WORLD BANK DEVELOPMENT LOAN PORTFOLIO OPTIMIZATION

Maximizing Potential Poverty Reduction

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Computational Optimization DNSC 6208 Final Project Report

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Introduction

The World Bank's (WB) Mission Statement is to "End extreme poverty within a generation and boost shared prosperity". One of the ways in which the WB aims to achieve this objective is through the lending of Development Policy Loans. These loans are designed to help the borrower achieve sustainable growth and poverty reduction through a program of policy and institutional actions. DPLs may be extended to member countries of the WB or their political subdivisions (Operations Policy & Country Services , 2012). The World Bank bases its decision to extend a Development Policy Loan on its risk assessment of the borrower's institutional and policy framework, the adequacy of its macroeconomic policy framework, and the borrower's commitment to and ownership of the reform program to be supported by the operation.

We have come up with a hypothetical scenario, based off of the 2012 World Bank Development Policy Lending Retrospective report, wherein we seek to optimize a development loan portfolio with the intention of maximizing the potential for poverty reduction subject to budgetary, risk, and return constraints.

Problem Definition and Data Sources

Loan portfolio optimization has been in use by financial managers since the 1950's when Nobel Laureate Harry Markowitz, using the concepts of efficient portfolios and efficient frontiers triggered a revolution in the development of modern finance (Markowitz, 1952). Traditionally loan portfolio optimization is focused on how to obtain the best possible performance for an organization, typically by maximizing returns subject to some constraint on risk or vice versa. In our case, we will attempt to optimize a portfolio in a way which maximizes the potential for poverty reduction, in-line with our lending institutions mission statement, subject to the budgetary, risk, return and disbursement requirements.

For this project we utilized the 2012 World Bank Development Policy Lending Retrospective report or guidance on how Development Policy Lending has operated in the past and goals for the future. However, we also used information gathered from the World Bank's open data source: World Development Indicators to fill in data for things such as country population, GDP, poverty etc.

We set out framing our problem by first identifying the countries which would be included in our set of developing countries eligible for the DPL loans. From the World Development Indicators (WDI) data set on the WBs website we were able to identify 138 countries which were then classified into six distinct regions which are summarized below, a complete list of all countries and there regions can be found in Appendix A..

Figure 1: Region Summary

Region	Abbreviation	Number of Countries	Population Below Poverty Line (millions)
East Asia & Pacific	EAP	24	211
Europe & Central Asia	ECA	20	40
Latin America & Caribbean	LCR	26	192.7
Middle East & North Africa	MNA	13	74.5
South Asia Region	SSA	8	482.9
Sub-Saharan Africa	SSA	47	446.9

As you can see in the table above, we were able to determine the amount of people living below the national poverty line within each region as well as for each country. This parameter will be the basis for determining our loan portfolios potential impact on poverty.

Next we identified four indicators from the WDI set which we felt could be used as a measure of risk for each country, the Country Political & Institutional Assessment (CPIA) scores. The World Bank created the CPIA to rate countries against a set of 16 criteria grouped into four clusters previously mentioned[1]. They are on a scale from one to six with six being the least risky. By averaging the four CPIA clusters, economic management, structural policies, policies for social inclusion and public sector management, we created a single risk score for each country. Countries for which there were no CPIA scores available in the WDI set were assigned a score of 2. A complete list of each countries CPIA score please see Table 2 in the Appendix.

In addition to each countries CPIA score we also collected data for each country's GDP which was then used to calculate the maximum loan amount allowed for each country. Which also led us to a decision about what type of loans to offer. After some careful research we decided to structure our loan portfolio around three different types of loans, a 10 year, 15 year and a 20 year loan. Where each country was able to borrow a maximum loan amount of up to 0.5% of their GDP for a 10 year loan, 1.5% for a 15 year loan and 2.5% for a 20 year loan. For each loan duration and each country we have a separate maximum loan amount, interest rate, and risk score. The interest rates were based off the LIBOR rate of 0.69% plus a premium of 0.75%, 1.05%, and 1.35% respectively for each of the possible loan durations. A complete list of each countries figures can be found in the Tables section of the Appendix..

We next decided that we needed to provide a minimum level of support to our model when determining how to disburse the loan amounts and so we developed region specific quotas. The regional quotas as a percent of the total amount loaned were 5% for East Asia & Pacific, 5% for Europe & Central Asia, 10% for Latin America & Caribbean, 5% for Middle East & North Africa, 5% for South Asia, and 20% for Sub-Saharan Africa. Finally, based upon our research of the 2012 retrospective report, we decided that the World Bank budget should be $70 billion USD, their minimum portfolio risk should be 3.0, and their minimum portfolio return should be 1.5%.

Optimization Model and Formulation

With all of our data gathered and structured in a manner we could use for optimization we then began defining and formulating our model. We first started with defining our sets:

Sets

R = set of regions {1, 2, 3, 4, 5, 6}

C = set of countries {1, 2, 3, … 138}

L = set of loan durations {1, 2, 3}

G = set of countries within each region

Parameters

P_c = Millions of people below the national poverty line for each country

B = World Bank budget, set to $70 billion USD

M_{cl} = Maximum amount that can be loaned to each country for a certain loan duration

I_l = Interest rate for a certain loan duration

S_{cl} = Risk score of a country for a certain loan duration

Q_r = Regional loan quotas

Decision Variables

For our decision variables we decided to use a continuous variable to determine the amount loaned to a country for a specific loan type. However, we also needed to a binary decision variable for each country-loan option.

x_{cl} = Size of loan to each country for a certain loan duration, continuous

y_{cl} = Whether or not loan is disbursed to each country for a certain loan duration, binary.

Objective Function

Developing our objective function was one of the hardest parts of the entire project. We ultimately decided to explore the impact of maximizing the average loans dollar to person in poverty ratio. That is, we divided each loan amount by the country's population living under poverty and then sought to maximize the average value of all the loan values. To accomplish this we realized that we would make our objective function non-linear, however with access to the commercial solver Knitro, which can handle non-linear mixed integer programs we did not feel that this would be a problem

$$max \frac{\sum_{c=1}^{C} \sum_{l=1}^{L} \frac{x_{cl}}{p_c}}{\sum_{c=1}^{C} \sum_{l=1}^{L} y_{cl}}$$

Constraints

Finally, we came up with several constraints which were needed to enforce the requirements discussed previously.

