Effect of Consumption of Non-Durable Goods on Greenhouse Gas Emissions in the U.S. and Brazil: An Empirical Analysis

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Abstract:

This paper explores how consumption of nondurable goods in the United States and Brazil is linked to greenhouse gas emissions, specifically carbon dioxide (CO_2), nitrous dioxide (N_2O), and methane (CH_4). Non-durable goods pollute the environment through production, transportation, consumption, and decomposition. The overconsumption of non-durable goods such as food, fuel, cosmetics, tobacco, and clothing are causing deforestation, loss of soil, soil pollution, and many more. After measuring the levels of pollutants from 2003-2017, they are compared to non-durable good consumption rates. This paper uses a collection of data from St. Louis Federal Reserve Economic Data (FRED) regarding consumption indicators, the United States Department of Agriculture (USDA), Natural Resources Conservation Service Soils (NRCSS) database for evidence of global land degradation, the EPA (Environmental Protection Agency), and the ERS (Economic Research Services). The model used in this paper is based off a Brandão et al. (2018) model used to study the impact of agriculture and fuel consumption on GHG emissions. As developed economies continue to evolve as consumption powerhouses, air pollution becomes an increasing worry.

JEL Classification: Q1, Q3, L6, L9,

Keywords: Environmental Economics; Greenhouse Gas Emissions; Methane; Nitrous Dioxide; Carbon Dioxide; Nondurable Goods; Consumption; Production.

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1.0 INTRODUCTION

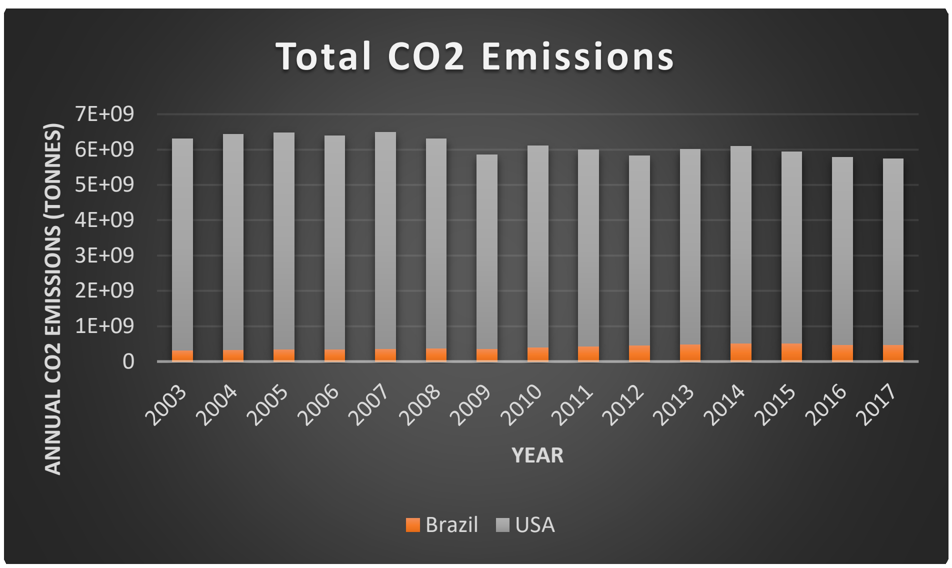
The consumption of non-durable goods plays a key role in the greenhouse gas emissions polluting Earth's atmosphere. Developed countries like the United States and Brazil are consumption powerhouses, ranked number one and eight, respectively. The consumption of non-durable goods in these countries leads to an unsustainable production. Production is crucial, especially since non-durable goods are the least regenerative. Great strides have been made in the last six decades to improve the regenerative processes of paper, rubber, and plastic. Unfortunately, non-durable goods expand beyond these three to include goods such as food, textiles, clothing, fuel, and cosmetics.

This study aims to enhance understanding of what non-durable goods have the greatest impact on GHG emissions, what sectors are the largest contributors, and which of the three gases modeled see the greatest increase from consumption. From a policy perspective, this analysis is important because a further understanding of an individual good's impact of a specific gas will allow us to narrow our target for reduction. We will be able to focus on sectors of production, exact gases, increasing public awareness on the products they use and the food they eat, and policies that can reduce air pollution with an attainable goal in mind instead of a general target of particulates in the air. The relevance of this study is that Brazil's non-durable goods manufacturing has increased 11% in the past 15 years while the US has decreased by 8%, but the US has 21% more air pollution. This study seeks to weigh the consumption trends in each sector against each other to determine what each country is doing better or worse than the other.

