IF A PICTURE IS WORTH A THOUSAND WORDS, WHAT IS A VIDEO WORTH?

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Congressional sponsorship–cosponsorship relationships have been shown to be important predictors of many variables of interest, ranging from legislative influence to party polarization. Generally, in these studies cosponsorship matters because it is indicative of an underlying working relationship (Fowler, 2006a, 2006b). However, many of the dependent variables in these studies are not social in nature (Tam, Cho, & Fowler, 2010; Waugh, Pei, Fowler, Mucha, & Porter, 2011). Indeed, legislative influence is certainly affected by the degree to which a member of Congress is connected, but a number of things predict whether a representative can pass amendments on the House floor. Similarly, the polarization of roll call votes certainly has a social component, but, at the same time, polarization can occur for a variety of reasons, none of which have to do with interpersonal relationships. Given that, in the study discussed in this chapter I ask a simple, yet important, question: Do

sponsorship–cosponsorship relationships predict polarized social interactions on the House floor?

For network analysis scholars this question is of particular import since it is often assumed that sponsorship–cosponsorship ties capture the underlying "social fabric" of Congress (Tam Cho & Fowler, 2010). However, to date these relationships have not been used to predict actual social interactions in the U.S. House of Representatives. Even though network studies are more interested in quantifying social connectedness as opposed to predicting it, one would imagine that if sponsorship–cosponsorship relationships have a social component then they are likely to be correlated with something as simple as the degree to which Republicans and Democrats talk with one another. In this way, measuring actual social interactions may give us new insights into resolving one of the fundamental problems when using sponsorship–cosponsorship relationships as a proxy for social interactions: at best, these relationships capture a social interaction that took place days, if not months, prior. At worst, these relationships have little to no social component and instead are grounded entirely in other political considerations, such as reelection and making good public policy. If these ties are shown to reasonably predict social interactions on the House floor, then it suggests that cosponsorship can be used to capture important interpersonal dynamics.

Fortunately C-SPAN gives us a way to answer this question. Since its launch in 1979, C-SPAN has gone to great lengths to give viewers the opportunity to observe the intricacies of the House floor. With the advent of the C-SPAN Archives' online Video Library, C-SPAN programming become increasingly accessible, which is why it is peculiar that no scholar has taken the opportunity to analyze the dynamics captured in these videos. The question becomes, why analyze floor videos? Simply put, these videos contain the social interactions network legislative scholars have been seeking to measure since Caldeira and Patterson's (1987) influential work on political friendship in the legislature. These authors found that members of legislatures tend to flock together, at least in terms of their demographic characteristics. What I will show in this chapter is that members of Congress actually flock together on the floor of the U.S. House of Representatives, and do so in a meaningful way. In the next two sections I will explain why this relationship is not only understandable but entirely predictable given what we know about sponsorship–cosponsorship relationships and video motion.

SPONSORSHIP–COSPONSORSHIP

Members of Congress cosponsor legislation for a variety of reasons, many of which are not social. For example, Fenno (1973) argues that legislators pursue three main goals: reelection, influence with the legislature, and pursuing good public policy. Campbell (1982) later argued that each of these goals can influence cosponsorship activity. However, most cosponsorships are attached to legislation that never makes it to the House floor, suggesting that ultimately cosponsorship could be purely symbolic (see, for example, Mayhew, 1974). Wilson and Young (1997) go as far as to say that cosponsorship is an overrated cue that, at best, signals one's expertise, meaning it is has no real effect on the legislative process.

More recently, scholars have begun to slowly revise this view. For example, bills with a large number of cosponsors are more likely to receive committee consideration, even though ultimately floor success is difficult to demonstrate (Browne, 1985; Krutz, 2005). Similarly, cosponsorship can send a strong signal within the House about one's ideological leanings that can then be used by one's colleagues to infer information about the content of legislation (Alemán, Calvo, Jones, & Kaplan, 2009; Kessler & Krehbiel, 1996). Along these same lines, Koger (2003) argues that cosponsorship can be used by members of Congress to signal their legislative priorities to their constituents. Thus, it is not too surprising that the characteristics of a legislator's constituency (Hall, 1996; Rocca & Sanchez, 2008) and electoral margin (Koger, 2003) are important predictors of whether he or she will cosponsor a bill. Collectively, this means that cosponsorship can be used as a commitment device, meaning that if members of Congress renege on their cosponsorship obligations, future legislative success could be jeopardized (Bernhard & Sulkin, 2013).

Although these scholars would certainly admit that some personal contact happens, for the most part the social aspect of cosponsorship has been left to the network sciences (for a review, see Ward, Stovel, & Sacks, 2011). Here, when members of Congress solicit cosponsors they often send "Dear Colleague" letters in which sponsors of bills attempt to recruit potential cosponsors whom they think would help their bill's success in the legislature. Given that, "the closer the relationship between a sponsor and a cosponsor, the more likely it is that the sponsor has directly petitioned the cosponsor for support. It is also more likely that the cosponsor will trust the sponsor or owe

the sponsor a favor, both of which increase the likelihood of cosponsorship. Thus, the push and pull of the sponsor–cosponsor relationship suggest that even passive cosponsorship patterns may be a good way to measure the connections between legislators" (Fowler, 2006b, p. 455). In essence, this means that individuals who sponsor and cosponsor together are more likely to have a meaningful working relationship as compared to those who do not.

