Political Polarization as a Co-adaptive Process *

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Abstract

Political polarization is often characterized as a consequence of changes in media technology and content. We argue, in contrast, for an account that views political polarization in media and the public as a co-adaptive process. This paper begins with a brief review of cultural evolution and co-adaptation, and then considers the application of similar ideas to over-time change in media and the public. Using formal models, we suggest that – in combination with any one of a range of well-established human biases such as in-group bias or cognitive dissonance – a reciprocal/co-adaptive (rather than unidirectional) relationship can best account for real-world dynamics. We consider the implications of these findings for our understanding of media "effects" and innovation in the design of communication platforms in modern representative democracy.

Keywords: political communication; co-adaptation; media technology; political polarization

Major technological innovations like television and the Internet have fundamentally changed the ways in which we learn about and engage with politics (e.g., Bimber, 2003; Shah et al., 2001; Neuman, 2016). VCRs allowed for "time-shifting" and increased diversification in television program viewership (Van den Bulck, 1999). Cable launched the 24-hour television news

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cycle and entertainment news programs (Baum, 2002). Social media facilitated the rise of incidental, rather than intentional, news exposure (Feezell, 2018). Small technological changes matter as well. Increasing the length of tweets led to more constructive but less empathic political discussions on Twitter (Jaidka et al., 2019), while allowing for a "respect" rather than simply a "like" button reduces partisan comments in online news (Stroud et al., 2017). Both large and small differences in technological "affordances" (Faraj and Azad, 2012) shape the design, reach, processing, and consequences of political information.[1]

The claim that technological change affects the ways in which we interact with the political world around us is not contentious, of course. There is a long history of work detailing the effects of communications technology on politics generally (e.g., Innis, 1951; Abramson et al., 1988; Neuman, 2010), and a growing body of work suggesting that technological change was fundamental to the growth of political polarization in particular (e.g., Prior, 2007; Persily and Tucker, 2020). Technology does not develop in a vacuum, however – it is a consequence of human efforts to solve human problems. Just as users adapt in response to technology, technological adaptations reflect designers' responses to users.

The objective of the current paper is to highlight the advantages of a more explicitly interactive, *co-adaptive*, explanation in accounting for trends in communications technology and politics. We first highlight a few ideas in the vast literatures on cultural evolution, coevolution and co-adaptation. Second, we connect these to the relevant literatures on technology and politics, and political polarization. Third, we use formal models to explore the relevance of co-adaptive models in our understanding of technology and political polarization.

We argue that work in political communication would benefit from the kind of joint consideration of technology and politics that a co-adaptive approach encourages, i.e., a consideration that highlights both endogeneity and cumulative long-term effects. The narrower argument – and the novel contribution to the study of political polarization in particular – is that the observed trends in political polarization are more likely to be the consequence of co-adaptation of technology and politics than they are to be the result of simple unidirectional effects of technology on politics. This is one inference we draw from the modeling exercise below. It is a more complex –

[1] Also see, e.g., Halpern and Gibbs (2013); Lane et al. (2019); Wise et al. (2006).

but we believe also more realistic – story than the technology-driven account of political polarization that is dominant in both academic work and public debate.

Cultural Evolution and Co-adaptation

There are vast literatures on cultural evolution and co-adaptation, and we will not attempt to review them in detail here. Even so, there are a few key themes in these literatures that are worth highlighting given our current objective.

The literature on cultural evolution suggests that some adaptations evident in humans are cultural in nature (Boyd and Richerson, 1995). Whereas biological evolution is inherited through genes, cultural evolution is the product of social learning. “Culture” in this literature is defined rather broadly, including, for instance, attitudes or beliefs, traditions, knowledge, and technologies(Boyd et al., 2013). The general dynamic behind cultural evolution is captured concisely in some existing reviews of the field: “When information is costly, natural selection will favor cognitive mechanisms that allow individuals to extract adaptive information, strategies, practices, heuristics, and beliefs from other members of their social group at a lower cost than through alternative individual mechanisms” (Henrich and McElreath, 2003, pg. 128) . “Like genes, cultural traits can be more or less adaptive depending on the environment and spread accordingly” (Creanza et al., 2017, pg. 7783).

The development of language depends on both biological (inherited) and cultural (learned) factors, for instance (e.g., Fay and Ellison, 2013; Smith and Kirby, 2008). Indeed, cultural evolutionary work on language may offer some particularly useful illustrations for scholars of media. A word emerges due to some communicative need, and it either becomes part of the lexicon or disappears based on its ongoing communicative clarity, ease of use, etc. A similar storyline can be told about the emergence of hashtags in social media (e.g., Cunha et al., 2011; Zappavigna, 2015): their appearance was based on the need for more efficiency in identifying the theme of tweets; and the durability of hashtags generally, and specific hashtags too, is the product of their clarity and efficiency in the context of social media interactions.

How might a cultural-evolutionary approach help us understand technology and political communication? Human evolution (both biological and cultural) is affected by technology, broadly defined; and as noted above, technology is one component of what the cultural evolution literature regularly characterizes as culture. A simple starting point, then, is to acknowledge that technological developments can have an impact on the adaptive value of different traits and behaviors. But the notion that we adapt in response to cultural/technological change is less important for our purposes than the recognition that culture and genes interact. Recent work on culture-gene co-evolution or dual inheritance theory highlights exactly this point. Evolution is driven not just by the independent effects of genes and culture, but also by the ways in which genes and culture interact over time. Genetic adaptations encourage cultural adaptations, and *vice versa*.

The literature on cultural niche construction (e.g., Jones et al., 1994) provides a storyline that may be especially relevant for our purposes. This work focuses on the ways in which cultural context, developed by humans, affects human evolution — not just through gene-culture interactions but through culture-culture interactions (e.g., Creanza et al., 2012). Cultural adaptations are thus partly a consequence of prior cultural adaptations. We might for instance view portable music players as a cultural/ technological adaption to the urban commuting environment (which itself is also a cultural/ technological adaption), insofar as the chaotic, impersonal nature of urban commuting encourages us to seek out means of gaining more control over our personal space (e.g., Grassi et al., 2009; Ito et al., 2009).

This body of work illustrates well the notion that the kind of co-adaption we are considering is entirely human-driven – humans develop technology, humans respond to that technology, and so on. Put differently: technology is not adapting on its own, it is adapting because humans produce technological changes. In one sense, then, the co-adaptation we consider below is not so much about humans and technology as it is about human users of technology and human designers of technology. Humans produce an environment (or niche) in which political communication then occurs; political communication shifts as a consequence, and then shifting demands and interests then lead to other design changes.

Note also that the portable music player example is helpful in identifying that the changes we consider are primarily (short-term) adaptive rather than (long-term) evolutionary. Most of the dynamics we might consider in political communication reflect changes that occur with a lifetime rather than across generations, after all; and if change occurs within a generation it is not genetic/evolutionary. Adaptation and evolution often overlap, however; cultural evolutionary dynamics often reflect both adaptive and evolutionary processes; and “evolutionary” theory and models are regularly used to understand a combination of short- and long-term phenomena (e.g., Boyd et al., 2011; Creanza et al., 2017). To be clear: the use of “evolutionary” models in the literature, and in the present case, does not depend on dynamics occurring exclusively through long-term change.

