Online Appendix: Quantifying Political Relationships

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A Details on the Event Data

A.1 BBN ACCENT Machine-Coding System

The news reports were machine-coded by BBN ACCENT, an automatic information extraction system developed by Raytheon BBN Technologies. The coder proceeds in several steps.

First, it processes the meta-data of the input document (the news report), such as the publication date and its source.

Second, it breaks the document into its sentences and proceeds with sentence-level extraction. This entails a number of processes, among others tokenization, name extraction, and classifying the relations between the entities in the sentence. Each of those processes is done by a separate model that has been trained using example data. For each news report, the first six sentences are coded. The focus is on the first six sentences because news reports are typically written in the "inverted pyramid" style, where the most important information (who, what, where, when) appears in the first few sentences of an article.

Third, once the sentence-level processing for the entire document is completed, the document-level extraction takes place. This entails finding the entities that are the main actors in the event, and categorizing the nature of the event. To do so, the categorical coding scheme developed by the Conflict and Mediation Event Observation (CAMEO) project is used (Gerner, Schrodt and Yilmaz, 2009). CAMEO consists of 20 top-level verb categories (with a total of around 350 subcategories) that classify the nature of the reported events. For example, some verb categories are "make optimistic comment," "express intent to settle dispute," or "accuse of aggression." The full list of CAMEO codes can be found at `http://eventdata.parusanalytics.com/cameo.dir/CAMEO.Manual.1.1b3.pdf`.

Finally, filters are applied to remove historical events and exact duplicates.

For more details, especially of technical nature of the ICEWS and ACCENT event coding, see Ramshaw et al. (2011), Boschee, Natarjan and Weischedel (2013), and Schrodt and Van Brackle (2013). The final product for each event is four pieces of information: the event date, the event source, the event target, and the event type. The ICEWS data were publicly released to Dataverse in early 2015 and can be found at `http://dx.doi.org/10.7910/DVN/28075`. Under the same address, there are also documents with a more detailed technical description of the event coder, including examples and evaluations.

Note that ACCENT has been released to the research community. Information about contact points at Raytheon BBN to obtain access is available from the author upon request.

A.2 ICEWS Event Data Suitability and Limitations

As I show in the article, using the machine-coded ICEWS events as source material allows me to derive a measure of public political relationships that involves hundreds of socioeconomic actors in a multitude of venues over many years. I also discuss issues of data breadth and accuracy, but due to space constraints only in a relatively brief manner. In this section, I provide a more detailed discussion of the suitability and limitations of the ICEWS data.

The goal of the ICEWS project is to aide policy analysts to predict political crises around the globe. Given this, one may wonder whether the event collection skews towards violent events. While ICEWS tries to forecast rebellions or ethno-religious violence, it also focuses on domestic political crises, which are often non-violent (see O'Brien, 2010, 2013). For example, the mass demonstrations in Greece around 2011 would qualify as such an event. Thus, the project aimed to assemble an event collection that reflects the activities of countries' main socio-political actors as accurately as possible, whether they be violent or not. It therefore relies on a large number of national and international news sources (see Section A.3), which should provide an extensive collection of events. The events are filtered to exclude reports on e.g. sports or entertainment, but socio-political events are retained, no matter whether they were violent or not.

A related concern is whether the CAMEO coding scheme is equipped to classify events between domestic actors, given that it was originally developed for the study of interstate conflict mediation.[1] This is reflected in many of the verb categories (e.g. "grant diplomatic recognition", "expel or withdraw peace-keepers", "use weapons of mass destruction"), which will hardly apply in settings outside of international conflict. However, the scheme is now commonly used to code domestic interactions as well, and many of the verb categories are more likely to apply to within-country interactions (e.g. "threaten to impose curfew", "engage in violent protest"). Of course, one may nevertheless wonder whether the use of CAMEO skews the event collection towards violence, or whether non-violent events are classified less accurately. It is certainly true that CAMEO is not perfect for my purposes, and new verb dictionaries addressing its weaknesses are in development.[2] However, note that CAMEO is used to machine-code events that are able to successfully forecast domestic political crises, which are often non-violent. As such, CAMEO can accurately classify news stories reporting conflict and cooperation between domestic political actors. Recall that in the example sentence in the article ("Economics Minister Michael Glos, of the government's conservative CDU/CSU coalition partner, attacked a draft proposal from Justice Minister Brigitte Zypries"), the key verb is "attack," a term often associated with violence. However, it is assigned the CAMEO code "criticize or denounce," correctly capturing the non-violent nature of the interaction. Furthermore, if the CAMEO coding fails to capture actual relations among domestic actors, this should make it harder to find any results in the analysis.

More broadly, language is complex and difficult to quantify, especially since context is often crucial for understanding. A potential concern about the data is thus the accuracy of the machine-coding. The first piece of evidence addressing this question comes from studies of BBN ACCENT. The algorithm's developers report that in a validation study, the machine-coding was judged to be correct in between 68 percent and 75 percent of cases,

[1] See `http://eventdata.parusanalytics.com/cameo.dir/CAMEO.Manual.1.1b3.pdf`, Ch. 1.

[2] See `http://ploverdata.org/`.

using a sample of 500 event codings for each of three top-level CAMEO event codes (Boschee, Natarjan and Weischedel, 2013).[3] This compares well with the available alternative, which is human coding. Even well-trained coders are prone to errors (Mikhaylov, Laver and Benoit, 2012). For example, King and Lowe (2003) evaluate event type coding done by trained undergraduates and find them to be correct in only 25 to 50 percent of cases. This is about as accurate as their machine-coding, which was done by a comparatively simple algorithm. Given advances in this area over the last decade, the machine-coding of the news reports in this article is likely at least as accurate as human coding would be, and quite possibly better. And importantly, the dichotomization of the events into cooperative and conflictual will further decrease coding errors. Sticking with the example sentence above, even if the machine-coding had misclassified "attack" as "use unconventional mass violence" rather than as "criticize or denounce," it would still correctly be considered a conflictual interaction.

Nevertheless, as with any source, there are some limitations to the event data. For one, media reports tend to focus on high-level political and social actors. Ministers, party leaders, or party spokespersons are well represented, while the activities of e.g. backbencher MPs are less likely to be reported. Similarly, unions or nationwide protest movements are more likely to be covered than societal actors at the local level. A second characteristic of the data is that just like other commonly used sources in the study of political communication (press releases, parliamentary speeches), it only represents public events. However, one advantage of media-based data compared to existing approaches is that it captures interactions not just in a single venue, but in many of them: press releases, parliamentary speeches, interviews, campaign events, and so on. Of course, how and in which venues actors communicate with each other publicly may differ between countries depending on their laws, culture, and institutions. It is therefore important to address this challenge to the comparability of the event data and the cooperation scores in one's analysis, for example by ensuring that findings are robust to accounting for potentially unobservable cross-national differences (e.g. through country or country-year fixed effects).

Finally, note that I do not weight the interactions in any way, so they are all treated equally. Of course, some interactions reported in the news are very important, whereas others are rather trivial. However, there is to date no procedure to systematically determine the relative importance of interactions that can be scaled and applied to hundreds of thousands of events. But while the volume of the event data makes it infeasible to determine the importance of the interactions, it at the same time compensates for it: Some events are more important than others for a relationship, but if we observe enough events, the balance of cooperative and conflictual ones between two actors is likely to be an adequate reflection of their overall relationship.

[3] Accuracy rates in an evaluation using all 20 top-level CAMEO event codes vary between 58 percent and 88 percent. More details are available under `http://dx.doi.org/10.7910/DVN/28075`.

A.3 Sources

Table 1: Top 10 news report sources

Source	Proportion of all Events
Agence France-Presse	0.159
Reuters News	0.130
Associated Press Newswires	0.105
Irish Times	0.046
Athens News Agency	0.041
Dow Jones International News	0.038
The Scotsman	0.032
BBC Monitoring European	0.032
Xinhua News Agency	0.032
London Evening Standard	0.031

List of all Sources: Note that a number of the sources originate from countries outside of Europe. However, reports from these sources still cover exclusively domestic events from one of the 13 Western European countries I consider in this article. ICEWS uses sources from around the world and employs an algorithm that identifies and deletes duplicate events. Thus, events reported by e.g. Xinhua News Agency likely are also reported by a European outlet such as Agence France-Presse or the BBC, but the de-duplification algorithm at times may only retain the report of a non-European source.

AAP Bulletins, Ad Dustour, Agence Europe, Agence France-Presse, Agence Ivoirienne de Presse, Agencia Diarios y Noticias, Agencia EFE - Servico em portugues, Agency Tunis Afrique Press (Arabic), AGERPRES, AKIpress, Al Ahdath Al Maghribia, Al Arabiya, Al Dia, Al Gomhuriah, Al Ittihad, Al Jazeera English, Al Rai, Al Rayah, Al Shabiba, Al-Bawaba News, Algerie-Focus, All Africa, Americas Review World of Information, Anadolu News Agency, ANSA - Spanish Service (BASP), ANSA- Servicio Economia en Latinoamerica, AP Spanish Worldstream, APANEWS, ARKA - News (Armenia), As Safir, Asharq Alawsat, Asia Pulse, Associated Press Newswires, Athens News Agency, Australian Associated Press, Australian Broadcasting Corporation (ABC) News, Baladna, Baltic Business Weekly, Baltic Daily, Bangkok Post, BBC Monitoring, BBC Monitoring Africa, BBC Monitoring Americas, BBC Monitoring Asia Pacific, BBC Monitoring Caucasus, BBC Monitoring Central Asia, BBC Monitoring Central Europe and Balkans, BBC Monitoring European, BBC Monitoring Former Soviet Union, BBC Monitoring Latin America, BBC Monitoring Media, BBC Monitoring Middle East, BBC Monitoring Newsfile, BBC Monitoring South Asia, BBC Monitoring Ukraine & Baltics, Black Sea Press, BNS Baltic Business News, Bulgarian News Agency, Calgary Herald, Canada NewsWire, Cape Argus, Cape Times, Central News Agency English News, Channel NewsAsia, China Daily, CNN: Breaking News, Corporate Argentina, CTK Daily News, Daily Dispatch, Daily News, Daily Star, Daily Telegraph, Deutsche Welle, DJ em Portugues, Dow Jones Business News, Dow Jones Emerging Markets Report, Dow Jones en Espanol, Dow Jones International News, Dow Jones News Service, EFE News Service, El Clarin, El Comercio, El Cronista, El Economista, El Mercurio, El Nacional, El Norte, El Nuevo Dia, El Observador Economico, El Pais, El Pais - English Edition, El Universal, El Watan, eMarrakech, Esmerk Danish News, Esmerk Finnish News, Esmerk Swedish News, EurActiv.fr, Euronews, Europolitique, FARS News Agency, Folha de Sao Paulo, Gazeta do Povo, Guardian Unlimited, HINA, Hindustan Times, Horizons, Il Sole 24 Ore, India Today, Indo-Asian News Service, Inter Press Service, Interfax News Service, Irish Times, ISI Emerging Markets Africawire, Israel Faxx, IT Market Statistics, ITAR Tass, Jeune Afrique.com, Jiji Press English News Service, Joins.com, KBS World News - French Edition, Korea Newswire, Korea Times, Kuwait News Agency, Kyodo News, L' Orient-Le Jour, L'Essor, L'Expression, La Nacion, La Republica, Latin America News Digest, Latvian News Agency, Le Figaro, Le Journal de l'Ile de la Reunion, Le Monde, Le Progres Egyptien, Le Quotidien, Le Temps, Libya News Agency (LANA), Lithuanian News Agency - ELTA, London Evening Standard, Mainichi Daily News, Market Wire, Middle East and North Africa Today, Mist News, Mural, National Iraqi News Agency, New Straits Times, New Zealand Herald, New Zealand Press Association, Noticen: Central American & Caribbean Affairs O Estado de Sao Paulo, O Globo, Oman News Agency, Organisation de la Presse Africaine, Organisation of Asia-Pacific News Agencies, PACNEWS, the Pacific News Agency Service, Panorama Brasil - Portugues, PARI Daily, Philippine Daily Inquirer, PNA (Philippines News Agency), Polish News Bulletin, Prime-News (Georgia), Reforma, Resource News International, Reuters - Noticias Latinoamericanas, Reuters EU Highlights, Reuters News, RIA Novosti, RIA Vesti, Rompres, Russia & CIS General Newswire, SAINT (South Atlantic Islands News Team), SAPA (South African Press Association), Saudi Press Agency, SBS World News Headline Stories, SeeNews, Servicio Universal de Noticias, SITA Slovenska Tlacova Agentura, South China Morning Post, Spiegel Online International, Straits Times, Sueddeutsche Zeitung, Syrian Arab News Agency, Taipei Times, TASR - Tlacova Agentura Slovenskej Republiky, Telecompaper Americas, Thai News Service, The Asian Wall Street Journal, The Australian, The Christian Science Monitor, The Courier-Mail, The Economist, The Hindu, The Jakarta Post, The Japan Times, The Jerusalem Post, The Korea Herald, The Mercury, The Moscow News, The Moscow Times, The Nation (Thailand), The New York Times, The News, The Oil Daily, The San Diego Union-Tribune, The Scotsman, The Sydney Morning Herald, The Times of India, The Toronto Star, The Tripoli Post, The Wall Street Journal, The Wall Street Journal Asia, The Wall Street Journal Europe, The Washington Post, Trend News Agency (Azerbaijan), Turan Information Agency (Azerbaijan), Turkish Daily News, Ukrainian National News Agency, United News of Bangladesh Limited, Unknown, UPI Energy Resources, USA Today, UzReport.com, Vietnam News Agency Bulletin, What The Papers Say, WPS: What the Papers Say, Xinhua News Agency, Yemen News Agency (Arabic), Yemen News Agency (SABA), Yogam Communications SARL, Yonhap English News.

A.4 Cooperative and Conflictual CAMEO Codes

The news stories were classified into cooperative and conflictual events based upon the CAMEO coding scheme available at `http://eventdata.parusanalytics.com/cameo.dir/CAMEO.Manual.1.1b3.pdf` In this section, I list the CAMEO codes for each category. Note that many CAMEO codes are irrelevant for domestic interactions in Western European countries (e.g. "Use unconventional mass violence", "Engage in ethnic cleansing") and do not show up in the data. However, I list them for the sake of completeness.

A.4.1 CAMEO Codes for Cooperative Events

- 013: Make optimistic comment
- 017: Engage in symbolic act
- 018: Make empathetic comment
- 019: Express accord
- 020: Make an appeal or request, not specified below
- 021: Appeal for material cooperation, not specified below
- 0211: Appeal for economic cooperation
- 0212: Appeal for military cooperation
- 0213: Appeal for judicial cooperation
- 0214: Appeal for intelligence
- 022: Appeal for diplomatic cooperation (such as policy support)
- 023: Appeal for aid, not specified below
- 0231: Appeal for economic aid
- 0232: Appeal for military aid
- 0233: Appeal for humanitarian aid
- 0234: Appeal for military protection or peacekeeping
- 026: Appeal to others to meet or negotiate
- 027: Appeal to others to settle dispute
- 028: Appeal to engage in or accept mediation
- 030: Express intent to cooperate, not specified below
- 031: Express intent to engage in material cooperation, not specified below
- 0311: Express intent to cooperate economically
- 0312: Express intent to cooperate militarily
- 0313: Express intent to cooperate on judicial matters
- 0314: Express intent to cooperate on intelligence

- 032: Express intent to engage in diplomatic cooperation (such as policy support)
- 033: Express intent to provide material aid, not specified below
- 0331: Express intent to provide economic aid
- 0332: Express intent to provide military aid
- 0333: Express intent to provide humanitarian aid
- 0334: Express intent to provide military protection or peacekeeping
- 034: Express intent to institute political reform, not specified below
- 0341: Express intent to change leadership
- 0342: Express intent to change policy
- 0343: Express intent to provide rights
- 0344: Express intent to change institutions, regime
- 035: Express intent to yield, not specified below
- 0351: Express intent to ease administrative sanctions
- 0352: Express intent to ease popular dissent
- 0353: Express intent to release persons or property
- 0354: Express intent to ease economic sanctions, boycott, or embargo
- 0355: Express intent to allow international involvement (non-mediation)
- 0356: Express intent to de-escalate military engagement
- 036: Express intent to meet or negotiate
- 037: Express intent to settle dispute
- 038: Express intent to accept mediation
- 039: Express intent to mediate
- 040: Consult, not specified below
- 041: Discuss by telephone
- 042: Make a visit
- 043: Host a visit
- 044: Meet at a “third” location
- 045: Mediate
- 046: Engage in negotiation
- 050: Engage in diplomatic cooperation, not specified below
- 051: Praise or endorse
- 052: Defend verbally
- 053: Rally support on behalf of
- 054: Grant diplomatic recognition

- 055: Apologize
- 056: Forgive
- 057: Sign formal agreement
- 060: Engage in material cooperation, not specified below
- 061: Cooperate economically
- 062: Cooperate militarily
- 063: Engage in judicial cooperation
- 064: Share intelligence or information
- 070: Provide aid, not specified below
- 071: Provide economic aid
- 072: Provide military aid
- 073: Provide humanitarian aid
- 074: Provide military protection or peacekeeping
- 075: Grant asylum
- 080: Yield, not specified below
- 081: Ease administrative sanctions, not specified below
- 0811: Ease restrictions on political freedoms
- 0812: Ease ban on political parties or politicians
- 0813: Ease curfew
- 0814: Ease state of emergency or martial law
- 082: Ease political dissent
- 083: Accede to requests or demands for political reform, not specified below
- 0831: Accede to demands for change in leadership
- 0832: Accede to demands for change in policy
- 0833: Accede to demands for rights
- 0834: Accede to demands for change in institutions, regime
- 084: Return, release, not specified below
- 0841: Return, release person(s)
- 0842: Return, release property
- 085: Ease economic sanctions, boycott, embargo
- 086: Allow international involvement, not specified below
- 0861: Receive deployment of peacekeepers
- 0862: Receive inspectors
- 0863: Allow humanitarian access

- 087: De-escalate military engagement
- 0871: Declare truce, ceasefire
- 0872: Ease military blockade
- 0873: Demobilize armed forces
- 0874: Retreat or surrender militarily

A.4.2 CAMEO Codes for Conflictual Events

- 011: Decline comment
- 012: Make pessimistic comment
- 016: Deny responsibility
- 024: Appeal for political reform, not specified below
- 0241: Appeal for change in leadership
- 0242: Appeal for policy change
- 0243: Appeal for rights
- 0244: Appeal for change in institutions, regime
- 025: Appeal to yield, not specified below
- 0251: Appeal for easing of administrative sanctions
- 0252: Appeal for easing of political dissent
- 0253: Appeal for release of persons or property
- 0254: Appeal for easing of economic sanctions, boycott, or embargo
- 0255: Appeal for target to allow international involvement (non-mediation)
- 0256: Appeal for de-escalation of military engagement
- 090: Investigate, not specified below
- 091: Investigate crime, corruption
- 092: Investigate human rights abuses
- 093: Investigate military action
- 094: Investigate war crimes
- 100: Demand, not specified below
- 101: Demand material cooperation, not specified below
- 1011: Demand economic cooperation
- 1012: Demand military cooperation
- 1013: Demand judicial cooperation
- 1014: Demand intelligence cooperation
- 102: Demand diplomatic cooperation (such as policy support)

- 103: Demand material aid, not specified below
- 1031: Demand economic aid
- 1032: Demand military aid
- 1033: Demand humanitarian aid
- 1034: Demand military protection or peacekeeping
- 104: Demand political reform, not specified below
- 1041: Demand change in leadership
- 1042: Demand policy change
- 1043: Demand rights
- 1044: Demand change in institutions, regime
- 105: Demand that target yields, not specified below
- 1051: Demand easing of administrative sanctions
- 1052: Demand easing of political dissent
- 1053: Demand release of persons or property
- 1054: Demand easing of economic sanctions, boycott, or embargo
- 1055: Demand that target allows international involvement (non-mediation)
- 1056: Demand de-escalation of military engagement
- 106: Demand meeting, negotiation
- 107: Demand settling of dispute
- 108: Demand mediation
- 110: Disapprove, not specified below
- 111: Criticize or denounce
- 112: Accuse, not specified below
- 1121: Accuse of crime, corruption
- 1122: Accuse of human rights abuses
- 1123: Accuse of aggression
- 1124: Accuse of war crimes
- 1125: Accuse of espionage, treason
- 113: Rally opposition against
- 114: Complain officially
- 115: Bring lawsuit against
- 116: Find guilty or liable (legally)
- 120: Reject, not specified below
- 121: Reject material cooperation

