Agricultural support policies and GHG emissions from agriculture in Latin America: relationships and policy implications for climate change

Políticas de apoyo a la agricultura y emisiones de GEI de la agricultura en América Latina: relaciones e implicaciones políticas para el cambio climático

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Abstract

Domestic support policies for farmers and agriculture, through their price effect, have been deemed potentially environmentally harmful; for example, in developing countries, agricultural prices have been set below the world market prices, aiming to secure low retail prices for urban consumers. This practice has lowered producer prices, and thereby prevented farmers from adopting ecofriendly production techniques. This study uses policy data —market price support (MPS) and general service support estimates (GSSE) as shares of total support estimate (TSE)— and greenhouse gases (GHG) data for main crops and livestock sectors in 18 Latin-American countries and it applies cluster analysis to construct a typology that highlights patterns between policy incentives for agricultural crops and activities and GHG emissions. The results suggest that an increase in the TSE and/or MPS comprising a large share of the TSE leads to an increase in GHGs. Conversely, GHGs fall when GSSE comprise a larger share of the TSE.

Keywords: agricultural greenhouse gas emissions, total support estimate, general service support estimate, producer single commodity transfers, Latin American countries.

Resumen

Las políticas internas de apoyo a los agricultores y la agricultura, a través de su efecto sobre los precios, pueden ser potencialmente dañinas para el medio ambiente; por ejemplo, en los países en desarrollo, los precios agrícolas se han fijado por debajo de los precios del mercado mundial, con el objetivo de asegurar precios minoristas bajos para los consumidores urbanos. Esta práctica reduce bajar los precios al productor y, por lo tanto, es un obstáculo que los agricultores adopten técnicas de producción ecológicas. En este estudio, se utilizan datos de políticas —soporte de precios de mercado y estimaciones de apoyo a los servicios generales como porcentajes de la estimación del apoyo total— y datos de gases de efecto invernadero (GEI) para los principales cultivos y sectores ganaderos en 18 países latinoamericanos, además de aplicarse análisis de conglomerados para construir una tipología en la que se destacan patrones entre políticas de incentivos para cultivos y actividades agrícolas y emisiones de GEI. Los resultados sugieren que un aumento en la estimación del apoyo total y/o en el soporte de precios de mercado, que comprende una gran parte, conduce a un incremento en los GEI. Por el contrario, estos caen cuando las estimaciones de apoyo a los servicios generales comprenden una mayor parte de la estimación del apoyo total.

Palabras clave: emisiones de gases de efecto invernadero por la agricultura, estimación del apoyo total, estimación de apoyo a los servicios generales, transferencias de producto único al productor, países de América Latina.

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1
Introduction

Agricultural activities directly and indirectly contribute 25% of the Global Greenhouse Gas (GHG) emissions (OECD 2017), which, in turn, contribute toward climate change. Moreover, governments may rely on price distorting incentives for farmers, which lead to environmental degradation. Lankoski (1997) presents the following two examples of the potential relationship between the price effect of such policies and environment effects. The first example focuses on developing countries where agricultural prices are set below the world market prices to secure low retail prices for urban consumers. This practice lowers producer prices and keeps farmers from adopting ecofriendly production techniques. A second example points to the low application efficiency of subsidized inputs which in turn leads to pollution. Notwithstanding, Just and Antle (1990) show the pollution mitigating effects of appropriate policy measures. Thus, to adopt appropriate measures, it is important to evaluate the GHG emissions implications of domestic agricultural support policies. This evaluation has become possible because of the availability of data on both agricultural and farmer support policies and on agricultural GHG emissions.

The Food and Agriculture Organization Statistical Database (FAOSTAT) offers data on GHG emissions from agriculture. The Inter-American Development Bank's (IDB) Agrimonitor database provides data on the agricultural policy measures for the Latin American countries (LACs). These include policy measures at the producer level, such as the market price support (MPS) and direct support (DS). With a few exceptions, most domestic agricultural support policies in the LACs rely on the MPS, and do so through border measures (*e.g.,* tariffs and quotas) and the domestic price support for a basket of goods (Egas & De Salvo 2018). The availability of these databases should facilitate policy and related comparisons across countries and time. These comparisons can help policymakers and practitioners to design and apply, respectively, consistent policies that both support farmers and mitigate pollution.

Despite the stated importance of resource efficiency and climate change, there is limited empirical evidence on the relationship between GHG emissions and domestic agricultural support policies for the LACs. The few empirical studies that discuss this relationship are Ackerman *et al.* (2018), for Uruguay, and Josling (2016) and Josling *et al.* (2017), for Jamaica. This limited attention can be attributed to the serious challenges in this research area. First, it is difficult to understand the environmental impacts of the agricultural policy and other reforms (*e.g.,* trade reforms) (Lankoski 1997, Balogh and Jámbor 2020). Second, there is an inadequate understanding of the interactions in the relationship between agriculture and environment, that is, interactions between trade, environment, agricultural policy reforms, and policy coordination; for example, there is little evidence on the endogeneity, because of the possible reverse causation between environment and trade effects. Third, there is little and contradictory evidence of the income effects for the LACs. These effects can be depicted through the so-called «environmental Kuznets curve» (EKC), whereby an initial growth in the per capita income leads to a decline in the environmental quality, which starts improving after income grows to a certain level. Fourth, the analysis of agricultural GHG emissions should focus on the sequestration of agricultural GHG emissions, the level of energy use, and the changes in land use. While the present study bridges the empirical gap, it does not address the last three aforementioned research challenges. Specifically, this study poses the following research questions:

- How have the agricultural support policies evolved in the LACs and what is the current level of support? Particularly, how is the correlation between the MPS and general support service estimates (GSSE) and GHGs?
- What is the relationship between the *selected* agricultural products (*e.g.,* rice) and activities (*e.g.,* livestock) contributing the most to GHG emissions *and* the levels and types of incentives given to farmers producing them?
- Is there a typology of the relationship between the farmers' incentives and the total agricultural GHG emissions in the LACs, after accounting for other appropriate indicators such as trade policy, institutions, and governance?

By answering these questions, the study aims to achieve the following:

- Measure the level and composition of the agricultural and farmer support in the selected LACs, by statistically summarizing its evolution in the past decade and its correlation with GHG emission indicators.
- Analyze GHG emissions for *common* agricultural crops and activities in the LACs (*e.g.,* rice production) aiming at finding a correspondence of these emissions with economic incentives in agriculture, providing a consistent mapping between the emissions in the FAOSTAT database and the policies in Agrimonitor and comparing different indicators of emissions with the indicators of the incentives for the selected crops and agricultural activities in the sampled LACs (similar to Josling *et al.* 2017).
- Find patterns in the relationships between GHG emissions and policy incentives in agriculture, by applying cluster analysis.
- Discuss policy implications of the identified relationship and patterns.

The next section presents a brief literature review. Section 3 describes the datasets and methods used. Section 4 discusses the results of the data and correlation analyses. Section 5 discusses the cluster analysis results. The last two sections present policy implications (section 6) and conclusions, limitations of the study and suggestions for future research (section 7).

2
Brief literature review on agricultural support policies and GHG emissions from agriculture

Agriculture[1] is, throughout the world, an economic sector that has spurred great deal of discussion about support policies, and rather recently about GHG emissions. Major challenges in such discussions include *(i)* how to quantify both agricultural support policies and GHG emissions from agriculture, and *(ii)* how to assess the complex relationship between agriculture and GHG emissions —on the one hand— and agriculture and GHG emissions *and* agricultural support policies —on the other hand (not to mention other policies/events that might also affect the agricultural sector and emissions)—. These discussions are important because of the role that agriculture performs in the economic development of the nations and because of the role that GHG emissions have on climate change, and more so knowing that climate change in turn affects agriculture —the latter, however, is not addressed in our research.

Organization for Economic Cooperation and Development (OECD) research has developed and published definition and measurements of agricultural support that span more than two decades. OECD (2022), the latest of such reports, evaluates agricultural support in 54 countries: 38 OECD countries, the 5 non-OECD EU Member States, and 11 emerging economies (among which are 6 LAC: Argentina, Paraguay, Chile, Colombia, Costa Rica, and Mexico). This report focuses on how agriculture and agricultural policies may contribute to climate change mitigation, which underscores the importance of the beforementioned subject. For LAC, the Inter-American Development Bank (IADB) has been applying —in the past few years— the OECD methodology to measure agricultural support in the region (De Salvo *et al.* 2019, Egas and De Salvo 2018, Gurria *et al.* 2016) publishing results not only at the regional level but also by countries. The latest report is for Guyana (Gachot *et al.* 2022) and one of the first reports was for Central America and Dominican Republic (Arias 2007).

There is indeed a complex relation between agriculture and GHG emissions. First, there is an endogenous, two-way relation because agriculture produces GHG but in turn such emissions may affect agricultural production and activities; for instance, for LAC through extreme climate events and/or rendering some areas no longer suitable for agriculture (Cardenas *et al.* 2021). And these

1 Hereby narrowly defined to include crop farming and livestock farming.

complex relations become even more complex when consumption of agricultural products (Garnett 2009) and agricultural support policies (and other policies) are added. Second, agriculture may play a prominent role in efforts to address climate change, which has been extensively discussed particularly in the context of developed countries (Horowitz and Gottlieb 2010, Franks and Hadingham 2012) but only recently for LAC and other developing economies has the issue been addressed (Arango *et al.* 2020, Tongwane and Moeletsi 2018). Lastly, and key for our research, agricultural support policies may impact GHG emissions, but this issue has yet to be fully discussed (Laborde *et al.* 2021).

As suggested in studies on agriculture and the environment, it is necessary to link the measurement of environmental performance indicators with the characteristics of different policy measures (*e.g.,* OECD 2005). Hence, our study analyzes the relationships between the GHG emissions (CO_2e, taken from FAOSTAT) and the domestic support (transfers to farmers and agriculture) for a selected set of crops and agricultural activities in the LACs. This allows a comparison between the experiences of different LACs across time, and thereby contributes toward establishing patterns and useful policy implications for the region. To the best of our knowledge, this issue is yet to be addressed.

3 Data and methods

3.1. Data

We extract data on agricultural support policies from the Agrimonitor database. Table A1 in the Annex summarizes the data periods available in Agrimonitor for each of the selected countries.

We extract emissions data from the FAOSTAT database. When we performed our research, the FAOSTAT database presented emissions data from 1961 to 2017 or 2019, depending on the variable and level of disaggregation. FAOSTAT provides data on GHG emissions from agriculture and land use, sorted by type of gas, country, and year. The agricultural land use emissions include emissions from cropland, grassland, net forest conversion, and the combustion of organic soils and humid tropical forests. However, the present study does not directly account for all these emissions, rather it uses only total emissions from agriculture (and from certain crops and activities) by adding carbon dioxide (CO_2) emissions with other trace gases emissions converted into carbon dioxide equivalent (CO_2e) via the global warming potentials (GWP) coefficients.

For the cluster analysis, we collect in addition indicator data from public databases such as the World Bank's Word Development Indicators and the World Trade Organization's tariffs database.

3.2. Methods

Figure 1 summarizes our research methods, which comprise of two parts.

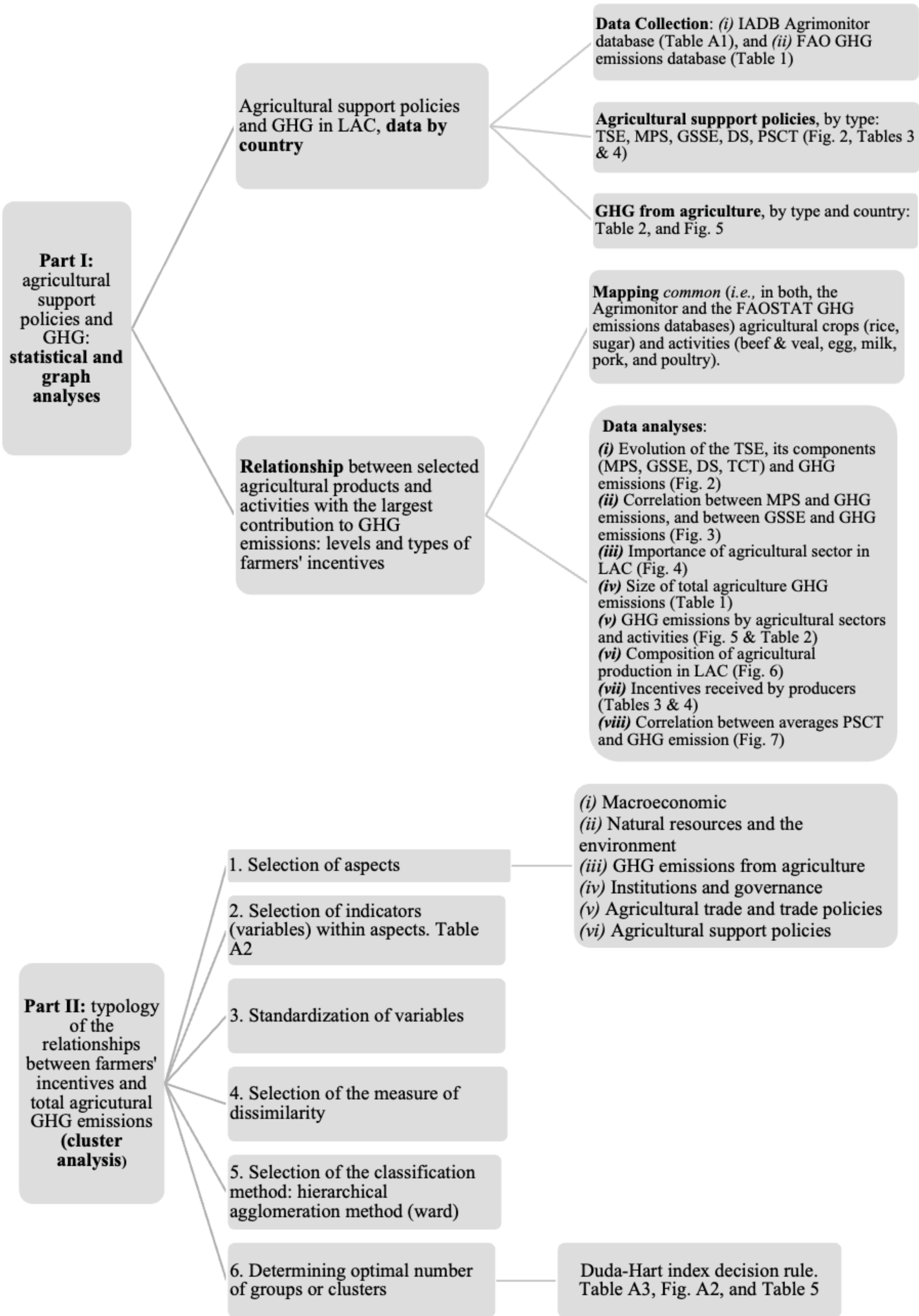


Figure 1
Outline of research methods

3.2.1. Part I: analyzing GHG emissions and agricultural policies

We collect data on the domestic agricultural support policy, *i.e.,* the total support estimate (TSE), by components (MPS, GSSE, and DS), for 18 LACs.[2] These agricultural incentives focus on the agricultural activities and commodities that are present in both the FAOSTAT and Agrimonitor databases. Based on data availability, we select rice and livestock farming (*i.e.,* beef and veal, egg, milk, pork, and poultry). We also include sugar, for its importance in the analysis of policy support.

We use the FAOSTAT database to collect data on the emissions from the primary production process, and not the entire product life cycle. Different crops and agricultural activities may emit different types of GHGs. However, for the purpose of computation, FAOSTAT converts the different trace emissions to CO_2e, which is expressed in gigagrams. This measurement is used throughout the study.

We then map the policy indicators for the selected agricultural commodity/activity with its GHG emissions to allocate emissions, by taking the same type of crop and livestock activity from both databases.

Finally, we compare the agricultural policies' incentives, by the selected commodities, with their corresponding emission indicators across countries.

Josling *et al.* (2017) also engage in the costing of emissions by applying a price to the CO_2 emissions and comparing different environmental indicators with agricultural indicators/policies. However, the CO_2 market is new or non-existent in most LACs. Moreover, the available data on CO_2 prices reflect the price volatility of CO_2 in the recent past, rendering it difficult to «pick» a price (when available) for a LAC during the sampled period.

