sum of all the offsets in all compliance account of CITSS database.

Figure 10. Variables considered to analyze the relation between Allowance Prices and Offsets. Sources of data: Compliance instrument reports from Q2 2014 to Q1 2023, Auctions Reports; ARB Offsets credits issuance table; Available at: https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/cap-and-trade-program-data; https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/program-data/compliance-instrument-report.

2. 3 Choice of case studies

Case studies options were shaped by the desire to study carbon markets implemented in the US. Here, carbon policies are mature enough to be explored yet have not received the amount of attention they deserve. The willingness to consider just initiatives within the United States, of course, has drastically lowered the number of possibilities.[81]

Luckily, data about these case studies are easily available, detailed and constantly updated. All of them have plenty of supporting documents that explain their functioning, their legal framework and their rules and agreements. Along with that, they enjoy widespread academic literature and have been discussed from different environmental economics perspectives. Furthermore, it is not difficult to find complete reports about various details of these carbon markets. This dissertation considers just two of the three options: California cap and trade and RGGI.

Of course, both have the only necessary condition to become a case study: the possibility of surrendering offsets to comply with environmental obligations. Belonging to the same geographical area, also shrinks down the possible drivers for offsets demand.

There are different reasons why California is a good fit when it comes to study offsets. First of all, it is one of the biggest carbon markets in the world. It has a broad coverage in terms of emissions and it is often cited both by academics and public opinion.

From its very first years, it has constantly issued a high number of offset credits. Hence, the period is large enough (almost 10 years) to obtain some insights about its trends. Moreover, CARB developed a well-defined framework to deal with offsets. It settled rules by which every emitter must abide, built bodies to check credits and divided offsets into different categories.

[81] These are: The Regional Greenhouse Gas Initiative, California Cap and Trade and Washington Cap and Invest

California is a particularly interesting subject due to the appreciation that capped entities have shown for offsetting their emissions. Offset-related credits have been largely used for compliance by different sectors in all three periods. Thus, it is the perfect example of a carbon market with an elevated request for offsets. Moreover, since the aggregated usage is split into different sectors, it is also the proper situation to probe offset use at the firm level.

Along with that, in California offsets have seen plenty of controversies. They have been debated by businesses, citizens and politicians. These are different points of view that allowed this investigation to consider the phenomenon as a whole.

The existence of some shared features between RGGI and California has made the Regional Greenhouse Gas Initiative also an interesting case to study carbon offsets in the US. First and foremost, it is the other major commitment that the US has right now to fight climate change and one of the oldest efforts to deal with it. Due to its continuous changes, it is frequently discussed in the literature. Plus, it is "old" enough to have plenty of data about its performance and all these data are available since it is transparent in disclosing data, like California. Again, it has a well-defined protocol for offsetting that set the rules for the main attributes that a project must have to obtain credits.

Of course, it has some discrepancies with California cap and trade. Without going into too much detail, they have different caps with different coverage, different quantitative limits on offsetting and other differences that may help in explaining offsetsing at the market level. However, what makes RGGI intriguing is that, even though it authorized offsets since its very beginning, almost no offsetting project has been financed up to this day. In this sense, it is the perfect example of an ETS with a low (if not nil) use.

It is from the comparison of these two opposite situations that some fascinating insights about macro variables driving upward and downward the request for offsets can be obtained.

2. 4 Data analysis

To perform a correct analysis, data needs to be cleaned. Cleaning is a fundamental step for reaching reliable conclusions. The whole process was performed in Excel.[82]

To conduct this study, it was necessary to obtain data about capped entities for different periods in both California and RGGI markets. These were contained in different datasets that have been unified. After removing duplicates data, some variables have been added to the aforementioned ones:

- Market: whether offsets credits were valid in California cap and trade or RGGI.
- Left the market in period 2: entities that are present in period 1 but not in period 2
- Left the market in period 3: entities that are present in period 1 and/or 2 but not in period 3
- New Entrants period 2: entities that joined the market in period 2
- New Entrants period 3: entities that joined the market in period 3
- Newcomers used offsets: entities that have been in the market for just 1 period and used offsets
- Starting using offsets in period 3: entities that use offsets from period 3 (without accounting for the period they have joined the market)
- Have never used offsets: entities that are present for all three periods and have never used offsets for compliance

These are all dummy variables (yes/no) fundamental for having a panorama of the behavior of regulated entities. Moreover, some quantitative information has been added:

[82] Excel is a calculation software inside the office package powered by Microsoft

- % of offsets: percentage of offsets used by a firm with respect to its total compliance obligation
- Absolute offsets change: absolute change in offsets used by a firm from the previous year
- % offsets change: percentage change in offsets used by a firm from the previous year.

Variable	Formula
% of Offsets	$\frac{\text{Total Offsets Surrendered}}{\text{Full Compliance Obligation}}$
Absolute offsets change	$\text{Offsets}_t - \text{Offsets}_{t-1}$
% offsets change	$\frac{(\text{Offstes}_t - \text{Offsets}_{t-1})/}{\text{Offsets}_{t-1}}$

Figure 11. Variables considered and their computation.

The database ended up having 877 observations for 19 variables. Summary statistics for the aggregated variables (i.e. total offsets for compliance, total allowances for compliance and so on) and for general data (such as the number of participants) in each period were calculated. Moreover, it includes statistical data (i.e. average, standard deviation, median and so on). This is useful to obtain a general view of firms behavior and to spot differences in time. Summary statistics were computed for the entire time range too.

Analyzing offsets across sectors, instead, demanded a little bit more effort. Data about offsets and information about sectors were contained in different reports, respectively compliance reports and emissions reports. The first one contains instruments surrendered for compliance, while the second display the GHG produced by every firm in California along with the sector of that firm. This paper is not interested in emissions as a whole, but only in the ones that are capped by California cap and trade.[83] Accordingly, data about emissions was dropped and the ones about sectors were kept.

In order to couple each firm with its NAICS code, the two reports were merged. The initial idea was to merge them accordingly to their ID, yet different types of ID (CARB ID and ARB ID) were employed. Therefore, the primary key became the variable "covered emissions". This was useful to assign the same CARB ID to equal entities in the same database. Then, the two databases have been merged according to CARB ID. This was made in BigQuery[84] with the "FULL OUTER JOIN" command.

To double-check this process, correspondence between legal names has been browsed. If they were different, a manual breakdown was performed. There were not so many mismatches, and all have been cleared thanks to research on companies official websites.[85] Unfortunately, it was not possible to assign a sector to every capped entity. To avoid gaps, missing emitters NAICS codes were retrieved from public databases, official documents or company websites. If nothing was found, that specific firm was incorporated in the "no sector" option. In this way, no cell was left blank. Finally, from the NAICS code were gathered the first two figures.[86]

Summary statistics have been computed to analyze which sector surrendered more offsets. Variables considered were averages, percentages, sums, medians and so on.

Finally, the relationship between allowance prices and offsets has been dissected thanks to econometric tests performed in R's environment.[87] This process was largely conducted based on Chung et al (2018) and Shrestha and Bhatta (2018).

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[83] Note that sometimes not all the emission of an industry are capped by California cap and trade.

[84] BigQuery is a SQL (structured-query-language) available online and powered by Google.

[85] Often mismatches were due to firms that changed their name or have been acquired/merged by/with some other firms.

[86] The first two numbers of a NAICS code represent the general sector to which an industry belongs.

[87] R is an open-source programming language. The code used for analysis is showed in Annex I.

To perform it, quarterly data for five (1 dependent and 4 independent) variables are considered. Thus, every variable has 36 observations.

Some precautions have been undertaken before starting the analysis. Firstly, the observations have been transformed into time-series. Secondly, descriptive statistics were computed. Thirdly, the presence of seasonality and trends has been checked. Moreover, to have a general idea of the relationships, a correlation with the Pearson coefficient was computed.

After the setting-up phase, the analysis started. Note that analysis has been performed on the natural logarithm of the variables. Moreover, the first difference has been considered too.

When working with a time series, the first necessary thing to do is to verify if that specific time series is stationary or it is not. There are different procedures to test for it. In this study, all the Augmented Dickey Fueller (ADF) Test, the Philip-Perron (PP) unit root test and the Kwiatkowski-Phillips-Schimidt-Shin (KPSS) test are performed.

The results of these tests are fundamental, since the choice of the model to be employed is based on them. The nature of the variables favor the choice of an Autoregressive Distributed Lag Model (ARDL).

To effectively estimate an ARDL model, it is necessary to determine the proper lag-length of the variables. To determine it, this research uses the information approach, considering both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Based on these determinations, the ARDL model is estimated.

Co-integration among variables is considered too. Here, the ADRL bound co-integration test is employed to understand if some co-integration relations exist. If it exists, to assess the mixture of long-term and short-term relationship between the dependent variable and the independent ones, an Error Correction Model (ECM) will be implemented. The aim is to obtain a throughout view of the relation between allowance prices and offsets.

Note that, ideally, after this last step a Granger Causality Test could have been done to verify if one variable granger-cause another. However, determine causality is out of the scope of this study. Furthermore, the sample size is too small to perform an efficient Granger causality test based on Vector Autoregression (VAR) model.

Task	Test	Function in R
Stationarity	ADF test, PP test, KPSS test	ur.df(), adf.test(),kiss.test(),pp.test()
Optimal Lag Length	AIC, BIC	ardlBound(…, ic = c("BIC", "AIC")
Short term relations among variables	ARDL model	ardlBound() ardl()
Co-integration	ARDL bound co-integration test	ardlBound()
Long term and Short term relations	ECM model	ardlBound(… ECM = TRUE)

Figure 12. Tasks to perform, tests done and relative functions in R.

2. 4. 1 Methodological issues

The main concern with this work comes from its mixed approach.

It is not new that qualitative analysis relies heavily on the researcher's knowledge. As a consequence, it could be that some important explanatory elements go missing in the process. To minimize this possibility, broad literature about offsets has been reviewed as a prerequisite in order to have a complete framework.

Another major downside is that this study employs some observed data to infer details about variables that are difficult to estimate. These variables do not only depend on the data observed, since there may be other elements that influence the term. As a consequence, it is not easy to discern what is the effect of every single entity. Thus, when something is inferred, it is important to always keep this issue in mind, avoiding generalizing effects that maybe are caused by other variables.

One more pitfall is the consequence of the short time range. Even though 10 years may seem enough, they are just three periods of California cap and trade. It is difficult to generalize conclusions with such a short time span considered.

However, the only solution is to reproduce the research when more data is available.

Missing sectors for some emitters are an issue as well. They have been reduced to the minimum, but they are still present. The solution was to label them as "no sector"[88] and compute relevant statistics for them too. Luckily, their incidence on general data was negligible. They could be dropped, but they were kept for completeness.

Furthermore, sectoral analysis requires a lot of specific information about sectors and the costs for firms. As predictable, these are not easy to find, since managers strive to keep this competitive information private. In this case, the best bet is to try estimating a firm's costs and internal policies either by its behavior or the literature about that sector (if any).

The relations between offsets and allowances raised some methodological troubles too.

The major one is surely the population size. Even though it is not that small for quarterly data,[89] it is hard to operate correct forecasting with a small population. In this specific case, however, it was not possible to overcome it since the data evaluated were all the data available at the time this study was performed. What decreases the incidence of this situation is the fact that this research does not aim to predict future allowance prices in relation to offsets, but just to obtain a general overview of their relationship. In this sense, econometric analysis is flanked by strong knowledge of offsets theory while interpreting the results.

Finally, there is the possibility that some explanatory aspects have been ignored in conducting the analysis. Indeed, there are several other variables (economic and not) that could probably influence the final allowance price. Due to the small population size, it was not possible to include all the variables that may influence offsets. Moreover, with such a small sample it was hard to conduct a granger causality test based on a VAR model. This, however, can be done in the future

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[88] There are 4 different entities classified as "No sector". The period with more "No sector" firms is period 2.

[89] In their book, Hanke and Sichern (2008) suggest a minimum from 2s to 6s, with s as the seasonal period. Thus, with quarterly data: 2x4 = 12 and 6x4 = 24.

when more data will be available. Furthermore, if more detailed reports become available, it will be possible to avoid utilizing proxies and focus on measured data.[90]

2. 5 Literature review

How to increase the capacity of an ETS while minimizing the costs that come with it is a continual question that has strongly earned its room in the academic field. Economists, once they recognized climate change as a problem, have long debated the most cost-effective methods to mitigate its effects. As a result, there is a quite broad literature that examines cap and trade and its several components, such as the decision of the right cap, types of auctioning, grandfathering vs auctioning to distribute allowances, the possibility of market links and the consequences of the offsets presence.

As the main focus of this paper is carbon offsets and their demand, to determine what are the features that make them more used in some markets and sectors rather than others, a literature review about carbon pricing and offsets is fundamental for understanding the context of this paper. Moreover, it seems reasonable to review the different contributions about the two case studies considered.

A pollution rights market was first theorized by John Dales (1968). Even though his research focused on pollution of regional waters and not emissions, he settled up the logic of current cap and trade systems. The regulator sets a cap on pollution, releases several permits equal to that cap and the market supply and demand mechanism will do its job in setting the right price. It also considers the possibility of banking permits, the necessity to avoid raising the cap and the possibility of newcomers. However, Dales limits his contribution to a theoretical

[90] To avoid incurring in the omitted variable bias, correlation has been tested among the five considered variables and other variables that are often proposed by studies about allowance price determinants. These are: oil price, natural gas price, California GDP, electricity price, coal price; average temperature in California, Business Confidence Index and banking lending rate. Amongst those, just California GDP and electricity price have a significative correlation both with one regressor and the regressand. This instance will be further considered lately.

proposal of this innovative solution, since it was impossible for him to empirically test it.

One of the first mathematical demonstrations was in Montgomery (1972). In his paper, the author shows how marketable permits amongst firms aiming at reducing their production cost could minimize the price of achieving environmental standards. Also, he demonstrated that a market equilibrium in pollution licenses exists. Unfortunately, the results can be applied just to some specific markets, since it is difficult to generalize its main assumption of concentrations as a linear function. Moreover, it considers just one pollutant.

Pearce and Turner (1990) broaden the considerations about a pollution rights market, giving economic-based explanations about how permits would reach the right price. Moreover, their paper raises multiple points in favor of permits marketability: it minimizes costs, adjusts for new entrants and inflation, presents an opportunity for non-polluters and avoids spatial and technological lock-in issues.

In a recent analysis, Economides *et al*. (2018) review a model for cap and trade, concluding that whatever the initial allocation of permits is, the outcome will be the same and that it will be cost-effective. Hence, the initial allocation can serve other purposes without losing efficiency. Finally, they consider two potential cases where efficiency may not be achieved: a) when a firm has excessive market power; b) when there are transaction costs. However, it does not consider possible solutions in that matter.

Turning to political economy considerations, Cullenward and Victor (2020) show the necessity to reconsider the role of the market to achieve effective reductions. They claim that theoretical predictions may fail to be upheld in reality due to political issues. The proposed solution is an industrial policy coupled with an international strategy guided by investments, experimentation, learning and scaling.

Difficulties coming from carbon pricing are also highlighted by Mildenberger (2020). In his book, he identifies the biggest problem of climate policies: double representation. It entails polluters enjoying representation on both the left and right wing of the political spectrum, blocking every kind of green proposal. This is a quite difficult problem to solve. Indeed, almost every policy aiming at effectively reducing emissions will impose costs on workers (loss of jobs), investors, and producers.

As studies about ETS advance, research about instruments that come with it has proliferated too. There are plenty of papers dealing with different aspects of it, such as: cap and trade challenges (Wagner 2013), price collars (Fell, Burtraw, Morgenstern, Palmer, and Preonas, 2010), optimal auction format (Khezr and MacKenzie, 2021), the determination of an optimal emission cap, market links (Weitzman 2020, Wilson 2019, Flachsland 2009) and carbon offsets.

Consideration about carbon offsets varies within a broad range: from necessary instruments to let a cap and trade system be accepted by major businesses to a condition to emit more uncapped emissions. For this reason, they are a topic that enjoys a lot of (often with opposite conclusions) commentary in the academic world.

One of the main concerns about offsets is whether or not they succeed in reducing emissions and their effect on allowance prices. Ramseur (2008) develops a cost-benefit analysis of carbon offsets presence in a cap and trade system. He foresees the dominion of offsets in early decades due to their low cost. The main concern is whether the inclusion of offsets will dispatch the appropriate price signal to encourage the development of long-term mitigation technologies. Fairness is another major issue.

Bertini et al (2022) consider the situation where carbon offsets can be purchased to achieve a net-zero corporate carbon footprint in a static model. The result is that it is optimal for a firm to go net zero if the compensation cost is lower than the demand-enhancing effect of reducing the carbon footprint. What offsets lack, however, is the incentive to invest in green technologies.

Calel *et al*. (2021) propose an innovative quantitative approach to identify projects that should have been built anyway without a subsidy. The logic behind it is to identify some Blatantly Infra-marginal Projects that will function as a lower threshold for the number of subsidy misallocations. In a nutshell, this means that there are some projects that are built with a subsidy even if some other more profitable ones were built without it. The strength of this idea is that it is not necessary to estimate the net benefits.

Allen et al. (2020) define some features that offsets must have to properly tackle emissions. In this sense, offsets should cut emissions, be of high quality and their strategy should be constantly revised to keep up with an evolving context. Moreover, carbon removal offsetting should be preferred to emissions reduction ones, favoring long-lived storage of emissions through long-term agreements.

Turning to the relationship between offsets and allowance prices, Chung et al. (2018) examine the relations between allowance prices and some other variables, on which there are also CERs, in the third phase of EU ETS. The result is that CER and EUA have not a granger-causal relationship, even though it was present in all the previous periods, as other studies demonstrated.[91]

Solutions for improving offsets are another major topic in this literature.

Bushnell (2010) relates the concept of additionality to the one of adverse selection. In his opinion, not all offsets are the same. As a consequence, they should not be treated as they are. To solve this problem, he proposed a programmatic approach that can lower transaction costs of review, help access a wider array of activities and give the possibility to focus on risks. His idea is not to eliminate offsets, but rather to reform the approach to deal with them.

Wara and Victor (2008) argue for a reform of the CDM, since the credits it grants are not backed up by real reductions or these reductions could have been achieved at lower prices. Their solution was to implement a climate fund focused on those projects where investments are needed along with an infrastructure deal program when money is not enough to hit the target.

McNish (2012) proposes the transformation of the offset program into a fund-based offsetting system. It consists of an investment fund controlled and run by a government or an international public sector actor. Considered a giant risk pool, the offset fund will add additional resources to the ones that the project receives from other investors. In this way, it will improve efficiency, risk management and environmental quality. The problem with this idea is distributional: if shared in a

[91] To know more about this topic take a look to: Christiansen et al. (2005), Alberola et al. (2008), Koch et al. (2014), Chevallier (2011), Barrieu and Fehr (2011).

common pool, how can resources be fairly distributed? The answer depends on the value that the regulator gives to environmental integrity, supply response and price moderation.

Along with these studies, Victor and Cullenward (2008) highlight the failure of the CDM in engaging developing countries, one of the main purposes for which it was created. Focusing particularly on the US, they developed a four-step solution pushing for the increase of investment in R&D to create new low-emissions energy.

Finally, Cullenward and Victor (2020) were less indulgent about offsets. Thanks to a political framework, they recognize that offsets exist because they are believed to lower polluter costs and extend the incentives of carbon pricing in different sectors. Yet, it is not so, and many times offsets are of low quality, local and not additional. From this point of view, they make no sense and fail in maintaining the promises that were made. The natural conclusion is the necessity to get rid of offsets. This is probably one of the most severe conclusions.

A brief description of contributions regarding the two case studies seems necessary to have an idea of the general context.

WCI and California Carbon Market have been analyzed from different points of view. Bornenstein, Bushnell and Wolak (2017) estimate a probability distribution of possible allowance prices in California cap and trade in 2030. The prices obtained by making different assumptions about the measure implemented (i.e. safety valve, speed bumps, lower prices ceiling) ranges between 52 USD and 40 USD.[92] Not so different were the results of their more recent research (Bornenstein, Bushnell, Wolak and Zaragoza-Watkins (2019)): the price of permits in the market would be either extremely low or extremely high if no restrictions exist. In greater detail, there is a high probability that the market could end up with excessive allowances, leaving the price close to the administrative floor.

Cullenward (2014) claims that the carbon price is still too low to be determinant. As a consequence, one of the main worries for policymakers should be to raise the minimum price.

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92 Both are considered in 2015 US Dollars.

In this regard, ARB (2010) conducts a study to examine the impact of different case studies on different aspects of California carbon market. Amongst these cases, there is one where offsets are not allowed. Not surprisingly, in this situation allowances price is higher than in the case of offset presence. The outcomes show that offsets can contain costs within a cap-and-trade program and prevent higher energy prices for California businesses and residents.

Badgley *et al*. (2022) focus on the forest offsets program. Using a quantitative approach, it concludes that this program creates an incentive to generate offsets that do not reflect real climate benefits. Moreover, in another study, Badgley *et al*. (2022) conclude that the buffer pool for forest offsets is not well-suited to assure that credit offsets remain out of the atmosphere for at least 100 years. Both of these studies show a problem with the forest offsets program.

Turning to RGGI, investigations aspire to assess its impact on the environment and the economy; and to discuss the relevant issues that it encounters during its implementation.

Hibbard *et al*. (2018) perform a 360-degree commentary of RGGI, showing that: it succeeded in achieving CO2 emissions reductions; member states have used their proceeds creatively and their use has an economic impact; RGGI's payment for out-of-state fossil fuels has been reduced; new jobs have been created. Yet, it shows a lack of investment in R&D initiatives.

Similar is the vision of Murray and Maniloff (2015) that, helped by a difference in difference model, try to understand how much emissions reductions were due to RGGI. It shows that it was the outcome of a combination of RGGI, complementary policy and asymmetry effects of the economic recession. However, RGGI seems to be the largest factor affecting the decline (once controlled for the other factors). Chan and Morrow (2019) confirmed this claim. Thanks to a difference in difference approach, they revealed that RGGI not only succeeded in achieving its target of reducing CO2 emissions but also succeeded in reducing SO2 emissions. It also acknowledges the presence of leakages, yet it does not consider them so damaging to the environment. Yan (2021) obtained the same results: RGGI causes a decrease in coal and natural gas consumption, but it also entails the presence of leakages.

Ramseur (2013) considers offsets within RGGI. In his opinion, low emissions allowance prices and/or a not so containing emissions cap are the reasons why no offsets project was developed yet.

Of the opposite view is Stevenson (2018), according to which RGGI has not achieved the outcomes it was supposed to.

As it may seem clear, the debate about carbon offsets is dominated by assessments of carbon offsets outcomes and the possible solutions to fix offsets inability to tackle climate change. Most of the contributions, reasonably, seem to focus on the Clean Development Mechanism. Even when it comes to interpreting the relation between offsets credits and allowance prices, the sole focus is the EU ETS and the relations between EUAs and CERs.

Only in the last few years California offsets program started to be considered. Nonetheless, in this program only the forest protocol and its controversies saw a quite high interest. RGGI offsets program, instead, has limited (to no) literature.

To the best of my knowledge, there are no studies about the demand for offsets and its determinant within the US carbon market. The relation between offsets availability and allowance price in these markets seems to be seldom considered.

This paper aims to fill this gap. Starting from the solid contribution in the academic literature about cap and trade modeling and offsets evaluation, it considers offsets political economy in an innovative fashion, hoping to give a new interesting viewpoint to the analysis of this phenomenon.

Chapter 3

The demand for carbon offsets

3. 1 The demand for carbon offsets and its drivers

It is not an easy task to understand how "green" a firm concretely is. Overstating the results, or "greenwashing", is becoming more and more common when emitters publicly sponsor sustainable initiatives. Even worse, they have a natural aversion to disclose information about internal strategies to tackle climate change. Making public this strategy, indeed, may give a competitive advantage to other businesses in the game. Moreover, instruments for compliance can be used also for speculation: allowances (and offsets) can be bought when the price is low and sold when they are overpriced.[93]

Offset strategies make no exception to the unwritten law of secrecy. As a consequence, guessing the demand for this tool is extremely difficult. Offsetting is also a controversial and debated practice, so firms are even more silent about their interest in these initiatives. Thus, at the end of the year, the only available data are the number of offset credits surrendered for compliance and those within the CITSS database.

Nevertheless, these data make evident that a broad variance exists in this kind of practice between different cap and trade markets and even between different sectors in the same system. These differences suggest that some rules implemented in an ETS and some sector-specific features favor the use of offsets.

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[93] Speculative investors held 46% of RGGI allowances in 2021; and around 20% of California allowances the same year. Moreover, asset managers like Pacific Investment Management Co. LLC and Krane Funds Advisors LLC have started to offer carbon market instruments to their portfolios.. See e.g.: Rives K. (2022), Private Investors flocking to cap-and-trade markets as prices and returns soar, S&P500 Market Intelligence, available at: https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/private-investors-flocking-to-cap-and-trade-markets-as-prices-and-returns-soar-70450498.

