# Repeated Cross-Sections in Survey Data

HENRY E. BRADY and RICHARD JOHNSTON

## Abstract

Examples of repeated cross-sections (RCS) include daily tracking polls of political opinions during campaigns, monthly Current Population Surveys of unemployment, yearly national health interview surveys, and quadrennial election studies of presidential voting. Each iteration is a distinct sample, as opposed to panels in which the same people are interviewed two or more times. By asking the same questions on repeated survey samples from the same population, RCS studies allow us to track trends and to establish causal inferences. One analytic challenge is to maintain both the representativeness and the comparability of samples as fieldwork methods or sources change. The longer the span covered by an RCS, the likelier it is that the universe will change. For an RCS spanning decades, populations can change in fundamental ways. The universe of content also changes, as issues of one period are redefined or even rendered irrelevant in another. Extracting trends from RCS data typically requires smoothing to separate signal from noise, especially where samples or subsamples are small, but this can lead to bias due to excessive smoothing or to mistaking noise for signal because of sampling variability when there is not enough smoothing. By deploying time the RCS design enables certain kinds of causal inference, but many alternative micro-processes are observationally equivalent, and so the RCS benefits from being combined with the panel design.

## INTRODUCTION

Repeated cross-sections (RCS) have been with us for decades. They appeared as soon as an initial sample survey was followed by a second one that used the same questions for a sample of the same population. Only in recent years have we come to recognize the importance and utility of these data. Knowing about trends has intrinsic value, and for many indicators this requires broadly comparable mass survey data repeated over time. And time is absolutely critical for establishing causal inferences that are the gold-standard for good science.

For high-quality causal inferences from observational data, the starting point is typically the panel survey, where the same persons are interviewed

*Emerging Trends in the Social and Behavioral Sciences*. Edited by Robert Scott and Stephen Kosslyn.
© 2015 John Wiley & Sons, Inc. ISBN 978-1-118-90077-2.

repeatedly so that individual change can be tracked and individual differences controlled. However, panels bring costs and benefits and are rarely available in key historical moments. In their stead, we commonly resort to pseudo-panels, or RCS.

At the microscopic extreme is daily sampling, increasingly common in the study of electoral campaigns. Early studies of primary-election dynamics (Bartels, 1988; Brady & Johnston, 1987) relied heavily on a 1984 weekly RCS conducted as part of the American National Election Study (ANES). Johnston, Blais, Brady, and Crête (1992) narrowed the focus to daily variation in their pathbreaking study of a Canadian election campaign. This became the model for the massive National Annenberg Election Study (Johnston, Hagen, & Jamieson, 2004). New modes, especially the maturation of Web-based surveys, and generally falling fieldwork costs are enabling more researchers to get in on the action. The distinctive claim of daily sampling is *granularity*. This is critical if, for example, shifts in preference or perception are to be attributed to campaign events. But the logic of RCS extends well beyond a daily or weekly time scale, as we show in the next section. Monthly or quarterly surveys are a staple for government statistical agencies. Even annual or quadrennial surveys are now accumulating enough waves for dynamic analysis.

At the same time, we now recognize that initially unrelated surveys can be lined up over time and analyzed together, especially as we think through item equivalence and missing data problems. Brady and Kaplan (2012, 2012), for example, assembled weekly and bi-weekly data from various sources for a microscopic analysis of opinion in the collapse of the Soviet Union. Berinsky, Powell, Schickler, and Yohai (2011) portray opinion shifts in the 1930s and 1940s in America, in some cases on a monthly time scale. Stimson (1999) takes virtually the entire postwar period as his time span for annual readings of Americans' policy mood.

If the incorporation of time is a distinctive feature of the RCS, the *scale* of time critically affects both the conduct of fieldwork and the analysis of data after the fact. The shorter the time units the greater the burden on design and execution of the sample to ensure daily samples that are truly random. The longer the overall temporal span, the greater the burden on analysis to deal with changes in the composition of the population.

## WHAT ARE REPEATED CROSS-SECTIONAL SURVEYS?

RCS surveys involve the repeated administration of the same (or similar) questions to a sample from the same (or a similar) survey population. Unlike panel surveys, the same people are not necessarily interviewed in every survey; instead, typically a new sample is drawn each time the survey is fielded.

