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Elections, Ethnicity and Political Instability

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Elections, Ethnicity and Political Instability

Abstract

This article provides a new perspective on the impact of elections on violent political instability in ethnically divided states. A number of scholars argue that elections may provoke large-scale violence in ethnically divided states. In this article we theorize that elections have a pacifying effect in the most ethnically fractionalized countries as they reduce endemic uncertainty and encourage coalition-building, lowering the rate at which electoral losers discount the future. Probit regressions using cross-national data for the period 1960-2010 support the notion that instability onsets are less likely in ethnically fractionalized states during election periods, and especially in the year after a national election. (103 words)

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Introduction

We examine how elections in ethnically divided states impact the probability of violent political instability. Armed conflict, coups and mass killings after electoral contestation in ethnically divided states would appear to be common. Examples include civil war in Cote d'Ivoire following presidential elections in 2010, genocide in Burundi following the 1993 elections and the military coup and Islamist insurgency after general elections in Algeria in 1992. Yet, for every example of elections provoking ethnic war and violence, there are numerous examples of elections that were followed by periods of peace, even in states with ethnic divisions. Presidential elections in Zambia in 2008 and 2011 were not followed by onsets of civil war, severe repression or coups. Papua New Guinea, one of the most ethnically diverse nations on the planet has a long history of parliamentary democracy while nearby Fiji has been beset by post-election coups since 1987 (Reilly 2001). What explains why elections in some circumstances of ethnic diversity, but not in others, witness serious and violent political instability? In this article we build on existing qualitative work (Horowitz 1985; Reilly 2001) and argue that elections in ethnically *fractionalized* states reduce the probability of violent political instability. That is, where there are numerous, evenly sized ethnic groups the chances of coups, onsets of civil war or very severe repression are lower in election periods and especially the year after an election. We do not expect that this pacifying effect of elections holds in polarized or ethnically homogenous states.

Quantitative studies of conflict onset have not generally considered ethnic structure as conditioning the impact of elections on instability, despite the prevalence of ethnic divisions and elections as a cause of violent conflict in journalistic accounts (Gettleman 2008) and in theory (Horowitz 1985, p. 33). Fjelde and Høglund come closest to our interests with their (2016) study of electoral violence. Fjedle and Høglund (2016) show that majoritarian electoral institutions have a strong impact on the probability of electoral violence in Africa where there is a large, excluded, ethnic group. Our interest, here, however, is in serious political instability that can be more clearly seen as something caused by elections in some cases, rather than endogenous to the electoral process itself. Electoral violence can be understood as a means of manipulating election results (Fjelde and Høglund 2016; Schedler 2002; Dunning 2011) while serious political instability can be seen as the use of violence to overturn or supersede predicted or actual electoral results. Studies of elections and violent conflict more generally tend to find that elections on their own and in the aggregate have little

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3 effect on political violence (Goldsmith 2015; Cederman, Gledistch and Hug 2013). Rather,
4 effects may be conditional on contextual factors such as the proximity of elections to periods
5 of no polling or armed conflict (Cederman, Gledistch and Hug 2013; Collier Hoeffler and
6 Soderbom 2008), the presence of strong institutions capable of enforcing electoral integrity
7 and leadership turnover (Flores and Noruddin 2012; Brancati and Snyder 2011; Salehyan and
8 Linebarger 2014) or opposition performance in the election (Wig and Rød 2014).¹ In the
9 theory section of this article we show that peace-inducing features of elections can also make
10 them conflict inducing and, therefore, absent other environmental conditions that push these
11 mechanisms in one direction or another, the impact of elections in violent conflict is
12 ambiguous.

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21 We argue that ethnic fractionalization is an important conditioning factor for two reasons: (1)
22 elections in fractionalized states reduce uncertainty in an especially information-poor
23 environment, and (2) elections in fractionalized states lower the rate at which actors discount
24 the future, thus reducing the incentives to pursue violent conflict soon after an election result.
25 We expect these effects to be strongest in the year after an election as this information is
26 revealed and new coalitions are forged. Elections provide little new information on
27 mobilization potential and do not-encourage coalition-building to the same extent in polarized
28 and homogenous settings, and thus we do not expect them to significantly change the
29 likelihood of instability in these contexts. Probit regressions of cross national data from 1960-
30 2010 indicate that elections in ethnically fractionalized states tend to reduce the probability of
31 instability in the year following an election, with weaker, but still negative effects in election
32 years and when an election is scheduled in the following year.

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43 The remainder of the article proceeds in five sections. First, we discuss the relationship
44 between elections and political instability and establish the general expectation that elections
45 have ambiguous effects on instability. We then focus on our expectations regarding elections
46 in ethnically fractionalized countries. Third, we specify the key dependent and independent
47 variables and methods of analysis. Fourth, our findings are presented and discussed. The
48 article concludes with some reflections on the significance of our findings and avenues for
49 future research.

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58 ¹ Salehyan and Linebarger (2014) do find a general effect of elections on violent events short of war in Africa.
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Elections and Violent Political Instability

It is important to first consider when elections might impact the likelihood of serious political instability in general. In any given non-election period we assume that a government and n sub-state groups (that may include factions within the state, especially the military and police) obtain some payoff $U_{\text{stability(pre-election)}}$ as a share of resources from the state in the form of government offices, jobs, ministerial posts, or preferred policies such as regional autonomy or increased ethnic rights (or protection of resources that are obtained autonomously from the state, such as illegal mining or trade). This payoff is weighed against those implied by a violent campaign to capture or increase power, or secede, which is itself a function of the expected chances of realizing gains through violence and the costs for doing so $U_{\text{conflict(pre-election)}}$. Depending on a number of factors, the relative costs and risks of violently challenging the status quo will vary between states and over time. Such factors might include mobilization capacity (Cederman, Wimmer and Min, 2010; Weidmann 2009) state capacity (Thies 2010), the likelihood of foreign support (Gleditsch 2007; Salehyan 2007), or rough terrain (Fearon and Laitin 2003). When the payoffs from $U_{\text{conflict(pre-election)}}$ approach, or exceed, $U_{\text{stability(pre-election)}}$ the likelihood of instability onset will be high.

For an election to change the probability of instability, positively or negatively, the payoffs implied by accepting a post-election bargain, $U_{\text{stability(post-election)}}$, or initiating a violent conflict in a post-election period, $U_{\text{conflict(post-election)}}$, must be *different* to the pre-election status-quo for at least one group (which may be the incumbent). Where elections do not change the calculations of actors as regards violent versus peaceful means of realizing power, we would not expect the probability of instability to change either. In general, we see four ways in which elections can change the probability of instability.

First, elections can redistribute political power and create a post-election bargain with *expected* payoffs that are *different* from the pre-election bargain. Elections might improve the expected distribution of benefits for the government and sub-state groups with the potential to initiate collective violence if, for example, the most threatening groups are compensated with ministerial posts or access to state power, or a new configuration of ‘winners’ is able to effectively deter the losers. On the other hand, elections might create losses that incentivise the use of violence to prevent or overturn them. Results that imply an incumbent loss, for example, have sometimes been followed by extreme repression to prevent those losses. One

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3 such case is the onset of genocide in Burundi following the 1993 presidential election, another
4 is the onset of civil war in Algeria following the 1992 election.
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8 Second, elections are, ideally, repeat events. Przeworski (2011) argues that elections can
9 introduce the ‘shadow of the future’ into calculations of civil conflict. Losers can recoup
10 present losses through future electoral contestation when there is some probability of winning
11 an election or making material gains through elections in the future, even in very authoritarian
12 states (Lust-Okar 2006). In other words, elections can change the rate at which electoral losers
13 *discount the future*. Where contestants believe that an election is a singular opportunity to
14 realize political gains, either because future elections will not be held, or will bring no benefit,
15 the future is heavily discounted, making violent action now more preferable. Where losers
16 believe that future elections are likely to be held, and deliver meaningful prospects of gain,
17 this discount rate will be lower, making violent conflict today less preferable. Sri Lanka’s first
18 presidential election in 1982, for example, may have convinced ethnic Tamil groups that
19 future elections were unlikely to result in any substantive leverage on the issue of autonomy
20 as the Tamil party won under 3% of the vote but constituted over 12% of the population. A
21 1982 referendum extended the term of parliament - dominated by the (Sinhalese) United
22 National Party - by 6 years, despite the majority Tamil provinces voting against it. Electorally
23 sanctioned exclusion from power may have convinced the Liberation Tigers of Tamil Eelam
24 (LTTE) that electoral competition could deliver neither tangible power in the sense of
25 parliamentary seats, nor certainty that the ‘rules of the game’ would be adhered to in the
26 future.
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41 Third, electoral mobilization can reveal information about the support of sub-state groups,
42 especially elites, even in very authoritarian states (Gandhi and Lust-Okar 2009: 405). A
43 number of studies suggest that autocratic leaders have difficulty obtaining information about
44 popular preferences (Kuran 1995) and hold elections as one way of obtaining this information
45 (Magaloni 2008; Fearon 2011). Elections thus provide a signal of the extent of popular
46 discontent and the probability of revolution (Wig and Rød 2014, p. 9). If the most ‘capable’
47 groups in terms of rebellion are better compensated, post-election, then elections can be
48 peace-inducing (Cox 2008; Fearon 1995; Walter 2009; Miller 2014). Alternatively, elections
49 can *create* uncertainty (Wig and Rød 2014). They might reveal that the government’s support
50 base is much lower than expected, and/or reveal elite splits or divisions in the military.
51 Fraudulent elections obscure the true distribution of popular support. It was the first scenario
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3 that sparked an attempt to overthrow the presidency of Samuel Doe in Liberia in 1985 (Ellis,
4 2007: 59-60).
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8 Finally, elections can enable sub-state groups to overcome collective action problems (or
9 intensify these collective action problems, Lichbach 1998). Mobilizing turnout at electoral
10 rallies, voter registration and polling booths requires an organizational infrastructure, and, to
11 the extent that these resources are fungible, electoral mobilization may make violent conflict
12 ‘cheaper’ compared to a pre-election period. Opposition groups might also be able to
13 overcome coordination problems in election periods and create powerful electoral coalitions
14 (Wahman 2013). This increased capacity might change opposition perceptions of the
15 likelihood of winning a military conflict, or imposing costs upon the government, thus
16 increasing the likelihood that this choice is made. Party leaders may also mobilize followers
17 based upon ethno-nationalist, or xenophobic, rhetoric, by promising large gains or
18 exaggerating past (pre-election) hardship, or by constructing the specter of catastrophic
19 consequences should the party lose. Election campaigning may also push the leaders of sub-
20 state groups to inflate the size of electoral losses, or create an extremist wing of the party that
21 places a lower value on accepting a post-election bargain. By altering the perceptions of the
22 payoffs implied by post and pre-election bargains, elections can change the likelihood of
23 instability.
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36 In sum, elections present losers with a choice of accepting a post-election bargain, or revising
37 it through the use of force. Elections can create higher or lower probabilities of instability
38 when they imply a post-election bargain that is different from the pre-election bargain. This
39 can occur by (1) changing the expected distribution of material benefits, (2) changing the rate
40 at which groups discount the future, (3) changing the level of uncertainty around capabilities
41 in armed conflict and (4) changing the capabilities of groups.
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47 *Ethnic Structure and Post-Election Stability*

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50 Each of these mechanisms has the potential to increase or decrease the likelihood of
51 instability, which strongly suggests any relationship between elections and instability will be
52 *conditional* on how environmental factors affect these mechanisms. Here we consider the
53 conditioning role of ethnic structure. Following the work of Horowitz (1985, 1993) we expect
54 that the effects of elections vary as the fractionalization of ethnic groups within a state
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3 changes. States with a fractionalized ethnic structure have a large number of ethnic groups
4 that each makes up a relatively small proportion of the overall (or politically relevant)
5 population. Homogenous societies, on the other hand, tend towards a single ethnic group that
6 makes up a large proportion of the population. Kenya is an example of a fragmented ethnic
7 structure, where, according to Fearon's (2003) measures, there are 12 ethnic groups and the
8 largest makes up 28% of the population. Burundi is a more homogenous state, with the Hutu
9 majority making up roughly 81% of the population. Polarization, on the other hand, refers to
10 the extent to which ethnic groups approximate a bimodal or bipolar distribution of two,
11 equally sized, ethnic groups (Montalvo and Reynal-Querol 2010). Politics in Fiji, for example
12 are dominated by ethnic Fijians and Fijian Indians, who comprise roughly half of the
13 population each (Fearon 2003).
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23 First, situations of high ethnic fractionalization are likely to be low-information environments,
24 especially as regards the ability of groups to mobilize for violent conflict. Ethnic mobilization
25 is a function of group size and concentration (Weidmann 2009), but, crucially, other
26 organizational factors including intra-ethnic divisions that fluctuate over time (Warren and
27 Troy 2015; Cunningham 2013) and inter-group alliances (Fortini 2012). The ability of the
28 government or a governing coalition to monitor the support of different ethnic elites,
29 independent of elections, will decline as the number of ethnic groups increases, and there is
30 much literature suggesting that bargaining is difficult in such multi-group environments
31 (Cunningham 2011; Butcher 2015; Waltz 1979). Elections have the potential to reduce this
32 uncertainty in fractionalized settings. Elections provide incentives for elites to mobilize their
33 support base, even in authoritarian states (Brownlee 2007), and provide a 'noisy' signal about
34 the mobilization potential and size of different groups (Gandhi and Lust-Okar 2009; Magaloni
35 2006). Elections may also create incentives to form electoral coalitions, thus providing
36 information on relationships between ethnic elites. This information may allow the incumbent
37 or a new government to compensate the most capable groups. When the most capable groups
38 or coalitions are compensated, elections should have a differential and peace-inducing effect
39 in more fractionalized states as elections reveal relatively more information about the
40 mobilization potential of different ethnic elites. Absent the ability of elections to reduce these
41 information asymmetries, violent conflict may be a common way of resolving them (Fearon
42 1995; Walter 2009). Crucially, we expect the amount of information that elections reveal to
43 be greater in ethnically fractionalized states than in other ethnic structures. Where one group
44 dominates ethnic demographics, for example, elections are unlikely to reveal as much new
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3 information about mobilization potential for violent conflict because small changes in the
4 mobilization potential of one group or another are unlikely to change the overall balance of
5 power. Recent research highlights that ethnically fractionalized countries have particular
6 difficulty managing or effectively distributing the private benefits that arise from control of
7 the state, especially natural resource revenues (Wenegast and Basedau 2013; Esteban et al
8 2012). Elections can reduce the probability of such distributional conflicts by creating more
9 efficient bargains through provision of information in an especially information poor
10 environment.
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18 The uncertainty-attenuating effect of elections in fractionalized states is reinforced by the
19 likelihood that elections in fractionalized states reduce the rate at which elites discount the
20 future. Elections in fractionalized states are unlikely to determine a single winner. For the
21 ‘winner’ to form government, or to assume the position of head of state, they must attract the
22 support of other ethnic groups, often a large number of ethnic groups (Horowitz 1985; Reilly
23 2001a, 2001b, 2002). Electoral losers can extract concessions from the group most likely to
24 form government, such as ministerial positions or a fraction of the distribution of material
25 benefits that come from office. And to the extent that elections also lower uncertainty, these
26 concessions will map onto the most threatening groups more closely such that concessions
27 create a post-election bargain that is *better* for the most important (and threatening) sub-state
28 groups than the pre-election bargain. Crucially, coalition-building, in combination with the
29 presence of a minority of excluded ethnic groups, enables the junior partners of the winning
30 coalition to punish the electoral winner if they renege on the post-election bargain. This
31 should ease commitment problems between junior and senior partners and excluded ethnic
32 groups may calculate that another opportunity to revise the present distribution, either through
33 another election, or a re-shuffle of the coalition, is high. These might be through no-
34 confidence motions, regular elections or the entrenchment of a “hegemonic party” which is
35 not fully dominated by one group (Bieber and Wolff, 2005).
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49 The prospects of joining a governing coalition in the future, or mobilizing more effectively in
50 the next election should decrease the rate at which electoral losers discount the future and
51 make (peacefully) gambling on future elections preferable in relation to violent conflict. We
52 do not expect elections to have this effect in homogenous or polarized settings. In
53 homogenous settings elections are unlikely to change the discount rate of losing groups as
54 they cannot form coalitions with other groups to increase their share of political power in
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3 future elections. In polarized settings elections may actually lead to *higher* discount rates as
4 losing groups face a situation where the winning group has incentives to avoid future
5 elections. The winning group may create institutional mechanisms that prevent the rival
6 ethnic bloc from assuming power, whether it be through positions in the judiciary that prevent
7 constitutional changes, stacking the army with ethnic kin, or repression. In Zambia, for
8 example, the Movement for Multiparty Democracy (MMD) has dominated electoral politics
9 since ousting Kenneth Kaunda in the 1991 elections. In part, its endurance has rested upon the
10 ability of incumbents to distribute the spoils of office to fragmented regional and ethnic
11 constituencies and re-allocate their support base. Levy Mwanawasa was elected in a narrow
12 (and controversial) election in 2006. To generate the appearance of a clean break from the
13 older MMD elite, Mwanawasa prosecuted the former president, Chiluba, for corruption.
14 While this move alienated Chiluba's Bemba ethnic group, Mwanawasa was able to re-forge
15 an alliance in rural Zambia to continue the dominance of the party (Cheesman and Hinfelaar,
16 2010).
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28 In sum, the incentives for electoral losers to acquiesce to a post-election bargain over
29 attempting to revise that bargain through large-scale violence are stronger after elections in
30 highly fractionalized states. Elections reduce uncertainty to a greater degree in ethnically
31 fractionalized states and enable governments to create post-election coalitions that
32 compensate the most threatening groups. This requirement for coalition building also means
33 that electoral losers can plausibly believe that political gains can be made in the future
34 through institutional means, either through another election, or by joining a government
35 coalition. We do not expect the same mechanisms to operate in polarized and ethnically
36 homogenous settings and, therefore, do not expect that elections increase or decrease the
37 probability of violent political instability in these circumstances.
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46 Our first set of hypotheses imply two axes of comparison. First, we expect that election
47 periods will be significantly more peaceful than non-election periods in ethnically
48 fractionalized states. In our regression results (below) we expect that changing from a non-
49 election period to an election period reduces the probability of instability in a way that is
50 distinguishable from no effect. The second axis of comparison is across different ethnic
51 structures. While we expect a significant negative relationship between elections and
52 instability in fractionalized states we hold that the null hypothesis of 'no effect' cannot be
53 rejected in cases of polarized and homogenous ethnic structures. We expect that changing
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3 from a non-election period to an election period in these cases will not change the probability
4 of instability in a way that is confidently distinguishable from a zero effect.
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8 *H1a: Elections in ethnically fractionalized states significantly reduce the probability of*
9 *serious political instability.*
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12 *H1b: Elections in ethnically polarized states do not significantly increase or decrease the*
13 *probability of serious political instability.*
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17 *H1c: Elections in ethnically homogenous states do not significantly increase or decrease the*
18 *probability of serious political instability.*
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24 Our second set of hypotheses focus on *when* we expect elections to have pacifying effects in
25 ethnically fractionalized states. Our theoretical mechanisms also lead us to believe that the
26 negative effects of elections on instability in fractionalized states will be strongest in the year
27 after an election. Information about the ability of elites to mobilize is revealed after electoral
28 coalitions are consolidated or re-formed during this period (often over a considerable amount
29 of time), depending upon the performance of candidates in the election. We do not expect
30 strong negative effects in the election year, or the year preceding the election. While voting
31 occurs in election years, the results can take months to be announced, disputed and settled and
32 our information revealing mechanism should not apply in this circumstance. Similarly,
33 coalition building can occur before elections as voting blocs align themselves in order to
34 maximize the likelihood of being part of a government coalition (Horowitz 1985), but
35 defections can occur in the post-election period once it becomes clear which group is most
36 likely to form the governing coalition. We expect the coalition-building mechanism to apply
37 most clearly in fractionalized states in immediate post-election years, but be less applicable in
38 election years or the year preceding election years.
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51 There are also research design-based reasons to examine the impact of elections not only in
52 election years, but also in the year before after an election year. Collier, Hoeffler and
53 Soderbom (2009) notice a substitution effect where belligerents forgo violence in election
54 years only to rebel the year after an election when the results have been determined. We
55 should not claim that elections or election periods have a ‘pacifying’ effect without also
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checking for the presence of substitution effects, such as greater violence in the year of or prior to an election.

We do not explicitly theorise whether the general prediction of no significant effect of elections in polarized and fractionalized settings varies across pre- and post-election periods, although our results below do provide some initial inductive answers to this question. A prediction of no significant effect in polarized and homogenous settings also does not imply that there are not other features of states in these samples that make them prone to instability or make elections dangerous. These are not the focus of our article, except insofar as they may be correlated with ethnic demography, discussed below.

H2a: Elections in ethnically fractionalized states significantly reduce the probability of serious political instability in the year after an election.

H2b: Elections in ethnically fractionalized states do not significantly increase or decrease the probability of serious political instability in election years.

H2c: Elections in ethnically fractionalized states do not significantly increase or decrease the probability of serious political instability the year before an election.

Table 1 – Summary of Hypotheses

	Timing		
	t+1	t	t-1
Homogenous	No effect (H1c)	No effect (H1c)	No effect (H1c)
Polarized	No effect (H1b)	No effect (H1b)	No effect (H1b)
Fractionalized	No effect (H2c, H1a)	No effect (H2b, H1a)	Negative (H2a, H1a)

Research Design

This section deals with model identification, variable specification and methods of analysis. We first discuss our characterization of the outcome variable: the onset of serious political instability. Next we turn to a discussion of the key causal variables: elections, and ethnic

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3 structure. We then describe our choices for control variables and quantitative method. The
4 data are pooled annual time-series cross-sections for the period 1960-2010 with country-years
5 as the unit of observation. The lower and upper bounds of the time period are determined by
6 data availability.
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10 *Political Instability*

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14 For the dependent variable, political instability, we use Political Instability Task Force (PITF)
15 data, which include civil wars (revolutionary and ethnic), adverse (non-democratic) regime
16 changes, and instances of genocide or politicide (Marshall, Gurr, and Harff 2015). Political
17 instability is coded 1 for each country-year in which an onset of instability occurs as
18 identified by the PITF. We do not drop ongoing years of instability as other forms of
19 instability may emerge during ongoing episodes, which we think is an important dynamic to
20 capture, but it does not substantively change our results if we drop these cases.
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28 Our hypothesis does not specify which sort(s) of political instability might be associated with
29 elections, and we believe this would depend on numerous contextual factors. Types of
30 political instability also might substitute for each other, in Schedler's (2006, 15) terms, the
31 "actual outcomes of the conflictive interaction [are] open." The military may stage a coup if
32 they anticipate that electoral results will provoke rebellion, or the government may employ
33 severe repression to prevent a rebellion. Even though instability may manifest as a coup or
34 genocide/politicide in this case, other forms of instability were also likely to occur. Treating
35 these cases as 'zero' obscures the fact that these situations were at elevated risk of significant
36 political violence. Furthermore, our theory plausibly applies to different forms of instability.
37 We might expect a lower probability of ethnic wars in fractionalized settings as ethnic groups
38 abstain from violent campaigns and pursue institutional methods of realizing power, or
39 elections might deter coups as coalition-building leads to more ethnically diverse armed
40 forces (Horowitz 1985, p. 443). Nonetheless, we do disaggregate the results by instability
41 type in the robustness tests, and re-test the hypotheses using the UCDP/PRIO Armed Conflict
42 Dataset (Themner and Wallenstein 2014; Gleditsch et al 2002), data on Mass Killings from
43 Ulfelder and Valentino (Ulfelder and Valentino 2008) and coups data from Marshall and
44 Marshall (2015).
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57 *Elections and Ethnic Structure*

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4 We use data from the National Elections Across Democracy and Autocracy Project (NELDA;
5 Hyde and Marinov 2012) to code state-years in which national elections occur. Our initial
6 tests are based upon a variable coded “1” if any national election round ended in the country
7 in that year and “0” if not (based on the definition in Hyde and Marinov 2012). If there are
8 multiple rounds in a single election then we code an election at the end of the last round. We
9 examine the effects of elections at year $t-1$, t and $t+1$. In other words we examine situations
10 where an election has occurred in the previous year and the results are known, during an
11 election year, and when an election is anticipated in the following year. We also re-test the
12 hypotheses using the Institutions and Elections Project election data (IAEP: Wig, Hegre and
13 Regan 2015).

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23 To test the conditional relationship between ethnic structure and instability, we interact the
24 elections variable with a measure of ethnic fractionalization. We expect that the effect of an
25 election at $t-1$ will become more negative as ethnic demography is characterized by larger
26 numbers of ethnic groups that make up relatively small proportions of the total population.
27 Ethnic fractionalization is defined as ‘the probability that two individuals selected at random
28 from a country will be from different ethnic groups’ (Fearon 2003: 208). As with similar
29 measures, it approaches ‘1’ as the number of ethnic groups increases and the population share
30 of each group becomes more equal. Thus, highly fractionalized states are those with many,
31 equally sized groups while more homogenous states are those where one ethnic group makes
32 up a large proportion of the population. An interaction between fractionalization and elections
33 enables us to test whether the effect of elections varies across different ethnic demographics,
34 such that elections in fractionalized states have negative effects on instability. This reflects
35 our causal mechanism, as the necessity for coalition-building will increase with more, evenly
36 balanced, ethnic groups, as should uncertainty over mobilization potential. The main analyses
37 presented in this article use James Fearon’s (2003) dataset of ethnic groups to construct these
38 measures. All ethnic groups accounting for at least 1% of a country’s population are included
39 for all countries with at least 500,000 people (160 in 1990). Our multiplicative interaction of
40 ethnic fractionalization with elections attributes higher values to elections in very
41 fractionalized states.

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56 We are, however, cognizant of critiques of Fearon’s fractionalization index, especially that
57 some ethnic groups are not ‘politically relevant’ and inflate the extent to which states are
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3 ethnically fractionalized (Cederman and Girardin 2007). This is a strong critique because our
4 causal mechanism rests upon ethnic groups having the latent capacity to launch an armed
5 struggle, which may not be the case in some situations. Fearon's measure is also cross-
6 sectional, and does not change over time. The main alternatives are Daniel Posner's (2004)
7 Politically Relevant Ethnic Groups (PREG) data for Africa and the Ethnic Power Relations
8 (EPR) data (Cederman, Wimmer and Min, 2010).
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14 We have chosen Fearon's data for our main analysis, first, because our electoral bargaining
15 mechanism is more closely related to the horizontal relations *between* ethnic groups (which
16 Fearon's measure captures) where the state is 'up for grabs' following an election, the result
17 of which is ostensibly based on demographics and salient social cleavages, as opposed to the
18 vertical relations between the state and individual ethnic groups that may be more relevant
19 when the state is 'closed' to other groups. The EPR data also do not include 'clans' or 'tribes'
20 as viable ethnic units and states such as Papua New Guinea, El Salvador and Somalia are
21 attributed with fractionalization measures of zero, which we think misses an important
22 ascriptive dimension of electoral politics in these states. We are also concerned about the
23 potential endogeneity of conflict and 'politically relevant' ethnicity over time (see Esteban et
24 al 2012 for a similar critique). While there may only be one or two ethnic cleavages that are
25 politically relevant in relation to the state, there may be latent ethnic cleavages that are
26 socially relevant for both instability and electoral politics. The EPR project measures political
27 relevancy as a function of sub-state mobilization in the national political forum and state-
28 discrimination on an ethnic basis. When state leaders increase their discrimination against
29 sub-state groups, ethnicity may become 'politically relevant' as individuals seek security in
30 non-state identities. However, this discrimination may also increase the likelihood of large-
31 scale violence.
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46 In Liberia, for example, there were just two relevant ethnic groups in 1980 – 'Americo-
47 Liberians' and 'Africans'. When President Samuel Doe (an African from the Krahn ethnic
48 group) overthrew the Americo-Liberian aristocracy that had ruled for over 100 years he
49 created an ethnic minority regime by stacking the military with Krahn soldiers. According to
50 the EPR data the number of politically relevant ethnic groups rose to 4 in 1981 (and then to 5
51 in the reign of Charles Taylor). Doe's kleptocratic and violent rule led to a coup attempt and
52 ethnic massacres in 1985 and a full-scale, ethnic, civil war in 1989. We might infer from the
53 EPR data that ethnic homogeneity produced peace in Liberia while heterogeneity was
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3 responsible for the ethnic instability that started in 1985, 1989 and 2000. Yet, this conclusion
4 would obscure the fact that ethnic discrimination increased both the number of politically
5 relevant ethnic groups and the likelihood of war. In addition, Doe was only able to
6 discriminate on an ethnic basis from 1980 because ethnic cleavages existed that were denied
7 expression in the national stage (and thus not politically relevant) in previous years. In other
8 words, in some cases the EPR measure may be endogenous to the risk of conflict, not
9 exogenous. Nonetheless, as a robustness check we re-test our hypotheses using the EPR data.
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16 Our ethnic polarization measure is based upon the RQ formula developed by Montalvo and
17 Reynal-Querol (2005) using Fearon's data on group composition.² Higher values of 'ethnic
18 polarization' are obtained the closer the distribution of ethnic groups approximates a 50/50
19 bipolar structure (Esteban et al. 2012). Guatemala has the highest polarization score in our
20 index, 0.9856. North Korea is the least polarized country, at 0.005. We interact this variable
21 with our elections variable to capture the effect of elections in polarized settings. Polarization
22 is correlated with fractionalization (correlation coefficient of 0.64 in the data used in this
23 article) and there is some evidence that it increases the chances of civil wars and genocides
24 (Montalvo and Reynal-Querol, 2005). Moreover, states become more polarized for low- to
25 mid-range levels of fractionalization. For example, Guatemala has a fractionalization score of
26 about 0.5, but a polarization score of 0.98. The comparative category when polarization and
27 fractionalization are included in the models is a 'homogenous' setting where one ethnic group
28 is significantly larger than all others. These homogenous states have low values on both
29 fractionalization and polarization.
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41 *Control Variables*

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44 We have chosen control variables that are plausibly related to ethnic structure and instability
45 onset, in addition to the holding of elections. Goldstone et al. (2010) show that infant
46 mortality is an important predictor of political instability and ethnically diverse states tend to
47 have lower levels of economic growth (Easterly and Levine 1997). It is also plausible that
48 countries with low levels of human welfare may be among those not holding, or cancelling,
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55 ² We made one adjustment to Fearon's data when constructing the polarization index. PNG has an ethnic
56 fractionalization score of "1", making it the most fractionalized country on the planet. But, because each group
57 makes up less than 1% of the population the largest group size is "0". When we apply the RQ formula, this
58 obtains the odd result that PNG also becomes the most polarized state on earth. This is clearly inaccurate, and so
59 we adjusted the PNG polarization value at 0.01.
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3 elections. We have included the logged infant mortality rate (IMR) from the World Bank
4 Databank (2015). Events of political instability, such as civil wars, may have a contagion
5 effect (Gleditsch, 2007) and the number of surrounding countries with ongoing episodes of
6 internal conflict is likely to affect the chances of a state experiencing instability. Ethnic
7 diversity is also, plausibly, regionally clustered (in Central and Eastern Africa for example)
8 and regional instability could conceivably also interrupt a state's regular election cycle, for
9 example through preemptive repression (Danneman and Ritter 2014). To control for this we
10 have included the number of bordering states experiencing an episode of conflict using the
11 Major Episodes of Political Violence data (Marshall, 2015).
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20 Ethnically diverse societies may build institutions specifically designed to distribute power
21 between ethnic groups through consociational or proportional representation systems, as
22 opposed to majoritarian systems (Lipjhart 2004), although recent research suggests that
23 institutions reflect colonial history rather than design (Selway and Templeton 2012).
24 Proportional representation institutions may be peace-inducing, although whether this is the
25 case theoretically (Horowitz 1985; Jarstad 2008; Reilly 2001b) or empirically (Selway and
26 Templeman 2012; Reynal-Querol 2002; Norris 2002) is debated. We nonetheless control for
27 this possibility with an ordinal variable indicating the extent to which electoral rules involved
28 proportional representation, from the IAEP data (Fjelde and Högglund, 2014; Wig, Hegre and
29 Regan 2015). A strong predictor of instability is 'partial democracy with factions' – regimes
30 that mix factional political contestation with fairly open executive recruitment (Goldstone et
31 al. 2010). Ethnically diverse societies may build political institutions that are open, but
32 factional, as multiple ethnic power bases create demand for contestation, but contestation is
33 expressed through identity-based or parochial mobilization. We have controlled for this with a
34 variable indicating whether political competition was factional *and* executive recruitment was
35 open from the PolityIV dataset (Marshall, Jaggers and Gurr 2015).³ We have also controlled
36 for institutional democracy as democracies hold more elections and are less prone to some
37 forms of instability, using the polity dataset (Marshall, Jaggers and Gurr 2015). We control
38 for population along with many other studies examining violent instability (Fearon and Laitin
39 2003). We also include a cubic polynomial for "stability years" to correct for serial correlation
40 (Carter and Signorino 2010; Pang 2010).
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57 ³ Controlling for anocracy in this way also allows us to avoid the simultaneity concerns expressed by Vreeland
58 (2003).
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3 Finally we include two election-related variables. First, elections may be so dangerous in
4 ethnically fractionalized states that elites postpone or suspend them until ‘safe’ periods. In this
5 case we would observe a negative association between elections and instability, but this
6 would reflect endogeneity. To account for this we have controlled for whether the election in
7 question was cancelled or postponed using data from Hyde and Marinov (2012). We also
8 include a measure of whether the election was held early or late from the same source.
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13 *Methods of Analysis*

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18 Because the outcome variable is binary, the choice of statistical techniques for time-series
19 cross-sectional data is limited, and perhaps none is wholly satisfying. We run regular probit
20 models, but also test the hypotheses with random effects models to deal with issues of
21 heterogeneous effects across units, and with robust standard errors correcting for clustering on
22 countries (not shown, see the appendix). The results are similar or significantly improved
23 when using these modeling strategies, so the reported results can be considered conservative
24 (Rogers 1993; Arellano and Bonhomme 2011; Pang 2010). The coefficients and standard
25 errors of individual interaction terms and their first order terms do not have a straightforward
26 interpretation (Brambor, Clark and Golder 2006), and we model the first difference in the
27 predicted probability of instability when changing the relevant election variable from “0” to
28 “1” in states across twelve different scenarios described below and shown in Figure 3. We
29 include all first order terms in our analysis and used the Zelig program (version 4.1.1) in the R
30 software platform (version 3.1.1) to produce the estimates and simulate the marginal effects
31 (Imai et al. 2009). For the main results we have used multiple imputation with the Amelia II
32 package (Honaker et al 2012) to reduce the effects that missingness has on our inferences, but
33 again, the results are similar when we do not use multiple imputation.
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46 We have split the data into four groups of observations: (1) where there was an election in the
47 previous year, (2) where there was an election in that year, (3) where there was an election in
48 the year after and (4) where there was no election at time $t-1$, t , or $t+1$. The last group we
49 consider to be a ‘control’ sample where conflict outcomes are plausibly independent of
50 electoral calculations in a 3-year ‘election period’. For bivariate and multivariate tests we
51 include observations from the relevant election period and the control sample. For example,
52 regressions that assess the impact of elections at $t-1$ on instability use observations where
53 there was an election at $t-1$ and from the control sample only. With this method we are
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3 comparing the probability of instability in a given part of the electoral cycle with a constant
4 baseline probability of instability. Including observations with elections at time t in a model
5 of elections at time $t-1$ would not enable us to disentangle whether elections made instability
6 onsets more or less likely in relation to ‘election periods’ or ‘non-election periods’.⁴
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11 12 13 14 15 **Results**

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18 Figure 1 shows instability onsets (large circles) across the distribution of fractionalization and
19 polarization measures. The bottom panel of Figure 1 shows the control sample. The top panels
20 show distributions when elections were at $t+1$, t , and $t-1$. The colored panels represent
21 arbitrary cut-offs for structures that are ‘homogenous’, ‘polarized’ and ‘fractionalized’. Figure
22 1 also shows that fractionalization and polarization are positively correlated for
23 fractionalization scores of up to, roughly, 0.6 and negatively correlated for values above this.
24 This correlation should be expected as fractionalization and polarization are indexes
25 measuring different aspects of the same underlying data.
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Figure 1 here

Figure 1 shows initial support for our hypotheses. Instability onsets are relatively frequent in
fractionalized settlings in the ‘control’ sample – more frequent than in homogenous or
polarized settings. There are few onsets at high levels of fractionalization when there is an
election at $t-1$, and, to a lesser extent, when there is an upcoming election. Remarkably, there
was just one instability onset in a fractionalized state the year after an election from 1960-
2010 (India 1989). These fractionalized states are not a trivial sample of cases, and include
states that are typically considered to be at high risk of ethnic conflict such as Liberia, India,
the Democratic Republic of Congo, Cameroon, Gabon, Uganda, Kenya, Zambia, and Papua
New Guinea. The majority of states in the ‘fractionized’ category are also African states
where ethnicity plausibly motivates electoral choices (Carlson 2015; Andrews and Inman
2009; Fjelde and Høglund 2014). Table 3 shows the results of Pearson correlation tests of the

⁴ The results do not substantially change if we include observations with elections in the years not being estimated as an independent variable in the sample. An example would be if we included observations with elections at time t , and $t+1$ in a model estimating the effect of elections at $t-1$ on instability.

association between two dichotomous variables across homogenous, fractionalized and polarized settings. It shows the association between the mean onset rate in situations where there was an election at the indicated time, with the 'control' group, where there was no election at t-1, t, or t+1. It also shows the mean onset rates for these categories and the percentage of years in which elections were held. Table 2 shows the states that fall into the 'fractionalized' category in Figure 1 and the number of onsets in each country, along with the types of instability by category in the Political Instability Task Force typology.

Table 2 – Most Fractionalized Countries and Instability Onsets, 1960-2010.

Country	Instability	Rev. War	Eth. War	Adv. Reg.	Geno/Politicide
Burkina Faso	1	0	0	1	0
Cameroon	0	0	0	0	0
Democratic Republic of the Congo	3	1	2	1	1
Gabon	0	0	0	0	0
Ghana	2	0	0	2	0
India	4	1	3	0	0
Kenya	3	0	2	1	0
Liberia	4	3	0	1	0
Madagascar	1	0	0	1	0
Papua New Guinea	1	0	1	0	0
South Africa	2	1	1	0	0
Tanzania	0	0	0	0	0
Togo	0	0	0	0	0
Uganda	5	1	2	2	2
TOTALS	26	7	11	9	3

Table 3 – Associations between elections and instability across ethnic structures, 1960-2010⁵

	Election at t+1	Election	Election at t-1	Instability Onset	Elections	n
Homogenous	0.01	0.01	0.03	0.021	0.281	2487
Polarized	-0.03	-0.02	-0.04*	0.036	0.233	3748
Fractionalized	-0.09*	-0.04	-0.14***	0.037	0.223	674

⁵ The categories correspond directly to the shaded areas in Figure 1. Specifically, Homogenous = polarization < 0.6 & fractionalization < 0.5, Polarized = polarization >= 0.6, Fractionalized = polarization < 0.6 & fractionalization > 0.5.

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3 Table 3 suggests further support for our hypotheses. Elections are positively correlated with
4 instability onsets in homogenous countries, but negatively correlated in polarized scenarios.
5 The strongest negative associations exist in ethnically fractionalized countries, with a strong
6 and significant difference between instability onset rates when there was an election in the
7 previous year.
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12 These results are suggestive that elections have a pacifying effect in ethnically fractionalized
13 states, but do not take into account the control variables discussed earlier, and rely on
14 somewhat arbitrary cut-offs for categories of ethnic structure. We now turn to our regression
15 results. Figure 2 shows our main results as the marginal impact on the probability of
16 instability onset when moving each variable in the model from its 10th to its 90th percentile
17 value. The results for the interactions of elections with ethnic structure show the impact of an
18 election on the probability of instability when fractionalization and polarization are at their
19 90th percentile values (0.8177 and 0.854 respectively). The regression tables for these results
20 can be found in the online appendix accompanying this article, but, in brief, we find a
21 statistically significant negative relationship between our interaction of fractionalization and
22 elections at t-1.
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33 Figure 2 here.
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36 Figure 2 provides strong evidence that elections have a pacifying effect on instability in
37 ethnically fractionalized countries. On average, when there was an election in the previous
38 year, the probability of instability is roughly 1.3 percentage points lower than in other years.
39 The 95% confidence interval does not cross the ‘zero effect’ line. Somewhat surprisingly, we
40 also find a significant negative relationship between elections and instability when there is an
41 election due in the following year. Our results also suggest that the chances of instability
42 onset are lower the year before an election in ethnically polarized states but higher the year
43 following an election. This ‘substitution effect’ of elections and violence has been observed
44 elsewhere (Collier, Hoeffler and Soderbom 2009), but it applies to polarized rather than
45 fractionalized states in our sample. Many of our control variables point in the expected
46 directions and replicate earlier research.
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3 The results of Figure 2, however, are not easily interpreted. This is for two reasons: (a)
4 interaction terms in binary outcome models are not easily interpreted in terms of sign,
5 magnitude, or statistical significance and (b) fractionalization and polarization scores cannot
6 be changed independently of one another, as discussed previously. To obtain a more intuitive
7 sense of the results we simulated predicted probabilities of instability for twelve different
8 ethnic structures in the empirical distribution, moving from a homogenous to a polarized then
9 a fractionalized structure, with all other continuous variables held at their means and ordinal
10 and nominal variables at their modes. The ethnic structure scenarios correspond to
11 fractionalization and polarization measures for Greece, Paraguay, Vietnam, Swaziland, the
12 Dominican Republic, Guatemala, Brazil, Peru, Afghanistan, the Central African Republic,
13 Cameroon and Uganda. Figure 3 shows where these cases sit on the
14 polarization/fractionalization distribution.
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25 Figure 3 here.
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28 Figure 4 shows the results of these simulations as the distribution of (1000) simulated first
29 differences when changing from an election to a non-election period (at the specified time)
30 across the scenarios that reflect changing ethnic demographics. The upper and lower bounds
31 reflect the 95% confidence intervals of these distributions. Figure 4 suggests that the risk of
32 instability is significantly lower in ethnically fractionalized states the year after an election, is
33 similar to non-election periods in the year of an election, and is lower, but with some overlap
34 when there is a forthcoming election in the most fractionalized states. The clearest divergence
35 can be seen in highly fractionized states when there was an election in the previous year as the
36 election and non-election distributions diverge around the Afghanistan scenario (polarization
37 ~ 0.75 , fractionalization ~ 0.75). Interestingly the probability of instability is significantly
38 lower when an election is due in the following year for moderately fractionalized states (such
39 as Afghanistan) and the year following an election. We also see the 'substitution effect' in
40 polarized settings where the probability of instability is lower when an election is due, but
41 higher in the year following an election. Importantly, in none of the panels is the estimated
42 probability of instability higher for election periods in fractionalized states than non-election
43 periods. The level of uncertainty varies across the scenarios, but it would appear that elections
44 in ethnically fractionalized states are peace inducing, at least for the year following an
45 election.
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Robustness Tests

We ran additional tests to assess the robustness of our findings. These include the following: (1) using the EPR data for ethnic structure, (2) disaggregating elections into executive and legislative elections based on the criteria in Hyde and Marinov (2012), (3) disaggregating violent instability into its constituent types (revolutionary wars, ethnic wars, adverse regime changes), (4) tests with the UCDP/PRIO data for the onset of internal armed conflict (Themner and Wallensteen 2014, Gleditsch et al 2002), (5) ‘mass killing’ onsets (Ulfelder and Valentino 2008), (6) Coup and coup attempts from the Political Instability Task Force (Marshall and Marshall 2015), (6) using the IAEP data for national elections (Wig, Hegre and Regan 2015), (7) using random effects probit, (8) using only the sample of non-democratic states (states scoring less than +6 on the polity2 scale), (9) using only the fractionalization measure for our interactions and removing the polarization and elections interaction, (10) respecifying our independent variable with categorical measures of ‘multipolar’ and ‘non-multipolar’ structures’, and (11) re-testing the hypotheses on the EPR measures of ‘ethnic armed conflict’ and ‘non-ethnic armed conflict onsets’ (Bormann et al 2015). Figure 5 summarizes the results of these tests by displaying the mean effect and the upper and lower bound of the 95% confidence interval for the change in the predicted probability of instability when a non-election period is changed to an election period in a ‘fractionalized state’ (i.e., a state with fractionalization 0.8177). The more this upper bound lies above zero, the less confident we can be that the effect is actually negative.