In sum, in line with the literature on cultural evolution we argue that human behavior adapts to (human-designed) technological change, this changed behavior then affects further technological development, and these reciprocal effects cumulate.

Technology and Political Communication

There already is a body of work signaling the potential for co-adaptive theory in work on media and communication. For instance, the literature on media ecology views communication technology as an ecosystem in which humans interact with each other, responding to or conditioned by that technology. This is evident in seminal work by Innis (1951) and McLuhan and Fiore (2001), each of whom gave serious consideration to the impact of technology on the nature of communication (and human civilization). Subsequent work has further highlighted the ways in which communication technology can alter distributions of power and political party systems (e.g., Abramson et al., 1988; Bimber, 2003).

Similar arguments are evident in the growing literature on habits and automaticity in the use of mobile technology. Bayer et al. (2016) write that “Mobile technology has also rewired, or allowed individuals to rewire, the underlying cognition of everyday life” (pg 131). By their account, the development of mobile technology produced new expectations and norms surrounding social connectedness. The related literature outlines various ways in which we develop both conscious and unconscious responses to cues from mobile technology, and considers the implications of these responses to how we consume information, interact socially, and understand the world around us (e.g., Rosen et al., 2013; Greenfield, 2015).

Much of the classic media ecology literature is focused on the unidirectional impact of technology on individuals and societies.[2] Early work was nevertheless instrumental in highlighting the ways in which communication

[2] For a more thorough account of the literature, including discussion of the technological determinism that is often attributed to early work in this area, see Scolari (2012).

technologies can produce change at the individual and societal level. And some more recent approaches view interactions between technology and humans as more reciprocal in nature. Actor-network theory argues for the view that humans and non-human things – both concepts and materials, like communications technology – are fundamentally intertwined, interacting over time (Latour, 2007). Chadwick (2017)'s notion of a "hybrid media system" similarly offers a view of media technologies that coevolve, where the content of one communication platform adapts in response to the content of another.[3]

Coevolution and co-adaption have been evoked more explicitly in other research, and two contributions have been particularly influential on the argument made here. First, Stewart and Williams (1998), writing relatively early in what they describe as a new era of "multimedia," suggest that predictions about the impact that new media will have on society are difficult because user demands adapt to technological capabilities, and vice versa. Second, Acerbi (2016) argues for the potential value of cultural evolutionary models in thinking about the effects of digital media; and Acerbi (2020) traces the way in which the "prestige bias" (Henrich and Gil-White, 2001) both conditions and responds to social media in which there are readily available indications of prestige in the form of likes and followers.[4]

There clearly has been some consideration, implicit and explicit, of different kinds of co-adaptive theories in communication. This approach has

[3] Also see Finneman (2006) on the coevolution of digital media; and Mackay (2000)'s account of users' adaptations to the X-Windows system. Relatedly, Neuman (2016) draws on evolutionary theory in describing the fundamentally different digital environment in which communication now occurs. And endogeneity and reciprocal causation are featured in other media- and technology-focused research as well. Bhattacharya et al. (2019) outline, and propose models that account for, the coevolution of users' network structure and content on social media, for instance. Slater (2007) proposes a reinforcing spirals framework which acknowledges that media use is often affected by the same variables that it affects. These accounts are not about technological change *per se*; but Slater in particular is very clear in setting out an account of media effects in which media use and attitudes are endogenous. A similar argument is made about media as reflection, not just a driver, of public attitudes in Wlezien and Soroka (2024).

[4] For a related, earlier account of the impact of new media on cultural transmission, see Barkow et al. (2012). Also see the argument presented in Whitaker et al. (2022), focused on the coevolution of social networks (not social media but in-person networks) and cognitive dissonance (i.e., the impact of being confronted with attitudes that are contrary to one's own). In Whitaker et al.'s account, the nature of our net-works affects our experience of cognitive dissonance, and vice versa.

nevertheless had limited impact on the literature about political polarization.

Co-Adaptation and Political Polarization

There is a rich literature focused on the ways in which changes in media content and technology have led to a highly polarized political climate in the U.S. and elsewhere. There have been several excellent reviews of that work over the past decade (e.g., Prior, 2013; Tucker et al., 2018; Kubin and von Sikorski, 2021). The current section accordingly offers just a brief account of some central elements of that literature.

For much of the latter half of the twentieth century, the U.S. was not especially polarized. Increasing ideological polarization occurred alongside the introduction of cable news, due in part to increased competition for viewers across a broader range of news sources. This technological shift was amplified with the introduction of the Internet. Part of the polarizing dynamic was driven by an increasing emphasis on national over local news, and the consequent (a) increasing power of partisanship on voting decisions (Trussler, 2021) and (b) partisan 'sorting' across broad, national-level political affiliations (Törnberg, 2022).[5]

It was also partly attributable to an increased partisan filtering of news stories in partisan outlets (e.g., Baum and Groeling, 2008).[6] Social media platforms incentivized the expression of more strongly stated opinions because those opinions receive immediate, broad attention and circulation (e.g., Hiaeshutter-Rice and Weeks, 2021). That circulation encouraged strongly stated reactions, and political discussion accordingly became more polarized. The novel ways in which social media combines news and social information also encouraged us to form negative attitudes about those who disagree with us politically (Settle, 2018).

The prevalence of more ideological content – in legacy news and social media – is thus correlated with the rise of selective exposure, i.e., the tendency

[5]Indeed, recent work suggests that local news outlets' decreasing coverage of national political news, and focusing more on local issues, is associated with decreased polarization amongst the public (Darr et al., 2021).

[6]Increasingly ideological content is also not just an aspect of news coverage — adaptations in mobile and social media have been important to social movements, outside of news coverage, on both the left and right of the political spectrum, after all (e.g., Mundt et al., 2018; Munger and Phillips, 2022).

to select news stories and sources that are in line with our pre-existing beliefs (Stroud 2010). Selective exposure is straightforward when partisanship is an increasingly clear feature of content, after all. Partisan news tends to move strong ideologues even further towards the extremes of the political spectrum (Levendusky, 2013). And to the extent that partisans are exposed to out-partisan viewpoints – especially in the context of new digital media – those opposing views may actually push partisans more towards the extremes (e.g., Bail et al., 2018; Lau et al., 2017). Even coverage of polarization may push perceived polarization upwards (Levendusky and Malhotra, 2016); and coverage of polarization amongst elites or strong partisans tends to affect citizens views of other citizens more generally (Ploger, 2024). It is significant that there is a tendency for news coverage, particularly in a high-competition environment, to focus on more extreme candidates, and thus paint a picture of a U.S. House that is more extreme than it actually is (Padgett et al., 2019). Media – partisan, social, and mainstream legacy media – generate misperceptions about the magnitude of polarization, resulting in even more polarization (Wilson et al., 2020).

For all of these reasons, social media use tends to be associated with increased polarization (Lee et al., 2022), and there is a cross-national association between digital media use more broadly and political polarization (Lorenz-Spreen et al., 2023).