This approach avoids the costs of tracking people, eliminates the priming and learning that may carry over from previous interviews, and ensures the representativeness of samples by avoiding attrition. Although RCS do not have the power of equivalently sized panels, this is usually more than compensated for by their larger size. Although it is easiest to think in terms of sample surveys, some of the logic extends to firms and organizations and even to successive Congresses or Supreme Court terms (Lebo & Weber, 2014), although as we move away from sample surveys we enter the territory of "unbalanced panels" (Honaker & King, 2010) in which some entities fall in and out of the population.

Table 1 describes some of the major RCS data sets that come from political science, economics, sociology, demography, and public health—although the emphasis is on political science data. In every case, there are enough cross-sections that time-series analysis can be undertaken. Even the quadrennial ANES Presidential surveys now comprise 17 temporal observations from 1948 to 2012, and the new American Community Survey already has eight yearly observations. For many of the other surveys there are hundreds of time-series observations, and often parallel time series for geographic sub-aggregates such as states.

From Table 1 it emerges that RCS studies can differ in three fundamental ways:

- *Time between Cross-Sections*. The time between repetitions of the survey can vary more than three orders of magnitude from individual days in some election-campaign tracking studies to 2–4 years (1461 days) in social change and presidential election studies. This variation in the period can affect the appropriateness of the questions and the nature of the sample.
- *Number of Cross-Sections*. Although the number of cross-sections could be as few as two, we are generally interested in those cases where there are enough cross-sections so that temporal trends can be identified and analyzed. This means that we want at least 10–15 RCS, and preferably many more. All the surveys listed in Table 1 have seven or more time periods and the median number is about 80.
- *Number of Interviews at Each Time Point*. The number of interviews at each time point also varies by several orders of magnitude from 75 in some daily or weekly tracking polls to 60,000 for the monthly Current Population Survey to 3,000,000 in the annual American Community Survey. The number of interviews affects the statistical accuracy of the data and the degree to which it can be broken down by region and subpopulation.

**Table 1**
Examples of Time-Series Cross-Sectional Studies

| Time between Cross-Sections | Name of Study | Interviews at Each Time Point | # of Cross-Sections—Time Points | Panel or Unusual Features? | Subject Matter |
|---|---|---|---|---|---|
| Daily | Canadian Election Studies—1988 (and subsequent ones) | ≈75 | ≈50 | Post-election re-interview | Public opinion and campaign dynamics |
| | Annenberg National Election Studies (2000, 2004, 2008) | ≈100–250 | ≈365 | Panels inside RCS plus some post-election re-interviews | Public opinion and campaign dynamics |
| | German Longitudinal Election Studies (2005, 2009) | ≈85 in 2005<br>≈100 in 2009 | 41 in 2005<br>60 in 2009 | Post-election re-interview | Public opinion and campaign dynamics |
| Weekly or bi-weekly | American National Election 1984 Continuous Monitoring | ≈76 | 46 | — | Public opinion and campaign dynamics |
| | Soviet Collapse Data Set (1989–1991) | ≈1000–4000 | ≈80 | Irregular spacing | Participation and opinion during collapse of SU |
| Monthly | Roper Social and Political Trends Dataset (1973–1994) | ≈2000 | 207 | — | Political and social participation over time |

| | | | | | |
|---|---|---|---|---|---|
| | American Mass Public in 1930s and 1940s– | ≈3000 | 400 | Irregular spacing | Public opinion and voting over time |
| | Current Population Survey (1940; micro-data from 1962-present) | ≈60,000 | ≈600 | Rotating panels | Employment, poverty, welfare over time |
| | Survey of Consumer Sentiment (1952; micro-data from 1978-today) | ≈480 | ≈400 | — | Consumer sentiment over time |
| Quarterly | California Field Poll Data (1956–2006) | ≈1000 | 232 | — | Public opinion and voting over time |
| | Eurobarometer (2–5 times per year) | 1000+ per country | 39+ | — | Political and social trends, attitudes to EU |
| | US Consumer Expenditure Survey (1980 to present) | ≈7000 | ≈120 | Diary component | Consumer expenditures over time |

*(Continued Overleaf)*

**Table 1**
(*Continued*)

| Time between Cross-Sections | Name of Study | Interviews at Each Time Point | # of Cross-Sections—Time Points | Panel or Unusual Features? | Subject Matter |
|---|---|---|---|---|---|
| Yearly or biennially | General Social Survey (1972–2010) | ≈2000 | 27 | First annual, now 2-years | Social trends over time |
| | American National Election Studies (1956–2004) –Every 2 years | ≈1000–2000 | 25 | Some panels embedded | Political trends and elections |
| | Integrated National Health Interview Surveys (1963–2011) | ≈80000 | 49 | Continuous sampling | Health of population |
| | American Community Survey (2006-present) | ≈3,000,000 | 7 | Continuous sampling | Demographics, poverty, institutionalization status, employment |
| Quadrennially | American National Election Presidential Studies (1948–2012) | ≈1000–2000 | 17 | Some panels embedded | Political trends and elections over time |

