Non-response Bias in Candidate Surveys*

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Abstract

The study of parliamentary candidates has been in the rise in the recent years. The Comparative Candidates Survey (CCS) has been applied in more than 20 countries, but they are still the object of criticism. Some of these relate to their alleged low response rates, assuming the presence of bias and, thus, lack of validity. We assess this issue by focusing on the 2010 and 2015 British candidate surveys. We observe that there are clear predictors of non-response that coincide in both years, such as ethnicity, electoral success, and political parties. However, we find that those differential response rates do not always have a substantive effect on a series of attitudinal and behavioural responses. We argue that candidate surveys can produce valid estimates as long as we identify and correct for potential biases.

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I. Introduction

Understanding the attitudes, behaviours, and careers of political elites is of key importance in the study of political representation. Those who are in charge of making decisions within political parties have a great deal of responsibility in seeking levels of congruence with their potential electorate. Furthermore, there are questions about their levels of descriptive representation, which relate to their demographic origins and they ways in which they are selected (or elected) to their positions. Notwithstanding the importance of understanding such elites, mainstream studies on the topic are usually limited to those who already hold public offices, such as MPs, local government officials, or cabinet ministers.

Candidate studies, particularly in the shape of candidate surveys, are designed to overcome this limitation by targeting not only those who achieve public office, but also those who seek them. Candidates also represent a wider sample of those who hold decision powers within political parties and other structures. The way in which they behave, campaign, take position on key issues, and are selected, tells a detailed picture of the internal politics of the parties, as well as the way in which they relate to their electorate.

Regardless of the advantages that candidate surveys offer to study political elites, there are serious criticisms about their validity. Since the start of the Comparative Candidate Survey, in 2005, more than 30 elections in 24 countries have been studied using several waves with common questionnaires. This exercise allows for valid comparisons between different countries and across different political systems. However, the response rate amongst these studies has varied widely across countries and elections. For example, for the 2006 Czech election, only 16% of the candidates responded to the survey, which is a stark contrast to the 67% of respondents from Iceland in 2009. This has led to critics questioning the real validity of the data provided by these surveys, given the potential effects of non-response bias.

The purpose of this paper is to provide the first, to our knowledge, comprehensive study of non-response bias in candidate surveys. We take advantage to the existence of a novel dataset from the Britain's New Political Class project, funded by the Leverhulme Trust. The dataset contains demographic information from all the British parliamentary candidates since 1945, effectively creating a census of candidates. We use this data to compare it with the respondents of the 2010 and 2015 British Candidate surveys. We use different statistical models to focus on three sources of potential non-response bias: individual level factors, such as sex and party affiliation; contextual level variables, such as the marginality of the constituency and the racial composition of the electorate; and issues related to the application of the surveys, such as the availability of the candidates' home address, amongst others

Our results show that there are differences between respondents and non-respondents, particularly in terms of political party, incumbency, and electoral success. Candidates from the Conservative Party are less likely to respond to the surveys, as well as incumbent candidates in general. A similar difference is observed with those who won the election, and BME candidates. Finally, home address availability is also a strong predictor or response.

Although we find significant differences between both groups – respondents and non-respondents, those differences do not seem to affect the overall validity of the results. Using weighting strategies, we compare the results of a series of attitudinal variables to assess any significant differences between weighted and unweighted estimators. The differences observed are not substantive enough to be a cause of concern. Furthermore, with the right corrections such as post-stratification, we can improve relevant estimators, where needed.

II. The principles of non-response bias

In survey research, full populations are usually hard to reach and observe directly. Hence, researchers turn to samples to understand variables of interest from the whole population. However, in order to obtain valid measures about the population, the error contained in the samples should be accounted for.

Traditionally, studies have tried to solve this problem by using simple random samples (SRS), where the probability of getting sampled is, theoretically, the same for every individual in the population (or the sampling frame, to be more specific). Nevertheless, survey research (Riley et al., 2014; Baker et al., 2013; Wang et al., 2015) has also shown that such samples are increasingly more difficult to reach, and what usually happens is that some people decide not to respond to the requests for a survey. Such phenomenon is what we call non-response.

Non-response occurs when someone who is selected to be part of the sample decides not to answer it. The fact that someone decides not to respond is not a source of bias in itself. Non-response bias, on the other hand, consists in a systematic characteristic that distinguishes those who respond from those who do not (apart from the sole act of responding). Therefore, we are particularly interested when those features are correlated with our variables of interest. For example, most political polling is concerned with vote choices, but recent evidence from the UK (Sturgis et al., 2016) shows that supporters of the Conservative party are less likely to answer the surveys, which required several adjustments from pollsters. Conversely, when non-response occurs randomly, it is not the source of bias.

In formal terms, we specify the argument in the following way. Being Y our variable of interest and X the variables that predict non-response, we are not concerned when $cor(X, Y) = 0$. In that case, we can assume that non-response occurs at random, with respect to our variable of interest (or completely at random). The following case is more complicated, and refers to when $cor(X, Y) \neq 0$. In this situation, we need to find ways to account for the inherent bias in the sample. The worst case scenario is when $X = Y$, that is, that our variable of interest is the one that predicts non-response.

