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Who Are Your Neighbors? The Role of Ideology and Decline of Geographic Proximity in the Diffusion of Policy Innovations

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States adopt policy innovations within the confines of a dynamic American federal system, but our study of policy diffusion tends to be fairly static. Single-policy studies incorporate temporal variation, but for only one innovation. Macro-level analyses examine broad patterns, but often by completely pooling across policy and time. This makes it difficult to identify how diffusion patterns change over time, though Walker's early work explicitly identified such temporal instability. This study specifically examines how neighbor and ideological cues change in importance over time using a dataset of 556 policies adopted from 1960 to 2014. While the findings demonstrate the generality of many key internal, external, and policy-level determinants of adoption, there is variation in these effects across time. Most important is the relative stability of ideological similarity between adopters and declining influence of contiguous neighbors. Further, political polarization plays a role in conditioning neighbor and ideological cues.

KEY WORDS: policy diffusion, state politics, political polarization

各州在充满活力的美国联邦制度下进行着政策创新，但我们对政策扩散的研究往往是静态的。尽管各政策研究包含了时间维度的变化，但仅适用于某单一项的政策创新。宏观层面的分析考察了政策扩散的大致模式，但这通常需要进行跨越政策和时间的大规模整合。这使得我们难以确定扩散模式是如何随时间而发生变化的；对此，沃克的早期工作明确说明了这种时间不稳定性。本研究使用的数据集涵盖了*1960*年至*2014*年间被采用的*556*项政策，专门研究了邻州和意识形态因素的重要性随时间而发生的变化。虽然我们的研究结果证明，许多重要的内部、外部以及政策层面的决定因素具有普遍性，但是我们发现这些因素会因时间不同而存在差异。最重要的是，政策采用者之间意识形态的相似性是相对稳定的，而相邻州的影响则随时间而减小。此外，政治两极分化在调节邻州和意识形态因素的影响上也发挥着作用。

The context within which the states adopt policies is clearly not fixed. Scholars work diligently to understand how shifting patterns in political polarization, economic inequality, campaign spending, lobbying, and much more, shift who has power and how public goods and services are distributed. It stands to reason that as broader political, societal, and technological contexts change over time, so do the patterns

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and predominant mechanisms of policy diffusion within American federalism. In fact, studying how diffusion patterns change over time offers insight into the effects of broader societal changes on the ideas emerging from the laboratories of democracy. Alas, diffusion research quite often focuses on the patterns of spread for a single innovation or a group of fully pooled innovations, making it difficult to understand how mechanisms and determinants change systematically across policies or time. This article seeks to address this lacuna by answering the following questions: how does the relative importance of ideological and neighbor adoption cues change over time and what factors condition those cues?

Answering these questions is important not only for policy diffusion researchers, but anyone studying changes in American politics. For diffusion scholarship, it is necessary to clarify how the factors influencing the likelihood and speed of adoption may change over time and under what conditions they are expected to change. In terms of understanding American politics, policy diffusion illuminates how new ideas spread horizontally and vertically in our federal system. As phenomena like political polarization and growing economic inequality occur, we must ask ourselves how they change the ideas that are able to emerge and the mechanism by which those ideas are legitimized and spread.

In this article, I examine how macro-level patterns of policy diffusion change. Specifically, I test how geographic and ideological cues increase or decrease in importance over time. This is done by examining a large dataset of 556 policies from the State Policy Innovation and Diffusion (SPID) database (Boehmke et al., 2019) that were adopted by states between 1960 and 2014. Using pooled event history analysis (PEHA), I am first able to replicate a bevy of past findings regarding key external, internal, and policy-level determinants of adoption. This suggests that these determinants in fact have general effects across time and diverse policy domains, supporting the notion of a generalizable theory of diffusion (Berry & Berry, 2018). Second, I find that the influence of neighbor adoptions declined from 1960 to 2014, whereas the influence of ideologically similar adopters remained steady. Finally, while ideological cues matter for policy diffusion regardless of whether a policy is simple and/or highly salient, political polarization reduces the importance of cues from proximate neighbors. This suggests that polarization is playing a role in changing the importance of these cues over time.

Temporal Changes in Policy Diffusion Patterns

Before addressing how diffusion changes over time, it is necessary to provide some conceptual clarification. The diffusion literature focuses on the spread of policy innovations and the basic definition of an innovation is something that is new to a given unit considering adoption (Walker, 1969). This means that an innovation is not necessarily new to the entire social system but is new to each observed potential adopter. Fundamentally, a policy innovation “includes governmental forms, institutions, or specific policies” (Karch, 2007b). In contrast to technological adoption or health practice adoption, however, policies are more than just a clearly demarcated new product. They represent ideas. These can be ideas for solving pressing public problems or raising one's competitive advantage (Dye, 1990). They can be pushed explicitly or implicitly from above by the federal government (Welch & Thompson, 1980), emerge from lower level municipal governments (Shipan & Volden, 2006), or emerge horizontally due to competitive, normative, political, or problem-driven pressures (Berry & Berry, 2018). Thus, the study of policy diffusion is crucial for understanding how *ideas* emerge, are legitimized, and spread within the American federal system.

