

Textual fingerprints of risk of war

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Abstract

We compute the rate of textual signals of risk of war recognizable in series of consecutive political speeches about a disputed issue serious enough to entail an international conflict. The speeches concern Iran's nuclear program. We trace textual signals forewarning of risks of war that reactions to this affair lead to. The thrust of the textual analysis rests on the interplay of affiliation and power words in continuous texts, following D. C. McClelland's model for anticipating wars. The speeches are those of Iranian President Mahmoud Ahmadinejad, US Secretary of State Hillary R. Clinton, Iranian Grand Ayatollah Ali Khamenei, and Israeli Prime Minister Benjamin Netanyahu. Prefiguring a military confrontation before it occurs involves structuring information from unstructured data. Despite such imperfect knowledge, by the end of January 2012, our results show a receding risk of war on the Iranian side, but an increasing risk on the American one, while remaining ambiguous on the Israeli one.

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Wars are like the uncontrollably complex soliton waves. Solitons result from normal after-waves that superpose one onto another to multiplicative effect (Herman, 1992). Our matter concerns one of these waves, the latent threats buried in speeches by political elites about a disputed issue serious enough to entail a risk of war. Our purpose is to recognise textual signals prefiguring these threats in transnational databases of texts. We centred on the speeches of four political figures in Iran, Israel, and the USA about Iran's nuclear affair. For Iran, the figures are the Grand Ayatollah Sayyid Ali Khamenei and President Mahmoud Ahmadinejad. Iran's is a hybrid secular-clerical government (Hashemi and Postel, 2011), a reason for analysing not one governmental source of data, but two, Ayatollah Khamenei on the clerical side and President Ahmadinejad on the secular one. For now, clerical dominance remains the rule (Dalton, 2010). The other figures are Secretary of State Hillary Rodham Clinton, US

Department of State, and Prime Minister Benjamin Netanyahu of the State of Israel. The stakes justify the present study.

It is not our job to like or dislike the Iranian issue, which is our object, not our cause. In truth, it is the words about the affair that are our object, not the affair itself. Our job is (i) to concentrate on political speeches related to the issue, (ii) use empirical methods to sift and order the information received and processed, and (iii) winnow from these speeches recognizable signals about the risk of war. At day's end, our job is to reduce uncertainty by foreshadowing what might happen before it happens, that is, by building up an index of risk of war that changes before war breaks out. The future may not be predictable. Some may not even wish it to be predictable. 'The idea of the future being different from the present is so repugnant to our conventional modes of thought and behaviour that we, most of us, offer a great resistance to acting

on it in practice' (Keynes, 1937, p. 13). Using reason for forecasting human behaviours by looking for signals of possible events is worthier than palm reading to understand all that is unreasonable in man. Every day, we use the words 'expectation', 'yearning', 'curiosity', 'death', which signal a deep wish to peer into the future. A way to meet this wish without getting the future wrong is to focus on 'degrees of uncertainty about the future' (Tetlock, 2005, p. 45) and indeed about the risk of war.

The good news is that 'We can learn a great deal about people's underlying (...) motives by counting and categorising the words they use to communicate' (Newman *et al.*, 2003, p. 666). This is not to say that words of war or peace cause war or peace as a billiard ball would hit another, for there is no causal logic here. (Our concern is with a different logic, deeply rooted in a motive imagery model to be expounded later, one that points the way to a risk of war or a chance of peace). Nor is it to say that we can predict war or peace, or prove the risk of war, for the only proven risk of war is war itself. Even troop build-ups, a usually reasonable indicator, do not necessarily lead to war. It is to say that we can point to risks of war or peace from mere imperfect signals worth vigilance, no matter how much hiding, misrepresenting, or omitting the speeches contain. To make a signal of risk of war appear through the batches of speeches requires bringing them down to a single scale in a time sequence and then isolating the signal. Yet, whether issued from experts or from words, forecasts do fail sometimes (Tetlock, 1999, 2005). On this side, the problem is not only one of foreseeing risks. It is also one of deciding which is more costly (in expenses or in threat to lives): detecting a false signal of a war in the making (causing expenses only) or

missing a true signal of a war in the making (causing expenses and threat to lives). Even so, thinking there is war when there is not could lead to problems like anger or attacks, which may in turn cause a war. In this vein, social scientists have exploited various linguistic routes by raiding on words to look for signals of coming wars. Among the routes to analyse threatening or non-threatening political texts are historical accounts of collective memories (Garagozov, 2008, 2012; Wertsch, 2002) and media analysis (Heinrich and Tanaev, 2009). Other tools include dictionary-based linguistic indicators (Hogenraad *et al.*, 1995; Pennebaker *et al.*, 2003), motives analysis (Smith, 2008), associative measurements (Osgood, 1959), and stylistic indicators (Hart, 1984). Hart's DICTION (Hart and Lind, 2011), for example, is a dictionary to analyse political rhetoric, ideology, and style. Computer-readable dictionaries prevail for assessing mood in extensive political documents or in the media. Among mood dictionaries, there are, for example, Young and Soroka's (2012) LSD (Lexicoder Sentiment Dictionary), Whissell's (2009) DAL (Dictionary of Affective Language), or Pennebaker and Chung's (2008) LIWC (Linguistic Inquiry and Word Count). Finally, in a world where visibility is dim, using automated coding of texts to forecast events (Schrodt and Gerner, 2000) holds a contributive place apart. Schrodt's KEDS (Kansas Event Data System) project relies on news reports collated by news agencies: political event data analysis includes cluster analysis procedures and Markov chain models linking the distribution of present and future states.