Figure 5 here.

Figure 5 shows that elections do appear to have a fairly consistent, negative association with various types of political instability the year after an election in ethnically fractionalized settings. The only instance where the mean association is positive in the year after an election is for state-led mass killing events. All other forms of serious political violence have a zero, or negative association. There is a high degree of confidence in this negative association when the EPR data are used, for legislative elections, for ethnic wars, adverse regime changes, coups, when we use the IAEP data for elections, for UCDP/PRIO armed conflicts, in non-democracies, in models without the polarization variable and interaction, when we used a categorical indicator of ‘multipolar’ contexts and for EPR ethnic conflict onsets. The

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3 associations for executive elections, revolutionary wars and non-ethnic conflicts are more
4 ambiguous. In election years the uncertain results in the main analyses are reflected.
5 Instability onsets are less likely, on average (with the exception of legislative elections, ethnic
6 wars), but the upper level of the confidence interval crosses the zero-effect line for all of the
7 estimates. It is difficult to say whether election years are associated with instability onsets in
8 fractionalized countries with these data. Our results are generally more ambiguous for
9 forthcoming elections as well, although the probability of instability does appear to be lower
10 in the year before an election in the base model, for legislative elections, coups, mass killing
11 events, when we use the IAEP data, in non-democratic states, and in 'multipolar' ethnic
12 contexts. That adverse regime changes, coups and mass killings are generally less likely in
13 fractionalized states may reflect the fact that a different mechanism applies in pre-election
14 periods. These are all state-initiated instability events, which suggests that states may abstain
15 from mass-violence or coups in the pre-election phase, perhaps because of the public
16 resistance that may follow. The full results in the appendix suggest, however, that adverse
17 regime changes and coups might be less likely in the year before an election across ethnic
18 contexts (i.e the probability is significantly lower in polarized and some homogenous settings
19 as well). Overall, the robustness tests suggest that there is a fairly consistent negative
20 association between the year after an election and violent instability in ethnically
21 fractionalized states that is not sensitive to re-specifications of the independent variable, or
22 modeling assumptions, and appears to apply to the types of instability that the theory most
23 closely relates to (i.e ethnic wars, and internal armed conflicts). The weight of the evidence,
24 we believe, continues to support our hypotheses.
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43 **Conclusions**

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46 Our study revealed no compelling evidence to suggest that elections are dangerous in
47 ethnically fractionalized countries. On the contrary, elections in fractionalized states appear to
48 reduce the likelihood of major episodes of political violence. We believe that this is the case
49 because elections in such circumstances reduce endemic uncertainty and create incentives for
50 coalition building and the pursuit of power through institutional means. These results add
51 some nuance to the debate regarding elections in divided societies, and largely confirm the
52 ideas of Horowitz (1985). Elections are not always dangerous when there are ethnic divisions,
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3 but they can be. What matters is the number of ethnic divisions and the relative sizes of these
4 groups.
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8 Turning to policy implications, one note of caution is that our analysis does not suggest that
9 elections are never associated with, or provide the spark for, political violence *of any sort*.
10 Our dependent variable is serious political instability, specific forms of political upheaval
11 which usually involve considerable violence. It may be the case that elections are associated
12 with lower levels of civil or ethnic violence, or electoral violence, that do not qualify as
13 serious political instability as we define it here. Small-scale electoral violence in the highlands
14 of Papua New Guinea, for example, may be more reflective of such an effect. We see this as
15 an important area for further research, but our results may also suggest that even if these
16 elections involve election-related violence, this violence appears to be less likely to escalate to
17 episodes of major political instability. In general, elections should be considered to reduce the
18 short-term risk of major instability in ethnically fractionalized societies, and thus potentially
19 contribute to ethnic accommodation, which can foster sustainable political development. If
20 our theory and analysis are correct, leaders in such ethnically divided states, and concerned
21 external actors, should see elections more as tools to help peacefully channel existing
22 disagreements, than as events carrying exceptionally high risk of sparking instability in the
23 form of a coup or other democratic reversal, state collapse, or a civil war. Our analysis
24 suggests that external actors should pay close attention to the year of an election in a
25 fractionalized scenario, as presenting the highest risk of instability (but only equal to a non-
26 election period), and the year after an election in a polarized scenario. While it seems clear
27 from recent events that elections involve some risk of violence, our analysis strongly suggests
28 that they also hold potential for promoting political stability and peace, especially in societies
29 with fraught ethnic divisions.
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Figure 1 –Scatterplots, instability onsets in election and non-election periods

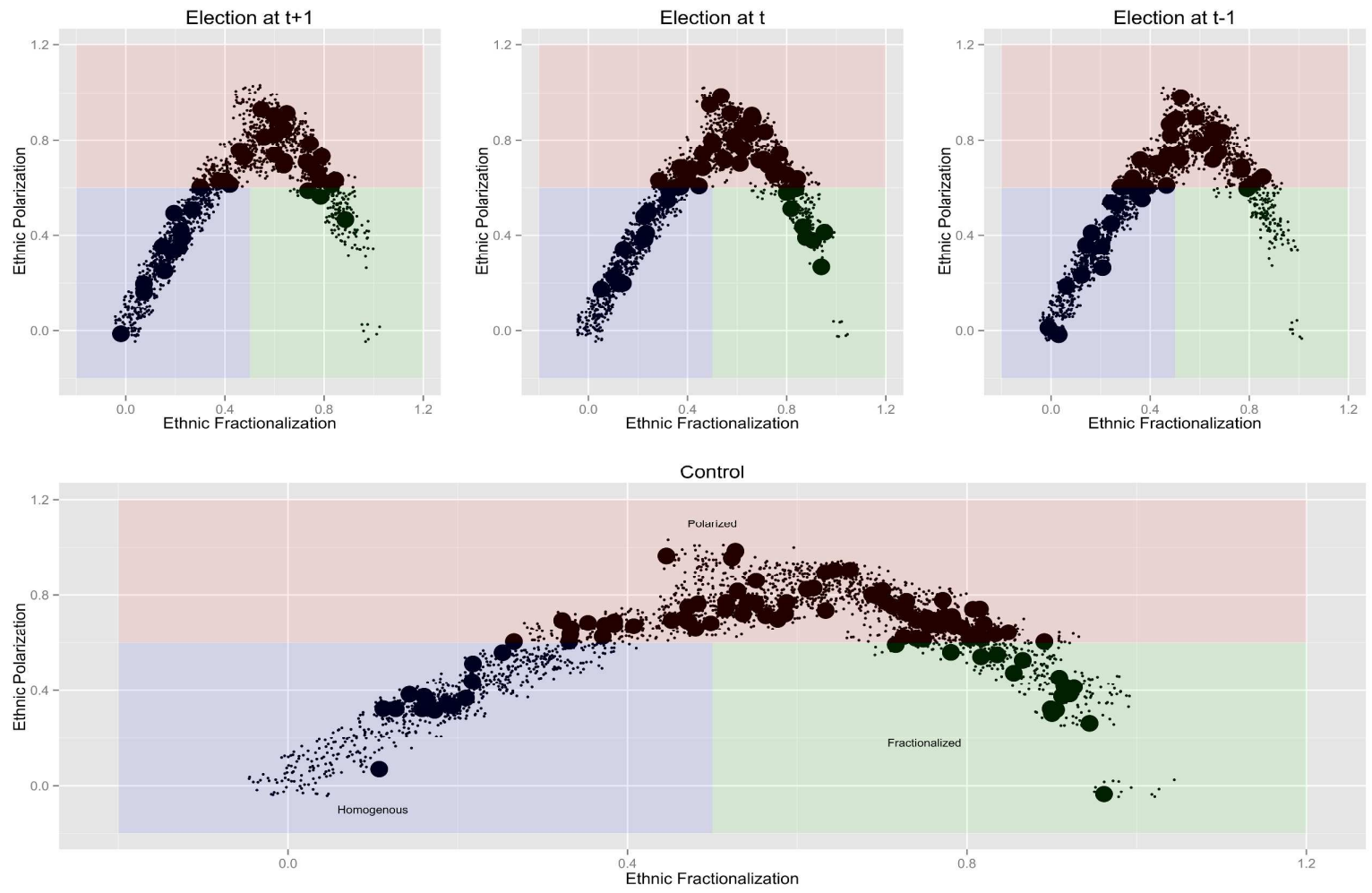
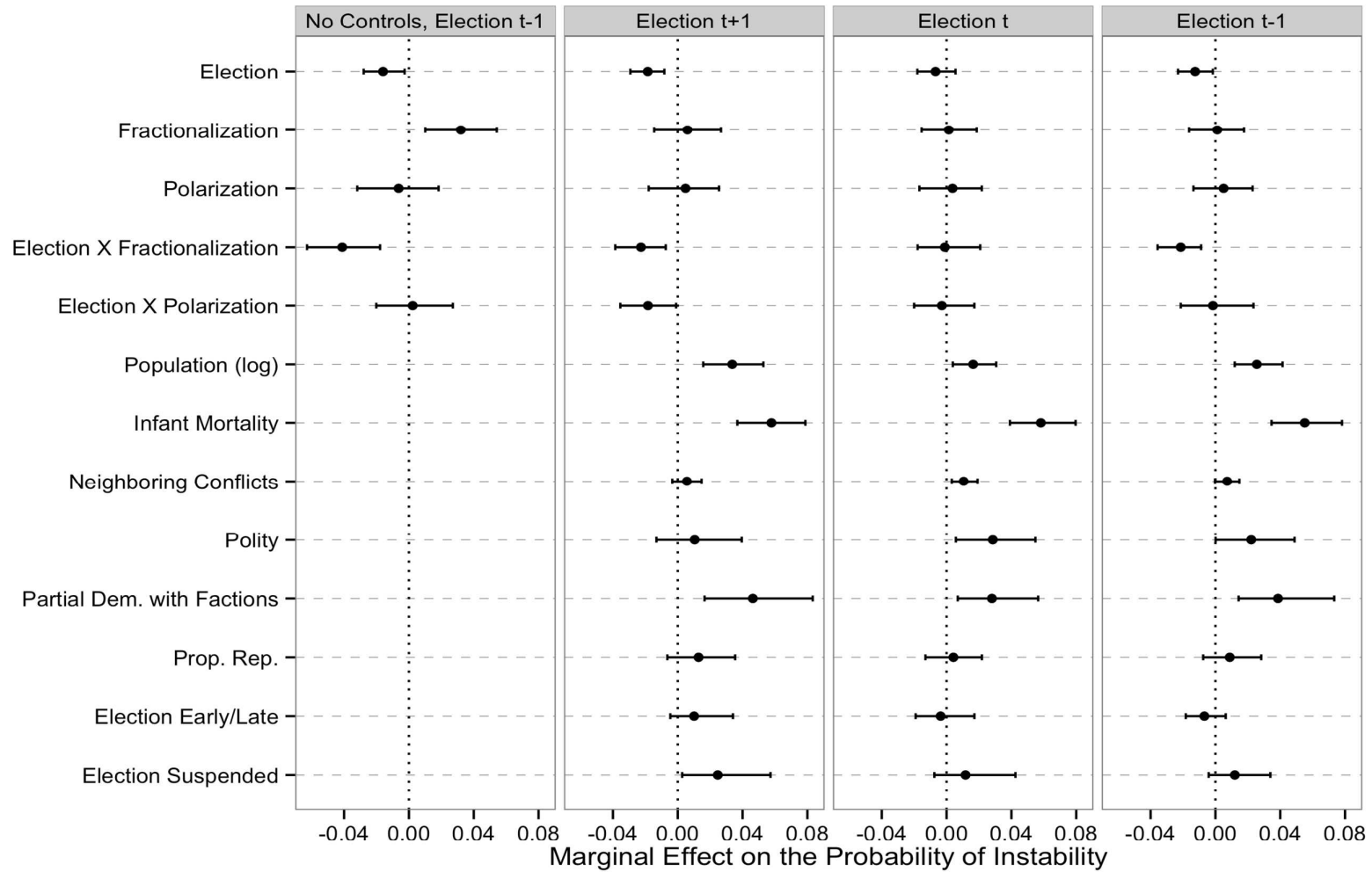
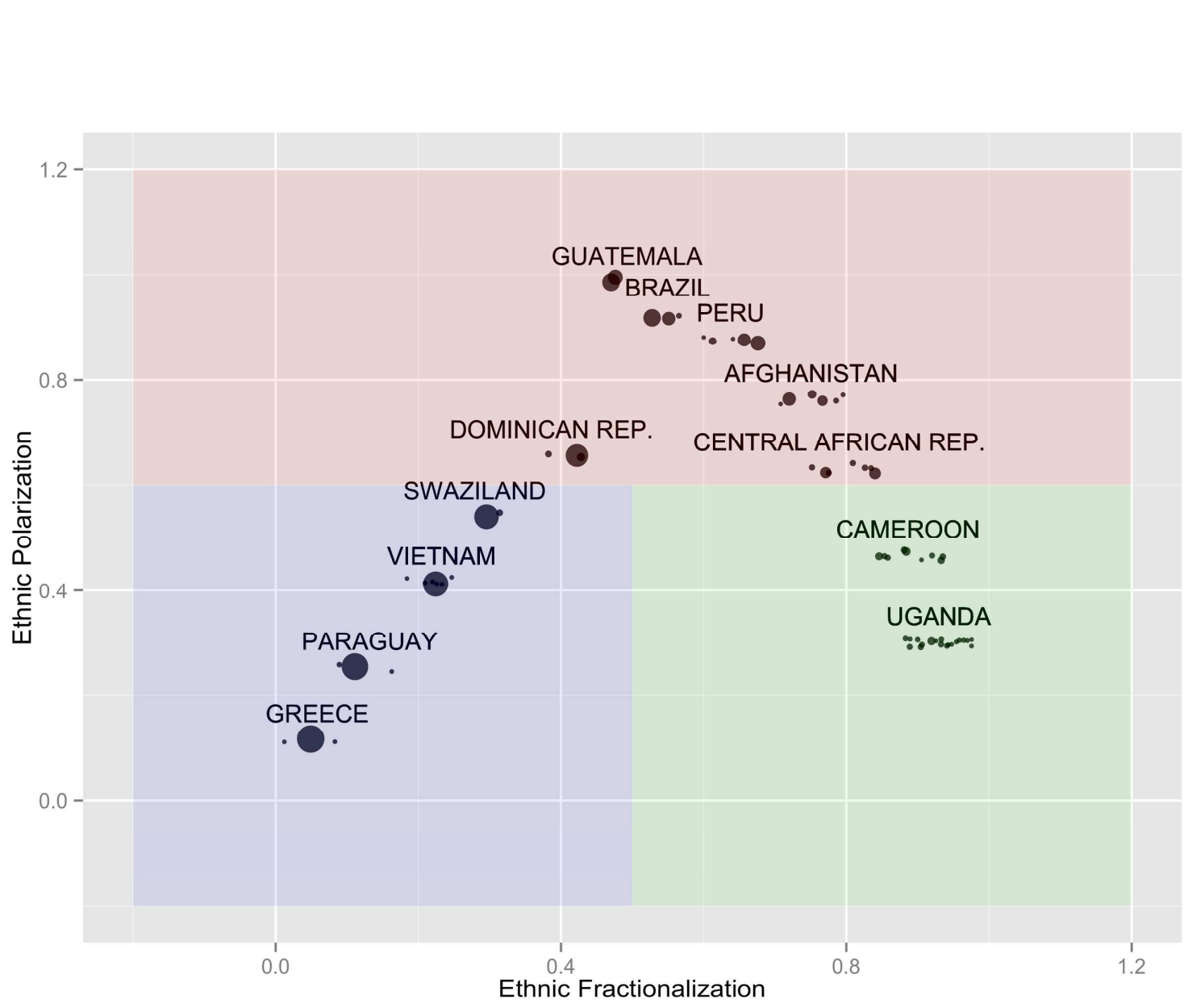


Figure 2 – First differences, elections, ethnic structure and the onset of instability, 1960-2010



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Figure 3 – Simulated scenarios in Figure 4



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Figure 4 – Simulated difference in the estimated probability of instability when changing from non-election to election years across ethnic structures

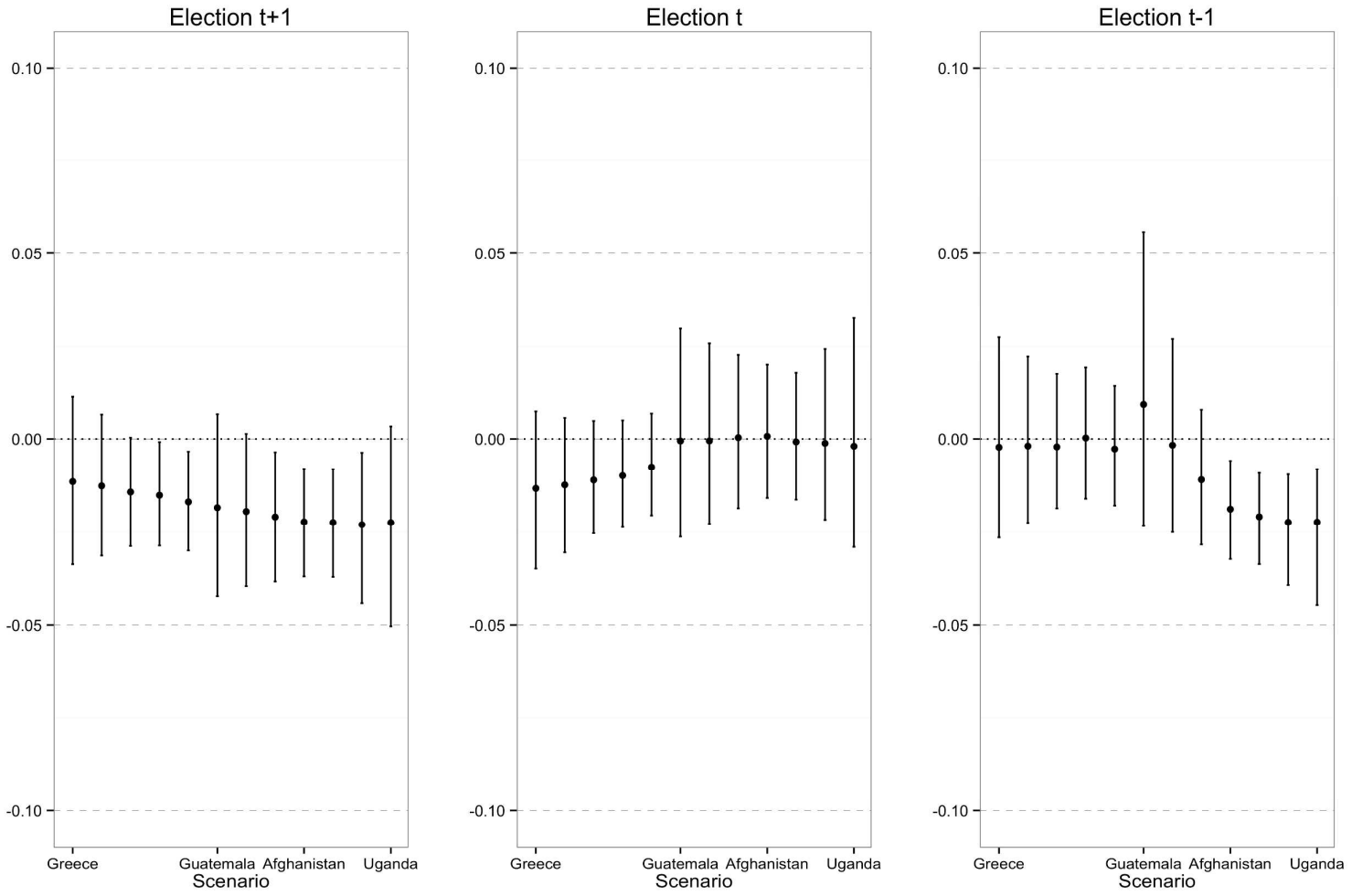
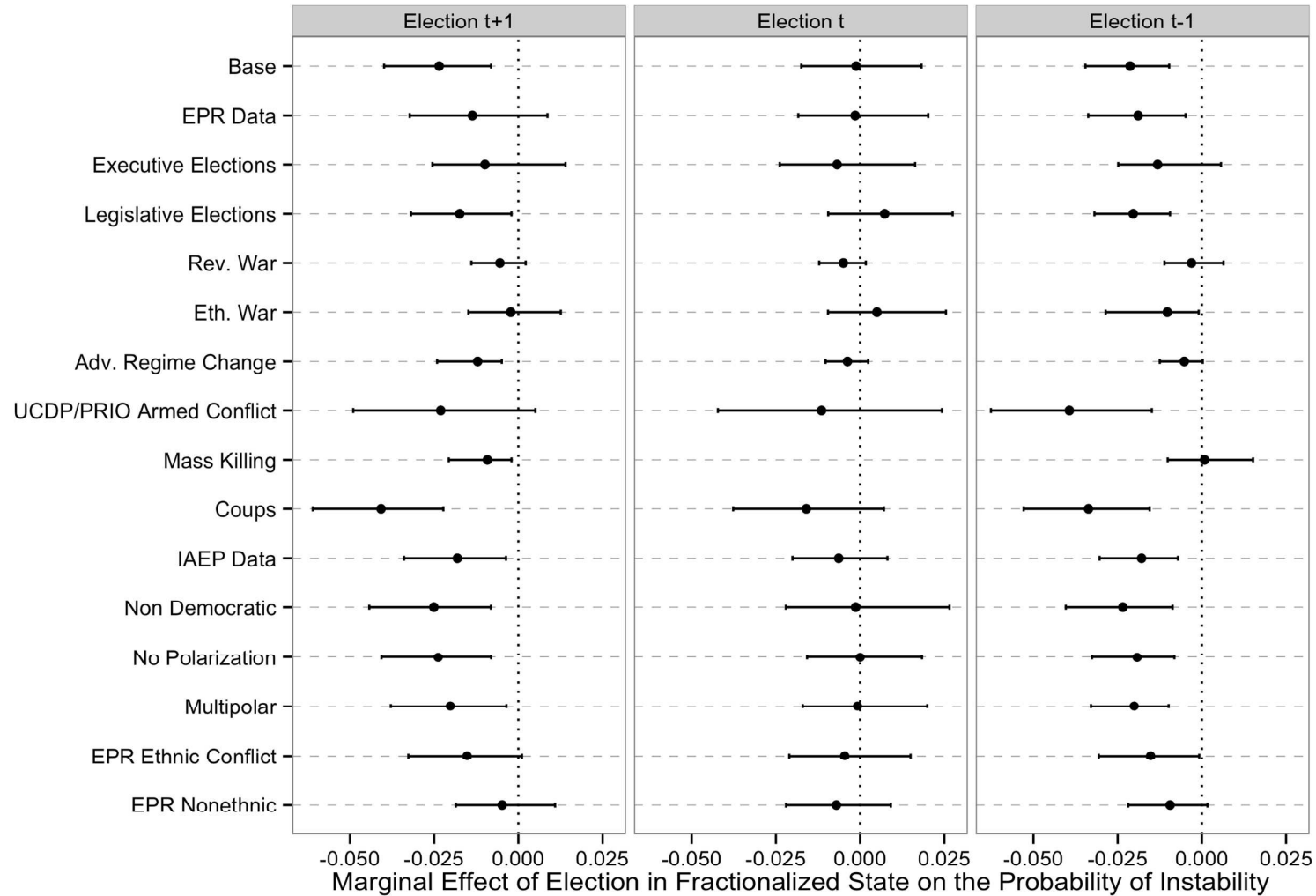


Figure 5 – Summary of robustness tests: First differences of the effect of an election on political instability in an ethnically fractionalized state



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Replication file for main analysis in 'Elections, Ethnicity and Political Instability'

Anonymous

7 July 2016

This R script will replicate the results in 'Elections, Ethnicity and Political Instability'. Files should be placed in the project directory, or set working directory to the location where the files are stored.

Required Packages and customised functions

```

require(ggplot2) # Version 2.1.0
## Loading required package: ggplot2
## Warning: package 'ggplot2' was built under R version 3.2.4
require(Amelia) # Version 1.7.4
## Loading required package: Amelia
## Loading required package: Rcpp
## ##
## ## Amelia II: Multiple Imputation
## ## (Version 1.7.4, built: 2015-12-05)
## ## Copyright (C) 2005-2016 James Honaker, Gary King and Matthew Blackwell
## ## Refer to http://gking.harvard.edu/amelia/ for more information
## ##
require(Zelig) # Version 4.2.1 - crucial - major changes to syntax have
occured since version 5.
## Loading required package: Zelig
## Loading required package: boot
## Loading required package: MASS
## Loading required package: sandwich
## ZELIG (Versions 4.2-1, built: 2013-09-12)
##
## +-----+
## | Please refer to http://gking.harvard.edu/zelig for full |
## | documentation or help.zelig() for help with commands and |
## | models support by Zelig. |
## | |
## | Zelig project citations: |
## |   Kosuke Imai, Gary King, and Olivia Lau. (2009). |
## |   ``Zelig: Everyone's Statistical Software,' |
## |   http://gking.harvard.edu/zelig |
## |   and |
## |   Kosuke Imai, Gary King, and Olivia Lau. (2008). |
## |   ``Toward A Common Framework for Statistical Analysis |
## |   and Development,' Journal of Computational and |
## |   Graphical Statistics, Vol. 17, No. 4 (December) |

```

```

1
2
3 ## | pp. 892-913. |
4 ## | | |
5 ## | To cite individual Zelig models, please use the citation |
6 ## | format printed with each model run and in the documentation. |
7 ## +-----+
8 ##
9 ## Attaching package: 'Zelig'
10 ## The following object is masked from 'package:ggplot2':
11 ##
12 ## alpha
13 ## The following object is masked from 'package:utils':
14 ##
15 ## cite
16 library(Hmisc) # Version 3.17-2
17 ## Loading required package: lattice
18 ##
19 ## Attaching package: 'lattice'
20 ## The following object is masked from 'package:boot':
21 ##
22 ## melanoma
23 ## Loading required package: survival
24 ##
25 ## Attaching package: 'survival'
26 ## The following object is masked from 'package:boot':
27 ##
28 ## aml
29 ## Loading required package: Formula
30 ##
31 ## Attaching package: 'Hmisc'
32 ## The following objects are masked from 'package:Zelig':
33 ##
34 ## combine, describe, describe.default, summarize
35 ## The following objects are masked from 'package:base':
36 ##
37 ## format.pval, round.POSIXt, trunc.POSIXt, units
38 require(texreg) # Version 1.36.4
39 ## Loading required package: texreg
40 ## Version: 1.36.4
41 ## Date: 2016-02-16
42 ## Author: Philip Leifeld (Eawag & University of Bern)
43 ##
44 ## Please cite the JSS article in your publications -- see
45 ## citation("texreg").
46 require(ZeligMultiLevel) # Version 0.7-1 - crucial
47 ## Loading required package: ZeligMultiLevel
48 ## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
49 ## logical.return = TRUE, : there is no package called 'ZeligMultiLevel'
50 # Customised functions
51
52 # Function to extract results from logit analyses of multiply imputed data
53 # with texreg
54
55 require(texreg)
56 extract.mi.logit <- function(model, ...) {
57
58   s <- summary(model, ...) # save the summary statistics
59   names <- rownames(s$coefficients) # extract coefficient names
60

```

```

1
2
3   co <- s$coefficients[,1] # extract the coefficient values
4   se <- s$coefficients[,2] # extract the standard errors
5   pval <- s$coefficients[,4] # extract the p-values
6   aic <- mean(s$all[[1]][[5]], s$all[[2]][[5]], s$all[[3]][[5]],
7   s$all[[4]][[5]], s$all[[5]][[5]])
8   rs <- s$r.squared # extract R-squared
9   adj <- s$adj.r.squared # extract adjusted R-squared
10  n <- nrow(model$impl$data) # extract number of observations
11  gof <- c(aic, n) #create a vector of GOF statistics
12  gof.names <- c("AIC", "Num. obs.") #names of GOFs
13  decimal.places <- c(TRUE, FALSE) #the last one is a count variable
14
15  tr <- createTexreg( # create a texreg object
16    coef.names=names,
17    coef=co,
18    se=se,
19    pvalues=pval, # p-values are only needed when
20    gof.names=gof.names, # signif. stars shall be printed
21    gof=gof,
22    gof.decimal=decimal.places # (optional)
23  )
24  return(tr) # return texreg object to texreg
25 }
26
27 setMethod("extract", signature=className("mi", "zelig"),
28   definition = extract.mi.logit)
29 ## [1] "extract"
30 # Function to simulate and extract first differences with multiply imputed
31 data and Zelig models.
32 # Requires the name of the model (model), the names of the variables that
33 need to be simulated as a strong vector (names), lower and upper bound of the
34 confidence intervals (c1, c2), a label for the model name (label) and the
35 number of imputed datasets (imps).
36
37 sims.mi.fd <- function (model, names, c1, c2, label, imps) {
38
39   results <- NULL
40   results.f <- NULL
41   margins <- NULL
42   model.name <- as.character(label)
43   names(names) <- "v1"
44   names <- as.data.frame(names)
45   names$v2 <- paste(names$v1, ".x1", sep="")
46   names$v3 <- paste(names$v1, ".x2", sep="")
47
48
49   ## sims for each variable in the names
50   for (i in 1:nrow(names)) {
51     ### take the first variable
52
53     x<-get(names[i,2])
54     x1<-get(names[i,3])
55     c <- sim(model, x=x, x1=x1)
56     object <- c
57
58     ### now extract the mi simulations from qi
59
60

```

```

1
2
3
4     for (i in 1:imps) {
5       a <- object[[i]]$qi[[5]]
6       results <- rbind(a, results)
7     }
8
9     results.f <- cbind(results.f, results)
10    results <- NULL
11
12  }
13
14  results.f <- as.data.frame(results.f)
15  titles <- as.character(names[,1])
16  names(results.f) <- titles
17
18  for (i in 1:ncol(results.f)){
19    mean <- mean(results.f[,i])
20    cil <- quantile(results.f[,i], prob=c1)
21    ci2 <- quantile(results.f[,i], prob=c2)
22    d <- as.data.frame(cbind(mean, cil, ci2))
23    d$variable <- as.character(names(results.f[i]))
24    margins <- rbind(margins, d)
25
26  }
27
28  margins <- as.data.frame(margins)
29  names(margins) <- c("mean", "low", "high", "variable")
30  margins$model <- model.name
31  return(margins)
32 }
33
34
35 # Multiplot function from Chang 2013 - 'R Grpahics Cookbook'.
36
37
38 multiplot <- function(..., plotlist=NULL, file, cols=1, layout=NULL) {
39   require(grid)
40
41   # Make a list from the ... arguments and plotlist
42   plots <- c(list(...), plotlist)
43
44   numPlots = length(plots)
45
46   # If layout is NULL, then use 'cols' to determine layout
47   if (is.null(layout)) {
48     # Make the panel
49     # ncol: Number of columns of plots
50     # nrow: Number of rows needed, calculated from # of cols
51     layout <- matrix(seq(1, cols * ceiling(numPlots/cols)),
52                      ncol = cols, nrow = ceiling(numPlots/cols))
53   }
54
55   if (numPlots==1) {
56     print(plots[[1]])
57
58   } else {
59
60

```

```

1
2
3   # Set up the page
4   grid.newpage()
5   pushViewport(viewport(layout = grid.layout(nrow(layout), ncol(layout))))
6
7   # Make each plot, in the correct location
8   for (i in 1:numPlots) {
9     # Get the i,j matrix positions of the regions that contain this subplot
10    matchidx <- as.data.frame(which(layout == i, arr.ind = TRUE))
11
12    print(plots[[i]], vp = viewport(layout.pos.row = matchidx$row,
13                                   layout.pos.col = matchidx$col))
14  }
15 }
16 }
17
18
19 # Function to generate robust standard errors. From King and Roberts (2015)
20
21 robust.se <- function(model, cluster){
22   require(sandwich)
23   require(lmtest)
24   M <- length(unique(cluster))
25   N <- length(cluster)
26   K <- model$rank
27   dfc <- (M/(M - 1)) * ((N - 1)/(N - K))
28   uj <- apply(estfun(model), 2, function(x) tapply(x, cluster, sum));
29   rcse.cov <- dfc * sandwich(model, meat = crossprod(uj)/N)
30   rcse.se <- coefest(model, rcse.cov)
31   return(list(rcse.cov, rcse.se))
32 }
33
34 # Function to generate robust, clustered standard errors. From King and
35 Roberts (2015)
36
37 cl <- function(dat, fm, cluster){
38   require(sandwich, quietly = TRUE)
39   require(lmtest, quietly = TRUE)
40   M <- length(unique(cluster))
41   N <- length(cluster)
42   K <- fm$rank
43   dfc <- (M/(M-1))*((N-1)/(N-K))
44   uj <- apply(estfun(fm), 2, function(x) tapply(x, cluster, sum));
45   vcovCL <- dfc*sandwich(fm, meat=crossprod(uj)/N)
46   coefest(fm, vcovCL) }
47
48
49
50 sims <- function (model, names, c1, c2, label, imps) {
51
52   results <- NULL
53   results.f <- NULL
54   margins <- NULL
55   model.name <- as.character(label)
56   names(names) <- "v1"
57   names <- as.data.frame(names)
58   names$v2 <- paste(names$v1, ".x1", sep="")
59
60

```

```

1
2
3 names$v3 <- paste(names$v1, ".x2", sep="")
4
5
6 ## sims for each variable in the names
7 for (i in 1:nrow(names)) {
8   ### take the first variable
9
10  x<-get(names[i,2])
11  x1<-get(names[i,3])
12  c <- sim(model, x=x, x1=x1)
13  object <- c
14
15  ### now extract the mi simulations from qi
16
17  for (i in 1:imps) {
18    a <- object[[i]]$qi[[5]]
19    results <- rbind(a, results)
20  }
21
22  results.f <- cbind(results.f, results)
23  results <- NULL
24
25 }
26
27 results.f <- as.data.frame(results.f)
28 titles <- as.character(names[,1])
29 names(results.f) <- titles
30
31 for (i in 1:ncol(results.f)){
32   mean <- mean(results.f[,i])
33   ci1 <- quantile(results.f[,i], prob=c1)
34   ci2 <- quantile(results.f[,i], prob=c2)
35   d <- as.data.frame(cbind(mean, ci1, ci2))
36   d$variable <- as.character(names(results.f[i]))
37   margins <- rbind(margins, d)
38 }
39
40 margins <- as.data.frame(margins)
41 names(margins) <- c("mean", "low", "high", "variable")
42 margins$model <- model.name
43 return(margins)
44 }

```

45 Read in the main dataframe

```
46
47
48 df <- read.csv("df-02-08-2016.csv")
49
```

50 Begin the analysis

51
52
53 Create 4 samples, 1 each for whether there was an election at t-1, t, and t+1, and a 'control' when
54 there was no election at t-1, t, and t+1. Create Figure 1 which shows the distribution of
55 inststability onsets across
56
57
58
59
60

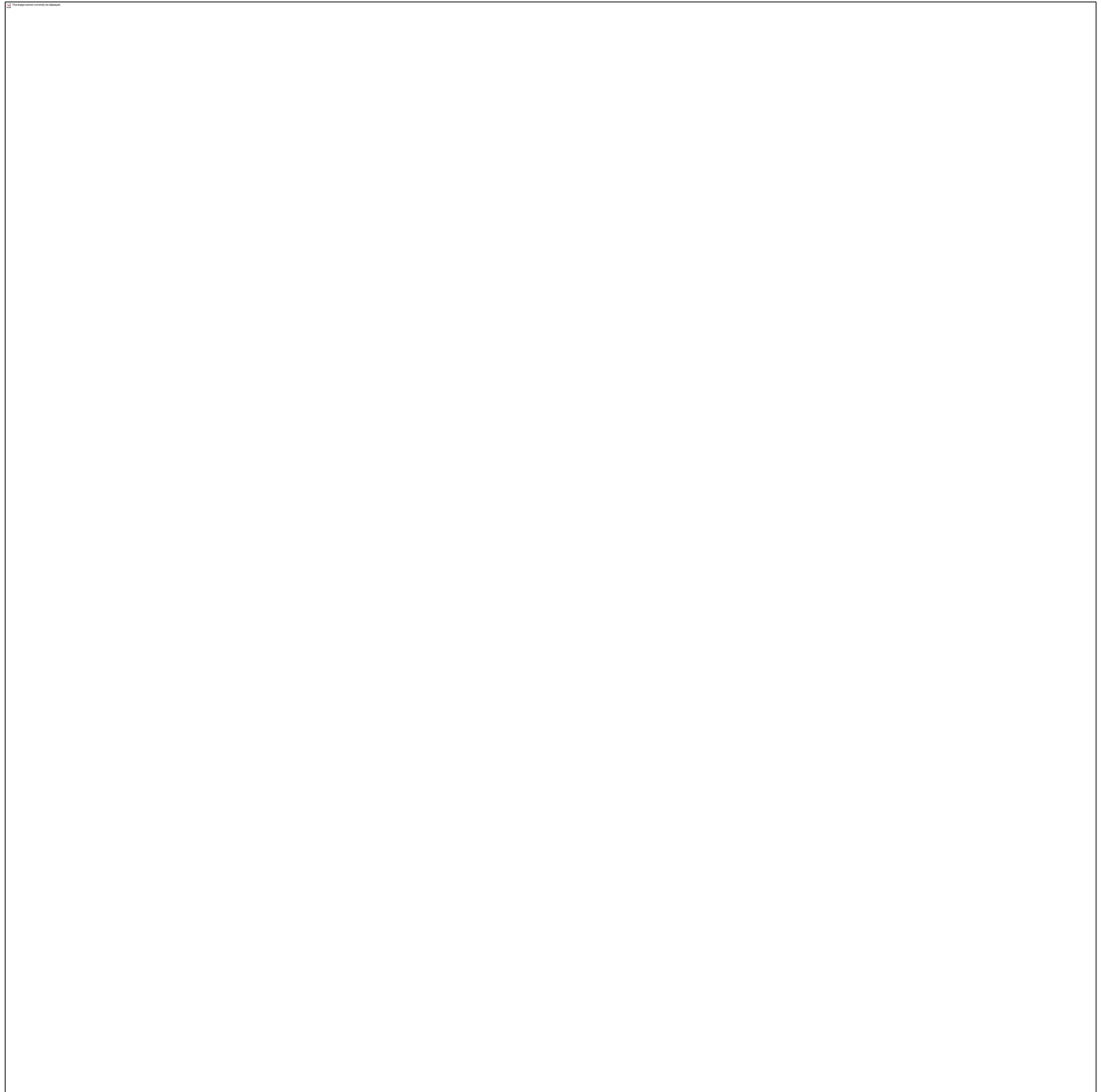
```

1
2
3 election.l1 <- subset(df, nld.election.l1==1)
4 election.t <- subset(df, nld.election==1)
5 election.f1 <- subset(df, nld.election.f1==1)
6 control <- subset(df, nld.election.l1==0 & nld.election==0 &
7 nld.election.f1==0)
8
9
10
11 # Distribution of instability onsets across fractionalization and
12 polarization scores - 'Control' group.
13
14 control.fig <- ggplot(control, aes(x=ef, y=polarization,
15 size=as.numeric(instab.st))) +
16   geom_point(position=position_jitter(width=.05, height=0.05))+
17   xlab("Ethnic Fractionalization")+ylab("Ethnic Polarization")+
18   guides(size=FALSE) + ggtitle("Control") + annotate("rect", xmin=0.5,
19 xmax=1.2, ymin=-0.2, ymax=0.6, alpha=.1,fill="green") +
20   annotate("rect", xmin=-0.2, xmax=0.5, ymin=-0.2, ymax=0.6,
21 alpha=.1,fill="blue") + annotate("rect", xmin=-0.2, xmax=1.2, ymin=0.6,
22 ymax=1.2, alpha=.1,fill="red") +
23   annotate("text", x=0.1, y=-0.1, label="Homogenous", size=3)+
24   annotate("text", x=0.75, y=0.18, label="Fractionalized", size=3) +
25   annotate("text", x=0.5, y=1.1, label="Polarized", , size=3)
26
27 # Election in the previous year
28
29 election.l1.fig <- ggplot(election.l1, aes(x=ef, y=polarization,
30 size=as.numeric(instab.st))) +
31   geom_point(position=position_jitter(width=.05, height=0.05))+
32   xlab("Ethnic Fractionalization")+ylab("Ethnic Polarization")+
33   guides(size=FALSE) + ggtitle("Election at t-1") + annotate("rect",
34 xmin=0.5, xmax=1.2, ymin=-0.2, ymax=0.6, alpha=.1,fill="green") +
35   annotate("rect", xmin=-0.2, xmax=0.5, ymin=-0.2, ymax=0.6,
36 alpha=.1,fill="blue") + annotate("rect", xmin=-0.2, xmax=1.2, ymin=0.6,
37 ymax=1.2, alpha=.1,fill="red")
38
39 # Election in that year
40
41 election.t.fig <- ggplot(election.t, aes(x=ef, y=polarization,
42 size=as.numeric(instab.st))) +
43   geom_point(position=position_jitter(width=.05, height=0.05))+
44   xlab("Ethnic Fractionalization")+ylab("Ethnic Polarization")+
45   guides(size=FALSE) + ggtitle("Election at t") + annotate("rect", xmin=0.5,
46 xmax=1.2, ymin=-0.2, ymax=0.6, alpha=.1,fill="green") +
47   annotate("rect", xmin=-0.2, xmax=0.5, ymin=-0.2, ymax=0.6,
48 alpha=.1,fill="blue") + annotate("rect", xmin=-0.2, xmax=1.2, ymin=0.6,
49 ymax=1.2, alpha=.1,fill="red")
50
51 # Election next year
52
53 election.f1.fig <- ggplot(election.f1, aes(x=ef, y=polarization,
54 size=as.numeric(instab.st))) +
55   geom_point(position=position_jitter(width=.05, height=0.05))+
56   xlab("Ethnic Fractionalization")+ylab("Ethnic Polarization")+
57   guides(size=FALSE) + ggtitle("Election at t+1") + annotate("rect",
58 xmin=0.5, xmax=1.2, ymin=-0.2, ymax=0.6, alpha=.1,fill="green") +
59
60

```

```
1
2
3   annotate("rect", xmin=-0.2, xmax=0.5, ymin=-0.2, ymax=0.6,
4   alpha=.1,fill="blue") + annotate("rect", xmin=-0.2, xmax=1.2, ymin=0.6,
5   ymax=1.2, alpha=.1,fill="red")
6
7   # Combine the three figures into figure 1
8
9
10  multiplot(control.fig, election.f1.fig, election.t.fig, election.l1.fig,
11  cols=3, layout=matrix(c(2,3,4,1,1,1), nrow=2, byrow=TRUE), linetype="dashed")
12  ## Loading required package: grid
13  ## Warning: Removed 120 rows containing missing values (geom_point).
14  ## Warning: Removed 35 rows containing missing values (geom_point).
15  ## Warning: Removed 36 rows containing missing values (geom_point).
16  ## Warning: Removed 35 rows containing missing values (geom_point).
```


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```
## [1] "dashed"
```

Now split the sample into ‘homogenous’, ‘polarized’ and ‘fractionalized’ states. The cutoffs are the same as the colours in Figure 1. Homogenous = $\text{frac} > 0.5$ & $\text{pol} > 0.6$, Polarized = $\text{pol} \geq 0.6$, fractionalized = $\text{frac} \geq 0.5$ & $\text{pol} \geq 0.6$. Then report the mean instability onset rates for these different samples and the correlations between the presence of elections at $t-1$, t , and $t+1$ and instability onsets.