Then, it becomes interesting to identify what are those characteristics that drive offset demand upward or downward. This could give policymakers an idea about the possible steps to undertake to curb down, when needed, offset use.

3. 2 Description of case studies and offsets protocols

Since it ranges considerably from ETS to ETS, a discussion about offset demand is helpful only if applied to some existing systems. In this study, the two markets considered are RGGI and California cap and trade. Since their regulation is the framework within the analysis develops, it is valuable to briefly discuss both ETSs main traits.

3. 2. 1 The Regional Greenhouse Gas Initiative

The Regional Greenhouse Gasses Initiative[94] is the first market-based, cap-and-invest regional initiative in the US. It is a cooperative effort among twelve different Eastern states to reduce carbon dioxide from power plants. It comprises Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont and Virginia. Its bureaucratic architecture authorizes external states to join RGGI and participating states to leave if not satisfied with the program and/or are facing internal political opposition to climate policies.[95]

Concretely, RGGI is the sum of the individual budget trading schemes located in every participating state. Each member has independent regulations that limit emissions of CO_2, issues allowances and decide for participation in the quarterly auction. There is no grandfathering in RGGI, and allowances can be obtained

[94] To have a complete idea of RGGI program take a look at: The Regional Greenhouse Gasses Initiative (2018), Model Rule, Part XX CO_2 Budget Trading Program. Almost all the information about RGGI are taken from there.

[95] For example, New Jersey left RGGI in 2011 and resumed participation in it in 2020. Virginia began its participation in 2021 and Pennsylvania in 2022.

merely through shared (among the states) quarterly auctions. Cost and emissions containment reserve mechanisms are in place during the bidding time.

The cap is set to be declining over time, aiming to constantly diminish pollution. Only CO_2 emissions coming from fossil fuel-fired electric power generators with a capacity of at least 25 megawatts are covered. For these entities, the "regulated sources", it is mandatory to hold allowances equal to the amount of CO_2 emitted in a three-years period.[96]

That is, RGGI is both limited in coverage (just CO_2 emissions) and in regulated entities (just power plants).

Since RGGI allows for offsetting, it has an offsets program.[97] CO_2 credits are awarded to those emitters that engage in projects which reduce or avoid emissions of CO_2 or equivalent and/or sequester carbon (in some sort of carbon capture and storage method). Reductions coming from these projects must have five attributes to be considered and recognized. They must be real, additional, verifiable, enforceable and permanent. The regulatory agency, through a standard-based approach, evaluates all of them. A quantitative limit exists too. Emitters can use offsets for compliance up to 3.3% of their obligation for each control period. Interestingly, some states do not award offsets credits,[98] still regulated sources can use those awarded by other members. According to the protocol, there are five macro-types of projects that an emitter can sponsor:

1. Landfill methane capture and destruction: projects that capture and destroy methane from landfills.
2. Sulfur hexafluoride: projects that prevent emissions of SF_6[99] to the atmosphere from equipment in the electricity transmission and distribution sector through capture and storage, recycling or destruction.

[96] RGGI Inc. (2023), RGGI 101 Factsheet, available at: https://www.rggi.org/program-overview-and-design/elements

[97] To know more about RGGI's offsets program take a look to: RGGI Inc-, Model Rule: Part XX CO_2 Budget Trading Program, issued 2017 and revised 2018.

[98] Those are: Massachusetts; New Hampshire, Rhode Island and Virgina.

[99] Sulfur Hexafluoride.

3. Forestry or afforestation: projects that entail reforestation, improve forest management or avoid conversion.
4. End-use efficiency: projects that reduce building sector emissions through reductions of on-site combustion of natural gas, oil or propane for end-use.
5. Avoided agricultural methane: projects that capture and destroy methane from animal manure and/or organic food waste through anaerobic digesters.

Finally, there are geographic limits imposed on offsets. A project qualifies to obtain credits exclusively if it is either located in a member state or in any state or US jurisdiction in which there exists a memorandum of understanding with RGGI regarding emissions.

3. 2. 2 California cap and trade

Assembly Bill 32[100] forces California to return to 1990 levels of GHG emissions. This entails an overall 15% reduction compared to the BAU scenario. To achieve this target, California imposed a statewide limit on emissions covering about 85% of California GHG, developing its cap and trade system. The golden state conceived this solution by keeping an eye on expanding possibilities. Indeed, its system is designed to link with other jurisdictions regulated by other ETS. As such, since 2014 it is tied with Quebec (Canada).

The cap imposed demanded maximum efforts from the beginning. In 2013, the first year of the program, it was settled 2% below the forecasted emissions level for that year. Then, it declines every year from 2015 to 2020. The cap is also comprehensive in its scope, with a coverage of about 450 entities.[101] Amongst those, there are electricity generators and large industrial facilities emitting at

[100] Assembly Bill No. 32, Air Pollution: Greenhouse gases: California Global Warming Solutions Act of 2006.

[101] 450 is the number of entities in 2023. The number of emitters covered kept increasing from 2013.

least 25 000 MTCO$_2$e annually, distributors of transportation, natural gas and other fuels. Moreover, the cap does not cover only CO_2 but many different pollutants.

Like every ETS, emitters have to hold and submit a number of allowances equal to their emissions at the end of every reporting period to avoid fines and penalties. Allowances are distributed via a mixed approach that couples grandfathering and auctioning. As time passes, the number of allowances given for free declines in favor of the auctioned ones (auctions are shared with Quebec). Permit trading and banking are permitted, and reserve mechanisms are in place during auctions.[102]

Offsetting is allowed and it is ruled by a protocol. ARB offsets credits are issued by CARB to those projects that reduce or capture GHG emissions. These are marketable credits and represent effective and verified GHG emissions reductions or removal from sources not restrained by California cap and trade. Bill 32 states that, to receive a credit, an offset must be real, permanent, quantifiable, verifiable, enforceable and additional to any GHG reduction that will otherwise occur. Furthermore, it should provide Direct Environmental Benefits (DEBS).

A quantitive limit exists on offsets amount: no more than 8% of the total compliance obligation can be fulfilled by these credits. This limitation is not fixed, it changes while periods go by, and varies from 8% (up to 2020) to 6% (2026-2030) passing by 4% in the years between 2020-2025.

Another restriction is given by what kind of projects can be financed. CARB approves offset credits just for initiatives contained in five different categories:

1. US Forestry: projects regarding re-forestation within the United States
2. Livestock Projects: projects associated with the installation of biogas control systems (BCS) on dairy cattle and swine farms.

[102] To know more about California cap and trade take a look at: California Air Resource Board (2019), Unofficial electronic version of the Regulation for the California Cap on Greenhouse Gas Emissions and Market-Based Compliance Mechanisms; California Air resource board (2015), Overview of ARB Emissions Trading Program; and California Air Resource Board (2012), Cap and Trade Regulation Instructional Guidance. Almost all the information about California Cap and Trade are taken from there.

3. Urban Forestry: projects that favor GHG removal due to the planting of trees and their maintenance.
4. Ozone Depleting substances: projects that entail reductions associated with the destruction of potential ozone-depleting substances within the US.
5. Mine Methane Capture: projects associated with the capture and destruction of CH_4[103] that would otherwise be released into the atmosphere due to mining operations.
6. Rice Cultivation: projects that achieve reductions in methane emissions from flooded rice fields.

By rules, all of these projects should be implemented within one US State to receive credits. However, CARB developed a sideline approach to issue offsets even to out-of-the-state projects. These are the sector-based credits, and are awarded for programs issued by subnational jurisdictions in developing countries.[104]

Feature	RGGI	California ETS
Members	12 Eastern States	California (linked with Quebèc)
Coverage	CO_2 from electric plants	Emissions from electric power, industrial and fuels
Allowances Distribution	Auctions	Auctions and Grandfathering
Offsets Protocol	Exists	Exists
Offsets Quantitative Limit	3.3%	8% (2013-2020); 4% (2020-2025); 6% (2026-2030)
Number of Offsets projects type	5	6

Figure 13. RGGI and California Cap-and-Trade main features.

[103] Methane

[104] To know more about California Offsets Program look at: CARB (2021), California's Compliance Offsets Program, available at: https://ww2.arb.ca.gov/our-work/programs/compliance-offset-program

3. 3 Market level drivers of offsets demand

At the market level, many features can drive offset demand upward or downward. This is a consequence of the uniqueness of every ETS, since none is built like another and each one operates in different political and economic contexts. Unfortunately, there is not that much literature about elements that influence carbon offsets demand.[105] Thus, the major insights within this chapter are inferred either by observation of data or by literature about different aspects of offsetting.

3. 3. 1 Quantitative limit

A quantitive limitation on offset usage is incorporated in almost every ETS model rule. Often, it is expressed as a percentage of the total compliance obligation of a specific entity in that period. It imposes an upper border that can not be crossed on credits that can be surrendered to abide with the regulation. The limit is a structural driver of offset demand: the higher the limit, the more credits coming from offsetting can be used without going against the regulation.

Dormady and Englander (2015) highlight the importance of the limit. They show that a ceiling on offsets credits that can be used for compliance constrains the ability of covered firms to optimize across compliance periods. Indeed, it could arise a situation where it is more profitable for firms to buy offsets credits, yet the limit discourages them from doing so. In turn, this increases the demand for allowances, making permits even more expensive.

As a consequence, less stringent jurisdictions (i.e with a higher quantitative limits) should experience a higher number of offsets used for compliances, while ETS with a lower limits should see the number of offsets to be extremely low.

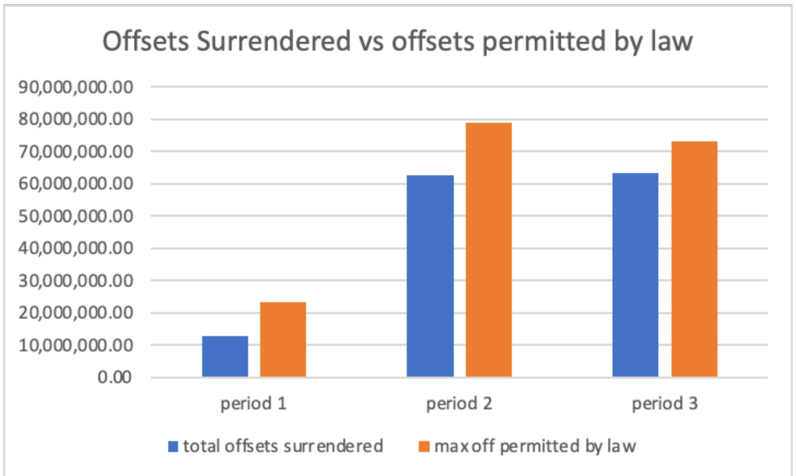
The data confirms this intuition. California cap and trade has seen the number of credits used for compliance regularly under the 8% limits. However, their

[105] To the best of my knowledge, the only paper that examine the relationship between offsets demand and other cap and trade factor is Dormady and Englander (2015).

number rose in time and peaked at 6.94% (on average) in period 3. In this last period, 86.81% of offsets allowed by law were used for compliance. The only period that experienced a little use of offsets is period 1 (4.39% and 54.88% of offsets used/offsets permitted by regulation). This could be a consequence of the shorter time spawn (2 years against the 3 years of periods 2 and3) of period 1 and that the first offsets credit was issued only at the end of 2013.[106] Moreover, offsets were a new tool, thus it could be that firms needed time to decide how to use them. Single-entity analysis reinforces this intuition: 277 (31% of the total[107]) emitters have used offsets in a percentage greater than 7.00%.

The role of quantitive limit becomes more clear if RGGI is taken into account. As mentioned above, RGGI has a lower limit (3.3% against the 8% of California). It is reasonable to see fewer credits in RGGI in absolute terms. Data confirms this relation. Merely one offsets project has been implemented during RGGI's whole life and it awarded an amount of 53,506 credits. This is less than 1% of the total credit surrendered.

a)



[106] The first offsets credit in California CaT was issued on the 23 of September 2013.

[107] Considering all the emitters (even same emitters repeated in different periods) and the sum of emitters for each period, that is 877 (period1: 263; period2: 306; period3: 308).

b)

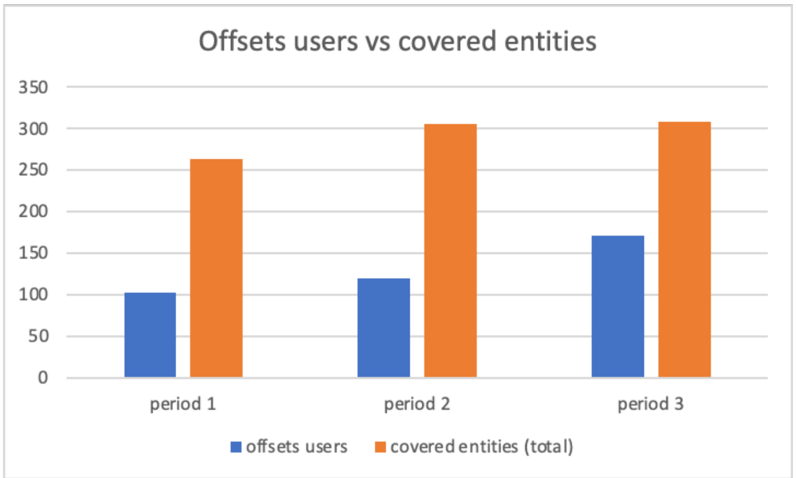


Figure 14. California offsets surrendered against offsets permitted by law (b) and California Offsets users vs covered entities for each period (b). Period 1: 2013-2014; period 2: 2015-2017; period 3: 2018-2020. Source: 2013-2014 Compliance Report; 2015-2017 Compliance Report; 2018-2020 Compliance Report. Available at: https://ww2.arb.ca.gov/;

In California, emitters get close to the 8% ceiling but never touch it. This could be a consequence of the difficulty to find projects that issue the precise amount of credits for a firm to reach the limit without crossing it. Considering the average of the credits issued per project compared to the average offsets allowed by law for every entity reinforce this. On average, every type of project awards a large amount of offset credits. Such a large amount may be the reason why, in California cap and trade, firms get close to the limit but never perfectly hit that.

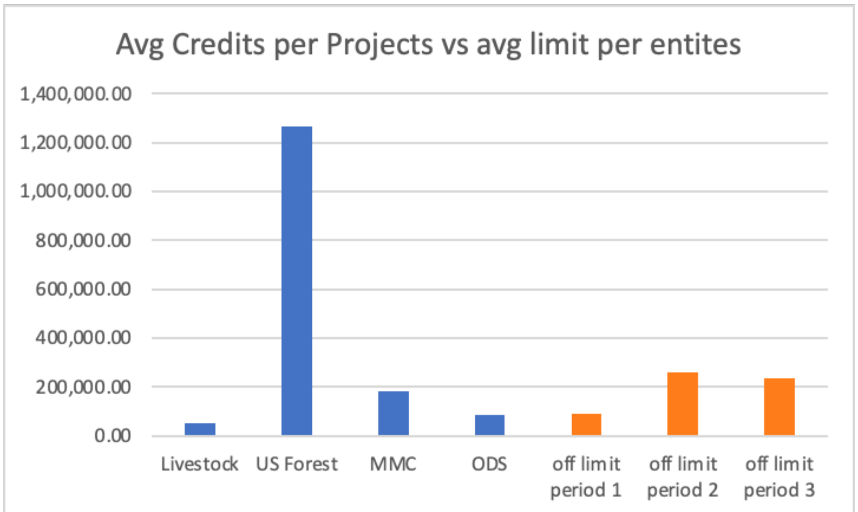


Figure 15. California average amount of credits issued per project compared to average quantitative limit per entity. MMC: mine methane capture; DOS: Ozone depleting substances. Note that Urban Forests and Rice cultivation have not been considered since no projects was developed in this areas. Period 1: 2013-2014; period 2: 2015-2017; period 3: 2018-2020. Source: 2013-2014 Compliance Report; 2015-2017 Compliance Report; 2018-2020 Compliance Report; table of offsets issued; offsets issued map. Available at: https://ww2.arb.ca.gov/;

That is, quantitative limits have a strong influence on the demand. They act like a ceiling that caps the use of offsets. Moreover, limits can reduce the liquidity of trading offsets since firms that hold enough offsets to meet their limitation will not demand this tool for that specific period.[108]

This structural characteristic can become even more determinant in curbing offsets demand when other features are strongly driving it upward. If this is the case, a quantitative limitation will play a fundamental role in stopping the demand for offsetting to skyrocket to a point that will undermine the effectiveness of a cap and trade system. Finally, it is important to impose qualitative limits (*i.e.* limits on project types, size, location and so on) along with quantitative ones. Otherwise, firms will purchase less expensive offsets even if they are of a low quality.[109]

3. 3. 2 Cap tightness

The cap is a primary feature of every ETS system. It determines directly the number of available allowances and indirectly their price. As such, in the literature, it is identified as one of the main determinants of offsets demand.[110] As a result, the cap should play an important role even within the US carbon markets.

In theory, ETS with a stringent cap should experience a stronger request for offsets. This is due to the cost of allowances. If, instead, the cap is not forcing

[108] Dormady N., Englander G. (2015), *Carbon Allowances and the demand for offsets: A comprehensive assessment of imperfect substitutes*, in «Journal of Public policy», p. 11

[109] See e.g; Dormady and Englander G. (2015), Wara and Victor (2008) or Bushnell (2010).

[110] Ramseur J. L. (2013), *The Regional Greenhouse Gas Initiative: Lessons Learned and Issues for Policymakers*, Washington, D.C., Congressional Research Service, CRS Report, p. 15.

any emissions reduction, the appetite for offsets will be very low, since emitters are not forced to abate. That is, the cap and offsets have an inverse relation: as the former drop, the latter expands (always up to the quantity limit). RGGI and California confirm these behaviors.

RGGI is an example of a loose cap with almost no offsets used. During its implementation, the cap has been above the actual level of emissions for a long period. As a consequence, covered entities did not need offsets to comply, since they had not the necessity to decrease their emission at all. They could just keep emitting the same as before and buying permits from an ETS with allowances in excess. In turn, this led to very cheap allowances. However, when the cap was re-estimated (2014), the number of offset credits did not increase as much. Two different conditions prevented the demand for offsets from soaring. One is that, even if re-estimated, the cap was not severe enough. Firms needed to reduce just a very small part of their emissions. Hence, abatement was not that costly to induce the need to divert toward different instruments. The other involves the possibility of allowances banking. In the first period, since the permits available were more than the ones required, there was a surplus of low-price permits. The possibility of banking led the firms to stockpile them to meet future obligations and/or sell them in the future. Thus, when the cap was reduced, firms surrendered banked allowances instead of buying new ones or employing different instruments (*i.e.* offsets). To deal with that, the cap has been re-estimated again considering banked allowances. Yet, it did not push for the use of different instruments. This is probably because firms still have a quite large amount of banked allowances.

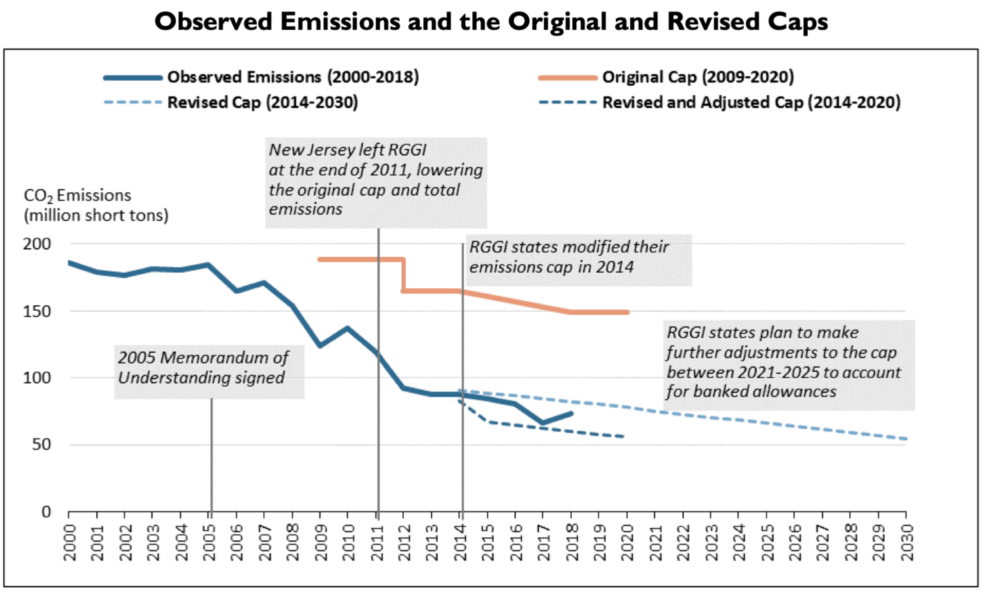


Figure 16. RGGI Cap against RGGI actual emissions. Source: Prepared by CRS (Congressional Research Service), observed state emission data (2008-2018) provided by RGG, in Ramseur J. L. (2019), T*he Regional Greenhouse Gas Initiative: Background, Impacts, and Selected Issues*, Washington, D.C., Congressional Research Service, CRS Report.

California confirms the role of the cap in the other sense. Its cap has been inferior than projected emissions since the very first year of its implementation. As a consequence, offsetting has always been elevated over time.

Considering the pattern displayed across periods by California emitters confirms the relationship between the maximum amount of emissions and offsetting. By law, the cap is settled to be diminishing over time, in order to effectively reduce emissions. Offsets, instead, followed the inverse path: they grow in number as the cap drops. Indeed, from period 1 to period 2 credits increased by more than 49 million. They also rise from period 2 to period 3. Even the number of users has soared. They went from 103 in the first period to 171 in the third (39% against 55% of total covered entities for that specific period[111]). That is, when the cap becomes stricter and stricter, firms look to different and cheaper ways to diminish emissions. Among these options, there are offsets.

Finally, offsets are more diffused in stringent systems since they are considered a way to indirectly enlarge the cap, reducing the burden of abating emissions.

[111] Note that the number of capped entities changes every periods. This could be due to: enlargement of the scope of the cap, merger and/or acquisitions, entities that shut down and leave the market, and so on.

Here, they are employed as a solution to keep the cap loose enough to avoid an uncontrolled boost in allowance price. This is the way of thought that authorities use when they justify the inclusion of offsets in cap-and-trade rules.

3. 3. 3 Allowance prices

Related to the cap are allowance prices. Price is not arbitrarily chosen, it is determined by the supply-and-demand mechanism of the market. The literature cites permit prices as one of the main rationales for firms to opt for offsets, and it is not difficult to understand why.[112]

Offsets credits and allowances are two of the three methods that emitters have to meet their ETS obligations. Not considering internal emissions reduction, which usually is the most expensive way, the remaining options can be considered as substitutes. Yet, Dormady and Englander (2015) show that they are imperfect substitutes.

Firms will employ a mixture of them. Entities are rational, thus they will use the cheapest method. For example, consider the case in which the cost of one permit is the same as the price of one credit. Here, the emitter is totally indifferent in picking allowances or offsets. Instead, if allowances are more expensive than offsetting, then the firm will turn to the latter to comply with the rules. In the real world, it is rare that they have the same price, rather is quite common that credits from offsets are cheaper than permits. According to these thoughts, ETS with pricey allowances should experience a massive use of offsets. Theoretically, the threshold that once passed makes offset the best option is the permit auction price. Technically, the difference between allowances and credits prices is named “price spread”.[113] The idea is that if the spread is positive, the demand for offsets will increase. Otherwise, the demand will diminish, since allowances will be the least expensive instrument.

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[112] Ramseur J. L. (2013), The Regional Greenhouse Gas Initiative: Lessons Learned and Issues for Policymakers, Washington, D.C., Congressional Research Service, CRS Report, p. 15.

[113] Dormady N., Englander G. (2015), *Carbon Allowances and the demand for offsets: A comprehensive assessment of imperfect substitutes*, in «Journal of Public policy», p. 5.

Comparing California ETS and RGGI proves the role played by allowance prices. RGGI low permit price is recurrently cited as one of the main features that maintain offset use low. The price has been almost negligible for more than 40 auctions, and it broke the threshold of 10$ just in the last months of 2021. Instead, in California allowances have never been sold under 11$, keeping soaring up to more than 20$ dollar. In the last auction, the price in California (26.80$) was more than double that of RGGI (12.99$). Turning to offsets, it is not easy to estimate their price. However, the voluntary offsets market provides an indication. Here, the price for one credit ranges between 3 to 8 USD.[114] Even though it is forecasted to rise in the future, at the moment it is a significant opportunity to drastically reduce abatement costs, especially for firms in California that will pay 1/5 of the allowances cost. Hence, it is not a surprise that California had a substantial use of offsetting while RGGI had almost none. In this case, what is effectively curbing the appetite for offsets is the quantitive limits imposed by CARB regulation, otherwise probably capped firms will surrender even more offsets.

If considered in term of price spreads, both California and RGGI confirm this relationship. Since the spread in California is larger than the RGGI one, it is plausible to expect a more intensive use of offsets. This is exactly what is happening.