First was a constraint to which kept the total amount loaned to less than our equal to the set budget:

$\sum_{c=1}^{C} \sum_{l=1}^{L} x_{cl} \leq b$ Budget

Second was a constraint which forced the model to keep a risk score of 3 or better:

$\sum_{c=1}^{C} \sum_{l=1}^{L} s_c x_{cl} \geq 3 \sum_{c=1}^{C} \sum_{l=1}^{L} x_{cl}$ Portfolio Risk

Similarly we wrote a constraint which forced the model to force a return of 1.5%:

$\sum_{c=1}^{C} \sum_{l=1}^{L} i_l x_{cl} \geq 0.015 \sum_{c=1}^{C} \sum_{l=1}^{L} x_{cl}$ Portfolio Return

This constraint served a dual purpose of keeping the loan amount less than the computed max amount as well as forcing our continuous variable to zero when the binary decision variable was zero.

$x_{cl} \leq m_{cl} y_{cl} \; \forall \; c \in C, l \in L$ Max loan

This constraint was developed to explore the effects of allowing only one loan per country.

$\sum_{l=1}^{L} y_{cl} \leq 1 \; \forall \; \mathrm{c} \in \mathrm{C}$ One loan

We also needed a constraint to enforce the regional quotas defined earlier. Note that we could not use the budget parameter and instead had to sum the total amount loaned. This was due to the constraint which allowed the total amount loaned to be less than or equal to budget.

$\sum_{c=1}^{C} \sum_{l=1}^{L} x_{cl} \geq q_r \sum_{c=1}^{C} \sum_{l=1}^{L} x_{cl} \quad \forall \; g \in G$ Region Quota

Lastly we have our non-negativity constraint for the continuous decision variable x and the binary constraint for y.

$x_{cl} \geq 0$ Non-negativity

$$y_{cl} = \begin{cases} 1, \text{if loan duration } l \text{ for country } c \text{ is used} \\ 0, \text{otherwise} \end{cases}$$ Binary

Solution Approach and Computational Experience

As we showed in the previous section, our model has a non-linear mixed integer objective function and therefore we decided to use the commercial solver Knitro developed by Zienna Optimization LLC. Therefore, solving this problem in excel was also not an option and therefore we turned to AMPL for model implementation.

While developing the AMPL implementation of the model we quickly learned that using a linear approximation of the objective function was a more efficient form of model building given the exceedingly long time needed to obtain an optimal integer solution. This process also had a secondary effect of providing us with an alternative, linear objective function, to evaluate alongside our original non-linear objective function.

Equation 1: Alternate Linear Objective Function

$$\frac{\sum_{c=1}^{C}\sum_{l=1}^{L} x_{cl}}{\sum_{c=1}^{C} p_c}$$

One drawback with this linear objective function was that it divided the total amount loaned by the entire population in poverty of our entire data set, rather than only those countries to which loans were made. However we felt that it was still valuable for model comparison given that we were able to find an optimal integer solution in about 93 seconds using Knitro.

Figure 2: AMPL Output for Linear Model

```
EXIT: All nodes have been explored. Integer feasible point found.

Final Statistics for MIP
------------------------
Final objective value               =  2.11789076613121e+001
Final integrality gap (abs / rel)   = 3.59e-004 /  1.69e-005 ( 0.00%)
# of nodes processed                =    28871
```

```
# of subproblems processed         =    28871
# of LP iterations                 =   245857
Total program time (secs)          =      93.948 (    93.922 CPU time)
Time spent in evaluations (secs)   =       3.080

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KNITRO 9.1.0: MIP: All nodes have been explored. Integer feasible point found.
objective 21.17890766; integrality gap 0.000359
28871 nodes; 28871 subproblem solves
```

When it came to solving our primary model using Knitro in AMPL we found ourselves with a model having 414 binary decision variables and 414 continuous variables and 561 linear inequalities. We initially gave our solver a max run time of 4 hours but did not obtain an optimal integer solution and therefore on our second run we set our max run time to sixteen hours. After 13.13 hours of total run time, only 8 minutes of which was actually in model evaluation, we obtained a locally optimal integer solution.

Figure 3: AMPL Output Non-Linear MIP

```
EXIT: Optimal solution found.
Final Statistics for MIP
------------------------
Final objective value              =  8.97441449254469e+002
Final integrality gap (abs / rel)  =-6.17e-005 / -6.88e-008 (-0.00%)
# of nodes processed               =     4601
# of subproblems processed         =     5418
Total program time (secs)          =   47287.375 ( 47285.266 CPU time)
Time spent in evaluations (secs)   =     428.921

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KNITRO 9.1.0: Locally optimal solution.
objective 897.4414493; integrality gap -6.17e-05
4601 nodes; 5418 subproblem solves
```

Results and Insights

The optimal objective function value for our primary non-linear MIP was $897.44 per person in poverty with a total of 12.408 billion USD loaned out to 11 countries. The optimal objective function value for our linear model had ab objective function value of $21.18 per person in poverty with a total of 30.674 billion USD loaned out to 111 countries. A comparison of the loan distributions broken down by region can be seen in the table below

Figure 4: Regional Loan Comparison

Region	Population in Poverty (Millions)	Non-Linear Model Loan Total (Millions USD)	Linear Model Loan Total (Millions USD)
East Asia & Pacific	211	729.70	2837.90
Europe & Central Asia	40	827.50	1873.25
Latin America & Caribbean	192.7	1240.53	3238.17
Middle East & North Africa	74.5	620.27	3509.72
South Asia	482.9	6506.24	12194.50
Sub-Saharan Africa	446.9	2481.06	7479.74

We can also perform the same side by side comparison of the two models and their impact on poverty, as measured by dollars per person in poverty by simply dividing the region total by the total population living under poverty for that region.

Figure 5: Regional Loan Impact Comparison

Region	Population in Poverty (Millions)	Non-Linear Model Impact $/person	Linear Model Impact $/person
East Asia & Pacific	211	3.46	13.45
Europe & Central Asia	40	20.69	46.83
Latin America & Caribbean	192.7	6.44	16.80
Middle East & North Africa	74.5	8.33	47.11
South Asia	482.9	13.47	25.25
Sub-Saharan Africa	446.9	5.55	16.74

As you can see, on a region basis the linear model has a greater impact per person than the non-linear model, at the expense of making 100 more loans and almost tripling the total amount loaned out. However when one compares the actual loan to person impacts at a country level the non-linear model clearly outperforms the linear model with the non-linear model having an average dollar to person in poverty ratio of $894. Whereas the linear models ratio is only 30,674 million USD divided by the total population in poverty in the countries loaned to, which was 1,056 million for a ratio of $29.04.

Conclusion

We have shown that it is possible to apply portfolio optimization to the World Bank's Development Policy Loans. Our formulation and solution is based upon specific parameters and constraints, some of which required us to make assumptions based upon our own research. We have also shown that based on the specific objectives of the decision makers, whether they want to help as many people a little bit or whether they want to help smaller amount of people a lot, we can build a model which optimizes those objectives while operating within specific constraints. Furthermore, we believe these models could be modified by the World Bank, or any other interested party, to reflect modified or additional parameters and constraints to better represent real world scenarios.