From this, scholars have used sponsorship–cosponsorship networks to study a variety of phenomena, such as an individual legislator's influence (Fowler, 2006a,b) and a legislature's ability to be generally productive (Tam Cho & Fowler, 2010). Of these, the use of these relationships to predict polarization is of particular import for this study (Zhang et al., 2008). Here, at a basic level these relationships are very intuitive. If bills have more cosponsorships from the opposition, then polarization is probably less likely. However, using network structures, researchers have uncovered an underlying social connectedness which both predicts and shapes partisan structures, giving us additional insights into how polarization changes over time (Waugh et al., 2011).

However, do sponsorship–cosponsorship relationships actually predict social interactions on the House floor? The answer to this question gets at the very nature of cosponsorship. At one extreme, if cosponsorship signals to the legislature one's position, then a bill that contains a lot of partisan cosponsors would send a very strong signal to the House floor about the nature of partisanship within the chamber. In essence, these bills may be viewed as being intentionally divisive, making bipartisan interactions less likely in this environment. At the other extreme, if sponsorship–cosponsorship relationships contain a social element, then they are indicative of the actual "social fabric" of the legislature, implying that more bipartisan cosponsors would be indicative of a more collegial environment in which walking across the aisle and talking to the opposition is encouraged. Either way, cosponsorship matters when it comes to the actual social interactions on the House floor.

Fortunately we can regularly observe these types of encounters on C-SPAN. Figure 11.1 shows a single frame from one of the videos I used for this study. This image shows the mingling that takes place after many floor votes. Later in this chapter I will demonstrate how one can predict the movement within this video by knowing the number of cosponsors from the opposing party. However, measuring video motion is easier said than done. From my understanding of the basic nature of video dynamics, I was convinced that
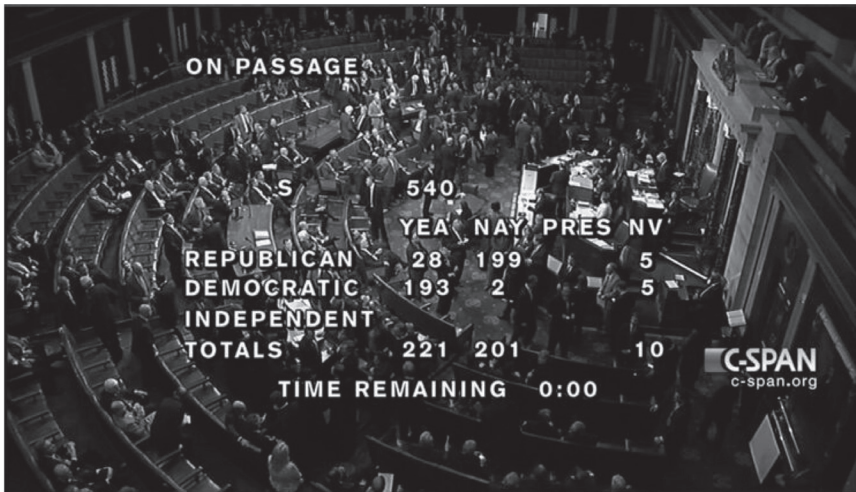
FIGURE 11.1 Overhead shot of members of Congress mingling after a roll call vote on the House floor.

some patterns should emerge, but the types of patterns were difficult to predict a priori. Thus, to help formulate testable hypotheses, I created an agent-based model (see the appendix to this chapter).

FORMULATING TESTABLE HYPOTHESES

In this simulation, members of Congress either seek out members of the opposition (bipartisanship) or they seek out members of their own party (polarization). All of these simulated interactions were recorded, then analyzed. Here, variations in pixel intensity are particularly useful. Specifically, how much do the pixels change from one frame to the next? Although this measure has never before been used to analyze motion in political science, variations of this measure have been employed by scholars in other fields, such as computer science (for a review see Zhan, Monekosso, Remagnino, Velastin, & Xu, 2008). Although unfamiliar, the measure itself is fairly easy to understand. If videos represent a series of pixel matrices, then the difference between one matrix and the next would indicate the degree to which a video changes from one frame to the next since each matrix represents a frame. If we assume more change is indicative of more motion, then tracking
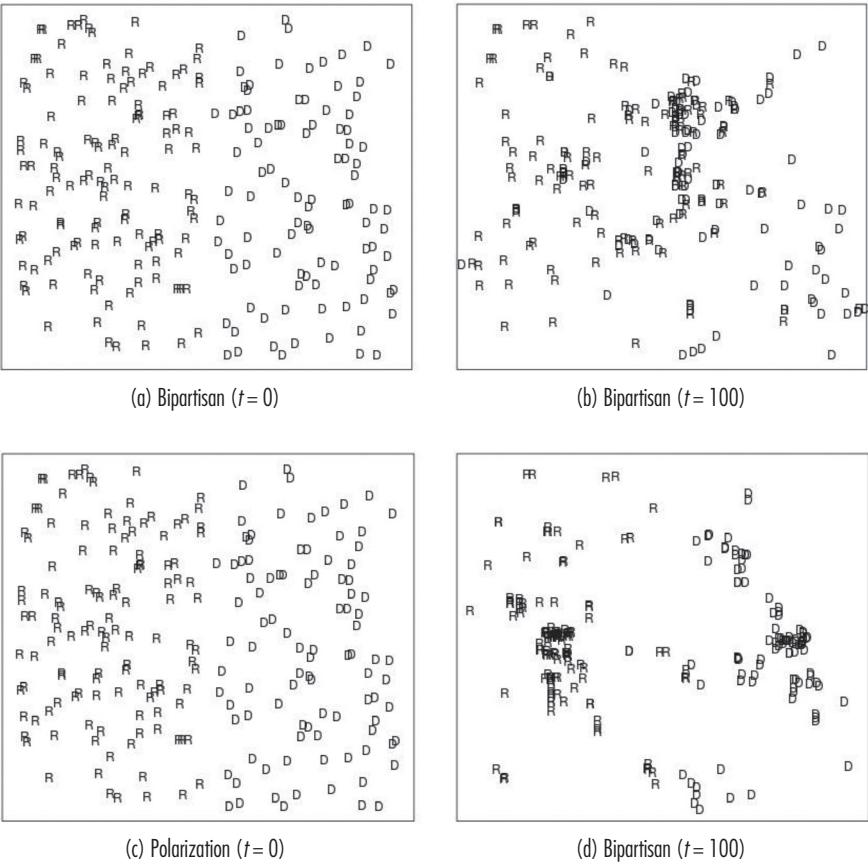
(a) Bipartisan (*t* = 0)