3.2.2. Part II: creating a typology of countries

A cluster analysis allows us to find patterns between countries, based on certain traits, and to explore possible explanations for such patterns (Grein *et al.* 2010). By applying clusters or conglomerates at the country level at different time periods, studies contrast situations showing how the clustering dynamics among countries can vary between the selected time periods. Our study applies the cluster analysis to examine possible patterns of agricultural policy and GHG emissions in the 18 LACs, in two points in time (2010 and 2017). The literature identifies a series of steps for conducting a cluster analysis (Kassambara 2017, Wong *et al.* 2020). Figure 1 lists the six steps, and we discuss them as follows.

2 Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay.

3.2.2.1. Selection of aspects and indicators

The selection of aspects and indicators depends on their relevance to the understanding of agricultural support in the LACs. For instance, Egas and De Salvo (2018) discuss trade and trade policy indicators when explaining the agricultural domestic support policies in the LACs. Ackerman *et al.* (2018) emphasize institutional setting when discussing producer support policies in Uruguay. Based on its relevance to the relationship between the agricultural policies and GHG emissions, we select indicators from six aspects: *(i)* macroeconomics, *(ii)* natural resources and the environment, *(iii)* GHG emissions from agriculture, *(iv)* institutions and governance, *(v)* agricultural trade and trade policy, and *(vi)* agricultural support policies. The indicators are listed, along with their data source, in Table A2 in the Annex.

3.2.2.2. Standardization of the variables

Objects can be clustered using several methods, the choice of which may depend on the type of data used and the study's objectives. For the continuous data used in this study, it may be suitable to use a hierarchical agglomeration, based on a variance procedure. In this case, to proceed, the data may be standardized. The data is given by a matrix of order *NxP,* where *N* represents the number of countries studied and *P* represents the number of selected variables or indicators. As it is of common knowledge, the standardization is conducted by subtracting the average from each value in the matrix (from a set of observations-countries, for a given variable) and dividing this result by its standard deviation. The standardization will yield a data matrix with comparable values, which will further facilitate cluster analysis.

3.2.2.3. Selection of the measure of dissimilarity

This stage involves a selection of the measure of heterogeneity, dissimilarity, or discontinuity. This measure is applied between countries. From the standardized data matrix, the distance matrix *D* of order *NxN* is constructed, where each coefficient d_{ij} represents the value of a dissimilarity coefficient for cases *i* and *j;* that is, the degree of distance between observations (in this case, countries). This matrix is symmetric; that is, $d_{ij} = d_{ji}$. In this process, all the distances must be greater than zero. According to the Euclidean distance (*i.e.,* between each pair of observations), the distance matrix of dissimilarities is represented by the formula:

$$d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2}$$

Where d_{ij} is the value of the distance between the units of analysis *i* and *j;* x_{ik} and x_{jk} represent the values of the variable *k* for the units *i* and *j,* respectively; and *p* is the number of variables whose values are to be compared.

3.2.2.4. Selection of the classification method

To obtain the classification by clusters, we apply the hierarchical agglomerative method. If we define *N* as the set of countries in the sample, from which we obtain the level $K = 0$ with *n* groups; then, at the next level, the two individuals with the greatest similarity (or least distance) will be grouped, which would yield *n*-1 groups. Following this procedure, we will continue to group the countries, until all the individuals in the sample are assigned to a group. This hierarchical method allows for the construction of a tree diagram for classification which is called a «dendrogram». In the dendrogram, one can follow the clustering procedure, the grouping level, and the measure of association between the groups. In the hierarchical agglomerative method, different strategies are used when uniting the groups at each level. We use the Ward's method —a commonly used hierarchical technique— to unite the groups at each level (Hair *et al.* 2010, Niembro 2017). Under the Ward's method, at each stage, the groups with the smallest increase in the total value of the sum of the squares of the differences within each group, of each individual, are joined to the centroid of the cluster (Everitt *et al.* 2011).

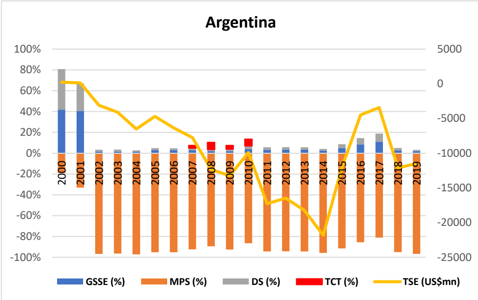
3.2.2.5. Determining the optimal number of groups or clusters

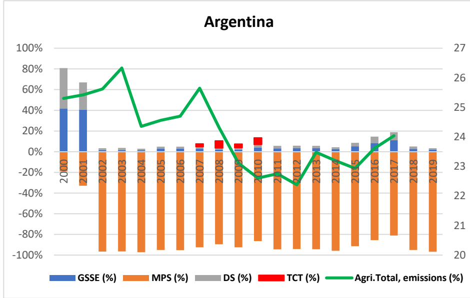
We use the Duda-Hart index (Duda *et al.* 2000) to determine the number of clusters formed. This index compares the sum of the squares of the intra-cluster errors in the next pair of groups to be combined. The decision criterion is based on choosing the number of clusters among the options reporting a relatively high Duda-Hart index for which the pseudo-*T*-square value is lower than the two neighboring options.

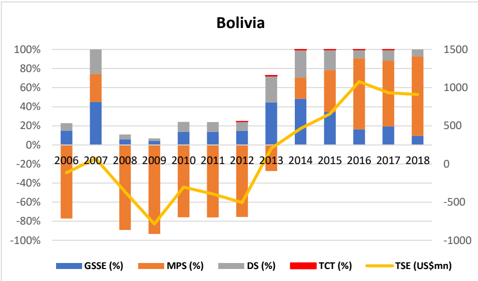
4
Agricultural support estimates and GHG emissions: results

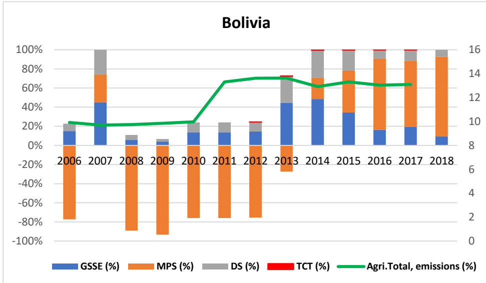
Graphs in the left column of Figure 2 and the text in the following bullet points summarize the composition of the agricultural support estimates for the 18 LACs and the evolution of the total TSE:

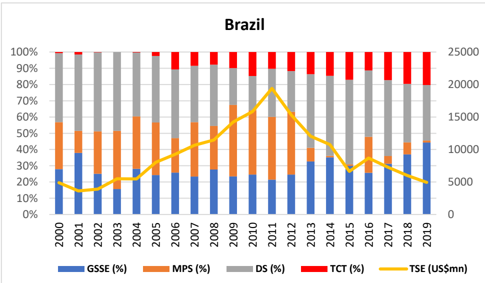
- As pointed out in the literature (Egas & De Salvo 2018), MPS represents the lion's share of agricultural support in most of the countries (notable exceptions are Brazil and Chile). In some countries, this share has been clearly increasing (Bolivia, Dominican Republic, Ecuador, and El Salvador), while it has been falling in certain countries (Honduras, Uruguay, and

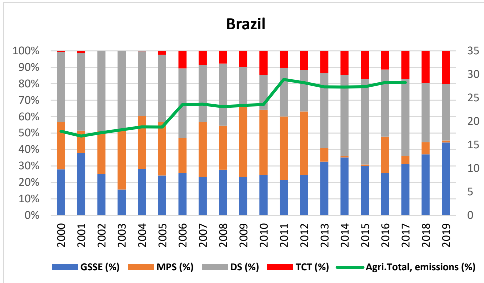

Argentina
GSSE (%)
MPS (%)
DS (%)
TCT (%)
TSE (US$mn)

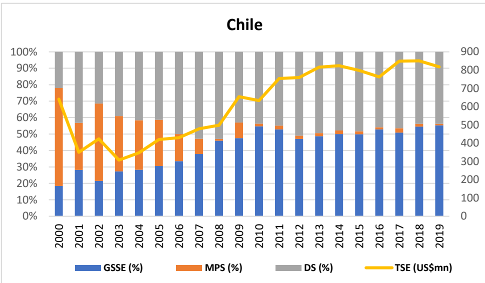

Argentina
GSSE (%)
MPS (%)
DS (%)
TCT (%)
Agri.Total, emissions (%)

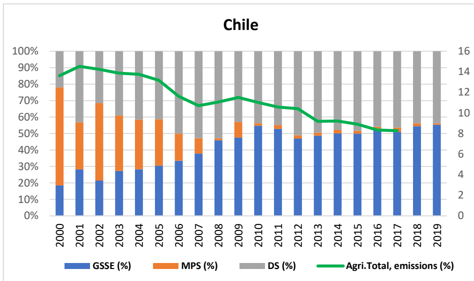

Bolivia
GSSE (%)
MPS (%)
DS (%)
TCT (%)
TSE (US$mn)

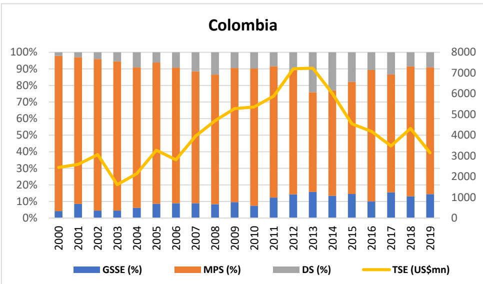

Bolivia
GSSE (%)
MPS (%)
DS (%)
TCT (%)
Agri.Total, emissions (%)

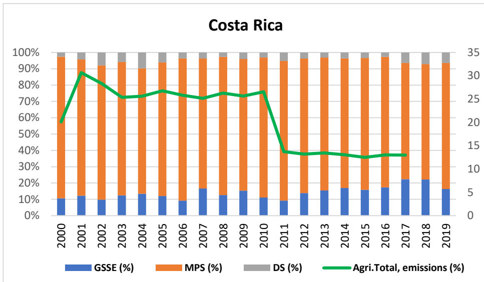

Brazil
GSSE (%)
MPS (%)
DS (%)
TCT (%)
TSE (US$mn)

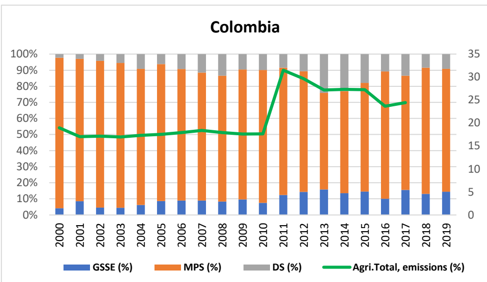

Brazil
GSSE (%)
MPS (%)
DS (%)
TCT (%)
Agri.Total, emissions (%)

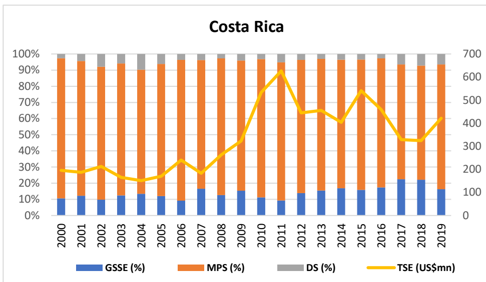

Chile
GSSE (%)
MPS (%)
DS (%)
TSE (US$mn)

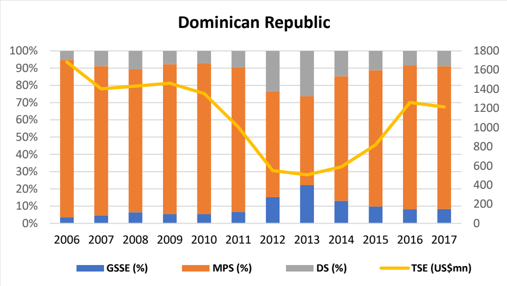

Chile
GSSE (%)
MPS (%)
DS (%)
Agri.Total, emissions (%)

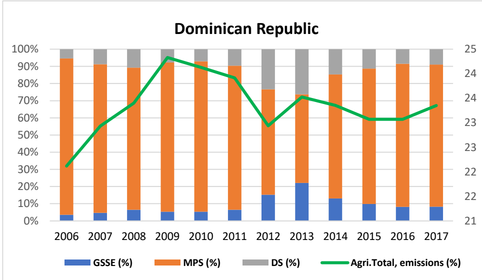

Colombia
GSSE (%)
MPS (%)
DS (%)
TSE (US$mn)

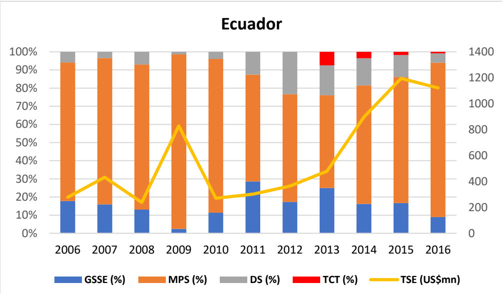

Costa Rica
GSSE (%)
MPS (%)
DS (%)
Agri.Total, emissions (%)

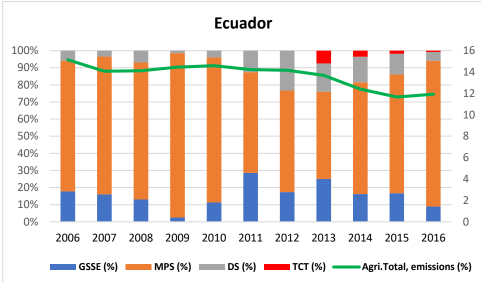

Colombia
GSSE (%)
MPS (%)
DS (%)
Agri.Total, emissions (%)

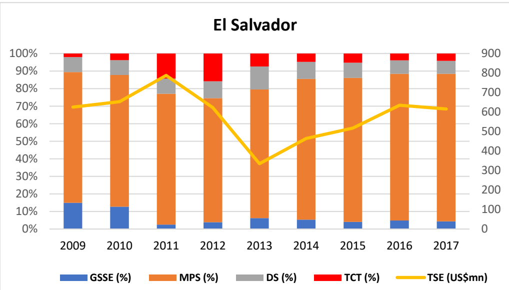

Costa Rica
GSSE (%)
MPS (%)
DS (%)
TSE (US$mn)

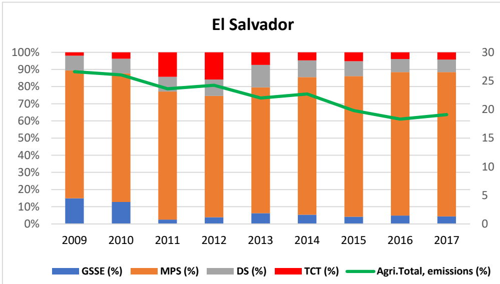

Dominican Republic
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
GSSE (%) MPS (%) DS (%) TSE (US$mn)

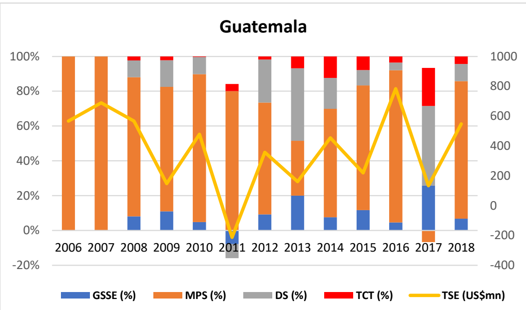

Dominican Republic
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
GSSE (%) MPS (%) DS (%) Agri.Total, emissions (%)

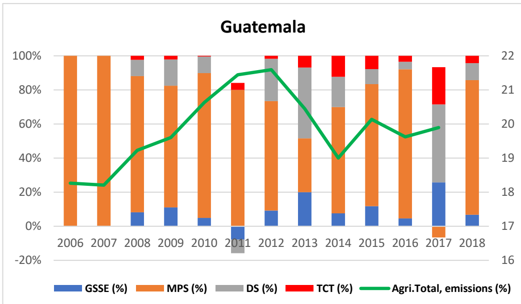

Ecuador
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
GSSE (%) MPS (%) DS (%) TCT (%) TSE (US$mn)

