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Temporal Analysis of Political Instability through Descriptive Subgroup Discovery

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This paper analyzes the Political Instability Task Force (PITF) data set using a new methodology based on machine learning tools for subgroup discovery. While the PITF used static data, this study employs both static and dynamic descriptors covering the 5-year period before onset. The methodology provides several descriptive models of countries especially prone to political instability. For the most part, these models corroborate the PITF's findings and support earlier theoretical works. The paper also shows the value of subgroup discovery as a tool for developing a unified concept of political instability as well as for similar research designs.

Keywords dynamic variables, political instability task force, subgroup discovery

Introduction

The study of intrastate conflict, from revolutions and coups to ethnic conflict, civil wars, and genocide, has been one of the most active fields in the post-World War II, and especially the post-Cold War social sciences. As a result, our knowledge about the onset and duration of such crises has increased markedly. Recently, the field has come to be dominated by quantitative studies, which have yielded impressive results about factors correlating closely with conflict. These studies, whether they employ regression models, econometric approaches, or other statistical methods, assume that the cases they code as “civil wars” (or whatever the dependent variable) are sufficiently alike to merit being grouped in a single category, and that all cases with a given outcome have developed along the same lines. This raises two potential methodological problems. First, can we be sure that all cases that are coded the same on their outcome variable are actually alike, and if not, how do we determine clusters of distinctive cases? And second, even if the cases are similar, can we rule out the possibility of equifinality, i.e., that different cases might have developed along different paths but ended up in the same state (George & Bennett, 2005)?

This paper presents results of an effort to apply the methodology of knowledge discovery in databases for the qualitative analysis of social science data. Specifically, we use the

recently developed method of subgroup discovery to solve the two methodological problems mentioned above. We employ this methodology to analyze data previously gathered by the Political Instability Task Force (PITF) to identify potential correlates of political instability. In the next section, we will give an overview of current literature on the causes and correlates of intrastate conflict, including the findings of the PITF. We then describe the data set and introduce the methodology. Subsequently, we discuss several possible descriptive models for the onset of political instability that emerge from the analysis. Finally, we offer some tentative conclusions drawn from these findings.

Review of the Literature

Current quantitative literature on intrastate conflict (as an umbrella term for ethnic conflicts, civil war, and similar phenomena of domestic political instability) is primarily concerned with the explanation of the onset, the severity (Lacina, 2006) and the duration of conflict (Fearon, 2004). A number of factors have been identified as positively affecting conflict onset. These include a lack of state capacity (Fearon & Laitin, 2003), low economic prosperity, lootable resources (Collier & Hoeffler, 2001), population size (Sambanis, 2004), earlier conflict in the same country or ongoing conflicts in neighboring countries (Esty et al., 1998b), and a “hybrid” regime type (Hegre et al., 2001). Population density and distance to the capital city can also affect conflict risk. However, the influence of these last variables is conditioned by the type of conflict (Buhaug & Rød, 2006). In contrast, several variables are considered either to be insignificant or to produce mixed results, among them ethno-linguistic fractionalization and rough terrain (Fearon & Laitin, 2003; Buhaug & Rød, 2006).

As Sambanis (2004) has pointed out, by employing different data sets using varying definitions of their dependent variable, these studies have sometimes come to starkly different conclusions. Instances of civil war that are coded in one data set are missing in another. Sambanis suggests that this might have skewed results, for example with regard to ethno-linguistic fractionalization: “The results presented here show that the estimated coefficients of most variables vary widely as a result of changes in the coded onset of civil war” (Sambanis, 2004: 855).

These studies, just like the PITF, employ static variables as causal factors for the explanation of conflict onset. Changes in these variables are implicitly recorded in new values for the next country-year cases in the data set. With very few exceptions (GDP growth), dynamic indicators per se are not considered to be relevant independent variables. This is in stark contrast to earlier literature on the social and political roots of conflict. Huntington, for example, theorized that political conflict may result from the modernization of society, which creates new demands for participation exceeding the institutional capacity of the political system (Huntington, 1969: 4).

The Political Instability Task Force

The PITF was founded in 1994 under the name State Failure Task Force (SFTF) at the request of the United States government (Esty et al., 1998a). The SFTF’s original aim, as the founding name implied, had been to identify the root causes of state failure. However, preliminary research showed that only 18 episodes of state failure had occurred in the initial time frame of 1955–1994, too few for meaningful quantitative analysis (Esty et al., 1995). As a result, the Task Force broadened the concept of state failure so that it included a wider range of phenomena, namely, adverse regime changes, genocides/politicides, revolutionary wars, and ethnic conflict. The SFTF acknowledged that this differed from the prior definition of state failure by renaming itself the Political Instability Task Force in 2003.