(b) Bipartisan (*t* = 100)

(c) Polarization (*t* = 0)

(d) Bipartisan (*t* = 100)

FIGURE 11.2 Images of initial and final states of each agent-based simulation. Note: Panels A and B represent where the agents began and ended after 100 time steps in the bipartisan simulation. Panels C and D show the same for the polarization simulation. In each, "D" and "R" represent Democratic and Republican members of Congress, respectively. Each representative was randomly placed when *t* = 0.

the change in the average pixel intensity as the agents move throughout the simulation would be useful for understanding the video dynamics produced by bipartisan versus polarized interactions.

With this in mind, consider Figure 11.2. Here, I show the initial and final positions of an agent-based model after 100 time steps. The details of this model can be found in the appendix to this chapter. The first thing to note is how the Democratic (represented by a "D") and Republican (represented by an "R") agents are positioned on either side of the board. In the Senate, this is formalized in the seating chart. In the House there are no assigned seats,

but seats are, by tradition, divided by party, with Democrats sitting to the Speaker's right and the Republicans sitting to the Speaker's left. This is why in the simulation Democrats begin on the right and Republicans begin on the left. As you can see, the same distribution of agents appears for both the bipartisan and polarization simulations. This is because each simulation uses the same initial conditions.

The question then becomes, how did the agents move during the course of the simulation? Videos of the simulations can be found online,[1] but for the purposes of this chapter let us consider how the average pixel intensity changed from one frame to the next. This is shown in Figure 11.3. Here, each frame of the bipartisan and polarization simulations are compared directly. Positive values imply that more change exists in the bipartisan simulations than in the polarization simulations. For example, at the 20th time step, the average change in pixel intensity was about 4 percent greater in the bipartisan simulation than in the polarization simulation. With this in mind, when comparing the bipartisan to polarization simulations, in the former, on average, pixel intensity changes more, suggesting more movement is present in the bipartisan simulation. This is not too surprising given where the agents began and where they ended. In the U.S. House, Democrats and Republicans sit on opposite sides of the aisle: If a Democrat wants to talk to a Republican, or vice versa, that person literally has to walk across the aisle. Given that, videos of bipartisan interactions should produce more motion than videos of partisan interactions, since less physical ground has to be covered in the latter.

Ultimately, this was the main theoretical drive behind this project, but the simulation revealed additional dynamics that I was not initially expecting. First, note the trajectory of the change in pixel intensity in Figure 11.3. Here we see a rapid increase in bipartisan motion early on, but the system eventually stabilizes. This also makes intuitive sense on the House floor. Although generally videos of bipartisan interactions include more motion, this motion happens early on as Republicans get out of their chairs and move to the other side of the aisle to interact with Democrats. Conversely, this same type of motion exists early on when observing partisan interactions, but instead of moving to the opposite side of the room, Republicans are remaining in their immediate neighborhood. However, the end result is the same: people standing around talking to one another. This is essentially what we see in the simulation. A rush of immediate movement, then stabilization.
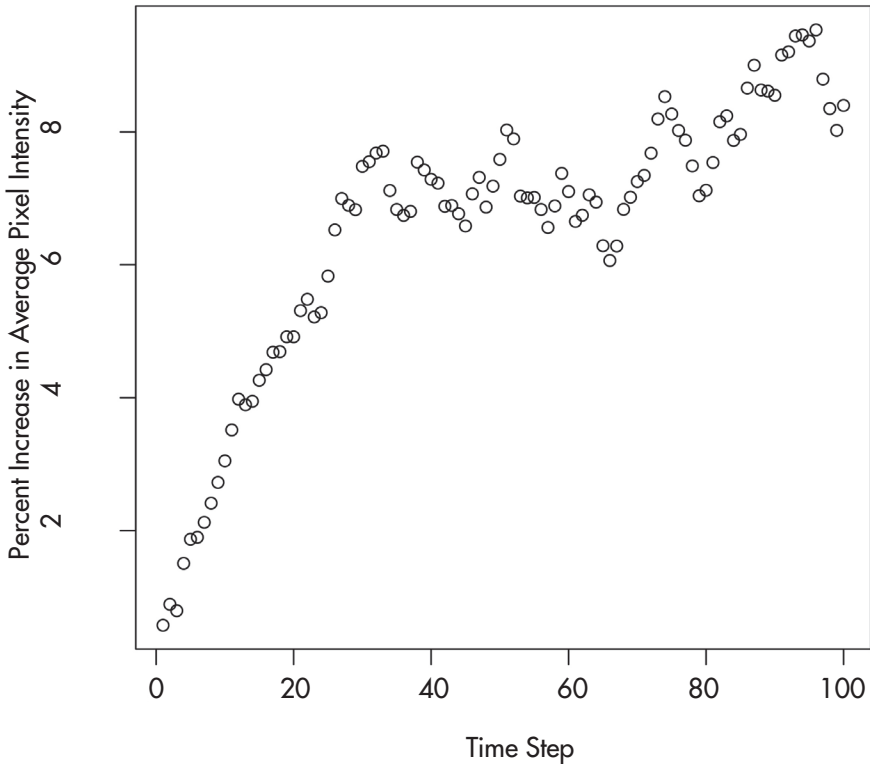
FIGURE 11.3 Results from an agent-based model of bipartisan versus polarized social interactions on the House floor. NOTE: This plot shows changes in pixel intensity from one frame to the next. Specifically, each point represents bipartisan pixel intensity minus polarized pixel intensity divided by bipartisan pixel intensity. Thus, positive values indicate that at that time step there was a greater change in pixel intensity in the bipartisan simulation as compared to the polarized simulation. Negative values would imply the inverse is true.

