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Model selection in observational media effects research: a systematic review and validation of effects

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ABSTRACT

Media effects research has produced mixed findings about the size and direction of the relationship between media consumption and public attitudes. We investigate the extent to which model choices contribute to these inconsistent findings. Taking a comparative approach, we first review the use of different models in contemporary studies and their main findings. In order to extend and validate this review, we consider the implications for national election studies attempting to measure media effects in election campaigns and recreate these models with the British Election Study 2005–2010 panel data. We compare the direction and size of effects of media content *on attitude change* across: between-subjects, within-elections models, in which the effects of individual-level variance in media exposure and content are assessed; within-subjects, within-elections models, which compare the effects of variance in media content for the same individual; and within-subjects, between-elections models that allow us to analyse the links between media content and exposure with attitude change over time. Our review shows some notable differences between models in terms of significance of effects (but not effect sizes). We corroborate this finding in the British campaign analysis. We conclude that to check the robustness of claims of media effects in observational data, where possible researchers should examine different model choices when evaluating media effects.

KEYWORDS
Media exposure; media effects; within-subjects models; between-subjects models; between-elections models

For decades, researchers viewed the media as having a minimal effect on opinion and behaviour (e.g. Klapper 1960). Although more recent work has revised those conclusions, the empirical record is still remarkably mixed, ranging from claims of 'minimal effects' to 'massive effects' (Pollock et al. 2015; Mondak 1995; Zaller 1996) to an apparent return to 'minimal effects' (Boyd and Bahador 2015b). With such heterogeneity in mind, Bartels described the body of research on media effects as 'one of the most notable embarrassments of modern social science' (Bartels 1993, 267), a state of affairs he attributed primarily to a combination of measurement error and the absence of longitudinal research designs

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The data and scripts to replicate the findings in this article can be accessed at Harvard Dataverse at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/7FYH0T

capable of detecting media effects (see also Mondak 1995). Zaller (2002) later raised an additional problem of research designs: the lack of attention to sample size and in particular the power of different sample sizes to pick up even medium to large media effects on shifts in voting preferences. Research on media effects in observational studies since then has responded to these seminal critiques in paying close attention to improving measures of exposure (e.g. Dilliplane 2014) and to estimating exposure to media content as well as media usage (e.g. Slater 2013; Stevens et al. 2011), but less so to the consequences of different design choices for observational data.

In this paper, we first revisit the validity of Bartels' and Zaller's claims with regard to contemporary research through a survey of statistical methods and substantive results in the published literature on media effects in leading political science and communication journals between 2011 and 2015.[1] This research has generally been focused on the US case, but we draw on a range of country-specific and cross-national studies which are increasing in number, with implications for research on media effects regardless of the country. We then examine these statistical methods in original analysis of the British general elections of 2005 and 2010 in order to validate and extend the findings of our review. In both the review and the validation, we assess the extent to which the statistical significance as well as the size and direction of 'media effects' is contingent on the methods employed. Examination of media effects often relies on election studies and a range of designs – post-election surveys (for example, the mainstay of the Australian Election Study); panel designs (such as the pre–post-election survey deployed in some New Zealand Election Studies and the British Election Study); or repeated cross-sections (e.g. New Zealand election studies (NZES) and British election study (BES)). Therefore, our analysis using the BES will be instructive for researchers using other election studies to study media effects. In addition, the BES analysis we present may also be informative because the British media system has been characterised as 'Liberal' along with those of New Zealand and Australia (Hallin and Mancini 2004).

Our focus is on media effects research using observational data – cross-sectional surveys and survey panels – for two reasons. First, despite their often-noted limitations, these types of data continue to represent the majority of published work on media and are particularly important in studies of media effects in election campaigns. Despite the recognised weaknesses of cross-sectional data, its greatest strength lies in the potential for studying people who have been exposed to real-world treatments (i.e. it captures people as they naturally encounter political information). It therefore behoves scholars to leverage the unique strengths of observational data to understand media effects. Second, Bartels' and Zaller's critiques of media effects research were directed at such observational studies. Given the development of new practices that purport to address their concerns, we need to take a step back and systematically evaluate the model choices media effects researchers make.

In the years following Bartels' critique, the scholarly community has developed new practices for estimating media effects with observational (non-experimental) data. These have generally focused on three areas: (1) better measures of exposure (e.g. Dilliplane, Goldman, and Mutz 2013; Prior 2009); (2) capturing variation in both media content and exposure by linking the two (e.g. Slater 2013); and (3) using methods that account for omitted variable bias or selection bias (e.g. within-subject designs, Barabas and Jerit 2009). The object of this paper is not to focus on measurement, which has been done elsewhere (e.g. Dilliplane, Goldman, and Mutz 2013), but rather on a comparison of models. In other words, we are interested mainly in how observational data have been used, whether it is linked to media content and how omitted variable bias has been accounted for and whether this all leads to different conclusions about the presence and direction of media effects.

We focus on three common methods used to examine media effects in observational studies: between-subjects models that utilise variation in media exposure and media coverage across respondents; within-subjects models that utilise variation in media coverage for the same individual during one election; and within-subjects models that utilise variation in media coverage and possibly exposure for the same individual across elections. The results of the review of published research show a degree of similarity in effect sizes but some differences in the likelihood of finding statistical significance, which in part can be ascribed to variation in the number of observations these models are based on. Our review of published research also reveals that the USA dominates studies of media effects. Over half the articles reported data from the USA and only slightly more than 10% of studies used cross-national data.