In its early stages, the PITF¹ compiled a data set encompassing 195 countries in the period from 1955 to 1994 (later updated to include events up to 2004).² Each country was described by 87 political, demographic, economic, social, and environmental variables that had been collected from different sources, including the World Bank and United Nations. In the above period, 131 instances of “state failure” (hereafter referred to as “positive cases”) had been recorded in 96 different countries. Since the PITF was trying to construct a predictive model, data from 2 years prior to the instability was combined with the outcome variable. The same procedure was employed for constructing negative (control) cases, three of which were added to the data set for each positive case. Control cases were defined as not having experienced instability during the 5-year period immediately preceding and following the sampling year.

The goal of the PITF is the development of statistical models that can be used to identify countries at greater risk of political instability (Esty et al., 1998b). Initially, single-variable correlations were used to detect potentially significant variables that were then subjected to multivariate logistic regression and neural network modeling. In its Phase I report, the Task Force identified a combination of three variables as providing the best predictive power: high infant mortality, partial democracy, and low trade openness. This global model was able to predict the positive cases with an accuracy of 60% (Esty et al., 1995). In the second and third phases, this model was refined by adding further independent variables, namely a large population and high population density as well as two or more bordering states with major civil conflict. Including these variables improved the model’s accuracy to 72%. There are differences in the predictive power of these six variables, with quality of life (for which infant mortality is a proxy) and regime type being the most robust. In addition, the PITF developed special models for specific outcome types (e.g., ethnic war) or selected geographical areas (e.g., sub-Saharan Africa, Muslim countries). These models usually attained a level of accuracy around 80%. However, with regard to the global model, it is doubtful whether substantial improvements in prediction accuracy can be realized with this data set and methodology without further loss of parsimony.

Despite these achievements, the PITF has been criticized on theoretical and methodological grounds. On a theoretical level, the most obvious charge against the PITF has long been that what it was studying was not state failure at all. This concept of state failure describes a breakdown of political order and state institutions and is at once both wider and quite different from the four kinds of political instability that the PITF included (Zartman, 1995). For example, state failure theorists would in most cases reject the notion that adverse regime change be considered as a positive case (unless it was particularly violent and took a long time to take effect). The PITF admitted as much in its first report (Esty et al., 1995), but continued to denote its positive cases “state failures,” thereby contributing to the confusion. The issue was further obscured by the PITF’s unwillingness to provide a clear definition of its dependent variable beyond a simple typology of events classified as state failure.

Even if this critique had merely been an issue of semantics, the lack of a theoretical core led to further problems. King and Zeng (2001) have pointed out that the different kinds of positive cases (adverse regime change, revolutionary war, ethnic war, genocide) actually were discrete types of events with quite distinct causes. This critique was somewhat countered by the PITF’s development of separate causal models for these outcome types.

¹To facilitate reading, we will refer to the task force as PITF even when talking about its work before its re-christening in 2003.

²In an intermediate step, the data set had been updated until 1999. This was the most current version of the data set when work on our project began, therefore the data set underlying the present paper covers events between 1955 and 1999. A public version of the data set, including documentation as well as all three reports is available on the PITF website at <http://globalpolicy.gmu.edu/pitf/pitfdata.htm>.

However, subsuming analytically distinct events into a single category at best reduces theoretical leverage; at worst, it produces misleading results (Sartori, 1970). It raises the danger of equifinality, since differences between positive cases can stem from divergent causal structures. One way to address this problem would be to disaggregate the dependent variable into clusters of related cases and then to analyze these clusters separately, as the PITF did through its development of separate models. However, this strategy then raises the question how such clusters should be determined. The PITF opted for a deductive approach, i.e., it defined the four kinds of positive outcomes on theoretical grounds. Such an approach again carries the risk for concept misformation: how can we be sure that, for example, revolutionary war and ethnic war are distinct groups of cases, or that all cases of adverse regime change are sufficiently alike to be considered the same class of events?

Other lines of criticism have pointed out the limitations of the PITF's approach. Schrodtt (2002) criticized the PITF and similar data-mining efforts as only producing correlations without addressing issues of causation. This point is illustrated by infant mortality—it is clear that infant mortality per se does not cause political violence. However, it is a good indicator for conditions of social squalor, which, in turn, are potential sources of conflict. And while causality and explanation were never on the PITF's agenda, it is important to be aware of this shortcoming. Finally, the limits of the global model are highlighted when looking at specific cases. Daun (2003) has conducted an independent single-case study of the representation of Colombia in the PITF data set: 4 country-years were included as either positive or negative outcomes; in three of these cases, the global model predicted the wrong result. This is a general weakness of the global model that is especially pronounced in “marginal” cases like Colombia, where violence takes a less ubiquitous form than, for example, in Somalia.

