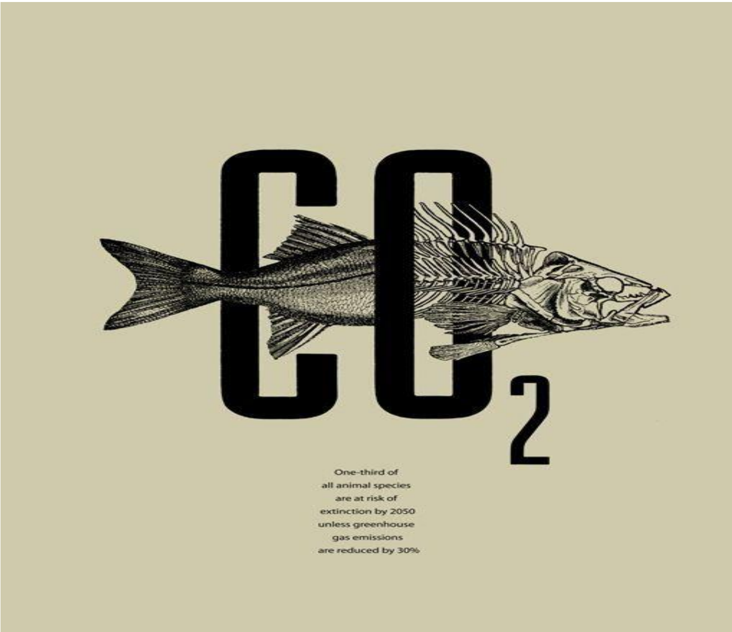

FACTORS AFFECTING GREENHOUSE GAS EMISSIONS

PROJECT REPORT

ABSTRACT

The report is about Green House Gases (GHG) Emissions in US and finding the true relationship between GHG emissions and the human activities. This report also presents the statistical significance of major factors affecting industry and energy sectors' GHG emissions.

SPEA-P507

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1. INTRODUCTION

"The warming of the climate system is unequivocal, and since the 1960s, many of the observed changes are unprecedented over decades to millennia." Greenhouse gases (GHG) from human activities are the most significant driver of observed climate change since the mid-20th century.

GHG Effects over climate change has been a hot topic of debates. There has been significant research work published over causes of GHG emissions and how they affect the global environment. But it comes to reality climate change and global warming are the last things on an individuals' mind.

While it is widely recognized that the emissions resulting from fossil fuel consumption are responsible for massive contributions to the global greenhouse effect, the true relationship between GHG emissions and various environmental changes is more complex. The greenhouse effect causes the atmosphere to retain heat which is ultimately resulting in an increase in Earth's surface temperature, ozone depletion, global warming etc.

In the United States, greenhouse gas emissions caused by human activities increased by 7 percent from 1990 to 2014. Since 2005, however, total U.S. greenhouse gas emissions have decreased by 7 percent. Reported emissions for 2010 were 6 percent below 2005 levels[1]. Carbon dioxide accounts for most of the nation's emissions and most of the increase since 1990[2].

In the context of the U.S. goal as stated in 2009, at the 15th meeting of the Conference of the Parties in Copenhagen, to achieve "in the range of a 17 percent GHG emission reduction by 2020 compared to 2005 levels"[*]

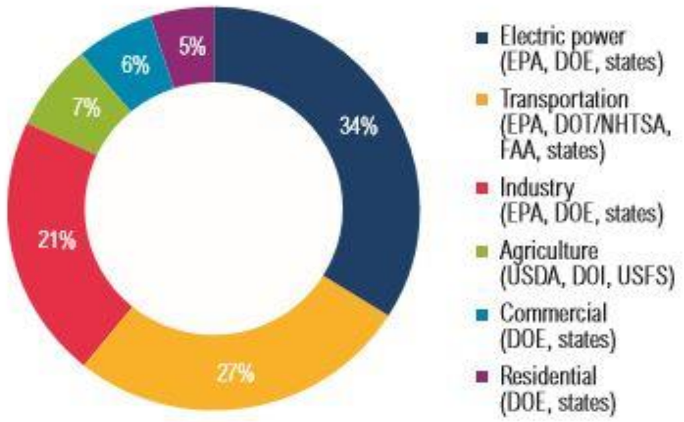
[*] The entire statement, available at http://unfccc.int/resource/docs/2011/ sb/eng/inf01r01.pdf, reads, "The United States communicated a target in the range of a 17 per cent emission reduction by 2020 compared with 2005 levels, in conformity with anticipated United States energy and climate legislation, recognizing that the final target will be reported to the secretariat in the light of the enacted legislation.

report examines key factors for the GHG emissions which can be controlled effectively and will be helpful for amending existing and draft emerging federal policies accordingly that are likely to reduce GHG emissions in the United States.

