Personality, Popularity, and Prosperity: Exploring Covariates of Israeli Foreign Policy Behavior (1979-2008) Using Discrete Sequence Pattern Recognition *

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Abstract

For the past several years we have been developing and exploring applications of a customized pattern recognition tool (`http://www.nkss.org`) for the study of sequences of political events, largely focusing on the Israeli-Palestinian conflict. Our efforts to date have been largely developmental and descriptive: we have firmly established that there are regular event patterns in this conflict and these change systematically—sometimes dramatically—but we have yet to ascertain the covariates of these changes. In this study, we will look at three possible factors: the personality characteristics of individual Israeli prime ministers measured in the Hermann-Young ProfilerPlus framework; prime minister and government approval ratings, based on an extensive time series we have collected from published polls in the Israeli press, and macroeconomic indicators such as GDP growth, unemployment, and exchange rates. We correlate these with various patterns of behavior over time, such as the frequency of basic tit-for-tat, unilateral concessions, unilateral escalations, and overall levels of conflict and cooperation has measured with the CAMEO Levant event data set (`http://web.ku.edu/keds/data.html`)

1 Introduction

In 2002, a methodological gauntlet was thrown done by Stephen Wolfram in his work, *A New Kind of Science*.[1] Though his book was not written from or for a social science perspective, several of his assessments are pertinent to that endeavor. Wolfram asserts that most modern scientific methods used in the physical and biological sciences are but idiosyncratic and limited derivations from something much more basic, more fundamental, and more powerful. In place of the continuous-variable mathematical structures that underlie classical mechanics and statistics, Wolfram's approach focuses on the discrete transformation of rule-based patterns. Simple rule-based pattern models can, through iteration, produce surprisingly complex behavior in physical and biological systems. Biochemists, for example, search for patterns in the amino acids coded by a strand of DNA, and then the patterns of those amino acids combine to produce the patterns formed by collections of proteins. Though the patterns in the DNA are simple in themselves, they can ultimately produce highly complex organisms, including human beings.

Conveniently for social scientists, humans do not only originate from patterns, but human psychology is intensely linked to the ability to perceive patterns and to find meaning in patterns (Newell and Simon 1972, Abelson 1973, Simon 1982, Anderson 1983, Kohonen 1984, Holland et al 1986, Margolis 1987, Khong 1992, Reber 1993, Political Psychology 2003). Indeed, it is not far off the mark to suggest the ultimate basis of all human epistemology is discrete pattern identification. As Wolfram puts it, "observers will tend to be computationally equivalent to the systems they observe," (Wolfram, 2002, 737) an observation we will explore shortly.

Simple introspection will show that many interactions in the world have no counterpart in continuous-variable operations, nor can we define every concept in terms of quantities. As Wolfram puts it, it is in many cases clear that the whole notion of continuity is just an idealizationalthough one that happens to be almost required if one wants to make use of traditional mathematical methods. (Wolfram, 2002, 729). The non-continuous nature of much of social reality is why we continue to have human diagnosticians, intelligence analysts, and police detectives. As rule-based pattern recognition devices, our own brains are more powerful—and typically utilize quite different mechanisms—than the most sophisticated mathematical and statistical methods, and at a deep level, we realize this fact anew every time we read a piece of quantitative research in the social sciences.

Mathematical and statistical approaches are a tiny and quite restricted subset of what the human brain is able to bring to bear on a subject matter in pursuit of understanding. This is not to say those approaches are not useful—they are very useful, particularly in realms involving large samples, high levels of noise, and variables that can be naturally operationalized using continuous measures. But they are elementary methods compared to what we already know how to do. As Wolfram puts it, "the field of mathematics as it exists today will come to be seen as a small and surprisingly uncharacteristic sample of what is actually possible" (Wolfram, 2002, 821).

Humans were built to make sense of complexity. In a sense, the way to move past the methodological discontent in our social science disciplines may be to discover more

[1] This section borrows heavily from Hudson, Schrodt and Whitmer 2007.

about how our minds in fact do this. "How we do this" is certainly the foundation of mathematical and statistical approaches, but that foundation could support much more in a methodological sense. If we can explore that "more," we will give ourselves more powerful and less constrained methodologies specifically geared towards the understanding of complexity.

Not only are individual humans built to make sense of complexity by the use of pattern recognition and rule-based behavior, many of the computational modeling projects in political science (Carbonell 1978, Thorson and Sylvan 1982, Sylvan and Chan 1984, Majeski 1987, Andriole and Hopple 1988, Sylvan, Goel and Chandrasekran 1990, Hudson 1991) have justifiably assumed that human collectives, including national bureaucracies do, too. Because of the rule-oriented nature of bureaucracies and the simplifications inherent in popular ideologies, one would be able systematically to extract an organizations rules and precedents from a sufficient quantity of debates, formal regulations and internal memoranda, and from these rules one could simulate much of the governmental decision-making process. The qualitative literature, for example Cyert and March (1963) and Allison (1971), has also long emphasized the rule-based nature of organizational decision-making. In much of their behavior, the bureaucracies are not acting *as if* they followed rules; they are instead *explicitly* following rules and are expected to do so, rule-following being a sine qua non of bureaucratic behavior. Thus, the rule-based pattern approach to social science is applicable not only at the level of individuals, but also at the levels of groups, organizations, and bureaucracies.

Since human understanding involves matching observed events to a rule-based pattern, the function of political discourse is to provide sufficient information to cause the audience to understand (i.e., pattern match) the situation in the same manner that the individual or collective transmitting the information understands it. Political information transfer is the attempt to stimulate pattern recognition in the mind of the audience and thereby trigger a desired behavior. This process can occur between competing organizations as well as within them, and, in democratic situations, in how an organization explains itself to the public. Signaling in a conflict situation involves exchanging messages with an opponent in an attempt to get the opponent to take, or refrain from taking, certain actions. Consequently we would expect to see in political behavior and its accompanying discourse, the explicit use of, and reference to, specific patterns of behavior from which rulesand hence intentions and purposescan be inferred. As a consequence we are calling these discrete sequence rule models, or DSR models.[2] This is a much more intuitive approach to social science explanation than is currently possible using standard statistico-mathematical techniques, and it is an approach that preserves, rather than obliterates, the agential nature of social interaction.

2 Discrete Sequence Rules

In order to visualize event data streams and the discrete sequence rules within those streams, we have developed the EP (Event Patterns) Tool, a web-based methodology that permits recoding of data, visualizing of events, and imputation of agent-based rules for interaction.[3]

[2]In a sense, then, we aim to implement *reverse* Wolfram modeling. Where Wolfram would posit rules and then observe resulting patterns, we are observing patterns that are the result of rules and we intend to postulate what those rules are, and ultimately subject those postulations to efforts at falsification.

[3]This section borrows heavily from Hudson, Schrodt and Whitmer 2007.

EP Tool currently resides at http://www.nkss.org . That site includes a number of data sets from the Kansas Event Data System (KEDS) project, and provides several well-documented facilities for recoding the data, specifying rules, and visualizing event data as discrete patterns rather than scaled aggregations. In particular, the inputs titled "patterns" and "display" allow a researcher to perform discrete pattern transformations on the graphic output. One can also experiment with hypothetical rules, then display whether those patterns account for any of the behavior in the set.

In our first exploratory experiments with DSR modeling using EP Tool, we have used it as a means to provide thick description of the signaling taking place between a dyad of nations. By examining what we are able to "see" in this initial exploration, and whether what we see has face validity, we will then be in a position to move beyond description to hypothesis generation and falsification in subsequent efforts. In this first exploration, then, we specified some very simple rules and then ascertained how well they accounted for the behavior in the Israel-Palestine dyad. We chose this dyad because it is highly active and has been the focus of sufficient media attention that we can be confident that the event data are a reasonably accurate description of the actual behavior in the system. Furthermore, event data on Israeli behavior has been analyzed using a variety of techniques, including vector autoregression (Goldstein et al 2001, Sprecher and DeRouen 2002), binary cross-sectional general estimating equations (DeRouen and Sprecher 2006), time-series cluster analysis (Schrodt and Gerner 2000), and event history models (Schrodt and Gerner 2004) and has generally produced credible results. The dyadic relationship between the Israelis and Palestinians, while certainly affected by the initiatives of third parties, is nevertheless quite internally reactive, as many scholars have noted (see for example Bickerton and Klausner 1998, Gauss 1998, Gerner 1994, Tessler 1994). After choosing a dyad on which to experiment, the next step was to devise a set of interaction rules whose use could be investigated.

Wolfram himself provides encouragement that the rules need not be many, and neither do they need be complex. For example, he states, "Simple and definite underlying rules can produce behavior so complex that it seems free of obvious rules" (Wolfram, 2002, 752). Indeed, Wolfram found that the most complex behavior could be obtained with sets of approximately three rules. We feel that there is reason to believe that the set of rules being employed by the Israelis and Palestinians in enacting what they feel to be meaningful behavior toward one another is also not very large, nor very complex. Signaling between organized human collectives, especially those in conflict, almost mandates that only a small set of simple rules be used in order to maximize the chances that the other group will understand the meaning intended by the action.

Furthermore, because international politics is a complex problem-solving environment, heuristics—simple rules used to partially solve complex problems—are of particular importance. Purkitt observes:

> To cope with limited cognitive capabilities, individuals selectively process information and use a limited number of heuristics or mental rules of thumb as cognitive aids in their effort to manage information. This apparently universal reliance on intuitive heuristics to solve all types of problems seems to be due to the need to compensate for the limitations of short-term memory and information processing capabilities. By using intuitive mental heuristics, people can develop

a problem attack plan which permits them to develop a subjectively acceptable problem solution. (Purkitt 1991,43)

For example, rational choice and balance of power theories are heuristics in the sense that they are relatively simple; they come with a complex set of side-conditions, and they are intended as general rules to guide decision-making without providing a complete specification of actions to be taken. To the extent that an heuristic is shared by the decision-makers in a political system—for example balance of power in 19th century European diplomacy or the Chicken game in 20th century nuclear deterrence—it reduces uncertainty and becomes self-validating.

For our initial explorations of the DSR method, we selected a set of rules that we believed were enacted between the Israelis and Palestinians on an aggregate level. These rules were chosen from a combination of the general theoretical literature and a qualitative assessments of what some experts in the field assert are the rules these specific actors do use (e.g. Bickerton and Klausner 1998, Gauss 1998, Gerner 1994, Goldstein et al 2001, Tessler 1994). These rules, like those of any formal model, constitute a simplification of the actual behavior driving the event-generating process.