Looking to California, there is another trend that documents the positive relation between offset use and allowance price. Considering this market through time, price of allowances has kept growing since 2013. It started from 11$ and touched 26$ in 2022. Along with that, credits surrendered rose too, from 12 billion to 60 billion in 2020.

[114] Holder M. (2021), Carbon offset prices set to increase tenfold by 2030, Business Green, https://www.greenbiz.com/article/carbon-offset-prices-set-increase-tenfold-2030.

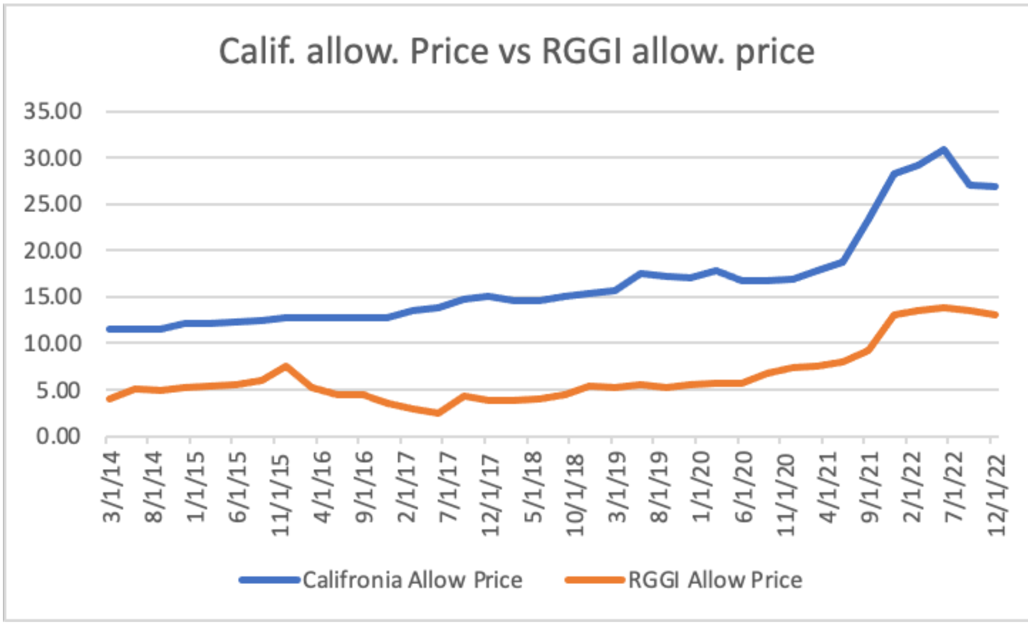

Figure 17. California Allowance prices (USD) against RGGI allowance prices (USD). Sources: RGGI Allowance Prices and Volumes; California Cap and Trade Program, Summary of California-Quebec joint auction settlement prices and result. Available at: https://www.rggi.org/auctions/auction-results/prices-volumes; and https://ww2.arb.ca.gov/sites/default/files/2020-08/results_summary.pdf.

3. 3. 4 Project types and geography

Logically, allowing a lot or a few types of projects can impact the use of offsets.

The more areas included, the more projects have the possibility to receive the good-to-go approval. In turn, more offsets become available and the spectrum of options becomes larger. As such, the possibility to find a proper offsets project increases if there are more areas in which offset can be awarded.

On the other hand, some areas constantly receive more attention (and investments) than others. Sometimes, the difference in credit issued and surrendered from projects in one area against another is substantial. If a system excludes those areas that usually get more investments, probably it will shrink the demand for offsets. Here, the difficulty is to know in advance toward what kind of projects the money will flow. It is challenging to understand why some kinds of initiatives are favored by emitters. It could be a matter of cost, technology development, return on the investment, internal policies or just a matter of preferences and/or availability.

Let's consider California cap and trade. Here, US forest projects have seen a bigger interest than the other areas. If this area was not included in the first place, California would have seen its offsets credits fall by more than 200 billion. This amount is more than the sum of all the other programs together. Nevertheless, reforestation is not the area that has seen more projects developed. Indeed, Ozone Depleting Substances projects[115] are the leaders in this matter.[116]

This could be the consequence of two different features of these projects. Re-forestation initiatives are often large. Hence, it is reasonable that a high amount of credits are issued for every single project. On the other hand, Ozone-depleting substance projects are usually small (are the third when offsets issued per project are taken into consideration), but since are implemented in a significant number, probably they are amongst the most profitable ones.

It is complex to guess why re-forestation received important investments, but cost definitely played a role in it. Planting trees is more effortless than developing ways to capture and store methane from mine. Moreover, the range of the cost for planting trees is not so wide, while for other projects it can vary quite a lot. For example, carbon capture prices can vary from 15$/t of CO_2 to 120$/t of CO_2[117], while planting trees has a cost of 607$ per acre[118] (approximately[119]) and the cost per tonne of CO_2 sequestered is less than 7$.[120]

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[115] Ozone Depleting Substances Projects 223; Us Forest Projects: 149; Livestock Projects: 144.

[116] Data from the California Air Resources Board (ARBOCs) Issuance, available at: https://webmaps.arb.ca.gov/ARBOCIssuanceMap/?extent=-17808695.9365%2C3307036.2385%2C-6615869.0107%2C9187183.9505%2C102100.

[117] IEA (2021), *Is carbon capture too expensive?*, IEA, Paris https://www.iea.org/commentaries/is-carbon-capture-too-expensive

[118] Note that 1 acre can contain from 100 to 200 tress. This lets the cost of planting a tree ranges from 6.07$ to 3.03$. The estimation of the number of trees for every acre is given by: Soll J. (2020), Can Planting a Trillion Trees save our planet?, Metro news, available at: https://www.oregonmetro.gov/news/power-trees#:~:text=Forests typically have 100 to,all those trees be planted?

[119] Reij C., Winterbottom R. (2017), *Can We Restore 350 Millions Hectares by 2030?*, World Resource Institute, https://www.wri.org/insights/can-we-restore-350-million-hectares-2030

[120] Wong Y. (2021), T*he Carbon Removal XPrize Winner Will Have to Beat $7 per Ton*, Terraformation, available at: https://www.terraformation.com/blog/the-carbon-removal-xprize-winner-will-have-to-beat-7-per-ton#.

Another element to consider is geography. This is a quite controversial point. It is logical to think that the more comprehensive the geographical coverage for projects implementation, the more cost-effectiveness opportunity will arise. Again, this is simply a matter of numbers: if the area is larger, the greater will be the number of opportunities. Along with that, the different possibilities will likely be even more cost-effective, since emitters can select those places where prices are very small. However, in the real world, as Cullenward and Victor (2020) pointed out, the story is different. Emitters prefer to be as close as possible, and jurisdictions build rules accordingly to this preference. As an example, California offsets are authorized only if originated within the US, otherwise, they must receive an ad-hoc sector-based approval. Up to now, all the projects developed are inside the US.

Not so different is the situation in RGGI: offsets must be developed within one of the members or in any other state that has some sort of agreement with RGGI. The only project developed at the time is in Maryland, a RGGI member.

As evident, location is playing a counterintuitive role in driving the demand for offsets. Enlarging the geographic coverage will not likely increase the number of offsets, at least under the current permit price ranges, that are low. If, as forecasted, allowance price increases, it is likely that firms will look toward out-of-the-state projects, which will be likely less expensive. Therefore, political entities must be careful when they have to decide in which location offsetting initiatives can be implemented.[121]

Furthermore, if a jurisdiction needs to drastically diminish the requests for credits, it should set a limit to at-home projects. As aforementioned, this is exactly the role of quantitative limits.

3. 3. 5 Risk of invalidation

Related to project type, there is the possibility of invalidation that every single credit carries with itself. Invalidation means that a credit previously issued is

[121] Cullenward and Victor (2020) disentangle politicians aspects that push authorities to favor local offsets rather than the ones abroad.

retired, and can no longer be used for compliance. This could happen for different reasons, such as double-issuance of credits (more than one program issues the same offsets for the same period); if the project does not abide by the local/international rules in terms of safety, environment, and health; and if there is an overstating of the reductions achieved (*i.e.* more credits have been issued than emissions effectively reduced).[122]

Dormady and Englander G. (2015) suggest that the risk of invalidation and offset demand have an inverse relation. Since firms will take into account the risk of *ex-pos*t invalidation, this will drive them toward other instruments for compliance to avoid this risk. However, the relationship is not straightforward, and there are different situations that can arise. Two factors are important in considering invalidation: its frequency for some kinds of projects and who will bear the cost of the retired credits.

Assessing the former is difficult. All the credit reductions claimed before the implementation of a project are just estimations. As a consequence, they can be wrong. Thus, in this case, a more cautious approach is to underestimate emissions reduction to avoid the cancellation of credits.

The second one is more straightforward to understand. Emitters will finance projects based on who will face the costs. Three different entities could face them: emitters, projects developer and the authority/state of the ETS. Logically, emitters will finance those projects where the bearers are either the state or the developer. A meaningful quota of investments will probably flood these projects. The downside of this strategy is that by avoiding the threat of invalidation, they will pay a premium price since it includes this risk for developers. The problem, if the developer does not bear the costs of invalidation, is that a moral hazard issue may arise. Indeed, it can develop dubious offsets projects without being worried that they will be the ones paying the future cost of invalidation. Instead, making the developer responsible could give them the incentive to undertake solid offset initiatives in order to avoid future losses deriving from seeing some credits invalidated.

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[122] California Air Resource Board (2015), California Air Resources Board Offset Credit Regulatory Conformance and Invalidation Guidance.

California demonstrates the preference of firms for developer-liability projects. There, the only area where the risk of invalidation is not on buyers is forest. This is due to the projects long-horizon lifespan that carries an elevated risk for invalidation. Not surprisingly, this area is the one that has issued more credits and constantly has the biggest number of credits submitted for compliance.

Another feature that may have influenced the demand for offsets in this market is the possibility to buy "golden" offsets. With this instrument, it is the broker offering credits that sustain the risk of invalidation (thus, it is neither the developer nor the emitter). As a consequence, these offsets are paid at a premium price. The effects of golden offsets on the demand for offsets it is not easy to forecast. In theory, they should increase the appetite for offsetting since now there is no more risk of invalidation. Nevertheless, since credits price increases, it reduces the price spreads, lowering the demand for offsets. Thus, the outcome may be a matter of which of these two effects prevails on the other at a specific point in time.

3. 3. 6 Carbon leakages

Finally, there is a practice that remains in the shadow yet can influence offset demand: leakages. It happens when a capped firm moves its production to a place where no environmental regulation is in place in order to drastically abate costs.

Leakage is not properly a feature of ETS. It is more an undesired consequence that authorities try to avoid to not undermine the efficiency of the policy. However, they do not achieve great outcomes in this matter. As a matter of fact, almost all ETSs have seen leakages to some extent.

Leakages and offsets appear to have an inverse relationship: the higher the leakages, the lower the offsets demand. With leakages a fourth way to abate emissions is introduced. Firms can re-locate, avoid costs imposed by regulation, not abate at all and import their services in the ETS-covered area. This reduces the emitter's compliance duty. In turn, the need for allowances, and offsets, will be reduced too.

Within RGGI states, leakage is a well-documented problem. It is estimated that the import of electricity from non-regulated sources is around 5-11% of annual electricity necessities.[123] Two situations lead to that: either emitters import electricity from out-of-the-state plants; or they increase the production by non-covered plants within the state. Hence, leakage can become an option for emitters within RGGI.[124] It is feasible that offsetting has been reduced by this possibility. Indeed, moving production can overcome offsetting in different ways: it does not require a long review by authorities, can not be reverted (*i.e.* has no risk of invalidation) and depends exclusively on the firm's preferences. As a consequence, leakages are a purely internal matter (as long as the authority does not find a way to avoid them), while offsetting heavily depends on external factors. Thus, firms will opt for moving away their production. The issue is that neither offsets nor leakages are good practices for the environment. Authorities should find a method to limit leakages without forcing the demand for offsets to drastically expand. This is not an easy task, but quantitive limits and some sort of tax on imported electricity can assist the change. Here, concerns shift to the political realm: none of the businesses covered will be happy in this context. Politicians will have the duty to deal with this tricky situation.

California, instead, handles leakages thanks to grandfathering (*i.e.* by giving more vulnerable businesses allowances for free). Yet, emitters in California are not planning to relocate out of the State, at the moment. Indeed, most of them are favoring a wait-and-see approach for figuring out the next moves. Yet, to keep costs low, they exploited the use of offsets.[125]

Moreover, there are also specific leakages concerns regarding offsets. These could be evident in the case of forestry projects. If, for example, a program wants

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[123] Ramseur J. L. (2013), *The Regional Greenhouse Gas Initiative: Lessons Learned and Issues for Policymakers*, Washington, D.C., Congressional Research Service, CRS Report

[124] Musgrove S. L., Taylor G. A., Valova R. R., Rábago K. R. (2017), *Emissions Leakage in RGGI: An Analysis of the Current State and Recommendations for a Path Forward*, Pace Energy and Climate Center, Pace University.

[125] Erickson H., gephart N., Goldstein A., Stevenson S. (2013), *The Demand for Carbon Offsets in the United States: a snapshot of US buyers on the Global Voluntary and California Compliance Market*, Master's Project Report, School of Natural Resource and Environment, University of Michigan.

to obtain credits by preventing trees to be cut down in a specific area, this can raise the price of woods and, in turn, increase de-forestation elsewhere.[126]

3. 4 Sector level drivers of offsets demand

Cap stringency, allowance prices, types of projects available and leakages are all features that describe why entities within different ETSs have distinct appetites for offsets.

However, even among emitters abiding by the same rules, differences exist in offsetting practices. To apprehend what drives offsets desirability at the micro-level, firms capped by California cap and trade are considered. Since it would be impossible to do a single unit analysis, they are grouped into the sector of operation based on NAICS 2017 classification. As a consequence, every entity is assigned to one (or more if it operates in more than one sector) two-digit NAICS code based on the classification displayed by CARB in its emissions reports (Figure 21). Every two digits-code contains various sub-sector. They are reported, but not considered in the analysis.

NAICS Sector	Definition
11	Agriculture, Forestry, Fishing and Hunting
21	Mining, Quarrying and Oil and Gas Extraction
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information

[126] To know more about offsets leakages and a possible solution, see e.g.: Filewod B., McCarney G. (2023), *Avoiding leakage from nature-based offsets by design*, Working Paper No. 415 , Centre for Climate Change Economics and Policy.

NAICS Sector	Definition
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
92	Public Administration

Figure 18. NAICS Sector and their relative description. Source: NAICS website, available at: https://www.census.gov/naics/?58967?yearbck=2017.

Classifying California emitters based on these codes (Figure 22) leads to predictable results. Most of the entities operate either in the utilities (22) or manufacturing (31-33), while Professional, Scientific and Technical Services (54) along with Management of Companies and Enterprises (55) have the smallest number of participants. By delving into this variance, it is possible to obtain interesting insights about the usage of offsets in different sectors.

Code		Number of Entities	
	Period 1	Period 2	Period 3
11	2	3	4
21	26	33	40
22	113	118	114
23	1	0	0
31	31	29	27
32	45	47	51

33	14	15	13
42	2	24	31
44	0	3	3
45	1	3	3
48	5	8	5
52	7	6	5
54	1	1	1
55	1	1	1
56	3	3	2
61	5	5	4
92	5	3	3
No Sector	1	4	1
Total	263	306	308

Figure 19. Number of California emitters for every code of NAICS classification. Sources: 2013-2014 Compliance Report; 2015-2017 Compliance Report; 2018-2020 Compliance Report. Available at: https://ww2.arb.ca.gov/.

3. 4. 1 Compliance obligation

How much a sector emits should be one of the main factors driving the use of offsets.

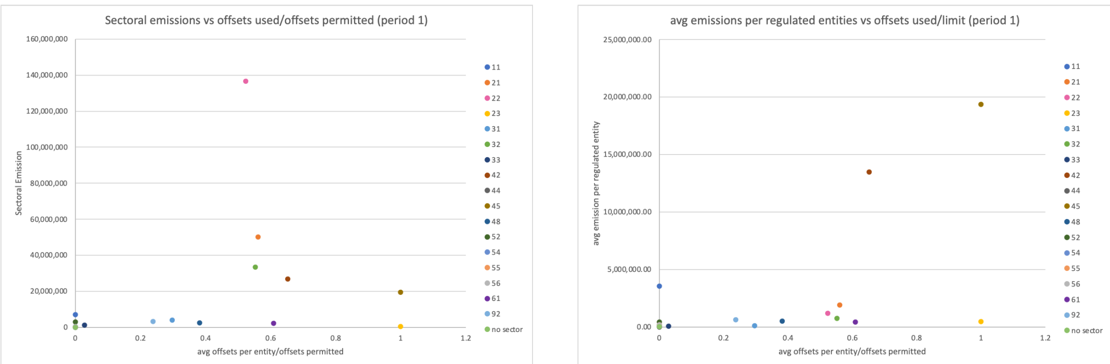
From a bureaucratic perspective, if a sector emits more than the other, it will have a higher obligation at the end of the period. So, it has to surrender a more significant number of permits compared to others. Since quantitive limitations are expressed as a percentage of total obligations, it has the legal possibility to submit a largest amount of offsets, if it touches the limit. An interesting situation can arise in this case. Some sectors may show the greater number of credits surrendered in absolute terms not because the others are more efficient in abating, but just because for structural limitations they can not cross an inferior threshold. By considering absolute terms, those sectors that emit more should be the ones that employ more offset too.

Data from California confirm this. The sectors that give in more offsets for compliance are Utilities in period 1 and Wholesale trade in periods 2 and 3. Not surprisingly, these sectors are also those with the biggest compliance duties. Nevertheless, considering just absolute numbers can be misleading, skewing the primacy toward high-emitting sectors. To avoid this, it is useful to look at offsets as a percentage of total compliance. In this matter, the sectors that displayed the three-period highest average are retail trade (44-45), which goes close to the 8% limit, and Construction (8%).[127]

Furthermore, it is interesting to analyze if the most polluting sectors surrender more offsets or rather are those sectors that have large units (*i.e*. have a high amount of emissions per entity) that tend to rely more on offsetting to decrease costs.

Data from California seems to favor the latter hypothesis. In period 2, between the three most polluting sectors, just two (wholesale trade and Mining) used more than 80% of permitted offsets. Instead, for some less pollutant sectors (such as Agriculture and Retail Trade) the ratio offsets used/offsets permitted almost equals 1. On the other hand, the six sectors with the highest average emissions per entity[128] are all employing offsets up to almost more than 85% of those that are permitted. This could be a consequence of the fact that since they buy more offsets it may be worth to pay the cost of the transaction. The situation is not so much different in period 3.

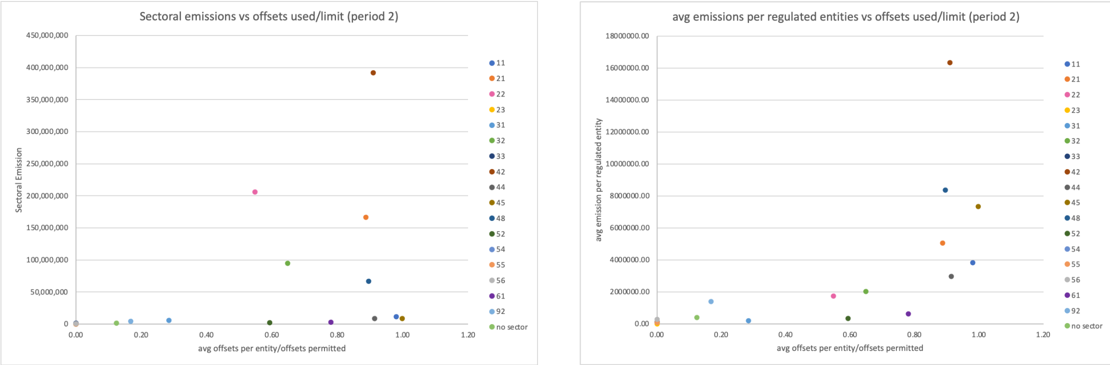
a)



127 Note the Sector 23 - Construction has been subject to cap and trade just in Period 1.

128 This is computed by dividing total emissions of a sector with the number of entities in it. It is useful to understand how large are entities composing a sector.

b)



c)

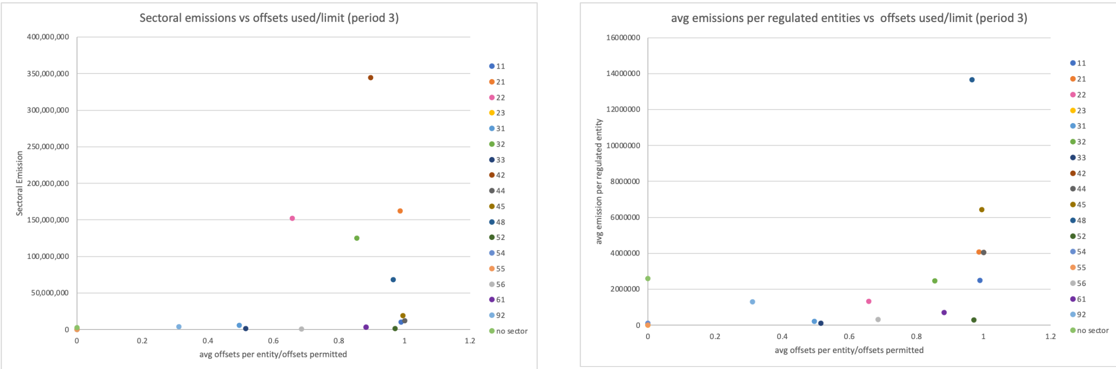


Figure 20. Sectorial emissions against offsets used/limit & avg emission per regulated entities against offsets used/limit for all the periods. a) period 1, b) period 2; c) period 3. Sources: 2013-2014 Compliance Report; 2015-2017 Compliance Report; 2018-2020 Compliance Report.

3. 4. 2 Sub-sector analysis: Utilities

The sectorial analysis can become more interesting by considering different subsections within a sector. Especially, the Utility sector in period 3 (NAICS code: 22) seems fascinating since sector 22 is the one that had more members for every period. Within it, there are 114 emitters divided into 9 different sub-sectors.

NAICS code	Description	Number of entities
221111	Hydroelectric power generation	6
221112	Fossil fuel electric power generation	50
221119	Other electric power generation	3
221121	Electric bulk power transmission and control	5
221122	Electric power distribution	41
221210	Natural gas distribution	6
221310	Natural gas distribution	1
221320	Sewage treatment facilities	1
221330	Steam and air	1
	TOTAL	114

Figure 21. Utility sub-sectors, their description and the number of emitters.

In this sector, most of the emitters are either generators of electric power from fossil fuels (50) or distributors of electric power (41). The ones that emit more, instead, are electric power distribution, electric bulk power transmission and control and fossil fuel electric power generators. The one with the greatest average emissions per entity is electric bulk power transmission and control.

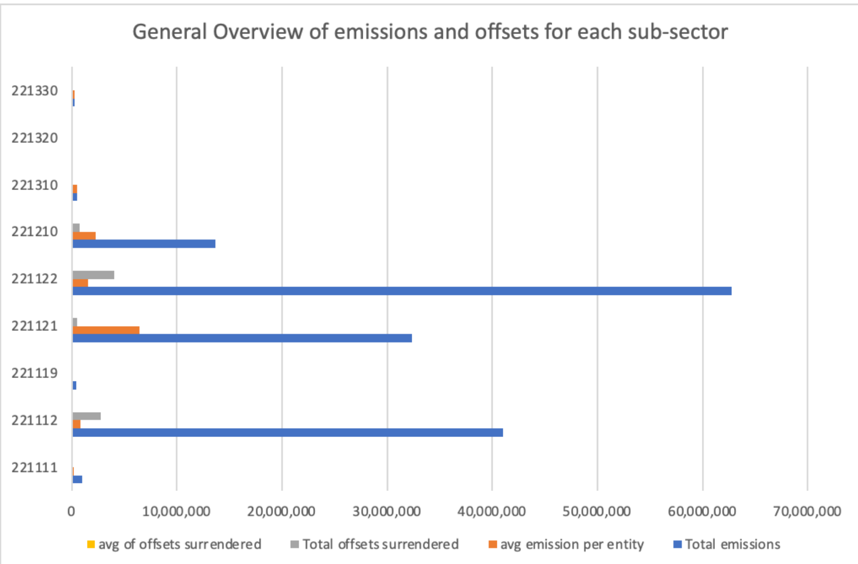


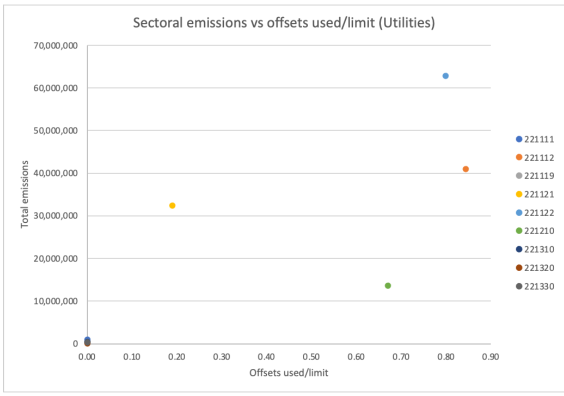
Figure 22. General overview of sub-sectors in the Utilities sector. Source: 2018-2020 Compliance period reports.