Depending on how these dimensions are combined, an RCS can be sensitive to different kinds of change. Larger samples with more interviews at each time point make it possible to distinguish true change from apparent change due to sampling variability. True change can come in two varieties. One is where the composition of the population is stable over time, but the units change their behaviors or attitudes. An obvious example is, where the members of an electorate decide that a candidate is better than they had originally thought, perhaps based on a performance in a debate. The other kind of change is compositional, where individuals do not change their proclivities but are themselves replaced by those with different characteristics. Both kinds of change can coexist in the population, but their relative prevalence and importance in samples depends on the interval between cross-sections and the total length of the data collection period. The shorter the time between cross-sections, the more that true change must reflect change in individuals' behavior or attitudes. Apart from sampling variability, change in the sample's propensities can have no other source but the conversion of its component individuals. As the span of the series increases, on the other hand, attention is forced to compositional change, which typically takes years to register. Again, the passage of time may make possible—may even be necessary for—individuals to change their attitudes or characteristics, but the longer the span the more inevitable it is that samples will also be drawn from populations comprising different individuals.

Depending on where a given RCS sits on the dimensions of time unit, overall duration, and sample size per time unit, various challenges must be faced. Commonly, addressing one challenge may only exacerbate another.

## COMPARABILITY VERSUS REPRESENTATIVENESS

### Comparability in Samples

At the high-frequency extreme of data collection the objective is to compare one day's results with those from the next day. To this end, the data collection strategy for each day should be identical, such that differences between the days are the product of something that has happened in the interval, *not* of differences in, say, accessibility or availability of respondents. However, if we require that the date of interview is the same as the date of release of the potential respondent's contact information to the field the sample will be very unrepresentative because many respondents will not be reached immediately. It takes time to "clear a sample," and we know that the longer a poll is in the field, the better it performs in providing predictions of elections (Lau, 1994). Even where prediction is not the objective it can be a factor in the credibility of the study. To combine granularity with representativeness, the key is to work equally hard to contact respondents as they are released to the field and to recognize that after a suitable number of days (perhaps a week), those people who are *interviewed* on a given day will constitute a random sample even though they come from different cohorts released on different days. This approach was successfully used with the Canadian studies, the National Annenberg Election Survey, and other studies. This implies careful management of the release and clearance of the sample and acceptance that the first days of fieldwork will not be useful for dynamic analysis (although the cases will be perfectly usable in analyses not involving time). A similar logic applies if the design involves changes in sampling fractions, although here model-based weighting can be employed (Brady & Johnston, 2006; Johnston & Brady, 2002).

Even when the intent is to provide a representative sample of some well-defined population (e.g., the United States), samples may differ over time because data come from different survey houses, interviewing is added in another language (e.g., Spanish), one method of interviewing is replaced by another (e.g., in-person by telephone), or sampling methods change (e.g., more sampling points, or shift from clustering to a simple random draw). For example, in their efforts to put together public opinion datasets on the American mass public in the 1930s and the 1940s, Berinsky and Schickler (2010) faced problems stemming from collecting surveys from four different survey organizations and the widespread use of quota sampling. They employed several model-based post-stratification methods to make the data comparable over time (Berinsky, 2006). Similarly, using a series of CBS/New York Times national polls from the 1988 election campaign, Gelman (2007) discussed the strengths and limitations of post-stratification weighting in the context of regression analysis. As Gelman notes, much more work has to be done to figure out the appropriate statistical methods for solving these problems. These problems are only compounded by the explosion in tracking polls and the salience of aggregators, such as FiveThirtyEight[1] or Pollster[2].