There is cause to wonder if we could ever read the entirety of the speeches we analyse (1,187,404 words in the present corpus, Table 1, to be

Table 1 The corpus

Texts	Divisions	Total number of words	No. of different words
Grand Ayatollah Sayyid Ali Khamenei	171 speeches over 47 months (3 January 2008 to 9 January 2012)	544,637	11,945
President Mahmoud Ahmadinejad	569 speeches over 42 months (14 March 2008 to 31 January 2012)	130,367	8,127
Secretary of State Hilary Rodham Clinton	105 speeches over 34 months (3 February 2009 to 10 January 2012)	173,894	8,373
Prime Minister Benjamin Netanyahu	202 speeches over 34 months (30 March 2009 to 1 February 2012)	338,506	12,826

expounded later) and decide from our reading on the risk of military confrontation contained in the streams of data. Our purpose is to reveal a layer of meaning buried in these speeches and to provide a vision of possible risks of military confrontation before it occurs, claiming no more than what the texts themselves can support. In war matters, troops and money usually count for far more than words. Yet, some circumstances plead for the weight of words in latent wars. For example, the existence and use of precision weaponry ('technological multipliers'), like guided missiles, need few combatants, so the usual forerunner signals of a war may be less visible. Pre-emptive unconventional wars too—biological, chemical, or cyber—may start without massive forces, thus blurring the usual signals of coming wars. The still unclaimed September 2010 version of the Stuxnet worm targeted Iranian industrial installations connected to nuclear infrastructures. This event shows what cyberwar looks like before leading up to a real war (Bronk, 2011). Relying on the words available may in these cases offer access to strategic intelligence that is otherwise scanty. Another use for words is when the actors of a war in the making deflect attention on war preparations using deceptive smokescreens (Chung and Pennebaker, 2011, p. 19). For example, Chung and Pennebaker read a drop in President G. W. Bush's use of the pronoun 'I' just after 9/11 and again with Hurricane Katrina (August 2005) as a way of shifting the attention from him. A last example shows that warriors themselves reckon with words. Preceding the August 2008 Russian intervention in Georgia, denial-of-service web attacks (not necessarily launched from Russia) blinded the Georgian governmental websites, pointing to the imminence of action (Markoff, 2008).

1 The Motivational Root of War and a Way to Assess the Risk of War

To track down and codify how nations develop patterns of violence over time, we took advantage of McClelland's (1975) motive imagery model. This model rests on the need for achievement, the need

for affiliation, and the need for power. Only the need for affiliation and the need for power form the basis for McClelland's model for forecasting wars. Intimacy, friendship, our loves and attachments define the need for affiliation. The will to have an impact on people or to get control over them forms the essential of the need for power. We best understand affiliation and power by contrast with what each is not for the other. One cannot love and be in control of the other. That would be like looking after a robot, predictable and obedient. In his chapter 9 'Love and power: the psychological basis of war', McClelland (1975, pp. 314–359) develops the notion of '*imperial motivation pattern*', which is the gap between a high need for power and a low need for affiliation. He shows how, in history, reformist zeal for social justice, that is, the use of one's own power to save others, irrespective of whether they like it, is often the link—not to be confused with the cause—between the '*imperial motivation pattern*' and later wars. The wider the gap, the greater the risk of war. Consider, for example, President Harry Truman's (1947) 'I believe that it must be the policy of the United States to support free peoples who are resisting attempted subjugation by armed minorities or by outside pressures'. This aura of collective enthusiasm runs like a recurring theme before every war, an axiom often running masked under the guise of helpfulness: the use of one's own power to save others—call it the rage to convince—is often the sign of wars to come. In Cioran's (1998, p. 30) words, 'One hardly saves a world without ruling it'.

All in all, the power-affiliation motive imagery matters because it lays out a way of linking different types of conflicts. This was a good enough reason to turn McClelland's view of the motivational root of wars into a tool to assess the risk of war in continuous texts, and use a procedure that guarantees the same treatment for each document. We do not ask judges to score speeches manually for the presence or absence of motive imagery. Rather, we draw on words of affiliation and words of power to build up a motive imagery dictionary on McClelland's model. The dictionary is then loaded in a suite of computerised content analysis programs set to carry out the menial work.

So, how do we fare with the motivational roots of war in assessing the risk of war? To test the truth of

the dictionary that we built on McClelland's model, we analysed stories and real-life documents about emerging conflicts. So far, we collated 36 corpora totaling 4,169,687 words.¹ We expected each of these accounts to display similar profiles characterised by increases of the index of risk of war, that is, an increasing gap between the need for power (rising) and the need for affiliation (falling) before the outbreak of the conflict. Among fictional materials (Hogenraad, 2003), William Golding's (1954) *'Lord of the Flies'* is emblematic of a peaceful start giving way to a conflict. The novel relates the survival story of a group of boys who, after a plane crash, set up a fragile community on a deserted island. After initially enjoying their freedom, the group soon divides into fearsome gangs, which turn the paradise island into a nightmare of fears and death. Chapter after chapter, the motive imagery indicator reliably tracks the emerging conflict within the group. In Tolstoy's (1997) *'War and Peace'*, the epic story of a family life during the Napoleonic wars from 1805 to 1812, the gap between the need for power and the need for affiliation increases linearly as expected. We extended tests of the motive imagery dictionary to real-life accounts of conflicts. In particular, we matched up diplomatic documents preceding the outbreak of past wars (Hogenraad, 2005, 2008) to the word-based index of risk of war. We assessed the likelihood of these past wars before they broke out. Confirmation of a likely war occurred, for example, in our analysis of the Anglo-American intervention in Iraq using the speeches of President George W. Bush and Prime Minister Tony Blair from 11 September 2001 to 20 March 2003 (Hogenraad, 2005). We also confirmed a likely war in the analysis of the speeches that preceded the military confrontation between Georgia and Russia of August 2008 (Hogenraad and Garagozov, 2010). Over the year 2008, the risk of war was increasing in the speeches of President Medvedev of Russia. That risk was increasing too among US Secretary of State Condoleezza Rice and European leaders. But the risk of war was decreasing in the speeches of President Saakashvili. The grudging conciliatoriness of President Saakashvili seemingly contradicted his final twist when he finally rushed to war. Yet

appeasement turned out to be a correct estimate of the risk of war when it appeared Saakashvili had perhaps been trapped into a war he did not want (Popjanovski, 2009, pp. 153–155).