Both the first and the second scenarios are workable options. In the former, we do not need to do anything, and the sample we obtain can provide valid and unbiased estimates of the population. In the latter, we can also obtain valid an unbiased estimates, but we need to assess the size and direction of the bias, and find ways to control for it. In the third scenario, the situation is more difficult, as we need to rely on heavy assumptions to account for the bias. Nevertheless, to our knowledge, none of such analyses have been produced in the case of candidate surveys.

i. Response rates and non-response bias

A simple, yet naive, criticism to candidate surveys relies on the low response rats obtained by some of the participating countries. In simple, the argument goes by saying that low response rates produce an insurmountable lack of validity. Hence, the results obtained by the candidate surveys would not be able to produce accurate pictures of the attitudes and behaviours of parliamentary candidates, even after assuming a low or nonexistent measurement error.

This is not a new criticism to survey research, low response rates have been historically blamed for low external validity of estimates. However, this argument has been consistently dismantled in the literature. Leslie Leslie (1972) explored this issue using data from the US, his findings show that low response rates are not a direct source of bias, particularly when we investigate fairly homogeneous groups (such as parliamentary candidates).

A similar argument is made by Groves (2006) when discussing the cases when non-response rates are related to non-response bias. In his view, the main question is not about how many people responded the survey, but what makes them respond (or not) and how that relates to our variables of interest. Furthermore, his analysis finds no clear empirical link between non-response rates and bias. The main issue with non-response, according to Groves, arises in the case of probability samples, where non respondents are usually replaced. In those cases, it is important to study the sources of non-response to account for them in the sampling process and later.

One way to account for differential non-response is to target those who are less likely to respond using incentives. This option has been studied in the past (Rogelberg and Stanton, 2007) and focuses on the role of external data sources to help assessing and correcting the bias. Recent research (Bailey, 2017) tries techniques within the survey, such as experiments and opt-in questions, to assess both survey and item non-response[1], with successful results.

Beyond the debates about how to assess non-response bias, the main issue is whether low response rates are closely – and linearly – associated with non-response bias. Groves and Peytcheva (2008) aim to settle the debate with a large meta-analysis of survey studies. Their main findings show that the relationship is not direct, and that high response rates are not directly related to lower bias. In their view, survey researchers should focus on understanding the differences between respondents and non-respondents, both at the individual and survey basis. This is exactly what we aim on this paper.

ii. Bias in small-group surveys

The study of non-response bias on small groups is fairly underdeveloped. Even more in the case of elite populations, such as parliamentary candidates. The field where this topic has been covered more widely is in the study of rallies, protests, and manifestations.

Rüdig (2010) used a combination of face-to-face and mail surveys to assess the non-response bias of protesters in Glasgow. His findings show that there are several variables, usually associated to individual resources (e.g. education, income, higher cost of participating in the protest) that are also associated with a higher probability of responding to the mail survey. He also finds that women are more likely to respond. Rüdig uses the face-to-face surveys, which reached a near perfect response rate, as a comparison point for the mail survey.

Porter and Whitcomb (2005) have similar findings on their study of non-response among higher education students. Apart from individual resources, measured with income-related variables, they authors find a great role of different personality traits on the probability of response. Furthermore, they also find that women are more likely to take the survey than men.

[1] In this paper we focus on survey non-response, but we acknowledge the relevance of understanding the low response on some items above others.

Bundi et al. (2016) study a different aspect of survey responses, but with a similar population as candidate surveys. They focus on misrepresentation in legislative surveys by comparing the responses given by legislators and their positions on the same issues obtained through other sources. Their findings show relevant differences, and also provide useful insight on different forms of asking sensitive information from legislators. However, their focus is not on non-response, but on misrepresentation.

Apart from these three studies, the literature on survey research and small populations is rather scarce. Rogelberg et al. (2003) focus on organisational surveys and study the size of non-response bias. Their findings show that the type of questions and the topics covered in the survey are closely associated to the probability of response. In the study of crowds and rallies, Seidler et al. (1976) in their seminal study show the first systematic approach to survey rally participants. Their concern with non-response is covered with, in their opinion, a near random approach to sampling.

In the study or candidate survey, to the best of our knowledge, there is no systematic study of non-response rates and bias. Furthermore, we believe that this paper contributes to both the particular debate about how to improve candidate surveys, and to the general debate about elite research and access.

III. Empirical strategy to study non-response in candidate surveys

One of they main problems assessing non-response in candidate surveys is that, more often than not, there is no available information about the whole population of candidates. Only a few of electoral authorities compile a full list of candidates that contain relevant information for the study of non-response bias, such as education levels. In the particular case of the United Kingdom, the electoral administration takes place at the local level, which means that there is no official compilation of the information.

We take advantage of the work from the "Britain's New Political Class" project, that has collected information from parliamentary candidates since 1945. The project has created, in practice, near perfect information about the whole sampling frame of candidate studies. That allows us to compare directly the relevant characteristics of respondents and non-respondents. We also include data from the parliamentary constituencies in which the candidates are running.

We use hierarchical regression models (described below) to analyse the role of the different predictors, focusing on three different areas: individual characteristics of the candidates, contextual variables of the constituencies where the candidates are running, and variables related to the way in which the survey is conducted. We believe that the interplay of these three layers can account for the different reasons behind the decision of responding or not.

Finally, we use the information from the models to assess the potential relation between the variables that predict non-response and certain attitudinal variables of interest. We use a raking algorithm to produce post-stratification weights, and then use them to study the difference between weighted and unweighted estimates.

i. Description of the data

Our data come from a variety of sources, such as the Parliamentary Candidates UK (`www.parliamentarycandidates.org`) endeavour, that hosts different projects studying parliamentary candidates. We also include data from the British Election Study Results dataset, and the 2010 UK General Election dataset collected by Norris and Singleton (2010). To construct the sampling frames, as described above, we use the "Britain's New Political Class" datasets, that contain information about the candidates' demographics and careers.