We did impose some delimiting assumptions in our use of DSR models. First, following the practice of most of the quantitative literature in the field, we are treating both sides as unitary actors, despite the fact that behavior by the Palestinians in particular is quite decentralized, notably in the oftentimes divergent agendas of the generally secular Fatah movement and the Islamic militant groups such as Hamas. There is no necessity in the DSR method to take this approach, but it simplified our experiments at this initial exploratory stage. Furthermore, there is reason to believe—and this contention is supported by earlier empirical work in various statistical frameworks—that there is likely to be sufficient consistency at the aggregate level that we should be able to find some patterns even with this rough assumption. Second, we examined a simple dichotomy of conflict behavior and cooperative behavior, though that, too, is not demanded by the model, and KEDS data can support behavioral distinctions of very fine grade. Again, we used this crude dichotomy to simplify our initial explorations of the DSR method.

3 Data

3.1 Event Data

The event data used in this study were coded into the CAMEO scheme (Gerner et al 2009) using `TABARI`, a computer program that creates event data from machine-readable text (.[4]

The events were coded from Reuters News Service lead sentences obtained from the NEXIS data service for the period May 1991 through May 1997, the Reuters Business Briefing service for June 1997 through September 1999, and the Factiva data service for October 1999

[4] Discussions of machine coding can be found in Gerner et al. (1994), Schrodt and Gerner (1994), and Bond et al. (1997) and King and Lowe 2003. The codebook for CAMEO can be downloaded from `http://web.ku.edu/keds/data.dir/cameo.html`

through August 2008.[5]

The coding software, coding dictionaries and data are available at the KEDS web site, `http://web.ku.edu/keds`. Following the standard practice of the KEDS project, the event data were run through a "one-a-day filter" that discarded multiple instances of any source-target-event occurring in a single day: this eliminates duplicate and developing stories, albeit at the cost of eliminating some true multiple events, particularly acts of violence during high conflict periods.

The analysis considers two dyads: Israeli actions towards the Palestinians, and Israeli actions towards Lebanon. For the Palestinians this includes actions towards both state and sub-state actors having PSE or PAL as the primary code in the CAMEO actor coding system[6] In the CAMEO actor coding framework, we use this for Palestinian quasi-state entities, the Palestine Liberation Organization and the post-Oslo Palestinian Authority. PAL refers to ethnic Palestinians and includes the actions of Palestinian non-state actors such as Hamas and Islamic Jihad. The data set contains 17,427 events involving this dyad for the period 15 April 1979 to 31 August 2008.

3.2 Polling data

Our initial source for the PM popularity data was a data set assembled by Rafi Ventura. This data was collected as follows

> All surveys were conducted either by the Guttman Institute for Applied Social Research (1948-1995) or by the Guttman Center at the Israel Democracy Insitute (later dates). The respondents in all surveys are Israeli citizens. All samples are representative samples of the adult population (age 18 onwards). The surveys were conducted face-to-face till the mid-80s and via telephone in later years.

The Ventura data, while of high quality, was relatively sparse, so we extensively augmented this with polling data reported in the Lexis/Nexis database.[7]. The search keyword was `poll* AND Israel` and variations on that, notably combinations of Prime Minister names with `poll*`. This search string was very broad and there was considerable information that was not relevant, but this appears to have located every available poll.

The breadth of the search was necessitated the inconsistent manner of reporting on polls from news agencies and other media outlets. For example, some of them would only mention a poll result in one sentence in the middle of the text. So there was some amount of digging, including reading news stories in detail to find other details. Some articles indicated polling numbers done in the past, without noting a margin of error or any other details, which involved some archival and internet research to track down those numbers.

Search results were usually in the thousands, so we restricted this search string to certain dates that would make the results more manageable: LexisNexis will not allow more than

[5]These data are available through June 2009, and we in fact are now maintaining a global data set in near-real-time—daily updates—using the Reuters RSS feeds: contact Schrodt for details.

[6]PSE is the ISO-3166-1 Alpha3 code for "Palestinian Occupied Territories."

[7]We also used Factiva to check if it provide additional information beyond Lexis-Nexis; in fact Lexis-Nexis had the most information

1,000 results, so if we could get it below about 900, we knew the results covered everything available on Lexis-Nexis.

There were two other important resources. First, the Independent Media Review Analysis (http://www.imra.org.il), a media organization in Israel, includes a daily digest of various newspaper articles, including polling by Gallup and other companies. Whenever possible, we would try to confirm the information available on the site with other sources, and did not find any major discrepancies. IMRA was particularly useful from around 1996 until 2008, and some parts of the data, especially the data points for Netanyahu, are dominated by information obtained from this source.

Second, http://Angus-Reid.com, which compiles public polling about various topics around the world, has been helpful in some instances. Whenever possible, this data was confirmed with the search results from the LexisNexis database. No discrepancies were found.

The data were averaged monthly: the number of polls used in the average ranged from 1 to a high of 18 (January 2001). In about half a dozen cases, we had no polls during a month and took the average of the prior and next month. Very little polling data is available on Lexis-Nexis or any of our other sources prior to June 1994 so we are not using this variable prior to that point. A file with all of the disaggregated polling data, and the sources for each point, is available from the authors.

Figure 1 shows the time series for this data by prime minister. The conspicuous feature of the data, obviously, is the very strong tendency of opinion to decline over time—the correlation between the popularity and months in office is -0.24, significant at the 0.001 level.

3.3 Economic data

We collected information about economic indicators for all the years for which polling was available. Data was collected from the National Bank of Israel and the Israeli Central Bureau of Statistics.

GDP At current prices, original data, N.I.S. Thousands. GDP data was retrieved from the Central Bureau of Statistics in Israel, from the Time-Series data-bank. Data was available since 1980. The website is: http://www1.cbs.gov.il/ts/ Path: National Account (Data Up To 1995); Sna68 (Data From 1980 through 1995)—Gross Domestic Product).

Change in GDP. This information was retrieved from the Bank of Israel Series Database, Section National Accounts, Subsection GDP and use of resources. Website:
http://www.bankisrael.gov.il/series/en/export/html/?series=BI.PCT.GDP.Q_FP-06

Unemployment data - Persons aged 15 years and over This includes the residents of East Jerusalem and persons who did not work in the country during the previous 12 months. Data was retrieved from the International Labor Organization's LABORSTA database. Website: http://laborsta.ilo.org/.

Inflation rate (averaged based on CPI, with seasonal adjustment) Data retrieved from Bank of Israel Series Database. Section: princes and inflation expectation. Subsection: underlying inflation andgroups of prices. Website: http://www.bankisrael.gov.il/series/en/export/html/?series=PN.R&start=1981-02&end=2009-07

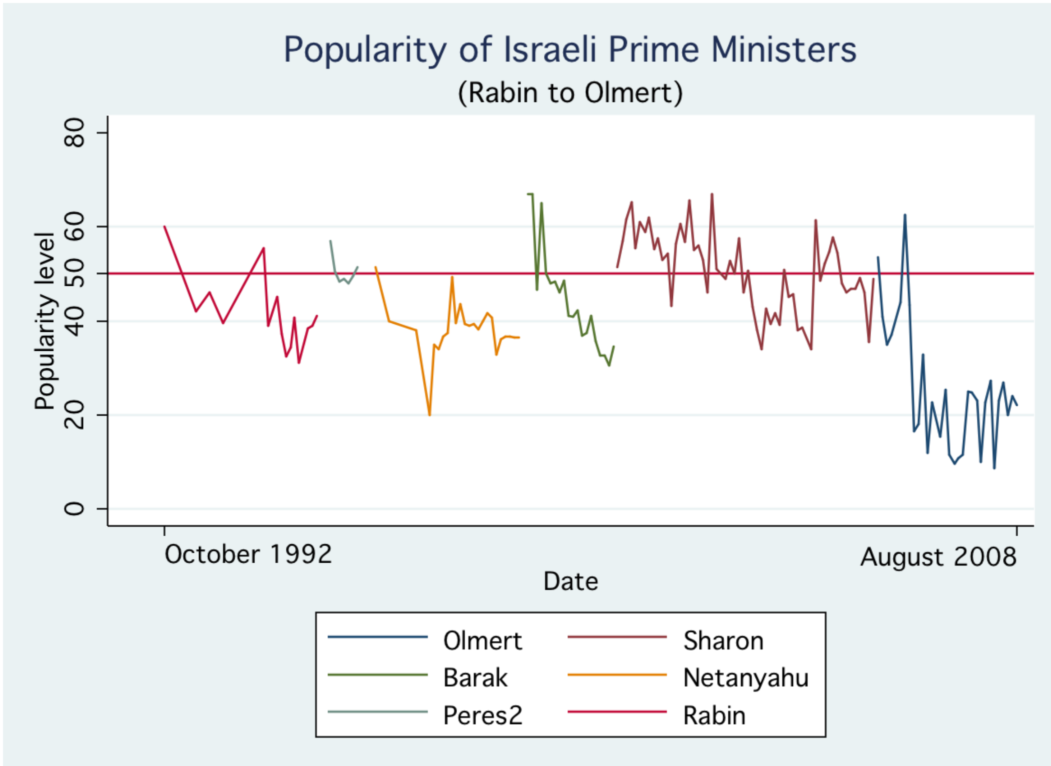

Figure 1: Public opinion time series for Israeli prime ministers

Exchange rate: NIS/dollar representative exchange rate, monthly with seasonal adjustment. Retrieved from the Bank of Israel Series Database. Section: exchange and interest rates and foreign currency reserves. Subsection: Representative exchange rates. Website: `http://www.bankisrael.gov.il/series/en/export/html/?series=MAT01.MA&start=1970-02&end=2009-08`

3.4 Personality data

The covariates on prime minister personality are based on the work of Hermann (1984, 2005) and the work Walker and Schafer and Young (WSY; Young 2001, Walker, Schafer and Young 2005, Walker and Schafer 2006) and were originally tabulated in Astroff (2008). We considered six indicators:

- **BACE** (Hermann): Belief in Ability to Control Events. This variable shows how effectual the leader believes he is and can be.

- **CC** (Hermann): Conceptual Complexity. This variable shows whether the leader is able to see shades of gray or only absolutes in black and white.

- **TASK** (Hermann): Task/Affect Orientation. The higher the score on this variable, the more the leader is focused on completing tasks; the lower it is, the more the leader is focused on maintaining relationships.

- **PWR** (Hermann): Need for Power
- **SC** (Hermann): Self Confidence
- **DISTRUST** (Hermann): Distrust of Others. This measures the degree to which the leader views others as untrustworthy, perhaps even out to "get" him

We considered three versions of these indicators: raw scores; Z-scores standardized on the set of Israeli primes ministers, and Z-scores standardized on a set of all world leaders.