U.S. government GHG projections suggest that additional policy action is likely to be necessary to achieve the president's GHG reduction target and continue significant emissions reductions after 2020.

Additional policies such as standards for existing power plants, additional energy efficiency standards for appliances and equipment, and policies that reduce HFC consumption, can drive additional reductions in 2020 and beyond.

FIGURE 1: Key Sectors and Legal Authorities[1]



Source: Adapted from Bianco and Litz 2010, using EPA 2012.
Note: The LULUCF sector is excluded.

Figure 1 depicts these authorities across the major GHG-emitting sectors. In addition, states and local governments can pass their own laws that can lead to reductions in GHG emissions.

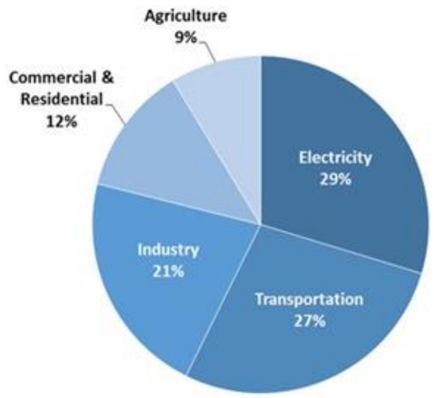
The U.S. Department of Energy (DOE) has the authority to set energy efficiency standards for appliances and commercial equipment. Moreover, the National Highway Transportation Safety Authority (NHTSA) has the authority over fuel efficiency of vehicles. The U.S. Environmental Protection Agency (EPA) has the authority to regulate GHG emissions. Agencies such as U.S. Federal Aviation Administration (FAA), which oversees air traffic, the U.S. Department of Agriculture (USDA), which governs agricultural and forest lands can greatly affect the GHG emissions[1].

2. OUR MODEL

Our aim is to identify which human activities contribute the most to GHG emissions which can be used to formulate policies to curb the GHG emissions.

2.1. IDENTIFICATION OF THE MODEL AND ITS THEORETICAL BASE

FIGURE 2: Total U.S. Greenhouse Gas Emissions by Economic Sector in 2015[4]



From above figure, industry, electricity, and transportation sectors majorly constitute the GHG emissions. Even though we know the overview of GHG emissions across the sectors, the real causes and their effects are required to be studied to mitigate the GHG emissions at the source level. Thus, to study the major human activities which contributes to these sectorial GHG emissions, we performed analysis of the root causes. Factors such as exports (trade), cement production, fisheries production, population, GDP, and agriculture are few worthy of investigation. There are few studies which relate each of the factors mentioned here to the GHG emissions.

Trees reduce GHG emissions since they intake CO_2 which is one of the major greenhouse gas (GHG), and in turn release oxygen. Thus, deforestation causes increase in

GHGs. Increase in population leads to increase in market demands which results in more production at the cost of increased fossil fuels and electricity which leads to GHG emissions on a large scale[4].

Cement production industry contributes heavily to GHG emissions, since the production of 1 ton of cement results in an equal amount of release of CO_2, adding to the GHG emissions[5]. As per the World Trade Organization, the expansion of international trade has resulted in an increase in GDP. “The factors affecting this trade increase are the technological changes, IT revolution, open trade, and investment policies. These factors have resulted in easy trade and coordination of production of parts and components of goods.”[2] Expansion of trade has resulted in increased energy consumption which in turn leads to increased GHG emissions. “U.S. Petroleum supplies 95 per cent of the total energy used by world transport making it a significant source of greenhouse gas emissions.”[2] Thus, theoretically, and conceptually there is proof of these factors affecting GHG emissions.

The global agriculture related emissions have increased by 8 percent and are projected to increase 15 percent above 2010 level by 2030[4]. “These increases are driven by population growth and changes in dietary preferences in the developing economies”[3]. We believed that these factors will be inter-related and required in-detail statistical analysis as there is not sufficient statistical evidence for their root contribution towards GHG emissions.