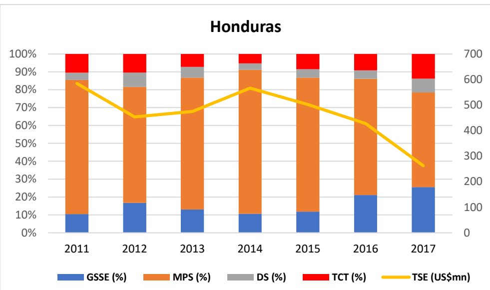

Ecuador
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
GSSE (%) MPS (%) DS (%) TCT (%) Agri.Total, emissions (%)

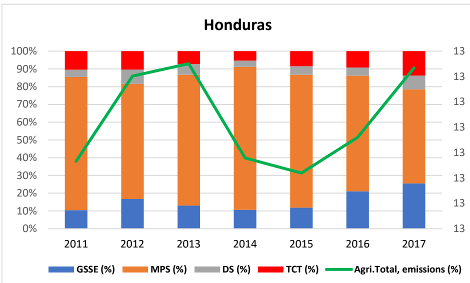

El Salvador
2009 2010 2011 2012 2013 2014 2015 2016 2017
GSSE (%) MPS (%) DS (%) TCT (%) TSE (US$mn)

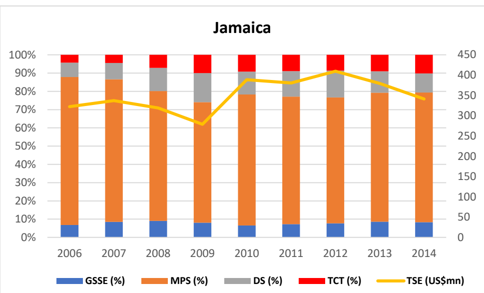

El Salvador
2009 2010 2011 2012 2013 2014 2015 2016 2017
GSSE (%) MPS (%) DS (%) TCT (%) Agri.Total, emissions (%)

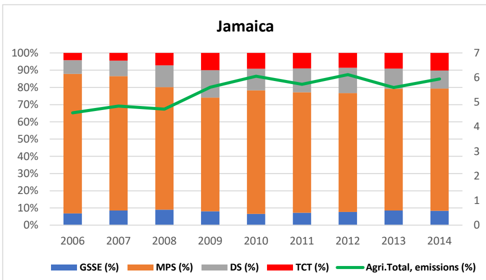

Guatemala
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GSSE (%) MPS (%) DS (%) TCT (%) TSE (US$mn)


Guatemala
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GSSE (%) MPS (%) DS (%) TCT (%) Agri.Total, emissions (%)


Honduras
2011 2012 2013 2014 2015 2016 2017
GSSE (%) MPS (%) DS (%) TCT (%) TSE (US$mn)


Honduras
2011 2012 2013 2014 2015 2016 2017
GSSE (%) MPS (%) DS (%) TCT (%) Agri.Total, emissions (%)


Jamaica
2006 2007 2008 2009 2010 2011 2012 2013 2014
GSSE (%) MPS (%) DS (%) TCT (%) TSE (US$mn)


Jamaica
2006 2007 2008 2009 2010 2011 2012 2013 2014
GSSE (%) MPS (%) DS (%) TCT (%) Agri.Total, emissions (%)

Notes: MPS = Market Price Support. DS = Direct Support. GSSE = General Services Support Estimates. TCT = Total Consumer Transfers. TSE = Total Support Estimates. Except for Chile, reliance on MPS (orange bars) is predominant.

Figure 2

Total Support Estimate (TSE), its components, and GHG emissions for LACs

Source: MPS, DS and GSSE shares in TSE are calculated using data from Agrimonitor.

Mexico, though the last two countries recently present some increase). However, this type of agricultural support does not exist for Paraguay, whereas Argentina and Bolivia present a negative MPS. For Argentina, a negative MPS can be attributed to the taxes on agricultural exports, such as the export of soybeans. This negative MPS leads to holding the domestic agricultural output prices lower than the international prices. It also reflects the transfer of revenues from producers to consumers and taxpayers (Lema *et al.* 2018).

- Direct support to farmers represents the smallest share in most countries, except for Mexico and Paraguay.
- General Support Services are not given to the farmers directly, but to the sector. This may include services such as inspection and control, development and maintenance of infrastructure, marketing and promotion, public stockholding, agricultural knowledge, and innovation system. GSSE has been increasing in some countries (Brazil, Chile, Costa Rica, Honduras, and Paraguay). Although fluctuating, this increase was also observed for Uruguay. GSSE has the largest share of TSE only in few countries (Chile, Uruguay, and Brazil).
- Comparing the first with the last year, in Figure 2, left column, we see an increase in the TSE in some countries (Bolivia, Chile, Costa Rica, Ecuador, Panama, Peru, and Uruguay), while a decrease in the others (Argentina, Dominican Republic, Honduras, Mexico, and Nicaragua). In the sampled period, this level was more or less the same in Brazil, Colombia, El Salvador, Guatemala, Jamaica, and Paraguay.

In Figure 2, it is also compared the shares of the different agricultural support estimates with the total agricultural GHG emissions for each country, which is expressed in terms of CO_2e emissions (graphs in the right column):

- It is interesting to see the cases in which an increase in the TSE and/or MPS with a large share of TSE goes along an increase in the agricultural GHG emissions (however small or large the level of these emissions from agriculture might be). These countries are Bolivia, Brazil, Honduras, Jamaica, Peru, and the Dominican Republic.
- Unlike the aforementioned finding, an increase in TSE together with GSSE comprising a larger share of the total TSE leads to a fall in GHG emissions in Chile and Uruguay.

It is relevant to note that countries should report the national inventories of GHGs and their intended nationally determined contribution (INDC) to the United Nations framework convention on climate change (UNFCCC). The most up-to-date national inventory varies by year for each country. The methodology for calculating the national GHG inventories is given by the Intergovernmental

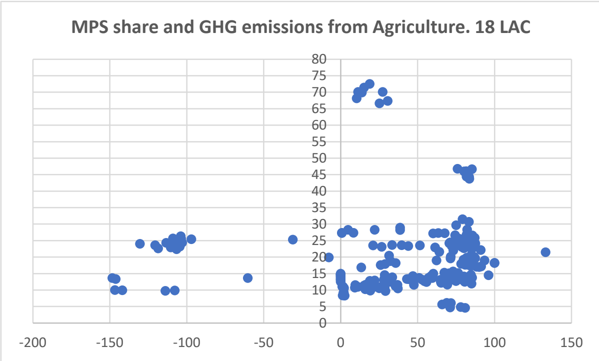
Panel on Climate Change of 2006 (IPCC 2006). The IPCC classifies the gases coming from the following main sectors: *(i)* energy; *(ii)* industrial processes and product use; *(iii)* agriculture, forestry and other uses, and land use changes (AFOLU); and *(iv)* waste. For the AFOLU sector, the IPCC presents measurements of the total CO_2e emissions and the shares of the total CO_2, methane (CH_4), nitrous oxide (N_2O), fluorinated gases, perfluorinated compounds (PFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3). For the AFOLU sector, emissions are measured from enteric fermentation, manure management, rice cultivation, agricultural land use, and biomass burning, among others (IPCC 2006, and the FAOSTAT database).

Besides measurements of national GHG inventories in AFOLU, concerns about climate change can be materialized through the design of agricultural support policies and programs that include climate change mitigation and adaptation. However, in this region, only Brazil, Uruguay, and Peru have been applying policies based on the Climate Smart Agriculture (CSA) approach (Egas & De Salvo 2018). This approach can help countries to promote technology adoption for low-carbon agriculture and climate change adaptation, among the other initiatives.

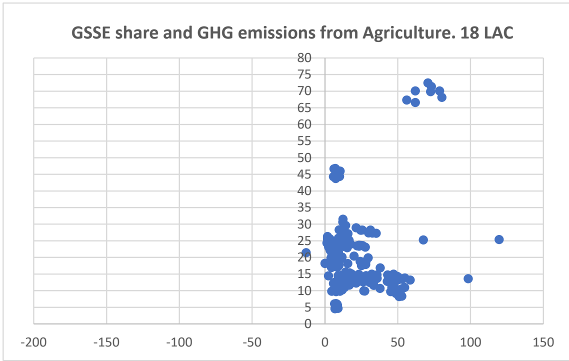
To further explore the agricultural policy-GHG emissions relationship visually, for the 18 LACs, Figure 3 part (a), on the left, shows the correlation between the MPS share in TSE and GHG emissions, and Figure 3 part (b), on the right, shows the correlations between the share of GSSE in TSE and GHG emissions. This figure suggests a positive relationship between the MPS share and CO_2 emissions (Figure 3, part a), whereas there is an ambiguity in the relationship between the GSSE share and the GHG emissions (Figure 3, part b). Even after excluding the countries with outlier data (Argentina, Bolivia, and Uruguay), Figure 3 part (c) still suggests a positive relationship between the MPS share and GHG emissions, whereas Figure 3 part (d) now suggests a negative relationship between GSSE shares and emissions. All these figures support the idea that producer incentives based on prices may be more harmful to the environment, at least in terms of the amount of GHG emissions. Hence, further studies should be performed to account for any significant causality, and the channels, in these relationships.

These results give rise to questions regarding the *importance of the agricultural sector in these economies,* the *size of agriculture emissions,* and *what the composition of agricultural production in the 18 LACs is.* Moreover, given the focus of this study on agricultural support, it is important to examine *how large are the incentives for the producers and commodities* and *whether the commodities with the largest GHG emissions are the ones that receive the most (price) support.* The following paragraphs present data to answer these questions.

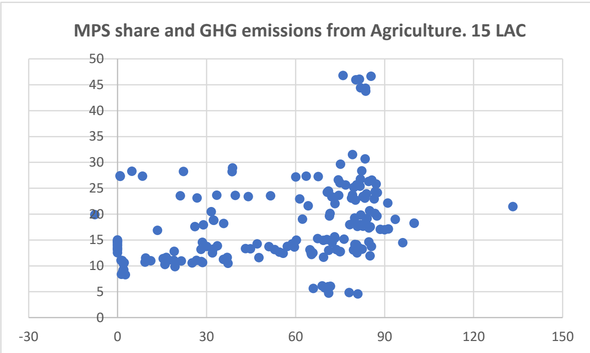
Part (a)



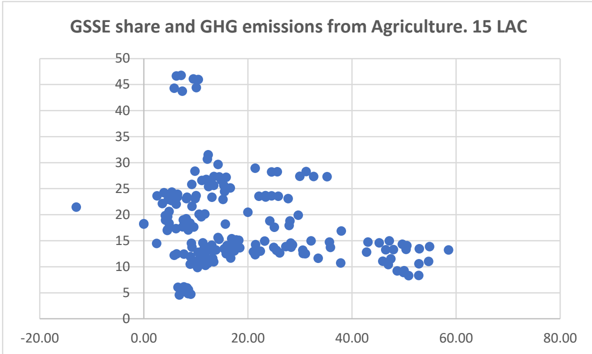
Part (b)



Part (c)



Part (d)



Notes: parts (a) and (b) include data from all 18 LACs in the sample. Parts (c) and (d) exclude country outliers: Argentina, Bolivia, and Uruguay, where Argentina has all the MPS in negative values (a valid interpretation of the lack of protection via prices for producers in that country). Bolivia also presents several years, but not all, with negative MPS values. Uruguay has the highest GHG emissions share of agriculture in the whole sample. The latest year for which emissions are available in FAOSTAT is 2017; thus, for some countries, we have missing agricultural support data for 2018 and 2019, though the countries may have data on MPS and GSSE.

Figure 3

Correlations: main TSE components and GHG emissions for LACs

Source: MPS and GSSE shares in TSE are calculated using data from Agrimonitor. GHG emissions shares from agriculture —in total emissions by country and year— are taken from FAOSTAT. These are measured as CO_2 equivalent (SAR definition).

Although in the process of development, agricultural production loses its share of GDP to other sectors (mostly services), its contribution to GDP still accounts for over 4 % in the LACs (except for Panama, which is currently at 2 %). The sector’s GDP share is more than 8 % in Bolivia, Ecuador, Guatemala, Honduras, Nicaragua, and Paraguay (hereby data on agricultural GDP and employment from the World Bank’s Word Development Indicators). Notably, agriculture still occupies a sizable employment share in the LACs (except for Argentina). For most of these countries, male employment in agriculture still plays a significant role. Male employment in this sector accounts for around 20 % (Colombia, Costa Rica, El Salvador, Jamaica, Mexico, Panama, and Paraguay), around 30 % (Bolivia, Ecuador, and Peru), and above 40 % (Guatemala, Honduras, and Nicaragua) of the total employment. In the Andean countries (Bolivia, Ecuador, and Peru), female and male occupy equal agricultural employment shares in total employment. These employment figures do not account for the indirect employment or production generated, for instance, from the allied sectors (*e.g.,* agrifood or services industries).

Concerning the emission levels, from 2000 to 2017, we find a sizeable share of agricultural GHG emissions in the total CO_2e emissions in some LACs (Table 1). Uruguay presents the largest agricultural GHG emissions during the period. However, in the past decade, Uruguay witnessed a decline in these GHG emissions, which accounted for 80 % of the total emissions in 2003 and was down to 66 % in 2017 —with an average of 73 % during the 2000-2017 period—. Countries representing a sizeable share *and* an increasing trend of these emissions are Brazil, Colombia, Nicaragua, and, to some extent, Dominican Republic and Guatemala. Conversely, Jamaica, accounted for the lowest share of agricultural GHG emissions, followed by Chile, Mexico, Ecuador, and Costa Rica. Moreover, these countries showed a decreasing trend in such emission shares. Eight countries represented an average share of above 20 % of the total agricultural GHG emissions, for the period 2000-2017 (Argentina, Brazil, Colombia, Costa Rica, Dominican Republic, El Salvador, Nicaragua, and Uruguay). The remaining ten countries comprised an average share of 6 % to 19 % of agricultural GHG emissions in the total emissions during the sampled period.