4 Event Aggregations and Patterns

4.1 Event aggregations

For the event counts, we use the following general classes of events based on the CAMEO two-digit cue categories:

Table 1: Aggegration of CAMEO categories

verbal cooperation	CAMEO categories 01 to 05
material cooperation	CAMEO categories 06 to 09
verbal conflict	CAMEO categories 10 to 14
material conflict	CAMEO categories 15 to 20

This reduces the number of distinct event categories that can be used as independent variables to a manageable amount and is also likely to reduce the effects of coding error somewhat, since only broad categories of events are being considered.

4.2 Event patterns

The event patterns that we analyze here follow those we studied in Hudson, Schrodt and Whitmer (2007). These are based on occurrences of, and departures from the classic "tit-for-tat" (TFT) approach immortalized by Rapoport and, more recently, Axelrod (1984). Country experts have asserted that the Israelis and Palestinians consciously use this rule; and it has long been known that reciprocity is one of the strongest patterns in event data (for example Dixon 1986, Ward and Rajmaira 1992, Goldstein and Freeman 1990, Goldstein and Pevehouse 1997). We consider the following patterns.

- <u>Conflictual Tit-for-tat</u>:
  Two or more incidents of material conflict by Palestinians directed towards Israel reciprocated within three days by four or more incidents of material conflict by Israel directed towards Palestinians [8]

[8] The different thresholds of conflict for the two sides are an adjustment we have been using to deal with the fact that the data contain substantially more events by Israel towards the Palestinians than vice versa.

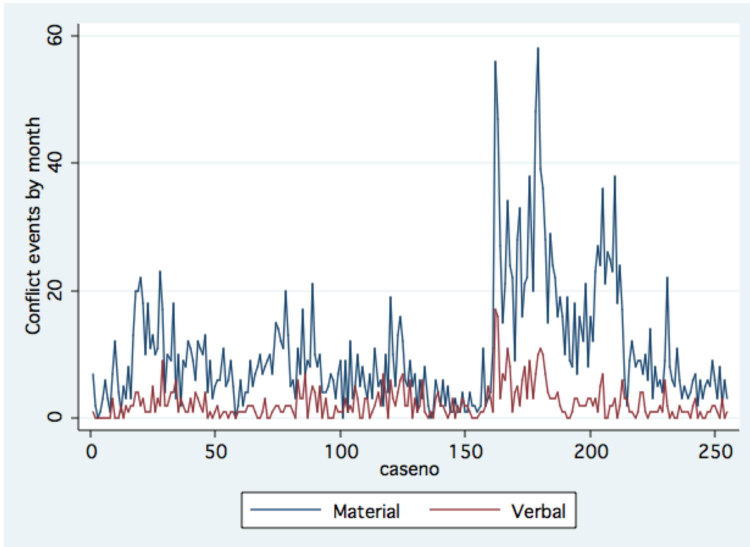

Figure 2: Monthly conflict events, Israel to Palestinians

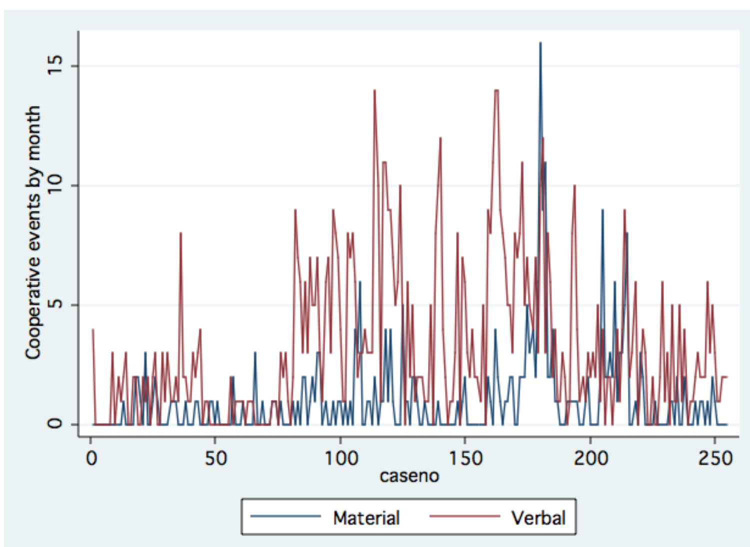

Figure 3: Monthly cooperation events, Israel to Palestinians

- Cooperative Tit-for-tat:
  One or more incidents of material cooperation by Palestinians directed towards Israel reciprocated within three days by one or more incidents of material cooperation by Israel directed towards Palestinians

- Olive1:
  Zero incidents of material cooperation by Palestinians directed towards Israel within three days followed by one or more incidents of material cooperation by Israel directed towards Palestinians. The olive-branch rule is the standard gambit for breaking out of the mutually-destructive DD/DD/.../DD sequence in the classical prisoners dilemma game.

- Olive2:
  One or more incidents of material conflict by Palestinians directed towards Israel in a period three to six days earlier followed by one or more incidents of material cooperation by Israel directed towards Palestinians

- Provocation:
  Zero incidents of conflictual tit-for-tat by Palestinians directed towards Israel followed by one or more incidents of material conflict by Israel directed towards Palestinians. This is the complement of an olive branch.

In the EP Tool, where Israel is actor "B", these measures are labeled, respectively, *AthenB, ACthenBC, noACthenBC, oliveB* and *noAthenB*.

5 Results: Exploratory Qualitative Concordance Assessment

Following the graphically-rich approach of Wolfram (2002), in Hudson, Schrodt and Whitmer (2007), we make a number of observations about the utility of using the pattern recognition built into the human visual cortex and its accompanying wetware as a means of making at least a first cut at determining possible causal relationship in our data. In particular, the EP-Tool makes extensive use of color (as well as glyphs), which can be easily generated and displayed on computer screens.[9]

Figures 4 and 5 provide a variant on this approach, first simplifying the indicators, which are aggregated by quarter rather than month, into a small number of categories, then displaying these with a color coding.[10]. Our objective is to see whether these blocks of color indicate any general qualitative rules that relate the personality, popularity and economic

Some of this is probably an artifact of the reports; some of it simply the greater military capacity of Israel. The threshold can be easily adjusted in the `EP Tool` and is somewhat arbitrary; based on our earlier work with the data, these values give a time series that still has a fair amount of detail that is lost if we set the values higher, while still not overwhelming the series with day-to-day variation, which occurs if the values are set lower.

[9] Though probably not on the display technologies likely to be available at the APSA Toronto meeting...

[10] The color of the PMs name means nothing and is there for visual organization.

indicators to the strategic profiles of the PMs. These results can then be used to guide our more conventional statistical analyses.

5.1 Coding for the tables

We trichotomized rule use into 3 categories for a first cut at exploration. Unprovoked aggression was one category, then tit-for-tat reciprocity (conflictual or cooperative) in a second, and then unprovoked peace-making efforts in a third. Though such simplification is not ideal, for exploratory purposes, it gives us a rough measure of the basic nature of the rule under use.

These categories of rule use are different than raw counts of conflict and cooperation events we will analyze later. Rule use means that we discerned an actual, purposive strategy to use conflict and cooperation in certain ways. Not only is it a strategy, but it is a strategy whose use is meant to be seen and recognized by the opponent, being repeated often enough to rise above the noise: it is a classical situation of signaling. Rule use profile change means we are seeing an actual change in strategic choice.

We then examined the mix of strategies in use during any quarter, assessing it for predominance of one type of strategy or another. We created a five-point scale that represents a *rule use profile*, that it, the profile represents the choice by the leadership to signal to its opponents with a particular set of strategic rule use.

5.1.1 Rule Use Profile Key

- blue: exclusive use of unprovoked cooperation as a strategy
- green: significant use of unprovoked cooperation as a strategy, even though reciprocity and some unprovoked aggression may occur.
- yellow: fairly balanced rule use
- orange: significant use of unprovoked aggression, even though reciprocity and some unprovoked cooperation may occur
- red: almost exclusive use of unprovoked aggression as a strategy

5.1.2 Popularity and Prosperity

The popularity and "prosperity" indicators were also placed in three categories to allow for a more discrete style of qualitative analysis. We are currently looking only at change in GDP as a measure of prosperity; our regression analyses will also look at the unemployment and exchange rate indicators.

color	category	GDP growth	popularity
blue	good	>2%	>40%
yellow	average	0% - 1.9%	30% - 39%
red	bad	<0%	<29%

5.1.3 Personality

Personality is used essentially as the default explanation for the rule use profile that we see—in other words, we posit invariant behavior based on unchanging personality type. Obviously that is not a credible general hypothesis, but it can help us to tease out the effects of popularity and prosperity. If the behavior is largely invariant, were attributing it to personality for exploratory purposes.

The letter codes in this column are based on the Hermann variables in the order given in Section 3.4; the coding is A=Avg; H=High, L=Low, VH=Very High, and VL=Very Low based on the standard deviation cut-points using Z-scores standardized for the Israeli PM cohort. The choice of color is somewhat subjective and based on Hudson's 25 years' use of the Hermann framework.

- Green: personality predisposes towards cooperatve initiatives towards opponents (Peres, Rabin, and Olmert)
- Yellow: personality does not seem to predispose towards a particular rule use strategy (Shamir and Barak)
- Orange: personality predisposes towards conflict as a general rule use strategy with opponents (Netanyahu and Sharon)

5.1.4 Personality Prediction

This column is coded Y/N based on a comparison of the predicted color of the PM's personality (green, yellow, or orange) to the color of the overall rule use profile in that quarter.

5.2 Observations from the Exploratory Concordance Assessment

1. Personality plays a more important role for some PMs than others. If we look at the percentage of time that the predicted thrust of foreign policy towards the Palestinians, as based on personality, matches the resulting behavior, we get:

Shamir	24%
Rabin	18%
Peres	0%
Netanyahu	18%
Barak	14%
Sharon	47%
Olmert	9%

This table seems to indicate that the rule use profile of Ariel Sharon was most closely linked to his personality, of all the Israeli prime ministers examined. That is, the type of rule use profile we would expect from Sharon based on his personality does match the observed rule use profile during his tenure as prime minister.