For their part, Chung and Pennebaker (2011) reviewed the usefulness of the motive imagery model to screen out threatening communications that they define as 'explicit planning of an aggressive action while at the same time concealing the planned action from the target' (p. 18). One can begin, they continue, to appreciate how word counts can betray intentions and future actions (p. 19). And intentions are what motive imagery hits on. Using trained human scorers, Smith *et al.* (2008; see also Winter, 2011) found increased levels of power imagery and lower levels of integrative complexity in terrorist groups than in non-terrorist groups. Frisch (2010) found that both integrative complexity (Suedfeld and Tetlock, 1977) and motive imagery measures were in accordance to predict intents of the actors of the August 2008 Russian intervention in Georgia. There are also measures of affiliation and power to explore the First Israeli-Palestinian Oslo Accords of 1993 (Tripscha *et al.*, 2006).

2 The Embarrassment of Ambiguity: In Praise of Vagueness

It may not have been lost on observers of language that the vagueness of language gnaws away at the credibility of textual analyses. By vagueness, we mean a language that evokes no specific facts or knowledge, and suggests an unwillingness to communicate clearly (Empson, 2004; Péladeau, 2005). Vague and evasive words defeat clarity indeed. But there is another way to see vagueness that does not give it a bad name. What tells against a negative view is the sense in which ambiguity can be productive because it allows ideas to evolve. At the moment an idea is molded into a frozen form like an overspecific word, it is drained and less likely to lead to innovative solutions in negotiation, as when discussing a draft agreement for example (Doonan and Foster, 2001, p. 97). In *'The Ambiguity Advantage'*, Wilkinson (2006) has described a

progression running from ambiguity, risk, vagueness, confusion down to chaos. But he shows also how leaders can use ambiguity, lead others through chaos, and create opportunities for them.

The question of vagueness is way beyond the prospect of this study. Besides, broaching the rate of stylistic vagueness, that is, words with a diffuse meaning (Sebeok, 1960, pp. 370–371), in the analysis of the content of textual data brings a confusion of levels. Yet different levels can sometimes be brought into useful confrontation. We had to make a point, but we are still in need of a corrective. On one side, we did not enter vague words in the motive imagery dictionary. Vague expressions like *more or less*, *somewhat*, *aspect*, *something*, and so on fill everyday language, which only the context of situation can clear up (Malinowski, 1935, p. 11). On the other side, there are other ways, besides vague words, for ambiguity to sneak into language, like calculated ambivalences, insinuations, or dubious wordplays as used in racist and populist speeches (Wodak, 2003, 2007, p. 217). Even the ‘war on terror’ label remains vague in the 9/11 context (Reese and Lewis, 2009), whereas its parts enter in the motive imagery dictionary. As Orwell (1981, p. 167) said ‘When the general atmosphere is bad, language must suffer’. In truth, the quasi-opposites of vagueness, that is, dogmatism, authoritarianism, or certainty, more often caught the attention of social scientists on the idea that one could not achieve one without failing the other. Hart (1984; Hart and Lind, 2011), Rokeach (1960), and indeed Ertel (1972) are among those who dug at dogmatism. Hart set up a computer-aided text analysis with dictionary (DICTION). One subcategory of DICTION, CERTAINTY, taps words expressed with full authority (*crowd*, *army*, *fully*, *always*, for example). From this set, another set of words expressing ambiguity is subtracted (*somewhere*, *perhaps*, *seems*, for example) to draw a final score of CERTAINTY. Incidentally, one notices a partial overlap between entries such as *crowd* or *army* in the COLLECTIVES subcategory of DICTION and the NEED FOR POWER category of the motive imagery dictionary.

The imperfect solution we devised, not to correct but to evaluate the rate of vagueness in our serial

data, is this. We brought to bear Hiller’s (1971) Communication Vagueness Scale to follow the rate of vagueness in the series of speeches. In this way, unable to get away with ambiguity, we could at least keep an eye on it. To put it simply, in a high-strung interplay, one would expect the language of a party open to settlement to contain more and more vague and evasive words, leaving doors open. And one would expect the opposite from a party resolved to reject negotiation, that is, a language with fewer and fewer ambiguous words, leaving no chance for ideas to evolve, or to repeat them in slightly different versions. This is what we found in the analysis of the communications that preceded the conflict between Georgia and the Russian Federation (January to August, 2008) over the separatist regions of Abkhazia and Southern Ossetia (Hogenraad and Garagozov, 2010, p. 22). President Saakashvili was open to negotiate with the separatist regions; his statements contained an increasing number of vague words over time, not unlike a strategy of survival. President Medvedev on the contrary was determined on the Georgian question and his statements were gaining in precision.

To sum up, we have a purpose (detecting signals of coming war or appeasement) equipped with proper tools (prevision-oriented dictionaries), a procedure (computer-aided content analysis), and data (political speeches transferred from official web sites) we will present soon. The tools are the motive imagery dictionary detailed to make the risk of war or the chance of appeasement emerge from the data, and the vagueness dictionary detailed to evaluate the rate of vagueness in the statements.