Finally, the end points of each simulation also reveal another unanticipated dynamic. This can be seen in panels B and D in Figure 11.2. Here, we see that the bipartisan simulation produces one large centralized cluster, whereas the polarization simulation produces two clusters on either side of the board. Again, this makes intuitive sense. If Democrats are moving toward Republicans and Republicans are moving toward Democrats, they are likely to meet in the middle of the room since both are beginning on opposite sides. Certainly, some may wander all the way to other side, but, for the most part, this is irrational since the goal is to interact with members of the opposition. This is most likely to happen right in the middle of the House floor. Thus, when we observe bipartisan interactions, Republicans do not cross the aisle to talk

to Democrats. Rather, Republicans and Democrats meet with each other in the aisle itself. Conversely, partisan interactions are more likely to take place away from the aisle because this is the easiest place for a given to party to congregate since this location minimizes the distance between all party members.

Collectively, the results from this simulation imply that videos of bipartisan interactions are more likely to produce motion than videos of partisan interactions. On a very basic level, this has to do with the positioning of Democrats and Republicans in the U.S. House of Representatives. If they typically sit on opposite sides of the aisle, then a bipartisan environment will tend to produce more motion because members of Congress have to cover a greater distance on the House floor. Similarly, in these instances, the interactions are more likely to be clustered toward the center of the video, whereas partisan interactions are more likely to be clustered toward either side. In both instances, these relationships are going to be more pronounced toward the beginning of the video as compared to the end, since the beginning of the video captures the initial sorting which eventually stabilizes once conversations begin. Thus, if sponsorship–cosponsorship ties can predict social polarization, then we should find evidence of the following relationships when it comes to video motion.

Hypothesis 1: Videos associated with bills that have more cosponsors from the opposite party as compared to the sponsor's party should have, on average, a greater change in pixel intensity than videos associated with bills where the inverse is true. This general relationship should be more pronounced toward the beginning of the video.

Hypothesis 2: Videos associated with bills that have more cosponsors from the opposite party as compared to the sponsor's party should have, on average, more centralized pixel clustering than videos associated with bills where the inverse is true. Again, this general relationship should be more pronounced toward the beginning of the video.

DATA AND MEASURES

To test these hypotheses, a research assistant captured videos similar to the one shown in Figure 11.1 using C-SPAN's Video Library. To make the starting and ending point of each video more definable, the video was stopped once the House cameras moved away from this overhead shot. On average, this

took place after 2 minutes and 30 seconds. Although we plan to obtain video for every floor vote in the 113th U.S. House of Representatives, for an initial demonstration I decided to find bills in which every cosponsor was from the opposition. Unsurprisingly, these were quite rare, but I was able to find 6 bills of this nature. Once these were found, I then examined the number of cosponsors each had. For the most part, these bills only had a couple of cosponsors each. With this in mind, I then looked for bills that had no cosponsors from the opposite party. To make these bills similar, I only considered bills that had fewer than 10 cosponsors. This yielded the bills outlined in Table 11.1.

All of the bills listed in Table 11.1 are sponsored by Republicans. This is partially by design. When I examined the bipartisan bills, I found that all of these were sponsored by Republicans and cosponsored by Democrats. Thus, I restricted the partisan bills to those sponsored by Republicans. Ultimately, this only eliminated one bill from consideration (H.R. 338). Excluding this bill did not significantly affect the results, but it should be kept in mind.