Prior work identifies specific technological changes that quite clearly contributed to increasing polarization. The essentially random rollout of Fox News across the U.S. has allowed researchers a fair bit of leverage in identifying the causal effect of partisan cable news, for instance. Fox News shifted the nature of electoral competition, altering Republican candidates' perceptions of Democratic incumbents' vulnerability (Arceneaux et al., 2020). Fox News also appears to have increased local Republican vote shares and right-wing ideological extremism, and contributed to polarization both in Congress and amongst the public (e.g., Clinton and Enamorado, 2014; Martin and Yurukoglu, 2017). Relatedly, changes in algorithms appear to have produced shifts in the prevalence of local Republican versus Democratic party posts on Facebook (Reuning et al., 2022).

That said, the relationship between digital technology and political polarization is only partly captured by a literature that emphasizes the effects of technology on polarization. It is almost certainly also the case that growing polarization affects the development of communications technology, and that produces further polarization, and so on. It is of some significance, after all, that partisan polarization in the U.S. was apparent well before the rise of social media, and first amongst representatives rather than the public (e.g., Levendusky, 2010).

Viewed in this context, Fox News should be regarded not just as an exogenous shock to the system facilitated by the invention of cable, but rather the adaptation of cable technology to capitalize on increasing polarization in Congress alongside emerging ideas amongst the U.S. public. Indeed, prior work suggests that the design of cable news programming in the first place was *not* entirely exogenous – it was premised on the belief that there was a latent (and not-latent) interest in more partisan programming (Collins, 2004; Morris, 2005). Acknowledging this fact does no harm to any of the afore mentioned literature. That work does not argue that the creation of Fox News was entirely exogenous, after all, it is simply that the endogeneity of cable news development is in most (if not all) cases temporally prior to the period focused on in analyses of its effects. The endogeneity of the change in media technology simply rests in the background of this and other accounts of political polarization.

Similar dynamics are evident in the development of social media, which has clearly been adapted *to* political polarization. Some technological adaptions in response to a highly polarized atmosphere have been intended to reduce that polarization: for instance, social media platforms have made efforts to identify and reduce the circulation of highly partisan misinformation (e.g., Jennings and Stroud, 2021). Other technological adaptions have sought to capitalize on a highly partisan atmosphere, where the creation of new social networks like Parler and Truth Social are perhaps the most recent, most obvious examples, created in order to circumvent the perceived censoring of right-leaning discussion on existing social media (e.g., Aliapoulios et al., 2021). Each of these media adaptations was a response to an environment that is an outcome of prior interactions between politics and technology.

One objective of the current paper is thus to make more explicit a more reciprocal, cumulative account of political polarization. This storyline, evident in some reviews of the field (including Prior (2013)), is about *co-adaptation*, whereby those who design technology respond to demands from those who use it, and then users' preferences and priorities adapt, prompting additional changes in technology. We do not regard any of these claims as especially contentious. Indeed, we suspect that most of them are widely accepted even if they are not explicitly acknowledged with much regularity. But recognizing the endogeneity of technological change in particular has important implications for how we understand both past media "effects" and future possibilities. This is especially evident when we consider the co-adaptive relationship between media and public polarization more formally.

Polarization in the Public and Media

Before turning to our models we define our key variables, beginning with polarization amongst the public. Note first that the existing literature has identified different variants of polarization, including ideological polarization (focused on policy attitudes) and affective polarization (focused on assessments of in- versus out-partisans). The distinction between ideology and affect is of some significance, but it is also worth nothing that these forms of polarization also appear to be strongly correlated – in part because policy differences can lead to affective responses (Rogowski and Sutherland, 2016; Webster and Abramowitz, 2017; Riera and Madariaga, 2023).

Media content and technology plays an especially large role in the literature on affective polarization, and so we focus on that aspect of polarization here.[7] We thus begin with a standard empirical indicator of affective polarization, i.e., "the tendency for partisans to dislike and distrust those from the other party" (Druckman et al., 2021, p. 28). To do so, we rely on data from the American National Election Studies, and the classic measure of affective polarization amongst the public: party thermometer scores for the Democratic and Republican parties.

Thermometer scores ask respondents to rate a variety of groups and parties on a 100-point scale, where higher values indicate "warmer" assessments.[8] The left panel of Figure 1 shows trends across four different aggregations of thermometer scores for Democrats (blue) and Republicans (red), both for themselves (in-party ratings) and for the other party (out-party ratings).

[7] Although we believe that our argument can be applied to other conceptions of polarization as well.

[8] The wording of the National Election Study thermometer question battery is as follows: "I'd like to get your feelings toward some of our political leaders and other people who are in the news these days. I'll read the name of a person and I'd like you to rate that person using something we call the feeling thermometer. Ratings between 50 degrees and 100 degrees mean that you feel favorable and warm toward the person. Ratings between 0 degrees and 50 degrees mean that you don't feel favorable toward the person and that you don't care too much for that person. You would rate the person at the 50 degree mark if you don't feel particularly warm or cold toward the person."

Ratings for the opposing party are much lower, of course. Most importantly where polarization is concerned, the gap between the in- and out-party ratings grows over time, driven primarily by declining evaluations for the out-party.

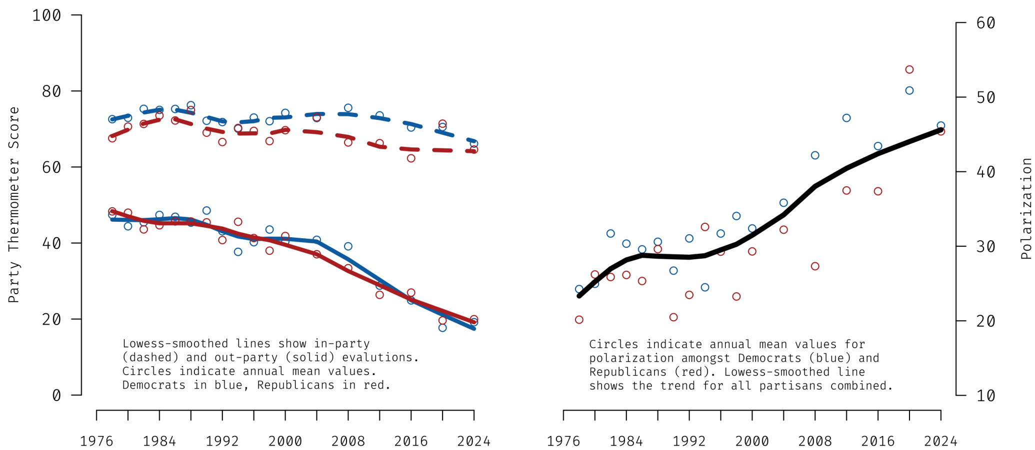

Figure 1: Left: In- and out-party evaluations. Lines show average feeling thermometer ratings that Democrats (blue) and Republicans (red) assign each party over time. Right: Affective polarization. Lines show the difference between in-party and out-party assessments amongst Democrats, Republicans, and all partisans combined. Data are from the American National Election Study 1948-2020 Time Series Dataset combined with the preliminary release of the 2024 dataset.