## COMPARABILITY OF SURVEY QUESTIONS

The questions asked on RCS often change over time because better versions are constructed, because times change and questions must be modified, or simply because different investigators have different beliefs about good

1. FiveThirtyEight (blog). http://fivethirtyeight.com/ (accessed 15 November 2014).
2. Huffington Post. Pollster. http://elections.huffingtonpost.com/pollster (accessed 10 September 2012).

questions. The problems created by these changes range from modifications at one point in time (e.g., a new way to measure unemployment or a new way to ask about liberal-conservative identification) to a mélange of different ways of answering a similar question (e.g., the popularity of some political figure asked with 3, 5, or 10 point scales and with different words such as "approve," "trust," or "support"). Brady and Kaplan (2012, 2012) approached this problem by simultaneously modeling trends in the data and the question formats using methods from test theory. Stimson (1999, Appendix 1) considered an extreme version of this problem in which he wanted to build factor scores (typically for a "liberal-conservative" dimension) from dated items with only partially overlapping cases.

## BIAS VERSUS VARIABILITY

One of the major reasons for considering RCS is to analyze trends, but in many cases samples are so small that simply "connecting the dots" risks confusing sampling variability for real change. Even when there are large samples, a focus on small sub-populations quickly leads to the same problem. Identifying real change requires smoothing.

But how much? The simplest approach is simply to estimate a linear trend. This may have the appeal of visual clarity but typically it provides far too much smoothing. The truth is, we commonly lack a theory of events that would tell us the shape of their impact over time that would guide smoothing, especially for highly granular variants of the RCS. Shaw (1999) gives an inventory of events that might populate a Presidential campaign and outlined alternative time paths of effect. However, this is a primer on shapes to look for; no real theory distinguishes the various paths. Hill, Lo, Vavreck, and Zaller (2013) stake a strong claim for a particular path for impact from campaign ads, and this may be a starting point for thinking about how discrete events, such as debates, might play out.

For the most part, however; we lack a strong basis on which to stake dynamic claims. In statistics, this problem has spawned an enormous literature on nonparametric smoothing techniques, such as the roughness penalty approach (Eubank, 1999; Green & Silverman, 1994), kernel smoothing (Bowman & Azzalini, 1997; Hardle, 1990), local polynomial modeling (Fan & Gijbels, 1996), the least squares spline approach (Smith, 1979), and the free-knot approach of Mao and Zhao (2003). Examples in political data are still rare but already the field shows variety. Brady and Johnston (2006) discuss this "bias versus sampling variability" problem in the context of daily cross-sections. They recommend a kernel smoothing approach and an optimum smoothing criterion based on variances in the variable of interest. Brady and Kaplan (2012, 2012) use least squares regression splines (Smith,

1979) with pre-chosen knots to estimate changes in public opinion in RCS. Matthews and Johnston (2010) propose a semi-parametric component for the economy that uses cubic smoothing splines with fixed equivalent degrees of freedom. For a similar problem, Johnston and Partheymüller (2012) use thin-plate regression splines (Wood, 2003) which estimate knot locations and flexible functional forms. Four papers, four approaches. We hope that in the coming years experts in nonparametric regression turn their attention to RCS data, to suggest better ways of choosing knot locations, equivalent degrees of freedom, and, indeed, the smoothing method itself.

Smoothing issues apply not just to the description of population and subpopulation trends over time. They also enable estimation of associations—and, critically, *changes* in the associations—among variables over time. How, for example, are public attitudes and leadership approval related to one another? How do events affect public attitudes? How do changes in employment or marital status affect the up-take of social welfare programs? How do changes in health status affect political participation, employment, marriage, education, or a host of other things? What is correlated with changes in party identification over time?

Before we can answer these questions we must get a better grip on a number of issues: How can we build models which simultaneously include covariates and smooth the data? How can we separate cross-sectional association (e.g., party identification with policy attitudes) from time series association (changes in party identification with changes in policy attitudes)? Johnston and Brady (2002) propose a method for separating time-series from cross-sectional effects that starts with a specific model of opinion change. Earlier, these same authors (Johnston *et al*., 1992) proposed a simple step function representation of varying parameters. Linear interactions of factors with time have been ventured (e.g., Bartels, 2006a). Mebane and Wand (1997) seem to be the first to try to extract patterns in individual transitions from early US and Canadian RCS campaign data. Pelzer, Eisinga, and Franses (2002) built on work by Moffitt (1993) and Franklin (1989) to take this further. In truth, we do not have plausible theories for the exact time path of varying coefficients. This points, again, to debates over how smoothing methods help identify how true temporal change in one variable relates to true change in another one. Eubank *et al*. (2004) use a smoothing spline to estimate a varying coefficient model. The Brady and Kaplan (2012), Johnston and Partheymüller (2012), and Matthews and Johnston (2010) references cited earlier include covariates in their model as interaction terms with time. All these approaches assume an absence of autocorrelation across successive days, an assumption forced by the fact that the data are, after all, not panels. Lebo and Weber (2014) propose a solution that involves multi-level modeling. The strengths and weaknesses of these methods need to be assessed, and new methods must be developed which will allow for the flexible modeling of temporal trends and the incorporation of covariates in models.