- 1211: Reject economic cooperation
- 1212: Reject military cooperation
- 122: Reject request or demand for material aid, not specified below
- 1221: Reject request for economic aid
- 1222: Reject request for military aid
- 1223: Reject request for humanitarian aid
- 1224: Reject request for military protection or peacekeeping
- 123: Reject request or demand for political reform, not specified below
- 1231: Reject request for change in leadership
- 1232: Reject request for policy change
- 1233: Reject request for rights
- 1234: Reject request for change in institutions, regime
- 124: Refuse to yield, not specified below
- 1241: Refuse to ease administrative sanctions
- 1242: Refuse to ease popular dissent
- 1243: Refuse to release persons or property
- 1244: Refuse to ease economic sanctions, boycott, or embargo
- 1245: Refuse to allow international involvement (non mediation)
- 1246: Refuse to de-escalate military engagement
- 125: Reject proposal to meet, discuss, or negotiate
- 126: Reject mediation
- 127: Reject plan, agreement to settle dispute
- 128: Defy norms, law
- 129: Veto
- 130: Threaten, not specified below
- 131: Threaten non-force, not specified below
- 1311: Threaten to reduce or stop aid
- 1312: Threaten with sanctions, boycott, embargo
- 1313: Threaten to reduce or break relations
- 132: Threaten with administrative sanctions, not specified below
- 1321: Threaten with restrictions on political freedoms
- 1322: Threaten to ban political parties or politicians
- 1323: Threaten to impose curfew
- 1324: Threaten to impose state of emergency or martial law

- 133: Threaten with political dissent, protest
- 134: Threaten to halt negotiations
- 135: Threaten to halt mediation
- 136: Threaten to halt international involvement (non-mediation)
- 137: Threaten with repression
- 138: Threaten with military force, not specified below
- 1381: Threaten blockade
- 1382: Threaten occupation
- 1383: Threaten unconventional violence
- 1384: Threaten conventional attack
- 1385: Threaten attack with WMD
- 139: Give ultimatum
- 140: Engage in political dissent, not specified below
- 141: Demonstrate or rally, not specified below
- 1411: Demonstrate for leadership change
- 1412: Demonstrate for policy change
- 1413: Demonstrate for rights
- 1414: Demonstrate for change in institutions, regime
- 142: Conduct hunger strike, not specified below
- 1421: Conduct hunger strike for leadership change
- 1422: Conduct hunger strike for policy change
- 1423: Conduct hunger strike for rights
- 1424: Conduct hunger strike for change in institutions, regime
- 143: Conduct strike or boycott, not specified below
- 1431: Conduct strike or boycott for leadership change
- 1432: Conduct strike or boycott for policy change
- 1433: Conduct strike or boycott for rights
- 1434: Conduct strike or boycott for change in institutions, regime
- 144: Obstruct passage, block, not specified below
- 1441: Obstruct passage to demand leadership change
- 1442: Obstruct passage to demand policy change
- 1443: Obstruct passage to demand rights
- 1444: Obstruct passage to demand change in institutions, regime
- 145: Protest violently, riot, not specified below

- 1451: Engage in violent protest for leadership change
- 1452: Engage in violent protest for policy change
- 1453: Engage in violent protest for rights
- 1454: Engage in violent protest for change in institutions, regime
- 150: Demonstrate military or police power, not specified below
- 151: Increase police alert status
- 152: Increase military alert status
- 153: Mobilize or increase police power
- 154: Mobilize or increase armed forces
- 155: Mobilize or increase cyber-forces
- 160: Reduce relations, not specified below
- 161: Reduce or break diplomatic relations
- 162: Reduce or stop material aid, not specified below
- 1621: Reduce or stop economic assistance
- 1622: Reduce or stop military assistance
- 1623: Reduce or stop humanitarian assistance
- 163: Impose embargo, boycott, or sanctions
- 164: Halt negotiations
- 165: Halt mediation
- 166: Expel or withdraw, not specified below
- 1661: Expel or withdraw peacekeepers
- 1662: Expel or withdraw inspectors, observers
- 1663: Expel or withdraw aid agencies
- 170: Coerce, not specified below
- 171: Seize or damage property, not specified below
- 1711: Confiscate property
- 1712: Destroy property
- 172: Impose administrative sanctions, not specified below
- 1721: Impose restrictions on political freedoms
- 1722: Ban political parties or politicians
- 1723: Impose curfew
- 1724: Impose state of emergency or martial law
- 173: Arrest, detain, or charge with legal action
- 174: Expel or deport individuals

- 175: Use tactics of violent repression
- 176: Attack cybernetically
- 180: Use unconventional violence, not specified below
- 181: Abduct, hijack, or take hostage
- 182: Physically assault, not specified below
- 1821: Sexually assault
- 1822: Torture
- 1823: Kill by physical assault
- 183: Conduct suicide, car, or other non-military bombing, not specified below
- 1831: Carry out suicide bombing
- 1832: Carry out vehicular bombing
- 1833: Carry out roadside bombing
- 1834: Carry out location bombing
- 184: Use as human shield
- 185: Attempt to assassinate
- 186: Assassinate
- 190: Use conventional military force, not specified below
- 191: Impose blockade, restrict movement
- 192: Occupy territory
- 193: Fight with small arms and light weapons
- 194: Fight with artillery and tanks
- 195: Employ aerial weapons, not specified below
- 1951: Employ precision-guided aerial munitions
- 1952: Employ remotely piloted aerial munitions
- 196: Violate ceasefire
- 200: Use unconventional mass violence, not specified below
- 201: Engage in mass expulsion
- 202: Engage in mass killings
- 203: Engage in ethnic cleansing
- 204: Use weapons of mass destruction, not specified below
- 2041: Use chemical, biological, or radiological weapons
- 2042: Detonate nuclear weapons

A.5 List of Actors

A.5.1 Political Parties

- **Austria**: SPO, FPO, OVP, Greens, BZO
- **Belgium**: CD&V, CDH, Ecolo, Groen, MR, N-VA, PS, SP.A, SPIRIT, VB, VLD
- **Denmark**: Venstre, Social Democrats, DKF, DPP, SF, Liberal Alliance, Radikale Venstre
- **Finland**: Centre, Green League, Left Alliance, NCP, PS, SDP, SFP
- **France**: EELV, FN, MoDem, PCF, PS, RPR, UMP
- **Germany**: CDU/CSU, FDP, Grune, PDS/Linke, SPD
- **Greece**: PASOK, ND, KKE, Syriza, XA, ANEL
- **Ireland**: Fianna Fail, Fine Gael, Labour, Sinn Fein
- **Italy**: LN, FI, AN, DL, DS, PRC, UdC, PD, PdL, M5S, SC
- **Netherlands**: CDA, D66, GL, LPF, PvdA, PVV, VVD
- **Portugal**: CDS-PP, CDU, PS, PSD
- **Spain**: PP, PSOE
- **United Kingdom**: Labour, Conservative, LibDem

A.5.2 Non-Partisan Political Actors

Table 2: Top 5 non-partisan political actors: Austria

Source	Proportion of all Country Events
Austria	0.262
Police (Austria)	0.162
Government (Austria)	0.038
Other Authorities / Officials (Austria)	0.036
Party Member (Austria)	0.022

Table 3: Top 5 non-partisan political actors: Belgium

Source	Proportion of all Country Events
Belgium	0.282
Police (Belgium)	0.183
Government (Belgium)	0.062
Royal Administration (Belgium)	0.061
Other Authorities / Officials (Belgium)	0.040

Table 4: Top 5 non-partisan political actors: Denmark

Source	Proportion of all Country Events
Denmark	0.293
Police (Denmark)	0.254
Government (Denmark)	0.076
Military (Denmark)	0.041
Royal Administration (Denmark)	0.034

Table 5: Top 5 non-partisan political actors: Finland

Source	Proportion of all Country Events
Finland	0.268
Police (Finland)	0.185
Government (Finland)	0.063
Legislature (Finland)	0.032
Oversight Court (Finland)	0.021

Table 6: Top 5 non-partisan political actors: France

Source	Proportion of all Country Events
France	0.246
Police (France)	0.145
Government (France)	0.042
Military (France)	0.033
Court Judge (France)	0.027

Table 7: Top 5 non-partisan political actors: Germany

Source	Proportion of all Country Events
Germany	0.234
Police (Germany)	0.145
Government (Germany)	0.058
Military (Germany)	0.031
Other Authorities / Officials (Germany)	0.024

Table 8: Top 5 non-partisan political actors: Greece

Source	Proportion of all Country Events
Police (Greece)	0.237
Greece	0.198
Ministry (Greece)	0.036
Other Authorities / Officials (Greece)	0.028
Legislature (Greece)	0.015

Table 9: Top 5 non-partisan political actors: Ireland

Source	Proportion of all Country Events
Ireland	0.214
Police (Ireland)	0.095
Government (Ireland)	0.072
Court Judge (Ireland)	0.069
Ministry (Ireland)	0.040

Table 10: Top 5 non-partisan political actors: Italy

Source	Proportion of all Country Events
Italy	0.210
Police (Italy)	0.180
Government (Italy)	0.053
Court Judge (Italy)	0.028
Ministry (Italy)	0.026

Table 11: Top 5 non-partisan political actors: Netherlands

Source	Proportion of all Country Events
Netherlands	0.241
Police (Netherlands)	0.201
Government (Netherlands)	0.059
The Hague	0.051
Other Authorities / Officials (Netherlands)	0.034

Table 12: Top 5 non-partisan political actors: Portugal

Source	Proportion of all Country Events
Police (Portugal)	0.180
Portugal	0.162
Government (Portugal)	0.110
Legislature (Portugal)	0.077
Political Parties (Portugal)	0.033

Table 13: Top 5 non-partisan political actors: Spain

Source	Proportion of all Country Events
Spain	0.248
Police (Spain)	0.197
Court Judge (Spain)	0.053
Other Authorities / Officials (Spain)	0.026
Member of the Judiciary (Spain)	0.023

Table 14: Top 5 non-partisan political actors: United Kingdom

Source	Proportion of all Country Events
Police (United Kingdom)	0.227
United Kingdom	0.196
Military (United Kingdom)	0.032
Court Judge (United Kingdom)	0.027
Ministry (United Kingdom)	0.023

A.5.3 Societal Actors

Table 15: Top 5 societal actors: Austria

Source	Proportion of all Country Events
Citizen (Austria)	0.298
Men (Austria)	0.059
Criminal (Austria)	0.041
Lawyer/Attorney (Austria)	0.035
Josef Fritzl	0.032

Table 16: Top 5 societal actors: Belgium

Source	Proportion of all Country Events
Citizen (Belgium)	0.352
Criminal (Belgium)	0.051
Men (Belgium)	0.037
Protester (Belgium)	0.031
Lawyer/Attorney (Belgium)	0.027

Table 17: Top 5 societal actors: Denmark

Source	Proportion of all Country Events
Citizen (Denmark)	0.285
Men (Denmark)	0.086
Protester (Denmark)	0.059
Criminal (Denmark)	0.034
Muslim (Denmark)	0.033

Table 18: Top 5 societal actors: Finland

Source	Proportion of all Country Events
Citizen (Finland)	0.290
Armed Gang (Finland)	0.092
Men (Finland)	0.058
Business (Finland)	0.036
Criminal (Finland)	0.032

Table 19: Top 5 societal actors: France

Source	Proportion of all Country Events
Citizen (France)	0.296
Men (France)	0.034
Lawyer/Attorney (France)	0.030
Criminal (France)	0.024
Children (France)	0.020

Table 20: Top 5 societal actors: Germany

Source	Proportion of all Country Events
Citizen (Germany)	0.262
Men (Germany)	0.045
Lawyer/Attorney (Germany)	0.042
Business (Germany)	0.030
Criminal (Germany)	0.028

Table 21: Top 5 societal actors: Greece

Source	Proportion of all Country Events
Citizen (Greece)	0.227
Protester (Greece)	0.059
Men (Greece)	0.043
Criminal (Greece)	0.035
Children (Greece)	0.030

Table 22: Top 5 societal actors: Ireland

Source	Proportion of all Country Events
Citizen (Ireland)	0.352
Men (Ireland)	0.085
Irish Republican Army	0.033
Business (Ireland)	0.029
Criminal (Ireland)	0.023

Table 23: Top 5 societal actors: Italy

Source	Proportion of all Country Events
Citizen (Italy)	0.279
Lawyer/Attorney (Italy)	0.064
Protester (Italy)	0.041
Men (Italy)	0.029
Criminal (Italy)	0.021

Table 24: Top 5 societal actors: Netherlands

Source	Proportion of all Country Events
Citizen (Netherlands)	0.302
Men (Netherlands)	0.088
Criminal (Netherlands)	0.069
Lawyer/Attorney (Netherlands)	0.041
Party Member (Netherlands)	0.033

Table 25: Top 5 societal actors: Portugal

Source	Proportion of all Country Events
Citizen (Portugal)	0.272
Men (Portugal)	0.032
Criminal (Portugal)	0.031
Party Member (Portugal)	0.014
People Associated with the Opposition (Portugal)	0.014

Table 26: Top 5 societal actors: Spain

Source	Proportion of all Country Events
Citizen (Spain)	0.310
ETA	0.139
Criminal (Spain)	0.043
Men (Spain)	0.036
Protester (Spain)	0.023

Table 27: Top 5 societal actors: United Kingdom

Source	Proportion of all Country Events
Citizen (United Kingdom)	0.317
Men (United Kingdom)	0.093
Criminal (United Kingdom)	0.029
Women (United Kingdom)	0.018
Children (United Kingdom)	0.016

A.6 Summary Statistics

A.6.1 Event Data by Country and Year

Table 28: Summary statistics of events by country

Country	Number of Events	Proportion Conflictual	Number of Actors
Austria	6434	0.532	175
Belgium	3694	0.498	191
Denmark	2583	0.6	152
Finland	1419	0.51	125
France	37236	0.527	424
Germany	22933	0.511	282
Greece	19425	0.547	263
Ireland	9581	0.592	251
Italy	19360	0.576	338
Netherlands	4271	0.616	181
Portugal	2835	0.48	148
Spain	45554	0.652	330
United Kingdom	74991	0.611	562
	250316	0.582	3422

Table 29: Summary statistics of events by year

Year	Number of Events	Proportion Conflictual	Number of Actors
2001	16646	0.555	1255
2002	13989	0.517	1207
2003	12401	0.507	1128
2004	21536	0.592	1354
2005	25407	0.596	1427
2006	23804	0.582	1439
2007	23243	0.580	1413
2008	20346	0.591	1342
2009	18060	0.612	1306
2010	16441	0.602	1268
2011	13378	0.613	1109
2012	15325	0.605	1178
2013	14964	0.612	1155
2014	14776	0.557	1234
	250316	0.582	3422

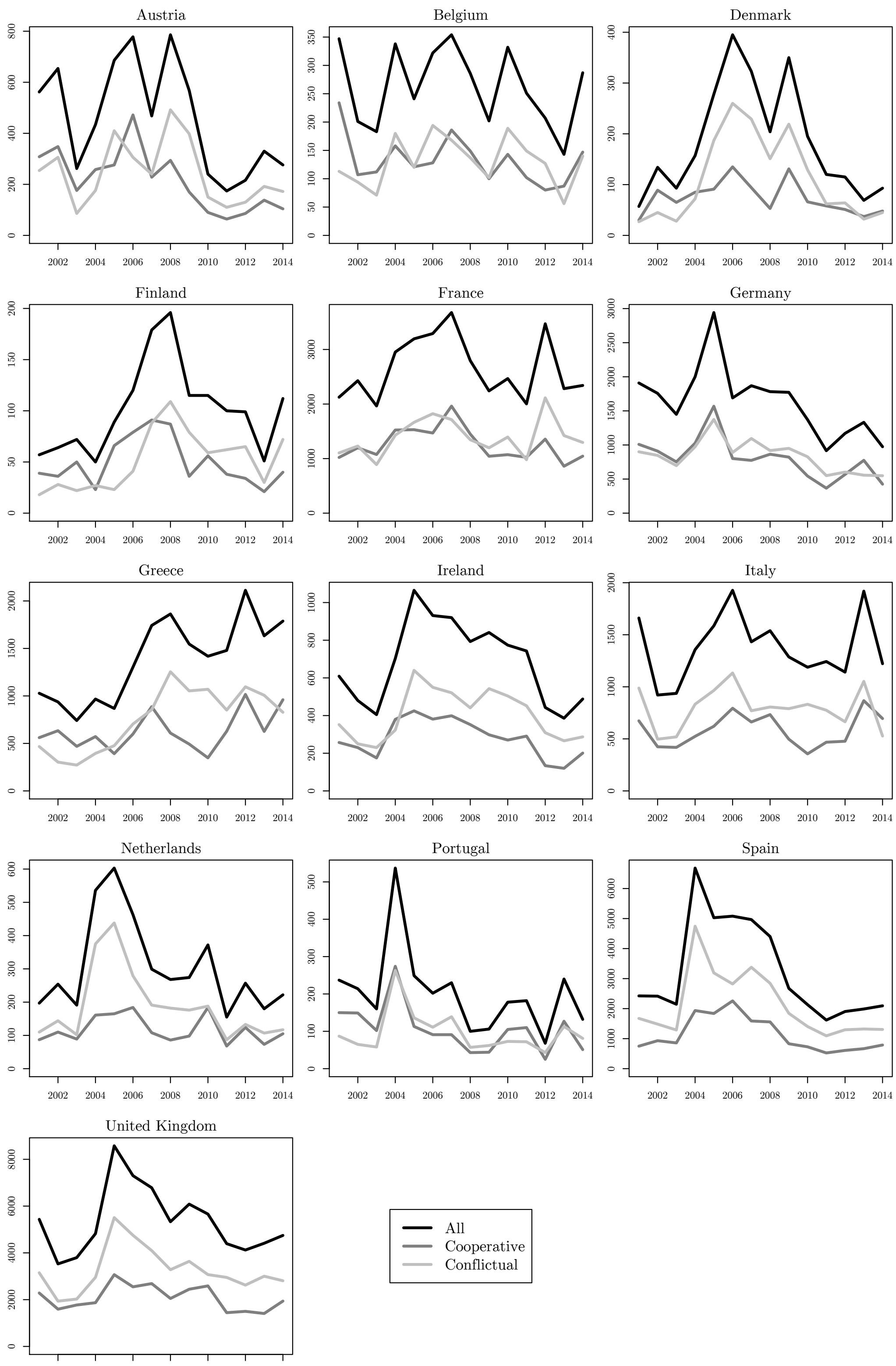

Figure 1: Number of events by country-year.

A.6.2 Cooperative and Conflictual Events

Table 30: Top 5 CAMEO categories for cooperative events, all interactions.

Event Type	Proportion of Events
Consult	0.093
Make an appeal or request	0.072
Express intent to meet or negotiate	0.054
Praise or endorse	0.040
Engage in negotiation	0.014

Table 31: Top 5 CAMEO categories for conflictual events, all interactions.