There are limitations to our review of the published research – such as direct comparisons of modelling choices across the same data – that lead us to extend and validate it using data on the British elections of 2005 and 2010 combined with media content. This analysis shows more clearly how systematic differences in media effects based on different research methods might arise: results based on within-elections models – both within and between subjects – are substantively different from results based on between-elections models. We conclude that while media effects research may have moved on in paying close attention to issues of measurement, there is still a relative lack of focus on the consequences of different methods that tap into different microprocesses underlying media effects. We recommend using more than one approach where possible, especially if the analyst is interested in disentangling the effects of exposure and of content.

1. The mechanisms of media effects

Most extant research has relied on one of the three observational methods for identifying media effects: between-subjects models, in which the effects of individual-level variance in media exposure and media content are assessed; within-subjects models, which compare the effects of variance in media content for the same individual; and between-elections models using, for example, panel surveys that allow us to measure attitudinal change over time. The challenge in these methods is to reflect both variation in exposure patterns (measured at the individual level and usually based on self-reports) and variation in media content or 'the message' (sometimes explicitly captured by linking media content to measures of exposure). Each method relies on different sources of variation, which in turn tap into somewhat different microprocesses of media effects.

1.1. *Between-subjects, within-election models*

Between-subjects models have long been a staple of the cross-sectional study of media effects. The comparison in this method is between respondents with varying levels of media usage for particular outlets – the source of variation generally derives from differences in reported exposure to general types of media (newspapers, radio, television and Internet) or to specific outlets (e.g. *The Guardian, The Sun* in the UK and *TV One* or *TV3* in New Zealand). In addition, there is variation between individuals in the media content they are exposed to: individuals who report reading *The Guardian* are exposed to different content than individuals reporting reading *The Sun*. As our review of published studies shows, however, linkage studies which combine self-reported exposure with actual media content still represent only about half of the media effects studies (with the other half not including any media content). Furthermore, there are problems inherent to between-subjects models. First, media usage is not randomly distributed. This implies that high and low media users (even of the same outlet) are likely to be different on factors, often unobserved, other than media usage (on this point, see Levendusky 2011; Soroka et al. 2013). If relevant variables are omitted in the empirical analysis, the purported relationship between media exposure and the dependent variable is likely to be biased (Morgan and Winship 2007; Pearl 2009). In recent years, matching techniques – attempts to replicate randomised experiments by selecting subgroups of 'treatment' and 'control' with similar distributions on covariates – have been applied to overcome this omitted variable bias (e.g. Ho et al. 2007). However, matching algorithms are far from a quick fix to identify media effects since one can only match on observables and not on unmeasured covariates (Levendusky 2011; Soroka et al. 2013). That is, 'while matching methods rely on a weaker functional form than regression models, matching cannot correct for an incorrect specification' (Keele and Minozzi 2013, 3). Second, as Zaller (1992) demonstrates, in high-intensity contexts such as election campaigns, media coverage tends to be relatively high, meaning that there is less variation in content across outlets or exposure, resulting in less variation across individuals, which may lower the possibility of discerning media effects (see also Mondak 1995).

1.2. *Within-subjects, within-elections models*

Within-subjects models seek to overcome omitted variable bias by comparing the same survey respondent to him or herself, an approach also known as 'within-survey, within-subjects' models (see for example Barabas and Jerit, 2009). Because variation is examined 'within' a subject across measures, unobserved factors correlated with (self-reported) media exposure are held constant. Barabas and Jerit (2009) draw upon nationally representative cross-sectional surveys that ask respondents multiple questions about different aspects of a political event (e.g. a battery of questions about proposals outlined in the President's State of the Union Address). The critical variation is thus in media content (rather than in content and media exposure in the case of between-individual comparisons). For example, if the amount of media coverage varies across topics (e.g. proposals in the president's address), differences in the outcome measures (e.g. knowledge about the proposals) can be attributed to the variation in media coverage. Similarly, Banducci, Giebler and Kritzinger (2017) link variation in the amount and tone of coverage of different parties to knowledge of the different parties' issue positions for that same individual. The within-subjects comparison approach retains the strengths of observational studies (examining people learning in the actual world), while improving the ability to make causal inferences about media influence by disentangling the effects of content from exposure. Multiple observations for the same respondents, i.e. 'stacked data', also have the advantage of increasing the number of observations per respondent. When paired with media content, within-subjects models are a very powerful method of estimating media effects using observational data.

1.3. *Within-subjects, panel design*

Instead of making a within-subjects comparison across similar questions at the same moment in time (i.e. in the same survey), panel methods examine responses to the same question within subjects at different moments in time where media coverage varies between observations (Ladd and Lenz 2009; Levendusky 2011). Differences in outcome measures between observations at T and $T + 1$ are likely due to an intervening factor such as media content or change in media exposure for a particular individual. As in within-subjects, within-elections models, individual-level characteristics that are unobserved but potentially correlated with (self-reported) media exposure are held constant. The additional advantage with this model is that one can compare change over time within the same individual and potentially disentangle separate effects of content and exposure.[2]

1.4. *Summary: designs and the microprocesses behind 'media effects'*

In general, a 'media effect' occurs when exposure to media content is accompanied by a change in attitude or behaviour that, in the estimate of the analyst, is not attributable to a third factor. Experimental methods, which are high on internal validity, are better than observational studies at controlling exposure to messages and observing the response. In observational studies, the probability of being exposed to a message is based on the both intensity of the message (an attribute of the media coverage and content) and news consumption behaviour (an attribute of individuals) (see in particular Zaller 1996). Minimally, in order to demonstrate a 'media effect', one needs to show that, after controlling for other potential confounding factors, those with more exposure to a message have different attitudes than those with less exposure. Each of the three observational research methods is based on a different mix of exposure and content, and each type of use is discussed in the literature as a 'media effect', yet the microprocesses underlying them and their ability to identify media effects in different contexts vary.