The main purpose of this study is to analyse non-response bias in candidate surveys. We focus on two particular surveys, the ones collected for the 2010 and 2015 elections. Both surveys were collected through a combination of postal and online questionnaires. We focus on these two elections as both are part of a larger network of candidate studies, the Comparative Candidate Study (CCS).

As explained above, one of the common criticisms of candidate surveys relate to low response rates. Figure 1 shows that those concerns are mostly unwarranted. The response rates of the recent two candidate surveys are comparable to the main public opinion survey in the UK, the British Election Study. Furthermore, the figure also compares the British surveys for wave 1 (2009-2013) against the response rates on the other participating countries. The UK surveys are well above the average of the CCS project.

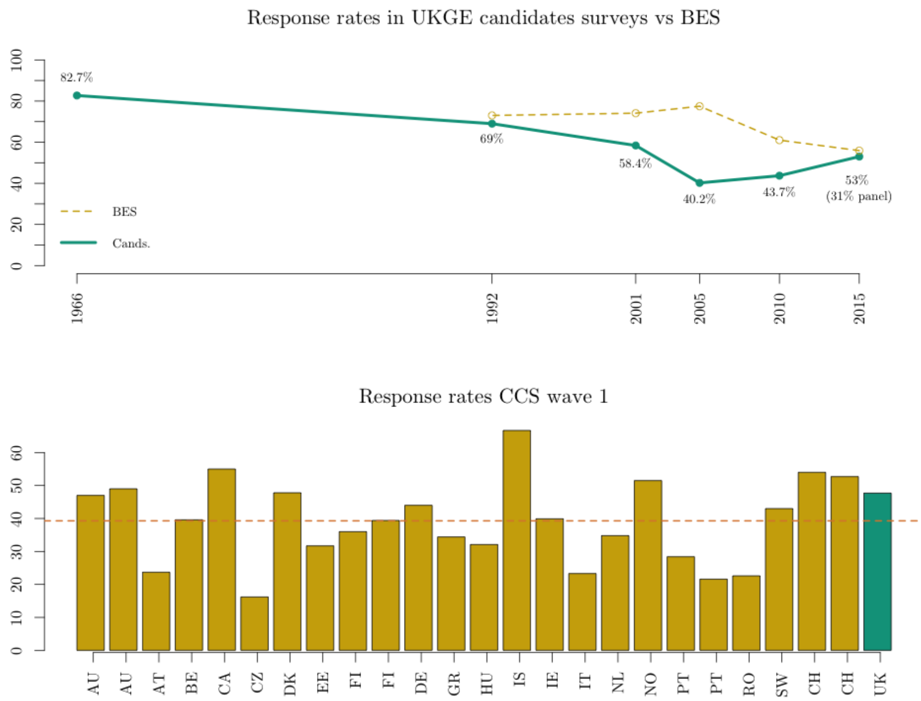


Figure 1: *(Above) Response rates of candidate studies over time; (Below) CCS response rates for wave 1 compared to UK 2010 study.*

ii. Models

In order to assess the potential bias, we use hierarchical logistic regression models, where we estimate both the individual effects on non-response and allow the intercepts to vary across each of the 632 British constituencies. That approach allows us to model the role of contextual variables into the individual level decision. The main dependent variable is whether the candidate responded the surveys or not.

We group the independent variable in three groups. The first one refers to individual level characteristics of the candidates, such as sex, whether the candidate can be identified as black or ethnic minority (BME), their political parties, whether they are incumbent, and whether they won the election[2].

The second group corresponds to contextual variables at the constituency level.

[2]The 2010 survey was fielded after the election, whereas the 2015 survey had pre and a post election waves

We included a variable measuring whether the constituency is a marginal one, the percentage of white population, the proportion of home owners, and the proportion of immigrants.

Finally, the third group corresponds to those variables related to the administration of the survey. We have included the availability of the candidates' address[3] and email (for 2010 only). For those candidates who did not publish their addresses, we used alternative ways of finding the information, such as contacting their election agents, looking at their addresses for concurrent elections, and requesting their details through their parties. For the 2015 election, the Conservative Party decided to send the surveys themselves, which ensured that all candidates had the correct address.

iii. Results

Figures 2A and and 2B show some of the descriptive statistics of our data. In particular, we look at the response rates for 2010 and 2015 between men and women, and by party. As we can observe, in both years the difference by sex is almost non-existent. Unlike the findings from other elite or small-group surveys, female candidates are not more likely to respond to the surveys. The political party, on the other hand, appears strongly associated with the decision to respond the survey. Particularly, conservative candidates are the least likely to respond in both years.

Table 1 shows the regression results for the 2010 survey. As it was hinted by the descriptive results, the Conservative Party candidates (the baseline category, therefore excluded from the table) are least likely to respond than candidates from other parties, with the exception of the candidates from the British National Party (BNP). This difference appears even even after controlling for other individual and contextual factors. Further, incumbent candidates and those who won the 2010 elections (but were not incumbents) are also less likely to respond. Finally, BME candidates also show a lower probability of response.

The contextual factors do not appear to make a significant difference after controlling for other independent variables. However, the two variables added that relate to the "contactability" of the candidates show significant results. As explaining above, the fact that a candidate did not disclose their address does

[3]Candidates in the UK are required to publish their home address, unless they opt-out. The addresses are published in the Statements of Persons Nominated (SOPNs) issued by every local authority. We collected the information from all SOPNs to assess which candidates publish their addresses and who does not.