2.0 TREND OF GASES AND CONSUMPTION RATES

Figure 1 is an overview of the total CO_2 emissions for Brazil and the US. CO_2 is the most abundant gas in the atmosphere from pollution. It is clear that the United States emits an average of 14.2 times of CO_2 as Brazil, but interestingly when other gases are factored in the US only emits six times as much as Brazil. This graph includes the United States' 202.5 million tonnes of fuel emissions (about 3.2%) and Brazil's 2.38 million tonnes of fuel emissions (0.5%) of aviation emissions. Because these numbers are exponential when using transportation as a separate variable, this study excludes aviation emissions.

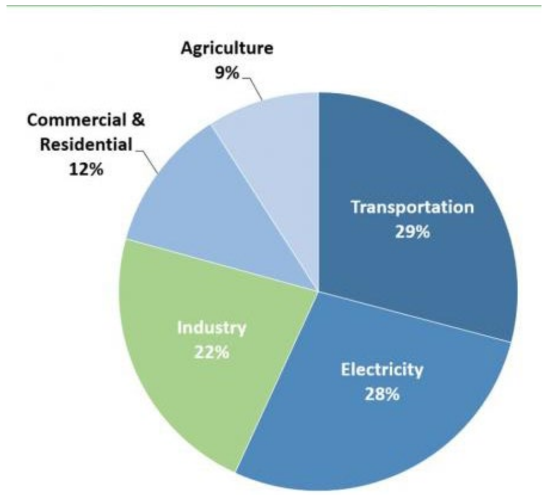
Figure 1:



Source: Oxford: Our World in Data

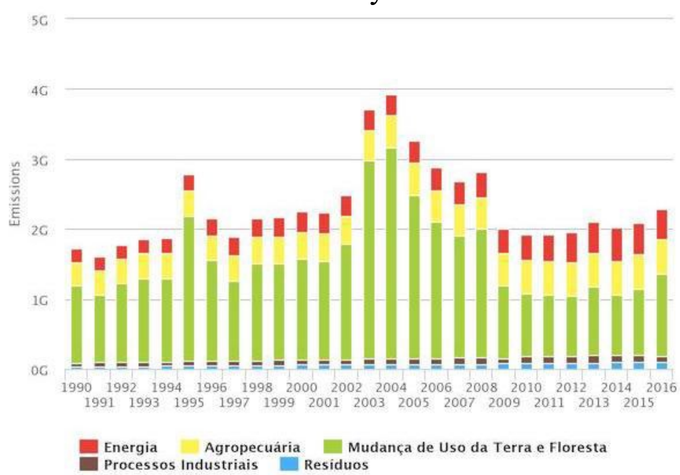
Figure 2 and 3 shows the breakdown of emissions by sector in 2017. This study excludes energy and forest degradation; The accounted for sectors show the US emitting the most from transportation and industry while Brazil emits the most from agriculture and comparatively less in industry. This proves its importance when the sectors are broken down into specific non-durable goods for a closer look into each sector.

Figure 2: US GHG Emissions by Economic Sector in 2017



Source: Organization for Economic Co-operation and Development

Figure 3: Brazil GHG Emissions by Economic Sector 1990-2016



Source: Climate Change Home News

3.0 Literature Review

As air quality becomes an increasing concern of the 21st century, researchers find evidence of significant contributing factors across all fields of study. One unifying variable lies at the center of all of it, consumption. Biing-Hwan and Yen (2014) indicate that Americans eat 77% more grain per day than recommended (6.7 ounces), while Brazilians eat just half of that per day (3.9 ounces). The 11% increase Brazil saw in non-durable goods manufacturing opposes the 8%

decrease the United States saw in 2017. Bernesson et al. back up the claims of Biing-Hwan and Yen (2014), stating that the GHG emissions from wheat production were 2,210kg CO2 eq. ha-1 (Bernesson et al., 2006). The results are almost the same as in this study; Wanhalinna (2010) has estimated GHG emissions of grain production as a part of carbon print of bread. GHG emissions for wheat were 720g kg-1 and for rye 900g kg-1. Grain yields were almost the same as in this study. This fact was a motivation for me to study what role each sector of non-durable good consumption plays in our air pollution. One of the underlying components of this, is what we consume. Grain consumption is responsible for large quantities of CO_2 being pumped into the atmosphere, and much of it is not directly calculated into GDP due to its role in livestock production. Agriculture is one of the leading causes of GHG emissions according to FAO (2002). Not only does fuel for machines and manufacturing contribute CO_2, but production inputs such as animal feed and manure fertilizer induce a high percentage of emissions in the agriculture sector (MMM, 2001).