Much of policy diffusion research is devoted to understanding what factors (i.e., determinants) shape the likelihood and speed of innovation adoption. For example, it is generally expected that states with greater slack resources (e.g., a larger tax base) are more likely to adopt innovations than those with fewer (Boehmke & Skinner, 2012). Additionally, there are attributes of innovations—complexity, salience, relative advantage, trialability, and observability—that condition the likelihood and speed of adoption (Makse & Volden, 2011). Finally, a variety of forces external to the states shape the likelihood and speed of adoption. Policy entrepreneurs and interest groups, for example, serve as vectors of policy transmission from state to state (Boushey, 2010). Positive experiences with innovations in other states may spread through citizen social networks and thus increase public support for an innovation (Pacheco, 2012). States learn from and are in competition with their neighboring states (Berry & Baybeck, 2005). Finally, ideological cues signal the political acceptability of an innovation (Grossback, Nicholson-Crotty, & Peterson, 2004). All the determinants examined in hundreds of published diffusion studies are essentially revealing the conditions by which an idea or set of ideas came to emerge, be legitimized, and spread (albeit not always totally) throughout the American federal system. Not every determinant, however, is relevant for each policy innovation, but there is a sense that we are testing a model of diffusion that is generalizable across policy and time (Berry & Berry, 2018).

It is unclear, however, why determinants differ across diverse policies and time periods, beyond the idiosyncrasies of individual innovations. Diffusion models thus tend to be highly contextualized and the generalizability of their findings is not readily apparent. Perhaps the most important conflicting results arise from tests of external determinants. Regionalism is long believed to influence policy diffusion (McVoy, 1940), though it can be difficult to determine whether the influence of surrounding states is due to policy learning, competition, or social contagion (Berry & Baybeck, 2005; Pacheco, 2012). More recently, scholars have been drawing attention to patterns of diffusion not associated with geographic neighbors, but ideological ones (Grossback et al., 2004). For instance, Hannah and Mallinson (2018) found that medical marijuana laws that began spreading in 1996 followed an ideological, as opposed to geographic, pattern of adoption.

Given that the very concept of diffusion implies a process of transfer from state to state via an underlying mechanism, meaning there is not simply independent and spontaneous replication due solely to forces internal to each state, understanding why different external determinants matter in different contexts is quite important. Alas, single-policy studies only examine a snapshot of time for a single innovation and it is thus difficult to say with confidence whether inconsistent findings for key diffusion determinants are due to differences in the policy context or the broader political context of the time being studied. I argue herein that both policy-level contexts and macro-political contexts that vary over time have a systematic effect on the probability of state innovation adoption. It is impossible to test all possible policy and political trends that condition policy and ideological learning cues, but I suggest three major suspects: policy complexity, salience, and political polarization. I now turn to establishing theoretical expectations for why geographic and ideological cues change over time and how these cues are conditioned by policy complexity, salience, and polarization.

Changing Adoption Cues

State governments have experienced a great deal of change in the last 100 years. Many states replaced or reformed their constitutions in the postwar era,[1] some reorganized their executive and judicial branches (Chackerian, 1996; Teaford, 2002), professionalized their legislatures (Teaford, 2002), changed the powers of key elites (Mooney, 2013), and either instituted term limits or had them imposed by voters (Kousser, 2005). The states also faced increasingly dense interest group environments (Gray & Lowery, 1993) and elite polarization (Shor & McCarty, 2011). They rode waves of public management reform (Moynihan, 2006), as well as the increasing use of direct democracy (Waters, 2003). Finally, professional organizations facilitated increasing interconnectedness among the states (Walker, 1971), but so did the rise of ideologically driven legislation mills, like conservative ALEC and progressive SIX (Hertel-Fernandez, 2019).

Given such substantial institutional and behavioral changes, it stands to reason that the internal and external predictors of policy diffusion are not static over time. In fact, when observing the period of 1870 to 1966, Walker (1969) observed both stability and change in the social, economic, and political correlates of policy innovativeness. Furthermore, while the regional clustering of diffusion for many policies was persistent in that era, states are increasingly in competition with peers beyond their immediate neighbors and are less limited in their ability to gather policy information from beyond their region. In fact, contiguity plays a smaller role in the overall structure of diffusion networks than previously thought (Desmarais, Harden, & Boehmke, 2015). Source states tend to have shared demographic and political features, *including the ideology of their residents*. The main question in this study is whether geographic proximity and ideological similarity have shifted in their importance as adoption cues over time.

Ideological cues serve to reduce uncertainty about the potential political consequences of a policy innovation (Grossback et al., 2004), whereas the more traditional conceptualization of policy learning captures the reduction of uncertainty about the effects of a policy choice. Geographic proximity, however, can also capture the mechanisms of competition and social contagion (Berry & Baybeck, 2005; Pacheco, 2012). I am not attempting to untangle the three in this paper, but instead I am considering the conditions under which we would expect geographic proximity to matter (be it through policy learning, competition, or social contagion) and the conditions under which we would expect ideological cues to matter for potential adopters. It is likely that both policy and political information are important for potential adopters but changing circumstances in American politics suggest that the weight of such information may change over time.