Subgroup Discovery Methodology

Cases in our analysis are represented by periods of 5 country-years without political instability. Positive cases encompass those periods immediately preceding a year with a recognized instability, while negative cases are those where political instability did not occur for at least another 5 years after the conclusion of the initial 5-year period. From each of the 87 variables available in the data set per country-year, we constructed 11 descriptors representing the 5-year time sequence. They are: mean value over 5 years; minimum value; maximum value; slope; standard deviation; range (maximum – minimum value); positive distortion (maximum – mean value); negative distortion (mean – minimum value); temporal distance between extremes (position of the minimum – position of the maximum value in years); relative distance of the minimum value in respect to the beginning of the time sequence; and relative distance of the maximum value in respect to the beginning of the time sequence.

These descriptors reflect both absolute (static) properties of the input variable (mean, maximum, minimum values, range, distortions), and temporal (dynamic) properties of the changes (slope, positions of the extremes, standard deviation). The result is that, due to the described data preparation phase, each case is represented by 957 numerical descriptors. The subgroup discovery algorithm that follows uses only these descriptor values as input.³

The set of cases consists of the group of positive cases P (countries experiencing political instability) and a control group of negative cases N (countries not experiencing

³It should be noted that the advantage of the applied subgroup discovery approach is that, due to the built-in anti-overfitting measures, the methodology can accept a large number of input variables even when the number of cases is relatively modest. For example, in the functional genomics domain successful experiments have been done with as much as 16,000 descriptors (Gamberger et al., 2004). In contrast to multivariate logistic regression modeling that needs to have explicit single-variable

political instability). The goal of the subgroup discovery algorithm is to construct rules that are true for positive cases and false for negative cases. It is not necessary that rules are true for all positive cases and false for all negative cases, but the intention is to find short rules that are true for large subsets of positive examples and at the same time that are false for large subsets of negative examples. Subgroup sizes are not defined in advance but the algorithm tends to make them as large as possible. A rule with ideal covering properties is true for all positive cases and not true for all negative ones. Positive cases covered by a rule are also called “true positives” and denoted by TP, while negative cases covered by the rule are called “false positives” (FP). All remaining negative cases not covered by the rule are called “true negatives” (TN). An ideal rule has $TP = P$ and $TN = N$, and because of $N = TN + FP$ the ideal rule has $FP = 0$.

The first step in the rule construction process is the construction of all possible “features” representing elementary rule building blocks. For descriptors on an interval scale the features have the form Descriptor > value or Descriptor < value. Examples from the PITF data set are ‘mean population density > 40.8 or slope of change of GDP per capita < 0.15. For each input descriptor, there can be many different features and the process of their construction is well defined. Practically for each pair of one positive and one negative case it is possible to construct one feature for every descriptor. For example, if we have a positive case with mean population density = 30 and a negative case with ‘mean population density = 35, then a feature ‘mean population density < 32.5 may be constructed. This feature will successfully discriminate between these two cases because it is true for the positive case and false for the negative one. Many features constructed this way can be immediately discarded if they are only true for a small number of positive cases or if they are false for a small number of negative cases. The reason is that such features are potentially bad rule building blocks because they may lead to results that are overfitted to the available data set and do not describe general relationships. All other features with reasonably good covering properties enter the rule construction process. For the PITF data set, we only accepted features that were true for at least 10 positive cases and, at the same time, that were false for 10 to 15 negative cases, depending on the total number of negative cases.

The central part of the rule construction process is the optimization algorithm searching for combinations of features with optimal covering properties on the given set of cases. It is assumed that features can be connected only by logical conjunction. This means that a combination of features is true for a case only if all features are true for the case and that a combination of features is false for a case if any of the features is false for it. In the subgroup discovery approach, the following rule quality measure Q is used as the optimization goal in the heuristic search of rules:

$$Q = TP / (FP + g)$$

where g is an appropriately selected generalization parameter. High quality rules will have a large Q value and they will cover most positive cases (large TP) and a low number of negative cases (small FP). The number of negative cases tolerated, relative to the number of positive ones covered by the rule, is determined by the parameter g . Rules presented in this work have been induced with g being in the range between 5 and 20. The quality of constructed rules is measured by two values: *sensitivity* which is equal to TP/P and which represents the proportion of positive cases classified as true positives, and *specificity* which

correlation tests in the preprocessing stage in order to reduce the number of inputs to ensure the construction of reasonable models, this approach allows even further expansion of the number of input descriptors.

is equal to TN/N and which represents the proportion of negative cases classified as true negatives. Very good rules have high sensitivity and high specificity, but rules can also be useful if only one of the values is very high.