```

1
2
3 sample <- na.omit(subset(df, select=c("instab.st", "ef", "polarization",
4 "nld.election.l1", "nld.election", "nld.election.f1", "nld.election.period",
5 "ccode", "year")))
6 sample$instab.st <- as.numeric(sample$instab.st)
7 sample$nld.election.f1 <- as.numeric(sample$nld.election.f1)
8 sample$nld.election.l1 <- as.numeric(sample$nld.election.l1)-1
9 sample$nld.election <- as.numeric(sample$nld.election)
10
11 homogenous <- subset(sample, ef<0.5 & polarization<0.6)
12 polarized <- subset(sample, polarization>=0.6)
13 fractionalized <- subset(sample, ef>=0.5 & polarization<0.6 )
14
15
16
17 # Instability rates and election rates across homogenous, polarized and
18 fractionalized settings
19 # As reported in Table 3.
20
21 # Mean instability
22 mean(homogenous$instab.st)
23 ## [1] 0.01900041
24 mean(polarized$instab.st)
25 ## [1] 0.03807723
26 mean(fractionalized$instab.st)
27 ## [1] 0.03951368
28 # Mean elections
29 mean(as.numeric(homogenous$nld.election))
30 ## [1] 0.2866584
31 mean(as.numeric(polarized$nld.election))
32 ## [1] 0.231704
33 mean(as.numeric(fractionalized$nld.election))
34 ## [1] 0.2294833
35 # Pearson correlations between elections and instability rates across
36 homogenous, polarized and fractionalized
37 # settings
38
39 library(Hmisc)
40
41 hom.f1 <- subset(homogenous, nld.election.f1==1 | nld.election.period==0,
42 select=c("instab.st", "nld.election.f1"))
43 hom.chi.f1 <- rcorr(as.matrix(hom.f1), type="pearson")
44 hom.chi.f1
45 ##
46 ##          instab.st nld.election.f1
47 ## instab.st          1.00          -0.01
48 ## nld.election.f1    -0.01           1.00
49 ##
50 ## n= 1416
51 ##
52 ## P
53 ##          instab.st nld.election.f1
54 ## instab.st          0.6381
55 ## nld.election.f1 0.6381
56 hom.t <- subset(homogenous, nld.election==1 | nld.election.period==0,
57 select=c("instab.st", "nld.election"))
58 hom.chi.t <- rcorr(as.matrix(hom.t), type="pearson")
59 hom.chi.t
60

```

```

1
2
3      ##           instab.st nld.election
4      ## instab.st           1.00        -0.02
5      ## nld.election       -0.02           1.00
6      ##
7      ## n= 1414
8      ##
9      ##
10     ## P
11     ##           instab.st nld.election
12     ## instab.st           0.5062
13     ## nld.election 0.5062
14     hom.l1 <- subset(homogenous, nld.election.l1==1 | nld.election.period==0,
15     select=c("instab.st", "nld.election.l1"))
16     hom.chi.l1 <- rcorr(as.matrix(hom.l1), type="pearson")
17     hom.chi.l1
18     ##           instab.st nld.election.l1
19     ## instab.st           1           NaN
20     ## nld.election.l1       NaN           1
21     ##
22     ## n= 720
23     ##
24     ##
25     ## P
26     ##           instab.st nld.election.l1
27     ## instab.st
28     ## nld.election.l1
29     ##### Polarized countries
30     pol.f1 <- subset(polarized, nld.election.f1==1 | nld.election.period==0,
31     select=c("instab.st", "nld.election.f1"))
32     pol.chi.f1 <- rcorr(as.matrix(pol.f1), type="pearson")
33     pol.chi.f1
34     ##           instab.st nld.election.f1
35     ## instab.st           1.00        -0.05
36     ## nld.election.f1     -0.05           1.00
37     ##
38     ## n= 2369
39     ##
40     ##
41     ## P
42     ##           instab.st nld.election.f1
43     ## instab.st           0.0201
44     ## nld.election.f1 0.0201
45     pol.t <- subset(polarized, nld.election==1 | nld.election.period==0,
46     select=c("instab.st", "nld.election"))
47     pol.chi.t <- rcorr(as.matrix(pol.t), type="pearson")
48     pol.chi.t
49     ##           instab.st nld.election
50     ## instab.st           1.00        -0.01
51     ## nld.election       -0.01           1.00
52     ##
53     ## n= 2364
54     ##
55     ## P
56     ##           instab.st nld.election
57     ## instab.st           0.567
58     ## nld.election 0.567
59
60

```

```

1
2
3 pol.l1 <- subset(polarized, nld.election.l1==1 | nld.election.period==0,
4 select=c("instab.st", "nld.election.l1"))
5 pol.chi.l1 <- rcorr(as.matrix(pol.l1), type="pearson")
6 pol.chi.l1
7 ##           instab.st nld.election.l1
8 ## instab.st           1           NaN
9 ## nld.election.l1     NaN           1
10 ##
11 ## n= 1506
12 ##
13 ##
14 ## P
15 ##           instab.st nld.election.l1
16 ## instab.st
17 ## nld.election.l1
18 ##### Fractionalized countries
19 frac.f1 <- subset(fractionalized, nld.election.f1==1 |
20 nld.election.period==0, select=c("instab.st", "nld.election.f1"))
21 frac.chi.f1 <- rcorr(as.matrix(frac.f1), type="pearson")
22 frac.chi.f1
23 ##           instab.st nld.election.f1
24 ## instab.st           1.0           -0.1
25 ## nld.election.f1     -0.1           1.0
26 ##
27 ## n= 409
28 ##
29 ##
30 ## P
31 ##           instab.st nld.election.f1
32 ## instab.st           0.0485
33 ## nld.election.f1 0.0485
34 frac.t <- subset(fractionalized, nld.election==1 | nld.election.period==0,
35 select=c("instab.st", "nld.election"))
36 frac.chi.t <- rcorr(as.matrix(frac.t), type="pearson")
37 frac.chi.t
38 ##           instab.st nld.election
39 ## instab.st           1.00           -0.03
40 ## nld.election     -0.03           1.00
41 ##
42 ## n= 408
43 ##
44 ##
45 ## P
46 ##           instab.st nld.election
47 ## instab.st           0.5026
48 ## nld.election 0.5026
49 frac.l1 <- subset(fractionalized, nld.election.l1==1 |
50 nld.election.period==0, select=c("instab.st", "nld.election.l1"))
51 frac.chi.l1 <- rcorr(as.matrix(frac.l1), type="pearson")
52 frac.chi.l1
53 ##           instab.st nld.election.l1
54 ## instab.st           1           NaN
55 ## nld.election.l1     NaN           1
56 ##
57 ## n= 257
58 ##
59 ##
60

```

```

1
2
3 ## P
4 ##           instab.st nld.election.l1
5 ## instab.st
6 ## nld.election.l1
7

```

8 The next section shows the results of the regression analysis. The first step is to use multiple
9 imputation to fill missing values of the data for three different samples (1) where there was an
10 election at t-1 and then no election in time t and t+1, and (2) where there was an election at t and
11 then no election in time t+1 and t-1, and (3) where there was an election at t+1 and then no
12 election in time t and t-1. The next step runs the probit models and displays the results, and the
13 final section simulated the marginal effects.
14
15

```

16 # We have selected all variables in the model. Three different samples are
17 imputed (1) where there was an election at t-1 and then no election in time t
18 and t+1, and (2) where there was an election at t and then no election in
19 time t+1 and t-1, and (3) where there was an election at t+1 and then no
20 election in time t and t-1.
21

```

```

22 # The following code creates 5 multiply imputed datasets for these 3 samples.
23 It uses a quadratic for imputing across time.
24

```

```

25
26
27
28 require(Amelia)
29 set.seed(12345)
30 a.out.l1 <- amelia(subset(df, select=c("instab.st", "nld.election.l1", "ef",
31 "polarization",
32 "ln.wdi.imr.l1", "polity2.lag.1",
33 "part.dem.fac.l1", "stabyrs", "stabyrs.2", "stabyrs.3", # Structural Controls
34 "ln.wdi.pop.l1", "nac.l1", "ccode",
35 "year", "pr.l1",
36 "nld.earlylate.l1",
37 "nld.suspend.l1"), year<=2010 &
38 is.na(ef)==F & nld.election==0 & nld.election.f1==0), idvars=c("stabyrs",
39 "stabyrs.2", "stabyrs.3"), m = 5, cs="ccode", ts="year", polytime=2,
40 noms=c("instab.st", "nld.election.l1" ))
41 ## -- Imputation 1 --
42 ##
43 ## 1 2 3 4 5
44 ##
45 ## -- Imputation 2 --
46 ##
47 ## 1 2 3 4
48 ##
49 ## -- Imputation 3 --
50 ##
51 ## 1 2 3 4 5
52 ##
53 ## -- Imputation 4 --
54 ##
55 ## 1 2 3 4 5
56 ##
57 ## -- Imputation 5 --
58 ##
59
60

```

```

1
2
3 ## 1 2 3 4 5
4 a.out <- amelia(subset(df, select=c("instab.st", "ef", "polarization",
5 "nld.election",
6 "ln.wdi.imr.l1", "polity2.lag.1",
7 "part.dem.fac.l1", "stabyrs", "stabyrs.2", "stabyrs.3", # Structural Controls
8 "ln.wdi.pop.l1", "nac.l1", "ccode",
9 "year", "pr.l1",
10 "nld.earlylate",
11 "nld.suspend"), year<=2010 & is.na(ef)==F
12 & nld.election.l1==0 & nld.election.fl==0), idvars=c("stabyrs", "stabyrs.2",
13 "stabyrs.3"), m = 5, cs="ccode", ts="year", polytime=2, noms=c("instab.st",
14 "nld.election" ))
15 ## -- Imputation 1 --
16 ##
17 ## 1 2 3 4 5
18 ##
19 ## -- Imputation 2 --
20 ##
21 ## 1 2 3 4 5
22 ##
23 ## -- Imputation 3 --
24 ##
25 ## 1 2 3 4 5
26 ##
27 ## -- Imputation 4 --
28 ##
29 ## 1 2 3 4 5
30 ##
31 ## -- Imputation 5 --
32 ##
33 ## 1 2 3 4 5
34 a.out.fl <- amelia(subset(df, select=c("instab.st", "ef", "polarization",
35 "nld.election.fl",
36 "ln.wdi.imr.l1", "polity2.lag.1",
37 "part.dem.fac.l1", "stabyrs", "stabyrs.2", "stabyrs.3", # Structural Controls
38 "ln.wdi.pop.l1", "nac.l1", "ccode",
39 "year", "pr.l1",
40 "nld.earlylate.fl",
41 "nld.suspend.fl"), year<=2010 &
42 is.na(ef)==F & nld.election.l1==0 & nld.election==0), idvars=c("stabyrs",
43 "stabyrs.2", "stabyrs.3"), m = 5, cs="ccode", ts="year", polytime=2,
44 noms=c("instab.st", "nld.election.fl" ))
45 ## -- Imputation 1 --
46 ##
47 ## 1 2 3 4 5
48 ##
49 ## -- Imputation 2 --
50 ##
51 ## 1 2 3 4
52 ##
53 ## -- Imputation 3 --
54 ##
55 ## 1 2 3 4
56 ##
57 ## -- Imputation 4 --
58 ##
59 ## 1 2 3 4 5
60

```

```
1
2
3 ##
4 ## -- Imputation 5 --
5 ##
6 ## 1 2 3 4 5
7 ### No controls, election at t-1
8
9 m.nc.l1 <- zelig(instab.st ~ nld.election.l1*ef +
10 nld.election.l1*polarization, model="probit", data=a.out.l1)
11 ##
12 ##
13 ## How to cite this model in Zelig:
14 ## Kosuke Imai, Gary King, and Olivia Lau. 2016.
15 ## "probit: Probit Regression for Dichotomous Dependent Variables"
16 ## in Kosuke Imai, Gary King, and Olivia Lau, "Zelig: Everyone's
17 Statistical Software,"
18 ## http://gking.harvard.edu/zelig
19 ##
20 tbl.1.1 <- extract.mi.logit(m.nc.l1)
21
22
23
24 ### Controls, election at t-1
25
26 m.l1 <- zelig(instab.st ~ nld.election.l1*ef + nld.election.l1*polarization +
27 ln.wdi.imr.l1 + polity2.lag.1 + part.dem.fac.l1 + stabyrs +
28 stabyrs.2 +stabyrs.3 + # Structural Controls
29 ln.wdi.pop.l1 + nac.l1 + pr.l1 + nld.earlylate.l1 +
30 nld.suspend.l1, model="probit", data=a.out.l1)
31 ##
32 ##
33 ## How to cite this model in Zelig:
34 ## Kosuke Imai, Gary King, and Olivia Lau. 2016.
35 ## "probit: Probit Regression for Dichotomous Dependent Variables"
36 ## in Kosuke Imai, Gary King, and Olivia Lau, "Zelig: Everyone's
37 Statistical Software,"
38 ## http://gking.harvard.edu/zelig
39 ##
40 tbl.1.2 <- extract.mi.logit(m.l1)
41
42 ### Controls, election at t
43
44 m.t <- zelig(instab.st ~ nld.election*ef + nld.election*polarization +
45 ln.wdi.imr.l1 + polity2.lag.1 + part.dem.fac.l1 + stabyrs +
46 stabyrs.2 +stabyrs.3 + # Structural Controls
47 ln.wdi.pop.l1 + nac.l1 + pr.l1 + nld.earlylate + nld.suspend,
48 model="probit", data=a.out)
49 ##
50 ##
51 ## How to cite this model in Zelig:
52 ## Kosuke Imai, Gary King, and Olivia Lau. 2016.
53 ## "probit: Probit Regression for Dichotomous Dependent Variables"
54 ## in Kosuke Imai, Gary King, and Olivia Lau, "Zelig: Everyone's
55 Statistical Software,"
56 ## http://gking.harvard.edu/zelig
57 ##
58 tbl.1.3 <- extract.mi.logit(m.t)
59
60
```

```

1
2
3   ### Controls, election at t+1
4
5   m.fl <- zelig(instab.st ~ nld.election.fl*ef + nld.election.fl*polarization +
6     ln.wdi.imr.l1 + polity2.lag.1 + part.dem.fac.l1 + stabyrs +
7     stabyrs.2 + stabyrs.3 + # Structural Controls
8     ln.wdi.pop.l1 + nac.l1 + pr.l1 + nld.earlylate.fl +
9     nld.suspend.fl, model="probit", data=a.out.fl)
10  ##
11  ##
12  ## How to cite this model in Zelig:
13  ##   Kosuke Imai, Gary King, and Olivia Lau. 2016.
14  ##   "probit: Probit Regression for Dichotomous Dependent Variables"
15  ##   in Kosuke Imai, Gary King, and Olivia Lau, "Zelig: Everyone's
16  ##   Statistical Software,"
17  ##   http://gking.harvard.edu/zelig
18  ##
19  tbl.1.4 <- extract.mi.logit(m.fl)
20
21  model.names <- c("No Controls, Election t-1", "Election t+1", "Election t",
22  "Election t-1")
23
24  table.1.1 <- htmlreg(list(tbl.1.1, tbl.1.4, tbl.1.3, tbl.1.2),
25  custom.model.names = model.names, caption="Elections and Violent Political
26  Instability, Base Model (shown in main text)", omit.coef = "(stab)" , stars =
27  c(0.01,
28  0.05, 0.1), caption.above=TRUE)
29

```

Show regression table with the results

table.1.1

Elections and Violent Political Instability, Base Model (shown in main text)

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.99*** (0.15)	-5.69*** (0.69)	-5.37*** (0.72)	-6.01*** (0.72)
nld.election.l1	-0.25 (0.27)			-0.11 (0.33)
ef	0.58*** (0.19)	0.16 (0.23)	0.03 (0.22)	0.03 (0.23)
polarization	-0.11 (0.23)	0.12 (0.26)	0.13 (0.27)	0.16 (0.27)
nld.election.l1:ef	-1.16** (0.51)			-1.63*** (0.59)
nld.election.l1:polarization	0.99* (0.52)			1.03* (0.61)
nld.election.fl		-0.32 (0.34)		
ln.wdi.imr.l1		0.37*** (0.08)	0.45*** (0.09)	0.45*** (0.09)
polity2.lag.1		0.01	0.02**	0.02*

		(0.01)	(0.01)	(0.01)
	part.dem.fac.l1	0.48***	0.34***	0.48***
		(0.13)	(0.13)	(0.13)
	ln.wdi.pop.l1	0.12***	0.07**	0.12***
		(0.03)	(0.03)	(0.03)
	nac.l1	0.04	0.09***	0.06*
		(0.03)	(0.03)	(0.03)
	pr.l1	0.06	0.02	0.05
		(0.05)	(0.05)	(0.05)
	nld.earlylate.fl	0.25		
		(0.22)		
	nld.suspend.fl	0.51**		
		(0.21)		
	nld.election.fl:ef	-0.31		
		(0.46)		
	nld.election.fl:polarization	0.08		
		(0.54)		
	nld.election		-0.46	
			(0.35)	
	nld.earlylate		-0.12	
			(0.23)	
	nld.suspend		0.19	
			(0.19)	
	nld.election:ef		0.33	
			(0.42)	
	nld.election:polarization		0.28	
			(0.49)	
	nld.earlylate.l1			-0.32
				(0.28)
	nld.suspend.l1			0.28
				(0.21)
	AIC	1105.99	1011.17	1078.80
	Num. obs.	3633	3710	3713
				3633

$p < 0.01$, $p < 0.05$, $p < 0.1$

Now simulate the marginal effects for each model. This section simulates the marginal effects for different scenarios in the data, moving from ethnically homogenized countries to ethnically heterogeneous ones. We've picked cases from each section of the polarization/fractionalization scatter (Figure 1) that reflect escalating fractionalization. These cases are Greece, Paraguay, Vietnam, Swaziland, Dominican Republic, Guatemala, Brazil, Peru, Afghanistan, Lebanon, Cameroon, Uganda

```

1
2
3 # Simulate the marginal effects for different scenarios in the data, moving
4 from ethnically homogenized countries to ethnically heterogenous ones. We've
5 picked cases from each section of the polarization/fractionalization sactter
6 (Figure 1) that reflect escalating fractionalization. These cases are Greece,
7 Parguay, Vietnam, Swaziland, Dominican Republic, Guatemala, Brazil, Peru,
8 Afghanistan, Lebanon, Cameroon, Uganda
9

```

```

10 require(foreign)
11 ## Loading required package: foreign
12 fearon <- read.dta("fearon.dta")
13 fearon <- subset(fearon, select=c("ef", "polarization", "country",
14 "ccodebg"))
15
16 fracmes <- c(fearon$ef[fearon$country=="GREECE"],
17 fearon$ef[fearon$country=="PARAGUAY"], fearon$ef[fearon$country=="VIETNAM"],
18 fearon$ef[fearon$country=="SWAZILAND"], fearon$ef[fearon$country=="DOMINICAN
19 REP."],
20           fearon$ef[fearon$country=="GUATEMALA"],
21 fearon$ef[fearon$country=="BRAZIL"], fearon$ef[fearon$country=="PERU"],
22 fearon$ef[fearon$country=="AFGHANISTAN"], fearon$ef[fearon$country=="CENTRAL
23 AFRICAN REP."],
24
25 fearon$ef[fearon$country=="CAMEROON"], fearon$ef[fearon$country=="UGANDA"])
26 polmes <- c(fearon$polarization[fearon$country=="GREECE"],
27 fearon$polarization[fearon$country=="PARAGUAY"],
28 fearon$polarization[fearon$country=="VIETNAM"],
29 fearon$polarization[fearon$country=="SWAZILAND"],
30 fearon$polarization[fearon$country=="DOMINICAN REP."],
31           fearon$polarization[fearon$country=="GUATEMALA"],
32 fearon$polarization[fearon$country=="BRAZIL"],
33 fearon$polarization[fearon$country=="PERU"],
34 fearon$polarization[fearon$country=="AFGHANISTAN"],
35 fearon$polarization[fearon$country=="CENTRAL AFRICAN REP."],
36
37 fearon$polarization[fearon$country=="CAMEROON"], fearon$polarization[fearon$co
38 untry=="UGANDA"])
39

```

```

40 # mes is an object with the values of polarization and fractionalization for
41 each of these scenarios.
42
43

```

```

44 mes <- as.data.frame(cbind(fracmes, polmes))
45

```

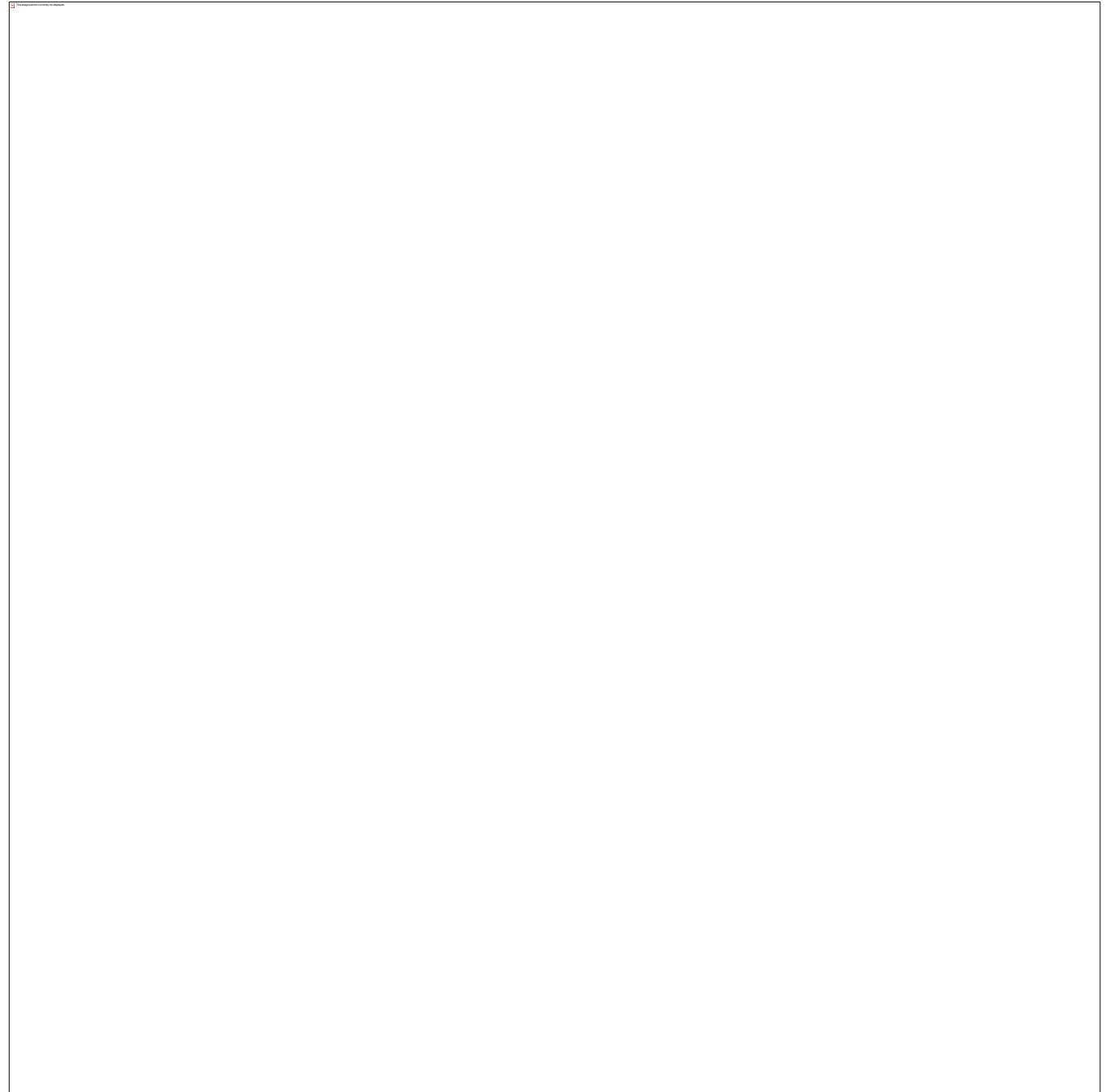
```

46 fearon$sim <- 0
47 fearon$sim[fearon$country=="GREECE" | fearon$country=="PARAGUAY" | fearon$country
48 == "VIETNAM" | fearon$country=="SWAZILAND" | fearon$country=="DOMINICAN
49 REP." | fearon$country=="GUATEMALA" |
50
51 fearon$country=="BRAZIL" | fearon$country=="PERU" | fearon$country=="AFGHANISTAN"
52 | fearon$country=="CENTRAL AFRICAN
53 REP." | fearon$country=="CAMEROON" | fearon$country=="UGANDA"] <- 1
54
55 fearon$label <- NA
56 for (i in 1:nrow(fearon)) { fearon$label[i][fearon$sim[i]==1] <-
57 fearon$country[i]}
58
59
60

```

```
1
2
3 # Now create the figure that shows which cases are being simulated (Figure 3)
4
5
6 ggplot(fearon, aes(x=ef, y=polarization, size=sim))+ geom_point()+
7   geom_text(aes(label=label), size=4, vjust=2) +
8   xlab("Ethnic Fractionalization")+ylab("Ethnic Polarization")+
9   guides(size=FALSE) + annotate("rect", xmin=0.5, xmax=1.2, ymin=-0.2,
10  ymax=0.6, alpha=.1,fill="green") +
11   annotate("rect", xmin=-0.2, xmax=0.5, ymin=-0.2, ymax=0.6,
12  alpha=.1,fill="blue") + annotate("rect", xmin=-0.2, xmax=1.2, ymin=0.6,
13  ymax=1.2, alpha=.1,fill="red")
14 ## Warning: Removed 148 rows containing missing values (geom_text).
15
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```
# The next set of code generates expected values for each of these data
# points in election and non-election periods
# and stores the first difference between these values.

# for election at t-1.
set.seed(12345)

# 95% confidence intervals

c1 <- 0.025
c2 <- 0.975
```

```

1
2
3
4 result.election.l1 <- NULL
5
6 for (i in 1:nrow(mes)) {
7   no.elect.x <- setx(m.l1, nld.election.l1=0, ef=mes$fracmes[i],
8 polarization=mes$polmes[i])
9   elect.x <- setx(m.l1, nld.election.l1=1, ef=mes$fracmes[i],
10 polarization=mes$polmes[i])
11   no.elect.s <- sim(m.l1, x=no.elect.x, x1=elect.x, num=10000)
12
13   mean.n <- as.numeric(c(mean
14                         (rbind(no.elect.s$imp1$qi[[5]],
15 no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
16 no.elect.s$imp5$qi[[5]])))
17
18   ci1.n <- as.numeric(c(quantile(rbind(no.elect.s$imp1$qi[[5]],
19 no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
20 no.elect.s$imp5$qi[[5]]), prob=c1)))
21   ci2.n <- as.numeric(c(quantile(rbind(no.elect.s$imp1$qi[[5]],
22 no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
23 no.elect.s$imp5$qi[[5]]), prob=c2)))
24   result.inside <- as.data.frame(cbind(mean.n, ci1.n, ci2.n))
25   result.inside$scen <- i
26   result.election.l1 <- as.data.frame(rbind(result.inside,
27 result.election.l1)) }
28
29 # Create the figure for simulations at time t-1
30
31 margins.2.1 <- ggplot(data = result.election.l1, aes(x = scen, y = mean.n,
32 ymin = ci1.n, ymax = ci2.n, label="Election (t-1)") ) +
33   geom_point()+
34   geom_point(position = position_dodge(width = 0.2)) +
35   geom_errorbar(position = position_dodge(width = 0.2), width = 0.1) +
36   theme_bw() +
37   theme(panel.grid.major.x = element_blank(),
38         panel.grid.minor.x = element_blank(),
39         panel.grid.major.y = element_line(colour="grey60",
40 linetype="dashed")) + geom_hline(yintercept=0, linetype="dotted") + xlab("")
41 + ylab("Marginal Effect on the Probability of Instability")+
42   scale_x_continuous(breaks=c(1, 6, 9, 12), labels=c("Greece", "Guatemala",
43 "Afghanistan", "Uganda") ) + xlab("Scenario") + ylab("")+
44   ylim(-0.1, 0.1)+ggtitle("Election t-1")
45
46
47 # For election at time t
48
49 set.seed(12345)
50
51 result.election <- NULL
52
53 for (i in 1:nrow(mes)) {
54   no.elect.x <- setx(m.t, nld.election=0, ef=mes$fracmes[i],
55 polarization=mes$polmes[i])
56   elect.x <- setx(m.t, nld.election=1, ef=mes$fracmes[i],
57 polarization=mes$polmes[i])
58   no.elect.s <- sim(m.t, x=no.elect.x, x1=elect.x, num=10000)
59
60

```

```

1
2
3
4   mean.n <- as.numeric(c(mean
5                           (rbind(no.elect.s$imp1$qi[[5]],
6   no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
7   no.elect.s$imp5$qi[[5]])))
8
9   cil.n <- as.numeric(c(quantile(rbind(no.elect.s$imp1$qi[[5]],
10  no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
11  no.elect.s$imp5$qi[[5]]), prob=c1))
12   ci2.n <- as.numeric(c(quantile(rbind(no.elect.s$imp1$qi[[5]],
13  no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
14  no.elect.s$imp5$qi[[5]]), prob=c2))
15   result.inside <- as.data.frame(cbind(mean.n, cil.n, ci2.n))
16   result.inside$scen <- i
17   result.election <- as.data.frame(rbind(result.inside, result.election)) }
18
19
20
21
22 margins.2.2 <- ggplot(data = result.election, aes(x = scen, y = mean.n, ymin
23 = cil.n, ymax = ci2.n, label="Election (t-1)")) +
24   geom_point()+
25   geom_point(position = position_dodge(width = 0.2)) +
26   geom_errorbar(position = position_dodge(width = 0.2), width = 0.1) +
27   theme_bw() +
28   theme(panel.grid.major.x = element_blank(),
29         panel.grid.minor.x = element_blank(),
30         panel.grid.major.y = element_line(colour="grey60",
31   linetype="dashed")) + geom_hline(yintercept=0, linetype="dotted") + xlab("")
32 + ylab("Marginal Effect on the Probability of Instability")+
33   scale_x_continuous(breaks=c(1, 6, 9, 12), labels=c("Greece", "Guatemala",
34   "Afghanistan", "Uganda")) + xlab("Scenario") + ylab("")+
35   ylim(-0.1, 0.1)+ggtitle("Election t")
36
37 ##### For election at time t+1
38
39 set.seed(12345)
40
41 result.election.f1 <- NULL
42
43
44 for (i in 1:nrow(mes)) {
45   no.elect.x <- setx(m.f1, nld.election.f1=0, ef=mes$fracmes[i],
46   polarization=mes$polmes[i])
47   elect.x <- setx(m.f1, nld.election.f1=1, ef=mes$fracmes[i],
48   polarization=mes$polmes[i])
49   no.elect.s <- sim(m.f1, x=no.elect.x, x1=elect.x, num=10000)
50
51   mean.n <- as.numeric(c(mean
52                           (rbind(no.elect.s$imp1$qi[[5]],
53   no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
54   no.elect.s$imp5$qi[[5]])))
55
56   cil.n <- as.numeric(c(quantile(rbind(no.elect.s$imp1$qi[[5]],
57   no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
58   no.elect.s$imp5$qi[[5]]), prob=c1))
59
60

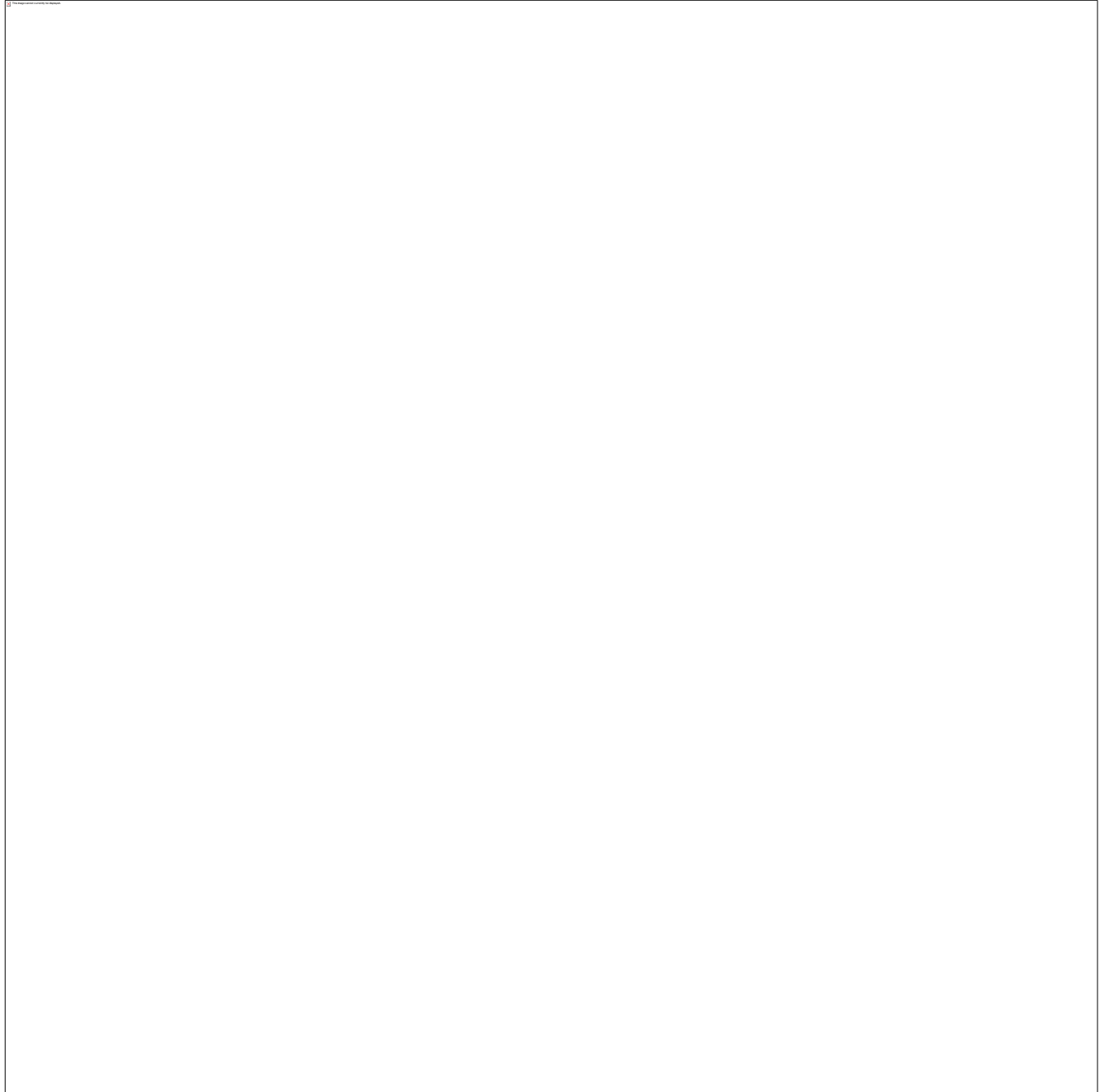
```

```

1
2
3     ci2.n <- as.numeric(c(quantile(rbind(no.elect.s$imp1$qi[[5]],
4 no.elect.s$imp2$qi[[5]], no.elect.s$imp3$qi[[5]], no.elect.s$imp4$qi[[5]],
5 no.elect.s$imp5$qi[[5]]), prob=c2)))
6     result.inside <- as.data.frame(cbind(mean.n,ci1.n, ci2.n))
7     result.inside$scen <- i
8     result.election.f1 <- as.data.frame(rbind(result.inside,
9 result.election.f1)) }
10
11
12 margins.2.3 <- ggplot(data = result.election.f1, aes(x = scen, y = mean.n,
13 ymin = cil.n, ymax = ci2.n, label="Election (t-1)")) +
14   geom_point()+
15   geom_point(position = position_dodge(width = 0.2)) +
16   geom_errorbar(position = position_dodge(width = 0.2), width = 0.1) +
17   theme_bw() +
18   theme(panel.grid.major.x = element_blank(),
19         panel.grid.minor.x = element_blank(),
20         panel.grid.major.y = element_line(colour="grey60",
21 linetype="dashed")) + geom_hline(yintercept=0, linetype="dotted") + xlab("")
22 + ylab("Marginal Effect on the Probability of Instability")+
23   scale_x_continuous(breaks=c(1, 6, 9, 12), labels=c("Greece", "Guatemala",
24 "Afghanistan", "Uganda")) + xlab("Scenario") + ylab("")+
25   ylim(-0.1, 0.1)+ggtitle("Election t+1")
26
27
28 result.election.l1$model <- "election.l1"
29 result.election$model <- "election.t"
30 result.election.f1$model <- "election.f1"
31
32 # bind all of the simulation results together
33
34 sims.results <- as.data.frame(rbind(result.election.l1, result.election,
35 result.election.f1))
36
37 write.csv(sims.results, "sims.csv")
38
39 # Produce Figure 4
40
41 multiplot(margins.2.3, margins.2.2, margins.2.1, cols=3)
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Next is showing the marginal effects of moving each variable in the model from the 10th to the 90th percentile value as reported in Figure 2. These are the effects for models 1-4. First process is to set the x's for each variable in the model, then the first differences are simulated for each x variable, stored, and recalled at the end to create Figure 2.

```
# Now, we are using the three probit models above to extract the mean, and  
95% CIs for the first difference for each variable in these models after  
moving them from their 10th (q1) to their 90th percentile value (q2) in the  
data.
```



```

1
2
3 # first step is to set the x's for every variable in the model.
4
5 q1 <- 0.10
6 q2 <- 0.90
7
8 nld.election.l1.x1 <- setx(m.nc.l1, nld.election.l1=0)
9 nld.election.l1.x2 <- setx(m.nc.l1, nld.election.l1=1)
10
11 ef.x1 <- setx(m.nc.l1, nld.election.l1=0, ef=quantile(na.omit(df$ef),
12 prob=q1))
13 ef.x2 <- setx(m.nc.l1, nld.election.l1=0, ef=quantile(na.omit(df$ef),
14 prob=q2))
15
16 polarization.x1 <- setx(m.nc.l1, nld.election.l1=0,
17 polarization=quantile(na.omit(df$polarization), prob=q1))
18 polarization.x2 <- setx(m.nc.l1, nld.election.l1=0,
19 polarization=quantile(na.omit(df$polarization), prob=q2))
20
21 # note here we are simulating the effects for an election in a 90th
22 percentile state on the fractionalization index.
23 nld.election.l1Xef.x1 <- setx(m.nc.l1, nld.election.l1=0,
24 ef=quantile(na.omit(df$ef), prob=q2))
25 nld.election.l1Xef.x2 <- setx(m.nc.l1, nld.election.l1=1,
26 ef=quantile(na.omit(df$ef), prob=q2))
27
28 # as above, election in 90th percentile state on the polarization scale.
29 nld.election.l1Xpolarization.x1 <- setx(m.nc.l1, nld.election.l1=0,
30 polarization=quantile(na.omit(df$polarization), prob=q2))
31 nld.election.l1Xpolarization.x2 <- setx(m.nc.l1, nld.election.l1=1,
32 polarization=quantile(na.omit(df$polarization), prob=q2))
33
34 model.2.1.names <- data.frame(c("nld.election.l1", "ef", "polarization",
35 "nld.election.l1Xef", "nld.election.l1Xpolarization"))
36
37 model.2.1.s <- sims.mi.fd(m.nc.l1, model.2.1.names, 0.025, 0.975, "No
38 Controls, Election t-1", 5)
39
40
41
42
43
44 ### election at t-1
45
46 q1 <- 0.10
47 q2 <- 0.90
48
49 nld.election.l1.x1 <- setx(m.l1, nld.election.l1=0)
50 nld.election.l1.x2 <- setx(m.l1, nld.election.l1=1)
51
52 ef.x1 <- setx(m.l1, nld.election.l1=0, ef=quantile(na.omit(df$ef), prob=q1))
53 ef.x2 <- setx(m.l1, nld.election.l1=0, ef=quantile(na.omit(df$ef), prob=q2))
54
55 polarization.x1 <- setx(m.l1, nld.election.l1=0,
56 polarization=quantile(na.omit(df$polarization), prob=q1))
57 polarization.x2 <- setx(m.l1, nld.election.l1=0,
58 polarization=quantile(na.omit(df$polarization), prob=q2))
59
60