2.2. DESCRIPTION OF DATA AND DATA SOURCES

Data for all the variables in our model except cement production is extracted from the World Bank Data Repository. The data for cement production is extracted from the U.S Geological Survey webpage. The description of variables and their units are given in Table A in the technical appendix section 5.

Our data variables cover the different sectors – agriculture, industry, transport and electricity that are identified as the major contributors to GHG emissions. The total GHG emissions is our dependent variable that our model seeks to capture.

2.3. MISSPECIFICATION

As all the initial variables collected have theoretical inter-relation between them, we expected to find severe multicollinearity. Also, due to limitation of the complete observations to small number (43), multicollinearity was highly possible. To remove severe multicollinearity and model it as linear regression problem, we might need to remove variables which may create specification bias or misspecification error. But as analysed in theoretical background, cement production, air transport, exports, fisheries production which are the major human activities among the variables collected and in one or other way ultimately affects the major causes of GHG emissions such as fossil fuel consumption, electricity consumption, and population.

3. MODEL ANALYSIS

We first considered all 10 variables that we believed (theoretically) affect GHG emissions as already studied by researchers in past. We included three different energy variables to identify the most significant one in GHG emissions.

Since we had 10 variables and just 43 observations, we did not run regression analysis directly on our model to avoid underfitting. (Underfitting occurs when a statistical model or machine learning algorithm cannot capture the underlying trend of the data.[8]) We performed bivariate analysis by regressing GHG on each one of the 10 dependent variables as shown in table 1. Based on bivariate regression results, we filtered out the variables that were insignificant with respect to GHG.

TABLE 1: Bivariate Analysis Results for GHG emissions against each independent variable

Independent Variable	**p-value**	**R^2**
airtrans	<0.0001	0.7884
electric	<0.0001	0.8063
energy	0.5652	0.0081
export	<0.0001	0.5774
fossil	<0.0001	0.5121
pop	<0.0001	0.7424
cement	<0.0001	0.6198
fish	<0.0001	0.3338
agriland	<0.0001	0.8038
gdp	<0.0001	0.7808

Energy use (among all the three energy variables) was dropped out since it was highly insignificant. We also dropped the variable fossil fuel consumption since we already had another variable, electricity consumption which is highly correlated to fossil fuel as electricity generation is majorly sourced by fossil fuel.

After bivariate analysis, we calculated correlation coefficients between 8 variables, and found both gdp(GDP) and pop(population) to be correlated with 5 variables. So, as next step towards minimizing multicollinearity, we removed both from model since these variables, are theoretically correlated.

TABLE 2: Correlation Matrix for the all the independent variables

Pearson Correlation Coefficients, N = 43 Prob > |r| under H0: Rho=0								
	airtrans	electric	export	pop	cement	fish	agriland	gdp
airtrans airtrans	1.00000	0.88802 <.0001	0.95348 <.0001	0.97490 <.0001	0.60925 <.0001	0.56077 <.0001	-0.96942 <.0001	0.98771 <.0001
electric electric	0.88802 <.0001	1.00000	0.83794 <.0001	0.94298 <.0001	0.56488 <.0001	0.81902 <.0001	-0.89420 <.0001	0.93525 <.0001
export export	0.95348 <.0001	0.83794 <.0001	1.00000	0.96452 <.0001	0.39481 0.0088	0.53318 0.0002	-0.94000 <.0001	0.96008 <.0001
pop pop	0.97490 <.0001	0.94298 <.0001	0.96452 <.0001	1.00000	0.51005 0.0005	0.68487 <.0001	-0.96236 <.0001	0.99577 <.0001
cement cement	0.60925 <.0001	0.56488 <.0001	0.39481 0.0088	0.51005 0.0005	1.00000	0.31396 0.0403	-0.56647 <.0001	0.56848 <.0001
fish fish	0.56077 <.0001	0.81902 <.0001	0.53318 0.0002	0.68487 <.0001	0.31396 0.0403	1.00000	-0.55548 0.0001	0.66085 <.0001
agriland agriland	-0.96942 <.0001	-0.89420 <.0001	-0.94000 <.0001	-0.96236 <.0001	-0.56647 <.0001	-0.55548 0.0001	1.00000	-0.96516 <.0001
gdp gdp	0.98771 <.0001	0.93525 <.0001	0.96008 <.0001	0.99577 <.0001	0.56848 <.0001	0.66085 <.0001	-0.96516 <.0001	1.00000

3.1. MODEL 1

We ran the first multivariate regression analysis, by regressing GHG on following 6 variables as shown in Table 3:

DV (Dependent Variable): GHG emissions (GHG)

IV (Independent variables): airtrans, electric, export, cement, fish and agriland.