This table may in fact underestimate the effects of personality effects. For example, Olmert is expected, on the basis of his personality, to favor cooperative initiatives towards opponents. In fact, his level of cooperation as a strategy in his rule use profile exceeds that

Quarter	PM	Provo-cative	Recipr-ocity	Olive	Popu-larity	Econ-omics	Personality	Personality Prediction
87-2	Shamir	20	0	0	2	1	LALLAL	n
1987-3	Shamir	11	0	5		2	LALLAL	y
1987-4	Shamir	0	0	0		3	LALLAL	n
1988-1	Shamir	28	11	5		1	LALLAL	n
1988-2	Shamir	29	0	5		3	LALLAL	n
1988-3	Shamir	22	0	5		1	LALLAL	n
1988-4	Shamir	52	0	5	1	2	LALLAL	n
1989-1	Shamir	24	0	0	1	3	LALLAL	n
1989-2	Shamir	18	0	6		2	LALLAL	n
1989-3	Shamir	16	0	0		2	LALLAL	n
1989-4	Shamir	22	0	2		3	LALLAL	n
1990-1	Shamir	11	0	4		1	LALLAL	y
1990-2	Shamir	24	0	0		2	LALLAL	n
1990-3	Shamir	5	0	10		2	LALLAL	n
1990-4	Shamir	0	0	5		1	LALLAL	n
1991-1	Shamir	4	0	0		3	LALLAL	y
1991-2	Shamir	0	0	5		1	LALLAL	n
1991-3	Shamir	0	0	6		1	LALLAL	n
1991-4	Shamir	8	0	13		1	LALLAL	n
1992-1	Shamir	11	0	11		2	LALLAL	y
1992-2	Shamir	13	0	3	1	2	LALLAL	y
1992-4	Rabin	31	0	3	1	2	VLVHALVHA	n
1993-1	Rabin	23	0	4		2	VLVHALVHA	n
1993-2	Rabin	27	0	0	1	3	VLVHALVHA	n
1993-3	Rabin	0	0	3	1	1	VLVHALVHA	n
1993-4	Rabin	5	10	8	2	1	VLVHALVHA	y
1994-1	Rabin	15	2	6		1	VLVHALVHA	n
1994-2	Rabin	8	19	8		3	VLVHALVHA	y
1994-3	Rabin	8	0	8	1	2	VLVHALVHA	n
1995-1	Rabin	18	4	9	2	1	VLVHALVHA	n
1995-2	Rabin	0	0	4	2	1	VLVHALVHA	n
1995-3	Rabin	12	0	3	1	3	VLVHALVHA	n
1995-4	Peres	24	0	8	1	2	ALAVLAA	n
1996-1	Peres	16	0	8	1	2	ALAVLAA	n
1996-2	Peres	0	0	10	1		ALAVLAA	n
1996-4	Netanyahu	8	12	3	1	2	HALVHHH	n
1997-1	Netanyahu	10	0	9		3	HALVHHH	n
1997-2	Netanyahu	12	8	10	2	1	HALVHHH	n
1997-3	Netanyahu	17	12	4	3	2	HALVHHH	n
1997-4	Netanyahu	11	0	5	2	3	HALVHHH	n
1998-1	Netanyahu	0	0	17	1	1	HALVHHH	n
1998-2	Netanyahu	13	0	3	1	3	HALVHHH	n
1998-3	Netanyahu	30	0	0	2	1	HALVHHH	y
1998-4	Netanyahu	14	0	2	2	2	HALVHHH	n
1999-1	Netanyahu	14	0	0	2	3	HALVHHH	y
1999-2	Netanyahu	0	0	0	2	1	HALVHHH	n

Figure 4: Quarters with Patterns and Personality by PM: Shamir to Netanyahu

Quarter	PM	Provo-cative	Recipr-ocity	Olive	Popu-larity	Econ-omics	Personality	Personality Prediction
1999-3	Barak	0	0	5	1	1	AHLHVLVL	n
1999-4	Barak	6	0	9	1	2	AHLHVLVL	n
2000-1	Barak	0	0	0	1	2	AHLHVLVL	n
2000-2	Barak	9	0	0	1	1	AHLHVLVL	n
2000-3	Barak	0	0	8	2	1	AHLHVLVL	n
2000-4	Barak	4	13	5	2	3	AHLHVLVL	y
2001-1	Barak	27	5	1	2	3	AHLHVLVL	n
2001-2	Sharon	20	9	4	1	3	VHVLVHHHVH	n
2001-3	Sharon	25	0	3	1	2	VHVLVHHHVH	y
2001-4	Sharon	19	11	6	1	3	VHVLVHHHVH	n
2002-1	Sharon	14	18	7	1	2	VHVLVHHHVH	n
2002-2	Sharon	8	15	9	1	2	VHVLVHHHVH	n
2002-3	Sharon	23	8	9	1	2	VHVLVHHHVH	n
2002-4	Sharon	22	10	7	1	3	VHVLVHHHVH	n
2003-1	Sharon	29	0	5	1	2	VHVLVHHHVH	y
2003-2	Sharon	24	0	6	1	2	VHVLVHHHVH	y
2003-3	Sharon	22	0	4	1	1	VHVLVHHHVH	y
2003-4	Sharon	19	0	5	2	3	VHVLVHHHVH	y
2004-1	Sharon	20	11	0	1	1	VHVLVHHHVH	n
2004-2	Sharon	29	0	5	1	2	VHVLVHHHVH	y
2004-3	Sharon	35	0	7	2	1	VHVLVHHHVH	y
2004-4	Sharon	35	0	8	1	3	VHVLVHHHVH	y
2005-1	Sharon	26	2	11	1	1	VHVLVHHHVH	n
2005-2	Sharon	11	0	11	1	2	VHVLVHHHVH	n
2005-3	Sharon	12	11	9	1	1	VHVLVHHHVH	n
2005-4	Sharon	14	0	5	1	3	VHVLVHHHVH	y
2006-1	Olmert	23	0	3	1	1	AVLHAVLA	n
2006-2	Olmert	8	0	5	1	1	AVLHAVLA	y
2006-3	Olmert	23	0	2	1	2	AVLHAVLA	n
2006-4	Olmert	0	0	9	3	3	AVLHAVLA	n
2007-1	Olmert	0	0	7	3	1	AVLHAVLA	n
2007-2	Olmert	0	0	0	3	2	AVLHAVLA	n
2007-3	Olmert	0	0	7	3	1	AVLHAVLA	n
2007-4	Olmert	0	0	7	3	2	AVLHAVLA	n
2008-1	Olmert	0	0	8	3	1	AVLHAVLA	n
2008-2	Olmert	15	0	5	3	2	AVLHAVLA	n
2008-3	Olmert	0	0	7	3	2	AVLHAVLA	n

Figure 5: Quarters with Patterns and Personality by PM: Barak to Olmert

which we would expect. If exhibiting even higher levels of cooperation than the expected cooperation can be viewed as concordant with his personality, then Olmerts personality would actually account for 72.

2. No relationship between popularity and the rule use profile is apparent from these exploratory charts. Negative public opinion doesn't push a PM necessarily towards conflict rule use profile or cooperative rule use profile. In fact, negative public opinion doesn't necessarily cause a PM to change at all—consider for example Olmert, whose poll ratings are at notoriously low levels,[11] but whose rule use is relatively invariant. But Sharon's rule use profile is relatively invariant, also, and his poll ratings are good. It is also interesting to note that prosperity and popularity dont go hand-in-hand in Israel: you can be popular when the economy is not doing well, and unpopular when it is.

3. There was an interesting time differential. For the first 3 PMs, Shamir, Rabin, and Peres, the first quarter of their time in office saw much more a conflictual rule use profile than the last quarter. For Netanyahu and Barak, the opposite was the case. Olmert turns more peaceful over the course of his tenure, as well. Generalizing (with Sharon as the exception), there seems to be a "Nixon" and an "anti-Nixon effect": if you start out with a hard line rule use profile, you can become a dove over time. But if you start out with cooperative rule use, you often end up becoming more hardline over time.

It is *possible* that this pattern gives us a hint of the reaction to the declining approval ratings: PMs attempt to correct those declines by reversing their earlier policies. However, since this never has any effect—the pattern of declining approval is true across all of the PMs for which we have data—the response of a PM to steady or improving approval remains a counterfactular.

Our overall conclusion from this stage of the analysis is that in certain cases the personality of a leader can be a very strong effect on rule use profile. Sharon certainly fits into this category, and with an expanded definition of concordance, Olmert does so as well. However, for most of the leaders, personality neither determines rule use profile nor its degree of changeability. Another interesting conclusion is that we see no obvious relationship between rule use profile and either popularity or prosperity. It may be that security issues, which would include first and foremost relations with the Palestinians, are more insulated from domestic variables such as these. This may suggest that for Shamir, Peres, Rabin, Barak, and Netanyahu, there are external variables, such as status of the relationship between the US and Israel, or variation in regional relationships, that may need to be examined. In future iterations of this project, we will examine both different cut-points for domestic variables, as well as including some external variables as well.

6 Results: Regression and Logit

In this section, we use conventional regression analysis to explore whether there are popularity, economic or personality variables that correlate with the occurrence of events and

[11] As widely reported, in two independent—if small sample—polls on 4-5 May 2007, Olmert was the first democratically-elected leader to achieve an approval rating statistically indistinguishable from zero

patterns.[12]

Table 2 shows the *Stata 10 reg* OLS regression results for number of incidents per month for our four event indicators and five pattern indicators as dependent variables, the popularity and economic variables as controls, and PM dummy variables.[13] The "exchangerate" variable correlates 0.81 with GDP and -0.67 with "inflation" and was not included due to collinearity concerns. This analysis covers the period August-1994 to August-2008 with the addition of a small number of pre-1994 points where we had popularity data. Numbers in (...) are standard errors; asterisks are the usual "*" for significance at the 0.05 level, "**" for the 0.01 level, and "***" for the 0.001 level, with additional color-coding of the significant coefficients. "cons" is the regression constant.

At first glance, Table 2 is rather easy to interpret, as virtually none of the coefficient are significantly different from zero, and the number that are—6 at the 0.05 significance level, and 1 at the 0.01 significance level—are consistent with significant results due to chance, given that there are 99 estimated coefficients in this table. Furthermore, there are *no* significant coefficients in the pattern variables, and the significant coefficients in the event variables are scattered randomly. In short, this appears to be a complete wash-out.

The one element suggesting otherwise are the R^2s and their significance levels, Six of the models are significant at the 0.001 level or higher—all of the event variables, *olive1* and *provoc*—and the R^2s for *matconf* and *provoc* are quite high for a sample of this size. This suggests—in fact in *provoc*, which has no coefficients significantly different from zero despite the high R^2, it requires—the possibility that the standard errors are inflated by colinearity. However, it is not at all evident for a simple correlation matrix of the independent variables where this colinearity is coming from—almost all of the bivariate correlations are below 0.35—and we clearly need to explore this further.

