When Groups Fall Apart: Measuring Transnational Polarization during the Arab Uprisings

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Abstract

Scholars continue to disagree as to what extent international social connections act as a conduit to influence contentious politics within states. To answer this question, we provide the first rigorous and real-time measure of transnational ideological diffusion across sectarian groups by employing a novel statistical method and new data to capture the transnational dynamics of polarization after the Arab Uprisings of 2011. As authoritarian governments fell, populations in several states polarized between secularists and Islamists over what kind of regime was to replace the ousted one. To examine these endogenous processes, we collected a comprehensive dataset on elite and citizen Twitter accounts in Cairo and Alexandria (Egypt) and Tunis (Tunisia) for a ten-month period during the critical year of 2013. Given the difficulty in directly measuring polarization, we also developed a new model, item response theory-vector autoregression (IRT-VAR), that allows us to incorporate measurement uncertainty while providing over-time estimates of transnational polarization. We show through our model that following catalytic events like regime ousters (such as the military coup against the Muslim Brotherhood in Egypt), we can separate the direct effects of these events on group polarization within a country from indirect transnational feedback happening through the channel of social media. [1]

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Introduction

International diffusion is a perennial and large question in comparative politics, straddling the intellectual boundary with international relations. When we observe similar policies, regimes, social movements, ideologies, or unrest across countries, are they caused by similar conditions in those countries, or have they spread internationally among the countries through some mechanism? The question implicates both our theories of politics and our empirical strategies. Galton's Problem captures the empirical issue: should observations of a phenomenon in several countries at once be treated as independent, or might autocorrelation be at work – for example, through transnational learning and imitation?

Skeptics of international diffusion remain, but the thesis that diffusion happens has strong momentum in the scholarly literature (Solingen 2012). Recent work has focused on empirical testing of theoretical claims about diffusion (Franzese Jr and Hays 2008). Our collective understanding of the phenomenon would advance greatly were we able to observe diffusion directly, but the actual international spreading of at least some categories of behavior is probably impossible. In this paper, we use social media to observe as directly as possible the diffusion of political contention across state boundaries using data from social media. Specifically, we investigate whether polarization between Islamists and secularists in Egypt and Tunisia was affected by events in Egypt in 2013, during the aftermath of the Arab Uprising. Although early studies are skeptical of diffusion of the Arab Uprising itself (Aday et al. 2012), there are theoretical reasons to believe that group polarization should indeed diffuse across national boundaries in cases such as this, where

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the two countries, for all their differences, share a majority religion and language, inhabit the same geographical region, and are open to transnational communication. Empirically, however, it is extremely difficult to disentangle the effects of those and other common conditions from actual diffusion of group conflict – that is, from people in Tunisia observing events in Egypt and moving further apart ideologically as a result.

Our dependent variable is change in group polarization. Group polarization is situational and hence may be short-lived; it is different from the stable, long-term social polarization (e.g. Red versus Blue America) that many social scientists study (Moulaert and Sekia 2003). An endogenous process triggered by exogenous events, group polarization is a way to conceive of how identities and preferences change in response to stimuli such as a public demonstration or a coup d'état. A stylized version runs as follows: At time t, an unmodeled stimulus takes place (e.g., Mohamed Bouazizi's self-immolation in Sidi Bouzid, Tunisia); at $t + 1$, the news spreads; at $t + 2$, a portion of the population of Sidi Bouzid becomes angry and identifies more strongly against the local and national government, as reflected in anti-government speech and action; at $t + 3$, news of that speech and action spreads; at $t + 4$, a portion of Sidi Bouzid's population becomes angry at the protesters and identifies more strongly with the government, as reflected in pro-government speech and action; at $t + 5$, news of that speech and action spread within Tunisia and beyond; and so on. Group polarization is self-reinforcing. It may be slowed, halted, or reversed by various developments, including coercion (censorship, physical force) by governments.

Its situational quality, specifically its dependence on exogenous events, makes group polarization impossible to predict, but therefore especially helpful in understanding complex chains of events such as the Arab Uprising itself and the various political events that followed. The group-polarization approach presupposes, with a long tradition in social theory, that people have multiple group affiliations; that belonging to one group entails defining oneself over against one or more alternative groups; that for a given individual at a given time a particular group affiliation may be more or less salient; that individuals respond to signals of friendship and hostility from one another; and hence that populations sometimes polarize along one axis of identity, temporarily submerging other axes of identity. Of particular interest after the Arab Uprising are (1) cross-polarization, or the shift from polarization along one axis (e.g., pro- versus anti-regime) to polarization along a cross-cutting axis (e.g., Islamist versus secularist), and (2) transnational polarization, i.e., simultaneous polarization along an identity axis in two countries.

Group polarization is a phenomenon of changing sentiment, identity, and preference. Measuring it with rigor has been difficult, and thus so has testing claims about what triggers it and what suppresses it. Salehyan and Gleditsch (2006) argue that refugee movements are one mechanism behind the international spread of civil war. Here we hypothesize that the growing use of social media is another mechanism for the diffusion of conflict along a particular identity axis. The availability of the resulting data, and advances in computing power, combine to allow researchers to measure changes in group polarization over time, as expressed in patterns of social media postings. In this paper, we present analysis of Twitter data during 2013 in Egypt and Tunisia. We measure the degree of Islamist-secularist polarization on a given day by the proportion of retweets by ordinary citizens of tweets of Islamist and secularist elites. (We identify the ideology of elites by the content of their tweets and known group membership.) A rising proportion of Islamist retweets among Islamists, for example, means that Islamism is becoming more salient for Islamists.

We choose this time period because Egypt went through a number of political events that seem prime candidates for triggers of group polarization. Most obvious is the July 3 coup d'état in which secularist military officers overthrew the elected government of Mohammed Morsi of the Muslim Brotherhood. In our models we specifically test for the effect of this coup (which we assume at least the timing of is exogenous) on endogenous polarization. We find that it has a statistically discernible long-term effect on the diffusion of group polarization across countries. At the same time, our model identifies other important polarizing events, some of which we identified beforehand, such as the military government's violent dispersal of pro-Morsi demonstrators in Cairo on August 14 (Daily News Egypt, https://dailynewsegypt.com/2013/08/14/live-updates-pro-morsi-sit-ins-dispersed/, retrieved on 11 August 2017), but others which we did not, including the promulgation of a draft constitution in Tunisia that undermined secularist notions of human rights (*Tunisia: Revise the Draft Constitution* 2013). In fact, our models show that these constitutional changes were the single most polarizing events during this time period, shifting the relative positions of ideological actors to a greater extent even than the anti-Morsi coup. We believe that this surprising level of polarization occurred because the Tunisian draft constitution divided people neatly along the secularist-Islamist axis, while the military coup divided some secularists along a pro- and anti-democracy cleavage.

In addition to our empirical and theoretical contributions, we offer a methodological advance by presenting a model that can incorporate both measurement uncertainty in using noisy Twitter data and the highly endogenous nature of polarization. Just as seismographs can measure the impact of stress underneath the earth's crust, we measure the unobserved but nonetheless quite powerful stress that occurs within and between social groups during group polarization. To do so, we designed a model based on item-response theory that we call an item response theory-vector autoregression (IRT-VAR) model. This method uses latent variables to represent the distance between ideological groups within countries via item-response theory, and incorporates multivariate time-series processes to allow these latent variables to influence each other over time and between countries. While item-response theory has been successfully applied to the study of ideology in social media (Barberá 2015), we advance this field by explicitly accounting for over-time endogeneity and the self-selected nature of Twitter samples.

In what follows, we explicate the logic of group polarization in an informal model. We include propositions about de-polarization and cross-polarization. We offer hypotheses about group polarization, and explain and defend our use of tweets in Egypt and Tunisia in 2013. We present the statistical model and data analysis. We close with thoughts for future research.

Group Polarization: An Informal Model

Polarization has been studied extensively by social scientists. Much of that work concerns social polarization, or segregation into groups that are stable over long periods of time (such as "Red America" and "Blue America"). By group polarization, we mean a process of segregation – not an equilibrium – that is relatively short-term or situational yet may be politically consequential.

Along with other scholars, we define polarization as a social construct, namely as progressive identity change that entails preference change. When two actors polarize, at time t, both actors may prefer a 50-50 allocation of goods; at $t + 1$, each may prefer a 60-40 allocation in its favor; at $t + 2$, a 75-25 allocation; and so on. At the limit of polarization, each side wishes the other destroyed.

Group polarization, then, is one way to formulate a progressive worsening of conflict; it does not cause conflict, in the sense of an independent variable causing a dependent one. Rather, polarization is conflict that is self-intensifying. Group polarization is endogenous, not in the sense that it is unrelated to pre-existing cleavages bur rather in the sense that, once triggered by exogenous events, it is self-exacerbating (Sambanis and Shayo 2013). It entails the altering of individuals' preferences and practices and creates new threats and opportunities for various actors, including actual and aspiring rulers (Owen and Inboden 2015, 55-61).

Stated informally, the basic group polarization model is simple. Assume a population of 100 persons, all 100 belonging to one half or another of x pairs of opposing social groups (labor or capital, democrats or authoritarians, Islamists or secularists, urban or rural, etc., etc.). Fifty are pro-democracy, fifty pro-authoritarian. These groups do not correlate significantly to any other groups; e.g., democrats are as likely to be Islamist as secularist. The population thus has cross-cutting cleavages. At time t, the population begins in an unbiased equilibrium, such that, although individuals may identify more strongly with one group affiliation than with others, in the population as a whole, no identity axis predominates; hence social interaction does not skew the distribution of resources, including information, to any of the social groups (Dunning and Harrison 2010). Now suppose that at $t+1$ three democrats – one Islamist and two secularist, and two urban and one rural – publicly beat an authoritarian. Assuming a relatively free flow of information, that event can trigger the polarization of the population along a democratic-authoritarian ideological axis, such that democrats and authoritarians care less and less about class, being urban or rural, or mosque-state questions and more and more about ideology. The endogeneity of group polarization implies that we can distinguish a *direct* effect from the beating (people observe the beating, feel threatened, and begin to polarize) from an *indirect* effect (people observe their confréres polarizing, and do likewise). If not disrupted, polarization by definition culminates in inter-group violence.

Transnational group polarization takes place when polarization spans two or more countries at once. Citizenship in a state amounts to yet another group affiliation, albeit normally an especially politically salient one that carries the advantages of a state apparatus. States are set up to foster group identity and loyalty vis-à-vis foreigners. They may use physical segregation, closed or semi-closed national borders, national economic integration, propaganda, history, threats of war, coercion, and other means to induce a strong national identity among citizens and hence a strong sense that foreigners are an "other." Yet, interaction – communication, trade, investment, travel – across state borders is normal, particularly among most countries in the twenty-first century. States vary in their capacity to build and maintain a national identity and to have that identity perpetually trump all other group affiliations, including transnational ones, across all conditions. Thus transnational group affiliations – ethnic, religious, ideological, class, sexual – are part of life for most people in most countries. Insofar as communication across state boundaries is uncensored by states, transnational group affiliations can yield transnational group polarization, as a direct effect (from observing the stimulus) produces an indirect effect (from observing others polarize). The informal model above may then incorporate democrats and authoritarians in a second state (and a third, a fourth, and so on).

Cross-polarization takes place when a group at time $t-1$ is not in unbiased equilibrium, but instead is polarized along one identity axis and at t an event triggers polarization along a different axis. In the example above, at t the population is segregated according to preference into Islamists and secularists. At $t+1$, three authoritarians (say, one Islamist and two secularist) publicly beat a democrat. At $t+2$, as Islamists and secularists who are democrats begin to identify more as democrats and less as Islamists or secularists. Polarization of the entire population along a democrat-authoritarian axis will commence.

Group de-polarization – understood as a diminution of speech and acts biased according to group affiliation – may set in when communication is censored or degraded or speech and action forcibly curtailed. The most obvious agent of de-polarization is a government, which typically has at least some of the means of censorship and coercion at its disposal. A government threatened by polarization into pro- and anti-government groups can be expected to try to slow, halt, or reverse it – or to trigger a cross-polarization that would weaken the anti-government group.

Justifying Assumptions

Social identity theory links the formation of groups and their degree of competition by means of the concept of polarization. Microfoundations for such a model are in philosophy and social theory. Assume that persons are not atomized individuals whose fundamental goal is to maximize their own exogenously derived utility and who value the gains and losses of others only insofar as those are instrumental to such maximization. Assume instead the persons depicted by traditions in sociology (Simmel 1955; Coser 1956): each individual is fundamentally a member of multiple social groups, and he identifies his interests to some extent with those of the groups to which he belongs and against opposing groups.

The logical foundations of this communal psychology is seen in the formula articulated by Spinoza and, later, Hegel: omnis determinatio est negatio, or “all determination is negation" (Melamed 2013). A thing must necessarily have properties, such as “short" or “cold." But properties only exist in contrast to other properties (Taylor 1975, 232-239). Human being contrasts to non-human being (animals, plants, rocks); female, to male; labor, to capital; old, to young; and so on. Having a self requires having an other. Having a property is equivalent to belonging to the set of things that have that property (Quine 1989, 22-26). Being female is equivalent to being a member of the set of persons that are female. Identity thus is social: who I am entails my group memberships.

Experimental evidence suggests that people, or at least some people, tend to think, feel, and act according to this in-group versus out-group logic. People tend to be self-interested, but their notion of “self" may expand to include persons in their social group whose existence requires contrast with some opposing or “out-group" (Mercer 1995). Indeed, these two identifications are mutually constitutive. As Simmel put the matter,

> "It appears to be necessary for us human beings, whose whole psychical nature is built upon our sensitiveness of difference, that a feeling of separateness should always exist alongside of the feeling of unity to make this latter perceptible and tangible" (Simmel 1898, 45-46).

Overlapping Social Groups and Different Saliencies

That individuals belong to multiple social groups, each with a corresponding anti-group, introduces a complication. For Simmel, an individual's identity consists of the unique overlap of the groups to which she belongs (Simmel 1955, 139-41). Yet, a given individual will identify more strongly with some of his groups than with others. Sometimes large groups of individuals may place greater weight on one particular group affiliation simultaneously, such that populations polarize along a particular axis of identity. Social-psychological literature posits at least two attributes of groups that lend them high salience. One is prestige or high status: experiments show that members of high-status groups are significantly more biased toward fellow members and against nonmembers than are members of low-status groups. Experiments also show that a second attribute is threat (physical, economic, status, etc.) – particularly among persons already highly committed to the group (Ellemers et al. 2002). A new threat – such as an attack on a group member by members of the opposing group – tends to arouse in such persons fears that they may be next, and so they tend to increase their biases toward that particular group affiliation. They identify more with it and against the threatening group. This experimental result is anticipated by Simmel:

> It is a fact of the greatest social significance, one of the few which are true almost without exception of group formations of every sort, that common antagonism against a third party under all circumstances tends to consolidate the combining group, and with much greater certainty than community in friendly relationships toward a third party (Simmel 1898, 45-46).

If these attributes of prestige and threat are associated with high salience, it should be the case that a rise in a group's status or jeopardy can render it more salient for its members. A rise in status may be triggered in politics by a victory in an election or a civil war, or an unexpectedly large public rally. A rise in threat may be brought on by physical violence, verbal abuse, or evidence (true or false) of discrimination or persecution against the group.