TABLE 3: Model 1 Findings

R-square	**96.75%**
Variable	***VIF***
Airtrans	47.86843
Electric	22.4918
Export	29.11771
Cement	4.17575
Fish	6.27855
Agriland	23.15159
Condition Index (COLLIN)	**866.1367**

The model showed serious multicollinearity issues, as interpreted from airtrans, electric and agriland which had *VIF values* >10 and *condition index* > 60.

3.2. MODEL 2

To remove multicollinearity, we ran auxiliary regression on each of the problematic variables. airtrans was the only variable that had its auxiliary R^2 value higher than the R^2 of the original model. Therefore, we ran the next multivariate regression model without airtrans.

TABLE 4: Model 2 Findings

R-square	**96.58%**
Variable	***VIF***
Electric	22.27183
Export	11.37046
Cement	2.14253
Fish	6.27477
Agriland	20.73613
Condition Index (COLLIN)	**770.28439**

The model had high multicollinearity, since electric, export and agriland had VIF values >10 and condition index was >60.

3.3. MODEL 3

To remove multicollinearity, we ran auxiliary regression on each of the problematic variables. None of the aux R^2 values were higher than the R^2 of the model 2. We ran 3 trial and error regression analysis by removing each of the problematic variables. The regression model without the feature agriland had the least VIF values and condition index. So, we ran the next multivariate regression model without agriland.

TABLE 5: Model 3 Findings

R-square	**95.42%**
Variable	***VIF***
Electric	15.36813
Export	5.23250
Cement	1.93223
Fish	5.09232
Condition Index (COLLIN)	**56.94305**

Unfortunately, we found multicollinearity, since electric had VIF value >10 and condition index was also >40.

3.4. MODEL 4

To remove multicollinearity, we ran auxiliary regression for the variable electric as dependent variable against remaining independent variables. The auxiliary R^2 value was lesser than the R^2 of Model 3. Also, we checked correlation matrix for the correlation between the four variables and found electric to be correlated with export and fish.

We ran another multivariate regression analysis without electric. This time, the resulting model had no multi-collinearity with each variable highly significant.

TABLE 6: Model 4 Findings

R-square	**87.68%**
Variable	***VIF***
Electric	15.36813
Export	1.51896
Cement	1.20603
Fish	1.42239
Condition Index (COLLIN)	**22.26537**

Model 4 shows significantly less multicollinearity. And as the no of observations were less and VIF merely more than 10, we considered variable electric in model for further diagnosis instead of dropping.

3.4.1. REGRESSION EQUATION:

ghg = 3373037 + 0.42654 * export + 28.79245 * cement + 81.69372 * fish + u

R^2 = 0.8768

After removing severe multicollinearity, we performed White test to check for heteroskedasticity. The model was devoid of heteroskedasticity.

Now that we had removed multicollinearity, we check for correlation between elements of series against others from same series as the data is time-series data at interval of 1 year. Therefore, performed auto-correlation testing using **Durbin – Watson statistic**. The DW statistic suggested **high positive auto-correlation**.

We ran both Cochrane-Orcutt's iterative process and Yule Walker's estimation to remove auto-correlation.

3.4.2. FINAL EQUATION USING COCHRANE- ORCUTT'S MODEL:

ghghat = 3977868.85 + 0.32798*export + 23.74982*cement + 52.41416*fish + u

R^2 = 0.87546

3.4.3. FINAL EQUATION USING YULE-WALKER'S MODEL:

ghghat2 = 3606443 + 0.3730*export + 25.4628*cement + 90.5568*fish + u

R^2 = 0.8758

Thus, after removing multicollinearity and autocorrelation, we selected the model obtained through **Yule-Walker's WLS estimation** as our final model since this estimation technique considers the first observation unlike Cochrane-Orcutt's iterative estimation.