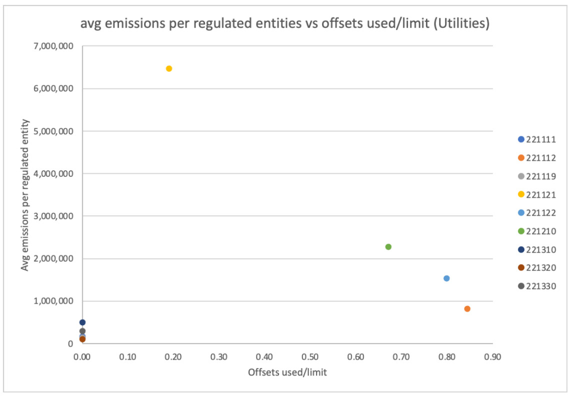
If this sub-sector follows the insights given by the sectorial analysis, it is possible to expect that electric bulk power transmission and control industries use the most offsets compared to the other codes.

In the utility sector, this is not the case. Fossil fuel electric power generation has the biggest offsets used/limit ratio, yet it is the second greatest emitter and has low average emissions per entity. Considering electric power distribution, it used almost 80% of offsets available by law. Instead, the sub-sector with the highest average emission per entity, electric bulk power transmission and control, employed less than the 20% of offsets allowed by law.

It is not easy to understand why this is the situation. Utilities are heavily regulated in California, yet this cap and trade has constantly faced leakages and/or resource shuffling.[129] Subsections with an elevated number of entities and significant emissions may imply that they have not experienced a high amount of firms relocating out of the state. Thus, they may use offsets to decrease compliance costs. Instead, sectors with high average emissions and a low number of entities may signify that either a few large firms remained within California borders while smaller ones have been relocated out of the state or that large firms employ resource shuffling.

Sub-sectorial competition can be a cause too. Sub-Sectors with higher competition may be more prone to use offsets to keep prices low and not lose customers in favor of other firms. If the number of covered entities is not so elevated, then a firm may avoid the use of offsets and increase the prices for its consumers. Strict regulation of this sector, can be another cause.





[129] See e.g: Cullenward (2014) and Cullenward and Weiskop (2013)

Figure 23. Sectoral emissions vs offsets used/limit (a) and average emissions per regulated entities vs offsets used/limit (b) within utilities sector. Source: 2018-2020 Compliance period reports.

3. 4. 3 Abatement cost

How much it costs for a firm to abate one single ton of emissions is the other major driver for offsets demand. Cost is strictly connected with the price of developing new technologies or new ways of production in a specific sector.

As seen at the beginning, abatement is an outlay represented by the MAC curve. If it is profitable, a firm will undergo all the other paths before effectively tackling its emissions. Between these, there is offsetting, which is currently the cheapest way. Thus, if a firm has to sustain a high abatement cost, it will try to use as many offsets as possible to decrease to the minimum the overall expenditures coming from abatement (composed of internal reductions, allowances, and offsetting). Moreover, theoretically, savings from the use of offsets can be re-invested to pay the cost of internal abatement or to develop new technologies to decrease it.[130] A firm with a low cost of abatement (*i.e.* more efficient), instead, is more flexible in its opportunities. If its emissions reduction costs are lower than allowances and offsets prices, it will abate as much as it can to accumulate proceeds from the sale of allowances in excess. It will not have intention to engage in projects that carry the risk of invalidation just to obtain credits. Unluckily, this situation is far away from the real world. However, decreasing emissions to sell allowances and obtain a profit instead of saving from submitting offset credits, remains a potential strategy for efficient firms.

The downside, in this case, is that it is impossible to know the actual MAC curve of a firm. This is a piece of sensible information that managers prefer to keep secret to avoid offering comparative advantages to competitors. Even firms in the same sector may have different MACs. What is possible to obtain is a general sectoral idea of the prices of reducing emissions. According to Wagner et al.

[130] Note that it is difficult to know if offsets savings are substantial enough to drive investment decisions. Indeed, it is likely that this is not the case.

(2011), sectors with the greatest abatement costs are agriculture, fuel production, industries and transportation. [131]In these areas, expenditures are pushed upward by the price of switching to sustainable fuels and the cost of developing new green technology. California system confirms the relation between MAC and offset. As expected, all of the less-efficient industries have an offsets used/total compliance ratio above the 7%, indicating the exploitation of offsetting.

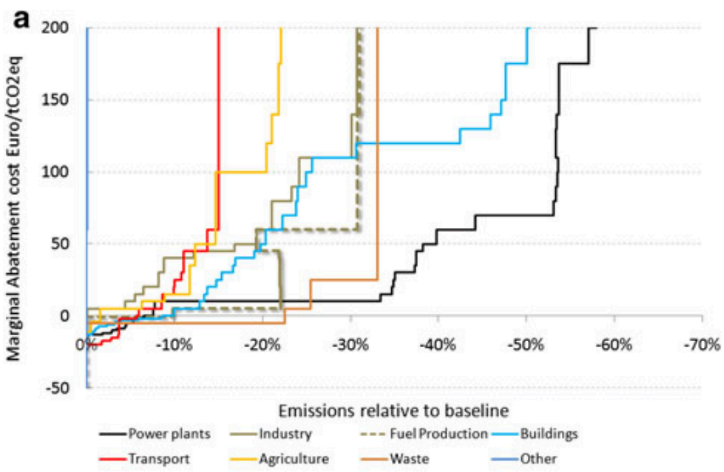


Figure 24. Sectoral cost curves for the US. Source: Wagner F., Amann M., Borken Kleefeld J., Cofala J., Höglund-Isaksson L., Purohit P., Rafaj P., Schöpp W., Winiwarter W. (2012), *Sectoral marginal abatement cost curves: implications for mitigation pledges and air pollution co-benefits for Annex I countries*, in «Sustainability Science», n. 7, p 178.

The cost of decreasing emissions is surely one of the main drivers of offset demand. However, what really will move upward or downward the demand is the combination of it and the sector's emissions intensity. If a sector is both poorly efficient and high-intensity in emissions, it will surrender the maximum amount available of offsets credit to reduce expenditures to an economically sustainable level. If, instead, a sector is extremely efficient and low in emissions, it will even not consider offsets, since opting for internal abatement will probably be the cheapest option.

[131] Wagner F., Amann M., Borken Kleefeld J., Cofala J., Höglund-Isaksson L., Purohit P., Rafaj P., Schöpp W., Winiwarter W. (2012), *Sectoral marginal abatement cost curves: implications for mitigation pledges and air pollution co-benefits for Annex I countries*, in «Sustainability Science», n. 7, pp 169-184.

3. 4. 4 Other factors

Along with costs and emission quantity, two more sector-specific components can impact how much firms may use offsets.

The first one is the competition. If a sector is highly competitive, a slight increase in prices by one single emitter can let customers look around for a less expensive option. In a sector with tons of competitors, customers will probably find one. A firm can not afford to raise its price or it will lose buyers. In an extreme situation, it can even be forced out of business. To bypass this problem, it will think about offsets to keep costs as low as possible. This behavior will be emulated by all of the members operating in that area. As a consequence, the more crowded the sector, the more likely is to experience a higher number of offsets to keep price low. If instead, there are fewer competitors, a firm can afford to increase its price without losing clients. For example, if there is just one factory in a specific sector, it does not worry about increasing prices, since there is nobody to whom customers can divert. In this sense, it does not need to use a controversial instrument, it could simply decide to raise prices and financing abatement or allowances purchase. It is important to note that this considers only competition by entities regulated by the same ETS. If regulated entities experience fierce rivalry by out of the state industries, they may choose to use offsets even if they are some sort of monopoly within their State. Thus, it is difficult to asses the relationship between competition and offsetting.

Related to competition is the possibility to pass reduction costs to buyers. Some kinds of industries can easily increase the final price paid for the service. For example, firms that supply household electricity can raise the customers' bills and be almost certain that none of them is going to change provider.[132] If this is the case, offsets use can be limited since covered entities will not bear the entire cost of the regulation. If, instead, a firm can not transfer the cost to its customer, maybe due to sectorial structural features or challenges from out of the state, offsets are a good option to decrease outlays. A firm that is selling digital

[132] Note that this may not be the case of US utilities market, since here the market is extremely regulated even in terms of pricing.

services, for example, can not inflate prices without consequences, even if it is the only one in that area. If it does so, it is easy for users to find a cheaper alternative proposed by out-of-the-state businesses. These are not subject to environmental requirements, therefore have inferior costs and lower prices. The possibility to transfer the cost on consumer, however, is also a consequence of restrictions on price that may exist in a specific sector.

California sectoral data favors the idea that crowded sector use more offsets. Indeed, sectors such as Mining and Manufacturing show a high percentage of offsets used for compliance. The only exception are utilities, but this can be a consequence of regulations or resource shuffling.

3. 5 Interaction between macro and micro drivers

In conclusion, it is worth remarking that macro and micro drivers do not act in isolation in the real world. They interact constantly, and their interrelation determines the demand for offsets by different sectors within different ETS in different periods. For this reason, it is challenging to estimate *ex-ante* the offsets quota that is going to be requested by emitters.

Authorities will have hard times if they want to intervene to curb a soaring demand, since it is challenging to disentangle what specific features are causing it. Moreover, jurisdictions can intervene directly only at the market level, leaving the firm-level intervention to an indirect type. This is a consequence of the fact that the latter operates in a framework built by the former.

Therefore, it is fundamental that each offset-targeting intervention is thoroughly assessed before being enforced to avoid unpredictable consequences.

Chapter 4

Carbon offsets and allowance prices

4. 1 Scope

The final part of this paper investigates the relationship between offsets and allowances. In its scope, it follows Chung et al. (2018) in the idea of discussing what influences allowances price; and Shrestha and Bhatta (2018) in terms of econometric methodology. The goal is to reckon whether or not offsets supply, demand and use have an effect on allowances auction price within California cap and trade.

4. 2 Models and procedure

The very first task to perform, when it comes to time series analysis, is to verify whether or not the variables are stationary.

A time series is defined as stationary when its mean, variance, and correlation structure do not change over time. Otherwise, it is non-stationary. If this is the case, and if nonstationarity is not properly addressed, estimations can contain biases, reducing the model's effectiveness. Concretely, there could be two different kinds of non-stationarity.

The first one is trend stationarity. It derives from the presence of a trend within the time series. De-trending (*i.e.* removing the trend) the series will transform it into stationarity.

The second one derives from the presence of a unit-root or a structural break. If the last observed value of a series is equal to its previous value plus an error term,[133] that series has a unit root. Structural breaks, instead, happen when a variable changes drastically during a specific point in time. Differencing[134] is usually the key to converting this kind of time series into stationary. In this case, the time series is said to be integrated of the *n* order, I(n).[135] The choice of the model is based on the nature of the variables.

In this research, an auto-regressive distributed lag (ARDL) model is employed. ARDL is an auto-regressive model that regresses the independent variables considering both the dependent variable's past values and the values of other regressors. It also allows different lags for different variables. Most importantly, Pesaran and Shin (1999) and Pesaran *et al*. (2001) claim that the ARDL model is useful in co-integration analysis to determine the relationships among economic variables regardless of the orders of integration of the regressor, as long as they are either I(0) or I(1). ARDL's general features are:

1. It is irrespective of whether the variables considered are I(0) or I(1).
2. It can not include variables that are I(2), otherwise it will be biased.
3. It is well-fitted for small samples.[136]
4. It is well-fitted only if just one long-run cointegration relation exists. If there is more than one, another approach[137] should be chosen.[138]

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133 In Mathematical terms: $y_t = \alpha y_{t-1} - \varepsilon_t$ with α

134 In Mathematical terms: $y_t - y_{t-n}$

135 Nkoro E., Uko A. K. (2016), *Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation*, in «Journal of Statistical and Econometric Methods», vol. 5, n. 4, pp 66-67.

136 Haug A.A. (2002), *Temporal Aggregation and the power of cointegration tests: a monte carlo study*, in «Oxford Bulletin of Economics and Statistics», n. 64, pp 399-412.

137 As the Johansen and Juselius (1990).

138 Nkoro E., Uko A. K. (2016), *Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation*, in «Journal of Statistical and Econometric Methods», vol. 5, n. 4, p 78.

According to Pesaran (1997), its formal specification is:

$$y_t = \alpha_0 + \alpha_1 t + \sum^{p}_{i=1} \phi_i y_{t-i} + \beta' x_t + \sum^{q-1}_{i} \beta_i^{*\prime} \Delta x_{t-i} + u_t \qquad (1)$$

With x_t as the *k*-dimensional I(1) variables that are not cointegrated and u_t as the disturbances with zero mean and constant variance and covariance. The limit of ARDL is that it helps in revealing just the short-term relations amongst variables.

If the emphasis is on the long-term horizon, cointegration must be considered. Cointegration means that there is a long-run equilibrium between economic variables that converges over time. A bounded cointegration test can be performed to verify it. Its result displays whether or not at least two variables are cointegrated (*i.e.* there is one cointegration relationship). If so, from the ARDL model can be derived an Error Correction Model (ECM) thanks to a linear transformation.[139] ECM's strength is that it considers short-run dynamics along with long-run equilibrium without losing long-run precious information. Pesaran et al. (1997) define the error correction representation of the ARDL as:

$$\Delta y = \alpha_0 + \alpha_1 t + \pi_{y,x} z_{t-1} + \sum \varphi' x \Delta z_{t-1} + w \Delta' x_t + u_t \qquad (2)$$

with $t = 1,2,\ldots$

4. 3 *Ex-ante* expectations

In the literature, the general conception of offsetting is that by permitting it, emitters abatement costs are drastically reduced. It diminishes also the necessity for allowances since emitters have one more instrument to comply with the rules. The natural consequence of a demand contraction, accordingly to basic economic

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[139] Banerjee A., Dolado j., Galbraith J., Hendry D. (1993), *Cointegration, Error Correction, and the Econetric Analysis of Non-stationarity Data*, Oxford, Oxford University Press.

theory, is a drop in that specific asset's price. Therefore, including offsets in a cap and trade system should decrease allowances price.

According to theory[140], it is reasonable to expect an inverse relation between offsets and allowance prices. However, determining *ex-ante* the relation between allowance prices and offsets is not straightforward. Market decisions, that drive both the demand for offsets and the demand for allowances, are determined by regulator's behaviors (that, in turn, depend on forecasted demand expectations); and firms' expectation of future demand conditions respectively to the present. It is not easy to estimate none of these situations. It is even harder to singularly forecast the possible relationships between allowance prices, offsets issued, offsets hold by firms and offsets used for compliance.

The same situation arises if the quantity of allowances and allowance prices relationship is considered. Theoretically, the higher the price of allowances, the higher the supply. However, it is not that straightforward. Since allowances are offered by regulators, they should predict in advance permits price, and then adjust the supply accordingly. Their price prediction, in turn, is based on the forecast of the demand by firms. The difference is within what is considered to be predominant, if supply or demand mechanisms. As a consequence, it is difficult to forecast the relation between allowance prices and allowances sold. Usually, if the demand is huge, the price tends to increase. The problem with this estimation is that it is not possible to observe demand, but rather it is considering quantity traded, which relies on the regulator's decisions.

Another blurred relationship is the one between the allowance prices and offsets in the general account. Credits within the latter do not have an expiration date, so can be transferred whenever a firm prefers.[141] There could be periods when their number is extremely elevated since firms finance projects forecasting a growth in price of credits rather than for immediate use. In such a decision, the firms' internal strategy plays a determinant role. As a consequence, it is challenging to discover a pattern. On this kind of account reside credits that are intended for banking. Usually, the highest the number of offsets banked, the more firms are

140 CARB 2010 report forecasted lower allowance prices in 2020 if offsets are allowed.

141 To use an offsets credit for compliance, a firm must move it to the compliance account.

expecting credits price to increase in the future. Otherwise, if firms think that prices will decrease in the future, they will not bank too many credits, since it will be more convenient to buy them at a lower price. Allowance price and offsets price are imperfect substitutes (Dormady and Englander (2015)). As such, an increase in the offsets price in the future, will decrease the price spread. In turn this may increase the demand for offsets. Thus, if banking is an indication of a future increase in price of offsets and it is significant it may point to an expansion of the demand for allowances. The effect of this on prices of allowances, however, it is unclear.

That is, it is not easy to guess in advance the potential connection between all of these variables, since all of them depend on different elements. Hopefully, the model will give some information about all of these reactions, pointing to those that are statically significant.

To sum up, these last paragraphs examine the following relations :

Relationship1: *Offsets issued and allowances auction price*

Relationship2: *Offsets in the compliance account and allowances auction price*
Relationship3: *Allowances sold in every auction and allowances auction price*

What must be considered, while discussing these hypotheses, is the role of the quantitative limit in the California cap and trade market. The ceiling is calculated on the total compliance obligation and is binding on offsets that are surrendered for compliance. As seen before, it appears to be significant in determining the number of offsets used for compliance. As a consequence, it is fundamental to take it into account in developing the different models.

4. 3. 1 General and compliance accounts

Highlighting the differences between compliance and general account in the CITSS database is necessary before starting the analysis to understand what kind of credits are included in each type of account. Both can hold offset credits, yet they have different purposes.

Firms capped by California cap and trade and that surrender instruments for compliance have both a general and a compliance account.

General accounts are those where firms store their compliance instruments. Credits coming from transfers, for example, go directly to this account. Here, entities can keep offsets and/or allowances as long as they want. The only restriction is the holding limit.However, only allowances are subject to that.

Compliance accounts, instead, are those accounts made purposely to submit allowances at the end of every period. Indeed, credits in this type of account are going to fulfill obligations at the end of every period. As a consequence, when the obligation is due, compliance credits are surrendered.

The relationship between general and compliance accounts is straightforward. Credits can flow from general to compliance account, but not *vice-versa*. As a result, once credits are transferred into compliance accounts, they are surely used for compliance.

Since offsets in the compliance accounts are used for compliance, the quantitative limit (the 8% limit on the use of offsets) applies only on these accounts. Instead, general accounts have no such limit in place. Hence, firms can hold as many credits as they want in their general account. Finally, the ceiling is not binding neither on credits issued, since those credits will go into general accounts, rather than in the compliance ones.

4. 4 Analysis

4. 4. 1 Descriptive statistics

Prior to starting, it is important to note that this research utilizes the natural logarithm of all the variables considered. Logarithm transformation, indeed, is an easy method to stabilize time series variance across time.[142] They are also easier to interpret. Thus, logarithms are computed for: allowances auction prices (allow_price); total allowances sold during a specific auction (allow_sold); total offsets issued in a specific quarter (*off_supp*); total amount of offsets held in all compliances (*comp_acc*) and all general accounts (*gen_acc*) of CITSS website.

To have a general framework of the environment that surrounds the outcomes, descriptive statistics can be considered. Figure 25 shows statistics for raw data (not-logged variables), while Figure 26 displays the log values for all the variables.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
allow_price	35	16.86	5.42	11.50	12.73	15.06	17.62	30.85
allow_sold	35	59,644,828	23,114,031	7,260,000	55,570,020	66,321,122	75,212,484	98,215,920
off_supp	35	6,911,807	5,568,131	1,166,531	3,518,873	4,838,031	8,242,116	24,245,973
gen_acc	35	42,182,452	23,776,545	10,072,343	20,382,774	43,680,604	54,092,958	89,334,980
comp_acc	35	4,507,783	4,608,214	0	980,780	3,352,986	7,766,990	19,095,889

	trimmed	mad	range	skew	kurt	se	IQR
allow_price	16.09	3.45	19.35	1.30	0.50	0.92	4.89
allow_sold	61449581.21	14758823.39	90955920.00	-0.85	-0.30	3906984.33	19642464.50
off_supp	6069836.07	2861619.63	23079442.00	1.46	1.39	941185.94	4723243.50
gen_acc	40662492.38	23789740.30	79262637.00	0.50	-0.75	4018969.72	33710183.50
comp_acc	3829658.07	3837330.55	19095889.00	1.25	1.15	778930.30	6786210.00

Figure 25. Raw Data descriptive statistics.

[142] To know more about this process and when it achieves its goal, take a look at: Luetkepohl (2009).

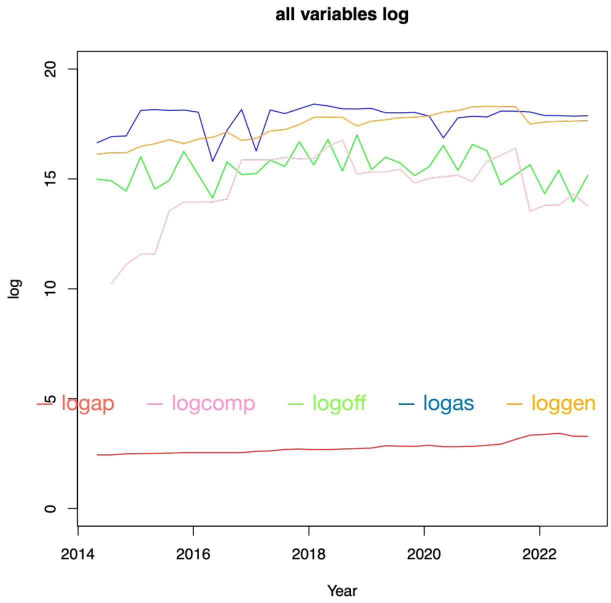

Figure 26. Chart of the natural logs for all the variables. logap = log(allow_price); logas = log(allow_sold); log(off_supp); loggen = log(gen_acc); logcomp = log(comp_acc).

Allowances sold experienced three major downturn in 2016, 2017 and 2020. It is reasonable to think that the last one was due to covid[143], while the dips in 2016 and 2017 may be the results of an interaction of factors. Indeed, in 2016 California cap and trade faced a lawsuit contesting the validity of the program. This made its future uncertain, and firms feared that allowances purchased could become useless. Moreover, at that time there was a surplus of previously purchased (*i.e*. banked) allowances. The uncertain future value of allowances played a role too.[144]

The presence of seasonality and trend[145] is tested for every variable. The results display that none of the regressors is seasonal, while *logap* and *logcomp* appear to have a trend.

[143] Note that the model below controls for Covid years.

[144] Charles B., Norin L., Monsen W (2016), Uncertainty and surplus allowances dog California cap-and-trade program, Norton Rose Fulbright, available at: https://www.projectfinance.law/publications/2016/august/uncertainty-and-surplus-allowances-dog-california-cap-and-trade-program/.

[145] The trend test used is the Mann-Kendall Trend Test.

Correlation is computed too. It does not define a significant and precise connection between variables, yet its coefficients provide general insights about the strength and directions of the relations between a couple of variables. It ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation). If it equals 0, there is no correlation. As noted, offsets in the general account appears to have a strong correlation with allowance prices and even a stronger correlation with credits in the compliance account. The latter arises doubts about multicollinearity, and it is addressed later on.

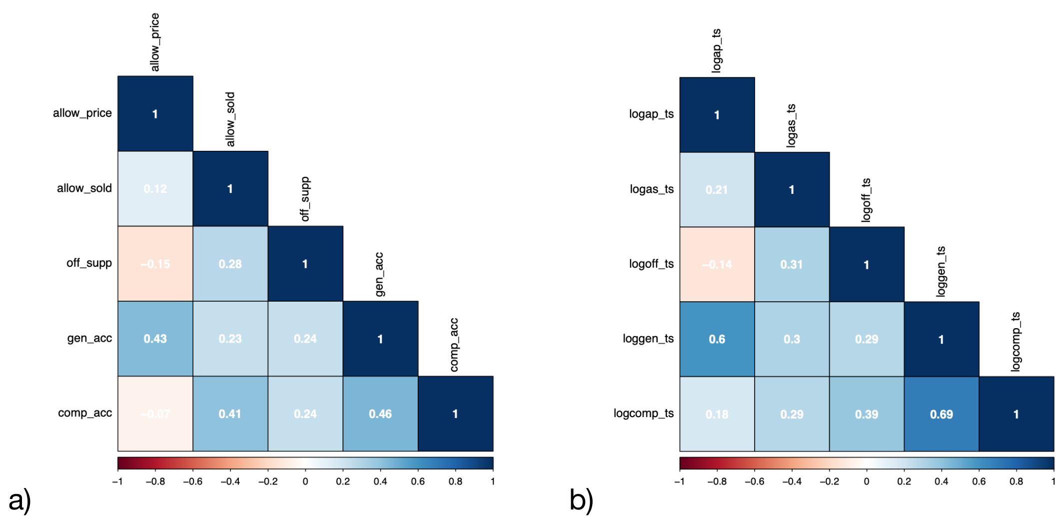

Figure 27. Correlogram of the raw data (a) and of their log (b). Interpretation: 0.0-0.2: almost nil correlation; 0.2-0.5: medium correlation; 0.5-0.8: high correlation; 0.8-1: very high correlation.