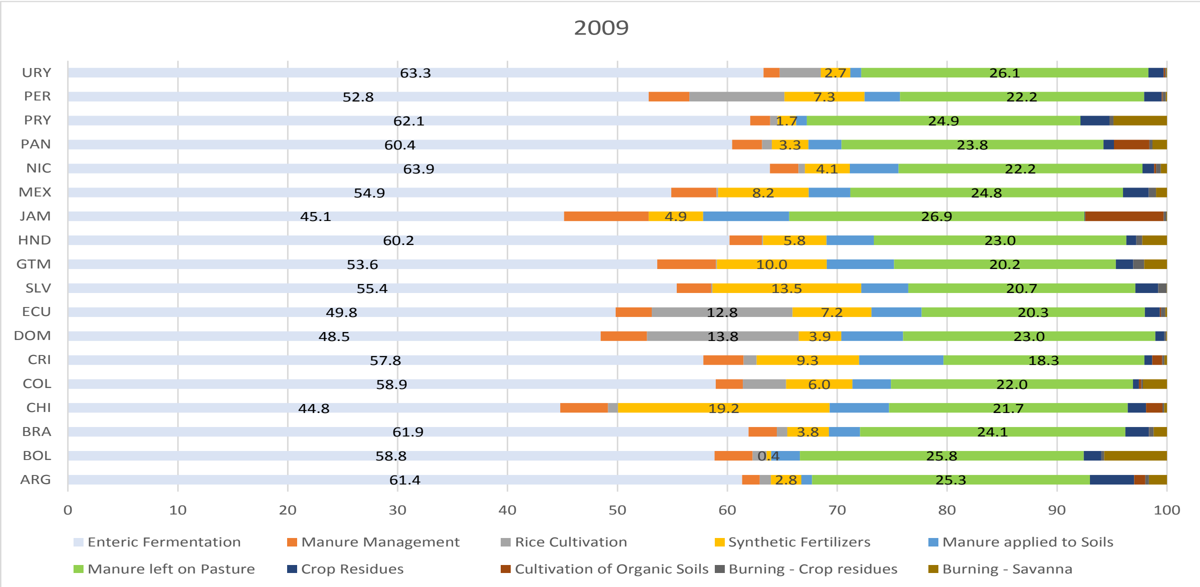
Agriculture consists of different sectors and activities, which produce GHG emissions of different amounts and intensities. In this regard, the literature has pointed out that some agricultural activities/sectors may be more polluting than the others, *e.g.,* livestock emits the highest agricultural GHGs (Josling *et al.* 2017 & Ackermann *et al.* 2018 for Jamaica and Uruguay, respectively). The activity

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average 2000-2017
ARG	25	25	26	26	24	25	25	26	24	23	23	23	22	23	23	23	24	24	24
BOL	13	14	15	15	14	14	10	10	10	10	10	13	14	14	13	13	13	13	13
BRA	18	17	18	18	19	19	24	24	23	23	24	29	28	27	27	27	28	28	23
CHI	14	15	14	14	14	13	12	11	11	12	11	11	10	9	9	9	8	8	11
COL	19	17	17	17	17	18	18	18	18	18	18	32	30	27	27	27	24	24	21
CRI	20	31	28	25	26	27	26	25	26	26	27	14	13	13	13	12	13	13	21
DOM	19	20	20	19	23	22	22	23	23	24	24	24	23	24	23	23	23	23	22
ECU	14	17	16	16	16	15	15	14	14	14	15	14	14	14	12	12	12	12	14
SLV	23	25	25	24	24	25	24	26	27	27	26	24	24	22	23	20	18	19	24
GTM	16	17	17	15	17	16	18	18	19	20	21	21	22	20	19	20	20	20	19
HND	9	11	11	12	12	12	13	12	12	13	13	13	13	13	13	13	13	13	12
JAM	8	7	7	8	7	7	5	5	5	6	6	6	6	6	6	6	5	5	6
MEX	12	12	12	12	12	11	11	11	10	10	11	11	11	11	11	11	11	10	11
NIC	16	16	16	17	16	17	15	15	15	15	15	44	47	46	46	47	44	44	27
PAN	15	15	16	15	15	15	15	15	15	15	15	15	15	15	16	14	13	13	15
PRY	17	19	18	19	18	18	12	13	13	13	14	13	14	14	15	15	15	15	15
PER	13	18	19	19	18	17	15	14	15	14	13	14	13	13	13	13	12	13	15
URY	77	78	79	80	78	77	76	77	70	70	72	70	68	70	71	67	67	66	73

Table 1
GHGs in Agriculture: share in total CO_2e emissions
Source: FAO (2020), FAOSTAT Agri-Environmental Indicators, Emissions shares: http://www.fao.org/faostat/en/#data/EM.

with the largest share of emissions is, by far, enteric fermentation; it makes up for about half or more of the total agricultural GHG emissions. This activity is followed by the manure-left-on-pasture that accounts for a fifth, and in some cases a fourth, of such emissions (Figure 4). The good news is that, in most LACs, both the activities registered a decline in emissions between 2009 and 2018 (Table 2). Conversely, during the same period, synthetic fertilizers —the third largest source of agricultural emissions— recorded

Part (a)



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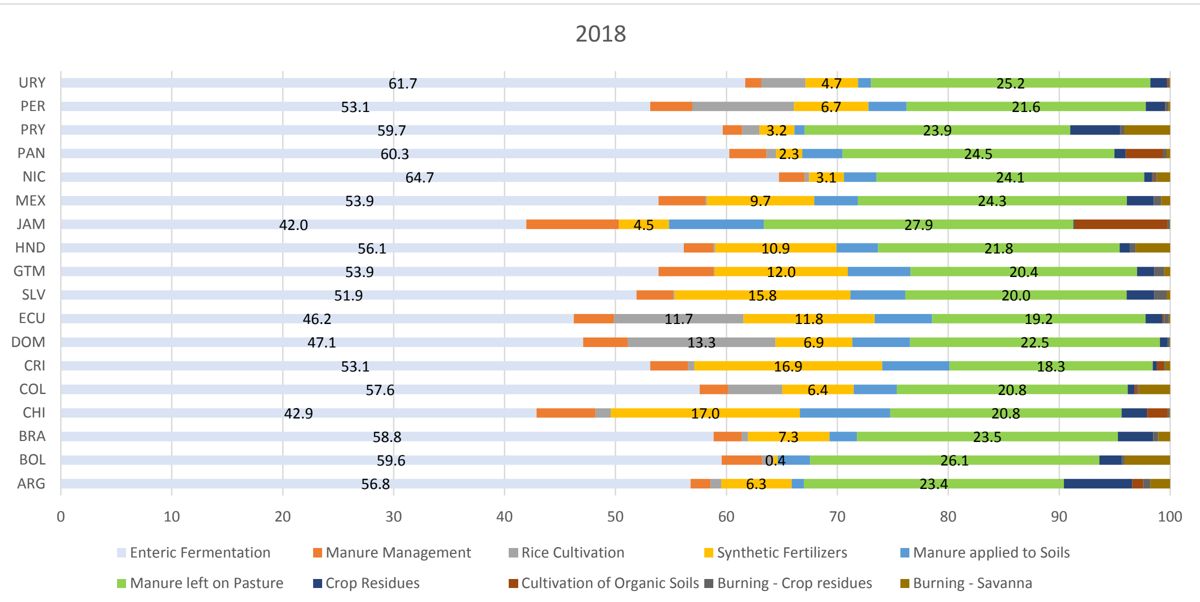


Notes: data for the sector Agriculture total combines the CH_4 and N_2O emissions from crop and livestock and other agricultural management activities.

Figure 4

Types of GHG emissions in Agriculture for selected LACs and selected years

Source: emissions estimated from the FAOSTAT dataset «Agriculture Total»: http://www.fao.org/faostat/en/#data/GT.

Type, Difference 2018-2009	ARG	BOL	BRA	CHI	COL	CRI	DOM	ECU	SLV	GTM	HND	JAM	MEX	NIC	PAN	PRY	PER	URY
Enteric Fermentation	-4.6	0.7	-3.1	-1.9	-1.4	-4.7	-1.4	-3.6	-3.5	0.3	-4.1	-3.2	-1.0	0.9	-0.2	-2.4	0.3	-1.6
Manure Management	0.2	0.2	0.0	1.0	0.1	-0.2	-0.2	0.3	0.2	-0.4	-0.2	0.7	0.1	-0.3	0.6	-0.1	0.1	0.0
Rice Cultivation	0.0	-0.3	-0.4	0.4	0.9	-0.6	-0.5	-1.1	0.0	0.0	0.0	0.0	0.0	-0.2	0.0	0.9	0.5	0.2
Synthetic Fertilizers	3.6	0.0	3.6	-2.2	0.4	7.6	3.1	4.6	2.3	2.0	5.2	-0.4	1.5	-1.0	-1.0	1.5	-0.6	2.0
Manure applied to Soils	0.1	0.3	-0.4	2.7	0.4	-1.6	-0.4	0.6	0.7	-0.5	-0.6	0.7	0.1	-1.5	0.6	-0.1	0.2	0.2
Manure left on Pasture	-1.9	0.3	-0.6	-0.9	-1.2	0.0	-0.4	-1.1	-0.7	0.2	-1.2	1.0	-0.6	1.9	0.7	-1.0	-0.7	-0.9
Crop Residues	2.2	0.4	1.0	0.6	0.1	-0.3	-0.1	0.2	0.4	-0.1	0.0	0.0	0.1	-0.3	0.1	1.9	0.1	0.1
Cultivation of Organic Soils	-0.1	0.0	0.0	0.4	0.0	-0.3	0.0	0.0	0.0	0.0	0.0	1.3	0.0	-0.1	0.1	0.0	0.0	0.0
Burning - Crop residues	0.3	0.0	0.0	0.0	0.0	-0.1	0.0	0.0	0.4	-0.1	0.0	0.0	0.0	-0.1	0.0	0.0	0.0	0.0
Burning - Savanna	0.1	-1.6	-0.1	-0.2	0.6	0.2	0.0	0.0	0.3	-1.6	0.8	0.0	-0.2	0.7	-1.0	-0.7	0.0	0.0
Total emissions (Gg), diff.	6,875	2,949	35,929	(1,903)	(1,479)	529	735	(2,313)	(877)	1,516	814	(59)	7,348	2,530	(142)	4,598	460	(1,638)
Total emissions (Gg) 2009	111,329	21,617	414,069	11,887	58,230	3,137	7,606	13,594	3,112	7,788	5,692	589	81,360	7,454	3,344	22,475	23,129	25,267
Total emissions (Gg) 2018	118,204	24,566	449,999	9,984	56,751	3,666	8,341	11,281	2,235	9,304	6,506	530	88,708	9,984	3,202	27,074	23,589	23,629

Table 2

Types of GHG emissions in Agriculture for LACs: totals and difference between 2009 and 2018

Source: emissions estimated from the FAOSTAT dataset «Agriculture Total»: http://www.fao.org/faostat/en/#data/GT.

considerable increments in almost all the LACs. Rice cultivation represents an important source of agricultural GHG emissions in the Dominican Republic, Ecuador, Colombia, Peru, and Uruguay. Between 2009 and 2018, 11 out of the 18 LACs recorded an increase in the total agriculture emissions; these countries are Argentina, Bolivia, Brazil, Costa Rica, Dominican Republic, Guatemala, Honduras, Mexico, Nicaragua, Paraguay, and Peru (Table 2).

Concerning the policy incentives to the agricultural producers, one important indicator of such incentives is the Producer Single Commodity Transfers (PSCT). As per the OECD, PSCT is «the annual monetary value of gross transfers from consumers and taxpayers to agricultural producers, measured at the farm gate level, arising from policies linked to the production of a single commodity such that the producer must produce the designated commodity in order to receive the transfer» (OECD 2016, p. 110). The PSCT includes, by definition, market price support policies, which capture the transfers associated with policies affecting the price of a particular commodity. The PSCT also includes budgetary and other transfers to producers from policies based on a single commodity; that is, besides MPS, the PSCT may include payments based on the input use (*e.g.,* variable input use, fixed capital formation, and on-farm services), payments based on the current A/An/R/I (area/animal numbers or revenue/income), production required, and payments based on non-current A/An/R/I production required. Thus, the PSCT includes price and payment measures that can potentially bring in environmentally harmful incentives to producers. To appraise the relative importance of the PSCT, the methodology provided by the OECD offers the percentage producer single commodity transfers (%PSCT), which is calculated as the percentage share of the PSCT of gross receipts for a given commodity.

All these indicators can be calculated at the individual commodity and at national (aggregate) levels. The OECD *Producer Support Estimate (PSE) Manual* (OECD 2016) provides a list of the «standard set of individual commodities». This list comprises the 7 commodities included in our study: beef and veal, eggs, milk, pig meat, poultry, rice, and refined sugar, as well as 11 others.[3] According to

3 The rest of the commodities included in the OECD list of standard set of individual commodities are wheat, maize, barley, sorghum, oats, rye, rapeseed, soybeans, sunflower, sheep meat, and wool.

this manual, the commodities in the complete list were selected «[…] because they represented a significant proportion of agricultural production in a large number of OECD countries and receive support policies» (OECD 2016, p. 98). Moreover, as the OECD manual points out, a standard set of commodities allows comparisons between countries at the national (aggregate) and individual commodity levels or between a subset of commodities. Thus, this study selects these seven commodities —a subset of those in the OECD standard set of individual commodities—, because of the following reasons: first, they still contribute a sizable share to the production value, with a combined share in total production value between 25 % to 72 %, depending on the year and country; second, most of the seven commodities are present in all the sampled LACs (Figure 5);

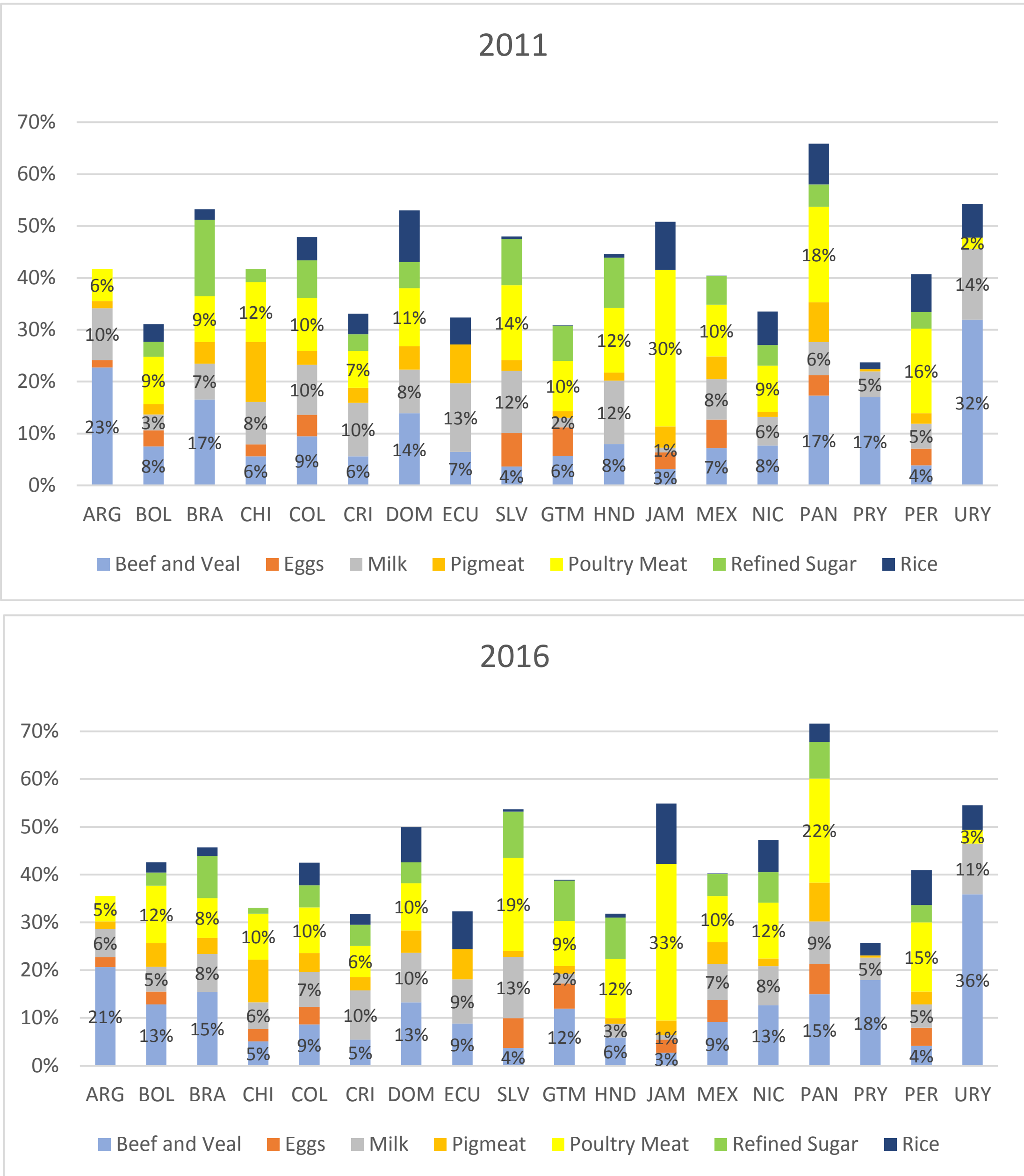


Figure 5
Share in value of production of selected crops and livestock activities, 2011 and 2016
Source: value of production shares calculated using data from Agrimonitor.

third, except for sugar, all the commodities have a comparable counterpart in the GHG emissions database from FAOSTAT. In other words, by focusing on the selected subset of commodities, we can compare the size of the policy incentives for the producers and commodities in the selected countries and check whether the commodities with the largest GHG emissions receive the maximum support (price or total).

Figure 5 highlights not only the importance of beef and veal, milk, and poultry in the value of production (VoP) of the 18 LACs but also the relative importance of sugar production (Brazil, Honduras, and Nicaragua), pork (Chile and Panama), and rice (Ecuador, Colombia, and Dominican Republic).