Brito et al. states that fuel consumption from the transportation industry is responsible for nearly a quarter of fuel emissions in Brazil (Brito et al., 2019). Transportation accounts for 29% of the United States fuel emissions, and technologies investments are said to bring massive relief to the emissions currently produced by the trucking industry. Guerrero (2014) suggests in his analysis that investment in technology that increases the speed of shipments could be the key to reducing emissions from the trucking industry. Heng and Lim (2011) say that with new technology investment in trucking, the industry could increase output and decrease GHG emissions by 11% with abatement costs between \$26 and \$94 million.

4.0 DATA AND EMPIRICAL METHODOLOGY

4.1 Data

This study uses panel data from 2003-2017. This paper uses a collection of data from St. Louis Federal Reserve Economic Data (FRED) regarding consumption indicators, the United States Department of Agriculture (USDA), Natural Resources Conservation Service Soils (NRCSS) database for evidence of global land degradation, the EPA (Environmental Protection Agency), and the ERS (Economic Research Services). The empirical analysis utilizes the non-durable goods manufacturing index, consumption percentages for agriculture, cosmetics, plastic, paper, livestock, rubber, fuel, waste, textiles, and clothes. Greenhouse gas emissions were measured using data that described levels of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), and what contributes the most to each gas. Summary statistics for each of the variables can be seen below in Table 1.

Table 1: Summary Statistics

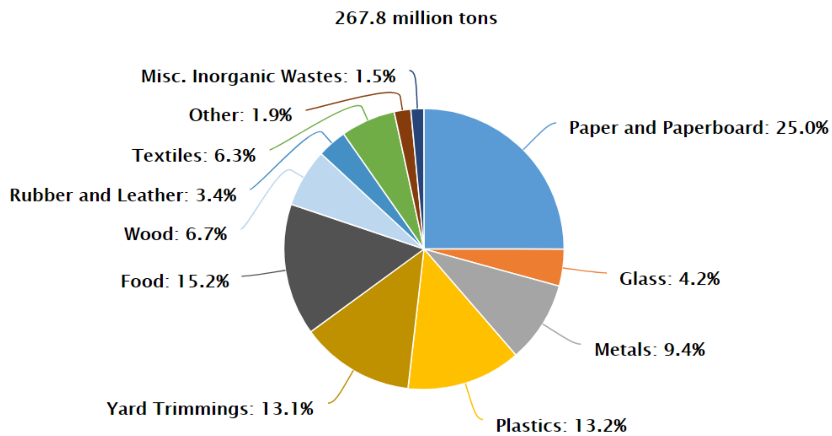
Interval Variable Summary Statistics
(maximum 500 observations printed)

Data Role=TRAIN

Variable	Role	Mean	Standard Deviation	Non Missing	Missing	Minimum	Median	Maximum	Skewness	Kurtosis
Agriculture	INPUT	579.8923	10.06026	15	0	563.2432	582.1805	597.2466	-0.16486	-0.66434
Beef	INPUT	27.54087	2.129693	15	0	24.672	27.289	30.311	0.080054	-1.72616
Brazil_Production	INPUT	103.7598	4.178092	15	0	99.28357	102.4297	110.7863	0.647233	-1.09582
CH4	INPUT	679.4708	17.15747	15	0	654.8979	687.549	702.3034	-0.22811	-1.8209
CO2	INPUT	5704.475	318.7291	15	0	5270.749	5572.585	6130.552	0.178752	-1.66974
Chicken	INPUT	46.45667	1.440112	15	0	44.45	46.6	49	0.169115	-0.91877
Corn	INPUT	9.742667	0.965937	15	0	7.72	9.66	11.08	-0.65592	0.24281
Fuel	INPUT	8571.533	220.7212	15	0	8190	8623	8886	-0.20946	-1.14451
Industry	INPUT	1459.562	60.05485	15	0	1319.18	1459.276	1546.506	-0.54964	0.707185
N2O	INPUT	374.3529	13.04613	15	0	348.8761	374.5466	400.2526	0.121359	0.329106
Paper	INPUT	-1.64855	3.274664	11	4	-10.2246	-1.19707	2.44613	-1.86771	5.023793
Pork	INPUT	22.4454	0.924389	15	0	20.896	22.773	23.709	-0.6048	-0.95792
Rice	INPUT	5.564667	0.27206	15	0	5.184	5.534	6.001	0.094809	-1.32603
Rubber_and_Plastic	INPUT	-0.41016	6.964441	11	4	-16.3942	1.41425	8.98372	-1.37242	2.104139
Waste	INPUT	144.2827	9.887922	15	0	130.9554	146.1286	160.5478	0.160869	-1.34925
Wheat	INPUT	2.993333	0.215892	15	0	2.6	2.97	3.55	0.802755	2.661726

Subtle outlier variables in skewness and kurtosis are due to some goods explaining the data well for one of the gases, but not all of the gases. For example, fuel combustion explains Carbon Dioxide but not Methane, and beef production explains Methane but not Nitrous Dioxide. Each of the gases are measured in metric tons (Mt). They were then converted to CO_{2eq}, which standardizes all gases as CO2 equivalents by a measure of 10^{-9}. Production of non-durable goods was weighed against consumption to include factory and transportation emissions. The Waste variable accounts for 63% of landfill totals, totaling only non-durable waste as seen in Figure 4.