Social-psychological literature notes that people vary by level of commitment to various groups. In equilibrium some city-dwelling Islamists identify more as urban and less as Islamist; others identify more as Islamist as less as urban. This kind of heterogeneity could in principle stifle polarization, because low-commitment group members could try to exit or hide from the group rather than take the risks that come with strongly identifying with it. Against that possibility, Tilly writes that, following a triggering event, highly committed group members mediate and broker polarization by spreading information about the threat or increased status and about ongoing polarization. Such brokers may propagandize by exaggerating and inventing symbolic events. Public discourse turns to what is to be done; those who hold extreme views tend to have more influence in such times and moderates either are quiet or move toward the extreme (Tilly 2005, 143-44). Smith (2012) models allocation decisions in a game comprising two social groups, each comprising two types of actors: "behavioral" actors who are biased to favor their own group members, and "rational" actors who are unbiased. The model shows that "rational" across will come to act like "behavioral" ones and favor allocation of goods to their own group.

It stands to reason that the low-commitment actors posited by Ellemers, Kortekaas, and Ouwerkerk (1999) would behave like Smith's "rational" actors. In sum, an exogenous event that either raises the prestige of social group A or threatens group A may cause people who belong to multiple overlapping groups A through Z to identify more strongly with A and against $\neg A$ and less with B and against $\neg B$, etc. Increases in status and in threats may be simultaneous: an increase in A's status may simultaneously threaten members of $\neg A$ and thus cause them to identify more as $\neg A$s and against group A. Large public anti-government demonstrations, as take place during a typical political spring, can both raise the status of being anti-government and simultaneously threaten those who identify with the government. And again, polarization tends to feed on itself:

as members of A observe members of $\neg A$ identifying more as $\neg A$s, members of A will identify still more strongly with A; and so on, in what we call an indirect effect.

For that reason, we are interested in establishing that, in general, (1) transnational ideological groups do react to each other's latent polarization, (2) that relatively exogenous events like the coup against Mohammed Morsi in July of 2013 will affect the direction of this polarization, and (3) that these exogenous events also induce endogenous polarization as groups' polarization increases in response to their ideological allies' polarization. We are not trying to ascertain conditions under which polarization does not diffuse – only whether it sometimes does so. Thus we select on the explanatory variable of an exogenous stimulus of polarization.

Our two countries are Egypt and Tunisia. It is important to have theoretically informed reasons for assuming that two states are candidates for international diffusion (Zhukov and Stewart 2013). We choose Egypt and Tunisia because they are part of an ex ante identifiable cultural, ethnic, and geographical region and the two were open to some of the same media, including satellite television and Internet platforms.

Hypotheses

We propose to test the following hypotheses based on this theory:

H1 As the latent ideological position of Islamists or secularists changes in one state, the latent ideological position in the like-minded group in the other state will also change.

H2 After the coup against Mohammed Morsi, in each country the difference in latent ideological positions between Islamists and secularists will diverge in direct reaction to the coup (direct effect).

H3 After the coup against Morsi, in each country the difference in latent ideological positions between Islamists and secularists will increase from each group's reaction to their ideological allies' shift in saliency in the other country (indirect effect).

H4 After the coup against Morsi, in each country the difference in group polarization between Islamists and secularists from the direct reaction to the coup and each group's reaction to their ideological allies' shift in the other country (combined effect) will be greater than the direct reaction to the coup alone (direct effect).

We operationalize these hypotheses by estimating the latent space within which people identify themselves with respect to these polarizing cleavages. To accomplish this, we collected data on ideological actors in Egypt and Tunisia from Twitter, as we described in the next section. To test these hypotheses, we need to be able to trace out the endogenous processes of polarization; we must address what Solingen (2012, 638) calls "the challenge of establishing when outcomes can be considered outcomes."

The event that we can identify a-prior as potentially polarizing is the coup that overthrew Egypt's Islamist President Mohammed Morsi in July of 2013, as it seemed likely that the average secularist and the average Islamist would react differently. Other polarizing events occurred and our model should be able to identify them, but we focus our attention first on the coup because we believe based on prior information it should be a directly polarizing phenomenon as it removed Islamists from power and ended democratization in Egypt. However, to date no one has been able to say for sure how much and to what extent Morsi's coup affected group polarization because group polarization in these countries was and is an ongoing endogenous process, making it very difficult to disentangle cause and effect.

Data Collection

Analyzing these phenomena quantitatively is difficult because we need good measures of group identity across countries that also vary over time. The heavy use of social media during the Arab Uprising provides some of the first available data that we can use to examine the predictions of the theory. We chose to use Twitter due to its public nature and the ability to closely track elite users, or those users with a large number of followers. We collected a sample of influential Egyptian and Tunisian Twitter users that are broadly representative of political thinking & discourse within these countries.

To obtain the sample, we started with a universe of tweets from the early stage of the Arab Uprising, December 2010 to April 1st, 2011 that all matched the search keywords “Cairo", “Alexandria" and “Tunis" in the user self-reported location field in Twitter.[2] While this dataset comprised 11 million tweets, it nonetheless did not capture all the important or influential users because it is quite common for Twitter users to either not report their location or to list a location that is not geographic in nature. For these reasons, to identify influential users who were not in this sample, we parsed the tweets in order to identify those users that had received the largest number of retweets and mentions during that time period. In this way, even if an influential user was not a part of the original sample, we were able to locate most of the popular Twitter users in the country by analyzing the content of the tweet database.

We curated the resulting list of elite users, both by removing accounts that were later abandoned and by adding in accounts that were created later in time. In general, Twitter in 2011 was dominated by well-educated secular elites with a flair for democracy, while Islamists and pro-regime figures were later to adopt Twitter as a medium. For example, in Egypt we added the account for Mohammed Morsi, the Islamist president affiliated with the Muslim Brotherhood, and in Tunisia we added Rached Ghannouchi, long considered to be the guiding force of the Islamist Nahda movement in Tunisia. The full list of users selected for analysis is available in the appendix.

2. The particular reason we started with this dataset is because we had access to these tweets from a prior research project. These tweets were purchased through the Gnip corporation (now owned by Twitter).

	Democracy Coding	Religion Coding
Percent Agreement	38.9% (83)	61% (130)
Percent Disagreement	72% (77)	28% (30)

Note: Rows sum to one.

Table 1: Coding Agreement for Anti/Pro Democratic and Islamist-Secularist Twitter Users

The final sample amounted to 155 Twitter users, 58 from Tunisia and 95 from Egypt. The larger number from Egypt reflects the much larger Twitter-sphere in the country and hence the need to obtain a broader sample of users. We then had two graduate assistants code the user list along two axes: Islamist-Secularist and Pro/Anti Democracy. The graduate assistants used polarizing search words on the elites' Twitter feeds, such as common hash tags in the Arab Uprising (Steinert-Threlkeld 2017), and also looked at published writings or newspaper articles about these users. If a user did not have any political content that expressed their own opinions they were removed from the sample (primarily media accounts).

Through this process, we found elite users on at each possible combination of religion and democracy perspectives. While Islamist and secularist were relatively easy to diagnose given the heightened salience of Islamist groups in politics during this time period, diagnosing an elite's views on democracy proved to be a significantly greater challenge. The reason for this difficulty is because of the strong normative bias against expressing pro-authoritarian discourse during this time period, although some users were willing to tweet their skepticism of democracy and the Arab Spring. For others, we coded their anti-democratic views based on their membership in pro-authoritarian parties in Egypt and Tunisia. However, in general our coding strategy was much more successful for coding religious sympathies than pro or anti-democratic perspectives.

Table 1 illustrates this tendency for the coders to agree much more on the Islamist-secularist coding than on the pro/anti democracy coding. While the coders did not agree on 77 of the users, or roughly half, for the pro/anti democracy cleavage, they only disagreed on 30 of the Islamist/secularist cleavage codings. Furthermore, several of the remaining disagreements for Islamism and secularism were easy to resolve by addressing accidental coding mistakes. For users for which there did not appear to be very clear evidence, we defaulted to secularism given that the majority of the users tended to be secular. In addition to these binary classifications, we also had the graduate coders record their confidence in their assessment on a scale of 0 to 100. We further reviewed cases that had an uncertainty of less than 50 percent. In general, these users did not tweet as much on political topics and their ideology is relatively unknown. We excluded these users for the analyses we report here as their lack of ideological content makes them uninteresting to this analysis.

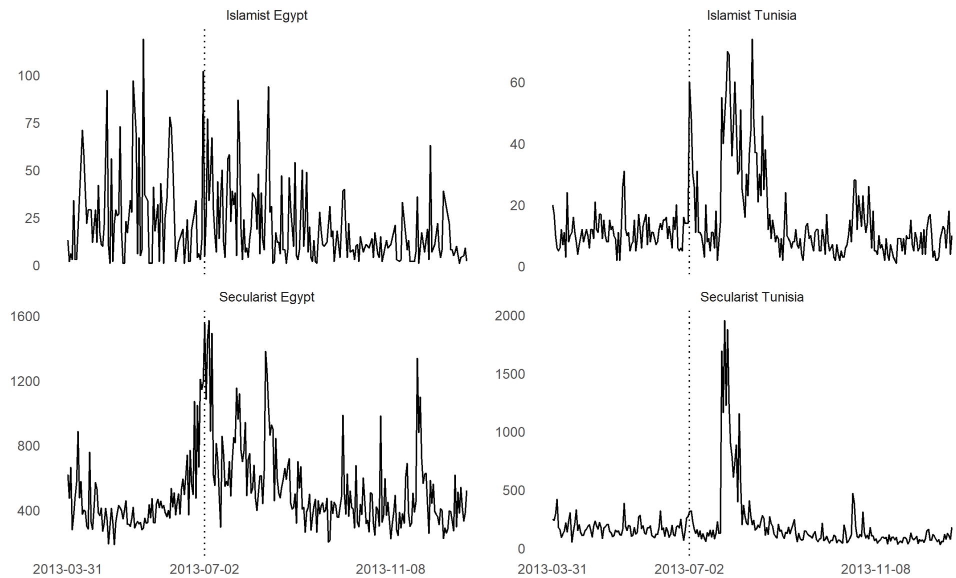
As a result, we chose to focus on the Islamist-secularist distinction in this paper because there are more observable indicators for this cleavage during the time period in question, such as tweets supporting or opposing the Muslim Brotherhood. In addition, adding an explicit second dimension would make the ensuing model more complicated, and is an issue we leave to future research.

With this finished list of 155 elite users, we then collected their full tweet histories from March 31st, 2013 to December 31st, 2013. This 1.7 million list of tweets was then filtered down to 1.2 million tweets that constitute each user's own composed tweets by removing all of each user's retweets. Using Twitter's open API, the retweets of all of these 1.2 million original tweets was then downloaded as a list of user IDs for each user per day for a total of 275 days. The use of the open API represents a limitation in the data collection because only 100 re-tweets of a given retweet may be downloaded; however, this limit was rarely reached in practice because very few of the tweets in question had more than 100 retweets. Even ex-President Mohammed Morsi, who has more than a million twitter followers, averaged only a few hundred re-tweets per tweet during 2013. Nonetheless, this data must still be understood as a sample of the full number of retweets, especially for users with a very large popular following.

The final database comprises a set of elites j and citizens i in which the outcome is the number of times that i retweeted j for each 24-period in the sample.[3] We took these retweets and we

3. As has become more well-known, automated Twitter accounts known as bots are able to inflate follower counts and amplify users' messages. However, because our inference is based on the curated list of elite users–none of whom are bots–the issue of bots is of minimal concern in this analysis as the measurement model is robust to purely mechanical retweeting. In addition, at this earlier stage in Twitter's development, bots were much less likely to be

Figure 1: Count of Retweets by Ideological Group Over Time



calculated how many times a specific user/citizen retweeted each elite within the 24-hour period. We then appended this data together for all the elites in our sample. We removed all citizens who did not re-tweet at least three different elites during the entire time period, resulting in a final dataset of 1,835,824 citizen-elite interactions with a total of 96,848 unique citizen Twitter users, or an average of 43 retweets per user of elites during the sample period. We then expanded this dataset by including all absent interactions in the dataset; i.e., for every 24-period, we include zeroes for all elites which a citizen did not retweet. This dramatically expands the size of the data to 19,933,100 observed and possible interactions. Including zeroes is important so that we do not assume that each citizen had an equal chance of retweeting all the elite Twitter accounts in the sample.

The set of elites is further divided into four groups based on the RA coding: Islamists in Egypt and Tunisia versus secularists in Egypt and Tunisia. We can then think of each group having an average position in an ideological ideal point space that varies over the number of days in the sample. We do not account for the pro- and anti-democracy axis, so for that reason these estimates implicitly average over this cleavage within ideological groups. Figure 1 shows the number of

used as a tool of statecraft as is now more often the case.

retweets of elite users aggregated to each coded ideological affiliation and by day in the sample. As can be seen, Twitter account activity varies tremendously over time, with prominent spikes around July when the Egyptian military overthrew the Muslim Brotherhood president Mohammed Morsi.

Modeling Ideological Polarization Over Time

We are not the first to collect and analyze Twitter data on polarization, including in the Middle East. Rather, our primary contribution in the empirical study of polarization is in our modeling strategy, which incorporates both uncertainty over the underlying measures of inter-group distance and an explicit method for analyzing endogenous polarization. This meta-model, which we term item-response theory-vector autoregression (IRT-VAR), provides single summary measures of difficult-to-identify effects that reflect our underlying uncertainty in the data.

Understanding measurement uncertainty is very important for Twitter analysis, and has bedeviled previous work in the subject. Generally speaking, scholars have applied some kind of model or aggregation algorithm to Twitter data before running statistical models, such as sentiment coding (Jamal et al. 2015; Siegel et al. 2018), network statistics (Freelon, Lynch, and Aday 2015) and the use of particular keywords or hashtags (Weber, Garimella, and Batayneh 2013). However, while these methods can be applied directly to the study of fully observable Twitter behavior such as the spread of known hashtags or keywords (Steinert-Threlkeld 2017), the study of ideological polarization requires an assumption that the aggregation used accurately reflects the underlying social process that the analyst wishes to identify. When it comes to identifying latent social cleavages, the observed Twitter data is rarely of interest, but rather whether and to what extent the observed data provides information on latent cleavages. While we know that this information exists, it can be frustratingly hard to extract.

For this reason, even as Twitter data opens up new opportunities for studying group formation processes in near real-time, it also presents imposing hurdles because the medium is not designed

Figure 2: Selected Tweets Responding to a Tweet from U.S. President Donald Trump

for easy interpretation or classification. The short character limit on tweets and the way in which tweet replies are structured invite users to write tweets using sophisticated (or at the very least obtuse) irony and sarcasm. As a result, even native speakers have trouble discerning the meaning of a tweet without spending time reading the context within which it was written. An illustration of this problem can be seen in Figure 2, which shows tweets sent in response to a tweet from U.S. President Donald Trump. As can be seen, the tweets include ambiguous slang and miniature icons as expressions of ironic dissent, which even an experienced Twitter user may have trouble deciphering. For example, one user responded "Globalist", which is usually taken as a term of criticism directed by right-leaning users towards left-leaning users, but in this context appears to be ironically applied as an epithet against the right-leaning President Trump.

Furthermore, discerning the meaning of tweets is doubly difficult in Arabic-language Twitter as existing computational linguistic models are usually limited to Western languages, and regional variants of Arabic, in addition to its non-standard Roman transliterations[4], make it hard to apply sentiment analysis without manually coding very large datasets. As a result, decisions over how to aggregate and measure tweets can have a strong influence on the results, and also make it difficult to compare across studies given the disparity in measurement strategies. In essence, the models and statistics that are computed on the aggregated data do not reflect the underlying uncertainty in the measurement of whichever latent social process the study is trying to capture.