3 Method

3.1 Texts

We summarise in Table 1 the database of speeches (1,187,404 words) in the English translations available. We indexed the speeches for their day, month, and year of production. We suspended collating the series of speeches after January 2012. We collated the speeches of Ayatollah Khamenei from the web site of the Supreme Leader of Iran (Supreme Leader of Iran, Grand Ayatollah Sayyid Ali Khamenei, *All speeches*). We collated the speeches of President

Ahmadinejad from the web site of the Iranian Presidency (President Mahmoud Ahmadinejad, *All speeches*). The first speech with mention of Iran by Secretary of State Hillary Clinton in the new Obama administration was on 3 February 2009 (Secretary of State Hillary R. Clinton, *All speeches*). Finally, we started collating the data of Prime Minister Netanyahu with his speech of 30 March 2009 (Prime Minister Benjamin Netanyahu, *All speeches*).

3.2 Computer-aided content analysis, motive imagery dictionary, and vagueness dictionary

We enter the texts in consecutive order, with codes to slice the texts. We then run a computer-aided content analysis procedure, PROTAN (for PROTOCOL Analyzer) (Hogenraad *et al.*, 1995), to trawl the data using computer-readable dictionaries organised into hierarchical categories. Computer-aided content analysis itemises and orders words into lists and numbers. The procedure involves entering, pruning declensions and verb forms, arranging texts into frequency tables and then looking for matches between words in a dictionary and words in a text. One then counts the number of word matches in the categories, and takes the percentage of the number of matches in each category. Dictionaries can be of two types, category-based and norm-based. Both types are useful assets for the humanities and the study of natural language. Category-based dictionaries rest on some theory that they embody (Wilson, 2011). Norm-based ones refer to some semantic property like concreteness or emotions. Building dictionaries of either type is time-consuming. Vincze and Bestgen (2011) have recently developed and validated a new automatic procedure for expanding lexical norms by analysing co-occurrences in texts. With adaptations, their procedure could be extended to category-based dictionaries (Y. Bestgen, personal communication).

The category-based motive imagery dictionary (version 6.0, 2012) is a database of needs for affiliation (837 entries, English words and roots) and needs for power (1724 entries) (Table 2). The dictionary is designed so any word assigned to one category cannot be present in another one except

Table 2 Affiliation and power categories of the motive imagery dictionary (V 6.0, 2012)

Category	Subcategory	No. of entries	Examples
Affiliation		843	
	Affection	105	Mate, sweetheart
	Social behavior	87	Answer, escort
	Affiliation	473	Accompany, courteous
	Affect loss	34	Alone, indifference
	Affect participants	61	Dad, mistress
	Affect words	41	Family, nostalgic
Power	Positive affect	43	Affable, thoughtful
		1,769	
	Power	984	Ambition, justice
	Power gain	48	Emancipate, nominate
	Power loss	65	Captive, weak
	Power ends	12	Plead, recommend
	Power conflicts	269	Adversary, invade
	Power cooperation	68	Arbiter, reciprocal
	Power authoritative participants	99	Patriarch, detective
	Power ordinary participant	28	Emissary, orator
	Power doctrine	27	Conservatism, dogma
	Power authority	36	Legitimate, reign
	Residual power words	133	Colonialism, terrorize

in its superordinate category. For example, in Table 2, the entry *sweetheart* in subcategory *AFFECTION* can be assigned only to the higher up category of *AFFILIATION* and to no other one. The text words being set in alphabetical order, each text word is then compared with the dictionary entries also set alphabetically, until a match is found. The matches are then recorded, summed, and averaged over the unit chosen (by month in the present study).

Lastly, we quantified how much vagueness there was in our documents, using Hiller’s Communication Vagueness Scale (Hiller *et al.*, 1969; Hiller, 1971). The scale comprises 362 vague words and expressions (*aspect, function, factor, more or less, about, sort of, you know, considerations, many, process, variety, situation, very*). For clarity, these words are ordered into 10 categories of vagueness such as *AMBIGUOUS DESIGNATION, APPROXIMATION, INDEFINITE AMOUNT, MULTIPLICITY, and others*

(Péladeau, 2005). There is no semantic homogeneity in the scale we used, with permission (J. H. Hiller, personal communication), to assess vagueness in our documents. We computed a global rate of vagueness from the vagueness scale (the percentage of the number of vague words to the total number of words in the section of the document under analysis). Hiller's scale detected item clarity in questionnaires (Ford *et al.*, 2000). The scale also correlated with writing quality in students' essays (Hiller *et al.*, 1969). Authors used Hiller's scales to evaluate the efficacy of teaching programs (Land, 1981) and the effect of discourse markers on reading comprehension (Chaudron and Richard, 1986). Another use of Hiller's procedure has been as a cognitive aid for improving information communication and for helping information processing in psychological treatment (Rosenthal and Downs, 1985). Eventually, vagueness scales could be applied profitably to evaluate the quality of scientific writing (Hogenraad *et al.*, 1992). Because vagueness characterises style and not content, it can be extended from its origin in education to other kinds of written documents, political for example.

4 Results

Statistical treatments comprise (i) removing auto-correlations, (ii) regression and resampling statistics, and (iii) identifying cutoff-points in the regression profiles. (i) Speeches of any political figure carry traces of previous speeches by the same figure. To ensure independent observations, we randomise data. It is impossible to randomise textual data because the temporal order is part of the information carried by them: serial texts impinge on one another. Dependencies in the temporal order of texts create apparent changes without genuine ones. We remove the systematic dependency in the temporal series (autocorrelation) from the data (Hogenraad *et al.*, 1997). (ii) Because texts are unrepeatable events, one cannot analyse the sampling error. It then becomes necessary to simulate observations we do not have using those we have. To evaluate how stable is the statistical estimator, we ran systematically 20,000 bootstrapped

simulations of the regressions to capture the confidence region of the boundary values of unique textual data (Diaconis and Efron, 1983; Hogenraad and McKenzie, 1999). The bootstrap method we used is part of SimStat for Windows (Péladeau, 1996). (iii) Under the seemingly smooth increases or decreases of risk of war, we want to know if there are turning points (waterfalls or cliffs) hidden in the time sequences. We used the CART (Classification and Regression Trees) non-parametric procedure (Breiman *et al.*, 1993; Efron and Tibshirani, 1991) of statistical decision-making that hierarchically splits data into progressively smaller turning points. Unlike single change-point tests (Siegel and Castellan, 1988), CART identifies several such points, building trees by recursive statistical decisions (McKenzie and Low, 1992). The result is a hierarchical structure in which each discontinuity reveals a transition within the time trend.