Cues from Neighboring States

Regional definitions hold an important place in American history and the study of the states. Frederick Jackson Turner (1932) argued that regions are important for the development of shared cultures and identities in the states (see also Elazar, 1966). Policy diffusion studies have used both region (typically Census region) and contiguity as markers of the influence of local adopters. The two are not identical concepts, however, given that some contiguous states may not fall within the same Census region and, likewise, some states in the same Census region are not contiguous. The primary focus of diffusion research, however, tends to be the effect of contiguous adopters.

Historically, neighboring states not only were more likely to have a similar history and culture, but they were also close enough for communications between state government officials. Policy learning is best tied to the "laboratories of democracy" conceptualization, in that states are learning from each other to solve problems that do not stop at state borders. It remains, to an extent, easier to know what is happening in a neighboring state than in those farther away. Media markets overlap, local travel is easy, elected and hired members of state government may serve in regional organizations together, and more. Even if it becomes easier for states to gather policy information from those beyond their borders, neighbors are still more likely to have shared culture and common problems and thus may look to learn from each other before reaching further for policy solutions.

There are also a variety of economic spillovers between neighbors that foster competition and emulation. Natural resources do not stop at state borders, nor do population centers (i.e., labor), transportation networks, and more. Such spillovers bring shared problems as well as opportunities for learning and competition (Berry & Baybeck, 2005). For example, in the rare instances when manufacturers move, they tend to move to neighboring states (Conroy, Deller, & Tsvetkova, 2017). Thus both state and local governments offer incentives, or remove regulatory burdens, in order to retain or lure economic activity from their neighbors.

Finally, social contagion is predicated on the idea that citizens will observe policies and their outcomes in neighboring states and will update their related political preferences accordingly (Pacheco, 2012). Meaning, if they come to understand, through cross-state media coverage and/or members of their social network from a neighboring state, that a policy is working well, they will become favorable to the policy. In the aggregate, enough changes from either opposition or neutral positions to supportive ones will shift public opinion and thus encourage policy adoption.

All three of the above mechanisms are potentially occurring when diffusion scholars observe patterns of neighbor adoptions influencing diffusion. But how might these mechanisms change in their influence on adoption over time? Early diffusion research expected information to spread in concentric circles from regional innovators to their neighbors (McVoy, 1940). This made a great deal of sense in a time when Pennsylvania legislators were more aware of new ideas coming out of New York than California, but the country has become metaphorically smaller with the development of interstate networks (Walker, 1971) and growth in national professional gatherings (e.g., the National Governors Association). In fact, Walker predicted that social and political changes would alter geographic patterns of diffusion, but his suppositions remain largely untested (Desmarais et al., 2015).

States also face economic competition not only from their neighbors, but across the entire country. While there are still regional niches in some industries, the recent competitive bidding process for Amazon's HQ2 illustrates the lengths to which governments across the country are willing to go in their competition with each other. In terms of social contagion, given that as of 2010, 59 percent of U.S. citizens reside in the state in which they were born (U.S. Census Bureau, 2011), citizens are still highly likely to have many social contacts within their own state and in neighboring states. Of course, not all regions are equal in their population mobility and moves within counties and across states have been on the decline since the late 1940s (Ihrke, 2017), which makes neighbor effects due to citizen networks *more* likely. Conversely, the rise of social media, with its potential for widespread social contagion (Bond et al., 2012), could in fact *weaken* the effect of neighbor contagion. Importantly, Desmarais et al. (2015) found that only 10 to 20 percent of ties in state diffusion networks—from 1960 to 2009—were between contiguous states. Meaning, the vast majority were between noncontiguous states. This means that contiguity is certainly still part of the policy diffusion story, but it is clearly not the entire story.

Given the above, it is likely that the influence of contiguous neighbors weakened during the latter half of the twentieth century.

> *Contiguous Neighbor Hypothesis: The probability of adopting an innovation increases as the proportion of a state's neighbors previously adopting the policy increases, though this effect has declined in strength over time.*

This does not mean that cross-state social networks, economic competition, and learning/emulation among neighbors are now irrelevant. But the question is whether other cues, like ideology, have become, relatively speaking, more influential.

Ideological Information Cues

There is limited, but growing, evidence that the relative ideology of previous adopters is a component of a state's decision to innovate (Boehmke & Skinner, 2012; Grossback et al., 2004; Volden, 2006). In fact, ideology is one facet of source states who surpass neighbor states in terms of diffusion ties. Conservative states are less likely to follow liberal states in adopting an innovation, and vice versa (Desmarais et al., 2015). Furthermore, local officials are less likely to consider innovations from ideologically dissimilar jurisdictions (Butler, Volden, Dynes, & Shor, 2017). This occurs because adoption by ideologically similar states reduces the *political* uncertainty surrounding a policy, whereas neighbor adoptions are thought to reduce policy success uncertainty (Grossback et al., 2004). While ideological similarity and geographic proximity overlap to a degree (e.g., California and Oregon), it is not complete (e.g., California and Arizona).