To respond to these concerns, we focus on a single type of Twitter-based behavior–retweets–and design a model that combines measurement with direct statistical analysis of group polarization. By so doing, our model only has to make two basic assumptions: 1) retweets are a signal of underlying ideological agreement and 2) our codings of elite Twitter users as Islamist or secularist are accurate. The first assumption has been shown to be valid through analyses of the political content of retweet networks (Conover et al. 2011). Every time a Twitter user clicks on the retweet icon by a tweet, they immediately broadcast it to their followers, signaling that the user believes this tweet is a message worth amplifying to their network.[5] The second assumption of coding elite Twitter accounts, while still an assumption, is relatively transparent and easy to replicate, and we include the entire set of coding decisions in the appendix as a reference. All other analysis of ideology that we present in this paper flows from the model and incorporates the full uncertainty in accurately identifying the underlying social process of polarization relative to the irrelevant noise in the content of users' tweets.

To adequately model these phenomena, we borrow ideas from two distinct literatures in statis-

4. Arabic-speaking social media users often write posts in an informal system known as Arabizi that matches Arabic letters with numbers when there is no Roman equivalent. However, users often made ad-hoc decisions in deciding how to transliterate Arabic vowels and verbal constructions, rendering it difficult to impossible to perform systematic grammatical analysis of the texts.

5. Even though some users will say that their retweets do not signal agreement, in general it is rare to observe personal accounts retweeting ideological enemies, as it is counter to the very idea of a personal account to amplify views that are reprehensible to one's own.

tics: time-series econometrics, in particular vector auto-regression, and the item-response theory literature on estimating latent concepts. Item-response theory has been used in political science for estimating the latent positions of actors based on roll-call voting datasets (Clinton, Jackman, and Rivers 2004), and more recently, through social media and campaign finance contributions (Bonica 2014; Barberá 2015). Item-response theory (IRT) has also been applied to difficult measurement problems, in particular the construction of democratization indices from a variety of coding sources (Coppedge et al. 2017; Treier and Jackman 2008). Item response models estimate latent traits for individual cases that can be divided into two distinct groups, such as raters and countries, lawmakers and bills, or in our sample, citizen and elite Twitter users.

The main advantage of these models is that they are designed to provide latent estimates of fundamentally unobservable quantities, such as political ideology. For that reason, there is a strong connection between IRT and factor analysis (Takane and Leeuw 1986), and similar concerns over the interpretation of the latent scores are justified. The latent dimension estimated by an IRT model will be the lowest-variance explanation of the observed data, but further prior knowledge and post-estimation validation is necessary to confirm that the results correspond with the concept of interest. We are confident in our application of this technique to the data because of our prior coding of users into similar ideological groups. For that reason, the resulting estimates will reflect these latent cleavages instead of arbitrary social behaviors or groupings. In other words, we anchor the model in our prior knowledge about elite users, and rely on the retweet patterns of ordinary users to see how these ideological networks are changing over time. As such, we define the latent scale in our model as inter-group salience rather than ideology per se because we are examining group polarization (a relatively short-lived phenomenon) instead of changes in the content of the ideologies.

The existing application of time series modeling to IRT is limited despite the fact that political science has many time-varying variables with considerable measurement error. This paper builds on the approaches of Martin and Quinn (2002) and Kropko (2013) who use random-walk priors on latent-traits to incorporate change in ideal points over time. In time-series lingo, these latent traits become integrated variables that exhibit an infinite memory process: any shifts in the ideal points are remembered in the time series over time (Box-Steffensmeier et al. 2014, Ch. 5). While this type of autocorrelation is appropriate for long-term time series, our focus on short-run dynamics suggest we use a model that is based around stationary ideological groups, i.e., that groups receive temporal shocks causing heightened salience of ideological divides for a short period of time and then return to an average level of social affinity (Ch. 2). In reality, ideological groups can exhibit both kinds of variation, with ideological development over the long-term leading to innovation in beliefs, while in the short-term the ideology of these groups is relatively fixed and it is the salience of these ideological divides that varies (Owen 2010). For this reason, we do not adopt the approach of Park (2011), who models “preference regimes" as showing stasis over time with brief moments of change in a form of punctuated equilibrium, which is a model more suited for studying long-term changes in networks.

Finally, in addition to examining change over time, our research explores transnational ideological polarization. We want to know whether an increase in Islamist-secularist polarization in Egypt causes changes in Islamist-secularist polarization in Tunisia. For that reason, we need to look at multivariate time-series techniques, i.e., vector autogression (VAR). Vector autoregression involves the estimation of lags of different time series in the same equation (Sims 1980), and has been used in political science to study time series that interact with each other for several decades (Freeman, Williams, and Lin 1989). Our main innovation in this paper is to jointly fit a VAR and an IRT model so that the VAR can fully incorporate the measurement error present in the Twitter data.

The primary purpose in employing a VAR as the inferential method is that it enables us to track the endogenous feedback effects of the ideal points of Islamists and secularists on each other over time. To set up this model, we start with two time series that represent the latent ideal points of different religious groups: y_{cgt} and x_{-cgt}. These series are observed at discrete time units t and each belong to the same group $g \in \{Secularist, Islamist\}$ but different countries $c \in \{Tunisia, Egypt\}$. In a VAR framework, we can use the following equation to signify these series influencing each other through their prior period lags. The parameters β_{cgIN} and β_{cgOUT} control the relative influence of prior period lags:

$$y_{cgt} = \gamma_{cg} + \beta_{cgIN} y_{cgt-1} + \beta_{cgOUT} x_{-cgt-1} + \beta_{gcx} X + \epsilon_{cgt} \tag{1}$$

$$x_{-cgt} = \gamma_{-cg} + \beta_{-cgIN} x_{-cgt-1} + \beta_{-cgOUT} y_{cgt-1} + \beta_{g-cx} X + \epsilon_{-cgt} \tag{2}$$

To make the model stochastic, we include ϵ_{cgt} and ϵ_{-cgt} as white noise (stationary) errors so long as β_{cgIN} and β_{cgOUT} meet the VAR stability conditions (Zivot and Wang 2006, 386-387).[6] So long as these parameters meet the stability conditions, the latent ideal points will over time return to their long-run equilibrium value γ_{cg} (i.e., the intercept). Substantively, these parameters provide estimates of how quickly a time series will return to its long-term mean given an exogenous shock (β_{cgIN}) and the strength of influence of the other time series (β_{cgOUT}).[7]

We also include an additional parameter in each series, β_{gcx}. This parameter does not vary over time and rather represents the effect of the exogenous event X, which equals 1 after the coup against President Morsi in Egypt and 0 before the coup. As such, we can use β_{gcx} as a direct measure of the long-term polarizing effect of the coup on each of the series. A null hypothesis of no effect of the coup would be the case in which $\beta_{gcx} = 0$.

Given that we have two groups and two countries, we have two sets each of ideal points series y_{cgt} and x_{-cgt} for a four time-series system (Tunisian secularists and Islamists and Egyptian secularists and Islamists). While we could pair each series with every other series, we instead chose to only pair each ideological group with their co-religionists in the other country. We impose this restriction because we aim to identify the effect of transnational polarization, and also because the within-country groups are separately related through the IRT model that we explicate in the appendix.

6. Loosely speaking, a VAR is stationary if the eigenvalues of the coefficients of the lags in the VAR have a modulus less than one. In essence, if these coefficients are too large in absolute terms relative to each other, the VAR will move away from its equilibrium level in either a random or explosive direction.

7. We only include one lag of each series in our VAR equation because the time series are themselves latent variables, and as such the normal lag selection procedures for VARs do not apply. We would prefer as well to keep the model as parsimonious as possible.

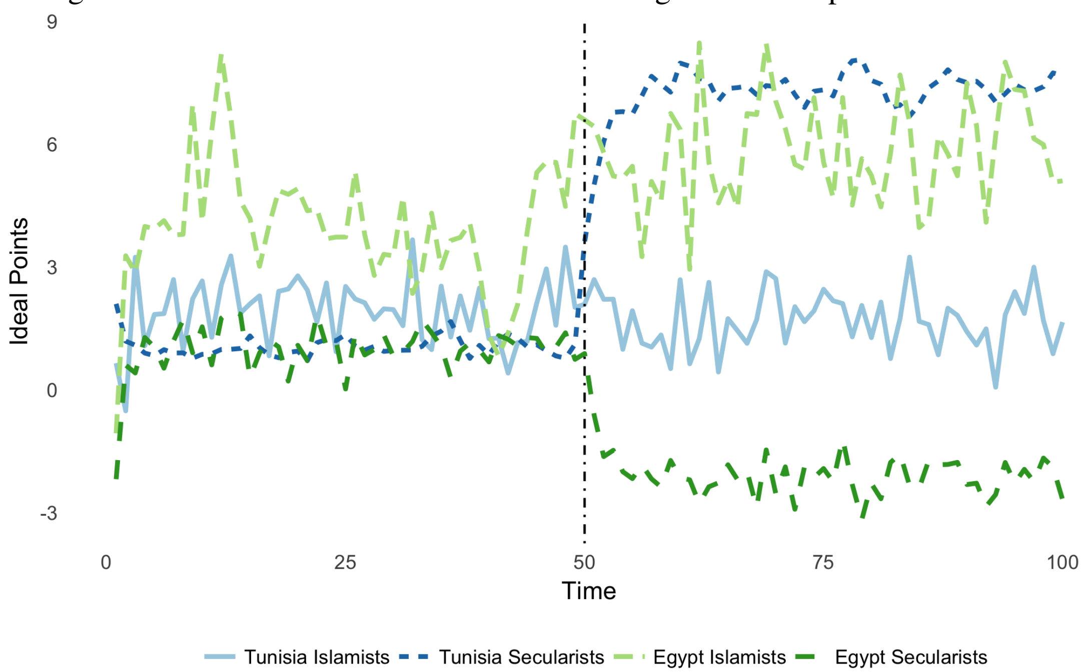
Given this framework, we are able to track endogenous changes in the latent ideal point time series via the coefficients β_{cgIN} and β_{cgOUT} that provide evidence of how reactive groups are to their own prior ideological position and to the position of other groups. A small value of β_{cgOUT} will imply that a religious group is relatively insensitive to the actions of their foreign co-religionists, and a larger value that the religious group is very sensitive to what happens in other countries. On the other hand, a small value of β_{cgIN} implies that a religious group is relatively insensitive to its own prior position in the latent space. As such, a low value of this parameter also signifies the stability of the series. Supposing that the religious group experienced some kind of shock that heightened the salience of religious divides, a lower β_{cgIN} will imply that the group return quickly to the long-term mean of the series (the intercept γ_{cg}). By contrast, a higher value of β_{cgIN} implies that the religious group is unstable and is unlikely to return quickly to a long-term mean. If $\beta_{cgIN} = 1$ the series is very unstable and may not ever return to a long-term mean.

However, we need to obtain the ideal point series themselves (y_t and x_t) in order to calculate all of these effects. As we mentioned earlier, we cannot directly measure ideological agreement on Twitter. We could try to create relevant time series by aggregating our Twitter data around the content of tweets using particular key words or hashtags, such as the Arabic phrases for sectarian terms. However, as we mentioned earlier, that would make our analysis heavily dependent on the particular set of keywords we chose to employ. For that reason, to estimate the underlying latent estimates using a more principled approach, we turn to item-response theory (IRT).

We provide a full explication of how we combine IRT and the VAR in Appendix B as well as explain how we can estimate this model using Bayesian inference. In essence, we use IRT to create the time series which are then fed into the VAR. IRT converts the raw Twitter data into four latent variables that represent the group-level ideal points of each of the religious-country groups. Because our IRT model employs the ideal point formulation (Clinton, Jackman, and Rivers 2004), the resulting latent variables can be interpreted as the relative salience of the groups in a latent social space in which users are making decisions about whom to retweet. Distance in this space then represents the closeness of these groups to each other in terms of ideologically-inclined retweet patterns. For example, as group polarization increases within countries, users will only retweet those elites who are close to their ideological ideal point, and we would expect the group-level ideal points to move farther apart in the latent space. Empirically that polarization would be expressed as more strongly polarized retweet patterns, but the IRT model is able to reduce that high-dimensional and rather noisy data down to a single estimate of relative group polarization with a credible interval to indicate our uncertainty in its true location. In other words, the group polarization estimate represents how users might think about and classify different people as belonging to these ideological groups, with periods of heightened polarization corresponding to more cleanly defined groups.

To test the model, we simulated data by generating group-level ideal points corresponding to the VAR equation above. The simulated "true" latent time series, each of which is paired with another time series representing an ideological group in different country, is shown in Figure 3. As can be seen, the two sets of time series each follow a pattern over time that is roughly stationary.

Figure 3: Simulated Data for the Vector Auto-regressive Component of IRT-VAR



The vertical line in Figure 3 shows the time period where an exogenous event X occurs and β_{gcx} has a non-zero value, which will shift the long-run equilibrium of each time series depending on the value of β_{gcx}. In addition to the summary estimate of β_{gcx}, we can also use the values of β_{cgIN} and β_{cgOUT} to calculate impulse-response functions (IRFs) for a shock to the elite group's ideal points coming from the group's own time series, or the indirect effect coming from a shock to a different group's time series. We can express this mathematically as the derivative of an exogenous shock ϵ_{cgt} with respect to the value of the ideal point α_{cgt} at time points after the shock from $t + n, n \in \{1, 2, ...10\}$:

$$\frac{\partial \alpha_{cg(t+n)}}{\partial \epsilon_{cgt}} \tag{3}$$

This IRF essentially measures the decaying (if the time series is stable) average effect of a shock to the latent ideal points over time, and provides a straightforward measure of the endogenous nature of group polarization. We can use this same framework to calculate other IRFs of interest, including the influence of an exogenous shock to co-religionists in another country,

$$\frac{\partial \alpha_{cg(t+n)}}{\partial \epsilon_{-cgt}} \tag{4}$$

the influence of the exogenous event X,

$$\frac{\partial \alpha_{cg(t+n)}}{\partial \beta_{gcx}} \tag{5}$$

the influence of the exogenous event X working through its polarizing effect on ideological allies in another country (i.e., indirect effects of the exogenous event):

$$\frac{\partial \alpha_{cg(t+n)}}{\partial \beta_{g-cx}} \tag{6}$$

and the combined influence of the exogenous event X on the within-country group α_{cgt} and the other country group α_{-cgt} (the combined effect):

$$\frac{\partial \alpha_{cg(t+n)}}{\partial \beta_{gcx} \partial \beta_{g-cx}} \tag{7}$$

Crucially, each of these effects incorporates the endogenous nature of these processes, allowing for heightened polarization in prior time periods to influence the present, ad infinitum. To summarize the model, then, we can match these estimates to our hypotheses to provide very specific null hypothesis tests of our arguments that, as we have noted, incorporate our measurement uncertainty in using Twitter data into the tests. We show how this model relates to our hypotheses in Table 2.