Concerning again the incentives received by the producers of these commodities, Table 3 and Table 4 illustrate the value and percentage share, respectively, of such PSCT incentives. Broadly speaking, it is possible to group the countries into three categories by the average amount of PSCT given to some or all these commodities:

- Negative support: Argentina for beef and veal, milk, and poultry; Bolivia for beef and veal, poultry, and sugar; Brazil for pig meat, and poultry; Guatemala for beef and veal, eggs, milk, and rice; and Nicaragua for beef and veal and milk.
- Zero or very low support: Chile (except for sugar and a couple of years for milk; Chile gives zero support to the other commodities); Paraguay (this country gives zero support to all commodities) and Uruguay (except for poultry, Uruguay also gives zero support to the rest of commodities), and Mexico (except for sugar, low support for the rest of commodities).
- Significant support: the rest of the nine countries provide significant support (in relation to the size of the sector) for most of the selected commodities. These countries are Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Honduras, Jamaica, Panama, and Peru.

ARGENTINA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	(1,873.9)	(2,367.6)	(5,390.6)	(2,032.4)	(2,068.1)	(3,011.3)	(3,054.4)	(2,392.4)	(1,684.3)	273.3	3.6	3.4	(1,512.7)	(1,756.6)	(1,919)
Eggs	30.8	43.2	104.0	93.2	65.7	158.8	150.5	200.0	172.4	153.2	81.5	82.1	106.0	121.7	112
Milk	(503.4)	(686.7)	(1,231.0)	(247.0)	(1,126.4)	(840.0)	(409.9)	(944.6)	(1,365.8)	(527.3)	107.6	69.1	(1,477.6)	(808.4)	(714)
Pigmeat	45.9	55.7	113.8	104.5	83.3	169.3	170.4	222.0	195.6	186.3	100.8	128.1	138.7	143.0	133
Poultry Meat	(525.6)	(480.8)	(463.5)	(685.0)	(202.4)	348.6	125.4	(231.0)	(609.9)	(614.5)	91.5	113.4	(1,061.6)	(632.0)	(345)
Subtotal	(2,826.1)	(3,436.2)	(6,867.4)	(2,766.7)	(3,247.9)	(3,174.6)	(3,018.0)	(3,146.0)	(3,292.0)	(528.9)	385.1	396.0	(3,807.1)	(2,932.3)	(2,733)
Total	(6,602)	(8,312)	(13,800)	(14,269)	(11,538)	(18,136.4)	(17,319.0)	(19,135.1)	(22,582.1)	(12,998.9)	(5,116.8)	(4,123.9)	(12,530.4)	(11,752.7)	(12,730)

BOLIVIA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	(15.6)	(15.8)	(330.5)	(655.7)	(304.1)	(211.6)	(357.6)	(34.7)	(40.9)	(103.7)	218.0	231.7	239.9	n.a.	(106)
Eggs	-	-	-	-	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	-	n.a.	0
Milk	(1.7)	(1.8)	(0.4)	(2.2)	8.1	7.8	52.7	88.1	79.5	110.0	117.4	105.1	109.3	n.a.	52
Pigmeat	(72.3)	(61.2)	(4.3)	(96.1)	(18.9)	(11.2)	(14.6)	(24.2)	31.9	94.8	76.9	68.0	62.8	n.a.	2
Poultry Meat	(68.5)	(61.4)	(4.9)	(119.4)	(23.3)	120.3	(105.2)	(23.6)	(21.0)	(201.1)	(61.6)	2.9	(139.5)	n.a.	(54)
Refined Sugar	-	0.0	(31.4)	(64.7)	(86.2)	(150.1)	(170.4)	(132.5)	(87.5)	(40.9)	(68.7)	(88.6)	(42.6)	n.a.	(74)
Rice	31.1	43.1	50.4	49.3	74.1	59.4	31.4	60.6	77.9	109.8	77.0	89.4	114.1	n.a.	67
Subtotal	(127.0)	(97.1)	(321.1)	(888.8)	(350.3)	(185.5)	(563.7)	(66.1)	39.8	(31.1)	359.0	408.5	344.0		(114)
Total	(124)	16	(307)	(631)	(326)	(442)	(605)	(93)	97	248	675	543	622		(25)

BRAZIL	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	61.7	189.1	(59.0)	1,836.7	1,899.9	1,589.1	(1,787.6)	170.6	158.1	126.3	29.3	0.9	104.1	98.8	316
Milk	9.0	(160.4)	(80.1)	2,486.0	1,326.7	872.5	93.7	42.8	40.2	47.6	813.5	0.2	0.8	1.0	392
Pigmeat	(117.6)	(187.7)	(254.3)	(24.9)	727.9	(92.5)	(263.9)	28.7	31.3	24.7	(138.8)	0.0	4.8	4.2	(18)
Poultry Meat	(262.7)	(433.2)	(611.1)	(75.6)	31.2	(256.5)	(604.5)	35.5	34.2	26.2	(332.2)	0.0	10.4	4.8	(174)
Refined Sugar	75.8	96.3	116.5	105.5	327.5	170.3	167.2	171.7	56.1	40.5	38.0	33.6	14.3	12.3	102
Rice	659.3	878.5	880.4	1,071.8	822.1	801.9	163.9	532.8	35.4	25.4	18.7	21.5	13.2	9.8	424
Subtotal	425.4	382.5	-7.6	5399.5	5135.3	3084.9	-2231.1	982.1	355.3	290.6	428.5	56.3	147.7	130.8	1,041
Total	3,305	5,320	5,076	7,729	7,850	10,261	7,469	2,956	1,808	1,123	2,832	1,372	971	544	4,187

CHILE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Eggs	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Milk	-	25.7	-	56.4	-	-	-	-	-	-	-	-	-	-	6
Pigmeat	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Poultry Meat	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Refined Sugar	16.9	12.8	3.8	3.6	6.5	10.8	9.5	8.7	7.3	7.8	5.8	6.0	7.9	4.1	8
Subtotal	17	38	4	60	7	11	9	9	7	8	6	6	8	4	14
Total	71	44	6	62	10	17	15	15	17	14	10	22	14	7	23

COLOMBIA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	346.7	578.5	223.0	290.4	(2.9)	(5.3)	170.9	278.3	(2.7)	(2.9)	(4.6)	(3.7)	302.5	32.7	157
Eggs	78.5	83.2	115.4	104.3	125.8	134.8	150.9	143.1	152.0	120.9	114.8	118.4	146.0	138.5	123
Milk	257.5	195.0	385.1	716.9	670.7	615.5	930.0	624.7	696.0	395.1	339.1	508.0	847.4	484.2	547
Pigmeat	56.7	145.6	285.1	231.6	270.3	238.6	271.0	301.2	225.8	131.8	304.7	201.8	169.7	179.5	215
Poultry Meat	204.9	473.9	577.4	540.6	725.7	1,141.2	1,387.5	1,082.5	772.0	105.0	126.2	(11.1)	58.5	654.8	560
Refined Sugar	329.7	287.7	310.3	443.4	575.9	357.5	292.7	333.6	480.0	490.5	197.6	93.8	121.7	-	308
Rice	257.1	333.3	674.7	599.5	620.2	740.5	894.0	666.4	655.7	740.9	800.6	566.3	499.6	525.7	612
Subtotal	1,531.0	2,097.1	2,570.9	2,926.7	2,985.7	3,222.8	4,096.9	3,429.7	2,978.8	1,981.4	1,878.3	1,473.5	2,145.4	2,015.5	2,524
Total	2,399	3,231	3,800	4,331	4,503	4,716	5,502	5,356	4,148	3,227	3,381	2,503	3,430	2,410	3,781

COSTA RICA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	11.1	31.4	2.4	-	-	-	-	-	-	-	-	-	0.0	-	3
Milk	22.7	-	36.8	-	107.7	156.2	41.0	32.2	-	76.2	11.0	-	0.0	-	35
Pigmeat	24.1	30.7	39.0	36.5	45.1	41.0	46.7	51.3	52.1	44.9	44.7	47.1	46.6	47.9	43
Poultry Meat	72.6	43.0	85.9	128.4	156.9	163.5	128.2	118.4	114.4	126.9	123.4	98.3	68.8	79.2	108
Refined Sugar	17.3	-	-	-	-	-	14.6	64.1	61.9	79.6	73.1	24.8	54.0	74.0	33
Rice	33.4	23.5	37.1	62.5	98.9	128.1	109.6	75.7	65.2	71.7	69.5	44.4	40.1	43.1	64
Subtotal	181.3	128.6	201.2	227.4	408.7	488.7	340.2	341.7	293.4	399.2	321.7	214.5	209.4	244.1	286
Total	209.3	145.5	222.4	260.2	457.1	537.0	368.0	372.6	321.7	438.1	366.8	235.1	229.5	325.9	321

DOMINICAN REP.	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	414.4	172.2	77.3	195.8	102.0	(71.7)	(144.3)	(131.2)	(112.0)	(160.7)	(81.5)	130.3			33
Milk	130.6	122.6	88.9	142.5	133.0	111.3	124.2	44.3	108.9	135.5	354.0	172.8			139
Pigmeat	139.1	95.9	95.5	60.5	34.3	12.1	(16.9)	37.0	0.4	58.1	92.8	80.7			57
Poultry Meat	364.9	334.0	291.8	264.9	336.6	324.3	272.1	248.9	298.5	328.0	161.7	56.9			274
Refined Sugar	11.4	3.2	45.1	59.3	17.4	(10.1)	(80.2)	(56.6)	(1.0)	2.9	(0.4)	(12.6)			(2)
Rice	176.5	214.2	289.7	199.1	146.8	123.7	95.0	94.2	71.4	76.6	113.2	145.7			146
Subtotal	1237.0	942.1	888.4	922.1	770.1	489.7	250.0	236.5	366.3	440.3	639.9	573.8			646
Total	1,229.9	972.9	974.0	943.7	846.8	628.8	299.8	197.9	322.8	459.3	736.4	700.5			693

ECUADOR	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	39.1	53.1	-	75.6	4.2	10.4	8.0	10.7	10.5	-	-				19
Milk	-	-	-	291.7	-	-	-	-	-	24.4	124.6				40
Pigmeat	77.0	103.4	105.5	160.3	145.3	139.0	179.6	115.5	134.0	159.6	119.2				131
Rice	32.0	86.3	21.3	52.4	-	-	-	53.9	192.5	284.2	265.1				90
Subtotal	148.1	242.8	126.7	580.0	149.5	149.4	187.6	180.2	336.9	468.2	508.9				280
Total	148.1	242.8	141.8	588.2	179.2	150.4	188.8	211.7	517.3	732.6	713.4				347

EL SALVADOR	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal				14.9	12.4	17.2	30.2	9.3	11.1	1.3	6.6	12.1			13
Eggs				n.a.	n.a.	13.2	(14.7)	(16.5)	(51.7)	(61.1)	(61.9)	(76.7)			(38)
Milk				150.0	141.6	88.8	108.2	72.3	37.7	16.9	19.7	81.1			80
Pigmeat				12.2	23.7	4.8	7.2	9.1	8.7	11.9	8.8	8.0			10
Poultry Meat				28.5	61.9	121.6	137.8	142.6	152.2	181.6	197.8	283.0			145
Refined Sugar				42.8	47.4	50.2	63.7	63.1	64.8	47.0	55.5	54.5			54
Rice				6.3	7.8	2.2	1.4	2.0	3.2	5.7	2.6	1.0			4
Subtotal				254.4	294.8	298.0	333.7	281.8	226.1	203.4	229.0	363.2			276
Total				281.2	322.2	535.8	396.3	234.1	388.2	440.5	538.7	459.6			400

GUATEMALA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	(5.6)	(11.2)	(27.6)	(11.7)	(142.6)	(348.5)	89.4	(230.4)	(162.8)	(112.0)	(183.8)	(271.6)	(190.0)		(124)
Eggs	53.5	(35.1)	(94.8)	(4.5)	17.8	(26.3)	49.7	65.6	(9.4)	(211.0)	56.4	(225.1)	(253.5)		(47)
Milk	(8.0)	(45.0)	(61.7)	7.0	(1.4)	(26.7)	(23.0)	(67.1)	(81.2)	(30.8)	(9.3)	(23.9)	(6.4)		(29)
Pigmeat	(10.8)	(21.9)	10.1	27.5	30.8	31.8	1.8	3.5	(17.5)	13.2	12.5	14.2	8.2		8
Poultry Meat	129.7	208.5	262.8	243.5	260.6	231.0	174.8	181.6	241.1	283.7	289.8	294.8	278.7		237
Refined Sugar	117.0	306.7	217.3	66.8	36.0	91.2	157.6	245.8	384.0	401.6	504.3	468.2	542.4		272
Rice	0.3	0.5	(2.3)	(1.0)	0.5	(2.3)	(0.7)	(1.1)	(1.0)	1.3	0.6	0.7	(1.1)		(0.4)
Subtotal	276.1	402.6	303.7	327.7	201.5	-49.9	449.7	197.9	353.3	346.0	670.4	257.4	378.3		317
Total	508.9	624.5	408.4	94.4	334.5	(239.9)	220.4	47.0	250.6	136.4	581.3	(1.1)	340.4		254

HONDURAS	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal						(1.1)	0.5	50.7	54.7	50.3	12.5	66.8			33
Milk						56.2	54.9	14.4	12.3	6.0	9.0	18.1			24
Pigmeat						(0.9)	1.0	5.2	(0.7)	4.3	2.4	(1.0)			1
Poultry Meat						128.1	128.7	104.7	110.4	85.3	96.5	(17.8)			91
Refined Sugar						23.8	6.1	43.2	68.0	73.2	67.2	41.4			46
Rice						14.8	17.0	(2.0)	(2.0)	1.8	1.7	1.8			5
Subtotal						220.9	208.1	216.3	242.6	220.9	189.2	109.3			201
Total						371.6	250.9	272.0	354.6	295.7	208.5	125.0			268

JAMAICA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	1.1	7.1	7.2	2.2	4.6	1.2	0.4	0.5	0.4						3
Eggs	8.6	4.4	1.0	1.1	0.5	1.0	1.6	6.1	0.6						3
Milk	0.7	1.3	0.7	2.4	0.5	0.3	1.3	0.0	0.0						1
Pigmeat	0.2	0.3	0.5	0.4	0.5	0.9	1.0	0.8	0.7						1
Poultry Meat	143.9	147.1	130.4	106.5	138.9	172.2	171.9	162.7	174.1						150
Refined Sugar	10.5	14.7	17.3	26.9	37.7	57.0	75.3	52.4	27.9						36
Subtotal	165.0	174.9	157.1	139.4	182.8	232.6	251.5	222.5	203.6						192
Total	177.4	182.6	157.7	132.5	186.7	229.7	251.7	220.4	204.3						194

MEXICO	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	194.6	394.1	352.8	310.0	351.5	324.2	323.4	276.6	282.4	142.9	191.7	143.3	100.4	-	242
Eggs	(3.0)	-	-	(5.7)	-	(13.7)	-	417.4	-	-	(2.8)	-	-	-	28
Milk	283.1	-	17.9	384.9	0.3	(12.3)	63.3	-	-	589.5	148.9	-	-	118.4	114
Pigmeat	45.8	36.2	150.6	171.3	52.4	(2.1)	16.8	22.1	24.7	34.2	49.2	7.4	148.4	31.5	56
Poultry Meat	309.2	614.1	384.4	494.1	575.2	797.5	843.3	708.7	379.9	-	(3.3)	-	-	546.4	404
Refined Sugar	318.6	763.6	586.9	2.4	333.5	102.8	616.6	-	213.6	403.3	212.8	905.9	1,053.3	943.0	461
Rice	8.3	9.9	-	-	4.3	7.0	4.5	2.0	8.9	0.0	-	-	-	3.6	3
Subtotal	1156.5	1817.9	1492.6	1357.0	1317.4	1203.4	1867.8	1426.9	909.5	1170.0	596.4	1056.6	1302.1	1642.9	1,308
Total	2,600.6	3,205.2	2,761.6	2,054.0	3,164.0	2,741.8	3,044.4	2,065.4	1,875.8	2,547.6	1,640.2	2,708.7	3,288.4	3,513.0	2,658