Figure 4: Breakdown of Landfill Components



Source: Organization for Economic Co-operation and Development

4.2 Empirical Model

We follow Brandão et al. (2018) and model the impact of agriculture and fuel consumption on GHG emissions. This study adapted and modified to model in Figure 5.

Figure 5: Brandão et al. (2018) Model

$$E_{MDA} = \sum_{A} PAxFE_{MD}x10^{-9}$$

Where, EMDA=emission of CH4 from manure management by animal type A (Gg CH4); PA=animal herd of a given type A (heads); FEMD=emission factor of CH4 from manure management of a given animal type A (g/CH4/animal/year); 10−9=conversion factor from g to Gg. We added the following variables in Table 2.

Table 2: Variable Descriptions

AGR	Agriculture sector (includes crops, livestock, and manure fertilizer)
TRAN	Transportation sector (includes commercial and personal fuel, excludes airplane fuel)
IND	Industry sector (excludes all services and durable goods manufacturing)
COM	Commercial sector (includes paper, plastic, and rubber)
VOC	Volatile Organic Compounds (includes cleaning products and cosmetics)
W	Waste (includes 63% of landfill emissions)
N2O	Nitrous Oxide
CO2	Carbon Dioxide
CH4	Methane

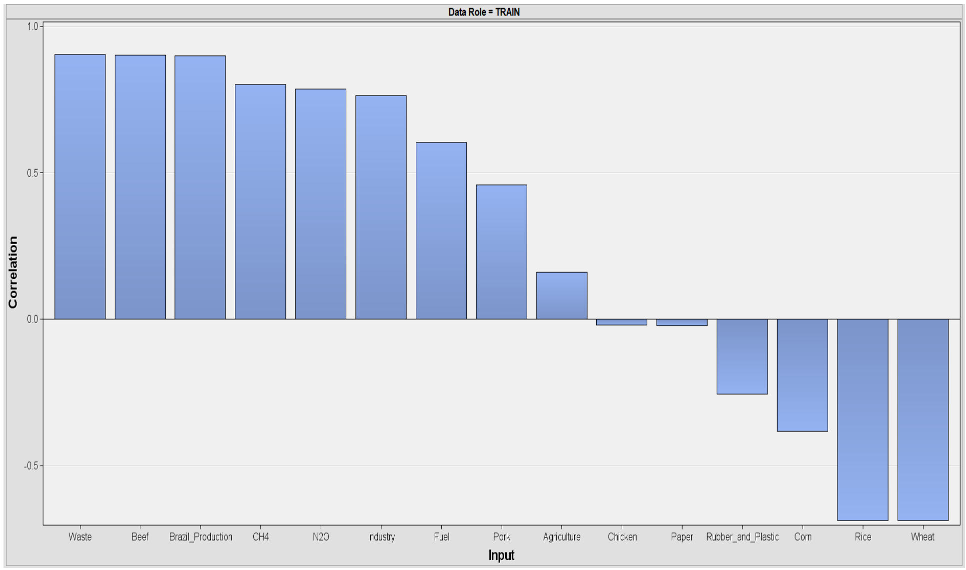
The model could be rewritten as follow:

$$\Delta CO2_{eq} = \beta_0 + \beta_1 AGR + \beta_2 TRAN + \beta_3 IND + \beta_4 COM + \beta_5 VOC + \beta_6 W + \beta_7 N20 + \beta_8 CO2 + \beta_9 CH4 + x_{i,\,t}$$

5.0 EMPIRICAL RESULTS

All variables were found to be statistically significant at the 1% level. The correlation coefficients are represented below in Figure 6. As we can see, Waste, Beef, and Production are the most positively correlated with our dependent variable, $CO2_{eq}$ and the largest polluting grains, Rice and Wheat are the most negatively correlated.

Figure 6: Correlation Coefficients



Figures 7-12 and Tables 3-8 show the empirical output from the least angle regression model. The LARs model utilized a Schwarz Bayesian Criterion instead of the AIC due to its larger penalty term. The larger penalty term helps us narrow down the most influential indicators because the data has a wide array of highly correlated variables with specific gases. The least angle regression was used to solve problems of overfitting that are present with simple OLS regression techniques. We notice here that Due to high volumes in comparison to other sectors, CO2 emissions from fuel and N2O emissions from landfills own most of the market shares.