An example of a real rule constructed for the PITF domain consisting of two features is the following: position of the maximum population value > 2.5 (maximum population is reached in the second half of the 5-year cycle) and 'difference between maximum and minimum values of infant mortality > 7.2 '. This rule has a sensitivity of 42% (it is true for 50 of 118 positive examples) and a specificity of 78% (it is false for 179 of 229 negative examples where data for both descriptor values is present). This rule is actually the base for the model F1 presented in this work. The transformation from the rule form into the descriptive form is the result of a statistical comparison of the subgroup of 50 positive cases described by the rule on the one hand and all available negative cases on the other. As expected, all positive examples that are true for the rule have increasing population (maximum value near the onset of instability) and large differences in infant mortality in a 5-year period. Moreover, these cases have also significantly decreasing infant mortality characterized by a significant negative slope for infant mortality as well as a significant positive slope for total population. Therefore, the main properties of the model are described as "countries characterized by *significantly increasing population* as a result of *rapidly decreasing infant mortality*." There can also be other significant differences between the subgroup of positive cases and all negative cases. These differences are listed in the model description as additional but not necessary properties. In the current example, model F1 has "decreasing GDP" (detected as the negative mean value of the slope of GDP for selected positive cases in contrast to the positive mean value that characterizes negative cases) and "growing urban population" as additional characteristics.

The other models presented in this work have been constructed the same way. Although the induced rules should have high predictive accuracy characterized by high sensitivity and specificity values, the real relevance of rules lies in the automatic detection of relevant subgroups of positive cases. Analysis of the statistical properties of these subgroups necessitates the evaluation and interpretation of underlying concepts during the transformation from rule form into model descriptions by an expert in the topic under study. Thus, the advantage of the methodology is that it actively includes human background knowledge and experience into the data analysis process. The disadvantage is that the process may result in different model descriptions depending on the expertise and preferences of the involved social scientist. Initially, the process can be influenced by selecting higher or lower values for the generalization parameter, g , during the rule generation process. Later, the expert can significantly influence the model description by highlighting different additional properties of the model. Also, the approach does not eliminate Schrod's critique of the PITF's approach (see above) in that it still detects correlation and not causation. Nevertheless, the human evaluation of hypotheses leaves enough freedom for experts to try to detect and incorporate causation into theories that are built based on the induced hypotheses. It also allows us to avoid the pitfalls of concept misformation through the inductive creation of subgroups.

The methodology used in this work represents recent advances in the field of intelligent data analysis. It has already been successfully applied in the fields of medicine (Gamberger et al., 2003), functional genomics (Gamberger et al., 2004), and chemistry (Baker et al., 2004), but it is yet to be generally accepted as a standard approach of data analysis. A goal of this study is to demonstrate its applicability to the social sciences and stimulate broader awareness of its potentials, while methodological details are outside the scope of this paper (Gamberger & Lavrač, 2002).

The computational aspect of the methodology is relatively complex because it makes use of a complete Inductive Learning by Logic Minimization (ILLM) system implemented

at the Rudjer Boskovic Institute, Zagreb. Outside researchers interested in the application of the methodology can access the Data Mining Server, publicly available at <http://dms.irb.hr>, which enables the use of the subgroup discovery tool with user-submitted data. The server presents a very simple and user-friendly interface to the data analysis process, but is limited to 250 cases and 50 descriptors for the sake of public availability. To allow for more complex experiments, please contact the authors of the paper.

The Experimental Setting

In the first phase, we experimented with a data set consisting of 118 positive and 259 negative (control) examples. This data set will be referred to as the F set. The positive cases included all examples for which a preceding 5-year period of political stability existed. Selection of negative examples was relatively random but the intention was to include negative cases, where possible, both for countries which had also generated a positive case, as well as a number of negative examples from countries which did not experience political instability, preferably in the same time periods when positive cases had been generated for other countries. The results obtained were very helpful to illustrate the methodology and its potentials, although later evaluation by a political scientist showed that some positive cases had been included in the data set even though they had not been independent states for the entire preceding 5-year period, raising doubts about the reliability of data. Moreover, expert analysis showed that relying on negative examples drawn from stable and developed countries produced biased results that more often reflected other, more general socio-economic differences between these countries and positive cases rather than differences in political stability as such.