```

```
1
2
3
4 nld.election.l1Xef.x1 <- setx(m.l1, nld.election.l1=0,
5 ef=quantile(na.omit(df$ef), prob=q2))
6 nld.election.l1Xef.x2 <- setx(m.l1, nld.election.l1=1,
7 ef=quantile(na.omit(df$ef), prob=q2))
8
9 nld.election.l1Xpolarization.x1 <- setx(m.l1, nld.election.l1=0,
10 polarization=quantile(na.omit(df$polarization), prob=q2))
11 nld.election.l1Xpolarization.x2 <- setx(m.l1, nld.election.l1=1,
12 polarization=quantile(na.omit(df$polarization), prob=q2))
13
14 ln.wdi.pop.l1.x1 <- setx(m.l1,
15 ln.wdi.pop.l1=quantile(na.omit(df$ln.wdi.pop.l1), prob=q1),
16 nld.election.l1=0)
17 ln.wdi.pop.l1.x2 <- setx(m.l1,
18 ln.wdi.pop.l1=quantile(na.omit(df$ln.wdi.pop.l1), prob=q2),
19 nld.election.l1=0)
20
21 ln.wdi.imr.l1.x1 <- setx(m.l1,
22 ln.wdi.imr.l1=quantile(na.omit(df$ln.wdi.imr.l1), prob=q1),
23 nld.election.l1=0)
24 ln.wdi.imr.l1.x2 <- setx(m.l1,
25 ln.wdi.imr.l1=quantile(na.omit(df$ln.wdi.imr.l1), prob=q2),
26 nld.election.l1=0)
27
28 nac.l1.x1 <- setx(m.l1, nac.l1=quantile(na.omit(df$nac.l1), prob=q1),
29 nld.election.l1=0)
30 nac.l1.x2 <- setx(m.l1, nac.l1=quantile(na.omit(df$nac.l1), prob=q2),
31 nld.election.l1=0)
32
33 polity2.lag.1.x1 <- setx(m.l1,
34 polity2.lag.1=quantile(na.omit(df$polity2.lag.1), prob=q1),
35 nld.election.l1=0)
36 polity2.lag.1.x2 <- setx(m.l1,
37 polity2.lag.1=quantile(na.omit(df$polity2.lag.1), prob=q2),
38 nld.election.l1=0)
39
40 part.dem.fac.l1.x1 <- setx(m.l1,
41 part.dem.fac.l1=quantile(na.omit(df$part.dem.fac.l1), prob=q1),
42 nld.election.l1=0)
43 part.dem.fac.l1.x2 <- setx(m.l1,
44 part.dem.fac.l1=quantile(na.omit(df$part.dem.fac.l1), prob=q2),
45 nld.election.l1=0)
46
47 pr.l1.x1 <- setx(m.l1, pr.l1=quantile(na.omit(df$pr.l1), prob=q1),
48 nld.election.l1=0)
49 pr.l1.x2 <- setx(m.l1, pr.l1=quantile(na.omit(df$pr.l1), prob=q2),
50 nld.election.l1=0)
51
52 nld.earlylate.l1.x1 <- setx(m.l1, nld.earlylate.l1=0, nld.election.l1=1)
53 nld.earlylate.l1.x2 <- setx(m.l1, nld.earlylate.l1=1, nld.election.l1=1)
54
55 nld.suspend.l1.x1 <- setx(m.l1, nld.suspend.l1=0, nld.election.l1=1)
56 nld.suspend.l1.x2 <- setx(m.l1, nld.suspend.l1=1, nld.election.l1=1)
57
58
59
60
```

```
1
2
3 model.2.2.names <- data.frame(c("nld.election.l1", "ef", "polarization",
4 "nld.election.l1Xef", "nld.election.l1Xpolarization", "ln.wdi.pop.l1",
5 "ln.wdi.imr.l1", "nac.l1", "polity2.lag.1",
6 "part.dem.fac.l1", "pr.l1",
7 "nld.earlylate.l1", "nld.suspend.l1"))
8
9 model.2.2.s <- sims.mi.fd(m.l1, model.2.2.names, 0.025, 0.975, "Election t-
10 1", 5)
11
12
13 # Election at t
14
15
16 nld.election.x1 <- setx(m.t, nld.election=0)
17 nld.election.x2 <- setx(m.t, nld.election=1)
18
19 ef.x1 <- setx(m.t, nld.election=0, ef=quantile(na.omit(df$ef), prob=q1))
20 ef.x2 <- setx(m.t, nld.election=0, ef=quantile(na.omit(df$ef), prob=q2))
21
22 polarization.x1 <- setx(m.t, nld.election=0,
23 polarization=quantile(na.omit(df$polarization), prob=q1))
24 polarization.x2 <- setx(m.t, nld.election=0,
25 polarization=quantile(na.omit(df$polarization), prob=q2))
26
27 nld.electionXef.x1 <- setx(m.t, nld.election=0, ef=quantile(na.omit(df$ef),
28 prob=q2))
29 nld.electionXef.x2 <- setx(m.t, nld.election=1, ef=quantile(na.omit(df$ef),
30 prob=q2))
31
32 nld.electionXpolarization.x1 <- setx(m.t, nld.election=0,
33 polarization=quantile(na.omit(df$polarization), prob=q2))
34 nld.electionXpolarization.x2 <- setx(m.t, nld.election=1,
35 polarization=quantile(na.omit(df$polarization), prob=q2))
36
37 ln.wdi.pop.l1.x1 <- setx(m.t,
38 ln.wdi.pop.l1=quantile(na.omit(df$ln.wdi.pop.l1), prob=q1), nld.election=0)
39 ln.wdi.pop.l1.x2 <- setx(m.t,
40 ln.wdi.pop.l1=quantile(na.omit(df$ln.wdi.pop.l1), prob=q2), nld.election=0)
41
42 ln.wdi.imr.l1.x1 <- setx(m.t,
43 ln.wdi.imr.l1=quantile(na.omit(df$ln.wdi.imr.l1), prob=q1), nld.election=0)
44 ln.wdi.imr.l1.x2 <- setx(m.t,
45 ln.wdi.imr.l1=quantile(na.omit(df$ln.wdi.imr.l1), prob=q2), nld.election=0)
46
47 nac.l1.x1 <- setx(m.t, nac.l1=quantile(na.omit(df$nac.l1), prob=q1),
48 nld.election=0)
49 nac.l1.x2 <- setx(m.t, nac.l1=quantile(na.omit(df$nac.l1), prob=q2),
50 nld.election=0)
51
52 polity2.lag.1.x1 <- setx(m.t,
53 polity2.lag.1=quantile(na.omit(df$polity2.lag.1), prob=q1), nld.election=0)
54 polity2.lag.1.x2 <- setx(m.t,
55 polity2.lag.1=quantile(na.omit(df$polity2.lag.1), prob=q2), nld.election=0)
56
57 part.dem.fac.l1.x1 <- setx(m.t,
58 part.dem.fac.l1=quantile(na.omit(df$part.dem.fac.l1), prob=q1),
59 nld.election=0)
60
```

```

1
2
3 part.dem.fac.l1.x2 <- setx(m.t,
4 part.dem.fac.l1=quantile(na.omit(df$part.dem.fac.l1), prob=q2),
5 nld.election=0)
6
7 pr.l1.x1 <- setx(m.t, pr.l1=quantile(na.omit(df$pr.l1), prob=q1),
8 nld.election=0)
9 pr.l1.x2 <- setx(m.t, pr.l1=quantile(na.omit(df$pr.l1), prob=q2),
10 nld.election=0)
11
12 nld.earlylate.x1 <- setx(m.t, nld.earlylate=0, nld.election=1)
13 nld.earlylate.x2 <- setx(m.t, nld.earlylate=1, nld.election=1)
14
15 nld.suspend.x1 <- setx(m.t, nld.suspend=0, nld.election=1)
16 nld.suspend.x2 <- setx(m.t, nld.suspend=1, nld.election=1)
17
18 model.2.3.names <- data.frame(c("nld.election", "ef", "polarization",
19 "nld.electionXef", "nld.electionXpolarization", "ln.wdi.pop.l1",
20 "ln.wdi.imr.l1", "nac.l1", "polity2.lag.1",
21 "part.dem.fac.l1", "pr.l1", "nld.earlylate",
22 "nld.suspend"))
23
24 model.2.3.s <- sims.mi.fd(m.t, model.2.3.names, 0.025, 0.975, "Election t",
25 5)
26
27 # Election at t+1
28
29 nld.election.f1.x1 <- setx(m.f1, nld.election.f1=0)
30 nld.election.f1.x2 <- setx(m.f1, nld.election.f1=1)
31
32 ef.x1 <- setx(m.f1, nld.election.f1=0, ef=quantile(na.omit(df$ef), prob=q1))
33 ef.x2 <- setx(m.f1, nld.election.f1=0, ef=quantile(na.omit(df$ef), prob=q2))
34
35 polarization.x1 <- setx(m.f1, nld.election.f1=0,
36 polarization=quantile(na.omit(df$polarization), prob=q1))
37 polarization.x2 <- setx(m.f1, nld.election.f1=0,
38 polarization=quantile(na.omit(df$polarization), prob=q2))
39
40 nld.election.f1Xef.x1 <- setx(m.f1, nld.election.f1=0,
41 ef=quantile(na.omit(df$ef), prob=q2))
42 nld.election.f1Xef.x2 <- setx(m.f1, nld.election.f1=1,
43 ef=quantile(na.omit(df$ef), prob=q2))
44
45 nld.election.f1Xpolarization.x1 <- setx(m.f1, nld.election.f1=0,
46 polarization=quantile(na.omit(df$polarization), prob=q2))
47 nld.election.f1Xpolarization.x2 <- setx(m.f1, nld.election.f1=1,
48 polarization=quantile(na.omit(df$polarization), prob=q2))
49
50 ln.wdi.pop.l1.x1 <- setx(m.f1,
51 ln.wdi.pop.l1=quantile(na.omit(df$ln.wdi.pop.l1), prob=q1),
52 nld.election.f1=0)
53 ln.wdi.pop.l1.x2 <- setx(m.f1,
54 ln.wdi.pop.l1=quantile(na.omit(df$ln.wdi.pop.l1), prob=q2),
55 nld.election.f1=0)
56
57
58
59
60

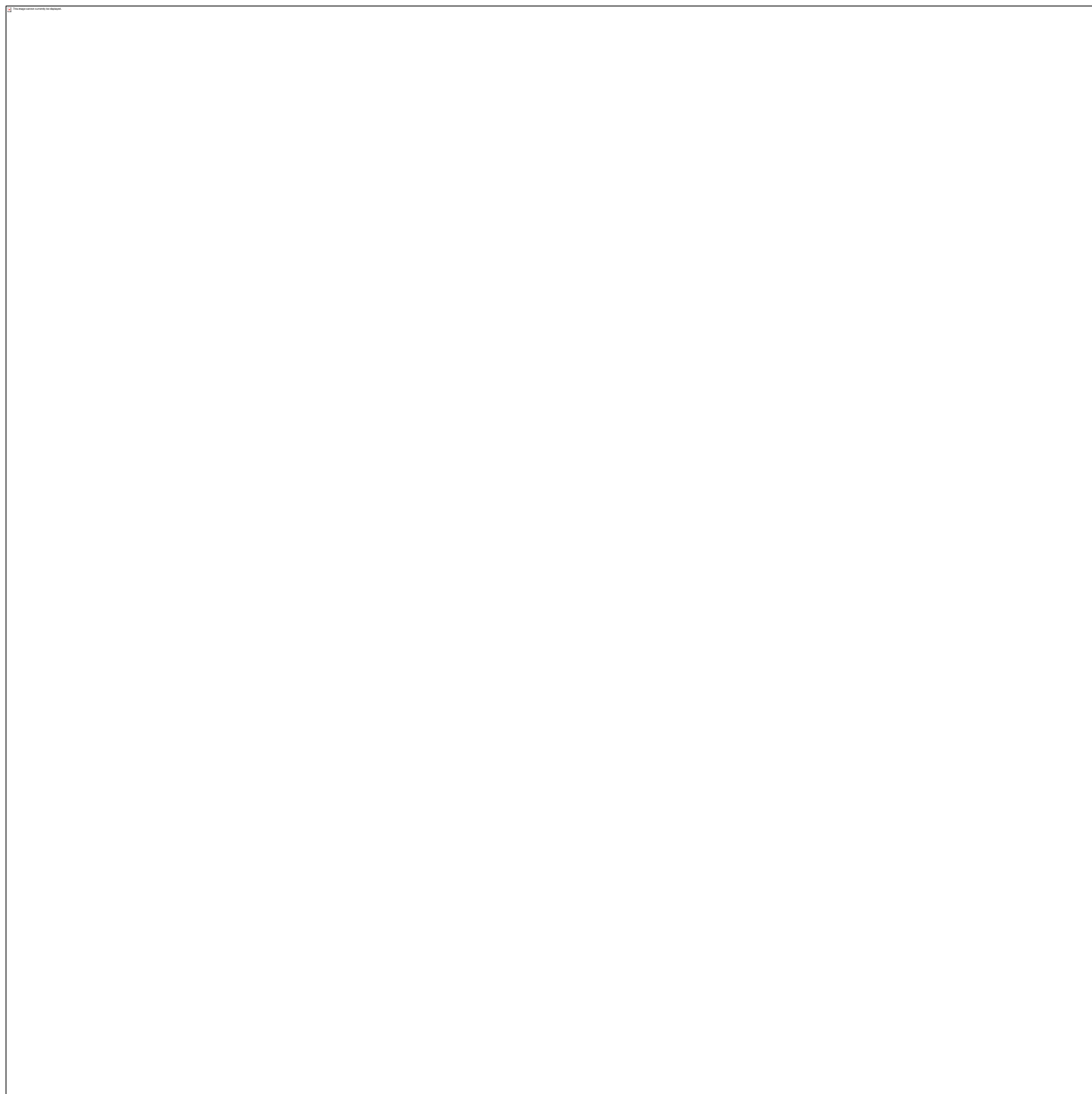
```

```

1
2
3   ln.wdi.imr.l1.x1 <- setx(m.f1,
4   ln.wdi.imr.l1=quantile(na.omit(df$ln.wdi.imr.l1), prob=q1),
5   nld.election.f1=0)
6   ln.wdi.imr.l1.x2 <- setx(m.f1,
7   ln.wdi.imr.l1=quantile(na.omit(df$ln.wdi.imr.l1), prob=q2),
8   nld.election.f1=0)
9
10  nac.l1.x1 <- setx(m.f1, nac.l1=quantile(na.omit(df$nac.l1), prob=q1),
11  nld.election.f1=0)
12  nac.l1.x2 <- setx(m.f1, nac.l1=quantile(na.omit(df$nac.l1), prob=q2),
13  nld.election.f1=0)
14
15  polity2.lag.1.x1 <- setx(m.f1,
16  polity2.lag.1=quantile(na.omit(df$polity2.lag.1), prob=q1),
17  nld.election.f1=0)
18  polity2.lag.1.x2 <- setx(m.f1,
19  polity2.lag.1=quantile(na.omit(df$polity2.lag.1), prob=q2),
20  nld.election.f1=0)
21
22  part.dem.fac.l1.x1 <- setx(m.f1,
23  part.dem.fac.l1=quantile(na.omit(df$part.dem.fac.l1), prob=q1),
24  nld.election.f1=0)
25  part.dem.fac.l1.x2 <- setx(m.f1,
26  part.dem.fac.l1=quantile(na.omit(df$part.dem.fac.l1), prob=q2),
27  nld.election.f1=0)
28
29  pr.l1.x1 <- setx(m.f1, pr.l1=quantile(na.omit(df$pr.l1), prob=q1),
30  nld.election.f1=0)
31  pr.l1.x2 <- setx(m.f1, pr.l1=quantile(na.omit(df$pr.l1), prob=q2),
32  nld.election.f1=0)
33
34  nld.earlylate.f1.x1 <- setx(m.f1, nld.earlylate.f1=0, nld.election.f1=1)
35  nld.earlylate.f1.x2 <- setx(m.f1, nld.earlylate.f1=1, nld.election.f1=1)
36
37  nld.suspend.f1.x1 <- setx(m.f1, nld.suspend.f1=0, nld.election.f1=1)
38  nld.suspend.f1.x2 <- setx(m.f1, nld.suspend.f1=1, nld.election.f1=1)
39
40  model.2.4.names <- data.frame(c("nld.election.f1", "ef", "polarization",
41  "nld.election.f1Xef", "nld.election.f1Xpolarization", "ln.wdi.pop.l1",
42  "ln.wdi.imr.l1", "nac.l1", "polity2.lag.1",
43  "part.dem.fac.l1", "pr.l1",
44  "nld.earlylate.f1", "nld.suspend.f1"))
45
46  model.2.4.s <- sims.mi.fd(m.f1, model.2.4.names, 0.025, 0.975, "Election
47  t+1", 5)
48
49
50  figure1 <- as.data.frame(rbind(model.2.1.s,
51  model.2.2.s,model.2.3.s,model.2.4.s))
52  figure1$variable <- sub(".f1", replacement="", x=figure1$variable)
53  figure1$variable <- sub(".lag.1", replacement="", x=figure1$variable)
54  figure1$variable <- sub(".l1", replacement="", x=figure1$variable)
55  order.f1 <- rev(c("nld.election", "ef", "polarization", "nld.electionXef",
56  "nld.electionXpolarization", "ln.wdi.pop", "ln.wdi.imr", "nac", "polity2",
57  "part.dem.fac", "pr",
58  "nld.earlylate", "nld.suspend"))
59
60

```

```
1
2
3 figure1$model2 <- factor(figure1$model, levels = c("No Controls, Election t-
4 1", "Election t+1", "Election t", "Election t-1"))
5 figure1$variable <- factor(figure1$variable, levels=order.f1, labels =
6 rev(c("Election", "Fractionalization", "Polarization", "Election X
7 Fractionalization", "Election X Polarization",
8
9 "Population (log)", "Infant Mortality", "Neighboring Conflicts", "Polity",
10 "Partial Dem. with Factions", "Prop. Rep.",
11
12 "Election Early/Late", "Election Suspended")))
13
14 # This is storing the effect for the summary of robustness tests figure.
15 base <- subset(figure1, variable=="Election X Fractionalization")
16
17 # Create Figure 2
18
19
20 ggplot(data = figure1, aes(x = variable, y = mean, ymin = low, ymax = high))
21 +
22   geom_point()+facet_grid(~model2) +
23   geom_point(position = position_dodge(width = 0.2)) +
24   geom_errorbar(position = position_dodge(width = 0.2), width = 0.1) +
25   coord_flip() +
26   theme_bw() +
27   theme(panel.grid.major.x = element_blank(),
28         panel.grid.minor.x = element_blank(),
29         panel.grid.major.y = element_line(colour="grey60",
30 linetype="dashed")) + geom_hline(yintercept=0, linetype="dotted") + xlab("")
31 + ylab("Marginal Effect on the Probability of Instability")
32
33
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47
48 This final section shows the table of most fraternalized states with the numbers of onests of each
49 type (Table 2)

50
51 # Table 2 - Instability onsets and types in fractionalized states
52
53 require(dplyr)
54 ## Loading required package: dplyr
55 ##
56 ## Attaching package: 'dplyr'
57 ## The following objects are masked from 'package:Hmisc':
58
59
60

```

1
2
3
4   ##
5   ##   combine, src, summarize
6   ## The following objects are masked from 'package:Zelig':
7   ##
8   ##   combine, summarize
9   ## The following object is masked from 'package:MASS':
10  ##
11  ##   select
12  ## The following objects are masked from 'package:stats':
13  ##
14  ##   filter, lag
15  ## The following objects are masked from 'package:base':
16  ##
17  ##   intersect, setdiff, setequal, union
18  fractionalized <- subset(df, ef>=0.5 & polarization<0.6)
19  fractionalized$instab.st <-
20  as.numeric(as.character(fractionalized$instab.st))
21  fractionalized <- fractionalized %>% tbl_df() %>% group_by(cname) %>%
22  summarise(instab.sum=sum(instab.st), rwar.sum=sum(rwar.st),
23
24  ewar.sum=sum(ewar.st), areg.sum=sum(areg.st),
25
26  gppl.sum=sum(gppl.st))
27  # show the table
28  fractionalized
29  ## Source: local data frame [14 x 6]
30  ##
31  ##           cname instab.sum rwar.sum ewar.sum areg.sum
32  ##           (fctr)   (dbl)     (int)   (int)   (int)
33  ## 1      Burkina Faso         1         0         0         1
34  ## 2      Cameroon           0         0         0         0
35  ## 3  Democratic Republic of the Congo  3         1         2         1
36  ## 4      Gabon              0         0         0         0
37  ## 5      Ghana              2         0         0         2
38  ## 6      India              4         1         3         0
39  ## 7      Kenya            3         0         2         1
40  ## 8      Liberia           4         3         0         1
41  ## 9      Madagascar        1         0         0         1
42  ## 10     Papua New Guinea    1         0         1         0
43  ## 11     South Africa        2         1         1         0
44  ## 12     Tanzania            0         0         0         0
45  ## 13     Togo                0         0         0         0
46  ## 14     Uganda              5         1         2         2
47  ## Variables not shown: gppl.sum (int)

```

The code below creates Figure 4, which shows the cases simulated, along with their distribution of ethnic groups represented as increasingly large circles depending upon their proportion of the total population.

```

51
52  # Fearon graph reported in figure 4.
53  require(foreign)
54
55
56  fearon <- read.dta("fearon.dta")
57  require(dplyr)
58  fearon <- rename(fearon, ccode=ccodebg)
59
60

```



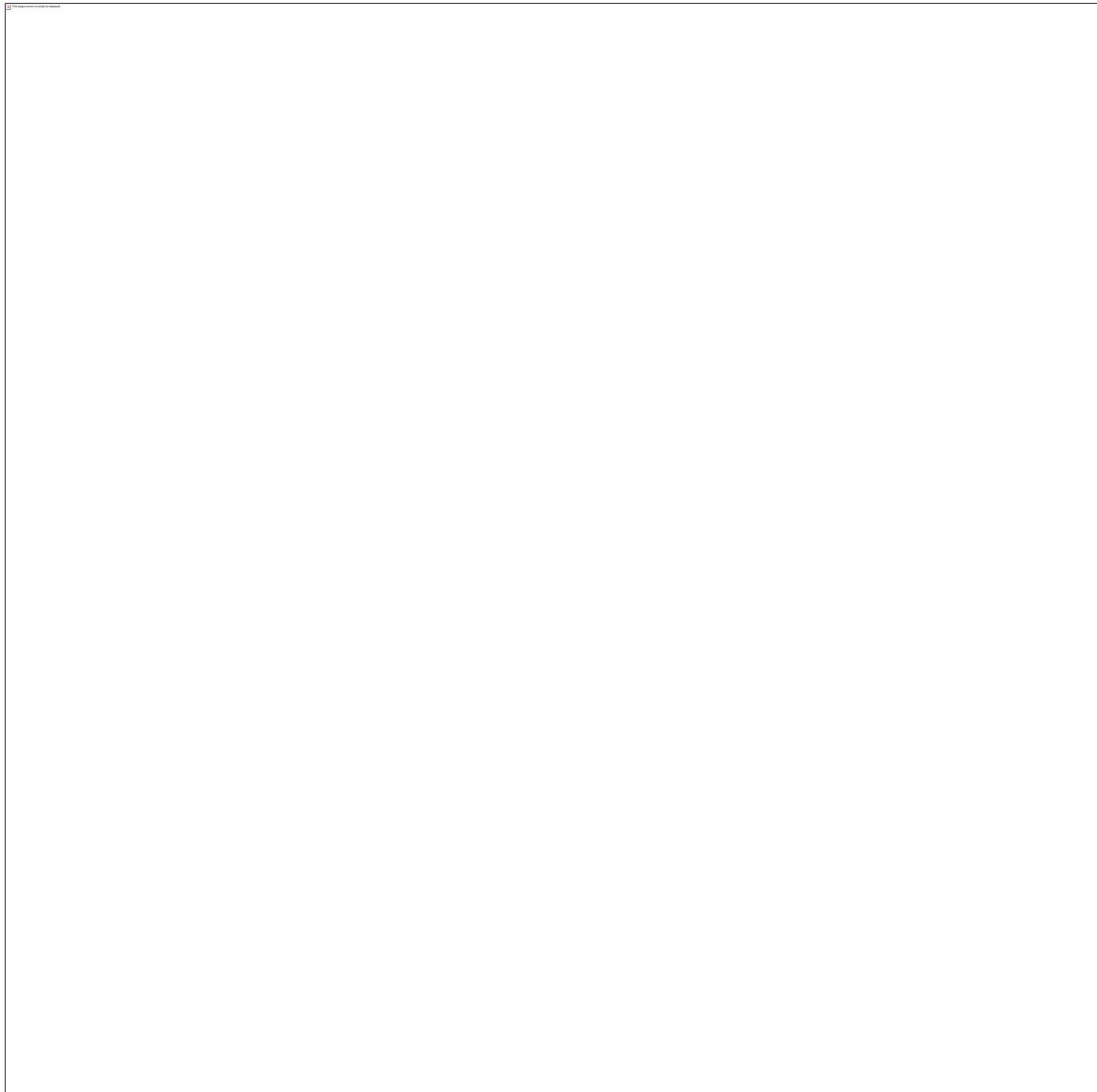
```

1
2
3 fearon.grp <- read.csv("fearongroupdata.csv")
4
5 fearon.pol <- subset(fearon, select=c("ccode", "polarization"))
6 fearon <- merge(fearon.grp, fearon.pol, all.x=T)
7
8 fracmes <- c(fearon$ef[fearon$country=="GREECE"],
9 fearon$ef[fearon$country=="PARAGUAY"], fearon$ef[fearon$country=="VIETNAM"],
10 fearon$ef[fearon$country=="SWAZILAND"], fearon$ef[fearon$country=="DOMINICAN
11 REP."],
12 fearon$ef[fearon$country=="GUATEMALA"],
13 fearon$ef[fearon$country=="BRAZIL"], fearon$ef[fearon$country=="PERU"],
14 fearon$ef[fearon$country=="AFGHANISTAN"], fearon$ef[fearon$country=="CENTRAL
15 AFRICAN REP."],
16
17 fearon$ef[fearon$country=="CAMEROON"], fearon$ef[fearon$country=="UGANDA"])
18 polmes <- c(fearon$polarization[fearon$country=="GREECE"],
19 fearon$polarization[fearon$country=="PARAGUAY"],
20 fearon$polarization[fearon$country=="VIETNAM"],
21 fearon$polarization[fearon$country=="SWAZILAND"],
22 fearon$polarization[fearon$country=="DOMINICAN REP."],
23 fearon$polarization[fearon$country=="GUATEMALA"],
24 fearon$polarization[fearon$country=="BRAZIL"],
25 fearon$polarization[fearon$country=="PERU"],
26 fearon$polarization[fearon$country=="AFGHANISTAN"],
27 fearon$polarization[fearon$country=="CENTRAL AFRICAN REP."],
28
29 fearon$polarization[fearon$country=="CAMEROON"], fearon$polarization[fearon$co
30 untry=="UGANDA"])
31
32 mes <- as.data.frame(cbind(fracmes, polmes))
33
34 fearon$sim <- 0
35 fearon$sim[fearon$country=="GREECE"|fearon$country=="PARAGUAY"|fearon$country
36 == "VIETNAM"|fearon$country=="SWAZILAND"|fearon$country=="DOMINICAN
37 REP."|fearon$country=="GUATEMALA"|
38 fearon$country=="BRAZIL"|fearon$country=="PERU"|fearon$country=="AFGHANISTAN"
39 |fearon$country=="CENTRAL AFRICAN
40 REP."|fearon$country=="CAMEROON"|fearon$country=="UGANDA"] <- 1
41
42 fearon$label <- NA
43 for (i in 1:nrow(fearon)) { fearon$label[i][fearon$sim[i]==1] <-
44 fearon$country[i]}
45
46 fearon.fig <- subset(fearon, sim==1)
47
48
49 # Create the plot (Figure 3)
50
51 ggplot(fearon.fig, aes(x=ef, y=polarization, size=gpro)) +
52 geom_point(position=position_jitter(width=0.05, height=0.01), alpha=.8)+
53 geom_text(aes(label=country), size=4, vjust=-1) +
54 xlab("Ethnic Fractionalization")+ylab("Ethnic Polarization")+
55 guides(size=FALSE) + annotate("rect", xmin=0.5, xmax=1.2, ymin=-0.2,
56 ymax=0.6, alpha=.1, fill="green") +
57
58
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60

```

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```
    annotate("rect", xmin=-0.2, xmax=0.5, ymin=-0.2, ymax=0.6,  
alpha=.1,fill="blue") + annotate("rect", xmin=-0.2, xmax=1.2, ymin=0.6,  
ymax=1.2, alpha=.1,fill="red")
```



1
2
3 Readme: Replication material for Elections, Ethnicity and Political Instability
4

5 There are 9 files (including this one) in the replication materials:
6

- 7
8 **analysis-replication-07-07-2016.html** – file that replicates results and figures
9 reported in the main text.
10
11 **analysis-replication-07-07-2016.Rmd** – R markdown file with code to replicate
12 results and figures reported in the main text.
13
14 **appendix-02-08-2016.pdf** – Results reported in online appendix.
15
16 **appendix-02-08-2016.Rmd** – R markdown file with the code to
17 reproduce the findings reported in the online
18 appendix.
19
20 **df-02-08-2016.csv** – Main data frame used in the analysis. Is
21 loaded in both the analysis and appendix Rmd
22 files.
23
24 **fearon.dta** – Fearon (2003) measures of
25 fractionalization and polarized. Used in
26 producing Figures in both analysis and appendix
27 files.
28
29 **fearongroupdata.csv** – Fearon (2003) measures of ethnic group
30 sizes. Used in producing Figure 3 in the analysis
31 file.
32
33 **epr-conflict.csv** – Onsets of ethnic conflict extracted from
34 the GROW-up platform (Bormann et al 2016).
35 Used only in the final part of the online
36 appendix.
37
38
39
40
41
42
43
44
45

46 Please ensure that you set the working directory to the source file location when running the
47 replication materials in R.
48
49
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Online Appendix for Elections, Ethnicity and Political

Instability

28 September 2015

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20 **Summary of Robustness Tests** **75**
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23 **References** **76**
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27 **Introduction**
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30 This document shows the results of robustness tests and further exploration of the results shown in “Elections,
31 Ethnicity and Political Instability”. In each section the same tests shown in the main document are replicated
32 with the specific changes made (i.e tests for elections at t+1, t, and t-1, with and without control variables).
33 The tests discussed in this document include using the Ethnic Power Relations (EPR) data for measures
34 of ethnic fractionalization and polarization, disaggregating election types into executive and legislative
35 elections, disaggregating instability types and testing the hypotheses on alternative data for the dependent
36 variable, in addition to using the Institutions and Elections Project (IAEP) to measure the presence of
37 elections. We also test random effects probit models to account for the fact that observations within countries
38 are probably not independent, show the regression tables displayed in the main document with robust
39 standard errors clustered on the country and test that the results hold in non-democratic contexts.
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50 **Results Reported in the Main Document**
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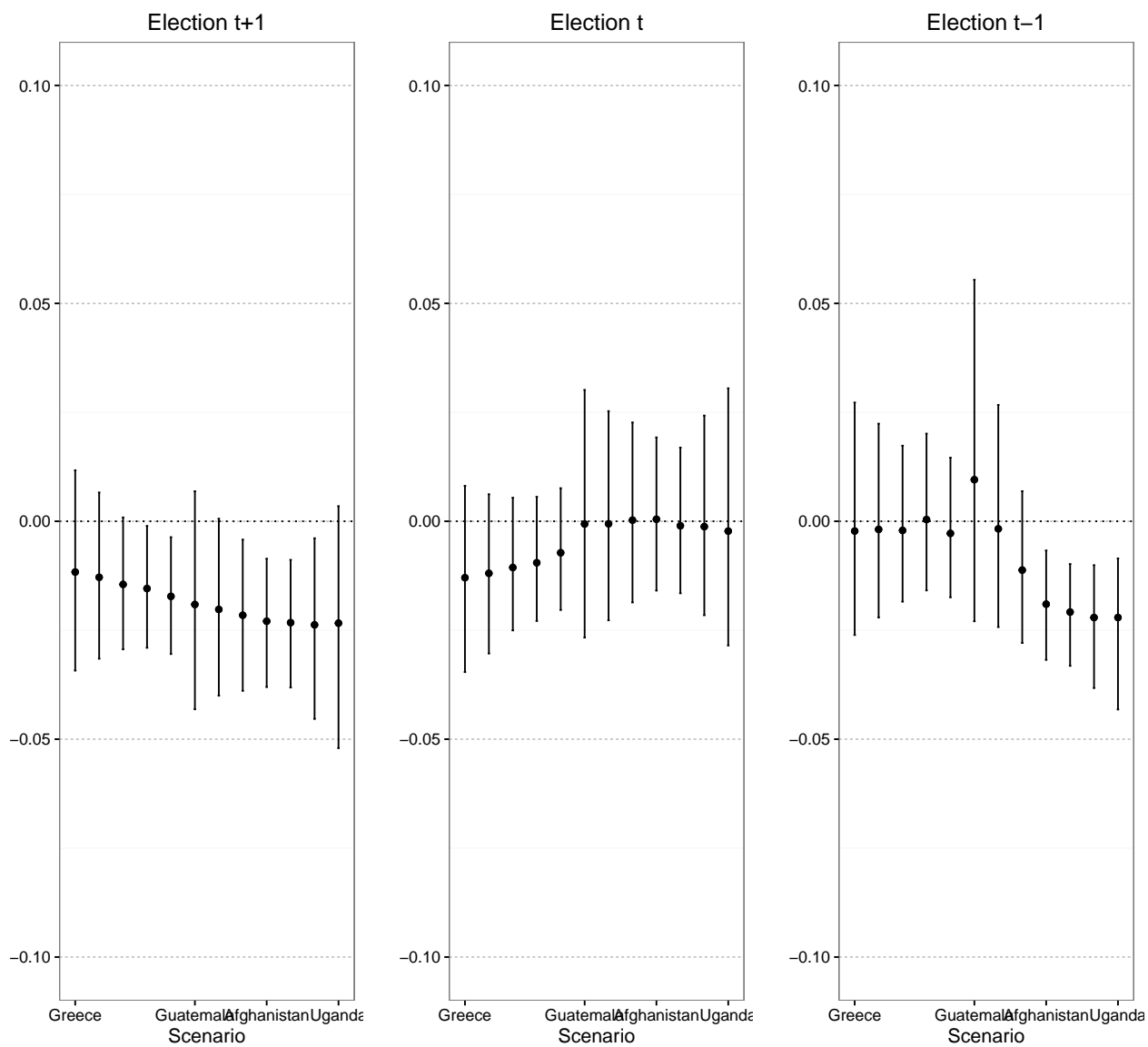
53 The results below are those reported in the article. These results also include the regression tables, which
54 were not included in the main text.
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Table 1: Elections and Violent Political Instability, Base Model (shown in main text)

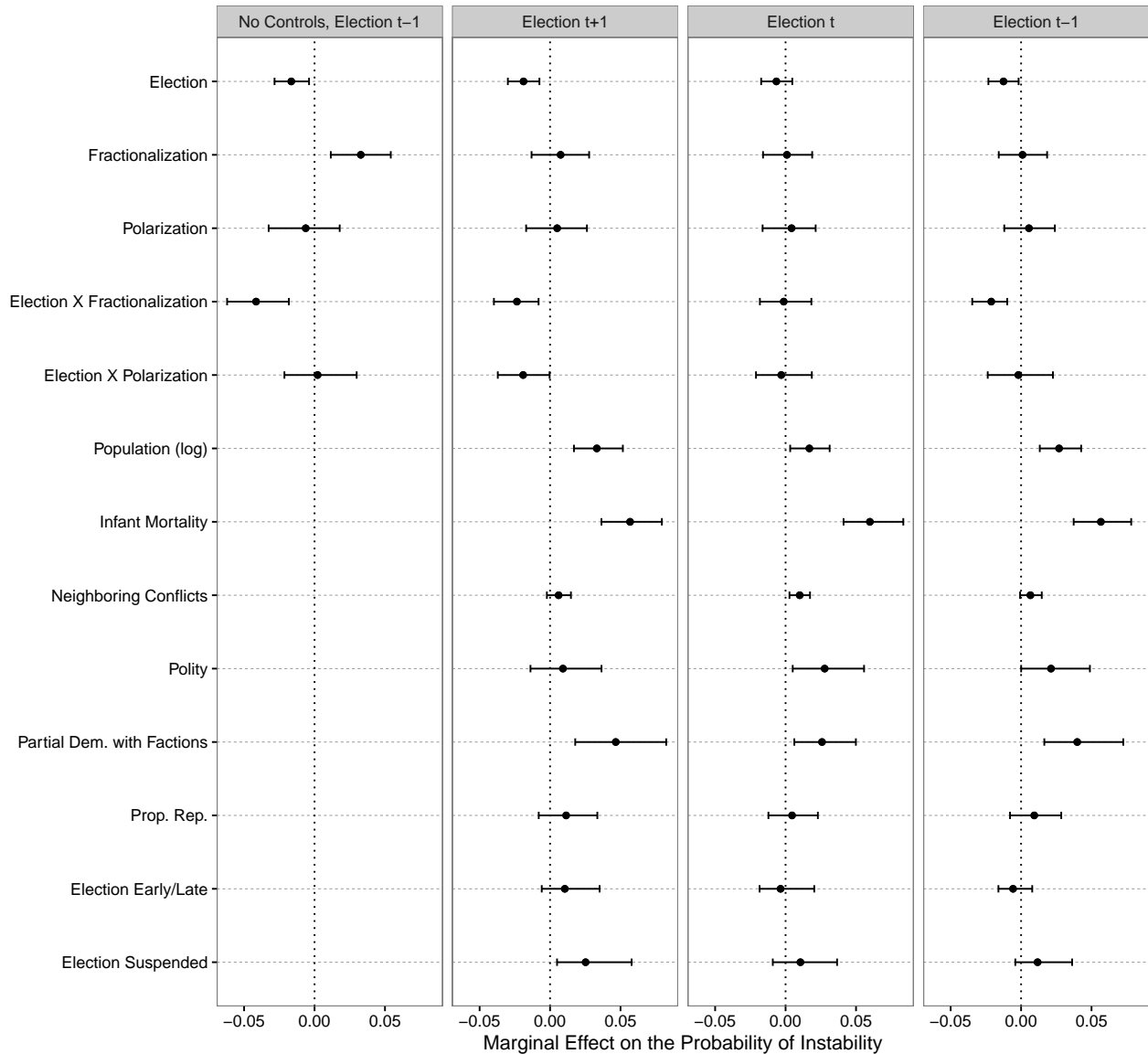
	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.99*** (0.15)	-5.69*** (0.69)	-5.37*** (0.72)	-6.01*** (0.72)
nld.election.l1	-0.25 (0.27)			-0.11 (0.33)
ef	0.58*** (0.19)	0.16 (0.23)	0.03 (0.22)	0.03 (0.23)
polarization	-0.11 (0.23)	0.12 (0.26)	0.13 (0.27)	0.16 (0.27)
nld.election.l1:ef	-1.16** (0.51)			-1.63*** (0.59)
nld.election.l1:polarization	0.99* (0.52)			1.03* (0.61)
nld.election.f1		-0.32 (0.34)		
ln.wdi.imr.l1		0.37*** (0.08)	0.45*** (0.09)	0.45*** (0.09)
polity2.lag.1		0.01 (0.01)	0.02** (0.01)	0.02* (0.01)
part.dem.fac.l1		0.48*** (0.13)	0.34*** (0.13)	0.48*** (0.13)
ln.wdi.pop.l1		0.12*** (0.03)	0.07** (0.03)	0.12*** (0.03)
nac.l1		0.04 (0.03)	0.09*** (0.03)	0.06* (0.03)
pr.l1		0.06 (0.05)	0.02 (0.05)	0.05 (0.05)
nld.earlylate.f1		0.25 (0.22)		
nld.suspend.f1		0.51** (0.21)		
nld.election.f1:ef		-0.31 (0.46)		
nld.election.f1:polarization		0.08 (0.54)		
nld.election			-0.46 (0.35)	
nld.earlylate			-0.12 (0.23)	
nld.suspend			0.19 (0.19)	
nld.election:ef			0.33 (0.42)	
nld.election:polarization			0.28 (0.49)	
nld.earlylate.l1				-0.32 (0.28)
nld.suspend.l1				0.28 (0.21)
AIC	1105.99	1011.17	1078.80	1000.78
Num. obs.	3633	3710	3713	3633

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Impact of Elections on Probability of Violent Political Instability Across Simulated Ethnic Structures, Results in Main Article



First Differences for Elections and Violent Political Instability, Results in Main Article



Using the Ethnic Power Relations Data for Ethnic Structure

This section shows the results displayed in the main analysis, but when using the ethnic fractionalization measure from the Ethnic Power Relations data version 3.01 (Wimmer, Cederman, and Min 2009). We constructed the fractionalization measure in the same way as in Fearon’s ethno-linguistic fractionalization data (i.e with the Herfindahl index) except using the groups and group population data from the Ethnic Power Relations Data. Using the EPR data in this way raises a number of additional issues as not all ethnic groups add up to 100% in the data. The results should be interpreted to reflect the fractionalization

and polarization scores of the ethnic groups that are ‘politically’ relevant. Countries where ethnicity is not relevant have been assigned fractionalization scores of “0” and polarization scores of “0”.

Scatterplots, Elections, Ethnic Structure and Violent Political Instability, EPR data

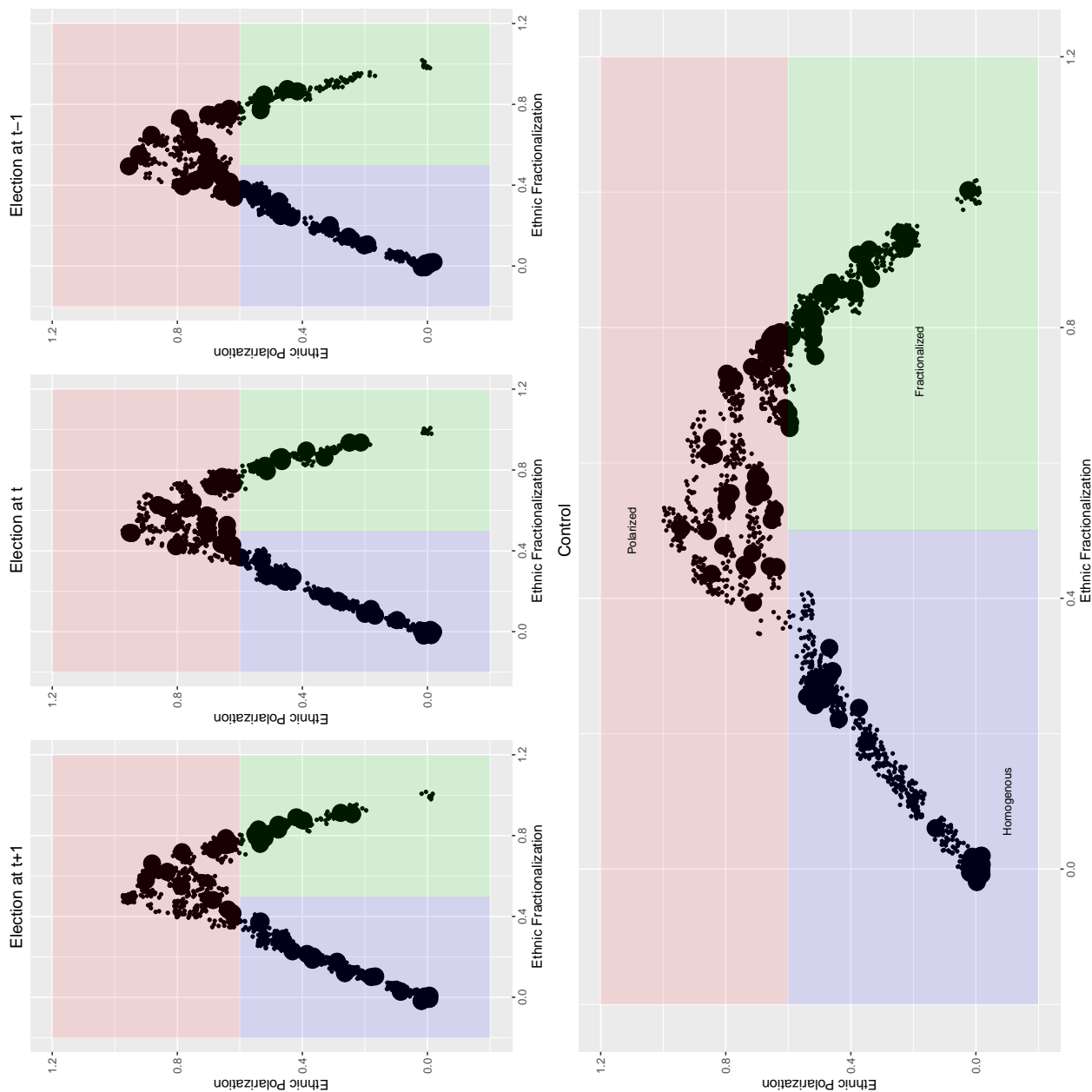
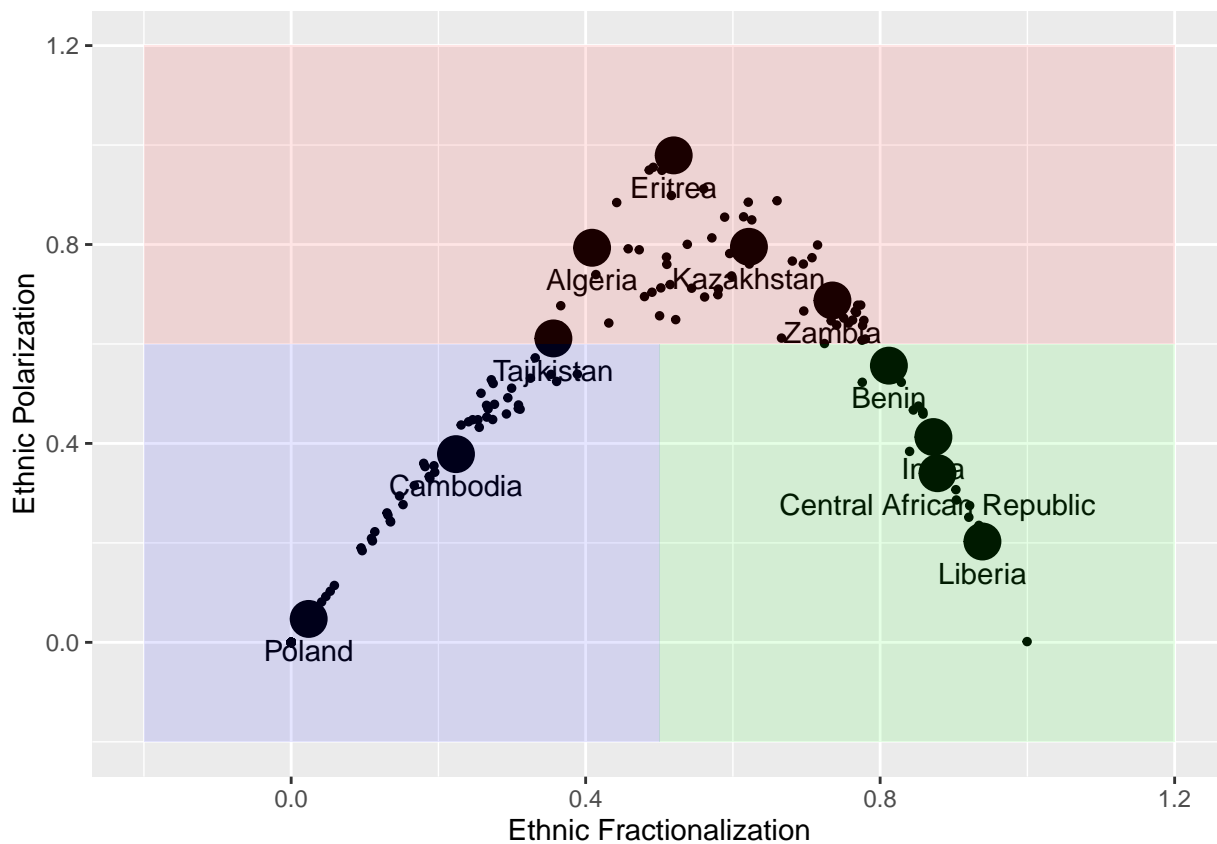