Event Type	Proportion of Events
Arrest, detain, or charge with legal action	0.151
Criticize or denounce	0.067
Accuse	0.054
Investigate	0.045
Demand	0.029

Table 32: Top 5 CAMEO categories for cooperative events, interactions between two political parties only

Event Type	Proportion of Party/Party Events
Consult	0.235
Praise or endorse	0.086
Make an appeal or request	0.072
Express intent to meet or negotiate	0.062
Engage in negotiation	0.037

Table 33: Top 5 CAMEO categories for conflictual events, interactions between two political parties only

Event Type	Proportion of Party/Party Events
Criticize or denounce	0.122
Accuse	0.087
Demand	0.029
Reject	0.026
Reduce relations	0.010

Table 34: Top 5 CAMEO categories for cooperative events, interactions between two non-partisan political actors only

Event Type	Proportion of Non-Partisan/Non-Partisan Events
Consult	0.104
Express intent to meet or negotiate	0.069
Make an appeal or request	0.057
Praise or endorse	0.052
Provide humanitarian aid	0.012

Table 35: Top 5 CAMEO categories for conflictual events, interactions between two non-partisan political actors only

Event Type	Proportion of Non-Partisan/Non-Partisan Events
Investigate	0.131
Use conventional military force	0.059
Arrest, detain, or charge with legal action	0.051
Confiscate property	0.048
Criticize or denounce	0.044

Table 36: Top 5 CAMEO categories for cooperative events, interactions between societal actors only

Event Type	Proportion of Societal/Societal Events
Make an appeal or request	0.073
Consult	0.027
Provide humanitarian aid	0.021
Express intent to meet or negotiate	0.017
Return, release person(s)	0.013

Table 37: Top 5 CAMEO categories for conflictual events, interactions between societal actors only

Event Type	Proportion of Societal/Societal Events
Use unconventional violence	0.139
Accuse	0.075
Criticize or denounce	0.065
fight with small arms and light weapons	0.051
Use conventional military force	0.044

Table 38: Top 5 CAMEO categories for cooperative events, interactions between one political party and one non-partisan political actor only

Event Type	Proportion of Party/Non-Partisan Events
Consult	0.181
Express intent to meet or negotiate	0.094
Praise or endorse	0.082
Make an appeal or request	0.081
Host a visit	0.060

Table 39: Top 5 CAMEO categories for conflictual events, interactions between one political party and one non-partisan political actor only

Event Type	Proportion of Party/Non-Partisan Events
Criticize or denounce	0.064
Demand	0.042
Accuse	0.034
Reject	0.024
Investigate	0.024

Table 40: Top 5 CAMEO categories for cooperative events, interactions between one political party and one societal actor only

Event Type	Proportion of Party/Societal Events
Make an appeal or request	0.148
Consult	0.096
Express intent to meet or negotiate	0.073
Praise or endorse	0.037
Engage in negotiation	0.023

Table 41: Top 5 CAMEO categories for conflictual events, interactions between one political party and one societal actor only

Event Type	Proportion of Party/Societal Events
Criticize or denounce	0.121
Accuse	0.104
Demand	0.034
Reject	0.029
Demonstrate or rally	0.024

Table 42: Top 5 CAMEO categories for cooperative events, interactions between one non-partisan political and one societal actor only

Event Type	Proportion of Non-Partisan/Societal Events
Make an appeal or request	0.047
Express intent to meet or negotiate	0.033
Return, release person(s)	0.020
Consult	0.016
Praise or endorse	0.009

Table 43: Top 5 CAMEO categories for conflictual events, interactions between one non-partisan political and one societal actor only

Event Type	Proportion of Non-Partisan/Societal Events
Arrest, detain, or charge with legal action	0.354
Investigate	0.064
Use conventional military force	0.041
Use unconventional violence	0.038
Criticize or denounce	0.035

B Additional Information for Latent Factor Networks Models

B.1 Further Details on the Latent Factor Networks Models

In this section, I provide further technical information on the latent factor network models I use to estimate the relationship scores. The discussion draws on Hoff (2008), Hoff (2015) and Minhas, Hoff and Ward (2016).

Suppose we are interested in estimating the relationships among a set of n actors, for whom we observe dyadic interactions. We represent these interactions in an $n \times n$ sociomatrix $\mathbf{Y}$. An entry y_{ij} summarizes the direct dyadic interactions between i and j. In my case, they are $y_{ij} = \ln\left(\frac{m^{+}_{ij}+1}{m^{-}_{ij}+1}\right)$. I treat the interactions as symmetric, so $y_{ij} = y_{ji}$, although it is possible to estimate sender and receiver-specific relationship scores using directed data (see Section B.4 below). The diagonal of $\mathbf{Y}$ is undefined.

The idea behind the latent factor model is that each actor can be represented through an unobserved, K-dimensional vector of characteristics $\boldsymbol{u}_i$. They are estimated in the following way:

$$\begin{aligned} y_{ij} &= \alpha + a_i + a_j + \epsilon_{ij} + \boldsymbol{u}_i' \boldsymbol{\Lambda} \boldsymbol{u}_j \\ a_1, \dots, a_n &\sim \text{i.i.d. } \mathcal{N}(0, \sigma_a^2) \\ \{\epsilon_{ij}\} &\sim \text{i.i.d. } \mathcal{N}(0, \sigma_e^2) \end{aligned} \tag{1}$$

As explained in the article, the random effects a_i, a_j, and ϵ_{ij} capture first-order and second-order dependencies, which are across-node heterogeneity (implying within-node heterogeneity of ties) and reciprocity.

Denote the $n \times n$ matrix that captures the remaining variance of $\mathbf{Y}$ not explained by the other terms in Equation (1) by $\mathbf{M}$. The eigenvalue decomposition theorem states that any square matrix, such as $\mathbf{M}$, can be written as $\mathbf{M} = \mathbf{U\Lambda U}'$, where $\mathbf{U}$ is a matrix of eigenvectors and $\boldsymbol{\Lambda}$ a diagonal matrix with the corresponding eigenvalues on the diagonal. The term $\mathbf{U\Lambda U}'$ thus captures the remaining variance in $\mathbf{Y}$ not accounted for by the other parameters. Note that an element m_{ij} of $\mathbf{M} = \mathbf{U\Lambda U}'$ is $\boldsymbol{u}_i' \boldsymbol{\Lambda} \boldsymbol{u}_j$.

Importantly, $\mathbf{U\Lambda U}'$ is able to capture two characteristics of networks: homophily and stochastic equivalence. Stochastic equivalence refers to a pattern where dyads or groups of nodes have similar relationship patterns. Homophily refers to the idea that relationships between nodes who have similar characteristics are stronger. The similarity of the latent factors $\boldsymbol{u}_i$ and $\boldsymbol{u}_j$ captures stochastic equivalence, and $\boldsymbol{\Lambda}$ gives the degree of homophily. If $K = 1$, then the latent factors as well as $\boldsymbol{\Lambda}$ are simply scalars, so $u_i \lambda u_j$. If positive homophily is observed then $\lambda > 0$, whereas negative homophily results in $\lambda < 0$. When $\lambda > 0$ (which is the case in the estimations presented in this article), then actors with similar latent positions u_i and u_j (both positive or both negative, and of larger magnitude) are predicted to have a large positive y_{ij}, whereas actors with dissimilar latent positions (one positive and one negative, and of large magnitude) are predicted to have a large negative y_{ij}. $\mathbf{U\Lambda U}'$ thus provides a low-dimensional representation of the complex set of interactions in $\mathbf{Y}$, net of node-specific characteristics and dyadic reciprocity. The latent factor models are estimated in a Bayesian framework using an MCMC algorithm.

B.2 Estimation Details and MCMC Convergence

To estimate the latent spaces, I aggregate the events recorded in ICEWS at the country-year level and estimate a total of 182 latent factor network models (14 years for 13 countries). Each latent space is estimated via MCMC sampling using the `amen` package in R (Hoff, 2015). There is a burn-in period of 10,000 followed by 100,000 iterations. Given a thinning interval of 100, the size of the posterior samples is 1,000. I have estimated models both with a unidimensional as well as a two-dimensional latent space. However, the latter do not show variation on the second dimension, so I focus on the latent spaces with $K = 1$.

The following figures show traceplots for all 182 latent network estimations. In all cases positive homophily is observed, so $\lambda > 0$. The left panels show the posterior draws for the variance components σ_a^2 and σ_e^2, and the right panels show the posterior draws for the overall intercept α.