Table 2: Hypotheses and Associated Tests from our Model

Hypothesis	Definition	Expected Outcome
H1	As the latent ideological position of Islamists or secularists changes, the latent ideological position in the like-minded group in the other state will also change.	$\frac{\partial \alpha_{cg(t+n)}}{\partial \epsilon_{-cgt}} \neq 0$ for all $c \in C$ and $g \in G$
H2	After the coup against Mohammed Morsi, the difference in latent ideological positions between Islamists and secularists will diverge in direct reaction to the coup (direct effect).	$\frac{\partial \alpha_{cg(t+n)}}{\partial \beta_{gcx}} \neq 0$ for all $c \in C$ and $g \in G$
H3	After the coup against Mohammed Morsi, the difference in latent ideological positions between Islamists and secularists will diverge from each group's reaction to their ideological allies' shift in latent ideological position (indirect effect).	$\frac{\partial \alpha_{cg(t+n)}}{\partial \beta_{g-cx}} \neq 0$ for all $c \in C$ and $g \in G$
H4	After the coup against Mohammed Morsi, the difference in latent ideological positions between Islamists and secularists from the direct reaction to the coup and each group's reaction to their ideological allies' shift will be greater than the direct reaction to the coup alone (combined effect).	$\frac{\partial \alpha_{cg(t+n)}}{\partial \beta_{gcx} \partial \beta_{g-cx}} \neq 0$ for all $c \in C$ and $g \in G$

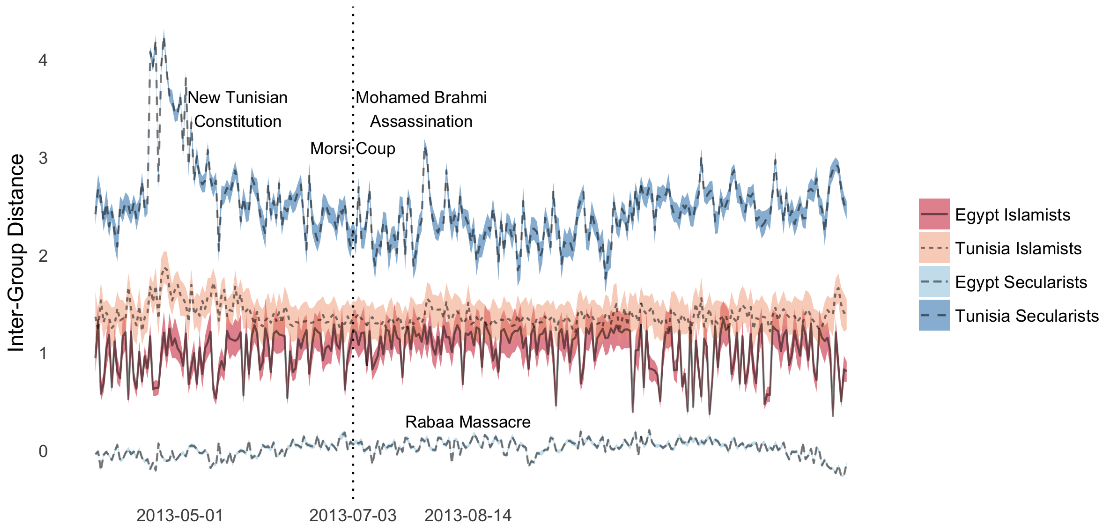
As this model has not been previously estimated in the literature, we also perform a simulation study in which we sample from the data-generating process and test to make sure we can recover both the parameter values and the correct values of the IRFs. The results of this simulation in Appendix B show that our use of Bayesian inference is able to capture the latent process given data simulated from the same DGP as the model. In the appendix we also discuss how we employ the method of Kubinec (2017) to adjust the ideal point estimates for self-selection via a 2-stage hurdle model. This adjustment is very important for accurate estimation because Twitter users tend to self-select which tweets they are likely to see on a given day because only those elites they have previously chosen to follow on Twitter will show up in their Twitter feed.

Model Results

Estimating this model using full Bayesian inference would be computationally prohibitive given the size of the data and the tens of thousands of model parameters. To address this big data issue, we employ variational Bayesian inference in which we estimate an approximation to the true posterior by minimizing the Kullback-Leibler divergence between the true posterior and a Normal approximation using the Stan estimation engine (Kucukelbir et al. 2015). Any additional error created by the use of an approximation is a minimal concern given the size of the data and the asymptotic properties of minimizing KL divergence (Grimmer et al. 2011; Kucukelbir et al. 2015). Our variational estimation produced 18,123 each of discrimination δ_j for all of the citizens in the model, but we will focus on the four group parameters that varied over time, α_{cgt}, with one for each country-ideological pairing: Tunisian secularists, Egyptian secularists, Tunisian Islamists, and Tunisian secularists, as they are our primary focus for inference.

We first present a plot showing the estimated ideal points for the four ideological groups along with a vertical line showing when the military coup against Mohammed Morsi occurred. The confidence intervals on the chart reflects the 10%-90% density region of the approximated posterior, hereafter referred to as the high-posterior density (HPD) interval. From this chart we can make useful descriptive inferences. The average position over-time of the time series gives us a sense of the general level of polarization in the data during this time period. First, it is clear that in terms of latent inter-group distance, the Islamists are much closer to each other than are the secularists in either country. Substantively, this finding means that Islamist Twitter users share much more in terms of the ideological nature of their retweet patterns relative to secularists. Secularists in both countries are farther apart in our latent space because citizens' tweet patterns would not indicate much ideological salience across the groups' networks. That is not to say that there is no relation, just that in relation to Islamists they share less in common with users across borders. The fact that the Islamists are generally closer to each other in the latent space than to their co-ethnics is a telling first sign of polarization as it implies that they tend to have more in common with their foreign ideological allies than their fellow citizens.

Figure 4: Estimated Ideal Point Locations for Transnational Ideological Groups



It is worthwhile to compare Figure 4 with Figure 1 that showed the raw counts of retweets. While Figure 1 had spikes around notable events like the coup against Morsi, the estimated ideal points in Figure 4 do not generally share these spikes and certainly not in the same proportions. The reason for this disparity is the work of the IRT-VAR measurement model, which will only pick up on changing proportions of tweets among users in terms of the pre-coded ideological groups. This disparity between raw data and the measured ideal points provides strong evidence of the face validity of the method.

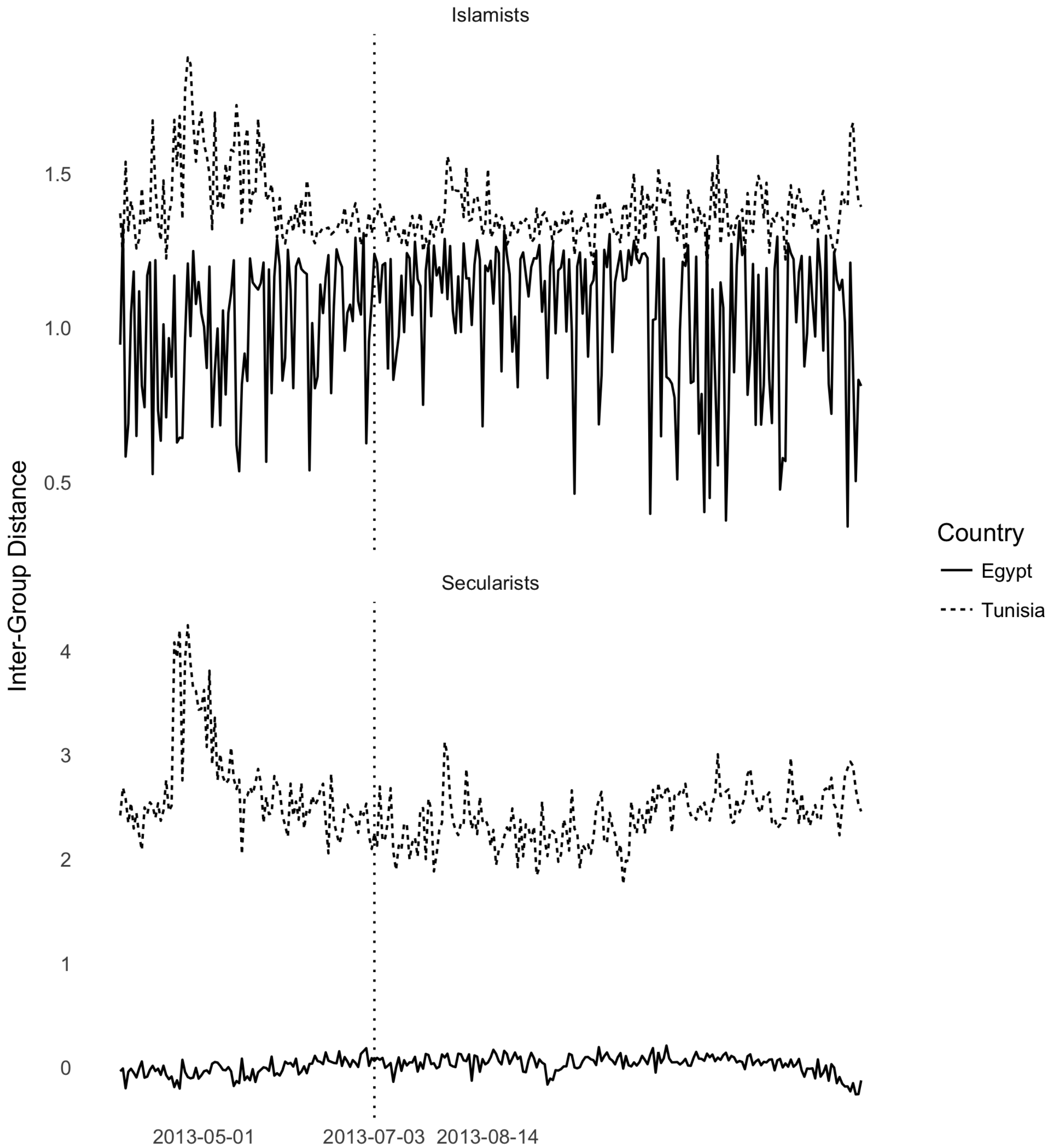
In addition, Figure 4 reveals that other events seemed to have a greater effect in terms of shifting ideal points than the Morsi coup that we had previously identified. The single largest movement appears in the ideal points of Tunisian secularists, and can be traced to the promulgation of a draft constitution that occurred on April 25, 2013. This draft modified wording in the constitution that diluted language about human rights in favor of Tunisia's "cultural specificities" that was widely interpreted as an attempt by the ruling Islamist party in Tunisia to provide guarantees that the relatively secular human rights language could not be used against Islamic norms (*Tunisia: Revise the Draft Constitution* 2013). With the caveat of hindsight, it makes sense that this event would prove to be so directly polarizing as it involved a change to the basic law of Tunisia's governance that corresponded closely to latent social cleavages without activating cross-cutting issues such as support for democratic values.

Other events are also noticeable from the plot, including the assassination of Mohammed Brahmi, a secularist politician, allegedly by Islamist radicals in July of 2013. We also see a noticeable spike in the Egyptian Islamists ideal points during the time of the Rabaa massacre, when the Egyptian military violently suppressed a sit-in by Muslim Brotherhood members opposing the coup against Mohammed Morsi. Given that these spikes in ideal points conform closely to events that we can identify as polarizing, but which we did not necessarily identify in advance (especially Tunisia's draft constitution), the estimated latent dimension appears to correspond closely to our label of group-level salience.

To see the relationships better, we show these trend lines without HPD intervals and overlapping country/ideological groups in Figures 4 and 6. While it can be difficult to spot patterns in time series with the naked eye, it is very clear that Islamists track with each other much more than secularists do in general, and that Tunisians tended to mirror each other more closely than Egyptians. Furthermore, while the opposing groups within countries are on average the same distance apart, Egyptian secularists and Islamists are farther apart on average than their Tunisian counterparts. We can use the distance between time series as a measure of the relative polarization between groups. Figure 7 looks at whether this group-level difference between Islamists and secularists is greater in Egypt or Tunisia over time. During the Tunisian constitutional crisis, within-country polarization (i.e., difference in ideal point locations) in Tunisia was significantly greater than Egypt's, but after Morsi's coup, Egypt's within-country polarization remained consistently higher than Tunisia's until the end of 2013. This plot shows that our basic intuition concerning Morsi's coup is correct–the coup heightened polarization in Egypt relative to Tunisia–although it does not help us understand transnational mechanisms of diffusion.

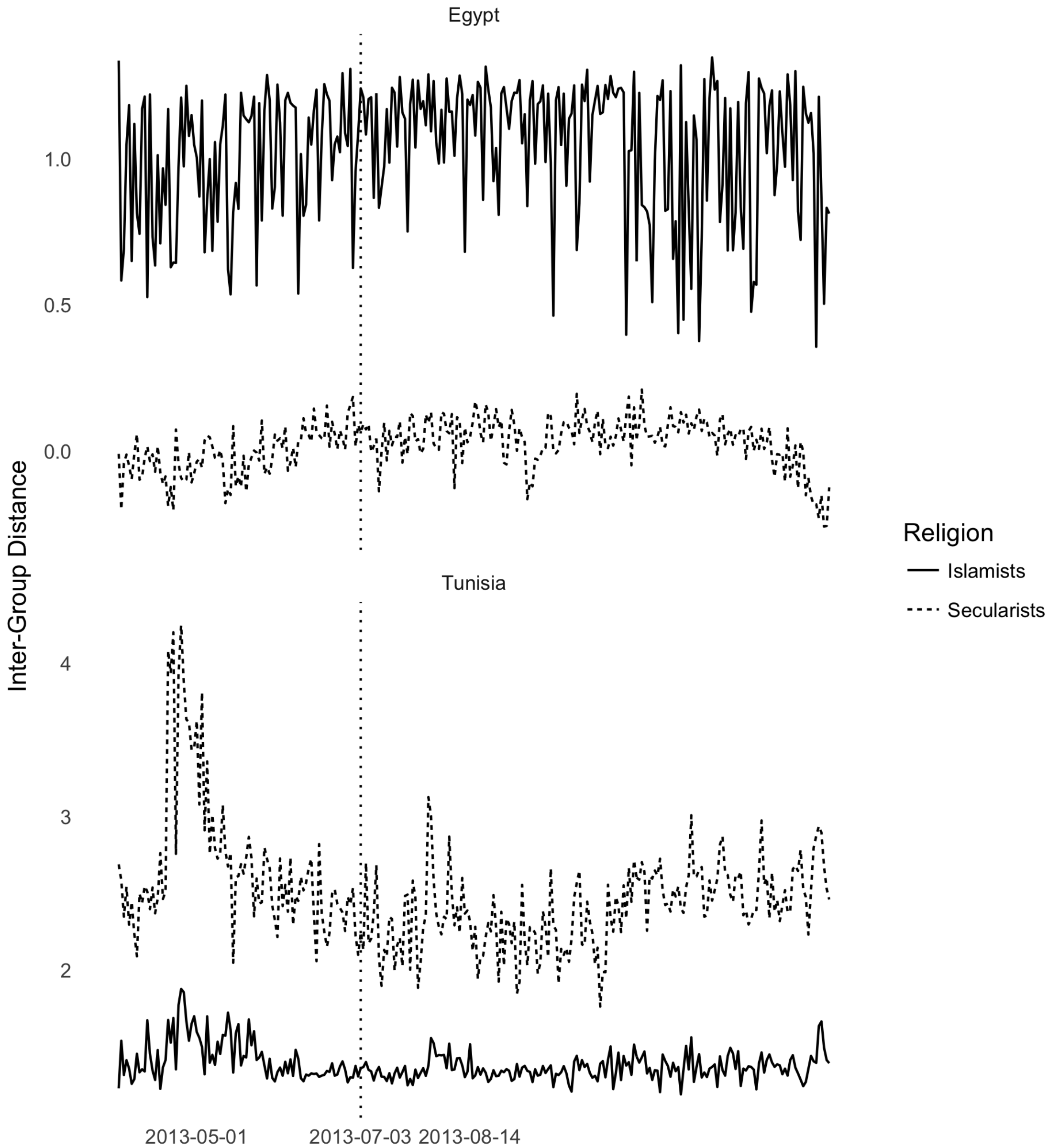
To do so, we present the parameters from the VAR component of the model in Figure 8. This plot of the posterior densities of the adjustment parameters β_{cgIN} and β_{cgOUT} provides a precise definition of how ideological groups react to each other and to their own prior history. First, β_{cgIN} captures how strongly the ideological group is influenced by its recent past as opposed to its long-

Figure 5: Estimated Ideal Point Locations by Religion



run value. In other words, a higher value of β_{cgIN} implies that the ideological group is relatively unstable and likely to drift in an uncertain direction, whereas a lower value of β_{cgIN} means that the ideological group remains fixed around its long-term inter-group distance and, although it will respond to shocks, its position in the system is relatively fixed. What is of interest with these parameters is that they are considerably higher for Tunisian groups than for Egyptian groups.