For each video, pixel intensity was relatively easy to obtain. Basically, once videos are broken into frames, one can assess the change in pixel intensity by comparing one frame to the next. Here, comparisons were made using the Euclidean distance, calculated by row. A greater Euclidian distance between one frame and the next would indicate greater motion, since the greater distance would imply greater change between the two associated pixel matrices. Ironically, the most difficult part of this calculation was actually dividing the videos into individual frames. This was done using ffmpeg software and resulted in 2,008 images, one for each second of video. From this point, each image had to be compared to every other image in a given video.[2]

To determine whether pixels were clustered centrally, I first partitioned each frame into two distinct clusters using the algorithm outlined in Chapter 2 of Kaufman and Rousseeuw (1990), which can be implemented using the *cluster* package in R software. Then, using the position of each cluster's center, I calculated how far the cluster was from the middle of the frame, again using the Euclidian distance. In this instance, greater values would imply the clusters were further from the middle, whereas smaller values would imply they were more centrally located. Given that, I expected the cosponsorship ratio to be a positive predictor of pixel intensity and a negative predictor of pixel clustering. As suggested in the previous section, I expected these relationships to be more pronounced toward the beginning of the video. Thus,

TABLE 11.1   *Bills Selected for This Study*

Bill Number	Date	Title	Sponsor
Bipartisan Bills			
HR 1067	3/12/2013	To make revisions in Title 36, United States Code	Rep. Bob Goodlatte (R)
HR 1162	3/14/2013	Government Accountability Office Improvement Act	Rep. Darrel Issa (R)
HR 1412	4/9/2013	Department of Veterans Affairs Expiring Authorities Act of 2013	Rep. Mike Coffman (R)
HR 2374	6/14/2013	Retail Investor Protection Act	Rep. Ann Wagner (R)
HR 2747	7/19/2013	Streamlining Claims Processing for Federal Contractor Employees Act	Rep. Tim Walberg (R)
HR 2848	7/30/2013	Department of State Operations and Embassy Security Authorization Act	Rep. Edward Royce (R)
Partisan Bills			
HR 668	2/13/2013	To amend Section 1105(a) of Title 31, United States Code	Rep. Luke Messer (R)
HR 767	2/15/2013	To amend the Energy Policy Act of 2005	Rep. Kevin Cramer (R)
HR 1582	4/16/2013	Energy Consumers Relief Act of 2013	Rep. Bill Cassidy (R)
HR 1911	5/9/2013	Bipartisan Student Loan Certainty Act of 2013	Rep. John Kline (R)
HR 2879	7/31/2013	Stop Government Abuse Act	Rep. Lynn Jenkins (R)
HR 3210	9/2/2013	Pay Our Military Act	Rep. Mike Coffman (R)

NOTE: For bipartisan bills, all of the cosponsors were from the opposition, meaning that since all of these bills were sponsored by Republicans, all of the cosponsors were Democrats. For partisan bills, all of the cosponsors were Republican. The dates indicate when the bill was introduced and the titles were obtained online from the Library of Congress.

these measures were also calculated using the first 10 percent of the video. I expected these relationships to be the same, but the coefficients to be greater in size. Ultimately, even though both variables operate in the predicted direction, greater support is found when comparing pixel intensity, which is where we now turn.

RESULTS

Figure 11.4 shows box plots for average and early pixel intensity for both the bipartisan and partisan bills outlined in the previous section. In each, the solid line represents the median value, and the borders of each box capture the 25th and 75th quantiles. The whiskers extend to the minimum and maximum values. Grey boxes indicate a t-test comparing the bipartisan and partisan bills was statistically significant at the .05 level. For example, the average pixel intensity for bipartisan bills (6.84) is approximately 4 percent higher than the average pixel intensity for partisan bills (6.55). Although this difference is slight, it is statistically significant ($t = -2.23$, $df = 11$, $p \leq .05$) which is impressive given that only 12 bills were used.

Similar evidence is found for early pixel intensity. Here, bipartisan bills tended to produce more early motion (7.05) than do partisan bills (6.74). Again, this difference was slight (approximately 5 percent) and statistically significant ($t = -2.33$, $df = 11$, $p \leq .05$). Moreover, as predicted, in both instances pixel intensity changed more in the early portions of the video as compared to the video overall. However, this difference was only significant for bipartisan bills ($t = -2.99$, $df = 16$, $p \leq .05$), where early motion was approximately 3 percent higher than overall motion. In Figure 11.4 this can be seen using the dashed boxes. These indicate that early motion is significantly ($p \leq .05$) higher than average motion. As you can see, even though early motion is higher for partisan bills as compared to overall motion, this difference is not statistically significant at the .05 level ($t = -1.09$, $df = 16$, $p \leq .05$). Collectively, these results provide evidence consistent with the first hypothesis.

When I considered pixel clustering a similar story was found. Pixels were more centralized in videos of bipartisan bills, and this relationship was more pronounced early in the video. However, unlike pixel intensity, none of these relationships were statistically significant at the .05 level. This can be seen in
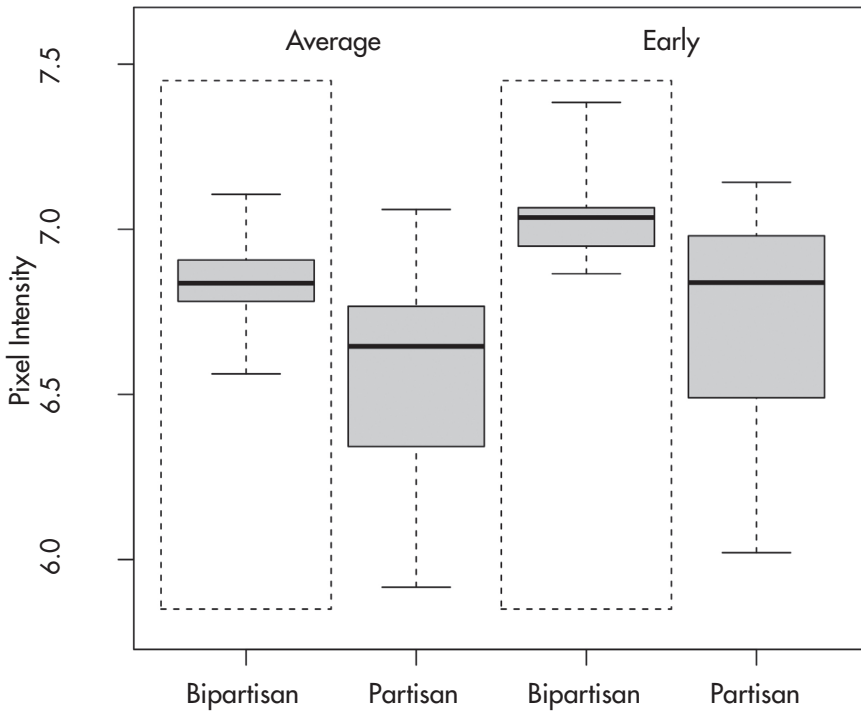
FIGURE 11.4 Comparing pixel intensity in bipartisan versus polarized social interactions on the House floor. NOTE: Grey box plots indicate there is a significant ($p \le .05$) difference between average and early pixel intensity. Significance was determined using a two-sample *t*-test where unequal variance was assured.

