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Abstract

CO_2 mitigation policies are one of the main tools to reduce CO_2 emissions from industries. Unfortunately, the link between GDP growth and emissions trends has not been directly addressed. In this document, we propose a method for decomposing the growth of CO_2 emissions based on information from national accounts, which breaks down the rate of variation of emissions into three components: scale, composition, and mitigation. This method directly measures the effectiveness of mitigation efforts at the national level. Using Chilean data for the last two decades, we show that, without mitigation attempts, total CO_2 emissions would have increased nearly 50 percentage points more than the actual number.

Resumen

Las políticas de mitigación de CO_2 son una de las principales herramientas para reducir las emisiones de CO_2 de las actividades económicas. Desafortunadamente, el vínculo entre el crecimiento del PIB y la tendencia de las emisiones no se ha abordado directamente. En este documento, proponemos un método para descomponer el crecimiento de las emisiones de CO_2 basado en información de las cuentas nacionales, que divide la tasa de variación de las emisiones en tres componentes: escala, composición y mitigación. Este método mide directamente la efectividad de los esfuerzos de mitigación a nivel nacional. Usando datos chilenos de las últimas dos décadas, mostramos que, sin intentos de mitigación, las emisiones totales de CO_2 habrían aumentado casi 50 puntos porcentuales más que el número real.

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*The views expressed are those of the author and do not necessarily represent the views of the Central Bank of Chile or its board members.

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1. Introduction

Anthropogenic greenhouse gas (GHG) emissions are one of the main drivers of climate change. Most of these emissions come from using fossil fuels to produce goods and services by industries.[1] GHG emanations are also expected to grow as the gross domestic product (GDP) increases. However, the coupling between both figures is not yet clearly determined. For instance, changes in the composition of GDP can alter the relation between overall economic activity and GHG emissions. Also, the mitigation policies that incentive the use of cleaner technologies can also decouple the trend between both variables.

A well-known GHG mitigation policy is the Intended Nationally Determined Contributions (NDCs), where countries have pledged to reduce emissions, which describes the national actions that they intend to take to reach the Paris Agreement's long-term temperature goal of limiting warming to well below 2°C above pre-industrial levels. The main sectors included in the NDCs are energy, industrial process and product use, waste, and land. At the same time, the GHG targets can be formulated to cover all significant GHGs or only a subset of them[2]. NDCs are comparable among economies, and their accomplishment can be measured over time.

Checking the effectiveness of countries' mitigation efforts to achieve NDCs goals is critical to disentangling the main forces that drive GHG emissions through economic activity production. For instance, in a scenario of high GDP growth, GHG emissions can increase even when mitigation policies are effective. On the other hand, if the composition of the GDP changes towards less pollutant activities, CO_2 emissions can decrease even if no mitigation policies have been adopted. In this study, we propose a simple and direct decomposition method which measures how economic growth, GDP composition and mitigation efforts affect CO_2 emissions. By matching national inventory reports of GHG emissions and national accounts data, we break down the emissions growth rate into three main effects: scale, composition, and mitigation.

The scale effect measures how GDP growth affects GHG emissions. The composition effect accounts for the change in emissions trend from industries heterogeneity when contributing to emissions and production. Finally, the mitigation effect reflects how the change in emissions intensity within economic activities affects total emissions.[3] For instance, the mitigation effect can operate through adopting more efficient technologies or upgrading technologies from those that use fossil fuels to others based on renewals.

One advantage of this structural decomposition is that it accounts for the GHG mitigation gains relative to the actual value produced by the different industries following the national accounts methodology. This feature lets policymakers directly relate the transition path to NDCs' goals with economic activity trends. The correct assessment of the link between both variables –emissions and economic activity– is essential to keep track of the transition to a zero-carbon stage.

Our method is closely related to previous work on emissions trend decomposition. Following the seminal work of (Copeland & Taylor, 1994), several authors have estimated a detailed measurement of composition and mitigation effects while narrowing the analysis to the manufacturing sector. (Levinson, 2009; 2015) shows that manufacturing emissions between 1987 and 2001 declined by 25 percent while output grew approximately the same amount; the author finds that efficiency gains in emissions mainly explain the difference. Similar

[1] See (Lee, et al., 2023).

[2] The main GHG are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorochemicals (PFCs), sulfur hexafluoride (SF_6) and nitrogen trifluoride (NF_3).

[3] See (UNEP, 2022) for a formal treatment of mitigation in the context of climate change.

results can be found in Canada (Cherniwchan & Najjar, 2021), Germany (Rottner & von Graevenitz, 2021), Sweden (Ustyuzhanina, 2021), and China (Zhang, 2012).[4]

For the Chilean case, (Accorsi, López, & Sturla, 2018) estimate a structural decomposition model based on the input-output framework for the period 2008-2013, finding that as the economy tilts its production to services, the composition effect plays an essential role in reducing emissions. On the other hand, (Cansino, Sánchez-Braza, & Rodríguez-Arévalo, 2018), using a decomposition analysis based on the log-mean divisia index, show that the energy intensity effect is the primary driver factor of Chile's CO_2 emissions between 1991 and 2013.

In the present study, we estimate the Chilean GHG growth decomposition for 1996-2020, using emissions data from the Chilean inventory report on GHG and national accounts (NA) data. The level of aggregation in NA allowed to include six main industries: agriculture-forestry, fishing, mining, manufacturing, utilities, trade-accommodation-food, and transport.

Emissions from the activities, as mentioned earlier, increased 63.7% between 1996 and 2020, while their value added in terms of volume grew by 91.7%. Therefore, according to the scale effect, GHG emissions should have almost doubled without mitigation attempts and with a constant GDP composition. On the other hand, if we consider the scale and composition effects, emissions from these economic activities would have increased by 114.6%. This number shows that cleaner sectors have lost preponderance in overall production over the last twenty years.