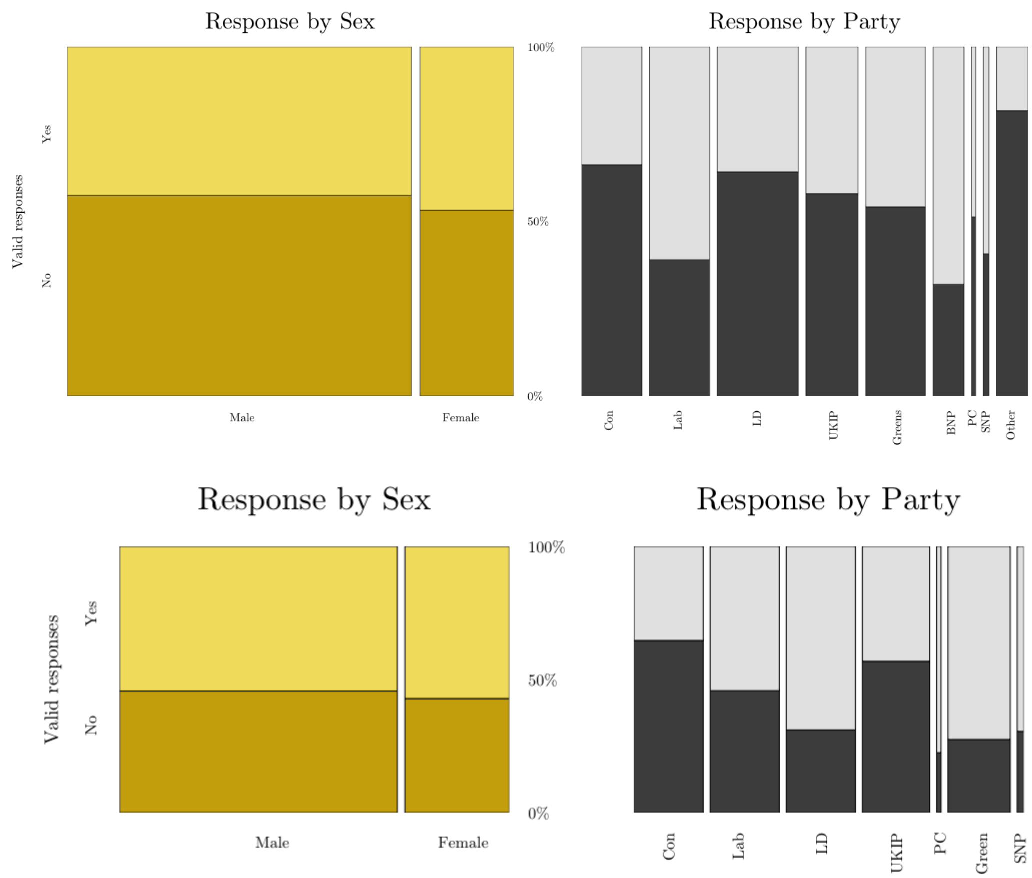


Figure 2: *(A - above) 2010 Candidate survey responses; (B - below) 2015 Candidate survey responses.*

not mean that we were not able to send them the survey. Thus, what we observe here is the association between the decision of withholding the address and their decision to respond. Finally, the coefficient for the email availability is difficult to interpret. A large number of email addresses in 2010 were assigned by the political parties, or where simply contact addresses created for the campaign.

The results from the 2015 survey, shown in Figure 2, present a similar picture than the 2010 results. The Conservative party candidates are the least likely to respond, with the exception of the UKIP candidates (which have no significant difference from the Conservatives). BME, incumbent, and winners are also less likely to respond.

We also observe a similar pattern in 2015 with respect to contextual variables. None of the constituency level variables show a significant relationship with the

Table 1: *Regression results for 2010 survey*

	Individual Factors	Contextual factors	Individuals & Contextual	"Contactability"	Full Model
Intercept	$-.32$ $(.10)^{**}$	-2.02 $(.38)^{***}$	-1.62 $(.43)^{***}$	$-.08$ $(.07)$	$-.68$ $(.45)$
Female	$.04$ $(.08)$		$.04$ $(.08)$		$.09$ $(.09)$
BME	$-.60$ $(.16)^{***}$		$-.49$ $(.16)^{**}$		$-.32$ $(.17)$
Labour	$.57$ $(.12)^{***}$		$.56$ $(.12)^{***}$		$.46$ $(.13)^{***}$
Green	1.08 $(.15)^{***}$		1.09 $(.16)^{***}$		1.04 $(.16)^{***}$
BNP	-1.18 $(.17)^{***}$		-1.16 $(.17)^{***}$		-1.90 $(.19)^{***}$
UKIP	$.02$ $(.13)$		$.01$ $(.13)$		$-.53$ $(.14)^{***}$
Other party	$-.21$ $(.12)$		$-.18$ $(.12)$		$-.55$ $(.13)^{***}$
Plaid Cymru	$.34$ $(.33)$		$.35$ $(.33)$		$.05$ $(.35)$
SNP	$.80$ $(.28)^{**}$		$.85$ $(.28)^{**}$		$.73$ $(.30)^{*}$
LibDem	$.90$ $(.12)^{***}$		$.90$ $(.13)^{***}$		$.84$ $(.13)^{***}$
Incumbent	$-.55$ $(.15)^{***}$		$-.54$ $(.15)^{***}$		$-.55$ $(.15)^{***}$
Won election	$-.44$ $(.13)^{**}$		$-.42$ $(.14)^{**}$		$-.30$ $(.14)^{*}$
Marginal const.		$.15$ $(.07)^{*}$	$.18$ $(.08)^{*}$		$.22$ $(.08)^{**}$
White %		$.01$ $(.00)$	$.01$ $(.00)$		$.01$ $(.00)$
Turnout '05		$.02$ $(.01)^{**}$	$.01$ $(.01)$		$.01$ $(.01)$
Migrants %		$.05$ $(.06)$	$.02$ $(.06)$		$.04$ $(.07)$
Professional %		$.00$ $(.01)$	$.00$ $(.01)$		$.00$ $(.01)$
Provide home add.				$.64$ $(.07)^{***}$	$.33$ $(.08)^{***}$
Email availab.				-1.01 $(.07)^{***}$	-1.46 $(.08)^{***}$
BIC	5280.79	5532.82	5253.34	5324.85	4918.18
Log Likelihood	-2586.39	-2737.37	-2547.86	-2645.81	-2371.99
Num. obs.	4056	4019	4007	4064	4007