Between-subjects, within-elections effects largely stem from variation in media consumption behaviour in terms of days, hours or types of media consumed and across individuals. Controlling for variation in an individual's characteristics, 'media effects' in this comparison are presumed to be caused by variation in coverage by different outlets or by the level of exposure. Within-subject, within-elections effects stem from variation in content across issues in the same outlet that is consumed by the same individual. The comparison is not between individuals but of the individual with him or herself. Thus, the trade-off in terms of detecting media effects is that variation in media exposure is enhanced, but the attributes of the individual – habitual news reception in Zaller's (1992) terms – do not vary: what this model picks up is the influence of variation in media content rather than individual characteristics. Within-subjects, between-elections effects stem from differences in media consumption within an individual but add the dimension of time. The focus is now on comparing media at two (or more) points in time and their relationship with the (change in) attitudes and behaviours of an individual at two (or more) points in time. In this comparison, we are still comparing two relatively high-intensity media events – elections – but there could be additional variation in media exposure within individuals because different elections vary, for example, in competitiveness and the issues that are top of the agenda. This could hold more promise of identifying media effects if there is variation in the political content of media reports across elections for the same individual or if exposure for the individual varies between the two elections.

2. Media effects in the literature

In order to gain initial perspective on contemporary research methods and findings regarding media effects, we analyse recent published research for (1) the use of different kinds of research methods and (2) findings of effects of different sizes and statistical significance.

We collected all articles that were published in leading political science and communication journals between 2011 and 2015, based on the top 10 journals as reported by Google Scholar.[3] We searched for 'media', 'media' and 'politics' or 'media' and 'political' in the abstract to identify potentially relevant articles, and within those articles, we searched for the pertinent analyses. This provided us with a total of 73 model outcomes in 18 articles of relevance for our purposes in that they directly addressed media effects on public opinion, political attitudes or knowledge with observational, large-N data (see the Appendix for the list of papers).[4] We coded the models containing these outcomes on a number of features but most importantly the kind of method design they employed (see Table 1).[5] Of the models coded for analysis, 54 of 73 outcomes (74%) relied on a between-subjects comparison versus a within-subjects comparison (over time or at one time point). Roughly one-half of the models about media effects did not include any measure of media content (36/73 = 49%), despite Zaller's (1996, 18) warning of the necessity of knowing 'the content of the mass communication to which individuals are exposed' in order to be able to observe media effects.[6]

To determine if such methodological choices are in any way related to the model outcomes, we first calculated for each the average *d* effect size statistic, as calculated by $2 * t/\sqrt{df}$.[7] This is a measure of the substantive size of the reported effect with larger effect sizes denoting larger substantive effects. We find that – on average – within-subjects models report larger effect sizes (d = 0.12) than between-subjects models (d = 0.10). Furthermore – across designs – the presence of media content is associated with smaller average effect sizes (d = 0.09 versus d = 0.12). These differences are mostly driven by between-subjects models that include media content, which report the smallest average effect size (d = 0.08).[8] It is interesting to note that models that do not include media content – and by definition cannot distinguish between the effects of media exposure and media content – report the average largest effect size.

So model choices relate (modestly) to the reported *size* of relationships. What of statistical significance? For this outcome, the results are more pronounced: in 63% of

Table 1. Breakdown of media effects models and outcomes.

Model	Media content	Number of models	Average effect size	Proportion of significant results
Between-subjects	No	29	0.12	0.41
Within-subjects	No	8	0.12	0.62
Between-subjects	Yes	25	0.08	0.36
Within-subjects	Yes	11	0.12	0.63

cases, within-subjects models reported significant coefficients compared to 38% of between-subjects models (this difference is significant, even controlling for the number of observations). Of models with measures incorporating media content, 44% of outcomes reported significant results compared to 46% of outcomes without media content.

These results imply that we are likely to have found ourselves in a scenario in which – in the published literature on media effects – model choices may have had some effect on both effect sizes and significance of media effects. However, factors like variation in control variables, measurement of media content and, most importantly, differences among respondent groups raise the question whether these results are indeed driven by model choices per se. To tease out the possible impact of these other factors, we need to make a comparison of models, keeping their context and – most importantly – the individuals on which they are based the same. To such a comparison, we turn next in our analysis of media effects in the UK elections.

3. Media effects in British elections: the effects of visibility and tone on party evaluations

We now proceed to extend our analysis of methods in published media effects articles with a comparison of models estimated on data from the British general elections of 2005 and 2010. The role of the media in British elections is particularly relevant as there is widespread recognition of media effects in British elections.[9] British consumption of news media is high: about 9 in 10 people (89%) reported using television as their main source of information on political issues during the 2005 general election campaign and more than half (54%) said they read their local newspaper for the same purpose (Deacon et al. 2005, 31), with similar numbers saying that they watched some television about news and current affairs each week (90%), or read a daily newspaper (58%) in the 2010 election. Most national newspapers in Britain are partisan and take a clear and explicit party line in their editorials and their reporting of daily news (Newton and Brynin 2001), albeit the strong pro-Conservative bias of many newspapers in the 1980s dissipated without being replaced by equivalent sentiment towards (New) Labour (Bartle 2005) or towards subsequent Conservative-led and Conservative governments.