References

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3. "World Development Indicators." Data. The World Bank Group, 2015. <http://data.worldbank.org/indicator>.
4. Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 77-91.
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Appendix

Table 1 (Regions):

Country	Region
Afghanistan	South Asia
Albania	Europe & Central Asia
Algeria	Middle East & North Africa
American Samoa	East Asia & Pacific
Angola	Sub-Saharan Africa
Argentina	Latin America & Caribbean
Armenia	Europe & Central Asia
Azerbaijan	Europe & Central Asia
Bangladesh	South Asia
Belarus	Europe & Central Asia
Belize	Latin America & Caribbean
Benin	Sub-Saharan Africa
Bhutan	South Asia
Bolivia	Latin America & Caribbean
Bosnia and Herzegovina	Europe & Central Asia
Botswana	Sub-Saharan Africa
Brazil	Latin America & Caribbean
Bulgaria	Europe & Central Asia
Burkina Faso	Sub-Saharan Africa
Burundi	Sub-Saharan Africa
Cabo Verde	Sub-Saharan Africa
Cambodia	East Asia & Pacific
Cameroon	Sub-Saharan Africa
Central African Republic	Sub-Saharan Africa
Chad	Sub-Saharan Africa
China	East Asia & Pacific
Colombia	Latin America & Caribbean
Comoros	Sub-Saharan Africa
Congo, Dem. Rep.	Sub-Saharan Africa
Congo, Rep.	Sub-Saharan Africa
Costa Rica	Latin America & Caribbean
Cote d'Ivoire	Sub-Saharan Africa
Cuba	Latin America & Caribbean
Djibouti	Middle East & North Africa
Dominica	Latin America & Caribbean
Dominican Republic	Latin America & Caribbean
Ecuador	Latin America & Caribbean

Egypt, Arab Rep.	Middle East & North Africa
El Salvador	Latin America & Caribbean
Eritrea	Sub-Saharan Africa
Ethiopia	Sub-Saharan Africa
Fiji	East Asia & Pacific
Gabon	Sub-Saharan Africa
Gambia, The	Sub-Saharan Africa
Georgia	Europe & Central Asia
Ghana	Sub-Saharan Africa
Grenada	Latin America & Caribbean
Guatemala	Latin America & Caribbean
Guinea	Sub-Saharan Africa
Guinea-Bissau	Sub-Saharan Africa
Guyana	Latin America & Caribbean
Haiti	Latin America & Caribbean
Honduras	Latin America & Caribbean
India	South Asia
Indonesia	East Asia & Pacific
Iran, Islamic Rep.	Middle East & North Africa
Iraq	Middle East & North Africa
Jamaica	Latin America & Caribbean
Jordan	Middle East & North Africa
Kazakhstan	Europe & Central Asia
Kenya	Sub-Saharan Africa
Kiribati	East Asia & Pacific
Korea, Dem. Rep.	East Asia & Pacific
Kosovo	Europe & Central Asia
Kyrgyz Republic	Europe & Central Asia
Lao PDR	East Asia & Pacific
Lebanon	Middle East & North Africa
Lesotho	Sub-Saharan Africa
Liberia	Sub-Saharan Africa
Libya	Middle East & North Africa
Macedonia, FYR	Europe & Central Asia
Madagascar	Sub-Saharan Africa
Malawi	Sub-Saharan Africa
Malaysia	East Asia & Pacific
Maldives	South Asia
Mali	Sub-Saharan Africa
Marshall Islands	East Asia & Pacific
Mauritania	Sub-Saharan Africa

Mauritius	Sub-Saharan Africa
Mexico	Latin America & Caribbean
Micronesia, Fed. Sts.	East Asia & Pacific
Moldova	Europe & Central Asia
Mongolia	East Asia & Pacific
Montenegro	Europe & Central Asia
Morocco	Middle East & North Africa
Mozambique	Sub-Saharan Africa
Myanmar	East Asia & Pacific
Namibia	Sub-Saharan Africa
Nepal	South Asia
Nicaragua	Latin America & Caribbean
Niger	Sub-Saharan Africa
Nigeria	Sub-Saharan Africa
Pakistan	South Asia
Palau	East Asia & Pacific
Panama	Latin America & Caribbean
Papua New Guinea	East Asia & Pacific
Paraguay	Latin America & Caribbean
Peru	Latin America & Caribbean
Philippines	East Asia & Pacific
Romania	Europe & Central Asia
Rwanda	Sub-Saharan Africa
Samoa	East Asia & Pacific
Sao Tome and Principe	Sub-Saharan Africa
Senegal	Sub-Saharan Africa
Serbia	Europe & Central Asia
Seychelles	Sub-Saharan Africa
Sierra Leone	Sub-Saharan Africa
Solomon Islands	East Asia & Pacific
Somalia	Sub-Saharan Africa
South Africa	Sub-Saharan Africa
South Sudan	Sub-Saharan Africa
Sri Lanka	South Asia
St. Lucia	Latin America & Caribbean
St. Vincent and the Grenadines	Latin America & Caribbean
Sudan	Sub-Saharan Africa
Suriname	Latin America & Caribbean
Swaziland	Sub-Saharan Africa
Syrian Arab Republic	Middle East & North Africa
Tajikistan	Europe & Central Asia

Tanzania	Sub-Saharan Africa
Thailand	East Asia & Pacific
Timor-Leste	East Asia & Pacific
Togo	Sub-Saharan Africa
Tonga	East Asia & Pacific
Tunisia	Middle East & North Africa
Turkey	Europe & Central Asia
Turkmenistan	Europe & Central Asia
Tuvalu	East Asia & Pacific
Uganda	Sub-Saharan Africa
Ukraine	Europe & Central Asia
Uzbekistan	Europe & Central Asia
Vanuatu	East Asia & Pacific
Venezuela, RB	Latin America & Caribbean
Vietnam	East Asia & Pacific
West Bank and Gaza	Middle East & North Africa
Yemen, Rep.	Middle East & North Africa
Zambia	Sub-Saharan Africa
Zimbabwe	Sub-Saharan Africa

Table 2 (Risk Scores):