But why might ideological cues be more important today than in the 1960s? I argue that there are two key developments. The first is political polarization and the second is the rise of the ALEC and, more recently, SIX. It is no secret among scholars or pundits that political polarization plays an important role in modern American politics. Granted, polarization is not unique to the modern era, but it has become increasingly relevant in American politics as the parties became more strongly linked to ideological poles and partisans sorted accordingly (Levendusky, 2009). While varying in degree, polarization has affected the states (Shor & McCarty, 2011). Ideology has thus become an increasingly important cue regarding the acceptability of candidates and policies (Caughey, Warshaw, & Yiqing, 2017). Given these changes, states with greater polarization in their legislature should be more attentive to ideological cues, as individual members' ability to remain in office depends more on their ability to display ideological bona fides, as opposed to demonstrating their effectiveness in solving problems.

Ideology Polarization Hypothesis: As polarization increases, the effect of ideological distance becomes increasingly negative.

Neighbor Polarization Hypothesis: As polarization increases, the positive effect of neighbor adoptions declines in strength.

Republicans presently have a powerful troika of nonstate actors—ALEC, State Policy Network (SPN), and Americans for Prosperity (AFP)—that support the spread of conservative legislation among the states (Hertel-Fernandez, 2019). Each arm plays a different role in state policymaking and they have not all existed for the same amount of time. ALEC is the oldest, founded in 1973, and produces model legislation. The organization claims to be focused on free market policies, but has also dabbled in stand your ground laws, voting restrictions, and more throughout its history. SPN, founded in 1992, provides research in support of conservative policy initiatives. Finally, AFP, founded in 2004, is focused on electioneering. All three gained increasing importance in the late 2000s, as Republicans made substantial gains in controlling state legislatures and governorships. Though preceded by other organizations, SIX was founded in 2012 to provide a progressive policy counterweight to ALEC. This marked, to some degree, a turn for progressives from a focus on national politics to an increasing focus on the states.

Given both the trend toward greater polarization in state chambers over the past two decades and the growth of ALEC's influence since 1973, the effect of ideological cues should increase from 1960 to 2014. Whereas, in the past, a state's neighbors were likely more similar in terms of citizen demographics and demands on government, the concept of "neighbors" is shifting to an ideological frame, where legislators want to not only know whether a policy works, but also whether it will benefit them in the next primary election. This is not to say that ideological cues did not matter in the past, but I am arguing that an implication of our current polarized environment in the United States is the increased importance of ideological information.

Ideological Distance Hypothesis: The probability of adopting an innovation declines as the average ideology of previously adopting states is further from a considering state; and this effect has gotten stronger over time.

It is also likely that policy attributes condition whether ideological cues matter for a given policy. Whereas legislators tend to seek innovations that are highly salient and require fewer resources (Karch, 2007a), there are also technically complex innovations that tend to diffuse more slowly (Nicholson-Crotty, 2009) due to the greater practical risks of poorly formulated policy. Of course, when legislators seek information on such complex policies, they tend to rely on easily accessible information, which would logically include the experiences of contiguous neighbors. Thus, ideological cues should be weaker for complex policies.

Complexity Hypothesis: The effect of ideological cues is stronger for noncomplex policies than complex policies.

Furthermore, if ideological cues are signals of ideological bona fides, which assist legislators in position taking for the next election, then these cues should be the strongest for issues that are highly salient to the public. It is on those highly salient issues where *political* failure is of greatest risk to legislators. Thus, ideological cues should be more impactful for highly salient policies.

Salience Hypothesis: As salience increases, the strength of the effect of ideological cues also increases.

Methods and Data

In order to test the changing dynamics of policy diffusion, it was necessary to assemble a large dataset of policies across a wide span of time. In 2018, a team of policy diffusion scholars released the State Policy Innovation and Diffusion (SPID) dataset (Boehmke et al., 2019). In all, SPID contains over 700 policies adopted by the states between 1691 and 2017. To test the arguments presented above, I utilized 556 policies that spread among the states between 1960 and 2014.[2] A start year of 1960 was chosen because many of the covariates included in this analysis are not measured before 1960.

Dependent Variable

The dependent variable for this analysis is a dichotomous indicator of whether a state (i) adopted a given policy innovation (p) in a year (t).[3] Thus, the unit of analysis is the state-policy-year. As is common in event history analyses, states remain in the dataset until they adopt a given policy and then they drop out for that policy.