This analysis of the British elections is intended to extend and validate the findings from our survey of the published literature, which we mentioned may have contained variation in control variables, measurement of media content and differences among respondent groups. In contrast, the UK models are based on the same respondents in the same country using – where necessary – the same control variables, thus accounting for unobserved factors related to audience and model specification. Since media effects may be a function of both content and exposure, we focus on newspaper consumption for which we have content data across a variety of outlets both in 2005 and in 2010 (using data gathered by a team of coders in the Communications Department at Loughborough University). Yet we cannot explicitly account for exposure and content of, for example, television and online media because the lack of coded content for both the 2005 and 2010 campaigns and the impossibility of retroactively obtaining such data. As such, our newspaper consumption models represent newspaper-specific estimates of media effects.

We are again interested in whether model choices affect both the size and the significance of modelled media effects. As with our survey of the media effects literature, we compare the results of a between-subjects model within a cross-sectional survey, a

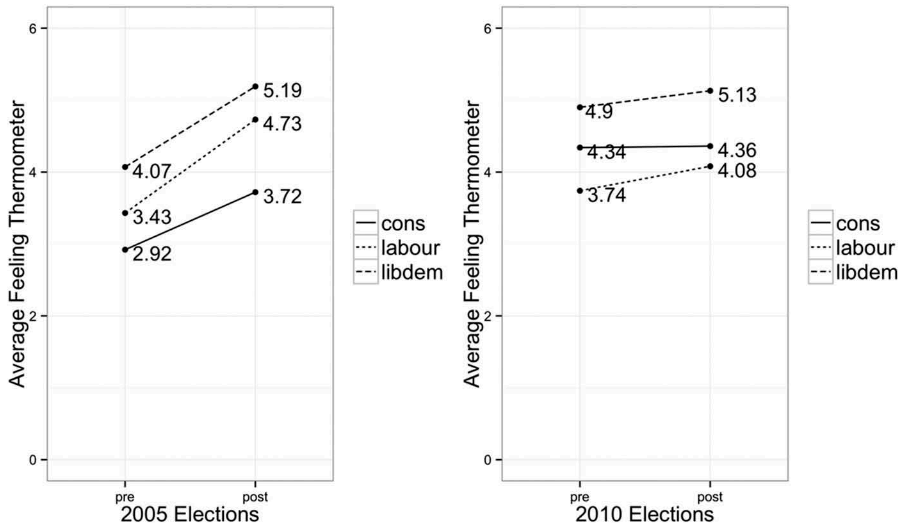

Figure 1. Campaign effects in the 2005 and 2010 elections.

within-subjects model that is also within-survey and a within-subjects model, between-surveys (panel data). Our UK analysis is in two ways more restrictive than our analysis of the published results. First, since we have access to media content in both the 2005 and 2010 elections, we include this in all our models. Second, since for both the 2005 and 2010 elections we have at our disposal pre-campaign and post-campaign survey results, we focus on change in party evaluations rather than post-campaign levels alone, which represents a stronger test of causal influence than a purely cross-sectional model.

For the independent variables in this analysis, we concentrate on two salient and commonly examined aspects of media exposure: the amount of coverage of a candidate or party (visibility) – widespread media effects are less likely when the probability of exposure is low (Zaller 1996) – and its tone (e.g. Althaus and Kim 2006; Stevens et al. 2011) – more negative coverage is likely to diminish evaluations of candidates or parties. We analysed whether the relative visibility and tone of coverage of the three major UK parties at the time – Labour, the Conservatives and the Liberal Democrats – in national newspapers in Britain shifts readers' evaluations of those parties using each of the three models.

These comparisons require that there was change in party evaluations during these campaigns that could be attributable to media reports. Figure 1 shows that in 2005 there was a greater change in evaluations than in 2010 but that there was change in both campaigns, though in 2010 this was mainly for Labour. In 2005, the ratings for Labour increased by 38% (from 3.43 to 4.73) – a change of 1.3 points on a 10-point scale. Conservative evaluations improved by 27% and Liberal Democrat evaluations by 28% (from 4.07 to 5.19). These shifts in evaluations of the parties indicate what could be considered the maximum potential net impact of media coverage on party evaluations in the campaign.

4. Data and measurement

A comparison of the three models requires measures of the visibility and tone of media coverage of Labour, the Conservatives and the Liberal Democrats at two or more points in time and repeated individual-level measures of media consumption and party favourability ratings at two or more points within- and between-elections. The data we use that satisfy these requirements come from two sources. Individual-level survey responses are taken from the 2005–2010 BES panel data set (Clarke et al. 2010), which has repeated measures of the thermometer ratings of Labour, Conservative and Liberal Democrat parties, of newspaper readership at each election, and also of key control variables at each election. The media content variables we use were gathered by a team of coders in the Communications Department at Loughborough University, which analysed election coverage in 2005 and 2010 from 10 daily national newspapers also asked about in the BES (see Stevens et al. 2011; Stevens and Banducci 2013). This team coded all articles about the election in newspapers from the front page, the first two pages of the domestic news section, the first two pages of any specialist section assigned to the coverage of the campaign and the pages containing and facing a newspaper's leader editorials for the duration of the campaign. Using the Loughborough content analysis, we operationalise party visibility by the number of stories in which at least one party actor appeared. Tone refers to the number of stories in which party actors were featured promoting their policies minus the number of articles in which actors were featured defending their own policies from attack. In the analysis that follows, we divide the tone and visibility variables by 20 so that a positive one-unit change denotes a 20-article increase (see the Appendix for the distribution of visibility and tone scores for all newspapers included in the analysis).