Figure 7: Brazil Variable Effect: Target N2O

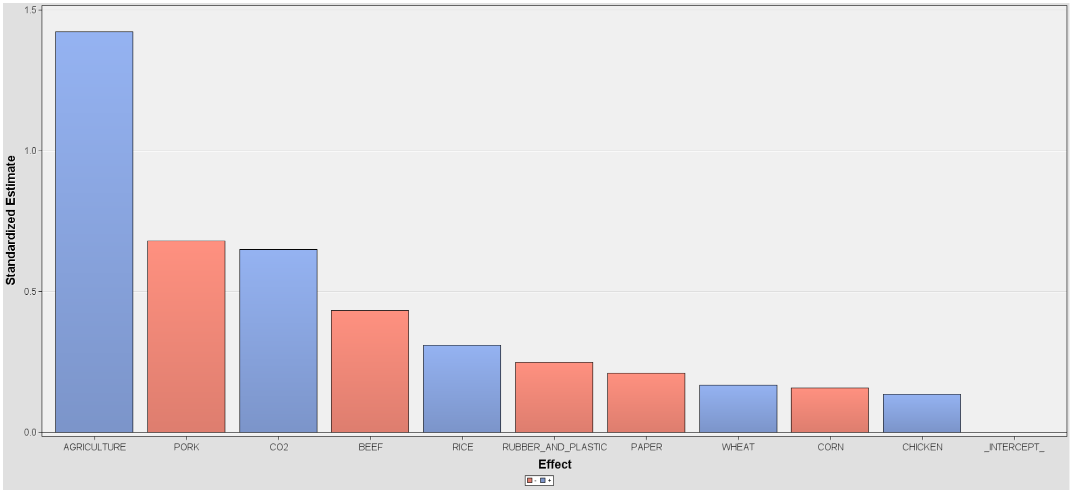


Table 3: Brazil LAR Selection Summary: N2O Target

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The GLMSELECT Procedure

Data Set                                       WORK._TMP_TRAIN
Dependent Variable                                         N2O
Selection Method                                           LAR
Stop at Specified Number of Effects                        200
Choose Criterion                                           SBC
Effect Hierarchy Enforced                                 None


Number of Observations Read         15
Number of Observations Used         11


        Dimensions

Number of Effects       16
Number of Parameters    16




The GLMSELECT Procedure

                 LAR Selection Summary

         Effect                  Number
 Step    Entered             Effects In           SBC

    0    Intercept                    1       55.7866
------------------------------------------------------
    1    Agriculture                  2       52.9059
    2    CO2                          3       37.3056
    3    Wheat                        4       35.7886
    4    Pork                         5       34.9035
    5    Corn                         6       37.0669
    6    Beef                         7       38.2997
    7    Chicken                      8       38.3870
    8    Rubber_and_Plastic           9       36.4822
    9    Rice                        10       27.9747
   10    Paper                       11        -Infty*

             * Optimal Value of Criterion
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Figure 8: Brazil Variable Effect: CH4 Target