Country	**10 year**	**15 year**	**20 year**
Afghanistan	2.65	1.99	1.33
Albania	1.00	0.75	0.50
Algeria	1.00	0.75	0.50
American Samoa	1.00	0.75	0.50
Angola	2.67	2.00	1.34
Argentina	1.00	0.75	0.50
Armenia	4.13	3.10	2.07
Azerbaijan	1.00	0.75	0.50
Bangladesh	3.27	2.45	1.63
Belarus	1.00	0.75	0.50
Belize	1.00	0.75	0.50
Benin	3.51	2.63	1.75
Bhutan	3.68	2.76	1.84
Bolivia	3.56	2.67	1.78
Bosnia and Herzegovina	3.60	2.70	1.80
Botswana	1.00	0.75	0.50
Brazil	1.00	0.75	0.50
Bulgaria	1.00	0.75	0.50
Burkina Faso	3.77	2.83	1.88

Burundi	3.24	2.43	1.62
Cabo Verde	3.94	2.96	1.97
Cambodia	3.43	2.57	1.71
Cameroon	3.23	2.42	1.61
Central African Republic	2.50	1.88	1.25
Chad	2.60	1.95	1.30
China	1.00	0.75	0.50
Colombia	1.00	0.75	0.50
Comoros	2.76	2.07	1.38
Congo, Dem. Rep.	2.88	2.16	1.44
Congo, Rep.	3.04	2.28	1.52
Costa Rica	1.00	0.75	0.50
Cote d'Ivoire	3.18	2.39	1.59
Cuba	1.00	0.75	0.50
Djibouti	3.09	2.32	1.55
Dominica	3.77	2.83	1.88
Dominican Republic	1.00	0.75	0.50
Ecuador	1.00	0.75	0.50
Egypt, Arab Rep.	1.00	0.75	0.50
El Salvador	1.00	0.75	0.50
Eritrea	1.99	1.49	1.00
Ethiopia	3.44	2.58	1.72
Fiji	1.00	0.75	0.50
Gabon	1.00	0.75	0.50
Gambia, The	3.27	2.45	1.63
Georgia	4.44	3.33	2.22
Ghana	3.68	2.76	1.84
Grenada	3.54	2.66	1.77
Guatemala	1.00	0.75	0.50
Guinea	2.97	2.23	1.48
Guinea-Bissau	2.53	1.89	1.26
Guyana	3.35	2.51	1.68
Haiti	2.83	2.13	1.42
Honduras	3.32	2.49	1.66
India	3.70	2.78	1.85
Indonesia	1.00	0.75	0.50
Iran, Islamic Rep.	1.00	0.75	0.50
Iraq	1.00	0.75	0.50
Jamaica	1.00	0.75	0.50
Jordan	1.00	0.75	0.50
Kazakhstan	1.00	0.75	0.50

Kenya	3.86	2.89	1.93
Kiribati	2.91	2.18	1.45
Korea, Dem. Rep.	1.00	0.75	0.50
Kosovo	3.59	2.69	1.80
Kyrgyz Republic	3.55	2.66	1.78
Lao PDR	3.36	2.52	1.68
Lebanon	1.00	0.75	0.50
Lesotho	3.47	2.60	1.73
Liberia	3.13	2.34	1.56
Libya	1.00	0.75	0.50
Macedonia, FYR	1.00	0.75	0.50
Madagascar	3.02	2.26	1.51
Malawi	3.07	2.30	1.53
Malaysia	1.00	0.75	0.50
Maldives	3.23	2.43	1.62
Mali	3.38	2.54	1.69
Marshall Islands	2.64	1.98	1.32
Mauritania	3.29	2.47	1.65
Mauritius	1.00	0.75	0.50
Mexico	1.00	0.75	0.50
Micronesia, Fed. Sts.	2.69	2.02	1.35
Moldova	3.86	2.89	1.93
Mongolia	3.36	2.52	1.68
Montenegro	1.00	0.75	0.50
Morocco	1.00	0.75	0.50
Mozambique	3.62	2.71	1.81
Myanmar	2.95	2.21	1.48
Namibia	1.00	0.75	0.50
Nepal	3.38	2.53	1.69
Nicaragua	3.76	2.82	1.88
Niger	3.46	2.59	1.73
Nigeria	3.58	2.68	1.79
Pakistan	3.07	2.30	1.53
Palau	1.00	0.75	0.50
Panama	1.00	0.75	0.50
Papua New Guinea	3.25	2.44	1.63
Paraguay	1.00	0.75	0.50
Peru	1.00	0.75	0.50
Philippines	1.00	0.75	0.50
Romania	1.00	0.75	0.50
Rwanda	3.93	2.94	1.96

Samoa	4.00	3.00	2.00
Sao Tome and Principe	3.05	2.29	1.53
Senegal	3.82	2.86	1.91
Serbia	1.00	0.75	0.50
Seychelles	1.00	0.75	0.50
Sierra Leone	3.27	2.45	1.63
Solomon Islands	2.93	2.20	1.47
Somalia	1.00	0.75	0.50
South Africa	1.00	0.75	0.50
South Sudan	2.09	1.57	1.05
Sri Lanka	3.52	2.64	1.76
St. Lucia	3.65	2.74	1.83
St. Vincent and the Grenadines	3.73	2.79	1.86
Sudan	2.36	1.77	1.18
Suriname	1.00	0.75	0.50
Swaziland	1.00	0.75	0.50
Syrian Arab Republic	1.00	0.75	0.50
Tajikistan	3.31	2.48	1.65
Tanzania	3.76	2.82	1.88
Thailand	1.00	0.75	0.50
Timor-Leste	3.06	2.29	1.53
Togo	2.97	2.23	1.48
Tonga	3.46	2.59	1.73
Tunisia	1.00	0.75	0.50
Turkey	1.00	0.75	0.50
Turkmenistan	1.00	0.75	0.50
Tuvalu	2.77	2.08	1.38
Uganda	3.72	2.79	1.86
Ukraine	1.00	0.75	0.50
Uzbekistan	3.38	2.54	1.69
Vanuatu	3.44	2.58	1.72
Venezuela, RB	1.00	0.75	0.50
Vietnam	3.79	2.84	1.90
West Bank and Gaza	1.00	0.75	0.50
Yemen, Rep.	2.99	2.24	1.50
Zambia	3.42	2.56	1.71
Zimbabwe	2.26	1.69	1.13

Table 3 (Poverty):