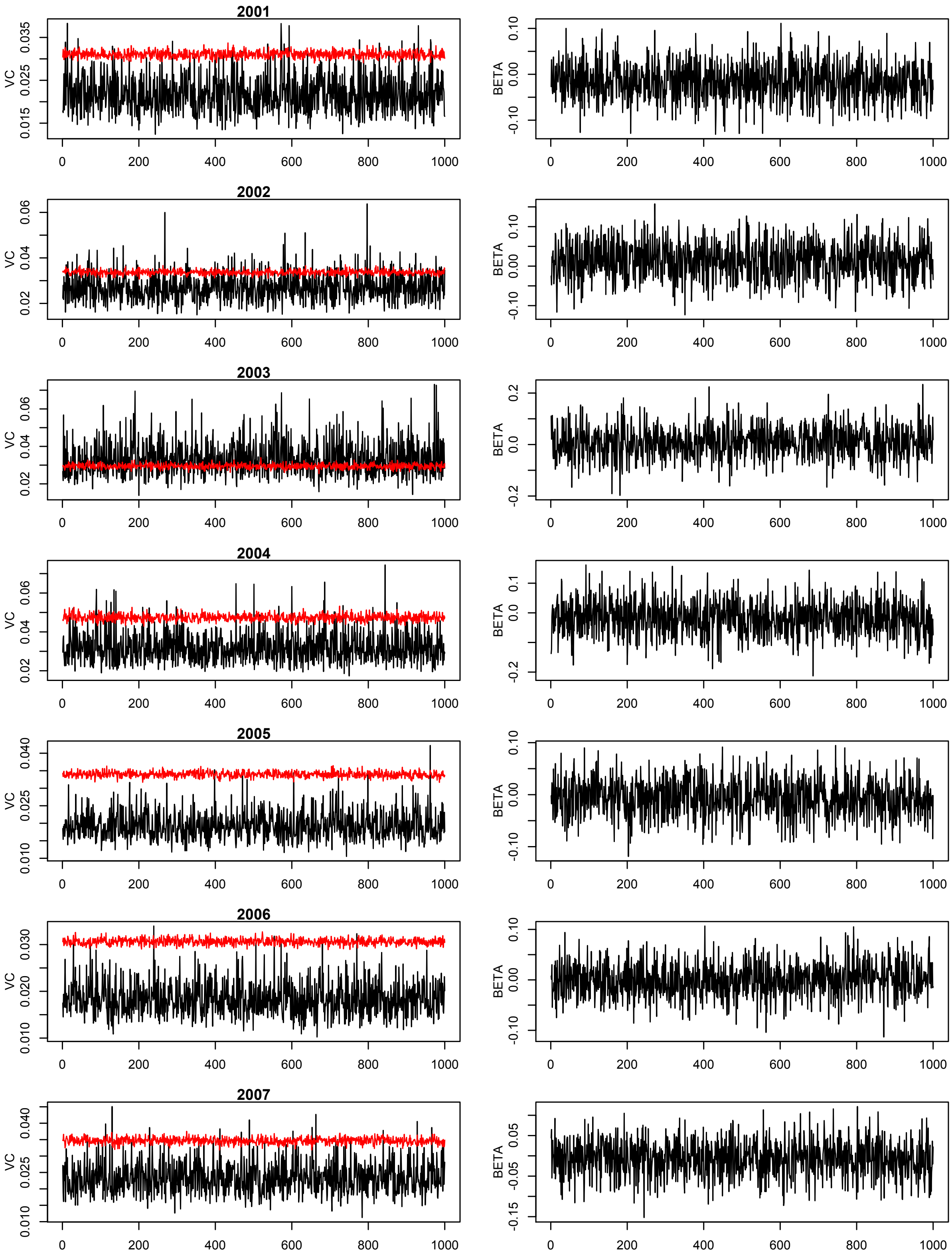

Figure 2: Convergence Diagnostics, Austria

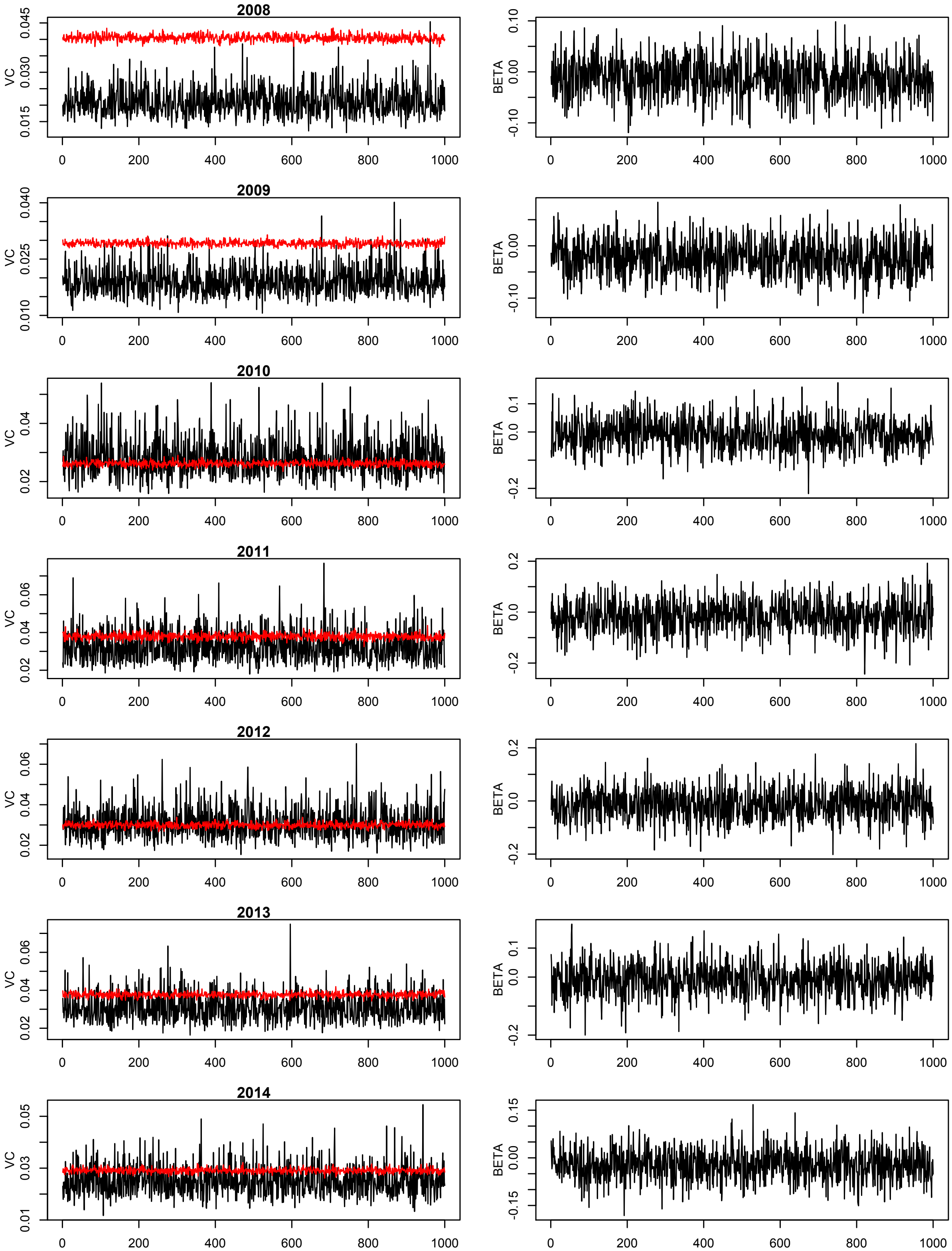

Figure 3: Convergence Diagnostics, Austria

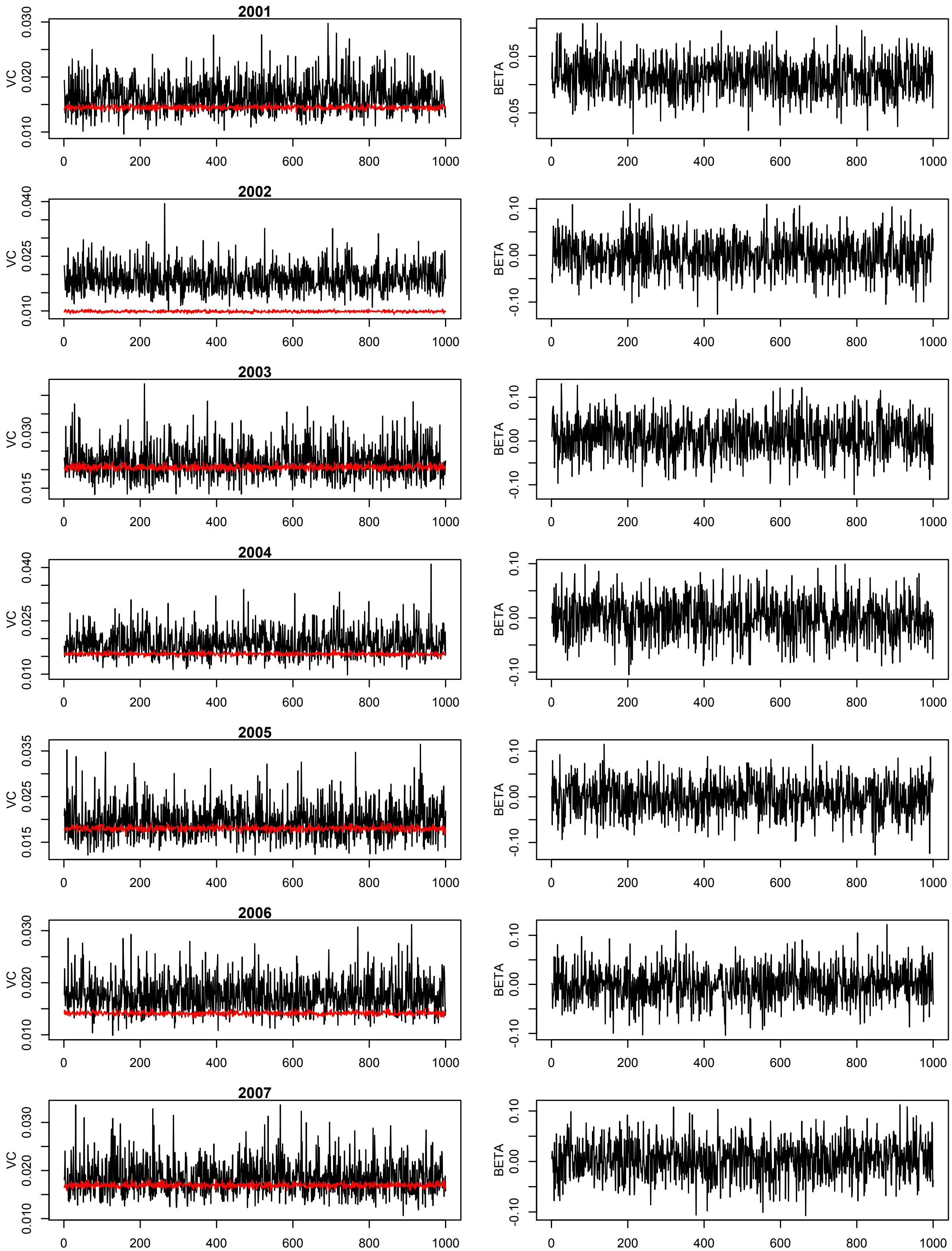

Figure 4: Convergence Diagnostics, Belgium

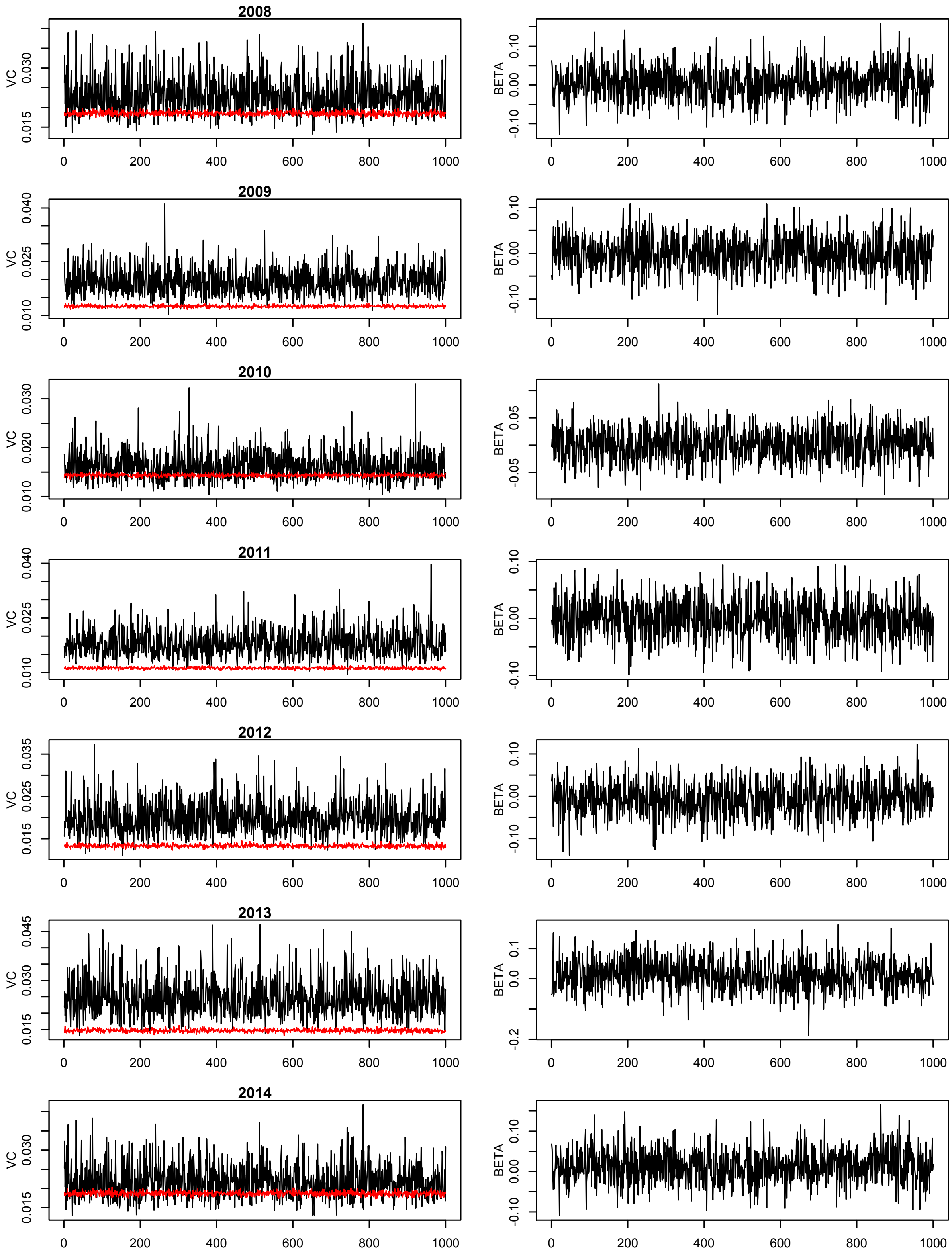

Figure 5: Convergence Diagnostics, Belgium

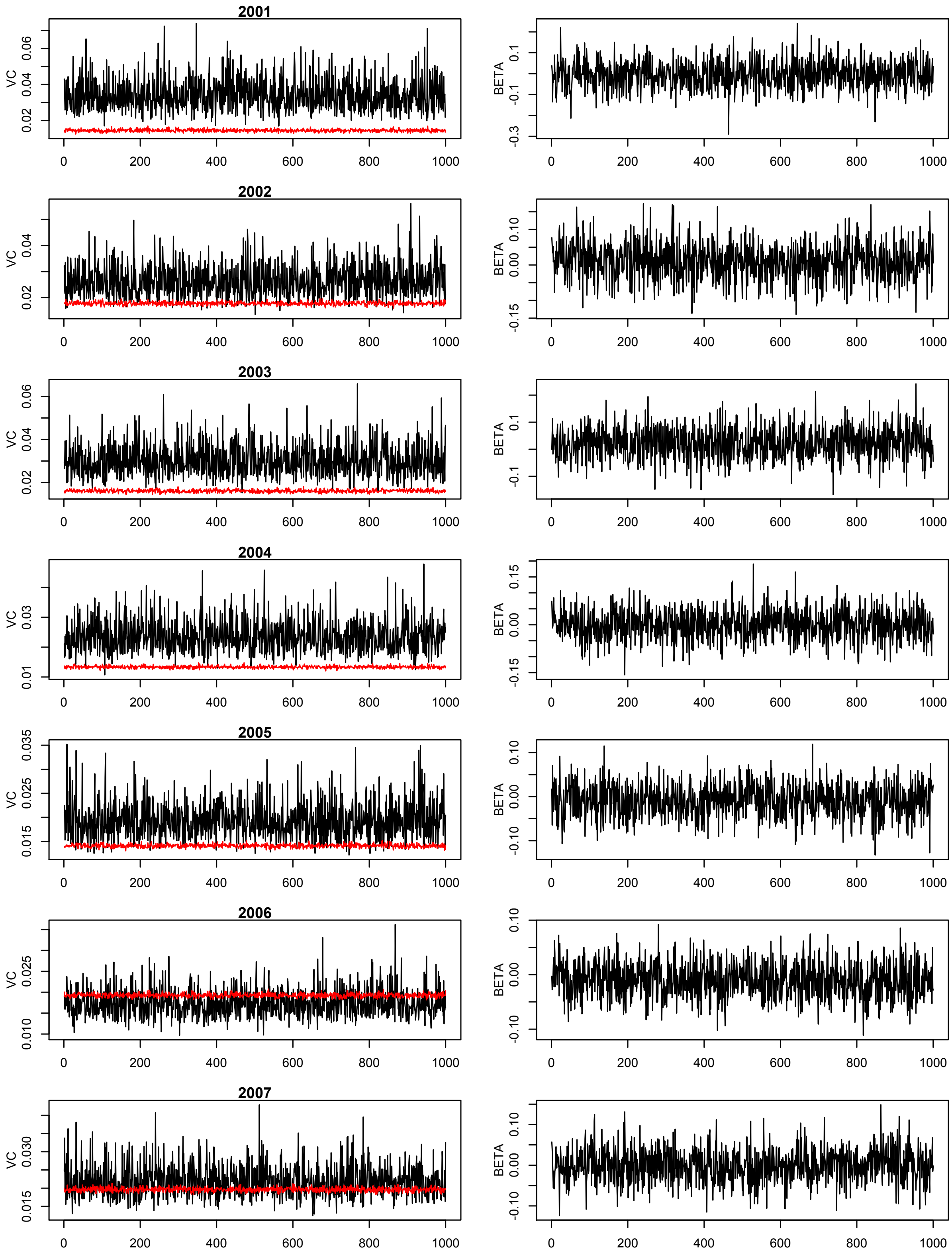

Figure 6: Convergence Diagnostics, Denmark

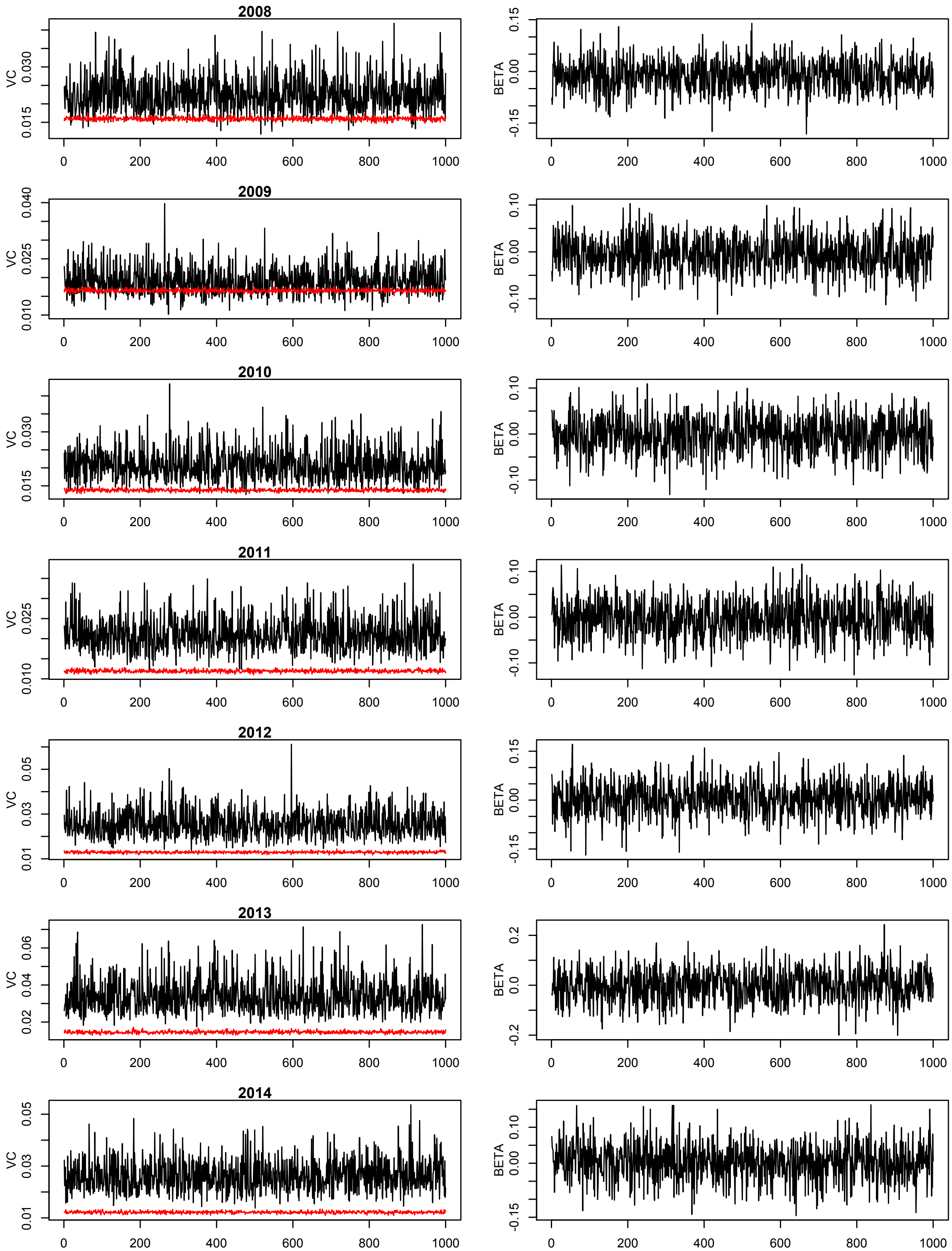

Figure 7: Convergence Diagnostics, Denmark

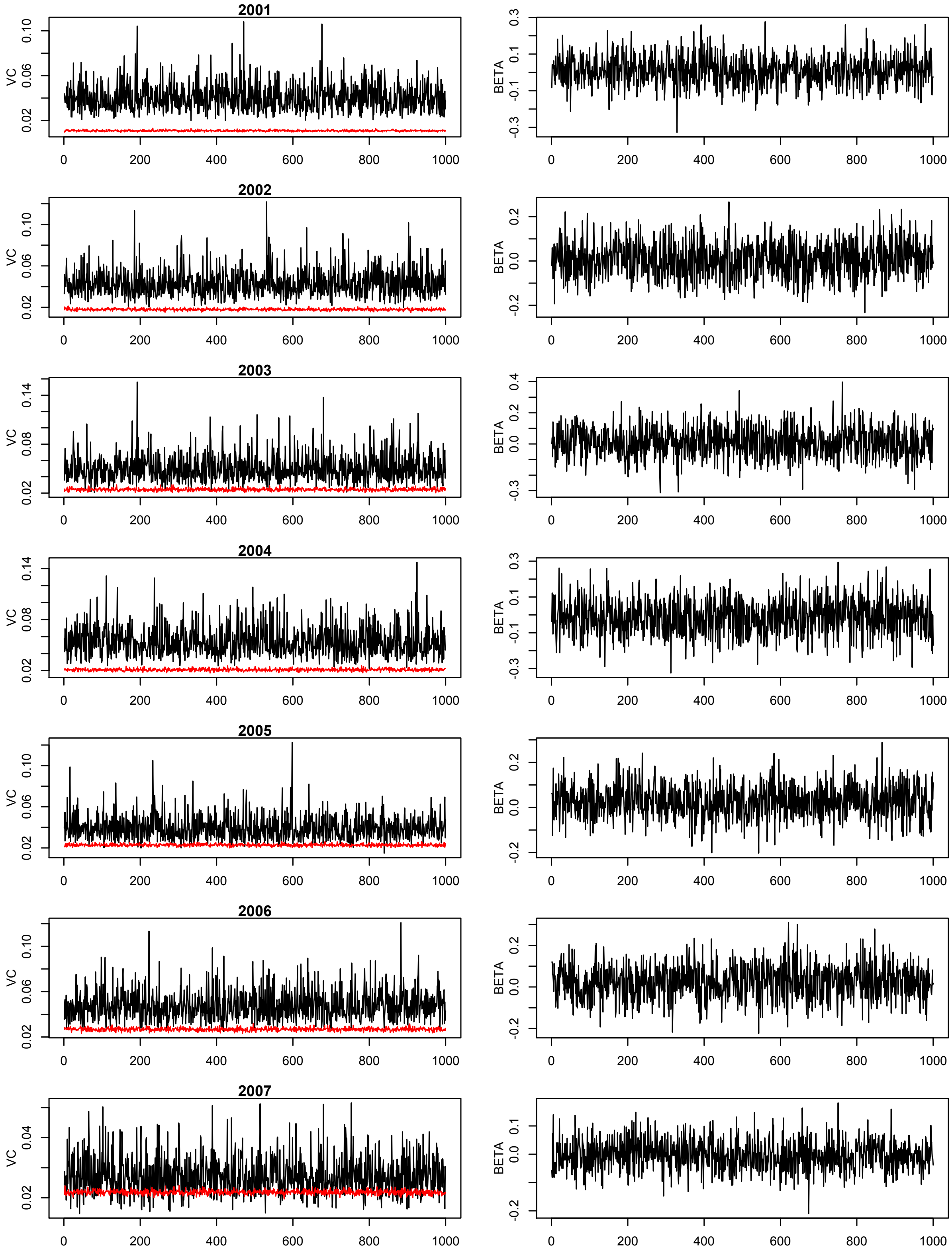

Figure 8: Convergence Diagnostics, Finland

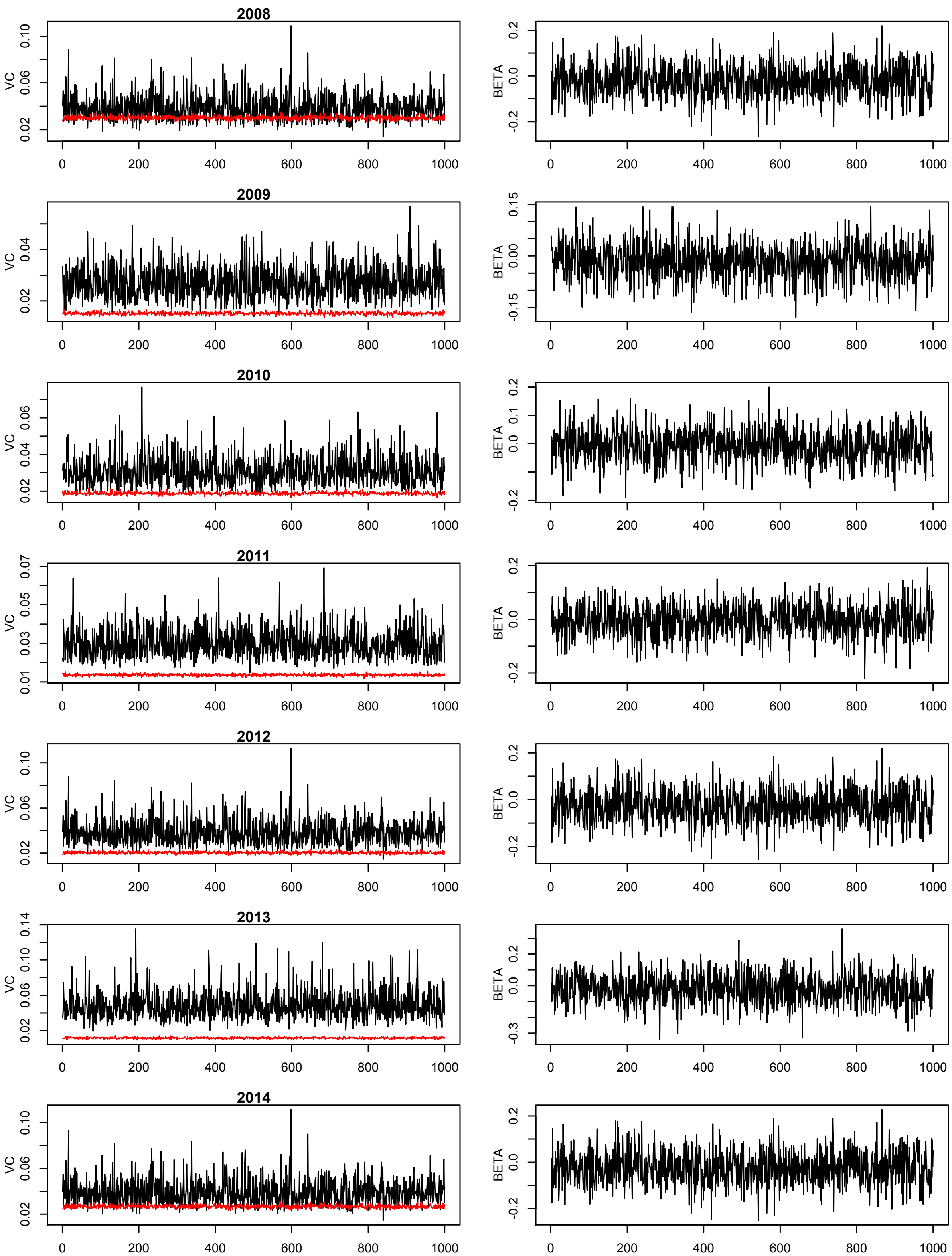

