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THE FAILED STATE: CAN IT BE PREDICTED? AN APPLICATION OF RANDOM FOREST FOR VARIABLE MODEL SELECTION

By

Beth Ann Stewart

A thesis submitted in partial fulfillment of the requirements for the degree

Of

MASTER OF ARTS

In

Political Science

Table of Contents

| Chapter 1 Introduction pp. | 1-5 |
|--|-------|
| Research Question | 1 |
| Outline points what this paper will do | 1-2 |
| Why use data to answer the question | 3 |
| Why address the question of the failed state | 3 |
| Chapter 2 Literature Review pp. | 5-16 |
| Failed state and other definitions reviewed | 5-8 |
| Working definition of the failed state for this paper | 8 |
| Chapter 3 Methodology | 16-41 |
| R as a computer language and Random Forest. | 16-19 |
| Hmisc (Harrell Miscellaneous)Correlation matix | 20 |
| Boruta | 20-21 |
| Where raw data came from | 22-23 |
| Source and method for original failed state ranking for model. | 23-26 |
| Baseline ranking from CIA world factbook information | 23-26 |
| Age and Condition of Populous. | 25 |
| Type of Government as a factor | 25-26 |
| State of the Economy of each state as a factor | 26 |
| Working through R for one of the many data sets. | 26-38 |
| Table 1 Check the tally of missing variables (Chart of results) | 28 |
| Run data through Hmisc (Results from R listed) | 28 |
| Table 2 Correlation Matrix showing relationships between variables | 30 |
| Run Random Forest | 31-36 |
| R code for random forest in our first data set | 31 |
| R results from Random Forest | 28-33 |

| | Table 3 Random Forest results of one data set | 33 |
|--------------------------|---|--------------------|
| | Graph enough trees | 32 |
| | Table 4 Graph Error % by Random Forest and Node Purity. | 35 |
| | Table 5 Partial dependence plots graphs. | 36-37 |
| Run Bor | ruta | 38 |
| | Table 6 results from Boruta | 38 |
| Chapter 4 Final model | and failed state analysis | 41-66 |
| | Random Forest final results | 42 |
| | Table 7 Random forest graph findings final model | 43 |
| | Partial dependence plot graphs with dependent variables | 45-52 |
| | Boruta confirmed result list. | 45 |
| | Table 8 Final variable set. | 53 |
| | Final variable categories | 54-56 |
| | Economy | 54 |
| | Health | 55 |
| | Government overall. | 55 |
| | Social and Individual Rights | 55-56 |
| | Failed state examples Yugoslavia, Rwanda and Syria | 56-66 |
| | Yugoslavia | 56-59 |
| | Rwanda | 59-63 |
| | Syria | 63-66 |
| | Surprise Findings | 66-68 |
| Conclusion | | 69-71 |
| Bilbiography | MLA format | 72-79 |
| Country reconcile list . | A _I | ppendix 1 (5pages) |
| Failed state ranking cro | eated from CIA world fact book info Ap | pendix 2 (4 pages) |

| R code language used for all data groups before the fina | |
|--|--|
| Hmisc results Correlation matrix for final statistical run | |
| Complete Boruta results from final run programAppendix 5 (2 pages) | |
| Boruta confirmation variable list for final model | |
| Final run2rf. Final model randomForest resultsAppendix 7 (1 page) | |

Introduction: The Failed State: Can It Be Predicted?

Research Question

Is it possible to identify the predictive characteristics for failed states using statistics?

This research is an application of R¹ and Random Forest² with previously mined data³ as a means to approach this political science question.

This research and the resulting paper is intended to do three things. **First**, give a working definition of the failed state for this project. **Second**, illustrate the rationale for using statistics, R⁴ as the platform and the randomForest⁵ package to create a model to identify predictor variables for the failed state. **Third**, evaluate multiple predictor variables arrived at through the methodology for the statistical model being created, which will distinguish strong correlations between the variables and a states' current stability status. This is an appraisal evaluated through

¹ http://cran.r-project.org/. R is the computer language platform used in this model. It is an open source language, meaning, anyone can use it without license and can create compatible software packages for others. Those who choose to use R or any of the packages associated with are encouraged to allow access to their package on one of the networks where CRan is maintained. R programming code resources were used to configure this statistical model and are cited as they are used in subsequent chapters of this work.

² Wiener, Matthew and Andy Liaw. "Classification and Regression by randomForest" R.News, 2002, Vol2 no.3. pgs 18-22. RandomForest is a downloadable software package from the CRan network site. It has been used for statistical purposes and has been touted as a reliable computer learning regressionary tree program. The predictability and reliability as such of this software has been expanding over more than just the hard sciences. (list uses of randomForest here)

The data for this statistical model was obtained from the following sources that utilize data mining and other data collection techniques that is openly available for research and other uses- The political Terror Scale www.poitical terrorscale.org, The World Bank www.worldbank.org/data, The CIA Factbook www.cia.gov/library/publications/the-world-factbook, (CIRI) The Cingranelli-Richards Human Rights Dataset www.humanrightsdata.org, Freedom House www.freedomhouse.org, and the United Nations http://data.un.org Data mining is defined as any mass list of data collected. It can be 5 years of collecting information on telephone calls, or all of the diagnoses billed from Medicaid, Blue Cross and Kaiser insurance companies. The massiveness of the data collected is traditionally produced from collective computer sources and stored and can be with no particular use in mind. Due to the nature of the massiveness of the data, data mining is a very expensive endeavor and is usually performed by large institutions or companies. Theinformation age has enabled sharing of such data if there is a use. Privacy problems arise when people feel that certain shared information may be harmful to them in some way. For example, a diagnosis may prevent someone from getting a job if the information was automatically accessible without personal authorization.

⁴ Ibid 1

⁵ Ibid 2

R⁶ and randomForest⁷ within it as identified through the methodology. **Finally**, we will look at several failed states to help illustrate the usefulness of the statistical model created.

Data is everywhere with today's information age. Where we work, how we vote, our medical ailments, and where we live right down to a street view of our home address⁸ is being tracked, filtered, stored and used to identify various things about people and their habits.⁹
Information covering economics, government authority, civil societies, access to health care, authoritarian regimes, international disputes, human rights violations, economic solvency, unemployment rates and now even cellular phone records are being collected by individual databases through international institutions, governments, scholars, and NGO's.¹⁰ Thousands of variables - bits of information, are collected into these databases, but almost no one is using them because of an inability to process it, resulting in a true "information overload"¹¹. The challenge presented is how to utilize this mass of international data to address a real question thereby resulting in something concrete and constructive.

Data sets have become so large and unwieldy that even current technology cannot handle all the data in today's world of increasing speed and optimizing software programs.¹² The data is

6.

⁶ Ibid 1

⁷ Ibid 2

⁸ 'Google Earth' http://www.google.com/earth/index.html.

⁹ "Big Data: The Next Frontier for Innovation, Competition, and Productivity", McKinsey Global Institute, Technology & Innovation, McKinsey & Company.

http://www.mckinsey.com/insights/mgi/research/technology_and_innovation/big_data_the_next_frontier_for_in novation. and Brown, Brad, Michael Chui, and James Manyika. "Are you ready for the era of 'big data'." *McKinsey Quarterly* 4 (2011): 24-35.

¹⁰ Ibid 8

¹¹ King, Gary, "Ensuring the Data-Rich Future of the Social Sciences", *Science*, 331 (2011), 719–721.

¹² Ibid 9

being collected faster and at greater proportions far surpassing processing capabilities.¹³ In the words of John Naisbitt, "We are drowning in information, and starved for knowledge".¹⁴.

So how do we filter through the cacophony of information in this data din? Most researchers who look at data indices are suffocated by their enormity. Rarely are these data monoliths put into practice because a majority of people really don't know how to use the information to solve a problem or answer a question, rendering this data essentially useless. Conversely, however, this mass of information being stored presents endless possibilities for those willing to filter through it and harness it into a workable medium. The desire to do just that has led me to attempt to use a quantitative approach in evaluating the failed state and to identify predictive variables contained therein. It is my hope that a quantitative approach to the failed state question will lend credibility to the field of political science, which has traditionally been considered a soft science, and create a platform and new direction for future research through the computer language of R¹⁶ and the software package of randomForest¹⁷ within in it.

We might as well start with one more question: Why address the question of the failed state? Since the 9/11 attacks in the United States against the World Trade Center and the Pentagon, the U.S. has considered failing states to be a growing concern. Unstable regimes and porous borders create havens for human and drug trafficking, while weapons of mass destruction

¹³ Ibid 9

¹⁴ Naisbitt, John. *Megatrends 2000* (Avon, 1991).

¹⁵ Jakulin, Aleks. "A Rant on the Virtues of Data Mining: Statistical Modeling, Causal Inference, and Social Science", Statistical Modeling, causal Inference, and social Science, 2012

http://andrewgelman.com/2007/08/a_rant_on_the_v/ [accessed 11 July 2012]. Aleks is not the first to discuss the problems of data mining. It has become a concern with our current administration regarding the collection phone records from Verizon users and whether the massive collection of private information is truly helpful in fighting domestic terrorism. For other source see ibid 3.

¹⁶Ibid 1

¹⁷Ibid 2

¹⁸ Mallaby, Sebastian. *The World's Banker: A Story of Failed States, Financial Crises, and the Wealth and Poverty of Nations* (Penguin Books, 2006).

undermine the stability of economic development and challenge international security.¹⁹ Al Qaida terrorist groups are growing in numbers in Iraq, Syria, and Somalia.²⁰ The United States is interested in protecting their economic interest globally-a view that is supported by the National Security Strategy published by the Clinton Administration stipulating "selective U.S. engagement around the world".²¹ There is a dichotomy and debate between intervention of a failed state and self-determination underpinned by conflicting economic and strategic interests. Each year the United States submits millions of dollars from its already tapped coffers to address these international concerns. Egypt is one such example.²² Propping up countries, intervening with troops, funding favored rebel groups against authoritarian regimes from the objective of protecting the United States' interests have left the U.S., a country already in deficit, in an even greater financially challenged position.²³ It is agreed by pundits that it is far better to prop up a regime than to fix a failed/collapsed state thus making this research question so important.²⁴

Although a majority of work in the political science field and the failed state has been qualitative, I believe it is possible to identify characteristics of failed states using statistical methods from information provided through data that has been mined.²⁵ This mined data coupled with the statistical model detailed in the methodology may make it more likely to predict failed

.

¹⁹ Rotberg, Robert I., "Failed States in a World of Terror", *Foreign Affairs*, 81 (2002), 127. And (Wyler, 2008)

Williamson, Richard S. "Nation-Building: The dangers of Weak, failing and Failed States", The Whitehead Journal of Diplomacy and International Relations. Winter/Spring (2007). 14. www.journalofdiplomacy.org.

²¹ Dorff, Robert H., "Democratization and Failed States: The Challenge of Ungovernability", *Parameters, US Army War College Quarterly - Summer 1996*, 1996, 17–31. The Clinton administration dealt with not only the tragedy of the Balkans but also the genocide in Rwanda in 1994. Dealing with the aftermath of problems created from failed states justified concluding that avoiding the failed state is a far more amenable prescription than recreation of state.

²² There has been a developing foreign policy since the Truman administration giving aid to countries as part of the United States foreign policy goals. Since 9-11, the focus has altered somewhat in its emphasis to prop up states economically and gain a political chess piece in the future global negotiations. Radelet, Steven. "Bush and Foreign Aid", Foregin Affairs. Vol.82, No.5.(Sept-Oct, 2003) pp. 104-117. www.jstor.org/stable/20033686.

²³ Charles T. Call, "The Fallacy of the Failed State". Third World Quarterly, 29 (2008), 1491-1507.

²⁴ Ibid 20. Ibid 21.

²⁵ Ibid 3

or faltering states once these characteristics are determined. There has already been a great deal of work done on identifying characteristics of the failed state and its precursors, but again, the bulk of information on this topic is rendered in qualitative form.

Literature Review

The failed state dilemma is poised at the top of policy makers globally. This being said, it comes as no surprise the amount of research done to elucidate this topic. Exhaustive endeavors by preceding researchers have yet to come up with even a concise definition of the "failed state". Unfortunately most of these scholars hold in reserve a definitive statement for the failed state. Although a good number have suggestions for remediation, as well as descriptions for what can usually be found in the failed state, the vagueness or lack of definition leads the reader to assume that a country can be deemed a failed state if all of the identifiers illustrated by these respective scholars are present.

Rosa Brooks deems a failed state the opposite of what a state is. In short, basically the demise of the state constitutes a failed state. In her article *Failed States or the State as Failure*²⁷ she portrays the following to be present in a failed state: violence ensues and government loses control of its territories.²⁸ This oversimplifies things by implying that all that needs to be present for the state to be considered failed are these events. Brooks also mentions a subset of a definition for what constitutes weak or failing states and further suggests remediation for these states being best applied in the form of some international trusteeship such as the United

²⁶ Ibid 23.

²⁷ Brooks, Rosa, "Failed States or the State as Failure?" The University of Chicago Law Review. 72 (2005), pp 1159-1196.

²⁸ Ibid24

Nations.²⁹ This particular view of a trusteeship to oversee states when they have failed is shared with Helmand and Ratner. In their article, *Saving Failed States*, they view three possible faltering state scenarios: the failed, the failing, and the states too new to decide on, suggesting that the United Nations charters' primary focus is for the right to self-determination rather than a concern for a states potential longevity.³⁰ Helman and Ratner are of the few scholars who define the failed state, although ambiguous, as a failed nation which occurs when it is "utterly incapable of sustaining itself as a member of the international community"³¹. This particular definition falls short given that the researcher is suggesting a United Nations protectorate as a government stand-in for intervention in the event of a failed or failing state.³²

Dorff approaches the definition of the failed state from the old adage "democracies do not fight other democracies"³³. He also pinpoints large financial markets and global economies as a problem for the smaller failed state because the smaller state will have a harder time rebuilding itself in the event of collapse. Egypt's overthrow of their presidential elect Mohammed Morsi, Libya's lack of an official government after the ousting of Gaddafi are two counter examples to his argument. A final point is his mention that new democracies go to war and occasionally transition to authoritarian regimes.³⁴ None of these opinions approach a definition for a failed state, but instead suggest what he believes should constitute a democracy.

Probably the largest and most well written contributor to the qualitative method of evaluating the failed state is Robert Rotberg. Numerous articles share a constant thread

²⁹ Ibid 24

³⁰ Helman, Gerald B and Steven R. Ratner, "Saving failed States". *Foreign Policy*. No.89 (Winter, 1992- 1993). Pp. 3-20.

³¹ Ibid 27

³² Ibid 27

³³ Dorff, Robert H., "Democratization and Failed States: The Challenge of Ungovernability", *Parameters, US Army War College Quarterly - Summer 1996*, (1996): 17–31.

describing several factors present in the failed state, but, yet again, no real definition is offered for the failed state. He mentions several levels of the failed state. These are failed states, collapsed states, and weak states, with collapsed states equal to utter and complete disintegration of government using Somalia as an illustration.³⁵ Like others scholars, he mentions characteristics of the failed state which include but are not limited to: a lack of food for the populace, a decrease in education, a decrease in medical infrastructure, an increase in government and elitist corruption, and a block of civil societies.³⁶ It is unfortunate, but all of these pseudo-definitions of a failed state are too numerous to list.

The Fund for Peace describes the a failing state as "One that is losing legitimacy, maintains few or no functioning state institutions, offers few or no public services and is unable to contain or deliberately inspires social fragmentation"³⁷. Furthermore they go on to say that a failed state is one in which it "forfeits the authority to make collective decision for the national population"³⁸. They continue by adding that a failing state "fails to interact in formal relations with other states as a fully functioning member of the international community"³⁹. I would argue that these two points should not define a failed state. They are better suited as identifiers of, but should not be included in the definition. Many states, regardless if it is positioned towards a division or collapse, still negotiate with other countries and trade goods. The Assad regime in Syria is one such example of this. The United Nations is in negotiations to decrease chemical weapon stores in that state.

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³⁵ Rotberg, Robert I., "Failed States in a World of Terror", *Foreign Affairs*, 81 (2002), 127 and Rotberg, Robert I. "Failed states, collapsed states, weak states: Causes and indicators." *State failure and state weakness in a time of terror* (2003): 1-25. PDF from the Brookings institute http://www.brookings.edu

³⁶ Rotberg, Robert I. *When States Fail: Causes and Consequences*. Princeton University Press. New Jersey. 2004 pp.7.

³⁷ Fund For Peace, Failed State Index. http://library.fundforpeace.org/fsi

³⁸ Ibid 34

³⁹ Ibid 34

Although prior qualitative review of the failed state has given us a better knowledge base of these characteristics associated with the failed state such as lack of a government head, refugee influx, and a decrease in literacy as well as a decrease in life expectancy, the fact remains that throughout all of this previous research there is still an obvious lack of a concrete, working definition of the failed state by which to analyze this respective research against. It is disappointing that a majority of these pundits are giving advice on how to remedy a problem they have not really defined. Charles Call at least recognizes this issue when he says in his article, *The Fallacy of the Failed State*, that because of a lack of consensus for the definition, the term should just be thrown out.⁴⁰

Failed State Definition

Taking all of the previous research into account and for the purposes of this paper, we define the failed state herein as failed when the following occurs-a total collapse of a government body and its respective institutions within defined and recognized geographic boundaries and/or a cessation of legitimacy in the government by its respective polity. A failed state can happen either by overthrow of a current regime either internally or externally. This definition allows civil war to be constituted as a failed state, as well as complete collapse of all infrastructures. Additionally, a failed state could be demonstrated by a secession of state, meaning state division of some sort as a result of civil war as was the case in Sudan and South Sudan⁴¹ recently, or

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⁴⁰ Ibid 23.

⁴¹ "Republic of South Sudan Declares Independence". http://www.betterworldcampaign.org/unpeacekeeping/web-features/south-sudan-declares-independence.html [accessed 12 December 2012].

ethnic cleavages as was present in the case in the former Yugoslavia⁴² as well as the former Soviet Union (U.S.S.R.).⁴³

Previous work in the form of indices and statistics offers a starting point for this and future such research in the field of political science. This includes but is not limited to the index of State Weakness in the Developing World created by Susan Rice and the Brookings Institute⁴⁴, The Mo Ibrahim index⁴⁵ focusing on Africa which gives a complete score definition of the failed state as well as a methodology and sources for raw data, the CIFP or the Country indicators for Foreign Policy⁴⁶ which lists data about foreign aid, and finally the Fund For Peaces' Failed State Ranking that is released annually by Foreign Policy. All of these entities have done a great deal of work on the fragility of states by using quantitative methods.

The Brookings Institute has a rather concise index titled "Index of State Weakness in the Developing World", in which Susan Rice and Patrick Stewart detail and categorize several lists of characteristics in which to gauge states fragility. These include economic, political, security and social welfare areas or 'baskets', Depending on the subcategories, all of these are weighed carefully, given a score and then the aggregate of that score goes into the basket and is tallied. 49

⁴² Laitin, David and Daniel Posner, "The Implications of Contructivism for Contructing Ethnic Fractionalization Indices", *The Comparative Politics Newsletter*, 12 http://todayinsci.com/QuotationsCategories/I_Cat/Information-Quotations.htm.

⁴³ Ibid 40.

⁴⁴Rice, Susan and Stewart Patrick. "Index of State Weakness in the Developing World", *The Brookings Institution* http://www.brookings.edu/research/reports/2008/02/weak-states-index.

⁴⁵ Mo Ibrahim Foundation | Methodology, Mo Ihabrim Foundation Index

http://www.moibrahimfoundation.org/IIAG-methodology [accessed 12 December 2012].

⁴⁶CIFP - Country Indicators for Foreign Policy. http://www4.carleton.ca/cifp/ [accessed 12 December 2012].

⁴⁷ Ibid 42.

⁴⁸ Ibid 44.

⁴⁹ Ibid 42

A very detailed effort to the indices for failed state evaluation includes the Mo Ibrahim Foundations Index of African Governance.⁵⁰ They focus on Africa in specific, and as such, are able to be more precise in their findings, pin pointing areas of weakness and/or challenge, that larger western world indicees are not able to. Consistent with most indexes, there are the traditional categories that the school of political science has deemed relevant to failed states: rule of law, economic areas, and human development to name a few.

Country Indications for Foreign Policy or CIFP⁵¹ is an online accessible publication for failed state ranking and index. Covering again the same sorts of indicators as others, this index also includes in its focus a human rights category and corruption figure. These details for human rights commonly have been lumped into rule of law for other indexes has previously not given full merit in its own category as it is here. Another different element this index has to offer is a category for corruption as well as political stability and violence. Produced by Carlton University in Canada, the raw data sources are listed so that other scholars may use it to further research.⁵²

Monty Marshall and Benjamin Cole also have produced a "State Fragility Index and Matrix"⁵³. Their index uses 0-5 as the basis for compiling scores. Political, security, economic and social indicators are scored and compiled into the 'matrix' which, again, basically is a table with the scores listed.⁵⁴

Probably the most notable contributor toward failed state research is from the Fund for Peace. Its Failed State Index comes out each year in the Foreign Policy publication advertising

⁵¹ Ibid 45

⁵⁰ Ibid 43

⁵²Ibid 45

Marshall, Monty and Benjamin Cole., "Global Report on Conflict, Governance and State Fragility 2008.", Foreign Policy Bulletin, 2008, 1–21.

⁵⁴ Ibid 45

the worst of the worst countries and failed states. 55 The Fund for Peace typically ranks 177 countries with a total ranking score of 120 where 1 is the lowest score to give a category with 120 points possible for complete failure. Each sub category within the framework is given a 1-10 score with one being the best and 10 the worst possible score in that particular group. 56 Their method is detailed through the Conflict Assessment System Tool (CAST) which was created in 2001⁵⁷. They describe this tool as an objective statistical assessment, implying that a statistical program was used to determine the final failed state ranking, or at least one was used to identify key areas projected as having relevancy for scoring the failed state. However, there is no mention in the methodology provided of a statistical program in CAST and/or how it works other than it separates the "relevant data from the irrelevant data".58, and that they use "human analysis to ensure that the software has not misinterpreted the raw data".59. When reviewing the CAST manual, it appears to be a very detailed rubric by which their data figures are derived. They use three main categories called "clusters of leading societal indicators of state decay and internal collapse". 60 These are social, economic and political/military identifiers. 61 For each of the subsets, they suggest the researcher to begin with a baseline number of 1. Depending on the researchers evaluation of the identifiers given, and using the prescribed definitions as a guide, then they add a point if the characteristic is present. These numbers are tallied. With the 12 individual characteristics, the total points possible are 120 for a failed state. 62

⁵⁵ Foreign Policy 2012

⁵⁶ Ibid 34

 $^{^{57}}$ Conflict Assessment System Tool (Cast) system, 2001. The manual can be located here.

http://library.fundforpeace.org/fsi

⁵⁸ Ibid 34

⁵⁹ Ibid 34

⁶⁰ Ibid 54

⁶¹ Ibid 54

⁶² Ibid 54

Unfortunately, the Fund for Peace does not offer their raw data so that others may use it to further this research. You can copy the findings each year and convert the numbers to a workable excel table or a comma separated value (csv)⁶³ file. However they suggest in CAST to use their rubric for your own subjective analysis.⁶⁴

Sadly, with the exception of the Mo Ibrahim Index⁶⁵, most of the producers of these failed state indices do lock away the raw data to protect their work. There is a plethora of raw data available electronically through NGO's and other institutions, but not all of it is in an accessible or workable standard. Some of it is offered in csv format, others provide only a chart with descriptions and numbers requiring it to be adapted and streamlined and into a functioning medium.

After review of all of the literature available and reviewing the mass of raw data, it became evident that out of all of this research, few if any had used statistics with their research and none of them were the product of a computer statistical model. The mention of statistical programs in past work is limited and altered depending on the interpretation, qualified, and altered if an analyzer (human form) deemed the statistical findings to be irrelevant. Wouldn't the question of the failed state would be more interesting if we could use the data and identify predictor variables for the failed state building a statistical model. How would we go about doing this? One of the considerations was to make the model in a format that anyone could use, not just someone with access to expensive supercomputer equipment, and it needed to be in a language that was probably not going to be considered extinct in the next few years like Fortran is now.

⁶³ CSV=comma separated file

⁶⁴ Ihid 54

⁶⁵ Ibid 43

Since there is a data surfeit, we have the ability to make more precise determinations about the failing state through more robust statistical methods. Although there are several different programs that are classification regression learning predictive tree models, we are using R⁶⁶ as the language platform with randomForest⁶⁷ as a software package in which to create the model. It was decided to use Random Forest and the predictor capabilities of the program for variable selection to create the model. Other options were SAS, SPSS and CART (Classification and Regression Trees), or IBM's InfoSphere Warehouse, however, both were unavailable due to cost as well as computer storage and ample processor speeds for which to run these complex programs. SAS and SPSS were omitted as statistical program possibilities due to a lack of availability. Both required either an expensive financial commitment that some universities are unwilling to carry, and/or a super processer that this size of dataset would require.

R⁶⁸ and randomForest⁶⁹ seemed to offer the potential to work through our question and circumvent the financial issues listed above. R⁷⁰ is a free language platform with open source downloadable from the CRan network. It has the ability to run smaller data sets or larger ones within certain parameters while offering the flexibility using a PC. All packages associated with R⁷¹ are offered as free packages from the CRan network that gives global downloadable access.⁷² These access locations are called mirrors. R is receiving increased recognition as a language

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⁶⁶ Cran network. Ibid 1

⁶⁷ randomForest Ibid 2

⁶⁸ Ibid 62

⁶⁹ Ibid 63

⁷⁰ Ibid 62

⁷¹ Ibid 62

⁷² The Cran network uses several mirrors. These mirrors reflect a geographical point on the globe. The users of this network choose a mirror site in which to access software packages. The closer the proximity, the shorter download time is the thought.

which allows the user great adaptability for multiple purposes as noted from the variety of current software program packages available.⁷³

Again, this paper and the method used to evaluate failed state predictors is meant to bring credit to a traditionally soft science field and provide a platform for further research. The best way to open a door is to create a model within a software program that anyone can re-create, through easy, accessible means. In this case the means are the accessible platform and the streamlined, downloadable, csv file raw data, further illustrating the rationale for choosing R.

Although 'R' itself has its challenges, namely that almost all its computer code has to be input manually — there are only a few graphical user interfaces for it. Many scholars are gravitating to it due to its exceptionally promising possibilities within the computer language of R and the benefits that its open source provides.⁷⁴

Recursive partitioning statistics, tree modeling and Random Forest therein, have been consistently showing reliable predictive results. 75 Random Forest differs from other regression tree machine learning programs by the following: in addition to the regression bootstrap method to determine node split, it also takes a random sample ⁷⁶ and runs this random sample against the root. What does this do exactly? Most statistical programs have some degree of error, due to biases of data supplied and the nature of the program itself looking for homogeneity in variables against the root. We build a forest of these like kind trees. With a random sample taken in the

⁷⁴ Open source is a term which means that it is not privately owned by a particular entity. There are no user rights given by anyone, and anyone can use the software. It is openly shared. However, proper citation for algorithms and software programs within the language are still required.

⁷⁵ Random Forest was used for gene selection applications. A paper on this describes how random forest does not over fit, can be used with large data sets and can still deal with noisy predictive variables. Diaz-Uriarte, Ramon and Sara Alvarex de Andres. "Gene Selection and Calssification of Microarray data using random forest". BMC Bioinformatics. 6 January 2006. http://www.biomedcentral.com/1471-2105/7/3. web access.