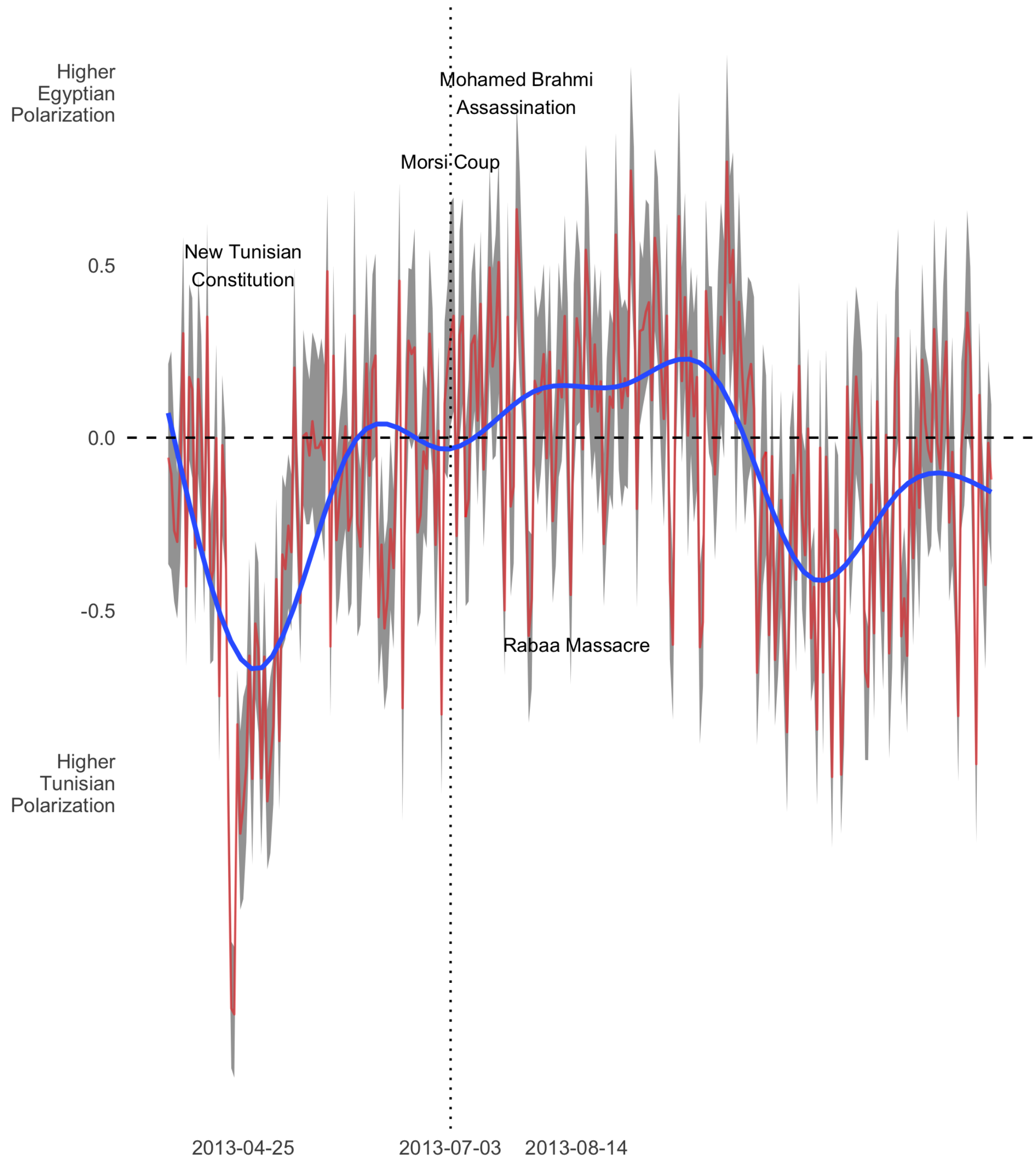
Figure 6: Estimated Ideal Point Locations by Country



Tunisian secularists have a value of β_{cgIN} that is close to 1, which is very high and means that these secularists do not appear to have a long-run mean to which they will return.[8] Tunisian Islamists have a much lower value, but still quite higher than the Egyptian Islamists, implying that it will take a longer time after some shock for the Tunisian Islamists to return to their own long-term average.

8. In other words, the series appears to be partially integrated of order 1.

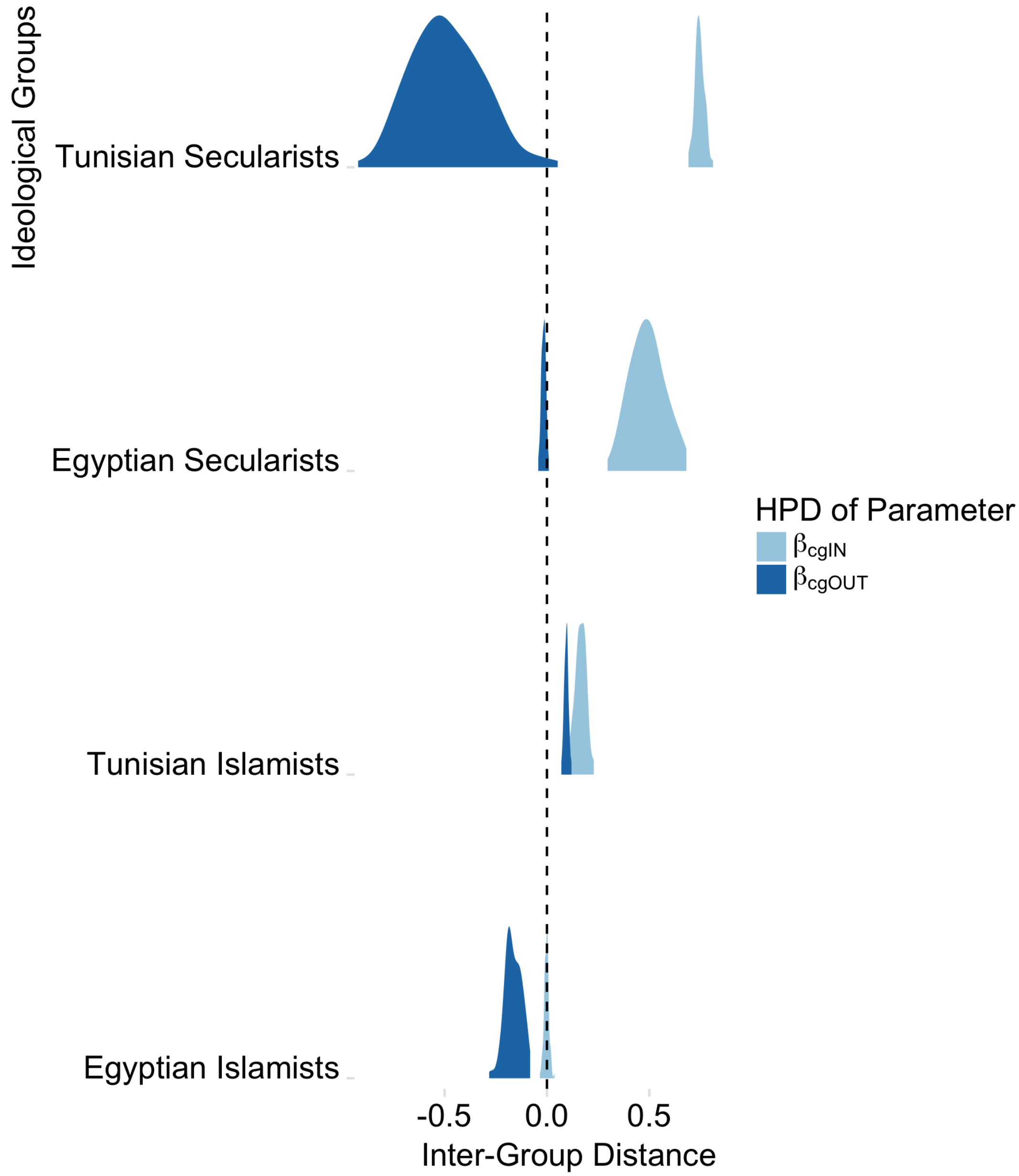
Figure 7: Comparison of Within-country Polarization Between Secularists and Islamists



By comparison, secularists and Islamists' positions in Egypt are relatively fixed, one could even say entrenched, with varying salience but relatively positions in the system.

The values of the β_{cgOUT} allow us to make statements about how each group is influenced by its foreign ideological allies. Of these parameters, Tunisian secularists have the highest absolute

Figure 8: Estimated Adjustment Parameters β_{cgIN} and β_{cgOUT} from IRT-VAR Model



value–albeit very imprecisely estimated–while Tunisian secularists by contrast have the lowest. Egyptian Islamists and Tunisian Islamists have β_{cgOUT} values that show they significantly influenced by foreign allies, and these parameters are very precisely estimated. In terms of transnational networks, it is clear that Islamists are influenced to a greater extent by foreign allies than are secularists.

Figure 9: Estimated Coup Effect β_{cgx} from IRT-VAR Model

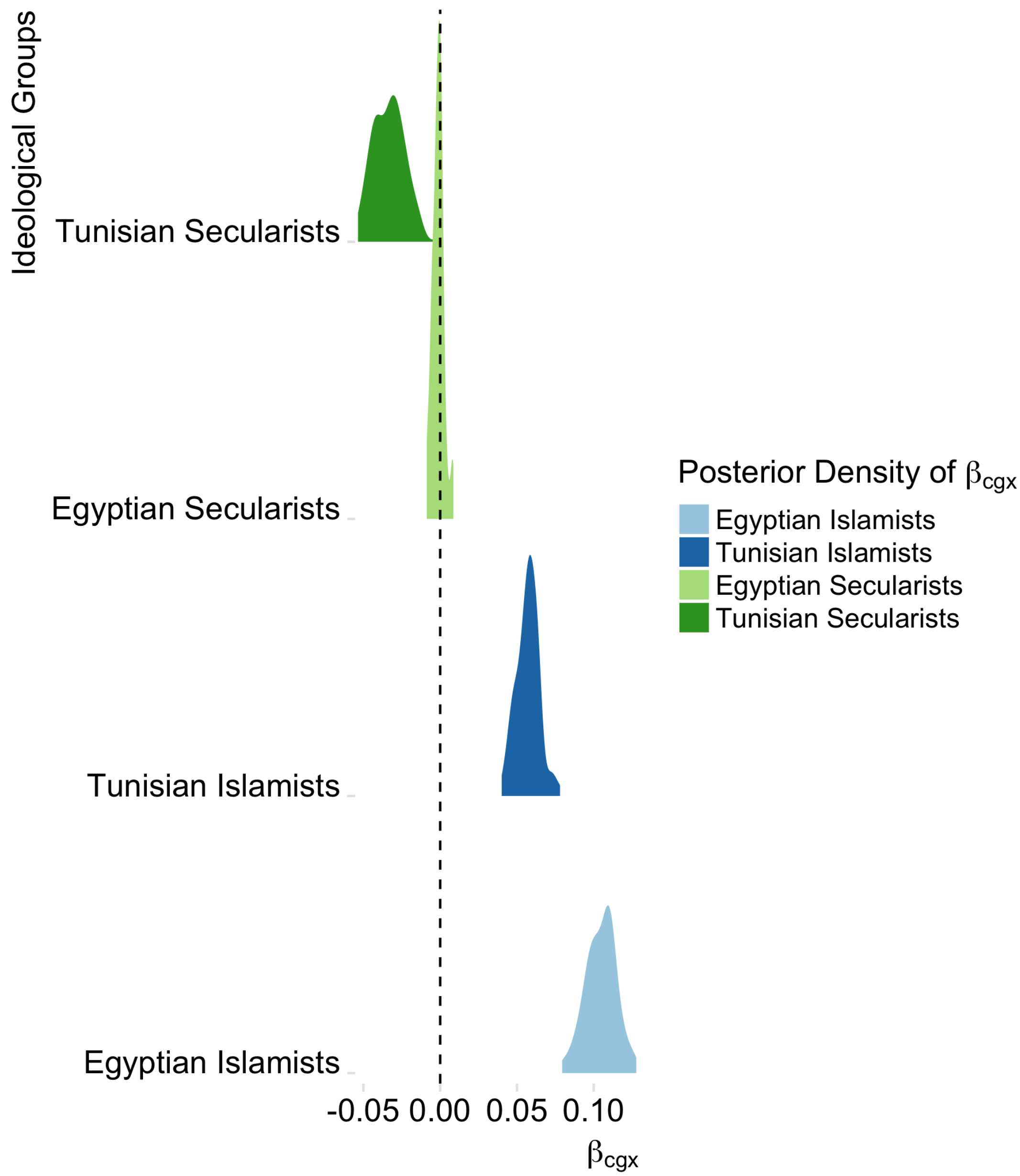
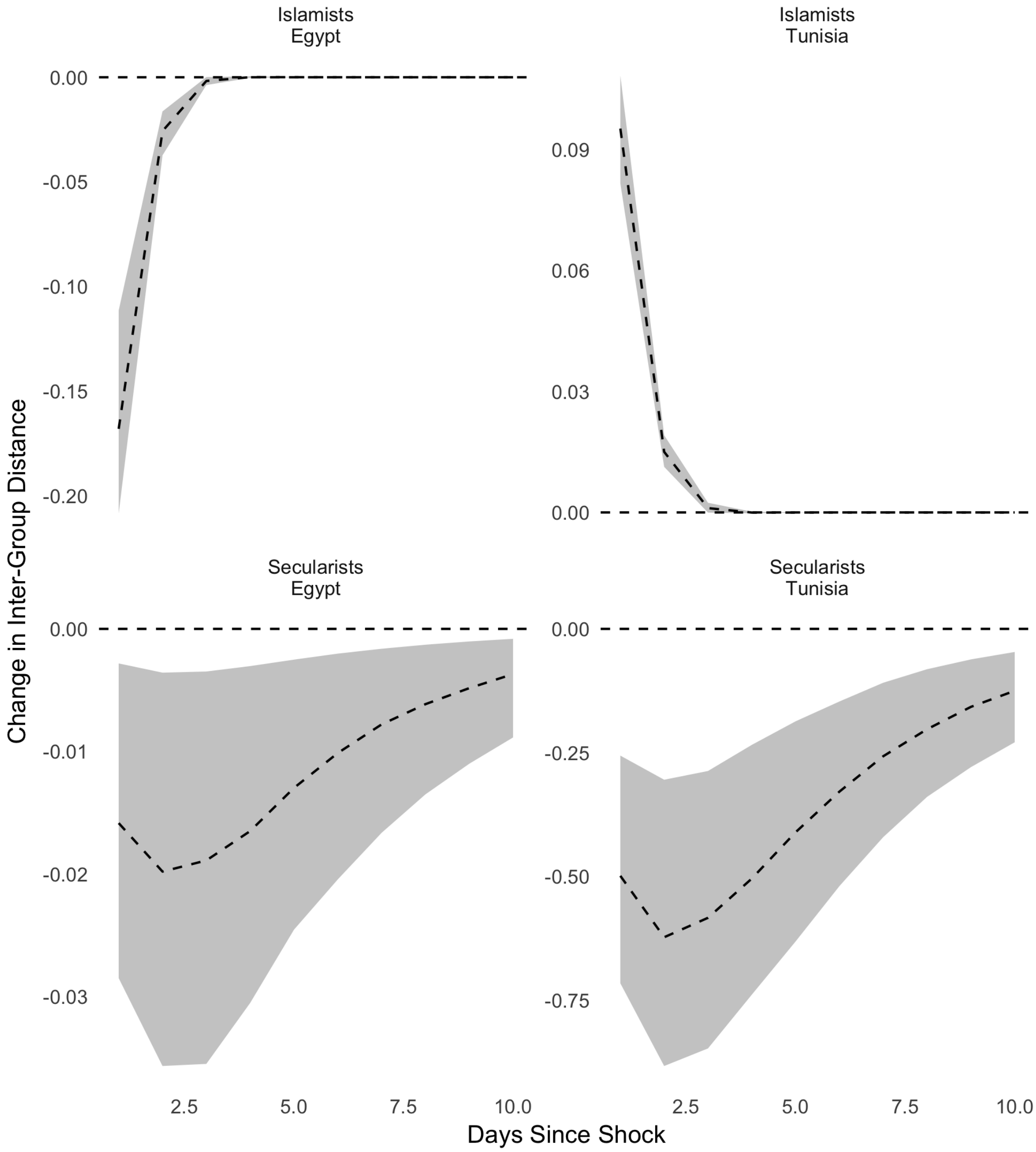