Country	Poverty
Afghanistan	30,551,674

Albania	2,897,366
Algeria	39,208,194
American Samoa	55,165
Angola	21,471,618
Argentina	41,446,246
Armenia	2,976,566
Azerbaijan	9,416,801
Bangladesh	156,594,962
Belarus	9,466,000
Belize	331,900
Benin	10,323,474
Bhutan	753,947
Bolivia	10,671,200
Bosnia and Herzegovina	3,829,307
Botswana	2,021,144
Brazil	200,361,925
Bulgaria	7,265,115
Burkina Faso	16,934,839
Burundi	10,162,532
Cabo Verde	498,897
Cambodia	15,135,169
Cameroon	22,253,959
Central African Republic	4,616,417
Chad	12,825,314
China	1,357,380,000
Colombia	48,321,405
Comoros	734,917
Congo, Dem. Rep.	67,513,677
Congo, Rep.	4,447,632
Costa Rica	4,872,166
Cote d'Ivoire	20,316,086
Cuba	11,265,629
Djibouti	872,932
Dominica	72,003
Dominican Republic	10,403,761
Ecuador	15,737,878
Egypt, Arab Rep.	82,056,378
El Salvador	6,340,454
Eritrea	6,333,135
Ethiopia	94,100,756
Fiji	881,065

Gabon	1,671,711
Gambia, The	1,849,285
Georgia	4,487,200
Ghana	25,904,598
Grenada	105,897
Guatemala	15,468,203
Guinea	11,745,189
Guinea-Bissau	1,704,255
Guyana	799,613
Haiti	10,317,461
Honduras	8,097,688
India	1,252,139,596
Indonesia	249,865,631
Iran, Islamic Rep.	77,447,168
Iraq	33,417,476
Jamaica	2,714,734
Jordan	6,460,000
Kazakhstan	17,035,275
Kenya	44,353,691
Kiribati	102,351
Korea, Dem. Rep.	24,895,480
Kosovo	1,824,000
Kyrgyz Republic	5,719,600
Lao PDR	6,769,727
Lebanon	4,467,390
Lesotho	2,074,465
Liberia	4,294,077
Libya	6,201,521
Macedonia, FYR	2,107,158
Madagascar	22,924,851
Malawi	16,362,567
Malaysia	29,716,965
Maldives	345,023
Mali	15,301,650
Marshall Islands	52,634
Mauritania	3,889,880
Mauritius	1,258,653
Mexico	122,332,399
Micronesia, Fed. Sts.	103,549
Moldova	3,558,566
Mongolia	2,839,073

Montenegro	621,383
Morocco	33,008,150
Mozambique	25,833,752
Myanmar	53,259,018
Namibia	2,303,315
Nepal	27,797,457
Nicaragua	6,080,478
Niger	17,831,270
Nigeria	173,615,345
Pakistan	182,142,594
Palau	20,918
Panama	3,864,170
Papua New Guinea	7,321,262
Paraguay	6,802,295
Peru	30,375,603
Philippines	98,393,574
Romania	19,981,358
Rwanda	11,776,522
Samoa	190,372
Sao Tome and Principe	192,993
Senegal	14,133,280
Serbia	7,164,132
Seychelles	89,173
Sierra Leone	6,092,075
Solomon Islands	561,231
Somalia	10,495,583
South Africa	53,157,490
South Sudan	11,296,173
Sri Lanka	20,483,000
St. Lucia	182,273
St. Vincent and the Grenadines	109,373
Sudan	37,964,306
Suriname	539,276
Swaziland	1,249,514
Syrian Arab Republic	22,845,550
Tajikistan	8,207,834
Tanzania	49,253,126
Thailand	67,010,502
Timor-Leste	1,180,069
Togo	6,816,982
Tonga	105,323

Tunisia	10,886,500
Turkey	74,932,641
Turkmenistan	5,240,072
Tuvalu	9,876
Uganda	37,578,876
Ukraine	45,489,600
Uzbekistan	30,243,200
Vanuatu	252,763
Venezuela, RB	30,405,207
Vietnam	89,708,900
West Bank and Gaza	4,169,506
Yemen, Rep.	24,407,381
Zambia	14,538,640
Zimbabwe	14,149,648

Table 4 (Max Loan, Millions USD):

Country	10 year	15 year	20 year
Afghanistan	$101,548,355	$203,096,710	$507,741,775
Albania	$64,616,201	$129,232,403	$323,081,007
Algeria	$1,050,917,053	$2,101,834,105	$5,254,585,263
American Samoa	$2,875,000	$5,750,000	$14,375,000
Angola	$620,891,209	$1,241,782,418	$3,104,456,045
Argentina	$3,049,444,855	$6,098,889,710	$15,247,224,276
Armenia	$52,160,848	$104,321,696	$260,804,239
Azerbaijan	$367,802,422	$735,604,844	$1,839,012,110
Bangladesh	$749,952,273	$1,499,904,545	$3,749,761,364
Belarus	$358,547,568	$717,095,137	$1,792,737,841
Belize	$8,121,471	$16,242,943	$40,607,356
Benin	$41,536,110	$83,072,221	$207,680,552
Bhutan	$8,906,307	$17,812,614	$44,531,535
Bolivia	$153,005,789	$306,011,577	$765,028,944
Bosnia and Herzegovina	$89,256,632	$178,513,265	$446,283,161
Botswana	$73,923,537	$147,847,073	$369,617,684
Brazil	$11,228,365,162	$22,456,730,324	$56,141,825,809
Bulgaria	$272,399,365	$544,798,731	$1,361,996,827
Burkina Faso	$57,912,780	$115,825,561	$289,563,902
Burundi	$13,572,535	$27,145,070	$67,862,676
Cabo Verde	$9,397,013	$18,794,026	$46,985,064
Cambodia	$76,193,448	$152,386,897	$380,967,242
Cameroon	$147,837,523	$295,675,047	$739,187,616
Central African Republic	$7,690,879	$15,381,757	$38,454,394