The difference between the actual emissions growth rate (63.7%) and the counterfactual that assumes only scale and composition effects (114.6%) exposes how the mitigation efforts have paid off in reducing GHG emissions, which in the case of Chile implies a decrease of 50.9 percentage points (p.p.). This result shows that Chilean economic activity emissions would have more than doubled in the last twenty years without cleaner technologies.

A caveat must be made regarding the proposed decomposition using NA data. Depending on the level of aggregation, emissions cuts due to changes in the production mix can be captured in the mitigation effect. For instance, if we consider manufacturing as one whole sector, changes in the production mix within manufacturing branches that imply a decrease in GHG emissions will be captured in the mitigation effect, overestimating this last effect. Hence, we extend the decomposition formula to further disaggregation levels to measure how the aggregation affects our previous estimation. This extension reveals the impact of sectors' aggregation, which can shed light on the direction and magnitude of the aggregate estimation bias. By including five manufacturing branches published in Chilean national accounts —food, beverages, and tobacco; pulp, paper, and printing; chemicals; non-metallic and natural metallic products; and machinery and equipment— to the extended formula, we were able to quantify the aggregation bias of the previous estimation. Our results show that if we treat manufacturing as a whole sector, the composition effect is underestimated (from 22.9 p.p. to 24.6 p.p.) with an equal and opposite impact regarding mitigation (from -50.9 p.p. to -52.6 p.p.).

[4] For studies that relate efficiency gains and international trade see (LaPlue & Erickson, 2020), and (Brunel & Levinson, 2021), and the literature cited there.

The paper is organized as follows: in the next section, we describe the decomposition theoretical framework. In section 3, we present the primary data sources used in this exercise, and in section 4, we show the main results. Section 5 extends the decomposition to more disaggregated data, and the last section concludes.

2. GHG emissions growth decomposition

Let $\mathcal{E}$ be an economy with I economic activities indexed by i. The production process involves using inputs that release pollution to the environment. We denote the emissions of activity i in year t as $e_t^i \geq 0$, which is measured in millions of tons of CO_2.[5] The total pollution emitted by economic activities in year t (E_t) is given by:

$$E_t = \sum_{i=1}^{I} e_t^i. \tag{1}$$

As pollution comes from production process activities, we assume that the activity i emissions depend linearly on the value produced as follows:[6]

$$e_t^i = \theta_t^i v_t^i, \qquad \forall i \in \{1, \dots, I\} \tag{2}$$

where v_t^i is the value produced, measured in millions of chain-linked Chilean pesos (CLP) and θ_t^i is the pollution intensity measured in tons of pollutants per million of chain-linked CLP. The parameter θ measures the degree of GHG that activities release due to their production process. For instance, if $\theta_{t-1}^i > \theta_t^i$, we say that activity i has become more efficient in year t as it releases a lesser amount of pollutant per value produced concerning the previous year. For our case, we assume that $\theta \in [0, \infty)$, so there are no economic activities that capture CO_2 from the environment in their production process.

We define V_t as the total value produced in the economy, measured in millions of chain-linked CLP. On the other hand, the nominal counterparts are denoted by $v_{N,t}^i$ and $V_{N,t} = \sum_i v_{N,t}^i$, respectively. To simplify notation, the growth rate of variable $X \in \{E, V\}$ in year t is written as $g_{X,t}$.

In contrast to constant price data, v_t^i is measured in chain-linked terms, meaning that the long-run volume measures are constructed by cumulating movements in short-term indices with different base periods. Chain-linked values update activity weights in total output yearly, allowing to keep track of relevant changes in relative prices that are not considered in a fixed-base index.[7] The caveat of the chain-linked index is that activity production cannot be added directly to compute aggregates which implies that the levels of θ_t^i cannot be compared across industries. However, as we will see below, this issue does not affect our proposed decomposition, as technological change is measured in terms of growth contributions that can be added between economic activities.

[5] We do not account for CO_2 sequestration.

[6] See appendix A for a derivation of this formula from a Cobb-Douglas production function.

[7] For chain-linked measures in NA see (Dippelsman, Josyula, & Métreau, 2016).

In practice, the non-additivity issue can be circumvented by calculating additive contributions to yearly percent changes from chain-linked volume series based on the Laspeyres method as follows:[8]

$$g_{V,t} = \sum_{i=1}^{I} \beta_{t-1}^{i} g_{v,t}^{i}, \tag{3}$$

where $\beta_t^i = \frac{v_{N,t}^i}{V_{N,t}}$ represents activity i share in aggregate nominal value.[9] The above formula allows for keeping track of activities' volume variations in comparable terms, which will prove to be useful in the decomposition formula below.

Employing equations (1) to (3), the annual growth rate in total emissions ($g_{E,t}$) can be decomposed into three main effects:

$$g_{E,t} = \underbrace{\sum_{i=1}^{I} \Delta_{t-1}^{i} g_{v,t}^{i}}_{\substack{\text{Composition}\\ \text{Effect}}} + \underbrace{\sum_{i=1}^{I} \alpha_{t-1}^{i} g_{\theta,t}^{i}}_{\substack{\text{Mitigation}\\ \text{Effect}}} + \underbrace{g_{V,t}}_{\substack{\text{Scale}\\ \text{Effect}}}. \tag{4}$$

In the above equation, $\alpha_t^i = e_t^i / E_t$ is activity i share in total emissions and $\Delta_t^i = \alpha_t^i - \beta_t^i$ is the difference between activity i's share in emissions and its share in total nominal value.[10] Each component on the right side of equation (4) captures a different driver of CO_2 emissions' evolution.