Our main dependent variable is constructed from 10-point feeling thermometers about the three parties, ranging from 0 (strongly dislike) to 9 (strongly like). These feeling thermometers were administered before and after the campaign in 2005 and 2010, which allows us to construct within-election and between-election models. Crucially, the thermometer items were administered for each party separately which allows us to make within-subjects models.

Our models are based on those respondents who responded both in 2005 and 2010 to the item 'How often do you read a daily morning newspaper – either the paper version or online?' by answering 'Everyday' or 'Sometimes', and who also reported the particular newspaper they read most often. An individual respondent's scores on the Tone and Visibility variables are thus the values of these variables for the newspaper they read most often.[10]

In the between-subjects model, we also control for a number of demographic variables that previous research tells us influence vote choice in Britain. *Education* is measured by two dummy variables, which denote low education and medium education groups (high education individuals form the excluded category). *Gender* is measured by a dummy variable with 0 denoting female and 1 denoting male. *Labour party identification, Conservative party identification* and *Liberal Democrat party identification* are dummy variables for individuals who identified with Labour, the Conservatives and the Liberal Democrats, respectively, in 2005 or 2010. To control for income effects on vote choice, we include a measure of *Income* on a 4-point income scale with 1 denoting the lowest income group and 4 the highest income group. *Race* is a dummy variable for which 1 denotes white respondents. In order to make sure that the models were estimated on the same respondents, we selected only those respondents with data on all variables in the models.

5. Analysis

5.1. *Between-subjects, within-elections models*

To investigate potential media effects on change in voter attitudes using between-subjects models, we first regress change in party evaluations across the campaign (that is, we subtract pre-campaign evaluations from post-campaign evaluations) on the media content variables and control variables. We then stack the data so that each row denotes a change in party evaluations (summing to a total of six rows per respondent: Labour 2005 and 2010, Conservatives 2005 and 2010 and Liberal Democrats 2005 and 2010), and we control for partisan identification, gender, race and income. Table 2 contains the results of an ordinary least squares (OLS) regression model.[11]

The results point in the same direction for tone and visibility: we find evidence that – across parties – an increase in a party's visibility is associated with a decrease in the change in party evaluations across the campaign (as evidenced by the significant negative coefficient for *visibility*). Furthermore, more negative reporting about a party is associated with a decrease in the change in party evaluations across a campaign (as evidenced by the significant negative coefficient for *tone*).

To capture the size of these effects, we simulate their first differences varying *visibility* (*tone*) from its lowest to its highest values and keeping all other (categorical) covariates at their modal values (Choirat et al. 2015; Imai, King, and Lau 2008). The results of these *first differences* simulations are shown in Figure 2. The results point in a similar direction: overall, the estimated effects for *visibility* and *tone* are estimated to be different from zero. What is more, their substantive size varies between 0 and 0.5 on a 10-point scale, which would have us conclude that media effects on changes in party evaluations in the British elections of 2005 and 2010 were limited and modest in size.

However, we should keep in mind that these results are not conclusive. After all, tone and visibility are not randomly distributed among media outlets and readers are not randomly distributed among outlets, so problems of selection and omitted variable bias, still a drawback of between-subjects models more generally, may affect these results as well.

5.2. *Within-elections, within-subjects models*

Within-subjects models seek to overcome omitted variable bias by comparing the same survey respondent to him or herself. By doing so, both observed and

Table 2. Between-subjects, within-elections models: content and exposure.

Change in party evaluations	
Visibility	−0.046** (0.018)
Tone	−0.120** (0.049)
Constant	0.740*** (0.270)
Observations	3312
R-squared	0.011
Adjusted R-squared	0.008
Residual standard error	1.600 (df = 3301)
F-statistic	3.600*** (df = 10; 3301)

Standardised coefficients and standard errors are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

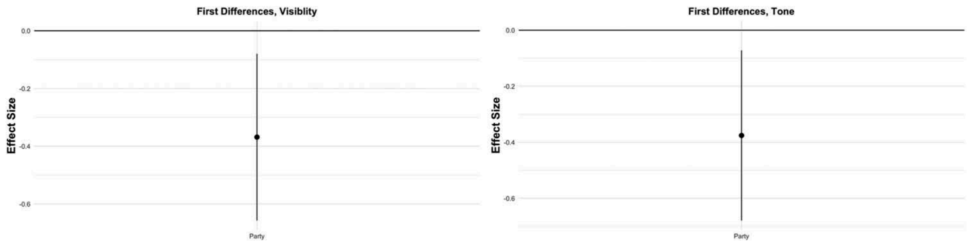

Figure 2. First differences, between-subjects, within-elections models.

unobserved stable differences between respondents accounted for by design. We are able to conduct such a within-subjects analysis because of two features of the data. First, we have multiple observations of changes in party evaluations – summing to a maximum of 6 – for each respondent, both in 2005 and in 2010, for Labour, the Conservatives and the Liberal Democrats. And second, we also have *visibility* and *tone* scores for each of those parties within the same newspaper. In essence, these different scores on newspaper content serve as 'within-subject' treatment variables for readers of that newspaper.

To prepare for a within-subjects analysis, we again stacked the BES data so that each row denotes a single observation of changes in party evaluations. These observations sum to a maximum of six for each individual: Labour 2005 and 2010; Conservatives 2005 and 2010; and Liberal Democrats in 2005 and 2010. We then estimate an OLS model, but this time we include fixed effects for individual respondents to account for stable between-individual variation. The results are presented in Table 3.

Substantively, the results are similar to the between-subjects, within-elections model: for a particular individual and newspaper, an increase in a party's visibility is associated with a decrease in the change in party evaluations across the campaign (as evidenced by the significant negative coefficient for *visibility*). What is more, as a party receives more negative reporting,this is associated with a decrease in the change in party evaluations across the campaign (as evidenced by the significant negative coefficient for *tone*).