Chad	$67,567,762	$135,135,524	$337,838,811
China	$46,201,352,260	$92,402,704,520	$231,006,761,301
Colombia	$1,892,076,634	$3,784,153,268	$9,460,383,170
Comoros	$2,994,629	$5,989,259	$14,973,147
Congo, Dem. Rep.	$163,454,484	$326,908,969	$817,272,422
Congo, Rep.	$70,429,261	$140,858,521	$352,146,303
Costa Rica	$248,105,447	$496,210,895	$1,240,527,237
Cote d'Ivoire	$155,310,133	$310,620,265	$776,550,663
Cuba	$360,000,000	$720,000,000	$1,800,000,000
Djibouti	$7,281,722	$14,563,445	$36,408,612
Dominica	$2,583,333	$5,166,667	$12,916,667
Dominican Republic	$305,818,384	$611,636,768	$1,529,091,920
Ecuador	$472,363,395	$944,726,790	$2,361,816,975
Egypt, Arab Rep.	$1,359,864,114	$2,719,728,229	$6,799,320,572
El Salvador	$121,295,500	$242,591,000	$606,477,500
Eritrea	$17,220,488	$34,440,976	$86,102,439
Ethiopia	$237,625,932	$475,251,865	$1,188,129,662
Fiji	$19,275,086	$38,550,171	$96,375,428
Gabon	$96,717,533	$193,435,066	$483,587,665
Gambia, The	$4,517,485	$9,034,970	$22,587,426
Georgia	$80,700,235	$161,400,470	$403,501,175
Ghana	$240,685,137	$481,370,275	$1,203,425,687
Grenada	$4,177,908	$8,355,817	$20,889,542
Guatemala	$268,983,547	$537,967,095	$1,344,917,737
Guinea	$30,720,660	$61,441,319	$153,603,298
Guinea-Bissau	$4,803,892	$9,607,785	$24,019,462
Guyana	$14,950,644	$29,901,288	$74,753,221
Haiti	$42,296,633	$84,593,267	$211,483,166
Honduras	$92,750,130	$185,500,260	$463,750,651
India	$9,383,985,996	$18,767,971,991	$46,919,929,978
Indonesia	$4,341,728,262	$8,683,456,525	$21,708,641,312
Iran, Islamic Rep.	$1,844,521,758	$3,689,043,516	$9,222,608,791
Iraq	$1,146,636,424	$2,293,272,847	$5,733,182,118
Jamaica	$71,811,313	$143,622,626	$359,056,565
Jordan	$168,392,501	$336,785,001	$841,962,504
Kazakhstan	$1,159,381,411	$2,318,762,821	$5,796,907,053
Kenya	$276,215,281	$552,430,562	$1,381,076,405
Kiribati	$844,758	$1,689,515	$4,223,788
Korea, Dem. Rep.	$140,000,000	$280,000,000	$700,000,000
Kosovo	$35,359,796	$70,719,592	$176,798,981
Kyrgyz Republic	$36,131,516	$72,263,033	$180,657,582

Lao PDR	$56,212,632	$112,425,265	$281,063,161
Lebanon	$221,762,091	$443,524,181	$1,108,810,453
Lesotho	$11,674,948	$23,349,896	$58,374,741
Liberia	$9,754,801	$19,509,601	$48,774,003
Libya	$370,997,643	$741,995,287	$1,854,988,217
Macedonia, FYR	$50,977,021	$101,954,041	$254,885,103
Madagascar	$53,067,470	$106,134,940	$265,337,351
Malawi	$18,526,934	$37,053,868	$92,634,670
Malaysia	$1,565,795,487	$3,131,590,974	$7,828,977,435
Maldives	$11,499,216	$22,998,432	$57,496,079
Mali	$54,713,637	$109,427,273	$273,568,183
Marshall Islands	$954,573	$1,909,146	$4,772,865
Mauritania	$20,790,915	$41,581,829	$103,954,573
Mauritius	$59,646,254	$119,292,508	$298,231,270
Mexico	$6,304,573,305	$12,609,146,610	$31,522,866,524
Micronesia, Fed. Sts.	$1,581,229	$3,162,457	$7,906,143
Moldova	$39,848,095	$79,696,190	$199,240,474
Mongolia	$57,582,048	$115,164,096	$287,910,240
Montenegro	$22,080,415	$44,160,831	$110,402,077
Morocco	$519,178,514	$1,038,357,028	$2,595,892,570
Mozambique	$78,151,514	$156,303,028	$390,757,570
Myanmar	$325,000,000	$650,000,000	$1,625,000,000
Namibia	$65,565,349	$131,130,698	$327,826,744
Nepal	$96,471,741	$192,943,482	$482,358,704
Nicaragua	$56,278,042	$112,556,084	$281,390,210
Niger	$37,037,092	$74,074,184	$185,185,461
Nigeria	$2,609,016,573	$5,218,033,147	$13,045,082,866
Pakistan	$1,161,433,906	$2,322,867,811	$5,807,169,528
Palau	$1,235,217	$2,470,434	$6,176,085
Panama	$213,240,500	$426,481,000	$1,066,202,500
Papua New Guinea	$76,446,870	$152,893,740	$382,234,351
Paraguay	$145,047,059	$290,094,117	$725,235,293
Peru	$1,011,749,235	$2,023,498,470	$5,058,746,174
Philippines	$1,360,332,774	$2,720,665,549	$6,801,663,872
Romania	$948,190,810	$1,896,381,620	$4,740,954,050
Rwanda	$37,606,309	$75,212,618	$188,031,545
Samoa	$4,009,580	$8,019,161	$20,047,901
Sao Tome and Principe	$1,553,423	$3,106,846	$7,767,116
Senegal	$73,958,495	$147,916,990	$369,792,475
Serbia	$227,598,255	$455,196,509	$1,137,991,273
Seychelles	$7,216,726	$14,433,452	$36,083,630

Sierra Leone	$20,681,404	$41,362,808	$103,407,019
Solomon Islands	$5,481,985	$10,963,969	$27,409,923
Somalia	$11,500,000	$23,000,000	$57,500,000
South Africa	$1,830,289,567	$3,660,579,134	$9,151,447,834
South Sudan	$59,022,034	$118,044,068	$295,110,169
Sri Lanka	$335,910,077	$671,820,153	$1,679,550,383
St. Lucia	$6,678,821	$13,357,641	$33,394,103
St. Vincent and the Grenadines	$3,546,791	$7,093,582	$17,733,955
Sudan	$332,829,447	$665,658,894	$1,664,147,235
Suriname	$26,493,939	$52,987,879	$132,469,697
Swaziland	$18,956,522	$37,913,043	$94,782,609
Syrian Arab Republic	$320,000,000	$640,000,000	$1,600,000,000
Tajikistan	$42,540,517	$85,081,035	$212,702,586
Tanzania	$166,125,187	$332,250,375	$830,625,937
Thailand	$1,936,260,821	$3,872,521,643	$9,681,304,107
Timor-Leste	$22,500,000	$45,000,000	$112,500,000
Togo	$21,692,879	$43,385,758	$108,464,396
Tonga	$2,331,295	$4,662,591	$11,656,477
Tunisia	$234,967,994	$469,935,988	$1,174,839,970
Turkey	$4,110,675,916	$8,221,351,832	$20,553,379,579
Turkmenistan	$209,254,386	$418,508,772	$1,046,271,930
Tuvalu	$191,612	$383,224	$958,059
Uganda	$107,468,077	$214,936,155	$537,340,387
Ukraine	$887,153,049	$1,774,306,098	$4,435,765,244
Uzbekistan	$283,978,282	$567,956,563	$1,419,891,408
Vanuatu	$4,141,186	$8,282,372	$20,705,930
Venezuela, RB	$2,191,417,824	$4,382,835,648	$10,957,089,120
Vietnam	$856,950,016	$1,713,900,033	$4,284,750,082
West Bank and Gaza	$33,000,000	$66,000,000	$165,000,000
Yemen, Rep.	$179,772,512	$359,545,023	$898,862,558
Zambia	$134,104,353	$268,208,706	$670,521,764
Zimbabwe	$67,450,000	$134,900,000	$337,250,000