NICARAGUA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal				(0.2)	-	-	-	-	-	(0.2)	(0.2)	(0.0)			(0.1)
Milk				(0.2)	-	-	-	-	-	(0.2)	(0.2)	(0.0)			(0.1)
Pigmeat				3.9	7.1	1.5	5.4	5.4	1.4	12.4	17.8	15.6			8
Poultry Meat				41.5	21.6	75.3	105.2	116.9	124.3	155.3	168.1	125.7			104
Refined Sugar				79.1	10.9	-	-	-	-	-	-	-			10
Rice				67.8	83.1	45.7	56.3	53.1	58.0	81.8	79.3	82.4			68
Subtotal				192.0	122.7	122.5	166.9	175.4	183.8	249.2	264.7	223.7			189
Total				225.9	122.7	161.2	181.8	175.8	206.2	294.1	332.4	237.0			215

PANAMA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal					103.7	99.5	46.2	90.4	57.3	65.2					77
Eggs					18.8	21.5	31.9	38.9	26.1	15.9					26
Milk					30.8	(0.6)	61.3	5.0	2.2	72.7					29
Pigmeat					49.4	47.3	55.3	55.4	52.3	76.7					56
Poultry Meat					5.7	37.3	30.5	4.0	4.6	47.0					22
Refined Sugar						(164.8)	(181.9)	(135.5)	(117.9)	(88.4)					(138)
Rice					19.4	35.5	56.0	59.7	21.8	59.1					42
Subtotal					227.8	75.7	99.4	118.0	46.3	248.4					136
Total					246.0	106.6	178.8	201.8	123.7	359.1					203

PARAGUAY	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-
Milk	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-
Pigmeat	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-
Rice	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	-	-	n.a.	-
Subtotal	n.a.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	n.a.	-
Total	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-

PERU	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	n.a.	n.a.	n.a.	n.a.	0.3	-	-	-	(46.4)	(48.4)	(30.8)	(54.5)	(24.4)	n.a.	(23)
Eggs	n.a.	n.a.	n.a.	n.a.	31.9	62.3	106.8	101.8	(8.2)	(8.8)	10.1	(10.5)	(8.8)	n.a.	31
Milk	n.a.	n.a.	n.a.	n.a.	3.7	0.3	0.2	0.1	(19.7)	(20.5)	48.2	18.1	134.7	n.a.	18
Pigmeat	n.a.	n.a.	n.a.	n.a.	-	0.04	1.5	42.4	44.0	136.2	169.0	182.8	198.6	n.a.	86
Poultry Meat	n.a.	n.a.	n.a.	n.a.	224.0	284.2	254.1	1.2	(21.0)	(21.6)	316.4	238.3	(20.0)	n.a.	140
Refined Sugar	n.a.	n.a.	n.a.	n.a.	1.6	124.1	119.0	87.3	0.1	58.3	18.5	-	114.4	n.a.	58
Rice	n.a.	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	-	n.a.	-
Subtotal					261.5	470.9	481.6	232.8	-51.3	95.1	531.3	374.1	394.6		310
Total					367.4	568.2	535.7	337.4	107.6	293.7	789.8	546.2	872.0		491

URUGUAY	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal				-	-	-	-	-	-	-	-				-
Milk				-	-	-	-	-	-	-	-				-
Poultry Meat				25.7	30.8	11.3	14.7	14.1	12.8	56.6	45.9				26
Rice				-	-	-	-	-	-	-	-				-
Subtotal				25.7	30.8	11.3	14.7	14.1	12.8	56.6	45.9				26
Total				36.2	35.0	30.3	21.5	27.0	36.3	84.6	59.1				41

Notes: PSCT in US$ million. Selected crops and activities, depending on data availability for each country, may include beef and veal, eggs, milk, pig meat, poultry, rice, and refined sugar.

Table 3
Incentives by selected crop and livestock activities (PSCT), total
Source: own construction using data on domestic support policies from Agrimonitor.

Concerning commodities, Table 4 also illustrates that the commodities receiving the highest support for most of the period are poultry meat, pork, and refined sugar.

ARGENTINA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	-43.7	-46.6	-97.6	-36.7	-25.7	-31.9	-31.7	-24.9	-17.8	2.7	0.04	0.03	-19.7	-24.4	-28.4
Eggs	10.6	11.5	17.7	20.6	11.7	26.0	17.3	20.6	20.0	14.9	8.9	10.8	12.8	17.1	15.8
Milk	-30.8	-29.4	-43.6	-10.1	-30.0	-20.3	-10.6	-22.1	-32.5	-14.3	4.1	2.1	-54.2	-27.3	-22.8
Pigmeat	16.3	18.8	25.7	26.1	17.2	29.3	27.9	31.6	27.1	22.9	15.1	15.2	23.3	24.8	23.0
Poultry Meat	-63.3	-43.2	-34.2	-56.4	-9.8	13.5	4.4	-7.7	-21.1	-23.6	4.0	5.0	-49.7	-27.6	-22.1

BOLIVIA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	-9.1	-8.4	-131.0	-287.4	-121.8	-74.4	-97.3	-8.4	-6.1	-14.5	30.8	32.0	32.3		-51.0
Eggs	-	-	-	-	0.005	0.002	0.01	0.05	0.01	0.01	0.01	0.01	-		0.01
Milk	-4.0	-3.6	-0.7	-3.6	7.2	6.7	29.5	35.8	29.4	39.4	41.3	42.5	46.2		20.5
Pigmeat	-101.3	-79.2	-4.1	-150.9	-28.0	-15.3	-18.3	-28.7	12.0	32.7	28.1	24.0	22.5		-23.6
Poultry Meat	-58.8	-44.6	-2.3	-60.9	-7.7	35.0	-19.9	-3.6	-3.2	-30.6	-9.3	0.4	-23.7		-17.6
Refined Sugar	-	0.001	-21.2	-42.6	-74.9	-135.8	-126.5	-92.9	-60.8	-27.6	-44.5	-45.7	-19.7		-53.3
Rice	28.8	45.4	39.8	46.8	62.8	45.5	19.1	43.7	53.7	71.9	65.9	63.8	72.4		50.7

BRAZIL	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	0.4	1.0	-0.2	8.1	7.0	5.0	-6.6	0.6	0.5	0.5	0.1	0.004	0.5	0.4	1
Milk	0.2	-2.0	-0.8	24.7	11.2	6.6	0.6	0.3	0.3	0.5	6.9	0.002	0.01	0.01	3
Pigmeat	-3.1	-4.0	-4.1	-0.5	9.9	-1.2	-3.8	0.4	0.4	0.5	-2.7	0.001	0.1	0.1	-0.6
Poultry Meat	-3.5	-4.0	-4.8	-0.6	0.2	-1.5	-4.2	0.2	0.2	0.2	-2.7	######	0.1	0.03	-1.4
Refined Sugar	0.9	0.9	1.0	0.8	1.5	0.6	0.7	0.9	0.4	0.4	0.3	0.2	0.1	0.1	0.6
Rice	26.4	29.7	20.0	26.3	20.5	20.2	4.3	12.1	1.0	0.9	0.7	0.7	0.5	0.4	12

CHILE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Eggs	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Milk	-	3.0	-	8.8	-	-	-	-	-	-	-	-	-	-	1
Pigmeat	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Poultry Meat	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Refined Sugar	9.1	9.1	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	4

COLOMBIA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	18.9	23.7	8.5	12.4	-0.1	-0.2	6.0	10.0	-0.1	-0.1	-0.2	-0.2	11.4	1.3	7
Eggs	14.5	12.1	12.5	12.3	12.5	12.1	12.6	12.6	12.6	12.5	12.1	12.3	12.4	12.7	13
Milk	16.8	9.9	16.2	33.4	27.5	23.6	33.0	21.6	24.3	19.4	18.1	22.7	35.1	19.4	23
Pigmeat	20.1	35.1	52.0	49.0	43.8	33.6	35.3	34.2	25.9	19.2	30.5	24.4	20.7	19.9	32
Poultry Meat	15.7	26.6	27.6	26.8	30.6	41.3	43.6	31.5	22.7	4.0	5.2	-0.4	2.1	20.8	21
Refined Sugar	27.4	27.9	30.3	30.4	34.2	18.4	17.8	23.9	30.5	36.8	16.6	7.8	11.8	-	22
Rice	44.4	42.2	50.0	50.3	60.0	60.8	65.4	55.4	62.3	64.7	64.6	46.7	45.2	45.3	54

COSTA RICA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	6.3	16.1	1.1	-	-	-	-	-	-	-	-	-	-	-	2
Milk	9.2	-	9.0	-	23.4	34.2	8.6	6.2	-	14.4	2.1	-	-	-	8
Pigmeat	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	31.5	32
Poultry Meat	36.2	21.6	34.8	44.3	49.1	51.9	39.7	34.4	32.2	36.9	37.6	30.2	22.7	27.3	36
Refined Sugar	17.3	-	-	-	-	-	6.1	23.8	24.5	33.0	32.7	11.2	24.7	32.8	15
Rice	61.0	39.6	41.3	45.2	62.3	72.1	68.6	55.0	50.9	65.1	61.6	55.9	49.7	54.7	56

DOMINICAN R	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	83.8	35.6	16.1	40.3	21.1	-14.4	-28.6	-25.4	-19.6	-28.9	-14.2	22.7			7
Milk	60.3	51.9	35.0	55.2	47.6	36.9	42.6	19.6	48.2	54.0	78.5	57.3			49
Pigmeat	62.5	48.9	50.8	42.9	23.3	7.5	-7.0	18.5	0.2	28.9	46.0	40.9			30
Poultry Meat	88.3	85.4	75.0	78.5	83.7	81.3	70.1	62.2	65.3	74.4	37.8	13.1			68
Refined Sugar	8.0	2.2	24.7	30.1	8.9	-5.6	-42.1	-33.6	-0.6	1.7	-0.2	-5.6			-1
Rice	57.7	56.8	58.5	50.7	37.4	32.3	28.1	26.7	21.8	24.2	34.5	42.6			39

ECUADOR	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	10.3	13.6	-	17.7	1.0	2.3	1.7	2.0	1.6	-	-				5
Milk	-	-	-	43.7	-	-	-	-	-	3.0	15.9				6
Pigmeat	25.9	26.7	27.7	39.9	33.6	27.8	34.1	28.9	24.1	27.9	22.4				29
Rice	9.3	17.8	6.9	17.5	-	-	-	9.3	31.1	39.2	39.3				15

EL SALVADOR	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal				17.2	13.9	24.2	35.4	13.3	15.1	1.7	9.1	16.7			16
Eggs				n.a.	n.a.	10.5	-11.2	-11.1	-32.1	-38.1	-50.2	-60.8			-28
Milk				57.4	46.6	38.1	44.0	28.7	14.5	6.9	7.8	27.4			30
Pigmeat				40.9	52.2	11.7	19.7	29.1	25.7	40.8	34.5	34.6			32
Poultry Meat				12.5	25.4	43.5	44.3	44.5	45.9	50.3	51.6	70.6			43
Refined Sugar				29.2	29.8	29.0	29.5	29.8	29.5	29.1	29.1	29.1			29
Rice				49.3	57.2	21.5	11.6	13.5	18.6	35.3	25.6	10.7			27

GUATEMALA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	-1.8	-3.4	-8.1	-3.7	-38.5	-95.7	16.1	-34.5	-22.0	-11.8	-22.3	-32.1	-19.0		-21
Eggs	20.3	-12.5	-31.9	-1.5	5.1	-7.6	13.1	15.1	-2.1	-48.8	15.5	-58.4	-68.6		-12
Milk	-7.4	-40.4	-54.6	6.7	-1.2	-22.7	-17.4	-58.0	-66.2	-22.1	-6.5	-15.9	-4.8		-24
Pigmeat	-13.8	-27.8	13.4	41.3	39.6	39.9	2.0	3.7	-16.5	12.0	11.1	12.3	7.3		10
Poultry Meat	31.4	44.8	51.3	46.8	42.9	37.7	32.5	31.6	38.0	42.1	44.8	42.0	48.4		41
Refined Sugar	44.5	97.5	66.2	19.3	12.9	21.2	33.5	43.0	63.9	70.3	86.5	77.0	90.5		56
Rice	5.7	8.4	-33.2	-14.8	5.7	-28.7	-5.9	-9.0	-7.9	10.7	5.2	6.4	-10.6		-5

HONDURAS	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal						-0.5	0.2	24.6	23.8	24.8	6.7	29.0			16
Milk						16.3	16.3	18.2	14.4	6.8	10.0	19.4			14
Pigmeat						-2.0	1.9	12.5	-1.6	10.0	6.5	-3.1			3
Poultry Meat						36.4	35.1	37.0	33.8	29.0	25.2	-4.9			27
Refined Sugar						8.6	1.9	14.9	23.3	26.0	24.8	14.3			16
Rice						72.3	72.7	-8.6	-6.0	5.1	6.9	8.0			21

JAMAICA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	4.1	28.4	27.2	9.8	20.3	4.5	1.6	1.6	1.6						11
Eggs	27.2	19.2	4.5	5.3	2.5	3.6	4.6	20.7	2.6						10
Milk	12.8	21.9	8.0	30.4	7.1	3.5	15.4	0.1	0.1						11
Pigmeat	2.1	2.2	2.5	2.4	2.7	2.7	2.7	2.7	2.6						3
Poultry Meat	64.0	56.2	55.1	50.5	61.5	68.7	66.2	64.2	64.3						61
Refined Sugar	18.9	22.0	25.0	42.6	57.6	59.8	56.4	50.7	24.5						40

MEXICO	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	6.0	10.8	9.4	9.2	9.1	8.3	8.3	6.4	5.6	2.7	4.1	2.9	2.2	-	6
Eggs	-0.2	-	-	-0.2	-	-0.5	-	9.5	-	-	-0.1	-	-	-	1
Milk	9.2	-	0.4	10.6	0.01	-0.3	1.5	-	-	14.0	4.1	-	-	2.2	3
Pigmeat	2.8	2.3	8.2	10.2	2.7	-0.1	0.7	0.9	0.8	1.4	2.2	0.3	6.1	1.1	3
Poultry Meat	8.9	14.6	9.1	11.5	12.3	16.1	15.6	11.8	6.3	-	-0.1	-	-	9.6	8
Refined Sugar	17.3	38.6	28.9	0.2	14.3	3.7	21.9	-	10.6	21.3	9.4	33.7	44.1	40.4	20
Rice	12.0	13.2	-	-	7.6	12.9	8.6	3.7	12.5	0.1	-	-	-	5.99	5

NICARAGUA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal				-0.1	-	-	-	-	-	-0.05	-0.1	-0.01			-0.02
Milk				-0.1	-	-	-	-	-	-0.1	-0.1	-0.01			-0.04
Pigmeat				18.2	30.8	6.5	19.5	17.8	4.6	35.2	39.9	34.3			23
Poultry Meat				27.7	14.2	32.0	38.6	40.2	40.2	48.5	52.7	39.2			37
Refined Sugar				29.7	4.6	-	-	-	-	-	-	-			4
Rice				53.5	57.9	27.2	32.1	31.0	33.0	49.1	42.6	43.2			41

PANAMA	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal					47.7	37.9	18.9	34.9	20.5	23.9					31
Eggs					35.6	35.9	37.6	39.7	27.4	13.9					32
Milk					27.6	-0.6	39.5	4.5	1.8	44.8					20
Pigmeat					48.9	40.8	43.1	41.5	37.2	51.9					44
Poultry Meat					2.4	13.3	9.9	1.2	1.2	11.9					7
Refined Sugar					n.a.	-252.1	-274.0	-203.0	-162.0	-126.5					-204
Rice					14.7	29.8	34.8	42.4	14.8	42.3					30

PARAGUAY	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-
Milk	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-
Pigmeat	n.a.	-	-	-	-	-	-	-	-	-	-	-	-	n.a.	-
Rice	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	-	-	n.a.	-