We again simulate the size of these media effects by means of an analysis of first differences (Choirat et al. 2015; Imai, King, and Lau 2008). The results of our simulations are displayed in Figure 3. In terms of their size, these effects are similar to the between-subjects, within-elections results: for a particular individual, as a party's visibility increases from lowest to highest point, this is associated with a decrease in evaluative change of about 0.40 point; as the tone of newspaper articles about that party is moved

Table 3. Within-subjects, within-elections models: content.

	Change in party evaluations
Visibility	−0.050** (0.019)
Tone	−0.110* (0.049)
Observations	3312
R-squared	0.240
Adjusted *R*-squared	0.094
Residual standard error	1.500 (*df* = 2758)
F-statistic	1.600*** (*df* = 553; 2758)

Standardised coefficients and standard errors are in parentheses.
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

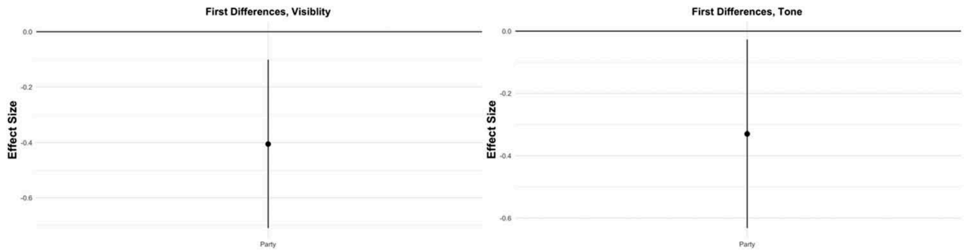

Figure 3. First differences, within-subjects, within-elections models.

from most positive to most negative, this is associated with a decrease in evaluative change of about 0.35 point.

We want to emphasise that the between-subjects within-elections, and the within-subjects, within-elections models are estimated on the same individuals and with the same dependent variable. Substantively, we conclude that content matters most since the results of the between-subjects, within elections (content + exposure) and the within-subjects, within elections (content) are very similar. But what if we compare media effects across campaigns? That is, what if we take into account changes in the environment between the 2005 and 2010 elections? To this question, we turn in the next section.

5.3. *Within-subjects, between-elections models*

With repeated observations for each individual in both 2005 and 2010, it is also possible for us to make models of the media effects of *visibility* and *tone* across elections. In particular, repeated observations allow us to compare the effects of media content changes from one election to the next (for a similar design, see Ladd and Lenz 2015). We construct a difference-in-differences design, modelling the differences in the changes in party evaluations in 2005 and 2010 as a function of the differences in the *tone* and *visibility* scores in both elections. This model gives us some leverage on whether changes in exposure to the same party influence change in party evaluations for a particular individual. We thus keep constant both party characteristics and stable individual characteristics and observe the effect of changes the campaign media environment.

In order to make between-elections models, we first subtract for all news-reading respondents their change in party evaluations in 2005 from their change in party evaluations in 2010. A positive score denotes that the change in party evaluations in the 2010 campaign was larger than the change in party evaluations in the 2005 elections, and a negative score denotes the opposite pattern. For the *tone* and *visibility* variables, we do the same: we subtract *visibility* (*tone*) in 2005 from *visibility* (*tone*) in 2010. We then again stack the data, such that we end up with the following information per individual: difference in the change in campaign evaluations (between 2005 and 2010) for Labour, for the Conservatives and one for the Liberal Democrats, as well as change in *visibility* and *tone* across both campaigns. We then estimate an OLS regression models for our dependent variable on the *visibility* and *tone* variables, including fixed effects for individual respondents. The results of this regression are reported in Table 4.

This time, our results point in the opposite direction than those of the between-subjects, within-elections, and the within-subjects, within-elections models: we find

Table 4. Within-subjects, between-elections models: content and exposure.

	Difference in change in party evaluations
Visibility	0.230*** (0.042)
Tone	−0.092 (0.060)
Observations	1656
R-squared	0.380
Adjusted *R*-squared	0.067
Residual standard error	1.800 (*df* = 1102)
F-statistic	1.200** (*df* = 554; 1102)

Standardised coefficients and standard errors are in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

evidence that a positive change in *visibility* across campaigns *increases* the difference in the change in party evaluations for a particular individual. That is, as the number of articles about a party increases between 2005 and 2010, this is associated with a positive increase in the change of party evaluations. Furthermore, we find no evidence for a significant effect of tone.

We again simulate the change in the probabilities of observing positive campaign effects and negative campaign effects varying *visibility* (*tone*).[12] The results are reported in Figure 4. Interestingly enough, the estimated effect of visibility on the change in party evaluations is estimated to be about four times the size (2) than the estimated effect sizes of our between-elections models.

Whereas the between-subjects, within-elections models and the within-subjects, within-elections models (mostly) indicated a negative effect of visibility on change in party evaluations, our analysis based on a within-subjects, between-elections model points us in the opposite direction: increasing party visibility increases the change in party evaluations, and tone is not found to have any effect, qualifying our results of the within-elections models.

5.4. *Tying the three models together*

We presented a framework comparing three different models of examining media effects, using between-and within-subjects models, could produce three possible outcomes: (1) similar results, (2) results that are similar in size but differ in terms of statistical significance and (3) results that differ in terms of statistical significance and size. Our analysis of published results led us to expect that the third outcome was most likely.