Table 5 (Optimal Solution – Loan Selection):

y_{cl}

	10 years	15 years	20 years
American Samoa	0	0	1
Belarus	0	1	0
Costa Rica	0	0	1
India	1	0	0
Jordan	0	0	1

Malaysia	1	0	0
Maldives	0	0	1
Montenegro	0	0	1
Nigeria	1	0	0
Palau	0	0	1
Seychelles	0	0	1

Table 6 (Optimal Solution – Amount of Loans):

x_{cl}

	10 years	15 years	20 years
American Samoa	-	-	$14,380,000
Belarus	-	$717,100,000	-
Costa Rica	-	-	$1,240,530,000
India	$6,448,740,000	-	-
Jordan	-	-	$620,265,000
Malaysia	$709,141,000	-	-
Maldives	-	-	$57,500,000
Montenegro	-	-	$110,400,000
Nigeria	$2,444,980,000	-	-
Palau	-	-	$6,180,000
Seychelles	-	-	$36,080,000

Table 7. Non-Linear Model AMPL Output (x[c,l],y[c,l])

x [*,*]	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	14.38
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	717.1	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0

y [*,*]	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	1
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	1	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0

16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	0	0
21	0	0	0
22	0	0	0
23	0	0	0
24	0	0	0
25	0	0	0
26	0	0	0
27	0	0	0
28	0	0	0
29	0	0	0
30	0	0	0
31	0	0	1240.53
32	0	0	0
33	0	0	0
34	0	0	0
35	0	0	0
36	0	0	0
37	0	0	0
38	0	0	0
39	0	0	0
40	0	0	0
41	0	0	0
42	0	0	0
43	0	0	0
44	0	0	0
45	0	0	0
46	0	0	0
47	0	0	0
48	0	0	0
49	0	0	0
50	0	0	0
51	0	0	0
52	0	0	0
53	0	0	0
54	6448.74	0	0
55	0	0	0
56	0	0	0

16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	0	0
21	0	0	0
22	0	0	0
23	0	0	0
24	0	0	0
25	0	0	0
26	0	0	0
27	0	0	0
28	0	0	0
29	0	0	0
30	0	0	0
31	0	0	1
32	0	0	0
33	0	0	0
34	0	0	0
35	0	0	0
36	0	0	0
37	0	0	0
38	0	0	0
39	0	0	0
40	0	0	0
41	0	0	0
42	0	0	0
43	0	0	0
44	0	0	0
45	0	0	0
46	0	0	0
47	0	0	0
48	0	0	0
49	0	0	0
50	0	0	0
51	0	0	0
52	0	0	0
53	0	0	0
54	1	0	0
55	0	0	0
56	0	0	0

57	0	0	0
58	0	0	0
59	0	0	620.265
60	0	0	0
61	0	0	0
62	0	0	0
63	0	0	0
64	0	0	0
65	0	0	0
66	0	0	0
67	0	0	0
68	0	0	0
69	0	0	0
70	0	0	0
71	0	0	0
72	0	0	0
73	0	0	0
74	709.141	0	0
75	0	0	57.5
76	0	0	0
77	0	0	0
78	0	0	0
79	0	0	0
80	0	0	0
81	0	0	0
82	0	0	0
83	0	0	0
84	0	0	110.4
85	0	0	0
86	0	0	0
87	0	0	0
88	0	0	0
89	0	0	0
90	0	0	0
91	0	0	0
92	2444.98	0	0
93	0	0	0
94	0	0	6.18
95	0	0	0
96	0	0	0
97	0	0	0

57	0	0	0
58	0	0	0
59	0	0	1
60	0	0	0
61	0	0	0
62	0	0	0
63	0	0	0
64	0	0	0
65	0	0	0
66	0	0	0
67	0	0	0
68	0	0	0
69	0	0	0
70	0	0	0
71	0	0	0
72	0	0	0
73	0	0	0
74	1	0	0
75	0	0	1
76	0	0	0
77	0	0	0
78	0	0	0
79	0	0	0
80	0	0	0
81	0	0	0
82	0	0	0
83	0	0	0
84	0	0	1
85	0	0	0
86	0	0	0
87	0	0	0
88	0	0	0
89	0	0	0
90	0	0	0
91	0	0	0
92	1	0	0
93	0	0	0
94	0	0	1
95	0	0	0
96	0	0	0
97	0	0	0

98	0	0	0
99	0	0	0
100	0	0	0
101	0	0	0
102	0	0	0
103	0	0	0
104	0	0	0
105	0	0	0
106	0	0	36.08
107	0	0	0
108	0	0	0
109	0	0	0
110	0	0	0
111	0	0	0
112	0	0	0
113	0	0	0
114	0	0	0
115	0	0	0
116	0	0	0
117	0	0	0
118	0	0	0
119	0	0	0
120	0	0	0
121	0	0	0
122	0	0	0
123	0	0	0
124	0	0	0
125	0	0	0
126	0	0	0
127	0	0	0
128	1.57E-16	0	0
129	0	0	0
130	0	0	0
131	0	0	0
132	0	0	0
133	0	0	0
134	0	0	0
135	0	0	0
136	0	0	0
137	0	0	0
138	0	0	0

98	0	0	0
99	0	0	0
100	0	0	0
101	0	0	0
102	0	0	0
103	0	0	0
104	0	0	0
105	0	0	0
106	0	0	1
107	0	0	0
108	0	0	0
109	0	0	0
110	0	0	0
111	0	0	0
112	0	0	0
113	0	0	0
114	0	0	0
115	0	0	0
116	0	0	0
117	0	0	0
118	0	0	0
119	0	0	0
120	0	0	0
121	0	0	0
122	0	0	0
123	0	0	0
124	0	0	0
125	0	0	0
126	0	0	0
127	0	0	0
128	0	0	0
129	0	0	0
130	0	0	0
131	0	0	0
132	0	0	0
133	0	0	0
134	0	0	0
135	0	0	0
136	0	0	0
137	0	0	0
138	0	0	0