Figure 9: Convergence Diagnostics, Finland

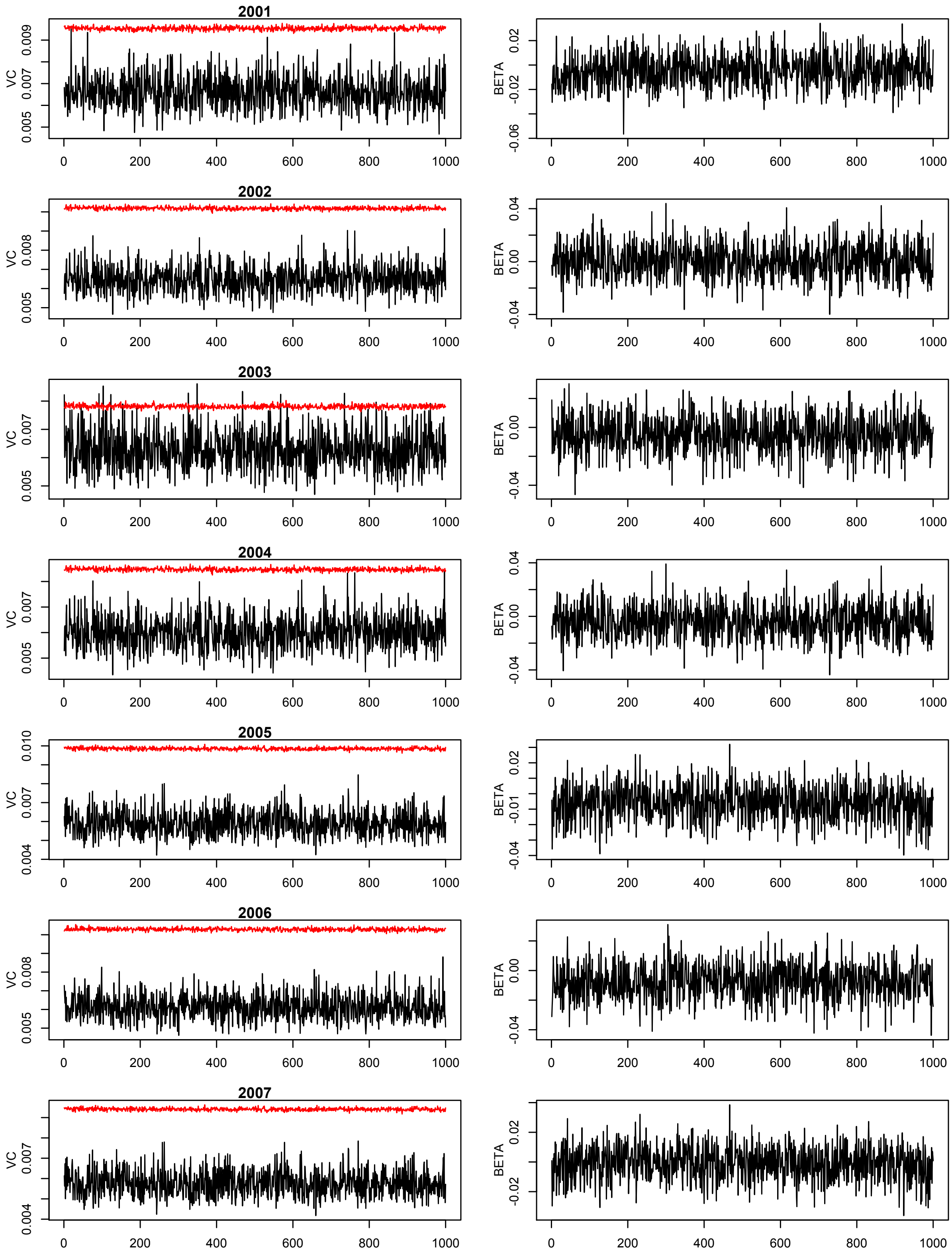

Figure 10: Convergence Diagnostics, France

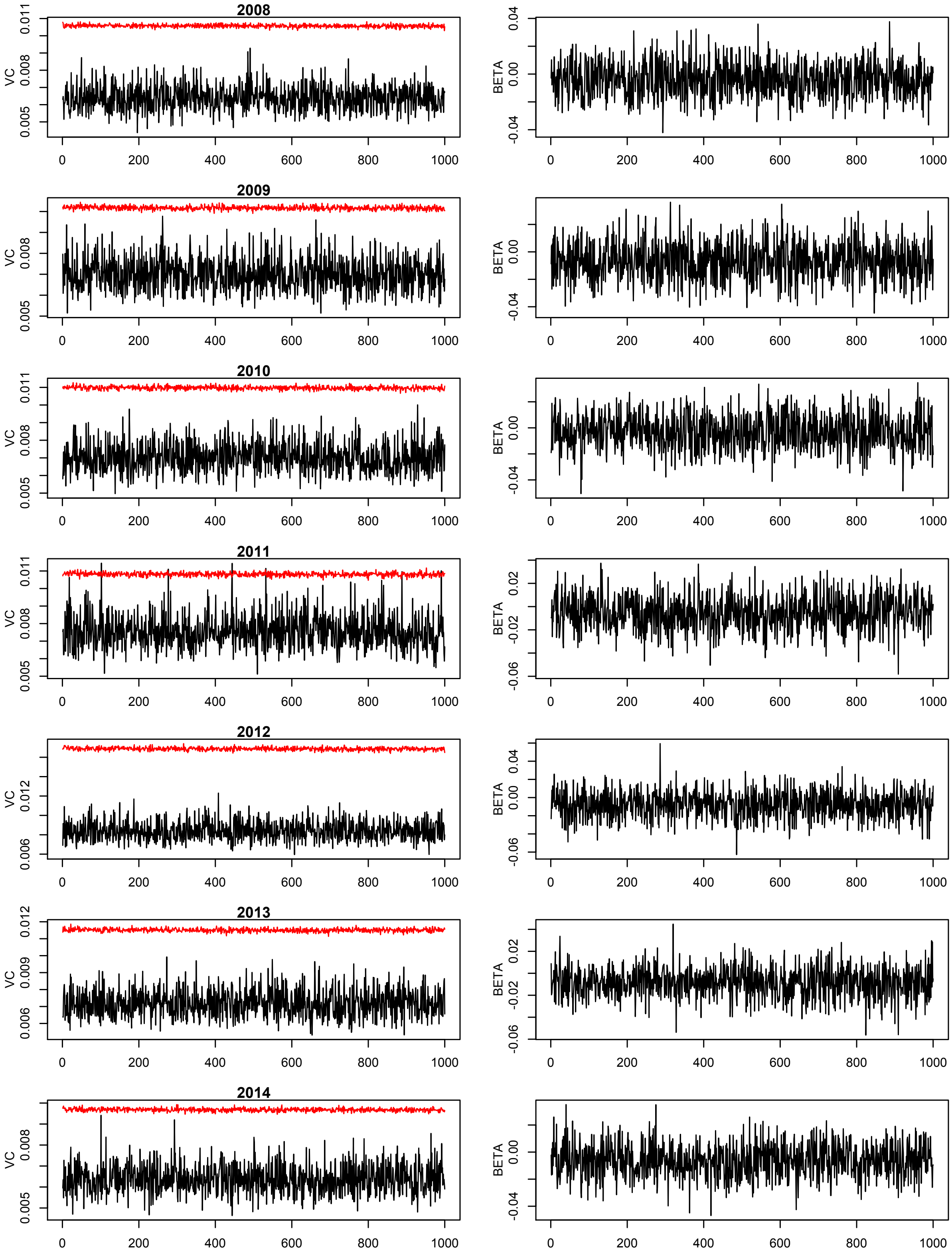

Figure 11: Convergence Diagnostics, France

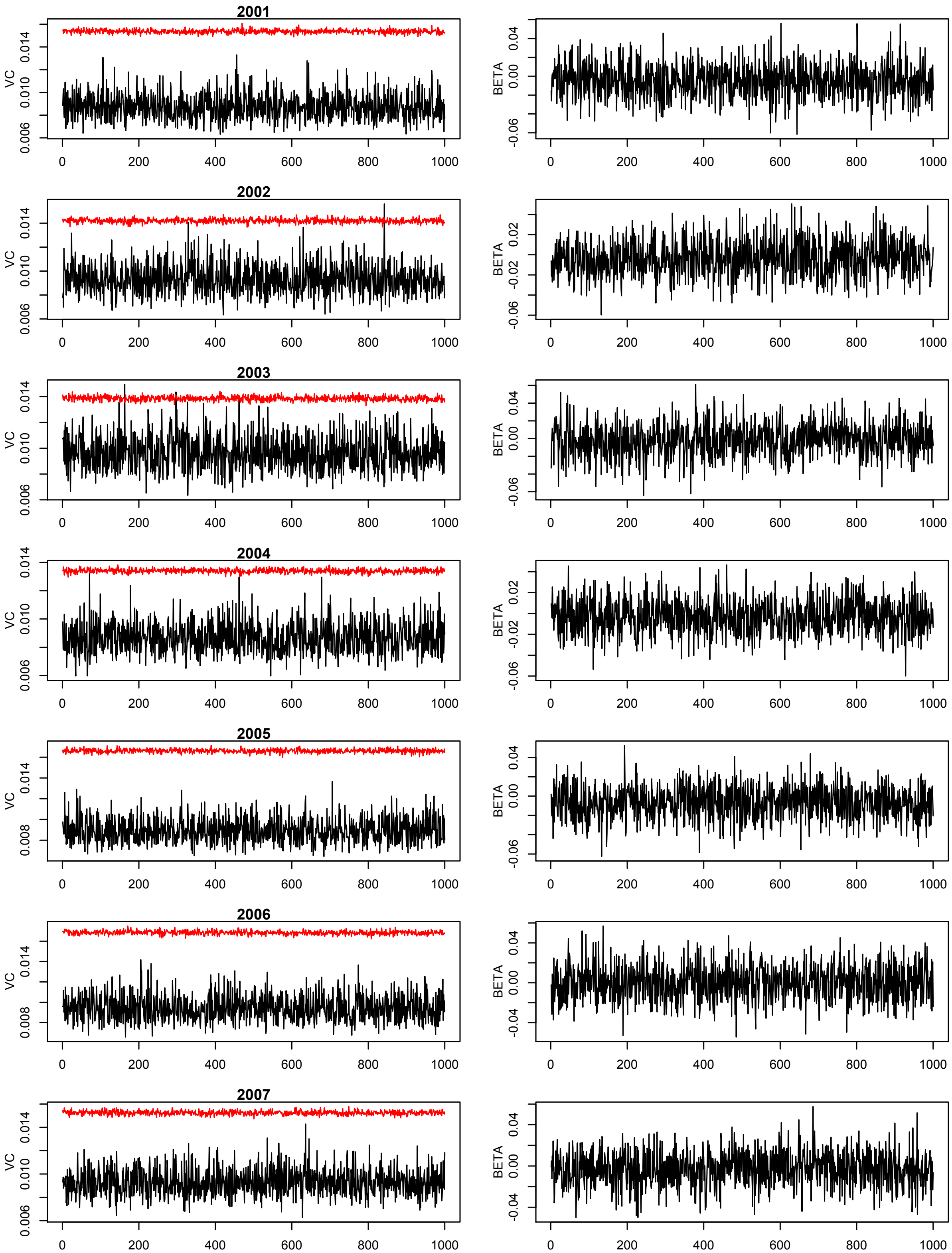

Figure 12: Convergence Diagnostics, Germany

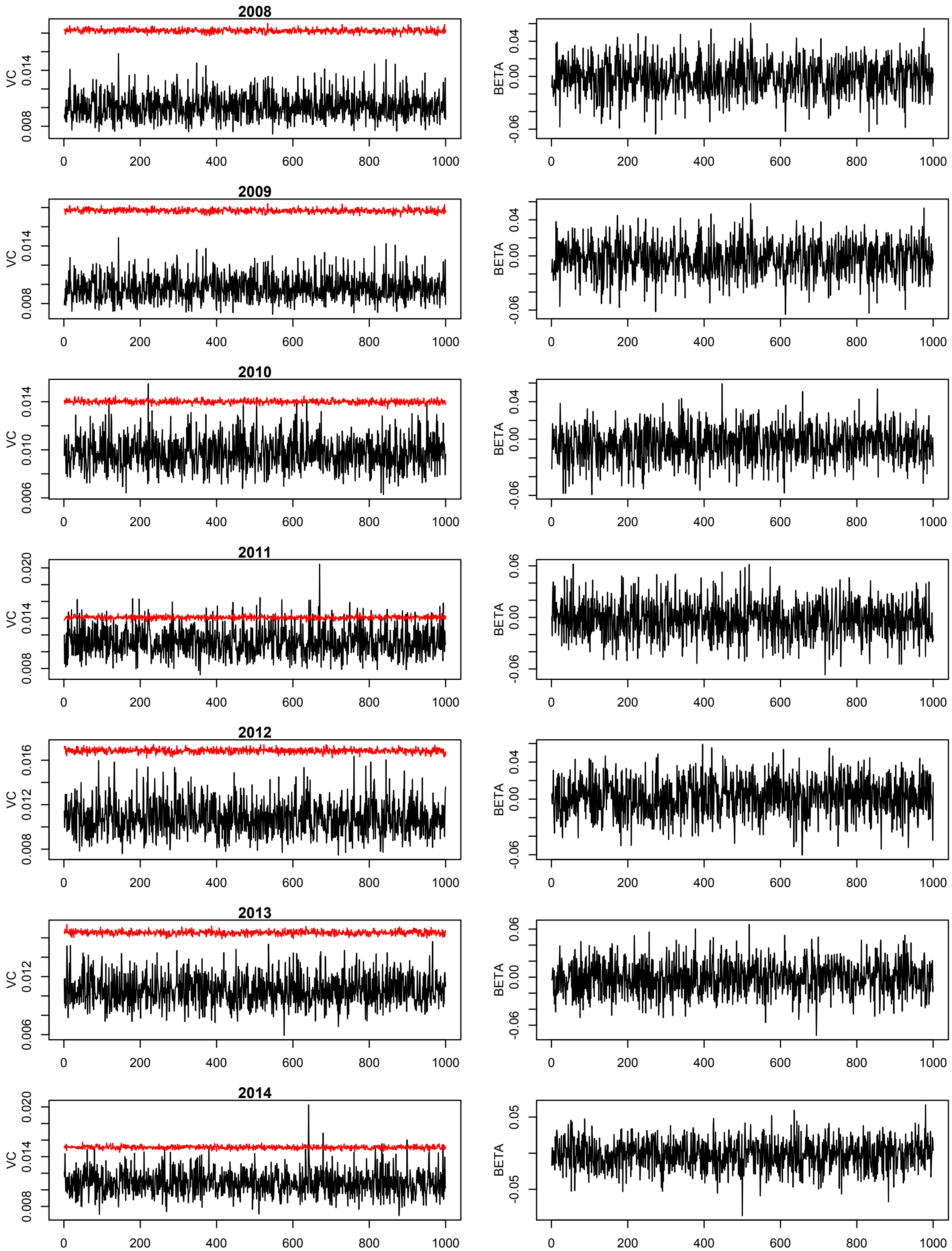

Figure 13: Convergence Diagnostics, Germany

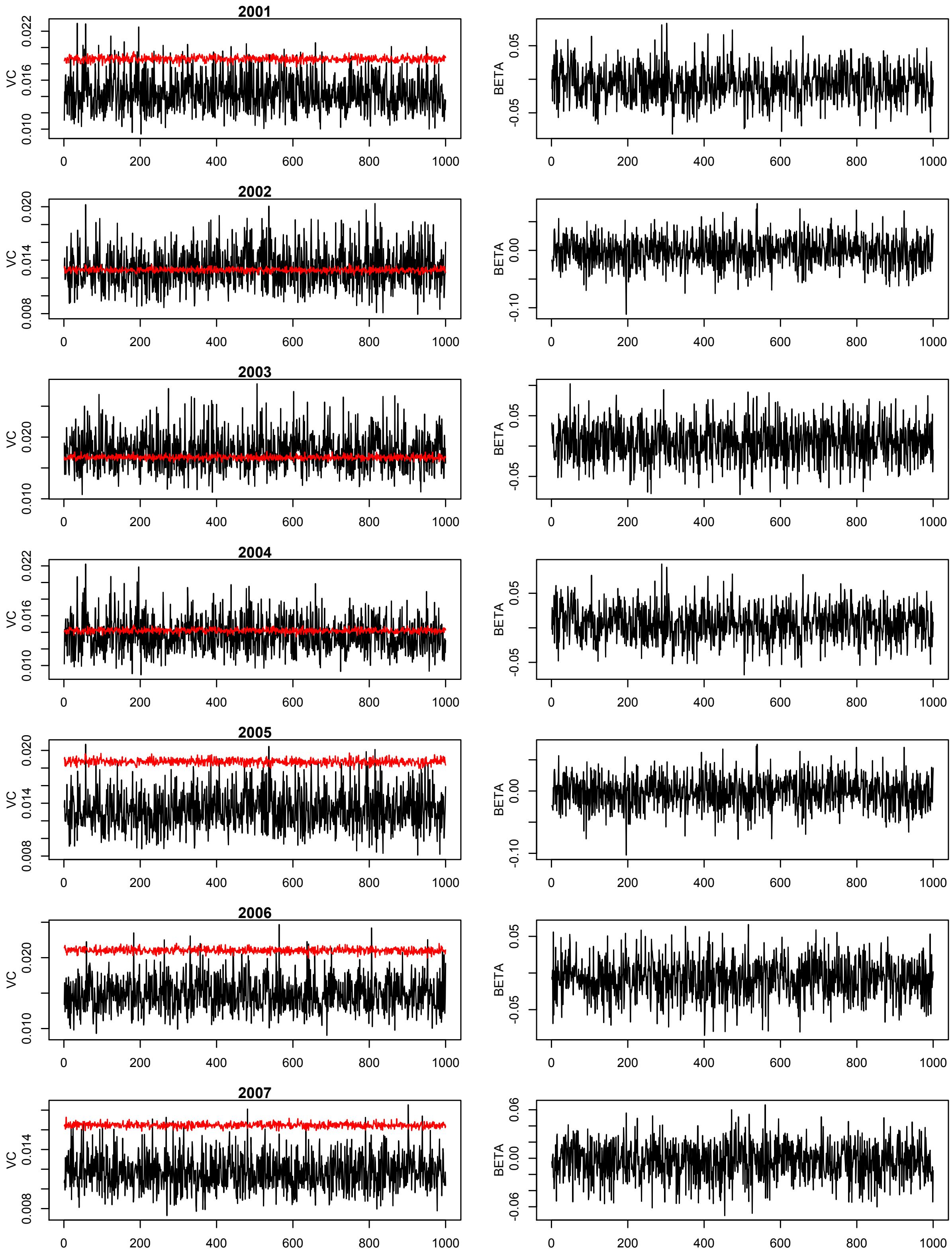

Figure 14: Convergence Diagnostics, Greece

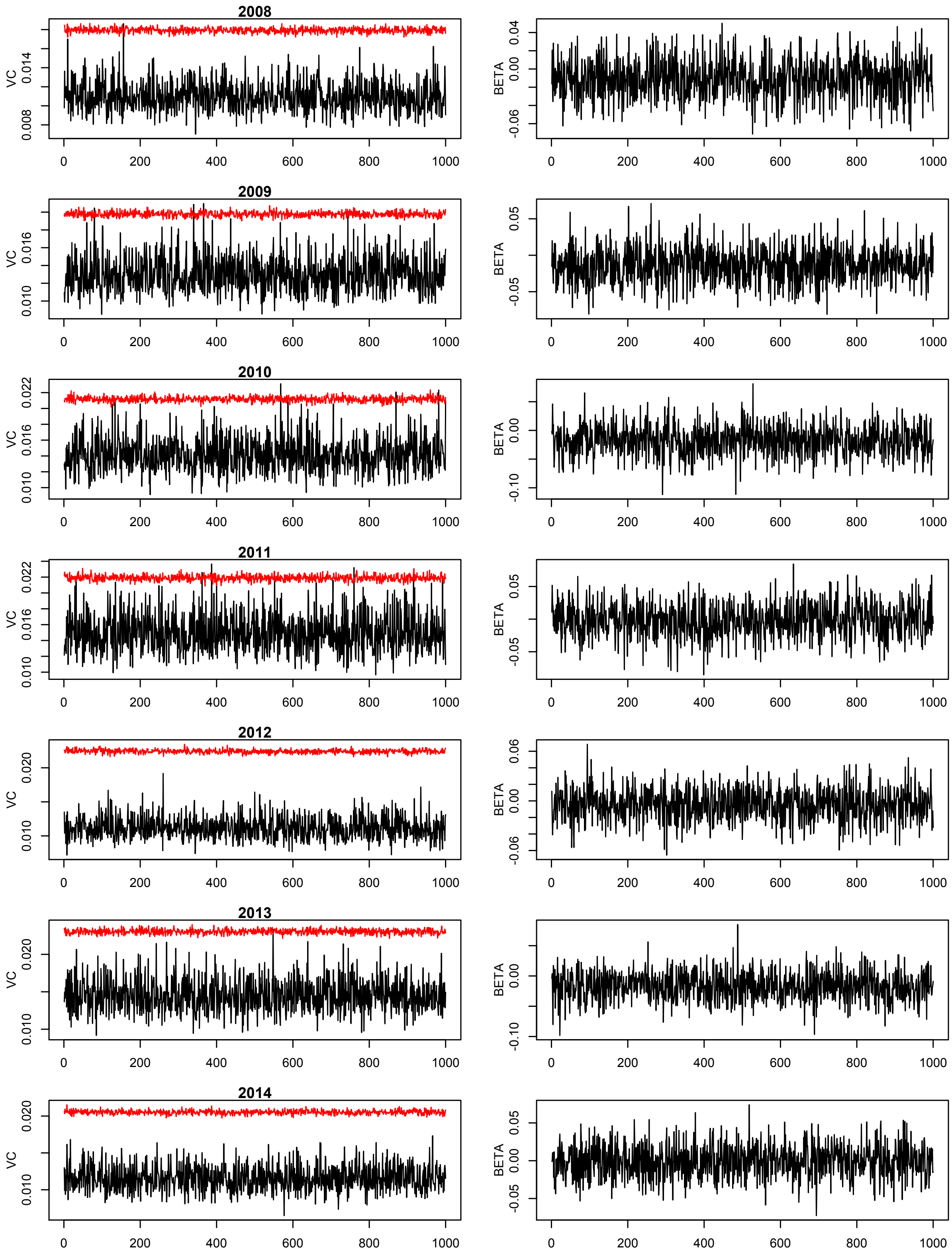

Figure 15: Convergence Diagnostics, Greece

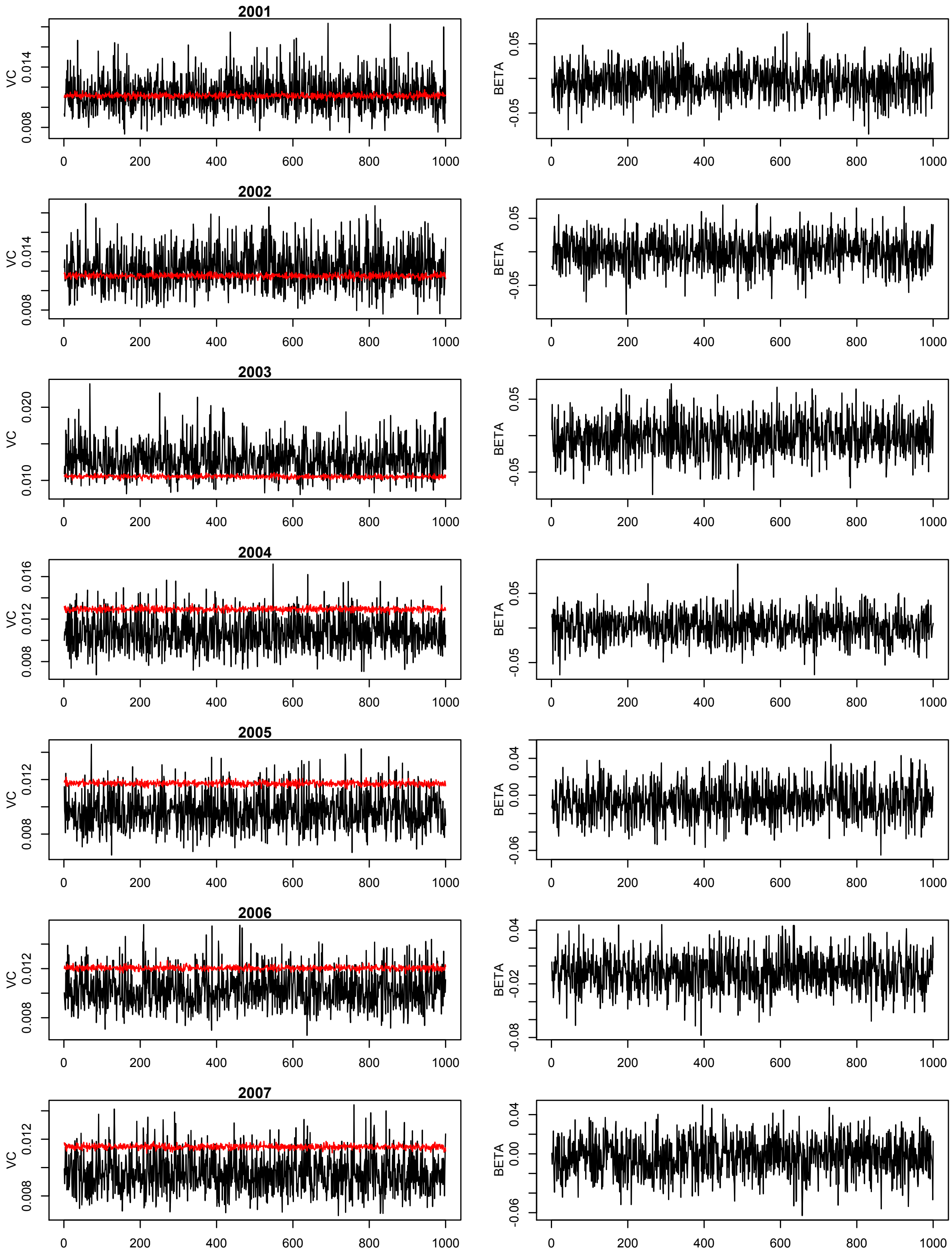

Figure 16: Convergence Diagnostics, Ireland