Independent Variables

The two key covariates of interest are *neighbor adoptions* and *ideological distance*. For the influence of past adopting neighbor states, I chose to use the proportion of a state's contiguous neighbors that have adopted an innovation prior to the current year (t). For *ideological distance*, I rely on the measure originated by Grossback et al. (2004) and used in a pooled adoption model by Boehmke and Skinner (2012):

$$\textit{Ideological Distance}_{itp} = \left| \textit{Ideology}_{it} - \frac{\overline{\textit{Ideology}_j} + \overline{\textit{Ideology}_k}}{2} \right|$$

Ideological distance is the absolute distance between the ideology of a state (i) that has not previously adopted a given policy (p) in an observed year (t) and the ideology of all previous adopters at the time they adopted the given policy (p). I use the revised 1960–2016 citizen ideology series from Berry, Ringquist, Fording, and Hanson (1998) as the measure of state ideology. Like Grossback et al. (2004), I upweight recent adopters, as their ideological cues are likely more relevant to states considering an innovation than those that adopted longer ago. This is done by adding the average ideology of adopters (k) from the most recent adoption year to the average ideology of the remaining older adopters (j) and dividing by 2.[4] Meaning, the ideology of the most recent adopters has equal weight to the set of all other past adopters. When interpreting the findings, it is important to keep in mind that this is a measure of ideological *distance*. Meaning, as previous adopters are more ideologically distant from a given state in a given year, that state should be less likely to adopt the policy.

In addition to these two variables, I include as controls a set of external, internal, and policy-level determinants that have demonstrated effects across a variety of policies in past diffusion research. *Congressional hearings* captures the explicit and implicit influence of the federal government on state adoption behavior (Karch, 2006; Welch & Thompson, 1980). It measures the percentage of total Congressional hearings in a given year by major policy topic.[5]

Internal characteristics of the states include *initiative availability*, *initiative qualification difficulty*, *legislative professionalism*, *slack resources (per capita income and population)*, *divided government*, and *polarization*. *Initiative availability* is a dichotomous indicator of a state's initiative status based on information from the Initiative & Referendum Institute (similar to Boehmke & Skinner, 2012).[6] While a dichotomous initiative availability measure can test whether initiative states as a whole innovate more quickly than non-initiative states, it is a blunt measure of the effect of initiatives.

Thus, I also include the Bowler and Donovan (2004) *initiative qualification difficulty* index. *Slack resources* are operationalized using state *population* and *per capita income*. Both are logged due to their skew. *Legislative professionalism* captures variation in the level of legislative resources available to states and is measured using Squire's (2012, 2017) index, which varies over time.[7] *Divided government* tends to be a drag on the spread of some innovations, but is also potentially productive for others (see Berry & Berry, 1990). It is measured using a dichotomous indicator, with 1 representing any combination of split party control and 0 representing single party control of the state legislature and governorship (Klarner, 2003). Finally, *polarization* is measured for the year 1993–2014 using Shor and McCarty (2011) updated scores. Specifically, I average the measures of ideological distance in each state's House and Senate to arrive at an average difference score.[8] A larger score means greater polarization in that state's legislature.

Finally, I include three policy-level measures that operationalize two concepts: salience and complexity. The measurement of policy-level attributes in policy diffusion research is relatively nascent (Makse & Volden, 2011), but salience and complexity have been found to impact the speed of policy adoption (Mallinson, 2016; Nicholson-Crotty, 2009). They are also the variables for which there are standard measures across diverse policies.[9] Salience is measured using the percentage of annual coverage in the *New York Times* and Gallup's *Most Important Problem (MIP)*.[10] They are matched to each policy using its major topic code, thus they capture the amount of attention paid to a general policy topic in a given year. For example, the major topic for health insurance portability (hiport) is health care (3) and thus the two measures capture media attention and public opinion regarding health care in year *t*. *Complex policy* is measured using Nicholson-Crotty's (2009) dichotomy.[11] Policies are complex if they fall into the energy, environmental pollution, health care (provision, finance, and licensing), taxation, trade, and fiscal regulation policy domains.

In addition to the above independent variables, interaction terms are included in several different model specifications to test the conditional expectations of the above hypotheses. Namely, *neighbor adoptions* × *year* and *ideological distance* × *year* test the primary hypotheses that both effects are changing over time. In two additional models, *ideological distance* × *complex policy* tests the hypothesis that policy complexity conditions ideological cues and *ideological distance* × *MIP* tests the hypothesis that issue salience among the public also conditions ideological cues. Finally, in an analysis of data from 1993 to 2014, *ideological distance* × *polarization* and *neighbor adoptions* × *polarization* test the hypotheses that polarization affects each of the signals by increasing the importance of ideology and decreasing the importance of contiguous neighbors.

Modeling Approach

There are two non-nested levels of observations in the dataset: policy and state. Thus, I estimate a multilevel logistic regression model, though random intercepts are only included for policies as there is little remaining variation in state intercepts once covariates are added.[12] The addition of random slopes to a pooled event history model is an effective means for estimating average effects across a heterogeneous collection of policies (Kreitzer & Boehmke, 2016), thus I include random slopes for *neighbor adoptions*.[13] To account for duration dependence, I include a log of time (Beck, Katz, & Tucker, 1998; Buckley & Westerland, 2004).[14]

Results

Before examining change over time, I first want to establish whether the diffusion determinants included in this analysis in fact have general effects when pooling policy and time. While there are recent efforts at identifying the broader patterns of policy diffusion across multiple policy domains, much diffusion research still relies on the single-policy EHA paradigm. With a multitude of conflicting results, it can be difficult to say with confidence whether the determinants that are often expected to matter for innovation adoption are in fact generalizable. The first column in Table 1 presents the results of a model that is completely pooled using all the available data.[15] Odds ratios and their 95 percent confidence intervals are reported for each effect. Many, though not all, of the determinants expected by policy diffusion theory exhibit statistically significant effects when fully pooled. But subsequent analysis will demonstrate that some of these effects are not consistent over time.