4. Regression Analysis Results

4.1. Final Regression Equation

After omitting insignificant variables and those which were creating issue of multicollinearity and autocorrelation, our final regression model is as follows:

$$\widehat{ghg} = \mathbf{3606443 + 0.3730*export + 25.4628*cement + 90.5568*fish} + \hat{u}$$

$$\mathbf{R^2 = 0.8758}$$

4.2. Final Regression Results.

The results of our regression analysis show a statistically significant relationship (F= 143.14, p <0.0001) between our dependent variable, *ghghat*, and our independent variables. Our R-squared value is 0.8758. This suggests that 87.58% of the variation in GHG (kt of CO_2 equivalent) can be explained due to changes in independent variables. The significance and standardized estimates of each of the independent variables is presented in appendix section \

5. Summary of GLM assumptions and near multicollinearity test

We performed through tests to check for multicollinearity and heteroskedasticity. Our model did not have any heteroskedasticity but it did have severe multicollinearity issues. We also confirmed that our model satisfied the GLM assumptions. We performed white test to test for heteroskedasticity, which yielded an insignificant p-value, reflecting that the model does not have any issues of heteroskedasticity. Detail results are given in appendix.

6. Conclusion

The results of our regression analysis complement our initial hypothesis that industrial activities such as cement production, exports of goods and services and total fisheries production contribute to the GHG emissions is correct. These activities increase the fuel and electricity consumption which in turn increase the GHG emissions. Fisheries production is the major contributor among these independent variables considered in the model. As explained earlier, a large amount of fuel is used in fisheries which results in GHG emissions[6]. Even cement production is a significant variable that adds to the GHG emissions. Each ton of cement releases approximately 1 ton of GHGs. Exports of goods and services also leads to an increase in GHGs but the effect is comparatively less.

Though the model has helped successfully identify the significance of specific industrial factors that lead to an increase in GHG emissions, there is scope for future research. The data in this model is from 1970-2012 for United States only. We could not consider multiple cross-sections due to missing values for other countries. Data should be collected from each industry to be able to identify the ones causing most problems and create policies to control the GHG emissions caused by them. There should be cap defined for the GHG emission allowed to each company. A rule should be put in place that forces the companies to plant trees for some level of GHG emission. Also, a cap should be placed on the permissible level of GHG emissions, violating which would result in some severe action such as shutting down the company. Such strict measures need to be in place since its human nature to ignore minor penalties until it doesn't affect his work or earnings severely. Making it compulsory to plant trees in order to help balance the GHG emissions caused by them will help keep in check, if not reduce the GHG emissions.

7. Technical Appendix

7.1. Included Variables

Initially we collected data for 10 independent variables that we thought affected the greenhouse gas emissions the most namely agricultural land, energy use, fossil fuel energy consumption, electric power consumption, population, GDP, exports of goods and services, total fisheries production, air transport (freight), cement production. All our data is compiled from world bank, except for cement production, which is extracted from the U.S geological Survey web portal. The variables and their data source are given in Table A.

The numbers for agricultural land, exports of goods and services and total fisheries productions were huge in the original data. To bring the data to a uniform range, we divide these data values by a suitable power of 10. The data for agricultural land extracted from the World bank site is converted to thousands of sq. km from sq.km. Exports of goods and services is converted to millions of US dollars. Similarly, total fisheries production is converted from metric tons to thousands of metric tonnes.

Table A. Data Sources

Variable Name	Variable description	Data Source
Agriland	Agricultural land (sq. km)	World Bank
Energy	Energy use (kg of oil equivalent per capita)	World Bank
Fossil	Fossil fuel energy consumption (% of total)	World Bank
Electric	Electric power consumption (kWh per capita)	World Bank
Ghg	Total greenhouse gas emissions (kt of CO2 equivalent)	World Bank
Pop	Population (People)	World Bank
Gdp	GDP-USD (Million US$ (2010))	World Bank
Export	Exports of goods and services millions US$)	World Bank
Fish	Total fisheries production (thousands metric tons)	World Bank
Airtrans	Air transport, freight (million ton-km)	World Bank
Cement	Portland Cement Production (thousand metric tonnes)	USGS – US Geological Survey

7.2. Overall Significance Test

In testing for the overall significance of our final equation, we have the following null and alternative hypotheses:

H_0: β2 = β3 = β4 = β5 = β6 = β7

H_1: Not H_0

Given an F statistic value of 143.14, and a p-value of <0.0001, we can reject H_0 at the 0.001 level of significance, indicating that there is statistically significant evidence of a relationship between GHGs (Greenhouse Gas Emissions) and the independent variables.