Table 2: Elections and Violent Political Instability, EPR Data

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.09*** (0.10)	-5.26*** (0.66)	-5.19*** (0.65)	-5.61*** (0.69)
nld.election.l1	-0.17 (0.21)			-0.20 (0.25)
epr.ef	0.54*** (0.17)	0.10 (0.20)	0.01 (0.20)	-0.00 (0.20)
epr.pol	0.16 (0.19)	0.13 (0.22)	0.25 (0.22)	0.19 (0.22)
nld.election.l1:epr.ef	-0.65 (0.42)			-0.95* (0.49)
nld.election.l1:epr.pol	0.52 (0.43)			0.76 (0.50)
nld.election.fl		-0.29 (0.25)		
ln.wdi.imr.l1		0.35*** (0.07)	0.45*** (0.08)	0.43*** (0.09)
polity2.lag.1		0.01 (0.01)	0.03*** (0.01)	0.02** (0.01)
part.dem.fac.l1		0.50*** (0.13)	0.35*** (0.13)	0.50*** (0.13)
ln.wdi.pop.l1		0.11*** (0.03)	0.06** (0.03)	0.10*** (0.03)
nac.l1		0.04 (0.03)	0.09*** (0.03)	0.06* (0.03)
nld.suspend.fl		0.46** (0.21)		
nld.earlylate.fl		0.20 (0.22)		
nld.election.fl:epr.ef		0.37 (0.38)		
nld.election.fl:epr.pol		-0.62 (0.46)		
nld.election			-0.05 (0.22)	
nld.suspend			0.19 (0.20)	
nld.earlylate			-0.13 (0.23)	
nld.election:epr.ef			0.14 (0.36)	
nld.election:epr.pol			-0.23 (0.41)	
nld.suspend.l1				0.24 (0.21)
nld.earlylate.l1				-0.31 (0.27)
AIC	1097.06	1007.10	1069.80	1006.79
Num. obs.	3633	3710	3713	3633

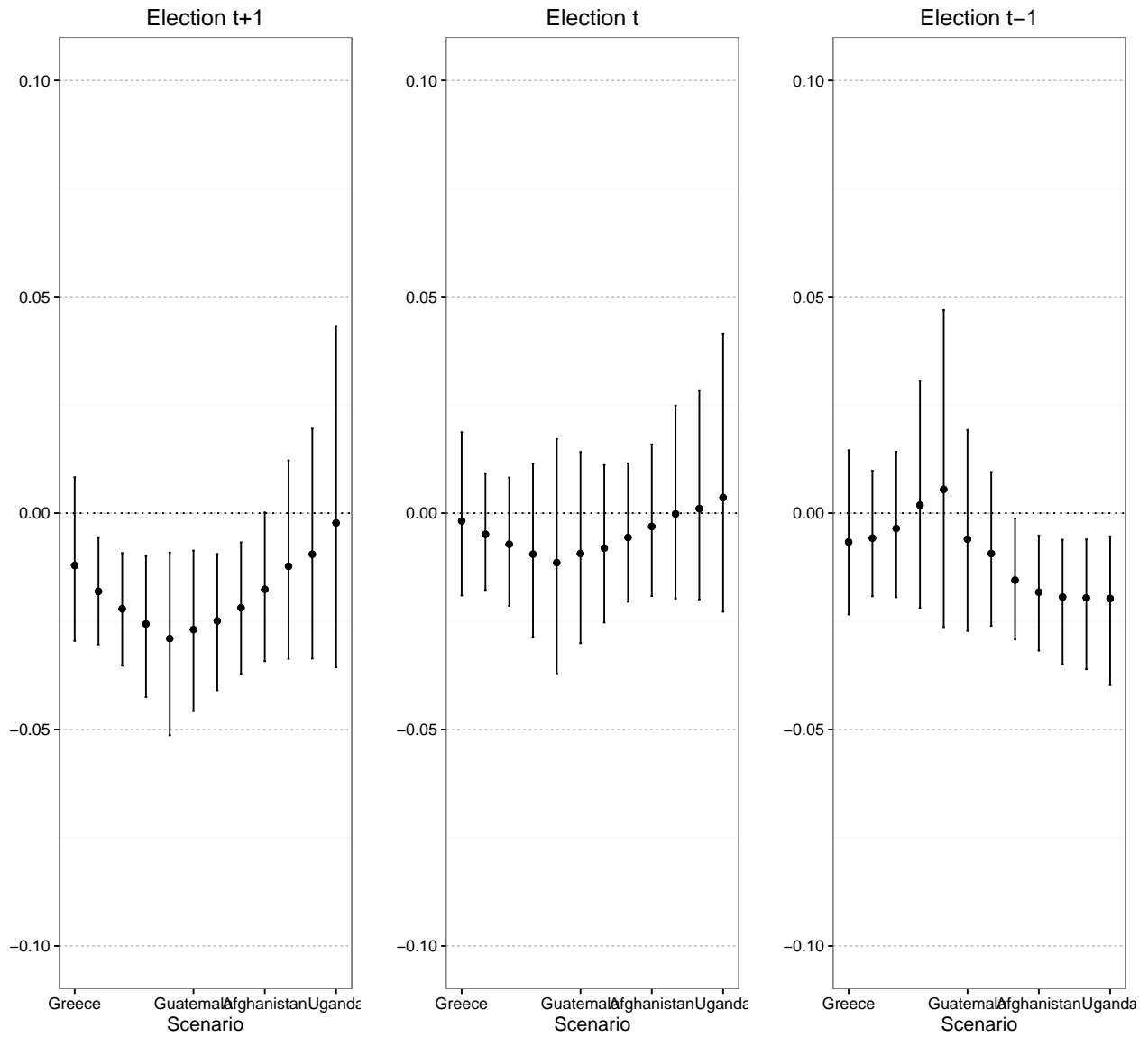
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Simulated Cases Across the Spectrum of Ethnic Polarization and Fractionalization, EPR data

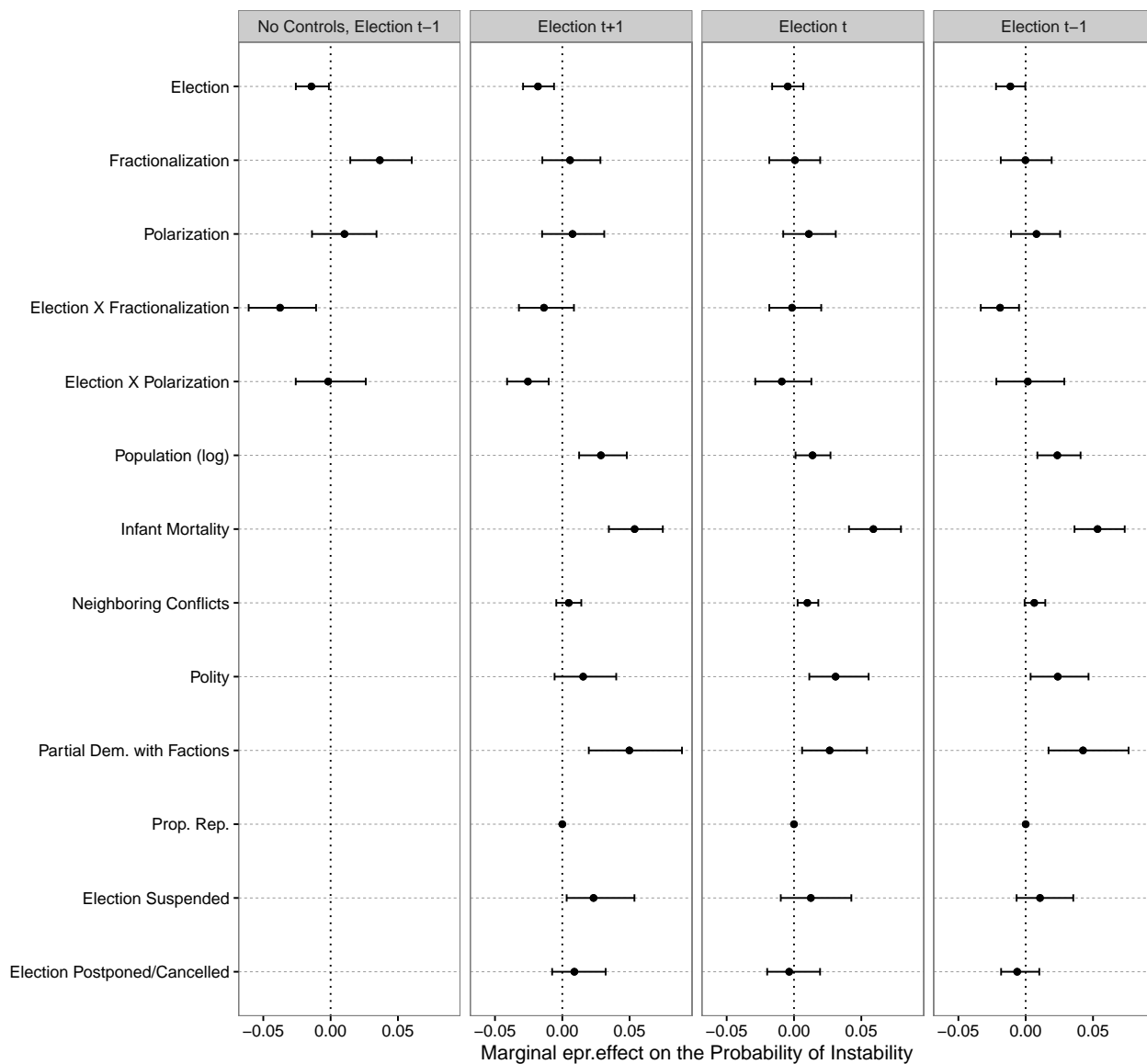


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Impact of Elections on Probability of Violent Political Instability Across Simulated Ethnic Structures, EPR Data



First Differences for Elections and Violent Political Instability, EPR data



Disaggregating elections

This section tests our results, but disaggregates the elections into ‘executive elections’ and ‘legislative elections’ as defined in the NELDA codebook (Hyde and Marinov 2012).

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Executive elections

This section tests our results, but uses executive elections as the election-related independent variable as defined in the NELDA codebook (Hyde and Marinov 2012).

Effects of Executive Elections Across Polarized and Fractionalized Settings

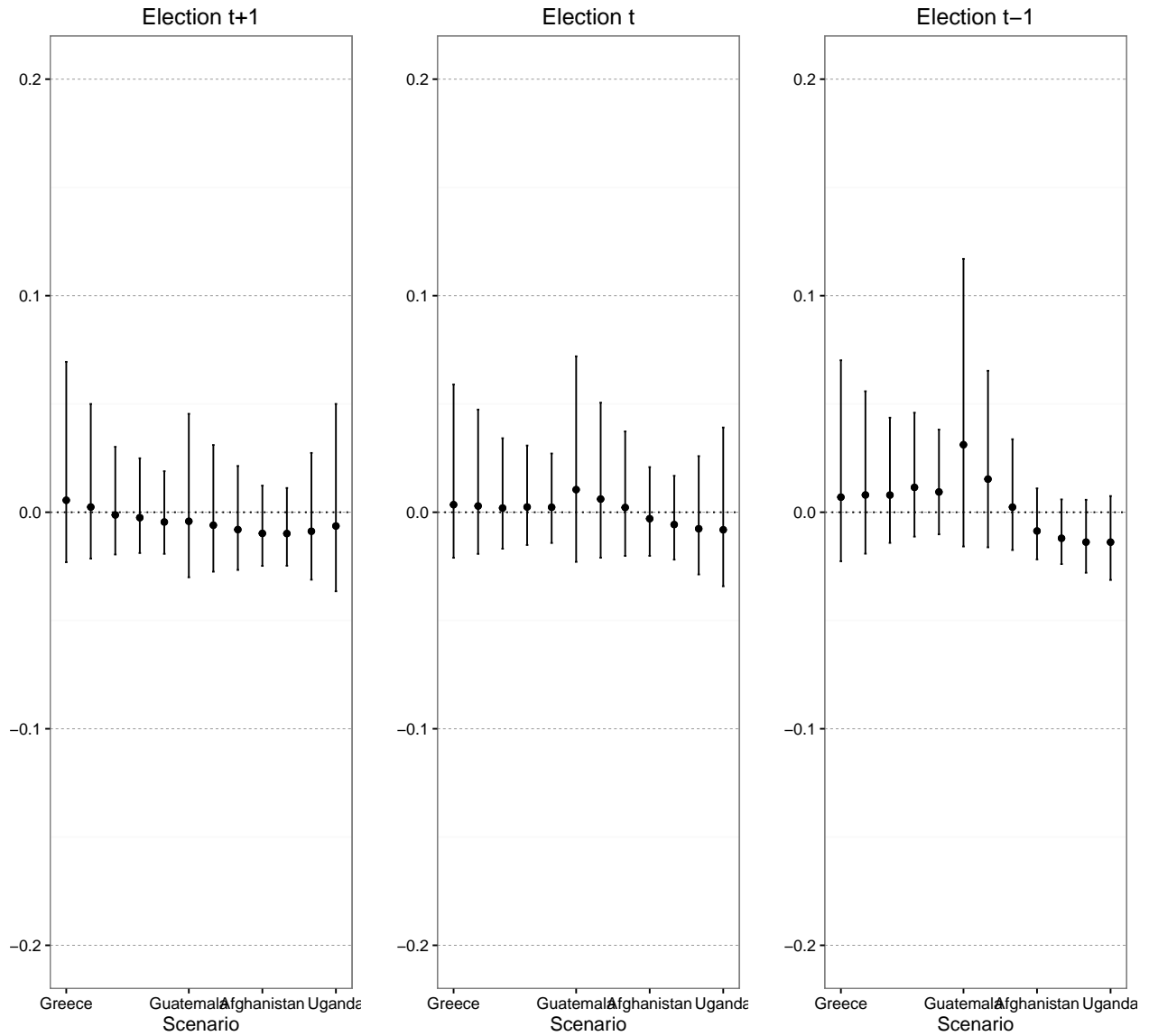
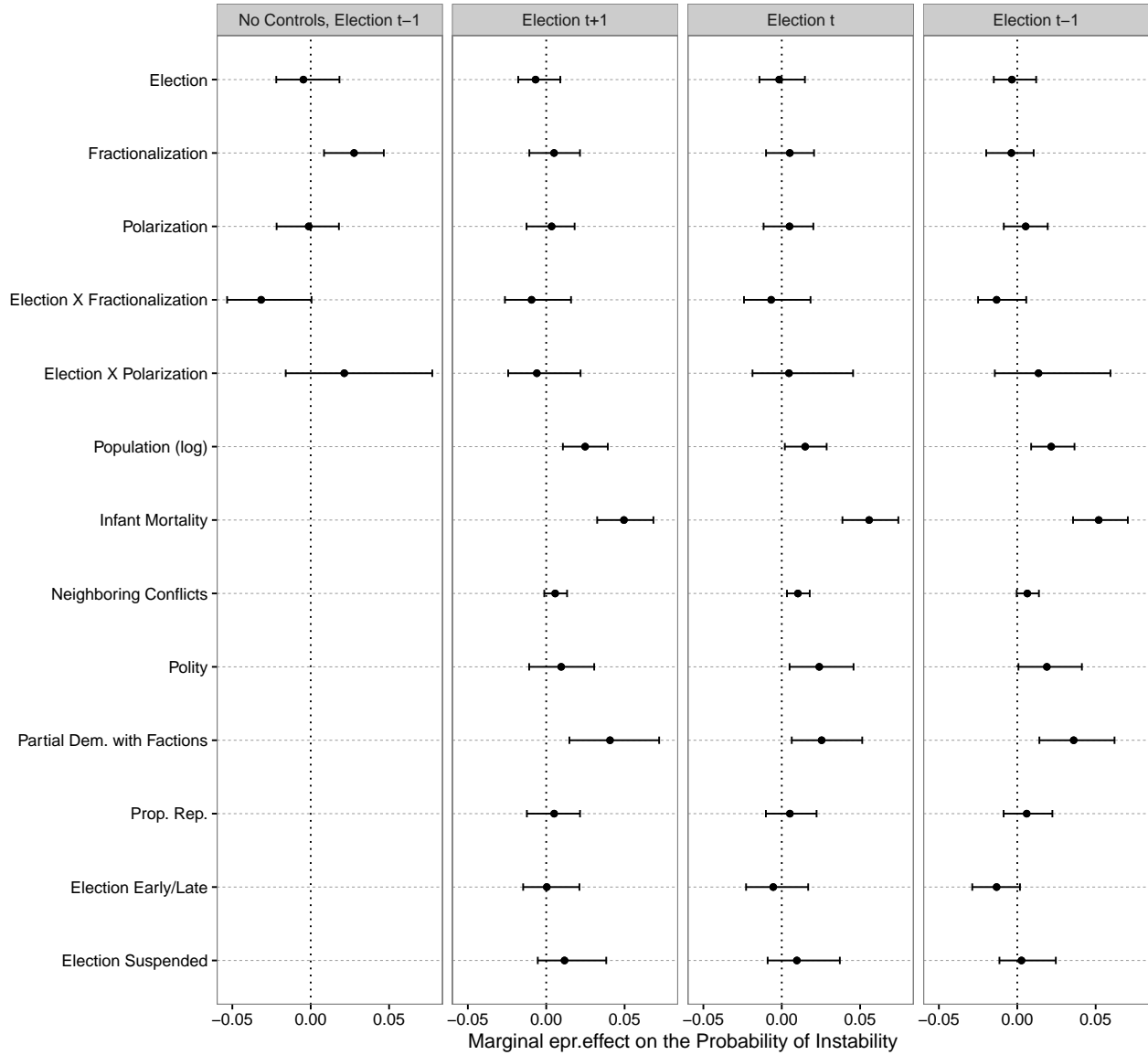


Table 3: Executive Elections and Violent Political Instability

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.07*** (0.13)	-5.54*** (0.75)	-5.46*** (0.66)	-5.81*** (0.73)
nld.exec.l1	-0.00 (0.42)			0.00 (0.44)
ef	0.54*** (0.18)	0.13 (0.21)	0.15 (0.21)	-0.10 (0.21)
polarization	-0.02 (0.21)	0.11 (0.24)	0.16 (0.24)	0.19 (0.25)
nld.exec.l1:ef	-1.36* (0.70)			-1.35* (0.79)
nld.exec.l1:polarization	1.03 (0.75)			0.99 (0.80)
nld.exec.f1		-0.01 (0.49)		
ln.wdi.imr.l1		0.38*** (0.09)	0.46*** (0.08)	0.46*** (0.08)
polity2.lag.1		0.01 (0.01)	0.02** (0.01)	0.02* (0.01)
part.dem.fac.l1		0.48*** (0.14)	0.36*** (0.13)	0.47*** (0.13)
ln.wdi.pop.l1		0.11*** (0.03)	0.07** (0.03)	0.11*** (0.03)
nac.l1		0.05 (0.03)	0.10*** (0.03)	0.06* (0.03)
pr.l1		0.03 (0.05)	0.03 (0.05)	0.03 (0.05)
nld.earlylate.f1		-0.02 (0.20)		
nld.suspend.f1		0.21 (0.18)		
nld.exec.f1:ef		-0.26 (0.63)		
nld.exec.f1:polarization		-0.03 (0.76)		
nld.exec			-0.07 (0.49)	
nld.earlylate			-0.17 (0.22)	
nld.suspend			0.16 (0.18)	
nld.exec:ef			-0.35 (0.60)	
nld.exec:polarization			0.33 (0.71)	
nld.earlylate.l1				-0.52* (0.27)
nld.suspend.l1				0.04 (0.18)
AIC	1113.20	1015.12	1070.15	1016.04
Num. obs.	3633	3710	3713	3633

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

First Differences for Executive Elections and Violent Political Instability



Legislative Elections

This section tests the impact of legislative elections on the probability of violent political instability as defined in the NELDA data (Hyde and Marinov 2012).

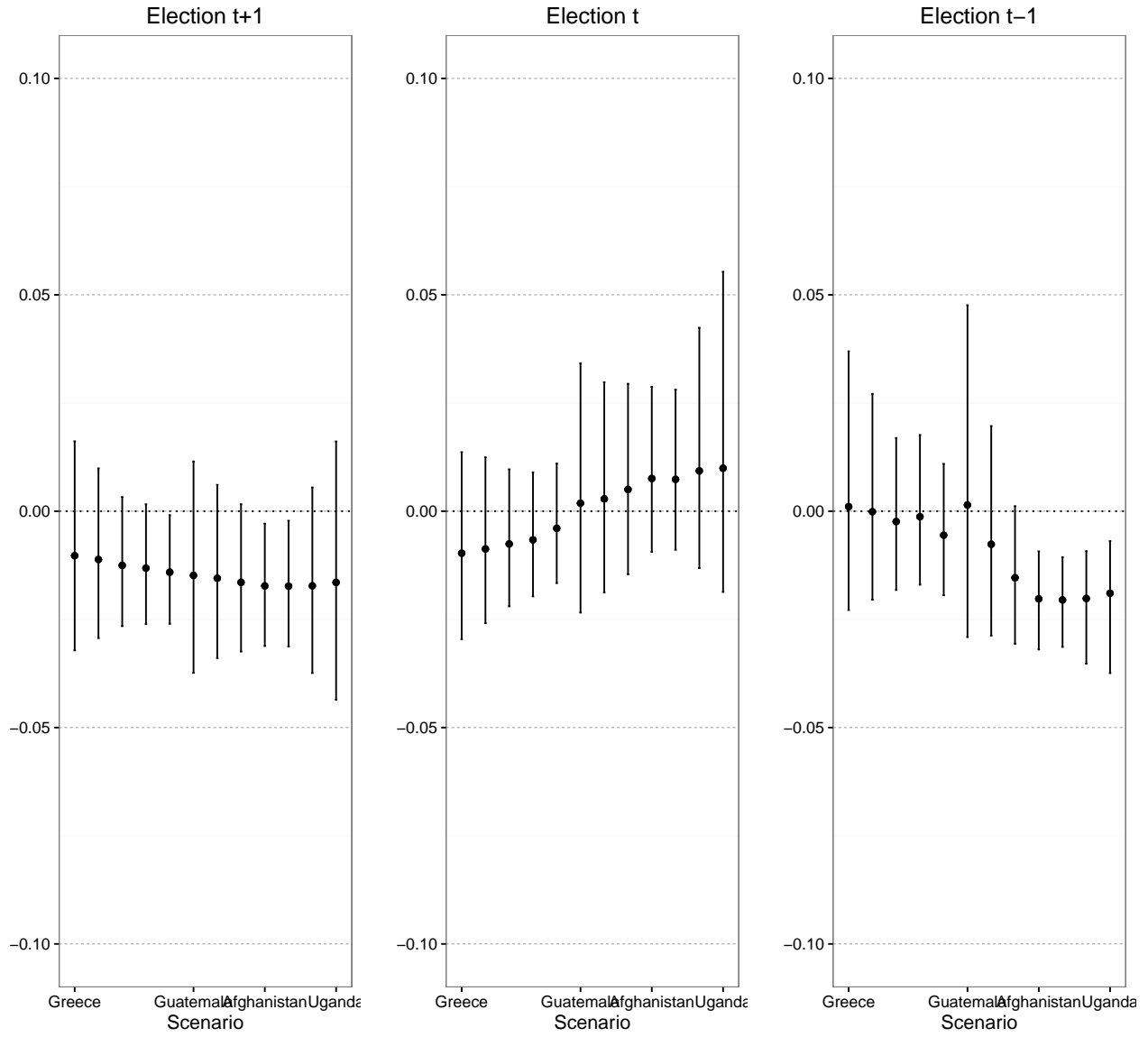
Table 4: Legislative Elections and Violent Political Instability

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.99*** (0.15)	-5.56*** (0.77)	-5.36*** (0.66)	-6.09*** (0.75)
nld.legpar.l1	-0.29 (0.29)			-0.02 (0.35)
ef	0.52*** (0.19)	0.11 (0.22)	-0.00 (0.22)	-0.03 (0.22)
polarization	-0.06 (0.23)	0.11 (0.26)	0.16 (0.26)	0.24 (0.26)
nld.legpar.l1:ef	-1.15* (0.60)			-1.73** (0.69)
nld.legpar.l1:polarization	0.98* (0.58)			0.87 (0.68)
nld.legpar.f1		-0.31 (0.36)		
ln.wdi.imr.l1		0.37*** (0.09)	0.46*** (0.08)	0.46*** (0.08)
polity2.lag.1		0.01 (0.01)	0.02** (0.01)	0.02** (0.01)
part.dem.fac.l1		0.48*** (0.14)	0.36*** (0.13)	0.46*** (0.13)
ln.wdi.pop.l1		0.12*** (0.03)	0.07** (0.03)	0.12*** (0.03)
nac.l1		0.05 (0.03)	0.09*** (0.03)	0.06* (0.03)
pr.l1		0.04 (0.05)	0.03 (0.05)	0.04 (0.05)
nld.earlylate.f1		0.13 (0.21)		
nld.suspend.f1		0.33* (0.18)		
nld.legpar.f1:ef		-0.14 (0.49)		
nld.legpar.f1:polarization		0.06 (0.57)		
nld.legpar			-0.37 (0.36)	
nld.earlylate			-0.19 (0.23)	
nld.suspend			0.12 (0.19)	
nld.legpar:ef			0.50 (0.43)	
nld.legpar:polarization			0.14 (0.50)	
nld.earlylate.l1				-0.42 (0.28)
nld.suspend.l1				0.26 (0.20)
AIC	1105.26	1007.88	1068.93	1004.90
Num. obs.	3633	3710	3713	3633

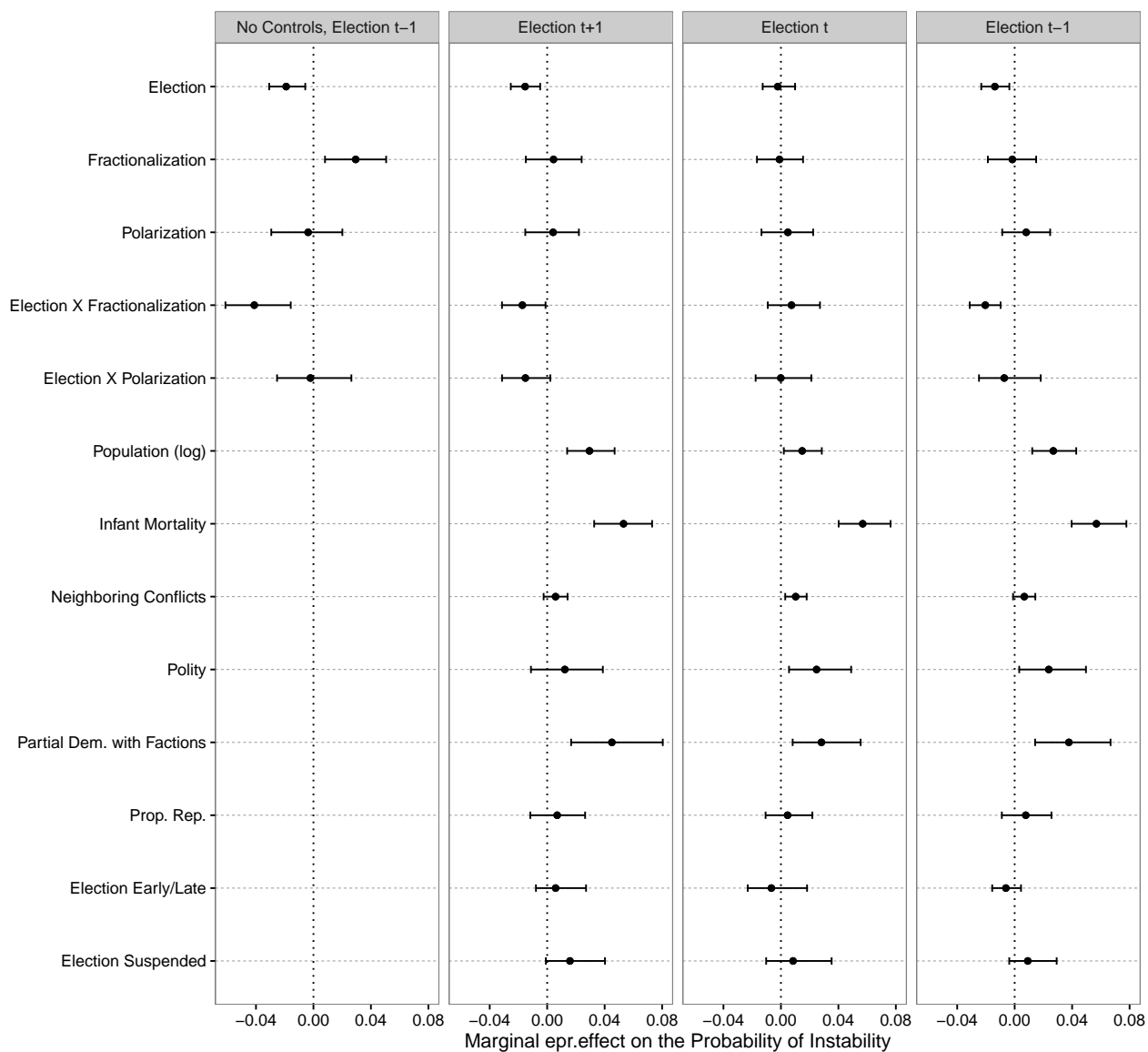
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Effects of Legislative Elections Across Polarized and Fractionalized Settings



First Differences for Legislative Elections and Violent Political Instability



Disaggregating Instability types

In this section we disaggregate ‘serious political instability’ into its four component forms and re-test the results on each. These four components are “revolutionary wars”, “ethnic wars” and “adverse regime changes” . For definitions of each form see (M. G. Marshall, Gurr, and Harff 2015). Note that we do not include a separate model for geno/politicide as there are no onsets of genocide or politicide in states with ethnic fractionalization scores over 0.75 and an election in the previous year. Although this would appear to support our contentions in the paper, it means that we cannot model the impact of an election in the previous year on the probability of geno/politicide in fractionalized states because, historically, there have

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3 been no such occurrences.
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7 **Revolutionary Wars**

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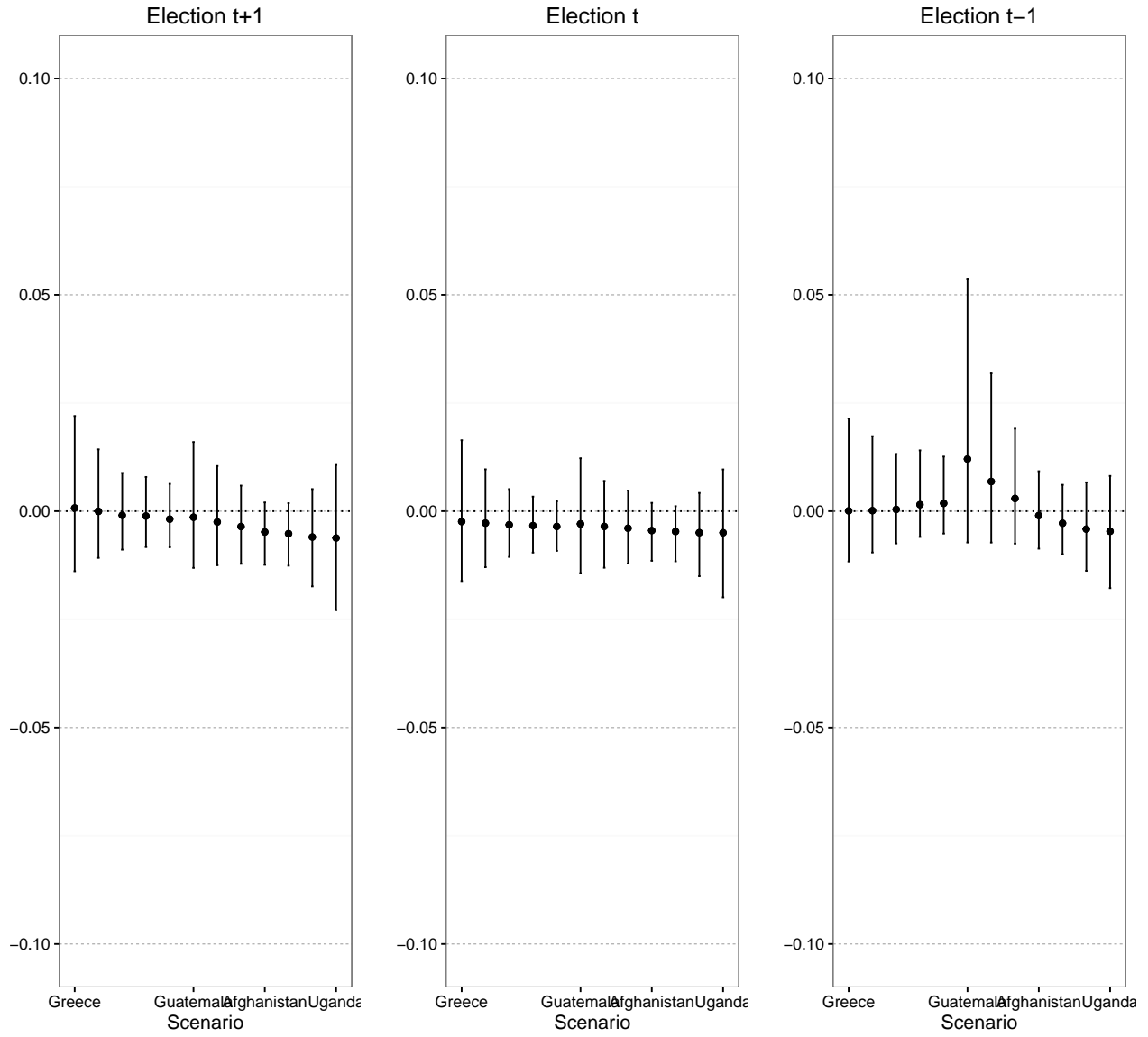
9
10 This section shows the results of our main regressions using the onset of revolutionary wars as the dependent
11 variable (M. G. Marshall, Gurr, and Harff 2015). Revolutionary wars are defined as “episodes of violent
12 conflict between governments and politically organized groups (political challengers) that seek to overthrow
13 the central government, to replace its leaders, or to seize power in one region.” (M. G. Marshall, Gurr, and
14 Harff 2015, 5)
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Table 5: Elections and Revolutionary Wars

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.51*** (0.25)	-5.41*** (1.17)	-5.69*** (1.23)	-6.17*** (1.17)
nld.election.l1	-0.70 (0.60)			-0.31 (0.69)
ef	0.61** (0.30)	0.25 (0.35)	0.16 (0.35)	0.21 (0.36)
polarization	-0.20 (0.36)	-0.01 (0.43)	0.01 (0.43)	0.13 (0.44)
nld.election.l1:ef	-0.44 (0.81)			-0.86 (0.87)
nld.election.l1:polarization	1.12 (0.87)			1.11 (0.97)
nld.election.f1		-0.01 (0.53)		
ln.wdi.imr.l1		0.41*** (0.14)	0.48*** (0.15)	0.47*** (0.15)
polity2.lag.1		-0.00 (0.02)	0.02 (0.02)	0.01 (0.02)
part.dem.fac.l1		0.35 (0.23)	0.13 (0.24)	0.15 (0.23)
ln.wdi.pop.l1		0.06 (0.05)	0.05 (0.05)	0.08 (0.05)
nac.l1		0.11** (0.05)	0.14*** (0.05)	0.14*** (0.05)
pr.l1		-0.00 (0.09)	-0.01 (0.09)	0.01 (0.09)
nld.earlylate.f1		0.52* (0.31)		
nld.suspend.f1		0.24 (0.34)		
nld.election.f1:ef		-0.76 (0.75)		
nld.election.f1:polarization		0.18 (0.89)		
nld.election			-0.47 (0.70)	
nld.suspend			0.72** (0.33)	
nld.election:ef			-0.16 (0.80)	
nld.election:polarization			0.14 (0.98)	
nld.earlylate.l1				-0.21 (0.44)
nld.suspend.l1				-0.28 (0.42)
AIC	387.54	380.60	357.42	379.88
Num. obs.	3633	3710	3713	3633

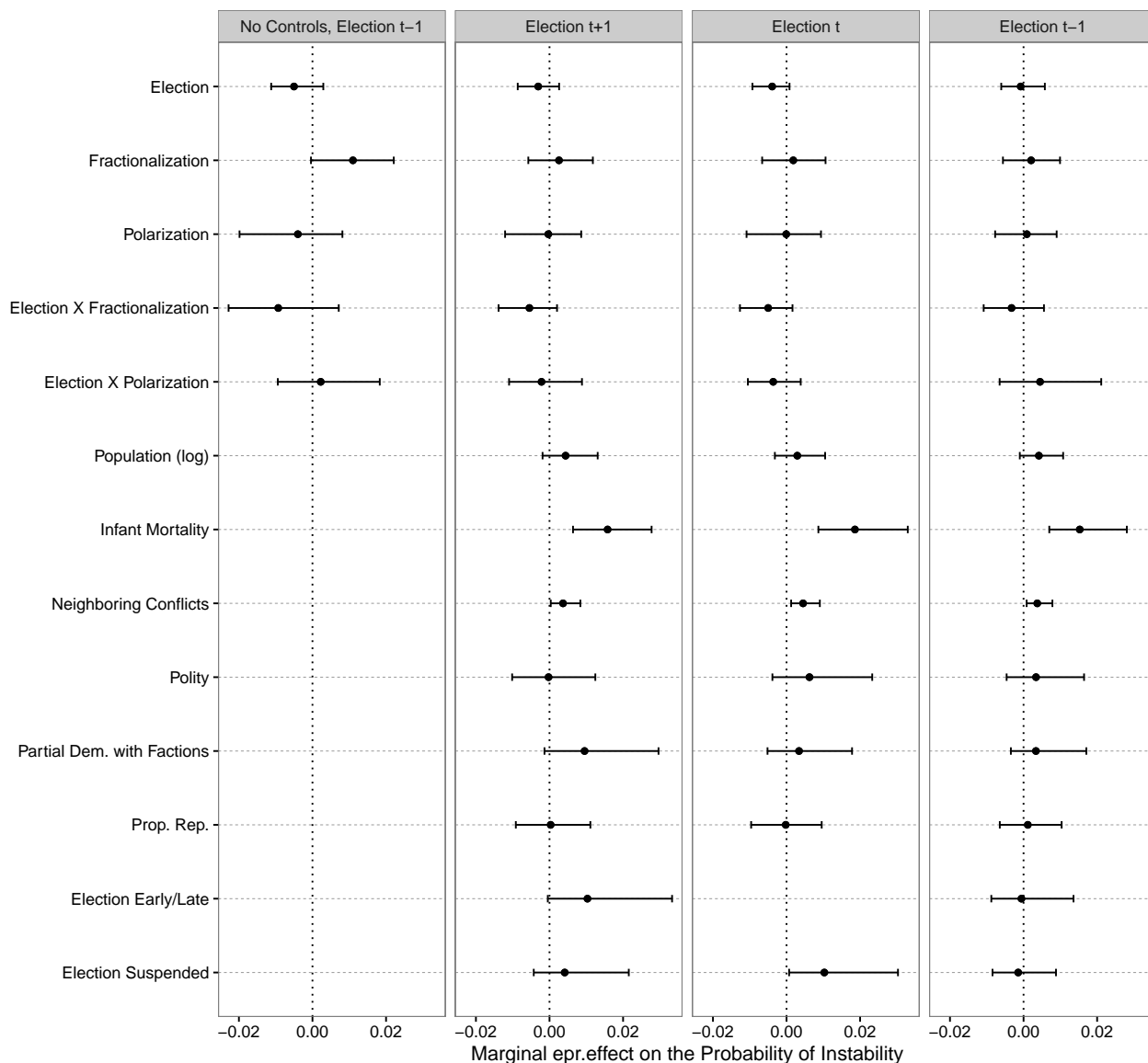
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Elections on Revolutionary War Onset in Polarized and Fractionalized Settings



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First Differences for Revolutionary War Onset



Disaggregating Instability types - Ethnic Wars

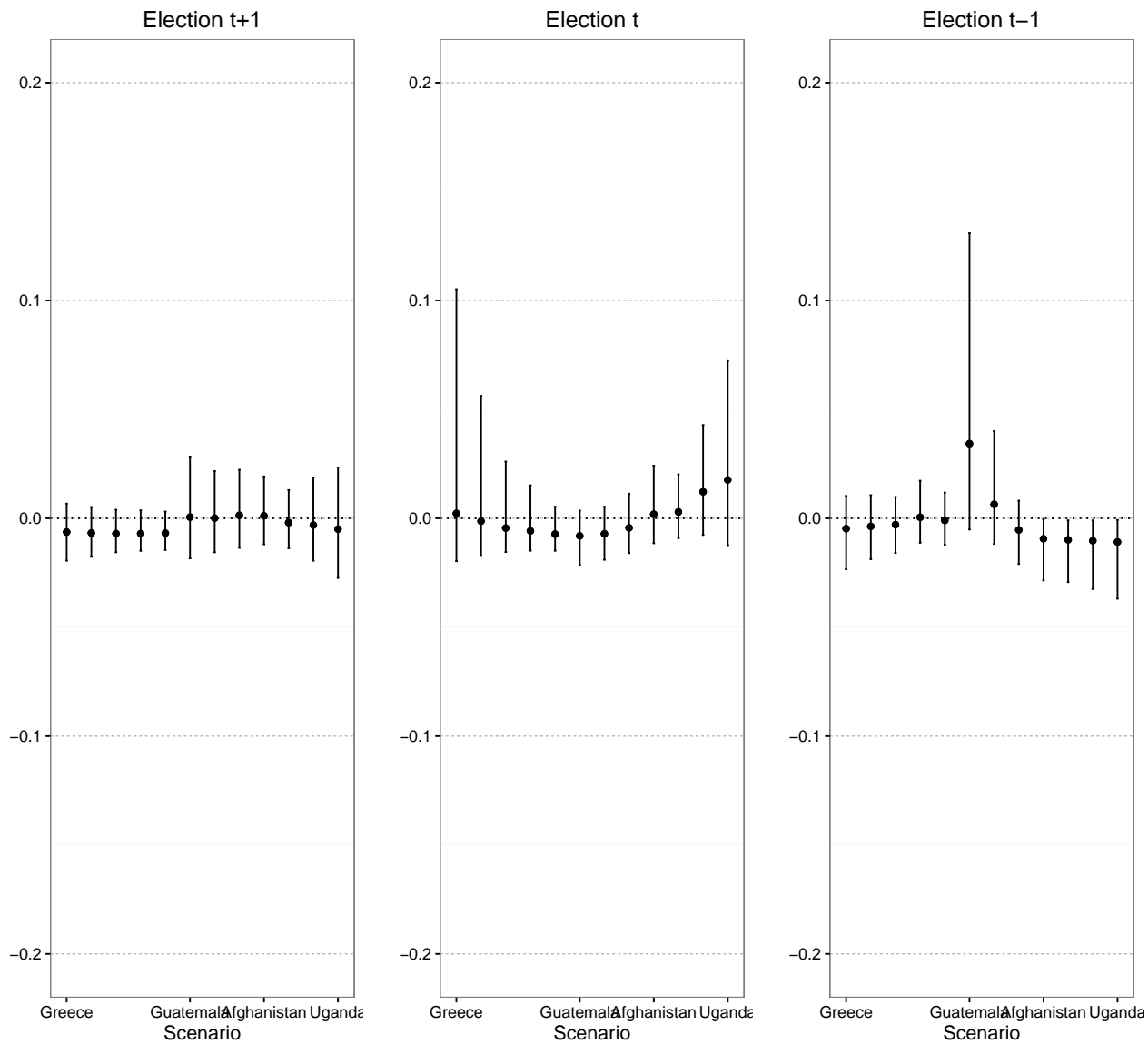
This section shows the results of our main regressions using the onset of ethnic wars as the dependent variable (M. G. Marshall, Gurr, and Harff 2015). Ethnic wars are defined as “episodes of violent conflict between governments and national, ethnic, religious, or other communal minorities (ethnic challengers) in which the challengers seek major changes in their status” (M. G. Marshall, Gurr, and Harff 2015, 6)