Of note is the replication of the interactive effect of salience and complexity on the likelihood of innovation adoption. This interactive effect has been shown for measures of adoption speed (Mallinson, 2016; Nicholson-Crotty, 2009); however, these results demonstrate that they also generally condition the likelihood that a state will adopt a policy innovation. Figure 1 displays both marginal effects and predicted probabilities for policy complexity and salience and their effect on policy innovation adoption.[16] High salience and low complexity, as well as low salience and high complexity policies have the highest probability of adoption. For complex policies, their adoption probability substantially decreases as salience increases. Thus, while noncomplex policies can spread quickly if they receive high priority among the public, salience is not able to overcome the hesitancy of legislators when they tackle complex legislation. In fact, it is likely that their high salience and high complexity encourage legislators to pause in order to better ensure policy success. I would note that for all of these results the absolute predicted probability is quite low, but this is to be expected given that adoption of an innovation from a crowded government and public agenda is an uncommon event. Thus, I would argue that even these small effects are substantively important. Having established that many of the effects expected by current diffusion theory are generalizable when completely pooling across policy and time, I now turn to examining how contiguity and ideology cues change over time.

Change Over Time

The second model in Table 1 tests the hypotheses that the effects of geographic and ideological proximity have changed from 1960 to 2014. This is done by interacting *neighbor adoptions* and *ideological distance* with a count of time that starts in 1960 and progresses through 2014. To interpret the effect, Figure 2 presents the marginal

Table 1. Results of All Pooled Models, Including Interaction with Year

Covariate	All Pooled	Year Interaction
External influences		
Neighbor adoptions	1.26* [1.21, 1.31]	1.31* [1.25, 1.37]
Ideological distance	0.87* [0.85, 0.89]	0.88* [0.86, 0.90]
Neighbor × Year		0.93* [0.90, 0.95]
Ideological distance × Year		0.98 [0.96, 1.00]
Congressional hearings	1.08* [1.03, 1.13]	1.08* [1.03, 1.13]
Internal characteristics		
Initiative available	1.24* [1.15, 1.33]	1.24* [1.15, 1.33]
Initiative qualification difficulty	0.94* [0.93, 0.96]	0.94* [0.93, 0.96]
Divided government	0.98 [0.94, 1.02]	0.98 [0.94, 1.02]
Legislative professionalism	0.98 [0.96, 1.01]	0.99 [0.96, 1.01]
log(Per capita income)	1.11* [1.01, 1.22]	1.09 [0.99, 1.20]
log(Population)	1.06* [1.03, 1.09]	1.06* [1.03, 1.09]
Policy characteristics		
Most important problem	1.07* [1.03, 1.12]	1.08* [1.03, 1.12]
Complex policy	1.20 [0.95, 1.52]	1.20 [0.94, 1.52]
MIP × Complex	0.78* [0.73, 0.84]	0.77* [0.72, 0.83]
New york times	1.08* [1.03, 1.13]	1.07* [1.02, 1.22]
Year	1.24* [1.12, 1.38]	1.32* [1.19, 1.47]
log(Time)	0.87* [0.83, 0.90]	0.85* [0.81, 0.88]
Intercept	0.04* [0.04, 0.05]	0.04* [0.04,0.05]
Policy intercepts	1.10 (1.05)	1.12 (1.06)
var(Neighbor adoptions)	0.11 (0.34)	0.12 (0.35)
N	299,599	299,599

Notes: 95% confidence intervals for reported odds ratios are in brackets. Standard deviations are in parentheses for variance components.
*$p < 0.05$.