The first term on the right side of equation (4), named composition effect, measures how the heterogeneity between activities tilts the evolution of total emissions. The heterogeneity is measured as activities' participation in emissions relative to the one in nominal value. For a given activity, the more significant the difference between α_t and β_t, the higher will be the incidence of its growth in terms of volume ($g_{v,t}^i$) in this component. For instance, the higher is the growth in activities that pollute more, and which also do not represent a large share of nominal GDP, the higher will be the composition effect, and so the growth in total emissions.

On the other hand, the mitigation effect in equation (4) shows how mitigation policies and technological change within economic activities influence GHG emissions; if activities reduce their pollution per unit of value produced (θ decreases), overall emissions will fall even if GDP and production mix remain constant. The mitigation effect is strongly related to the policies that help firms to invest in cleaner technologies.

From equation (2), the mitigation effect for activity i can be expressed in terms of observed variables since:

$$g_{\theta,t}^{i} \approx g_{e,t}^{i} - g_{v,t}^{i}.$$

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[8] Chain-linked volume measures in monetary terms based on the annually chain-linked Laspeyres formula will be additive in the reference year and the subsequent year.
[9] See appendix B for a derivation of equation (3).
[10] See appendix C for a derivation of equation (4).

Therefore, an activity becomes cleaner if the growth in GHG emissions is slower than the one observed in value ($g^i_{\theta,t} < 0$). This occurs, for instance, when the firms update their production process to one that uses inputs that pollute less or when their productivity increases over time.

Finally, the scale effect shows that the dynamics of overall GHG emissions should be equal to the economic growth if the technologies and activities mix remains constant.[11] In other words, all things equal, as the size of an economy increases, the demand for polluting inputs increases, and so does the pollution derived from them.

Each component in equation (4) can be directly computed using observed activity level data on emissions and production. The following section presents the data used to calculate the proposed decomposition.

3. Data

Our proposed growth decomposition relies mainly on two datasets: industries' GHG emissions and their production and added value measured in volume. Both datasets are then matched at an industry level.

Data on activities' pollutant emissions comes from the National Greenhouse Gas Inventory (NGHGI) published by the Chilean Ministry of Environment. The NGHGI measures anthropogenic GHG releases to the environment yearly, calculated per the 2006 IPCC[12] Guidelines for national greenhouse gas inventories. The NGHGI records emissions of carbon dioxide (CO_2) and the CO_2 equivalent counterparts from methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbon (HFC), perfluorocarbon (PFC), and sulphur hexafluoride (SF_6).[13] Emissions are estimated for the following sectors: Energy; industrial processes; product use; land use, land-use change and forestry (LULUCF); and waste. Each of these sectors is further subdivided into IPCC categories or subsectors. The years covered by the Chilean NGHGI range from 1990 to 2020 for all the above-mentioned pollutants.[14]

According to the NA activity breakdowns based on the International Standard Industrial Classification (ISIC rev4), emissions data is merged with industries' value added. The Central Bank of Chile (BCCh) publishes data on industries' value added for twenty-three economic activities, eight of which belong to the manufacturing sector. We set 1996 as the reference year and drop activities that do not present emissions in the NGHGI during the whole period. The list of remaining activities used in this study is shown in Table 1.

[11] We focus on activities that pollute the environment, i.e., the activities that do not present emissions during the relevant period are not considered in the analysis.
[12] Intergovernmental Panel on Climate Change.
[13] Also, the NGHGI includes other pollutants released to the environment such as nitrogen oxides (NO_X), carbon monoxide (CO), non-methane volatile compounds (VOC) and sulfur dioxide (SO_2). However, these pollutants are partially measured and not used this study.
[14] For further information on how sector emissions were computed see (Gomez, et al., 2006).

Table 1
Economic activities with GHG emissions

Agriculture-Forestry	
Fishing	
Mining	
Manufacturing	Food, beverages, and tobacco
	Pulp, paper, and printing
	Chemicals
	Non-metallic and raw metallic products
	Machinery and equipment
Utilities	
Trade, accommodation, and food	
Transport	

Note: Utilities include power generation, transmission and distribution, water, gas, and waste management.

The BCCh publishes the volume of value added as a chain-linked index, implying that the long-run volume measures are constructed by cumulating movements in short-term indices with different base periods. Chain-linked values update industry weights in total output yearly, allowing to keep track of relative prices changes that can be relevant. As mentioned in the previous section, the caveat of the chain-linked index is that activity production cannot be added directly to compute overall GDP.[15]

Table 2
CO_2 emissions
(kt)

	1996	2008	Average annual growth	2009	2020	Average annual growth
CO_2	50,863	75,232	3.3%	72,422	83,245	1.3%

Source: Authors' calculations based on NGHGI and NA data.

Table 2 shows the emissions dynamics for all the industries included in the study. The CO_2 average growth rate has declined in the last twenty years, from 3.3% in 1996-2008 to 1.3% in 2009-2020. The main contributors to this result are utilities and transport, where both activities increased their share of emissions over time. Conversely, agriculture-forestry-fishing and manufacturing have reduced GHG emissions over the same period (figure 2).[16]

[15] For chained-linked measures in NA see (Dippelsman, Josyula, & Métreau, 2016).

[16] As mentioned above, we only account for emissions for the selected industries and we do not subtract CO_2 captures by the Land Use, Land-Use Change and Forestry (LULUCF) sector.