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Baseline party: Conservative

decision to respond the survey. Finally, for 2015 we only focused on whether the candidates provided their home addresses or not, since we obtained the email addresses for all the 3174 candidates from that election. The results are, again, consistent with 2010, and those who provided their addresses are more likely to respond.

One way to assess the magnitude, and not only the significance, of the results is by estimating the change in probabilities for some of the variables. In this paper we focus on the role of incumbency, and study what is the difference n predicted probabilities between incoming and incumbent candidates. In order to account for the uncertainty around our estimates, we used pseudo-Bayesian simulations.

Figure 4 shows the difference between incumbents in 2010. As it can be observed, incumbents are roughly 0.1 points below non-incumbents, bringing the

Table 2: *Regression results for 2015 survey*

	Individual Factors	Contextual factors	Individuals & Contextual	"Contactability"	Full Model
Intercept	$-.03$ (.11)	.04 (.51)	.05 (.55)	$-.20$ (.10)*	.11 (.56)
Female	$-.05$ (.09)		$-.05$ (.09)		$-.05$ (.09)
BME	$-.75$ (.15)***		$-.77$ (.15)***		$-.77$ (.15)***
Labour	.70 (.12)***		.70 (.12)***		.98 (.16)***
LibDem	.97 (.13)***		.97 (.13)***		1.31 (.18)***
UKIP	$-.19$ (.13)		$-.19$ (.13)		.16 (.18)
Plaid Cymru	1.39 (.39)***		1.40 (.40)***		1.74 (.41)***
Green	1.06 (.14)***		1.05 (.14)***		1.40 (.19)***
SNP	1.33 (.32)***		1.35 (.32)***		1.61 (.33)***
Incumbent	$-.81$ (.15)***		$-.81$ (.15)***		$-.79$ (.15)***
Won election	$-.39$ (.16)*		$-.39$ (.16)*		$-.31$ (.16)
Marginal const.		$-.00$ (.07)	$-.02$ (.08)		$-.02$ (.08)
White %		.01 (.01)	.00 (.01)		.00 (.01)
Turnout '10		.00 (.01)	.00 (.01)		.00 (.01)
Non-Migrants %		$-.01$ (.01)	$-.00$ (.01)		$-.00$ (.01)
Professional %		$-.00$ (.02)	$-.00$ (.02)		.00 (.02)
Provide home add.				.47 (.10)***	.47 (.17)**
BIC	4069.56	4411.31	4108.01	4363.18	4108.35
Log Likelihood	-1990.43	-2181.47	-1989.51	-2173.53	-1985.64
Deviance	3980.87	4362.93	3979.01	4347.06	3971.29
Num. obs.	3174	3173	3173	3174	3173

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Baseline party: Conservative

probability to 0.22. In 2015 – Figure **??** – we see an increase in the difference in predicted probabilities between incumbents and non-incumbents (0.18).

In summary, our results allow us to study, for the first time, the main determinants of non-response on candidate surveys We observe a clear difference between political parties, and also between those who hold office and who do not. In terms of demographic characteristics, black and minority ethnic candidates are significantly less likely to provide their answers than white candidates.