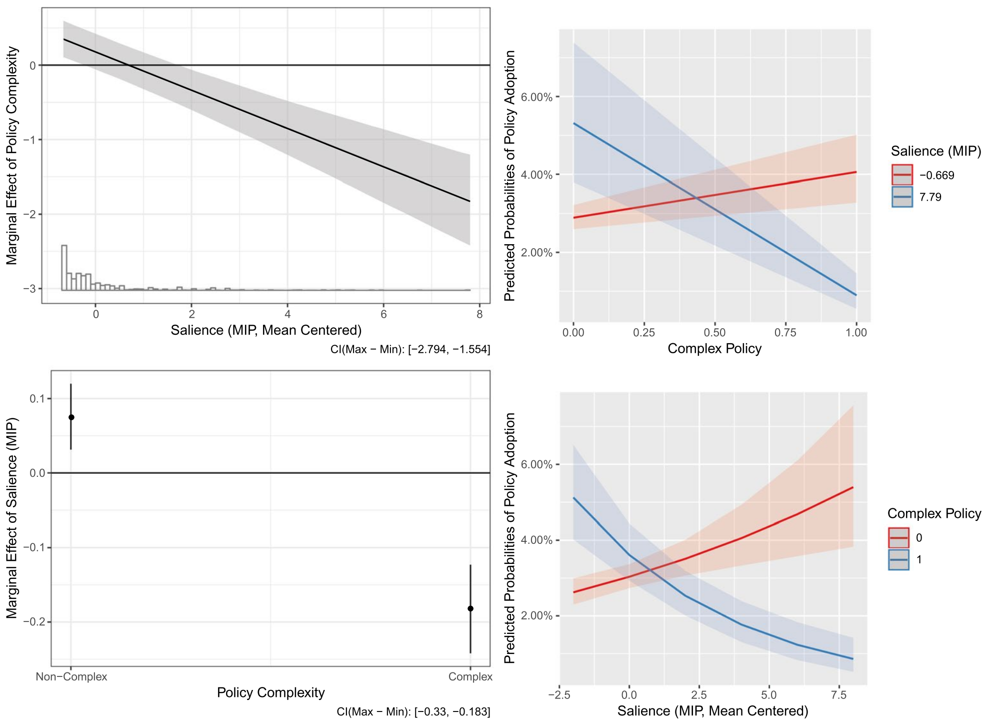

Figure 1. Marginal Effects and Predicted Probabilities for Policy Complexity and Salience. [Colour figure can be viewed at wileyonlinelibrary.com]

effects and predicted probabilities for both interactions. Both marginal effects plots support the basic conclusion of the beta coefficients, that there is a statistically significant decline in the effect of *neighbor adoptions* over time, but not *ideological distance*. The predicted probability plots, however, are far more interesting. The results for 1960 (red) and 2014 (blue) are plotted in each figure. For neighbor adoptions, the expected increase in predicted probability of adoption is evident in 1960, but in 2014 there is actually no statistically significant ($p < 0.05$) change in adoption probability as more neighbors adopt. This is evident from the overlapping confidence intervals across the entire span of the predicted probability line. The opposite is the case for ideological distance. In 1960, there is no statistically significant change in the predicted probability of adoption as distance increases, however there is a significant decline in the probability of adoption by 2014. This is evidence that supports the argument that contiguity cues—be they due to policy learning, competition, or social contagion—declined in influence over time while ideological cues increased.

Conditioning Effects of Policy Attributes and Political Polarization

These results raise the question of what changes in context may impact the import of geographic and ideological cues for legislators. Table 2 presents models testing the conditional effects of salience, complexity, and polarization on ideological

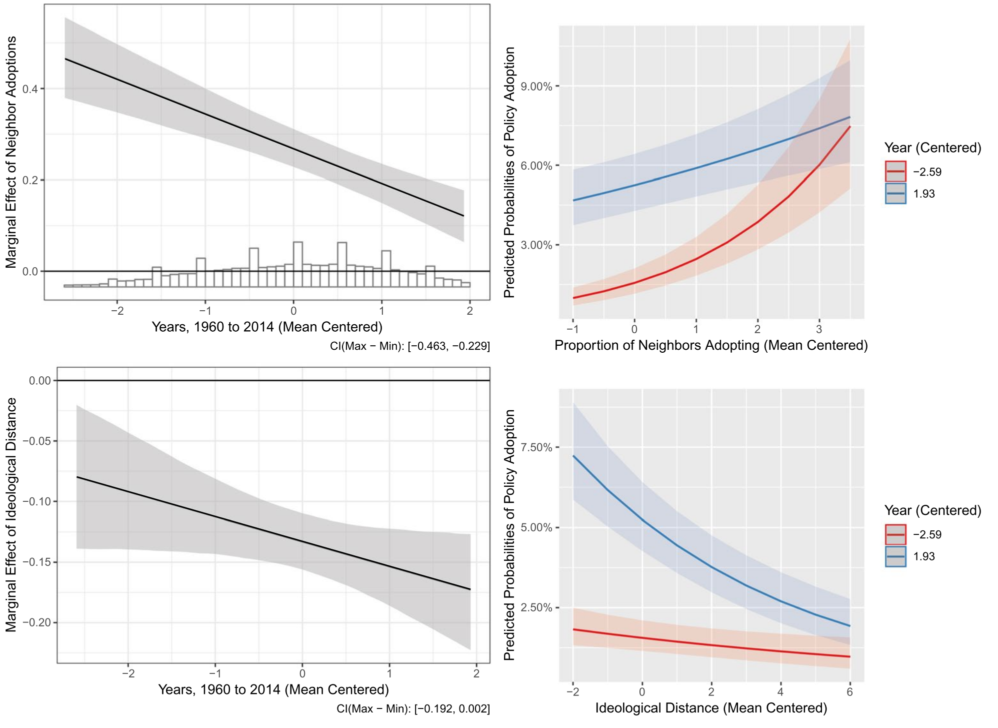

Figure 2. Marginal Effects and Predicted Probabilities for Neighbor Adoptions and Ideological Distance, Conditional on Time. [Colour figure can be viewed at wileyonlinelibrary.com]