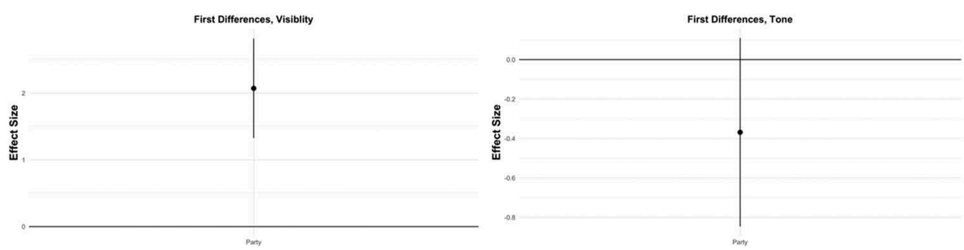

Figure 4. First differences, within-subjects, between-elections models.

Our analysis of the UK elections also shows that we find ourselves in the third scenario: across models, the effect sizes vary and differ in terms of statistical significance and direction. With these results in mind, if we had examined media effects using a within-subjects model, within-elections model alone we might have written a story about powerful British media and pervasive media effects in British elections with both media visibility and media tone having an effect on change in party evaluations. It is not that such a conclusion would be incorrect so much as it would be incomplete, as evidenced by the substantively different results the within-subjects, between-elections model generates.

Substantively, we have shown that the press appears to have affected voters' party evaluations in two British elections. Yet we would be mistaken to speak of clearly defined 'media effects' that point in one particular direction. Instead, the media effects we observed appear to a degree to be model dependent, in line with our analysis of media effects in published results. However, in many respects, our British data offer a better comparison since we are controlling for (some) unobserved factors that we introduced when comparing across designs and contexts. Furthermore, the results from three models are all based on the same survey respondents, whereas our analysis of the published literature is of course based on various groups of respondents. Nevertheless, the results of this validation exercise point us in the same overall direction: substantive conclusions about media effects appear in part to be driven by modelling choices.

6. Conclusion

Bartels' (1993) seminal article on media effects has received more attention for the points it made about problems of measurement than of modelling choices. While Bartels was particularly concerned that research be conducted using data that enable the discernment of effects that are likely to develop over long periods of time, we have argued that an additional and perhaps more pressing issue in contemporary media effects research is the heterogeneity of models coupled with the homogeneity of interpretation of findings as indicative of generalizable media effects. Our analysis of published results in leading political science and communication journals from 2011 to 2015 showed that between-subjects cross-sectional models continue to be most favoured; it also showed that both the size of the effects and the conclusions about their significance are model-dependent: within-subjects models – on average – are more likely than between-subjects models to report significant effect which are also somewhat larger in size. We confirm these findings in our analysis of the UK elections: size and significance of media effects correlate with model selection.

None of the analysed articles evaluate more than one model to gauge the robustness. Yet some studies present opportunities for doing so. For example, Goldman (2012) looks at the relationship between media exposure and changes in within-subject white racial prejudice in the 2008 presidential election using a fixed-effects model applied to national annenberg election survey (NAES) panel data. With regard to his fixed-effects model, he notes that: 'constant effects of individual characteristics (whether observable or unobservable) cannot produce spurious associations. This represents a huge improvement over most observational studies, which rely on potentially contaminated between-person variance' (Goldman 2012, 669). In contrast, we would argue that rather than presenting just a fixed-effects (or within-subjects models for that matter) model, a comparison of results with, for example, a between-subjects model would have been enlightening. If the results of both designs indeed point in the same direction, this would strengthen the substantive conclusion that 'exposure to Obama caused the largest reductions in prejudice among McCain supporters, Republicans, and conservatives' (663). If, however, both designs lead to different substantive conclusions, this would shed light on the robustness of the substantive findings in the paper, especially if the number of observations were to remain unchanged. Furthermore, it would allow us to disentangle whether it is media *content* or *exposure* that matters more.

More broadly, what do we learn from our analysis with respect to media effects? First, in the introduction, we depicted the empirical record with regard to media effects as ranging from 'minimal effects' to 'massive effects' (Pollock et al. 2015). Our analysis illustrates that one possible source of this heterogeneity, raised most prominently by Zaller (2002), is to be found in the variety of models combined with variation in the number of observations that have been used to disentangle these media effects. After all, even though all models had some form of change in party evaluations as a dependent variable, when it came to the role of media content, they pointed to different substantive conclusions. In essence, presenting these models side-by-side serves as a robustness check for each separately. Second, this research illustrates the contextual nature of media effects. Rather than thinking of media effects as an on–off phenomenon, we think of them as partly conditional on model features and their implied comparisons. Effect sizes, significance levels and causal arrows may not transcend beyond their local context, and as such it seems fruitful both theoretically and empirically that the field of media effects research moves beyond the 'minimal effects' versus 'massive effects' paradigms.

While, with our original analysis, we have demonstrated these differences in Britain, they are instructive for other national election studies where similar data collection efforts are used, such as New Zealand, or are being developed as in Australia. Given that the New Zealand Election Study uses a pre–post-design and has an across election panel within-subjects design (see www.nzes.org for description), our findings are particularly relevant. As the Australian Election Study collects its first between-elections panel data in 2016–2019, this will also present opportunities to look at Australian media effects with the different designs that we have employed and thus to establish the robustness of different 'media effects'.