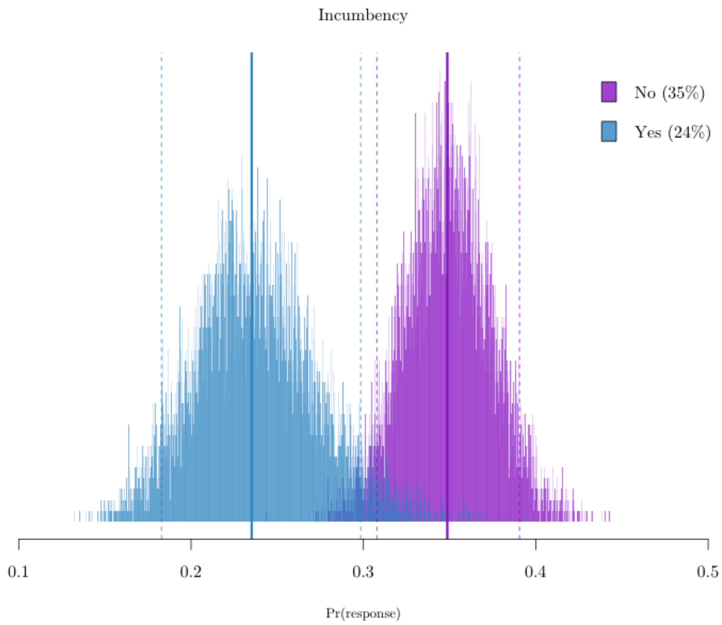


Figure 3: *Predicted probabilities for 2010 incumbents*

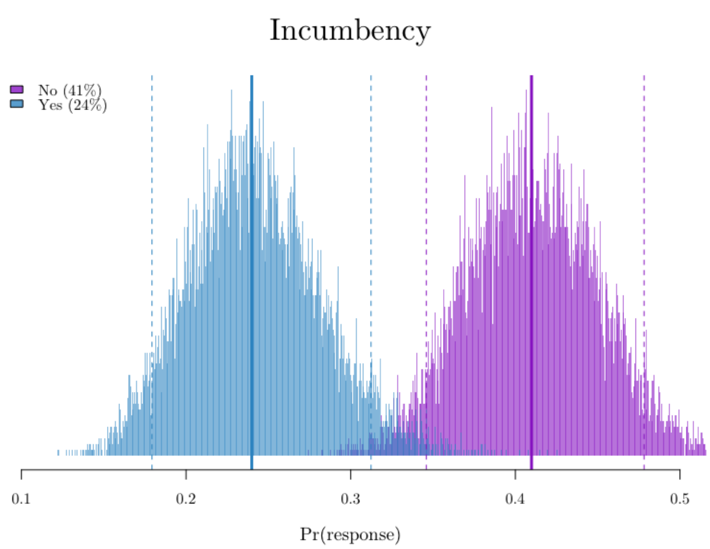


Figure 4: *Predicted probabilities for 2015 incumbents*

IV. Is there a substantial non-response bias?

As we discussed above, the concern about non-response is related mostly to our variables of interest. That is, when non-response does not happen randomly, we need to check the correlation between the predictors of non-response and those variables of interest in the survey. One way of assessing that is by studying the correlation directly, but that is not always possible, as the responses for our variables of interest might be dependent on the predictors of non-response. Alternatively, researchers have used weighting or post-stratification techniques as a catch-all approach, in the expectation that by creating weights, we can account for the systematic differences between respondents and non-respondents.

Although this might look like a sensible approach, there is an on-going discussion of the extent to which we can use weights beyond simple descriptions. Gelman (2007) argues that using weights on regression models is not always the best choice, and therefore discourages their use as a default. What is more important to us, blindly using survey weights does not allow us to assess whether our estimates are biased by non-response or not. If the unweighted estimators do not differ from the weighted ones, then we should not be too concerned about the potential bias.

Using the results from the previous sections, we estimated survey weights for all of our respondents, based on their parties, ethnicity, incumbency status, and electoral success. We used a raking algorithm to incorporate all of these variables into the same weight, and then produced descriptive statistics comparing the weighted and the unweighted estimations.

Figure 5 shows the difference, for 2010 (**??**) and 2015 (5B), between the weighted and the unweighted responses for the left-right self positioning scale. As we can observe, there is a small difference between both estimates, with the weighted average being closer to the right than the unweighted one. A simple explanation for this would be that conservative candidates are less likely to respond, and the weights seem to be accounting for that. However, in both years, the difference between the averages is not statistically significant, with *p*-values above the conventional $\alpha = 0.05$ threshold.

We then tried the same approach with another attitudinal question, this time focused on immigration. The candidate survey asked, in both years, a question about respondents' agreement with the statement that immigrants need to adjust to the UK customs.

We estimated the difference between weighted and unweighted responses for both years, by party. As it can be observed in Figure 6 A and B, the main differences do not take place in the distribution around the mean, but on the