4.1 Average risk of war

The average rate of risk of war in Ahmadinejad is 3.5 (min/max = 1.4/5.9, SD = 1.6, $N = 42$). In Khamenei, the rate is 1.3 (min/max = -0.6/3.4, SD = 1.0, $N = 47$). In Netanyahu, the rate is -1.0 (min/max = -2.4/0.3, SD = 0.6, $N = 34$). Lastly, in Clinton, the rate is -0.7, (min/max = -2.7/5.2, SD = 1.7, $N = 34$). The two extremes on a scale of average risk are Prime Minister Netanyahu and President Ahmadinejad. The average rate of risk for Ahmadinejad is way above that of the other political figures, even of Khamenei.

4.2 The course of the risk of war

The risk of war (Table 3) is receding linearly and significantly in the speeches of Ayatollah Khamenei (Fig. 1). President Ahmadinejad (Fig. 2) too relents, then does not, releasing a new energy in his speeches. The meaning of Figures 1 and 2 is that a change is taking place. In Khamenei, the mean speed of risk of war decreases at the slow rate of -0.02 (β ; Table 3) a month. In Ahmadinejad, the mean speed of risk of war decreases at the rate of -0.15 until month 28 included (November 2010) after which the speed increases at the slow rate of 0.002 until month 42 (January 2012). The trend toward making terms persists on the Iranian side in a way that it does not

Table 3 Risk of war: summary of statistical results (95% β confidence intervals are based on 20,000 resamplings)

Id	R^2	df	F	β	β CIs 95%
A. Khamenei	0.10	1,45	5.1*	-0.023	-0.04/-0.001 linear
M. Ahmadinejad ^a	0.29	2,37	7.5**	-0.145	-0.2/-0.06 linear
H. R. Clinton	0.14	1,32	5.1*	0.002	0.0007/0.004 quadratic
B. Netanyahu ^b	0.06	1,31	2.0 (<i>ns</i>)	0.06	0.01/0.3 linear
				0.01	-0.007/0.03 linear

^aTwo outliers.

^bOne outlier.

* $P < 0.05$; ** $P < 0.01$.

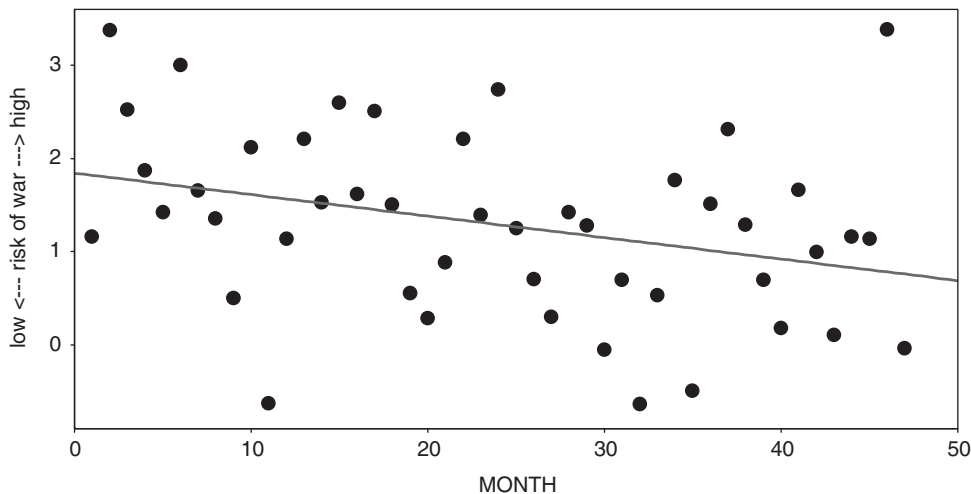


Fig. 1 The risk of war as assessed from the speeches of Ayatollah Khamenei (3 January 2008 to 9 January 2012) ($N = 47$ months). Distribution of Ayatollah Khamenei's speeches per month: 2008, months 1–12; 2009, months 13–23; 2010, months 24–35; 2011, months 36–46; 2012, month 47

elsewhere. Yet the sometimes unbecoming style of both Ayatollah Khamenei and President Ahmadinejad had made us expect changes in the opposite direction. With the noted decreasing trends, in both of them we found change-points inside the trends. In the Khamenei series, we found a shift down separating the period before January 2010 (month 24) ($M = 1.6$, $n = 24$, $SD = 0.9$) from that after (month 25, February 2010) ($M = 0.9$, $n = 23$, $SD = 0.9$). In the Ahmadinejad series, we identified a similar shift down, before August 2009 (month 15) ($M = 4.2$, $n = 15$, $SD = 0.9$) and after (month 16, September 2009) ($M = 3.0$, $n = 25$, $SD = 0.7$).

The course of the risk of war in the speeches of Secretary of State Clinton (Table 3 and Fig. 3) rises

linearly and significantly. This is a reverse direction to that of Khamenei and Ahmadinejad. In her speeches, the mean speed of risk of war increases at the rate of 0.06 a month. (By comparison, the mean speed of risk of war in the speeches of Prime Minister Blair before the Anglo-American intervention in Iraq was 0.02 a month over 72 months; Hogenraad, 2005, Fig. 3, p. 147). The increasing risk of war in Secretary Clinton's speeches comes as a surprise, considering the low rate of risk at the start—from a low point of -2.57 on month 1, to a high point of 0.13 on month 34. We ferreted out a first upward cutoff-point before May 2010 ($M = -1.5$, $n = 15$, $SD = 0.1$) and after May 2010 (month 16) ($M = -0.05$, $n = 19$, $SD = 1.6$).