Figure 11.5. Here, partisan bills produce, on average, less centralized pixel clustering (384.85) as compared to their bipartisan counterparts (378.69). As before, this difference is small (approximately 2 percent), but this time it is not statistically significant ($t = 0.28$, $df = 16$, $p > .05$). The same can be said when I compared early pixel clustering, where again partisan bills produce less centralized clustering, but this slightly larger difference (approximately 8 percent) was still insignificant ($t = 0.85$, $df = 13$, $p > .05$). All of these are consistent with the second hypothesis, but less confidence can be placed in these results.

For those convinced that social interactions matter in the U.S. House of Representatives, these results are important in and of themselves because they suggest bipartisan cosponsorship relationships are more likely to produce bipartisan social interactions as compared to their partisan counterparts.
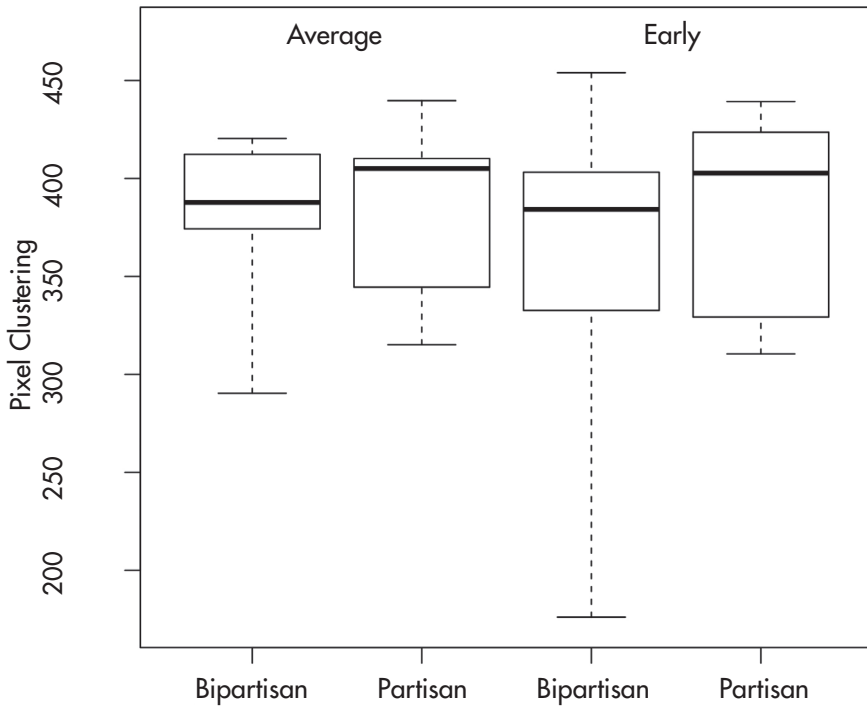
FIGURE 11.5 Comparing pixel clustering in bipartisan versus polarized social interactions on the House floor. NOTE: Grey box plots indicate there is a significant ($p \leq .05$) difference between average and early pixel clustering. Significance was determined using a two-sample t-test where unequal variance was assured.

However, others may be skeptical of whether these results are substantively important. In an attempt to convince this latter group, I considered whether pixel intensity and pixel clustering correlated with the number of yes votes each bill received. Here, I took the number of representatives voting yes, divided by the total number of representatives voting for the bill. I then determined the degree to which this measure correlated with those outlined in the previous paragraphs. When this was done, I found that average ($\rho = 0.34$) and early pixel intensity ($\rho = 0.41$) were both positively correlated with the vote margin, with the latter being not only higher but statistically significant at the .10 level ($t = 1.81$, $df = 16$, $p \leq .10$).

When I considered pixel clustering, I found a similar relationship. Again, both average ($\rho = -0.27$) and early pixel clustering ($\rho = -0.49$) were correlated

with the number of yes votes, and the latter was statistically significant, but this time at the .05 level ($t = -2.23$, $df = 16$, $p \leq .05$). As explained earlier, the measure of pixel clustering operates differently than the measure of pixel intensity. Here, larger values imply less clustering, making the direction of the correlations consistent with the previous results. Even with this caveat, the direction of causation is difficult to determine since the floor votes happened prior to the videos being analyzed, meaning it is impossible to determine whether bipartisan interactions contribute to more representatives voting yes or the other way around. Thus, more research is needed.