Table 6: Elections and Ethnic Wars

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.28*** (0.21)	-5.39*** (0.94)	-4.99*** (0.95)	-5.05*** (1.04)
nld.election.l1	-0.88* (0.48)			-0.64 (0.56)
ef	0.35 (0.27)	0.22 (0.32)	0.18 (0.32)	0.13 (0.32)
polarization	-0.12 (0.33)	0.12 (0.37)	0.08 (0.37)	0.08 (0.37)
nld.election.l1:ef	-3.76** (1.89)			-4.00** (1.85)
nld.election.l1:polarization	3.48** (1.39)			3.23** (1.38)
nld.election.f1		-1.57 (1.00)		
ln.wdi.imr.l1		0.14 (0.10)	0.16 (0.11)	0.17 (0.11)
polity2.lag.1		-0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)
part.dem.fac.l1		0.24 (0.20)	0.28 (0.23)	0.35* (0.20)
ln.wdi.pop.l1		0.15*** (0.04)	0.12*** (0.04)	0.12*** (0.05)
nac.l1		0.03 (0.05)	0.07 (0.05)	0.05 (0.05)
pr.l1		0.01 (0.07)	0.05 (0.07)	0.01 (0.08)
nld.earlylate.f1		-0.18 (0.40)		
nld.suspend.f1		0.23 (0.29)		
nld.election.f1:ef		1.04 (0.88)		
nld.election.f1:polarization		1.04 (0.94)		
nld.election			-2.28 (1.93)	
nld.earlylate			-0.11 (0.43)	
nld.suspend			0.07 (0.35)	
nld.election:ef			2.71 (1.65)	
nld.election:polarization			0.33 (1.30)	
nld.earlylate.l1				-1.66 (3.07)
nld.suspend.l1				0.46 (0.32)
AIC	489.14	501.71	481.12	474.20
Num. obs.	3633	3710	3713	3633

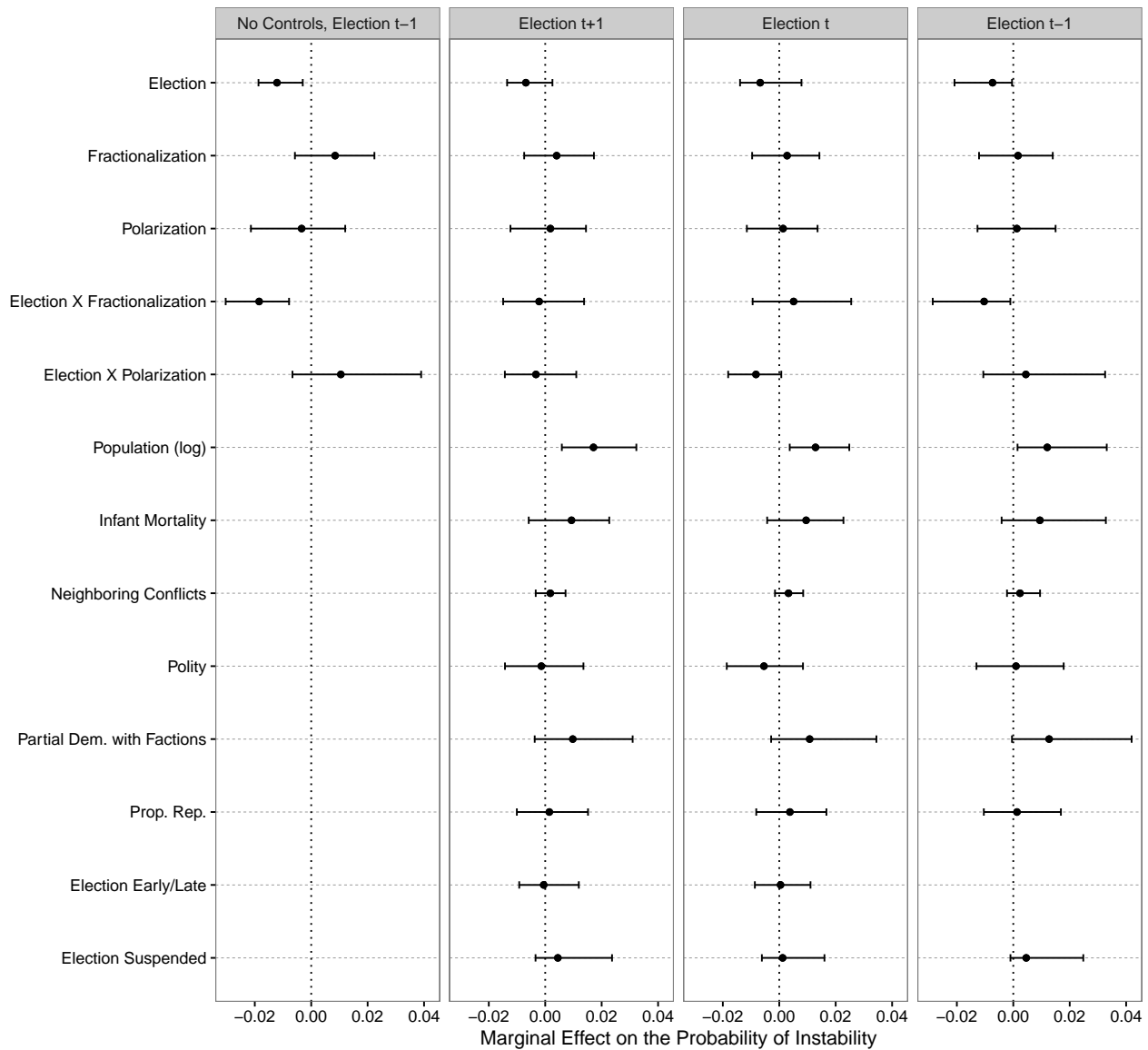
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Elections on Ethnic War Onset in Polarized and Fractionalized Settings



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First Differences for Ethnic War Onset



Disaggregating Instability types - Adverse Regime Changes

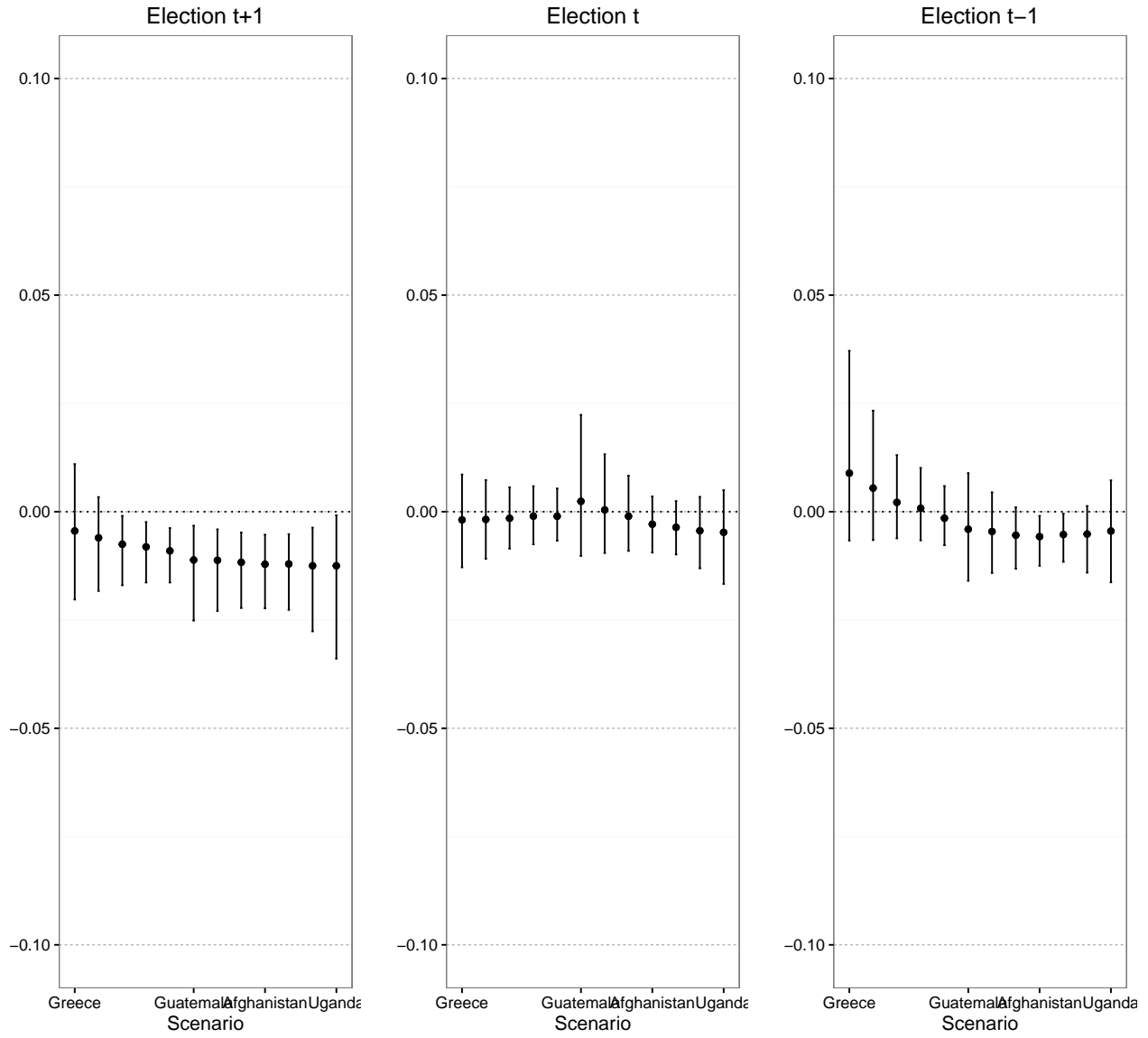
This section shows the results of our main regressions using the onset of adverse (non-democratic) regimes changes as the dependent variable (M. G. Marshall, Gurr, and Harff 2015).

Table 7: Adverse Regime Changes and Violent Political Instability

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.59*** (0.24)	-5.39*** (0.94)	-5.23*** (1.24)	-6.13*** (1.06)
nld.election.l1	0.38 (0.35)			0.48 (0.44)
ef	0.67** (0.28)	0.22 (0.32)	0.24 (0.34)	0.10 (0.33)
polarization	0.12 (0.33)	0.12 (0.37)	0.08 (0.39)	0.22 (0.40)
nld.election.l1:ef	-0.84 (0.58)			-1.18* (0.71)
nld.election.l1:polarization	-0.06 (0.63)			-0.23 (0.79)
nld.election.f1		-1.57 (1.00)	-0.25 (0.54)	
ln.wdi.imr.l1		0.14 (0.10)	0.51*** (0.15)	0.61*** (0.13)
polity2.lag.1		-0.00 (0.01)	0.04** (0.02)	0.04*** (0.01)
part.dem.fac.l1		0.24 (0.20)	0.79*** (0.18)	0.66*** (0.16)
ln.wdi.pop.l1		0.15*** (0.04)	-0.01 (0.05)	0.02 (0.05)
nac.l1		0.03 (0.05)	0.01 (0.06)	0.02 (0.05)
pr.l1		0.01 (0.07)	0.03 (0.08)	0.02 (0.07)
nld.earlylate.f1		-0.18 (0.40)	1.04*** (0.39)	
nld.suspend.f1		0.23 (0.29)	1.47*** (0.42)	
nld.election.f1:ef		1.04 (0.88)	-0.91 (0.86)	
nld.election.f1:polarization		1.04 (0.94)	-1.01 (1.02)	
nld.earlylate.l1				-0.26 (0.36)
nld.suspend.l1				0.30 (0.28)
AIC	573.50	501.71	438.95	495.57
Num. obs.	3633	3710	3710	3633

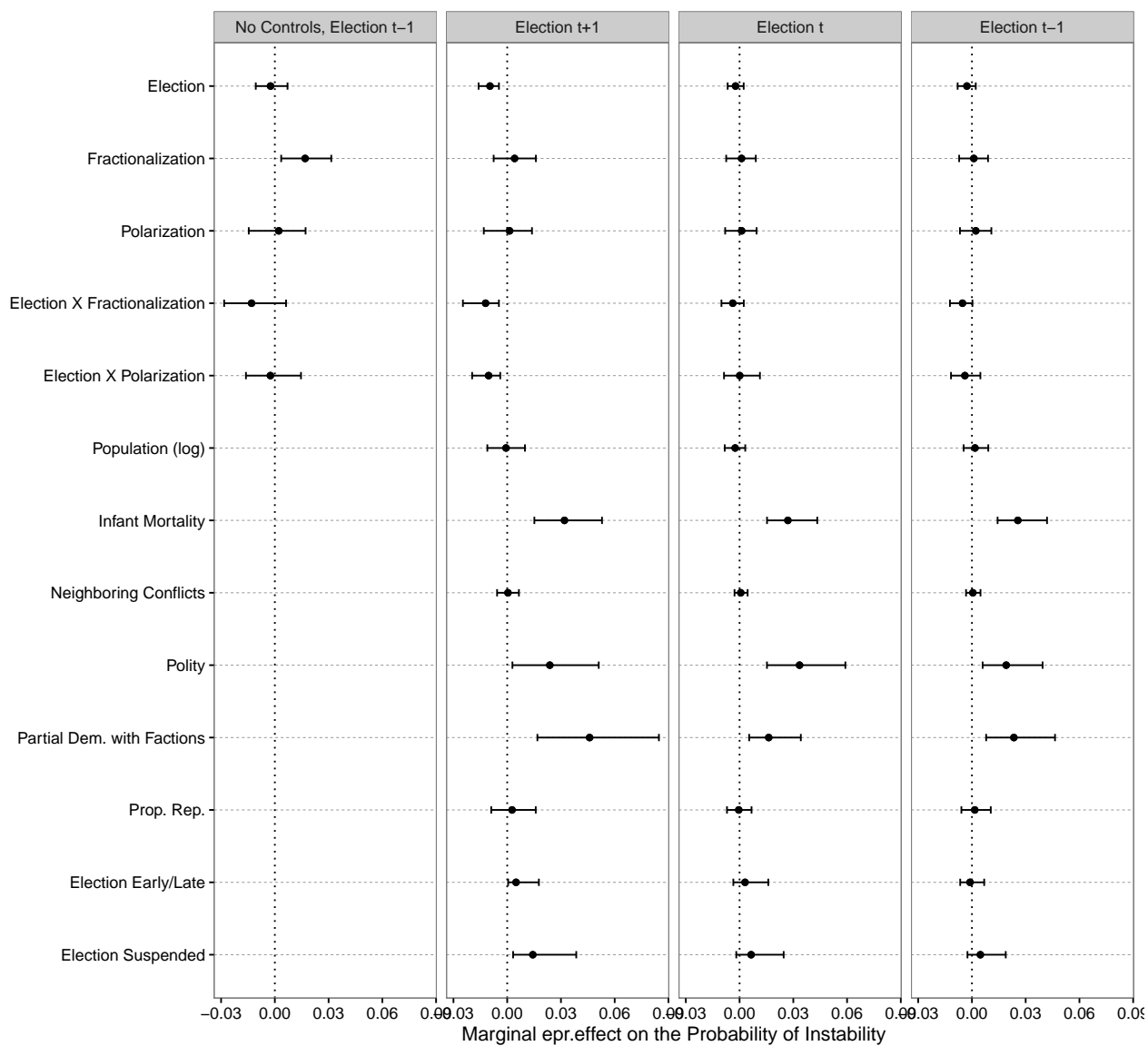
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Elections on Adverse Regime Change in Polarized and Fractionalized Settings



First Differences for Adverse Regime Changes

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Disaggregating instability types- UCDP Civil Wars.

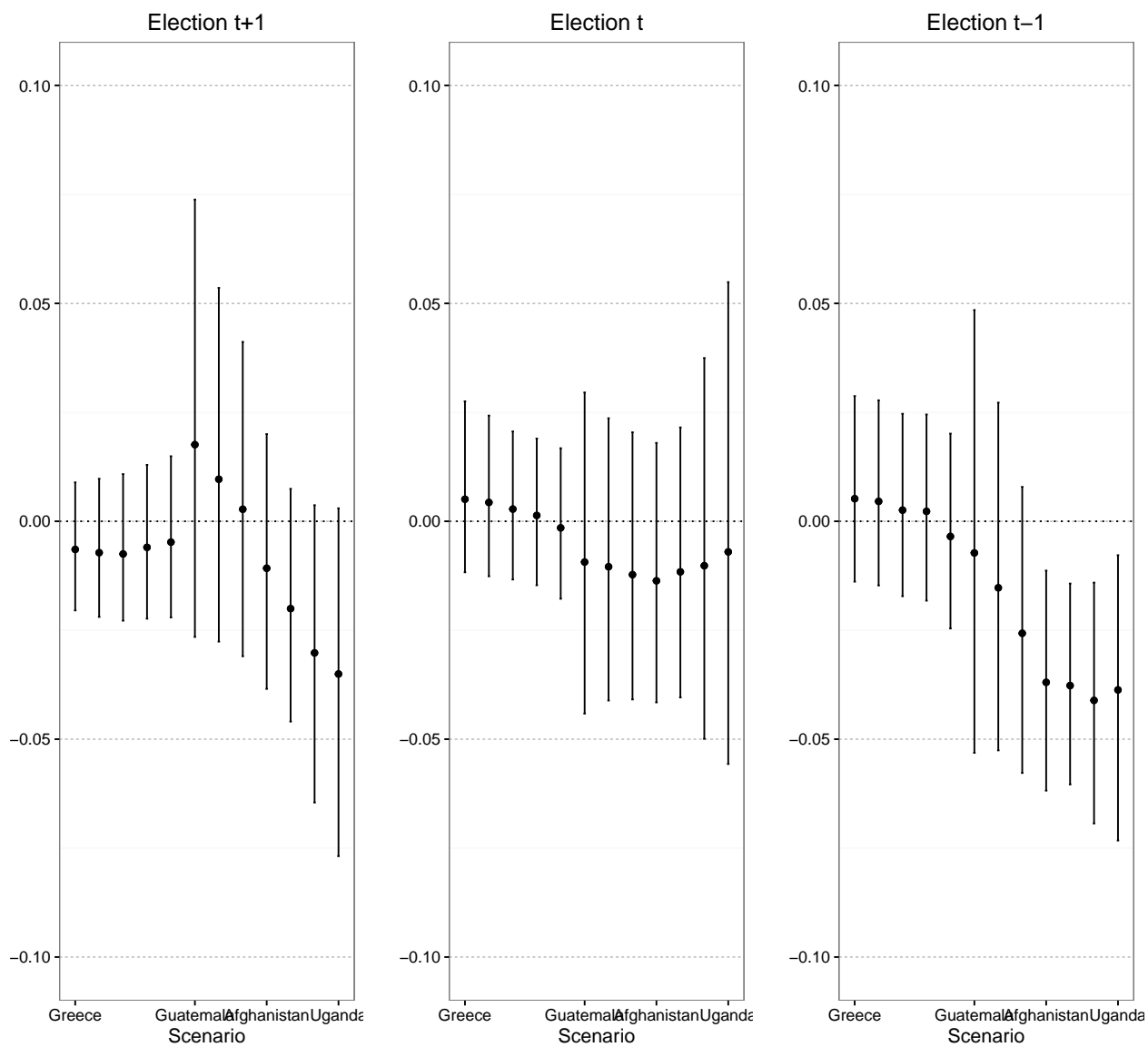
This section shows the impact of elections on UCDP civil wars in ethnically fractionalized states. The data come from the UCDP/PRIO Armed Conflict Monadic Conflict Onset and Incidence Data, version 4.13 (Themnér and Wallensteen 2014).

Table 8: Internal Armed Conflicts (UCDP/PRIO) and Violent Political Instability

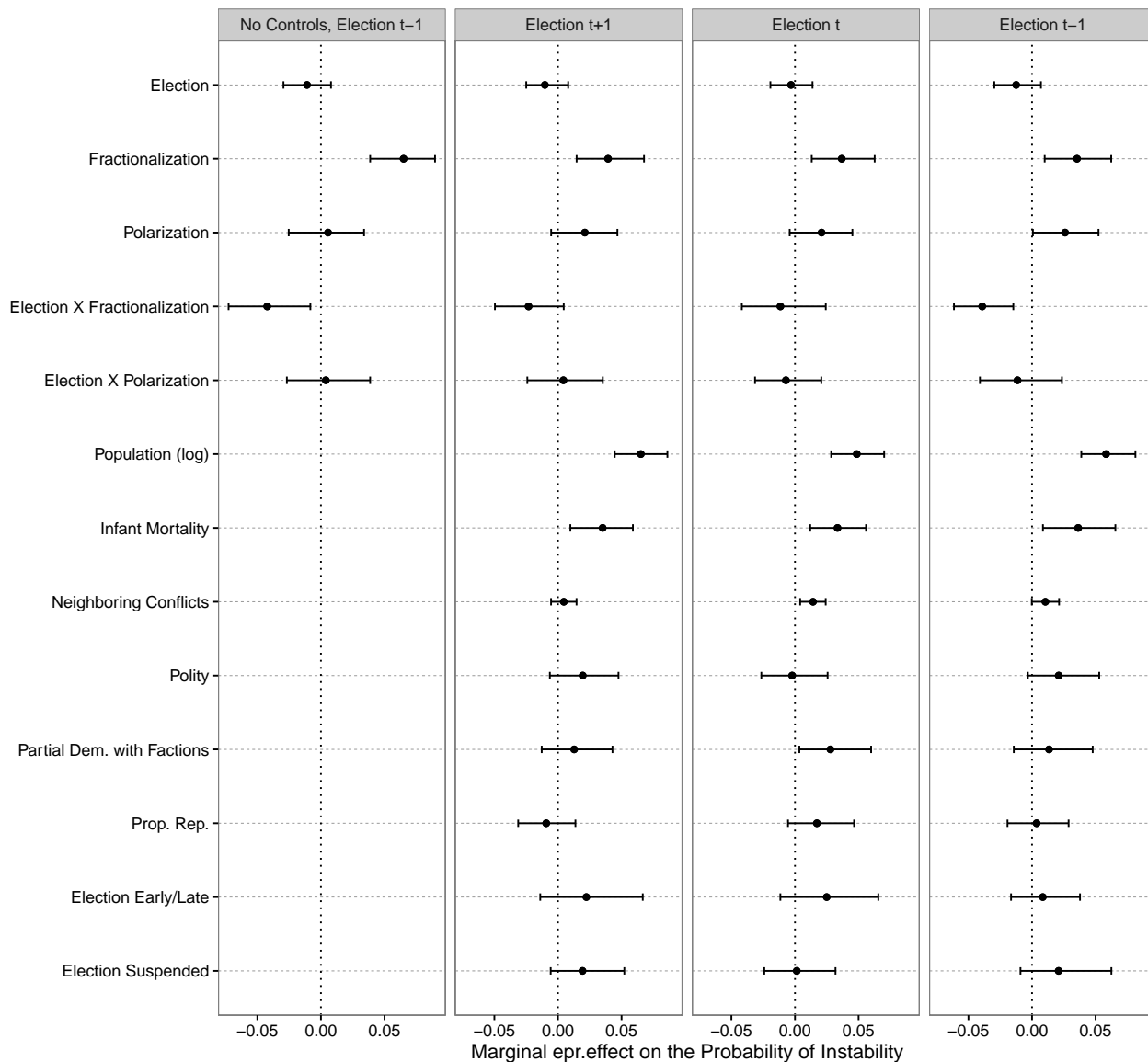
	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.17*** (0.21)	-5.84*** (0.59)	-5.52*** (0.68)	-6.01*** (0.61)
nld.election.l1	-0.07 (0.32)			0.19 (0.40)
ef	0.93*** (0.22)	0.71*** (0.25)	0.71*** (0.23)	0.69** (0.30)
polarization	0.10 (0.24)	0.44 (0.28)	0.45 (0.28)	0.56* (0.29)
nld.election.l1:ef	-0.74* (0.41)			-1.09** (0.47)
nld.election.l1:polarization	0.55 (0.47)			0.27 (0.57)
nld.election.f1		-0.44 (0.42)		
ln.wdi.imr.l1		0.17** (0.07)	0.18*** (0.07)	0.19** (0.08)
polity2.lag.1		0.01 (0.01)	-0.00 (0.01)	0.01 (0.01)
part.dem.fac.l1		0.12 (0.16)	0.29** (0.13)	0.13 (0.19)
ln.wdi.pop.l1		0.19*** (0.03)	0.16*** (0.03)	0.18*** (0.03)
nac.l1		0.03 (0.03)	0.09** (0.03)	0.07* (0.04)
pr.l1		-0.04 (0.05)	0.07 (0.05)	0.01 (0.05)
nld.earlylate.f1		0.26 (0.24)		
nld.suspend.f1		0.24 (0.17)		
nld.election.f1:ef		-0.27 (0.41)		
nld.election.f1:polarization		0.71 (0.50)		
nld.election			0.17 (0.34)	
nld.earlylate			0.25 (0.23)	
nld.suspend			-0.01 (0.20)	
nld.election:ef			-0.24 (0.42)	
nld.election:polarization			-0.16 (0.47)	
nld.earlylate.l1				0.12 (0.22)
nld.suspend.l1				0.28 (0.23)
AIC	1443.15	1470.74	1378.86	1325.28
Num. obs.	3633	3710	3713	3633

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Elections on UCDP Intrastate / Internationalized Intrastate Conflict Onset in Polarized and Fractionalized Settings



First Differences for UCDP Intrastate / Internationalized Intrastate Onset



Disaggregating Instability types - Ulfelder and Valentino Mass Killing Episodes

This section shows the impact of the elections and ethnic fractionalization interaction on episodes of mass killing, as defined by Ulfelder and Valentino ((Ulfelder and Valentino 2008)). The data come from the 2014 update, which can be found at (<https://github.com/ulfelder/cpg-statrisk-2014>).

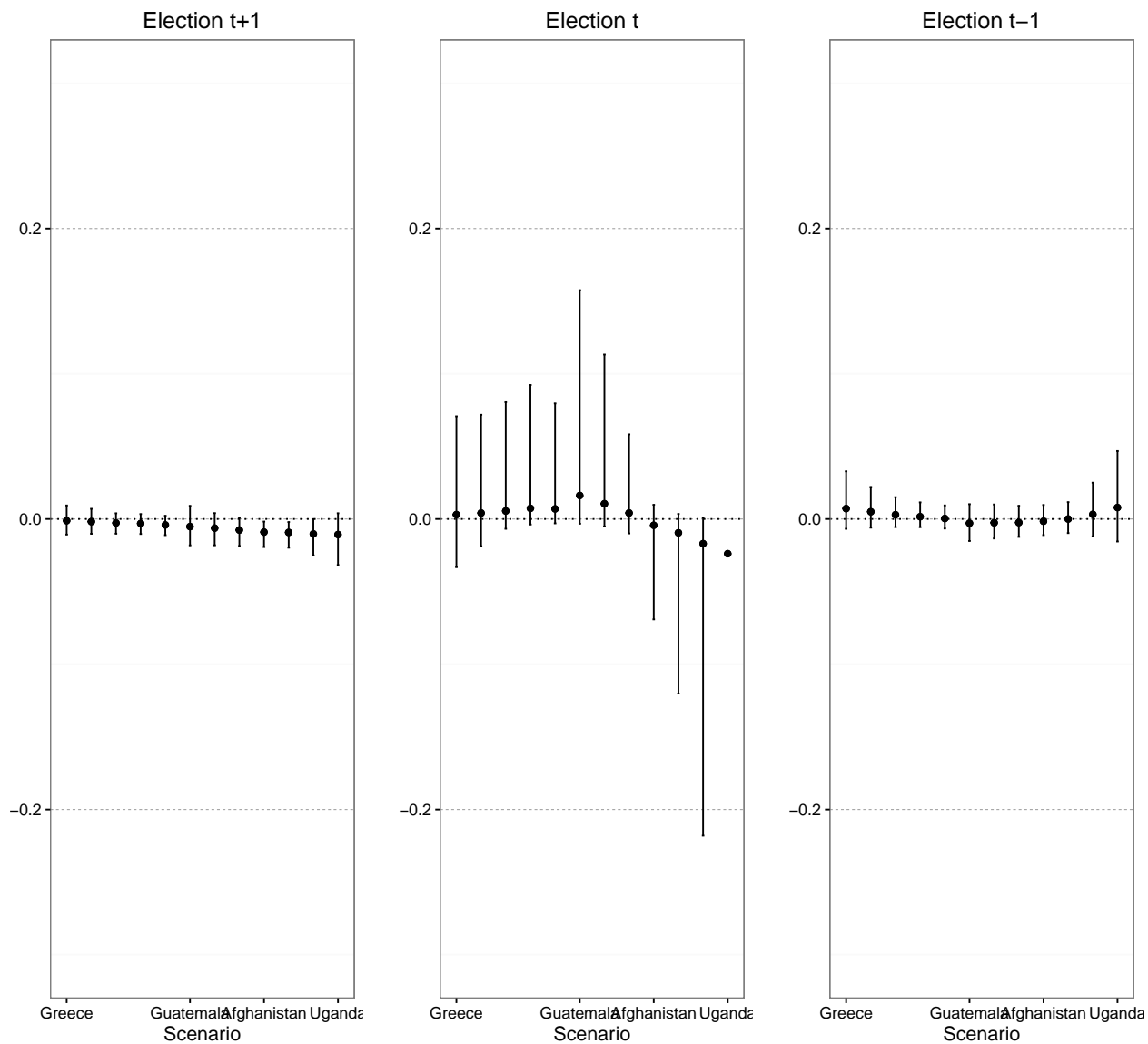
Table 9: Mass Killings and Violent Political Instability

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.62*** (0.26)	-4.47*** (1.06)	-5.33*** (1.04)	-5.51*** (1.03)
nld.election.l1	0.17 (0.40)			0.44 (0.46)
ef	0.83*** (0.29)	0.54 (0.35)	0.39 (0.34)	0.44 (0.33)
polarization	-0.12 (0.35)	0.12 (0.41)	0.14 (0.41)	0.13 (0.40)
nld.election.l1:ef	0.07 (0.50)			-0.08 (0.54)
nld.election.l1:polarization	-0.33 (0.59)			-0.63 (0.67)
nld.election.f1		-0.23 (0.57)		
ln.wdi.imr.l1		0.21 (0.13)	0.37*** (0.12)	0.34*** (0.12)
polity2.lag.1		-0.01 (0.02)	0.00 (0.02)	-0.00 (0.01)
part.dem.fac.l1		0.15 (0.26)	0.33 (0.22)	0.20 (0.20)
ln.wdi.pop.l1		0.09* (0.05)	0.08* (0.04)	0.10** (0.04)
nac.l1		0.02 (0.05)	0.07 (0.05)	0.05 (0.05)
pr.l1		-0.06 (0.09)	-0.02 (0.08)	0.03 (0.07)
nld.earlylate.f1		1.02*** (0.33)		
nld.suspend.f1		0.53 (0.34)		
nld.election.f1:ef		-0.89 (0.79)		
nld.election.f1:polarization		0.13 (0.91)		
nld.election			0.05 (0.52)	
nld.earlylate			-2.37 (104.37)	
nld.suspend			0.17 (0.28)	
nld.election:ef			-1.33* (0.77)	
nld.election:polarization			1.04 (0.83)	
nld.earlylate.l1				-0.08 (0.31)
nld.suspend.l1				0.27 (0.25)
AIC	509.00	425.84	473.54	495.97
Num. obs.	3633	3710	3713	3633

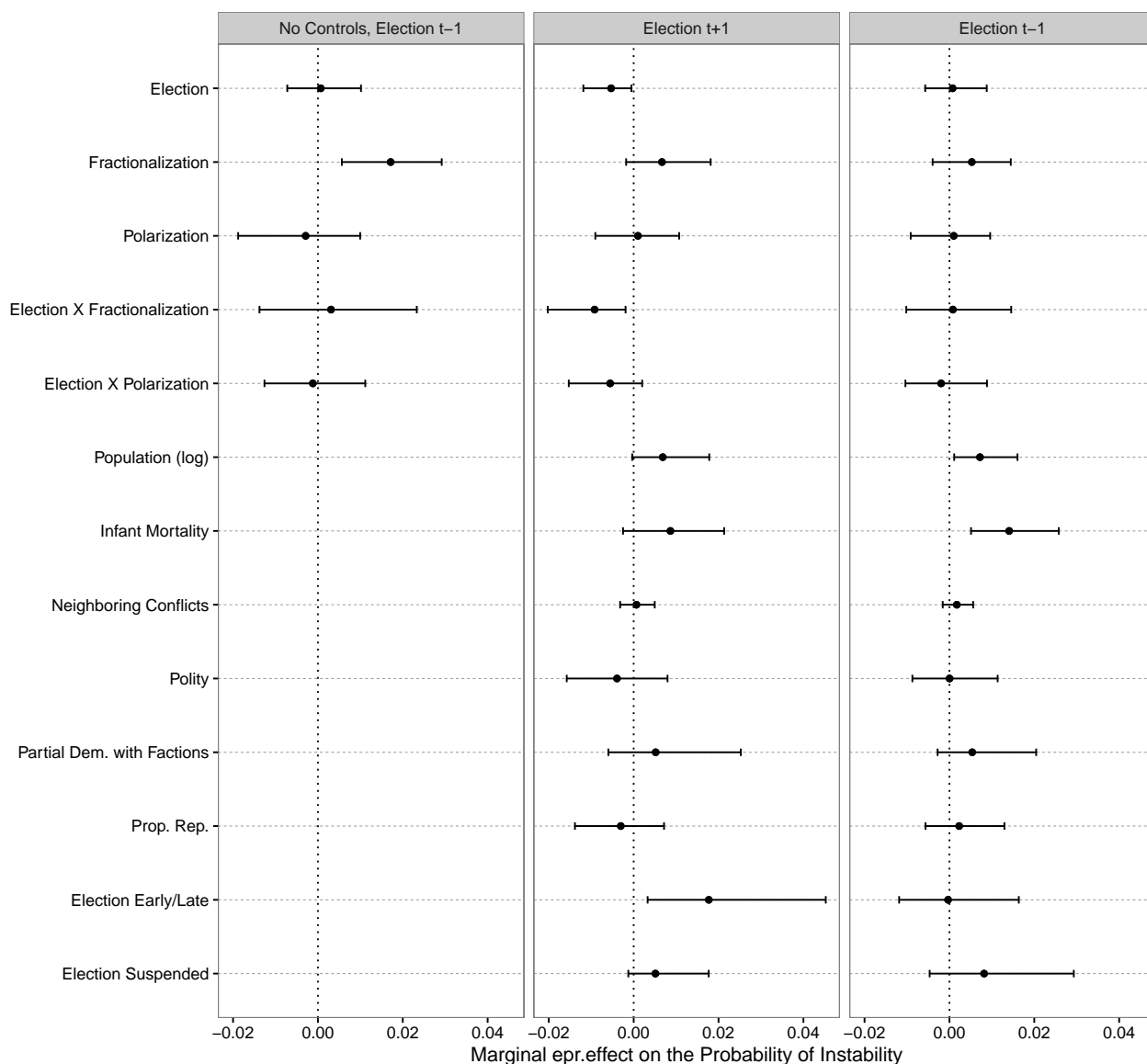
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Elections on Ulfelder and Valentino Mass Killing Onsets in Polarized and Fractionalized Settings

Warning: Removed 1 rows containing missing values (geom_errorbar).



First Differences for Ulfelder and Valentino Mass Killing Onsets



Disaggregating Instability Types - PITF Coups and Coup attempts.

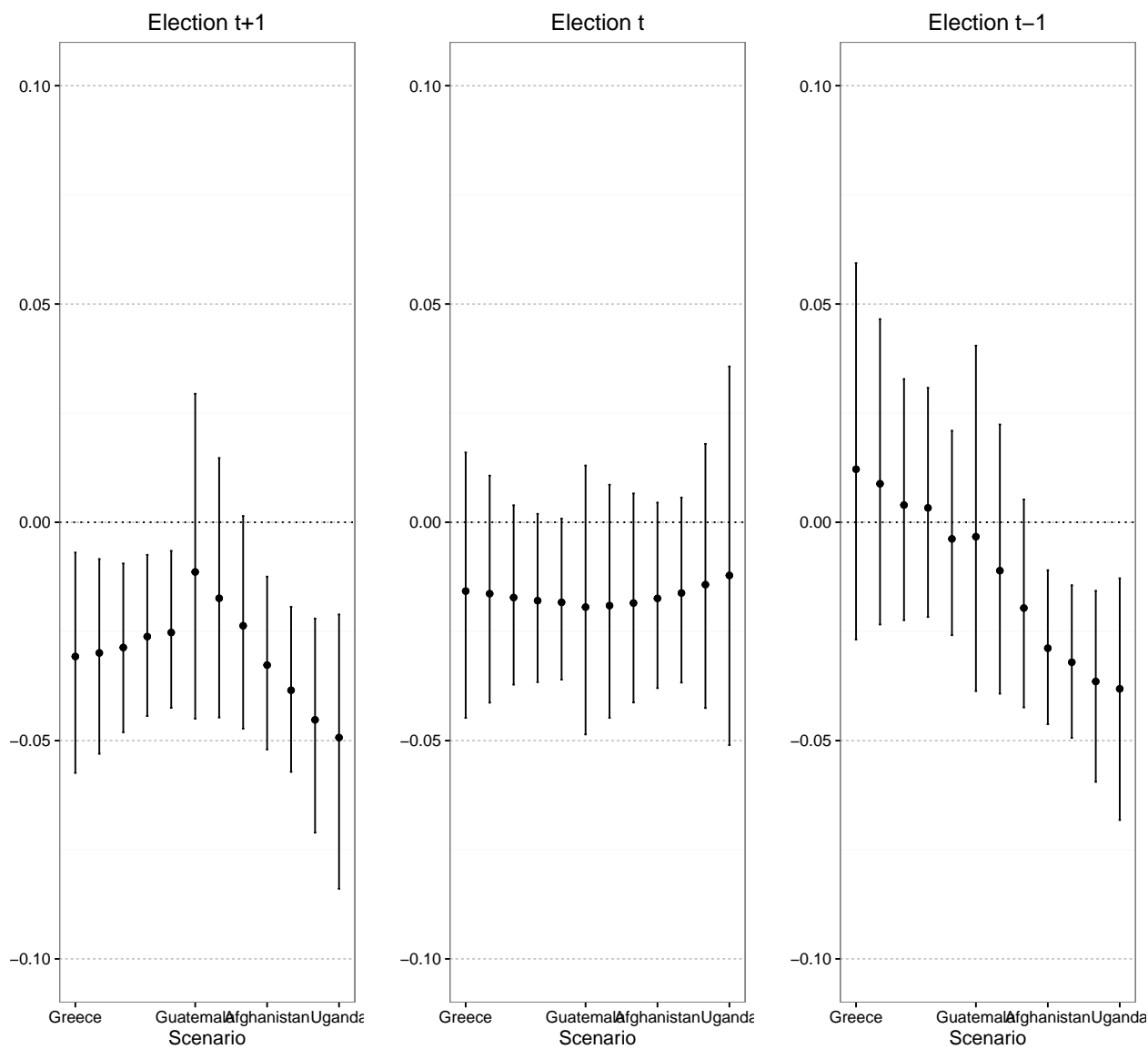
This section shows the impact of the elections and ethnic fractionalization interaction on successful and attempted coups, as defined in the Political Instability Task Force’s Coup d’etat Event Dataset, 2015 version ((M. Marshall and Marshall 2015)).

Table 10: Coups and Violent Political Instability

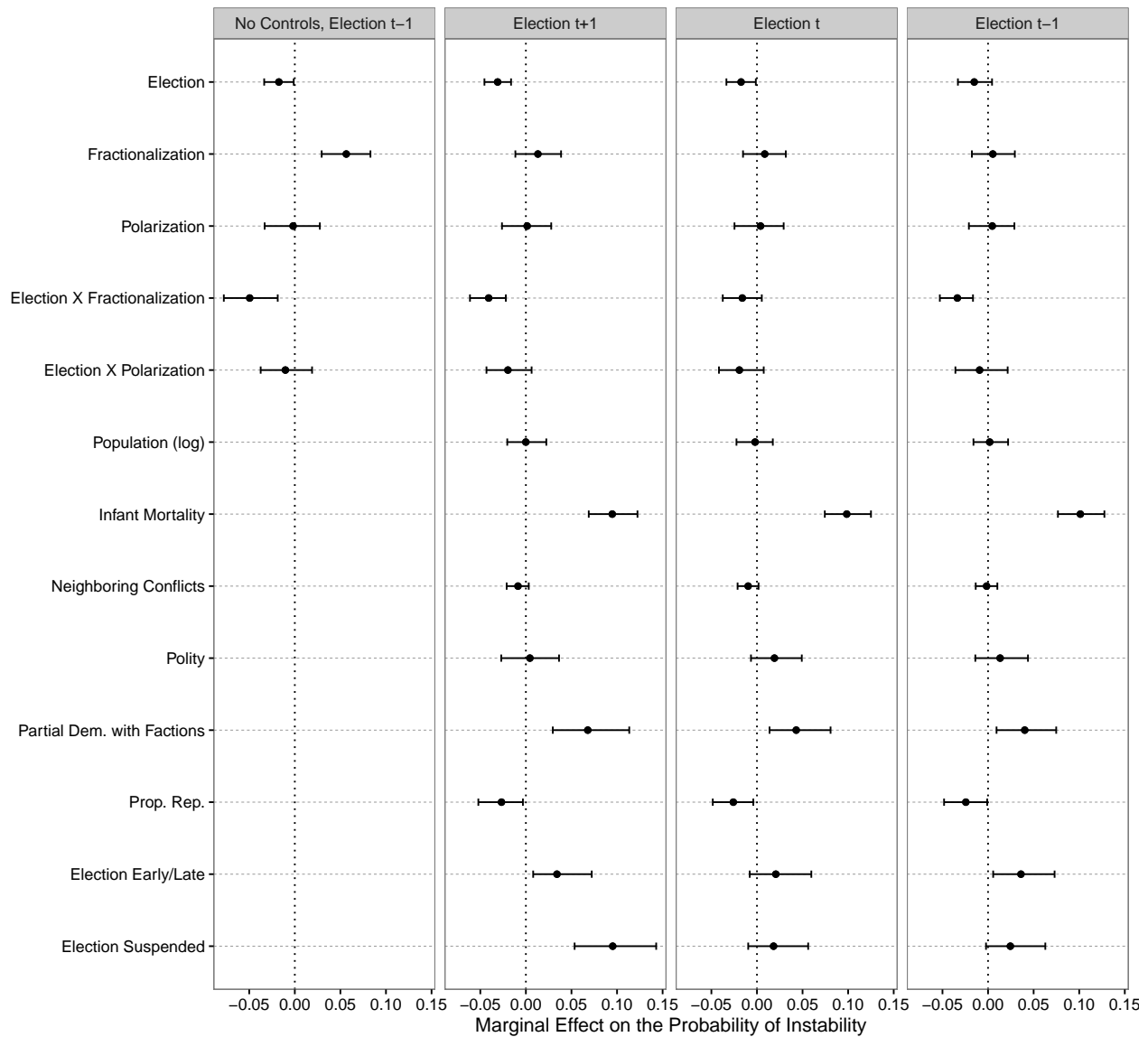
	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.89*** (0.14)	-3.36*** (0.58)	-3.50*** (0.60)	-3.71*** (0.56)
nld.election.l1	0.07 (0.23)			0.15 (0.27)
ef	0.70*** (0.17)	0.20 (0.20)	0.14 (0.19)	0.09 (0.20)
polarization	-0.02 (0.20)	0.03 (0.22)	0.08 (0.23)	0.09 (0.23)
nld.election.l1:ef	-0.76** (0.37)			-1.14*** (0.41)
nld.election.l1:polarization	0.25 (0.40)			0.37 (0.45)
nld.election.f1		-0.76** (0.33)		
ln.wdi.imr.l1		0.42*** (0.07)	0.47*** (0.07)	0.49*** (0.07)
polity2.lag.1		0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
part.dem.fac.l1		0.49*** (0.13)	0.36*** (0.13)	0.34*** (0.13)
ln.wdi.pop.l1		-0.00 (0.03)	-0.01 (0.03)	0.00 (0.03)
nac.l1		-0.04 (0.03)	-0.05 (0.03)	-0.01 (0.03)
pr.l1		-0.09** (0.05)	-0.10** (0.04)	-0.09** (0.05)
nld.earlylate.f1		0.51*** (0.19)		
nld.suspend.f1		0.97*** (0.17)		
nld.election.f1:ef		-0.45 (0.42)		
nld.election.f1:polarization		0.86* (0.48)		
nld.election			-0.27 (0.30)	
nld.earlylate			0.27 (0.20)	
nld.suspend			0.23 (0.19)	
nld.election:ef			0.14 (0.37)	
nld.election:polarization			-0.06 (0.43)	
nld.earlylate.l1				0.40** (0.17)
nld.suspend.l1				0.28 (0.18)
AIC	1580.10	1447.37	1448.92	1472.45
Num. obs.	3633	3710	3713	3633

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Elections on Successful Coups and Coup attempts - PITF in Polarized and Fractionalized Settings



First Differences for Successful Coups and Coup attempts - PITF



Using the IAEP data for elections.