Figure 9 shows the posterior densities for our β_{cgx} parameter that measures the total effect of Morsi's coup on each of the time series. As can be seen, these values are uniformly positive and statistically distinguishable from zero. Unsurprisingly, the effect on Egyptian Islamists is three times larger than for other groups. To interpret these values correctly, the relative position of each ideological group in Figure 4 must be kept in mind. Because Egyptian secularist are further down the scale than Egyptian Islamists, the positive values imply that 1) Egyptian Islamists moved away from Egyptian secularists after the coup and that 2) to a much lesser extent, Egyptian secularists also moved towards Islamists. Interestingly, the opposite logic holds for Tunisia: the coup caused Tunisian Islamists to move closer to the position of secularists, while secularists moved farther away, although substantively these movements are much smaller. These findings show how the simpler within-country interpretation available in Figure 7 needs to be adjusted to understand the specific reactions of different groups in the period after the coup.

While these revelations are substantively interesting, the value of β_{cgx} alone cannot answer the questions posed by our hypotheses because these static values do not capture feedback effects or time auto-correlation. To test our hypotheses precisely, we calculate the impulse-response functions (IRFs) mentioned previously to test the hypotheses in Table 2. First, we examine H1 in Figure 10, which involves testing a basic null hypothesis that we should be able to detect some kind of response in one ideological group from a unit shock to their foreign ideological allies. While this shock is substantively quite large, using a 1-unit shock is convenient as we can then interpret the y axis as representing the proportion of the shock that transfered from one country to another. As can be seen in Figure 10, a one-unit shock in a foreign ideological ally does result in movement in each group. Tunisian secularists show the greatest responsiveness, with more than 50% of the shock transferring across borders in the initial day after the shock, with the Egyptian and Tunisian Islamists showing sizable but smaller impacts of the 1-unit shock. Overall, this evidence supports our hypothesis 1 that groups should be responsive to their foreign ideological allies, with the caveat that we could not identify clear transnational influence on Egyptian secularists.

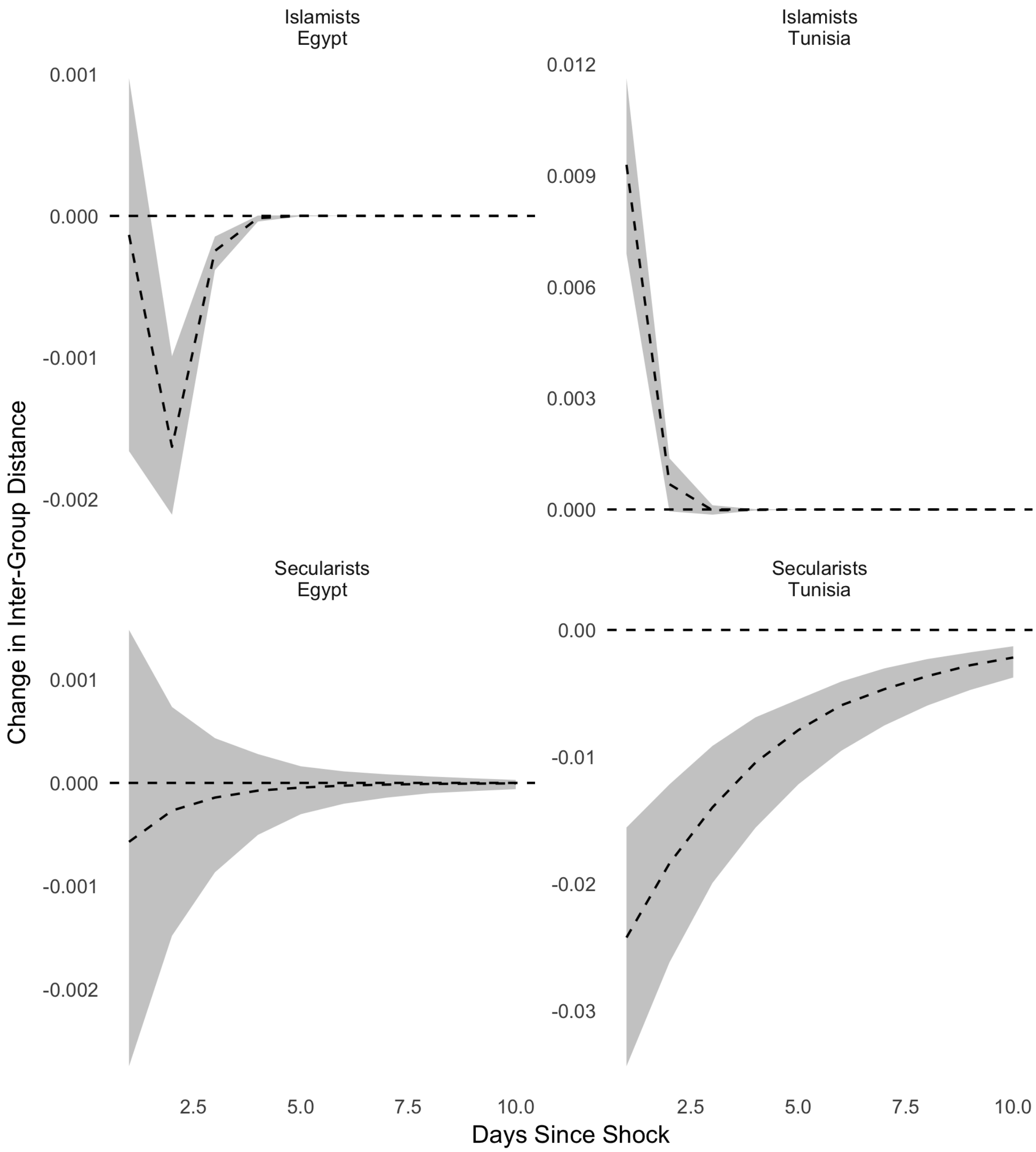
To test hypothesis 2, we can employ the same IRF technique except now we use the estimates for the Morsi coup effect β_{cgx} instead of a hypothetical 1-unit shock. In hypothesis 2, we are testing for the direct effect; i.e., whether the coup had a statistically distinguishable effect on each ideological group on itself over time. Figure 11 reveals that this direct effect does generally exist. Substantively, Egyptian Islamists and Tunisian Islamists have clear reactions to the coup, although the effects decay quickly, while the effect of the coup on Tunisian secularists is more durable over time.

Figure 10: IRF for 1-Unit Shock to Transnational Ideological Groups' Ideal Points



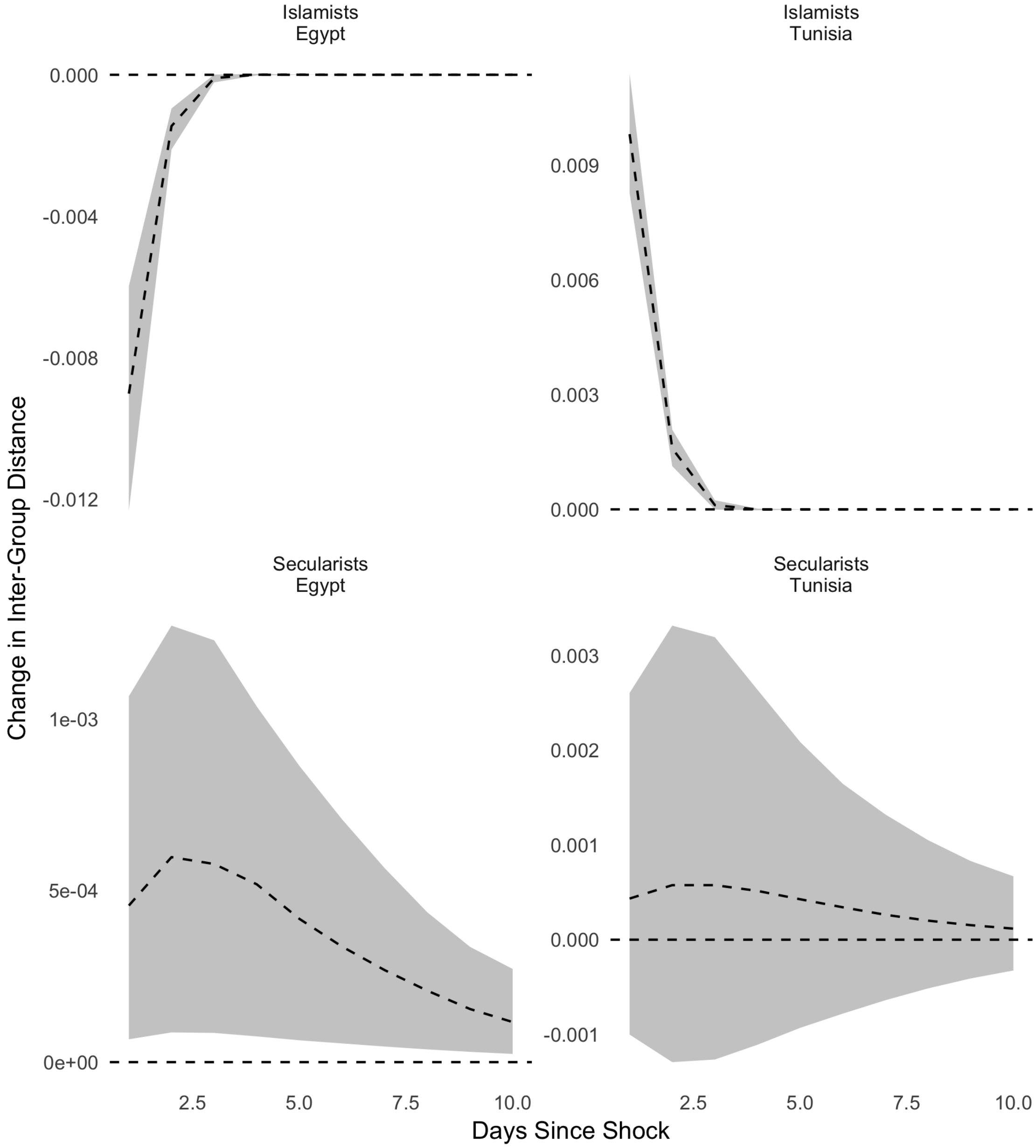
Next we test the indirect effect mentioned in hypothesis 3 of the Morsi coup, or the amount with which the shock of the coup transferred to ideological allies, in Figure 12. Unsurprisingly, these effects are substantially smaller than the direct effects in Figure 11. Interestingly, the indirect effects of Egyptian and Tunisian Islamists are almost identical because the smaller direct effect for Tunisian Islamists counterbalances Egyptian Islamists' greater sensitivity to transnational po-

Figure 11: IRF for Within-Time Series Direct Effect of Coup β_{cgx}



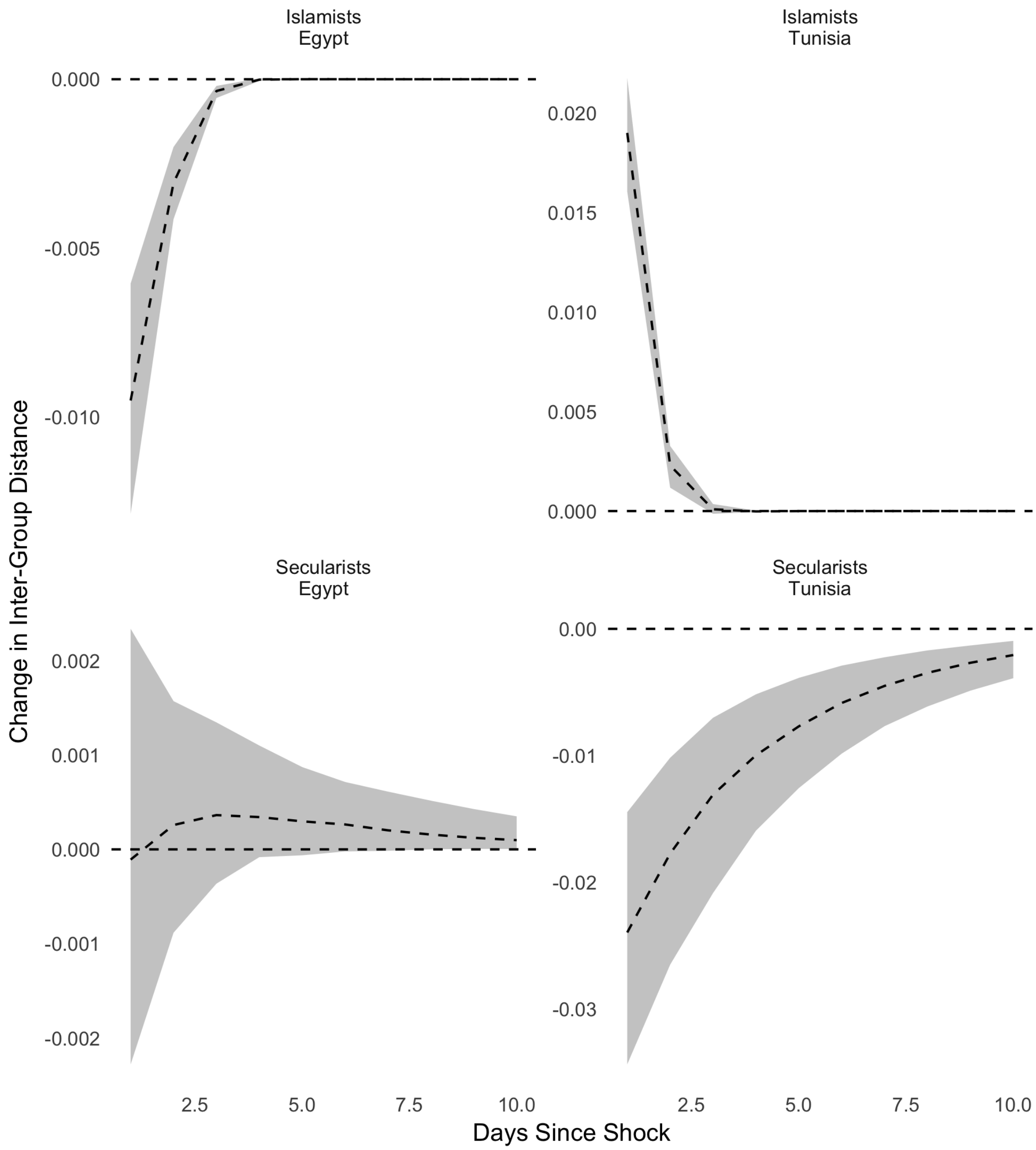
larization. Again, we would note that the secularists show relatively little responsiveness to the coup's effect on each other. Overall, the evidence shows that there are indeed indirect feedback effects of the coup across countries for ideological groups, although these indirect effects are most notable for Islamists.