Figure 2
CO_2 emissions by Industry
(as % of total)

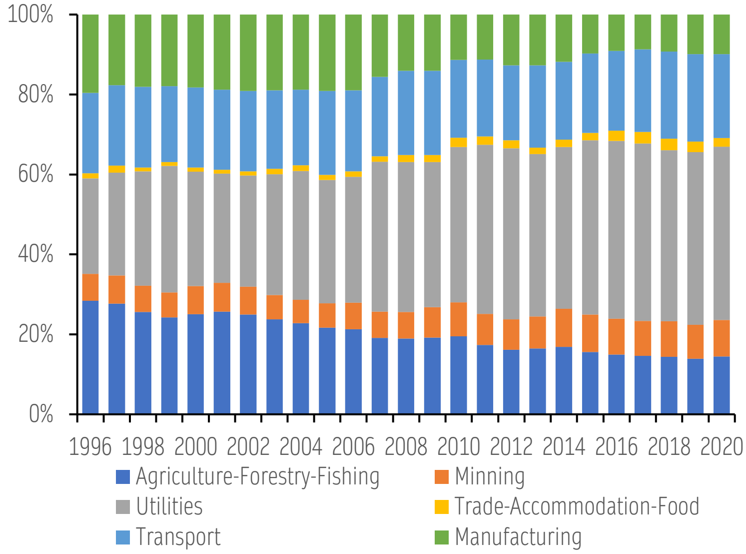
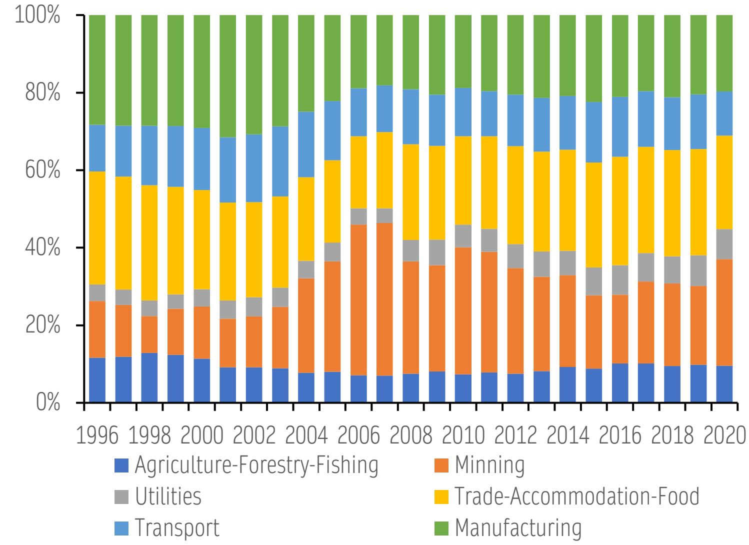


Figure 3
Nominal GDP by Industry
(as % of total)



Source: Authors's calculations based on NGHGI and NA data.

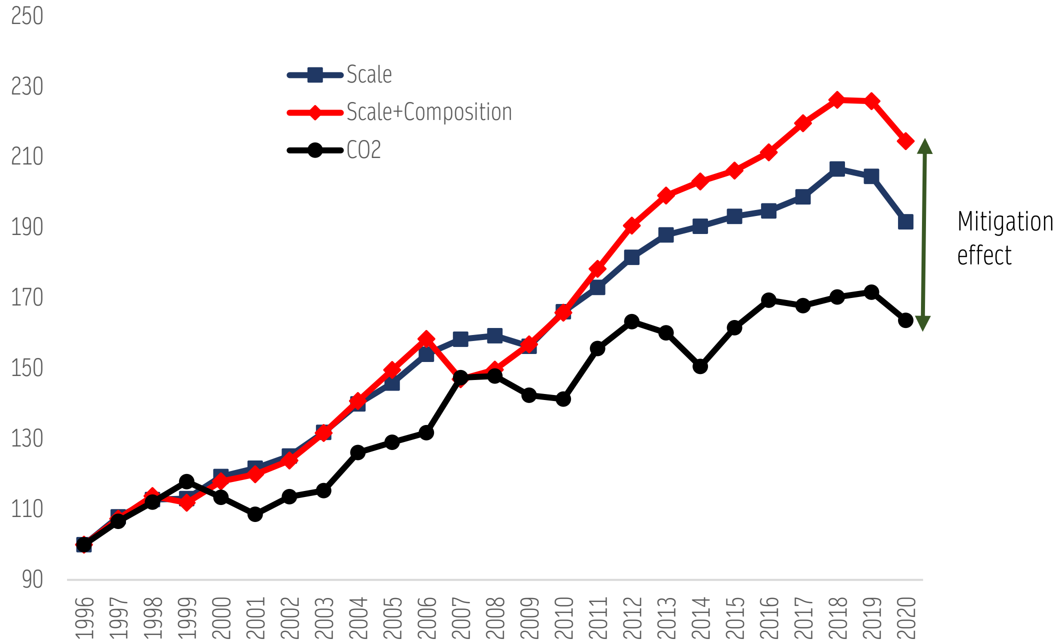
The composition of the nominal value produced shows a higher variability than the one observed in emissions. The activities with the most significant shares are trade, accommodation, and food; manufacturing; and mining, where mining has the largest variability in the period as it inherits the volatility in copper prices (figure 3).

The difference between activity shares in emissions and the one in nominal GDP is the primary driver of the composition effect. For the case of utilities, their share in emissions is more significant than its share in nominal value added; from equation (3), this implies that, as this activity grows in volume, its incidence to the composition effect will be positive. Conversely, as the manufacturing volume grows, its contribution will be negative to this effect, as its share in emissions is lower than its share in nominal value added.

4. CO_2 growth decomposition results

In this section, we present two counterfactual exercises that depict what would have been the evolution of CO_2 emissions if the different boosters had remained unchanged since 1996. The first exercise assumes that the composition and mitigation effects are null, i.e., emissions are driven only by the scale effect in this scenario. The second case assumes that only the mitigation effect is null. In this setting, we believe that the scale and composition effects determine the evolution of GHG emissions. Thus, the remaining difference between the second case result and the current trend in GHG emissions reveals the mitigation effect.