In general, we urge researchers to be precise in defining what is the media effect that they expect to find and with what type of design they intend to analyse it. For many authors, testing for media effects involves the examination of treatment effects with secondary data, as in this paper. Different models may lead to different conclusions, as a result of different microprocesses being tested, the implied treatment (e.g. *content* or *exposure*), statistical power or a combination of these. Where possible, before concluding that there were or were not 'media effects', researchers should subject their findings to additional tests with alternative models, for example, combining within-subjects, between-subjects or panel designs in order to identify and explain variation in effects and their sources. Such checks on the robustness of findings are now commonplace within other areas of political science research (Plümper and Neumayer 2012). In the absence of appropriate data for additional tests, our results suggest that researchers should, nevertheless, be more cautious about over-generalising the implications of their findings.

Notes

1. Citation counts suggest that media effects researchers have focused more on Bartels' criticisms: According to Google Scholar, the citation numbers for these two articles were 890 versus 89 at the time of writing (November 2017).
2. More generally, panel data also have other advantages (e.g. decomposing variation into a between-subjects and a within-subjects component), but there can be problems of non-random panel attrition (Bartels 1999; Frankel and Hillygus 2013), and they can require more advanced statistical techniques, such as corrections to standard errors in order to account for the longitudinal nature of the data.
3. This is not a meta-analysis, which would look at published and unpublished work over a wider range of journals and a greater time period; our intention here is simply to get a systematic idea of the methods that are being used in contemporary media effects research and whether they appear to provide different results. Another point where our survey of the published results departs from a meta-analysis is that it does not address factors like methods of coding, the inclusion of various independent factors as control variables, the way the researchers deal with 'no answers' or 'undecided' responses and whether or not measures such as interactions effects terms were included in the models. The journals we used were *American Journal of Political Science, American Political Science Review, Journal of Politics, Journal of Common Market Studies, Comparative Political Studies, Journal of European Public Policy, West European Politics, British Journal of Political Science, Annual Review of Political Science and Political Analysis for Political Science and New Media and Society, Journal of Communication, Public Relations Review, Journal of Computer-Mediated Communication, Journal of Pragmatics, Journalism, International Journal of Communication, Public Opinion Quarterly, Communication Research and Media, Culture and Society for Communication*.
4. We exclude papers that report the results from experimental designs from this analysis. A majority of these experiments took place in the lab with only a handful occurring out in the real world in the form of a field experiment or a quasi-experimental design. Since our emphasis in this paper is on a comparison of three models in detecting large-scale media effects, we choose to focus on observational studies alone. In order to be able to compare results with those of our UK analysis, we also exclude studies that have behavioural or emotional rather than cognitive dependent variables. The effect sizes in the observational studies we report are about half as large as the average effect size (d = 0.21) in the experimental results that we also collected.
5. NB: we only analysed one within-subjects design (Banducci, Giebler and Kritzinger 2017) with no time component. Because of that, we grouped it with the within-subjects over time models. Over Time models refer to panel, time-series or rolling cross-sectional designs in this analysis.
6. Although we do not report it in Table 1, the analysis of media effects articles also shows that a majority of studies are conducted in a single country with only a very small minority of papers making cross-country models even though there is reason to believe that media systems matter when it comes to media effects (Pollock et al. 2015; Schoonvelde 2014).
7. That is, d is estimated using the t-statistic multiplied by 2, divided by the square root of the degrees of freedom of the model. As such, it takes into account the number of observations the model is based on.
8. Since we considered knowledge, attitudes and evaluations as outcomes, we have also broken down our effect sizes for each of these outcomes separately. Because we did not find any systematic differences across outcomes, we decided to take them together in the presentation of our results.
9. This could be disputed on the grounds that the press in Britain is partisan, readers select outlets that accord with their partisan predispositions and what one observes is therefore selection effects rather than media effects. However, recent studies, for example Stevens et al. (2011), suggest that this account is simplistic and that there are short-term media effects on partisans in British elections. Research on partisan media in the USA also suggests effects that are not just an artefact of self-selection (Dilliplane 2014; Smith and Searles 2014).

10. For a discussion of self-reported items in media effects research, see Jerit et al. (2016).
11. To keep the regression output clear and concise, we did not include parameter estimates for the control variables in the table. The model displays the results of the regression of the change in party evaluations on party visibility, party tone, party identification, medium education dummy, low education dummy, gender, income and race. All regression tables were constructed using the Stargazer package in R (Hlavac 2013).
12. The lowest value (−1) for *visibility* and *tone* (−1) now denotes a situation where visibility (tone) is larger (more positive) in 2005 than in 2010, whereas the highest value (+1) denotes a situation where visibility (tone) is larger (more positive) in 2010 than in 2005.

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Appendix

Table A1. Tone and visibility in 2005 newspapers.

newspaper	lab vis	lab tone	cons vis	cons tone	libdem vis	libdem tone
1 daily mail / scottish daily mail	104	-16	52	5	26	3
2 daily telegraph	169	18	131	21	74	14
3 express	60	-5	44	6	8	1
4 financial times	121	38	78	11	31	3
5 guardian	153	25	105	17	64	15
6 independent	125	15	84	1	52	5
7 mirror/scottish mirror/daily record	118	26	78	1	36	3
8 times	96	20	75	5	40	7

Table A2. Tone and visibility in 2010 newspapers.

newspaper	lab vis	lab tone	cons vis	cons tone	libdem vis	libdem tone
1 daily mail / scottish daily mail	80	3	86	23	72	1
2 daily telegraph	108	-5	100	31	69	-1
3 express	94	3	89	35	61	3
4 financial times	99	1	91	28	60	3
5 guardian	88	-1	74	25	51	7
6 independent	85	7	77	24	54	5
7 mirror/scottish mirror/daily record	108	10	110	19	62	8
8 times	90	5	81	18	57	1

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