⁷⁶ Random sampling is also known as bagging or abbreviated as OOB meaning out of bag.

program, it allows the algorithm to be more accurate- fewer false positives, with a higher rate of node purity.⁷⁷ Large data sets can be very noisy and random forest has a lower error rate in the sample due to the random sampling. This is one of the few programs that use this factor programmed into the algorithm.⁷⁸

Due to its predictability, flexibility and discerning capabilities, it should come as no surprise that the medical field has been using statistical tree programs to elucidate possible treatment scenarios for patients with acute illness. One such study was done by three researchers looking at patients suffering from renal cancer. In an effort to use the least invasive measures possible for the highest recovery rate, they evaluated cases based on applicable variables. It is because of the predictability of the recursive tree partitioning statistical model, that they have been able to make sufficient progress to apply the model's results in the exam room for cancer treatment. Additionally, Furlanello has completed research using R and Random Forest evaluating the potential prevalence for tick-borne disease within the geographical boundaries of Trento, Italy where tick presence is common. At our own institution, Dr. Richard Culter et al produced the following research paper and work "Random Forest for Classification in

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⁷⁷ A node in tree modeling is defined as each place that a new tree is created. This node is a split from the parent tree. Node purity measures the accuracy of the split choice. For more information on nodes and tree modeling see explanation from Breiman and Cutler in randomForest software description. See ibid 2. For a graphed example of node purity in our research see table 3 and table 4.

⁷⁸ Ibid 2

Three articles can be referred to for further information regarding the use of random forest algorithms, their predictability and use in cancer research that is now being applied to the exam room. Carter, Hannah, et al. "Cancer-specific high-throughput annotation of somatic mutations: computational prediction of driver missense mutations." *Cancer research* 69.16 (2009): 6660-6667. Ma, Yan, et al. "Predicting cancer drug response by proteomic profiling." *Clinical cancer research* 12.15 (2006): 4583-4589. https://clincancerres.aacrjournals.org/content/12/15/4583.full, and Kim, Hyung L., et al. "Using protein expressions to predict survival in clear cell renal carcinoma." *Clinical cancer research* 10.16 (2004): 5464-5471.

expressions to predict survival in clear cell renal carcinoma." *Clinical cancer research* 10.16 (2004): 546 http://clincancerres.aacrjournals.org/content/10/16/5464.web.

⁸⁰ Furlanello et. All. 2003.

Ecology"⁸¹. In it, he describes the accuracy of the predictability for the program even with some missing data.

Aside from the social sciences, machine learning is being developed to mimic the brain for adaptation in cell phones and Google search algorithms. ⁸² If your personal wireless device and search programs can mark and learn your behavior from previous inputs and inquiries, it can take less time to provide you with results that the computer program predicts you are looking for, thereby making the device more useful. In addition, Machine learning may even be coming to a TSA near you. A recent article released suggests the future use of self serve security kiosks that predict behavior based on your belongings and where you live. The device gets more accurate as more people go through the scanner based on false negatives (commits to memory), such as mistaking an electric razor for a bomb. ⁸³

Methodology

The methodology used for this research includes a platform language called R into which a software package application called randomForest is employed. Random Forest is so named because it computes (for a sample illustration) like an upside-down forest of ancestral/family (genealogical) trees. The last trees "grown" in this forest equal the most frequently manifest predictor variables (characteristics) from the computational set, in which 'set' comes from the

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⁸¹ Cutler, Richard, Thomas EdwardsJr., Karen Beard et all. "Random Forests for Classification in Ecology." *Ecology*, 88(11) 2007. 2783-2792.

⁸²Some information on machine learning and smart phones can be found in the following article. Makeig, S.; Kothe, C., Mullen, T., Bigdely-Shamlo et all. "Evolving Signal Processing for Brain–Computer Interfaces," *Proceedings of the IEEE*, vol.100, no.Special Centennial Issue, pp.1567,1584, May 13 2012 http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6169943&isnumber=6259910

For detailed information regarding search engine responses to individual inquiry and changes to those algorithms a good article can be referred to here. Thelwall, Mike. "The responsiveness of search engine indexes." *Cybermetrics*5.1 (2001): 8. http://cybermetrics.cindoc.csic.es/articles/v5i1p1.pdf

⁸³ http://travel.yahoo.com/blogs/compass/security-machine-might-replace-local-tsa-agent-212342236.html

raw data initially input. Along with random forest as the predictive software, Hmisc and Boruta are used to assist in selecting final variables for the model.

RandomForest⁸⁴ works by 'growing' trees from the raw data input in which the data can be likened to nodes and branches or seeds to saplings. Some data 'seeds/seedlings' turn into more robust saplings than others based on the homogeneity of the variables determined by the program. It is considered a kind of bootstrap program⁸⁵ that also uses out of bag (OOB) sampling to stabilize the data results. For this research, a forest was 'grown' in Random Forest by using the failed state ranking subjectively predetermined as the dependent variable in the index for the source set, or seed, to continue with the tree growth analogy, which then splits into subsets using the Gini impurity index⁸⁶ that determined the node or branch of the split. The Random Forest programs job is to build or grow homogenous trees in which the objective is to split off the trees that begin to look unlike the rest of the forest. This process is repeated on each derived subset and is considered complete when the splitting or "growth" that the program generates no longer adds value (per the law of diminishing returns)⁸⁷ to the predictive resultant variables. Other forms of statistical methods like this are called regressive partitioning.⁸⁸ Classification and

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⁸⁴ For a detailed video explanation on randomForest you can look here for a five video series. https://www.youtube.com/watch?v=cQrvTYVN0ko

⁸⁵ The basic idea with a bootstrapping technique is to resample to data over and over. It is a way to determine the margin of error within a data set. This is employed in many R programs and in particular random Forest. For more information regarding the bootstrap method refer to Efron, Bradley, and Robert J. Tibshirani. *An introduction to the bootstrap*. Vol. 57. CRC press, 1994.pp.45-57.

⁸⁶ The Gini impurity is employed in random forest to determine when to split from the parent to grow another tree in the forest. Ibid 2.

⁸⁷ We use the term the law of diminishing returns to imply that adding another sampling does not yield any decreasing results. It is not meant to imply that adding further sampling will alter the results negatively after a certain number of samples taken.

Recursive partitioning in regression models refers to the questions posed in the algorithm. It usually is a statement that determines the split in tree models for variable selection. See Torsten, Hothorn, Kurt Hornik and Achim Zeileis; "Unbiased Recursive Partitioning: A Conditional Interence Franework" *Journal of Computational and Graphical Statistics*. Vol. 15, Iss.3. 2006. http://www.tandfonline.com/doi/abs/10.1198/106186006X133933

regression trees (CART),⁸⁹ machine learning,⁹⁰ and employing bootstrapping and random sampling techniques.⁹¹

To explain regression tree programs in another way, the data set is asked a series of if then questions. Each question leads to the next question. In other words, it is a set of binary decisions. In theory, for illustration only, y equals 1 in this example or the failed state. We then ask a series of yes and no questions regarding the other variables. Labeling three variables as A, B, C, the question posed might be is A>.50. If the answer is yes, then the node split could be to the left, if the answer is no, then the node split is to the right and the next question is dependent on how the last one was answered. The next question might be on the left node split of the tree if A>.50 then is B>.75 and so on. From the answers of these yes and no questions, the probability the A=Y is a percentage of the probability from the question. In our case A, B and C represent specific characteristics in our failed state data set. The probability of the answer to the question is derived mathematically. In short, the higher the probability a variable is close to y, determines which variables are chosen. ⁹² Leo Breiman describes this classifier question and response split (our example is A>.50) as a binary tree. ⁹³ Each tree split off makes up the forest. With each question that is answered, it develops pattern recognition. It is through this bootstrap algorithm that lends the predictability label commonly placed in these machine learning programs.

⁸⁹ Numerous articles discuss CART and its predictive characteristics. A good source can be found in the following article. Loh, Wei-Yin. "Classification and regression trees." *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 1.1 (2011): 14-23.

⁹⁰ Machine learning is another term for the computer creating predictive results based on input from the user over time. It is from information that the computer determines a pattern of behavior and predicts the users thinking.

⁹¹ These techniques described in this paper are over simplified. For specific algorithm and distinctive mathematical equations and descriptions of all process within this statistical software programs employed refer to ibid2, Hmisc and Boruta

⁹² Ibid 2

⁹³ Breiman, Leo, et al. *Classification and regression trees*. CRC press, 1984.

The end results in Random Forest are given with a percentage (%) of variance explained, as well as percentage (%) Inc MSE, also known as percentage increase over the Mean square error rate, and the Inc Node Purity, or increase of node purity. A percentage of variance explained is meant to tell the programmer how much variance in the variables could be explained. In other words, it is the probability percentage that was determined from the binary yes and no questions. If you look at the results from random forest on page (29) you can see that from one of our data sets, the percentage of variance explained was only 37.09%. So the program was able to predict accuracy 37 % of the time. This is not uncommon in very large noisy data sets that you are trying to whittle down. It is also because of this prediction accuracy rate that we used another program in conjunction with random forest to identify all relevant variables.

Percent increase mean square error as seen on table 3 and 4 illustrates a function of risk⁹⁴ or the percentage of the Gini impurity⁹⁵ being wrong corresponding to the "squared error loss",⁹⁶. As the percentage increases, the mean square error loss measured is less. We can see the %IncMSE on Table 4. The higher the percentage, the higher the predictability of a particular variable Mean Square Error measures the average of the squares of the errors. 97

The final item to evaluate in the random forest results are the Increase Node Purity as seen on Table 4. This increase just describes the probability of the decision made for the node split. The higher the node purity equals the higher the correlation to the failed state in our case.

⁹⁴ Grömping, Ulrike. "Variable importance assessment in regression: linear regression versus random forest." *The* American Statistician 63.4 (2009).

⁹⁵ Ibid 2

⁹⁷ In regression analysis MSE is sometimes referred to the "unbiased estimate of error variance" .It can also mean squared prediction error.

Hmisc, ⁹⁸ also referred to as Harrell Miscellaneous, is correlation matrix program. Using the spearman command within this software we can look for direct relationships between variables. When there is a large data set that you are trying to pare down, Hmisc ⁹⁹ can identify close relationships between two variables. When you have extremely similar variables, the excess variable is considered redundant and should be dropped.

Boruta¹⁰⁰ is a software package written in R. It was designed to be run with Random Forest to specifically identify all relevant and non relevant variables. Random Forest gives us a classification predictor variable set from the forest creation - in our case, those variables most significant to the failed state. However, it does not tell us degrees of relevance for all of the variables. In some schools it is necessary to know all relevant variables, not just the most relevant ones. For example, in the case of medical research, a patient is worked up for cancer and presents with four symptoms, however, none of the four are the actual tumor itself. Even though the four are not a tumor, loss of appetite, low blood count, headaches and vomiting may still suggest presence of a brain tumor. Therefore all symptoms are relevant and should not be omitted. In the case of the failed state, high unemployment, exodus of the intelligence community (brain-drain), and rebel groups gaining power may not individually indicate a failed state, but collectively would be considered relevant and warrant further evaluation for it.

Boruta¹⁰¹ is used in this methodology to pick out all relevant variables, not just the most relevant. We mentioned when describing random forest that there was a percentage of variance

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⁹⁸ Ibid 1. http://cran.r-project.org/web/packages/Hmisc/index.html

⁹⁹ Ibid 87

¹⁰⁰ For a summary of the Boruta process see Kursa, Miron B. and Withold R. Rudnicki. "Feature Selection with the Boruta Package". *Journal of Statistical Software*. September 2010 Vol. 36. Issue 11. http://www.jstoresoft.org. Ihid 89

that could not be explained. 102 Boruta makes up for this by its algorithm which was designed to specifically wrap around the random forest program and its results. The program works by creating a shadow of all attributes, then calculates a Z score on this variable set. The Z score takes into "account the fluctuations of the mean accuracy loss in the trees from random forest". 103 Next, a minimum and a maximum Z score if derived from the shadow attributes in the program. Boruta assigns a hit to every attribute that scored better than the Mean Z score attribute or MZSA. Attributes which have importance significantly lower than MZSA are deemed unimportant and conversely those attributes scoring higher than MZSA are identified as being important. These values of importance are assigned for all the attributes. 104 When we look at table 5, we can see the mean Z, median Z, Min Z and Max Z as well as the decision. The range for decision and the Z score is different for each variable as we can see from our table. It is however the decision that we deem most important. Again, each variable needed to have a percentage of hits within the range of the Z score calculated for each to be deemed important. These scores are produced just to understand the range, not to imply that we use one particular point of importance over another. As long as the hits are within the range of min to max, it is considered valid in this program.

Although this method is very different from traditional analogies of the failed state, this research and the methodology used to evaluate the research question is intended to bring heightened credibility to a traditionally soft science field and provide accessible opportunity for future research.

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¹⁰² See results from random forest page 32

¹⁰³ Kursa, Miron B., and Witold R. Rudnicki. "Feature selection with the Boruta package." (2010).

¹⁰⁴ For a detailed account about the Boruta program, its authors describe in detail the full workings and equations for it. Kursa, Miron and Witold R. Rudnicki."Feature Selection with the Boruta Package" *Journal of Statistical Software* Sept. 2010, VOI 36, Issue 11.

Even though R has its own idiosyncrasies, namely the necessity of learning to code in R a fair amount due to the few graphical user interface options, the advantages of R outweighs the idiosyncrasy and scholars are gravitating to it because of the opportunities and flexibility it offers.

Many tree-based models have been used for data research in the applied sciences, including, medical purposes-arriving at prognosis and best treatment of cancer patients based on variables processed using such models. Since data sets can be altered with variable condition changes, the applied sciences make good use of the findings offered by these models. However, there is no good reason the social sciences cannot and should not be making equal use of such modeling. With regard to the failed state, we can make new data sets available from countries that were not as internationally transparent at earlier dates, thereby allowing them to be included in the data mix-adding to the comprehensiveness and cohesiveness of the data and the model.

Raw data for the purposes of this model was gleaned from multiple resources. While collecting data, it was apparent that many data sets covered a specific area of government or function in the state, such as voting freedom, rule of law, women suffrage, or level of democracy. However, not all sources could be used because of the format of data storage. Freedom House has an annual publication that describes states as one of the three: NF (not free), PF (partially free), and F (free). Although statistical computing has been employed, the data stores for their interpretation are not readily available. International indices evaluating life expectancy based on access to health care (amount the government pays per individual for health

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¹⁰⁵ Ibid 3

¹⁰⁶ The data used fit a particular format. It needed to be numeric, and it had to be downloadable. If the data needed to be streamline and assigned values, other than freedom house, it was too time consuming and confusion to assign numeric values. Additionally, when assigning numeric values, there is no guarantee that it could be easily reproduced which would have been contrary to using accessible international data sources.

care), immunization rates, rate of curable diseases, drought conditions, access to education, and economic GDP were however used for our research purposes. Additionally, raw resource data (oil, minerals), agriculture information, information technology and the following were added: information on human trafficking/sexual slavery, FGM (female genital mutilation), organ theft, ethnocide, and states' solvency. The United Nations has made an attempt to make this data publicly available. 108

Incorporating as much of the good and useful bits of data derived from current indices and models, this research attempts to go even further by being more comprehensive and employing a unique methodology in this field to derive at a reliable and rather comprehensive predictive variable set, that can be resurrected or re-created for further research in the field through statistics.

After deciding on a software medium for which to create the failed state model, several other steps were essential in the process. In order to do this properly, it was necessary to list all the countries for which data was available. Several originating data sources came from countries other than the United States, in which a particular country's data was listed under a different name such as Republic of Korea, for example, which we will refer to as North Korea for our purposes. Individual countries were omitted from being included either because they lacked enough data or were missing sufficient data that could render them as useable/useful. These countries included but were not limited to Uzbekistan, Turkistan, among others. The reason(s) for a country demonstrating a dearth of data included the age of the country, (such as the abovementioned, of which two were former members of The USSR, now Russia, whose geographic

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¹⁰⁸ Ibid 3

 $^{^{107}}$ For a full list of original raw data resources see Ibid 3

boundaries have altered over recent years), resulting in a raw data gap. Also omitted were countries that had no data due to its provincial nature and/or its rule under others. Puerto Rico, for example, is a province of the United States and was therefore omitted. Scotland, Northern Ireland and the Falklands fall under the United Kingdom and were also left out of the study as was the Palestinian territories. Given this, a resultant and still sizable 200 countries are included in this research.

An original failed state ranking for each of the 200 countries was created in which to run the collective data against. I used the CIA World Factbook 110 as the main source of information in which to determine each states present viability. This ranking would be used for this comprehensive model in which to run all of the other data against. The ranking is from 1 to 5, with 1 being the farthest removed from being a failed state, and a 5 considered a failed state. At the original time of data collection (2009)¹¹¹, the only two states that ranked a 5 were Iraq and Somalia, according to the definition previously presented in this paper. There have since been some states that have failed, which would be appropriate to include for further study. These 1-5 rankings were used so that anyone could replicate them according to the same definition and evaluation method used herein.

Again, the baseline is a number one, similar to the Fund for Peace. If a 1 was given, the country had a democracy in place, a strong economy, high age expectancy for its respective population, no sanctions posed against it and no alerts for travelers to the country. Airports, schools, and highway infrastructures were in place and the government spent a substantial

¹⁰⁹ See appendix 1 for country reconcile list.

¹¹⁰ Ibid 3

¹¹¹ We began data collection in 2009 and as such, the results are based on the data collected during that this. World events however have not remained in 2009 and there are more examples and further data that was not available at the beginning of this research.

proportion of its revenue on its constituents. The rule of law was observed. The government was able to protect its own borders, and few if any refugees were exiting the country-spilling over into neighboring states or flowing into the country from bordering states.

The following key items pulled from the CIA World Factbook¹¹² were also considered for ranking: age of populous, type of government, and state of the economy that would warrant a change in the baseline score. These will be further detailed below.

Age and Condition of Populous

Consideration was given if over 70% of the population was under age 65. This would indicate that a state either has a short life-expectancy and/or a young populous was/is prominent. Resultant civil societies are fewer in the country due to the younger populous and government can also be weak with a predominantly younger populace. The birth rate, death rate, and migration rates significantly alter the average age of the residents. Any or all of these could be indicative of civil unrest which can create a state's inability to provide even for the basic needs of protecting its people. Additionally, health expenditures as a percentage of GDP was considered within this category, for example, the percentage of children under age five who were/are underweight. The literacy rate over age fifteen was also a factor. A number one was added to the base score accordingly given the considerations above.

Type of Government

The description for each respective state was evaluated from the CIA World Factbook. 113 We first looked to see if a government was identified. If no government was specifically

¹¹² Ibid 3

¹¹³ Ibid 3

identified, such as democratic, autocratic etc., or if the government structure was unclear, then a one was added to the score. If there was, for example, an Islamic republic associated with it— we know that Islamic republics are considered more unstable than democracies or a republic, a one was added to the score. If it was not clear about government type, but documentation suggested that there was no constitution in place, if there was not a separation in the branches of government, or if it was defined as an authoritarian regime, a point was added to the failed state baseline. Note, most stable or defined strong regimes were clearly stated as such in the CIA World Factbook.

State of the Economy

A critical question when looking at the failed state is whether the economy is being propped up by international actors or is solvent. A country's unemployment rate, its percentage of GDP inflation, the type of products that were/are produced by the state, i.e., whether the state is natural-resource abundant, or what other resourc(es)/industry is used to sustain itself as its main sources of revenue were all considered. If there was a particularly high unemployment rate and it was known that government workers had not been paid in awhile, another point was added. We deemed arrear wages owed as an indication of either potential state insolvency, or misappropriation of state funds by its leaders.

In addition to the categories above, I looked to see if there was mass exodus of refugees or refugee pours instead of traditional migration patterns. If a transfer of population was due to civil unrest or loss of rule of law, another point was added. 114

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¹¹⁴ See appendix 2

There were originally 600 plus variables from the data collected considered for 200 countries in this research, which needed to be condensed or simplified for working purposes. I divided the data into 20 separate files in which to read into the program R. R works by loading all of the data into ram at the same time. Some computer languages and software platforms/programs will take the command that you give it, then the processor picks it up, puts it into ram, runs it, puts it back into memory and picks up the next command thus leaving ram and the processor relatively unencumbered, fast and free. R does not do this. Although it is quick, adaptable, and can handle large data sets, R still likes reasonable sized data sets. There are limits due to processor speed and memory space on any PC. These sets are still larger than other statistical programs would be able to handle on a laptop, but they still needed to be divided.

Each data set was run in the same fashion to determine predictor variables for the failed state prior to arriving at a final data set. To detail the methodology employed, I will work through just one of the data sets (BF_BO).¹¹⁶

I checked a tally to determine how many missing variables were in the data set. 117

Our code

apply(BF BO, 2, function(x) length(which(is.na(x))))

If you look at Table 1, you can see that GDPpercap_2005 is missing data for 22 different countries in the list. Since we have 200 countries in the data set, this is not considered a large percentage missing, and therefore, would be acceptable to keep.

27

¹¹⁵ Because R loads all of the data into Ram at the same time, it can process all of the information there very quickly, however too much in a data set can be an issue for a regular PC. Chopping up the data therefore is helpful. ¹¹⁶ See appendix 3 for R code used.

¹¹⁷ See appendix 3 for full list of all R code employed.

Table 1

| Country | Failing_Rank | LifeBirth_2005 | AdultLit_2005 |
|----------------|----------------|-----------------|---------------|
| 0 | 0 | 16 | 14 |
| EnrolEduc_2005 | GDPpercap_2005 | LifeBirth_2006 | AdultLit_2006 |
| 11 | 22 | 15 | 14 |
| EnrolEduc_2006 | GDPpercap_2006 | HDI_2006 HDI_A1 | Reconcil_Rank |
| 11 | 19 | 21 | 21 |

After this, the data was run through a software package for R called Harrell Miscellaneous or Hmisc¹¹⁸ which was able to help look at the relationships between the variables in a correlation matrix.¹¹⁹

We use the spearman command in Hmisc.

Our Code

```
library(Hmisc)
r.results <- rcorr(as.matrix(BF_BO[,2:ncol(BF_BO)]), type="spearman")
r.results$r</pre>
```

The matrix in Table 2 produced through Hmisc¹²⁰ allows us to look at the relationship between variables prior to running the data through random forest.¹²¹ You can see the closer the

¹¹⁸ Harrel, Franck E. Jr. Cran 2012-10-25. 14:00:08 Http://biostat.mc.vanerbuilt.edu

¹¹⁹ See appendix 3 for all R code employed.

relationship between two variables is indicated by their numeric proximity to one another either positive or negative. The negative relationship indicates that as one variable goes up, the other goes down and vice verse. As a rule, any pair whose relationship is higher than .80, for the purpose of this paper, is deemed highly correlated and therefore one is redundant. In other words, both highly related variables predict in the same way usually necessitating the use of only one. For example GDP and GDP per Cap for the year 2006 could be highly correlated. We would therefore choose the one with a more complete data set for our purposes. Note is taken for all pairs bearing this relationship determined by Hmisc and are considered before final pairing prior to a Random Forest run.

For this particular data set you can see that HDI_A1Reconcil_Rank and HDI_2006 have a negative strong correlation of -0.999986410. So these two variables are noted for final selection of variables to omit one due to this relationship.

Again, all of the variables are run through Hmisc¹²³ prior to randomForest¹²⁴ to locate directly related variables in an effort to either further solidify a relationship validated eventually through randomForest¹²⁵ and Boruta¹²⁶, or to extract it from the data set due to its redundancy. The end goal of this exercise is to end up with a model of about twenty or so variables from the hundreds that we started with which show a predictable relationship to the failed state statistically through random forest and Boruta.

¹²⁰ Ibid 87

¹²¹ Ibid 2

¹²² See table 2

¹²³ Ibid 87

¹²⁴ Ibid 2

¹²⁵ Ibid 2

¹²⁶ Ibid 89

Table 2

| | Failing_Rank | LifeBirth_2005 | AdultLit_2005 | EnrolEduc_2005 |
|---------------------|----------------|----------------|---------------------|----------------|
| Failing_Rank | 1 | 0.06242993 | 0.02658016 | 0.076718941 |
| LifeBirth_2005 | 0.06242993 | 1 | 0.05348156 | -0.016884008 |
| AdultLit_2005 | 0.02658016 | 0.05348156 | 1 | 0.046367958 |
| EnrolEduc_2005 | 0.07671894 | -0.01688401 | 0.04636796 | 1 |
| GDPpercap_2005 | -0.26392859 | -0.06410334 | -0.03690866 | 0.086575672 |
| LifeBirth_2006 | 0.27416915 | 0.12889048 | 0.14461656 | 0.095038928 |
| AdultLit_2006 | 0.09985825 | 0.05220463 | 0.62730968 | 0.017374132 |
| EnrolEduc_2006 | 0.04383237 | 0.07998408 | 0.11584348 | 0.100154713 |
| GDPpercap_2006 | 0.01886463 | -0.0494695 | -0.04241028 | 0.066649035 |
| HDI_2006 | -0.63302928 | -0.03570063 | -0.19248299 | -0.005080359 |
| HDI_A1Reconcil_Rank | 0.63324142 | 0.03642339 | 0.19208394 | 0.005436544 |
| | GDPpercap_2005 | LifeBirth_2006 | AdultLit_2006 | EnrolEduc_2006 |
| Failing_Rank | -0.263928592 | 0.27416915 | 0.09985825 | 0.043832373 |
| LifeBirth_2005 | -0.064103335 | 0.12889048 | 0.05220463 | 0.079984084 |
| AdultLit_2005 | -0.036908664 | 0.14461656 | 0.62730968 | 0.115843482 |
| EnrolEduc_2005 | 0.086575672 | 0.09503893 | 0.01737413 | 0.100154713 |
| GDPpercap_2005 | 1 | -0.22368312 | -0.07090337 | 0.003077174 |
| LifeBirth_2006 | -0.223683119 | 1 | 0.30828696 | 0.112480037 |
| AdultLit_2006 | -0.070903368 | 0.30828696 | 1 | 0.175718904 |
| EnrolEduc_2006 | 0.003077174 | 0.11248004 | 0.1757189 | 1 |
| GDPpercap_2006 | -0.038675476 | -0.05839336 | -0.15373917 | 0.006740789 |
| HDI_2006 | 0.430028647 | -0.51835126 | -0.38356614 | -0.066614233 |
| HDI_A1Reconcil_Rank | -0.429583192 | 0.51815039 | 0.38339147 | 0.066481166 |
| | GDPpercap_2006 | HDI_2006 | HDI_A1Reconcil_Rank | |
| Failing_Rank | 0.01886463 | -0.633029282 | 0.633241415 | |
| LifeBirth_2005 | -0.0494695 | -0.03570063 | 0.036423385 | |
| AdultLit_2005 | -0.04241028 | -0.192482993 | 0.19208394 | |
| EnrolEduc_2005 | 0.06664903 | -0.005080359 | 0.005436544 | |
| GDPpercap_2005 | -0.03867548 | 0.430028647 | -0.429583192 | |
| LifeBirth_2006 | -0.05839336 | -0.518351257 | 0.518150389 | |
| AdultLit_2006 | -0.15373917 | -0.383566141 | 0.38339147 | |
| EnrolEduc_2006 | 0.00674079 | -0.066614233 | 0.066481166 | |
| GDPpercap_2006 | 1 | 0.028291663 | -0.028308809 | |
| HDI_2006 | 0.02829166 | 1 | -0.99998641 | |
| HDI_A1Reconcil_Rank | -0.02830881 | -0.99998641 | 1 | |

Next we tell R to run Random Forest after looking for incomplete data sets that we may want to omit depending, or impute separately outside of random forest. Random Forest will impute values on its own in missing data sets if we tell it. Again, if there is a significant amount of missing data, those variables were dropped prior to running the program. This particular data set does not have enough missing data to warrant dropping the variables prior to running Random Forest. I did a trial run on this data set and several others to determine if there was a significant difference between dropping values, imputing separately, or just running it through Random Forest and deemed that just running the data through Random Forest at this point without imputation was sufficient for our purposes.¹²⁷

Our Code

```
search()
library(randomForest)
str(BF_BO)
BF_BO$Failing_Rank
head(BF_BO)
BF_BO$FailingRank[BF_BO$FailingRank==NA,]
Incomplete <- BF_BO[!complete.cases(BF_BO),]
Incomplete
Incomplete$Country
set.seed(456)
BF_BO.rf=randomForest(Failing_Rank~.,data=BF_BO.data,importance=TRUE)
BF_BO.rf
```

⁻

¹²⁷ There is some degree of imputation automatically programmed into the software package of randomForest, however one has the ability to impute the data set prior to even running the program and beginning with a complete data set if desired. We omitted variables with large gaps in our data set so that we had a more clean result. For full list of R code employed See appendix 3.