Figure 4
CO_2 emissions decomposition
(1996=100)



Source: Authors' calculations based on NGHGI and NA data.

Under the first scenario, CO_2 emissions would have increased more than ninety percent in the last two decades (line Scale in Figure 4). However, CO_2 emissions increased by 63.7% (line CO_2 in Figure 4). The difference between both numbers encompasses the composition and mitigation effects.

The second counterfactual exercise, which allows GDP and its production mix to change over time while leaving emissions intensity (θ) constant, shows that GHG emissions would have increased by 116%, meaning that production has tilted towards more polluting activities in the last decades. This trend has increased in the previous quinquennia, as shown in Figure 4 (scale+composition line).

The remainder difference between the current level of CO_2 and the scale+composition counterfactual is due to the mitigation effect. In aggregate terms, economic activities have become cleaner in the last two decades, a tendency that has increased in the previous decade, more than compensating for the tilting of GDP towards more polluting activities.

Table 2 summarizes the previous results by splitting the CO_2 emissions growth rate between 1996 and 2020 into three effects. Without the mitigation effect, the GHG emissions would have grown 114.6% in 1996-2020, with a scale effect contributing 91.7 percentage points (p.p.) and composition adding 22.9 p.p. However, emissions only grew 63.7%, meaning that the mitigation effect had an incidence of -50.9 p.p. in total growth. Thus, even though emissions have increased over the last decades, they would have been more significant given the trends in economic activity.

Table 2
Emissions decomposition, 1996-2020
(In percentage points)

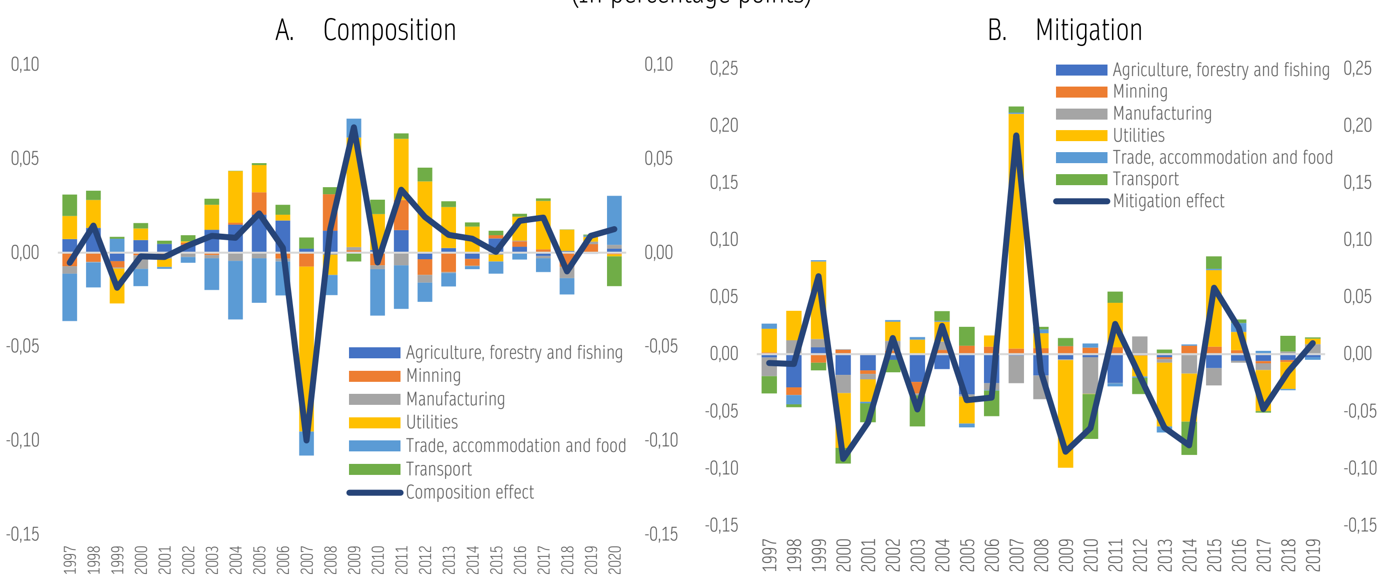
	Scale	Composition	Mitigation	Growth
CO_2	91.7	22.9	-50.9	63.7

Source: Authors' calculations based on NGHGI and NA data.

Detailed information on the composition and mitigation effects can be found in Figure 5.A and 5.B. Regarding the composition effect, utilities and trade, accommodation and food are the industries that contribute the most to its result; in the first case, due to fossil fuel power generation, which has a high emission coefficient and low added value and in the second to its high share in added value relative to its share in GHG emissions.

The drivers of the mitigation effect are depicted in Figure 5.B; utilities have the most significant contribution in absolute terms, followed by transport and agriculture, forestry, and fishing. Regarding utilities, in 2007, the mitigation effect was positive and the largest in the series, mainly because the power generation matrix changed, replacing natural gas with diesel due to gas import shortages[17]. As diesel power generation is more intensive on emissions and has higher production costs compared to gas, in 2007 the technology effect was positive and the composition effect was negative regarding utilities. In recent years, the utility effect has been mainly negative as the outburst of nonconventional renewable energies has replaced fossil fuels.[18]

Figure 5
Activities' contribution to main decomposition effects
(In percentage points)



Source: Authors' calculations based on NGHGI and NA data.