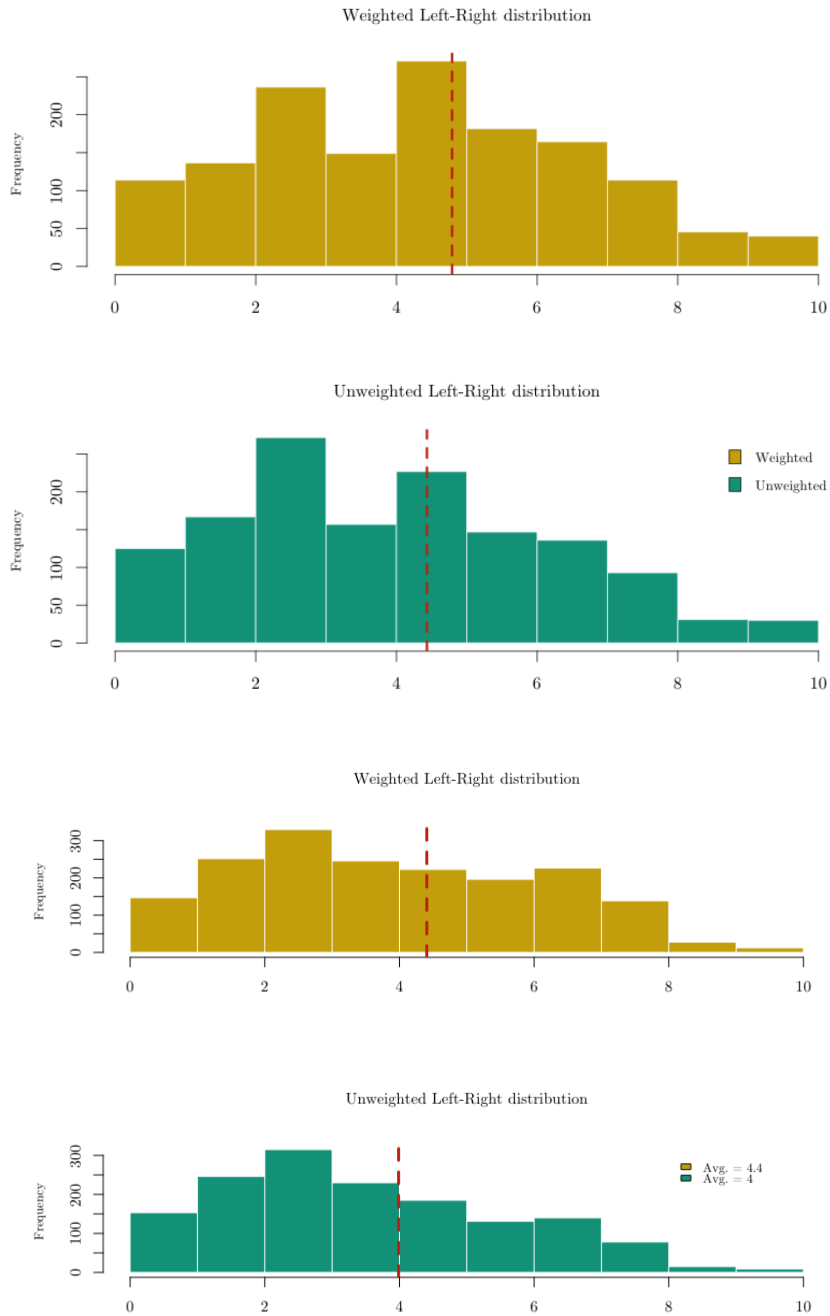
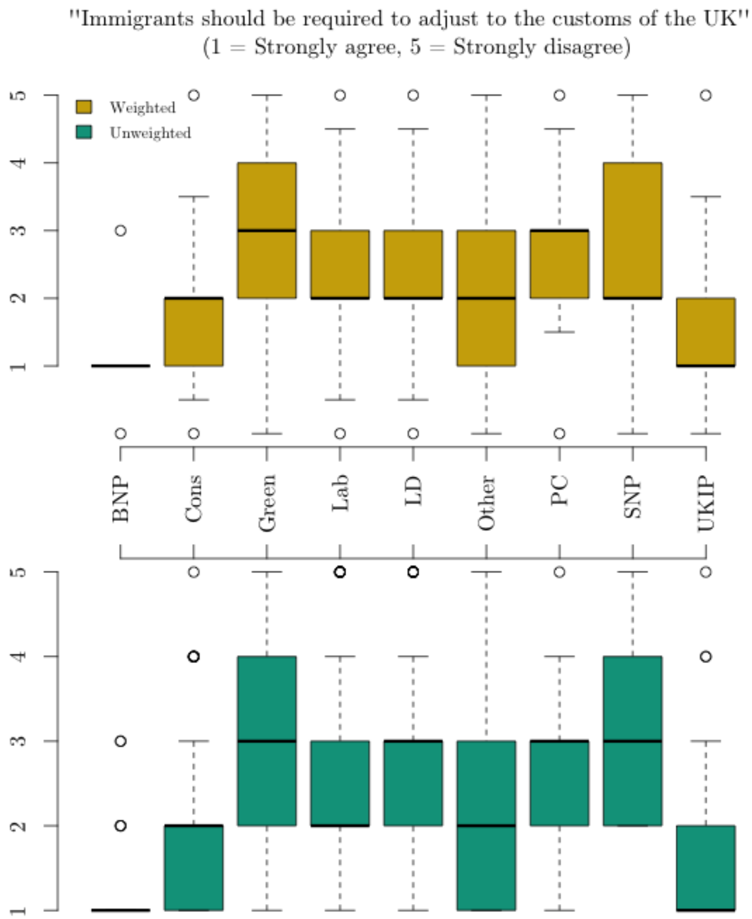


Figure 5: *(A - above) 2010 Left-Right responses; (B - below) 2015 Left-Right responses.*

means themselves. With the exception of the Scottish National Party candidates in 2010, we don not find any differences between the sets of estimates.

Finally, we focused on a more contingent issue. For the 2015 survey, candidates were asked about their position on the upcoming (at the time of the survey) Brexit referendum. As we can see in Figure 7, in this case we do observe a substantive (and statistically significant) difference between the weighted and unweighted sample. We see a decrease of the remain vote once we add the weights, which might be the outcome of accounting for the differential response rates by party.

Looking at the differences observed question by question might not be the more useful approach when it comes to the use of survey weights. However, it is important not to incorporate new sources of bias in our estimates when we do not need them. Survey weights are constructed using a combination of variables, and it is not always feasible to do some reverse engineering to disentangle which particular variable had more relevance for every single estimation. We call for caution when using weights, but more importantly, we show that they are not always necessary when it comes to candidate survey data. Furthermore, we take these results as a signal of the validity of the survey data.