To inquire more about the relationships between offsets and allowances, the correlation between allowance price and the difference of credits in the general accounts and those in the compliance ones[146] is considered. This spread, indicatively, represents credits that are banked, since those are offsets that are not used for compliance during a specific period. The correlation coefficient is extremely low (0.06), showing the absence of correlation between those two variables.[147]

[146] Δacc = loggen - logcomp

[147] Note that the correlation coefficient gives just a general idea of the relationship between two variables. So, cautions must be used while assessing it. Further analysis is needed to effectively claim whether or not banked allowances have an effect on prices or vice-versa.

4. 4. 2 Stationarity

Verifying that the dependent and independent variables are of order I(0) (are stationary) or I(1) (are stationary in their first differentiation) is crucial to implement an ARDL model that does not include biases. Here, different methods are performed to check for stationarity.

The first one is the augmented Dickey-Fuller test. It examines the presence of a unit root within a time series taking into consideration n-lag values. The null-hypothesis is the presence of a unit root, while the alternative hypothesis is that the series is stationary.

The Phillips-Perron test is another unit root test considered. Again, H0 assumes the presence of a unit root, while H1 tests its absence.

Finally, the Kwiatkowski-Phillips-Schmidt-Shin test is implemented. It has the hypothesis switched: the null-hypothesis indicates that the time series is stationary, while the alternative entails the presence of a unit root.

Stationarity tests

Variable	ADF	PP	KPSS
logap	2.3731	0.623	0.0472
logas	-4.0289	0.01	0.1
logoff	-1.7507	0.01	0.1
Loggen	-1.3502	0.769	0.01
logcomp	-3.8153	0.8317	0.0964

Figure 28. Stationarity tests results. Note: for the ADF is reported tau value, and for PP and KPSS is reported the p-value. The thresholds for ADF tau are: 0.01: -4.15; 0.05: -3.50; 0.1: -3.18.

Tests results show that *logap* is non-stationary, while *logas* is stationary of order 0 (I(0)). For *logoff*, *loggen* and *logcomp*, different tests point to divergent findings.

Due to the uncertainty about the nature of these time series, stationarity is inquired again on the first differences.

Stationarity tests

Variable	ADF	PP	KPSS
diffap	-0.0962	0.0129	0.1
diffas	-8.8295	0.01	0.1
diffoff	-6.8628	0.01	0.1
diffgen	-3.9021	0.01	0.1
diffcomp	-4.7760	0.01	0.03366

Figure 29. Stationarity tests results for differenced variables. Note: for the ADF is reported tau value, for PP and KPSS is reported the p-value. Thresholds for ADF tau are: 0.01: -4.15; 0.05: -3.50; 0.1: -3.18.

Differencing clears some doubts. If first differentiated, *logoff* and *loggen* become stationary. That is, they are integrated of at most order 1. Instead, *diffap* and *diffcomp* need some more attention.

The former exhibit stationarity for PP and KPSS tests but not for the ADF. To complement these findings, a Bruiting Variance Ratio test for a unit root is performed. It rejects the null-hypothesis of non-stationarity, thus it is possible to be quite sure that *logap* is stationary in the first order.

On the other hand, both ADF and PP tests consider *logcomp* as stationary, while the KPSS test fails to reject the null hypothesis at the 0.05 confidence level (it does not reject it for a = 0.01). Probably, acquiring more data will clear all these doubts. Anyway, a Bruiting Variance Ratio test confirms the stationary nature of the series. That is, *logcomp* is integrated in the first order too.

Thus, the stationarity tests performed clear the road for the development of an ARDL model. Indeed, the mixed orders and the absence of order (2) regressors make the ARDL the most suitable model.

Variables Order of Integration

Variable	Type
logap	I(1)
logas	I(0)
logoff	I(1)
loggen	I(1)
logcomp	I(1)

Figure 30. Variables Integration orders.

4. 4. 3 Optimal lag-length selection

Selecting the lag length is a crucial step in designing a sound model. A lag is a period back, and the length of the lag suggests how far away in time the model must go to obtain information. ARDL has two main features regarding lags: all the regressors do not need to have the same lag (ARDL is a distributed lag model), and the independent variable optimal lag is needed too (ARDL is autoregressive).

Different methods exist to determine the optimal lag length. The more frequently used one is the Information criterion. In a nutshell, it considers which model is best fitted for the estimation based on the lower Sum of Squared Residuals (SSR). The issue with this approach is that the more variables included, the lower the SSR. So, even not-useful regressors contribute to decreasing the SSR. To avoid the situation where the overfitted model is the best, the information criterion incorporates a penalization for the number of variables counted. In detail, two different formulas can be used: Akaike Information Criteria (AIC)[148] and Bayesian Information Criteria (BIC). The distinction stands within the penalization formula. It is not unusual that both the BIC and AIC give the same results. If this does not happen, Chung *et al*. (2018) suggest using BIC in the case of small samples, since AIC seems to contain biases in the measure of the actual differences.

[148] Developed by Akaike (1973)

For completeness, in this study both the AIC and BIC are considered. As predictable, they give the same results.

OPTIMAL LAG

Method	logap	logas	logoff	loggen	logcomp
AIC	4	4	4	4	3
BIC	4	4	4	4	3

Figure 31. Lag selection criteria results.

4. 4. 4 ARDL model

Once the optimal lag is chosen, it is possible to estimate the ARDL. In this case, it is an ARDL (4,4,4,4,3).

While composing the model, some problems arise. *Logcomp*, when plotted, seems to have a (quadratic) trend and a structural break. These are two characteristics that should not be included in any analysis. Luckily, there are several ways to deal with them.

Speaking of trends, there are two main approaches. One is to include it in the estimation, while the other is to de-trend the time series before considering it as a regressor.

Structural breaks have a two-fold approach too. Either observations after the break are not considered (risking data loss), or a dummy variable representing the break is included along with the other regressors. To deal with these concerns, three different ARDL models are estimated: one includes a trend in the model but not the structural break (*nt*), one with the de-trended version for the variable *logcomp* and no structural break (*dt*), and the last one with a dummy variable and the de-trended *logcomp* (*dtd*). The procedure of ignoring data after the break is not employed to avoid shrinking an already small sample.

Choosing among models is never an easy task. However, some indicators can help in this process.

The first one concerns the dummy variable. It is important to understand if it is statistically relevant, otherwise, it is just overfitting the model. In the case where it was considered, it did not appear to be relevant. Thus, it is not necessary to include it in the equation.

R^2 and Adjusted R^2 are other statistics used to compare models. It is important to be cautious with these. Both vary from 0 to 1 and describe the model's capacity of estimation. However, having a high R^2 is not always a synonym of a good model. Sometimes, it can be a cue for overfitting (*i.e.* too many independent variables are incorporated). If this is the case, by removing variables it should be reasonable to expect a more-reliable model. To assess this, a new ARDL without *loggen* has been estimated. Yet, the R^2 did not decrease that much.

Another reason why an elevated R^2 could happen is if the autoregressive variable (*i.e. logap*) is strongly autocorrelated. Probably, this is the case for all three models.

The last resort in picking a model, however, is to consider the knowledge and expectations surrounding it. In models *nt* and *dt*, the direction between dependent and independent variables is the same. What does it change, however, is its strength and statical significance. This is due to different estimations of the trend. Indeed, in *nt* the trend considered is linear, while in *dt* the *logcomp* has been de-trended of a quadratic trend. As a result, *Dt* can be a more satisfactory guess since it properly de-trends *logcomp*.

It is interesting to see if coefficients gives some insights about possible relations.

```
==============================================================================
Dt model
==============================================================================
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
______________________________________________________________________________

(Intercept)         -2.145740   0.613414  -3.498  0.01732 *
L(logap_purets, 1)   0.522184   0.183619   2.844  0.03608 *
L(logap_purets, 2)  -0.230202   0.239822  -0.960  0.38120
L(logap_purets, 3)  -0.638839   0.208374  -3.066  0.02792 *
L(logap_purets, 4)   0.595997   0.204572   2.913  0.03327 *
logas_purets         0.104180   0.018643   5.588  0.00253 **
L(logas_purets, 1)   0.066112   0.013081   5.054  0.00392 **
L(logas_purets, 2)   0.031980   0.014279   2.240  0.07525 .
L(logas_purets, 3)  -0.018662   0.012302  -1.517  0.18973
L(logas_purets, 4)   0.048059   0.014431   3.330  0.02077 *
logoff_purets       -0.074671   0.013428  -5.561  0.00259 **
L(logoff_purets, 1) -0.112561   0.017163  -6.559  0.00124 **
L(logoff_purets, 2) -0.101269   0.027411  -3.694  0.01408 *
L(logoff_purets, 3) -0.084058   0.027958  -3.007  0.02987 *
L(logoff_purets, 4) -0.061942   0.019301  -3.209  0.02375 *
loggen_purets        0.139748   0.055133   2.535  0.05223 .
L(loggen_purets, 1)  0.082759   0.044441   1.862  0.12162
L(loggen_purets, 2) -0.063737   0.039456  -1.615  0.16715
L(loggen_purets, 3)  0.106731   0.035659   2.993  0.03034 *
L(loggen_purets, 4)  0.131513   0.040491   3.248  0.02275 *
detlogcomp_ts       -0.023552   0.012040  -1.956  0.10781
L(detlogcomp_ts, 1)  0.038769   0.011784   3.290  0.02171 *
L(detlogcomp_ts, 2) -0.009259   0.011259  -0.822  0.44829
L(detlogcomp_ts, 3)  0.042386   0.012247   3.461  0.01803 *
covid               -0.033963   0.039816  -0.853  0.43261
______________________________________________________________________________
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
______________________________________________________________________________
Residual standard error: 0.02284 on 5 degrees of freedom
Multiple R-squared:  0.9988,     Adjusted R-squared:  0.993
F-statistic: 172.2 on 24 and 5 DF,  p-value: 8.752e-06
```

Figure 32. *Dt* model. It includes an already de-trended logcomp.

Both allowances prices and quantity sold during auction seem to be statically significant at almost all lags. Moreover, the relations between *logap* and *logas* is positive (except for logas at the third lag), while when *logap* regresses itself has a different influence depending on the lag.

Shifting the focus on offsets, their supply appears to be statistically significant. The model points toward a negative relation: if offsets supply expands, allowance prices will decrease. The greater availability of offset credits, indeed, enlarges abatement options for emitters. There will be even more possibilities to reduce costs, leading businesses to opt for offsetting. However, again, how much available offsets are effectively reducing allowance price depends also on the regulator's choice of the ceiling, since if it is low, the market will be flooded by offsets credits that can not be submitted by none of the cover entities. That is, those credits will becomes useless. Hence, the effect of a great supply of offsets, crossed the limit, may not be so influential on allowance price.

The number of offsets in general accounts is statistically significant only for lag(0) and lag(3) and (4). It has both negative and positive coefficients. This is presumably a consequence of the fact that credits in these accounts can be held as long as firms want, and they could either be transferred or used for compliance. That is, emitters can just stockpile credits without the willingness to use them. Credits in offsets accounts appear to be statically significant too.

One last condition must be considered for all of these models: multicollinearity. Multicollinearity occurs when two independent variables are strictly correlated. As aforementioned, *logcomp* and *loggen* have a powerful correlation. This is not a surprise, since credits within compliance accounts are transferred directly from general accounts.

To obtain reliable estimates, multicollinearity should be avoided, since it could bias the results. Thus, a brand-new ARDL that excludes *loggen* from the regressor is computed. The decision of getting rid of *loggen* rather than *logcomp* resides in the fact that credits in the latter are surely used for compliance,[149] while the ones in general accounts can be (and are) used even for speculation strategies. Hence, the new ARDL examines allowances prices using as regressors allowances sold, past allowances prices, offsets supply, offsets used for compliance and a dummy variable to see if it becomes significant.

[149] The *Compliance Account* is the account from which instruments are surrendered to the ARB at the end of a compliance period. (ARB (2017), User Guide - Volume III Conducting Transfers in the CITSS). Note that banking is not allowed on compliance account neither is allowed to transfer back credits from compliance to general account.

```
==============================================================================
Model without loggen (ngsh)
==============================================================================
Coefficients:
                     Estimate   Std. Error t value  Pr(>|t|)
_______________________________________________________________________________
(Intercept)           0.161401   0.380898   0.424    0.67538
L(logap_purets, 1)    1.107766   0.058565  18.915    2.51e-16 ***
logas_purets          0.017017   0.020323   0.837    0.41034
logoff_purets        -0.009076   0.015069  -0.602    0.55240
L(logoff_purets, 1)  -0.037495   0.015413  -2.433    0.02248 *
detlogcomp_ts         0.017025   0.013124   1.297    0.20640
dummyts              -0.198664   0.061955  -3.207    0.00366 **
covid                 0.003067   0.028292   0.108    0.91455
_______________________________________________________________________________
___
Signif. codes:  0 ’***‘0.001 ’**‘0.01 ’*‘0.05 ’.‘0.1 ’‘1
_______________________________________________________________________________
___
Residual standard error: 0.05635 on 25 degrees of freedom
Multiple R-squared:  0.9677,     Adjusted R-squared:  0.9587
F-statistic: 107.1 on 7 and 25 DF,  p-value: < 2.2e-16
```

Figure 33. *Ngsh* model. It includes an already de-trended logcomp and a dummy for the breaking point. Note. The optimal lag length has been computed based on BIC and is: (1, 0, 1,0).

This model shows how past allowances price and offsets supply of the previous quarter are statically significant. Offsets issued do not imply that firms already have obtained them, but just that they are available. This could be the explanation of the significance of the lagged level: credits issued are not immediately bought, but could be acquired in the next quarter due to the firm's internal policies or bureaucratic procedure time.

Anyway, *ngsh* clears some doubts about the relations: offsets supply is negatively connected to allowances prices, while the price itself and the quantity have a positive relation. Yet, none of those are significant.

Detlogcom, instead, requires a little bit of discussion. It does not result to be statistically significant and has a positive relation with allowances price. This may be controversial. A feasible explanation is that emitters surrender obligations not during every quarterly auction, but just at the end of the compliance period (that is at the end of the year). Thus, *logcomp* in a specific quarter could not be so influential in that same quarter prices. Moreover, holders can alternatively transfer credits to the compliance account every month of the year. As a consequence, there is a huge variability among these credits for every quarter. Reasonably, it could be expected to find the most elevated amount of credits is in

Q4 of every year and an even bigger amount in Q4 during the last year of the compliance period.

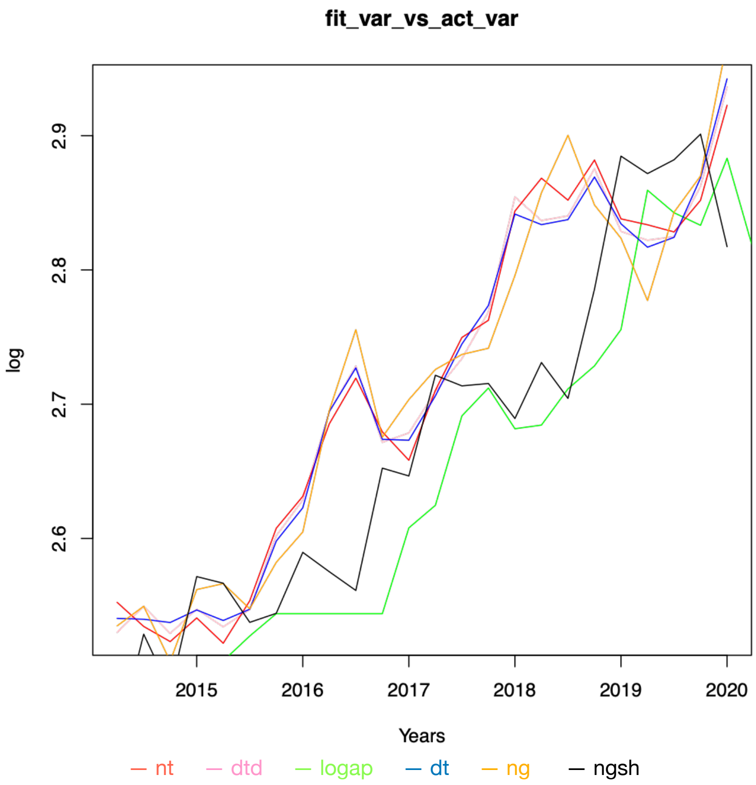

Figure 34. Estimated *logap* values for every model against real *logap* value.

4. 4. 5 Cointegration

An ARDL model clarifies only the short-term relation. Yet, some sort of longer-term relationship could exist between variables. To spot them, Pesaran et al. (2001) designed the Bound Cointegration Test. It looks after the null-hypothesis of no cointegration by creating two different bounds, I(0) and I(1), for every confidence level. Then, it computes the F-statistics and compares them. Three different cases can take place:

1. F < I(0): there is no cointegration.
2. F > I(1): there is at least one cointegration relation.
3. I(0) < F < I(1): the test is unspecified, so it is not possible to draw conclusions about long-term relations.

In this research, the F-bounds test has been computed on the model *ngsh*.

Bounf F (Wald) test		
F-statistics = 3.3927	p-value = 0.06019	
Bounds:	I(0)	I(1)
0.01	3.3354	4.3614
0.05	2.5680	3.4937
0.1	2.2191	3.0968

Figure 35. Bounds-F-test for cointegration in model *ngsh*.

As Figure 35 shows, the F-statistics lies in between the two bounds for $\alpha = 0.05$. Curiously, for $\alpha = 0.1$, it indicates the presence of some long-term relations. In this sense, these results could be misleading. To complete them, and have a clear idea of the situation, a Bound t-test for cointegration is performed too. It confirms the absence of co-integration.[150]

Bounf t test		
F-statistics = 2.105	p-value = 1	
Bounds:	I(0)	I(1)
0.01	-3.4441	-4.5826
0.05	-2.8650	-4.0002
0.1	-2.56891	-3.6661

Figure 36. Bounds-t-test for cointegration in model *ngsh*.

[150] Sam, McNown and Gosh (2019) explains how to all of three tests (F-test on lagged levels; t-test of lagged level of the dependent variable; and F-test on the lagged level of the independent variables) must point to the presence of cointegration to be sure of its existence.

Due to the absence of any long-term relationship, estimating an Error Correction Model will be pointless.

4. 4. 6 Diagnostic tests

The final step in building a model is adequacy checking. Firstly, no serial correlation should exist between residuals. The Durbin-Watson test looks exactly for this situation. When performed on *nhsg* model, it fails in rejecting the null hypothesis of no autocorrelation between residuals. The autocorrelation plot confirms this result.

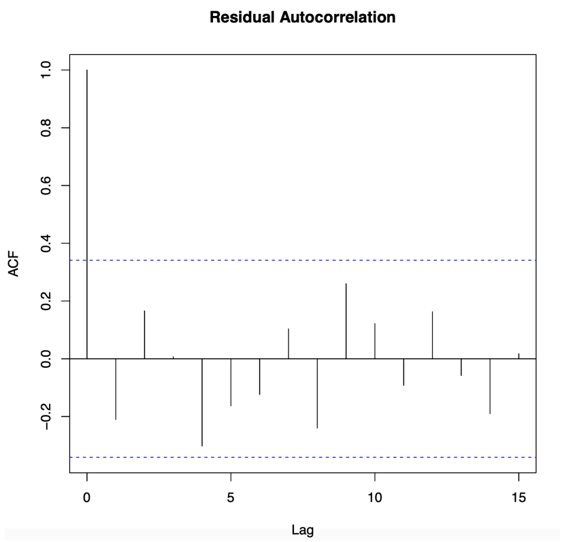

Figure 37. Residual Autocorrelation Plot.

Moreover, the residuals' normality distribution is tested. A Jarque-Bera test is employed, and it fails in rejecting the null-hypothesis of normally distributed residuals.

```
==============================================================================
Goodness of fit tests
==============================================================================
Type of test                                p-value

Jarque-Bera                                 0.5705

Durban Watson                               0.7596
```

Figure 38. JB and DW test results.

Heteroskedasticity is checked too. The Breusch-Pagan-Godfrey test confirmed the presence of heteroskedasticity. As a consequence, *ngsh* is computed again employing the White formula.[151] None of the variables changed its statistical significance.

```
==============================================================================
Ngsh model with robust standard error
==============================================================================
Coefficients
                     Estimate   Std. Error  t value    Pr(>|t|)

(Intercept)           0.1562582  0.2400687   0.6509     0.52083
L(logap_purets, 1)    1.1103601  0.0679674   16.3367    3.44e-15 ***
logas_purets          0.0164414  0.0171048   0.9612     0.34530
logoff_purets        -0.0086903  0.0135684  -0.6405     0.52747
L(logoff_purets, 1)  -0.0372971  0.0142490  -2.6175     0.01457 *
detlogcomp_purets     0.0174022  0.0123677   1.4071     0.17125
dummyts              -0.2010964  0.0826269  -2.4338     0.02212 *

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 39. *Ngsh* model with robust standard errors. Errors are computed with the White formula.

Finally, residual's CUSUM is considered. CUSUM stands for Cumulative sum, and it must not cross the significance level. *Ngsh* satisfies this stability condition.

[151] White Formula is robust to heteroskedasticity.

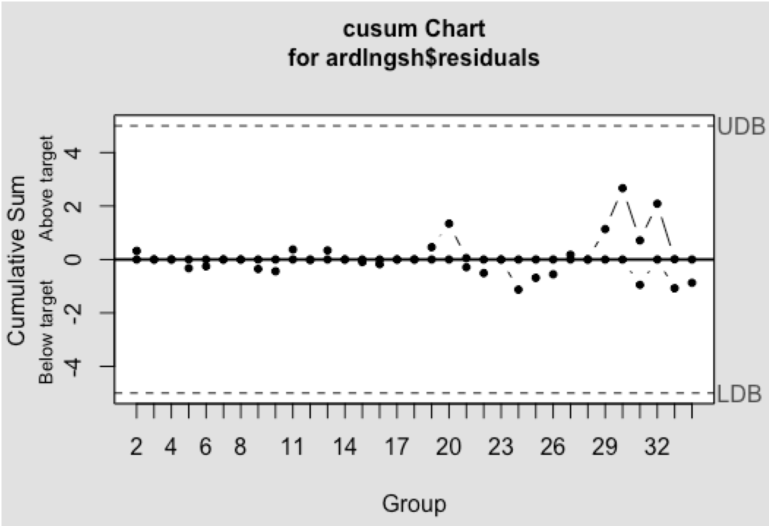

Figure 40. CUSUM plot of ngsh residuals.

4. 5 ARDL alternative model

Even though model ngsh appears to be the best-fitted model for discussing the relationship between offsets and the price of allowances, using logcomp as a regressor may be problematic.

This is due to the existing relationship between credits in the compliance account and the quantitative limit. The ceiling is imposed exactly on this account. The concern is that logcomp may be meaningfully determined by the limit.

The issue with the quantitative limit is that it is not possible to know its value for each quarter. Moreover, it is concretely imposed just during the end of the obligation year (and period). Nevertheless, since credits in this account can not be brought back to the general account or transferred, firms are attentive to not crossing this threshold in every quarter, not just in Q4. Considered in this term, the limit appears to have a strong influence on credits within the compliance account. If this is the case, the model *ngsh* could lose its significance, since credits in compliance accounts become determined also by a choice from the authority.

For this reason, a new ARDL model is estimated to discuss if the findings from previous models hold. In this case, instead of *logcomp*, is employed *loggen* as a regressor.

Again, it is important to note that this may not be the best approach. Indeed, the best approach should be to control for the ceiling and estimate a model with *logcomp*. However, due to the lack of data about the limit, this is not possible. Thus, the most cautious approach is to compute an ARDL model excluding *logcomp* to reduce the effect of the ceiling. Or, better, to reduce at least the direct effect of the ceiling on credits (since the aforementioned effect on the supply of offsets remains).

The major strength of considering credits in general accounts is that they did not depend on the quantitative limit at all. They are totally up to the willingness of the single entity. The weakness is that they display both credits that will be used for compliance and those that are used for banking. Thus, it is difficult to understand whether the effect on allowances price is due to credits for compliance or for banking.

As a consequence, in model *ncsh* allowances prices are regressed on their past prices, allowances sold, offsets supply and the sum of credits in all the general accounts.