The Results from randomForest

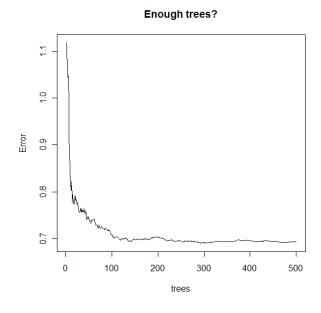
```
Call:
randomForest(formula = Failing_Rank ~ ., data = BF_BO.data, importance = TRUE)
Type of random forest: regression
Number of trees: 500
No. of variables tried at each split: 3
```

Mean of squared residuals: 0.6947214 % Var explained: 37.09

Next we graph these results and ask the question, do we have enough trees? Would running the program more times yield different results? We grew 500 trees in our sample.

Our code plot(BF BO.rf, lty=1, main="Enough trees?")

Enough Trees Graph



We can see from our graph that there appears to be little change in the error rate, roughly, after 250 trees where our line begins to flatten out. So we know that with this data set, it is not necessary to increase the amount of sampling employed/trees grown.

Next we plot and make a graph of the Random Forest results according to variable importance.

Our code

round(importance(BF_BO.rf), 2)
varImpPlot(BF_BO.rf)

Table 3

| | %IncMSE | IncNodePurity |
|----------------|---------|---------------|
| LifeBirth_2005 | -1.57 | 3.79 |
| AdultLit_2005 | 10.87 | 11.65 |
| EnrolEduc_2005 | 6.96 | 13.52 |
| GDPpercap_2005 | 8.35 | 22.23 |
| LifeBirth_2006 | 2.93 | 11.58 |
| AdultLit_2006 | 5.74 | 6.94 |
| EnrolEduc_2006 | -0.94 | 9.14 |
| GDPpercap_2006 | 3.45 | 11.22 |
| HDI_2006 | 20.15 | 49.14 |

As we mentioned earlier, the higher the node purity and the higher the percentage of increase of the mean square error rate indicates a higher correlation to the failed state. These two things are the predictor measure of accuracy in randomForest. 128 "In regression trees, node impurity is measured by MSE, therefore the second measure that averages cumulative reduction in node impurity due to splits by a variable over all trees is labels as mean decrease in MSE. When you permute the value of a variable in out of bag data and make a prediction, the

¹²⁸ Svetnik, Vladimir, et al. "Random forest: a classification and regression tool for compound classification and QSAR modeling." *Journal of chemical information and computer sciences* 43.6 (2003): 1947-1958.

expectation is that the MSE will increase, especially if the variable has some importance- hence the label % INC MSE or % increase MSE. 129

Our graph on Table 4 shows the variables for this particular data set in descending order of importance. According to the graph, we see variables that seem to have the highest ranking on node purity, and mean square error explained (the variables or characteristics that seem to be prevalent regarding our failed state ranking). These would be HDI_2006 and HDI_A1Reconcil_Rank. We took note of these two variables when Hmisc¹³⁰ was run in R¹³¹ which deemed these two variables to be almost identical in response to the failed state ranking. So, one of these will be dropped before determining the final model set. Next, it is always a good idea to look at partial dependence plots to see if there are any obvious relationships to take into account.¹³² The results are on Table 4 on the following page.

¹²⁹ Ibid 128

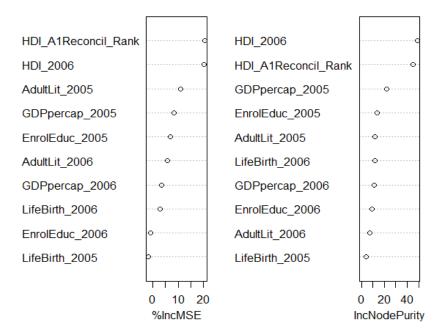
¹³⁰ lbid 87

¹³¹ Ihid 1

¹³² See appendix 3 for a complete list of all R code employed for this paper.

Table 4

BF_BO.rf



We graph all of the dependent variables using partial dependence plots ran through Random Forest with their results.

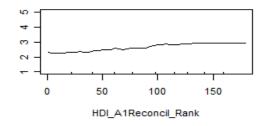
Our Code

```
imp<-importance(BF_BO.rf)
impvar<-rownames(imp)[order(imp[,1], decreasing=TRUE)]
par(mfrow=c(3,2))
for (i in seq_along(impvar)) {
   partialPlot(BF_BO.rf, BF_BO.data, impvar[i], xlab=impvar[i],
   main=paste("Partial Dependence on", impvar[i]), ylim=c(1,5))
   }
par(mfrow=c(1,1))</pre>
```

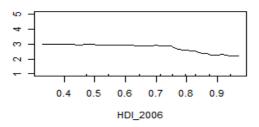
Table 5

Partial Dependence Plots

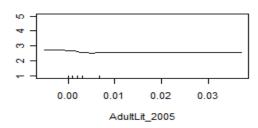
Partial Dependence on HDI_A1Reconcil_Rar



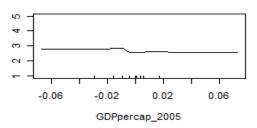
Partial Dependence on HDI_2006



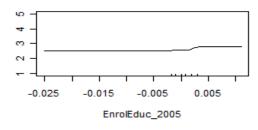
Partial Dependence on AdultLit_2005



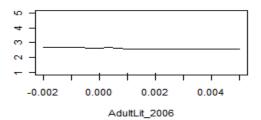
Partial Dependence on GDPpercap_2005



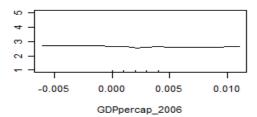
Partial Dependence on EnrolEduc_2005



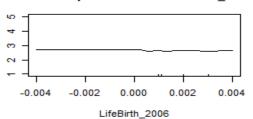
Partial Dependence on AdultLit_2006



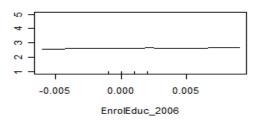
Partial Dependence on GDPpercap_2006



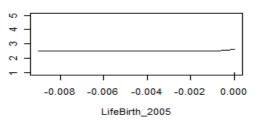
Partial Dependence on LifeBirth_2006



Partial Dependence on EnrolEduc_2006



Partial Dependence on LifeBirth 2005



There seems to be little obvious responding variables from these graphs, so we employ the Boruta program to identify all relevant variables. As previously mentioned, Boruta identifies all relevant variables.

Here is our code...¹³³

library(Boruta)

set.seed(498)

 $BF_BO.Boruta = Boruta(Failing_Rank \sim ., data = BF_BO.data, doTrace = 2, maxRuns = 400)$

BF_BO.Boruta

 $attr = attStats(BF_BO.Boruta)$

attr[order(-attr\$medianZ),]

 $^{^{133}}$ For all code employed in the making of the model see appendix 3

Table 6

| | Mean Z | Median Z | Min Z | Max Z | norm Hits | Decision |
|----------------------|------------|------------|-----------|-----------|------------|-----------|
| HDI_A1 Reconcil_Rank | 19.9603965 | 19.976504 | 16.847558 | 23.020708 | 1 | Confirmed |
| HDI_2006 | 18.932823 | 18.9644994 | 15.990646 | 21.516691 | 1 | confirmed |
| AdultLit_2005 | 9.0000899 | 9.0545373 | 6.348779 | 12.607887 | 0.99302326 | confirmed |
| GDP_percap_2005 | 8.693459 | 8.6262783 | 5.704974 | 11.813586 | 0.98837209 | confirmed |
| AdultLit_2006 | 6.1957459 | 6.213406 | 2.813337 | 9.729706 | 0.92790698 | confirmed |
| EnrolEduc_2005 | 5.9797098 | 5.9268323 | 2.311391 | 9.381075 | 0.88837209 | confirmed |
| LifeBirth_2006 | 2.6465938 | 2.6576754 | -1.351819 | 5.557084 | 0.43953488 | tentative |
| GDPpercap_2006 | 1.7449177 | 1.8202295 | -1.066098 | 4.13523 | 0.05116279 | rejected |
| EnrolEduc_2006 | -0.7323241 | -0.6133068 | -3.211732 | 1.076007 | 0 | rejected |
| LifeBirth_2005 | -0.9960767 | -0.9855453 | -3.39596 | 1.002132 | 0 | rejected |

We can see that the top two variables have a significant response to the ranking in table 5 and the range Boruta determined for each variable as well as hits associated with it. Note the top two variables that were previously identified as important through Random Forest, HDI_A1 Reconcil_rank and HDI_2006. In addition, we have other confirmed variables that we otherwise might have missed. Boruta determined the following variables to be relevant:

HDI_A1Reconcil_Rank, HDI_2006, AdultLit_2005, GDPpercap_2005, AdultLit_2006, and EnrolEduc_2005. From this data set HDI_A1Reconcil_Rank will be dropped. The others are saved into another file.

This method was employed for all of the twenty different sub-data sets, from the 600 plus original raw data variables, employed to create the model. The most relevant variables pulled from the different data sets were then subject to Random Forest and Boruta once more before the

final model and its variables were confirmed. This was a statistical manner of process and elimination to derive a final variable set.

So how does this model and method differ from previous research and why is this unique? First of all, most past research is offered in the form of an index, not a model created using statistics for variable selection, although it may be labeled as a model. The Fund for Peace Failed State Index that is published yearly in the Foreign Policy publication is an example. 134 The findings published are created through a CAST method¹³⁵ which is in part a statistical process as well an alteration of their statistical findings depending on the opinion of the analyst. Although qualitative interpretation is necessary in political science research, when creating any kind of index and rankings for a failed state, you can lose the opportunity to discover a variable and/or identifier that otherwise might be omitted from the data because it had not been considered before as being a key indicator of the failed state. If you are careful with what statistical program you choose and decrease variance error rates properly, you can use statistical programs for variable selection and then create a model useful for evaluating a states solvency and legitimacy. This is what we have done here as defined in the methodology. The CAST method referenced in the Fund for Peace is used to create an index. An index shows you where you are based on past events. CASTs' predictive capabilities are limited because the variables themselves were altered and the data used was altered based on the biases of the analyst. When the statistical program score is determined then altered or omitted by the researcher, it can bring all of the results into question, not to mention that you can miss something key to the research by assuming that it is a false positive.

¹³⁴ Ibid 55

¹³⁵ Ibid 57

To better illustrate this point of an index we can look at a very common index to Americans-the Standard and Poor's 500. This is a stock market index. ¹³⁶ The index itself demonstrates at any given point the demand for a stock or option on a stock and the price that the last person was willing to pay for it. With a documented history of stock prices for all companies in the index, one can look at past analysis of a stock's performance through any given company's public trading history. The stock price and the index do not make inferences for future performance and it does not predict future solvency of any given company. It merely represents where it is today and gives documentation where it was. Millions have been spent to come up with a predictive stock analysis model.

Although previous researchers employ statistical methods to come with their rankings for the failed state, their indices still just tell you where a country was yesterday. The purposed outlined in the methodology is to take all such raw data from international indices available and after formulating a failed state ranking score, using a machine learning algorithm, in this case Random Forest, to create a model that can derive key characteristics/variables from the program. This program then illustrates variables that have strong correlations or a relationship to an increased failed state ranking. As complex and comprehensive as the data collection and processing was, this construct ends up being a basic but very functional and useful model. ¹³⁷

Although this research has a main quantitative focus, qualitative means were used to evaluate the justification of the independent variable ranking numbers (original failed state ranking, aka independent variable, previously described) against three known failed states and

40

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¹³⁶ Kawaller, I.G., Koch, P.D. and Koch, T.W. (1987), "The Temporal Price Relationship between S&P 500 Futures and the S&P 500 Index". *The Journal of Finance*, 42: 1309–1329.

¹³⁷ See methodology section of this paper pp.

their conditions to demonstrate the validity of the model. Analysis of the results of this quantitative research and qualitative means of explanation is the subject of the next section.

Analysis of the data final model and failed state examples

After running all of the separate data clusters through the methodology described, what remains is a final variable set for our model. 138

Again, the first step in the final analysis was to look at the data set through Hmisc. ¹³⁹ By using the spearman command and the correlation matrix through Hmisc, we considered which variables may have a similar response, and could therefore be considered statistically redundant. Because Random Forest takes all of the variables into consideration when building the forest in the model, it is important to remove as many variables that are duplicates in an effort to explain the variation in the node selection, generating a more concise model.

We looked to make sure that there were no duplicates. Then we loaded up Random Forest and imputed any missing data. Imputation was done in the final model to make as complete of a data set as possible for the final run. Our goal was to have a final set of about twenty variables for this model. 140 We ran the data set through random forest and came up with a set of variables¹⁴¹then checked to make sure that we had enough trees and that the change over adding one more tree did not make a large difference.

 $^{^{138}}$ For a the raw data list used See Appendix 8

¹³⁹ See appendix 4 for Hmisc correlation matrix results table.

Note, we began with over 600 variables and ended with approximately 20 for model selection.

¹⁴¹ See appendix 7

Below is our results. 142

Random Forest Results

Type of random forest: regression

Number of trees: 500

No. of variables tried at each split: 17

Mean of squared residuals: 0.5901746

% Var explained: 45.91

A graph to view the results is found on Table 7.

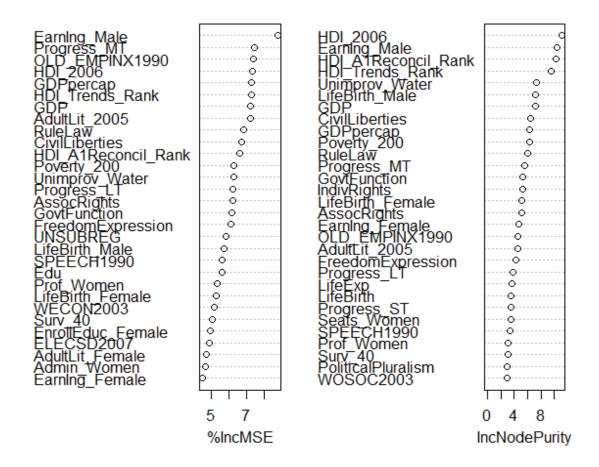
A few of the variables are rather obvious for showing a relationship. On our graph on Table 6 we see the male earnings, and HDI 2006 stand out at the top as having strong correlation to the failed state. Again, the higher the score indicates the higher the correlation to the failed state in both columns.

¹⁴² For full list of R code employed see appendix 3

42

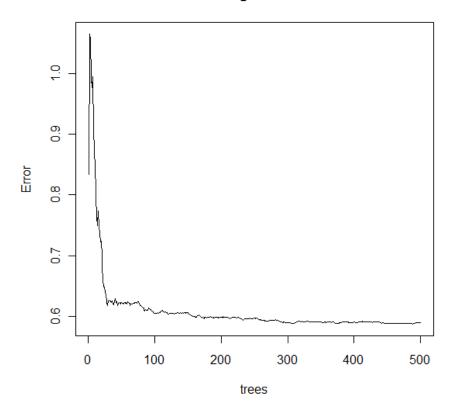
Table 7

run2.rf



Again we check to see if there were enough trees grown for the regression?

Enough trees?



The next step was to run Boruta¹⁴³. Although our Random Forest results graph gives us a nice look at the variables and their relationship to each other and the model, Boruta shows us all of the relevant variables after random forest has been run. 144 The final set of predictive variables for the failed state from this statistical practice are as follows under results in descending order of importance based on the statistical findings confirmed from the Random Forest regression paired with results from Boruta. 145

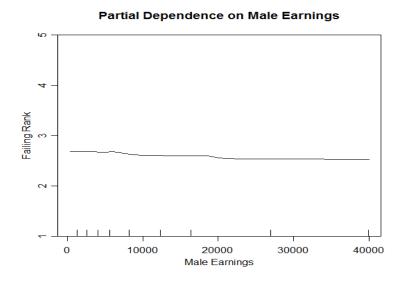
 $^{^{143}}$ See appendix 3 for R code employed. 144 See appendix 5 and 6

¹⁴⁵ See appendix 5 for Boruta results

Results

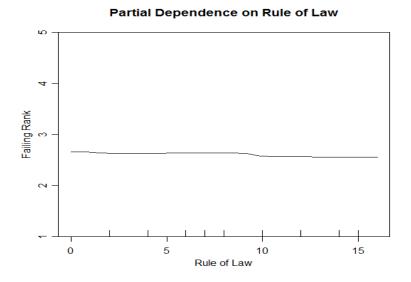
The results are Male earnings, rule of law, Human Development index, civil liberties, unimproved water, GDP, adult literacy, freedom of speech, associated rights, freedom of expression, life birth of males, poverty a percentage of the population, progress-mt, government function, followed by earnings per female, life birth female, individual rights, chance of survival over 40 years of age, political pluralism, progress-LT, Lifebirth, Life expectancy, WOSOC2003, Prof_Women, AdultLit_female, and education enrollment. ¹⁴⁶

Below are some individual partial plot graphs to show the relationships between the failed state ranking and variables confirmed in Boruta to have a statistical relationship.

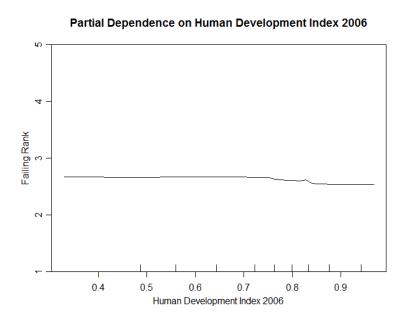


We can see in the male earnings partial plot that as earnings increase, the failed state ranking decreases. Male earnings is measured here as annual currency equal to U.S. dollars.

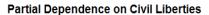
 $^{^{146}\,\}mbox{See}$ appendix 5 and 6 for the final model variables.

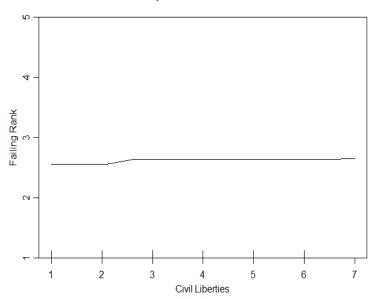


Rule of law is observed as a number scale based on several characteristics- Judicial process effectiveness and observance policing safeguards for civilians. You can see as the rule of law increases, the failed state ranking decreases.

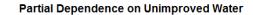


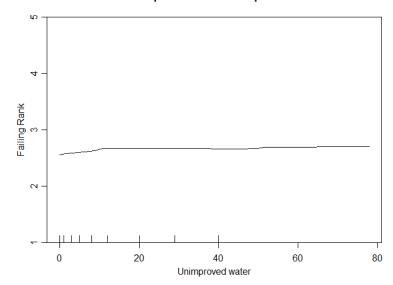
Here the human development index is measured on a percentage scale. It is meant to reflect a percentage of the population- .40 being 40 % and so on. As the failed state ranking goes down, the human development index increases.





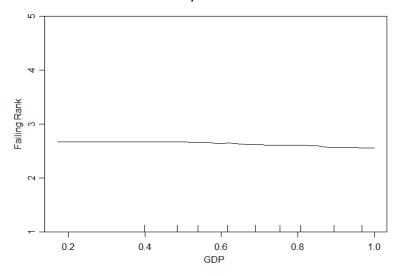
Civil liberties scale is a tally of overall civil liberties offered in a country. This relationship is a curious one. The curve is very slight. You can see that slowly as civil liberties increase, so does the failed state ranking. This finding was a surprise to me.



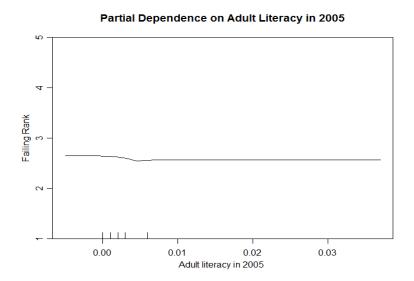


This partial plot shows a scale of the unimproved water in relationship to the percentage of the population that does not have access. It comes as no surprise that as the percentage of people without water improvements gets larger, so does the failed state ranking.

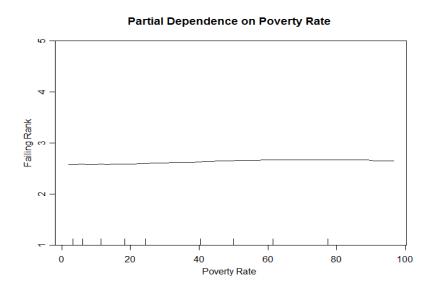




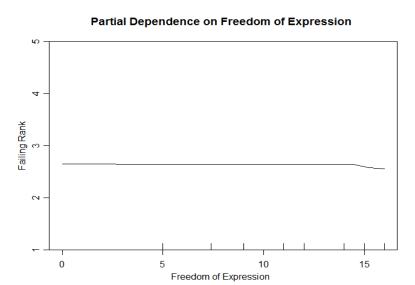
GDP is typically measured in U.S. dollars and is measured by the trillions. So a 1.0 would be one trillion and the percentages below that would be in the billions. Again we have a slightly discernible plot line that shows the failed state ranking going down as GDP increases.



Adult literacy is measured as a percentage of the population that can read. As literacy goes up, failed state ranking goes down.

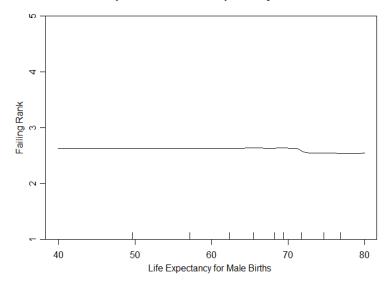


Poverty rate in the graph shows the complete spread of the population to 100%. Although a confirmed variable, this particular graph does not show an obvious relationship by itself. There is a slight decrease in the failed state at about the 90 % mark.



Freedom of expression is another variable measured in terms of score ranking from original data based on the amount of freedoms allowed. This encompasses freedom of speech, freedom of religion, and freedom of the press—the higher the measure of freedom of expression, the less chance of a failed state.

Partial Dependence on Life Expectancy for Male Births

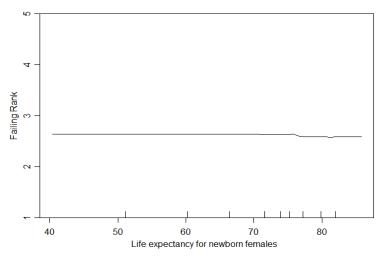


These numbers show the percentage of male boys born that live to age 5. The figure represents a percentage of the population of baby boys that survive to age 5. There are two different measures in the partial plots—life birth boys and a life expectancy for newborn females. It is widely known that baby boys do not fare as well as baby girls for survival particularly in food insecurity situations. Although the particular cause is unknown, regardless of medical research to determine otherwise, boys are more susceptible to respiratory failure and other problems associated with if proper care and nutrition is not available.¹⁴⁷

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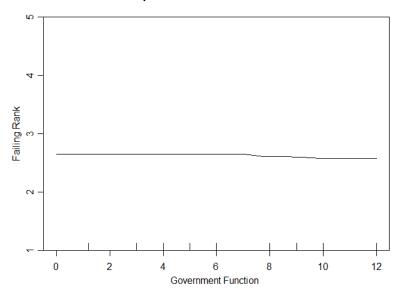
¹⁴⁷ Elsmén, Emma, Mårten Steen, and Lena Hellström-Westas. "Sex and gender differences in newborn infants: why are boys at increased risk?." *Journal of Men's Health and Gender* 1.4 (2004): 303-311.





Similar to life expectancy for male births, life expectancy for newborn females is graphed in the overall percentage of babies' likelihood to survive to age 5. As this rate increases, we can see on the graph that the failing rank decreases.

Partial Dependence on Government Function



Our last plotted example is government function. The numbers are a ranking of effectiveness for a government to function properly as a whole. Our plot shows a slight decrease of the failed state ranking as government function increases.

Table 8

| Male earnings | Rule of law | Human development | Civil liberties | |
|-----------------------|----------------------|----------------------|---------------------|--|
| | | index | | |
| Unimproved water | GDP | Adult literacy | Freedom of speech | |
| Associated rights | Freedom of | Life birth males | Poverty | |
| | expression | | | |
| Government progress | Government progress | Government function | Earnings per female | |
| mid term | long term | | | |
| Life birth female | Individual rights | Chance of survival | Political pluralism | |
| | | over 40 | | |
| Life births | Life expectancy | Womens social issues | Women professionals | |
| Adult literacy female | Education enrollment | | | |

Final model

Our final model employs the identifiers from table 7 for the failed state: Male earnings, rule of law, Human Development index, civil liberties, unimproved water, GDP, adult literacy, freedom of speech, associated rights, freedom of expression, life birth of males, poverty a percentage of the population, progress-mt, government function, followed by earnings per female, life birth female, individual rights, chance of survival over 40 years of age, political pluralism, progress-LT, Lifebirth, Life expectancy, WOSOC2003, Prof_Women, AdultLit_female, and education enrollment. ¹⁴⁸ So how do we make use of these variables? We found the most straightforward way to use the model was to categorize the variables similar to

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¹⁴⁸ See table 6

how the raw data was categorized from its original sources and then to look at the variables within failed state examples.

Final Variable Categories

The final variable set easily fits into four categories- *Economy* as a function of government, *Health* as a function of government, *Government overall*, and *Social and Individuals rights* wherein the government serves as a protector and supporter of these rights.

1. Economy- male earnings, female earnings, GDP (gross domestic product), and poverty a percentage of the population. Also included under this heading is government economic progress midterm and long term (listed in the data as progress MT and progress LT).

We know from studies conducted that states which employ economic solvency and growth have a higher ratio of well being and happiness than their non free nation counterparts including civil liberties and life expectancy. Earnings of individuals, and more importantly, poverty, are significant factors in the failed state evaluation. It has been documented that the impoverished are more likely to become terrorists and other criminals. People in general are malleable, and even more so when they are financially depressed. That being said, it is also important to point out that not all states with failed or collapsed economies become failed states. Iceland is one such example. Their economy completely collapsed, the government

¹⁴⁹ Dowd, Alan. "Freedom and Failed States." Fraser Forum Nov./Dec. 2012:15 print.