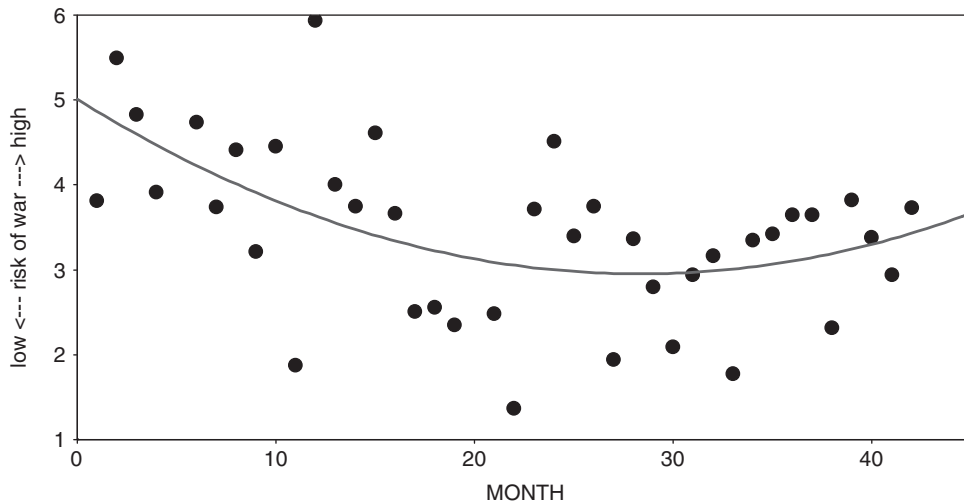


Fig. 2 The risk of war as assessed from the speeches of President Ahmadinejad (14 March 2008 to 31 January 2012) ($N=42$ months). Distribution of President Ahmadinejad's speeches per month: 2008, months 1–9; 2009, months 10–19; 2010, months 20–30; 2011, months 31–41; 2012, month 42

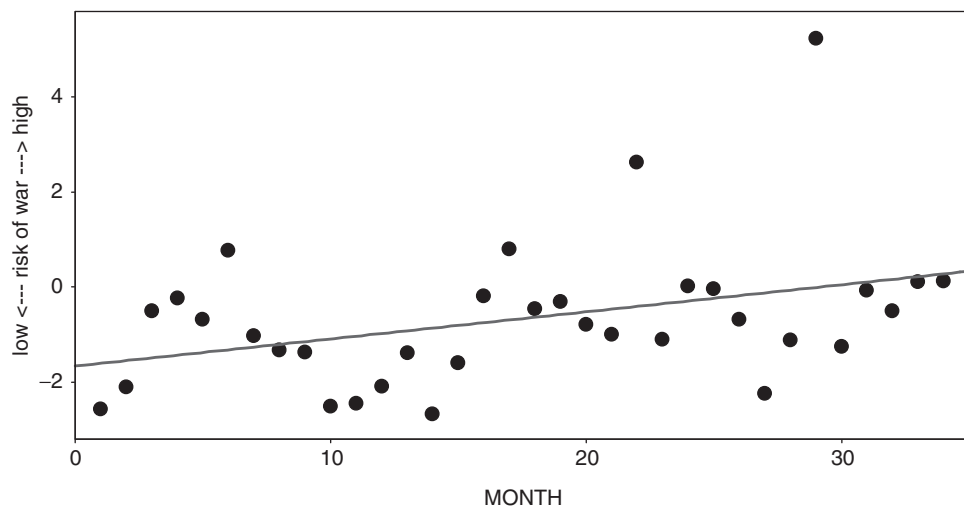


Fig. 3 The risk of war as assessed from the speeches of Secretary Clinton (3 February 2009 to 10 January 2012) ($N=34$ months). Distribution of Secretary Clinton's speeches per month: 2009, months 1–10; 2010, months 11–22; 2011, months 23–33; 2012, month: 34

We found a secondary downward shift within the first subperiod, before ($M = -1.0$, $n = 9$, $SD = 0.9$) and after November 2009 (month 9) ($M = -2.1$, $n = 6$, $SD = 0.5$). Finally, the course of the risk of war in the speeches of Prime Minister Netanyahu is not statistically significant (Fig. 4)

and shows no turning point. That does not mean the lack of statistical significance is meaningless or inconclusive. The absence of direction gives away the uncertainty associated with the expressed motives of the Israeli Prime Minister, which is informative in itself.