```
============================================================================
Ncsh model
============================================================================
Coefficients:
                     Estimate   Std. Error   t value    Pr(>|t|)
_____________________________________________________________________________

(Intercept)         -0.493835   0.606207    -0.815      0.4240
L(logap_purets, 1)   0.863757   0.073756     11.711     6.34e-11 ***
logas_purets         0.020159   0.021566     0.935      0.3601
L(logas_purets, 1)   0.019248   0.020649     0.932      0.3614
L(logas_purets, 2)   0.000324   0.020344     0.016      0.9874
logoff_purets       -0.020096   0.018887    -1.064      0.2989
L(logoff_purets, 1) -0.039495   0.019326    -2.044      0.0532 .
loggen_purets       -0.065565   0.063962    -1.025      0.3165
L(loggen_purets, 1)  0.129534   0.053098     2.440      0.0232 *
covid                0.007265   0.042684     0.170      0.8664
_____________________________________________________________________________
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
_____________________________________________________________________________
Residual standard error: 0.05973 on 22 degrees of freedom
Multiple R-squared:  0.9668,     Adjusted R-squared:  0.9532
F-statistic: 71.09 on 9 and 22 DF,  p-value: 3.544e-14
```

Figure 41. *ncsh* model. The model includes *loggen* as a regressor and excludes *logcomp*.

Comparing the results with those obtained in model *ngsh* give some insights into the different relationships. The first thing to note is that the allowances price is still highly significant and maintains the same sign. This confirms that the price of the previous quarter is significant in determining the current price. The quantity of Allowance sold is still not determinant

Offsets supply maintains the inverse relation with allowances prices and the statical significance (even though it loses a little bit of it) at the lagged level. Again, this could be a consequence of bureaucratic times needed to purchase offsets issued. The loss of significance, instead, can be a consequence of the fact that now even banked permits are considered. Indeed, in model *ngsh* the only variable that indirectly comprehended also banked permits was the offset supply, even if it considered them before they were effectively banked.

Finally, the most interesting relation is the one between *loggen* and allowances price. It appears that the coefficient for 1-lag delayed *loggen* is significant and positive. From these results, two different things can be inferred. The first one is that banking has a significant effect on allowances prices. Remember that *loggen* considers both banked and surrendered credits, and that before credits in compliance accounts were not significant. This suggests that banked credits are more determinant for allowances price rather than those used for compliance. The coefficient also shows a positive relation. This could be a consequence of the fact that if firms are holding credits in the general account and not in the compliance one, they are not willing to use them for compliance but prefer to stockpile them for the future, probably forecasting a price increase. As a consequence, the price of allowances might increase because firms need more allowances to comply.

Otherwise, it could be that firms in previous periods foresee a high price of permits in the remaining time before the compliance obligation, so they bank more. Then, more banking seems to lead to a higher allowances price later, and it is exactly what it does. This could be the consequence of an expected allowances shock that will increase permits price, increase banking at the moment the shock is forecasted, and leads to more expensive allowances once it takes place.[152]

[152] Note that all tests to inquire goodness of fitness have been performed on *ncsh* model. Residuals showed no autocorrelation, no heteroskedasticity, a normal-shape distribution and in the CUSUM plotting all but one points were inside the margin.

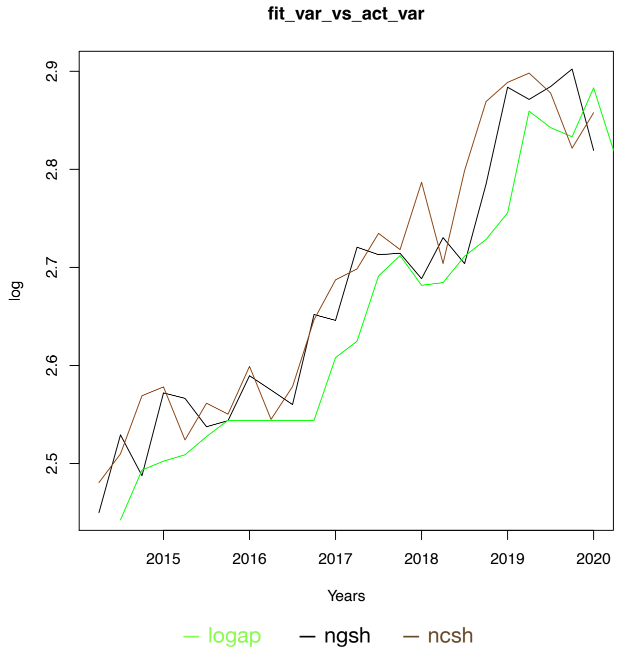

Figure 42. Estimated *logap* values for models *ngsh* and *ncsh* against real *logap* value.

4. 6 Final considerations

These last paragraphs show the relations between different elements that frame every cap and trade system. Past allowances prices and offsets issued are statically significant in explaining allowances price, while allowances sold and credits on compliance accounts seem not to be significant. What seems to be significant, instead, are credits hold in general account, maybe due to the possibility of banking. Moreover, suggestions have been given about the sign of relationship between some variables.

Unfortunately, this study is not exempt from downsides. What is likely most concerning is the sample size. Due to the period considered and data availability, it consists of a quantity of data slightly above the acceptable number. Another concern is the usage of proxies. Demand and supply are not easy to estimate. In this case, both proxies have been used. This entails the impossibility to observe real data. Another issue could be the possibility that some important variable in the relation between offsets and allowances price has been left out of the equation. Another major pitfalls was the impossibility to obtain quarterly data about the quantitative limit, and thus testing how determinant it is on offsets credits in compliance account was difficult. The only suggestion about this situation came from an analysis of all the three period. In this case, the limit appears significant in determining offsets use. Thus, this research has been limited by this constraint.

Further studies are essential to delve more into profundity in the relationship between allowances price and offsets as a whole. Ideally, it could be interesting to examine it in the other way round, by discussing if allowances prices are significant in determining offsets use. This could be done by means of a VAR (or VECM) model to inquire different relations at the same time.

Anyway, tha major improvement that this study can receive is to be performed again employing a model that takes into consideration the ceiling for offsets and either controls for it or use it as a regressor, to understand what is the role played by quantitative limits.

To develop both of these approach, this research should be proposed again when more data are available or when emitters start to disclose more information about their internal strategy. The first option is just a matter of time. The latter appears to be more problematic right now, but never say never.

Conclusion

This research adopted a political economy perspective to disentangle offsets demand. Through a mixed methods approach, it aimed to assess the effects of offsetting in both directions: factors influencing offsets and offsets influence on other cap and trade elements. The study is twofold: it examines the characteristics that affect the use of offsets by emitters regulated by the US carbon markets both at the market and sector level; then it delves into the relation between offsets and allowances price in California cap and trade.

Chapter one dealt with a description of cap and trade and offsetting, while chapter two showed the methodological choices undertaken to discuss the phenomena. Finally, chapters three and four developed the analysis of carbon offsets demand.

Using a quantitative approach supported by qualitative insights, this research identifies those ETS traits that may influence offsetting. It is possible to infer that quantitative limits, cap tightness, allowances price and project types are the elements that have a noteworthy impact on offsets use at the market level. At the firm level, instead, the two main drivers are the sector abatement cost and the sector emission intensity. Moreover, this study showed the significant relations between allowances and their past prices and between offsetting supply and banking of offsets. It did not show any relevance to the relation between allowances price and offsets used for compliance.

The results were in line with *ex-ante* expectations, and they confirmed that some elements in the cap and trade systems architecture affect the capped entities' appetite for carbon offsets. The relation between allowances price and offsets was difficult to disentangle due to the important role that the quantitative limit plays in determining offsets for compliance. For this reason, every conclusion about credits in the compliance account must be taken cautiously. What, surpassingly, appeared to have a significant effect on allowances price was credits banked within the general account of CITSS databases.

The major contribution of these findings is that they show several ETS components on which authorities can intervene if they want to decrease or increase the usage of offsets. This dissertation helps policymakers to forecast what are the possible effects on offsets of changes in structural elements of cap and trade systems. Even though here different factors are considered singularly, in the real world they interact with one another. Yet, the contribution of this discussion is that it indicates those adjustments that may decrease offset demand and the ones that will increase it. Anyway, it is always necessary to develop a tailor-made estimation of the interrelated effects based on the context by policymakers. Another important contribution is that it shows the importance of a ceiling of offsets in effectively curbing offsets use.

Unfortunately, there are some limitations that this study could not overcome. The main concerns were the small sample size and the necessity to use proxies to get insights on offsets.

As a consequence, further analysis seems necessary in the near future. It could be a good idea to perform this study again when more data becomes available to disentangle better the offsets phenomena. For example, the same approach could be employed considering different proxies and/or more variables to double-check if the outcomes do not change. Particularly, it will be extremely helpful to consider the quantitative limit of offsets. Furthermore, it would be fascinating to inquire about the same variables with a more complex econometric model (like a VAR, for example) to discuss the relations among the variables in all different directions.

This dissertation shows that it will not be painless to get rid of offsets and all the controversies that come along with them. What authorities can do, for the moment, is to create setups to dominate the increasing business appetite for offsets. It is compulsory to reduce offsets negative impacts and maximize the positive ones. Only when this is achieved, offsets will stop being just cost-saving tools and will become also emissions-reducing instruments.

Time is running out on the climate change clock, and humanity is already too late to be interested in solutions that reduce costs but not emissions.

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Annex I

```
#################################################################################################################
#                    Final Dissertation Cap 4
#*****************************************************************************************************************
# Program = Allowances and Offsets California Market
# Programmer = Luca Albertini
# Date first logger: 2023 03 05
#
#          Description: ARDL Model to estimate the relation between allowances prices and offsets in Califonria CaT.
#                    Section of the Luca Albertini Final dissertation for the master in International Politics and
Economics
#                    presented on July 2023.
#
#          Input files: in_data
#          Temp files: none
#          Output files: out_dat
#
#*****************************************************************************************************************
#set the working directory
#Luca's Macbook
setwd("~/Education/Master_Degree/Dissertation")
# set working directory
# setwd("")

#load needed packages
library("expss")
library("WDI")
library("reshape2")
require("normtest")
library("readxl")
library("reshape")
library("Hmisc")
library("tseries")
library("pastecs")
library("psych")
library("moments")
library("AER")
library("systemfit")
library("moments") # kurtosis and skewness calculations
library("stargazer") # table format for regression results
library("MASS")
library("lmtest") # required for coefci and coeftest
library("sandwich") # required for heteroskedastic robust standard errors calculation
library("plm")
library("gridExtra") # arrange graphs
library("olsrr") # Breusch-Pagan Test
library("fBasics") # dagoTest (approximates sktest)
library("ivpack")
library("ggplot2")
library("haven")
library("dplyr")
library("foreign")
library("broom")
library("estimatr")
library("Jmisc")
library("rccdates")
library("xts")
```

```
library("tis")
library("sos")
library("gridExtra")
library("corrgram")
library("urca")
library("dynlm")
library("tibble")
library("corrplot")
library("flexmix")
library("sos")
library("tsDyn") #VECM and VAR calculation
library("knitr")
library("vars")
library("seastests")
library("trend")
library("forecast")
library("ARDL")
library("dLagM")
library("lmtest")
library("egcm")
library("gamlss")
library("itsadug")
library("astsa")
library("pracma")
library("astsa")
library("tstools")
library("modelsummary")


###### this command might be useful to find to what package a function belongs
# findFn(function name)

# clear workspace
rm(list = ls())

###################################### USEFUL FUNCTIONS
############################################################

###### OUTLIERS
# count mild outliers
find_mild_out <- function(X) {
  iqr = IQR(X)
  lowerq = quantile(X)[2]
  upperq = quantile(X)[4]
  lowmildborder = lowerq - (iqr*1.5)
  upmildborder = upperq + (iqr*1.5)
  print(mild_outliers <- length(which( X > upmildborder | X < lowmildborder)))
}
# function to count total outliers
outliers <- function(X) {
  print(find_mild_out(X))}

###### QUANTS
quants <- function(series) {
  s <- series
  return(
    data.frame("Level" = s,
               "Logarithm" = log(s),
               "first log difference" = log(s) - lag(log(s)),
               "AnnualGrowthRate" = 100 * log(s / lag(s)),
               "1stLagAnnualGrowthRate" = lag(100 * log(s / lag(s))))
  )
}
```

```
# this command gives:
# the Xs of the series (the level--> in this case the GDP)
# the logarithm
# the annual growth rate
# the annual log rate lag

###### BIC
# Computation of the BIC
BIC2 <- function(model) {
  ssr <- sum(model$residuals^2)#sum of squared residual
  t <- length(model$residuals)#length of model residuals
  npar <- length(model$coef)#length of coefficent

  return(
    round(c("p" = npar - 1,
            "BIC" = log(ssr/t) + npar * log(t)/t,
            "R2" = summary(model)$r.squared), 4)
  )
}
################## population variance
var_pop <- function(X) {

  mean((X - mean(X))^2)}


#################### Interpreting augmented dickey fueller by Hank Roark
interp_urdf <- function(urdf, level="5pct") {
  if(class(urdf) != "ur.df") stop('parameter is not of class ur.df from urca package')
  if(!(level %in% c("1pct", "5pct", "10pct") ) ) stop('parameter level is not one of 1pct, 5pct, or 10pct')

  cat("========================================================================\n")
  cat( paste("At the", level, "level:\n") )
  if(urdf@model == "none") {
    cat("The model is of type none\n")
    tau1_crit = urdf@cval["tau1",level]
    tau1_teststat = urdf@teststat["statistic","tau1"]
    tau1_teststat_wi_crit = tau1_teststat > tau1_crit
    if(tau1_teststat_wi_crit) {
      cat("tau1: The null hypothesis is not rejected, unit root is present\n")
    } else {
      cat("tau1: The null hypothesis is rejected, unit root is not present\n")
    }
  } else if(urdf@model == "drift") {
    cat("The model is of type drift\n")
    tau2_crit = urdf@cval["tau2",level]
    tau2_teststat = urdf@teststat["statistic","tau2"]
    tau2_teststat_wi_crit = tau2_teststat > tau2_crit
    phi1_crit = urdf@cval["phi1",level]
    phi1_teststat = urdf@teststat["statistic","phi1"]
    phi1_teststat_wi_crit = phi1_teststat < phi1_crit
    if(tau2_teststat_wi_crit) {
      # Unit root present branch
      cat("tau2: The first null hypothesis is not rejected, unit root is present\n")
      if(phi1_teststat_wi_crit) {
        cat("phi1: The second null hypothesis is not rejected, unit root is present\n")
        cat("      and there is no drift.\n")
      } else {
        cat("phi1: The second null hypothesis is rejected, unit root is present\n")
        cat("      and there is drift.\n")
      }
    } else {
      # Unit root not present branch
      cat("tau2: The first null hypothesis is rejected, unit root is not present\n")
```

```
      if(phi1_teststat_wi_crit) {
        cat("phi1: The second null hypothesis is not rejected, unit root is present\n")
        cat("      and there is no drift.\n")
        warning("This is inconsistent with the first null hypothesis.")
      } else {
        cat("phi1: The second null hypothesis is rejected, unit root is not present\n")
        cat("      and there is drift.\n")
      }
    }
  } else if(urdf@model == "trend") {
    cat("The model is of type trend\n")
    tau3_crit = urdf@cval["tau3",level]
    tau3_teststat = urdf@teststat["statistic","tau3"]
    tau3_teststat_wi_crit = tau3_teststat > tau3_crit
    phi2_crit = urdf@cval["phi2",level]
    phi2_teststat = urdf@teststat["statistic","phi2"]
    phi2_teststat_wi_crit = phi2_teststat < phi2_crit
    phi3_crit = urdf@cval["phi3",level]
    phi3_teststat = urdf@teststat["statistic","phi3"]
    phi3_teststat_wi_crit = phi3_teststat < phi3_crit
    if(tau3_teststat_wi_crit) {
      # First null hypothesis is not rejected, Unit root present branch
      cat("tau3: The first null hypothesis is not rejected, unit root is present\n")
      if(phi3_teststat_wi_crit) {
        # Second null hypothesis is not rejected
        cat("phi3: The second null hypothesis is not rejected, unit root is present\n")
        cat("      and there is no trend\n")
        if(phi2_teststat_wi_crit) {
          # Third null hypothesis is not rejected
          # a0-drift = gamma = a2-trend = 0
          cat("phi2: The third null hypothesis is not rejected, unit root is present\n")
          cat("      there is no trend, and there is no drift\n")
        } else {
          # Third null hypothesis is rejected
          cat("phi2: The third null hypothesis is rejected, unit root is present\n")
          cat("      there is no trend, and there is drift\n")
        }
      }
      else {
        # Second null hypothesis is rejected
        cat("phi3: The second null hypothesis is rejected, unit root is present\n")
        cat("      and there is trend\n")
        if(phi2_teststat_wi_crit) {
          # Third null hypothesis is not rejected
          # a0-drift = gamma = a2-trend = 0
          cat("phi2: The third null hypothesis is not rejected, unit root is present\n")
          cat("      there is no trend, and there is no drift\n")
          warning("This is inconsistent with the second null hypothesis.")
        } else {
          # Third null hypothesis is rejected
          cat("phi2: The third null hypothesis is rejected, unit root is present\n")
          cat("      there is trend, and there may or may not be drift\n")
          warning("Presence of drift is inconclusive.")
        }
      }
    } else {
      # First null hypothesis is rejected, Unit root not present branch
      cat("tau3: The first null hypothesis is rejected, unit root is not present\n")
      if(phi3_teststat_wi_crit) {
        cat("phi3: The second null hypothesis is not rejected, unit root is present\n")
        cat("      and there is no trend\n")
        warning("This is inconsistent with the first null hypothesis.")
        if(phi2_teststat_wi_crit) {
```

```
        # Third null hypothesis is not rejected
        # a0-drift = gamma = a2-trend = 0
        cat("phi2: The third null hypothesis is not rejected, unit root is present\n")
        cat("      there is no trend, and there is no drift\n")
        warning("This is inconsistent with the first null hypothesis.")
      } else {
        # Third null hypothesis is rejected
        cat("phi2: The third null hypothesis is rejected, unit root is not present\n")
        cat("      there is no trend, and there is drift\n")
      }
    } else {
      cat("phi3: The second null hypothesis is rejected, unit root is not present\n")
      cat("      and there may or may not be trend\n")
      warning("Presence of trend is inconclusive.")
      if(phi2_teststat_wi_crit) {
        # Third null hypothesis is not rejected
        # a0-drift = gamma = a2-trend = 0
        cat("phi2: The third null hypothesis is not rejected, unit root is present\n")
        cat("      there is no trend, and there is no drift\n")
        warning("This is inconsistent with the first and second null hypothesis.")
      } else {
        # Third null hypothesis is rejected
        cat("phi2: The third null hypothesis is rejected, unit root is not present\n")
        cat("      there may or may not be trend, and there may or may not be drift\n")
        warning("Presence of trend and drift is inconclusive.")
      }
    }
  }
 } else warning('urdf model type is not one of none, drift, or trend')
 cat("========================================================================\n")
}

########## plot var fevd
plot.varfevd  <-function (x, plot.type = c("multiple", "single"), names = NULL,
             main = NULL, col = NULL, ylim = NULL, ylab = NULL, xlab = NULL,
             legend = NULL, names.arg = NULL, nc, mar = par("mar"), oma = par("oma"),
             addbars = 1, ...)
{
 K <- length(x)
 ynames <- names(x)
 plot.type <- match.arg(plot.type)
 if (is.null(names)) {
  names <- ynames
 }
 else {
  names <- as.character(names)
  if (!(all(names %in% ynames))) {
   warning("\nInvalid variable name(s) supplied, using first variable.\n")
   names <- ynames[1]
  }
 }
 nv <- length(names)
 #   op <- par(no.readonly = TRUE)
 ifelse(is.null(main), main <- paste("FEVD for", names), main <- rep(main,
                                    nv)[1:nv])
 ifelse(is.null(col), col <- gray.colors(K), col <- rep(col,
                             K)[1:K])
 ifelse(is.null(ylab), ylab <- rep("Percentage", nv), ylab <- rep(ylab,
                                   nv)[1:nv])
 ifelse(is.null(xlab), xlab <- rep("Horizon", nv), xlab <- rep(xlab,
                                 nv)[1:nv])
 ifelse(is.null(ylim), ylim <- c(0, 1), ylim <- ylim)
 ifelse(is.null(legend), legend <- ynames, legend <- legend)
```

```
  if (is.null(names.arg))
    names.arg <- c(paste(1:nrow(x[[1]])), rep(NA, addbars))
  plotfevd <- function(x, main, col, ylab, xlab, names.arg,
                       ylim, ...) {
    addbars <- as.integer(addbars)
    if (addbars > 0) {
      hmat <- matrix(0, nrow = K, ncol = addbars)
      xvalue <- cbind(t(x), hmat)
      barplot(xvalue, main = main, col = col, ylab = ylab,
              xlab = xlab, names.arg = names.arg, ylim = ylim,
              legend.text = legend, ...)
      abline(h = 0)
    }
    else {
      xvalue <- t(x)
      barplot(xvalue, main = main, col = col, ylab = ylab,
              xlab = xlab, names.arg = names.arg, ylim = ylim,
              ...)
      abline(h = 0)
    }
  }
  if (plot.type == "single") {
    #        par(mar = mar, oma = oma)
    #        if (nv > 1)
    #            par(ask = TRUE)
    for (i in 1:nv) {
      plotfevd(x = x[[names[i]]], main = main[i], col = col,
               ylab = ylab[i], xlab = xlab[i], names.arg = names.arg,
               ylim = ylim, ...)
    }
  }
  else if (plot.type == "multiple") {
    if (missing(nc)) {
      nc <- ifelse(nv > 4, 2, 1)
    }
    nr <- ceiling(nv/nc)
    par(mfcol = c(nr, nc), mar = mar, oma = oma)
    for (i in 1:nv) {
      plotfevd(x = x[[names[i]]], main = main[i], col = col,
               ylab = ylab[i], xlab = xlab[i], names.arg = names.arg,
               ylim = ylim, ...)
    }
  }
  #    on.exit(par(op))
}

###################################### PREPARE DATA
##########################################################

# load data from the Prices_r.csv (an excel file)
prices = read.csv("in_data/prices_raw.csv", header =  TRUE, sep = ",")
# have a quick look to the data
glimpse(prices)
# 36 observations of 10 variables

# preparation of the data set
#rename some variables
names(prices)[names(prices) == "Current.Auction.Settlement.Price"] <- "allow_price"
names(prices)[names(prices) == "Total.Current.Auction.Sold"] <- "allow_sold"
names(prices)[names(prices) == "Offsets.Supply..Total.amount.for.that.quarter."] <- "off_supp"
names(prices)[names(prices) == "Off.General.Account"] <- "gen_acc"
names(prices)[names(prices) == "Off.Compliance.Account"] <- "comp_acc"
names(prices)[names(prices) == "Date"] <- "date"
```

```
#select just the relevant variables
prices1 <- select(prices, date, allow_price, allow_sold,
          off_supp, gen_acc, comp_acc)
# 36 obs of 6 variables
#select just the year where there are infos (11/20113 to 08/2022)
prices1 <- dplyr::filter(prices1, date >= as.Date("2014-02-01"), date <= as.Date("2022-11-01"))
#set the right length for date
date <- prices1$date
# applying label to variables
prices1 = apply_labels (prices1,
             allow_price = "USD",
             allow_sold= "total allowances sold",
             off_supp = "offsets issued",
             gen_acc = "Total offsets in general account",
             comp_acc = "Total offsets in compliance account")
#convert data into numeric (if not already in that format)
prices1$allow_price <- as.numeric(prices1$allow_price)
prices1$allow_sold <- as.numeric(prices1$allow_sold)
prices1$off_supp <- as.numeric(prices1$off_supp)
prices1$gen_acc<- as.numeric(prices1$gen_acc)
prices1$comp_acc <- as.numeric(prices1$comp_acc)
# save data set in a folder
write.csv(prices1, file= "out_data/prices_cleaned.csv")
########### transform all the variables into time series
ap_ts <- ts(prices1$allow_price, start = c(2014, 2), end = c(2022,4), frequency = 4)
as_ts <- ts(prices1$allow_sold, start = c(2014, 2), end = c(2022,4), frequency = 4)
offsupp_ts <- ts(prices1$off_supp, start = c(2014, 2), end = c(2022,4), frequency = 4)
genacc_ts <- ts(prices1$gen_acc, start = c(2014, 2), end = c(2022,4), frequency = 4)
compacc_ts <- ts(prices1$comp_acc, start = c(2014, 2), end = c(2022,4), frequency = 4)
#add the "date" variables
date <- prices1$date
#transform "date" into date format
date <- as.Date(date)
#add all these time series into the same dataframe
prices_ts <- data.frame(date,ap_ts, as_ts, offsupp_ts,
             genacc_ts, compacc_ts)
#check the database
glimpse(prices_ts)
########### transform all variables into their natural logaritm
logap <- log(prices1$allow_price)
logas <- log(prices1$allow_sold)
logoff <- log(prices1$off_supp)
loggen <- log(prices1$gen_acc)
logcomp <- log(prices1$comp_acc)
#transform natlog in time series
logap_ts <- ts(logap, start = c(2014, 2), end = c(2022,4), frequency = 4)
logas_ts <- ts(logas, start = c(2014, 2), end = c(2022,4), frequency = 4)
logoff_ts <- ts(logoff, start = c(2014, 2), end = c(2022,4), frequency = 4)
loggen_ts <- ts(loggen, start = c(2014, 2), end = c(2022,4), frequency = 4)
logcomp_ts <- ts(logcomp, start = c(2014, 2), end = c(2022,4), frequency = 4)
#merge all the variables in the same dataframe
logall <- data.frame(date, logap_ts, logas_ts, logoff_ts,
           loggen_ts, logcomp_ts)
#transform date into date format
logall$date <- as.Date(logall$date)
# save data set in a folder (if needed)
write.csv(logall, file= "out_data/logprices.csv")
################ create the dataset without the 0
####################### remove the NA
#select just the year where there are infos (08/20114 to 08/2022)
logall_cor <- dplyr::filter(logall, date >= as.Date("2014-08-01"), date <= as.Date("2023-12-01"))
# note that the first observation has been removed since the log of 0 is not determined
#select just the relevant variables
```

```
logall_cor <- select(logall_cor, logap_ts, logas_ts, logoff_ts, loggen_ts, logcomp_ts)
#create a variable of logcomp without the 0
logas_pure <- logall_cor$logas_ts
logap_pure <- logall_cor$logap_ts
logoff_pure <- logall_cor$logoff_ts
loggen_pure <- logall_cor$loggen_ts
logcomp_pure <- logall_cor$logcomp_ts
#transform it into time series
logas_purets <- ts(logas_pure, start = c(2014, 3), end = c(2022,4), frequency = 4)
logap_purets <- ts(logap_pure, start = c(2014, 3), end = c(2022,4), frequency = 4)
logoff_purets <- ts(logoff_pure, start = c(2014, 3), end = c(2022,4), frequency = 4)
loggen_purets <- ts(loggen_pure, start = c(2014, 3), end = c(2022,4), frequency = 4)
logcomp_purets <- ts(logcomp_pure, start = c(2014, 3), end = c(2022,4), frequency = 4)
# create a database with these variable
log_pure <- data_frame(logap_purets, logas_purets, logoff_purets, loggen_purets, logcomp_purets)
#control for COVID
covid <- create_dummy_ts(end_basic = c(2022,4), dummy_start = c(2020,1), dummy_end = c(2021,3),
               sp = T, start_basic = c(2014,3), frequency = 4)
#add covid to the database
log_pure$covid <- covid
log_pure
######################################## DESCRIPTIVE STASTICS
############################################################
#general info about the variables that will be analyzed

#Summarize raw variables together
summary(prices1[,c("allow_price","allow_sold","off_supp", "gen_acc",
          "comp_acc")])
#create a dataset
stargazer(prices1[,c("allow_price","allow_sold","off_supp", "gen_acc",
           "comp_acc")], type ="text", median = TRUE, digits = 2, title = "Raw Data")
# inquire more statistics about the variables
desc1 <- describe(prices1[,c("allow_price","allow_sold","off_supp", "gen_acc",
                "comp_acc")], IQR = TRUE)
desc1 <- data.frame(desc1)
write.csv(desc1, "out_data/desc_stat.csv", row.names = F)
# insert the describe's results in a table
kable(desc1, digits = 2)

######################################## SINGLE VARIABLES ANALYSIS
##############################################################
# consider main variables alone.