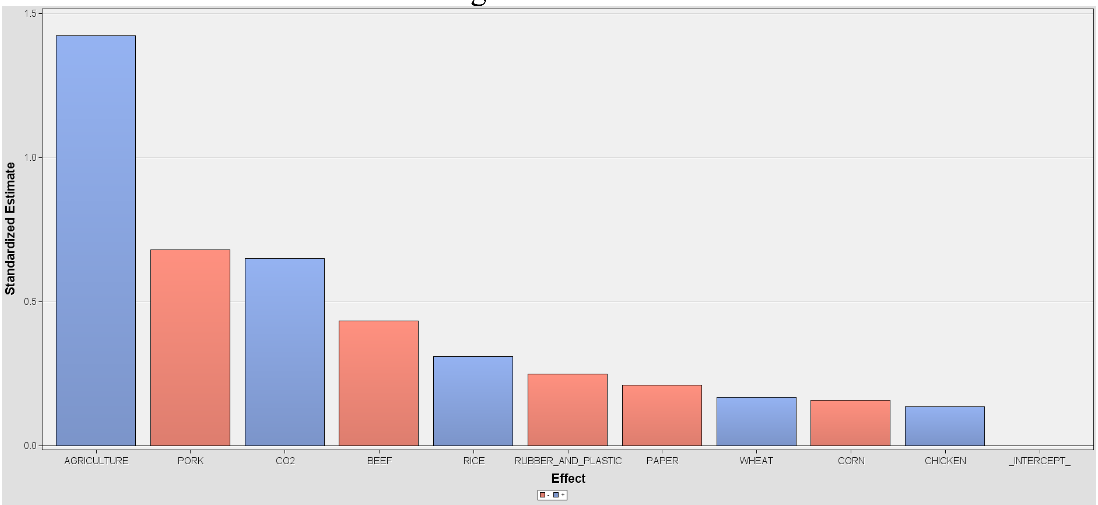

Table 4: Brazil LAR Selection Summary: N2O Target

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The GLMSELECT Procedure

Data Set                                    WORK._TMP_TRAIN
Dependent Variable                                      N2O
Selection Method                                        LAR
Stop at Specified Number of Effects                     200
Choose Criterion                                        SBC
Effect Hierarchy Enforced                              None


Number of Observations Read          15
Number of Observations Used          11


        Dimensions

Number of Effects       16
Number of Parameters    16




The GLMSELECT Procedure

                 LAR Selection Summary

         Effect                  Number
 Step    Entered               Effects In          SBC

    0    Intercept                      1      55.7866
------------------------------------------------------
    1    Agriculture                    2      52.9059
    2    CO2                            3      37.3056
    3    Wheat                          4      35.7886
    4    Pork                           5      34.9035
    5    Corn                           6      37.0669
    6    Beef                           7      38.2997
    7    Chicken                        8      38.3870
    8    Rubber_and_Plastic             9      36.4822
    9    Rice                          10      27.9747
   10    Paper                         11       -Infty*