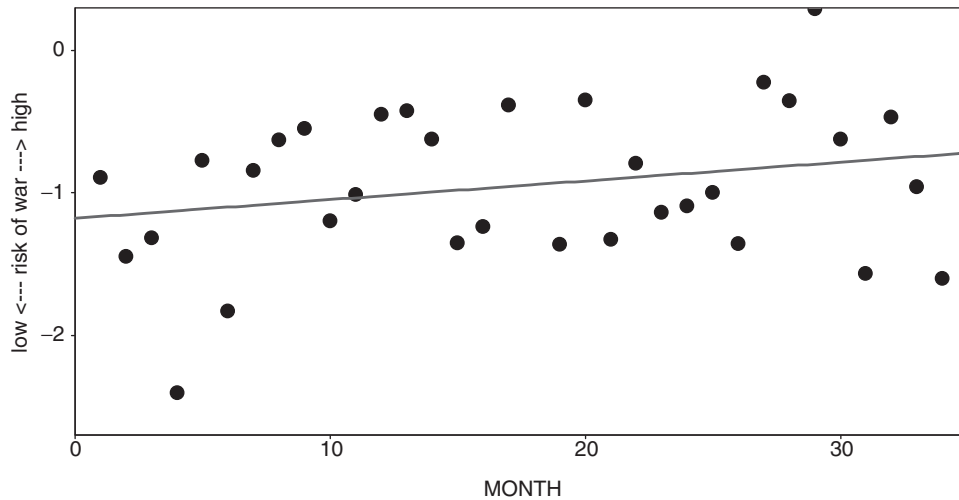


Fig. 4 The risk of war as assessed from the speeches of Prime Minister Netanyahu (30 March 2009 to 1 February 2012) ($N=34$ months days). Distribution of Prime Minister Netanyahu's speeches per month: 2009, months 1–10; 2010, months 11–21; 2011, month 22–32; 2012, months 33–34

Table 4 Vagueness of style: summary of statistical results (95% β confidence intervals are based on 20,000 resamplings)

Id	R^2	df	F	β	β CIs 95%
A. Khamenei	0.002	1,45	0.09 (<i>ns</i>)	0.001	−0.005/0.007 linear
M. Ahmadinejad ^a	0.14	1,39	6.2*	0.02	0.005/0.03 linear
H. R. Clinton	0.21	1,32	8.5**	0.03	0.005/0.05 linear
B. Netanyahu	0.18	1,32	7.1*	0.02	0.004/0.03 linear

^aOne outlier.

* $P < 0.05$; ** $P < 0.01$.

4.3 The course of the rate of vagueness

The average rate of vagueness is 6.7 in Ahmadinejad (min/max = 0/7.8, $SD = 1.2$, $N = 42$), 8.7 in Khamenei (min/max = 8/9.5, $SD = 0.3$, $N = 47$), 7.6 in Netanyahu (min/max = 6.4/8.4, $SD = 0.4$, $N = 34$), and 7.4 in Clinton (min/max = 6.1/9.2, $SD = 0.6$, $N = 34$). The course of the rate of vagueness increases linearly and significantly in Ahmadinejad, Clinton, and Netanyahu (but not Khamenei) (Table 4 and Figs 5–7). The speed of increase is slow in each data set, between 0.02 and 0.03 a month. The course of vagueness in Netanyahu adds up to the absence of direction noted earlier for the risk of war: his speeches remain in a lasting state of vagueness throughout. We further bothered to find correlations between the risk of war and the rate of vagueness. We found only one, in Clinton's speeches, a statistically

significant lagged one between the risk of war at T_0 and the rate of vagueness at T_{+1} ($r = 0.66$, $n = 33$, $p < 0.0001$, CI 95% = 0.37/0.86 using 20,000 resamplings). Changes in the risk of war in Clinton are followed in proportion by changes in the rate of vagueness one month later.

5 Discussion

War is an event of many layers and its beginnings are always invisible to the naked eye. We relied on the motive imagery model to enlarge our vision of risk while the usual signals of war are still hardly noticeable. To come to this, we assessed how the ratio of power to affiliation imagery that shapes the risk of war spread through the speeches over time. For now, the trends of risk of war in the

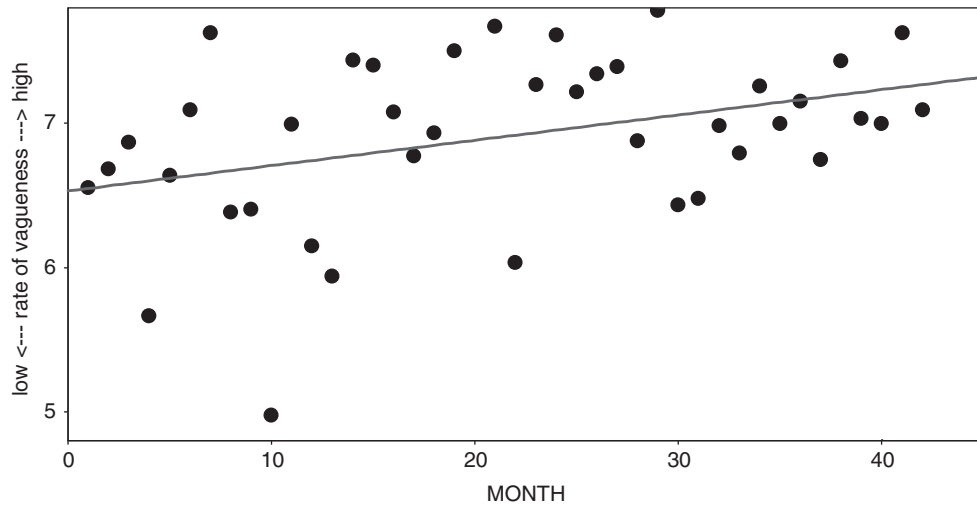


Fig. 5 The rate of vagueness in the speeches of President Ahmadinejad (14 March 2008 to 31 January 2012) ($N=42$ months). Distribution of President Ahmadinejad's speeches per month: 2008, months 1–9; 2009, months 10–19; 2010, months 20–30; 2011, months 31–41; 2012, month 42