PERU	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	n.a.	n.a.	n.a.	n.a.	0.1	-	-	-	-6.5	-7.4	-5.0	-8.7	-3.8	n.a.	-3
Eggs	n.a.	n.a.	n.a.	n.a.	8.5	13.9	21.6	18.2	-1.4	-1.5	1.8	-1.7	-1.4	n.a.	6
Milk	n.a.	n.a.	n.a.	n.a.	0.6	0.04	0.02	0.01	-2.6	-2.8	6.7	2.3	16.3	n.a.	2
Pigmeat	n.a.	n.a.	n.a.	n.a.	-	0.02	0.4	10.9	11.3	35.4	42.2	40.7	42.8	n.a.	20
Poultry Meat	n.a.	n.a.	n.a.	n.a.	11.0	12.6	10.0	0.05	-0.9	-1.0	14.7	10.2	-0.8	n.a.	6
Refined Sugar	n.a.	n.a.	n.a.	n.a.	0.5	28.2	26.9	20.2	0.02	12.6	3.4	-	26.7	n.a.	13
Rice	n.a.	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	-	n.a.	-

URUGUAY	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avrg. Period
Beef and Veal	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	n.a.	n.a.	n.a.	-
Milk	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	n.a.	n.a.	n.a.	-
Poultry Meat	n.a.	n.a.	n.a.	23.8	27.2	8.5	10.1	7.7	6.7	31.3	30.1	n.a.	n.a.	n.a.	18
Rice	n.a.	n.a.	n.a.	-	-	-	-	-	-	-	-	n.a.	n.a.	n.a.	-

Table 4

Incentives by selected crop and livestock activities (%PSCT), percentage share

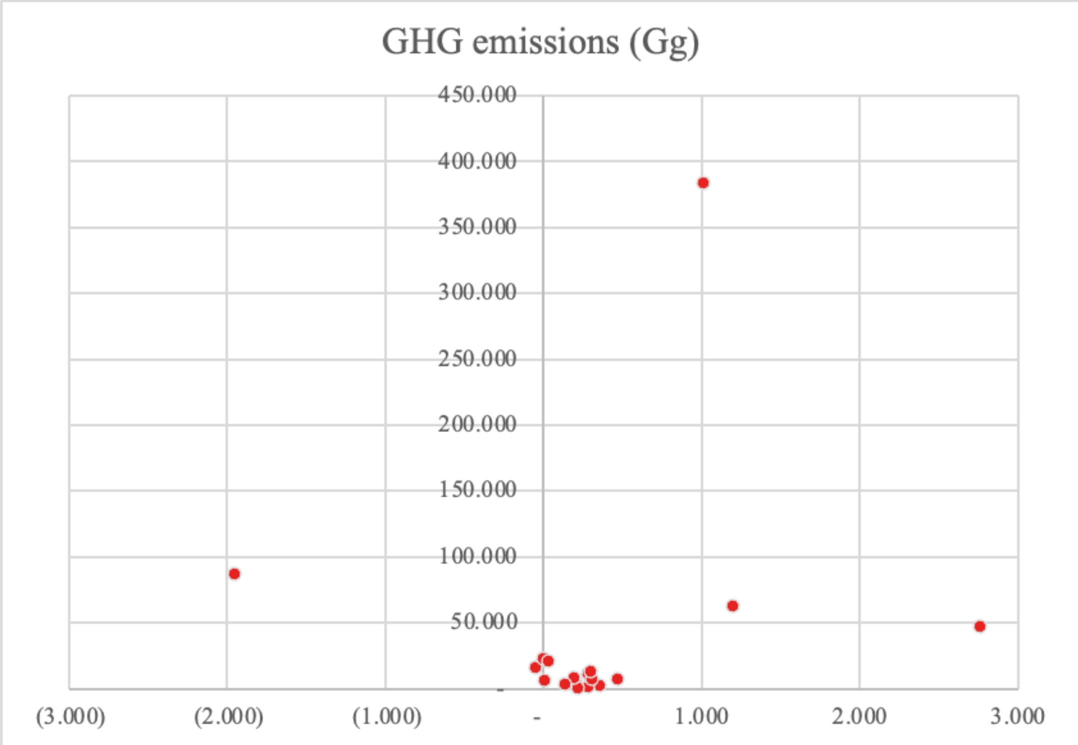
Source: own construction using data on domestic support policies from Agrimonitor.

In most LACs, the importance of policy support through PSCT denotes the importance of the MPS component of the PSE. This support has been provided through border measures such as tariffs, specific duties, and quotas, which increase domestic prices and, in turn, support farmers, as per Egas and De Salvo (2018). These authors also show that the exceptions are Chile, Uruguay, and Mexico, which record extremely low (or zero) levels of MPS; another country with this exception is Argentina, which records a negative MPS. These incentives are in line with those provided through PSCT, as also discussed in this study. Given that most LACs use policies that provide price incentives, it is necessary to determine the relationship between these price incentives and GHG emissions in these countries.

There are other transfers besides MPS in the PSCT. These transfers aim to improve access to inputs and increase productivity by reducing the costs of the purchased inputs (energy, fertilizers, etc.) and capital. These transfers are important in Brazil, Chile, and Mexico, whereas concessional credits that foster agricultural investment are key in Brazil and Colombia (Egas & De Salvo 2018). Policies that alter the composition and use of inputs may also lead to distortions in production and the use of inputs, and thereby impact GHG emissions.

In summary, the aforementioned details show the following: first, the largest GHG emitter is the livestock sector; second, the livestock sector's contribution to the VoP is highly important in some countries; it is fairly important in the rest of countries; third, given that beef and veal and milk —two sizable sectors in VoP— do not receive high support via prices,[4] and hence these commodities are not likely to exhibit a strong correlation between PSCT incentives and GHG emissions, it is not necessarily expected an overall strong correlation between PSCT incentives and GHG emissions. This is shown precisely through Figure 6 which depicts both the average PSCT (in US million) and the average GHG emissions (in gigagrams, Gg) for the period 2010-2017 in the 18 LACs. This finding suggests a slight positive correlation (including outlier observations) between these two indicators. It must be noted that the production and emissions depicted are contemporaneous. Lags may be possible; that is, it is possible that policies take time to affect production, and that emissions may increase at a later period. There are commodities that receive increasing support and record increasing emissions through time. These commodities are *pig meat* in Argentina and Bolivia; *rice* in Colombia (and somehow milk in this country), Costa Rica (until the early 2010s), the Dominican Republic (until the late 2000s), and Ecuador; *poultry* in Honduras (until mid-2010s), Jamaica, and Panama; and *milk* in Mexico.

4 Beef and veal receive low (Brazil, Ecuador, El Salvador, Honduras, Jamaica, Mexico, and Panama), zero (Chile, Costa Rica, Nicaragua, Paraguay, and Uruguay), or even negative (Argentina, Bolivia, Colombia, Dominican Republic, Guatemala, and Peru) support.



Notes: average PSCT in US$ million, and GHG emission in gigagrams (Gg). Selected crops and activities, depending on data availability for each country, may include beef and veal, eggs, milk, pig meat, poultry, and rice. Sugar is not included because there are no separate GHG emissions from sugar in the FAOSTAT database.

Figure 6
Average PSCT and GHG emissions, for selected crops and activities, 2010-2017
Source: own construction using data on domestic support policies from Agrimonitor and GHG emissions from FAOSTAT.

5
Cluster analysis results

We construct a typology of countries for both years, 2010 and 2017, using the methodology and variables summarized in Section 3 and Table A2 in the Annex, respectively. We construct five scenarios for each year based on five different sets of variables as follows:

Scenario 1: only agricultural support policy indicators

Scenario 2: only GHG emissions variables

Scenario 3: both agricultural support policy indicators and GHG emissions

Scenario 4: all the proposed variables (Table A2)

Scenario 5: using the variables in scenario 4 but excluding those for agricultural support policies

We conduct the analysis for 2010 and 2017 (considering the greater availability of data) to compare the interactions of the groups over time. Table 5 shows the different groupings based on the five scenarios for both years.

	2010	2017
Scenario 1: Agricultural support policies	**Group 1**: Argentina and Bolivia **Group 2**: Brazil, Chile, Mexico, Paraguay, Peru, and Uruguay **Group 3**: Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Nicaragua, and Panama	**Group 1**: Argentina, Brazil, Chile, Guatemala, Honduras, Mexico, Paraguay, and Uruguay **Group 2**: Bolivia, Colombia, Costa Rica, Ecuador, Nicaragua, and Peru. **Group 3**: Dominican Republic, and Panama **Group 4**: El Salvador, and Jamaica
Scenario 2: GHG emissions	**Group 1**: Argentina, Bolivia, Brazil, Colombia, Costa Rica, Honduras, Nicaragua, Paraguay, and Uruguay **Group 2**: Chile, El Salvador, Guatemala, Jamaica, Mexico, and Panama **Group 3**: Dominican Republic, Ecuador, and Peru	**Group 1**: Argentina, Brazil, Nicaragua, Paraguay, and Uruguay **Group 2**: Bolivia, Chile, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Panama, and Peru **Group 3**: Dominica Republic, and Ecuador. **Group 4**: Jamaica
Scenario 3: Agricultural support policies + GHG emissions	**Group 1**: Argentina, Bolivia, Brazil, Paraguay, and Uruguay **Group 2**: Chile, Ecuador, Mexico, and Peru **Group 3**: Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama **Group 4**: Dominican Republic and Jamaica	**Group 1**: Argentina, Brazil, Chile, Guatemala, Honduras, Mexico, Paraguay, and Uruguay **Group 2**: Bolivia, Dominican Republic, and Panama **Group 3**: Colombia, Costa Rica, Ecuador, Nicaragua, and Peru **Group 4**: El Salvador, and Jamaica
Scenario 4: Indicators from all aspects: macroeconomics, natural resources and the environment, emissions, agricultural trade and agricultural trade policy, institutions, and agricultural support policies	**Group 1**: Argentina, Bolivia, Paraguay, Uruguay **Group 2**: Chile, Peru **Group 3**: Brazil, Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Jamaica, Nicaragua, and Panama **Group 4:** Colombia, Ecuador, and Mexico	**Group 1**: Argentina, and Uruguay **Group 2**: Brazil, Guatemala, Mexico, and Paraguay **Group 3**: Chile, and Peru **Group 4**: Bolivia, Ecuador, Honduras, and Nicaragua **Group 5**: Colombia, Costa Rica, Dominican Rep., El Salvador, Jamaica, and Panama
Scenario 5: Indicators from all aspects, except agricultural support policies	**Group 1**: Argentina, Bolivia, Paraguay, and Uruguay **Group 2**: Chile, and Peru **Group 3**: Brazil, Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Jamaica, Nicaragua, and Panama **Group 4**: Colombia, Ecuador, and Mexico	**Group 1**: Argentina, and Uruguay **Group 2**: Chile, and Peru **Group 3**: Bolivia, Brazil, Guatemala, Honduras, Nicaragua, and Paraguay **Group 4**: Ecuador **Group 5**: Colombia, Costa Rica, Dominican Republic, El Salvador, Jamaica, Mexico, and Panama

Table 5
Cluster analysis results
Source: elaborated by the authors.

5.1. Scenario 1: agricultural support policies

As an illustration of the cluster analysis, consider scenario 1 for year 2010. Following Ward's method, we obtain the dendrogram shown in Figure A1 of the Annex. Recalling the decision rule to select the optimal number of clusters described in the research method section, choose the number of clusters with both a high value in the Duda-Hart index [Je (2) / JE (1)] and a low pseudo-T-squared surrounded by higher T-squared values; it can be seen in Table A3 that the formation of three groups fulfills this decision rule. In other words, a distinctive grouping can be obtained when such guidelines are applied. This may not be always the case. Thus, for scenario 1, year 2010, the three groups are summarized in Table 5.

These groups can be considered a distinctive grouping based on the agricultural support polices. As Figure 2 corroborates, group 1 comprises two countries (Argentina and Bolivia) with both negative MPS and negative TSE; group 2 comprises six countries (Brazil, Chile, Mexico, Paraguay, Peru, and Uruguay) with low or none MPS; group 3 comprises ten countries (the rest of the 18 LAC) that rely most on the MPS. These groupings conform with the discussion on MPS found in Egas and De Salvo (2018).

For year 2017, scenario 1 again constructs distinctive groupings, but this time there are four groups. In these four groups, the distinction is between countries that do not rely on MPS or rely much less on such support (those in group 1) and countries that rely more on MPS (those in groups 2 to 4). However, for the latter countries, we consider a few nuances, given that there are three groups, one with a greater dependence on MPS than that of the others; that is: group 2 has countries that rely on MPS, group 3 has countries that rely more on MPS than those in group 2, and group 4 has countries that show the highest dependence on MPS for that year.

5.2. Scenario 2: GHG emissions

The second scenario includes, for each country, indicators of CO_2e emissions from agricultural activities such as the emission shares from the production of beef and veal, eggs, milk, pig meat, poultry, and rice. It also includes the total agricultural emissions share in the total emissions as well as the amount of GHG emissions (expressed as CO_2e TNT/capita). Following the decision rule, we find a distinctive grouping of three groups for 2010 (Table 5).

In agriculture, the amount of expected agriculture emissions is determined by several factors such as the type of agricultural activity and production, emission intensities and productivity of the crops or activity, the level of development of an economy and its reliance on agricultural production, and the use of technology versus traditional production systems. Thus, for year 2010, group 1 includes countries with the highest emission shares from livestock activities such as enteric fermentation (Argentina, Brazil, Nicaragua, Honduras, Paraguay, and Uruguay; see Figure 5) and/or a high emission share of the beef and veal production (Bolivia, Colombia, and Nicaragua). A few of these countries produce a high volume of beef and veal (Argentina, Brazil, Paraguay, and Uruguay). Group 2, in contrast, includes countries with the lowest share of total agricultural emissions or low GHG emissions per capita (see Table 1, year 2010). Group 3 includes countries with a medium level of total agricultural emission shares and GHG emissions per capita.

For year 2017, we do not find a distinctive grouping, that is, the rule for choosing the optimal number of groups does not provide us with only one possible classification, but several. This allows for groupings of two, four, and even six countries. We choose to construct a grouping of four (Table 5, scenario 2, year 2017). If the choice were to have two groups, then group 1 would have remained the same and the other three groups would have conformed into one big group. Again, group 1 comprises countries with the highest emissions shares from livestock activities.

Comparing 2010 with 2017, groups 1 and 2 are similar. The only difference is that, from the 2010 cluster, some members of group 1 (Bolivia, Colombia, Costa Rica, and Honduras) and one member of group 3 (Peru) moved to group 2 in 2017; and Jamaica conformed to a one-country cluster in the second year. Thus, owing to the GHG emissions, the relationships between countries in 2017 remained like those in 2010, except for a few countries that conformed new groups (Jamaica) or moved to another group of lower emissions.

5.3. Scenario 3: agricultural support policies and GHG emissions

When accounting for the *combined* relationships among countries for the indicators of agricultural support policies *and* those of GHG emissions, in year 2010, we find two alternative groupings —clusters of four or six groups—. We choose the clustering of four groups (Table 5). It becomes more difficult to explain the groupings when more sets of variables are used. However, the members of the groups represent a combination of those found in Scenarios 1 and 2 for year 2010.

For year 2017, following the stopping rule, for the Duda-Hart decision rule, as per which the number of groups selected must correspond with the largest J and a lower T-squared located in between or next to a large T, we construct four groups (Table 5). The combined use of variables from emissions and agricultural support policies helped us to find groupings that are like those found in scenario 1, when using only agricultural support policies in the cluster analysis. For 2017, such policies seem to have a stronger influence (than those of emissions) in their cluster result.

5.4. Scenario 4: all indicators

When utilizing all the variables to conform the clusters, for 2010, we do not find a clear cut off point for the optimal number of groups. If we choose to conform four groups, their members are those indicated in Table 5.

As noted above, as the number of aspects and variables applied in cluster analysis increases, it becomes more difficult to find a distinctive number of groupings and to attribute to some particular characteristics the results we found. In any case, the aspects proposed include indicators discussed in the literature when analyzing agricultural support polices (see, for instance, Ackerman *et al.* 2018, Egas & De Salvo 2018). The cluster analysis using all the proposed variables is included because this allows a comparison of the final grouping with another scenario in which the variables corresponding to the agricultural support policies are excluded (Scenario 5). This contributes toward determining if there is any difference in the final number of groups owing to such policies. Thus, the following section will compare the results obtained from Scenarios 4 and 5.