             * Optimal Value of Criterion
```

Figure 9: Brazil Variable Steps: CO2 Target

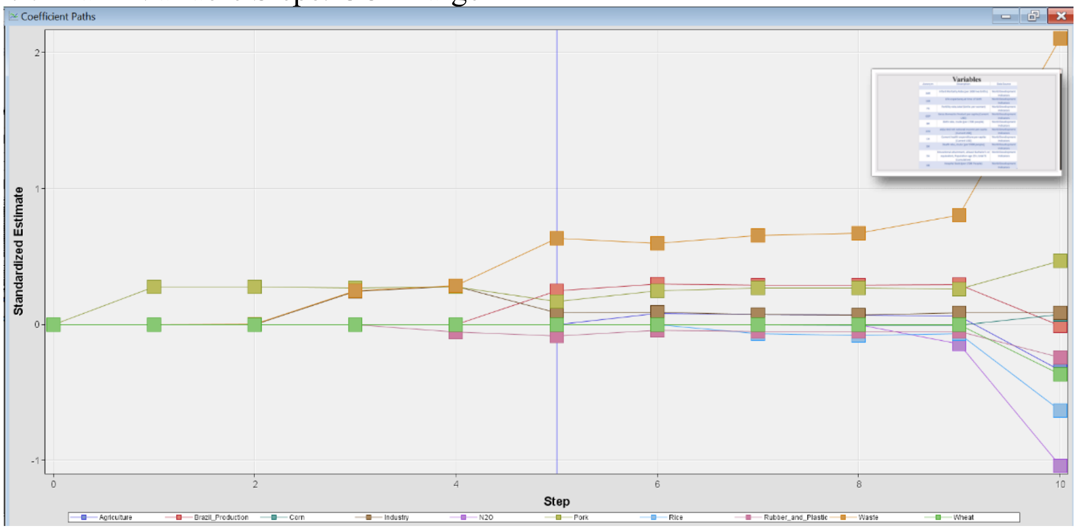

Table 5: Brazil LAR Selection: CO2 Target

The GLMSELECT Procedure

Data Set	WORK._TMP_TRAIN
Dependent Variable	CO2
Selection Method	LAR
Stop at Specified Number of Effects	200
Choose Criterion	SBC
Effect Hierarchy Enforced	None

Number of Observations Read	15
Number of Observations Used	11

Dimensions

Number of Effects	16
Number of Parameters	16

The GLMSELECT Procedure

LAR Selection Summary

Step	Effect Entered	Number Effects In	SBC
0	Intercept	1	123.8197
1	Brazil_Production	2	120.6046
2	Waste	3	117.1582
3	N2O	4	118.8953
4	Industry	5	102.0377
5	CH4	6	101.5353
6	Chicken	7	95.8364
7	Pork	8	96.8639
8	Corn	9	97.8218
9	Rice	10	96.0756
10	Rubber_and_Plastic	11	-Infty*

* Optimal Value of Criterion

Table 10: United States Variable Effect: N2O Target

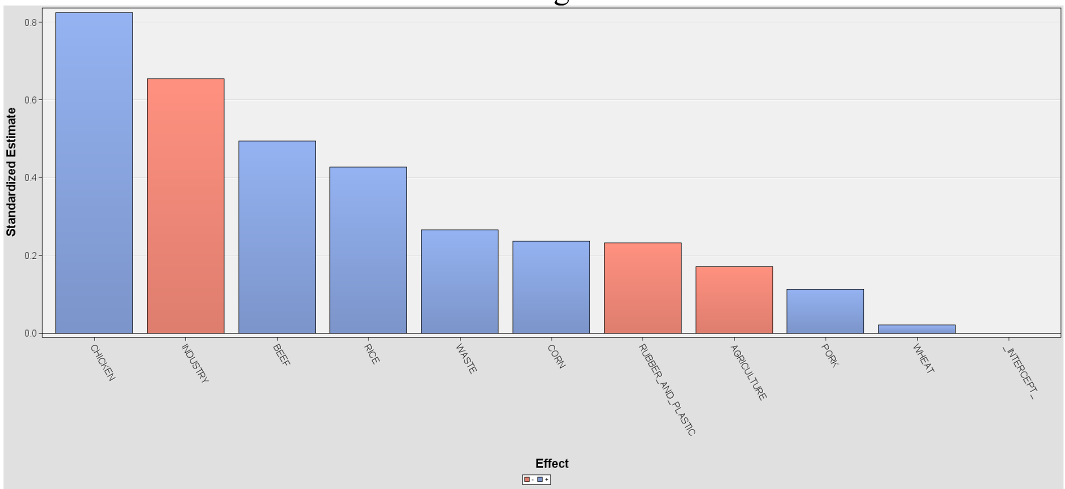

Table 6: United States LAR Selection Summary: N2O Target

The GLMSELECT Procedure

Data Set	WORK._TMP_TRAIN
Dependent Variable	N2O
Selection Method	LAR
Stop at Specified Number of Effects	200
Choose Criterion	SBC
Effect Hierarchy Enforced	None

Number of Observations Read	15
Number of Observations Used	11

Dimensions

Number of Effects	16
Number of Parameters	16

The GLMSELECT Procedure

LAR Selection Summary

Step	Effect Entered	Number Effects In	SBC
0	Intercept	1	-70.1197
1	Waste	2	-86.0683
2	Rice	3	-84.8122
3	Pork	4	-83.9933
4	Chicken	5	-91.0384
5	Corn	6	-91.8499
6	Industry	7	-106.4703
7	Wheat	8	-104.7728
8	Rubber_and_Plastic	9	-103.6236
9	Agriculture	10	-108.3574
10	Beef	11	-Infty*

* Optimal Value of Criterion

Figure 11: United States Variable Steps: CH4 Target

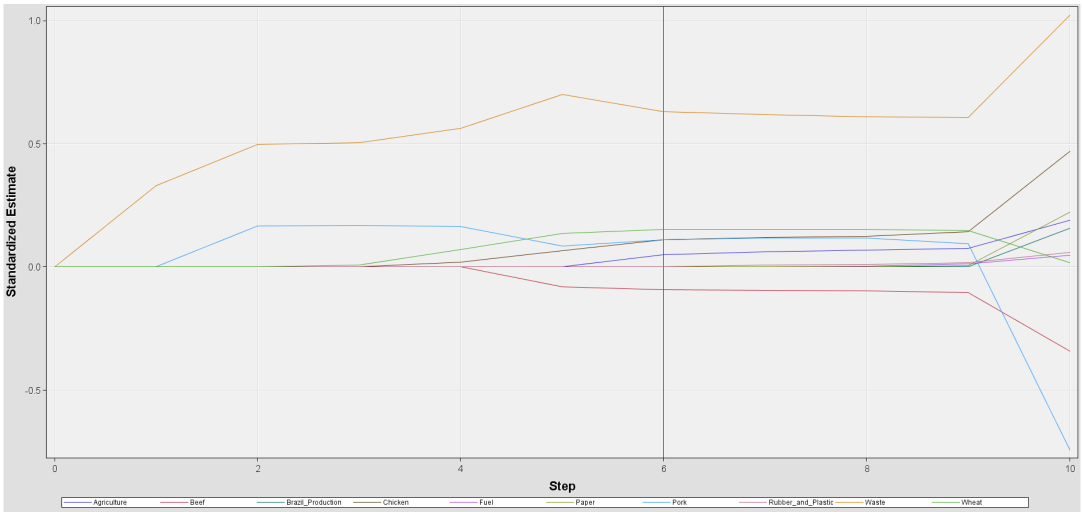

Table 7: United Sates LAR Selection Summary: CH4 Target

The GLMSELECT Procedure

Data Set	WORK._TMP_TRAIN
Dependent Variable	CH4
Selection Method	LAR
Stop at Specified Number of Effects	200
Choose Criterion	SBC
Effect Hierarchy Enforced	None

Number of Observations Read	15
Number of Observations Used	11

Dimensions

Number of Effects	16
Number of Parameters	16

The GLMSELECT Procedure

LAR Selection Summary