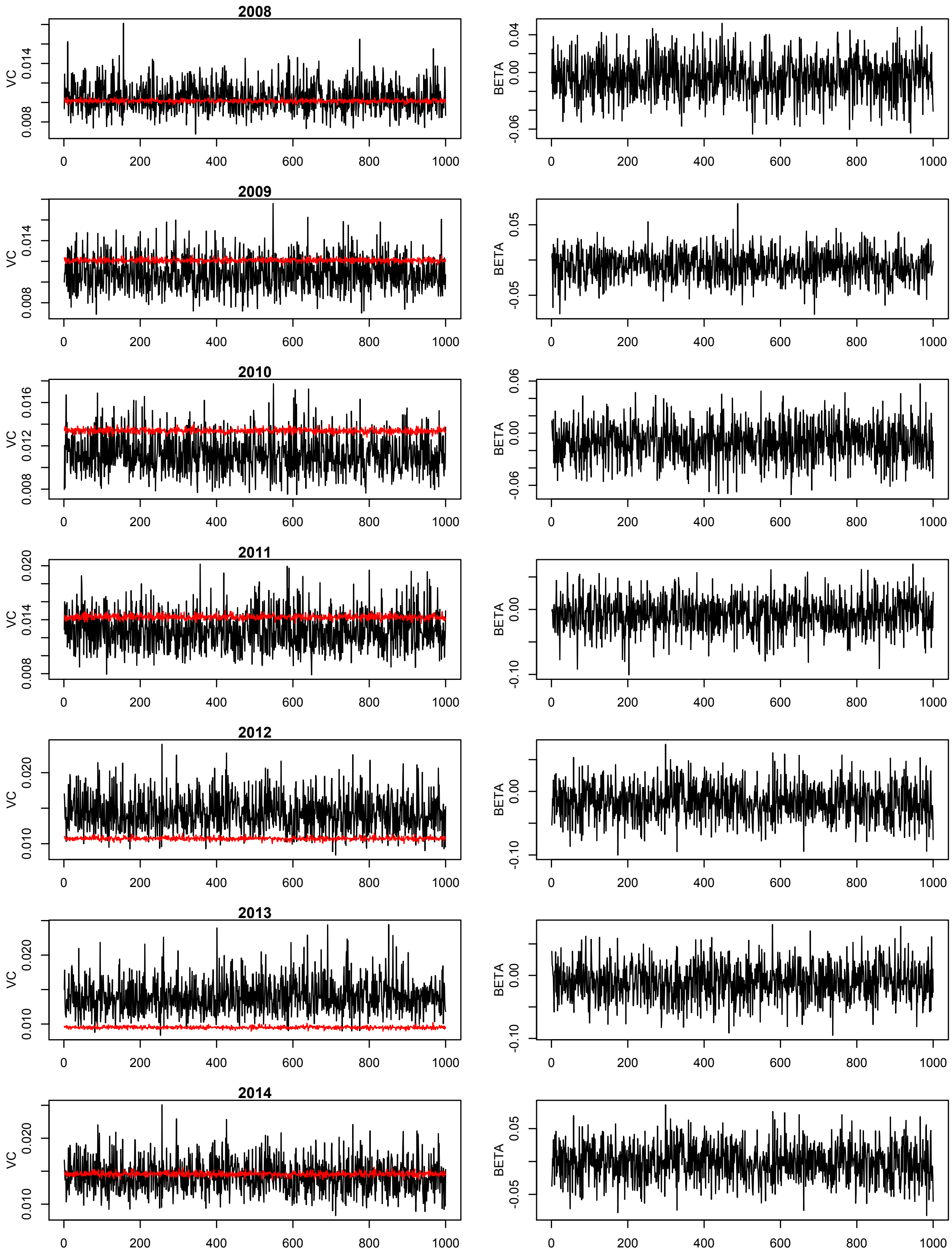

Figure 17: Convergence Diagnostics, Ireland

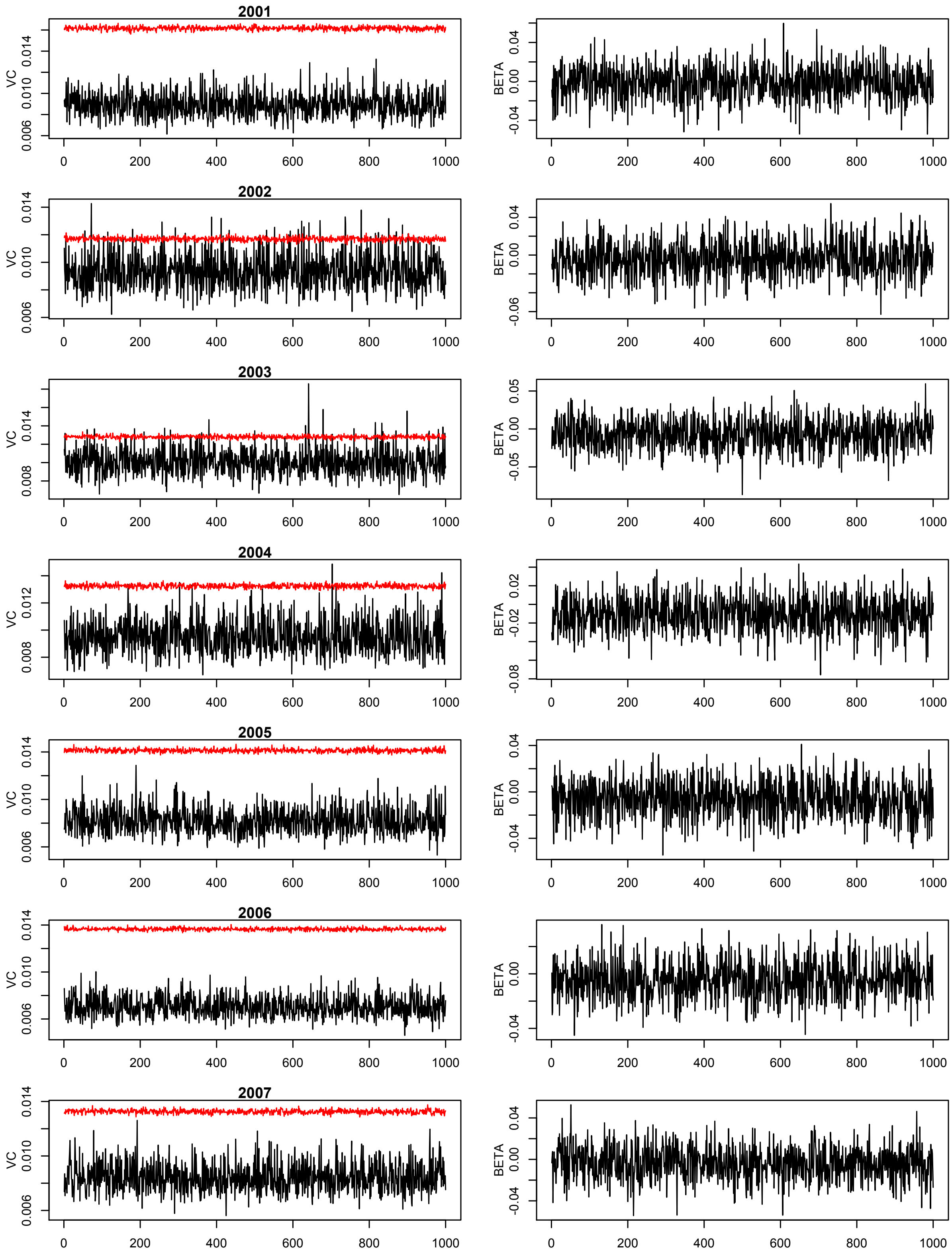

Figure 18: Convergence Diagnostics, Italy

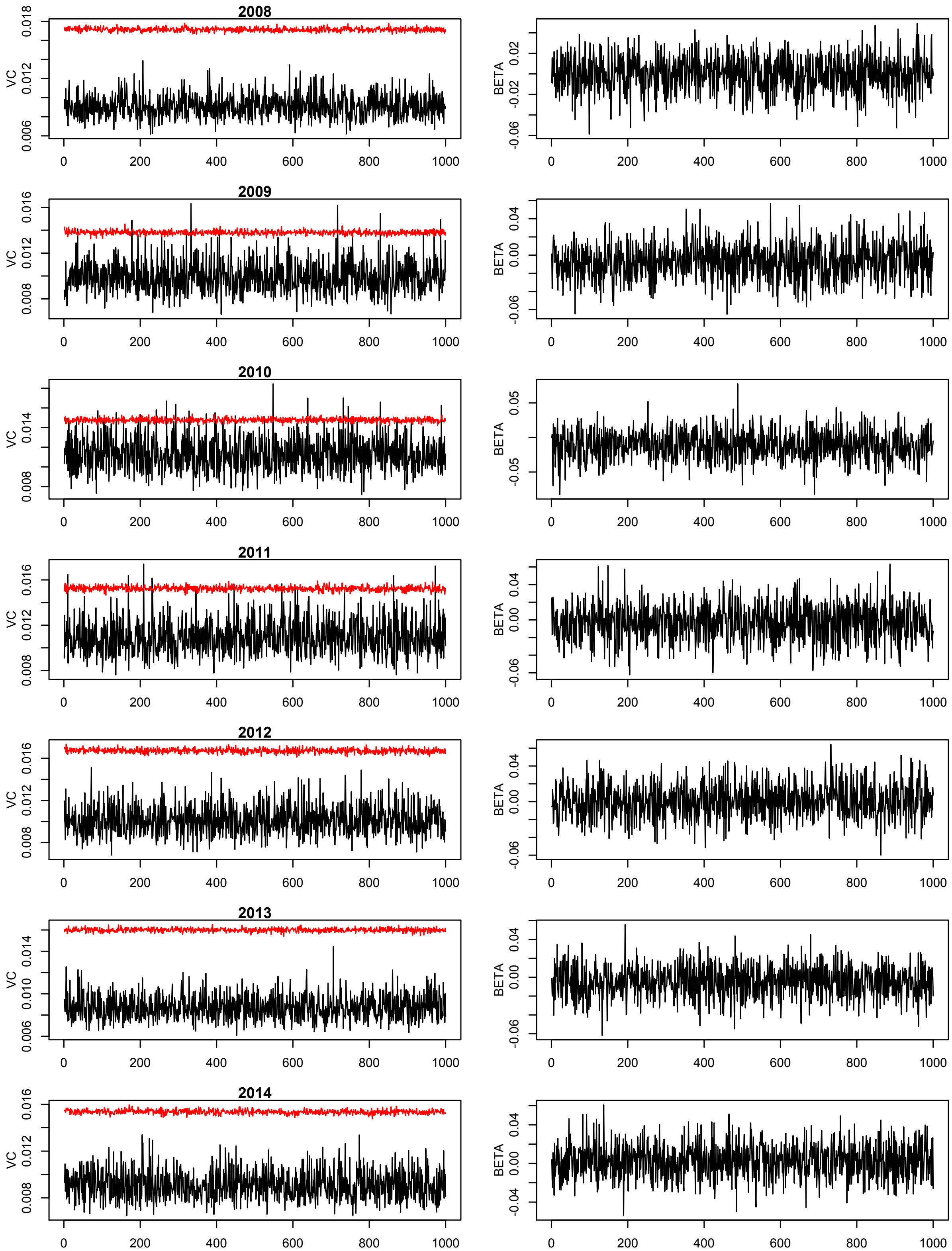

Figure 19: Convergence Diagnostics, Italy

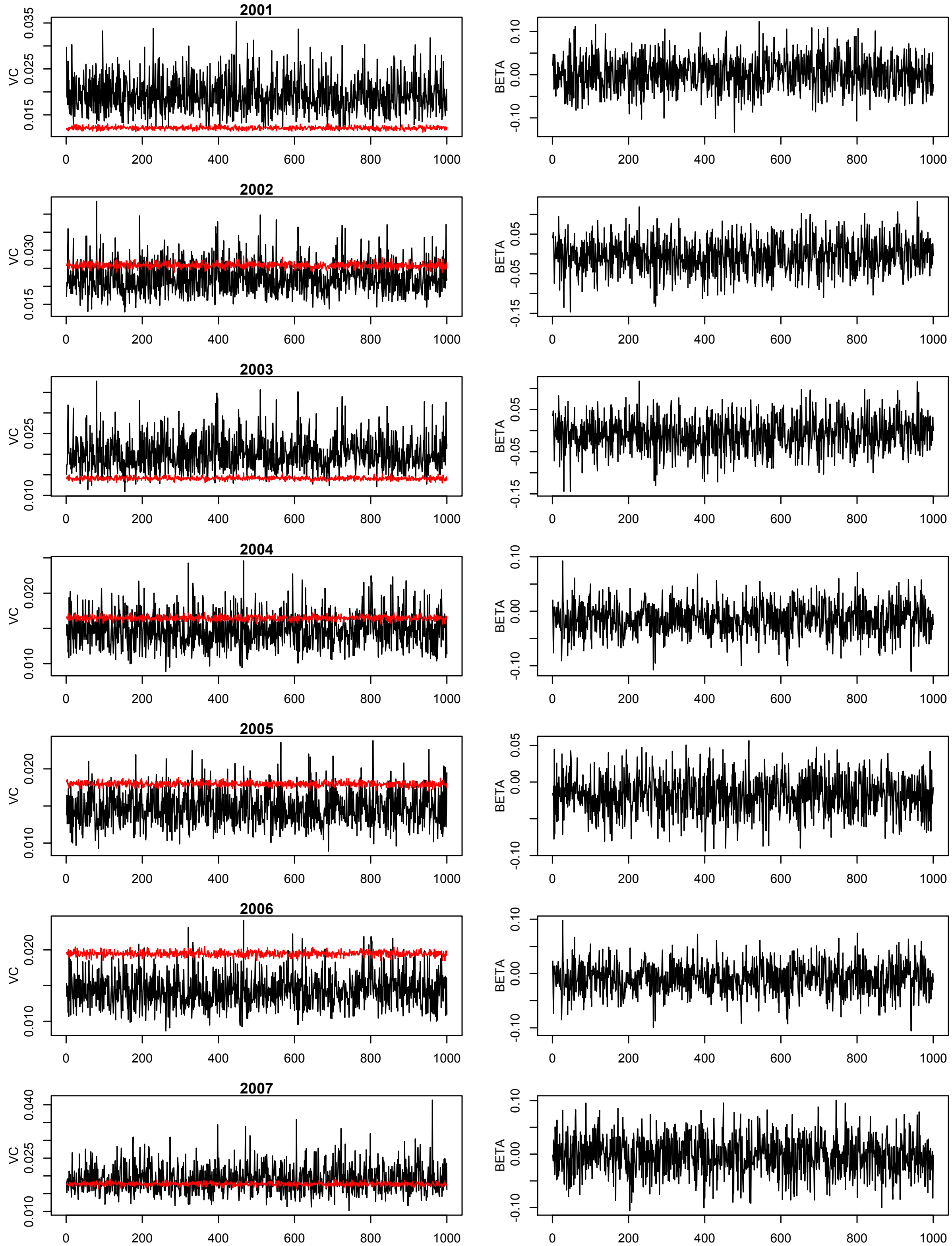

Figure 20: Convergence Diagnostics, Netherlands

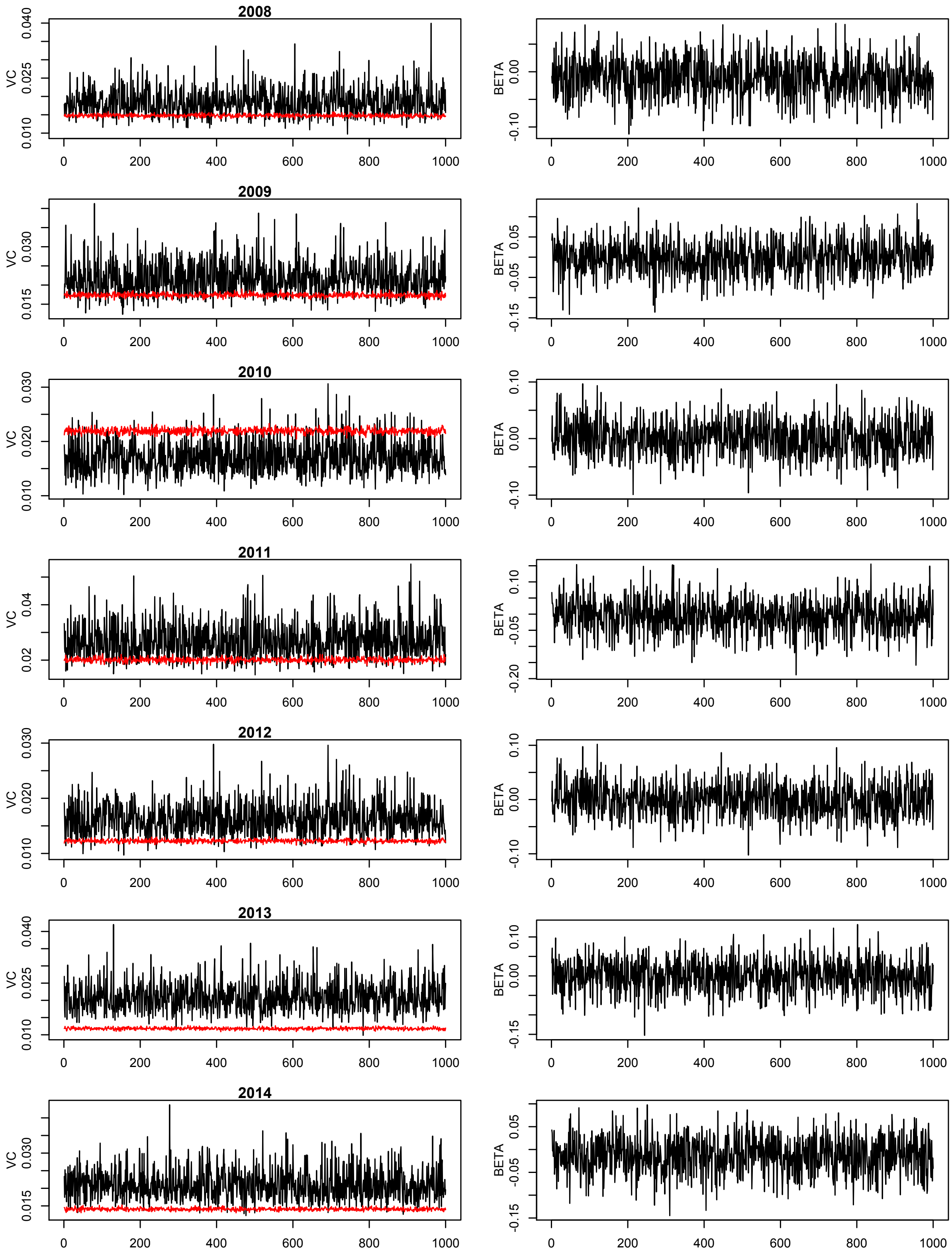

Figure 21: Convergence Diagnostics, Netherlands

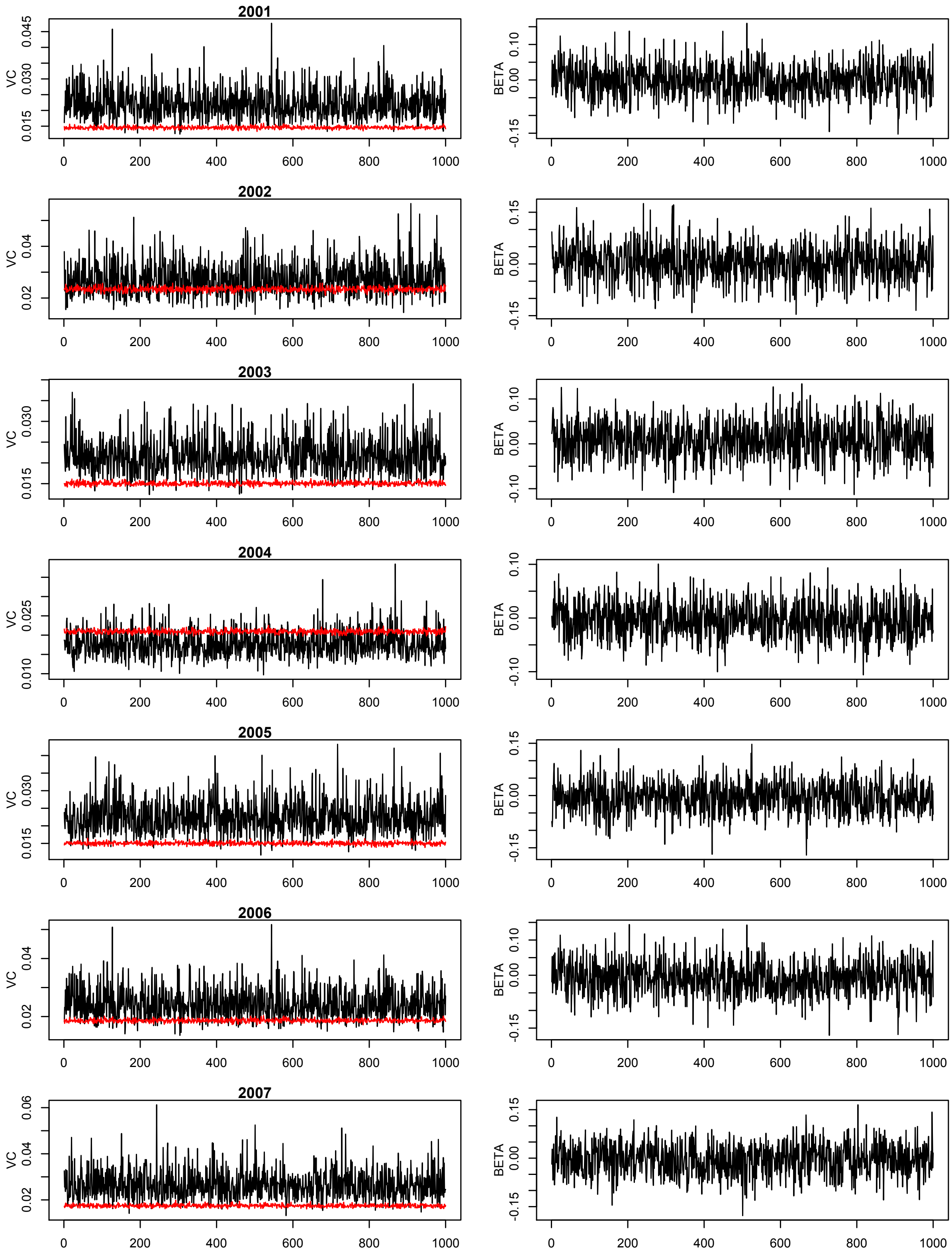

Figure 22: Convergence Diagnostics, Portugal

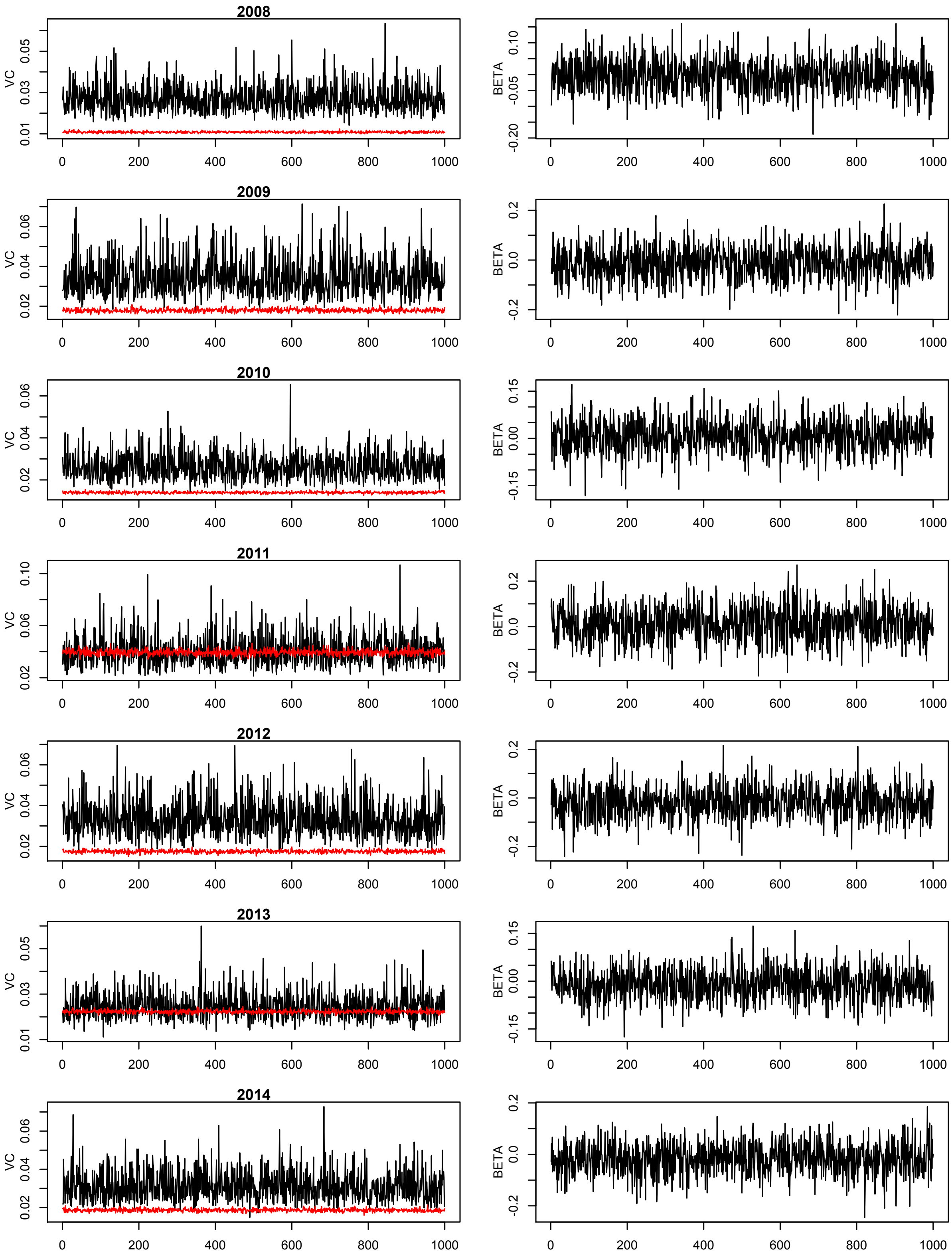

Figure 23: Convergence Diagnostics, Portugal

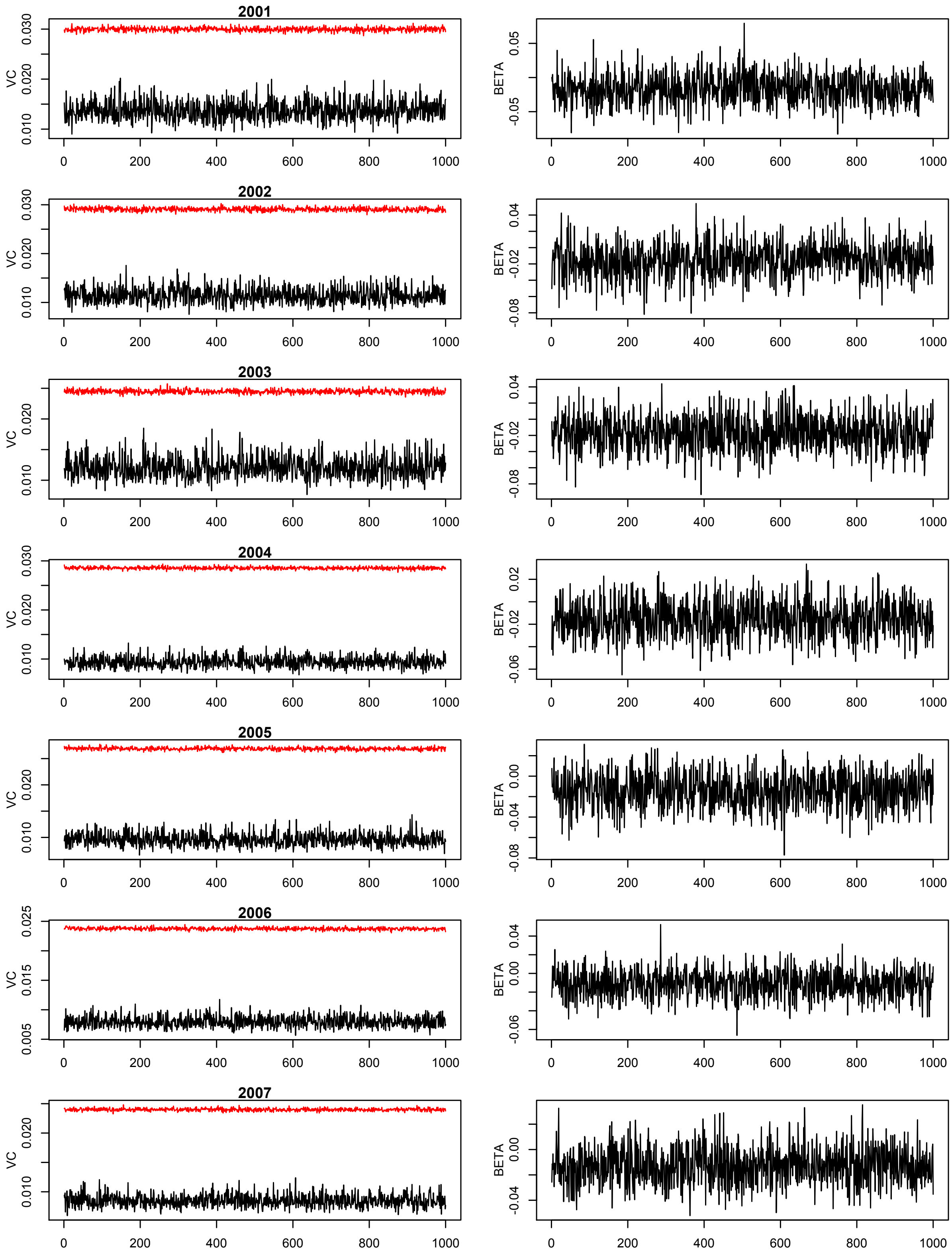