Again, for year 2017, we do not get a clear cut off point for the optimal number of groups. According to the decision rule, the number of groups we may choose is three or more. We choose a clustering of three, which corresponds to a combined first lower (not the lowest) in between the two higher pseudo-T-squared and a high (but not the highest) Je (see Table 5).

We may also choose to have five groups, which correspond to another even lower (but again, not the lowest), besides a higher pseudo-T-squared along with an even higher Je. Given the hierarchical approach, when choosing five groups, instead of three, the two other groups result from dividing the former group 1 into three groups (Table 5).

A comparison between the grouping of five in 2017 with that of 2010 reveals the similarity between the groups. However, again, given the large number of variables (44, see Table A2 in Annex 2), it is difficult to explain why the countries conform to such groups. We include this clustering to categorize countries based on the aspects discussed when analyzing agricultural support policies.

5.5. Scenario 5: all indicators, except for the agricultural support policies

When *excluding* indicators of the agricultural support policy in the cluster analysis for year 2010, we do not find a clear cut off point for the optimal number of groups. While there may be four or six groups, we construct a clustering of four groups, which turns out the same groupings as in year 2010 of Scenario 4, suggesting that excluding (or including) agricultural policy indicators make no difference in the groupings when the rest of all indicators are used for that year (Table 5).

For 2017, we find a distinctive clustering of five groups, when choosing the number of groups corresponding to the second lower T-squared to appear, as this is associated with a high Je. It must be noted that, when comparing Scenario 4 (all variables) with Scenario 5 (all variables, except agricultural support policies), with groupings of five, the members remain the same in two groups and are similar in the other three groups. Again, this could be taken as a suggestion that agricultural support policies were not an aspect to set the groupings apart when using all indicators; except for the case of Ecuador, which —when excluding agricultural support policies for the set of all variables in 2017— conforms a separate group by itself (group 4). See Table 5.

6
Policy implications

The LACs should widely adopt the practice of finding a correspondence between climate change mitigation measures and indicators of agricultural support policies. Indeed, as countries implement their INDC commitments to curb emissions of GHG, they can choose from a variety of agricultural policy measures and programs. Josling *et al.* (2017) propose a series of alternative policy measures which we discuss as follows:

1. Reduce the transfers to the highest GHG emitting sectors or activities, such as livestock (Figure 5). As pointed out by Josling *et al.* (2017), this practice can benefit if the goal were only to meet the INDC target. However, such sectors/activities produce goods for domestic and export sales. Moreover, some direct transfers might be directed to improve climate change adaptation and may also contribute toward climate change mitigation (*e.g.,* several programs in Uruguay such as the Development and Adaptation to Climate Change, as well as the Climate Insurance, both cited in Ackermann *et al.* 2018).

2. Reduce support to sectors with a high Agricultural Carbon Equivalent (ACE) to the production value ratio. ACE expresses the value of GHG emissions in local currency —which in turn requires a carbon price— and accounts for sequestration; however, in most cases, they are comparable to those accounting only GHG emissions, as the sequestration adjustment is not considerable according to Josling *et al.* (2017). The same caveats from point (1) apply here.

3. Reduce support to sectors with both high GHG emissions and high protection. This alternative would lead to a reduction in price distortions in agricultural markets. In this case, several caveats may apply. There is a likelihood that the major emitter sectors may not be the most protected ones (on the contrary, they may even be taxed, as in the case of beef in Argentina; see Tables 3 and 4). There is also a likelihood that the most protected sectors are those that produce goods for domestic markets (*e.g.,* potato and poultry) where transfers via price support for farmers may be considerable (*e.g.,* 40 % and 22 %, respectively, of the VoP on average, for Uruguay for 2014-2016; see Ackermann *et al.* 2018). Some of the most protected sectors might not be considered in the list of selected commodities when measuring PSCT due to their low share in VoP. Moreover, emissions usually capture totals, not the intensities of emissions of each product (*i.e.,* emissions for unit of product).

4. Increase support for sectors/commodities with a high ratio of the value of the sectors' output *net of support* to the cost of GHG emissions. Again, this requires a carbon price which is not widely or easily available for most LACs.

5. Apply complementary measures/programs to MPS that locate the source of GHG emissions.

6. Focus on changing management techniques in high-emitting sectors. Josling *et al.* (2017) indicate that, in the case of manure management, an improvement in management practices could be fostered by private incentives (taxes, subsidies, or direct regulations). The emphasis here is to change farming practices.

7
Concluding remarks

Although we did not expect a simple relationship between agricultural support policies and GHG emissions, our evidence suggests that the reliance on policies distorting output or input prices may lead to higher production or input use, and thereby cause environmental degradation through higher GHG emissions. Thus, results suggest that an increasing TSE and/or MPS representing a large share of TSE may lead to an increase in agricultural GHG emissions (Bolivia, Brazil, Honduras, Jamaica, and more recently Peru, and the Dominican Republic). However, when GSSE represents a large TSE share, these emissions may fall with a rise in TSE (Chile and Uruguay).

The level and share of agriculture in the total emissions of a country clearly depend on the type of the main crop and agricultural activity. When livestock activities represent a lion's share of the agricultural value of production, there may be a significant share in GHG emissions (Uruguay and Brazil). In these countries, inventory levels and CSA have been applied to account for such gases, as well as to set up mitigation programs. However, these practices and policies are the exception rather than the norm in LAC.

A cluster analysis allowed the grouping of countries by their agricultural support policies. This is in line with findings in other studies (Egas & De Salvo 2018), for groups with negative MPS, low MPS, and reliance on MPS. We also found other groupings of countries by their GHG emissions.

Our study has the following limitations:

First, there are other potential sources of GHG emissions in agriculture, which were not accounted for in the study such as energy, fuel use in agriculture, and change in land use; similarly, there are activities that contribute toward trapping or reducing emission (carbon sequestration) that were not discussed here.

Second, and as stressed in Ackermann *et al.* (2018), the methodology to measure agricultural support policies has two assumptions that imply either an underestimation or an overestimation of the support to farmers. Firstly, it is assumed that the agricultural support provided for the products included is similar to that of the products excluded in the list of selected products. The idea is that the products excluded are those with less weight in the VoP. However, these products can potentially have both lower exposure to the international markets and higher protection through border measures. Secondly, it is assumed that there are competitive markets throughout the production chain. However, in some LACs, it remains to be proven if the support is effectively transferred to the (small and micro) producers or if it is transferred to other levels in the chain. Thus, the first assumption may imply an underestimation of the true value of the support through prices, and the second one may imply an overestimation of the true value (see Ackermann *et al.* 2018).

Other limitations deal with leaving aside of the analysis the LACs' agricultural sector's vulnerability to climate change and issues of adaptation. As highlighted in a study, «efforts to increase the resilience of agriculture in the face of climate vulnerability could go hand-in-hand with the changes necessary to meet mitigation goals» (Josling *et al.* 2017, p. 29).

Future studies can explore the carbon *intensity* of crops and livestock activities and their relationship with productivity in the agricultural sectors of LACs, as well as the income effect of agricultural policies and its relationship with GHG emissions.

Future studies should also address the causal effects of agricultural support policies on emissions for LAC. As pointed out in the introduction, although it is difficult to assess such causality, among other reasons because there is still an inadequate understanding of the interactions between agriculture and the environment, and because despite the great efforts to collect data on agricultural support policies for LAC, there is still more to be done to have a consistently long span of such policy data for LAC.

8
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9 Annex

#	Country	First year	Last year
1	Argentina	1997	2019
2	Bolivia	2006	2018
3	Brazil	1995	2019
4	Chile	1990	2019
5	Colombia	1992	2019
6	Costa Rica	1995	2019
7	Dominican Republic	2006	2017
8	Ecuador	2006	2016
9	El Salvador	2009	2017
10	Guatemala	2006	2018
11	Honduras	2011	2017
12	Jamaica	2006	2014
13	Mexico	1986	2019
14	Nicaragua	2009	2017
15	Panama	2010	2015
16	Paraguay	2007	2018
17	Peru	2010	2018
18	Uruguay	2009	2016

Table A1

Agrimonitor database: periods available for selected countries

Source: Agrimonitor, *Results by Country,* as of July 2021, available on https://agrimonitor.iadb.org/en.

Aspect	Variable	Source
Macroeconomics: The macroeconomic aspects in LACs may influence the choice of agricultural support policies in these countries. For example, countries with a weak macroeconomic performance—low growth, higher fiscal deficits, and inflation—may have producer support policies based on price, as such countries may not have much scope to provide direct support or services to the producers owing to fiscal constraints. However, countries with a strong macroeconomic performance may have better producer support policies in the form of services or direct support. By including the general macroeconomic aspects in LACs, this study captures the differences in the aforementioned relationships.	GDP per capita (current US$). Current account balance (% of GDP) Inflation, consumer prices (annual %) Surplus (+) or deficit (-) of the Non-Financial Public Sector as a percentage of GDP.	"World Development Indicators" from the World Bank
Natural resources and the environment: Greater land availability, particularly agricultural land, and greater cultivation of such land may increase production, which in turn may result in environmental effects.	Total natural resources rents (% of GDP) Arable land (hectares per person) Arable land (% of land area) Agricultural land (% of land area) Forest area (% of land area) Total greenhouse effect emissions in kilotons of CO2e per capita	"World Development Indicators" from the World Bank

Agricultural GHG emissions: Greater dependence on price support may increase production and result in environmental effects through, for instance, higher emissions. The corresponding indicators for this aspect are the total agricultural emissions as a share in the country's total emissions. These agricultural emissions include the emissions from agricultural activities (according to the FAO classification) and those associated with crops receiving, on an average, a higher producer single commodity transfers (PSCT).	Agricultural total, GHG emission share in total GHG emissions (measured in CO2e)	FAOSTAT
	Beef and veal, GHG emission share in total GHG emissions (measured in CO2e)	
	Eggs, GHG emission share in total GHG emissions (measured in CO2e)	
	Milk, GHG emission share in total GHG emissions (measured in CO2e)	
	Pig meat, GHG emission share in total GHG emissions (measured in CO2e)	
	Poultry, GHG emission share in total GHG emissions (measured in CO2e)	
	Rice, GHG emission share in total GHG emissions (measured in CO2e)	
Agriculture, agric. trade, and trade policy: The substantial increase in the agricultural trade associated, among others, with the commodity price boom during the 2000s and mid-2010s may be relevant within a relationship framework comprising incentives and emissions. Thus, another relevant trade aspect for a typology of countries may include the environmental requirements of the export markets. This aspect would provide an understanding of the impact of agricultural production on emissions, in relation to the type of trading partner. In this regard, it must be noted that some LACs have entered into effect free trade agreements (FTAs) with the European Union or the United States; such agreements usually include environmental provisions.	Agriculture, forestry, and fishing, value added (% of GDP)	"World Development Indicators" from the World Bank
	Agricultural trade balance with developed countries (% GDP)	Trade Map
	Agricultural trade balance with word (% GDP)	
	MFN average applied tariff rate, agriculture	World Trade Organization
	MFN average tariff rate, animal products	
	MFN average tariff rate, dairy	
	MFN average tariff rate fruits, vegetables, plants	
	MFN average tariff rate, coffee, tea	
	MFN average tariff rate, cereals, and food preparations	
Institutions: It is important for countries to include certain GHG emissions commitments in their development plans. The fulfillment of commitments requires a respect toward law, political stability, government effectiveness, corruption control, and certain regulatory quality. It is also calls for the involvement of the civil society (public opinion) and accountability. These six indicators have been defined in the worldwide governance indicators published by the World Bank.	Voice and Accountability: citizens' ability to participate in the selection of their government and other freedoms.	"The Worldwide Governance Indicators" from the World Bank.
	Political Stability and Absence of Violence/Terrorism.	
	Government Effectiveness: government effectiveness, quality of public services and independence from political pressures.	
	Regulatory quality: quality and regulatory capacity of the government.	
	Corruption: extent to which public power is exercised for private gain.	
	Rule of law: the extent to which officers trust and respect the rules of society, contract enforcement, quality of the police and the courts.	
Agricultural support policies: According to the evidence from Agrimonitor, the dependence of some of the LACs on price-based support policy has been increasingly accentuated. Some products may receive more incentives than that of others, and some of these products may generate higher GHG emissions than that of others. Based on these differences, we include the following indicators by selected crops and agricultural activity: MPS, DS, GSSE, PSCT and Transfers to Consumers from Taxpayers (TCT).	General Service Support Estimate, GSSE (share in TSE)	AGRIMONITOR database from the Inter American Bank (IADB)
	Market Price Support, MPS (share in TSE)	
	Direct Support, DS (share in TSE)	
	Transfers to Consumers from Taxpayers, TCT (share in TSE)	
	Total Support Estimate, TSE (as a share of Value of Production)	
	Total Support Estimate, TSE (% of GDP)	
	Value of Production, VoP (% of GDP)	
	Percentage Producer Single Commodity (PPSC) for beef & veal	
	Percentage Producer Single Commodity (PPSC) for milk	
	Percentage Producer Single Commodity (PPSC) for pig meat	
	Percentage Producer Single Commodity (PPSC) for poultry	
	Percentage Producer Single Commodity (PPSC) for rice	

Table A2

Variables for cluster analysis

Source: elaborated by the authors.

Number of clusters	Je(2)/Je(1)	Pseudo T-squared
1	0.6976	6.94
2	0.5948	4.09
3	0.7552	2.59
4	0.6785	2.84
5	0.0000	.
6	0.4909	3.11
7	0.6943	1.76
8	0.5005	2.00
9	0.3673	1.72
10	0.3182	2.14
11	0.0000	.
12	0.0000	.
13	0.0000	.
14	0.2057	3.86
15	0.0000	.

Note: following the stopping rule implies choosing 3 groups.

Table A3
Duda-Hart stopping rule for the hierarchical cluster analysis of Scenario 1, year 2010
Source: elaborated by the authors.

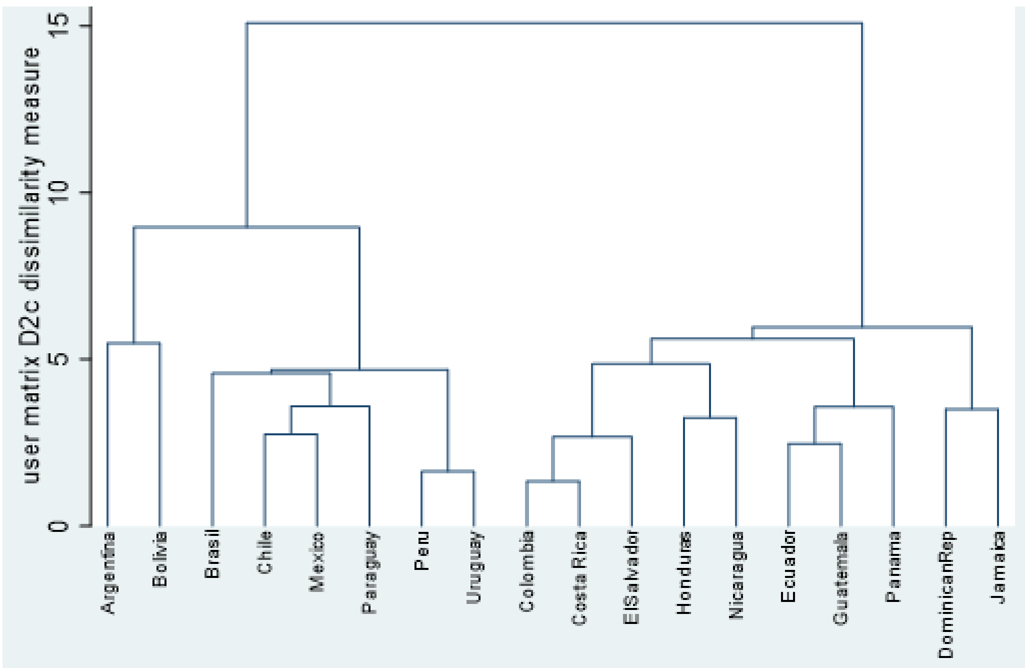

Figure A1
Cluster Analysis: dendrogram for Scenario 1, year 2010
Source: elaborated by the authors.