## CHANGES IN THE UNIVERSE

Most of the discussion so far assumes that comparisons are across basically unchanging universes of persons and content. The issues are ones of error, in sampling or in measurement. The longer the time span for the study, however; the more the analysis engages issues in the comparability of populations and of attitude domains.

### Universe of People

If we can assume that RCS surveys draw their sample from the same population over time, then the impact of an explanatory variable on different groups in the population (say the impact of a change in wages on female labor supply or the impact of a change in unemployment on presidential popularity among men) can be determined by looking at what happens to the dependent variables (female labor supply in the first instance and presidential popularity among men in the second) from one period to the next as changes occur in wages or unemployment. In effect, the fixed characteristic of a person (in this case his or her sex) is used to create a "pseudo-panel" of similar people whose reactions can be measured by conditioning on these characteristics. Tellingly, a pseudo-panel is sometimes called a *synthetic cohort*.

However, this method only works if the populations of each group stay the same from one period to the next, and this assumption is surely wrong, since day by day people age so that new people enter into the eligible population (by being born or by turning 18) and people die. In addition, the way in which a factor affects the dependent variable may change from one period to the next or its impact may depend upon the cohort of people exposed to the factor (and these cohorts might change because of emigration or immigration). These changes are probably negligible for relatively short time periods—maybe even as long as several years, but at some point they must be confronted. In sum, as time spans expand, we can no longer pretend that an RCS is a single synthetic cohort; "Age-Period-Cohort" problems must be confronted directly. A thought experiment illustrates the problem: in the 1980s, one could give a quite complete account of US politics and yet say nothing about Hispanics; could one imagine doing so today? Any attempt to track issue evolution over this span must allow for this transformation in the electorate's coalition possibilities (Shafer & Spady, 2014).

Certainly any study of long-term trends must take into account these kinds of changes that stem from changes in age, the impacts of the periods in which people live, and the cohorts of which they are a member. Sociologists have done the most to consider these factors. The classic work is Mason and Fienberg (1985), which considered ways to deal with the basic identification problem created by the fact that one's age (say 50) in a given period (say the year 1965) equals period minus cohort as defined by year of birth (1915). More recently, Yang Yang and Kenneth Land (2006) and Yang Yang (2006) have developed mixed (fixed and random effects) models of trend data in RCS surveys (e.g., the General Social Survey) which identify and estimate age, period, and cohort components of change. Another example of this line of research is Devereux's (2007) analysis of biases in synthetic cohort models. These papers suggest ways to deal with the non-fixity of the underlying population, and they should be further developed so that they can be combined with analyses that go beyond Age-Period-Cohort analysis.

### Universe of Content

The issues flagged above for the comparability of survey questions are compounded as time spans several decades. Some issue domains simply have no counterparts across the periods. Even persistent domains—race relations in the United States, to take an example—change their surface content. Questions from the 1950s about, say, school integration and rights to sit at lunch counters, would be almost incomprehensible to current respondents. The usual response is to go minimal and look for questions with maximum correspondence, often focusing on single items (Carmines & Stimson, 1989; Shafer & Johnston, 2006). Attempts to model the landscape more broadly do not have this luxury, and analysts are shifting to combinations of exploratory and confirmatory factor analyses (Claggett & Shafer, 2010) and to item-response theory (Shafer & Spady, 2014). Once again, better theories about how attitudes are affected by social and cultural change over time might be very useful (MacKinnon & Luke, 2002).

## CAUSAL INFERENCE

Describing trends and estimating associations between variables are important scientific tasks, but we often want to estimate causal impacts as well. This takes us back to where we started. True panel data have the advantage that we can control for fixed effects, add lagged endogenous variables, and develop dynamic models of change (Bartels, 2006b; Hsiao, 2003), which can eliminate many threats to making reliable inferences. The pseudo panel approach cannot do these things directly, but RCS surveys have some advantages over panels. Their temporal granularity makes it possible to detect changes that might be missed by panels spaced far apart (Brady & Johnston, 2006). They are less likely to suffer from panel attrition which can create selection bias problems for panel studies. Moreover, the sheer number of repeated temporal data points (sometimes in the hundreds compared to panel studies which rarely have more than five waves) makes it possible to study the impact of putative explanatory variables both as they go up and as they go down, which provides more leverage for causal inference.