######################### Allowances prices (ap)
# build separate dataframe for every variable to analyze it
allowances_prices <- select (prices_ts, ap_ts, date)
# look for the presence of outliers
invisible(capture.output(total_out_ap <- outliers(prices_ts$ap_ts)))
total_out_ap
# 5
# represent the allowances_prices
ap_plot <- plot.ts(ap_ts, col ="red", main ="Allowances_price",
          xlab = "quarter", ylab = "price", axes = TRUE)
ap_plot
# put the results in the dataframe
allowances_prices$logap_ts <- logap_ts
# transform it into numeric value
# insert label
allowances_prices = apply_labels (allowances_prices,
                 logap_ts = "log of allowances prices")
# check the structure of the dataframe
str(allowances_prices)
# Represent the log of ap
```

```
logap_plot <- plot.ts(logap_ts, col ="red", main ="Allowances prices log",
             xlab = "Years", ylab = "log_price", axes = TRUE)
logap_plot
# compute the growth rate
logap_gr <- growth.rate(logap_ts, lag =1, simple = T)
# plot the ap growth rate
ap_gr_plot <- plot.ts(logap_gr, col ="red", main ="allowances price growth rate",
             xlab = "Years", ylab = "Growth precentage", axes = TRUE)
ap_gr_plot
# save it

######################## allowances sold (as)
# build separate dataframe for every variable to analyze it
allowances_sold <- select (prices_ts, as_ts, date)
# look for the presence of outliers
invisible(capture.output(total_out_as <- outliers(prices_ts$as_ts)))
total_out_as
# 6
# represent the allowances_prices
as_plot <- plot.ts(as_ts, col ="blue", main ="Allowances_sold",
           xlab = "quarter", ylab = "price", axes = TRUE)
as_plot
# insert results in the dataframe
allowances_sold$logas_ts <- logas_ts
# labels
allowances_sold = apply_labels (allowances_sold,
                  logas_ts = "log of allowances sold")
# check the structure of the dataframe
str(allowances_sold)
# save the dataframe
# Represent the log of as
logas_plot <- plot.ts(logas_ts, col ="blue", main ="Allowances sold log",
             xlab = "Years", ylab = "log_price", axes = TRUE)
logas_plot
# compute the growth rate
logas_gr <- growth.rate(logas_ts, lag =1, simple = T)
# plot the as growth rate
as_gr_plot <- plot.ts(logas_gr, col ="blue", main ="allowances sold growth rate",
             xlab = "Years", ylab = "Growth precentage", axes = TRUE)
as_gr_plot

######################## Offsets Supply (off)

# build separate dataframe for every variable to analyze it
offsets <- select (prices_ts, offsupp_ts, date)
# look for the presence of outliers
invisible(capture.output(total_out_off <- outliers(prices_ts$offsupp_ts)))
total_out_off
# 4
# represent the offsets
off_plot <- plot.ts(offsupp_ts, col ="green", main ="Number of offsets issued",
            xlab = "quarter", ylab = "amount", axes = TRUE)
off_plot
# save it
# put the results in the dataframe
offsets$offsup_ts <- offsupp_ts
# labels
offsets = apply_labels (offsets,
              offsupp_ts = "log of offsets issued")
# check the structure of the dataframe
str(offsets)
# Represent the log of off
logoff_plot <- plot.ts(logoff_ts, col ="green", main ="log of offsets issued",
```

```
            xlab = "Years", ylab = "log_number", axes = TRUE)
logoff_plot
# save it
# compute the growth rate
logoff_gr <- growth.rate(logoff_ts, lag =1, simple = T)
# plot the off growth rate
off_gr_plot <- plot.ts(logoff_gr, col ="green", main ="Offsets issued growth rate",
            xlab = "Years", ylab = "Growth precentage", axes = TRUE)
off_gr_plot
# save it

######################## General account (genacc)

# build separate dataframe for every variable to analyze it
general <- select (prices_ts, genacc_ts, date)
# look for presence of outliers
invisible(capture.output(total_out_off <- outliers(prices_ts$genacc_ts)))
total_out_off
# 0
# represent the offsets
gen_plot <- plot.ts(genacc_ts, col ="orange", main ="Number of offsets in the general account",
          xlab = "quarter", ylab = "amount", axes = TRUE)
gen_plot
# save it
# put the results in the dataframe
general$genacc_ts <- genacc_ts
# labels
offsets = apply_labels (offsets,
             genacc_ts = "Log of offsets in general account")
# check the structure of the dataframe
str(general)
# Represent the log of off
loggen_plot <- plot.ts(loggen_ts, col ="orange", main ="log of offsets in general account",
            xlab = "Years", ylab = "log_number", axes = TRUE)
loggen_plot
# save it
# compute the growth rate
loggen_gr <- growth.rate(loggen_ts, lag =1, simple = T)
# plot the off growth rate
gen_gr_plot <- plot.ts(loggen_gr, col ="orange", main ="Offsets in general account growth rate",
            xlab = "Years", ylab = "Growth precentage", axes = TRUE)
gen_gr_plot
# save it

######################## Compliance account (compacc)

# build separate dataframe for every variable to analyze it
compt <- select (prices_ts, compacc_ts, date)
# look for the presence of outliers
invisible(capture.output(total_out_off <- outliers(prices_ts$gcompacc_ts)))
total_out_off
# 0
# represent the offsets
comp_plot <- plot.ts(compacc_ts, col ="pink", main ="Offsets in the compliance account",
           xlab = "quarter", ylab = "amount", axes = TRUE)
comp_plot
# save it
# put the results in the dataframe
compt$compacc_ts <- compacc_ts
# labels
offsets = apply_labels (offsets,
             compacc_ts = "Log of offsets in compliance account")
# check the structure of the dataframe
```

```
str(general)
# Represent the log of off
logcomp_plot <- plot.ts(logcomp_ts, col ="pink", main ="log of offsets in compliance account",
                xlab = "Years", ylab = "log_offset", axes = TRUE)
logcomp_plot
# save it
# compute the growth rate
logcomp_gr <- growth.rate(logcomp_ts, lag =1, simple = T)
# plot the off growth rate
comp_gr_plot <- plot.ts(logcomp_gr, col ="pink", main ="Offsets in compliance account growth rate",
                xlab = "Years", ylab = "Growth precentage", axes = TRUE)
comp_gr_plot
# save it

######################## Show all charts together
######### real values chart (for all the variables)
par(mfrow = c(2,3))
ap_plot <- plot.ts(ap_ts, col ="red", main ="Allowances_price",
            xlab = "quarter", ylab = "price", axes = TRUE)
ap_plot
as_plot <- plot.ts(as_ts, col ="blue", main ="Allowances_sold",
            xlab = "quarter", ylab = "price", axes = TRUE)
as_plot
off_plot <- plot.ts(offsupp_ts, col ="green", main ="Number of offsets issued",
            xlab = "quarter", ylab = "price", axes = TRUE)
off_plot
gen_plot <- plot.ts(genacc_ts, col ="orange", main ="Number of offsets in the general account",
            xlab = "quarter", ylab = "price", axes = TRUE)
gen_plot
comp_plot <- plot.ts(compacc_ts, col ="pink", main ="Offsets in the compliance account",
            xlab = "quarter", ylab = "price", axes = TRUE)
comp_plot
#save them
pdf("out_data/values_plot.pdf")
par(mfrow = c(2,3))
ap_plot <- plot.ts(ap_ts, col ="red", main ="Allowances_price",
            xlab = "quarter", ylab = "price", axes = TRUE)
ap_plot
as_plot <- plot.ts(as_ts, col ="blue", main ="Allowances_sold",
            xlab = "quarter", ylab = "price", axes = TRUE)
as_plot
off_plot <- plot.ts(offsupp_ts, col ="green", main ="Number of offsets issued",
            xlab = "quarter", ylab = "price", axes = TRUE)
off_plot
gen_plot <- plot.ts(genacc_ts, col ="orange", main ="Offsets in general account",
            xlab = "quarter", ylab = "price", axes = TRUE)
gen_plot
comp_plot <- plot.ts(compacc_ts, col ="pink", main ="Offsets in compliance account",
            xlab = "quarter", ylab = "price", axes = TRUE)
comp_plot
dev.off()

######### log charts (for all the variables)
par(mfrow = c(2, 3))
logap_plot <- plot.ts(logap_ts, col ="red", main ="Allowances prices log",
              xlab = "Years", ylab = "log_price", axes = TRUE)
logap_plot
logas_plot <- plot.ts(logas_ts, col ="blue", main ="Allowances sold log",
              xlab = "Years", ylab = "log_price", axes = TRUE)
logas_plot
logoff_plot <- plot.ts(logoff_ts, col ="green", main ="log of offsets issued",
              xlab = "Years", ylab = "log_number", axes = TRUE)
logoff_plot
```

```
loggen_plot <- plot.ts(loggen_ts, col ="orange", main ="log of offsets in general account",
              xlab = "Years", ylab = "log_number", axes = TRUE)
loggen_plot
logcomp_plot <- plot.ts(logcomp_ts, col ="pink", main ="log of offsets in compliance account",
               xlab = "Years", ylab = "log_offset", axes = TRUE)
logcomp_plot
# save them
pdf("out_data/log_plot.pdf")
par(mfrow = c(2, 3))
logap_plot <- plot.ts(logap_ts, col ="red", main ="Allowances prices log",
             xlab = "Years", ylab = "log_price", axes = TRUE)
logap_plot
logas_plot <- plot.ts(logas_ts, col ="blue", main ="Allowances sold log",
             xlab = "Years", ylab = "log_price", axes = TRUE)
logas_plot
logoff_plot <- plot.ts(logoff_ts, col ="green", main ="log of offsets issued",
              xlab = "Years", ylab = "log_number", axes = TRUE)
logoff_plot
loggen_plot <- plot.ts(loggen_ts, col ="orange", main ="log of offsets in general account",
              xlab = "Years", ylab = "log_number", axes = TRUE)
loggen_plot
logcomp_plot <- plot.ts(logcomp_ts, col ="pink", main ="log of offsets in compliance account",
               xlab = "Years", ylab = "log_offset", axes = TRUE)
logcomp_plot
dev.off()

######### growth rates charts (for all the variables), with a different command
par(mfrow = c(2, 3))
ap_gr_plot <- plot.ts(logap_gr, col ="red", main ="allowances price growth rate",
             xlab = "Years", ylab = "Growth precentage", axes = TRUE)
ap_gr_plot
as_gr_plot <- plot.ts(logas_gr, col ="blue", main ="allowances sold growth rate",
             xlab = "Years", ylab = "Growth precentage", axes = TRUE)
as_gr_plot
off_gr_plot <- plot.ts(logoff_gr, col ="green", main ="Offsets issued growth rate",
              xlab = "Years", ylab = "Growth precentage", axes = TRUE)
off_gr_plot
gen_gr_plot <- plot.ts(loggen_gr, col ="orange", main ="Offsets in general account growth rate",
              xlab = "Years", ylab = "Growth precentage", axes = TRUE)
gen_gr_plot
comp_gr_plot <- plot.ts(logcomp_gr, col ="pink", main ="Offsets in compliance account growth rate",
               xlab = "Years", ylab = "Growth precentage", axes = TRUE)
comp_gr_plot
# save it
pdf("out_data/diff_plot.pdf")
par(mfrow = c(2, 3))
ap_gr_plot <- plot.ts(logap_gr, col ="red", main ="allowances price growth rate",
             xlab = "Years", ylab = "Growth precentage", axes = TRUE)
ap_gr_plot
as_gr_plot <- plot.ts(logas_gr, col ="blue", main ="allowances sold growth rate",
             xlab = "Years", ylab = "Growth precentage", axes = TRUE)
as_gr_plot
off_gr_plot <- plot.ts(logoff_gr, col ="green", main ="Offsets issued growth rate",
              xlab = "Years", ylab = "Growth precentage", axes = TRUE)
off_gr_plot
gen_gr_plot <- plot.ts(loggen_gr, col ="orange", main ="Offsets in general account growth rate",
              xlab = "Years", ylab = "Growth precentage", axes = TRUE)
gen_gr_plot
comp_gr_plot <- plot.ts(logcomp_gr, col ="pink", main ="Offsets in compliance account growth rate",
               xlab = "Years", ylab = "Growth precentage", axes = TRUE)
comp_gr_plot
dev.off()
```

```
#clear the work space
dev.off()

########################### Plot all the logs in the same chart
# Draw first time series
logall_plot <- plot(logall$date,                    # Draw first time series
             logall$logap_ts,
             type = "l",
             col = "red",
             ylim = c(- 0, 20),
             xlab = "Year",
             ylab = "log")
# Draw  the other time series
lines(logall$date,                    # Draw 2 time series
   logall$logas_ts,
   type = "l",
   col = "blue")
lines(logall$date,                    # Draw 3 time series
   logall$logoff_ts,
   type = "l",
   col = "green")
lines(logall$date,                    # Draw 4 time series
   logall$loggen_ts,
   type = "l",
   col = "orange")
lines(logall$date,                    # Draw 5 time series
   logall$logcomp_ts,
   type = "l",
   col = "pink")
title(main = "all variables log")# add the title
par(xpd = TRUE)
legend("bottomright", legend = c("logap", "logas", "logoff", "loggen", "logcomp"),
    col = c("red", "blue", "green", "orange", "pink"), pch = 4, lty =1, cex = 0.8 )

#save it
pdf("out_data/all_var.pdf")
logall_plot <- plot(logall$date,                    # Draw first time series
             logall$logap_ts,
             type = "l",
             col = "red",
             ylim = c(- 0, 20),
             xlab = "Year",
             ylab = "log")
# Draw  the other time series
lines(logall$date,                    # Draw 2 time series
   logall$logas_ts,
   type = "l",
   col = "blue")
lines(logall$date,                    # Draw 3 time series
   logall$logoff_ts,
   type = "l",
   col = "green")
lines(logall$date,                    # Draw 4 time series
   logall$loggen_ts,
   type = "l",
   col = "orange")
lines(logall$date,                    # Draw 5 time series
   logall$logcomp_ts,
   type = "l",
   col = "pink")
title(main = "all variables log")
dev.off()
```

```
####################################### SEASONALITY and TRENDS
################################################
################  Plots to look for seasonality and trends
#ap_ts
logap_trend <- decompose(logap_ts)
plot(logap_trend)
#as_ts
logas_trend <- decompose(logas_ts)
plot(logas_trend)
#off_supp
logoff_trend <- decompose(logoff_ts)
plot(logoff_trend)
#genacc
loggen_trend <- decompose(loggen_ts)
plot(loggen_trend)
#compacc
logcomp_trend <- decompose(logcomp_purets)
plot(logcomp_trend)

################ SEASONALITY
############# Seasonality test - logged variables
isSeasonal(logas_purets, freq = 4) #FALSE
isSeasonal(logap_purets, freq = 4) #FALSE
isSeasonal(logoff_purets, freq = 4) #FALSE
isSeasonal(loggen_purets, freq = 4) #FALSE
isSeasonal(logcomp_purets, freq = 4) #FALSE
#no seasonality for any data

################### TREND
#### Use Mann-Kendall test to spot trend.
#H0: there is not a trend
#H1: a trend (positive or negative) exists
#if p-value < a reject H0
#tau is the strenght of the trend
############### natlogs
mk.test(logas_purets) #can not reject H0, no trend (0.4767)
mk.test(logap_purets) #reject H0, trend (2.431e-13)
mk.test(logoff_purets) #can not reject H0, no trend (0.8125)
mk.test(loggen_purets) #reject H0, trend (3.494e-08)
mk.test(logcomp_purets) #can not reject H0 for 0.05, no trend (0.1381)
#clear the environment
dev.off()

####################################### TREND ANALYSIS
##########################################################
#spot the trend for all the variables
trend(logap_purets) #trend
trend(logas_purets) #no trend, seasonality?
trend(logoff_purets) #no trend
trend(loggen_purets) #trend
trend(logcomp_purets) #trend?
#detrend the series

####### ATTENTION ON LOGCOMP
#it appears to have a quadratic trend
# de-trending
#set logcomp as time
t = time(logcomp_purets)
#transform it into quadratic
t2 = t^2
#(linear) model the trend
model2 = lm(logcomp_purets ~ t +t2)
#show it
```

```
summary(model2)
#extract the values
expected <- fitted.values(model2)
#change to numeric format
expectedn <- as.numeric(expected)
#change to ts object
expected_ts <- ts(expectedn, start = c(2014, 2), end = c(2022,4), frequency = 4)
#de-trend the series
detlogcomp_ts <- (logcomp_purets - expected_ts)
#show the new time series
plot(detlogcomp_ts)
#mk.test
mk.test(detlogcomp_ts)
#plot the original data and the trend
plot(ts(fitted(model2)), ylim=c(min(c(fitted(model2), as.vector(logcomp_purets))), max(c(fitted(model2),
as.vector(logcomp_purets)))),
     ylab='y', main = "logcomp")
lines(as.vector(logcomp_purets),type="o")
#compute the residuals
res.model2 = rstudent(model2)
plot(y = res.model2, x = as.vector(time(logcomp_purets)),xlab = 'Time',
     ylab='Studentized Residuals of model2',type='p')
abline(h=0)
#histogram for the residual
hist(res.model2, xlab = 'Standardized Residuals')
#normality chart for the residuals
qqnorm(res.model2)
qqline(res.model2, col=2, lwd=1, lty=2)
#build a datafram with the detrended variable
lognt_purets <- data.frame(logap_purets, logas_purets, logoff_purets,
                     loggen_purets, detlogcomp_ts)
#analyze the trend
trend(detlogcomp_ts)
#remove the structural break
detlogcomp21_ts <- ts(detlogcomp_ts, start = c(2014, 2), end = c(2021,1), frequency = 4)
#show the detrended variable
trend(detlogcomp21_ts)

##### create the dummy variable for Q1 2021
dummyts <- create_dummy_ts(end_basic = c(2022,3), dummy_start = c(2022,2), dummy_end = c(2022,4),
            sp = T, start_basic = c(2014,3), frequency = 4)
# add the dummy to the database
log_pure$dummyts <- dummyts
log_pure
plot.ts(detlogcomp_ts, main ="allowances price growth rate",
       xlab = "Years", ylab = "Growth precentage", axes = TRUE)

########################################  CORRELATION
############################################################
# study the correlation among all the variables with the pearson coefficient
# to have an idea of their relation

################## NATLOGS
#create a database with the correlation of the natlogs
corrlogs <- cor(logall_cor)
#show them
corrlogs
#plot the correlogram of all the natlogs
corrplot(corrlogs, title = "Log Correlation", type = "lower", method = "color",
       outline = T, addCoef.col = "white", tl.col = "black")
#save it
pdf("out_data/log_corr.pdf")
corrplot(corrlogs, type = "lower", method = "color",
```

```
        outline = T, addCoef.col = "white", tl.col = "black")
dev.off()
################## VARIABLES
price_cor <- select(prices1, allow_price, allow_sold,
                 off_supp, gen_acc, comp_acc)
corvar <- cor(price_cor)
#plot it
corrplot(corvar, type = "lower", method = "color",
        outline = T, addCoef.col = "white", tl.col = "black")
#save it
pdf("out_data/var_corr.pdf")
corrplot(corvar, type = "lower", method = "color",
        outline = T, addCoef.col = "white", tl.col = "black")
dev.off()
##### correlation between different loggen - logcomp and allow pric
diffacc <- (loggen_pure - logcomp_pure)
diffacc_ts <- ts(diffacc, start = c(2014, 3), end = c(2022,4), frequency = 4)
cor(diffacc_ts, logap_purets)
# correlation: 0.06826428.
#######################################  STATIONARITY
##########################################################
# Examine Stationarity
#################### AUTOCORRELATION
#plot the autocorrelation to have an idea of the stationarity of the data
# clear the space
dev.off()
# set the plot space in a way to contain 2 charts
par(mfrow = c(3, 2))
##### Allowances price
acf(na.omit(logap_ts), lag.max = 34, plot = F)
acf(na.omit(logap_ts), lag.max = 34, main ="log allowances price autocorrelation")
##### Allowances sold
acf(na.omit(logas_ts), lag.max = 35, plot = F)
acf(na.omit(logas_ts), lag.max = 35, main ="log allowances sold autocorrelation")
##### offsets supply
# compute autocorrelation and plot it
acf(na.omit(offsupp_ts), lag.max = 35, plot = F)
acf(na.omit(offsupp_ts), lag.max = 35, main ="log of offsets supply autocorrelation")
##### offsets general account
# compute autocorrelation and plot it
acf(na.omit(genacc_ts), lag.max = 35, plot = F)
acf(na.omit(genacc_ts), lag.max = 35, main ="log levels of offsets in general account autocorrelation")
##### compliance account
# compute autocorrelation and plot it
acf(na.omit(compacc_ts), lag.max = 35, plot = F)
acf(na.omit(compacc_ts), lag.max = 35, main ="log levels of offsets in compliance account autocorrelation")
#detrended logcomp
acf(na.omit(detlogcomp21_ts), lag.max = 34, plot = F)
acf(na.omit(detlogcomp21_ts), lag.max = 34, main ="detrended log levels of offsets in compliance account
autocorrelation")
# save it
pdf("out_data/autocorr.pdf")
par(mfrow = c(3, 3))
acf(na.omit(logap_ts), lag.max = 34, plot = F)
acf(na.omit(logap_ts), lag.max = 34, main ="Allowances price log autocorrelation")
acf(na.omit(logas_ts), lag.max = 35, plot = F)
acf(na.omit(logas_ts), lag.max = 35, main ="Allowances sold log autocorrelation")
acf(na.omit(offsupp_ts), lag.max = 35, plot = F)
acf(na.omit(offsupp_ts), lag.max = 35, main ="Offsets supply log autocorrelation")
acf(na.omit(genacc_ts), lag.max = 35, plot = F)
acf(na.omit(genacc_ts), lag.max = 35, main ="Offsets in general acc log autocorrelation")
acf(na.omit(compacc_ts), lag.max = 35, plot = F)
acf(na.omit(compacc_ts), lag.max = 35, main ="Offsets in compliance acc log autocorrelation")
```

```
acf(na.omit(detlogcomp21_ts), lag.max = 34, plot = F)
acf(na.omit(detlogcomp21_ts), lag.max = 34, main ="detrended log levels of offsets in compliance account autocorrelation")
dev.off()

# clear the space
dev.off()

#################### DICEKY-FUELLER TEST
# Run an augmented Dickey-Fueller test on the logged levels and on the first differences of the log
# Dickey-Fuller test on the logged levels
# compare the value with tau3
# H0: there is a unit root in the logged levels --> nonstationarity