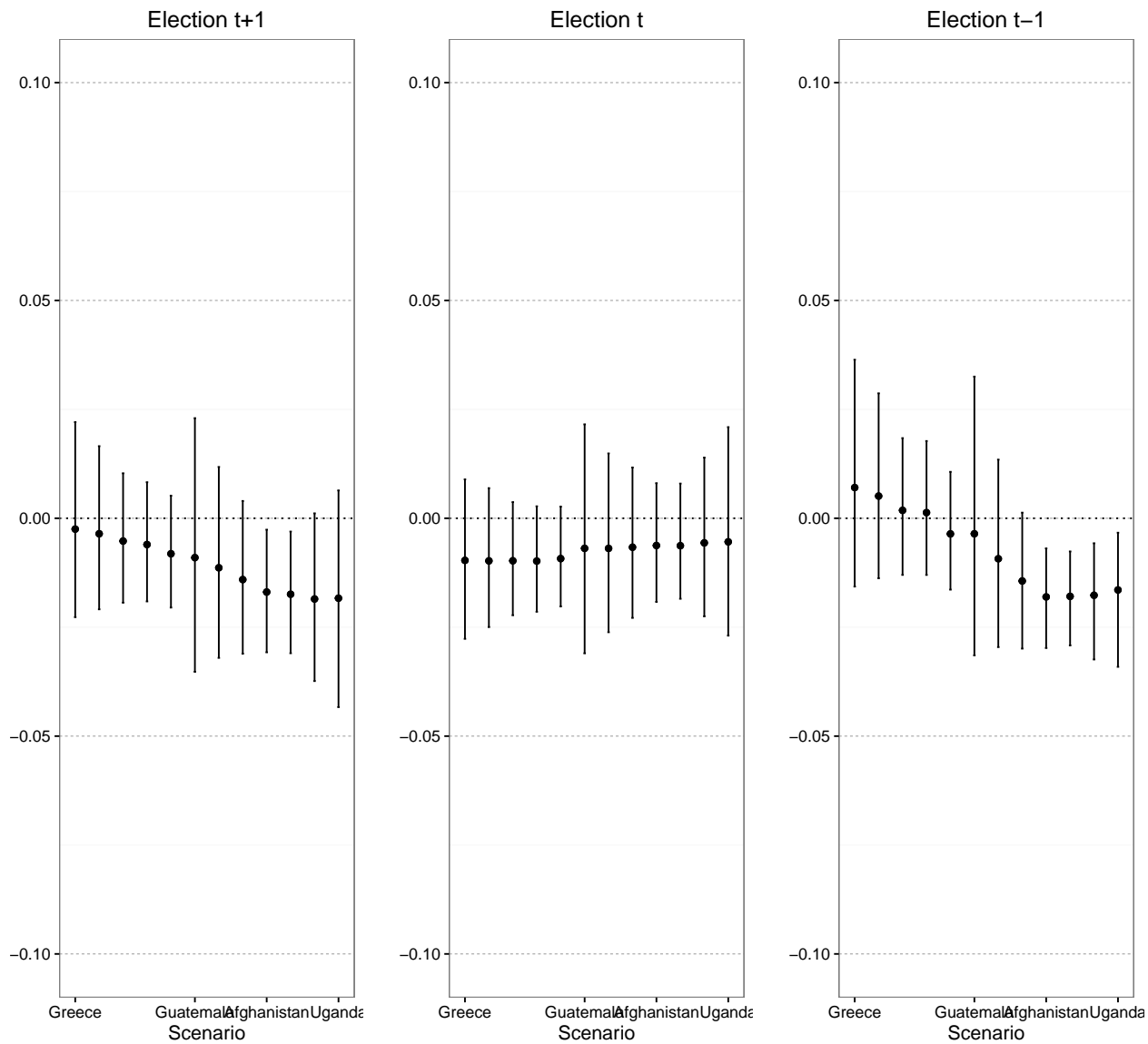
In this section we show the results of the interaction of ethnic fractionalization and elections on violent political instability, but in this test we use the data on elections from the Institutions and Elections Project (IAEP; (Wig, Hegre, and Regan 2015)). The election variable reflects any election that was held in the country-year (or at t-1, or t+1, as in the main analysis).

Table 11: Elections (IAEP) and Violent Political Instability

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.08*** (0.15)	-5.33*** (0.70)	-5.68*** (0.72)	-6.19*** (0.77)
election.l1	0.04 (0.25)			0.16 (0.30)
ef	0.54*** (0.19)	0.18 (0.23)	0.02 (0.23)	-0.02 (0.23)
polarization	0.05 (0.23)	0.21 (0.27)	0.24 (0.27)	0.33 (0.27)
election.l1:ef	-0.78* (0.46)			-1.24** (0.55)
election.l1:polarization	0.28 (0.48)			0.38 (0.58)
election.fl		-0.07 (0.31)		
ln.wdi.imr.l1		0.36*** (0.08)	0.51*** (0.09)	0.48*** (0.10)
polity2.lag.1		0.00 (0.01)	0.02** (0.01)	0.02** (0.01)
part.dem.fac.l1		0.45*** (0.13)	0.33** (0.13)	0.48*** (0.12)
ln.wdi.pop.l1		0.10*** (0.03)	0.07** (0.03)	0.12*** (0.03)
nac.l1		0.06* (0.03)	0.07** (0.03)	0.06* (0.03)
pr.l1		0.03 (0.05)	0.04 (0.05)	0.02 (0.05)
electpost.fl		0.54** (0.24)		
election.fl:ef		-0.50 (0.46)		
election.fl:polarization		0.15 (0.53)		
election			-0.41 (0.37)	
electpost			0.32 (0.28)	
election:ef			0.20 (0.44)	
election:polarization			0.17 (0.52)	
electpost.l1				0.29 (0.28)
AIC	1153.18	1023.66	1005.39	1041.50
Num. obs.	3794	3794	3779	3794

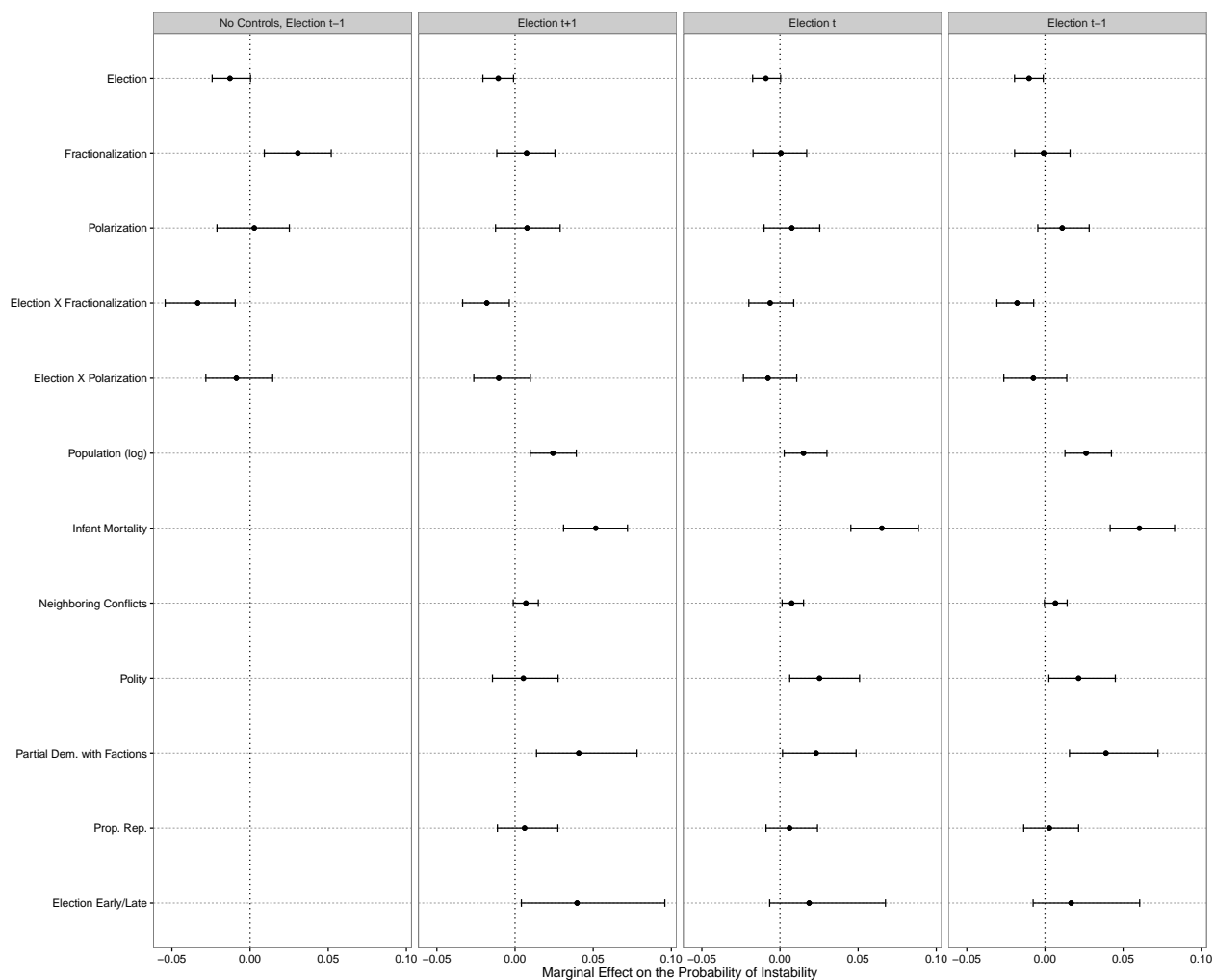
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of IAEP Elections Across Polarized and Fractionalized Settings



First Differences for IAEP Elections and Violent Political Instability

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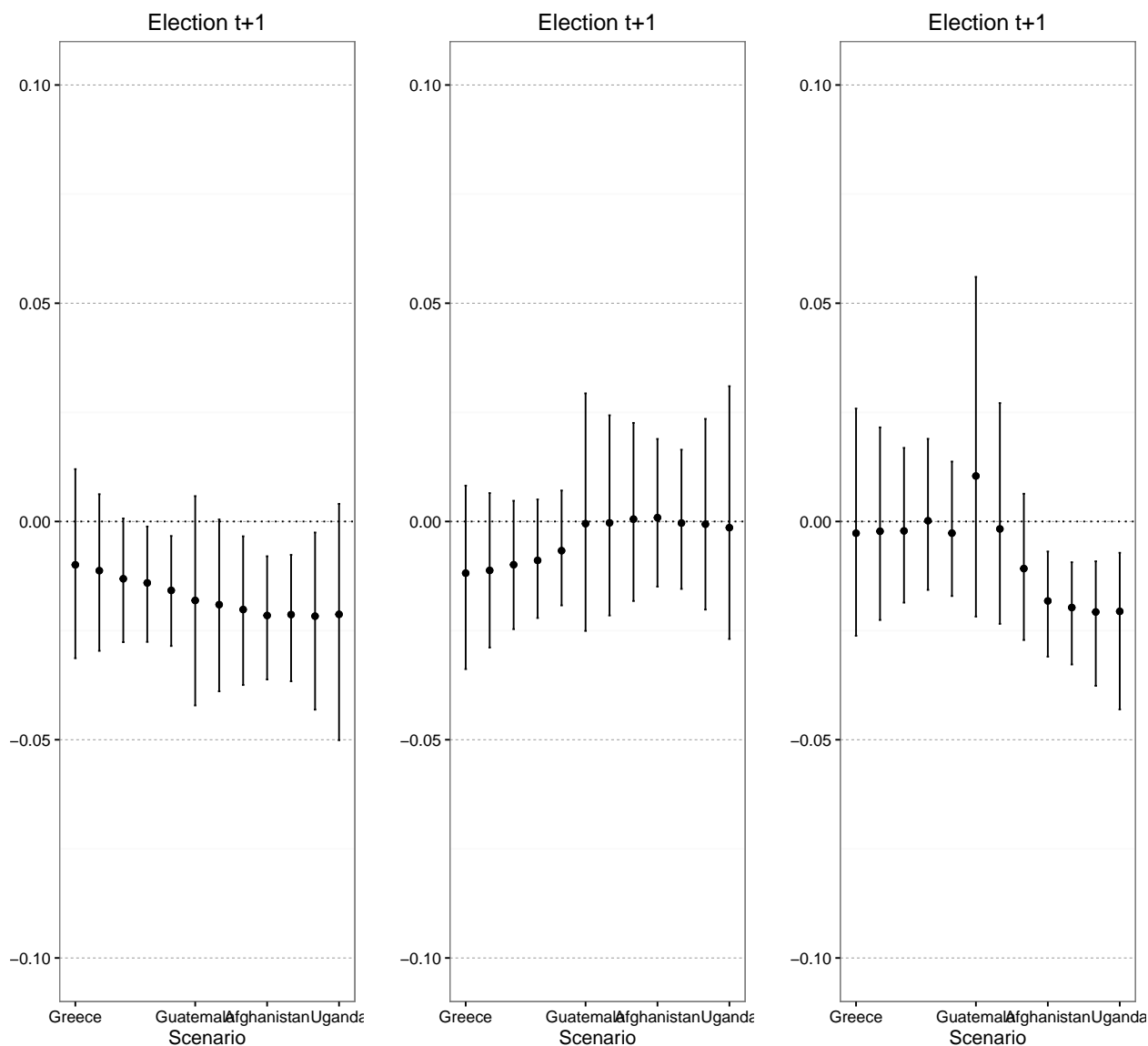


Alternative Modelling Strategies

In this section we show the results of random effects probit regressions with random intercepts for each country, and the results using robust standard errors clustered on countries.

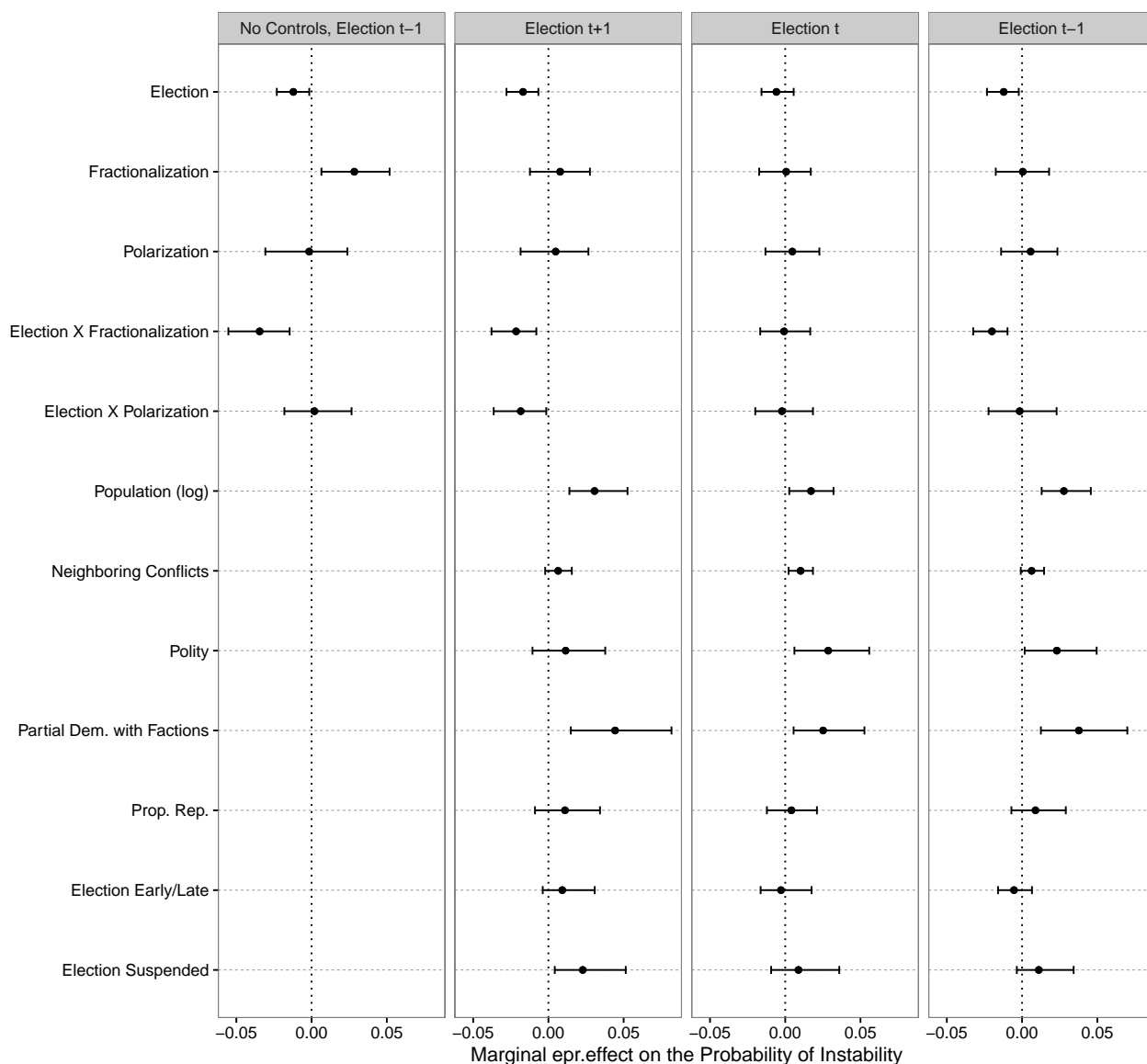
Random effects probit

Effects of Elections Across Polarized and Fractionalized Settings, Random Effects Probit Models



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First Differences for Elections and Violent Political Instability, Random Effects Probit Models.



Coefficients with clustered robust standard errors.

The table below shows the results of our main regressions using robust standard errors clustered on countries (ccode). These data are not multiply imputed.

Table 12: Elections and Violent Political Instability, Country Clustered Robust SEs

	Election t+1	Election t	Election t-1
(Intercept)	-5.92*** (0.75)	-5.60*** (0.72)	-6.54*** (0.89)
nld.election.fl	-0.38 (0.32)		
ef	0.17 (0.25)	0.03 (0.22)	0.01 (0.25)
polarization	0.05 (0.29)	0.09 (0.29)	0.13 (0.30)
ln.wdi.imr.l1	0.39*** (0.10)	0.49*** (0.10)	0.51*** (0.11)
polity2.lag.1	0.00 (0.01)	0.02* (0.01)	0.02* (0.01)
part.dem.fac.l1	0.45*** (0.12)	0.32** (0.13)	0.42*** (0.13)
ln.wdi.pop.l1	0.14*** (0.03)	0.08*** (0.03)	0.14*** (0.04)
nac.l1	0.02 (0.03)	0.08** (0.03)	0.05 (0.04)
pr.l1	0.05 (0.05)	0.04 (0.05)	0.03 (0.05)
nld.earlylate.fl	0.30 (0.26)		
nld.suspend.fl	0.41 (0.25)		
nld.election.fl:ef	-0.41 (0.46)		
nld.election.fl:polarization	0.28 (0.45)		
nld.election		-0.46 (0.36)	
nld.earlylate		-0.08 (0.23)	
nld.suspend		0.07 (0.21)	
nld.election:ef		0.08 (0.50)	
nld.election:polarization		0.53 (0.53)	
nld.election.l1			0.03 (0.25)
nld.earlylate.l1			-0.48 (0.31)
nld.suspend.l1			0.22 (0.21)
nld.election.l1:ef			-1.36*** (0.53)
nld.election.l1:polarization			0.60 (0.52)
AIC	881.89	937.69	851.77
BIC	985.04	1041.19	954.85
Log Likelihood	-423.95	-451.84	-408.89
Deviance	847.89	903.69	817.77
Num. obs.	3190	3256	3176

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. <https://mc.manuscriptcentral.com/comppolstud>

Impact of Elections on Instability in Non-democratic States

This replicates the models in the main analysis, but in the sample of non-democratic states. Non-democratic states are defined here as those scoring less than 6 on the polity index (ranging from -10 to 10).

Impact of Elections on Instability in Non-democratic States Across Simulated Ethnic Structures.

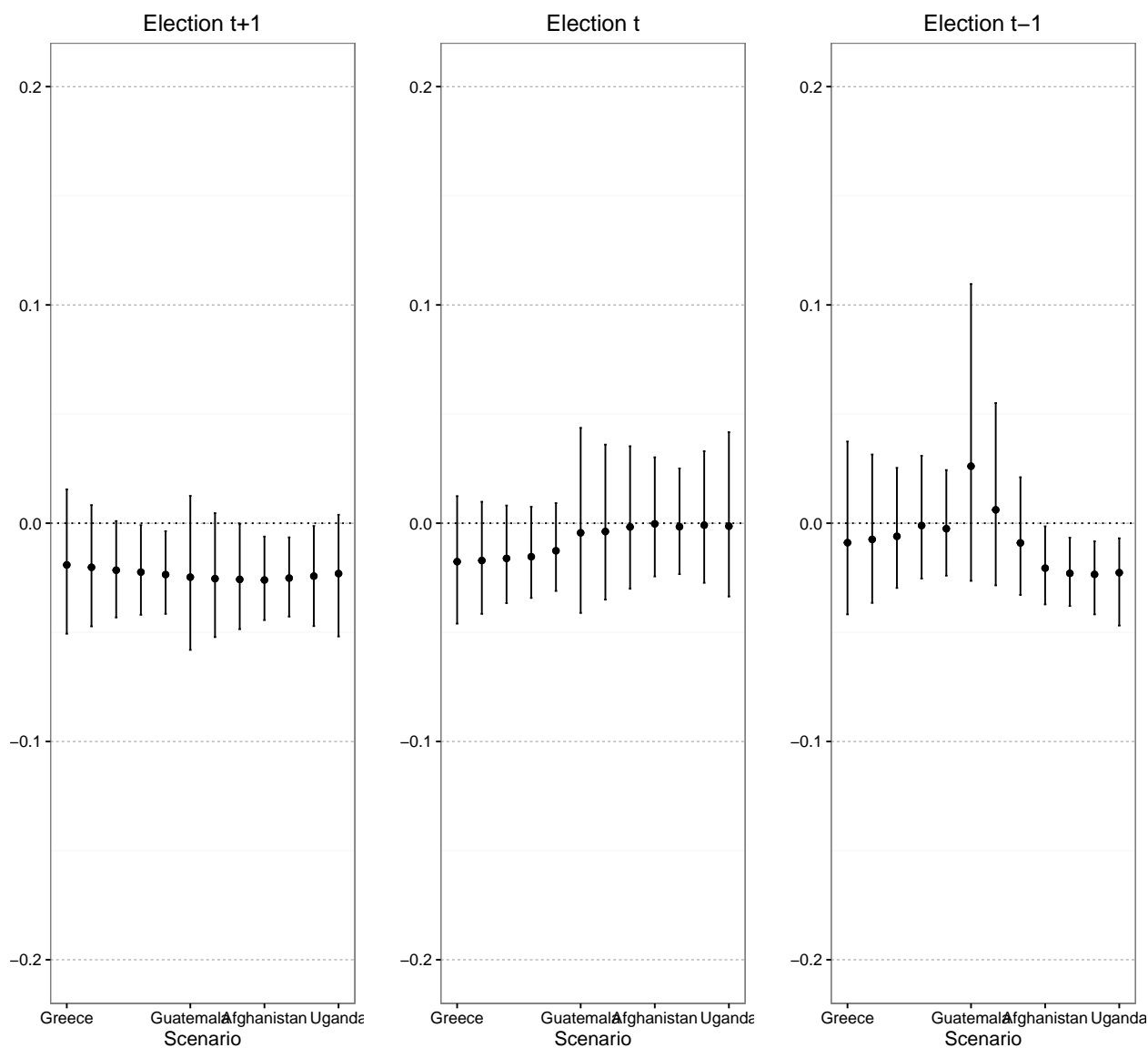
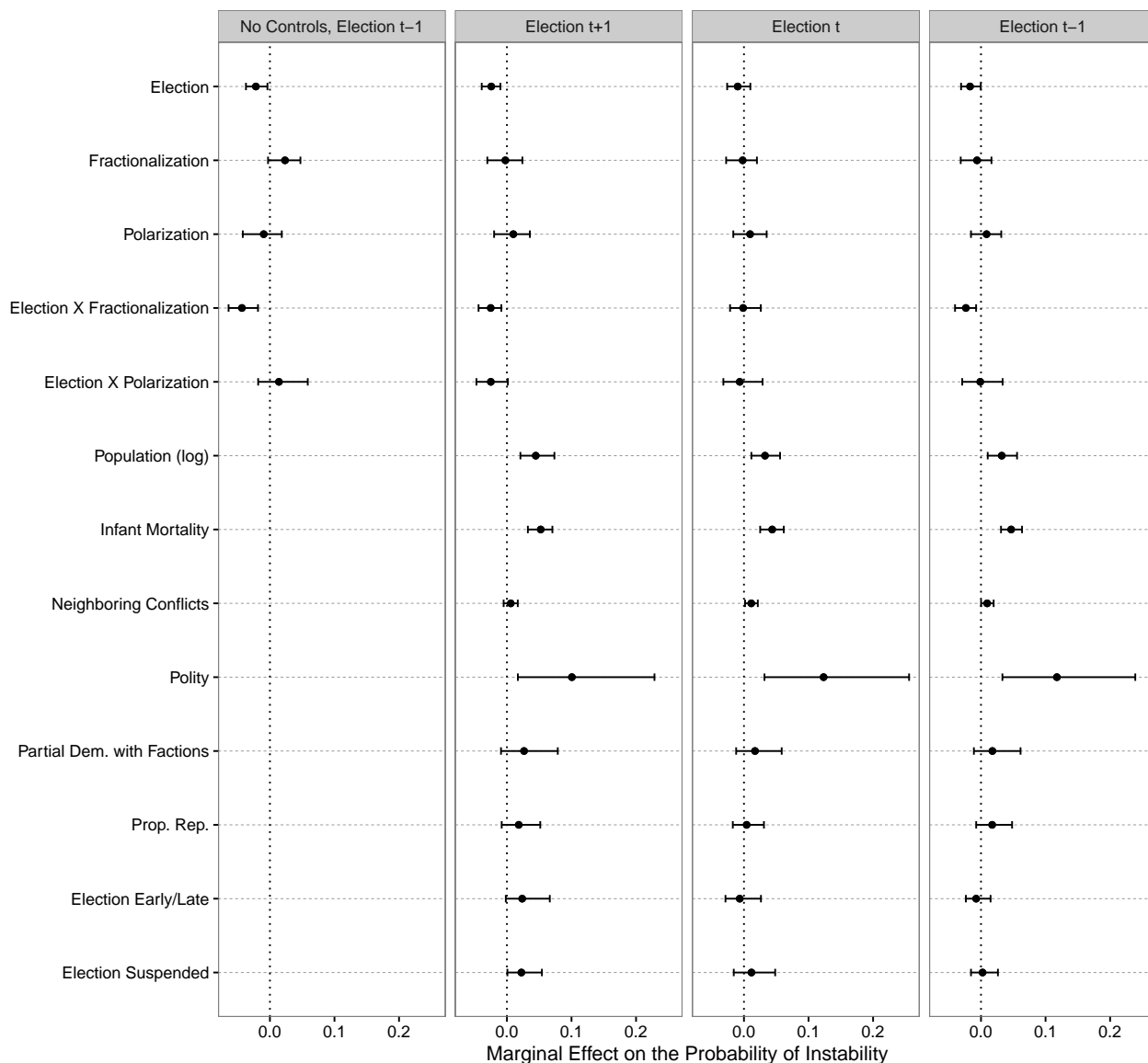


Table 13: Elections and Violent Political Instability, Non-Democracies

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.85*** (0.17)	-5.99*** (0.87)	-5.47*** (0.83)	-5.89*** (0.85)
nld.election.l1	-0.52 (0.40)			-0.32 (0.44)
ef	0.40* (0.21)	-0.04 (0.25)	-0.02 (0.25)	-0.11 (0.26)
polarization	-0.16 (0.26)	0.20 (0.29)	0.22 (0.29)	0.22 (0.29)
nld.election.l1:ef	-1.67** (0.73)			-1.65** (0.80)
nld.election.l1:polarization	1.81** (0.71)			1.37* (0.76)
nld.election.f1		-0.46 (0.41)		
ln.wdi.imr.l1		0.37*** (0.10)	0.34*** (0.09)	0.42*** (0.11)
polity2.lag.1		0.04** (0.02)	0.05*** (0.02)	0.05*** (0.02)
part.dem.fac.l1		0.25 (0.20)	0.17 (0.20)	0.19 (0.20)
ln.wdi.pop.l1		0.14*** (0.04)	0.11*** (0.04)	0.12*** (0.04)
nac.l1		0.04 (0.04)	0.08** (0.04)	0.07** (0.04)
pr.l1		0.07 (0.06)	0.02 (0.06)	0.07 (0.06)
nld.earlylate.f1		0.46* (0.26)		
nld.suspend.f1		0.46* (0.24)		
nld.election.f1:ef		-0.22 (0.52)		
nld.election.f1:polarization		0.15 (0.60)		
nld.election			-0.59 (0.45)	
nld.earlylate			-0.20 (0.30)	
nld.suspend			0.18 (0.23)	
nld.election:ef			0.48 (0.50)	
nld.election:polarization			0.27 (0.57)	
nld.earlylate.l1				-0.49 (0.44)
nld.suspend.l1				0.03 (0.29)
AIC	808.36	788.26	816.87	748.58
Num. obs.	2468	2536	2500	2468

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

First Differences for Elections and Violent Political Instability, Non-democratic states



Test with alternative measure of independent variable

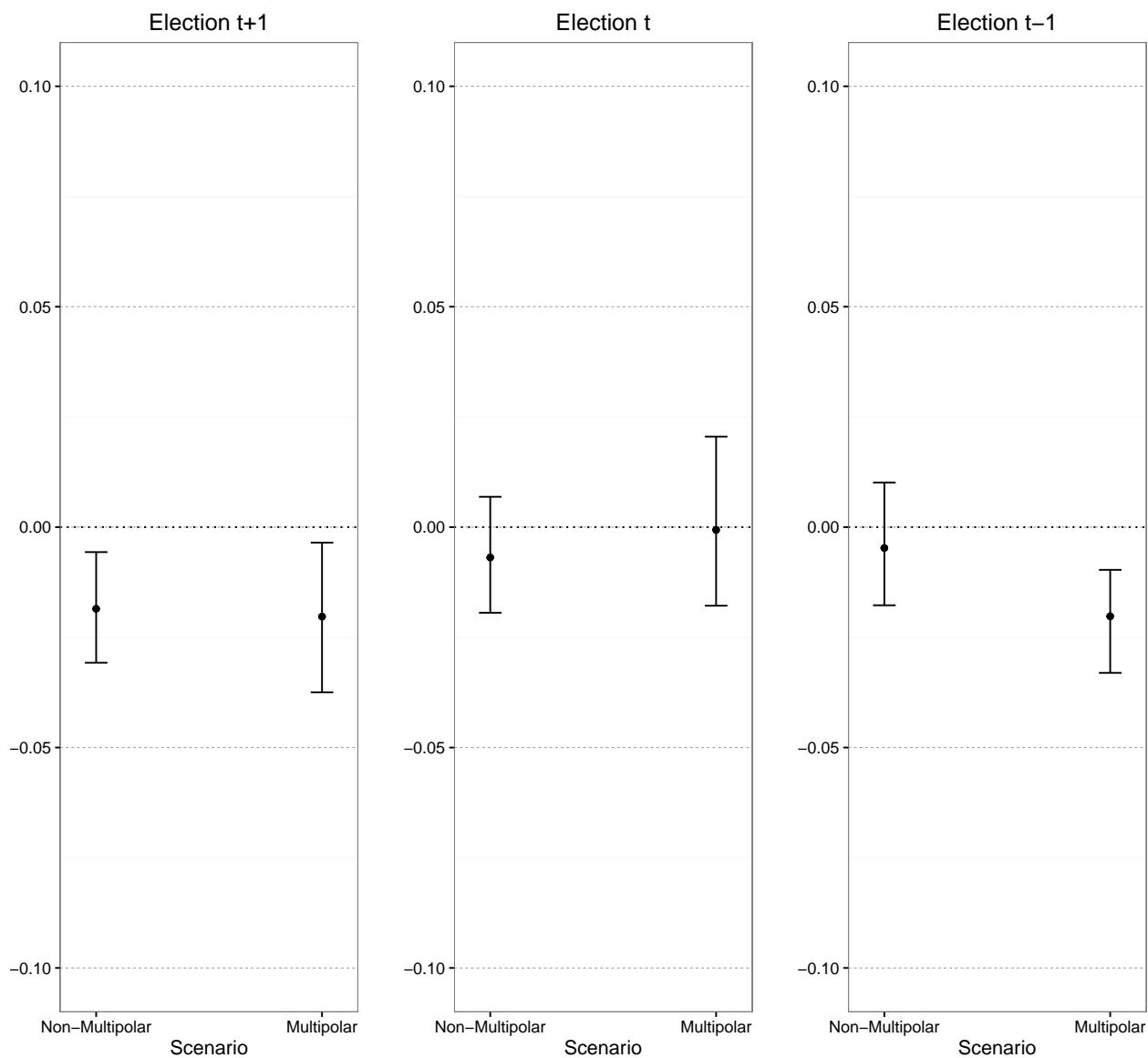
This section tests hypothesis 1 with a dichotomous measure of a ‘multipolar’ ethnic demography. The variable “Multipolar” was constructed in the following way. States where the largest ethnic group was more than 50% of the population were coded ‘hegemonic’. States where the largest group was less than 49% of the population and the second largest group was more than 30% were coded as ‘bipolar’ and states that were neither hegemonic nor bipolar were coded as multipolar.

Table 14: Elections and Violent Political Instability, Alternative Independent Variable

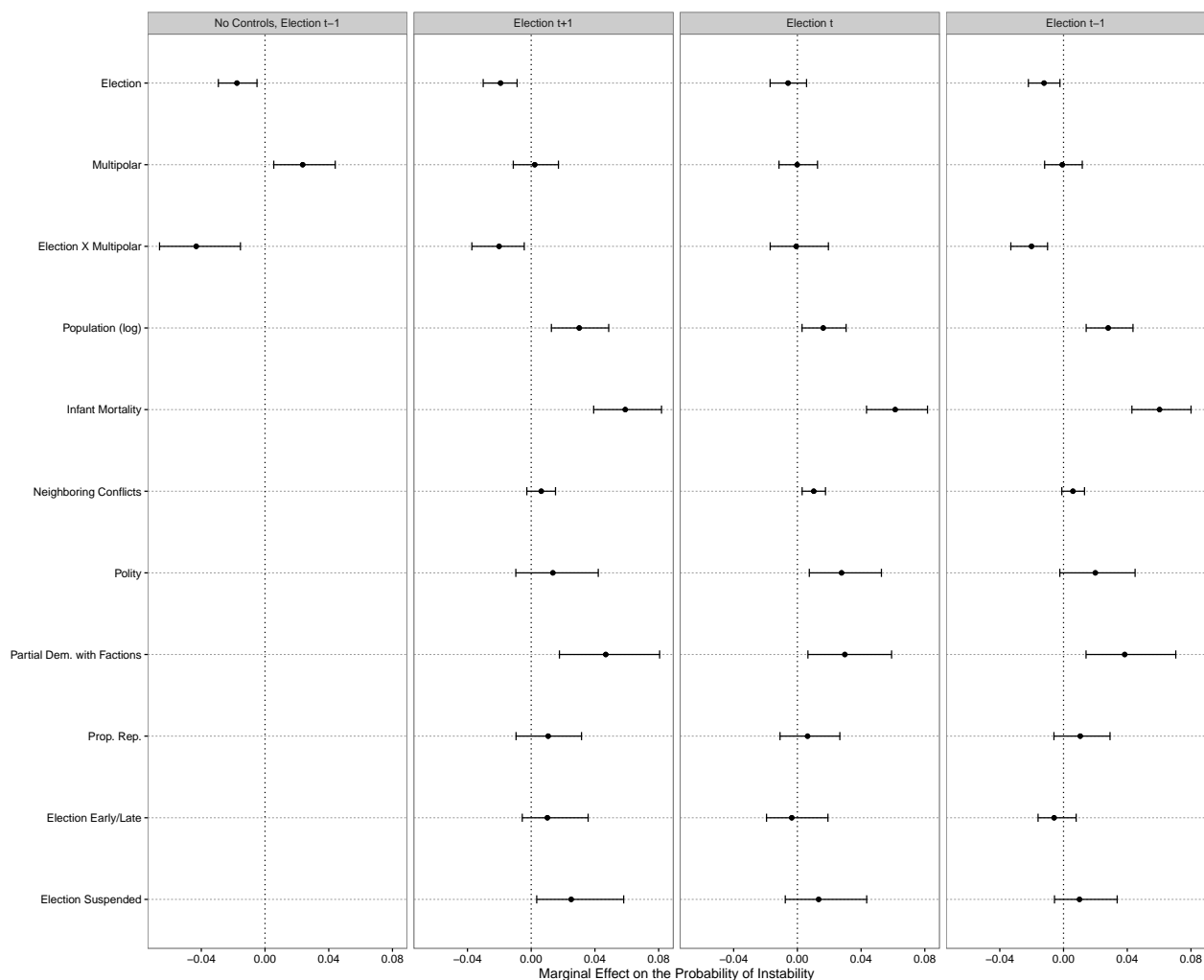
	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.82*** (0.06)	-5.47*** (0.67)	-5.36*** (0.64)	-6.17*** (0.67)
nld.election.l1	-0.11 (0.10)			-0.10 (0.14)
frac.f	0.24** (0.09)	0.03 (0.11)	-0.01 (0.11)	-0.02 (0.11)
nld.election.l1:frac.f	-0.56** (0.26)			-0.76*** (0.29)
nld.election.fl		-0.42*** (0.16)		
ln.wdi.imr.l1		0.39*** (0.08)	0.47*** (0.08)	0.49*** (0.08)
polity2.lag.1		0.01 (0.01)	0.02*** (0.01)	0.02* (0.01)
part.dem.fac.l1		0.47*** (0.13)	0.37*** (0.13)	0.47*** (0.13)
ln.wdi.pop.l1		0.11*** (0.03)	0.07** (0.03)	0.12*** (0.03)
nac.l1		0.05 (0.03)	0.09*** (0.03)	0.05 (0.03)
pr.l1		0.05 (0.05)	0.03 (0.05)	0.06 (0.05)
nld.earlylate.fl		0.25 (0.22)		
nld.suspend.fl		0.50** (0.21)		
nld.election.fl:frac.f		-0.02 (0.22)		
nld.election			-0.14 (0.14)	
nld.earlylate			-0.12 (0.23)	
nld.suspend			0.21 (0.19)	
nld.election:frac.f			0.12 (0.20)	
nld.earlylate.l1				-0.32 (0.28)
nld.suspend.l1				0.25 (0.21)
AIC	1106.67	1009.51	1068.76	986.49
Num. obs.	3633	3710	3713	3633

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Effects of Election Across Multipolar and Non-Multipolar Ethnic Structures



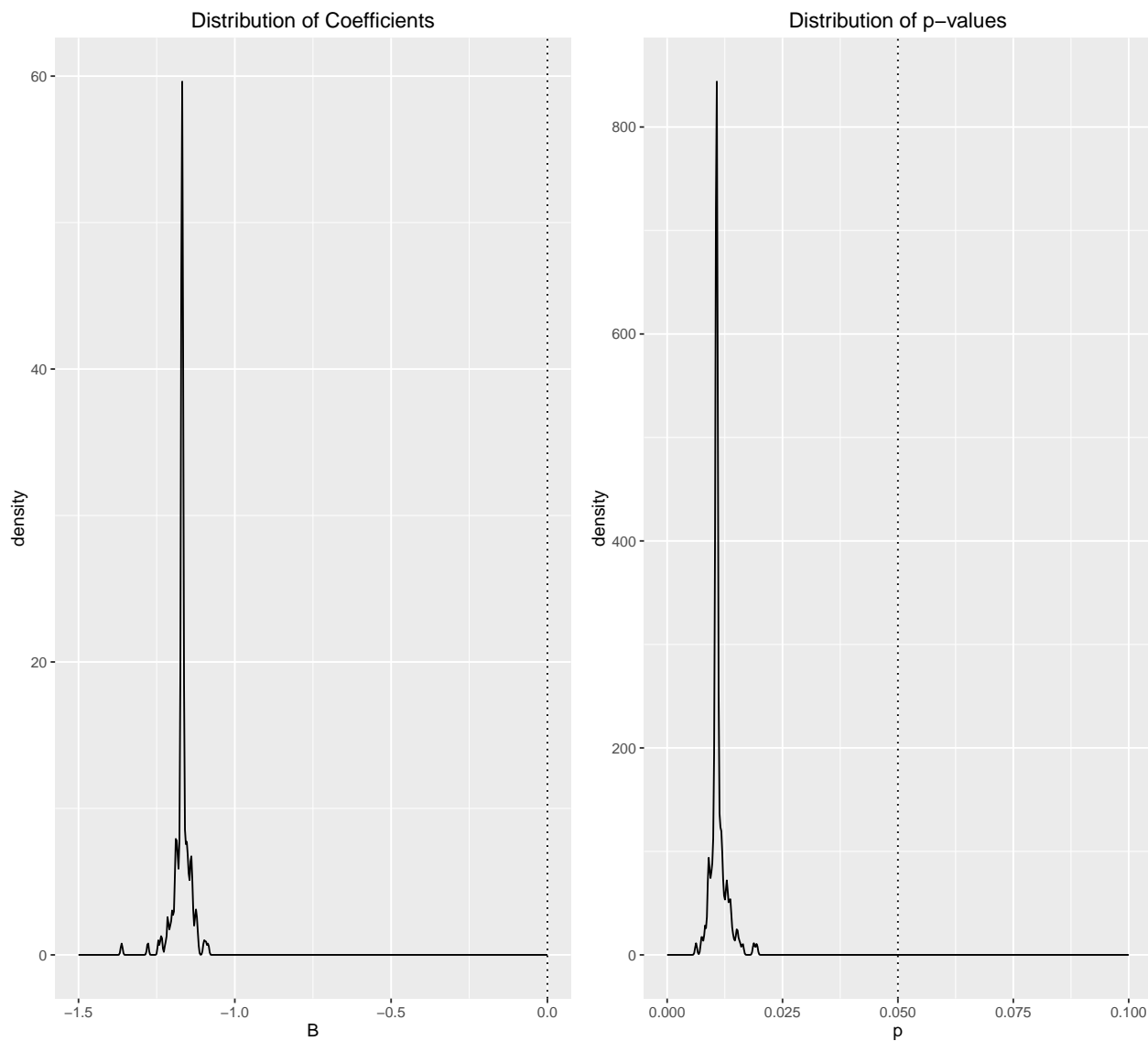
First Differences for Elections and Violent Political Instability



Considering Influential Observations

Our fractionalization variable is cross sectional, and it may be a concern that one case is heavily influencing our results. To assess the extent to which this was the case we ran the base regression with an election at t-1 169 times removing one country from the sample each time, then replacing it. We stored the coefficients and p-values for each regression and the distributions obtained are shown below. As the figure suggests there is no scenario when a country is removed that also results in the p-value for our interaction term moving above 0.05 or the coefficient moving below -1.0. This suggests that our results are not the product of any single country influencing the results.

Distribution of coefficients and p-values with single countries removed



Results without polarization included

This section shows our results when we do not include the polarization and elections interaction as shown in the main results. The first order polarization term is also excluded as a variable in the model. The only interaction term in the models below is the fractionalization and elections interaction.