To circumvent the problems detected in the first phase, we then designed two additional experiments. Positive cases remained the same in both experiments: There are 87 cases of political instability that satisfied the conditions that the countries had been independent and stable for at least 5 years before political instability set in and that the 5-year period started after 1955. In the first of these experiments, which will be referred to as the M data set, negative cases were constructed using countries that had never experienced political instability. For each such country (99 in total) two negative cases were constructed with randomly chosen 5-year periods, taking care that these two periods are at least 20 years apart. If it was not possible to guarantee a 20-year interval (because of the relatively recent independence of a country), a minimum distance of 10 years was employed, and if this was still not possible, only a single case was constructed for the country. In total, this gave us 181 negative cases for the M set. This set is intended to highlight immanent properties that differentiate unstable countries from stable ones.

In the second experiment, a different data set (the S set) was constructed with the aim of detecting which variables were most successful in predicting why and when similar countries remained stable or became unstable. To do that, the negative cases in the S set were taken only from countries that had experienced political instability at some other point. For each such country, we tried to find two periods of 5 years which could serve as negative cases: one which was before the onset of instability and another one after its termination. For each negative case, a minimum distance of 10 years to the positive case had to be present. If this was not possible, negative cases with a shorter distance (but not less than 5 years) were accepted. For some countries that experienced a particularly long period of instability (or that had only recently become independent), it was only possible to construct a single negative case, or, for a few countries, no negative case at all. However, it was possible to extract a few additional negative cases from countries which had experienced instability but were dropped from the data set because reliable data had not been present for at least 5

years prior to the onset of instability (see above). This produced a total count of 96 negative cases for data set S.

In the following section we present the results from the analysis of the data sets. It should be pointed again that the method of subgroup discovery does not produce hard and fast results, but helps formulate specific hypotheses through the inductive discovery of subgroups of cases sharing characteristics overlooked otherwise. Therefore, the induced models were later evaluated by asking how well they conform to theory, other research findings and expert knowledge on political instability.

General Political Instability Models (Induced from the F Set)

From the data set constructed in the first phase (F set), it was possible to detect increasing population and a change in GDP per capita as the most relevant driving forces for political instability. The following specific models were constructed:

Model F1

Countries characterized by *significantly increasing population* as a result of *rapidly decreasing infant mortality*. Additional, but not necessary, characteristics are decreasing GDP per capita and growing urban population. Such countries are more likely to suffer an adverse regime change than other countries. An example of such a case would be South Korea in 1961. Model sensitivity is 42% and specificity is 78%. This pattern closely resembles theoretical models from the literature on modernizing and developing countries. Numerous forces of social change coincide: growing demographic pressure coupled with urbanization provide for a tight job market and social dislocation, creating the structural conditions for conflict. An economic recession then becomes the proximate cause of violent conflict. This model agrees with the explanations by Huntington outlined above.

Model F2

Small countries with an *increasing number of conflict in bordering states* in combination with *increasing trade openness*. Additional characteristics are small size, a strongly decreasing GDP per capita and decreasing population. The most frequent outcomes are ethnic wars and complex cases (a combination of several different outcome variables). Bosnia in 1992 is a typical representative of this concept. Model sensitivity is 32% and specificity is 87%. F2 does not lend itself to a parsimonious interpretation like F1 does. It is potentially interesting because it does not agree with existing theories of political instability. The combination of the factors “neighboring conflicts” and “trade openness” is very unusual. While such a combination might seem plausible on the surface (a relatively open society “importing” the seeds of conflict), it is more likely that this model is either a collection of individual outlier cases or that it is held together by omitted background variables. Another possibility is that the key causal variable in F2 is the “increasing number of neighboring countries in conflict” one, which had already been found as contributing to conflict by the PITF and in further research (de Waal, 2000: 1–34). In this case, the other descriptor (trade openness) would be an epiphenomenon, i.e., a factor that correlates with the neighboring conflicts variable without there being a relevant connection between the two.