DISCUSSION

Although the techniques used in this study may be unfamiliar to political scientists, the results are very intuitive. If Democrats and Republicans sit on opposite sides of the aisle, then bipartisan interactions simply require more effort because individuals have to stand up and walk to the other side of the room. Conversely, in instances of polarization, members of Congress just stay put, meaning motion is less likely. Although it is impossible to comment about the content of these conversations, these results seem to tell a simple and uncontroversial story: Bipartisan bills are associated with bipartisan social interactions.

For years, network scholars have been using sponsorship–cosponsorship ties to capture the "social fabric" of Congress. Even though many legislative scholars are beginning to accept this argument, others are reluctant to believe that cosponsorship is anything more than a symbolic gesture to win points either within the legislature or within one's own district. This study provides evidence that sponsorship–cosponsorship relationships may contain some social element, at least when it comes to polarization. Note that this is not the same as claiming that sponsorship–cosponsorship ties are indicative of interpersonal relationships since I am unable to determine whether the sponsors of the bills in question actually talked to their cosponsors on the House floor. However, although untested, the results seem to be consistent with this claim.

For legislative scholars, this study is entirely consistent with cosponsorship being important for legislative signaling. Members of Congress know what they are doing when they solicit cosponsors from their own party. They

are signaling to the legislature that party matters. Similarly, when members of Congress go out of their way to find cosponsors from the opposition, they are likely attempting to emphasize the importance of bipartisanship. Both of these affect social interactions on the House floor, either directly or indirectly. Directly, bipartisan bills may actually signal to those on the House floor to move across the aisle as a sign of solidarity for an important bipartisan effort. Indirectly, members of Congress know that a partisan bill is coming up for a vote, which is why they choose to stand with each other to demonstrate party unity. Either way, these underline an important social dynamic that many have suspected, but few have actually observed and quantified.

Fortunately C-SPAN gives us the opportunity to begin to test these and other related questions. No scholar has yet used C-SPAN for this purpose. The C-SPAN Video Library is an extraordinary resource, but to date we have only scratched the surface of what we can do with it. Social interactions take place all the time on the House floor. Many scholars argue these matter for a variety of reasons. With this chapter I demonstrate how we can begin to actually measure the extent of these relationships without relying on proxies such as cosponsorship. Does social polarization predict polarization in roll call votes? Did Democrats talk more to Republicans before 2008? How did the Gabrielle Giffords shooting affect the social dynamics on the House floor? I argue that we can begin to answer these types of questions using these videos. Although not perfect, this study provides a useful starting point for these efforts.

NOTES

1. The polarization simulation can be found at https://www.youtube.com /watch?v=lNLzsizM4fY. The bipartisanship simulation can be found at https://www .youtube.com/watch?v=mkrzQQXZtSg.

2. This was done using Amazon's Elastic Computing Cloud.

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APPENDIX
Simulating Social Interactions
on the House Floor

Videos are extraordinarily complex. Each frame of a video represents a matrix of pixels. When the video is in color, there are actually three matrices that combine to form the image. Given that, most videos are converted to grayscale when analyzed. When this is done, each cell of the matrix represents a pixel that ranges from 0 to 1, where 0 is white and 1 is black. Thus, a grayscale image that is 480 by 640 pixels can be represented by a single matrix of equivalent size. Ultimately, this implies that videos are essentially a time series of matrices, with one image representing a predetermined length of time.

Agent-based models are particularly useful for analyzing video, especially if the video involves crowds (for review see Zhou et al., 2010). Generally, agent-based models are useful for studying systems which contain the following characteristics: (1) the system is composed of interacting agents; and (2) the system exhibits emergent properties—that is, properties arising from the interactions of agents that cannot be deduced by aggregating the properties of the agents themselves (Axelrod & Tesfatsion, 2006). I argue that C-SPAN videos contain each of these characteristics.

First, when Democrats walk across the aisle and talk with Republicans they are, by definition, interacting agents. In fact, social polarization itself is grounded in these interactions. Second, when we watch these encounters on C-SPAN, we are actually observing the result of a complex process that produced the video we see on the screen. Indeed, by simply watching the video from afar it is difficult to deduce who is talking to whom. Given that, not only is an agent-based model useful for understanding the types of video dynamics we should see on the House floor, but from a theoretical standpoint an agent-based model may be the only way to study these dynamics at all.

In the model used for this study, I first created a space in which the agents could move. This space was a simple 250 by 250 matrix. At the beginning of the simulation, I created 218 agents: 122 Republicans and 96 Democrats. This partisan split (which was randomly assigned) was chosen because it closely

resembles the 113th U.S. House of Representatives, which was 54 percent Republican. Once this was done, I randomly assigned each agent two vision parameters, one of which allowed the agent to look north and south while the other allowed the agent to look east and west. These vision parameters were randomly drawn from a uniform distribution that ranged from 1 to 200, meaning at one extreme agents could only look one space around them while at the other extreme they could look almost across the room. After this, each agent was assigned a movement parameter, which was randomly drawn from a uniform distribution that ranged from .50 to 1. This variable captured the degree to which an agent was likely to move. Although I wanted to make it more likely than not that an agent would move, I also wanted to allow some agents to be less willing to budge as compared to others. Similarly, I made some agents faster than others, meaning at any given time step some could move more spaces than others. This parameter was also set using a random uniform distribution (min. = 1, max. = 10). Finally, although the goal of this simulation was to mimic social interactions, some agents may be social butter-flies, meaning that instead of just talking to one person they want to mix and mingle. This was captured using a variable randomly drawn from a uniform distribution which ranged from 0 to .25, meaning that on average agents are not going to jump from one agent to another, but some may.