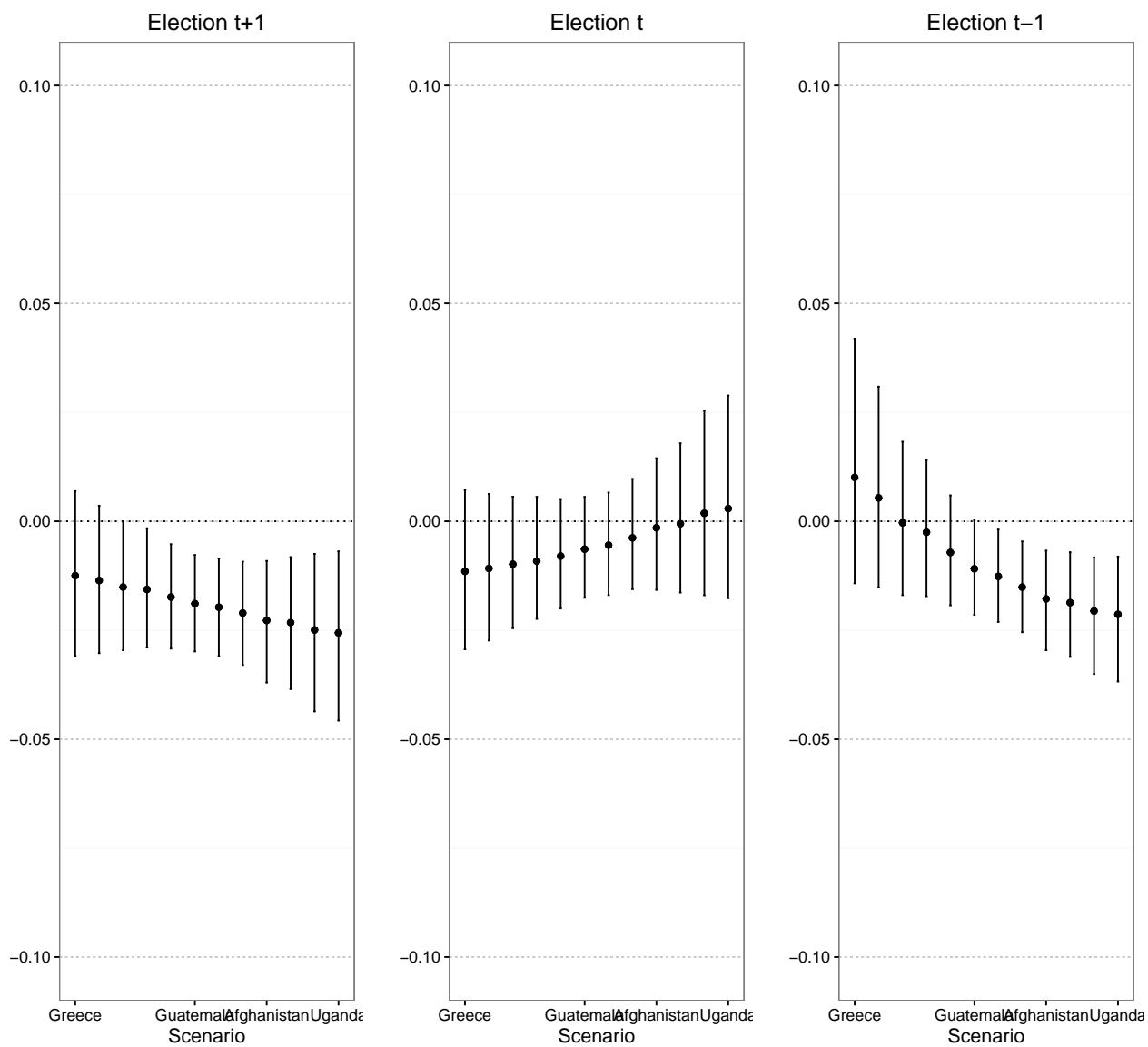
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Table 15: Elections and Violent Political Instability, Polarization Removed

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.04*** (0.11)	-5.56*** (0.65)	-5.22*** (0.69)	-5.74*** (0.69)
nld.election.l1	0.07 (0.20)			0.20 (0.23)
ef	0.55*** (0.18)	0.20 (0.21)	0.07 (0.21)	0.09 (0.21)
nld.election.l1:ef	-0.58 (0.35)			-0.93** (0.40)
nld.election.fl		-0.30 (0.25)		
ln.wdi.imr.l1		0.36*** (0.08)	0.44*** (0.09)	0.43*** (0.09)
polity2.lag.1		0.01 (0.01)	0.02** (0.01)	0.02* (0.01)
part.dem.fac.l1		0.49*** (0.13)	0.36*** (0.13)	0.50*** (0.13)
ln.wdi.pop.l1		0.12*** (0.03)	0.07** (0.03)	0.11*** (0.03)
nac.l1		0.05 (0.03)	0.09*** (0.03)	0.07* (0.03)
pr.l1		0.06 (0.05)	0.03 (0.05)	0.06 (0.05)
nld.earlylate.fl		0.25 (0.22)		
nld.suspend.fl		0.51** (0.21)		
nld.election.fl:ef		-0.26 (0.40)		
nld.election			-0.32 (0.25)	
nld.earlylate			-0.12 (0.23)	
nld.suspend			0.20 (0.19)	
nld.election:ef			0.38 (0.38)	
nld.earlylate.l1				-0.36 (0.28)
nld.suspend.l1				0.27 (0.21)
AIC	1105.94	1007.51	1075.88	1001.93
Num. obs.	3633	3710	3713	3633

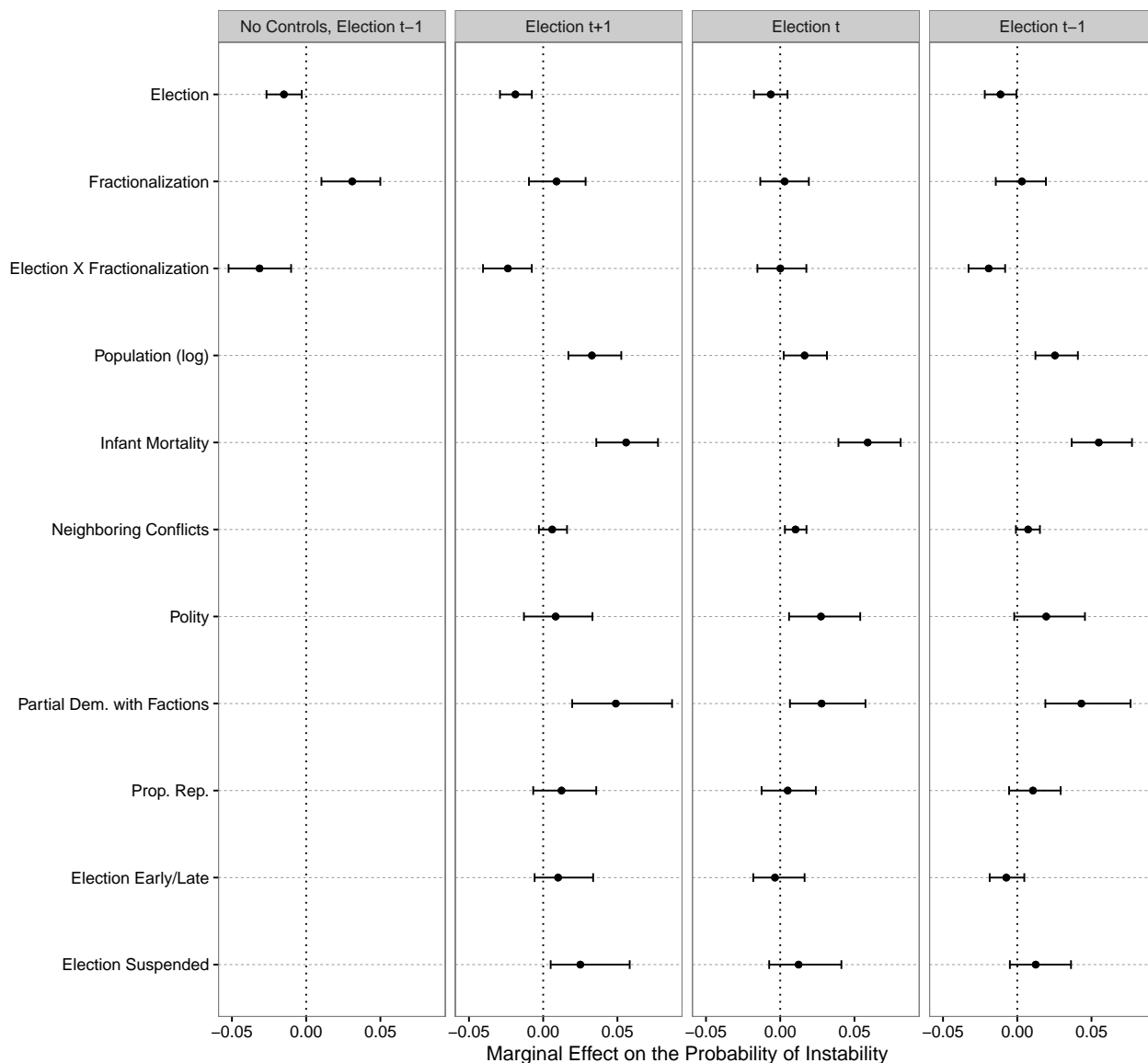
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Impact of Elections on Probability of Violent Political Instability Across Simulated Ethnic Structures, No Polarization



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First Differences for Elections and Violent Political Instability, No Polarization



Results across subsets of the data

In this section we subset the data into ‘fractionalized’, ‘polarized’ and ‘homogenous’ states and run a simplified model, due to the lower number of observations. We include variables that have significant and predicted effects in the expected direction on instability in the base model. These controls are the most likely to represent (and be controlling for) genuine alternative explanations. These variables are: log population, log infant mortality rate, neighboring countries in conflict, polity2 score, partial democracy with factions. We also include country-fixed effects in these models so that we are controlling out country-level factors and

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3 comparing election and non-election periods within the same country.
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Fractionalized States

Table 16: Elections and Violent Political Instability, Fractionalized States (Country Fixed Effects)

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-5.89 (500.30)	-8.99 (5.70)	-11.29 (464.99)	-21.19 (638.36)
nld.election.l1	-0.62** (0.25)			-0.93*** (0.30)
nld.election.fl		-0.25 (0.21)		
ln.wdi.imr.l1		0.97* (0.52)	0.84** (0.40)	1.63*** (0.55)
polity2.lag.1		0.01 (0.02)	0.03 (0.02)	0.03 (0.02)
part.dem.fac.l1		0.94*** (0.32)	0.49 (0.32)	1.03*** (0.35)
stabyrs		0.03 (0.06)	0.02 (0.05)	0.14* (0.08)
stabyrs.2		-0.00 (0.00)	-0.00 (0.00)	-0.01* (0.01)
stabyrs.3		0.00 (0.00)	0.00 (0.00)	0.00** (0.00)
ln.wdi.pop.l1		0.15 (0.29)	0.02 (0.26)	0.38 (0.39)
nac.l1		0.02 (0.10)	-0.00 (0.09)	-0.08 (0.11)
nld.election			0.11 (0.19)	
AIC	372.02	381.15	409.97	326.17
Num. obs.	865	878	850	865

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Polarized States

Table 17: Elections and Violent Political Instability, Polarized States (Country Fixed Effects)

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.78*** (0.07)	-10.49 (691.18)	-10.54 (639.97)	-10.39 (663.71)
nld.election.l1	-0.11 (0.13)			-0.19 (0.18)
nld.election.fl		-0.33* (0.19)		
ln.wdi.imr.l1		0.38* (0.21)	0.46** (0.20)	0.45 (0.32)
polity2.lag.1		0.05** (0.02)	0.07*** (0.02)	0.07*** (0.02)
part.dem.fac.l1		-0.06 (0.26)	-0.02 (0.23)	-0.03 (0.25)
stabys		0.07 (0.05)	0.12** (0.05)	0.08* (0.05)
stabys.2		-0.00 (0.00)	-0.01** (0.00)	-0.01** (0.00)
stabys.3		0.00 (0.00)	0.00** (0.00)	0.00** (0.00)
ln.wdi.pop.l1		0.06 (0.30)	0.01 (0.23)	0.01 (0.39)
nac.l1		0.01 (0.09)	0.07 (0.09)	0.08 (0.09)
nld.election			0.06 (0.16)	
AIC	515.89	524.49	573.04	556.14
Num. obs.	1704	1741	1761	1704

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Homogenous States

Table 18: Elections and Violent Political Instability, Homogenous States (Country Fixed Effects)

	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-1.98*** (0.10)	-24.04 (839.56)	-12.01 (819.14)	-9.48 (766.86)
nld.election.l1	-0.07 (0.18)			-0.16 (0.33)
nld.election.fl		-0.24 (0.32)		
ln.wdi.imr.l1		0.93* (0.49)	0.89* (0.49)	1.04** (0.41)
polity2.lag.1		-0.00 (0.04)	0.03 (0.03)	0.04 (0.04)
part.dem.fac.l1		0.89 (0.55)	0.45 (0.49)	0.65 (0.54)
stabys		-0.03 (0.10)	-0.07 (0.10)	-0.14 (0.11)
stabys.2		0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
stabys.3		0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
ln.wdi.pop.l1		0.69 (0.84)	0.11 (0.69)	-0.10 (0.49)
nac.l1		0.21 (0.15)	0.22 (0.16)	0.31* (0.16)
nld.election			-0.47 (0.34)	
AIC	233.30	246.14	242.82	237.30
Num. obs.	1064	1091	1102	1064

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Ethnic wars in the EPR dataset

Table 19: Elections and Ethnic Civil War (EPR Dependent Variable)

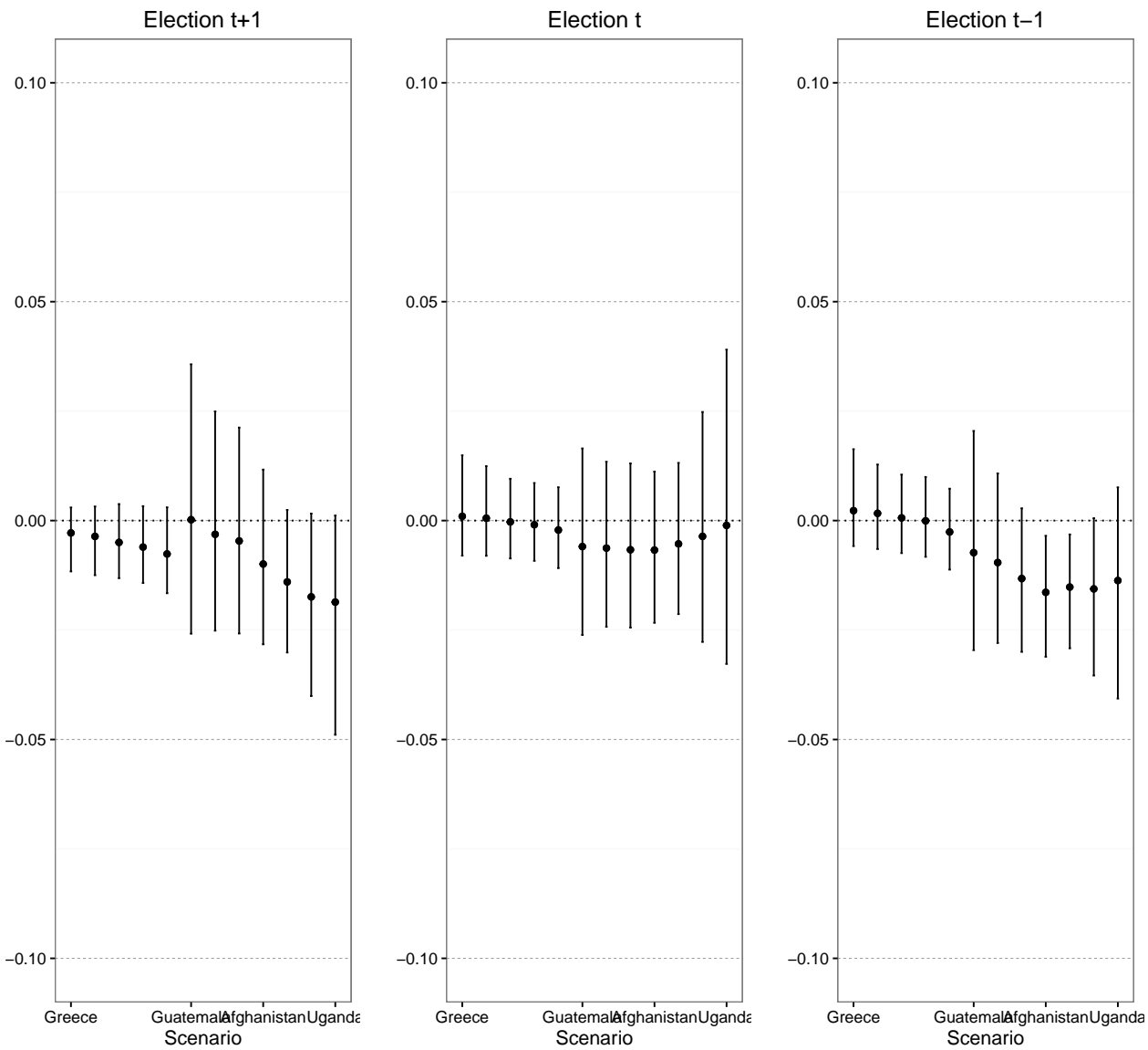
	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.71*** (0.27)	-6.24*** (0.98)	-5.63*** (0.96)	-7.27*** (1.04)
nld.election.l1	0.13 (0.42)			0.28 (0.53)
ef	0.93*** (0.30)	0.76** (0.35)	0.82** (0.35)	0.82** (0.37)
polarization	0.11 (0.35)	0.44 (0.40)	0.47 (0.40)	0.59 (0.41)
nld.election.l1:ef	-0.97 (0.66)			-1.24* (0.74)
nld.election.l1:polarization	0.35 (0.71)			0.07 (0.81)
nld.election.f1		-1.69 (1.08)		
ln.wdi.imr.l1		0.19* (0.10)	0.16* (0.10)	0.22** (0.10)
polity2.lag.1		0.01 (0.01)	0.00 (0.01)	0.02 (0.01)
part.dem.fac.l1		0.05 (0.21)	0.16 (0.20)	0.02 (0.20)
peaceyears		-0.05* (0.03)	-0.04* (0.03)	-0.06** (0.03)
peaceyears.2		0.00 (0.00)	0.00 (0.00)	0.00* (0.00)
peaceyears.3		-0.00 (0.00)	-0.00 (0.00)	-0.00* (0.00)
ln.wdi.pop.l1		0.17*** (0.05)	0.13*** (0.04)	0.21*** (0.05)
nac.l1		-0.01 (0.05)	0.10** (0.05)	0.03 (0.05)
pr.l1		-0.00 (0.07)	0.03 (0.07)	-0.00 (0.07)
nld.earlylate.f1		0.51* (0.29)		
nld.suspend.f1		0.70*** (0.27)		
nld.election.f1:ef		0.43 (0.91)		
nld.election.f1:polarization		1.47 (0.96)		
nld.election			0.06 (0.55)	
nld.earlylate			0.25 (0.27)	
nld.suspend			0.21 (0.28)	
nld.election:ef			-0.07 (0.58)	
nld.election:polarization			-0.24 (0.67)	
nld.earlylate.l1				0.39 (0.29)
nld.suspend.l1				0.06 (0.36)
https://mc.manuscriptcentral.com/compolstud				
AIC	493.37	492.89	517.21	471.52
Num. obs.	3160	3227	3252	3160

***p < 0.01. **p < 0.05. *p < 0.1.

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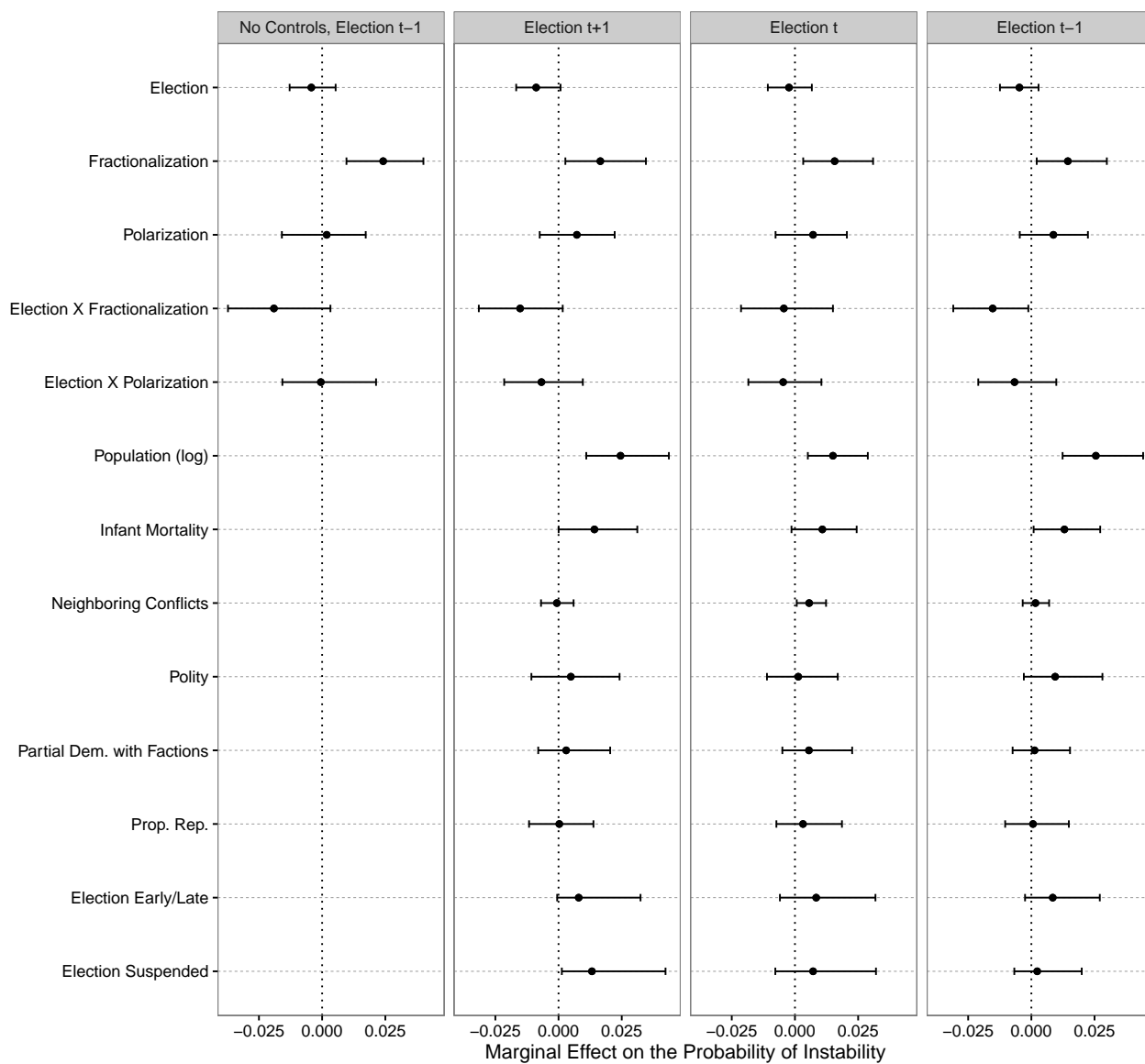
Impact of Elections on Probability of Violent Political Instability Across Simulated Ethnic Structures, EPR Ethnic Armed Conflict

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First Differences for Elections and Violent Political Instability, EPR Ethnic Armed Conflict



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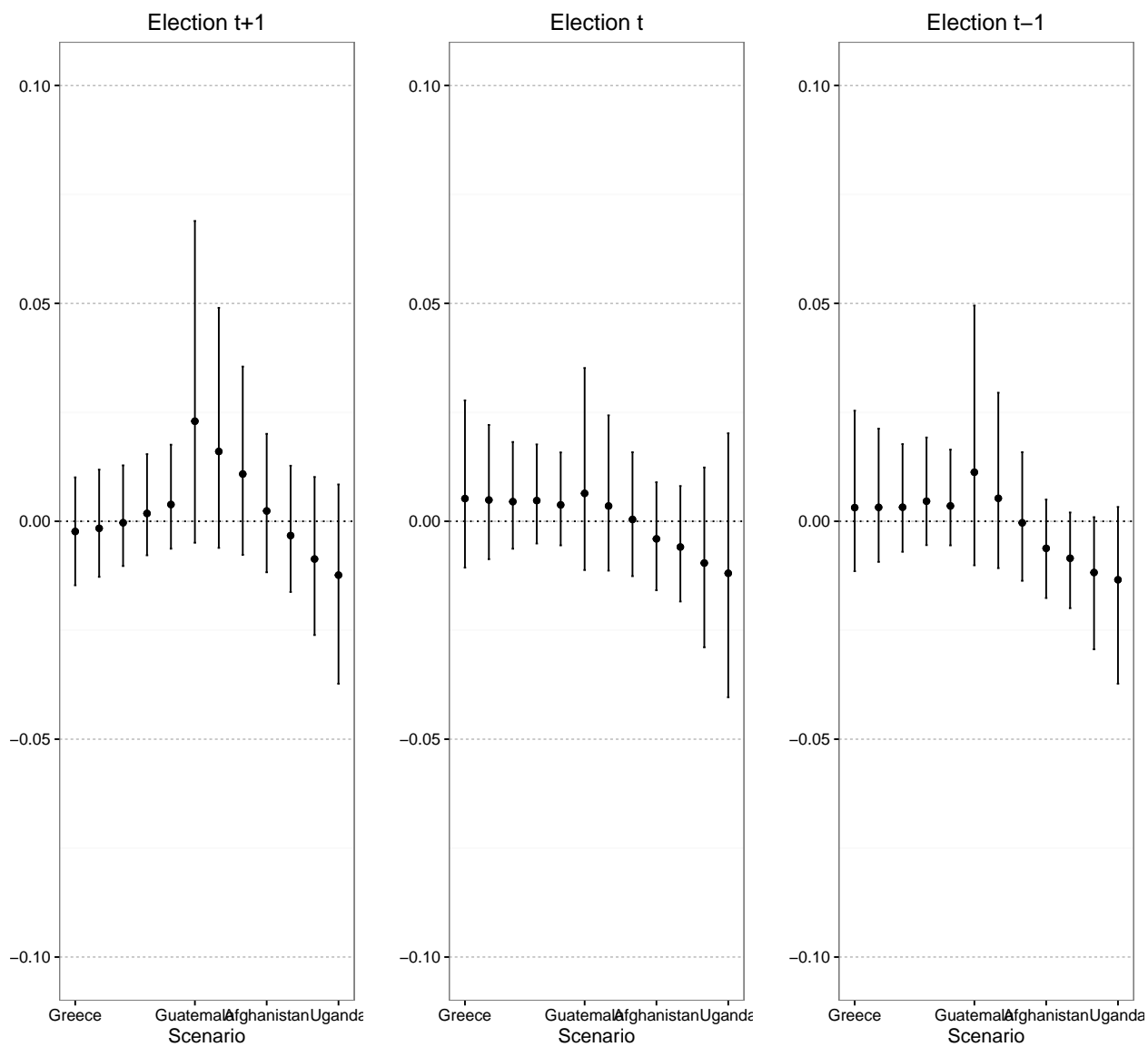
Non-ethnic wars in the EPR dataset

Table 20: Elections and Non-Ethnic Civil War Onset (EPR Data for DV)

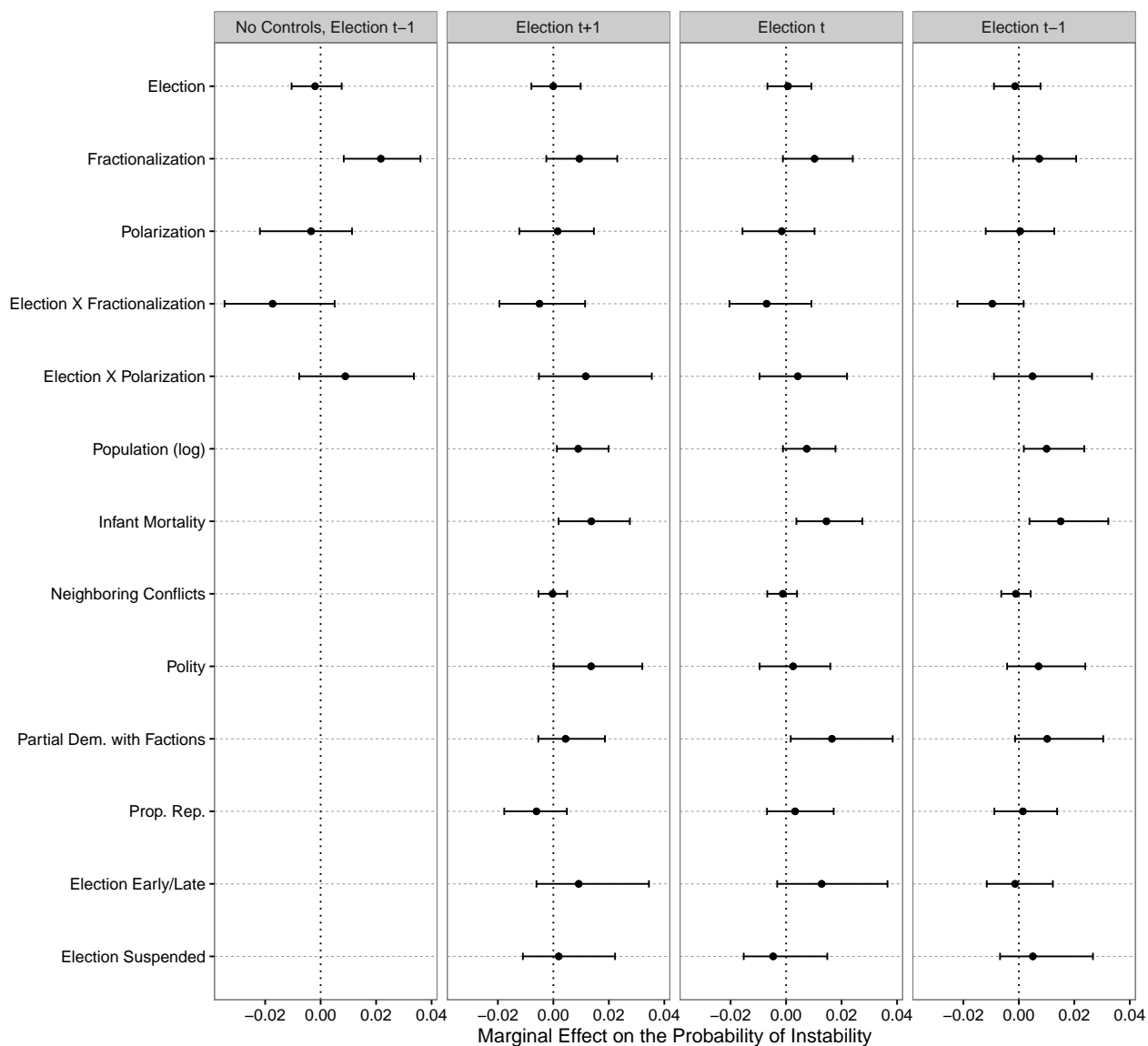
	No Controls, Election t-1	Election t+1	Election t	Election t-1
(Intercept)	-2.58*** (0.26)	-4.77*** (0.93)	-4.42*** (0.93)	-5.27*** (0.98)
nld.election.l1	-0.05 (0.42)			0.10 (0.47)
ef	0.90*** (0.29)	0.51 (0.33)	0.56* (0.33)	0.49 (0.34)
polarization	-0.13 (0.34)	0.10 (0.39)	-0.07 (0.39)	0.04 (0.39)
nld.election.l1:ef	-1.20* (0.69)			-1.44* (0.74)
nld.election.l1:polarization	0.97 (0.72)			0.89 (0.79)
nld.election.f1		-0.40 (0.53)		
ln.wdi.imr.l1		0.22** (0.10)	0.24** (0.11)	0.28** (0.11)
polity2.lag.1		0.02* (0.01)	0.01 (0.01)	0.01 (0.01)
part.dem.fac.l1		0.12 (0.18)	0.41** (0.18)	0.30 (0.18)
peaceyears		-0.02 (0.03)	-0.07** (0.03)	-0.04 (0.03)
peaceyears.2		0.00 (0.00)	0.00** (0.00)	0.00 (0.00)
peaceyears.3		-0.00 (0.00)	-0.00* (0.00)	-0.00 (0.00)
ln.wdi.pop.l1		0.09** (0.04)	0.07* (0.04)	0.10** (0.04)
nac.l1		-0.00 (0.05)	-0.02 (0.05)	-0.02 (0.05)
pr.l1		-0.09 (0.07)	0.03 (0.07)	0.01 (0.07)
nld.earlylate.f1		0.25 (0.24)		
nld.suspend.f1		0.01 (0.27)		
nld.election.f1:ef		-0.54 (0.62)		
nld.election.f1:polarization		1.12 (0.70)		
nld.election			0.22 (0.41)	
nld.earlylate			0.32 (0.23)	
nld.suspend			-0.38 (0.40)	
nld.election:ef			-0.88 (0.62)	
nld.election:polarization			0.38 (0.69)	
nld.earlylate.l1				-0.13 (0.32)
nld.suspend.l1				0.17 (0.29)
https://mc.manuscriptcentral.com/compolstud				
AIC	481.04	516.16	510.25	472.07
Num. obs.	3204	3285	3282	3204

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Impact of Elections on Probability of Violent Political Instability Across Simulated Ethnic Structures, Non-Ethnic Armed Conflicts (EPR)



First Differences for Elections and Violent Political Instability, Non-Ethnic Armed Conflicts (EPR)

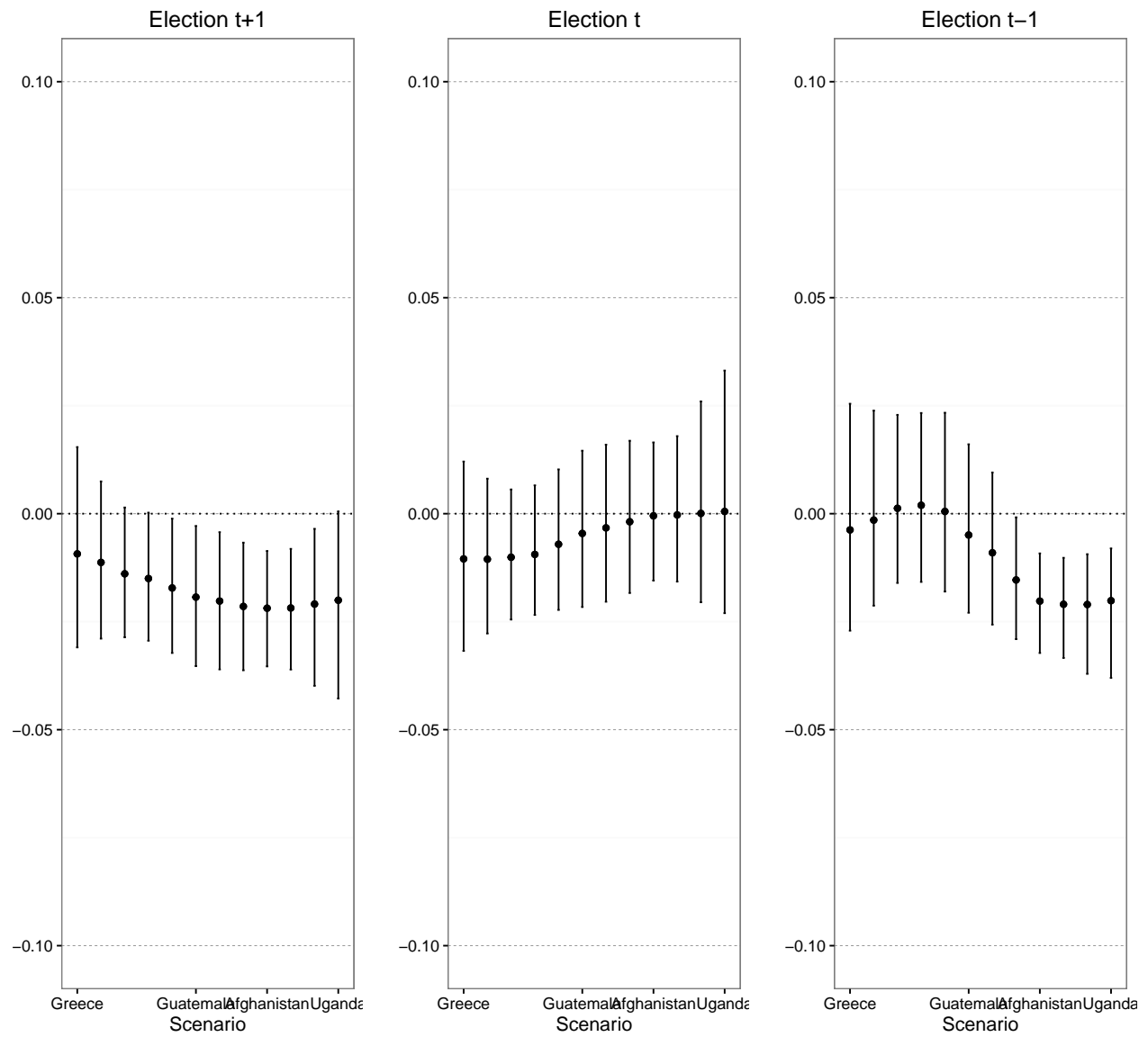


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Square of the EF index instead of the polarization measure

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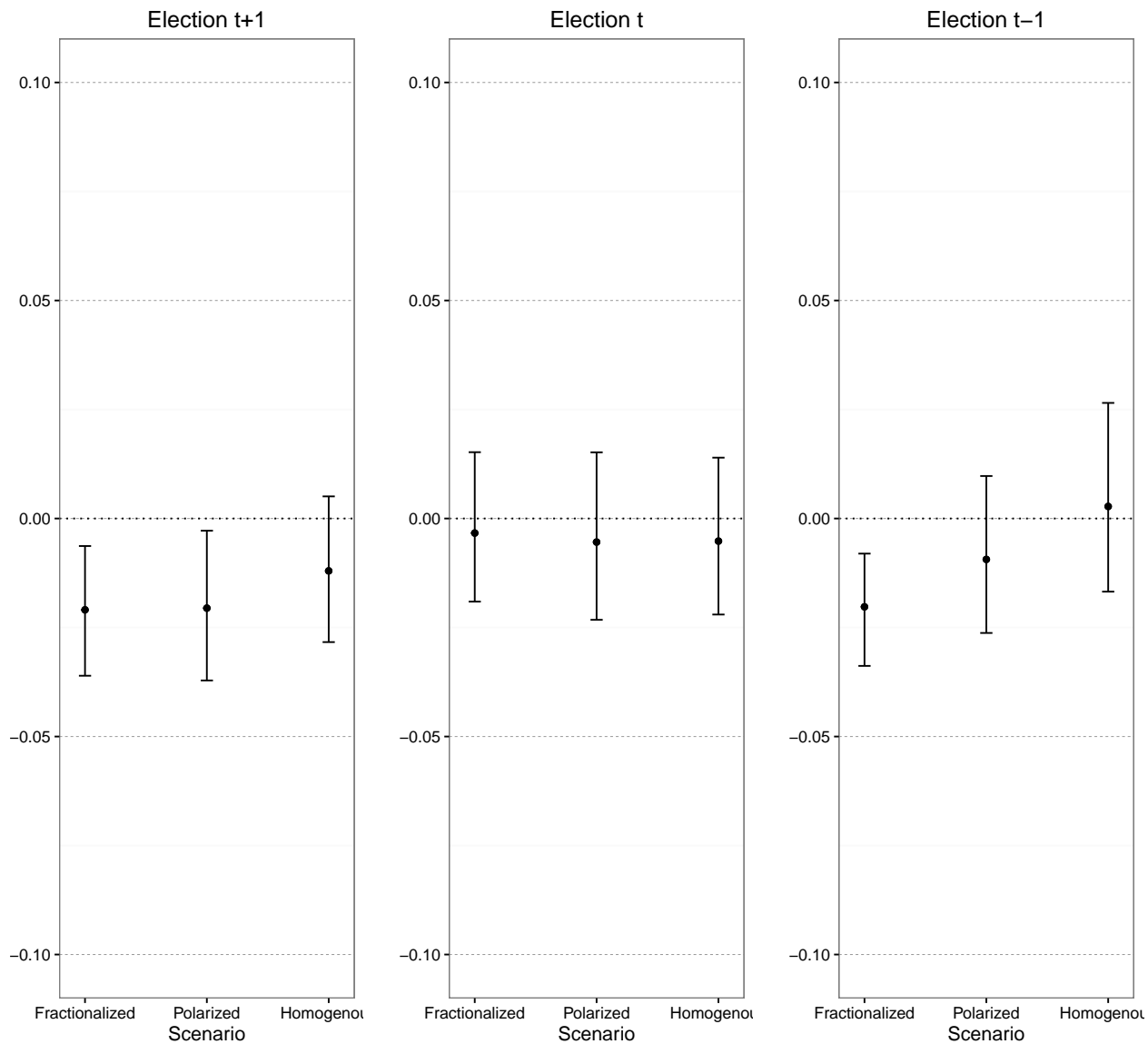


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3 **Categorical indicators of low, medium and high fractionalization**
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6 Low fractionalization is $ef \leq 0.33$, medium is $ef > 0.33$ & $ef < 0.66$, high is $ef \geq 0.66$
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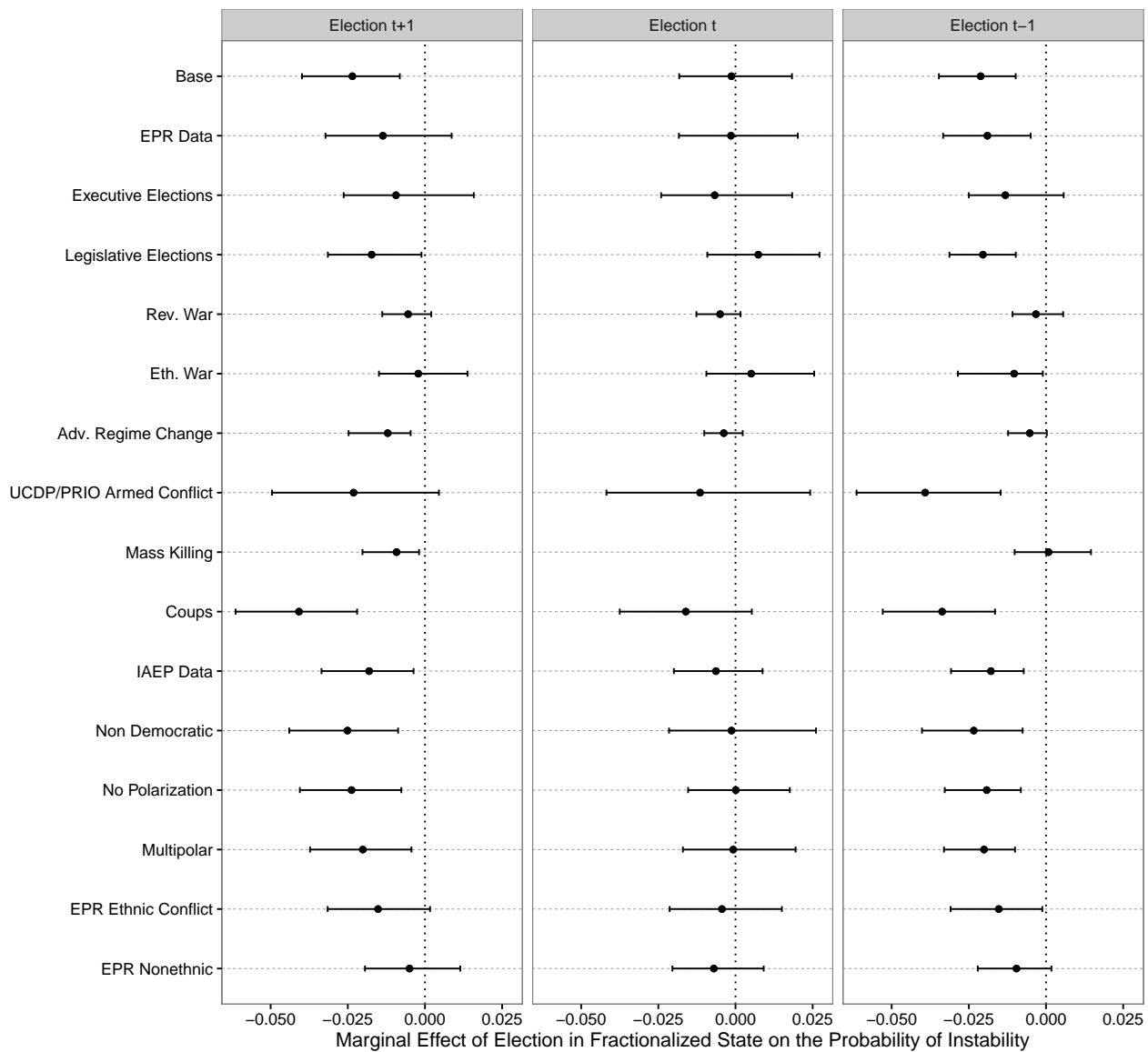
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Summary of Robustness Tests



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