Model F3

Countries characterized by *increasing population* and *increasing GDP per capita* and *increasing cropland*. Additional characteristics are regime type stability and decreasing trade

openness. The most likely outcome is an adverse regime change, with Argentina 1973 being an example. Model sensitivity is 19% and specificity is 93%. There are some similarities with F1: firstly, both models include an increasing population. Secondly, while F3 includes an increase in GDP, the countries in F1 exhibit a decrease. This is not the contradiction it may seem—Clément (2004) has indicated that the economic shift in itself is relevant, but not its direction. These similarities again lead us to the issue of social and economic change. The model conforms to Huntington's explanation, in that it looks at a static regime in a situation of change. The regime is unable or unwilling to adapt to the changing circumstances, which leads to a violent confrontation that effects regime change. The descriptors increasing cropland and decreasing trade openness do not add explanatory value. Beyond infrequent conflicts between pastoralists and nomads in some parts of sub-Saharan Africa, there is no theoretical reason why increasing cropland should contribute to conflict. Decreasing trade openness might suggest international isolation of the country, possibly as a result of a crackdown by the government, but this is highly speculative and merely reinforces the importance of the regime variable. Accuracy characteristics and overlapping between models are illustrated in Figure 1.

The conditions used in all three models are based on complex descriptors related to temporal changes of input descriptors. The result justifies the temporal approach to the

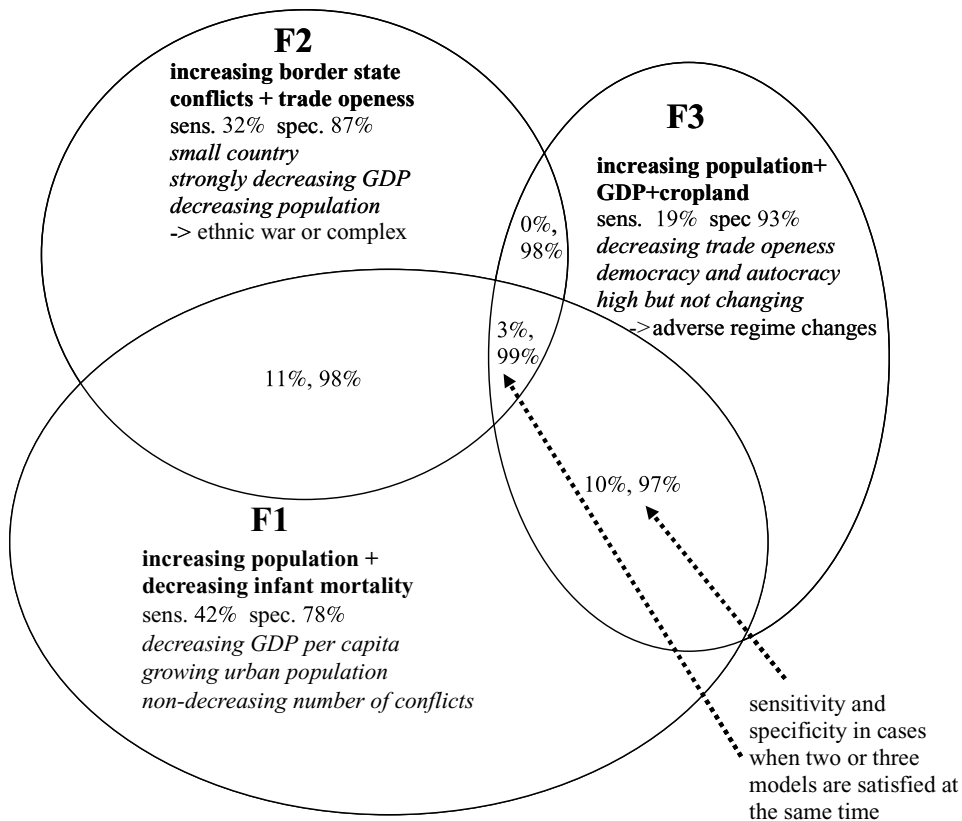


FIGURE 1 Models of the general concept of political instability with respective sensitivity and specificity values. The OR combination of at least one of the three satisfied models has a sensitivity of 68% and a specificity of 65%. The results are based on 118 positive and 259 control cases.

analysis of the PITF data set. But the results allow the conclusion that dynamic conditions are more relevant than the absolute values of these variables in analyzing political instability. For example, “changing quality of life or increasing GDP per capita” can have a much larger impact on political stability than the actual absolute values of infant mortality and GDP per capita. Additionally, some variables have different implications for different models. One example is GDP per capita: in model F3, increasing GDP is a necessary condition while models F1 and F2 both detect decreasing GDP as an additional, but not necessary characteristic of unstable countries. Furthermore, we have an increasing total population in models F1 and F3 as a necessary condition and a decreasing population in model F2 as an additional characteristic. These results demonstrate the importance of partitioning the group of positive cases into subgroups. In other words, different countries seem to follow different paths toward political instability.