With this initial setup in mind, what are the agents doing in the simula-tion? In the initial time step of the polarization simulation, each agent first decides whether to move. If the agent chooses to move, it then looks north, south, east, and west for agents around it. The degree to which an agent can see other agents is constricted by its vision. Once it obtains a list of potential targets, it selects only targets that are from its own party, meaning Democratic agents select only Democrats and Republican agents select only Republicans. Then, from these potential targets the agent determines the closest and moves in that direction. This motion is first determined by taking a number of steps north, south, east, and west equal to each agent's speed. Once these potential moves are calculated, the agent selects the move that minimizes the distance between it and the partisan target. After this move is made, the agent then re-cords its position and the ID of the target. In some instances, the agent will be unable to find a target. When this happens, the agent randomly moves (equal to the agent's speed) either north, south, east, or west.

From this point, the simulation continues in a similar fashion in sub-sequent time steps, with two caveats. First, if an agent has already found a

target, then it proceeds to move toward that target. This was done because I assume that agents are seeking out their friends in the legislature. Generally, these friendships are stable, meaning they tend to select one friend and stick with that selection. Thus, if the agent does not have a partisan target, then the agent follows the process outlined above to find one. Second, in subsequent time steps the agent can decide if it wants to find a new target. If it does, then its current partisan target is removed from its memory and it finds a new one using the process outlined in the previous paragraph. Of course all of this assumes that the agent has selected to move in the given time step. If the agent has not selected to move, then it stays put. Although somewhat different the bipartisan simulation is essentially the same, except instead of trying to find targets from its own party, each agent is trying to find targets from the opposition, meaning Democratic agents seek out Republicans and Republican agents seek out Democrats.

Undoubtedly, real social interactions on the House floor are more complex than the model presented here, but I think this model can capture some of this complexity. First, embedded within the two simulations is polarization versus bipartisanship. In terms of the former, agents are seeking out members from their own party, whereas in the latter agents are seeking out members from the opposition. In the future, I will vary these two strategies by agent, but in the short-term, this is exactly what I think of when I think of polarized social interactions. Here, members of Congress refuse to talk to the opposition. Conversely, in a bipartisan environment, members of Congress are literally willing to reach (or walk) across the aisle. This model captures some of this dynamic.

Second, although vision seems somewhat silly, this parameter captures a combination of things. Indeed, some people are able to see further than others, but vision primarily captures the degree to which a member of Congress is actually willing to look out onto the House floor and find someone to talk to. In instances where vision is low, an agent is unwilling to look further than its local neighborhood. Conversely, when vision is high, the agent looks beyond its immediate vicinity for potential targets. However, the agent is not irrational, meaning that even if other potential targets are found elsewhere, the agent is not going to expend energy to move toward those targets when perfectly acceptable targets are standing one or two spaces over.

Finally, speed captures both the physical limitations of a given agent and the energy by which an agent is willing to move toward its objective. For

example, imagine that a representative is excited about mingling with a member of the opposition: This representative is likely to move toward the member of the opposition with greater purpose than would be a member of Congress who is not excited. The same can be said about polarization: If members of Congress are extremely polarized, then they may move more quickly to their fellow partisans than to others. Thus, speed not only captures the degree to which an agent moves from one space to the next, but also the motivation it has for achieving the objective, be it partisan or bipartisan.

When one observes the videos of the polarization[1] and bipartisan simulations,[2] three patterns emerge. First, the bipartisan simulation produces more motion. This is understandable given the initial starting points and motivations of the agents. In each simulation, Republicans and Democrats begin on opposite sides of the aisle. Thus, to find a member of the opposition, the agents have to cover more ground. This ultimately produces more motion.

Second, at the end of each simulation we see a great deal of clustering, but the locations of the clusters differ. In the partisan simulation, the clustering takes place on either side of the aisle. Conversely, in the bipartisan simulation, the clustering takes place in the middle of the screen. Again, from the agents' perspectives this makes sense. If agents are interested in interacting with members of the opposition, they will walk toward the opposition, but they will actually never cross the aisle since their opponents are doing the same. Thus, they meet in the center. Those in the partisan simulation want to talk only to members of their own party, which makes moving from their present location irrational. Instead, these agents simply want to cluster on their side of the aisle. This is readily apparent from the videos associated with each simulation.

Finally, the endpoint of each simulation is the same: agents standing around talking to one another. Given that, regardless of whether one is observing the bipartisan or the partisan simulation, the majority of the movement happens early on. In these moments, the agents are frantically sorting themselves based on the rules assigned at the beginning of the simulation. Once they find someone to talk with, they have little reason to move. Thus, the general motion and clustering patterns outlined above are more pronounced earlier in the simulation.

I encourage the reader to observe the interactions for themselves. Even though many of these relationships are demonstrated empirically, these videos

will help the reader understand each of the hypotheses tested in the associated chapter. Agent-based models are extraordinarily complex, which sometimes makes understanding them difficult. However, in this instance I argue that the agent-based model helps to clarify the results. I hope this appendix helps to achieve this end.

Notes

1. The polarization simulation can be found here at https://www.youtube.com/watch?v=lNLzsizM4fY.

2. The bipartisanship simulation can be found here at https://www.youtube.com/watch?v=mkrzQQXZtSg.

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