¹⁵⁰ Maleckova, Jitka. *Root causes of Terrorism: Myths, Reality and Ways Forward*. Routledge. New York. 2006. Pp. 33-43.; and Bjorgo, Tore and Jitka Maleckova Root Causes of Terrorism: Myths, Reality and Ways Forward. Routledge New York. 2005. Pp. 33.

administration resigned, new officials were elected and implemented a course of policies to regain state solvency.¹⁵¹

- **2. Health-** HDI (health development index) This includes world health standards with access to vaccinations and other medical intervention available within the state, unimproved water (we know that bacteria disease processes such as tuberculosis, dysentery and the plague thrive in unclean areas where toilets are located close by the water source¹⁵²), life births (the number of life births overall), life births male (the number of life male births), and life expectancy over the age of 40. ¹⁵³
- **3. Government** government functioning overall and the rule of law.

A stable government is one that can protect individual rights, provide social and other institutions that instill safety as well as a respected judicial process. A respected judicial process is necessary for rule of law to be recognized. Without it, vigilante groups and individual factions gain strength weakening a society.¹⁵⁴

4. Social and Individual rights-civil liberties, freedom of speech, associated rights, freedom of expression, education enrollment, adult literacy, adult literacy in females and number of women in professional job positions as well as women's social rights for 2003 (WOSOC2003).

¹⁵¹ The breakdown of the banking system in 2008 led to a transition of government in Iceland. For many countries, chaos would ensue. This was not the case with Iceland. See Ingimundarson, Valur, "A crisis of Affluence: The Politics of an Economic Breakdown in Iceland." *Irish Studies in International Affairs*. Vol 21, vol 21. 2010 pp. 57-69. http://ria.metapress.com/content/e41405167wvr06h3/

¹⁵² See the World Health Organization for details about drinking water standards and waste management. http://www.who.int/topics/water/en/.

¹⁵³ For a list of all original data sources see ibid 3.

¹⁵⁴ The groups that rise up in the wake of a failed state or fill a role that a failing government no longer offers are not included in this list such as the civil society structures that grew when Somalia became a failed state. Lemarchand, Rene. "Uncivil states and civil societies: how illusion became reality." *Journal of Modern African Studies* 30.2 (1992): 177-191.

From the final variable set in table 7, we can evaluate former failed states to determine the value of the model. For this we use three examples, the former Yugoslavia, Rwanda and Syria.

Failed State examples

Yugoslavia

To many it comes as no surprise that the former Yugoslavia failed given its warring tumultuous past. WWI began with the assassination of the Archduke Ferdinand in Sarajevo during 1914. There was a long standing animosity between those wanting to regain Serbian territory lost from Austrio-Hungarian wars of the past. To this day Serbs celebrate the battle of the blackbird where they actually lost as a defining moment of their strength and ability to persevere looking forward to the day that they can again be a united greater Serbia. Following WWI, WWII brought border changes and divisions with part of the region siding with German coalition in Croatia, and part of the region siding with Slavic neighbor states of the Soviet Union. The treatment of Serbs in Croatia during the Nazi era was brutal and not forgotten. The Croat Nazi's (Ustache) were tortuous to Serbs in what could be described sadistic. 157

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¹⁵⁵ Long standing clashes in the Balkans and an inability to come to peaceful terms between the Austro Hungarian empire and the Serbian factions led to global powers taking sides. For more information about the Balkans, David ¹⁵⁶ Owen gives a concise account. Owen, David. *Balkan Odyssey*. Harvest Book. Harcourt Brace & Company. New York. 1995. 7-17.

¹⁵⁷ The atrocities of the Ustache during the second world war are well known in the Balkans. See De Figueiredo Jr, Rui JP, and Barry R. Weingast. "Rationality of fear: political opportunism and ethnic conflict." *Military Intervention in Civil Wars* (1997).

Because of the states violent history, many researchers immediately come to the conclusion that it fell again after Marshall Tito died and that only his rule was able to maintain Yugolsav nationalism that could not be maintained by another head of state. 158

The entrenched problems are hard to ignore, however every failed state, and every non failed state has a history of which the United States is not exempt. We know that once the Soviet Union dropped back from support of Marshall Tito and Yugoslavia that he began a series of reforms in an effort to stabilize the region. Even though the country considered itself communist, each region was afforded some autonomy. Each region was allowed to have a central bank.

Trade was encouraged. Travel across borders in the regions and internationally was allowed.

Freedom of the press was observed and freedom of speech to some extent. Some factory workers were even known to strike for better working conditions. Taxes went to the larger collective.

Marshall Tito became known as a benevolent dictator and a liberal communist. He ruled for 34 years until his death in 1980. 159

For the most part, it appeared that this multicultural multi regional state was content due to the reforms set about. However if we look closely at the economy in 1978, something was happening in the state. The country lost about one million emigrants. ¹⁶⁰ Inflation was on the rise in this weak economy and industry was deteriorating in Serbian regions. Yugoslavia was importing large numbers of goods and was unable to export with the same stamina that they were

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¹⁵⁸ Denitch, Bogdan Denis. *Ethnic nationalism: The tragic death of Yugoslavia*. U of Minnesota Press, 1996.pp.51-70

There has been a great deal of study regarding the decentralization in an effort to create nationality regarding Tito's Yugoslavia. Some good articles regarding this are Nicholas R. Lang (1975). The Dialectics of Decentralization: Economic Reform and Regional Inequality in Yugoslavia. World Politics, 27, pp 309-335. doi:10.2307/2010123.; Furubotn, Eirik G., and Svetozar Pejovich. "Property rights, economic decentralization, and the evolution of the Yugoslav firm, 1965-1972." JL & Econ.16 (1973): 275.; and Dunn, W. N. "Communal federalism: Dialectics of decentralization in socialist Yugoslavia." Publius: The Journal of Federalism 5.2 (1975): 127-150.

able to consume.¹⁶¹ Everyone had a job, which was consistent with the communist ideal, however, work hours shrunk due to economic challenges. The former Austrio-Hungarian regions were more advanced and modern than their agrarian counterparts and as a result were sending much of their moneys to the central coffers to those underemployed provinces which created a source of resentment.¹⁶²

Old Croat nationalist factions rose stirring secessionist sentiments.¹⁶³ Tito squashed this in its tracks and limited the education. By 1980 oil and gas prices were out of control at a 60 % increase from 1979-1980. Staples such as butter and milk could no longer be found in the country. The gas pumps ran dry.¹⁶⁴

These events set the stage for the failed state. If we refer to our final failed state model, the following variables make sense given the events presented above. These are *GDP*, *Male earnings*, *female earnings*, *education enrollment*, *poverty*, *government function*, *rule of law*, *life expectancy*, *and survival age over 40*. In our model, we see a direct correlation to the failed state from the following identifiers in the history of Yugoslavia. A shrinking Gross domestic product was due to industrial inefficiency and a negative trade deficit. Male earnings and female earnings had been on the decline for some time. Education enrollment dropped after Croatia made a challenge to break up the federation during Tito's rule. Poverty was on the rise,

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¹⁶¹ Milanovic, Branko. "Poverty in Poland, Hungary, and Yugoslavia in the years of crisis", 1978-87. Vol. 507. World Bank Publications, 1990.

¹⁶² Two good articles discuss these situations Jovic, Dejan. "The Disintegration of Yugoslavia A Critical Review of Explanatory Approaches." *European Journal of Social Theory* 4.1 (2001): 101-120 and this book source Woodward, Susan L. *Socialist unemployment: the political economy of Yugoslavia, 1945-1990*. Princeton University Press, 1995.pp. 193-202.

¹⁶³ Malesevic, Sinisa. *Ethnicity and Federalism in Communist Yugoslavia and its successor states. Autonomy and ethnicity: negotiating competing claims in multi-ethnic states.* Cambridge University Press(2000): 147.

¹⁶⁴ Mesa-Lago, Carmelo. "Unemployment in a Socialist Economy: Yugoslavia." *Industrial Relations: A Journal of Economy and Society* 10.1 (1971): pp. 49-69.

¹⁶⁵ Ibid 164

and with all of these, government function and its inability to stimulate the economy faltered.¹⁶⁶ Once Tito died, these factors came to the forefront which his successors were unable to maintain. Eventually the Rule of law could no longer be observed and the county fell once again into civil war thereby dropping its life expectancy rate well below that of any stable state and the chance of survival age over 40 years of age took a steep decline. ¹⁶⁷

Rwanda

A thousand hills mark the landscape surrounded by sinuous, graceful rivers pooling into turquoise lakes. Pastoral lands lie in the valley offering fine grazing areas for cattle while cultivated terraced hills rise up into the sky. White blankets of pyrethrum flowers sway in the landscape. Conical peaks from the Virunga Mountains create a backdrop to the West housing what was once one half of the worlds remaining mountain gorilla population. Beset by the Democratic Republic of Congo, Burundi, Uganda, and Tanzania, this is Rwanda.

For those that have seen this country, it is as picturesque as it sounds. However, in 1994, Rwanda's population had shrunk by approximately 3,800,000. The result of a massive genocide left 800,000 dead and displaced three million to the bordering states. Within three months, the Interahamwe militia almost completed its task of eradicating what they believed to be pests, cockroaches, *Inyenzi* from the earth. It has been said that the murders were so numerous, blood from these killings caused Lake Victoria to run red. 169

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¹⁶⁶ Ihid 164

¹⁶⁷ A good resource for the effects of civil war and life expectancy can be seen here. Mackenbach, Johan P.

[&]quot;Political conditions and life expectancy in Europe, 1900–2008." *Social Science & Medicine* 82 (2013): 134-146. ¹⁶⁸ Keane, Fergal. *Season of Blood: A Rwandan Journey*. London WC2R ORL England: Penguin Books. 1995. Pp. 10.

Neuffer, Elizabeth. *The Key to My Neighbors House: Seeking Justice in Bosnia and Rwanda*. New York. Picador.2002. pp. 84-86.

Rwanda is a fascinating case study. It is one of the smallest and most densely populated countries in Africa. In this restrained area, three different ethnic groups have coexisted for hundreds of years -Twa, Hutu and Tutsi. As a result of a former Belgian and German protectorate, cultural distinctions and ethnic differences were defined by features and measurements of the skull by the Belgians. Identification cards were issued. Favored positions went to the Tutsi. Eventually this economic class disparity led the Hutus to overthrow the government and place Hutu preferences in power. Regardless of identification cards and transition in power, there was a point where these groups had intermarried before the identity cards declared their differences. These ethnic classes did not formerly recognize physical distinctions amongst themselves.

So what happened in Rwanda? What is for certain is this country fell into civil war and genocide in 1994. A massive machete slaughter left indelible images in the minds of those who saw bodies of people along shorelines and littered throughout the landscape. Due to the sheer systematic brutality of the genocide, most researchers focus on ethnic division as the reason for the failed state and miss perhaps even more significant problems that began long before ethnic foment gave rise to genocide.

We know that through the beginning of colonialism in 1897 and up to the time of the genocide in 1994, Rwanda basically subsisted in agriculture. During the Belgian colonial

¹⁷⁰ Smith, David Norman. "The psychocultural roots of genocide: Legitimacy and crisis in Rwanda." *American Psychologist* 53.7 (1998): 743.

¹⁷¹ Mamdani, Mahmood. *When victims become killers: Colonialism, nativism, and the genocide in Rwanda*. Princeton University Press, 2001.

An in depth analysis of the Rwandan genocide can be found in "Leave none to tell the Story: Genocide in Rwanda" written by Alison Des Forges. Human Rights Watch. New York. 1999.

occupation, roughly about 90 % of Rwandans practiced agriculture¹⁷³, with 75% of the farm land being used to cultivate coffee.¹⁷⁴ Cash cropping was introduced by Belgium and land tenure to foreign plantation owners was allowed with these limited land resources for pyrethrum production (an insecticide) and coffee. The transfer of precious land to foreigners left little for food propagation for the indigenous peoples. Rwandan struggled under these foreign landowner accommodations. It did not take long for economic hardship to cause negative sentiments amongst the people.

In 1959 Hutus overthrew the Tutsi ruling class that was originally instilled by the colonizers.¹⁷⁵ Tutsis fled to neighboring Uganda and Tanzania. They made an attempt to retake their position in 1963 through armed militia in the North, but were pushed back. All of the land of some 400,000 displaced Tutsis was available for Hutus, moreover, the elite Hutu groups. Abandoned land transferred to Hutus easily with no laws in place for repatriation of refugee flows.¹⁷⁶

Since 1980 Rwanda fell to overpopulation and unequal land distribution. Elite groups sought to control land and mineral rich areas. The elite groups were called "abaryi- meaning eaters", ¹⁷⁷ by rural poor, and comprised of both Hutu and Tutsi. This exploitive group took any opportunity for advancement and comfort that they could to the extreme. At one point, 95% of the population covered 43% of the cultivated land area. The population growth had surpassed food production at this point. It was even more problematic because the choice of food

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¹⁷³ Bigagaza, Jean, Carolyne Abong, and Cecile Mukarubuga. "Land scarcity, distribution and conflict in Rwanda." *Scarcity and Surfeit: The Ecology of Africa's Conflicts, ACTS Press, Nairobi/Institute for Security Studies, Pretoria*(2002): 85-156.

¹⁷⁴ Schoenbrun, David L. "A Past Whose Time Has Come: Historical Context and History in Eastern Africa's Great Lakes" *History and Theory* 32:4. Dec. 1993. Pp. 34.

¹⁷⁶ Van Der Meeren, Rachel. "Three decades in exile: Rwandan refugees 1960-1990." *J. Refugee Stud.* 9 (1996): 252. ¹⁷⁷ Ibid 171 pp.52.

consumption was a tuber akin to the sweet potato. Tubers traditionally take up more land space. Education was offered to elite groups or those that could afford it. Extreme poverty ran among the rural population. To make matters worse, an economic crisis hit Rwanda in the late 1980's and coffee prices were beginning to spiral. At the time of the genocide, Rwanda had the highest population density within its state in the entire African continent. 179

In the 1990's, high unemployment, land tenure programs benefitting elites and a massive drought left this overpopulated country and its people hungry. The elite groups used propaganda to blame poverty on the Tutsis and instilled fear in the Hutus that Tutsis were going to kill them. Fueled by the belief that they would gain land and loot from those they killed, the genocide was swift. It would be second generation Tutsis displaced from 1959 that made up the Rwandan Patriotic Front who eventually stopped the genocide.

From our model variables, *Male earnings, rule of law, adult literacy, poverty,*government function, earnings per female, political pluralism, education enrollment and

professional women in the population, GDP, HDI, and civil liberties, all are variables

determined in our model to be closely linked with or are precursors for the failed state and can be seen from the historical event prior to the genocide.

The earnings overall had significantly decreased in this nation, rule of law did not protect everyone, only those with privileges. Poverty was everywhere. GDP was down due to a decline

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¹⁷⁸ Grosse, Scott, Robert Ford, and Jennifer Olson. "MORE PEOPLE MORE TROUBLE: Population Growth and Agricultural Change in Rwanda (A Case Study of the Population-Agriculture-Environment Nexus)." 1994 USAID http://pdf.usaid.gov/pdf_docs/pnabw925.pdf

¹⁷⁹ Gros, Jean-Germain. "Towards a taxonomy of failed states in the New World Order: decaying Somalia, Liberia, Rwanda and Haiti." *Third World Quarterly*17.3 (1996): 455-472.

¹⁸⁰ Ibid 177.

¹⁸¹ Gourevitch, Philip. We wish to inform you that tomorrow we will be killed with our families: Stories from Rwanda. Macmillan, 1998.

¹⁸² Ibid 175

in coffee prices. Hutu elites ruled the government, and education was for a selected group. However, even being Hutu did not grant income and security. The country was failing economically and there was not enough food. It took little to use propaganda as a tool to fuel mass killings.

When the genocide broke out, all of the other infrastructures failed as well. There was no more rule of law. Women's social issues were not respected. It was not uncommon for rape as a weapon to be used during the genocide, and chance of survival over 40 was gone.

Syria

Finally we look at the state of Syria. Syria shares borders with the following countries: Turkey, Israel, Iraq, Lebanon and Jordan. At one point Syria enjoyed trade with several partners and brought in some of its money from its oil reserves. Primarily a Muslim country, it allowed education, women in high positions and even women in the judicial system. It was at one time, by all accounts, a rather transitioning country regarding education, civil liberties and freedoms.

Long considered terrorist sympathizers by the United States for allowing Hezbollah (considered terrorists of Israel) to reside within its borders without impunity, sanctions were put in place. Syria became a haven for many Palestinian refugees following the 1967 Three Day War, in which Israel claimed the Golan Heights. The sanctions would mark the beginning of

¹⁸³ Kienle, Eberhard. "Syria, the Kuwait War, and the New World Order." *The Gulf War and the New World Order: International Relations of the Middle East*(1994): 383-398.

¹⁸⁴ Cardinal, Monique C. "Women and the judiciary in Syria: appointments process, training and career paths." *International Journal of the Legal Profession* 15.1-2 (2008): 123-139.

¹⁸⁵ Beres, Louis Rene, and Zalman Shoval. "On Demilitarizing a Palestinian Entity and the Golan Heights: An International Law Perspective." *Vand. J. Transnat'l L.* 28 (1995): 959.

an economic strangulation for Syria. ¹⁸⁶ Other maneuvers by the United States following these sanctions included, but were not limited to, restricting the use of U.S. dollars in Syria and the imposition of high taxes on any U.S. company doing business in Syria. This proved to be enough of financial burden to cause complete withdraw of American foreign investment in the state. ¹⁸⁷ Although laws were passed in Syria to entice foreign investment and protect property rights for those investments, the laws were poorly written leaving them, at times, open for ambiguous interpretation. ¹⁸⁸ An inability to use the dollar for international business in Syria coupled with corrupt, public officiators, lead prospective investors to mistrust that Syria could provide protection of their future potential investment. Most foreign investors had pulled out of the country leaving an economic void. ¹⁸⁹

Even though economic prospects looked bleak, the regime continued to look for progressive ways in which to open up trade and receive financial assistance from other countries. ¹⁹⁰ Strategically an opportunity presented itself in the first Gulf war. By siding itself with Saudi Arabia and Kuwait, Syria was able to trade that support in exchange for international aid. However, these funds and the opening of the oil trade did not do enough to entice its leaders to use the funding to create programs for its people. The government's main focus was on foreign investments and foreign business. ¹⁹¹ Now the country is lost in the chaos of civil war, with hundreds of thousands of its people killed, or displaced and starving.

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¹⁸⁶ Sen, Kasturi, Waleed Al-Faisal, and Yaser AlSaleh. "Syria: effects of conflict and sanctions on public health." *Journal of Public Health* 35.2 (2013): 195-199.

¹⁸⁷ Perthes, Volker. "The Syrian economy in the 1980s." *The Middle East Journal* (1992): 37-58.

Perthes, Volker. "The private sector, economic liberalization, and the prospects of democratization: The case of Syria and some other Arab countries." *Democracy without democrats* (1994): 243-269.

¹⁸⁹ Ibid 182

¹⁹⁰ Ibid 184

¹⁹¹ Ibid 179

From our final model, the following variables seem to fit within the framework of events in Syria. These are as follows; male earnings, rule of law, human development index, civil liberties, unimproved water, GDP, freedom of speech, associated rights, freedom of expression, life birth males and life birth females, poverty, government function, chance of survival over 40, life expectancy, professional women, womens social issues, and education enrollment.

After foreign trade left Syria, unemployment rose. Women usually are the first groups of people to lose their jobs. According to our model, the following factors reside in Syria and were prevalent before the civil war. Male earnings were down, female earnings declining, GDP declining, government function was declining, and the rule of law (protection of property rights) was not being properly observed. Pall of the other variables mentioned as indicators are obviously present due to the failed state. In civil war situations, life expectancy, life births, and babies surviving are diminished due to food insecurity and collapse of health care institutions. Muslim clerics have issued a fatwa granting people to eats dogs and cats because they are starving. The Assad regime seems to be expulsing any persons who exercise and speak in defiance of the regime, so the associated rights, freedom of expression, and freedom of speech are no longer observed in this country. When civilian areas are bombed, so are the infrastructures including power and water sources. It does not take much to contaminate a well from leaking gas pipes, or irrigation systems.

¹⁹² Moore, Pete W., and Bassel F. Salloukh. "Struggles under authoritarianism: Regimes, states, and professional associations in the Arab world." *International Journal of Middle East Studies* 39.01 (2007): 53-76.

¹⁹³Hunter, Stuart. "Clerics in Syria Issue Fatwa Allowing Citizens to Eat Dogs, Cats toPprevent Starvation". The World Post. Oct 16, 2013. http://www.huffingtonpost.com/2013/10/15/syria-eating-dogs-cats-cleric-fatwa_n_4101821.html

The civil war and the World Health Organization announced a polio outbreak in Syria and in the refugee flow areas of Turkey and Iraq, which can only mean that its people were not vaccinated. 194 If it is only small children that have not been vaccinated, we can assume that the health development index was on the decline at least a couple of years ago to not have enough vaccine on hand. With a decline of the HDI and an outbreak of polio aside from the civil war, we can note that life expectancy has been declining in the state for some time. We know that a lack of access to proper health care diminishes lifespan. If Syria had been more transparent, we may have additional indicators consistent with our model prior to the opposition clashes and the outbreak of civil war in 2011.

Surprising findings

There are two rather surprising indicators that pop up in our final model. The first being women's rights and women's issues. Their prevalence in the model is unmistakable. 195 Adult literacy in females, the number of professional women, women's social rights overall and earnings per female all have a strong correlation to the failed state.

Originally it was my belief that only ethnic protections and equality between ethnicities were prudent for harmony in a state. Furthermore, although gender issues were important, they did not weigh with as much significance. After reviewing the results, I discovered that I was wrong about this. The United Nations has mandates for protection of women's rights. Women that are discriminated against, typically receive less health care attention, less education and

¹⁹⁴ More Polio Cases is Syria to be Confirmed this Week-WHO Reuters http://www.reuters.com/article/2013/11/25/syria-crisis-polio-idUSL5N0JA2X720131125

¹⁹⁵ See table

lower wages than men.¹⁹⁶ FGM (Female genital mutilation) is a cruel practice against girls in some African states and is a practice still continued. The importance to marry girls off in societies where they are not allowed to work outside of the home became the impetus for this brutal practice. Men could be very selective about their brides with purity ranking as a must. To ensure this, families practice FGM to show a girl's worthiness to marry, or a "proof of purity" Although this practice has been condemned, it still continues. ¹⁹⁸ It is the individual rights that are not observed for women in the collective that lead to more harsh treatment and a harsher view of women. FGM is as abhorrent as male castration, which is a practice used to tame cattle bulls. After evaluations, it is apparent how these rights are so profoundly linked to the failed state. We only need to look to Afghanistan and Taliban rules imposed regarding women to see exactly how damaging it can be on a society.

The second surprise was regarding the civil liberties indicator in the model. The model showed that as civil liberties rise past a certain point in any given state, there was a positive relationship. In other words, as civil liberties increased past a particular threshold, so did the risk for a failed state. Malcolm Gladwell gave an example in *David and Goliath* that may shed some light on this. He suggests after some research, that there is a plateau regarding education, in which a person's value for it decreases—education is taken for granted, and a false sense of entitlement begins. ¹⁹⁹ This entitlement problem comes not from the generation of people who

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¹⁹⁶ See Ibid 3 <u>www.undata.org</u>. In 1980 the United Nations adopted a charter to protect women called CEDAW or Convenant on Women's Rights. Drinan, Robert Jr. *The Mobilization of Shame: A worldview of Human Rights*. Yale University Press. 2001. Pp. 35-44.

¹⁹⁷Fauziya Kassindja entered the United State requesting asylum on December 17, 1994 for fear or subjugation of female circumcision. Her accounts of this practice the health problems as well as the economic burdens if a girl cannot marry in Togo because of an absence of this are well documented in her journey Kassindja, Fauziya and Layli Miller. *Do they hear you when you Cry?* Random House. New York. 1998. Pp. 168.

¹⁹⁹ Galdwell, Malcolm. *David and Goliath: Underdogs, Misfits, and the Art of Battling Giants.* Little Brown and Company. New York. 2013. 39-62. Print.

had to scrape to save so that their child could go to college, or those that had to work and do well in school for a scholarship. It seems to be the following generation that is the nexus for a false sense of entitlement. Expectations have changed for kids receiving more. We can look at the recent case of a girl that had moved out of her home at age 17 who was suing her parents for financial support for current and future academics. Perhaps this is an example of why when civil liberties go up past a certain point the chance of a failed state does too. The entitlement expectations and proclivity against working for basics, sets people up for a fall if economies can no longer provide what those people understand as a given.

Another possible example of this is language interpreters. The United States encourages language individuality. Although English is the common language, electric companies offer two options, English and Spanish, in their automated system. Judicial and medical services must provide interpreters at the cost of the physician/medical community. In San Francisco, a huge melting pot area for immigration and tourism, there could be as many as 20 different languages-Spanish, Swahili, Persian, Arabic, Russian, Serbian, Portuguese, Italian, Chinese, Mandarin, Japanese, Korean, Vietnamese, Greek, French, and so on, although some research states that number to be even higher. Written driver exams in California are currently being offered in the following languages in addition to English -- Amharic, Arabic, Armenian, Cambodian, Chinese, Croatian, French, German, Greek, Hebrew, Hindi, Hmong, Hungarian, Indonesian, Italian, Japanese, Korean, Laotian, Persian/Farsi, Polish, Portuguese, Punjabi, Romanian,

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²⁰⁰Ly, Laura. "Student's Lawsuit Against Parnets for support loses first round in court". CNN Mar. 5, 2014. http://www.cnn.com/2014/03/04/justice/student-sues-parents-new-jersey/

²⁰¹In this article from the Bay Area of San Francisco the figure touted for diverse languages was recorded at 112. Hendricks, Tyche."Bay Area/ Report: 112languages Spoken in Diverse Region". SF Gate http://www.sfgate.com/bayarea/article/BAY-AREA-Report-112-languages-spoken-in-2692403.php

Russian, Samoan, Spanish, Tagalog/Filipino, Thai, Tongan, Turkish, and Vietnamese. ²⁰² When interpreters and language offerings go beyond, it could be considered an example of excessive civil liberties. Nationalism is no longer a goal or is even encouraged. Whether or not it would lead to a failed state is unknown.

Conclusion

Is it possible to identify the predictive characteristics for failed states using statistics with previously mined data? Furthermore, can the failed state be predicted?

In answer to the first question, we were able to construct a model that pinpoints indicators for the failed state. These markers appeared consistently and were prevalent in failed states from Random Forest and Boruta programs. Regression tree partitioning programs are being used in more fields of study than just the hard sciences. Through the process employed in the methodology, this paper has given a valid argument for the use of statistics and quantitative analysis in political science. Because of the nature of the statistical program and the methods employed, we were able to locate predictor variables/identifiers for the failed state by this model creation. However, this method would not have been possible without mined data sets.

There was a great deal of unavailable information regarding some countries due to lack of transparency or a short existence that would have given even more validity to the variables identified by their inclusion in the construct. Models created can only be as precise as the data available. It is possible that some variables would have had more importance if more countries could have been included. As it is, the model created was determined using no fewer than 200 countries, which was enough to provide sufficient data for our exercise. By assembling a model,

69

²⁰² http://www.dmv.ca.gov/dl/dl_info.htm#languages

the question of the failed state allows us to look at it through a different lens in the hopes of illustrating points we otherwise would not locate by qualitative means alone.

The variables identified for the model are Male earnings, rule of law, Human Development index, civil liberties, unimproved water, GDP, adult literacy, freedom of speech, associated rights, freedom of expression, life birth of males, poverty a percentage of the population, progress midterm, government function, followed by earnings per female, life birth female, individual rights, chance of survival over 40 years of age, political pluralism, progress long term, live births, life expectancy, WOSOC2003 (women's social issues for 2003), women in professions, female adult literacy, and education enrollment.