The right panel of Figure 1 offers an alternative summary of the data – and a single measure of polarization that is more similar to the hypothetical measure of polarization that we will focus on below. This is a standard measure of polarization in the field: the differences in between in- and out-party evaluations. The right panel of Figure 1 shows the measure for Democrats (blue) and Republicans (red) as circles, but the overall trend is easily captured using a combined measure, shows as a black line. There have been fluctuations around the trend, but the trend itself is very clear. The gap between party evaluations has roughly doubled over the past 40 years.[9]

[9]Note that the measure in Figure 1 is the standard survey-based measure of affective polarization, but there are of course alternative measures, including more policy-oriented measures for the public and for policymakers (e.g., McCarthy et al., 2008; Fiorina and Abrams, 2008; Hetherington, 2009).

Figure 1 sets out the empirical reality that we are trying to explain below. That said, in the models that follow we focus on polarization variables that are related to but also different from what is illustrated in Figure 1. Political polarization is an aggregate-level quantity, characterized by increasingly dissonant attitudes on policy issues across partisan lines, or by increasingly disparate evaluations of the in-party (or in-partisans) and the out-party (or out-partisans). But our models below necessarily depend on a version of polarization that is an individual-level phenomenon. We thus focus on a version of affective polarization defined, in line with recent work by Arceneaux and Bakker (2025), as a version of in-group bias. In our models, *public polarization* is the tendency for in- and out-groups to be defined by partisanship, and for individuals to increasingly have more positive views of their in-group than their out-group.

There is of course a large literature suggesting that humans are on balance predisposed towards in-group bias (e.g., Fischer and Derham, 2016; Mullen et al., 1992). And in-group bias is not the only well established bias in information processing that predisposes us towards political polarization: each of cognitive dissonance, motivated reasoning, and the use of partisan cues as information shortcuts (e.g., Druckman et al., 2013; Lodge and Taber, 2013; Petersen et al., 2013; Stroud, 2011) likely pull individuals in the direction of aggregate-level polarization.[10] These predispositions will play a central role in the models that follow.

Some previous work has used text analysis to identify polarization in news coverage, identified by increasingly different language used to discuss a range of policy issues (Hart et al., 2020; Chinn et al., 2020). The is one component of what we refer to as media polarization, although our conception of this variable is a fair bit broader. We use the term “media” to refer to the platforms and technologies that deliver content, as well as the content itself. There can be polarizing tendencies driven by cable news, or mobile technologies, or by particular online platforms, or by the content on those platforms, for instance. For our purposes below, we lump all of this together as “media.” And we define *media polarization* as the tendency for media to highlight and make salient partisan differences in attitudes, priorities or behavior.

[10]Also see a recent review in which Jost et al. (2022) outline a range of individual-level “cognitive–motivational” mechanisms that may help explain aggregate-level political polarization.

Modeling Technology and Polarization

Formal models, even extremely sparse models such as those we consider here, allow us to develop and test our intuition for what observations can be explained by a given set of assumptions (Smaldino, 2017; Page, 2018). In this instance we are interested in comparing what can be accounted for by a unidirectional model of polarization versus a co-adaptive one. As we will see, it is less plausible that the persistent rise in polarization evident in Figure 1 results from the unidirectional model implicit in much of the existing literature on media and polarization. Rather, a co-adaptive model that also incorporates human biases towards increasing polarization is more likely to have produced the dynamics we see in the U.S.

The Unidirectional Model

We first consider a simple unidirectional model in which exogenous changes in media affect the level of polarization in society. Note that this is essentially the structure that implicitly underlies the arguments in a good deal of the existing literature linking increasing polarization to cable technology and/or social media. (See the preceding section, as well as literature reviews including, e.g., Prior (2013); Tucker et al. (2018); Kubin and von Sikorski (2021); Arora et al. (2022).) In this literature, media technology impacts polarization through a variety of mechanisms including the affordances of selective exposure, emphasis on partisan content, and the use of partisan cues. Here we are agnostic about which of these mechanisms applies. We simply intend to capture an overarching model structure in which exogenous changes in media impact public polarization.

In order to focus on the aggregate dynamic interaction between media producers and media consumers, we represent the entire ecosystem of journalists, media firms, and technology platforms by a single variable, x, which, as noted above, we refer to simply as the polarization of the media. This omnibus variable x is meant to encompass any of the features of media from the literature that are thought to drive polarization. In other words, it is the independent variable describing media technology in a generic model of media technology's impact on public polarization. Similarly, we represent the public by a single variable, y, which we take as an aggregate indicator of polarization in the population.

To operationalize the idea that, over time, the level of polarization of public opinion adapts to the current media environment suppose that

$$y_t = y_{t-1} + \alpha(x_{t-1} - y_{t-1}) \tag{1}$$

for some $\alpha \in (0, 1]$.[11] To be clear: in this model, levels of public polarization (y) at time t are the product of public polarization in the previous time period (y_{t-1}) plus some adjustment that closes the gap between media polarization and public polarization in the previous time period ($x_{t-1} - y_{t-1}$). The rate of that adjustment, i.e., the rate at which the gap between public and media polarization is reduced, is controlled by α. Put differently, public polarization will adapt to become more similar to media polarization, where the parameter α determines the speed of that adjustment.

Note that equation (1) assumes that individuals have no predisposition towards in-group bias. The assumption is simply that public polarization will adapt to media polarization. It is however relatively straightforward (and much more realistic) to incorporate a human bias in the direction of increased polarization by replacing equation (1) with

$$y_t = y_{t-1} + \alpha(x_{t-1} - y_{t-1}) + \beta, \tag{2}$$

where $\beta \geq 0$ reflects the bias towards polarization. One interpretation of this new equation is that, at baseline, the public has a tendency towards increased polarization. If public polarization and technology polarization are already matched, so $x_{t-1} = y_{t-1}$, then equation (2) implies that $y_t = y_{t-1} + \beta$. Public polarization will accordingly increase by β in the next time period. It is important to note that equation (2) does not imply unbounded increases in polarization, however. That is, public polarization does not increase indefinitely if media remains fixed. This can be made clearer by rearranging equation (2) to pull the bias term inside the parentheses to obtain

$$y_t = y_{t-1} + \alpha\left(\left(x_{t-1} + \frac{\beta}{\alpha}\right) - y_{t-1}\right). \tag{3}$$

Note that equation (3) has exactly the same form as (1), albeit with x_{t-1} replaced by $x_{t-1} + \frac{\beta}{\alpha}$. Thus, as in equation (1), we can interpret (3) as capturing the tendency of public polarization to close the gap between its

[11] For convenience, we implicitly assume that x and y are measured in the same units, but more generally we could replace x_{t-1} in equation (1) by a monotonic transformation $f(x_{t-1})$ without impacting our model findings.

previous value y_{t-1} and a target level that depends on media polarization. But now, rather than approaching x_{t-1}, public polarization moves towards a target slightly greater than media polarization: $x_{t-1} + \frac{\beta}{\alpha}$. This feature of the model can also limit public polarization: if y_{t-1} exceeds the target level, $x_{t-1} + \frac{\beta}{\alpha}$, then the adaptive component in equation (3) pulls public polarization downwards.