######################## allowance prices
#ADF
summary(ur.df(logap_purets,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
#interpret the results
interp_urdf(ur.df(logap_purets,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: 2.3731 4.5005 5.0933
#try other tests to confirm the results
#adf test, =/ command
adf.test(logap_purets)
#pp test
pp.test(logap_purets, type = "Z(alpha)")
pp.test(logap_purets, type = "Z(t_alpha)")
#kpss test
kpss.test(logap_purets, null = "Trend")
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(logap_purets)

######################## allowance sold
# ADF
summary(ur.df(logas_purets,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(logas_purets,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: -4.0289 7.3448 10.355
#try other tests to confirm the results
#adf test, =/ command
adf.test(logas_purets)
adf.test(logas_purets)
#pp test
pp.test(logas_purets, type = "Z(alpha)")
pp.test(logas_purets, type = "Z(t_alpha)")
#kpss test
kpss.test(logas_purets)
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(logas_purets)

######################## offsets
#ADF
summary(ur.df(logoff_purets,
```

```
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(logoff_purets,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: -1.7507 2.63 3.9187
#try other tests to confirm the results
#adf test, =/ command
adf.test(logoff_purets)
#pp test
pp.test(logoff_purets, type = "Z(alpha)")
pp.test(logoff_purets, type = "Z(t_alpha)")
#kpss test
kpss.test(logoff_purets, null = "Level")
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(logoff_purets)

######################## general account
# ADF
summary(ur.df(loggen_purets,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(loggen_purets,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: -1.3502 0.9872 1.3681
#try other tests to confirm the results
#adf test, =/ command
adf.test(loggen_purets)
#pp test
pp.test(loggen_purets, type = "Z(alpha)")
pp.test(loggen_purets, type = "Z(t_alpha)")
#kpss test
kpss.test(loggen_purets)
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(loggen_purets)

######################## compliance account (removed 1 period)
#ADF
summary(ur.df(logcomp_purets,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(logcomp_purets,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: -3.8153 5.8072 8.7078
#try other tests to confirm the results
#adf test, =/ command
adf.test(logcomp_purets)
#pp test
pp.test(logcomp_purets, type = "Z(alpha)")
pp.test(logcomp_purets, type = "Z(t_alpha)")
#kpss test
kpss.test(logcomp_purets)
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(logcomp_purets)
#detrended logcomp
```

```
#ADF
summary(ur.df(detlogcomp_ts,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
#interpret the results
interp_urdf(ur.df(detlogcomp_ts,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: 2.3731 4.5005 5.0933
#try other tests to confirm the results
#adf test, =/ command
adf.test(detlogcomp_ts)
#pp test
pp.test(detlogcomp_ts, type = "Z(alpha")
#kpss test
kpss.test(detlogcomp_ts, null = "Level")
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(detlogcomp_ts)

#logcomp with no trend and no structural break
#ADF
summary(ur.df(detlogcomp21_ts,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
#interpret the results
interp_urdf(ur.df(detlogcomp21_ts,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
# result: 2.3731 4.5005 5.0933
#try other tests to confirm the results
#adf test, =/ command
adf.test(detlogcomp21_ts)
#pp test
pp.test(detlogcomp21_ts, type = "Z(t_alpha)")
#kpss test
kpss.test(detlogcomp21_ts, null = "Level")
#test for unit roots variance ratio (the rho is the variance, the p-value is as usual)
bvr.test(detlogcomp21_ts)

################################ DIFFERENCING I(1)
################################################
#to transform nonstationary series into stationry the techniques it so difference
#in this case a first order differencing will be made
#this is done for testing if an ARDL model can be implemented

######################## allowance prices
diffap <- diff(logap_purets)
summary(ur.df(diffap,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(diffap,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
#try other tests to confirm the results
#adf test, =/ command
adf.test(diffap)
# p-value 0.01 so i reject the null hypothesis
```

```
pp.test(diffap, type = "Z(alpha)")
#p-value 0.01295 so i reject the null hypothesis of nonstationrairty
pp.test(diffap, type = "Z(t_alpha)")
#p-value 0.02306 so i reject the null hypothesis of nonstationrairty
kpss.test(diffap, null = "Level")
# with the detrended data

######################## allowance sold
# ADF
diffas <- diff(logas_purets)
summary(ur.df(diffas,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(diffas,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
#try other tests to confirm the results
#adf test, =/ command
adf.test(diffas)
# p-value 0.01 so i reject the null hypothesis
pp.test(diffas, type = "Z(alpha)")
#p-value 0.01295 so i reject the null hypothesis of nonstationrairty
pp.test(diffas, type = "Z(t_alpha)")
#p-value 0.02306 so i reject the null hypothesis of nonstationrairty
kpss.test(diffas, null = "Level")

######################## offsets
#ADF
diffoff <- diff(logoff_purets)
summary(ur.df(diffoff,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(diffoff,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
#try other tests to confirm the results
#adf test, =/ command
adf.test(diffoff)
# p-value 0.01 so i reject the null hypothesis
pp.test(diffoff, type = "Z(alpha)")
#p-value 0.01295 so i reject the null hypothesis of nonstationrairty
pp.test(diffoff, type = "Z(t_alpha)")
#p-value 0.02306 so i reject the null hypothesis of nonstationrairty
kpss.test(diffoff, null = "Level")

######################## general account
diffgen <- diff(loggen_purets)
summary(ur.df(diffgen,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(diffgen,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
#try other tests to confirm the results
#adf test, =/ command
adf.test(diffgen)
pp.test(diffgen, type = "Z(alpha)")
```

```
pp.test(diffgen, type = "Z(t_alpha)")
kpss.test(diffgen, null = "Level")

######################## compliance account (removed 1 period)
#ADF
diffcomp <- diff(logcomp_purets)
summary(ur.df(diffcomp,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(diffcomp,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
#try other tests to confirm the results
#adf test, =/ command
adf.test(diffcomp)
pp.test(diffcomp, type = "Z(alpha)")
pp.test(diffcomp, type = "Z(t_alpha")
kpss.test(diffcomp, null = "Level")
kpss.test(diffcomp, null = "Trend")
ndiffs(logap_ts, test = "kpss")
#perform test with detrending
bvr.test(diffcomp, detrend = TRUE)
# detrended logcomp
diffdetlogcomp <- diff(detlogcomp_ts)
diffdetlogcomp <- ts(diffdetlogcomp, start = c(2014, 2), end = c(2021,1), frequency = 4)
summary(ur.df(diffdetlogcomp,
        type = "trend",
        lags = 8,
        selectlags = "BIC"))
interp_urdf(ur.df(diffdetlogcomp,
          type = "trend",
          lags = 8,
          selectlags = "BIC"))
#try other tests to confirm the results
#adf test, =/ command
adf.test(diffdetlogcomp)
# pp-tests
pp.test(diffdetlogcomp, type = "Z(alpha)")
pp.test(diffdetlogcomp, type = "Z(t_alpha)")
# kpss test
kpss.test(diffdetlogcomp, null = "Level")

########## MODEL TESTING
##################################### EXTERNAL TREND
################################################
#nt = no logcomp detrended mode, but trend integrated in the model
##################################### COMPUTE THE RIGHT LAG LENGTH
##################################
#compute the bound Wald test for cointegration
#this command estimated the ARDL, the related ECM, the right lag length and the cointegration test
ardlBICnt <- ardlBound(data = log_pure, logap_purets ~ logas_purets + logoff_purets +
      loggen_purets + logcomp_purets + trend(logcomp_purets), case = 3, p = NULL,
      remove = NULL, autoOrder = FALSE, ic = "BIC" , max.p = 4, max.q = 3,
      ECM = TRUE, stability = TRUE)
#BIC selection: 4, 4, 4,4,3
ardlAICmt <- ardlBound(data = log_pure, logap_purets ~ logas_purets + logoff_purets +
             loggen_purets + logcomp_purets + trend(logcomp_purets), case = 3, p = NULL,
            remove = NULL, autoOrder = FALSE, ic = "AIC" , max.p = 4, max.q = 3,
            ECM = TRUE, stability = TRUE)
#AIC selection: 4, 4, 4,4,3
```

```
############################################ ARDL
###################################################
#estimate the ARDL Model with shorter lags
ardlnt <- ardl(logap_purets ~ logas_purets + logoff_purets +
              loggen_purets + logcomp_purets + trend(logap_purets), data = log_pure, order = c(4, 4, 4,4,3))
ardlntsum <- summary(ardlnt)
se_ardlnt <- ardlntsum$coefficients[,2]
#plot to see the difference the model together and the the real price
#fv_sh <- fitted.values(ardlsh)
#fv_sh <- ts(fv_sh, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot(fv_sh)
fv_nt <- fitted.values(ardlnt)
fv_nt <- ts(fv_nt, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot the model estimation and the real values
plot.ts(fv_nt,type="l",col="red", main ="fit_val_vs_act_val",
       xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
#lines(fv_sh, col = "blue")
###### residual analysis (long lag model)
#save the residual
resnt <- ardlnt$residuals
resnt2 <- resnt^2
#show them
summary(resnt)
# look for residuals autocorrelation
acf(ardlnt$residuals, type = "correlation")
#save it
pdf("out_data/res_corr.pdf")
acf(ardlnt$residuals, type = "correlation")
dev.off()
# test for it with Durban Watson Test
dwtest(ardlnt)
# no correlation among residuals

############################################ COINTEGRATION
############################################
#perform a bound test to see if there is cointegration (long-model)
# if F > I(1) -> cointegration, if F < I(0) -> no cointegration
#if I(0) < F < I(1) test is not specified
#F bound test
bounds_f_test(ardlnt, alpha = 0.05, case = 5)
# T bounds test
bounds_t_test(ardlnt, alpha = 0.05, case = 5)

############################################ DETRENDED ANALYSIS
############################################
#dt = logcomp already detrended, without dummy
### add covid to lognt_purets
lognt_purets$covid <- covid
##########################################################################################
###########
#this command estimated the ARDL, the related ECM, the right lag length and the cointegration test
ardlAICdt <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
                loggen_purets + detlogcomp_ts, case = 3, p = NULL,
              remove = NULL, autoOrder = FALSE, ic = "BIC" , max.p = 4, max.q = 3,
              ECM = TRUE, stability = TRUE)
#BIC selection: 4,4,4,4,3
ardlAICdt <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
                loggen_purets + detlogcomp_ts, case = 3, p = NULL,
              remove = NULL, autoOrder = FALSE, ic = "AIC" , max.p = 4, max.q = 3,
              ECM = TRUE, stability = TRUE)
#AIC selection: 4,4,4,4,3
```

```
########################################## ARDL
##################################################
ardldt <- ardl(logap_purets ~ logas_purets + logoff_purets +
         loggen_purets + detlogcomp_ts + covid, data = lognt_purets, order = c(4,4,4,4,3,0))
summary(ardldt)
#fitted values
fv_dt <- fitted.values(ardldt)
fv_dt <- ts(fv_dt, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot the model estimation and the real values
plot.ts(fv_dt,type="l",col="orange", main ="Offsets in general account growth rate",
    xlab = "Years", ylab = "Growth precentage", axes = TRUE)
lines(logap_purets,col="green")
#lines(fv_sh, col = "blue")

###### residual analysis (long lag model)
#save the residual
resdt <- ardldt$residuals
resdt2 <- resdt^2
#show them
summary(resdt)
# look for residuals autocorrelation
acf(ardldt$residuals, type = "correlation")
#save it
pdf("out_data/res_corr.pdf")
acf(ardldt$residuals, type = "correlation")
dev.off()
# test for it with Durban Watson Test
dwtest(ardldt)
# no correlation among residuals

######################################### COINTEGRATION
###########################################
#perform a bound test to see if there is cointegration (short-model)
# if F > I(1) -> cointegration, if F < I(0) -> no cointegration
#if I(0) < F < I(1) test is not specified
ardldt
#double check the results of the bound test
bounds_f_test(ardldt, alpha = 0.05, case = 2)
# double check with the results of the t test
bounds_t_test(ardldt, alpha = 0.05, case = 3)

############################ DETRENDED AND DUMMY VARIABLE ANALYSIS
########################
#dtd: logcomp detrended and dummy vriable added for structural break
#add the dummy to the database
lognt_purets$dummyts <- dummyts
###########################################################################################
#this command estimated the ARDL, the related ECM, the right lag length and the cointegration test
ardlBICdtd <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
             loggen_purets + detlogcomp_ts, case = 3, p = NULL,
            remove = NULL, autoOrder = FALSE, ic = "BIC" , max.p = 4, max.q = 3,
            ECM = TRUE, stability = TRUE)
#BIC selection: 4,4,4,4,3
ardlAICdtd <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
             loggen_purets + detlogcomp_ts, case = 3, p = NULL,
            remove = NULL, autoOrder = FALSE, ic = "AIC" , max.p = 4, max.q = 3,
            ECM = TRUE, stability = TRUE)
#AIC selection: 4,4,4,4,3
########################################## ARDL
##################################################
ardldtd <- ardl(logap_purets ~ logas_purets + logoff_purets +
         loggen_purets + detlogcomp_ts + dummyts + covid,
         data = lognt_purets, order = c(4,4,4,4,3,0,0))
```

```
summary(ardldtd)
#fitted values
fv_dtd <- fitted.values(ardldtd)
fv_dtd <- ts(fv_dtd, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot the model estimation and the real values
plot.ts(fv_dtd,type="l",col="pink", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")

###### residual analysis (long lag model)
#save the residual
resdtd <- ardldtd$residuals
resdtd2 <- resdtd^2
#show them
summary(resdtd)
# look for residuals autocorrelation
acf(ardldtd$residuals, type = "correlation")
#save it
pdf("out_data/res_corr.pdf")
acf(ardldtd$residuals, type = "correlation")
dev.off()
# test for it with Durban Watson Test
dwtest(ardldtd)
# no correlation among residuals

############################################ COINTEGRATION
##############################################
#perform a bound test to see if there is cointegration (short-model)
# if F > I(1) -> cointegration, if F < I(0) -> no cointegration
#if I(0) < F < I(1) test is not specified
ardldtd
#double check the results of the bound test
bounds_f_test(ardldtd, alpha = 0.05, case = 2)
# double check with the results of the t test
bounds_t_test(ardldtd, alpha = 0.05, case = 3)

############################################# WITHOUT LOGGEN
#############################################
#ng = logcomp already detrended, without dummy
##################################################################################################
############
#this command estimated the ARDL, the related ECM, the right lag length and the cointegration test
ardlAICng <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
                detlogcomp_ts, case = 3, p = NULL,
                remove = NULL, autoOrder = FALSE, ic = "BIC" , max.p = 4, max.q = 3,
                ECM = TRUE, stability = TRUE)
#BIC selection: 4,4,3,4
ardlAICng <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
                 + detlogcomp_ts, case = 3, p = NULL,
                remove = NULL, autoOrder = FALSE, ic = "AIC" , max.p = 4, max.q = 3,
                ECM = TRUE, stability = TRUE)
#AIC selection: 4,4,3,4
ardlBoundOrders(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
            + detlogcomp_ts, ic = "BIC", max.q = 4, max.p =4)
############################################ ARDL
#################################################
ardlng <- ardl(logap_purets ~ logas_purets + logoff_purets
          + detlogcomp_ts + dummyts + covid, data = lognt_purets, order = c(4,4,3,4,0,0))
summary(ardlng)
ardlngsh <- ardl(logap_purets ~ logas_purets + logoff_purets
          + detlogcomp_ts + dummyts + covid, data = lognt_purets, order = c(1,0,1,0,0,0))
summary(ardlngsh)
#fitted values
```

```
fv_ng <- fitted.values(ardlng)
fv_ng <- ts(fv_ng, start = c(2014, 2), end = c(2020,1), frequency = 4)
fv_ngsh <- fitted.values(ardlngsh)
fv_ngsh <- ts(fv_ngsh, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot the model estimation and the real values
plot.ts(fv_ng,type="l",col="orange", main ="Offsets in general account growth rate",
        xlab = "Years", ylab = "Growth precentage", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_ngsh, col = "black")
#lines(fv_sh, col = "blue")
vif(ardlngsh)
#choice ardlngsh

###### residual analysis (long lag model)
#save the residual
resngsh <- ardlngsh$residuals
resngsh2 <- resngsh^2
#show them
summary(resngsh)
# look for residuals autocorrelation
acf(ardlngsh$residuals, type = "correlation")
#save it
pdf("out_data/res_corr1.pdf")
acf(ardlngsh$residuals, type = "correlation", main = "Residual Autocorrelation")
dev.off()
# test for it with Durban Watson Test
dwtest(ardlngsh)
# no correlation among residuals
#Breusch pagan test
bptest(ardlngsh)
#presence of heteroskedasticity
#compute robust standard error and re-estimate the model
ardlngsh_rob <- coeftest(ardlngsh, vcov = sandwich)
#normality of the residuals
jarque.bera.test(ardlngsh$residuals)
#residuals are normally distributed
#compute the cumsum for the residuals
library(qcc)
cusum1 <- cumsum(ardlngsh$residuals)
#cusum plot
cusum(ardlngsh$residuals)

########################################### COINTEGRATION
############################################
#perform a bound test to see if there is cointegration (short-model)
# if F > I(1) -> cointegration, if F < I(0) -> no cointegration
#if I(0) < F < I(1) test is not specified
ardlngsh
#double check the results of the bound test
bounds_f_test(ardlngsh, alpha = 0.05, case = 2)
# double check with the results of the t test
bounds_t_test(ardlngsh, alpha = 0.05, case = 3)

############################################ WITHOUT LOGCOMP
###########################################
#nc = logcomp is not considered, since it may be determined by the cap
###############################################################################################
############
#this command estimated the ARDL, the related ECM, the right lag length and the cointegration test
ardlAICnc <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
                   loggen_purets, case = 3, p = NULL,
                  remove = NULL, autoOrder = FALSE, ic = "BIC" , max.p = 4, max.q = 3,
                  ECM = TRUE, stability = TRUE)
```

```
#BIC selection: 3,3,2,3
ardlAICnc <- ardlBound(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
              + loggen_purets, case = 3, p = NULL,
             remove = NULL, autoOrder = FALSE, ic = "AIC" , max.p = 4, max.q = 3,
             ECM = TRUE, stability = TRUE)
#AIC selection: 3,3,2,3
ardlBoundOrders(data = lognt_purets, logap_purets ~ logas_purets + logoff_purets +
          + loggen_purets, ic = "BIC", max.q = 4, max.p =4)
############################################ ARDL
#####################################################
ardlnc <- ardl(logap_purets ~ logas_purets + logoff_purets
        + loggen_purets + covid, data = lognt_purets, order = c(3,3,2,3,0))
summary(ardlnc)
ardlncsh <- ardl(logap_purets ~ logas_purets + logoff_purets
         + loggen_purets + covid, data = log_pure, order = c(1,2,1,1,0))
summary(ardlncsh)
#fitted values
fv_nc <- fitted.values(ardlnc)
fv_nc <- ts(fv_nc, start = c(2014, 2), end = c(2020,1), frequency = 4)
fv_ncsh <- fitted.values(ardlncsh)
fv_ncsh <- ts(fv_ncsh, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot the model estimation and the real values
plot.ts(fv_nc,type="l",col="deeppink", main ="Offsets in general account growth rate",
     xlab = "Years", ylab = "Growth precentage", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_ncsh, col = "chocolate4")
#lines(fv_sh, col = "blue")
vif(ardlncsh)
#choice ardlngsh

###### residual analysis (long lag model)
#save the residual
resncsh <- ardlncsh$residuals
resncsh2 <- resncsh^2
#show them
summary(resncsh)
# look for residuals autocorrelation
acf(ardlncsh$residuals, type = "correlation")
#save it
pdf("out_data/res_corr_ncsh.pdf")
acf(ardlngsh$residuals, type = "correlation", main = "Residual Autocorrelation")
dev.off()
# test for it with Durban Watson Test
dwtest(ardlncsh)
# no correlation among residuals
#Breusch pagan test
bptest(ardlncsh)
#homoskedasticity
#normality of the residuals
jarque.bera.test(ardlncsh$residuals)
#residuals are normally distributed
#compute the cumsum for the residuals
cusumncsh <- cumsum(ardlncsh$residuals)
#cusum plot
cusum(ardlncsh$residuals)
plot(cusumncsh)

########################################### COINTEGRATION
############################################
#perform a bound test to see if there is cointegration (short-model)
# if F > I(1) -> cointegration, if F < I(0) -> no cointegration
#if I(0) < F < I(1) test is not specified
ardlncsh
```

```
#double check the results of the bound test
bounds_f_test(ardlncsh, alpha = 0.05, case = 2)
# double check with the results of the t test
bounds_t_test(ardlncsh, alpha = 0.05, case = 3)
#no cointegration

####################################### MODELS COMPARISON
#######################################
#plot the different fitted values in the same chart
plot.ts(fv_dtd,type="l",col="pink", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_nt, col = "red")
lines(fv_dt, col = "blue")
#save it
pdf("out_data/fit_vs_act.pdf")
plot.ts(fv_dtd,type="l",col="pink", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_nt, col = "red")
lines(fv_dt, col = "blue")
dev.off()
############# include all the model
plot.ts(fv_dtd,type="l",col="pink", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_nt, col = "red")
lines(fv_dt, col = "blue")
lines(fv_ng, col = "orange")
lines(fv_ngsh, col = "black")
lines(fv_nc,col="deeppink")
lines(fv_ncsh, col = "chocolate4")
#save it
pdf("out_data/fit_vs_act.pdf")
plot.ts(fv_dtd,type="l",col="pink", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_nt, col = "red")
lines(fv_dt, col = "blue")
lines(fv_ng, col = "orange")
lines(fv_ngsh, col = "black")
lines(fv_nc,col="deeppink")
lines(fv_ncsh, col = "chocolate4")
dev.off()
# just loggen and logcomp model
plot.ts(fv_ngsh,type="l",col="black", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_ncsh, col = "chocolate4")
#save it
pdf("out_data/fit_vs_act_compgen.pdf")
plot.ts(fv_ngsh,type="l",col="black", main ="fit_var_vs_act_var",
        xlab = "Years", ylab = "log", axes = TRUE)
lines(logap_purets,col="green")
lines(fv_ncsh, col = "chocolate4")
dev.off()
#include all the models in the same table
#nt
ardlnt_sum <- summary(ardlnt)
se_nt <- (ardlnt_sum$coefficients[,2])
#dt
ardldt_sum <- summary(ardldt)
se_nt <- (ardldt_sum$coefficients[,2])
```

```
#dtd
ardldtd_sum <- summary(ardldtd)
se <- nt <- (ardldtd$coefficient[,2])
####### unify all together

################################ DETRENDED LOGAP
##################################################
#this command estimated the ARDL, the related ECM, the right lag length and the cointegration test
detlogap <- detrend(logap_purets)
ardlAICng <- ardlBound(data = log_pure, logap_purets ~ logas_purets + logoff_purets +
              detlogcomp_ts, case = 3, p = NULL,
             remove = NULL, autoOrder = FALSE, ic = "BIC" , max.p = 4, max.q = 3,
             ECM = TRUE, stability = TRUE)
#BIC selection: 4,4,3,4
ardlAICng <- ardlBound(data = log_pure, logap_purets ~ logas_purets + logoff_purets +
              + detlogcomp_ts, case = 3, p = NULL,
             remove = NULL, autoOrder = FALSE, ic = "AIC" , max.p = 4, max.q = 3,
             ECM = TRUE, stability = TRUE)
#AIC selection: 4,4,3,4
########################################### ARDL
###################################################
ardlng <- ardl(logap_purets ~ logas_purets + logoff_purets
        + detlogcomp_ts + dummyts, data = log_pure, order = c(4,4,3,4,0))
summary(ardlng)
#fitted values
fv_ng <- fitted.values(ardlng)
fv_ng <- ts(fv_ng, start = c(2014, 2), end = c(2020,1), frequency = 4)
#plot the model estimation and the real values
plot.ts(fv_ng,type="l",col="orange", main ="Offsets in general account growth rate",
    xlab = "Years", ylab = "Growth precentage", axes = TRUE)
lines(logap_purets,col="green")
#lines(fv_sh, col = "blue")

###### residual analysis (long lag model)
#save the residual
resng <- ardlng$residuals
resng2 <- resng^2
#show them
summary(resng)
# look for residuals autocorrelation
acf(ardlng$residuals, type = "correlation")
#save it
pdf("out_data/res_corr.pdf")
acf(ardlng$residuals, type = "correlation")
dev.off()
# test for it with Durban Watson Test
dwtest(ardlng)
# no correlation among residuals

########################################## COINTEGRATION
############################################
#perform a bound test to see if there is cointegration (short-model)
# if F > I(1) -> cointegration, if F < I(0) -> no cointegration
#if I(0) < F < I(1) test is not specified
ardlng
#double check the results of the bound test
bounds_f_test(ardlng, alpha = 0.05, case = 2)
# double check with the results of the t test
bounds_t_test(ardlng, alpha = 0.05, case = 3)


###########################################################################################
##############################
```

THE END
###
##