In addition to using statistics to help answer our question, we also looked at three states qualitatively to help validate the variables chosen. Those states are the former Yugoslavia, Rwanda and Syria. Each of these states fit our definition of the failed state. There was enough history documented on all three to make reasonable qualitative illustrations for our variable model set and each state is distinctly different in its failure. Yugoslavia fell apart after the death of a long standing leader, was a former communist country, and is currently divided up into seven separate viable countries that are growing economically, (Serbia, Macedonia, Kosovo, Montenegro, Croatia, and Slovenia) with the exception of one that is under a United Nations protectorate—Bosnia-Herzegovina. Rwanda was a former colonial state that was ripped apart from a genocide that as well is growing economically. Syria is in the throes of civil war whose end is yet to be played out. All three are different and all had good documentation of past events and that allowed us to apply our variables for qualitative case analysis.

By using statistics as employed in the methodology, we hope to provide credit to the field of political science that is traditionally considered a soft science by enhancing the value of what we know through past research and opening the door to other methods of thinking

So, Can the failed state be predicted? Even after all of the research and deliberation taken, there are so many factors when dealing with failed states that there is no one size fits all model for predicting the failed state. The closest that I think we can come is to identify characteristics that show consistently to have a relationship with failed states. Along that vein, just because a state has several indicators present that are consistent with failed states, it is not necessarily a harbinger for a failed state.

States and whether or not they fail depends on so many factors. Society may be very tolerant, or conditioned to fill in the gaps where the government is lacking making it less likely to fail. In other situations it could take little to collapse the state. There are so many unknowns that it is very difficult to make a judgment about which states will fail and which will not.

My original belief was that states, which were propped up financially by wealthy nations, regardless of how unstable they were, would not fail due to external stability and support. However, Egypt proved this initial belief of mine to be wrong. Although this model is useful in identifying predictor variables, failed states themselves are too difficult to predict. There is no panacea for the failed state and there is no one predictor element for it. Although this model is very useful in identifying predictor variables, failed states themselves are too difficult to conclusively predict.

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Appendix 1

Country name reconciliation

Trend_Country Rank_Country

Afghanistan

Albania Albania
Algeria Algeria
Angola Angola

Antigua and Barbuda

Argentina Argentina
Armenia Armenia
Australia Australia
Austria Austria
Azerbaijan Azerbaijan
Bahamas Bahamas, The

Bahrain Bahrain Bangladesh Bangladesh **Barbados Barbados Belarus Belarus** Belgium Belgium Belize **Belize** Benin Benin **Bhutan Bhutan** Bolivia Bolivia

Bosnia and Herzegovina Bosnia and Herzegovina

Botswana Botswana Brazil Brazil

Brunei Darussalam

Bulgaria Bulgaria Burkina Faso Burkina Faso

Burma

Burundi Burundi
Cambodia Cambodia
Cameroon Canada Cape Verde Cape Verde

Central African Republic Central African Republic

Chad Chile Chile

China China
Colombia Colombia
Comoros Comoros

Congo, Republic of

Congo (Democratic Republic of

th Congo, Democratic Republic of

Costa Rica Costa Rica
Croatia Croatia
Cuba Cuba
Cyprus Cyprus

Czech Republic
Côte d'Ivoire
Côte d'Ivoire
Denmark
Djibouti
Dominica
Czech Republic
Côte d'Ivoire
Denmark
Djibouti
Djibouti
Dominica

Dominican Republic Dominican Republic

Ecuador Ecuador
Egypt Egypt
El Salvador El Salvador

Equatorial Guinea Equatorial Guinea

Eritrea Eritrea Estonia Estonia Ethiopia Fiji Finland Finland France Gabon Gabon

Gambia Gambia, The
Georgia Georgia
Germany Germany
Ghana Ghana
Greece Greece

Grenada

Guatemala Guinea Guinea

Guinea-Bissau Guinea-Bissau

Guyana Guyana
Haiti Haiti
Honduras Hong Kong, China (SAR) Hong Kong
Hungary Hungary
Iceland Iceland
India India

Indonesia Indonesia

Iran (Islamic Republic of) Iran

Iraq

Ireland Ireland Israel Israel Italy Italy Jamaica Jamaica Japan Japan Jordan **Jordan** Kazakhstan Kazakhstan Kenya Kenya

Kiribati

Korea, North Korea, South

Kuwait Kuwait

Kyrgyzstan Kyrgyz Republic

Lao People's Democratic

Korea (Republic of)

Republic Laos
Latvia Latvia
Lebanon Lebanon
Lesotho Lesotho
Liberia Liberia
Libyan Arab Jamahiriya Libya

Liechtenstein

Lithuania Lithuania Luxembourg Luxembourg

Macau

Macedonia (TFYR) Macedonia Madagascar Madagascar Malawi Malawi Malaysia Malaysia Maldives Maldives Mali Mali Malta Malta Mauritania Mauritania Mauritius Mauritius Mexico Mexico

Micronesia, Fed St.

Moldova Mongolia Mongolia

Montenegro, Republic of

Morocco Mozambique Mozambique Myanmar

Namibia Namibia Nepal Nepal

Netherlands
New Zealand
Nicaragua
Niger
Nigeria
Norway
New Zealand
Nicaragua
Niger
Niger
Nigeria
Norway
Norway

Occupied Palestinian Territories

Oman Oman Pakistan Panama Panama

Papua New Guinea Papua New Guinea

Paraguay Paraguay
Peru Peru
Philippines Philippines

Poland Poland
Portugal Portugal
Qatar Qatar
Romania Romania
Russian Federation Russia
Rwanda Rwanda

Saint Kitts and Nevis

Saint Lucia Saint Lucia

Saint Vincent and the

Grenadines Saint Vincent and the Grenadines

Samoa Samoa

Sao Tome and Principe São Tomé and Príncipe

Saudi Arabia
Senegal
Senegal
Serbia
Seychelles
Seychelles
Sierra Leone
Singapore
Singapore
Singapore
Singapore
Singapore

Slovakia Slovak Republic

Slovenia Slovenia

Solomon Islands
South Africa
South Africa
South Africa

Spain Spain
Sri Lanka Sri Lanka
Sudan Sudan
Suriname Suriname

Swaziland Swaziland
Sweden Switzerland Switzerland

Syrian Arab Republic Syrian Arab Republic

Taiwan

Tajikistan Tajikistan
Tanzania (United Republic of) Tanzania
Thailand Thailand
Timor-Leste Timor-Leste

Togo Tonga Tonga

Trinidad and Tobago Trinidad and Tobago

Tunisia Tunisia Turkey Turkey

Turkmenistan Turkmenistan

Uganda Uganda Ukraine Ukraine

United Arab Emirates
United Kingdom
United States
Uruguay
Uzbekistan
Uzbekistan
United Arab Emirates
United Kingdom
United States
Uruguay
Uzbekistan
Vanuatu

Venezuela (Bolivarian Republic

o Venezuela
Viet Nam Vietnam
Yemen Yemen
Zambia Zambia
Zimbabwe

Appendix 2

Original failed state ranking

| | Failing |
|----------------------------------|---|
| Country | Rank |
| Afghanistan | 4.5 |
| Albania | 2 |
| Algeria | 3 3 3 3 |
| Angola | 3 |
| Argentina | 3 |
| Armenia | 3 |
| Australia | 1 |
| Austria | 1 |
| Azerbaijan | 3 |
| Bahamas | 1 |
| Bahrain | 1 |
| Bangladesh | 3 |
| Barbados | 1 |
| Belarus | 2 |
| Belgium | 1 |
| Belize | 1 |
| Benin | 3 3 3 |
| Bhutan | 3 |
| Bolivia | 3 |
| Bosnia and Herzegovina | 4 |
| Botswana | 2 2 |
| Brazil | 2 |
| Bulgaria | 2 |
| Burkina Faso | 3 |
| Burma | 2 |
| Burundi | 3 |
| Cambodia | 2 3 2 3 3 3 |
| Cameroon | 3 1 |
| Canada | 1 |
| Cape Verde | 2 |
| Central African Republic | 4 4 |
| Chad | |
| Chile | 2 |
| China | 3 |
| Colombia | 4 |
| Comoros | 3 |
| Congo (Democratic Republic of th | 4 |
| Congo | 4 3 4 3 1 4 2 3 4 |
| Costa Rica Côte d'Ivoire | 1 |
| | 4 |
| Croatia | 2 |
| Cuba | 3 |
| Cyprus | 4 |

| Czech Republic | 1 |
|---------------------------------------|------------------|
| Denmark | 1 |
| Djibouti | 3 |
| - | 2 |
| Dominica | |
| Dominican Republic | 3 |
| Ecuador | 2 |
| Egypt | 2 |
| El Salvador | 2 |
| Equatorial Guinea | 4 |
| Eritrea | 4 |
| Estonia | 1 |
| Ethiopia | 3 |
| - | 4 |
| Fiji | 1 |
| Finland | |
| France | 2 |
| Gabon | 3 |
| Gambia | 3 |
| Georgia | 3 |
| Germany | 2 |
| Ghana | 2 |
| Greece | 1 |
| Guatemala | 3 |
| Guinea | 4.5 |
| Guinea-Bissau | 3 |
| Guyana | 3 |
| Haiti | 3 |
| Honduras | 2 |
| Hong Kong, China (SAR) | 2 |
| Hungary | 1 |
| Iceland | 2 |
| | 3 |
| India | 2 |
| Indonesia | 3 |
| Iran (Islamic Republic of) | 3 |
| Iraq | 4 |
| Ireland | 2 |
| Israel | 2 |
| Italy | 2 |
| Jamaica | 3 |
| Japan | 3 2 |
| Jordan | 2 |
| Kazakhstan | 3 |
| Kenya | 3 |
| Kiribati | 2 3 3 3 |
| Korea, North | 3 |
| Korea (Republic of) | 2 |
| Kuwait | 2 |
| | 3.5 |
| Kyrgyzstan Lao People's Democratic | 3.5 |
| Republic | 3 |
| | 2 |
| Latvia | 3 |
| Lebanon | 3 |

| Lesotho Liberia Libyan Arab Jamahiriya Liechtenstein Lithuania | 4 3 3 1 3 |
|--|-----------------------|
| Luxembourg Macau Macedonia (TFYR) | 1 2 3 |
| Madagascar | 4 |
| Malawi | 3 |
| Malaysia | 3 |
| Maldives | 4 |
| Mali | 3 |
| Malta | 2 |
| Mauritania | 3 |
| Mauritius | 2 |
| Mexico | 3 |
| Micronesia (Federated States of) | 3 |
| Moldova | 4 |
| Mongolia | 2 |
| Montenegro | 2 |
| Morocco | 3 |
| Mozambique | 3 |
| Namibia | 2 |
| Nepal | 4 |
| Netherlands | 1 |
| New Zealand | 4 |
| Nicaragua | 4 |
| Niger Nigeria | 4 |
| Norway | 1 |
| Oman | 2 |
| Pakistan | 4 |
| Panama | 2 |
| Papua New Guinea | 4 |
| Paraguay | 4 |
| Peru | 2 |
| Philippines | 4 |
| Poland | 2 |
| Portugal | 2 |
| Qatar | 2 |
| Romania | 5 |
| Russian Federation | 3 |
| Rwanda | 2 |
| Saint Lucia | 2 |
| Saint Vincent and the Grenadines | 2 |
| Samoa | 2 |
| Sao Tome and Principe | 2 |
| Saudi Arabia | 2 |
| Senegal | 3 |

| 0.11 | 2 |
|--------------------------------|--------|
| Serbia | 3 2 |
| Seychelles | 3 |
| Sierra Leone | |
| Singapore | 1 |
| Slovakia | 2 |
| Slovenia | 1 |
| Solomon Islands | 4 |
| South Africa | 2 |
| Spain | 2 |
| Sri Lanka | 4 |
| Sudan | 4 |
| Suriname | 2 |
| Swaziland | 3 |
| Sweden | 1 |
| Switzerland | 1 |
| Syrian Arab Republic | 2 |
| Taiwan | 2 |
| Tajikistan | 4 |
| Tanzania (United Republic of) | 2 |
| Thailand | 3 |
| Timor-Leste | 4 |
| Togo | 4 |
| Tonga | 1 |
| Trinidad and Tobago | 1 |
| Tunisia | 2 |
| Turkey | 3 |
| Turkmenistan | 4 |
| Uganda | 3 |
| Ukraine | 2 |
| United Arab Emirates | 1 |
| United Kingdom | 1 |
| United States | 1 |
| Uruguay | 2 |
| Uzbekistan | 4 |
| Vanuatu | 1 |
| Venezuela (Bolivarian Republic | |
| 0 | 2 |
| Viet Nam | 2 |
| Yemen | 2 |
| Zambia | 3 |
| Zimbabwe | 4 |
| | |

Appendix 3

R code language employed

```
getwd()
## Read the data from csv file
# ---This command pertains only to my computer
#----You will need to name it something else depending on where you save
vour files
AN BF <- read.csv("C:\\Users\\Beth\\Documents\\R\\csv data files for
thesis\\AN BF.csv", header=TRUE)
## Save the workspace as a name ex. AN BF.Rdata
##--you will need to name it something else for your computer specific
#--this tells it where to save the workspace at so that I can email
results or view later
save.image("C:\\Users\\Beth\\Thesis data analysis\\AN BF.Rdata")
## Print data
AN BF
## Check "structure"
str(AN BF)
## Tally the number of NAs in each column
apply(AN BF, 2, function(x) length(which(is.na(x))))
## Graphically exploring the dataset, looking for expected relationships
     with response
## and any strong correlations among predictor variables
# --> ncol(AN BF) is the number of columns in AN BF
      Plot columns (i.e., variables)
#plot(AN BF[,c(3:ncol(AN BF),2)]) # scatterplot matrix
\#pairs(AN BF[,c(3:ncol(AN BF),2)], panel = panel.smooth, lwd = 2, cex=
1.5, col="blue") # hmm...
pairs (AN BF[,c(3:ncol(AN BF),2)], panel = panel.smooth, lwd = 2, cex=
0.5, col="black") # hmm...
## Compute all pairwise correlations if desired
# This was done on all computation sets
library(Hmisc)
r.results <- rcorr(as.matrix(AN BF[,2:ncol(AN BF)]), type="spearman")</pre>
r.results$r
```

```
# Create multiple plots for columns indexed by i (turn on Graphics window
History|Recording first) If you do not turn on the graphics window
#recording, you will need to re run the set. It will not be saved.
for (i in seq(from=3, to=ncol(AN BF))){
   plot.data <- AN BF[, c(i,2)]# Extract a pair of variables to plot
   plot.data <- na.omit(plot.data) # Delete observations for which either</pre>
variable is NA
   plot(plot.data, ylim=c(1,5))# Plot
   lines(smooth.spline(plot.data))# Augment with smoothed curve
# --> PageUp/PageDown in Graphics window to see each plot
## Put object high in the list to determine comparison see attach in
intro book
search()
## Load randomForest package
library(randomForest)
## Look at structure of dataframe, and print values of Failing Rank
str(AN BF)
AN BF$Failing Rank
## Print data for first 5 countries
head(AN BF)
## Print observations where failing rank is missing
AN BF$FailingRank[AN BF$FailingRank==NA,]
## Identify countries with any missing data
Incomplete <- AN BF[!complete.cases(AN BF),]</pre>
# Print whole record for all countries with missing data
Incomplete
# Print just Country for all countries with missing data
Incomplete$Country
## Copy the full dataset
## If rows (i.e., countries) or columns (i.e., variables) are omitted
using the code below,
## then this new dataset will be overwritten. If there are no edits, then
this dataset will
## move forward into random forest modeling
AN BF.edited = AN BF
## --> Do this step only if necessary or desired
## Make a dataset that omits selected countries, e.g.,
# those with missing FailingRank
```

```
# or those with too many variables with missing data
# or those you want to drop for some other reason
# Replace the numbers in the c() list with appropriate row numbers to
drop specific countries
# Get a list of countries with row numbers
AN BF.edited$Country
# Drop countries in the list
AN BF.edited = AN BF.edited[-c(47,105,124,134,166,198),]
# Check new structure; there should be fewer "obs.", consistent with
fewer countries
str(AN BF.edited)
# List countries in the new dataframe
AN BF.edited$Country
## --> Do this step only if necessary or desired
## Make a dataset that omits selected variables, e.g.,
# those with so many missing values that imputation does not seem
sensible,
# or those you want to drop for some other reason (e.g., they are
redundant to other variables)
# or to look at a small subset of variables that look "important"
## KEEP IN MIND that the total number of variables will be different if
some are dropped
# Look at structure
str(AN BF.edited)
# Drop variables as desired by identifying columns in the c() list
AN BF.edited = AN BF.edited[,-c(4:11, 13:20)] # drop 4th through 11th,
and 13th through 20th
# Check new structure to be sure that you dropped what you meant to drop
str(AN BF.edited)
# --> Random forest modeling Choice #1:
     Using an imputed dataset.
# --> For any computation that uses random numbers, like imputation or
random forest
     modeling, you want to set a seed. Otherwise the computer will set
it by default
      from the computer clock and you will not be able to exactly
duplicate the analysis.
set.seed(120)
# --> If there are no missing values, then an Error will be reported
      and the AN BF.imputed object will not be created. Hence any
subsequent command
     that uses AN BF.imputed will not run.
# --> If your dataset has no missing values (either by default or because
you deleted
     all of the countries (rows) with missing data, then use
AN BF.edited in subsequent
      commands rather than AN BF.imputed
# --> This process drops the Country variable from the AN BF.imputed
object
      Impute missing values
AN BF.imputed <- rfImpute (Failing Rank ~ .,
AN BF.edited[,c(2:ncol(AN BF.edited))])
```

```
# --> Check that all cases are now complete
complete.cases(AN BF.imputed)
# --> Look at structure of new dataframe
str(AN BF.imputed)
# --> Copy imputed dataset into dataset AN BF.data to use in random
forest modeling
AN BF.data = AN BF.imputed
# --> Create a random forest object AN BF.rf
set.seed(456)
AN BF.rf=randomForest(Failing Rank~.,data=AN BF.data,importance=TRUE)
AN BF.rf
# --> OR Random forest modeling Choice #2:
      Using a complete dataset, either the original dataset if it had no
      missing values or an edited dataset that was made by dropping all
rows (countries)
      and/or columns (variables) with missing data.
# --> Copy imputed dataset into dataset AN BF.data to use in random
forest modeling,
      dropping the Country variable from the dataset object
AN BF.data = AN BF.edited[,c(2:ncol(AN BF.edited))]
# --> Create a random forest object AN BF.rf
set.seed(456)
AN BF.rf=randomForest(Failing Rank~.,data=AN BF.data,importance=TRUE)
AN BF.rf
# --> OR Random forest modeling Choice #3:
     Using a dataset that may have missing values, dropping all
observations (countries)
     with any missing data
# --> Copy imputed dataset into dataset AN BF.data to use in random
forest modeling,
      dropping the Country variable from the dataset object
AN BF.data = na.omit(AN BF.edited[,c(2:ncol(AN BF.edited))])
# --> Check structure of new dataframe
str(AN BF.data)
# --> Create a random forest object AN BF.rf
set.seed(456)
AN BF.rf=randomForest(Failing Rank~.,data=AN BF.data,importance=TRUE)
AN BF.rf
## --> Continuing with the analysis, regardless of Choice
round(importance(AN BF.rf), 2)
varImpPlot(AN BF.rf)
## to automatically save the plot
setwd("C:\\Users\\Beth\\Documents\\R\\graphs for thesis\\")
# change the file name to whatever the graph is
savePlot(filename="AN BF Variable importance",type="emf")
# multiple partial plots in 3 rows and 2 columns
imp<-importance(AN BF.rf)</pre>
```

```
impvar<-rownames(imp)[order(imp[,1], decreasing=TRUE)]</pre>
par(mfrow=c(3,2))
for (i in seq along(impvar)) {
 partialPlot(AN_BF.rf, AN_BF.data, impvar[i], xlab=impvar[i],
 main=paste("Partial Dependence on", impvar[i]), ylim=c(1,5))
par(mfrow=c(1,1))
# for individual partial plot
# make graphic a large 1 by 1 matrix
par(mfrow=c(1,1))
partialPlot(AN BF.rf, AN BF.data, LifeBirth Female,
xlab="LifeBirth Female",
  ylab="Failing Rank",
  main=paste("Partial Dependence on", "LifeBirth Female"), ylim=c(1,5))
savePlot(filename="C:\\Users\\Beth\\graphs for thesis\\AN BF Partial Plot
LifeBirth Female",
  type="emf")
##save new data objects in workspace
save.image("C:\\Users\\Beth\\Thesis data analysis\\AN BF.Rdata")
```

Appendix 4 Hmisc results

> r.results <- rcorr(as.matrix(run2[,2:ncol(run2)]), type="spearman")

> r.results\$r

| | Failing_Rank | AdultLit_2005 | EnrolEduc_2005 | GDPpercap_2005 |
|---------------------|--------------|---------------|----------------|----------------|
| Failing_Rank | 1.00000000 | 0.02697799 | 0.0851947516 | -0.248745710 |
| AdultLit_2005 | 0.02697799 | 1.00000000 | 0.0463679582 | -0.036908664 |
| EnrolEduc_2005 | 0.08519475 | 0.04636796 | 1.0000000000 | 0.086575672 |
| GDPpercap_2005 | -0.24874571 | -0.03690866 | 0.0865756720 | 1.000000000 |
| AdultLit_2006 | 0.11383769 | 0.62730968 | 0.0173741318 | -0.070903368 |
| HDI_2006 | -0.63596439 | -0.19248299 | -0.0050803591 | 0.430028647 |
| HDI_A1Reconcil_Rank | 0.63617671 | 0.19208394 | 0.0054365443 | -0.429583192 |
| PoliticalRights | 0.54707551 | 0.13005950 | -0.0520302616 | -0.006106872 |
| CivilLiberties | 0.57924598 | 0.15963461 | -0.0294325501 | -0.019184226 |
| ElectoralProcess | -0.50577277 | -0.10522731 | 0.0709697530 | -0.028558489 |
| PoliticalPluralism | -0.53421974 | -0.10544204 | 0.0469114557 | 0.010303929 |
| GovtFunction | -0.58038324 | -0.13948955 | 0.0049100816 | 0.033694092 |
| FreedomExpression | -0.56814373 | -0.12557831 | 0.0154502923 | 0.034476887 |
| AssocRights | -0.52849948 | -0.12270474 | 0.0344730690 | 0.022420902 |
| RuleLaw | -0.58514124 | -0.16048244 | 0.0164689720 | 0.005314687 |
| IndivRights | -0.60100901 | -0.20106521 | -0.0060573211 | 0.037086338 |
| FreedomStatus | 0.51773691 | 0.10652321 | -0.0473107770 | 0.029706782 |
| DISAP2005 | -0.38758761 | -0.03165168 | 0.1180226430 | 0.111951649 |
| Progress_ST | 0.18639658 | 0.21095045 | 0.2107104957 | 0.031337664 |

> library(Hmisc)

| GDP | -0.61502534 | -0.16067779 | 0.0063518756 | 0.536121130 | |
|-----------------|-------------|-------------|---------------|--------------|--|
| HDI_Trends_Rank | 0.63095719 | 0.19208394 | 0.0054365443 | -0.429583192 | |
| GDPpercap | -0.61405259 | -0.17096333 | 0.0003752598 | 0.536530316 | |
| LifeBirth | -0.60013753 | -0.13539150 | -0.0752368197 | 0.323006004 | |
| LifeExp | -0.59949005 | -0.13514304 | -0.0759409517 | 0.323116124 | |
| EarnIng_Female | -0.64474130 | -0.19459738 | 0.0286328439 | 0.499794543 | |
| Seats_Women | -0.25070402 | -0.06595705 | 0.0029300835 | -0.067054778 | |
| Admin_Women | -0.17601755 | -0.21298316 | 0.0094822142 | 0.011029314 | |
| Prof_Women | -0.10955402 | -0.41417724 | 0.0997921675 | -0.101032443 | |
| EarnIng_Male | -0.64237249 | -0.14544363 | 0.0001138583 | 0.528035283 | |
| OLD_EMPINX1990 | -0.44005004 | -0.21366489 | -0.0452510379 | 0.047151525 | |
| SPEECH1990 | -0.44005945 | -0.19672032 | -0.0529744104 | 0.159773558 | |
| ELECSD2007 | -0.43849507 | -0.03614708 | 0.0361889787 | -0.012454747 | |
| Progress_LT | 0.37626520 | 0.38514042 | 0.0581945032 | -0.015066378 | |
| Progress_MT | 0.16695333 | 0.47412163 | -0.0175123420 | -0.285973549 | |
| ALR | -0.31345794 | -0.26788428 | 0.0513533987 | 0.296765745 | |
| EdEnroll | -0.56001270 | -0.21732248 | 0.0362962298 | 0.336800456 | |
| Edu | -0.53535765 | -0.30806777 | 0.0282828324 | 0.305609882 | |
| WOSOC2003 | -0.44952592 | -0.19484411 | 0.0483556762 | 0.052507211 | |
| WECON2003 | -0.46219319 | -0.20606793 | 0.0634766221 | 0.097478129 | |
| WOPOL2006 | -0.16770512 | -0.15532932 | -0.0731181279 | -0.156219810 | |
| COW | 0.24864329 | 0.12362177 | -0.0537854023 | -0.192376986 | |
| POLITY | 0.25118226 | 0.12574111 | -0.0534191951 | -0.192376986 | |
| UNSUBREG | -0.24048531 | -0.26868746 | -0.0842922851 | 0.230426684 | |
| Unimprov_Water | 0.49786022 | 0.07333523 | 0.0072254627 | -0.285795748 | |

| LifeBirth_Female | -0.62169522 | -0.16466987 | -0.0333726257 | 0.324246198 |
|-------------------|-------------|-------------|---------------|--------------|
| LifeBirth_Male | -0.60210639 | -0.11294315 | -0.0735311434 | 0.324774683 |
| AdultLit_Female | -0.34737045 | -0.25754476 | 0.0343733840 | 0.258503467 |
| AdultLit_Male | -0.30301630 | -0.27829573 | 0.0422901288 | 0.319651425 |
| EnrollEduc_Female | -0.58448786 | -0.24265614 | 0.0049101929 | 0.333301306 |
| EnrollEduc_Male | -0.53936839 | -0.25156751 | 0.0162247103 | 0.334829837 |
| Surv_40 | 0.45933023 | 0.04103788 | 0.0203386340 | -0.326344043 |
| Poverty_200 | 0.44574928 | 0.13835996 | -0.1575469077 | -0.355751991 |
| POLPRIS1993 | -0.02558983 | 0.10134294 | -0.0436097234 | -0.062632650 |

| | AdultLit_2006 | HDI_2006 | HDI_A1Reconcil_Rank |
|--------------------|----------------|--------------|---------------------|
| Failing_Rank | 0.11383769 | -0.635964394 | 0.636176705 |
| AdultLit_2005 | 0.62730968 | -0.192482993 | 0.192083940 |
| EnrolEduc_2005 | 0.01737413 | -0.005080359 | 0.005436544 |
| GDPpercap_2005 | -0.07090337 | 0.430028647 | -0.429583192 |
| AdultLit_2006 | 1.00000000 | -0.383566141 | 0.383391470 |
| HDI_2006 | -0.38356614 | 1.000000000 | -0.999986410 |
| HDI_A1Reconcil_R | ank 0.38339147 | -0.999986410 | 1.000000000 |
| PoliticalRights | 0.24357341 | -0.537640929 | 0.537667453 |
| CivilLiberties | 0.27023625 | -0.589725614 | 0.589622200 |
| ElectoralProcess | -0.23420817 | 0.493383318 | -0.493352205 |
| PoliticalPluralism | -0.23018314 | 0.521081924 | -0.520920813 |
| GovtFunction | -0.25261465 | 0.560757399 | -0.560876071 |
| FreedomExpressio | n -0.22634208 | 0.519603014 | -0.519470930 |
| AssocRights - | 0.22636390 | 0.507611513 | -0.507318377 |