Immanent Danger of Political Instability

From the M data set, we induced immanent characteristics of countries that eventually experienced political instability. The most frequently detected properties are an increasing population, a small percentage of urban population, changes in labor force and a not completely democratic government (a Polity score below 7).⁴ The following specific models have been detected:

Model M1

Countries characterized by a *very low percentage of urban population (below 41%)* and a *change of leadership*. Additional characteristics are large changes in the total labor force and a changing level of democracy. A typical case of this model is Haiti in 1991. Model sensitivity is 25% and specificity is 89%.

Model M2

Countries characterized by *low percentage of urban population (below 55%)* and *changing infant mortality*. Additional characteristics are large changes in total labor force and increasing population. Jordan 1967 represents a good example of this model. Model sensitivity is 62% and specificity is 77%.

Model M3

Countries characterized by *low, but rapidly changing percentage of urban population (below 50%)*. Large changes in the total labor force represent an additional characteristic. One of the cases from M3 is South Africa 1967. Model sensitivity is 49% and specificity is 86%.

Models M1 to M3 conform to Huntington’s general proposition that modernizing societies are at a special risk of instability and conflict. Further, low percentage of urban population is a constant property that represents a necessary (if not sufficient) condition. The large segment of rural population indicates that these are underdeveloped and modernizing countries. A political crisis ensues when a proximate cause is added to this structural

⁴The Polity score is drawn from the Polity IV data set. It stands for the difference between the two variables showing the degree of democracy (DEMOC) and autocracy (AUTO) in a country. Since these have values between 0 and 10, the Polity score ranges from -10 (completely autocratic) to 10 (completely democratic). The Polity IV data set is available at <http://www.cidcm.umd.edu/inscr/polity/>.

condition, e.g., a change in leadership (M1), a change in the quality of life (M2), or increasing urbanization (M3).

The models M1 to M3, which describe the immanent features of unstable cases, seem very well suited to point out the crucial factors differentiating stable from unstable countries. The models rely more on attributes differentiating developing and developed countries. This is reflected primarily in the attribute “low percentage of urban population” that is present in all models, and the condition “changing labor force,” which is a supporting characteristic for these models. In contrast to models induced from the F data set, models describing immanent characteristics of politically unstable states have a somewhat higher accuracy. This shows that socioeconomic descriptors included into the PITF data set are better for differentiating between unstable and stable countries than for building concrete political instability models.

Specific Conditions for the Onset of Instability

In the S set, negative cases were generated only from the countries that had experienced instability in a time period at least 5 years prior to or after the negative case. Hence, we expected that the models induced would reflect specific conditions that contributed to the immediate onset of political instability. The following models have been constructed:

Model S1

Countries characterized by *rapidly changing infant mortality but no significant change in GDP per capita*. Additional characteristics are a relatively high maximum level of democracy, and a large agricultural population. This model is exemplified by Gambia 1994. Model sensitivity is 25% and specificity is 94%. The rapid change in infant mortality points toward major changes in the quality of life. A large agricultural population combined with a formal system of democracy and economic stagnation suggests that these are countries that were suffering from an economic crisis, possibly in combination with uneven development. The economic situation might then have been ripe for exploitation by elite actors capitalizing on popular unrest, which eventually led to regime change.

Model S2

Countries characterized by *semi-democracy (Polity score above -5) and a change in membership in regional organizations*. Additional characteristics are an increasing GDP and a changing size of forest cover. Albania 1996 is a typical representative of this subgroup. Model sensitivity is 26% and specificity is 93%. Having a democracy score somewhere between 0 and 7 on the Polity scale, these regimes can be considered anocracies. This model most likely captures countries in transition that had previously emerged from single-party or military rule and taken some steps towards a true polyarchy which makes their political system highly vulnerable. The variable “changing membership in regional organizations” is hard to interpret. A changing membership reflects either diplomatic realignment or deepening regional integration. Since semi-democracies are less stable than other regimes types (Hegre et al., 2001), inclusion of this variable means that this model most likely covers a group of countries in transition.

The models induced from the S set have low sensitivity scores and a relatively low level of accuracy. Beyond the regime characteristic (where both models exclude highly autocratic countries), the models have no common features. A possible interpretation for this phenomenon is that generalizing specific conditions for the onset of political instability

is a very difficult task. Instead, onset might be influenced more strongly by context- and case-specific factors. To understand the problem of political instability, it is necessary to integrate the models obtained from the S set with conditions detected in set M. This is especially relevant for the conditions based on the type of government. From set M we have learned that nondemocratic countries have a larger risk of instability while the S set points out the relative dangers of nonautocracy. These two specific properties, combined into the general proposition that semi-democracies are at a higher risk of instability, support the findings of the PITF as well as of the quantitative literature on civil war.