Figure 12: IRF for Within-Time Series Indirect (Transnational) Effect of Coup β_{cgx}



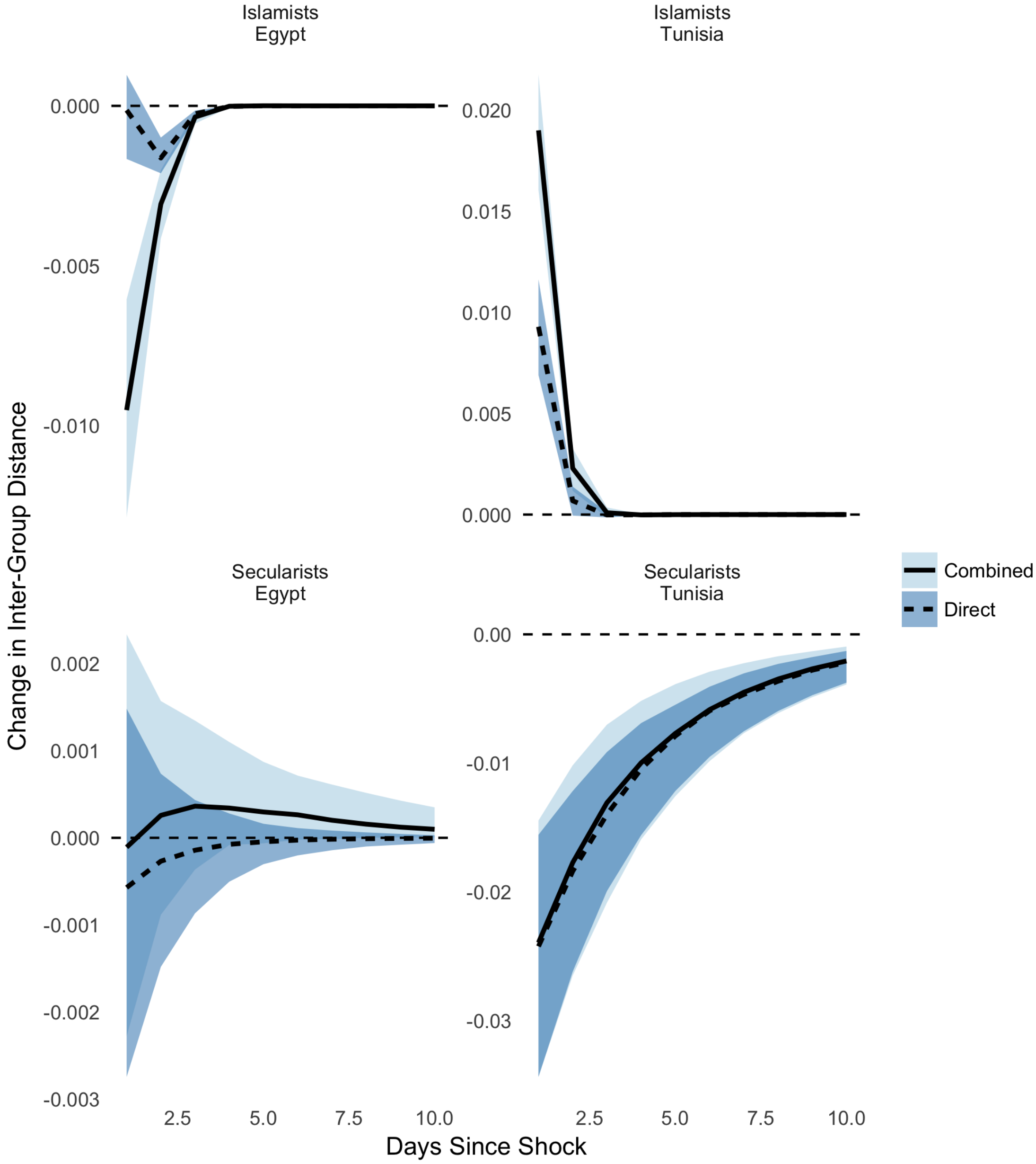
Finally, we examine hypothesis 4, which proposes that the combined effect of both the direct and indirect effects of the coup will also be greater than zero. In other words, once transnational polarization is taken into account, the coup actually has a greater total effect on moving the inter-group distance of ideological groups within countries. This hypothesis could be falsified if the direct and indirect effects counterbalanced each other, but as Figures 13 and 14 reveal, the com-

Figure 13: IRF for Within-Time Series Combined Effect of Coup β_{cgx}



bined effect is indeed greater than either the indirect or direct effect for Islamists. Figure 13 shows that the combined effects of the coup look similarly to the direct and indirect effects. What is interesting is to then overlay the combined effects on the direct effects, which we do in Figure 14. This plot makes the point that for Islamists, the combined feedback effects serve to heighten their movement in the latent space, while for secularists, this is not necessarily so. Secularists in Tunisia are

Figure 14: Comparison of IRF for Direct and Combined Effect of Coup β_{cgx}



largely indifferent to movement in their foreign ideological allies, while for secularists in Egypt, their co-religionists response to the coup does heighten their own response relative to the direct effect, although the difference is not very precise. In all, it is clear that the combined effects, or both the within-group effect of the coup and the feedback traveling across borders, prompt a higher level of salience and movement in the ideological space that corresponds to our theory of how ideological groups receive and transmit transnational polarization. Or to put it more colloquially, no ideological group is an island.

Discussion

The substantive interpretation of the movement of group-level ideal points presented in the previous section will require further theoretical development. Without having such precise measures of exactly how groups respond to each other in real time, we did not previously have the ability to come up with hypotheses that describe how Islamists and secularists will react to each other on a day by day basis. Furthermore, explanation of the exact trajectory of the ideal points over time will have to involve further specification of the sometimes conflicting determinants of group polarization that we presented in this paper. For example, in Tunisia, Islamists were under considerable pressure to dampen ideological conflict during this time period as they faced rising social unrest due to Islamist radical violence (McCarthy 2016). For that reason, after the coup in Egypt they may have feared supporting their co-religionists too publicly, lest they suffer a similar fate within their own country (Grewal 2016). This kind of suppression, or what we call de-polarization, may explain why Tunisian Islamists tended to move closer to Tunisian secularists in response to the coup, while the opposite occurred for Egyptian Islamists. We believe that our model's ability to identify these movements at a low level of granularity will provide fodder for further theoretical development of how group-level polarization actually occurs. As with modeling of other complex dynamic systems like weather patterns, we do not expect predictions to be deterministic, yet there is still much more we could learn empirically from this model.

In addition, because the model and data in this paper are novel, the external validity of this analysis is necessarily limited. We have not been able to measure this kind of ideological polarization precisely, and so we do not know whether the results we observe are substantively large relative to the universe of transnational sectarian polarization. Thus as is often the case, an increase in measurement precision also generates new hypotheses and areas for exploration. One of the main avenues for future inquiry is to apply this model to other countries, ideological groups, and time periods.

This study is further limited by the time range under consideration, approximately nine months during a period of political instability following the Arab Uprising. As we described in our theory section, endogenous polarization occurs within and between countries over time, so it can be difficult to obtain a long enough series to show all of the polarizing effects and their consequential after-shocks. For our data, we are limited in modeling dynamics before 2012 because many of the Islamists did not open Twitter accounts until the beginning of 2013, leaving limited ideological diversity prior to that date. This limited time series may explain why we do not observe an even larger polarizing effect of the anti-Morsi coup: by the beginning of 2013, groups had already become polarized, which would leave less room for yet more polarization to occur.

Yet even with those two previous caveats, our findings provide important insight into the underlying dynamics of transnational ideological polarization. It is difficult to study endogenous processes whether qualitatively or quantitatively, and we are able to analyze a very large dataset and reduce it down to the particular latent social cleavage of interest. Given how responsive the inter-group distance measure is to clearly polarizing events–some of which we did not identify in advance, such as the draft Tunisian constitution–our model's internal validity appears quite high.

As a result, the precision of the hypothesis tests we are able to implement in this paper enables us to identify the direct, indirect, and combined *transnational* effects of group polarization. Being able to separate these different components of the feedback process allows us to substantiate the major elements of the theory, and to support the central point of our paper that transnational linkages among ideological groups can endogenously heighten polarization independent of what is occurring within each group's country. While we are not the first to document such linkages, we are the first to directly measure this kind of transnational ideological polarization in a way that incorporates our uncertainty in measuring latent social cleavages.

Our analysis also raises questions that we had not considered before. The surprisingly unstable nature of Tunisian secularists shows that when the salience and inter-group distance is highly unstable for an ideological group, it can likewise have dramatic and unpredictable effects on ideological allies. While we do not consider our model incorrect–we do still believe that Tunisian secularists have long-term ideological beliefs that were not being revised under the short time period under study–the analysis does reveal that Tunisian secularists had a less fixed group identity than their foreign allies. Although we cannot with complete certainty tie these dynamics to observed outcomes in these countries, it is interesting to note that Tunisians were able, more broadly, to contain sectarian conflict and reach a political compromise in which the Islamist party stepped down for new elections, while sectarian conflict in Egypt resulted in brutal repression of Islamists that continues until today.

We would note as well the need to incorporate an explicit second dimension to ideological polarization, that of the pro- and anti-democracy axis, perhaps through the use of compensatory multi-dimensional IRT (Reckase 2009). We believe that this second dimension explains why the changes in the Tunisian constitution provoked a wider swing in inter-group distance than did the anti-Morsi coup. Pro-democratic secularists in both countries opposed the coup because of their commitment to democratic norms, which arguably reduced polarization or at least made it less likely for these secularists to adopt a more negative view of Islamists as a result of the coup. By comparison, the constitutional changes in Tunisia produced a much cleaner break along the secularist-Islamist cleavage. This difference between the two events is further validation that we were able to identify the secularist-Islamist cleavage among the diversity and noise present within the Twitter data.

One area of our data that we have not explored is the content of the tweets themselves. In fact, our empirical strategy is based in part on avoiding the challenging task of parsing tweets into useful categories. However, our approach to grounding the model in assigned ideological labels and retweets provides an avenue for incorporating text. A major challenge in text analysis is to know how to identify latent variables of interest underlying word counts (Slapin and Proksch 2008; Grimmer and Stewart 2013). By incorporating coded labels and retweets as a relatively direct measure of polarization, text could then be included as an additional source of information about polarization. This approach is similar to the recent efforts to find ways of estimating ideal points for legislators that combine both the text of legislation and legislators' observed votes (Lauderdale and Clark 2014). For these reasons, our model does not preclude analysis of text but rather helps provide an estimation framework for anchoring estimates of noisy Twitter data.

Conclusion

International diffusion of ideas and practices – including conflict – remains a vital area of study in comparative politics and international relations. For all of the theoretical and empirical progress in the study of diffusion, lacking have been studies demonstrating the spread of contention across national boundaries that account for pre-existing contention in the receiving country. In this paper we address this gap by putting forward a method of estimating the latent positions of ideological groups in Egypt and Tunisia during the tumultuous period of the Arab Uprising. We take advantage of Twitter's widespread usage to measure transnational polarization by showing how latent ideological scores change over time and also in tandem with similar ideological groups in other countries. The use of the IRT-VAR model allows for these estimates to incorporate measurement uncertainty while also providing useful summary measures of inter-group distance.

We find that the overthrow of Mohammed Morsi in a coup by the Egyptian military resulted in a long-term shift of the latent social cleavages of both secularists and Islamists in Egypt. This shock also eventually resulted in both groups moving farther apart from each other in the months ahead. The aftermath of the coup had its greatest effect on shifting the ideal points of Egyptian and Tunisian Islamists, with weaker effects on Egyptian and Tunisian secularists. Furthermore, for Islamists, we find that the combined effect of both the coup and the feedback each member of the group received from its foreign ideological ally resulted in greater movement in ideal points, and hence polarization, relative to each member of the group's individual response to the coup.

Of course, the spread of group polarization is only one narrow question in the general question of international diffusion. Mechanisms, the efficacy of diffusing and blocking agents, the diffusing phenomenon itself, and many other factors are needed to complete the picture. It is worth noting that thus far the political outcome in Tunisia – enduring if fragile democracy – is different from that in Egypt – a military-authoritarian secular regime. Still, it is important to establish empirically whether and through what mechanisms contentious politics can diffuse across national borders, and that is what we have done. Our findings open the door to further exploration of the determinants and measurement of transnational polarization during periods of political instability. This model provides a rich range of estimates and can pinpoint places at which polarizing events occurred. Furthermore, we can show how short-term shocks translate into long-term differences in polarization over time. We hope that this evidence stimulates more investigation of the determinants and effects of group feedback effects in ideologically polarized societies.