Tables 3 and 4 show the regression results for same dependent variables, popularity and economic controls, but with the Hermann personality variables in place of the PM dummies.[14] In Table 3, which reports the results for the event categories, we begin to see at least one credible pattern: high scores on the Hermann *task* and *power* variables correlate with the use of material conflict and verbal cooperation. The first effect would seem obvious in the context of this conflict—results and power-oriented leaders are more likely to use force—but the second is less so. This may reflect the fact that this conflict is heavily mediated,

[12] In additional analyses we are not reporting here, we explored used two additional techniques. First, since the PMs give us a panel design, rather than a traditional random sample, OLS regression may incorrectly estimate the standard errors. We ran the analyses with both a generalized least squares—Stata's `xtgls`—and a fixed-effects model—Stata's `xtreg,fe`. As expected, the estimated standard errors in these models were somewhat different than those in OLS, but none of these differences would affect the overall interpretation of the models.

We also used logit with a dichotomous variable indicating whether or an event-category or pattern was used at all during a month: this model would have the advantage of attenuating the effects of months where there were high frequencies of the event-category or pattern. Due to the fact that some of the PM dummies completely predict some of the variables (that is, some PMs have "1"s in all months for the variable) these results were more difficult to systematically interpret than the results of the panel-adjusted models, but again, are generally consistent with the OLS results. In particular, these models do not provide any additional evidence for the importance of the popularity variable.

[13] Shamir is the null dummy case.

[14] Because we are in a linear regression framework here, there is no difference in the significance between the raw scores and the Z-scored variables, since the Z-scores are just linear transformations of the raw scores.

Table 2: Events and Patterns: Prime Minister Dummies and Controls

	matconf	verconf	matcoop	vercoop	tftconf	tftcoop	olive1	olive2	provoc
popularity	-.048	.008	.030	.008	-.011	-.002	.021	.012	.003
	(.075)	(.022)	(.017)	(.027)	(.017)	(.001)	(.011)	(.013)	(.025)
gdp	-.117	-.016	-.002	-.021	-.016	-.000	-.005	-.008	-.034
	(.080)	(.024)	(.018)	(.028)	(.018)	(.001)	(.012)	(.013)	(.026)
gdpgrowth	-.645	-.217*	-.003	-.131	-.088	-.004	-.002	-.019	-.169
	(.336)	(.100)	(.076)	(.120)	(.076)	(.005)	(.051)	(.058)	(.111)
unemploy	.457	-.127	-.165	-.586*	-.088	.005	-.143	-.105	.362
	(.739)	(.220)	(.168)	(.263)	(.168)	(.012)	(.114)	(.127)	(.246)
inflation	-.380	-.119	-.020	-.067	.015	-.003	-.027	.002	-.193
	(.479)	(.143)	(.109)	(.171)	(.109)	(.008)	(.073)	(.082)	(.159)
sharon	24.74*	3.753	2.47	6.64	3.69	.062	2.31	2.23	6.71
	(10.74)	(3.21)	(2.44)	(3.84)	(2.45)	(.184)	(1.66)	(1.86)	(3.58)
barak	13.70	3.52	.753	7.64*	3.58	.071	.993	1.70	2.10
	(9.45)	(2.82)	(2.15)	(3.37)	(2.15)	(.162)	(1.45)	(1.63)	(3.14)
netanya	6.43	2.24	.906	5.82*	1.96	.031	1.000	1.17	1.11
	(7.49)	(2.24)	(1.70)	(2.67)	(1.71)	(.128)	(1.15)	(1.29)	(2.49)
peres	3.97	.584	1.25	2.08	.994	.026	.993	.896	.460
	(6.28)	(1.87)	(1.42)	(2.24)	(1.43)	(.108)	(.970)	(1.08)	(2.09)
rabin	3.96	.571	.277	4.91*	1.30	.004	.374	.758	.087
	(5.30)	(1.58)	(1.20)	(1.89)	(1.21)	(.091)	(.818)	(.916)	(1.76)
cons	9.90	2.93	.376	5.79*	1.23	.076	.632	.359	.503
	(7.89)	(2.35)	(1.79)	(2.81)	(1.80)	(.135)	(1.21)	(1.36)	(2.62)
N	176	176	176	176	176	176	176	176	176
R^2	0.384	0.162	0.180	0.178	0.093	0.036	0.205	0.077	0.442
Prob	0.000	0.001	0.000	0.000	0.121	0.861	0.000	0.257	0.000

and periods where there is a high level of violence tend to be accompanied by international pressure for talks with the other side. The actual *level* of verbal cooperation compared to material conflict is relatively low—a simple bivariate regression yields

$$\text{vercoop } = 0.084 \text{ matconf} + 2.37 \ (R^2 = 0.06 \text{ signif} < 0.001) \tag{1}$$

but the two are correlated. In short, we may be seeing an implementation of Theodore Roosevelt's "Speak softly but carry a big stick," albeit in this conflict, it is more "Carry a really big stick, but also occasionally speak."

The importance of the *task* and *power* variables are reinforced, if more weakly, in the results for the patterns reported in Table 4. In this table, *task* and *power* are the only variables if significant coefficients, and these occur on the TFT-conflict and provocation variables, consistent with these indicators correlating with a pattern of showing strength. The *olive1* variable is both significant and shows a relatively high R^2, but has no significant coefficients, again indicating the presence of collinearity; the remaining two models are nowhere near being significant.

As in the earlier model, the popularity and economic controls appear to have little or no effect in any of these models. The significant fit of the overall models are all significant at the 0.001 level or better in some of the models, suggesting again the possibility of colinearity effects in the *verconf*, *matcoop*and *olive1* models, which have no significant coefficients.

Given the lack of significant coefficients on the popularity and economic controls, and the confounding presence of collinearity, Tables 5 and 6 eliminate these controls and look only at the Hermann personality variables. These produce the strongest results of any of our models, particularly for the *matconf*, *tftconf* and *provoc* models. In these models, all of the personality variables have significant coefficients[15], suggesting all of these factors play into the variations of these behaviors.

The clearly counter-intutive result is the negative sign on *distrust*. This is almost certainly an artifact of collinearity—*distrust* has high positive bivariate correlations with *bace* (0.93), *task* (0.78) and *pwr* (0.69) and these interactions are almost certainly forcing the coefficient to a negative; the bivariate correlations between these behavioral indicators and *distrust* are all positive and significant.

We draw four general conclusions from this series of analyses. First, there do appear to be strong personality effects, which appear to support a "show strength" model focusing on power and task-orientation which is consistent with our qualitative understanding of this conflict. Second—and quite to our surprise, particularly given the amount of effort we put into assembling the data set—we are not seeing any discernible effects of the popularity variable; this result is consistent with the exploratory qualitative concordance analysis in section 5.

Third, and probably less surprising given the lack of a popularity result, we also aren't seeing economic effects. This is probably due to two factors. First, several of the economic variables are quite steady—Israel's economic condition has generally been steadily improving during almost the entire period—and there is little that would correlate with the high variation in Israeli-Palestinian relations. Second, given the generally strong economic indicators, we would expect to see any economic effects mediated through the popularity variable—that

[15] cc–cognitive complexity—is not significant in the *tftconf* model

Table 3: Events: Personality and Controls

	matconf	verconf	matcoop	vercoop
popularity	-.048	.008	.030	.008
	(.075)	(.022)	(.017)	(.027)
gdp	-.117	-.016	-.002	-.021
	(.080)	(.024)	(.018)	(.028)
gdpgrowth	-.645	-.217*	-.003	-.131
	(.336)	(.100)	(.076)	(.120)
unemploy	.457	-.127	-.165	-.586*
	(.739)	(.220)	(.168)	(.263)
inflation	-.380	-.119	-.020	-.067
	(.479)	(.143)	(.109)	(.171)
bace	135.522	32.575	19.526	-13.342
	(171.775)	(51.320)	(39.068)	(61.312)
cc	-3.821	6.255	11.361	64.343
	(131.365)	(39.246)	(29.877)	(46.888)
task	387.124***	52.467	10.076	103.803*
	(115.843)	(34.609)	(26.347)	(41.348)
pwr	766.862*	145.763	1.581	313.339*
	(311.909)	(93.186)	(70.939)	(111.330)
sc	94.999	15.496	.570	20.278
	(77.735)	(23.224)	(17.680)	(27.746)
distrust	-5156.207	-906.620	-36.502	-964.578
	(2949.448)	(881.181)	(670.812)	(1052.753)
cons	-465.029*	-79.496	-19.802	-172.184***
	(144.378)	(43.134)	(32.836)	(51.533)
N	176	176	176	176
R^2	0.384	0.162	0.180	0.178
Prob	0.000	0.001	0.000	0.000

Table 4: Patterns: Personality and Controls

	tftconf	tftcoop	olive1	olive2	provoc
popularity	-.011	-.002	.021	.012	.003
	(.017)	(.001)	(.011)	(.013)	(.025)
gdp	-.016	-.000	-.005	-.008	-.034
	(.018)	(.001)	(.012)	(.013)	(.026)
gdpgrowth	-.088	-.004	-.002	-.019	-.169
	(.076)	(.005)	(.051)	(.058)	(.111)
unemploy	-.088	.005	-.143	-.105	.362
	(.168)	(.012)	(.114)	(.127)	(.246)
inflation	.015	-.003	-.027	.002	-.193
	(.109)	(.008)	(.073)	(.082)	(.159)
bace	11.336	1.848	8.434	.902	45.974
	(39.236)	(2.954)	(26.508)	(29.673)	(57.159)
cc	17.532	.207	10.729	14.633	-22.564
	(30.006)	(2.259)	(20.271)	(22.692)	(43.712)
task	58.131*	.926	13.432	23.368	97.041*
	(26.460)	(1.992)	(17.876)	(20.011)	(38.547)
pwr	142.660*	2.094	19.715	52.425	177.147
	(71.245)	(5.364)	(48.133)	(53.880)	(103.788)
sc	10.577	.529	-.440	.726	28.298
	(17.756)	(1.337)	(11.996)	(13.428)	(25.866)
distrust	-690.796	-28.635	-17.276	-123.169	-1406.457
	(673.705)	(50.730)	(455.151)	(509.499)	(981.439)
cons	-83.859*	-1.754	-21.714	-35.835	-106.532*
	(32.978)	(2.483)	(22.280)	(24.940)	(48.042)
N	176	176	176	176	176
R^2	0.093	0.036	0.205	0.077	0.442
Prob	0.121	0.861	0.000	0.257	0.000