Figure 24: Convergence Diagnostics, Spain

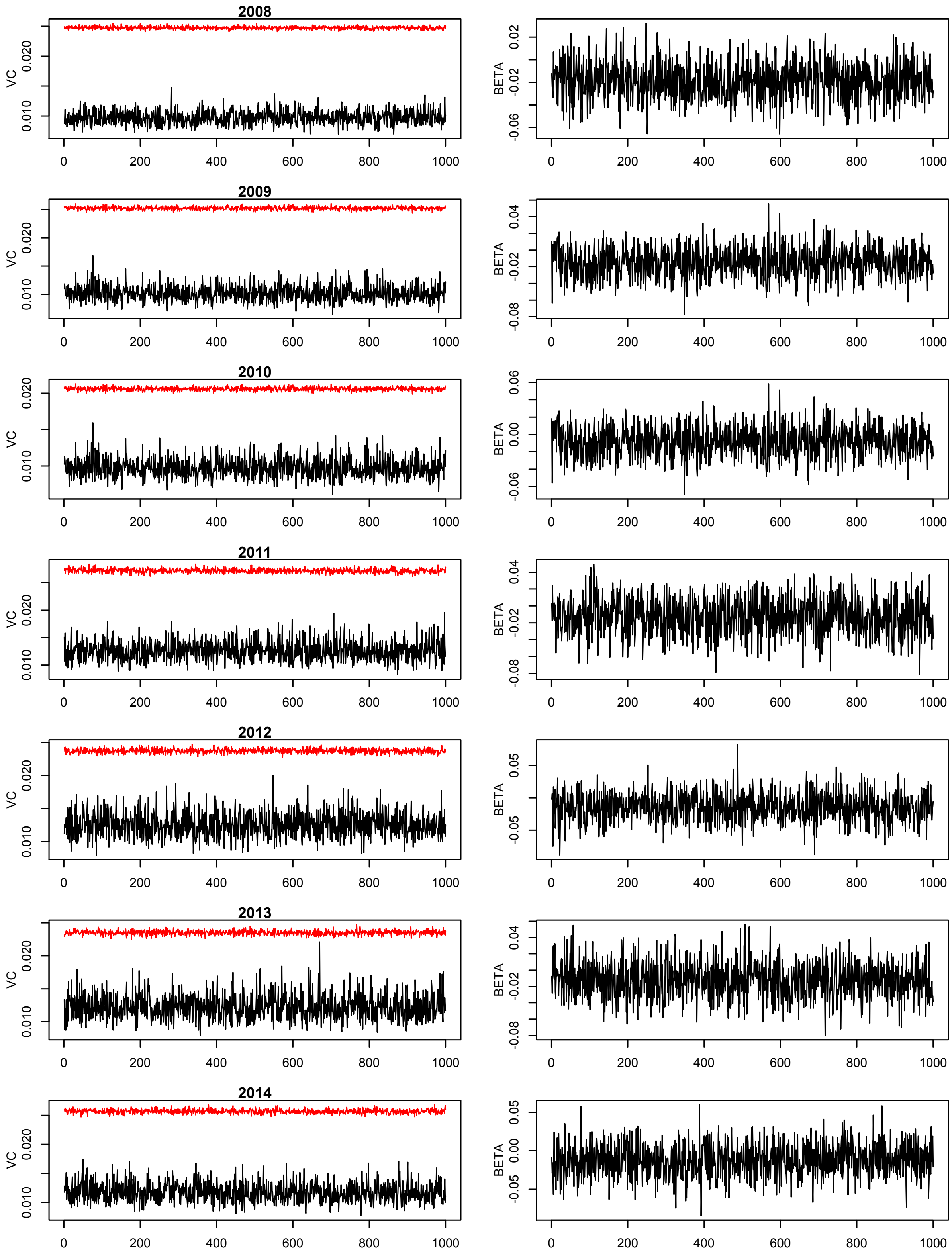

Figure 25: Convergence Diagnostics, Spain

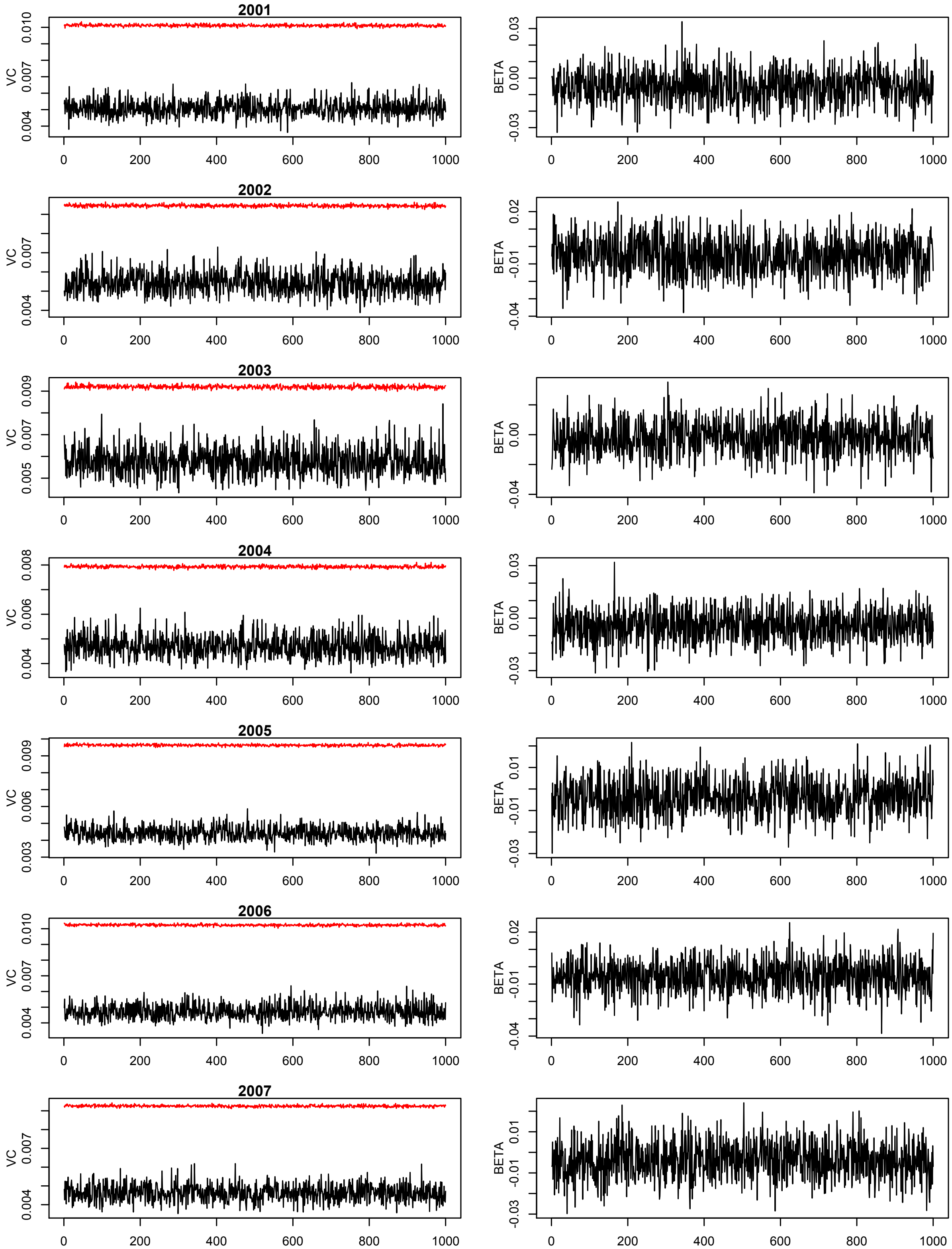

Figure 26: Convergence Diagnostics, United Kingdom

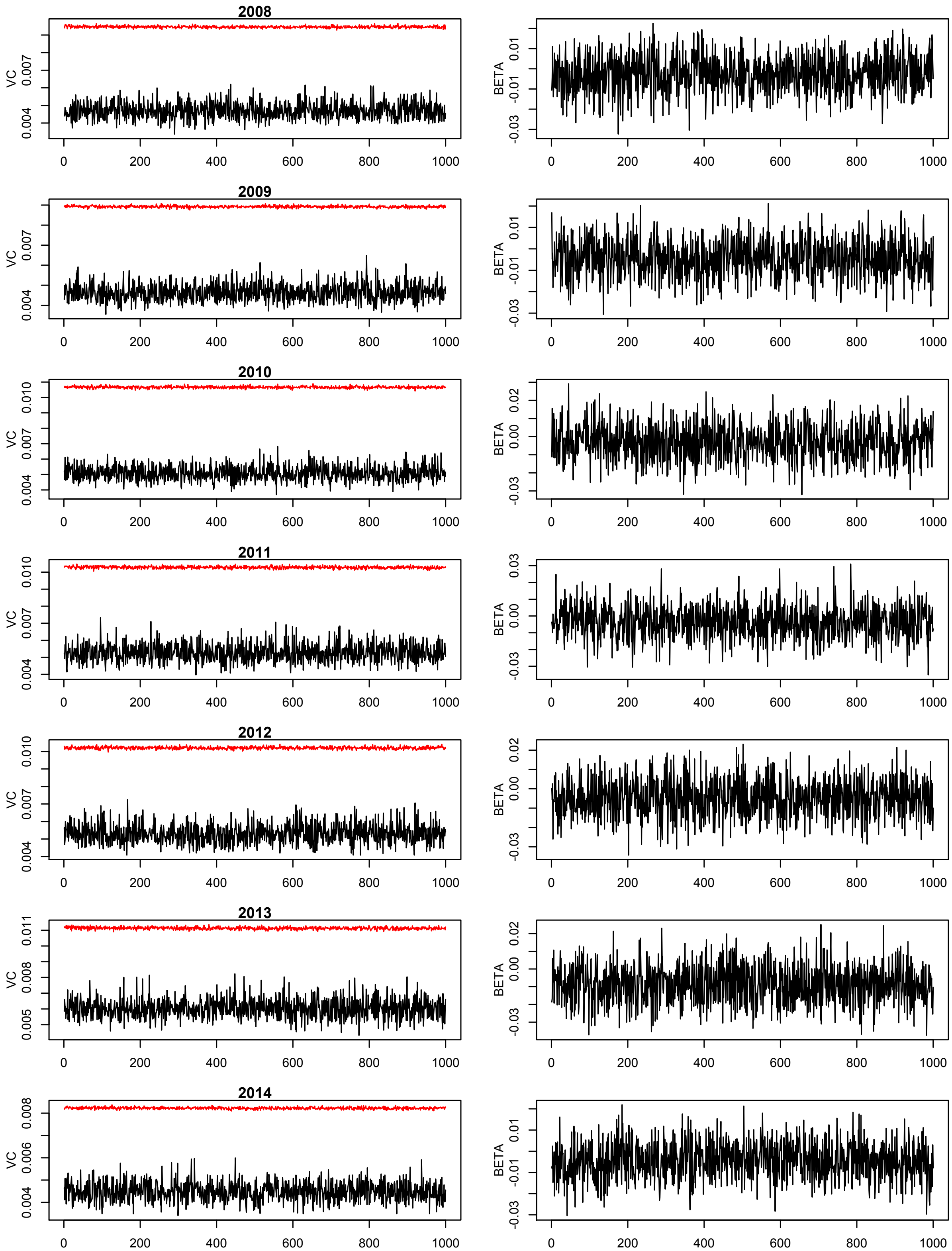

Figure 27: Convergence Diagnostics, United Kingdom

B.3 Relationship Scores with Uncertainty, Germany

Figure 1 of the article shows the relationship scores for a select set of party-dyads. Below, I show the relationship scores for all party-dyads for Germany in 2001, 2004, and 2008. In addition to the posterior means, I also include the 95% confidence intervals.