Appendix A: List of Elites

Username	Secularist/Islamist
slim404	Secularist_Tunisia
ooouups	Secularist_Tunisia
nawaat	Secularist_Tunisia
psycke	Secularist_Tunisia
karim2k	Secularist_Tunisia
riadheh	Secularist_Tunisia
mira404	Secularist_Tunisia
yassayari	Islamist_Tunisia
sarah_bh	Secularist_Tunisia
majdikhan	Secularist_Tunisia
maramirou	Secularist_Tunisia
marwen	Secularist_Tunisia
benmhennilina	Secularist_Tunisia
slimazzabi	Secularist_Tunisia
jnayna	Secularist_Tunisia
azyyoz	Secularist_Tunisia

arabasta1	Secularist_Tunisia
zinga_	Secularist_Tunisia
c_moii	Secularist_Tunisia
jasmintn	Secularist_Tunisia
sans_url	Secularist_Tunisia
indigo_light	Secularist_Tunisia
takriz	Secularist_Tunisia
sameh_b	Secularist_Tunisia
nayzek	Secularist_Tunisia
liliopatra	Secularist_Tunisia
eyaturki	Secularist_Tunisia
faiyla	Secularist_Tunisia
zizoo	Secularist_Tunisia
houeida	Secularist_Tunisia
malekk	Secularist_Tunisia
ahlemhc	Secularist_Tunisia
tom_z	Secularist_Tunisia
chiheb12	Secularist_Tunisia
zeinebturki	Secularist_Tunisia
khamousss	Islamist_Tunisia
may_mouna	Secularist_Tunisia
yamenbousrih	Secularist_Tunisia
ifikra	Secularist_Tunisia
blech_klem	Secularist_Tunisia
emnachebaane	Secularist_Tunisia
bidules	Secularist_Tunisia
khalilbm	Secularist_Tunisia
boukornineblog	Secularist_Tunisia

out__rage	Secularist_Tunisia
yhzami	Secularist_Tunisia
viagramoniak	Secularist_Tunisia
mounej	Secularist_Tunisia
maroo_king	Secularist_Tunisia
kiffegrave	Secularist_Tunisia
albawsalatn	Secularist_Tunisia
nizarus	Secularist_Tunisia
r_ghannouchi	Islamist_Tunisia
nahdhatunisie	Islamist_Tunisia
ali_larayedh	Islamist_Tunisia
yusraghkh	Islamist_Tunisia
ziedladhari	Islamist_Tunisia
bassemloukil	Secularist_Tunisia
mehdi_jomaa	Secularist_Tunisia
alaa	Secularist_Egypt
waelabbas	Secularist_Egypt
ghonim	Secularist_Egypt
nawaranegm	Secularist_Egypt
sandmonkey	Secularist_Egypt
elbaradei	Secularist_Egypt
zeinobia	Secularist_Egypt
3arabawy	Secularist_Egypt
amrmsalama	Secularist_Egypt
monasosh	Secularist_Egypt
kalimakhus	Secularist_Egypt
drbassemyoussef	Secularist_Egypt
gamaleid	Secularist_Egypt

salmaeldaly	Secularist_Egypt
yosrifouda	Secularist_Egypt
wael	Secularist_Egypt
monaeltahawy	Secularist_Egypt
alyaagad	Secularist_Egypt
galalamer	Secularist_Egypt
amrwaked	Secularist_Egypt
mand0z	Secularist_Egypt
adel_salib	Secularist_Egypt
hazem_azim	Secularist_Egypt
ahmadesseily	Secularist_Egypt
zeinabsamir	Secularist_Egypt
lilianwagdy	Secularist_Egypt
5orm	Secularist_Egypt
sarahcarr	Secularist_Egypt
gsquare86	Secularist_Egypt
minazekri	Secularist_Egypt
ahmednaguib	Secularist_Egypt
gemyhood	Secularist_Egypt
shokeir	Secularist_Egypt
heshoz	Secularist_Egypt
mennagamal	Islamist_Egypt
theboghdady	Secularist_Egypt
seksek	Secularist_Egypt
sarahngb	Secularist_Egypt
thebigpharaoh	Secularist_Egypt
h_eid	Secularist_Egypt
lastoadri	Secularist_Egypt

rashapress	Secularist_Egypt
minanaguib90	Secularist_Egypt
ahmad_khalil	Secularist_Egypt
naguibsawiris	Secularist_Egypt
mazloum	Secularist_Egypt
nabilelhalfawy	Secularist_Egypt
alnagar80	Secularist_Egypt
theadly	Secularist_Egypt
thesherio	Secularist_Egypt
kalnaga	Secularist_Egypt
midoo0	Secularist_Egypt
dr_heba_raouf	Islamist_Egypt
moftasa	Secularist_Egypt
ahmdalish	Secularist_Egypt
theonlywarman	Secularist_Egypt
pakinamamer	Secularist_Egypt
zelaky	Secularist_Egypt
embee	Secularist_Egypt
ahmada2	Secularist_Egypt
ramiii	Secularist_Egypt
mar3e	Secularist_Egypt
alaaaswany	Secularist_Egypt
alienzero	Secularist_Egypt
salmasaid	Secularist_Egypt
i3atef	Secularist_Egypt
loainagati	Secularist_Egypt
memam8	Secularist_Egypt
ayaabdullah	Secularist_Egypt

bassem_sabry	Secularist_Egypt
bothainakamel1	Secularist_Egypt
tarekshalaby	Secularist_Egypt
m3adel	Secularist_Egypt
amrrodriguez	Secularist_Egypt
malek	Secularist_Egypt
etharkamal	Secularist_Egypt
ssirgany	Secularist_Egypt
__safi__	Secularist_Egypt
hfakhry	Secularist_Egypt
hamzanamira	Islamist_Egypt
asmaamahfouz	Secularist_Egypt
egyptocracy	Secularist_Egypt
nasry	Secularist_Egypt
mohamedwaked	Secularist_Egypt
themiinz	Secularist_Egypt
muhammadmorsi	Islamist_Egypt
ikhwanweb	Islamist_Egypt
mushaweh	Islamist_Egypt
azzaelgarf	Islamist_Egypt
asmaaghazalll	Islamist_Egypt
alnourpartyeg	Islamist_Egypt
yonosmakhyoun	Islamist_Egypt
naderbakkar	Islamist_Egypt
gelhaddad	Islamist_Egypt
alqaradawy	Islamist_Egypt

Appendix B: Simulation Study of IRT-VAR

To construct the latent inter-group distance time series, we employ as our base specification the standard 2-PL IRT model that can be used to estimate the canonical ideal point model (Clinton, Jackman, and Rivers 2004). Formally, we use this model to predict the mean of a product of Gaussian-distributed random variables Y_{cgjt} (standardized retweet counts) with common variance σ_Y:

$$\prod_{C}^{c=1}\prod_{G}^{g=1}\prod_{J}^{j=1}\prod_{T}^{t=1} Y_{cgjt} \sim N(\delta_j \alpha_{cgt} - \beta_j, \sigma_Y) \tag{8}$$

In this model, α_{cgt} represent the latent ideal points of all the elites in each ideological group-country combination gc at each time point t, while δ_j represents how strongly ideological citizen j's retweet pattern is and β_j is a citizen-specific intercept. We know from Clinton, Jackman, and Rivers (2004) that we can interpret this model as citizens choosing to retweet an elite if and only if that elite's ideal point in a latent space is closer to the citizen's ideal point in the latent space than the ideal point of any other elite.

Given that we want to focus on relative changes in ideological polarization, we standardize Y_{cgjt} within users so that the outcome represents the relative weight of each ideological group in a user's tweet patterns. This standardization helps us to address the problem that some users tend to retweet at much higher rates in general than other users (Barberá 2015). It also significantly increases the speed of estimation relative to using a Poisson or other count model.

In order to estimate this model, we situate equation 8 in a Bayesian framework in which we define θ as the full set of parameters we can estimate in (8), and we want to know the most likely values of θ conditional on the observed data Y_{cgjt}:

$$p(\theta|Y_{cgjt}) \propto p(\theta)p(Y_{cgjt}|\theta) \tag{9}$$

Using this standard form of Bayesian inference, equation 8 becomes the likelihood $p(Y_{cgjt}|\theta)$, and we can then look at endogenous relationships between ideal point parameters via the priors of these parameters, $p(\theta)$. In particular, building on Martin and Quinn (2002) and Kropko (2013), we can model the vector auto-regression between the ideological groups g via priors on the α_{cgt}:

$$\alpha_{cgt} \sim N(\gamma_{cg} + \beta_{cgIN}\alpha_{cg(t-1)} + \beta_{cgOUT}\alpha_{-cg(t-1)} + \beta_{gcx}X + \beta_c I(c), \sigma_{cg}) \tag{10}$$

Equation 10 shows how any one elite group α_{cgt}'s latent score in time t is a function of its prior time period latent score, $\beta_{cgIN}\alpha_{cg(t-1)}$, and the latent score of the same group g but opposite country $-c$ in the previous time period, $\beta_{cgOUT}\alpha_{-cg(t-1)}$. As can be seen relative to equation 1, equation 10 substitutes the observed time series y_t and x_t with the latent ideal scores α_{cgt}, but otherwise has the same parameters β_{cgIN} and β_{cgOUT}. In other words, we use the IRT model to construct the time series by estimating the latent positions of the elite actors, but we are also able to directly estimate parameters of interest even with this measurement uncertainty. Because these priors are multiplied with the likelihood $p(Y_{cgjt}|\theta)$, we can then estimate a full joint density of both the IRT model and the vector autoregression between latent ideological positions so that uncertainty in both models is appropriately captured.

There are two other notable features of equation 10. First, we include exogenous regressors $\beta_{gcx}X$ and $\beta_c I(c)$. $\beta_{gcx}X$ represents a binary vector that equals 0 before a polarizing event occurs, and 1 afterward, so that we can directly measure the effect of polarizing events on the ideal points α_{cgt}. $\beta_c I(c)$ is an indicator function (dummy variable) that represents a fixed effect for countries and equals 1 when $c = Tunisia$ and 0 otherwise. We include this dummy variable as a way to help achieve identification of the rotation of the ideal points by constraining β_c to be positive (see (Bafumi et al. 2005) for a full discussion of ideal point identification). Finally, we include separate variance parameters σ_{cg} to directly model heteroskedasticity in the time series.

At this point, we have defined the IRT-VAR model that allows us to make time-series inferences on the over-time changes in the elite ideal points α_{cgt}. However, this model is only defined over the retweet counts in which we have observed a citizen j retweet one of the elites in a specific time period t. As mentioned in the previous section, we expand our observed data to include all the times that each citizen j *does not* retweet an elite in each time period, or $Y_{cgjt} = 0$. If we simply include those zeroes in our likelihood $L(Y_{cgjt}|\theta)$ as additional data, we will be making the very strong assumption that each citizen j looked at every tweet from every elite in time period t and decided whether or not to retweet each tweet. In fact, that assumption may not hold for any of the citizens in our data except for unusually thorough citizens who want to have all influential Twitter users in their feed. As a result, we are concerned about a form of selection bias in which citizens are only exposed to tweets from those elites who are ideologically proximate to them, either because 1) Twitter's recommendation algorithm suggests that they follow elites who are ideologically proximate or 2) the citizen prefers to have a network is full of ideological allies or 3) both of these factors in interaction.

For these reasons, we need a separate likelihood for the case when $Y_{cjgt} = 0$. To do so, we incorporate the missing-data mechanism employed by Kubinec (2017), in which a hurdle model is used to account for missing data in an ideal point model when missingness is plausibly a function of the value of a person's ideal points. Given that this missingness pattern is very likely present in our data for the reasons previously described, we define a new likelihood $L(Y_{cjgt} = 0|\lambda)$ conditional on a different set of parameters λ:

$$L(Y_{cjgt} = 0|\lambda) = \prod_{C}^{c=1} \prod_{G}^{g=1} \prod_{J}^{j=1} \prod_{T}^{t=1} logit^{-1}(\delta_{Aj}\alpha_{cgt} - \eta_{Aj}) \tag{11}$$

What should be noted about this model is that we now have a Bernoulli-distributed random variable $Y_{cjgt} = 0$, and so we predict this probability using a logit link function of the parameters in λ. These parameters represent a separate IRT equation with the same elite ideal points α_{cgt} but separate discrimination parameters for the citizens δ_{Aj}. These separate set of citizen parameters represent a citizen's latent willingness to look at tweets from across ideological spectrum that is independent of that citizen's own individual ideal point, or what could be thought of as that citizen's desire to be informed of tweets from across the ideological spectrum. We include citizen intercepts η_{Aj} that represent missingness that is ignorable, which will occur if $\delta_{Aj} = 0$ and the probability of a citizen seeing a tweet is equal to that citizen's average number of tweets per group for the sample period. Ignorable missingness can occur if, for example, a citizen does not see tweets because they are working or on vacation. Importantly, in either case, the elite ideal points α_{cgt} that are our focus of inference will adjust to the uncertainty in this first-stage selection model. Our revised Bayesian model can then be written as follows in terms of the joint distribution of $Y_{cjgt} = 0$, $Y_{cjgt} \neq 0$, λ and θ:

$$p(\theta, \lambda | Y_{cgjt} \neq 0, Y_{cgjt} = 0) \propto p(\theta) p(\lambda) \cdot \tag{12}$$

$$[L(Y_{cgjt} = 0|\lambda) + (1 - L(Y_{cgjt} = 0|\lambda)) L(Y_{cgjt} \neq 0|\theta)] \tag{13}$$

To finish our model specification, we include here our prior distributions for all other parameters in the model:

$$\eta_{Aj} \sim N(0, \sigma_\eta) \tag{14}$$

$$\delta_j \sim N(0, 5) \tag{15}$$

$$\delta_{Aj} \sim N(0, 5) \tag{16}$$

$$\gamma_{cg} \sim N(0, 3) \tag{17}$$

$$\beta_{gcx} \sim N(0, 3) \tag{18}$$

$$\beta_{cgIN} \sim N(0, 1) \tag{19}$$

$$\beta_{cgOUT} \sim N(0, 1) \tag{20}$$

$$\alpha_{cg1} \sim N(0, 1) \tag{21}$$

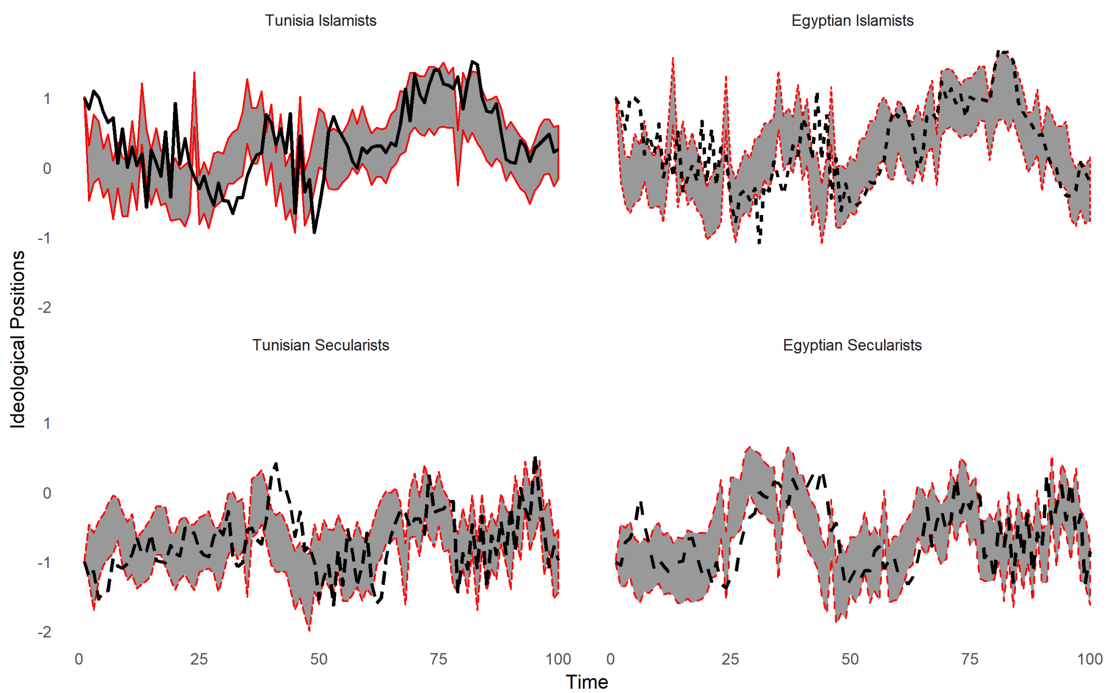
$$\sigma_\eta \sim E(1) \tag{22}$$

$$\sigma_{cg} \sim E(1) \tag{23}$$

$$\sigma_\delta \sim E(1) \tag{24}$$

What is important to note about the prior distributions is that because the outcome is standardized, each standard deviation of 1 for a prior distribution corresponds to a standard deviation of 1 in the outcome if the prior has a Normal distribution. As such, the $N(0,3)$ and $N(0,5)$ represent weak priors, while the β_{cgIN} and β_{cgOUT} parameters receive stronger unit Normal priors in order to bias the model towards stationarity (although we do not impose a hard constraint). The hierarchical prior on η_{Aj} is used for both regularization, as there are many citizens in the model, and for identification (Bafumi et al. 2005). We also put a tight prior on the first time point of the elite ideal points α_{cg1} to help identify the scale of the ideal points as well as fixing the overall variance σ_Y at 1.

Figure 15: Recovery of True Parameter Values



Finally, Figure 15 shows the performance of the model at recovering the latent time series using Bayesian MCMC estimation within the Stan framework (Carpenter et al. 2017). While the recovery is not perfect, it is able to follow the same path of the generated data. The uncertainty around the latent process will by necessity be larger because the time series themselves are unobserved.

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