The equation capturing variation in media polarization over time is comparatively simple. If we view changes in media as the product of random, exogenous changes unrelated to public polarization, then we can specify the evolution of technology polarization as follows

$$x_t = \max(0, x_{t-1} + \epsilon_t), \tag{4}$$

where current technology polarization (x_t) is always greater than or equal to zero and is a function of prior technology polarization (x_{t-1}) plus random changes (ϵ_t) – where those changes represent technology innovations that occur entirely independently of polarization in either the media or the public.

We view the model specified by equations (3) and (4) as being very similar to the storyline implicit in much of the literature connecting public polarization to media technology. In this account, individuals are predisposed towards in-group bias, and there are random shocks to media technology. These shocks change the degree to which media encourage or discourage polarization, and this has implications for public polarization.

Figure 2 illustrates how the system specified by equations (3) and (4) responds when there is a polarization increasing shock to media, a polarization decreasing shock to media, or a polarization increasing shock followed by an equal magnitude decreasing shock. The scale for our hypothetical indicator of polarization (on the vertical axis) is the same for both media (x) and the public (y). We set the initial value of polarization in both to 10 rather than 0, both here and in subsequent simulations, to suggest a mild amount of polarization; however, since our model scale is arbitrary, this choice carries no actual significance. So it is easier to see the public adapt to media, we leave human bias (β) at 0. Throughout $\alpha = .3$ and both x and y update over 40 time periods (shown on the horizontal axis).

We note three aspects of these results. First, while public polarization adapts gradually to changes in media, outside of shifts due to the assumed exogenous shocks, media do not change. Second, in the long run, both media and public polarization converge to a stable equilibrium. And third, the

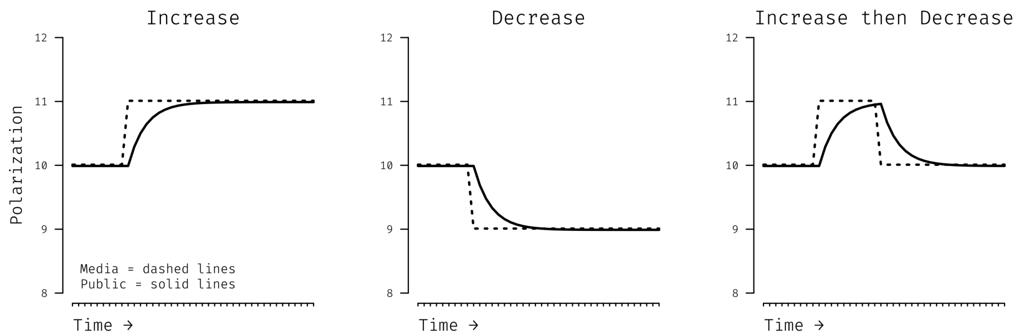

Figure 2: Three depictions of the unidirectional model of technology's influence on polarization.

effects of an initial polarization increasing shock to media are completely offset by a later equal magnitude polarization decreasing shock. Thus, there is no "path dependence" in this model system (Page, 2006).

It is possible to examine what the typical evolution of media and public polarization predicted by the unidirectional model specified in equations (3) and (4) looks like by simulating these variables under an assumed distribution of stochastic shocks. We run 10,000 such simulations, under the assumption that $\epsilon_t \sim N(0, 1)$. Figure 3 shows results assuming that there is *no* human bias, i.e., when $\beta = 0$. The left panel of Figure 3 shows the first three of these simulations. In this and subsequent cases, the media series from a particular simulation run is displayed in the same color as its corresponding public series. Note that by assumption this model produces a random walk for the polarization value of media, and polarization in the public follows with a lag. Sometimes polarization goes up, and sometimes it goes down, but there is no consistency to these changes.

The fact that polarization is as likely to decrease as increase is clearer in the right panel of Figure 3, which shows the kernel density plot for the final level of public polarization across all 10,000 simulations. Note that the distribution is centered around 10 – the same value for polarization at the beginning of the time series. Once formalized, then, the idea that the increase in polarization depicted in Figure 1 results from public opinion adapting to random shocks to media technology seems rather far-fetched. Without some force driving media towards increasing polarization, it would mean something like the flipped coin for shocks to media technology happened to come up heads forty times in a row.

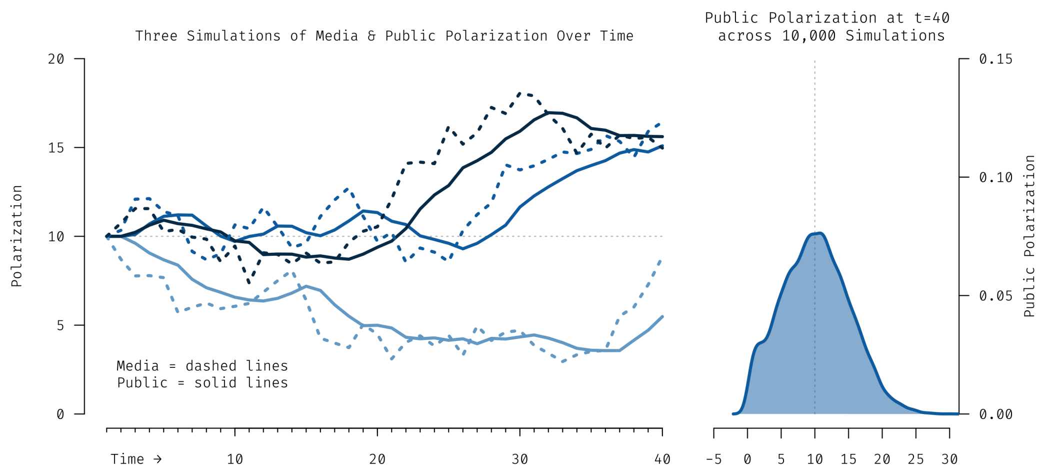

Figure 3: Left: Three simulations for a closed loop model in which public polarization adapts to technology. Right: Kernel density plot for the level of polarization after 40 time steps from 10,000 simulations.

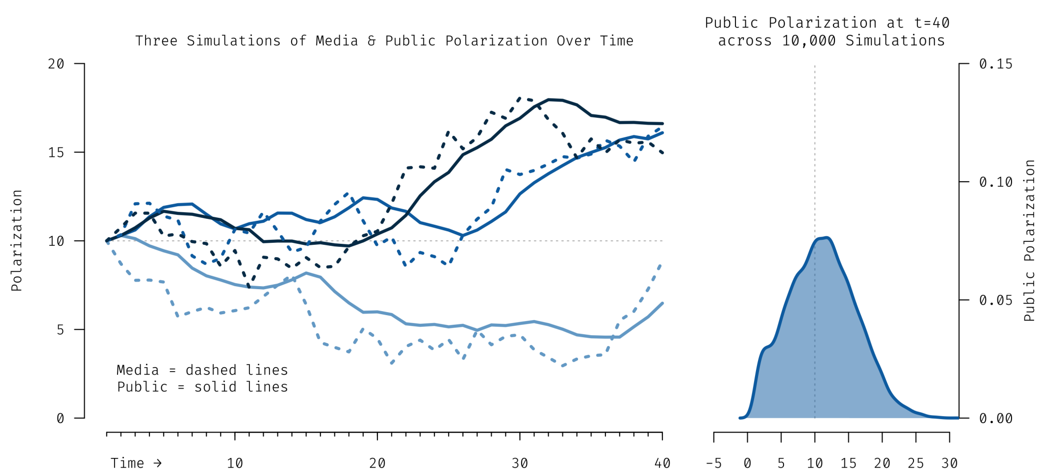

Figure 4: Left: Three simulations for a closed loop model in which public polarization adapts to technology, taking human bias into account. Right: Kernel density plot for the level of polarization after 40 time steps from 10,000 simulations.