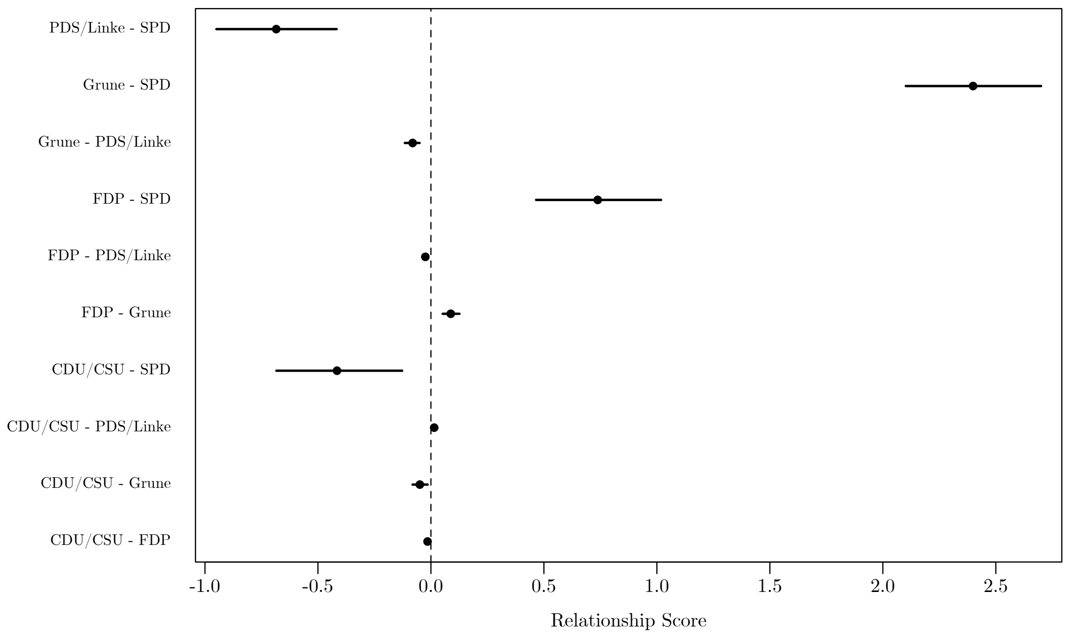

Figure 28: Relationship Scores, Germany, 2001. Scores for all party-dyads, with 95% confidence intervals.

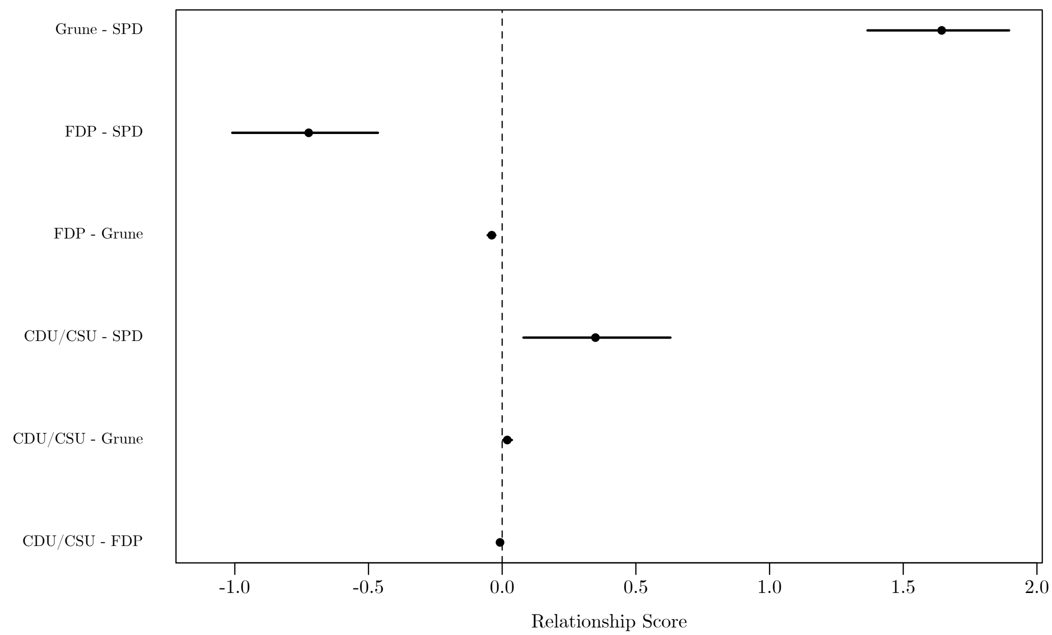

Figure 29: Relationship Scores, Germany, 2004. Scores for all party-dyads, with 95% confidence intervals.

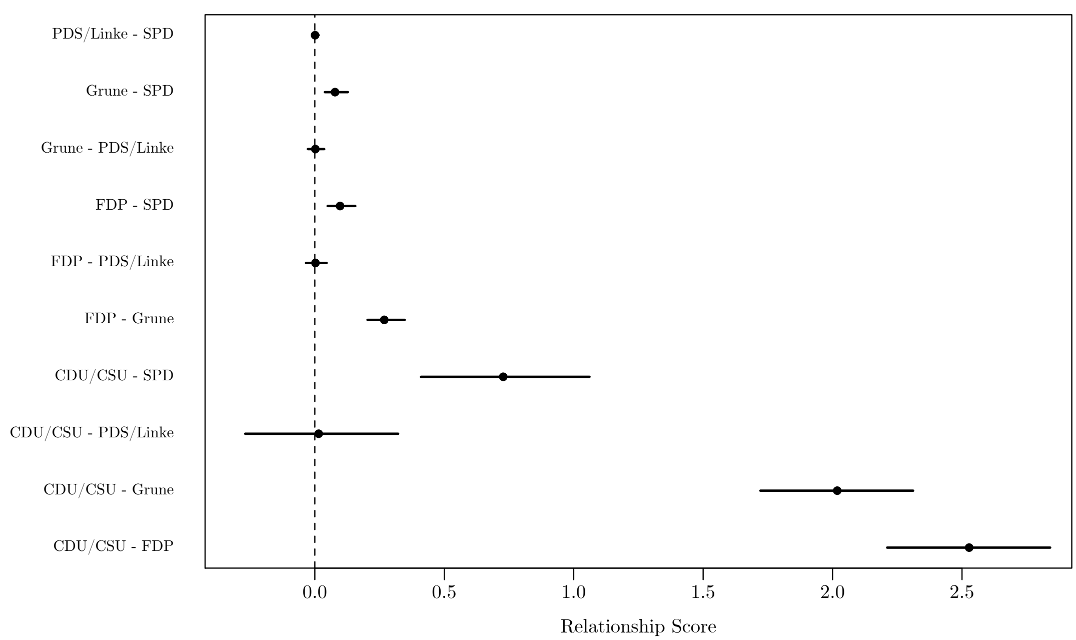

Figure 30: Relationship Scores, Germany, 2008. Scores for all party-dyads, with 95% confidence intervals.

B.4 Extension to Directed Data

In the manuscript, by construction $y_{ij} = y_{ji}$, so the interactions are assumed to be symmetric. The ICEWS data code the sender and the receiver of a given interaction, which makes it possible to construct a dependent variable $y_{ij} = \ln\left(\frac{m_{ij}^{+}+1}{m_{ij}^{-}+1}\right)$, where m_{ij}^{+} denotes the number of cooperative interactions where i is the sender and j the receiver, and m_{ij}^{-} denotes the same for conflictual interactions. The latent factor model in Equation (1) can be adapted for directed data as follows:

$$\begin{aligned} y_{ij} &= \alpha + a_i + b_j + \epsilon_{ij} + \boldsymbol{u}_i' \boldsymbol{v}_j \\ \{(a_1, b_1), \ldots, (a_n, b_n)\} &\sim \text{i.i.d. } \mathcal{N}(0, \Sigma_{ab}) \\ \{(\epsilon_{ij}, \epsilon_{ji}) : i \neq j\} &\sim \text{i.i.d. } \mathcal{N}(0, \Sigma_e) \end{aligned} \tag{2}$$

with

$$\Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \text{ and } \Sigma_e = \sigma_e^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$$

The major difference is that instead of $\boldsymbol{u}_i' \boldsymbol{\Lambda} \boldsymbol{u}_j$ the multiplicative effect $\boldsymbol{u}_i' \boldsymbol{v}_j$ is estimated. Each actor is now represented through *two* unobserved, K-dimensional vectors of characteristics, $\boldsymbol{u}_i$ and $\boldsymbol{v}_i$. The former describes i's behavior as a sender, and the latter as a receiver. The representation of $\mathbf{M}$ as $\mathbf{UV}'$ is justified by the singular value decomposition theorem.

In addition to the relationship scores based on symmetric data discussed in the manuscript, I have also estimated a full set of 182 models using the asymmetric approach given in Equation (2) with $K = 1$. Each model is estimated via MCMC sampling using the `amen` package in R (Hoff, 2015). There is a burn-in period of 10,000 followed by 100,000 iterations. Given a thinning interval of 100, the size of the posterior samples is 1,000.

Figure 31 plots the annual directed relationship scores for all party-dyads. The horizontal axis shows $u_i v_j$ and the vertical axis gives $u_j v_i$. The diagonal line shows where dyads would fall if the relation of i towards j was exactly the same as the one of j towards i. Generally, the points fall along the 45 degree line, so if i has a conflictual relation towards j, j also has a conflictual relation towards i as well. The one exception is 2009, where there is little relation between the two. However, note that in that year relations among political parties are mostly neutral because of the demands of the Great Recession (see Weschle, 2017).

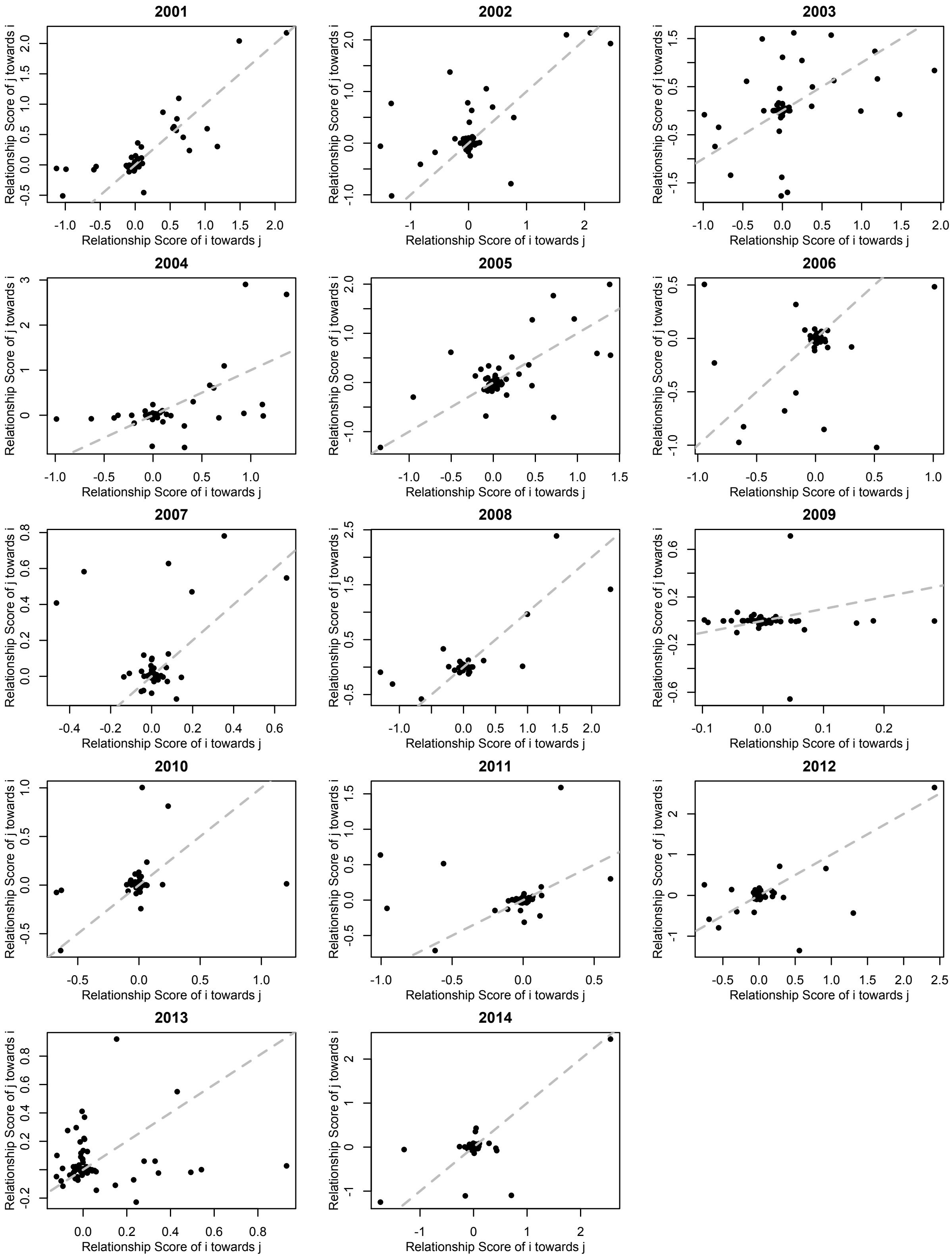

Figure 31: Directed Relationship Scores for Political Parties, 2001-2014.

C Additional Information for Regressions

C.1 Summary Statistics of Regression Data

Table 44: Summary statistics of variables used.

	Mean	Std. Dev.	Min	Max
Cooperation Score	0.05	0.44	-2.63	3.90
Coalition	0.18	0.39	0.00	1.00
Opposition	0.26	0.44	0.00	1.00
Delta CMP Left-Right	20.68	17.09	0.00	97.22
Delta CMP Multiculturalism	2.93	3.84	0.00	25.09
Delta Vote Share	12.81	10.43	0.00	39.50
Election Year	0.30	0.46	0.00	1.00
Number of Parties	4.85	1.20	2.00	8.00
Population (log)	16.77	1.08	15.17	18.23
Number of Events	1190.28	1294.62	50.00	8577.00
Mean Cooperation Score	0.03	0.31	-2.55	3.88

C.2 Additional Regression Results

Table 45: Regression results including all control variables. 95 percent confidence intervals in parentheses.

	(1)	(2)	(3)
Coalition	0.127	0.152	0.179
	(-0.018, 0.272)	(0.005, 0.299)	(0.021, 0.336)
Opposition	-0.041	-0.061	-0.065
	(-0.097, 0.015)	(-0.133, 0.011)	(-0.154, 0.024)
$\lvert\Delta$ CMP Left-Right$\rvert$	0.001	0.001	0.001
	(-0.001, 0.002)	(-0.001, 0.003)	(-0.001, 0.003)
$\lvert\Delta$ CMP Nationalism/Multiculturalism$\rvert$	-0.006	-0.008	-0.011
	(-0.013, 0.001)	(-0.015, -0.001)	(-0.022, -0.001)
$\lvert\Delta$ Vote Share$\rvert$	0.001	-0.001	-0.001
	(-0.004, 0.005)	(-0.006, 0.004)	(-0.007, 0.004)
Election Year	0.061	0.046	
	(-0.002, 0.124)	(-0.028, 0.120)	
Number of Parties	-0.025	0.002	
	(-0.055, 0.004)	(-0.057, 0.060)	
Population (log)	0.027	0.596	
	(-0.041, 0.095)	(-2.082, 3.272)	
Number of Events	0.000	0.000	
	(0.000, 0.000)	(0.000, 0.000)	
Mean Cooperation Score	15.920	14.049	
	(5.944, 27.575)	(4.467, 25.719)	
Constant	-0.278	-9.937	0.076
	(-1.339, 0.785)	(-54.541, 34.673)	(-0.035, 0.186)
Country and Year FE		✓	
Country-Year FE			✓
N	1150	1150	1150
R^2	0.060	0.090	0.216

Table 46: Regression Results, Election Years Only. 95 percent confidence intervals in parentheses.

	(1)	(2)	(3)
Coalition	0.103	0.114	0.144
	(-0.111, 0.317)	(-0.091, 0.319)	(-0.072, 0.360)
Opposition	-0.096	-0.103	-0.125
	(-0.169, -0.027)	(-0.201, -0.007)	(-0.230, -0.020)
$\lvert\Delta$ CMP Left-Right$\rvert$	0.000	0.000	0.000
	(-0.002, 0.002)	(-0.002, 0.003)	(-0.002, 0.003)
$\lvert\Delta$ CMP Nationalism/Multiculturalism$\rvert$	0.003	0.006	0.000
	(-0.009, 0.015)	(-0.010, 0.022)	(-0.015, 0.015)
$\lvert\Delta$ Vote Share$\rvert$	-0.001	-0.003	-0.003
	(-0.008, 0.005)	(-0.009, 0.003)	(-0.010, 0.003)
Number of Parties	-0.035	0.036	
	(-0.076, 0.004)	(-0.095, 0.167)	
Population (log)	0.042	2.124	
	(-0.070, 0.154)	(-2.446, 6.688)	
Number of Events	0.000	0.000	
	(0.000, 0.000)	(0.000, 0.000)	
Mean Cooperation Score	18.614	14.984	
	(2.977, 40.611)	(-8.106, 44.806)	
Constant	-0.420	-35.667	0.119
	(-2.180, 1.346)	(-111.773, 40.585)	(0.004, 0.234)
Country and Year FE		✓	
Country-Year FE			✓
N	296	296	296
	0.020	0.145	0.216

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