| RuleLaw | -0.27063823 | 0.583854020 | -0.583960295 | |
|-----------------|-------------|--------------|--------------|--|
| IndivRights | -0.34219384 | 0.678043783 | -0.677946806 | |
| FreedomStatus | 0.19605599 | -0.471143216 | 0.471388847 | |
| DISAP2005 | -0.07118428 | 0.262089640 | -0.261888802 | |
| Progress_ST | 0.37397963 | -0.369489759 | 0.369453013 | |
| GDP | -0.31272355 | 0.948860645 | -0.948753536 | |
| HDI_Trends_Rank | 0.38339147 | -0.999986410 | 1.000000000 | |
| GDPpercap | -0.30870351 | 0.949518323 | -0.949401975 | |
| LifeBirth | -0.32445711 | 0.933804154 | -0.933910191 | |
| LifeExp | -0.32460445 | 0.933611095 | -0.933715522 | |
| EarnIng_Female | -0.36146429 | 0.944190621 | -0.944079757 | |
| Seats_Women | -0.17863925 | 0.234579623 | -0.234277889 | |
| Admin_Women | -0.33580786 | 0.097385503 | -0.096904181 | |
| Prof_Women | -0.52336985 | 0.183156326 | -0.183604211 | |
| EarnIng_Male | -0.29610494 | 0.945450902 | -0.945398688 | |
| OLD_EMPINX1990 | -0.32388648 | 0.535366893 | -0.534776509 | |
| SPEECH1990 | -0.28245655 | 0.453809977 | -0.453614801 | |
| ELECSD2007 | -0.08909162 | 0.336264402 | -0.336110085 | |
| Progress_LT | 0.50145411 | -0.329182148 | 0.328977227 | |
| Progress_MT | 0.50059414 | -0.301268607 | 0.301322252 | |
| ALR | -0.49664107 | 0.783320844 | -0.783357978 | |
| EdEnroll | -0.35110492 | 0.869987845 | -0.869750559 | |
| Edu | -0.48087588 | 0.878686428 | -0.878678679 | |
| WOSOC2003 | -0.29256171 | 0.582607567 | -0.582167447 | |
| WECON2003 | -0.25238499 | 0.535259247 | -0.535613835 | |

| WOPOL2006 | -0.23135683 | 0.163696811 | -0.163358018 |
|-------------------|-------------|--------------|--------------|
| COW | 0.24906459 | -0.320214957 | 0.319751441 |
| POLITY | 0.25102791 | -0.323124617 | 0.322670043 |
| UNSUBREG | -0.26096317 | 0.535796463 | -0.535898864 |
| Unimprov_Water | 0.25045758 | -0.818641841 | 0.818749607 |
| LifeBirth_Female | -0.36299199 | 0.944966912 | -0.945028365 |
| LifeBirth_Male | -0.28515211 | 0.907627106 | -0.907730341 |
| AdultLit_Female | -0.49747863 | 0.781164289 | -0.781269133 |
| AdultLit_Male | -0.47851905 | 0.774360538 | -0.774483085 |
| EnrollEduc_Female | -0.36894932 | 0.875091255 | -0.874780774 |
| EnrollEduc_Male | -0.36054954 | 0.855759263 | -0.855338871 |
| Surv_40 | 0.23032515 | -0.912202239 | 0.912346423 |
| Poverty_200 | 0.32868043 | -0.900733054 | 0.900777519 |
| POLPRIS1993 | 0.11815877 | -0.040827919 | 0.040728055 |

| | PoliticalRights | CivilLiberties | ElectoralProcess |
|-------------------|-----------------|----------------|------------------|
| Failing_Rank | 0.547075510 | 0.57924598 | -0.50577277 |
| AdultLit_2005 | 0.130059496 | 0.15963461 | -0.10522731 |
| EnrolEduc_2005 | -0.052030262 | -0.02943255 | 0.07096975 |
| GDPpercap_2005 | -0.006106872 | -0.01918423 | -0.02855849 |
| AdultLit_2006 | 0.243573412 | 0.27023625 | -0.23420817 |
| HDI_2006 | -0.537640929 | -0.58972561 | 0.49338332 |
| HDI_A1Reconcil_Ra | nk 0.537667453 | 0.58962220 | -0.49335220 |
| PoliticalRights | 1.000000000 | 0.94438207 | -0.96647555 |
| CivilLiberties | 0.944382071 | 1.00000000 | -0.90561801 |

| ElectoralProcess | -0.966475546 | -0.90561801 | 1.00000000 |
|--------------------|--------------|-------------|-------------|
| PoliticalPluralism | -0.967481136 | -0.94134063 | 0.93654853 |
| GovtFunction | -0.954280257 | -0.93319625 | 0.90849406 |
| FreedomExpression | -0.930052221 | -0.95643997 | 0.90285641 |
| AssocRights | -0.932795167 | -0.95032841 | 0.91222590 |
| RuleLaw | -0.917431831 | -0.96034533 | 0.86626369 |
| IndivRights | -0.890894294 | -0.94611591 | 0.85111308 |
| FreedomStatus | 0.937147439 | 0.91540259 | -0.90272355 |
| DISAP2005 | -0.391567826 | -0.40905383 | 0.37371707 |
| Progress_ST | 0.317109346 | 0.33829808 | -0.28972384 |
| GDP | -0.442463905 | -0.49958798 | 0.40239230 |
| HDI_Trends_Rank | 0.539304614 | 0.59112281 | -0.49542701 |
| GDPpercap | -0.441896707 | -0.49894869 | 0.40206948 |
| LifeBirth | -0.507694662 | -0.54861081 | 0.46441242 |
| LifeExp | -0.507705510 | -0.54860926 | 0.46435705 |
| EarnIng_Female | -0.509087205 | -0.57436627 | 0.47139797 |
| Seats_Women | -0.169129208 | -0.17236039 | 0.19086848 |
| Admin_Women | -0.361237884 | -0.40966564 | 0.37493256 |
| Prof_Women | -0.295592576 | -0.33614707 | 0.32507414 |
| EarnIng_Male | -0.446632862 | -0.50253177 | 0.40700874 |
| OLD_EMPINX1990 | -0.780963004 | -0.82143790 | 0.76257253 |
| SPEECH1990 | -0.666586757 | -0.69026029 | 0.64663094 |
| ELECSD2007 | -0.755801678 | -0.70969433 | 0.77142590 |
| Progress_LT | 0.494528115 | 0.48357841 | -0.47228754 |
| Progress_MT | 0.238795444 | 0.25357905 | -0.23140550 |

| ALR | -0.243760973 | -0.32802901 | 0.21199600 |
|-------------------|--------------|-------------|-------------|
| EdEnroll | -0.533041298 | -0.56538314 | 0.50561786 |
| Edu | -0.527754903 | -0.57763833 | 0.48754296 |
| WOSOC2003 | -0.518549263 | -0.53657407 | 0.49574777 |
| WECON2003 | -0.400483310 | -0.47706851 | 0.36419705 |
| WOPOL2006 | -0.283918798 | -0.26337799 | 0.32338703 |
| COW | 0.431596041 | 0.40458068 | -0.47683045 |
| POLITY | 0.432444811 | 0.40580153 | -0.47756970 |
| UNSUBREG | -0.158068240 | -0.21357927 | 0.12505431 |
| Unimprov_Water | 0.351939023 | 0.41801113 | -0.32900479 |
| LifeBirth_Female | -0.551280260 | -0.59265864 | 0.50950617 |
| LifeBirth_Male | -0.503672481 | -0.54320037 | 0.45627579 |
| AdultLit_Female | -0.312993139 | -0.40503189 | 0.27375188 |
| AdultLit_Male | -0.208135977 | -0.30488029 | 0.17642967 |
| EnrollEduc_Female | -0.562310994 | -0.59900844 | 0.53738141 |
| EnrollEduc_Male | -0.556681752 | -0.57583493 | 0.53276849 |
| Surv_40 | 0.303058505 | 0.37749767 | -0.25048339 |
| Poverty_200 | 0.362890124 | 0.43846568 | -0.37244534 |
| POLPRIS1993 | -0.081042729 | -0.10071660 | 0.09601165 |
| | | | |

| | PoliticalPluralism | GovtFunction | FreedomExpression |
|----------------|--------------------|--------------|-------------------|
| Failing_Rank | -0.53421974 | -0.580383241 | -0.56814373 |
| AdultLit_2005 | -0.10544204 | -0.139489546 | -0.12557831 |
| EnrolEduc_2005 | 0.04691146 | 0.004910082 | 0.01545029 |
| GDPpercap_2005 | 0.01030393 | 0.033694092 | 0.03447689 |

| AdultLit_2006 | -0.23018314 | -0.252614647 | -0.22634208 |
|--------------------|---------------|--------------|-------------|
| HDI_2006 | 0.52108192 | 0.560757399 | 0.51960301 |
| HDI_A1Reconcil_Ran | k -0.52092081 | -0.560876071 | -0.51947093 |
| PoliticalRights | -0.96748114 | -0.954280257 | -0.93005222 |
| CivilLiberties | -0.94134063 | -0.933196247 | -0.95643997 |
| ElectoralProcess | 0.93654853 | 0.908494055 | 0.90285641 |
| PoliticalPluralism | 1.00000000 | 0.923494518 | 0.93779808 |
| GovtFunction | 0.92349452 | 1.000000000 | 0.91280740 |
| FreedomExpression | 0.93779808 | 0.912807405 | 1.00000000 |
| AssocRights | 0.93330145 | 0.915465117 | 0.93549627 |
| RuleLaw | 0.91224945 | 0.933803260 | 0.91087741 |
| IndivRights | 0.89299595 | 0.905044854 | 0.90060008 |
| FreedomStatus | -0.91974729 | -0.902664602 | -0.90618026 |
| DISAP2005 | 0.37945792 | 0.383428782 | 0.40070885 |
| Progress_ST | -0.33597210 | -0.342695504 | -0.33543631 |
| GDP | 0.42316464 | 0.483143061 | 0.44266516 |
| HDI_Trends_Rank | -0.52247071 | -0.562402070 | -0.52160841 |
| GDPpercap | 0.42253974 | 0.482644200 | 0.44210896 |
| LifeBirth | 0.48506752 | 0.550043225 | 0.48420775 |
| LifeExp | 0.48538163 | 0.550045073 | 0.48435014 |
| EarnIng_Female | 0.49844387 | 0.535347044 | 0.52168965 |
| Seats_Women | 0.18328646 | 0.225743100 | 0.18597150 |
| Admin_Women | 0.35284200 | 0.359516889 | 0.44221571 |
| Prof_Women | 0.28336206 | 0.273163706 | 0.32873791 |
| EarnIng_Male | 0.43187645 | 0.477569699 | 0.44749025 |

| OLD_EMPINX1990 | 0.78297788 | 0.757665157 | 0.80487406 |
|-------------------|-------------|--------------|-------------|
| SPEECH1990 | 0.67512572 | 0.626532197 | 0.69412965 |
| ELECSD2007 | 0.74897516 | 0.716874361 | 0.73179197 |
| Progress_LT | -0.48545143 | -0.470533818 | -0.48946443 |
| Progress_MT | -0.22253641 | -0.266235441 | -0.26388118 |
| ALR | 0.22059275 | 0.251771897 | 0.24473839 |
| EdEnroll | 0.52428097 | 0.534959435 | 0.54515082 |
| Edu | 0.51863372 | 0.536301315 | 0.52927285 |
| WOSOC2003 | 0.52192920 | 0.519593835 | 0.51619965 |
| WECON2003 | 0.42172581 | 0.451772451 | 0.42449170 |
| WOPOL2006 | 0.28983042 | 0.319381565 | 0.26854649 |
| COW | -0.44038776 | -0.400209546 | -0.43980920 |
| POLITY | -0.44002721 | -0.400294334 | -0.44047418 |
| UNSUBREG | 0.15186514 | 0.219719529 | 0.14879431 |
| Unimprov_Water | -0.32313126 | -0.388489008 | -0.35152331 |
| LifeBirth_Female | 0.52711606 | 0.586949170 | 0.52089614 |
| LifeBirth_Male | 0.48775935 | 0.547114909 | 0.47604969 |
| AdultLit_Female | 0.29396018 | 0.312303603 | 0.33988979 |
| AdultLit_Male | 0.19503127 | 0.209660277 | 0.23070431 |
| EnrollEduc_Female | 0.55225074 | 0.570115864 | 0.58038723 |
| EnrollEduc_Male | 0.55314618 | 0.553605437 | 0.55801022 |
| Surv_40 | -0.28051412 | -0.330858260 | -0.27705276 |
| Poverty_200 | -0.35086536 | -0.330064088 | -0.36027229 |
| POLPRIS1993 | 0.07560226 | 0.083667815 | 0.08423979 |

| | AssocRights | RuleLaw | IndivRights | FreedomStatus |
|--------------------|----------------|--------------|--------------|---------------|
| Failing_Rank | -0.52849948 | -0.585141242 | -0.601009011 | 0.51773691 |
| AdultLit_2005 | -0.12270474 | -0.160482436 | -0.201065212 | 0.10652321 |
| EnrolEduc_2005 | 0.03447307 | 0.016468972 | -0.006057321 | -0.04731078 |
| GDPpercap_2005 | 0.02242090 | 0.005314687 | 0.037086338 | 0.02970678 |
| AdultLit_2006 | -0.22636390 | -0.270638227 | -0.342193842 | 0.19605599 |
| HDI_2006 | 0.50761151 | 0.583854020 | 0.678043783 | -0.47114322 |
| HDI_A1Reconcil_Rai | nk -0.50731838 | -0.583960295 | -0.677946806 | 0.47138885 |
| PoliticalRights | -0.93279517 | -0.917431831 | -0.890894294 | 0.93714744 |
| CivilLiberties | -0.95032841 | -0.960345328 | -0.946115911 | 0.91540259 |
| ElectoralProcess | 0.91222590 | 0.866263688 | 0.851113081 | -0.90272355 |
| PoliticalPluralism | 0.93330145 | 0.912249446 | 0.892995954 | -0.91974729 |
| GovtFunction | 0.91546512 | 0.933803260 | 0.905044854 | -0.90266460 |
| FreedomExpression | 0.93549627 | 0.910877407 | 0.900600076 | -0.90618026 |
| AssocRights | 1.00000000 | 0.903326452 | 0.885020554 | -0.90136027 |
| RuleLaw | 0.90332645 | 1.000000000 | 0.931369185 | -0.88168204 |
| IndivRights | 0.88502055 | 0.931369185 | 1.000000000 | -0.85831940 |
| FreedomStatus | -0.90136027 | -0.881682038 | -0.858319402 | 1.00000000 |
| DISAP2005 | 0.38118166 | 0.432924509 | 0.369896233 | -0.35271356 |
| Progress_ST | -0.33471537 | -0.355973721 | -0.380730152 | 0.28981361 |
| GDP | 0.43337011 | 0.496219039 | 0.578128934 | -0.39208645 |
| HDI_Trends_Rank | -0.50939190 | -0.585429370 | -0.678846180 | 0.47366464 |
| GDPpercap | 0.43282714 | 0.495879650 | 0.577812135 | -0.39143285 |
| LifeBirth | 0.48174530 | 0.544982791 | 0.658314168 | -0.44294170 |
| LifeExp | 0.48177880 | 0.545050979 | 0.658454835 | -0.44312918 |

| EarnIng_Female | 0.50724006 | 0.562206268 | 0.649822354 | -0.45731312 |
|-------------------|-------------|--------------|--------------|-------------|
| Seats_Women | 0.18437541 | 0.163147897 | 0.221796528 | -0.16207905 |
| Admin_Women | 0.33993477 | 0.337255567 | 0.384615868 | -0.40714043 |
| Prof_Women | 0.34134516 | 0.255117953 | 0.338858575 | -0.35722876 |
| EarnIng_Male | 0.42999730 | 0.497813821 | 0.579064548 | -0.39733073 |
| OLD_EMPINX1990 | 0.78413832 | 0.781591654 | 0.797511578 | -0.75761771 |
| SPEECH1990 | 0.66621572 | 0.677234948 | 0.645810485 | -0.62820321 |
| ELECSD2007 | 0.73334098 | 0.674335003 | 0.657062292 | -0.70252407 |
| Progress_LT | -0.50133830 | -0.495151192 | -0.454295814 | 0.43065155 |
| Progress_MT | -0.28944305 | -0.267498165 | -0.249489918 | 0.20248102 |
| ALR | 0.23055692 | 0.315209240 | 0.440868437 | -0.23085994 |
| EdEnroll | 0.51493520 | 0.542042851 | 0.639029384 | -0.49623731 |
| Edu | 0.51217872 | 0.567452431 | 0.653799772 | -0.47999164 |
| WOSOC2003 | 0.49893105 | 0.519890606 | 0.586038828 | -0.47310460 |
| WECON2003 | 0.41038567 | 0.497486442 | 0.529785454 | -0.36614451 |
| WOPOL2006 | 0.29613894 | 0.281660408 | 0.308042765 | -0.25010797 |
| COW | -0.44038177 | -0.330050915 | -0.399929792 | 0.40967098 |
| POLITY | -0.44177458 | -0.331039965 | -0.401823014 | 0.40869999 |
| UNSUBREG | 0.16477765 | 0.235176206 | 0.281042755 | -0.11539730 |
| Unimprov_Water | -0.33562526 | -0.392918140 | -0.528129756 | 0.34662068 |
| LifeBirth_Female | 0.52316189 | 0.586472988 | 0.690726399 | -0.47985685 |
| LifeBirth_Male | 0.46576345 | 0.547383904 | 0.650316358 | -0.43232995 |
| AdultLit_Female | 0.29741171 | 0.396186680 | 0.511588335 | -0.29893103 |
| AdultLit_Male | 0.20988682 | 0.297066927 | 0.434626371 | -0.20098864 |
| EnrollEduc_Female | 0.54704469 | 0.569474757 | 0.663271666 | -0.51802528 |

| EnrollEduc_Male | 0.54254824 | 0.554376602 | 0.654744983 | -0.49900439 |
|--------------------|-----------------|--------------|--------------|----------------|
| Surv_40 | -0.26576987 | -0.366238058 | -0.509423077 | 0.27980503 |
| Poverty_200 | -0.32478002 | -0.374444664 | -0.577836871 | 0.34788749 |
| POLPRIS1993 | 0.08413205 | 0.121352091 | 0.063788973 | -0.11349798 |
| | | | | |
| | DISAP2005 | Progress_ST | GDP H | OI_Trends_Rank |
| Failing_Rank | -0.38758761 | 0.186396584 | -0.615025342 | 0.630957186 |
| AdultLit_2005 | -0.03165168 | 0.210950449 | -0.160677791 | 0.192083940 |
| EnrolEduc_2005 | 0.11802264 | 0.210710496 | 0.006351876 | 0.005436544 |
| GDPpercap_2005 | 0.11195165 | 0.031337664 | 0.536121130 | -0.429583192 |
| AdultLit_2006 | -0.07118428 | 0.373979628 | -0.312723547 | 0.383391470 |
| HDI_2006 | 0.26208964 | -0.369489759 | 0.948860645 | -0.999986410 |
| HDI_A1Reconcil_Ra | ınk -0.26188880 | 0.369453013 | -0.948753536 | 1.000000000 |
| PoliticalRights | -0.39156783 | 0.317109346 | -0.442463905 | 0.539304614 |
| CivilLiberties | -0.40905383 | 0.338298082 | -0.499587983 | 0.591122806 |
| ElectoralProcess | 0.37371707 | -0.289723843 | 0.402392298 | -0.495427012 |
| PoliticalPluralism | 0.37945792 | -0.335972100 | 0.423164636 | -0.522470713 |
| GovtFunction | 0.38342878 | -0.342695504 | 0.483143061 | -0.562402070 |
| FreedomExpression | 0.40070885 | -0.335436314 | 0.442665160 | -0.521608412 |
| AssocRights | 0.38118166 | -0.334715366 | 0.433370113 | -0.509391904 |
| RuleLaw | 0.43292451 | -0.355973721 | 0.496219039 | -0.585429370 |
| IndivRights | 0.36989623 | -0.380730152 | 0.578128934 | -0.678846180 |
| FreedomStatus | -0.35271356 | 0.289813608 | -0.392086446 | 0.473664641 |
| DISAP2005 | 1.00000000 | -0.186140329 | 0.221342877 | -0.259035915 |
| Progress_ST | -0.18614033 | 1.000000000 | -0.344958752 | 0.370078027 |

| GDP | 0.22134288 | -0.344958752 | 1.000000000 | -0.948297203 |
|-----------------|-------------|--------------|--------------|--------------|
| HDI_Trends_Rank | -0.25903592 | 0.370078027 | -0.948297203 | 1.000000000 |
| GDPpercap | 0.22147235 | -0.345790416 | 0.999931693 | -0.948935449 |
| LifeBirth | 0.26513770 | -0.352263957 | 0.833822966 | -0.934383154 |
| LifeExp | 0.26473927 | -0.352857381 | 0.833632469 | -0.934191704 |
| EarnIng_Female | 0.22887747 | -0.364341646 | 0.978015304 | -0.944079757 |
| Seats_Women | 0.04473292 | -0.317611843 | 0.202271461 | -0.234277889 |
| Admin_Women | 0.18362819 | -0.279127896 | 0.067554861 | -0.096904181 |
| Prof_Women | 0.11569655 | -0.123055354 | 0.100230381 | -0.183604211 |
| EarnIng_Male | 0.22555541 | -0.337840527 | 0.996558785 | -0.945398688 |
| OLD_EMPINX1990 | 0.27764863 | -0.436269104 | 0.492423385 | -0.535376728 |
| SPEECH1990 | 0.26300561 | -0.339644790 | 0.428210199 | -0.455012769 |
| ELECSD2007 | 0.28562614 | -0.194780171 | 0.277367920 | -0.339494526 |
| Progress_LT | -0.33144596 | 0.705702841 | -0.282749414 | 0.324108154 |
| Progress_MT | -0.20802465 | 0.444662631 | -0.363772452 | 0.309781939 |
| ALR | 0.17478155 | -0.202458784 | 0.643701196 | -0.781870544 |
| EdEnroll | 0.26815289 | -0.370891184 | 0.785950124 | -0.871269345 |
| Edu | 0.26020411 | -0.382997453 | 0.770789921 | -0.879901290 |
| WOSOC2003 | 0.21412116 | -0.237325519 | 0.462973744 | -0.582167447 |
| WECON2003 | 0.27278146 | -0.096584536 | 0.458737671 | -0.537212014 |
| WOPOL2006 | 0.06807546 | -0.316652805 | 0.157701313 | -0.170307815 |
| COW | -0.17106958 | 0.228187740 | -0.298374653 | 0.322819710 |
| POLITY | -0.17106958 | 0.228187740 | -0.300163329 | 0.325753957 |
| UNSUBREG | 0.07847913 | -0.114679649 | 0.499518812 | -0.534262955 |
| Unimprov_Water | -0.18781652 | 0.243267313 | -0.753166914 | 0.819719911 |

| LifeBirth_Female | 0.27737620 | -0.348840356 | 0.842526913 | -0.945028365 |
|--------------------|------------------|--------------|--------------|----------------|
| LifeBirth_Male | 0.27163446 | -0.341296762 | 0.811933637 | -0.907730341 |
| AdultLit_Female | 0.18938942 | -0.245197400 | 0.650438786 | -0.781269133 |
| AdultLit_Male | 0.15826266 | -0.142696589 | 0.652076244 | -0.774483085 |
| EnrollEduc_Female | 0.26854813 | -0.363403320 | 0.785921633 | -0.874780774 |
| EnrollEduc_Male | 0.22618480 | -0.373896956 | 0.770073414 | -0.855338871 |
| Surv_40 | -0.23300095 | 0.117368340 | -0.777336240 | 0.912840903 |
| Poverty_200 | -0.16810924 | 0.108158514 | -0.872796237 | 0.900777519 |
| POLPRIS1993 | 0.16626303 | 0.004667582 | -0.037407175 | 0.031312138 |
| | GDPpercap | LifeBirth | LifeExp | EarnIng_Female |
| Failing_Rank | -0.6140525937 | -0.60013753 | -0.59949005 | -0.64474130 |
| AdultLit_2005 | -0.1709633321 | -0.13539150 | -0.13514304 | -0.19459738 |
| EnrolEduc_2005 | 0.0003752598 | -0.07523682 | -0.07594095 | 0.02863284 |
| GDPpercap_2005 | 0.5365303159 | 0.32300600 | 0.32311612 | 0.49979454 |
| AdultLit_2006 | -0.3087035120 | -0.32445711 | -0.32460445 | -0.36146429 |
| HDI_2006 | 0.9495183229 | 0.93380415 | 0.93361109 | 0.94419062 |
| HDI_A1Reconcil_Rar | nk -0.9494019747 | -0.93391019 | -0.93371552 | -0.94407976 |
| PoliticalRights | -0.4418967068 | -0.50769466 | -0.50770551 | -0.50908720 |
| CivilLiberties | -0.4989486933 | -0.54861081 | -0.54860926 | -0.57436627 |
| ElectoralProcess | 0.4020694792 | 0.46441242 | 0.46435705 | 0.47139797 |
| PoliticalPluralism | 0.4225397408 | 0.48506752 | 0.48538163 | 0.49844387 |
| GovtFunction | 0.4826442003 | 0.55004323 | 0.55004507 | 0.53534704 |
| FreedomExpression | 0.4421089590 | 0.48420775 | 0.48435014 | 0.52168965 |
| AssocRights | 0.4328271449 | 0.48174530 | 0.48177880 | 0.50724006 |
| RuleLaw | 0.4958796501 | 0.54498279 | 0.54505098 | 0.56220627 |

| IndivRights | 0.5778121352 | 0.65831417 | 0.65845484 | 0.64982235 |
|-----------------|---------------|-------------|-------------|-------------|
| FreedomStatus | -0.3914328516 | -0.44294170 | -0.44312918 | -0.45731312 |
| DISAP2005 | 0.2214723527 | 0.26513770 | 0.26473927 | 0.22887747 |
| Progress_ST | -0.3457904160 | -0.35226396 | -0.35285738 | -0.36434165 |
| GDP | 0.9999316931 | 0.83382297 | 0.83363247 | 0.97801530 |
| HDI_Trends_Rank | -0.9489354491 | -0.93438315 | -0.93419170 | -0.94407976 |
| GDPpercap | 1.0000000000 | 0.83794165 | 0.83773381 | 0.97929943 |
| LifeBirth | 0.8379416466 | 1.00000000 | 0.99998194 | 0.82415754 |
| LifeExp | 0.8377338052 | 0.99998194 | 1.00000000 | 0.82403356 |
| EarnIng_Female | 0.9792994261 | 0.82415754 | 0.82403356 | 1.00000000 |
| Seats_Women | 0.2025850564 | 0.21750504 | 0.21703789 | 0.25052324 |
| Admin_Women | 0.0503443778 | 0.01578032 | 0.01587339 | 0.19479311 |
| Prof_Women | 0.0810177699 | 0.06930289 | 0.07026724 | 0.23616332 |
| EarnIng_Male | 0.9964874387 | 0.83960348 | 0.83934879 | 0.96892852 |
| OLD_EMPINX1990 | 0.4923361838 | 0.49735919 | 0.49798006 | 0.54505062 |
| SPEECH1990 | 0.4281404912 | 0.42805210 | 0.42850965 | 0.45880964 |
| ELECSD2007 | 0.2769346237 | 0.30917901 | 0.30930671 | 0.34058225 |
| Progress_LT | -0.2833374441 | -0.23367557 | -0.23324271 | -0.37816095 |
| Progress_MT | -0.3646709621 | -0.14368549 | -0.14395040 | -0.40452957 |
| ALR | 0.6467152834 | 0.63511461 | 0.63477045 | 0.69960511 |
| EdEnroll | 0.7916238904 | 0.76990497 | 0.76971710 | 0.81314903 |
| Edu | 0.7741427422 | 0.76786393 | 0.76755524 | 0.81711841 |
| WOSOC2003 | 0.4629864693 | 0.50605863 | 0.50630742 | 0.53674096 |
| WECON2003 | 0.4583230317 | 0.50723892 | 0.50647449 | 0.49472439 |
| WOPOL2006 | 0.1584373116 | 0.13928635 | 0.13922371 | 0.19467112 |