Table 5: Events: Personality Only

	matconf	verconf	matcoop	vercoop
bace	340.741***	59.248*	35.929*	11.426
	(63.065)	(19.143)	(13.565)	(22.262)
cc	-144.966*	-5.770	12.310	53.604*
	(50.392)	(15.296)	(10.839)	(17.788)
task	340.074***	36.094	5.468	32.555
	(69.042)	(20.957)	(14.851)	(24.372)
pwr	601.377***	92.725	-23.859	131.954*
	(184.044)	(55.866)	(39.589)	(64.968)
sc	196.366***	25.172*	4.375	8.924
	(37.635)	(11.424)	(8.095)	(13.285)
distrust	-8343.829***	-1135.444*	-151.329	-389.287
	(1642.733)	(498.648)	(353.366)	(579.895)
cons	-396.484***	-61.384*	-17.511	-88.770***
	(76.392)	(23.188)	(16.432)	(26.966)
N	255	255	255	255
R^2	0.321	0.111	0.175	0.246
Prob	0.000	0.000	0.000	0.000

Table 6: Patterns: Personality Only

	tftconf	tftcoop	olive1	olive2	provoc
bace	34.391*	1.024	24.640*	24.069*	122.947***
	(13.613)	(.986)	(9.467)	(10.157)	(23.033)
cc	-4.103	-.049	8.782	4.438	-61.388***
	(10.877)	(.787)	(7.565)	(8.116)	(18.404)
task	36.196*	.622	6.665	10.055	108.207***
	(14.903)	(1.079)	(10.365)	(11.119)	(25.216)
pwr	82.363*	2.090	-8.879	10.496	184.095*
	(39.727)	(2.877)	(27.630)	(29.642)	(67.218)
sc	18.897*	.393	4.108	6.193	69.692***
	(8.124)	(.588)	(5.650)	(6.061)	(13.745)
distrust	-890.115*	-20.267	-141.840	-291.559	-2825.078***
	(354.600)	(25.685)	(246.624)	(264.576)	(599.978)
cons	-52.861*	-1.211	-15.976	-19.948	-122.196***
	(16.490)	(1.194)	(11.468)	(12.303)	(27.900)
N	255	255	255	255	255
R^2	0.082	0.022	0.192	0.079	0.329
Prob	0.001	0.474	0.000	0.002	0.000

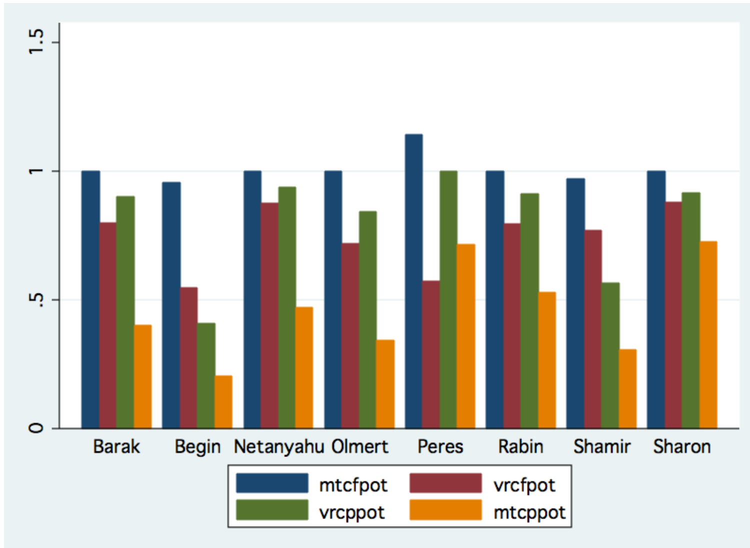

Figure 6: PM Behavior Vectors: Events

is, PMs would respond to the economy not directly, but following declines in popularity due to economic problems—and since we aren't finding popularity effects, this casual path is not active.

Finally, we've got some problems with collinearity that might be masking some effects. In particular, we need to look at a comparison between models that use the controls only, versus the models that use the personality variables only.

7 Results: Discriminant Analysis

This section and the next pursue the possibility of defining PMs not by their behaviors on a single indicator, but rather their profile across a set of indicators. The underlying logic here is that just as we characterized the PMs by a set of personality measurements, we can do the same with a set of behavioral characteristics. Figures 6 and 7, for example, show the proportion of months of their time in office that each of the PMs in our data set engaged in a category of event or pattern of behavior. In some cases, these are fairly similar: for example the overall event profile of Barak, Netanyahu, Olmert and Peres shown in Figure 6. In other cases—pretty much all of the profiles in Figure 7—they are quite distinct.[16]

Ideally, we would like to be able to connect the multivariate personality measures to the multivariate event and pattern measures. Unfortunately, the available tools for this are rather limited.[17] Consequently for exploratory purposes, we are going to simplify the problem by using two different multivariate techniques—discriminant analysis and correspondence

[16]The contrast between these two figures is another good illustration of the fact that pattern counts—which measure responses to the other side—can be quite distinct from event counts.

[17]The rarely used method of canonical correlation comes closest to the problem we've just described in the sense that it takes multiple variables on both the left and right-hand side of the equation: we may experiment with this in the future.

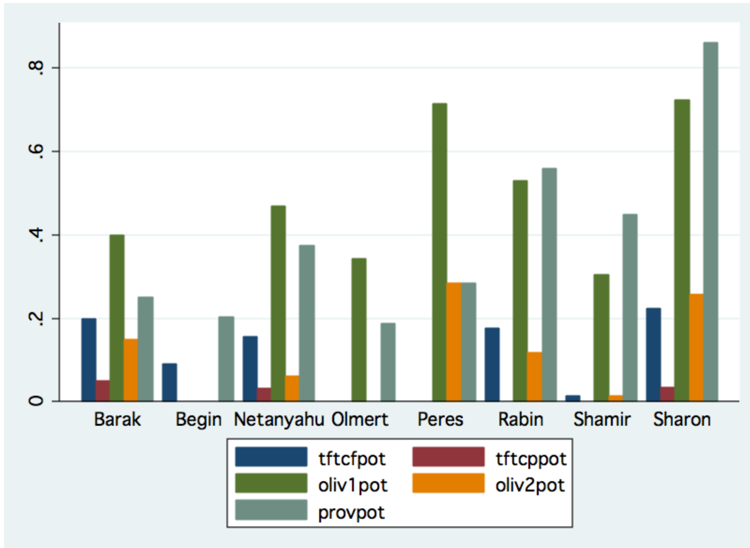

Figure 7: PM Behavior Vectors: Patterns

analysis (CA)—that will use the event and pattern variables to either classify (discriminant) or cluster (CA) the prime ministers using these variables.

Discriminant analysis is a relatively well-known linear classification technique; Klecka (1980) is a standard reference.[18] Our analysis was done using the `State 10 discrim lda` routine.[19]

Table 7 shows the classification table of a discriminant analysis with the PM-months as the cases and counts of event types and patterns as the discriminating variables.[20] The discriminant analysis now includes Menachem Begin: we did not have popularity or personality data on Begin, but we do have event and pattern data for him and included months back to

[18] As so often occurs in matters statistical, Wikipedia (http://en.wikipedia.org/wiki/Linear_discriminant_analysis; accessed 27 Aug 09) provides a really nice summary of the method:

> Linear discriminant analysis (LDA) and the related Fisher's linear discriminant are methods used in statistics and machine learning to find the linear combination of features which best separate two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.
>
> LDA is closely related to ANOVA (analysis of variance) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. In the other two methods however, the dependent variable is a numerical quantity, while for LDA it is a categorical variable (i.e. the class label).
>
> LDA is also closely related to principal component analysis (PCA) and factor analysis in that both look for linear combinations of variables which best explain the data. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities.

[19] `discrim knn` produces generally comparable results.

[20] We have not included the economic controls because the monotonic character of GDP and exchange rate means that these classify almost perfectly. Popularity is a very poor classifier since the pattern of popularity decline is almost identical for each PM.

Table 7: Discriminant analysis classification by events and patterns

	Classified PM								
True PM	PER	SHM	RAB	NET	BAR	SHR	OLM	BEG	Total
Peres	3	0	0	2	0	0	2	1	8
	37.5%	0.0%	0.0%	25.0%	0.0%	0.0%	25.0%	12.5%	100%
Shamir	1	25	2	3	0	6	21	11	69
	1.4%	36.2%	2.9%	4.3%	0.0%	8.7%	30.4%	15.9%	100%
Rabin	2	7	6	4	6	3	6	1	35
	5.7%	20.0%	17.1%	11.4%	17.1%	8.5%	17.1%	2.8%	100%
Netan.	0	5	1	9	7	1	3	7	33
	0.0%	15.1%	3.0%	27.2%	21.2%	3.0%	9.0%	21.2%	100%
Barak	0	0	3	6	4	1	1	5	20
	0.0%	0.0%	15.0%	30.0%	20.0%	5.0%	5.0%	25.0%	100%
Sharon	5	7	4	1	5	32	4	0	58
	8.6%	12.0%	6.9%	1.7%	8.6%	55.1%	6.9%	0.0%	100%
Olmert	0	4	5	0	1	1	14	7	32
	0.0%	12.5%	15.6%	0.0%	3.1%	3.1%	43.7%	21.8%	100%
Begin	0	7	0	1	0	1	3	36	48
	0.0%	14.5%	0.0%	2.0%	0.0%	2.0%	6.2%	75.0%	100%
Total	11	55	21	26	23	45	54	68	303
	3.6%	18.1%	6.9%	8.5%	7.5%	14.8%	17.8%	22.4%	100%

January 1980.

Three characteristics are evident from Table 7. First, the overall accuracy is not particularly good—the main diagonal elements (that is, correct classifications) are only 42.6% of the total. However, the degree of classification varies substantially

Accuracy	PM
>50%	Begin, Sharon
30% - 40%	Peres, Shamir, Olmert
<30%	Rabin, Netanyahu, Barak

The distinctiveness of Begin and Sharon comes as little surprise. The low classification accuracy of Rabin and Netanyahu—both considered fairly strong personalities with distinctive ideological profiles—is more surprising, and in both cases, may be an effect of the fact that both were involved in the "Oslo process" of negotiations with the Palestinians that resulted in them "playing against type." In the case of Rabin, this took the form of "Nixon in China," where a PM with a record of strong actions against the Palestinians was critical in willingly initiating the Oslo peace process.