7.3. Parameter Estimates for Final Model

$\hat{\beta}_1$ = 3606443 is the intercept where the regression plane crosses the Y axis when all independent variables are equal to zero.

$\hat{\beta}_2$ = 0.3730; A one unit increase in exports results in a 0.3730 unit increase in total GHGs

$\hat{\beta}_3$ = 25.4628; A one unit increase in the cement production results in a 25.46 unit increase in total GHGs.

$\hat{\beta}_4$ = 90.5568; A one unit increase in total fisheries production results in 90.5568 unit increase in total GHGs.

7.4. Tests for Near Multicollinearity

We performed thorough tests to check for multicollinearity and heteroskedasticity. Our initial model did not have any heteroskedasticity but it did have severe multicollinearity issues. We also confirmed that our model satisfied the GLM assumptions. Even though dropping a variable from the model is not the best way forward in case of multicollinearity, our model had severe multicollinearity issues that couldn't be sorted using other methods. Multicollinearity is a problem with the model and a different sample might have less multicollinearity. But due to the limited observations the sample size could not be increased. In case our had near multicollinearity issues, we could have let them be, but severe issues cannot be ignored. Since each variable was somehow related to the other independent variables in the model, it's effect might be duplicative, hence causing severe multicollinearity issues. Thus, we removed the problematic variables with the understanding that the other independent variables in the final model are somehow covering the effect of those variables. We tested for multicollinearity using correlation table, variation inflation factor (VIF), tolerance (TOL) and condition index (COLLIN). Our final model had VIF values below 10, hence did not indicate any multicollinearity issues.

7.5. Test for Autocorrelation

Autocorrelation is usually seen in time series data and our data set is no exception to this. To test for autocorrelation, we performed Durbin-Watson test, which confirmed our suspicions. Significant value of Pr<DW reflects positive autocorrelation. To remove autocorrelation, we performed iterative Cochrane-Orcutt as well as Yule Walker methods. Both the methods yield similar results and successfully remove autocorrelation from the model. The Yule Walker is preferred in this case, since the observations are less. Yule Walker includes the first observation during the correction, unlike Cochrane-Orchutt. The R2 of this model is 87.579, which means that cement production, exports and fisheries production explain most of the variation in the model.

7.6. Dataset

year	agriland	energy	fossil	popgrowth	electric	ghg	pop	gdp	export	fish	airtrans	cement
1970	4344	7569.077	95.91877	1.165003	7236.657	5400504	205052000	4779684.39	51900	2962.979	5151.2	68947
1971	4333	7644.525	95.64381	1.264334	7517.305	5440421	207661000	4937197.78	59710	3050.82	5540.8	72861
1972	4323	7940.998	95.36676	1.070523	8076.409	5704297	209896000	5197055.47	62964	2946.225	6283	76708
1973	4312	8163.604	94.97719	0.954477	8573.194	5912971	211909000	5490331.80	70844	2978.682	7060.1	79444
1974	4301.58	7909.586	94.15645	0.91366	8449.928	5756864	213854000	5461938.30	95270	3053.006	7255.4	75194