Notably, the story does not change fundamentally when we introduce human bias into the unidirectional model. Figure 4 shows results based on a unidirectional system in which $\beta = 0.3$. These results are scarcely different from Figure 3. Outcomes still do not lean strongly towards polarization – that is, in this instance, even when humans are inclined towards polarization, the aggregate trend is not necessarily polarization. Random shocks to media technology can still push the system either towards or away from increased polarization. The only difference is that the levels of public polarization are on balance slightly higher. To be clear: in this univariate system, taking human bias into account does not systematically produce high polarization.

The Co-adaptive Model

Our unidirectional model suggests that human biases towards polarization do not on their own inevitably lead to polarization. Because of the adaptive component of equation (2), more readily identifiable in equation (3), increasing public polarization can be pulled downwards by media polarization.

Now we consider a co-adaptive model in which media not only influences polarization in public opinion, but polarization in public opinion also feeds back to affect media. In other words, if the population becomes more (or less) polarized, media–perhaps driven by the pressure of commercial competition–adapt to provide a platform that best serves that level of public polarization. We can modify our previous model to incorporate this feedback by retaining equation (3) but changing equation (4) to

$$x_t = \max(0, x_{t-1} + \gamma(y_{t-1} - x_{t-1}) + \epsilon_t) \quad (5)$$

for some $\gamma \in (0, 1]$. The new term in this equation, $\gamma(y_{t-1} - x_{t-1})$, specifies that media polarization will adjust to become more similar to public polarization, where the parameter γ controls the speed at which media moves to close the gap.

Figure 5 depicts three runs of the simulation of this closed loop model with the same parameters as shown for Figure 2 and $\gamma = .3$. Unlike in the results from the unidirectional model depicted in Figure 2, now both media and public polarization gradually adjust after an initial shock to media. One possible intuition for such a model is that its closed loop structure might create a reinforcing feedback that would either push the system towards higher and higher or lower and lower levels of polarization, where the direction of change would be determined by the random initial shocks that get the ball rolling. For example, an initial increase in media polarization would push public opinion polarization higher resulting in further increases in media polarization and so on. However, as Figure 5 illustrates, instead there is a

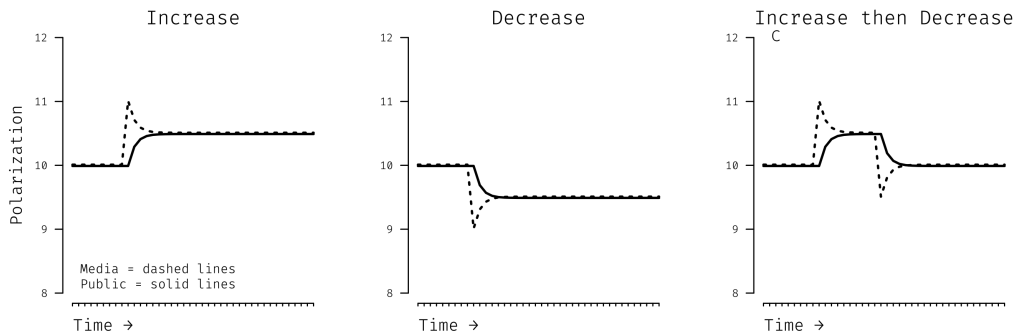

Figure 5: Three simulations of a closed loop model in which public polarization adapts to technology and technology adapts to public polarization.

balancing effect where an initial increase in media polarization results in a subsequent reversion in media polarization back towards its previous level.

To see why, consider the left panel of Figure 5. The initial polarization increasing shock to technology occurs at time $t = 10$. At that time, public polarization is $y_{10} = 10 + .3(10 - 10) = 10$ and media is $x_{10} = \max(0, 10 + .3(10 - 10) + 1) = 11$. In the next time step, public polarization responds by increasing to $y_{11} = 10 + .3(11 - 10) = 10.3$ but technology polarization now *decreases* to $x_{11} = \max(0, 11 + .3(10 - 11)) = 10.7$. Then public polarization increases further to $y_{12} = 10.42$ and media polarization decreases to $x_{12} = 10.58$. This pattern of marginally decreasing increases in y and marginally decreasing decreases in x continues until the two variables asymptotically approach a stable limit point at $x_\infty = y_\infty = 10.5$.[12] Whenever there is a shock resulting in a change in media polarization away from public polarization, public polarization adjusts part of the way to close the gap, and then in the subsequent step media polarization inevitably reverses course to move back closer to public polarization.

Does the trajectory of media and public polarization change when the system is co-adaptive rather than unidirectional? In absence of human bias, it does not. The left panel of Figure 6 depicts results from the first three (of 10,000) simulations of the co-adaptive model specified in equations (1) and (5), when $\beta = 0$. As in Figures 3 and 4, there is no consistent pattern

[12] The fact that the long run equilibrium is exactly half way between the value of media and public polarization immediately after the shock is an artifact of the choice to have the adjustment rates α and γ equal to one another in these simulations. If α and γ are not equal, the long run equilibrium will be closer to whichever variable adjusts more slowly.

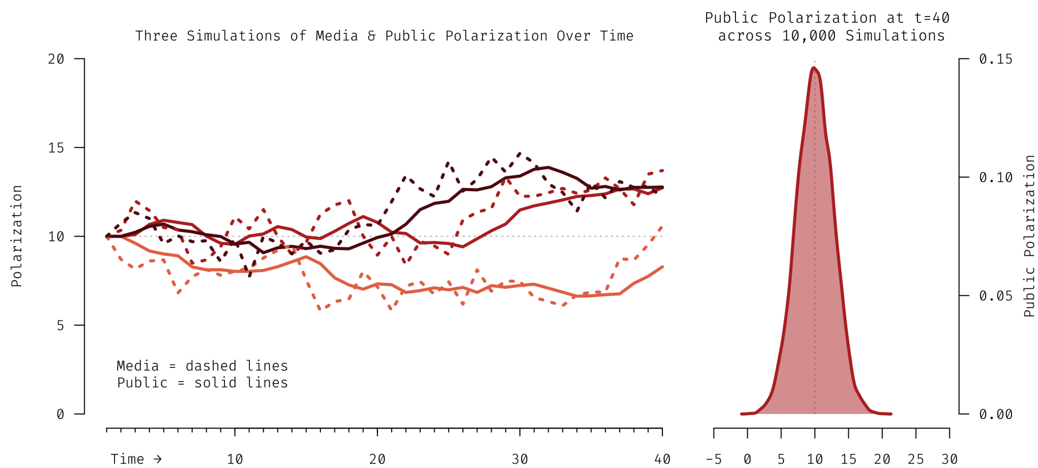

Figure 6: Left: Three simulations for a closed loop model in which public polarization adapts to technology and technology adapts to public polarization. Right: Kernel density plot for the level of polarization after 40 time steps from 10,000 simulations