Netanyahu's situation is even more complex since he came into office while the Oslo

Table 8: Discriminant analysis classification by patterns only

	Classified PM								
True PM	PER	SHM	RAB	NET	BAR	SHR	OLM	BEG	Total
Peres	3	0	0	0	0	0	2	3	8
	37.5%	0.0%	0.0%	0.0%	0.0%	0.0%	25.0%	37.5%	100%
Shamir	3	14	3	2	0	8	9	30	69
	4.3%	20.2%	4.3%	2.9%	0.0%	11.5%	13.0%	43.4%	100%
Rabin	4	5	4	2	3	3	3	11	35
	11.4%	14.2%	11.4%	5.7%	8.5%	8.5%	8.5%	31.4%	100%
Netayahu	3	3	3	1	3	1	5	14	33
	9.0%	9.0%	9.0%	3.0%	9.0%	3.0%	15.1%	42.4%	100%
Barak	3	2	0	0	3	1	2	9	20
	15.0%	10.0%	0.0%	0.0%	15.0%	5.0%	10.0%	45.0%	100%
Sharon	7	8	1	0	3	34	1	4	58
	12.0%	13.7%	1.7%	0.0%	5.1%	58.6%	1.7%	6.9%	100%
Olmert	3	3	1	0	0	1	7	17	32
	9.3%	9.3%	3.1%	0.0%	0.0%	3.1%	21.8%	53.1%	100%
Begin	0	2	0	0	3	2	0	41	48
	0.0%	4.1%	0.0%	0.0%	6.2%	4.1%	0.0%	85.4%	100%
Total	26	37	12	5	15	50	29	129	303
	8.5%	12.2%	3.9%	1.6%	4.9%	16.5%	9.5%	42.5%	100%

peace process still had some momentum, but did not favor it, and the process gradually fell apart during his tenure in office. Consequently while Netanyahu presumably had hawkish inclinations, the situation during his tenure in office allowed little opportunity to express these.[21]

Figures 6 and 7 showed that the overall profiles appeared more distinctive in the pattern domain than in the event domain, so Table 8 presents the results of classification based only on the five pattern variables. Because discriminant is a linear method, the overall accuracy with fewer variables will necessarily be lower than that of the earlier analysis—only 35.3% of the cases are classified correctly—but there are a couple of interesting contrasts between the two models.

First, the focus solely on pattern *increases* the classification accuracy for the two most distinctive cases, Sharon and Begin: these increase by about 3% and 10% respectively. Second, the pattern for Netanyahu is quite intriguing, with almost no correct classifications, about 60% of the classifications spread almost uniformly across all of the post-Begin cases, and then about 40% classified as Begin. By this characterization, then, Netanyahu pattern-based behaviors about an even mix of "generic prime minister", and the hard-line Menachem Begin. However, Ehud Barak—generally quite different ideologically from Netanyahu—also

[21] Our data do not include Netayahu's current tenure but, arguably, he is in much the same situation today as well.

has almost the same classification profile, though we would note that Netanyahu managed to look like Begin despite being engaged in the Oslo process, whereas Barak did this during the second Palestinian *intifada*.

8 Results: Correspondence Analysis

Correspondence analysis (CA) is another method of dealing multidimensional data, with a specific emphasis on simultaneously clustering cases and characteristics in a manner that places the characteristics in the same geometrical vicinity as the cases best represented by those characteristics. It was originally developed in France by Benzerci in the 1960s and 1970s for linguistic applications (see Benzreci 1992); the standard English-language treatment is Greenacre (1984, 1993)

Garson (n.d.) describes the method as follows

> Correspondence analysis is a method of factoring categorical variables and displaying them in a property space which maps their association in two or more dimensions. ... Correspondence analysis is a special case of canonical correlation, where one set of entities (categories rather than variables as in conventional canonical correlation) is related to another set.
>
> Correspondence analysis starts with tabular data, usually two-way cross-classifications, though the technique is generalizable to n-way tables with more than two variables. The variables must be discrete: nominal, ordinal, or continuous variables segmented into ranges. The technique defines a measure of distance between any two points, where points are the values (categories) of the discrete variables. Since distance is a type of measure of association (correlation), the distance matrix can be the input to principal components analysis, just as correlation matrices may be the input for conventional factor analysis. However, where conventional factor analysis determines which variables cluster together, correspondence analysis determines which category values are close together. This is visualized on the correspondence map, which plots points (categories) along the computed factor axes.
>
> Source: http://faculty.chass.ncsu.edu/garson/PA765/correspondence.htm; accessed 27 Aug 2009

In order to use CA on this data, we reduced the time series data to two tables. In each case, the rows are the PMs. In one table, the columns are the total number of uses of event types and patterns; in the other the columns are the number of months in which each event type or pattern was used at least once. CA works only with relative frequencies, so standardization by the number of months in office is not required.

Figures 8 and 9 show the CA graphs based on the total counts of events and patterns and patterns only respectively. The most conspicuous feature in figure 8 is a fairly clear delineation of the two dimensions: the X-axis involving decreasing levels of conflict,[22] and

[22]The sign of the axis is a free-parameter; this computation just happened to put conflict on the left and cooperation on the right

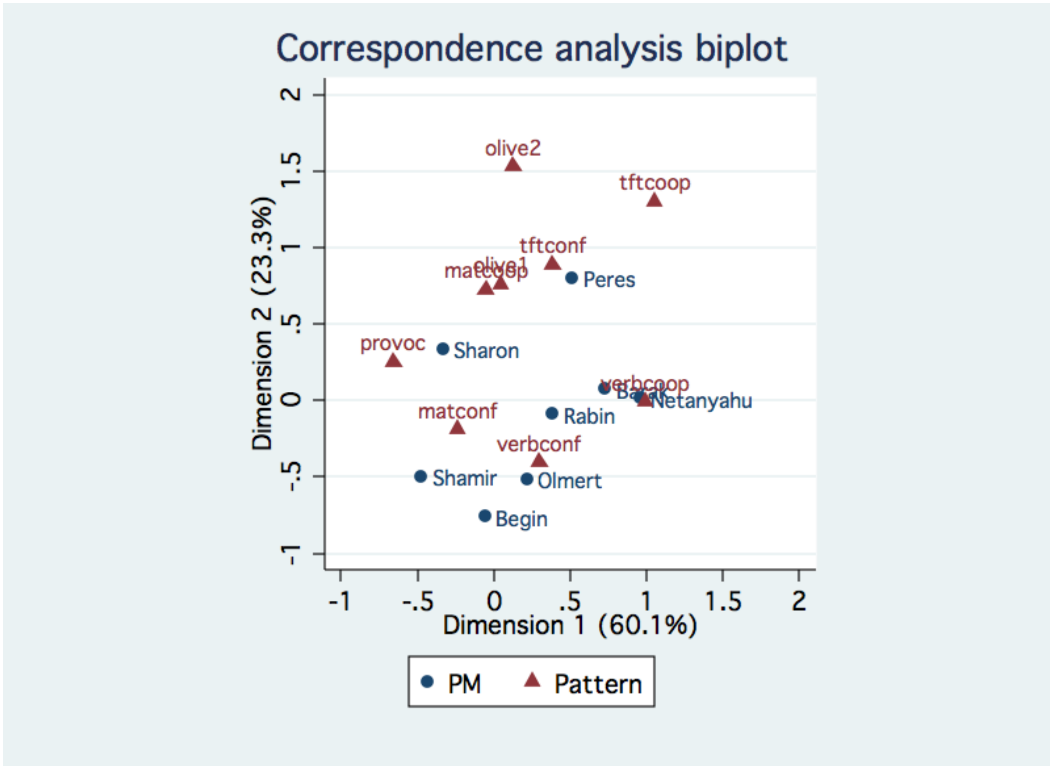

Figure 8: Correspondence Analysis: Total Events and Patterns by PM

the Y-axis differentiating events (lower) and patterns (higher). As we saw in the earlier discriminant analysis, Barak and Netanyahu are almost indistinguishable and Begin is a clear outlier (though unlike the discriminant, nowhere near the Netanyahu/Barak cluster).

Rabin is near the center of the graph, which probably reflect his mix of *olive1* and *provoc* behaviors, as reflected in the histograms in Figure 7. The initially counter-intuitive placement is Peres, who is even more of an outlier than Begin. Based on the profiles in Figure 7, this is probably due to Peres's disproportionate use of the *olive1* strategy; we would also note that Peres is only in the data for 10 months, so we have only a very small sample of his behaviors.

Figures 10 and 11 show the CA graphs based on the number of *months* that particular event categories and patterns were used rather than the total counts. Figures 10 is particularly difficult to interpret: the X-axis seems to differentiate the patterns and events, as we saw on the Y-axis of Figure 8, but there is no clear interpretation of the Y-axis and Peres, for once, is actually central. Figure 11 is clearer, with a conflict-cooperation dimension on the Y-axis, and the usual placement of Begin and Peres as outliers on opposite ends of the graph. Based on this sample, the total counts appear to provide a better characterization than the total months.