The case of agriculture, forestry and fishing is worth mentioning since it mainly presents gains in emissions efficiency over the last two decades. Part of this result reflects the productivity gains in crops as new fertilizers

[17] For the Chilean generation matrix in 2017 see (Pastén, 2012).
[18] For an overview of recent energy policies in Chile see (Simsek, Lorca, Urmee, Bahri, & Escobar, 2019).

achieve a higher production yield over the same land extension, which does not translate into a similar increase in CO_2 growth.[19] Even more, there has been a decline in emissions from enteric fermentation due to a decreased cattle population.[20]

5. Aggregation bias

Our results rely on the assumption that, within industries, firms are homogeneous. However, if there is a further disaggregation level within sectors, the composition and mitigation effects, as given by equation (3), could be biased depending on how these sub-activities contribute to GHG emissions.

The heterogeneity within sectors can be added to the proposed decomposition to account for the change in the estimated effects concerning their more disaggregate counterparts. We extend the previous formula as follows: For each economic activity i, assume that there are N_i sub-activities that compose the aggregate. For activity i and component $j \in \{1, \dots, N_i\}$, emissions are denoted by e_t^{ij} and nominal value added by v_t^{ij}. Accordingly, the shares on total emissions and nominal value added of each component are given by $\alpha_t^{ij} = e_t^{ij}/E_t$ and $\beta_t^{ij} = v_{N,t}^{ij}/V_{N,t}$, respectively.

Thus, if we consider the disaggregation within economic activities, the CO_2 growth rate can be rewritten as[21]:

$$g_{E,t} = \underbrace{\underbrace{\sum_{i=1}^{I}\sum_{j=1}^{N_i}\Delta_{t-1}^{ij} g_{v,t}^{ij}}_{\substack{\text{Disaggregated} \\ \text{Composition Effect}}} - \underbrace{\sum_{i=1}^{I}\alpha_{t-1}^{i}\sum_{j=1}^{N_i}\Delta_{t-1}^{ij} g_{v,t}^{ij}}_{\text{Aggregation bias}}}_{\substack{\text{Aggregated Composition} \\ \text{Effect}}} + \underbrace{\underbrace{\sum_{i=1}^{I}\sum_{j=1}^{N_i}\alpha_{t-1}^{ij} g_{\theta,t}^{ij}}_{\substack{\text{Disaggregated} \\ \text{Mitigation Effect}}} + \underbrace{\sum_{i=1}^{I}\alpha_{t-1}^{i}\sum_{j=1}^{N_i}\Delta_{t-1}^{ij} g_{v,t}^{ij}}_{\text{Aggregation bias}}}_{\substack{\text{Aggregated Mitigation} \\ \text{Effect}}} + \underbrace{g_{V,t}}_{\substack{\text{Scale} \\ \text{Effect}}}, \tag{5}$$

where $\Delta_t^{ij} = \alpha_t^{ij} - \beta_t^{ij}$. As shown in equation (5), if further disaggregation is not controlled for in the data, the estimated composition and mitigation effects could differ from their actual effects, as compositional changes within economic activities could be included in the mitigation effect.

The aggregation bias term in equation (5) can be either positive or negative, conditional on how emissions and production are distributed between the subsectors. Suppose the sub-activities that pollute more do not represent a large share of the overall production within the economic activity. In that case, the aggregation bias will be positive, overestimating the mitigation effect and underestimating the composition effect with an equal and opposite magnitude.

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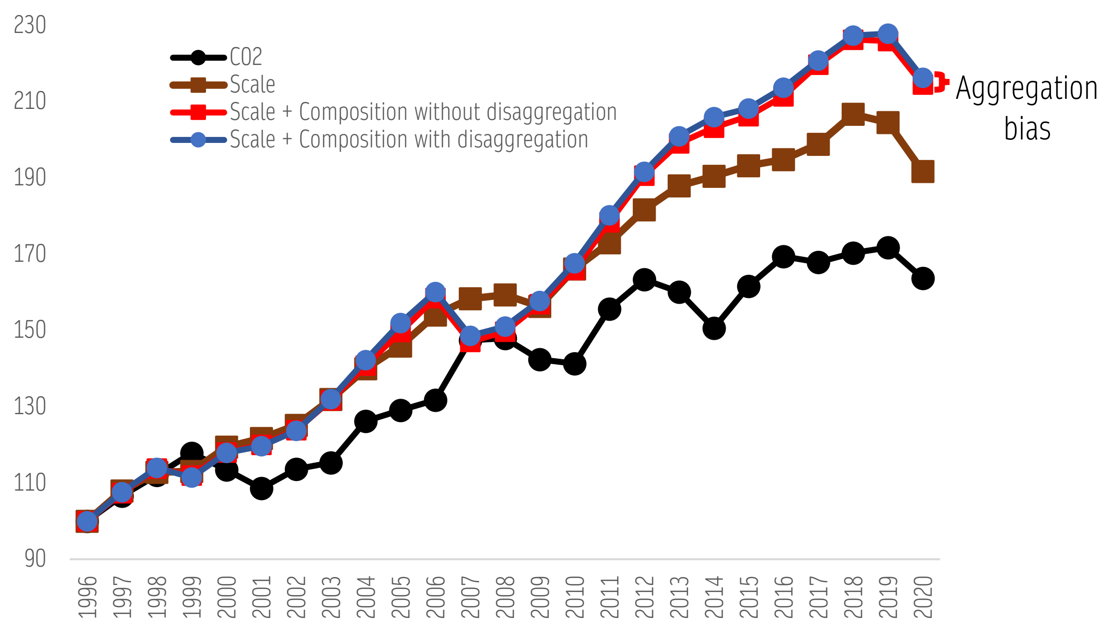
[19] See (Castilla, Meza, Vicuña, Marquet, & Montero, 2019).

[20] See (Ministerio del Medio Ambiente, 2018).

[21] See Appendix D for a full derivation of equation (5).

Figure 6
CO_2 emissions decomposition accounting for manufacturing branches
(1996=100)



Source: Authors' calculations based on NGHGI and NA data.