| COW | -0.2973598540 | -0.33543274 | -0.33605617 | -0.32135794 |
|---|--|--|--|---|
| POLITY | -0.2991590202 | -0.33939192 | -0.34001246 | -0.32420799 |
| UNSUBREG | 0.5003862977 | 0.43119729 | 0.43050861 | 0.51639909 |
| Unimprov_Water | -0.7535790801 | -0.75996768 | -0.75976670 | -0.74140477 |
| LifeBirth_Female | 0.8444795609 | 0.97360003 | 0.97351211 | 0.84242189 |
| LifeBirth_Male | 0.8168677092 | 0.97839665 | 0.97844064 | 0.79425037 |
| AdultLit_Female | 0.6508321166 | 0.64332259 | 0.64333636 | 0.70126492 |
| AdultLit_Male | 0.6578247547 | 0.64284146 | 0.64261901 | 0.68865925 |
| EnrollEduc_Female | e 0.7919008732 | 0.77614331 | 0.77576137 | 0.81747997 |
| EnrollEduc_Male | 0.7756068110 | 0.75986940 | 0.75976247 | 0.80654687 |
| Surv_40 | -0.7838840485 | -0.97104955 | -0.97090280 | -0.74592066 |
| Poverty_200 | -0.8726763129 | -0.81007999 | -0.80958456 | -0.85819232 |
| DOI DDIC4000 | | | | |
| POLPRIS1993 | -0.0366780385 | -0.01074270 | -0.01153954 | -0.07091042 |
| POLPRIS1993 | -0.0366780385 Seats_Women | -0.01074270 Admin_Women | -0.01153954 Prof_Women | -0.07091042 EarnIng_Male |
| Failing_Rank | | | | |
| | Seats_Women | Admin_Women | Prof_Women | EarnIng_Male |
| Failing_Rank | Seats_Women -0.250704020 | Admin_Women -0.176017553 | Prof_Women -0.10955402 | EarnIng_Male -0.6423724890 |
| Failing_Rank AdultLit_2005 | Seats_Women -0.250704020 -0.065957054 0.002930084 | Admin_Women -0.176017553 -0.212983161 | Prof_Women -0.10955402 -0.41417724 | EarnIng_Male -0.6423724890 -0.1454436332 |
| Failing_Rank AdultLit_2005 EnrolEduc_2005 | Seats_Women -0.250704020 -0.065957054 0.002930084 | Admin_Women -0.176017553 -0.212983161 0.009482214 | Prof_Women -0.10955402 -0.41417724 0.09979217 | EarnIng_Male -0.6423724890 -0.1454436332 0.0001138583 |
| Failing_Rank AdultLit_2005 EnrolEduc_2005 GDPpercap_2005 | Seats_Women -0.250704020 -0.065957054 0.002930084 -0.067054778 | Admin_Women -0.176017553 -0.212983161 0.009482214 0.011029314 | Prof_Women -0.10955402 -0.41417724 0.09979217 -0.10103244 | EarnIng_Male -0.6423724890 -0.1454436332 0.0001138583 0.5280352831 |
| Failing_Rank AdultLit_2005 EnrolEduc_2005 GDPpercap_2005 AdultLit_2006 | Seats_Women -0.250704020 -0.065957054 0.002930084 -0.067054778 -0.178639248 0.234579623 | Admin_Women -0.176017553 -0.212983161 0.009482214 0.011029314 -0.335807860 | Prof_Women -0.10955402 -0.41417724 0.09979217 -0.10103244 -0.52336985 | EarnIng_Male -0.6423724890 -0.1454436332 0.0001138583 0.5280352831 -0.2961049378 |
| Failing_Rank AdultLit_2005 EnrolEduc_2005 GDPpercap_2005 AdultLit_2006 HDI_2006 | Seats_Women -0.250704020 -0.065957054 0.002930084 -0.067054778 -0.178639248 0.234579623 | Admin_Women -0.176017553 -0.212983161 0.009482214 0.011029314 -0.335807860 0.097385503 | Prof_Women -0.10955402 -0.41417724 0.09979217 -0.10103244 -0.52336985 0.18315633 | EarnIng_Male -0.6423724890 -0.1454436332 0.0001138583 0.5280352831 -0.2961049378 0.9454509020 |
| Failing_Rank AdultLit_2005 EnrolEduc_2005 GDPpercap_2005 AdultLit_2006 HDI_2006 HDI_A1Reconcil_R | Seats_Women -0.250704020 -0.065957054 0.002930084 -0.067054778 -0.178639248 0.234579623 cank -0.234277889 | Admin_Women -0.176017553 -0.212983161 0.009482214 0.011029314 -0.335807860 0.097385503 -0.096904181 | Prof_Women -0.10955402 -0.41417724 0.09979217 -0.10103244 -0.52336985 0.18315633 -0.18360421 | EarnIng_Male -0.6423724890 -0.1454436332 0.0001138583 0.5280352831 -0.2961049378 0.9454509020 -0.9453986883 |
| Failing_Rank AdultLit_2005 EnrolEduc_2005 GDPpercap_2005 AdultLit_2006 HDI_2006 HDI_A1Reconcil_R PoliticalRights | Seats_Women -0.250704020 -0.065957054 0.002930084 -0.067054778 -0.178639248 0.234579623 tank -0.234277889 -0.169129208 | Admin_Women -0.176017553 -0.212983161 0.009482214 0.011029314 -0.335807860 0.097385503 -0.096904181 -0.361237884 | Prof_Women -0.10955402 -0.41417724 0.09979217 -0.10103244 -0.52336985 0.18315633 -0.18360421 -0.29559258 | EarnIng_Male -0.6423724890 -0.1454436332 0.0001138583 0.5280352831 -0.2961049378 0.9454509020 -0.9453986883 -0.4466328621 |

| GovtFunction | 0.225743100 | 0.359516889 | 0.27316371 | 0.4775696993 |
|-------------------|--------------|--------------|-------------|---------------|
| FreedomExpression | 0.185971498 | 0.442215711 | 0.32873791 | 0.4474902451 |
| AssocRights | 0.184375405 | 0.339934766 | 0.34134516 | 0.4299972951 |
| RuleLaw | 0.163147897 | 0.337255567 | 0.25511795 | 0.4978138208 |
| IndivRights | 0.221796528 | 0.384615868 | 0.33885857 | 0.5790645480 |
| FreedomStatus | -0.162079051 | -0.407140434 | -0.35722876 | -0.3973307312 |
| DISAP2005 | 0.044732921 | 0.183628187 | 0.11569655 | 0.2255554050 |
| Progress_ST | -0.317611843 | -0.279127896 | -0.12305535 | -0.3378405273 |
| GDP | 0.202271461 | 0.067554861 | 0.10023038 | 0.9965587854 |
| HDI_Trends_Rank | -0.234277889 | -0.096904181 | -0.18360421 | -0.9453986883 |
| GDPpercap | 0.202585056 | 0.050344378 | 0.08101777 | 0.9964874387 |
| LifeBirth | 0.217505038 | 0.015780324 | 0.06930289 | 0.8396034837 |
| LifeExp | 0.217037886 | 0.015873395 | 0.07026724 | 0.8393487930 |
| EarnIng_Female | 0.250523239 | 0.194793105 | 0.23616332 | 0.9689285159 |
| Seats_Women | 1.000000000 | 0.270869136 | 0.18667163 | 0.1784800887 |
| Admin_Women | 0.270869136 | 1.000000000 | 0.55485570 | 0.0420527458 |
| Prof_Women | 0.186671630 | 0.554855704 | 1.00000000 | 0.0667365342 |
| EarnIng_Male | 0.178480089 | 0.042052746 | 0.06673653 | 1.0000000000 |
| OLD_EMPINX1990 | 0.236425236 | 0.469473720 | 0.48713535 | 0.4775406420 |
| SPEECH1990 | 0.177913979 | 0.310264796 | 0.33900404 | 0.4133956730 |
| ELECSD2007 | 0.157554716 | 0.363321334 | 0.25589523 | 0.2750814259 |
| Progress_LT | -0.388169020 | -0.506690502 | -0.48862085 | -0.2970980108 |
| Progress_MT | -0.196966648 | -0.426243305 | -0.45877489 | -0.3362294137 |
| ALR | 0.061867572 | 0.336560100 | 0.72111654 | 0.6393366456 |
| EdEnroll | 0.220086604 | 0.313123196 | 0.39774960 | 0.7925933599 |

| Edu | 0.252111644 | 0.284347355 | 0.53006250 | 0.7691794038 |
|------------------|----------------|--------------|-------------|---------------|
| WOSOC2003 | 0.315631002 | 0.218239084 | 0.30404428 | 0.4715750217 |
| WECON2003 | 0.272065282 | 0.181219324 | 0.19969313 | 0.4598045349 |
| WOPOL2006 | 0.604778945 | 0.283548146 | 0.30742148 | 0.1138004288 |
| COW | -0.297051758 | -0.440053046 | -0.35137358 | -0.2823579907 |
| POLITY | -0.294671714 | -0.436909318 | -0.34906891 | -0.2845457792 |
| UNSUBREG | 0.024909241 | -0.130753189 | 0.10268971 | 0.5175127387 |
| Unimprov_Water | -0.079555154 | -0.078664586 | -0.34315640 | -0.7614439130 |
| LifeBirth_Female | 0.211445138 | 0.071581215 | 0.14638385 | 0.8475594521 |
| LifeBirth_Male | 0.176071927 | -0.048765160 | -0.03498290 | 0.8216308951 |
| AdultLit_Female | 0.110621594 | 0.484909922 | 0.76123810 | 0.6312161088 |
| AdultLit_Male | 0.084503479 | 0.298121065 | 0.66249830 | 0.6393441558 |
| EnrollEduc_Fema | le 0.241279557 | 0.354479909 | 0.44256899 | 0.7923355699 |
| EnrollEduc_Male | 0.231503934 | 0.243843228 | 0.31778511 | 0.7793121338 |
| Surv_40 | 0.058021832 | 0.119456396 | -0.08131274 | -0.7819010019 |
| Poverty_200 | 0.033583030 | -0.158697531 | -0.44135115 | -0.8726723790 |
| POLPRIS1993 | -0.197988003 | 0.162749872 | -0.08437014 | -0.0380039848 |
| | | | | |
| | OLD_EMPINX1990 | SPEECH1990 | ELECSD2007 | Progress_LT |
| Failing_Rank | -0.44005004 | -0.44005945 | -0.43849507 | 0.3762651980 |
| AdultLit_2005 | -0.21366489 | -0.19672032 | -0.03614708 | 0.3851404190 |
| EnrolEduc_2005 | -0.04525104 | -0.05297441 | 0.03618898 | 0.0581945032 |
| GDPpercap_2005 | 0.04715152 | 0.15977356 | -0.01245475 | -0.0150663778 |
| AdultLit_2006 | -0.32388648 | -0.28245655 | -0.08909162 | 0.5014541149 |
| HDI_2006 | 0.53536689 | 0.45380998 | 0.33626440 | -0.3291821480 |

| HDI_A1Reconcil_Rar | nk -0.53477651 | -0.45361480 | -0.33611009 | 0.3289772272 |
|--------------------|----------------|-------------|-------------|---------------|
| PoliticalRights | -0.78096300 | -0.66658676 | -0.75580168 | 0.4945281148 |
| CivilLiberties | -0.82143790 | -0.69026029 | -0.70969433 | 0.4835784137 |
| ElectoralProcess | 0.76257253 | 0.64663094 | 0.77142590 | -0.4722875357 |
| PoliticalPluralism | 0.78297788 | 0.67512572 | 0.74897516 | -0.4854514301 |
| GovtFunction | 0.75766516 | 0.62653220 | 0.71687436 | -0.4705338180 |
| FreedomExpression | 0.80487406 | 0.69412965 | 0.73179197 | -0.4894644320 |
| AssocRights | 0.78413832 | 0.66621572 | 0.73334098 | -0.5013383031 |
| RuleLaw | 0.78159165 | 0.67723495 | 0.67433500 | -0.4951511919 |
| IndivRights | 0.79751158 | 0.64581048 | 0.65706229 | -0.4542958140 |
| FreedomStatus | -0.75761771 | -0.62820321 | -0.70252407 | 0.4306515455 |
| DISAP2005 | 0.27764863 | 0.26300561 | 0.28562614 | -0.3314459622 |
| Progress_ST | -0.43626910 | -0.33964479 | -0.19478017 | 0.7057028413 |
| GDP | 0.49242339 | 0.42821020 | 0.27736792 | -0.2827494144 |
| HDI_Trends_Rank | -0.53537673 | -0.45501277 | -0.33949453 | 0.3241081536 |
| GDPpercap | 0.49233618 | 0.42814049 | 0.27693462 | -0.2833374441 |
| LifeBirth | 0.49735919 | 0.42805210 | 0.30917901 | -0.2336755693 |
| LifeExp | 0.49798006 | 0.42850965 | 0.30930671 | -0.2332427055 |
| EarnIng_Female | 0.54505062 | 0.45880964 | 0.34058225 | -0.3781609535 |
| Seats_Women | 0.23642524 | 0.17791398 | 0.15755472 | -0.3881690204 |
| Admin_Women | 0.46947372 | 0.31026480 | 0.36332133 | -0.5066905022 |
| Prof_Women | 0.48713535 | 0.33900404 | 0.25589523 | -0.4886208475 |
| EarnIng_Male | 0.47754064 | 0.41339567 | 0.27508143 | -0.2970980108 |
| OLD_EMPINX1990 | 1.00000000 | 0.77460682 | 0.69534922 | -0.5355617404 |
| SPEECH1990 | 0.77460682 | 1.00000000 | 0.55443025 | -0.4176353812 |

| ELECSD2007 | 0.69534922 | 0.55443025 | 1.00000000 | -0.3245204985 |
|------------------|--------------|-------------|-------------|---------------|
| Progress_LT | -0.53556174 | -0.41763538 | -0.32452050 | 1.0000000000 |
| Progress_MT | -0.40202385 | -0.34352434 | -0.06792083 | 0.7919880748 |
| ALR | 0.30970633 | 0.29745039 | 0.02979096 | -0.2878564298 |
| EdEnroll | 0.56010413 | 0.48052365 | 0.35425991 | -0.3103162348 |
| Edu | 0.54606318 | 0.48764977 | 0.31206605 | -0.4099386334 |
| WOSOC2003 | 0.49251539 | 0.37783498 | 0.44614226 | -0.3801598251 |
| WECON2003 | 0.33522117 | 0.21321660 | 0.23521544 | -0.2600356638 |
| WOPOL2006 | 0.34076020 | 0.28633839 | 0.28113094 | -0.5105660558 |
| cow | -0.45336005 | -0.40182438 | -0.38610086 | 0.3722806275 |
| POLITY | -0.45336005 | -0.40182438 | -0.38870418 | 0.3722806275 |
| UNSUBREG | 0.14366330 | 0.14071129 | 0.01704218 | -0.0358309671 |
| Unimprov_Water | -0.30211017 | -0.20691605 | -0.13969818 | -0.1467339396 |
| LifeBirth_Female | 0.52328551 | 0.44733515 | 0.35168314 | -0.2554354370 |
| LifeBirth_Male | 0.46373397 | 0.40611520 | 0.30260348 | -0.2067137361 |
| AdultLit_Female | 0.36739624 | 0.33679783 | 0.11260743 | -0.3524624705 |
| AdultLit_Male | 0.22850463 | 0.26926067 | 0.02782055 | -0.1308524609 |
| EnrollEduc_Femal | e 0.61640865 | 0.50627071 | 0.37255657 | -0.3512610793 |
| EnrollEduc_Male | 0.59704596 | 0.52249694 | 0.37903893 | -0.3196311891 |
| Surv_40 | -0.16995938 | -0.14573340 | -0.11494207 | -0.1357613206 |
| Poverty_200 | -0.41974258 | -0.35720897 | -0.17851424 | -0.0995636806 |
| POLPRIS1993 | 0.16663888 | 0.16979913 | 0.11046769 | -0.0008901446 |

| | Progress_MT | ALR | EdEnroll | Edu |
|--------------------|-----------------|-------------|-------------|-------------|
| Failing_Rank | 0.166953325 | -0.31345794 | -0.56001270 | -0.53535765 |
| AdultLit_2005 | 0.474121630 | -0.26788428 | -0.21732248 | -0.30806777 |
| EnrolEduc_2005 | -0.017512342 | 0.05135340 | 0.03629623 | 0.02828283 |
| GDPpercap_2005 | -0.285973549 | 0.29676574 | 0.33680046 | 0.30560988 |
| AdultLit_2006 | 0.500594139 | -0.49664107 | -0.35110492 | -0.48087588 |
| HDI_2006 | -0.301268607 | 0.78332084 | 0.86998785 | 0.87868643 |
| HDI_A1Reconcil_R | ank 0.301322252 | -0.78335798 | -0.86975056 | -0.87867868 |
| PoliticalRights | 0.238795444 | -0.24376097 | -0.53304130 | -0.52775490 |
| CivilLiberties | 0.253579050 | -0.32802901 | -0.56538314 | -0.57763833 |
| ElectoralProcess | -0.231405497 | 0.21199600 | 0.50561786 | 0.48754296 |
| PoliticalPluralism | -0.222536415 | 0.22059275 | 0.52428097 | 0.51863372 |
| GovtFunction | -0.266235441 | 0.25177190 | 0.53495944 | 0.53630131 |
| FreedomExpressio | n -0.263881177 | 0.24473839 | 0.54515082 | 0.52927285 |
| AssocRights | -0.289443046 | 0.23055692 | 0.51493520 | 0.51217872 |
| RuleLaw | -0.267498165 | 0.31520924 | 0.54204285 | 0.56745243 |
| IndivRights | -0.249489918 | 0.44086844 | 0.63902938 | 0.65379977 |
| FreedomStatus | 0.202481017 | -0.23085994 | -0.49623731 | -0.47999164 |
| DISAP2005 | -0.208024651 | 0.17478155 | 0.26815289 | 0.26020411 |
| Progress_ST | 0.444662631 | -0.20245878 | -0.37089118 | -0.38299745 |
| GDP | -0.363772452 | 0.64370120 | 0.78595012 | 0.77078992 |
| HDI_Trends_Rank | 0.309781939 | -0.78187054 | -0.87126935 | -0.87990129 |
| GDPpercap | -0.364670962 | 0.64671528 | 0.79162389 | 0.77414274 |
| LifeBirth | -0.143685490 | 0.63511461 | 0.76990497 | 0.76786393 |
| LifeExp | -0.143950403 | 0.63477045 | 0.76971710 | 0.76755524 |

| EarnIng_Female | -0.404529572 | 0.69960511 | 0.81314903 | 0.81711841 |
|-------------------|--------------|-------------|-------------|-------------|
| Seats_Women | -0.196966648 | 0.06186757 | 0.22008660 | 0.25211164 |
| Admin_Women | -0.426243305 | 0.33656010 | 0.31312320 | 0.28434736 |
| Prof_Women | -0.458774894 | 0.72111654 | 0.39774960 | 0.53006250 |
| EarnIng_Male | -0.336229414 | 0.63933665 | 0.79259336 | 0.76917940 |
| OLD_EMPINX1990 | -0.402023852 | 0.30970633 | 0.56010413 | 0.54606318 |
| SPEECH1990 | -0.343524337 | 0.29745039 | 0.48052365 | 0.48764977 |
| ELECSD2007 | -0.067920834 | 0.02979096 | 0.35425991 | 0.31206605 |
| Progress_LT | 0.791988075 | -0.28785643 | -0.31031623 | -0.40993863 |
| Progress_MT | 1.000000000 | -0.42781082 | -0.32816473 | -0.43873754 |
| ALR | -0.427810818 | 1.00000000 | 0.76689011 | 0.95864218 |
| EdEnroll | -0.328164726 | 0.76689011 | 1.00000000 | 0.92813212 |
| Edu | -0.438737541 | 0.95864218 | 0.92813212 | 1.00000000 |
| WOSOC2003 | -0.207658142 | 0.47095063 | 0.58011156 | 0.62243956 |
| WECON2003 | -0.221221104 | 0.36734596 | 0.48800403 | 0.52185017 |
| WOPOL2006 | -0.279218525 | 0.03244329 | 0.21021147 | 0.24374177 |
| COW | 0.207228959 | -0.22311851 | -0.32824409 | -0.31774911 |
| POLITY | 0.207228959 | -0.22787155 | -0.32987344 | -0.31991744 |
| UNSUBREG | -0.244513363 | 0.45981070 | 0.41477683 | 0.52354723 |
| Unimprov_Water | 0.103882909 | -0.71180189 | -0.68517154 | -0.72342384 |
| LifeBirth_Female | -0.173785850 | 0.68045771 | 0.77700460 | 0.79999632 |
| LifeBirth_Male | -0.084527411 | 0.57825863 | 0.71929312 | 0.72394323 |
| AdultLit_Female | -0.461882532 | 0.98795545 | 0.79562163 | 0.95333856 |
| AdultLit_Male | -0.377919197 | 0.97792447 | 0.75787133 | 0.93429857 |
| EnrollEduc_Female | -0.305663675 | 0.80426747 | 0.98913223 | 0.93424261 |

| EnrollEduc_Male | -0.294358015 | 0.76212639 | .97913605 | 0.91862005 |
|--------------------|-----------------|-------------|--------------|-------------|
| Surv_40 | 0.007564762 | -0.67562759 | -0.72025543 | -0.72516882 |
| Poverty_200 | 0.081558116 | 0.74751902 | -0.77429968 | -0.77325255 |
| POLPRIS1993 | -0.043714061 | -0.07480341 | 0.04188898 | -0.02770853 |
| | | | | |
| | WOSOC2003 | WECON2003 | WOPOL2006 | cow |
| Failing_Rank | -0.44952592 | -0.46219319 | -0.167705119 | 0.24864329 |
| AdultLit_2005 | -0.19484411 | -0.20606793 | -0.155329317 | 0.12362177 |
| EnrolEduc_2005 | 0.04835568 | 0.06347662 | -0.073118128 | -0.05378540 |
| GDPpercap_2005 | 0.05250721 | 0.09747813 | -0.156219810 | -0.19237699 |
| AdultLit_2006 | -0.29256171 | -0.25238499 | -0.231356829 | 0.24906459 |
| HDI_2006 | 0.58260757 | 0.53525925 | 0.163696811 | -0.32021496 |
| HDI_A1Reconcil_R | ank -0.58216745 | -0.53561383 | -0.163358018 | 0.31975144 |
| PoliticalRights | -0.51854926 | -0.40048331 | -0.283918798 | 0.43159604 |
| CivilLiberties | -0.53657407 | -0.47706851 | -0.263377994 | 0.40458068 |
| ElectoralProcess | 0.49574777 | 0.36419705 | 0.323387027 | -0.47683045 |
| PoliticalPluralism | 0.52192920 | 0.42172581 | 0.289830416 | -0.44038776 |
| GovtFunction | 0.51959383 | 0.45177245 | 0.319381565 | -0.40020955 |
| FreedomExpression | n 0.51619965 | 0.42449170 | 0.268546492 | -0.43980920 |
| AssocRights | 0.49893105 | 0.41038567 | 0.296138942 | -0.44038177 |
| RuleLaw | 0.51989061 | 0.49748644 | 0.281660408 | -0.33005092 |
| IndivRights | 0.58603883 | 0.52978545 | 0.308042765 | -0.39992979 |
| FreedomStatus | -0.47310460 | -0.36614451 | -0.250107974 | 0.40967098 |
| DISAP2005 | 0.21412116 | 0.27278146 | 0.068075463 | -0.17106958 |
| Progress_ST | -0.23732552 | -0.09658454 | -0.316652805 | 0.22818774 |

| GDP | 0.46297374 | 0.45873767 | 0.157701313 | -0.29837465 |
|-----------------|---------------|-------------|--------------|-------------|
| HDI_Trends_Rank | · -0.58216745 | -0.53721201 | -0.170307815 | 0.32281971 |
| GDPpercap | 0.46298647 | 0.45832303 | 0.158437312 | -0.29735985 |
| LifeBirth | 0.50605863 | 0.50723892 | 0.139286354 | -0.33543274 |
| LifeExp | 0.50630742 | 0.50647449 | 0.139223710 | -0.33605617 |
| EarnIng_Female | 0.53674096 | 0.49472439 | 0.194671124 | -0.32135794 |
| Seats_Women | 0.31563100 | 0.27206528 | 0.604778945 | -0.29705176 |
| Admin_Women | 0.21823908 | 0.18121932 | 0.283548146 | -0.44005305 |
| Prof_Women | 0.30404428 | 0.19969313 | 0.307421476 | -0.35137358 |
| EarnIng_Male | 0.47157502 | 0.45980453 | 0.113800429 | -0.28235799 |
| OLD_EMPINX199 | 0 0.49251539 | 0.33522117 | 0.340760201 | -0.45336005 |
| SPEECH1990 | 0.37783498 | 0.21321660 | 0.286338389 | -0.40182438 |
| ELECSD2007 | 0.44614226 | 0.23521544 | 0.281130940 | -0.38610086 |
| Progress_LT | -0.38015983 | -0.26003566 | -0.510566056 | 0.37228063 |
| Progress_MT | -0.20765814 | -0.22122110 | -0.279218525 | 0.20722896 |
| ALR | 0.47095063 | 0.36734596 | 0.032443289 | -0.22311851 |
| EdEnroll | 0.58011156 | 0.48800403 | 0.210211471 | -0.32824409 |
| Edu | 0.62243956 | 0.52185017 | 0.243741766 | -0.31774911 |
| WOSOC2003 | 1.00000000 | 0.58861929 | 0.266380310 | -0.20251010 |
| WECON2003 | 0.58861929 | 1.00000000 | 0.202627212 | -0.11308328 |
| WOPOL2006 | 0.26638031 | 0.20262721 | 1.000000000 | -0.45789340 |
| COW | -0.20251010 | -0.11308328 | -0.457893401 | 1.00000000 |
| POLITY | -0.20237719 | -0.11341916 | -0.447453499 | 0.99999273 |
| UNSUBREG | 0.33823082 | 0.32748210 | -0.088216223 | 0.17380078 |
| Unimprov_Water | -0.36619890 | -0.27642488 | 0.039763432 | 0.24633418 |