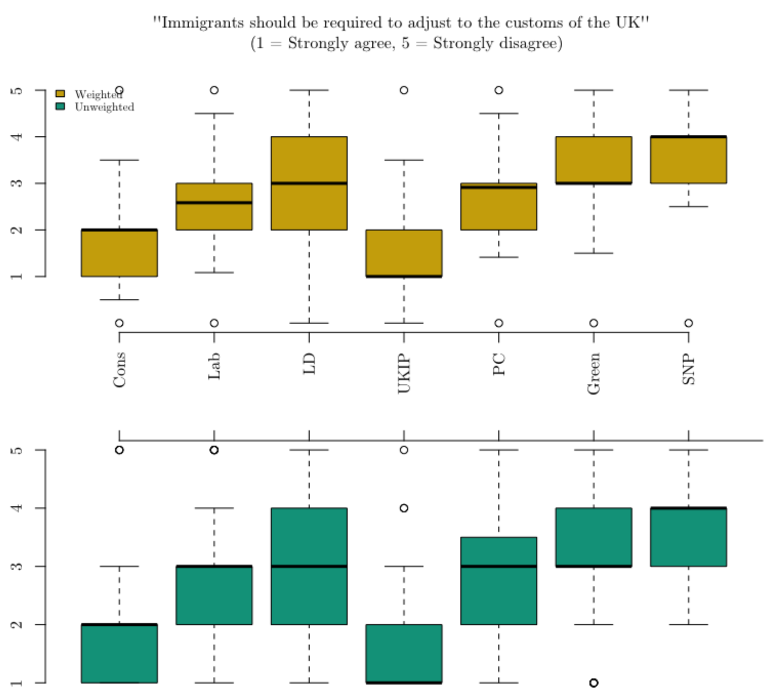


Figure 6: *(A - above) 2010 Immigration responses by party; (B - below) 2015 Immigration responses by party.*

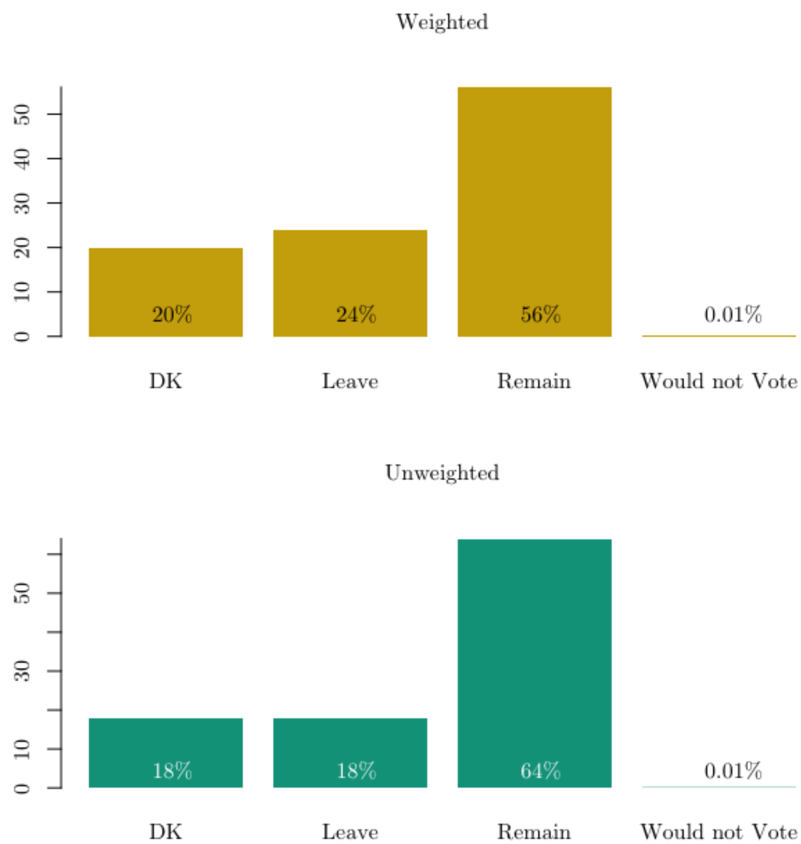


Figure 7: *Vote choices for the Brexit referendum.*

V. The road ahead: Plans for a future research agenda

The agenda for candidate studies is growing. Every wave of the CCS brings more countries into the study, and researchers around the world are increasingly interested in expanding the study of political elites from legislators to candidates. One of the traditional, but we believe mostly unwarranted, criticism relates to the response rates of candidate surveys. In this sense, candidate surveys could not provide the adequate validity to obtain substantive results from them. Thus, they are not fit for rigorous academic research. We dispute that claim.

Our results above show two things. First, that there are differential response rates, explained by demographics (ethnicity), party affiliation, and position. Second, that once accounted for, those differences do not produce a large amount of bias on several descriptive estimates.

In the future, researchers will need to develop more fine-tuned variables to investigate other determinants of non-response, and observe whether they matter in terms of descriptive statistics. We are particularly concerned about the role of the survey team as a source of bias. Although all teams aim for consistency, there are situations out of the team's control that create differences in the way certain candidates are reached; we need to account for them. Furthermore, we need to investigate other individual incentives to respond, such as the difference between front and backbenchers (for incumbents), and between those who have previous political experience and those who are new to the job.

Another contribution of our work is to highlight the relevance of building accurate datasets of candidates, alongside the application of the survey. Where possible, we recommend survey teams to produce an accurate picture of their sampling frames by collecting data from all available sources. This way, survey teams will be able to provide weights or more sophisticated post-stratification variables to account for potential non-response bias.

Finally, we also believe that we need to continue studying non-response within the surveys (i.e. item non-response). Not all candidates respond to all questions, and it is important to incorporate the vast knowledge that household survey researchers have created into the study of small groups of elites. This will also increase the validity of the instruments.

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