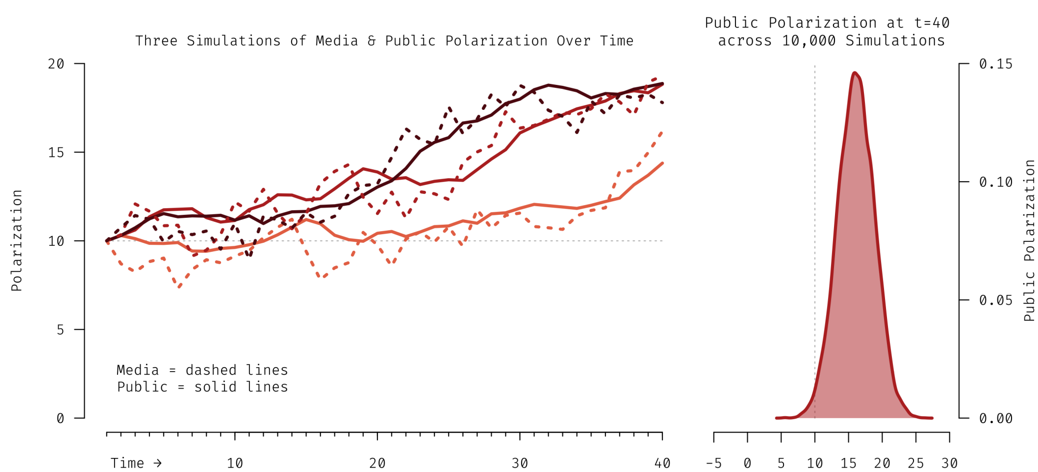

Figure 7: Left: Three simulations for a closed loop model in which public polarization adapts to technology and technology adapts to public polarization, taking human bias into account. Right: Kernel density plot for the level of polarization after 40 time steps from 10,000 simulations

of changes – but the changes that do appear are in this instance somewhat dampened by the balancing feedback of media adjusting to match the public. If anything, this form of co-adaptation limits the probability of steadily and steeply increasing (or decreasing) polarization. This is clearer in the right panel of Figure 6, which shows the distribution of simulated public polarization when $t = 40$ across all 10,000 simulations. Note that the distribution in this instance is narrower, and still centered around the starting point for polarization, 10.

The situation is very different when there is a combination of human bias and co-adaption, however. Figure 7 shows results when $\beta = 0.3$ – and all three simulations in Figure 7 trend steadily towards increased polarization. In this instance, the combination of human bias and co-adaptive media technology inevitably produces an environment in which both media and the public are strongly polarized. This is especially clear in the right panel of Figure 7, where the distribution for polarization is now well above 10.

Comparing Outcomes Across Models

We can of course make some more direct comparisons between the outcomes from the preceding four models. Table 1 shows three different ways of thinking about the differences between the models. The first column shows the mean value of public polarization across all 10,000 simulations at T=40. The second column shows the percentage of values at T=40 are above 10, the starting value of public polarization. Each of these measures captures the impact of models at the *end* of the time series. The third column, however, shows the percentage of time steps, over the entire 40 steps across 10,000 simulations, in which public polarization increases. This captures the likelihood at any given point in time that polarization will be increasing.

Model	Mean	% above 10	% changes > 0
Unidirectional	10.12	50%	50%
Unidirectional + Human Bias	11.12	58%	52%
Co-adaptive	10.01	50%	50%
Co-adaptive + Human Bias	16.11	99%	67%

Table 1: Outcomes Across Four Models of Public and Media Polarization. Cells show the mean value of public polarization, and the percentage of values above 10 after 40 time steps from 10,000 simulations, and the percentage of time steps in which public polarization increases, where $\alpha = 0.3$, $\gamma = 0.3$, and $\beta = 0.3$.

In the unidirectional model without bias the mean level of polarization at the end has scarcely increased from its starting point, and only 50% of the simulations end with a value above the starting point. At any given point in time, there is a 50% chance that polarization is increasing. Roughly the same is true for the unidirectional model with bias and the co-adaptive model without bias, each of which produce only slightly more polarization. For the co-adaptive model, however, mean polarization at the end of the time series is 16.11, the likelihood of increasing polarizatin at any given point in time is 67%, and 99% of the simulations end above 10.

We can also plot the four kernel density plots from Figures 3, 4, 6, and 7 together, as in Figure 8. Results for the unidirectional models are shown in the left panel and results for the co-adaptive models are in the right panel. Note that the left panel shows two nearly identical distributions, where the one that takes bias into account has shifted just slightly – about $\beta/\alpha = 1$ – to the right. The right panel shows starker differences between two distributions: one in which human bias is not taken into account, centered around 10, and another in which the combination of human bias and a co-adaptive relationship between the public and media produces increased polarization.

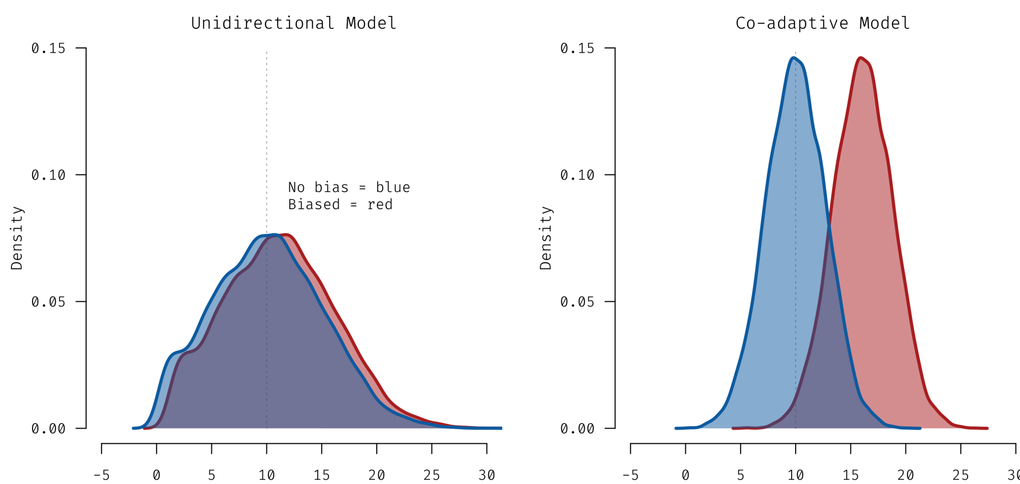

Figure 8: Kernel density for the level of polarization after 40 time steps from 10,000 simulations each of the unidirectional model with and without bias and the co-adaptive model with and without bias, where $\alpha = 0.3$, $\gamma = 0.3$, and $\beta = 0.3$.