| LifeBirth_Female | 0.56308752 | 0.52017891 | 0.143488228 | -0.33712566 |
|--------------------|---------------|-------------|----------------|------------------|
| LifeBirth_Male | 0.49210614 | 0.51803166 | 0.074404337 | -0.27554074 |
| AdultLit_Female | 0.47765532 | 0.41276705 | 0.075854979 | -0.26410404 |
| AdultLit_Male | 0.46543166 | 0.43044057 | -0.002795757 | -0.19551815 |
| EnrollEduc_Female | 0.60667646 | 0.48877221 | 0.217017531 | -0.35573554 |
| EnrollEduc_Male | 0.60346675 | 0.47171015 | 0.244185671 | -0.34165320 |
| Surv_40 | -0.44860193 | -0.39624077 | 0.160426244 | 0.14670704 |
| Poverty_200 | -0.47884870 | -0.26578781 | 0.045208838 | 0.45346564 |
| POLPRIS1993 | -0.08513338 | -0.07721172 | -0.077233747 | -0.01313319 |
| | | | | |
| | POLITY | UNSUBREG | Unimprov_Water | LifeBirth_Female |
| Failing_Rank | 0.25118226 | -0.24048531 | 0.497860223 | -0.621695220 |
| AdultLit_2005 | 0.12574111 | -0.26868746 | 0.073335230 | -0.164669871 |
| EnrolEduc_2005 | -0.05341920 | -0.08429229 | 0.007225463 | -0.033372626 |
| GDPpercap_2005 | -0.19237699 | 0.23042668 | -0.285795748 | 0.324246198 |
| AdultLit_2006 | 0.25102791 | -0.26096317 | 0.250457585 | -0.362991989 |
| HDI_2006 | -0.32312462 | 0.53579646 | -0.818641841 | 0.944966912 |
| HDI_A1Reconcil_Ra | nk 0.32267004 | -0.53589886 | 0.818749607 | -0.945028365 |
| PoliticalRights | 0.43244481 | -0.15806824 | 0.351939023 | -0.551280260 |
| CivilLiberties | 0.40580153 | -0.21357927 | 0.418011129 | -0.592658639 |
| ElectoralProcess | -0.47756970 | 0.12505431 | -0.329004794 | 0.509506166 |
| PoliticalPluralism | -0.44002721 | 0.15186514 | -0.323131263 | 0.527116060 |
| GovtFunction | -0.40029433 | 0.21971953 | -0.388489008 | 0.586949170 |
| FreedomExpression | o -0.44047418 | 0.14879431 | -0.351523310 | 0.520896137 |
| AssocRights | -0.44177458 | 0.16477765 | -0.335625261 | 0.523161888 |
| | | | | |

| RuleLaw | -0.33103997 | 0.23517621 | -0.392918140 | 0.586472988 |
|-----------------|-------------|-------------|--------------|--------------|
| IndivRights | -0.40182301 | 0.28104275 | -0.528129756 | 0.690726399 |
| FreedomStatus | 0.40869999 | -0.11539730 | 0.346620679 | -0.479856849 |
| DISAP2005 | -0.17106958 | 0.07847913 | -0.187816516 | 0.277376205 |
| Progress_ST | 0.22818774 | -0.11467965 | 0.243267313 | -0.348840356 |
| GDP | -0.30016333 | 0.49951881 | -0.753166914 | 0.842526913 |
| HDI_Trends_Rank | 0.32575396 | -0.53426296 | 0.819719911 | -0.945028365 |
| GDPpercap | -0.29915902 | 0.50038630 | -0.753579080 | 0.844479561 |
| LifeBirth | -0.33939192 | 0.43119729 | -0.759967685 | 0.973600030 |
| LifeExp | -0.34001246 | 0.43050861 | -0.759766698 | 0.973512113 |
| EarnIng_Female | -0.32420799 | 0.51639909 | -0.741404772 | 0.842421889 |
| Seats_Women | -0.29467171 | 0.02490924 | -0.079555154 | 0.211445138 |
| Admin_Women | -0.43690932 | -0.13075319 | -0.078664586 | 0.071581215 |
| Prof_Women | -0.34906891 | 0.10268971 | -0.343156397 | 0.146383852 |
| EarnIng_Male | -0.28454578 | 0.51751274 | -0.761443913 | 0.847559452 |
| OLD_EMPINX1990 | -0.45336005 | 0.14366330 | -0.302110165 | 0.523285508 |
| SPEECH1990 | -0.40182438 | 0.14071129 | -0.206916049 | 0.447335154 |
| ELECSD2007 | -0.38870418 | 0.01704218 | -0.139698178 | 0.351683140 |
| Progress_LT | 0.37228063 | -0.03583097 | -0.146733940 | -0.255435437 |
| Progress_MT | 0.20722896 | -0.24451336 | 0.103882909 | -0.173785850 |
| ALR | -0.22787155 | 0.45981070 | -0.711801887 | 0.680457711 |
| EdEnroll | -0.32987344 | 0.41477683 | -0.685171545 | 0.777004600 |
| Edu | -0.31991744 | 0.52354723 | -0.723423839 | 0.799996316 |
| WOSOC2003 | -0.20237719 | 0.33823082 | -0.366198897 | 0.563087523 |
| WECON2003 | -0.11341916 | 0.32748210 | -0.276424885 | 0.520178914 |

| WOPOL2006 | -0.44745350 | -0.08821622 | 0.039763432 | 0.143488228 |
|-------------------|-------------|-------------|--------------|--------------|
| cow | 0.99999273 | 0.17380078 | 0.246334180 | -0.337125659 |
| POLITY | 1.00000000 | 0.17292447 | 0.251605004 | -0.340739787 |
| UNSUBREG | 0.17292447 | 1.00000000 | -0.413491279 | 0.456023246 |
| Unimprov_Water | 0.25160500 | -0.41349128 | 1.000000000 | -0.768605053 |
| LifeBirth_Female | -0.34073979 | 0.45602325 | -0.768605053 | 1.000000000 |
| LifeBirth_Male | -0.27979946 | 0.43086550 | -0.733549774 | 0.964120746 |
| AdultLit_Female | -0.27008632 | 0.40519893 | -0.686108232 | 0.686362803 |
| AdultLit_Male | -0.20319155 | 0.45978534 | -0.663447142 | 0.676071346 |
| EnrollEduc_Female | -0.35707027 | 0.44728070 | -0.715088308 | 0.784095526 |
| EnrollEduc_Male | -0.34342533 | 0.45027903 | -0.659576416 | 0.765674889 |
| Surv_40 | 0.15333332 | -0.43544862 | 0.772388458 | -0.963847399 |
| Poverty_200 | 0.45346564 | -0.35442418 | 0.820479393 | -0.837943852 |
| POLPRIS1993 | -0.01233003 | -0.12073769 | 0.050677702 | -0.008748074 |

| | LifeBirth_Male | AdultLit_Female | AdultLit_Male |
|-------------------|----------------|-----------------|---------------|
| Failing_Rank | -0.60210639 | -0.34737045 | -0.303016305 |
| AdultLit_2005 | -0.11294315 | -0.25754476 | -0.278295726 |
| EnrolEduc_2005 | -0.07353114 | 0.03437338 | 0.042290129 |
| GDPpercap_2005 | 0.32477468 | 0.25850347 | 0.319651425 |
| AdultLit_2006 | -0.28515211 | -0.49747863 | -0.478519052 |
| HDI_2006 | 0.90762711 | 0.78116429 | 0.774360538 |
| HDI_A1Reconcil_Ra | nk -0.90773034 | -0.78126913 | -0.774483085 |
| PoliticalRights | -0.50367248 | -0.31299314 | -0.208135977 |
| CivilLiberties | -0.54320037 | -0.40503189 | -0.304880291 |

| ElectoralProcess | 0.45627579 | 0.27375188 | 0.176429674 |
|--------------------|-------------|-------------|--------------|
| PoliticalPluralism | 0.48775935 | 0.29396018 | 0.195031270 |
| GovtFunction | 0.54711491 | 0.31230360 | 0.209660277 |
| FreedomExpression | 0.47604969 | 0.33988979 | 0.230704308 |
| AssocRights | 0.46576345 | 0.29741171 | 0.209886819 |
| RuleLaw | 0.54738390 | 0.39618668 | 0.297066927 |
| IndivRights | 0.65031636 | 0.51158834 | 0.434626371 |
| FreedomStatus | -0.43232995 | -0.29893103 | -0.200988635 |
| DISAP2005 | 0.27163446 | 0.18938942 | 0.158262655 |
| Progress_ST | -0.34129676 | -0.24519740 | -0.142696589 |
| GDP | 0.81193364 | 0.65043879 | 0.652076244 |
| HDI_Trends_Rank | -0.90773034 | -0.78126913 | -0.774483085 |
| GDPpercap | 0.81686771 | 0.65083212 | 0.657824755 |
| LifeBirth | 0.97839665 | 0.64332259 | 0.642841458 |
| LifeExp | 0.97844064 | 0.64333636 | 0.642619014 |
| EarnIng_Female | 0.79425037 | 0.70126492 | 0.688659251 |
| Seats_Women | 0.17607193 | 0.11062159 | 0.084503479 |
| Admin_Women | -0.04876516 | 0.48490992 | 0.298121065 |
| Prof_Women | -0.03498290 | 0.76123810 | 0.662498295 |
| EarnIng_Male | 0.82163090 | 0.63121611 | 0.639344156 |
| OLD_EMPINX1990 | 0.46373397 | 0.36739624 | 0.228504628 |
| SPEECH1990 | 0.40611520 | 0.33679783 | 0.269260675 |
| ELECSD2007 | 0.30260348 | 0.11260743 | 0.027820554 |
| Progress_LT | -0.20671374 | -0.35246247 | -0.130852461 |
| Progress_MT | -0.08452741 | -0.46188253 | -0.377919197 |

| ALR | 0.57825863 | 0.98795545 | 0.977924466 |
|-------------------|-------------|-------------|--------------|
| EdEnroll | 0.71929312 | 0.79562163 | 0.757871330 |
| Edu | 0.72394323 | 0.95333856 | 0.934298575 |
| WOSOC2003 | 0.49210614 | 0.47765532 | 0.465431660 |
| WECON2003 | 0.51803166 | 0.41276705 | 0.430440575 |
| WOPOL2006 | 0.07440434 | 0.07585498 | -0.002795757 |
| COW | -0.27554074 | -0.26410404 | -0.195518151 |
| POLITY | -0.27979946 | -0.27008632 | -0.203191549 |
| UNSUBREG | 0.43086550 | 0.40519893 | 0.459785342 |
| Unimprov_Water | -0.73354977 | -0.68610823 | -0.663447142 |
| LifeBirth_Female | 0.96412075 | 0.68636280 | 0.676071346 |
| LifeBirth_Male | 1.00000000 | 0.58399850 | 0.592186928 |
| AdultLit_Female | 0.58399850 | 1.00000000 | 0.944558859 |
| AdultLit_Male | 0.59218693 | 0.94455886 | 1.000000000 |
| EnrollEduc_Female | 0.72150993 | 0.83267605 | 0.777986944 |
| EnrollEduc_Male | 0.70876193 | 0.78295499 | 0.760698974 |
| Surv_40 | -0.95364803 | -0.65647340 | -0.678031206 |
| Poverty_200 | -0.76409930 | -0.74054700 | -0.753288865 |
| POLPRIS1993 | -0.03345465 | -0.09169500 | -0.127909467 |

| | EnrollEduc_Female | EnrollEduc_Male | Surv_40 | Poverty_200 | |
|----------------|-------------------|-----------------|--------------|-------------|--|
| Failing_Rank | -0.584487855 | -0.539368391 | 0.459330231 | 0.44574928 | |
| AdultLit_2005 | -0.242656142 | -0.251567513 | 0.041037876 | 0.13835996 | |
| EnrolEduc_2005 | 0.004910193 | 0.016224710 | 0.020338634 | -0.15754691 | |
| GDPpercap_2005 | 0.333301306 | 0.334829837 | -0.326344043 | -0.35575199 | |

| AdultLit_2006 | -0.368949324 | -0.360549539 | 0.230325148 | 0.32868043 |
|--------------------|------------------|--------------|--------------|-------------|
| HDI_2006 | 0.875091255 | 0.855759263 | -0.912202239 | -0.90073305 |
| HDI_A1Reconcil_R | ank -0.874780774 | -0.855338871 | 0.912346423 | 0.90077752 |
| PoliticalRights | -0.562310994 | -0.556681752 | 0.303058505 | 0.36289012 |
| CivilLiberties | -0.599008441 | -0.575834930 | 0.377497673 | 0.43846568 |
| ElectoralProcess | 0.537381411 | 0.532768488 | -0.250483394 | -0.37244534 |
| PoliticalPluralism | 0.552250743 | 0.553146183 | -0.280514121 | -0.35086536 |
| GovtFunction | 0.570115864 | 0.553605437 | -0.330858260 | -0.33006409 |
| FreedomExpression | n 0.580387235 | 0.558010221 | -0.277052760 | -0.36027229 |
| AssocRights | 0.547044694 | 0.542548239 | -0.265769869 | -0.32478002 |
| RuleLaw | 0.569474757 | 0.554376602 | -0.366238058 | -0.37444466 |
| IndivRights | 0.663271666 | 0.654744983 | -0.509423077 | -0.57783687 |
| FreedomStatus | -0.518025279 | -0.499004394 | 0.279805034 | 0.34788749 |
| DISAP2005 | 0.268548131 | 0.226184800 | -0.233000949 | -0.16810924 |
| Progress_ST | -0.363403320 | -0.373896956 | 0.117368340 | 0.10815851 |
| GDP | 0.785921633 | 0.770073414 | -0.777336240 | -0.87279624 |
| HDI_Trends_Rank | -0.874780774 | -0.855338871 | 0.912840903 | 0.90077752 |
| GDPpercap | 0.791900873 | 0.775606811 | -0.783884048 | -0.87267631 |
| LifeBirth | 0.776143312 | 0.759869397 | -0.971049547 | -0.81007999 |
| LifeExp | 0.775761366 | 0.759762466 | -0.970902801 | -0.80958456 |
| EarnIng_Female | 0.817479968 | 0.806546867 | -0.745920658 | -0.85819232 |
| Seats_Women | 0.241279557 | 0.231503934 | 0.058021832 | 0.03358303 |
| Admin_Women | 0.354479909 | 0.243843228 | 0.119456396 | -0.15869753 |
| Prof_Women | 0.442568988 | 0.317785114 | -0.081312738 | -0.44135115 |
| EarnIng_Male | 0.792335570 | 0.779312134 | -0.781901002 | -0.87267238 |

| OLD_EMPINX1990 | 0.616408646 | 0.597045958 | -0.169959381 | -0.41974258 |
|-------------------|--------------|--------------|--------------|-------------|
| SPEECH1990 | 0.506270707 | 0.522496939 | -0.145733401 | -0.35720897 |
| ELECSD2007 | 0.372556567 | 0.379038930 | -0.114942066 | -0.17851424 |
| Progress_LT | -0.351261079 | -0.319631189 | -0.135761321 | -0.09956368 |
| Progress_MT | -0.305663675 | -0.294358015 | 0.007564762 | 0.08155812 |
| ALR | 0.804267466 | 0.762126386 | -0.675627589 | -0.74751902 |
| EdEnroll | 0.989132226 | 0.979136050 | -0.720255435 | -0.77429968 |
| Edu | 0.934242606 | 0.918620050 | -0.725168824 | -0.77325255 |
| WOSOC2003 | 0.606676459 | 0.603466749 | -0.448601931 | -0.47884870 |
| WECON2003 | 0.488772213 | 0.471710145 | -0.396240771 | -0.26578781 |
| WOPOL2006 | 0.217017531 | 0.244185671 | 0.160426244 | 0.04520884 |
| COW | -0.355735540 | -0.341653198 | 0.146707043 | 0.45346564 |
| POLITY | -0.357070267 | -0.343425333 | 0.153333321 | 0.45346564 |
| UNSUBREG | 0.447280705 | 0.450279027 | -0.435448617 | -0.35442418 |
| Unimprov_Water | -0.715088308 | -0.659576416 | 0.772388458 | 0.82047939 |
| LifeBirth_Female | 0.784095526 | 0.765674889 | -0.963847399 | -0.83794385 |
| LifeBirth_Male | 0.721509933 | 0.708761930 | -0.953648031 | -0.76409930 |
| AdultLit_Female | 0.832676053 | 0.782954991 | -0.656473398 | -0.74054700 |
| AdultLit_Male | 0.777986944 | 0.760698974 | -0.678031206 | -0.75328887 |
| EnrollEduc_Female | 1.00000000 | 0.950588524 | -0.734593928 | -0.78947687 |
| EnrollEduc_Male | 0.950588524 | 1.000000000 | -0.696624100 | -0.77008772 |
| Surv_40 | -0.734593928 | -0.696624100 | 1.000000000 | 0.84005624 |
| Poverty_200 | -0.789476871 | -0.770087719 | 0.840056241 | 1.00000000 |
| POLPRIS1993 | 0.002826840 | -0.003617385 | 0.069253787 | 0.04562134 |

POLPRIS1993

| Failing_Rank | -0.0255898293 | |
|----------------------------------|----------------|--|
| AdultLit_2005 | 0.1013429388 | |
| EnrolEduc_2005 | -0.0436097234 | |
| GDPpercap_2005 | -0.0626326501 | |
| AdultLit_2006 | 0.1181587651 | |
| HDI_2006 | -0.0408279188 | |
| HDI_A1Reconcil_Rank 0.0407280549 | | |
| PoliticalRights | -0.0810427293 | |
| CivilLiberties | -0.1007165983 | |
| ElectoralProcess | 0.0960116461 | |
| PoliticalPluralism | 0.0756022558 | |
| GovtFunction | 0.0836678147 | |
| FreedomExpression | n 0.0842397884 | |
| AssocRights | 0.0841320530 | |
| RuleLaw | 0.1213520914 | |
| IndivRights | 0.0637889728 | |
| FreedomStatus | -0.1134979799 | |
| DISAP2005 | 0.1662630290 | |
| Progress_ST | 0.0046675815 | |
| GDP | -0.0374071747 | |
| HDI_Trends_Rank | 0.0313121378 | |
| GDPpercap | -0.0366780385 | |
| LifeBirth | -0.0107427044 | |
| LifeExp | -0.0115395365 | |

EarnIng_Female -0.0709104240

Seats_Women -0.1979880035

Admin_Women 0.1627498716

Prof_Women -0.0843701437

EarnIng_Male -0.0380039848

OLD_EMPINX1990 0.1666388810

SPEECH1990 0.1697991341

ELECSD2007 0.1104676872

Progress_LT -0.0008901446

Progress_MT -0.0437140614

ALR -0.0748034120

EdEnroll 0.0418889821

Edu -0.0277085323

WOSOC2003 -0.0851333812

WECON2003 -0.0772117227

WOPOL2006 -0.0772337466

COW -0.0131331859

POLITY -0.0123300264

UNSUBREG -0.1207376868

Unimprov_Water 0.0506777018

LifeBirth_Female -0.0087480741

LifeBirth_Male -0.0334546492

AdultLit_Female -0.0916950032

AdultLit_Male -0.1279094666

EnrollEduc_Female 0.0028268399

EnrollEduc_Male -0.0036173847

Surv_40 0.0692537874

Poverty_200 0.0456213392

POLPRIS1993 1.0000000000

Appendix 5

Boruta Results

| | meanZ | medianZ | MinZ | maxZ | normHits | Decision |
|---------------------|-----------|------------|-------------|-----------|-------------|-----------|
| Earnings_Male | 7.5653348 | 7.61574141 | 5.62706888 | 9.1626948 | 1 | Confirmed |
| RuleLaw | 7.2269491 | 7.24433719 | 5.52997138 | 8.8762238 | 0.988372093 | Confirmed |
| HDI_2006 | 7.1866486 | 7.1866486 | 5.14013860 | 8.7759338 | 0.993023256 | Confirmed |
| CivilLiberties | 6.8686380 | 6.86319630 | 4.91997208 | 8.5750299 | 0.983720930 | Confirmed |
| HDI_Trends_Rank | 6.8536475 | 6.86042117 | 4.87929152 | 8.6574353 | 0.993023256 | Confirmed |
| HDI_A1Reconcil_Rank | 6.8452700 | 6.81835583 | 5.12679428 | 8.0973620 | 0.983720930 | Confirmed |
| Unimprov_Water | 6.6564019 | 6.67225343 | 4.51076947 | 8.8205913 | 0.986046512 | Confirmed |
| GDP | 6.6169581 | 6.62964347 | 4.46632684 | 8.3413279 | 0.990697674 | Confirmed |
| GDPpercap | 6.2931513 | 6.29969632 | 4.27561374 | 8.1365522 | 0.979069767 | Confirmed |
| AdultLit_2005 | 6.2511449 | 6.25854794 | 3.09400413 | 8.7155516 | 0.972093023 | Confirmed |
| OLD_EMPINX1990 | 6.2073087 | 6.19752575 | 4.38881210 | 8.1476327 | 0.981395349 | Confirmed |
| SPEECH1990 | 6.0579632 | 6.08588915 | 4.08820884 | 8.1382888 | 0.981395349 | Confirmed |
| AssocRights | 5.9671259 | 5.99573419 | 4.27390405 | 7.9370283 | 0.974418605 | Confirmed |
| FreedomExpression | 5.7410892 | 5.76290319 | 3.49786690 | 7.3398607 | 0.951162791 | Confirmed |
| LifeBirth_Male | 5.6573027 | 5.68556470 | 3.98608757 | 7.3172314 | 0.960465116 | Confirmed |
| Poverty_200 | 5.6490511 | 5.64273889 | 3.14818815 | 7.8794205 | 0.953488372 | Confirmed |
| Progress_MT | 5.5719758 | 5.57905495 | 2.32761442 | 8.8394059 | 0.925581395 | Confirmed |
| GovtFunction | 5.1842169 | 5.21516588 | 2.96044392 | 7.2070137 | 0.937209302 | Confirmed |
| EarnIng_Female | 5.1028746 | 5.11616863 | 3.02722566 | 6.6882073 | 0.923255814 | Confirmed |
| LifeBirth_Female | 4.9941838 | 4.98939272 | 3.30842873 | 6.5874214 | 0.918604651 | Confirmed |
| IndivRights | 4.6878620 | 4.69553060 | 2.87892855 | 6.0394965 | 0.879069767 | Confirmed |
| Surv_40 | 4.6333056 | 4.68902042 | 2.44154473 | 6.5107425 | 0.853488372 | Confirmed |
| PoliticalPluralism | 4.5062036 | 4.56515515 | 2.24433515 | 6.3954653 | 0.858139535 | Confirmed |
| Progress_LT | 4.2859354 | 4.30972021 | 1.41009088 | 6.8003917 | 0.758139535 | Confirmed |
| LifeBirth | 4.2858806 | 4.28981423 | 2.32090565 | 5.7975827 | 0.788372093 | Confirmed |
| LifeExp | 4.3010242 | 4.28807632 | 2.43150986 | 5.8614181 | 0.811627907 | Confirmed |
| WOSOC2003 | 4.1252955 | 4.15395539 | 1.77189964 | 6.4879093 | 0.748837209 | Confirmed |
| Prof_Women | 3.7511920 | 3.75191040 | 0.08118345 | 6.7700336 | 0.644186047 | Confirmed |
| AdultLit_Female | 3.6046336 | 3.63583989 | 0.55961701 | 5.9450258 | 0.595348837 | Confirmed |
| EdEnroll | 3.6333366 | 3.63400835 | 0.67176580 | 5.9917663 | 0.602325581 | Confirmed |
| Edu | 3.5193391 | 3.55918045 | 1.46595564 | 5.3803870 | 0.576744186 | Confirmed |
| WECON2003 | 3.3732770 | 3.44016899 | 0.61099550 | 5.2298595 | 0.576744186 | Confirmed |
| ALR | 3.2495458 | 3.31780422 | 0.22254339 | 5.6346212 | 0.500000000 | tentative |
| ELECSD2007 | 3.2311754 | 3.27815260 | 1.44269147 | 4.6636778 | 0.530232558 | tentative |
| EnrollEduc_Female | 3.0572417 | 3.08717811 | -0.10882993 | 4.7724718 | 0.451162791 | tentative |
| ElectoralProcess | 3.0180520 | 3.02968905 | 0.61180720 | 4.6845675 | 0.441860465 | tentative |
| UNSUBREG | 2.9483912 | 2.97085340 | -0.33628087 | 5.2695729 | 0.372093023 | Rejected |
| EnrollEduc_Male | 2.3966204 | 2.49947707 | 0.21855017 | 4.1032037 | 0.044186047 | Rejected |
| Admin_Women | 2.4125390 | 2.46138761 | -0.03207636 | 5.0965314 | 0.046511628 | Rejected |
| DISAP2005 | 2.3155786 | 2.42296135 | -0.12588872 | 3.8365676 | 0.039534884 | Rejected |

| FreedomStatus | 2.3195119 | 2.39226313 | 1.34870207 | 3.4686590 | 0.023255814 | Rejected |
|-----------------|------------|-------------|-------------|-----------|-------------|----------|
| PoliticalRights | 2.3078427 | 2.33610723 | 0.78141876 | 3.9903609 | 0.037209302 | Rejected |
| AdultLit_2006 | 2.0403918 | 2.16197379 | -0.49526028 | 3.8913776 | 0.030232558 | Rejected |
| Seats_Women | 2.0162893 | 2.15040620 | -0.09587335 | 3.8431321 | 0.018604651 | Rejected |
| AdultLit_Male | 1.8612782 | 1.94466891 | -0.69211584 | 3.6519175 | 0.020930233 | Rejected |
| GDPpercap_2005 | 1.3826995 | 1.38390337 | -0.33042109 | 2.7468396 | 0.000000000 | Rejected |
| POLITY | 1.3979751 | 1.36354068 | -0.89501749 | 3.8497572 | 0.011627907 | Rejected |
| Progress_ST | 1.3538738 | 1.29000299 | -0.39833326 | 3.2319258 | 0.009302326 | Rejected |
| COW | 0.9262780 | 0.98860094 | -0.81726879 | 2.5140436 | 0.002325581 | Rejected |
| EnrolEduc_2005 | -0.1828905 | -0.07425007 | -2.61312323 | 1.5092043 | 0.000000000 | Rejected |
| POLPRIS1993 | -1.0636480 | -0.92910357 | -3.63456161 | 1.1545708 | 0.000000000 | Rejected |

Appendix 6

Boruta results

| EarnIng_Male | Confirmed |
|---------------------|-----------|
| RuleLaw | Confirmed |
| HDI_2006 | Confirmed |
| CivilLiberties | Confirmed |
| HDI_Trends_Rank | Confirmed |
| HDI_A1Reconcil_Rank | Confirmed |
| Unimprov_Water | Confirmed |
| GDP | Confirmed |
| GDPpercap | Confirmed |
| AdultLit_2005 | Confirmed |
| OLD_EMPINX1990 | Confirmed |
| SPEECH1990 | Confirmed |
| AssocRights | Confirmed |
| FreedomExpression | Confirmed |
| LifeBirth_Male | Confirmed |
| Poverty_200 | Confirmed |
| Progress_MT | Confirmed |
| GovtFunction | Confirmed |
| Earning_Female | Confirmed |
| LifeBirth_Female | Confirmed |
| IndivRights | Confirmed |
| | |

| Surv_40 | Confirmed |
|--------------------|-----------|
| | |
| PoliticalPluralism | Confirmed |
| Progress_LT | Confirmed |
| LifeBirth | Confirmed |
| LifeExp | Confirmed |
| WOSOC2003 | Confirmed |
| Prof_Women | Confirmed |
| AdultLit_Female | Confirmed |
| EdEnroll | Confirmed |

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