1975	4301.58	7656.264	93.09795	0.985986	8522.394	5539255	215973000	5451141.22	126651	3065.741	6999.6	63249
1976	4301.58	8100.562	93.00562	0.95022	8968.776	5868460	218035000	5744744.60	138707	3272.174	7438.2	67580
1977	4303.31	8285.571	92.4223	1.005772	9337.724	6048233	220239000	6009496.75	149515	3211.927	7920.6	72629
1978	4281.63	8438.403	91.74381	1.059573	9560.545	6054465	222585000	6343726.02	159350	3636.483	8406.8	77262
1979	4281.63	8327.042	91.80293	1.103577	9700.695	6135463	225055000	6545183.14	186885	3722.375	8658.1	76323
1980	4281.63	7942.253	91.42607	0.95959	9862.365	5896083	227225000	6529173.87	230129	3871.666	8615.4	69588
1981	4281.63	7647.538	90.83195	0.981415	9976.694	5830249	229466000	6698571.36	280773	3931.248	8606.9	66162
1982	4313.99	7259.079	90.04312	0.953318	9544.461	5534118	231664000	6570568.95	305239	4214.408	8295.8	58369
1983	4313.99	7199.119	89.45507	0.914379	9742.006	5524778	233792000	6874947.75	283209	4421.466	9284.5	64724
1984	4313.99	7443.32	88.90104	0.865817	10282.37	5761217	235825000	7374006.18	276996	5048.228	10293.1	71395
1985	4313.99	7456.263	88.30167	0.886129	10414.21	5776898	237924000	7686570.95	302383	5043.441	9672.2	71539
1986	4313.99	7376.096	87.65663	0.924164	10424.43	5731026	240133000	7956493.69	303209	5253.141	10619	72498
1987	4269.48	7622.173	87.37781	0.893829	10886.86	5743633	242289000	8231927.43	321000	6077.501	12023.2	72122
1988	4269.48	7849.754	87.07724	0.907999	11298.33	6185748	244499000	8577995.35	363944	6028.323	13875.6	70988
1989	4269.48	7890.287	87.09329	0.944406	11531.93	6221392	246819000	8893710.53	444601	5860.605	14651	71267
1990	4269.48	7671.773	86.43784	1.129651	11713.33	6136094	249623000	9064413.77	504291	5936.132	14791.4	71310
1991	4269.48	7631.468	85.69474	1.336261	12134.17	6073644	252981000	9057698.44	551874	5607.652	14486.2	67193
1992	4254.29	7677.401	85.57482	1.386886	12014.96	6137498	256514000	9379735.50	594932	5688.778	15617.6	69585
1993	4229.48	7709.497	86.11796	1.31868	12261.52	6282704	259919000	9637289.60	633053	6025.071	16343	73807
1994	4211.39	7757.831	85.91213	1.226296	12455.16	6374979	263126000	10026408.99	654800	6043.96	19083.8	77948
1995	4201.39	7763.755	85.46934	1.190787	12659.61	6365297	266278000	10299024.62	720939	5712.653	19622.9	76906
1996	4163.06	7844.468	85.51006	1.163412	12854.3	6577713	269394000	10689963.36	812813	5454.047	21676.4	79266
1997	4148.85	7828.581	86.45649	1.20396	12889.83	6724414	272657000	11169624.85	867590	5493.228	25478.8	82582
1998	4145.88	7803.698	86.08659	1.165715	13154.76	6749016	275854000	11666663.21	953806	5180.987	25757.9	83931
1999	4138.87	7923.224	85.7846	1.14834	13281.87	6808138	279040000	12213269.67	952981	5310.497	27292.2	85952

2000	4143.99	8056.864	85.88083	1.112769	13671.05	6969124	282162411	12713058.21	991980	5216.83	30171.98	87846
2001	4149.44	7827.886	86.34598	0.989741	13046.61	6821236	284968955	12837135.35	1096835	5462.163	27924.57	88900
2002	4130.64	7843.345	86.24908	0.927797	13296.18	6981787	287625193	13066422.98	1026713	5483.648	29554.68	89732
2003	4139.25	7794.236	86.27839	0.859482	13307.49	6991255	290107933	13433168.20	1002509	5534.652	34205.55	92843
2004	4115.21	7881.579	86.12431	0.925484	13388.59	7244272	292805298	13941713.40	1040279	5602.988	37450.12	97434
2005	4117.84	7846.5	86.01854	0.921713	13704.58	7182808	295516599	14408093.84	1181507	5475.187	37357.64	99319
2006	4092.148	7697.653	85.62647	0.964254	13583.27	6994087	298379912	14792303.79	1308901	5378.772	39881.9	98167
2007	4128.576	7758.166	85.61471	0.951055	13657.45	7128952	301231207	15055395.30	1476316	5296.214	40617.74	95464
2008	4133.126	7488.082	84.96822	0.945865	13663.43	6648991	304093966	15011490.54	1664625	4861.785	39313.6	86310
2009	4099.607	7056.784	84.15425	0.876651	12913.71	6604069	306771529	14594842.18	1841942	4715.028	35097.67	63907
2010	4084.262	7160.97	84.15059	0.835992	13394.05	6713349	309346863	14964372.00	1587742	4893.331	39353.26	66447
2011	4046.693	7026.902	83.71405	0.76385	13240.13	6571654	311718857	15204019.63	1852335	5520.449	39621.91	67895
2012	4087.065	6867.106	83.45825	0.761808	12954.9	6343841	314102623	15542161.72	2106371	5521.244	39111.34	74151

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