In the previous section, we treated manufacturing as one overall industry without considering the different branches that compose it. NA data measures the production of its sub-activities, and the NGHGI also measures their emissions, allowing us to assess the aggregation bias[22]. As pictured in Figure 6, the aggregation of manufacturing branches underestimates the composition effect, mainly explained by the contribution of non-metallic and raw metallic, and food, beverages, and tobacco industries.

Once manufacturing activities are included, the composition effect increases from 22.9 to 24.6 p.p. while the mitigation effect goes from -50.9 to -52.6 p.p., both increasing in absolute terms (see Table 3). The aggregation bias (1.6 p.p.) represents 7.6% and 3.4% of the estimated composition and mitigation effects, respectively. Even though the magnitudes would seem high, the primary signal that mitigation efforts have paid off over the last twenty years remains the same.

Table 3
Decomposition of emissions accounting by manufacturing branches, 1996-2018
(In percentage points)

	Scale	Composition	Mitigation	Growth
CO_2	91.7	24.6	-52.6	63.7

Source: Authors' calculations based on NGHGI and NA data.

[22] The list of branches within the manufacturing industry is shown in table 1.

6. Conclusions

The path to a net zero carbon stage is one of the main concerns among the different economies. To achieve this goal, economies have committed to several mitigation policies to reduce emissions from economic activities. Unfortunately, disentangling how mitigation attempts reduce activities' emissions has not been tackled in aggregated terms hindering the accountability of these compromises.

In this paper, we propose a simple method that isolates the effect of aggregate mitigation attempts, measuring the efficiency gains in GHG emissions relative to the value produced as measured by national accounts. By linking both variables –emissions and economic activity– we provide a helpful mitigation indicator that can be compared across countries. The method decomposes the emissions' yearly growth rate into scale, composition, and mitigation.

For the case of Chile, we find that the composition effect has increased over the last years mainly because utilities have increased their share in emissions while maintaining their share in value produced. Without the mitigation effect, total emissions from economic activities would have increased by 114.6% instead of the actual number of 63.7% in the period 1996-2018. The difference of 50.9 percentage points can be attributed to more efficient technologies that release less GHG per unit of value produced.

Our method works with aggregated data that can give biased results if different disaggregation levels within economic activities are not accounted for. Hence, we extend our result to the next level of aggregation and show how the bias behaves between the composition and mitigation effects. This term sheds light on the under or sub-estimation of these effects when dealing with aggregated information. We extend the previous results for the Chilean case by including the different manufacturing branches. In this exercise, the mitigation effect slightly increases in absolute terms as the branches that emit the most also contribute less to overall manufacturing production.

Further analysis needs to be done regarding other pollutants such as nitrogen oxides (NO_X), carbon monoxide (CO), non-methane volatile compounds (VOC) and sulphur dioxide (SO_2) as they too are released to the environment through the production process. Unfortunately, the Chilean NGHGI does not fully cover all the emissions of these pollutants, preventing a robust analysis at the moment.

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Appendix

A. Emissions technology

Let's assume that the production function of activity i is Cobb-Douglas with constant returns to scale:

$$y_{i,t} = A_i \prod_{j=1}^{I} \left(x_{j,t}^i\right)^{\alpha_{j,t}^i} \qquad \text{for} \quad i \in \{1, \dots, I\},$$

where $y_{i,t}$ is output, $x_{j,t}^i$ measures input j and A_i is the usual productivity factor which we assume constant. For now on, we drop the activity index for simplicity. We think that firms maximize profits under competitive markets where prices are $(p_1, \dots, p_I)$, for simplicity we assume that prices do not change over time.

Each input, once used to produce other goods, emits CO_2; the emission factor is $\phi \geq 0$ measured in tons of CO_2 per unit of input. For instance, the use of x_j units of input j emit $\phi_j x_j$ tons of CO_2 to the environment. If an input does not emit CO_2, we set $\phi = 0$.

From first-order conditions, overall emissions can be written as:

$$e_t = \sum_{j=1}^{I} \phi_j x_{j,t} = \theta_t y_t, \qquad \text{where } \theta_t = \sum_{j=1}^{I} \alpha_{j,t} \frac{\phi_j p}{p_j}.$$

Hence, if technology remains constant ($\alpha_{j,t} = \alpha_j$ for all t and j), we have that the growth rate of emissions is equal to the growth rate of production. On the other hand, if we vary θ only in activities k and s we have:

$$d\theta_t = d\alpha_{k,t} \frac{\phi_k p}{p_k} + d\alpha_{s,t} \frac{\phi_s p}{p_s} = p d\alpha_{k,t} \left(\frac{\phi_k}{p_k} - \frac{\phi_s}{p_s}\right),$$

since $d\alpha_{k,t}^i + d\alpha_{s,t}^i = 0$. Therefore, emissions intensity will fall if the technology becomes more intensive in inputs that pollute less per CLP.

B. Chain-linked index method and growth decomposition with annual data

For an economy with I industries, let the quantity and prices for year $t \in \{0, \dots, T\}$ be given by $q_t = (q_{1,t}, \dots, q_{I,t})$ and $p_t = (p_{1,t}, \dots, p_{I,t})$, respectively.