Starting with Deaton (1985), econometricians have developed and expanded on the pseudo-panel concept. After Franklin's (1989) and Moffitt's (1993) papers made some conceptual breakthroughs, many others have followed (Collado, 1997; Pelzer, Eisinga, & Franses, 2002, 2005; Ridder & Moffitt, 2007; Verbeek, 2008; Verbeek and Nijman, 1993; Verbeek & Vella, 2005). Athey and Imbens (2006; see also Abadie, 2005; Manski & Pepper, 2012) used the Neyman-Rubin-Holland counterfactual outcomes approach to develop a very general framework for thinking about "nonparametric identification, estimation, and inference for the average effect of the treatment for settings where RCS of individuals are observed in a treatment and a control group, before and after the treatment" (432). Even if RCS designs can be sensitive to fine temporal distinctions, the patterns they identify can be consistent with quite different micro-mechanisms. Lenz (2009), for example, notes that shifts in coefficients that Johnston *et al*. (1992, 2004) attribute to priming are observationally equivalent to effects from learning and opinion change. He deploys true panels to identify the mechanisms.

For high-frequency RCS designs, campaign studies for example, it is possible to combine repetition of cross-sections with true panels. Canadian Election Studies are, in one sense, just pre-post panels, with the first wave released in a rolling manner. Even this simple design gives causal leverage, provided the key questions appear at each wave (Johnston & Partheymüller, 2012; Lenz, 2009). More elaborate designs, including a proper baseline, would be more effective for inference, if at the cost of representativeness. And such designs are starting to appear, thanks to the power and flexibility of the online mode. Goldman (2012) uses the five-wave RCS-panel combination, part of the 2008 National Annenberg Election Survey (http://www.annenbergpublicpolicycenter.org/political-communication/naes/), for an account of racial politics. Faas and Blumenberg (2013) apply the design to election and referendum campaigns in the German state of Baden-Württemburg.

## CONCLUSIONS

As mentioned earlier, RCS have been with us for a long time. With hindsight, we now see the commonalities—but also the distinctions—among such data sets. The critical groundwork has been divided among economists, sociologists, political scientists, and others, with the effect that one disciplinary groups proceeds largely in ignorance of the others. Now we are poised to learn from each other. The possibilities for future discoveries are exciting. No less exciting are the opportunities to repurpose data and learn about our past.

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## HENRY E. BRADY SHORT BIOGRAPHY

**Henry E. Brady** is Dean of the Goldman School of Public Policy and Class of 1941 Monroe Deutsch Professor of Political Science and Public Policy at the University of California, Berkeley. He received his PhD in Economics and Political Science from MIT in 1980, and he has written extensively on political methodology. He is coauthor or coeditor of nine books including coeditor of *Rethinking Social Inquiry* (2004), *Capturing Campaign Effects* (2006), and the *Oxford Handbook of Political Methodology* (2008). He has been president of the American Political Science Association, president of the Political Methodology Society, and director of the University of California's Survey Research Center from 1998 to 2009. He was elected a Fellow of the American Academy of Arts and Sciences in 2003, a Fellow of the American Association for the Advancement of Science in 2006, and a Fellow of the Political Methodology Society in 2008. He received the Career Achievement Award of the Political Methodology Society in 2012.

## RICHARD JOHNSTON SHORT BIOGRAPHY

**Richard Johnston** (PhD Stanford) is Professor of Political Science and Canada Research Chair in Public Opinion, Elections, and Representation at the University of British Columbia. He has also taught at the University of Toronto, the California Institute of Technology, Harvard University (Mackenzie King chair, 1994–1995), and the University of Pennsylvania. He was an Associate Member of Nuffield College, Oxford, a Marie Curie Research Fellow at the European University Institute, and official visitor at MZES, Mannheim. He is the author or coauthor of five books, three on Canadian politics and two on US Politics. He has coedited three other books and has written numerous articles and book chapters. In 2007–2008 he was President of the Canadian Political Science Association. He was Principal Investigator of the 1988 and 1992–1993 Canadian Election Studies and Research Director for the National Annenberg Election Survey (Penn), 2000–2008. Much of his work focuses on elections and public opinion, with special reference to the role of mass communications and campaigns.

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