While the point estimates in these results are of course contingent in part on the assumed values of α, γ and β, as well as our ending the simulations after 40 time periods, our general findings are robust to changes in these parameters. For example, Table 2 shows mean final values of polarization, the percent of simulations ending with polarization above ten, and the percent of changes over time in which public polarization is increasing, for decreasing values of β under two different assumed values for γ.

Model	Mean	% above 10	% changes > 0
where $\alpha = 0.3$ & $\gamma = 0.3$...			
$\beta = 0.3$	16.11	99%	67%
$\beta = 0.2$	14.08	93%	61%
$\beta = 0.1$	12.04	77%	56%
$\beta = 0.05$	11.02	65%	53%
where $\alpha = 0.3$ & $\gamma = 0.1$...			
$\beta = 0.3$	13.450	81%	58%
$\beta = 0.2$	12.34	72%	56%
$\beta = 0.1$	11.19	62%	53%
$\beta = 0.05$	10.61	56%	51%

Table 2: Outcomes in the Co-adaptive Model With Varying Values of β. Cells show mean values of public polarization, and the percentage of values above 10, after 40 time steps from 10,000 simulations.

Looking first at the top panel of Table 2, note that reducing the bias, β, by a third (to 0.2) makes only a slight different to outcomes – it is still the case that 93% of simulations end above ten in this instance. More importantly, even very small levels of human bias shift the outcomes of a co-adaptive model: a β of 0.05 still leads to increased polarization at T=40 for 64% of 10,000 simulations.[13] Very low values for human bias clearly limit the degree to which a co-adaptive model ends with high polarization. As noted above, however, there is a large body of work suggesting human biases are significant.

[13] Any discussion about the magnitude of parameters in our model must, of course, be linked to the units for our measure of polarization. While we measure polarization on an abstract scale, the units of that scale are set by our specification of the distribution of ϵ in equations (4) and (5). Specifically, setting the standard deviation of the distribution of ϵ to one, pins all other differences to a scale in terms of this standard deviation. For example, a β of 0.3 is equivalent to roughly one third of a standard deviation in the random exogenous shocks to media polarization. The adaptation parameters, α and γ, are unitless percentages. We have relied on what we regard as moderate levels of adaptation in public and the media – in each case, adaptation that closes 30% of the gap between the series over one time period.

What if media polarization adapted more slowly to the public? The bottom panel of Table 2 shows descending values of β again, this time where γ is equal to 0.1 rather than 0.3. The effects of human bias are in these instances more muted. When β is equal to 0.3, for instance, just 81% rather than 99% of the simulations end with public polarization above 10. In every case in the bottom panel, the percentage of upward changes in public polarization over time is less than 60%. Both the magnitude of human bias and the rates of adaption matter for the degree to which our system is destined for polarization. We take up this issue again in the discussion that follows.

Discussion

Our results do not provide evidence that political polarization in the U.S. is necessarily the outcome of co-adaptation in media and the public. Simple unidirectional models driven by technological change alone *can* lead to polarization, after all. But, given the parameters above, the likelihood of such a system resulting in increased levels of polarization is roughly 0.5. In contrast, the likelihood that a co-adaptive system will, in the presence of well-established human biases, produce increased polarization in media and the public may be as high as 0.99.

This is a striking difference in outcomes, to be sure. We nevertheless believe that most of what we have argued is uncontentious and widely recognized even if it rarely finds its way into discussions of media and political polarization. Accounts of polarization that focus on the effects of media innovations without taking into account the endogeneity of those innovations are not wrong, of course, but they provide only part of the story.

The models outlined above are intentionally simple and could be extended in several important (and likely more accurate) ways. First and foremost, even as we have explored the impact of changing values of α, β or γ, we have assumed that they are static over time – even as there are good reasons to believe that this is not the case. The speed with which media can adapt to public polarization has almost certainly changed over the long term. Digital news consumption provides minute-to-minute analytics about the stories that audiences find most engaging, after all (e.g., Neheli, 2018). We should consequently expect news producers to be able to respond to the public more quickly than was feasible even several years ago; and given what are likely constant, incremental improvements in news analytics, shifts in the value of

γ may occur over the short term as well. It may similarly be the case that the public has a more steady flow of information about media polarization – either through increased physical access to news through mobile technology (Dunaway and Searles, 2022), or the increased prevalence of public affairs content mixed in to other content on social media (Tewksbury et al., 2001; Kim et al., 2013; Settle, 2018).

Moreover, α and γ may be endogenous to the co-adaptive system outlined above. The increased prevalence of polarization-relevant cues in media content may increase α, for instance, and the realized benefits of news analytics may lead to even more detailed analytics, increasing γ. The speed of the adaptive process may accordingly vary over time. So too may the magnitude of human bias, β. Negativity biases vary in response to the valence of the news environment (Lamberson and Soroka, 2018; Soroka, 2014), for example. Context is relevant to the magnitude of in-group bias (Brewer, 1979) and cognitive dissonance (DeBono and Edmonds, 1989) as well. In short: there are good reasons to consider extending our co-adaptive system to include endogenous variation in α, β and γ.[14]

There also are reasons to expect heterogeneity in the magnitude of α, β and γ across partisans. We have focused on a system with a single "public," and a single "media." But is reasonable to think that the magnitude of human biases varies across partisan groups; that media focused on one set of partisans adapts more quickly or slowly to their targeted audiences' preferences; and that audiences vary in their inclination to adapt to media polarization as well. Although we have not considered these possibilities in any detail above, they are easily incorporated into extensions of our models.

In the meantime, recognizing the very strong likelihood that political polarization is the result of co-adaptation between media and the public is important not only for our understanding of polarization, but also of media effects more generally. Wlezien and Soroka (2024) argue that media *content* regularly reflects rather than affects public preferences; we argue that the media *outlets and technologies* that deliver that content are endogenous to public preferences as well. The effects of media content and technologies may

[14] It is similarly possible to build models that more explicitly allow for heterogeneity across individuals in bias (β) and adaptation to media polarization (α), and heterogeneity across media outlets or technologies in adaptation to public polarization (γ) as well. Consider for instance the possibility that, at any given point in time, online media are faster to adapt to public polarization than legacy media; or that one partisan group is faster to respond to media polarization than another.

be over-estimated as a result.

Just as importantly, our simulations also highlight the potential for innovations in media to have either deleterious or corrective effects on public polarization. Our co-adaptive models portray a system in which media necessary moves *towards* the public. We view this as an accurate assessment of most media outlets/platforms/technologies as they currently exist. But results in Table 2 have made clear the impact of reducing the speed of media adaptation; and it is certainly possible to design media in ways that counteract rather than compound human biases. There already are good examples of exactly this, including prior (albeit now defunct) efforts by Facebook to reduce the circulation of highly partisan misinformation (Jennings and Stroud, 2021), ongoing efforts to practice "constructive journalism" (Bro, 2019), or the development of news apps with algorithms explicitly oriented towards providing more balanced content (e.g., AllSides or SmartNews).

We are unsure whether these kinds of corrective changes to media are feasible or advisable, of course. Our simulations do nevertheless suggest that what we currently see in American political polarization is the consequence of a co-adaptive process. Taking this co-adaptation into account, both in modeling and empirical analysis, is important for our understanding of the sources – and possibly also the solutions – for growing political polarization.

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