For year $t = 0$, overall production is given by $V_0 = \sum_{i=1}^{I} p_{i,0} q_{i,0}$ which is set to 100. For year $t = 1$, overall production in volume terms is given by:

$$V_1 = 100 \cdot \frac{\sum_{i=1}^{I} p_{i,0} q_{i,1}}{\sum_{i=1}^{I} p_{i,0} q_{i,0}}.$$

For subsequent years, the chain-linked index is computed as follows:

$$V_t = 100 \cdot \frac{\sum_{i=1}^{I} p_{i,0} q_{i,1}}{\sum_{i=1}^{I} p_{i,0} q_{i,0}} \cdot \frac{\sum_{i=1}^{I} p_{i,1} q_{i,2}}{\sum_{i=1}^{I} p_{i,1} q_{i,1}} \cdots \frac{\sum_{i=1}^{I} p_{i,t-1} q_{i,t}}{\sum_{i=1}^{I} p_{i,t-1} q_{i,t-1}} = V_{t-1} \cdot \frac{\sum_{i=1}^{I} p_{i,t-1} q_{i,t}}{\sum_{i=1}^{I} p_{i,t-1} q_{i,t-1}}.$$

Therefore, the growth rate in chain-linked terms between two periods is given by

$$\frac{V_t}{V_{t-1}} = \frac{\sum_{i=1}^{I} p_{i,t-1} q_{i,t}}{\sum_{i=1}^{I} p_{i,t-1} q_{i,t-1}}, \quad \text{which implies} \quad \frac{V_t}{V_{t-1}} - 1 = \frac{\sum_{i=1}^{I} p_{i,t-1} q_{i,t-1} \cdot \left(\frac{q_{i,t}}{q_{i,t-1}} - 1 \right)}{\sum_{i=1}^{I} p_{i,t-1} q_{i,t-1}},$$

i.e., industries contribution to overall growth is its share in nominal value times its real growth.

C. GHG growth decomposition

From equation (1), the annual growth rate in emissions is given by:

$$g_{E,t} = \sum_{i=1}^{I} \alpha_{t-1}^{i} g_{e,t}^{i}, \tag{A1}$$

where $\alpha_t^i = e_t^i / E_t$. On the other hand, since value added is measured in chain-linked CLP, it is not direct to measure total value as the sum of activities value added. However, we can express the growth rate of total value added as the sum of activities' growth contributions ($c_{i,t}$) as $g_{V,t} = \sum_{i=1}^{I} c_t^i$. Adding and subtracting the above expression in (A1) leads to the following:

$$g_{E,t} = \sum_{i=1}^{I} \alpha_{t-1}^{i} g_{e,t}^{i} - \sum_{i=1}^{I} c_t^i + g_{V,t}. \tag{A2}$$

Finally, since $g_{e,t}^i = g_{\theta,t}^i + g_{v,t}^i$ from equation (2) and using the fact that growth contributions can be computed as $c_t^i = \beta_{t-1}^i g_{v,t}^i$, we can rewrite equation (A2) as:

$$g_{E,t} = \sum_{i=1}^{I} \alpha_{t-1}^{i} \left(g_{\theta,t}^{i} + g_{v,t}^{i} \right) - \sum_{i=1}^{I} \beta_{t-1}^{i} g_{v,t}^{i} + g_{V,t}. \tag{A3}$$

Rearranging terms leads to equation (4).

D. Structural decomposition with a higher level of disaggregation

Let's assume that each economic activity i is composed by N_i subactivities. Then, each component in equation (4) can be rewritten as:

$$g_{v,t}^{i} = \sum_{j=1}^{N_i} \beta_{t-1}^{ij} g_{v,t}^{ij} = \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{v,t}^{ij} - \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij},$$

Thus, for the technology component, we have:

$$g_{\theta,t}^{i} = g_{e,t}^{i} - g_{v,t}^{i} = \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{e,t}^{ij} - \sum_{j=1}^{N_i} \beta_{t-1}^{ij} g_{v,t}^{ij} = \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{\theta,t}^{ij} + \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij}.$$

Replacing in equation (3)

$$g_{E,t} = \underbrace{\sum_{i=1}^{I} \Delta_{t-1}^{i} \left\{ \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{v,t}^{ij} - \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij} \right\}}_{\substack{\text{Composition} \\ \text{Effect}}} + \underbrace{\sum_{i=1}^{I} \alpha_{t-1}^{i} \left\{ \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{\theta,t}^{ij} + \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij} \right\}}_{\substack{\text{Mitigation} \\ \text{Effect}}} + \underbrace{g_{V,t}}_{\substack{\text{Scale} \\ \text{Effect}}}.$$

Thus,

$$\begin{aligned} g_{E,t} = \sum_{i=1}^{I} \Delta_{t-1}^{i} \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{v,t}^{ij} + \sum_{i=1}^{I} \beta_{t-1}^{i} \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij} - \sum_{i=1}^{I} \alpha_{t-1}^{i} \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij} \\ + \sum_{i=1}^{I} \alpha_{t-1}^{i} \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{\theta,t}^{ij} + \sum_{i=1}^{I} \alpha_{t-1}^{i} \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij} + g_{V,t}. \end{aligned}$$

Rearranging terms we have:

$$g_{E,t} = \underbrace{\underbrace{\sum_{i=1}^{I} \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij}}_{\substack{\text{Disaggregated} \\ \text{Composition Effect}}} - \underbrace{\sum_{i=1}^{I} \alpha_{t-1}^{i} \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij}}_{\text{Aggregation bias}}}_{\substack{\text{Aggregated Composition} \\ \text{Effect}}} + \underbrace{\underbrace{\sum_{i=1}^{I} \sum_{j=1}^{N_i} \alpha_{t-1}^{ij} g_{\theta,t}^{ij}}_{\substack{\text{Disaggregated} \\ \text{Mitigation Effect}}} + \underbrace{\sum_{i=1}^{I} \alpha_{t-1}^{i} \sum_{j=1}^{N_i} \Delta_{t-1}^{ij} g_{v,t}^{ij}}_{\text{Aggregation bias}}}_{\substack{\text{Aggregated Mitigation} \\ \text{Effect}}} + \underbrace{g_{V,t}}_{\substack{\text{Scale} \\ \text{Effect}}}.$$

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