Step	Effect Entered	Number Effects In	SBC
0	Intercept	1	-8.3368
1	Waste	2	-14.3231
2	Pork	3	-24.8250
3	Wheat	4	-23.2579
4	Chicken	5	-29.0463
5	Beef	6	-51.6060
6	Agriculture	7	-53.8029
7	Rubber_and_Plastic	8	-52.3263
8	Fuel	9	-50.4793
9	Paper	10	-49.0478

Figure 12: United States Variable Steps: CO2 Target

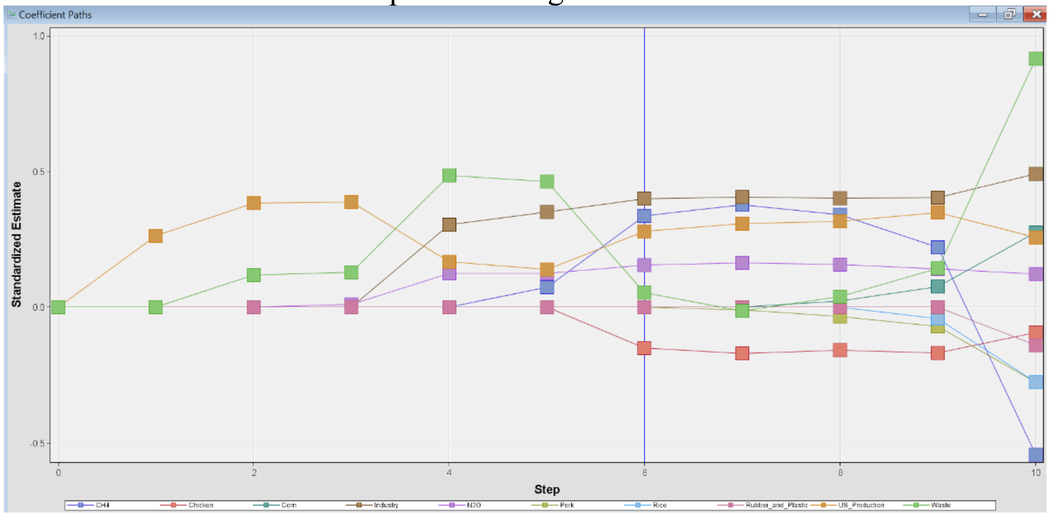

Table 8: United States LAR Selection Summary: CO2 Target

The GLMSELECT Procedure

Data Set	WORK._TMP_TRAIN
Dependent Variable	CO2
Selection Method	LAR
Stop at Specified Number of Effects	200
Choose Criterion	SBC
Effect Hierarchy Enforced	None

Number of Observations Read	15
Number of Observations Used	11

Dimensions

Number of Effects	16
Number of Parameters	16

The GLMSELECT Procedure

LAR Selection Summary

Step	Effect Entered	Number Effects In	SBC
0	Intercept	1	123.8197
1	US_Production	2	120.6046
2	Waste	3	117.1582
3	N2O	4	118.8953
4	Industry	5	102.0377
5	CH4	6	101.5353
6	Chicken	7	95.8364
7	Pork	8	96.8639
8	Corn	9	97.8218
9	Rice	10	96.0756
10	Rubber_and_Plastic	11	-Infty*

* Optimal Value of Criterion

5.0 CONCLUSION AND POLICY IMPLICATIONS

The US emits just over 6 times as much CO_2eq as Brazil. Dominating GHG contributions with more than a 30% margin are waste, beef, rice, pork. Wheat, 2,330kg CO_2eq, and rye, 2,270kg CO_2eq, had higher N_2O emissions per hectare than oats had with 1,800kg CO_2eq and barley with 1,930kg CO_2eq. The leading factor was a higher concentration of nutrient-manure fertilizer. Rubber and plastic consumption have a larger effect on CO_2, N_2O, and CH_4 than plastic. Paper has averaged a 1.9% (US) and 0.8% (Brazil) decrease in consumption since 2007, while plastic and rubber have seen about 3% increases each year. Policies should explore alternatives to plastic that do not involve paper, such as grocery stores who are switching to paper bags instead of plastic. The US relies on natural gas for energy 2.5 times less than Brazil, who relies on energy sources such as the high-emitting coal. The US should decrease grain consumption, as it is a top three factor in all GHG emissions and only top three factor in one category for Brazil.

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