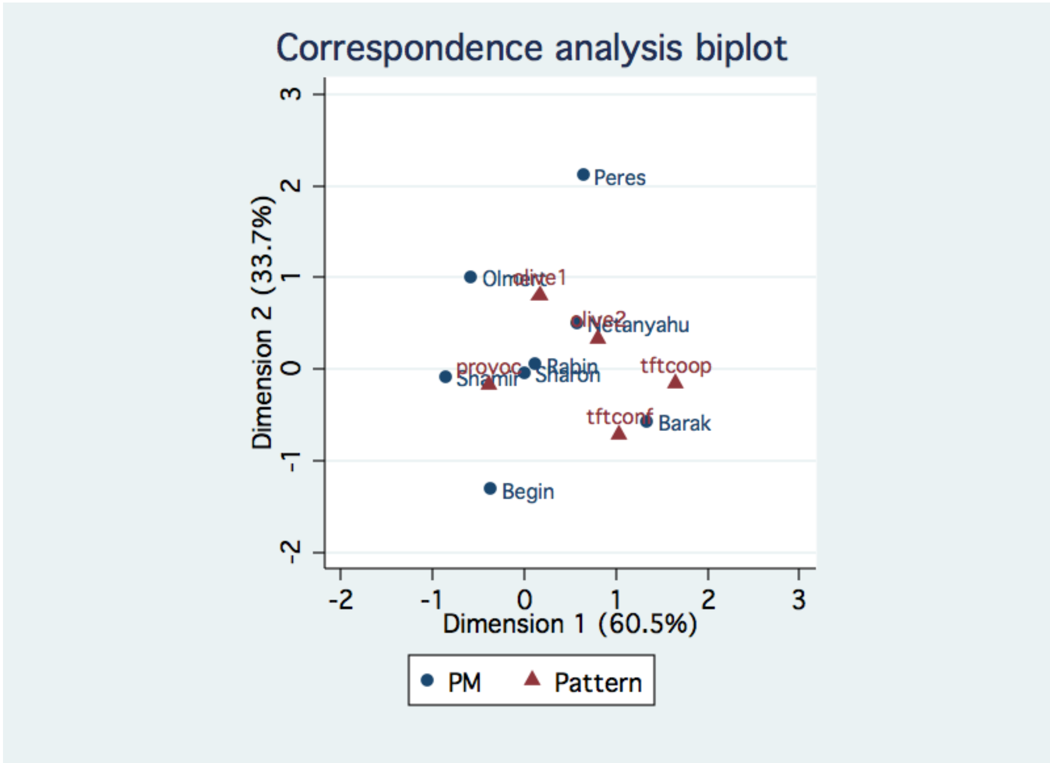

Figure 9: Correspondence Analysis: Total Patterns by PM

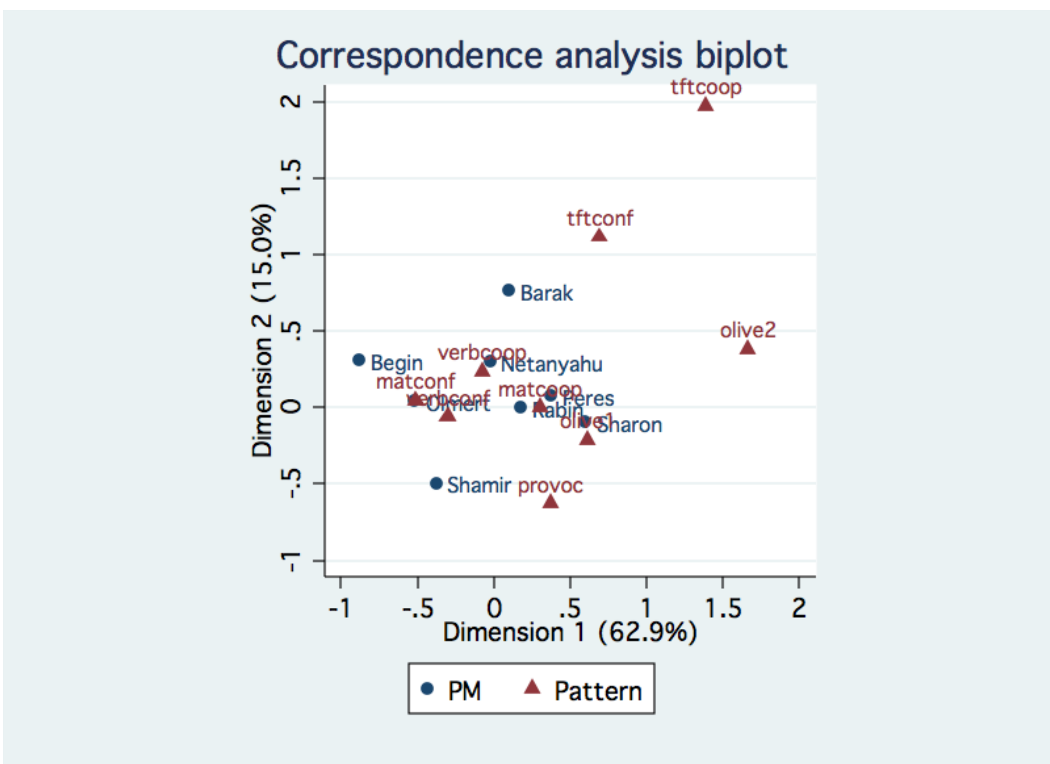

Figure 10: Correspondence Analysis: Months with Events and Patterns by PM

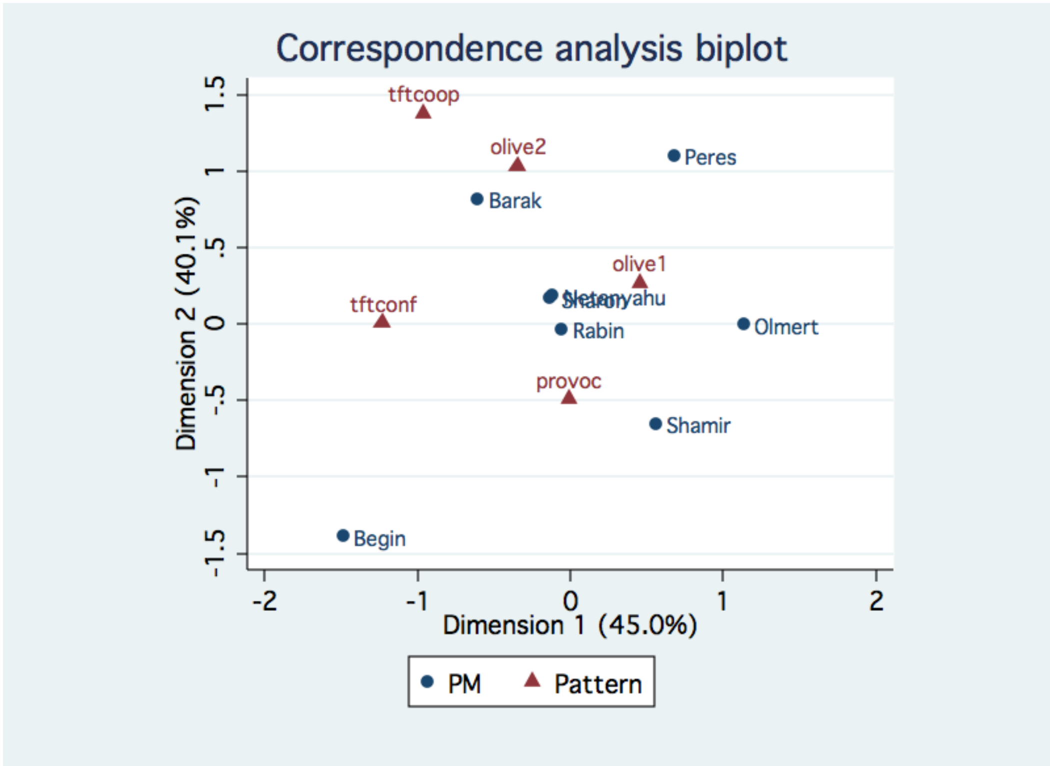

Figure 11: Correspondence Analysis: Months with Patterns by PM

9 Conclusion

The results of this exercise have been mixed, and we readily admit that this may be because we ran out of time to develop a more sophisticated system for categorizing rule use profile, which was to have been the centerpiece of this effort. However, if we view this paper as a very rough first attempt at investigating the relative effects of personality, popularity, and prosperity on Israeli PM strategy towards their opponents, the Palestinians, we do see some interesting observations.

First, popularity and prosperity seem not to matter in Israeli PM strategy towards the Palestinians (as reflected in rule use profile and changes in that profile). At first glance, this is counterintuitive. Israeli politics are very volatile, and sinking fortunes often result in the dismissal of governments. Israeli PMs also often have to appease coalition partners, and so have even more incentive to maintain their popularity. However, no matter how we sliced and diced it, we could see no effect of popularity on Israeli PM strategy towards the Palestinians. It may be that this particular issue is inherently insulated from domestic political effects, and that the logic of the conflict with the Palestinians and perhaps the relationship with external actors, such as the United States, are more important drivers of PM strategy.

Likewise, we see virtually no effect for prosperity, as well. This may be due to the fact that Israel did not suffer any great economic shocks during this period, and thus the variation in sconomic fortunes across PMs was not large. The Israeli economy generally prospered throughout the tenure of all the PMs that we examined.

Personality, on the other hand, did seem to play a significant role for several of the

PMs, particularly Sharon and Olmert.[23] The rule use profile of these two prime ministers corresponded in large measure with the general predispositions of their personalities. This finding was reinforced by the significant association found in the regression analysis between several personality traits, particularly need for power and task orientation, on the one hand, and a conflictual rule use profile on the other.

Interestingly, we find that situational imperatives can force dissimilar PM personalities to adopt similar rule use profiles. The oddest couple here are Barak and Netanyahu: each was forced to look more like the other than "himself." As noted, this is because Netanyahu was forced by the logic of the situation at hand to adopt more reciprocal and cooperative measures than his personality would have suggested; and Barak was forced to adopt more aggressive measures than his personality would have suggested. It is interesting to note that this "going against the grain" may explain the volatility of the rule use profiles of Barak and Netanyahu: of all the Israeli PMs examined, these two had the greatest variation in rule use profile across the quarters of their tenure. Indeed, if the Palestinian side were looking at consistency of signal to determine the strength of Israeli will in their mutual struggle, there would have been no consistency to observe in the tenure of these two PMs. As these two governed during an especially important and sensitive time in Israeli-Palestinian relations, one wonders whether more effective governance would have resulted from a closer match between the personality of the PM and the strategic requirements of the time period in question.

We did find some evidence for a "Nixon in China" effect. PMs who were able to move towards a more stable strategy of cooperation by the end of their tenure had started out their tenure with a much more conflictual rule use profile.

The two efforts to use linear combinations of event and pattern vectors characterize PMs were less successful except to the extent that they provided some information on distinguishing between "typical" Israeli PMs and outliers such as Sharon and Begin. The linear discriminant approach did not provide a particularly high level of classification accuracy, and the results if the correspondence analysis were very mixed. We continue to believe that finding a method of characterizing these as vectors is the route to go, but these methods did not take us as far as we had hoped they would.

On a more abstract level, this exercise has shown that it is possible to tease out purposive strategic moves from event data. To date, most analysis of event data has examined levels of cooperation and conflict, but has been unable to distinguish whether these are reactive or purposive. The development of the concept of "rule use profile," as well as the more basic distinctions such as differentiating whether conflict occurs as a tit-for-tat response versus occurs without provocation, is we believe, a major step forward. It rests upon a new technology, EP Tool, that is designed to hunt for specified strategies among all the buzz and noise inherent in event data.

To finally see strategy and signaling in event data has long been a goal of ours, and we feel that EP Tool has helped us make unprecedented progress in this regard. This paper was meant to go a step further, in turning those identified strategies into a strategic profile. We feel that in this paper we have taken that next step forward in a fashion that is more awkward than we had hoped. Instead of a relatively sophisticated operationalization of the

[23] and, based on his position as an outlier, possibly Begin, but we couldn't test this directly.

concept of rule use profile, we found ourselves stuck with a crude trichotomy because we ran out of time. We hope that future iterations of this exercise, with a more finely developed operationalization, will result in additional interesting and significant observations, aside from those few we were able to discern in this effort.

10 Appendix: CAMEO Code Summary, Version 0.9B2

01: MAKE PUBLIC STATEMENT
02: APPEAL
03: EXPRESS INTENT TO COOPERATE
04: CONSULT
05: ENGAGE IN DIPLOMATIC COOPERATION
06: ENGAGE IN MATERIAL COOPERATION
07: PROVIDE AID
08: YIELD
09: INVESTIGATE
10: DEMAND
11: DISAPPROVE
12: REJECT
13: THREATEN
14: PROTEST
15: EXHIBIT FORCE POSTURE
16: REDUCE RELATIONS
17: COERCE
18: ASSAULT
19: FIGHT
20: ENGAGE IN UNCONVENTIONAL MASS VIOLENCE

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