Toward a Unified Concept of Political Instability

The induced models and their expert evaluation allow for the extraction of some general conclusions about the causes of political instability. A very simple proposition to be inferred is that instability and its onset are a very complicated process that cannot be predicted solely from static socioeconomic data. In that respect, our results confirm those reported by the PITF. However, the induced models allow for some further theorizing.

Summarizing the results, we can say that instability is characteristic of countries with a high share of rural population undergoing significant social, economic or political change. Fast population growth and a change in GDP are important supporting indicators. A fully developed, “mature” system of democracy seems to be able to absorb problems associated with social change, and a high level of democracy is a key characteristic of countries without immanent danger of instability. Onset of political instability usually happens in periods of political transition. This is a fairly trivial observation, but it has to be pointed out that a hybrid regime is not a sufficient condition by itself; it needs to be accompanied by periods of rapid or unbalanced economic and social changes to escalate into crisis. Other proximate risk factors seem to be changes in the country’s leadership as well as conflict in neighboring countries.

Our exclusion of positive cases where the country in question had not been independent for at least 5 years before instability set in might have introduced selection bias. However, such bias, if present at all, will likely have caused us to underestimate the robustness of the factors identified. Previous research (Fearon & Laitin, 2003) has shown that countries are at a significantly higher risk for conflict for a few years after independence. While they propose no theory as to why this might be the case, our findings support the notion that this increase is due to the attendant political transition which is accompanied by social and economic change. In addition, newly independent countries since 1945 have usually been overwhelmingly poor which correlates strongly with large population growth. All of these are factors that show up as highly relevant in our model.

Discussion and Conclusions

The relevance of the work presented in this paper lies in the effort to use the novel methodology of subgroup discovery that had not previously been used to analyze social science data. The methodology is able to produce results that go beyond those obtained by other quantitative studies. What the new methodology provides is a) the automatic detection of relevant subconcepts and b) a concise description of subgroups through co-occurring variables.

As regards the first point, the automatic detection of subgroups is relevant whenever a complicated target concept like political instability can be more effectively described by breaking it down into different but potentially nonexclusive subconcepts. The advantage of the subgroup discovery approach is that expert knowledge is not necessary for this step. More importantly, expert-generated subgroups might be inappropriate: in our research, neither

regional nor religious properties show up as central features or as descriptive properties of the induced subgroups. As to the type of instability, it should be noted that models F1 and F3 predominantly describe adverse regime changes while F2 mainly corresponds to ethnic wars and complex cases (see Figure 1). This suggests that ethnic wars and adverse regime changes really have different causal backgrounds.

Additionally, different subgroups may have the same relevant variables but with opposite effects. For example, models F1 and F2 identified decreasing GDP per capita as an indicator of crisis while F3 included increasing GDP per capita as a crucial variable. In such cases, the search for globally relevant variables may completely fail to detect such descriptors even though they are relevant for each subconcept. In this way the subgroup discovery approach may prevent such important variables from being overlooked.

The second advantage of this methodology is the explicit construction of models by co-occurring factors in a form directly and easily interpretable by researchers with expertise about cases or the subject matter. In this paper, expert evaluation showed that most models corresponded to existing research results on mass political violence. Even when single variables or whole models were identified as not directly useful these variables or models may be subjected to further analysis, e.g., in the form of process tracing (George & Bennett, 2005). We cannot expect a revolutionary, novel theory about political instability from the methodology at hand, but the results are relevant because they give some added weight to previously existing theories, such as Huntington's theory of political development.

From a methodological point of view, the agreement between induced models and existing research demonstrates that the methodology is able to detect relevant correlations from the available data without expert knowledge. This will be useful for future applications of this methodology, especially for disciplines and problems without a sufficiently developed theoretical background.

The results demonstrate the relevance of the temporal analysis of available data. Although there are variables (like the percentage of urban population or the level of democracy) where absolute or mean values are relevant, a complete understanding of the problem is not possible without analyzing changes in the values of the variables. Changes in total population, GDP and infant mortality seem to have an especially high significance. Interestingly enough, the absolute values of these variables have not been detected as relevant.

The final advantage of the applied methodology is that it can accept a large number of input variables even when the number of cases is modest. In contrast to multivariate logistic regression modeling which needs to have preliminary single-variable correlation tests in order to reduce the number of inputs and ensure the construction of reasonable models, in the subgroup discovery approach a further expansion of the number of input variables is possible. This enables an effective handling of temporal properties of input variables, which may also be relevant for other applications in the social sciences.

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