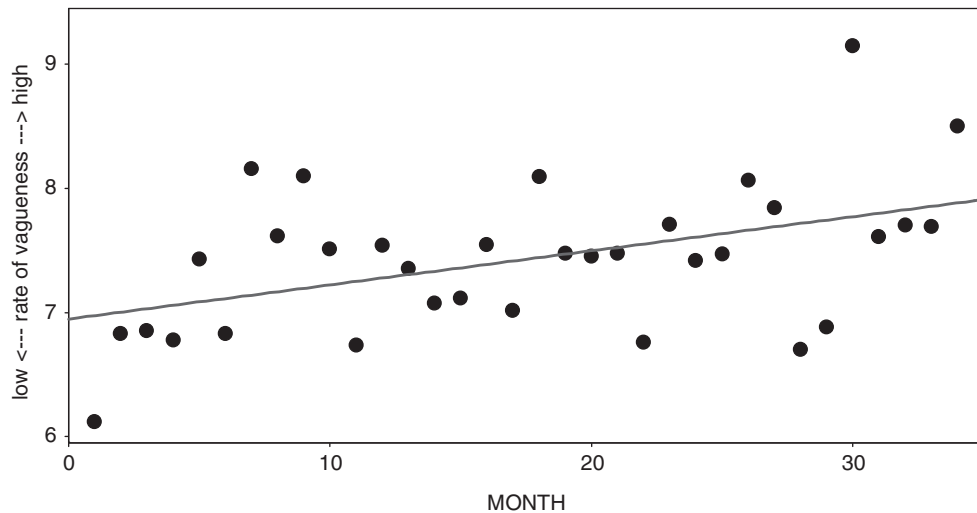


Fig. 6 The rate of vagueness in the speeches of Secretary Clinton (3 February 2009 to 10 January 2012) ($N=34$ months). Distribution of Secretary Clinton's speeches per month: 2009, months 1–10; 2010, months 11–22; 2011, months 23–33; 2012, month: 34

speeches of Ayatollah Khamenei, and, with a nuance, of President Ahmadinejad, chart a cautious course toward appeasement. The reversal of the sign of the trend after the 28th month in Ahmadinejad—he is not all easing—hints he is not indifferent to external pressures. But this minor dissonance confirms the otherwise general pattern toward

settlement. On the other hand, the rising trend of risk of war in the speeches of Secretary of State Clinton flags foreseeing a persisting enforcement of pressures on Iran. A warning bell, and maybe more. The Israeli speeches keep their ambiguous line, indeed as if entangled in conflicting forces. Risks of war are analysable and workable, but this

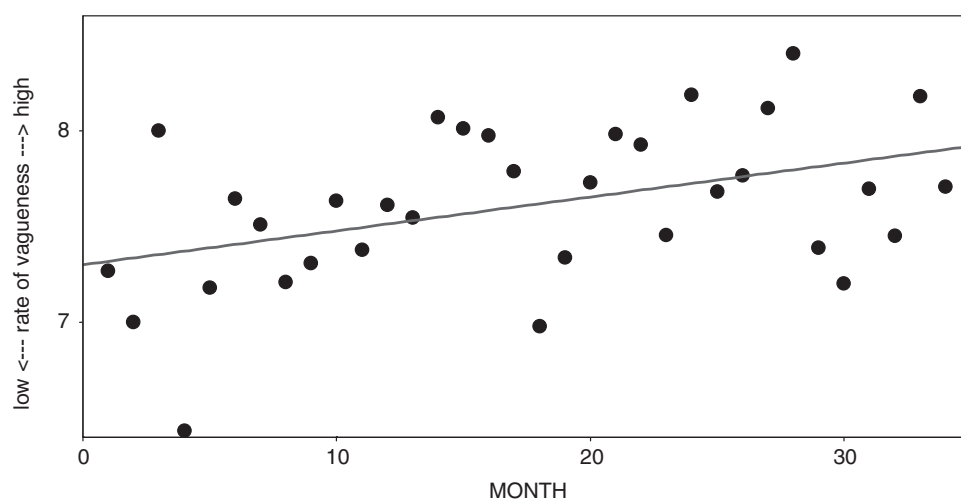


Fig. 7 The rate of vagueness in the speeches of Prime Minister Netanyahu (30 March 2009 to 1 February 2012) ($N=34$ months days). Distribution of Prime Minister Netanyahu's speeches per month: 2009, months 1–10; 2010, months 11–21; 2011, month 22–32; 2012, months 33–34

ambiguity as lack of visibility is not. Just the same, it is difficult to imagine that words bear no relation to events.

Playing martial language against vagueness of language, we noticed the rate of vagueness increased in Ahmadinejad, Clinton, and Netanyahu. But the context of the increases does not mean the same for each of them. Being vague in Iran is not the same as being vague in Washington or Jerusalem. On one side, a martial language like Clinton's, woven with signals of ambiguity, looks like a paradoxical blurred show of confidence. This view is reinforced by the solid lagged correlation in Clinton's speeches between risk of war and rate of vagueness one month later. On the other side, an appeasing language like Ahmadinejad's, woven with more signals of ambiguity, is coherent. Beyond these nuances, vagueness that leaves doors open is helpful in a dispute, even on the Israeli side. At any rate, one would have more to fear from the opposite, that is, an increasingly martial language woven with a decreasing rate of vagueness locking the stance of the disputants. The speeches of President Medvedev in the August 2008 intervention in Georgia (Hogenraad and Garagozov, 2010, p. 22) are a case in point.

Ultimately, what we cared about was to foreshadow a risk of war from political speeches. We

used a measure of vagueness to modulate that evaluation of risk. With this, we have reached the limit of what one can do to warn of a risk of war using only words. What comes out is that codifying words of motive imagery as links—not causes—prefiguring wars in the making led us to recognise an undeniable risk. However partial this knowledge, we cannot know what knowledge may be useful in the future, except as an inducement to think about conflicts through the words of the other. At least known risks can be handled. It is always the unknown, writes Robert Harris (2011, p. 49) (in his recent novel about an automated computer-content analysis artifact run amok!), that is most frightening.

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Note

- The list of corpora used to validate the English, French, and Spanish versions of the motive imagery dictionary is available at <https://www.dropbox.com/s/17sphwk0vzrhdttd/Corpus%20of%20War%20and%20Peace.pdf>