	9602.861	717.1	2085.335
	Total	12405.3	

	3	1	7
	Total	11	

Table 8: Linear Model AMPL Output (x[c,l],y[c,l])

x [*,,*]	1	2	3
1	101.55	0	0
2	1.62E-27	2.11148	1.65E-24
3	0	3.31E-24	1.65E-24
4	2.88	0	1.65E-24
5	620.89	0	0
6	0	0	0
7	0	104.32	0
8	367.8	0	1.65E-24
9	749.95	0	0
10	0	0	1.65E-24
11	8.12	3.31E-24	0
12	41.54	0	0
13	0	17.81	0
14	0	306.01	3.31E-24
15	0	178.51	0
16	0	0	0
17	0	3.31E-24	0
18	0	0	1.65E-24
19	0	115.83	0
20	13.57	0	0
21	0	18.79	0
22	76.19	0	3.31E-24
23	147.84	0	0
24	7.69	0	0
25	67.57	0	0
26	0	0	0
27	0	0	0
28	2.99	3.84E-16	1.65E-24
29	163.45	0	0
30	70.43	4.44E-16	0
31	248.11	3.31E-24	0
32	155.31	0	0

y [*,*]	1	2	3
1	1	0	0
2	0	1	0
3	0	0	0
4	1	0	0
5	1	0	0
6	0	0	0
7	0	1	0
8	1	0	0
9	1	0	0
10	0	0	0
11	1	0	0
12	1	0	0
13	0	1	0
14	0	1	0
15	0	1	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	1	0
20	1	0	0
21	0	1	0
22	1	0	0
23	1	0	0
24	1	0	0
25	1	0	0
26	0	0	0
27	0	0	0
28	1	0	0
29	1	0	0
30	1	0	0
31	1	0	0
32	1	0	0

33	360	0	0
34	7.28	4.44E-16	0
35	2.82E-16	5.17	0
36	305.82	3.31E-24	0
37	0	3.31E-24	1.65E-24
38	0	0	0
39	121.3	0	1.65E-24
40	17.22	4.44E-16	0
41	0	475.25	3.31E-24
42	19.28	0	1.65E-24
43	0	0	0
44	4.52	0	0
45	0	161.4	0
46	0	481.37	0
47	0	8.36	0
48	268.98	0	0
49	30.72	0	0
50	4.8	6.62E-24	1.65E-24
51	14.95	0	0
52	42.3	0	0
53	92.75	0	0
54	9383.99	0	0
55	0	0	0
56	1844.52	0	1.65E-24
57	0	0	0
58	71.81	3.31E-24	1.65E-24
59	0	0	1.65E-24
60	0	0	1.65E-24
61	0	552.43	1.62E-27
62	0.84	0	0
63	0	0	0
64	0	70.72	0
65	0	72.26	0
66	56.21	0	0
67	0	0	1.65E-24
68	0	23.35	0
69	9.75	0	3.31E-24
70	371	0	0
71	50.98	3.31E-24	1.65E-24

33	1	0	0
34	1	0	0
35	0	1	0
36	1	0	0
37	0	0	0
38	0	0	0
39	1	0	0
40	1	0	0
41	0	1	0
42	1	0	0
43	0	0	0
44	1	0	0
45	0	1	0
46	0	1	0
47	0	1	0
48	1	0	0
49	1	0	0
50	1	0	0
51	1	0	0
52	1	0	0
53	1	0	0
54	1	0	0
55	0	0	0
56	1	0	0
57	0	0	0
58	1	0	0
59	0	0	0
60	0	0	0
61	0	1	0
62	1	0	0
63	0	0	0
64	0	1	0
65	0	1	0
66	1	0	0
67	0	0	0
68	0	1	0
69	1	0	0
70	1	0	0
71	1	0	0

72	53.07	0	0
73	18.53	0	0
74	0	0	0
75	11.5	0	0
76	54.71	0	0
77	0.95	1.06E-16	0
78	20.79	4.44E-16	0
79	59.65	3.31E-24	0
80	0	0	1.65E-24
81	1.58	0	1.65E-24
82	0	79.7	0
83	57.58	0	0
84	22.08	3.31E-24	0
85	519.18	0	1.65E-24
86	0	156.3	0
87	325	0	0
88	4.44E-16	3.31E-24	0
89	96.47	0	0
90	0	112.56	0
91	37.04	0	0
92	2609.02	0	0
93	1161.43	0	0
94	1.24	0	0
95	213.24	0	1.65E-24
96	76.45	0	0
97	0	0	1.65E-24
98	1011.75	0	1.65E-24
99	0	3.31E-24	0
100	0	0	1.65E-24
101	0	75.21	0
102	5.48E-20	8.02	2.22E-16
103	1.55	0	0
104	9.86E-32	147.92	0
105	227.6	0	1.65E-24
106	7.22	3.31E-24	1.65E-24
107	20.68	0	0
108	5.48	0	0
109	11.5	0	1.65E-24
110	0	0	0

72	1	0	0
73	1	0	0
74	0	0	1
75	1	0	0
76	1	0	0
77	1	0	0
78	1	0	0
79	1	0	0
80	0	0	0
81	1	0	0
82	0	1	0
83	1	0	0
84	1	0	0
85	1	0	0
86	0	1	0
87	1	0	0
88	0	0	0
89	1	0	0
90	0	1	0
91	1	0	0
92	1	0	0
93	1	0	0
94	1	0	0
95	1	0	0
96	1	0	0
97	0	0	0
98	1	0	0
99	0	0	0
100	0	0	0
101	0	1	0
102	0	1	0
103	1	0	0
104	0	1	0
105	1	0	0
106	1	0	0
107	1	0	0
108	1	0	0
109	1	0	0
110	0	0	0

111	59.02	0	0
112	0	671.82	0
113	0	13.36	0
114	2.12E-16	7.09	0
115	332.83	0	0
116	26.49	0	1.65E-24
117	18.96	0	0
118	320	0	1.65E-24
119	42.54	0	0
120	0	332.25	0
121	0	3.31E-24	0
122	22.5	0	0
123	21.69	0	0
124	2.33	0	3.31E-24
125	234.97	0	0
126	0	0	1.65E-24
127	209.25	0	1.65E-24
128	0.19	0	0
129	0	214.94	1.62E-27
130	0	0	0
131	283.98	0	0
132	0	8.28	0
133	0	0	0
134	0	1713.9	0
135	33	3.31E-24	1.65E-24
136	179.77	0	0
137	134.1	0	0
138	67.45	0	0
	24539.26	6135.041	2.22E-16

111	1	0	0
112	0	1	0
113	0	1	0
114	0	1	0
115	1	0	0
116	1	0	0
117	1	0	0
118	1	0	0
119	1	0	0
120	0	1	0
121	0	0	0
122	1	0	0
123	1	0	0
124	1	0	0
125	1	0	0
126	0	0	0
127	1	0	0
128	1	0	0
129	0	1	0
130	0	0	0
131	1	0	0
132	0	1	0
133	0	0	0
134	0	1	0
135	1	0	0
136	1	0	0
137	1	0	0
138	1	0	0
	81	29	1