Table 2. Main Results of Models Testing the Conditional Effects of Salience, Complexity, and Polarization on Neighbor Adoptions and Ideological Distance

Covariate	Salience Interaction	Complexity Interaction	Polarization
Neighbor adoptions	1.26* [1.21, 1.31]	1.26* [1.21, 1.31]	1.37* [1.27, 1.48]
Neighbor adoptions × Polarization			0.93* [0.89, 0.97]
Ideological distance	0.87* [0.85, 0.89]	0.87* [0.85, 0.89]	0.91 [0.82, 1.01]
Ideological distance × MIP	1.00 [0.98, 1.02]		
Ideological distance × Complexity		1.02 [0.96, 1.08]	
Ideological distance × Polarization			0.96 [0.89, 1.04]
Most important problem (MIP)	1.07* [1.03, 1.13]	1.07* [1.03, 1.13]	1.03 [0.97, 1.10]
Complex policy	1.20 [0.95, 1.52]	1.21 [0.95, 1.53]	1.31 [0.98, 1.76]
N	299,599	299,599	

Notes: 95% confidence intervals for reported odds ratios are in brackets. Standard deviations are in parentheses for variance components. Full results included in the Supplemental Information.
*$p < 0.05$.

and neighbor adoption cues. Note that only the odds ratios and 95 percent confidence intervals for the main variables of interest are included. The full results are provided in the online supplement. At first pass, it appears that policy characteristics have little impact, and polarization conditions the effect of neighbor adoptions, but not ideological distance. Figure 3 displays marginal effects and predicted probabilities for the salience and complexity interactions, while Figure 4 displays the same for the polarization interactions. Figure 3 confirms that there is little distinction in the effect of ideology due to policy salience or complexity. While more salient and less complex policies were expected to be more susceptible to ideological dues, it is quite interesting that all policies are subject to these cues. Thus, it may not be only simple policies or nonprofessional legislatures that are influenced by ideologically laden policies that can be copied from sources like ALEC (Garrett & Jansa, 2015; Jansa, Hansen, & Gray, 2019). Even technical policies are impacted by ideological learning, not just policy learning.Turning to the conditioning effect of polarization, Figure 4 presents some evidence that both cues are impacted by legislative polarization, though differently. In terms of neighbor adoptions, they have the characteristic positive increase in probability in the lowest polarization legislatures, but that effect becomes essentially flat for highly polarized legislatures. Of course, by the time most neighbors adopt, it is impossible to tell a difference in adoption probability across different legislatures. For ideological distance, the expected negative effect is found in states with highly polarized legislatures, but the effect flattens for the

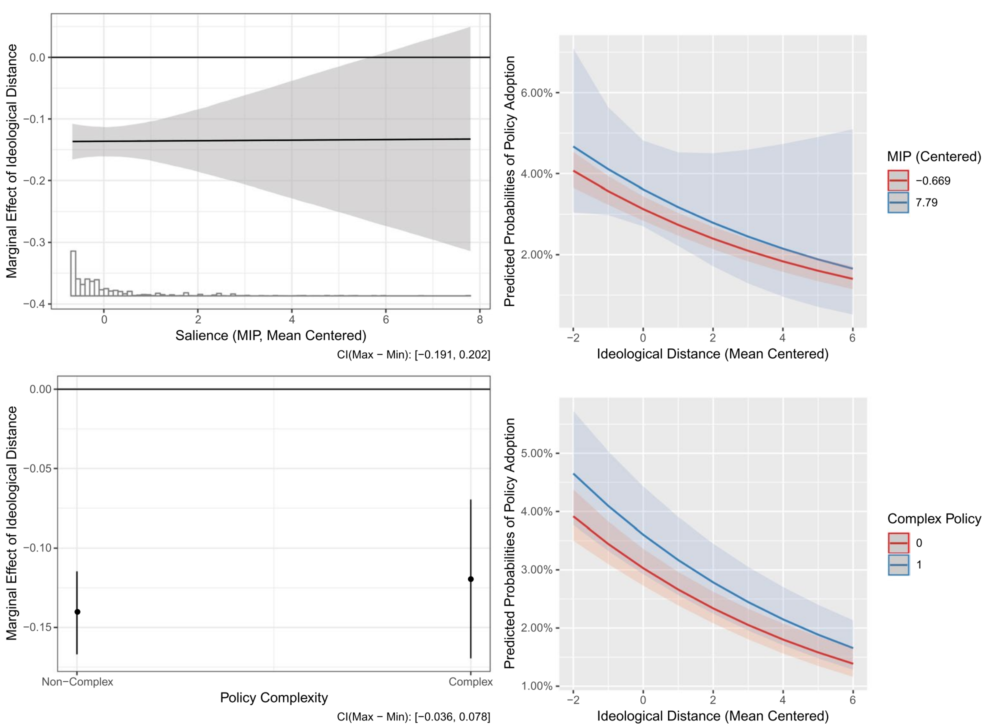

Figure 3. Marginal Effects and Predicted Probabilities of Ideological Distance, Conditional on Policy Salience and Complexity. [Colour figure can be viewed at wileyonlinelibrary.com]

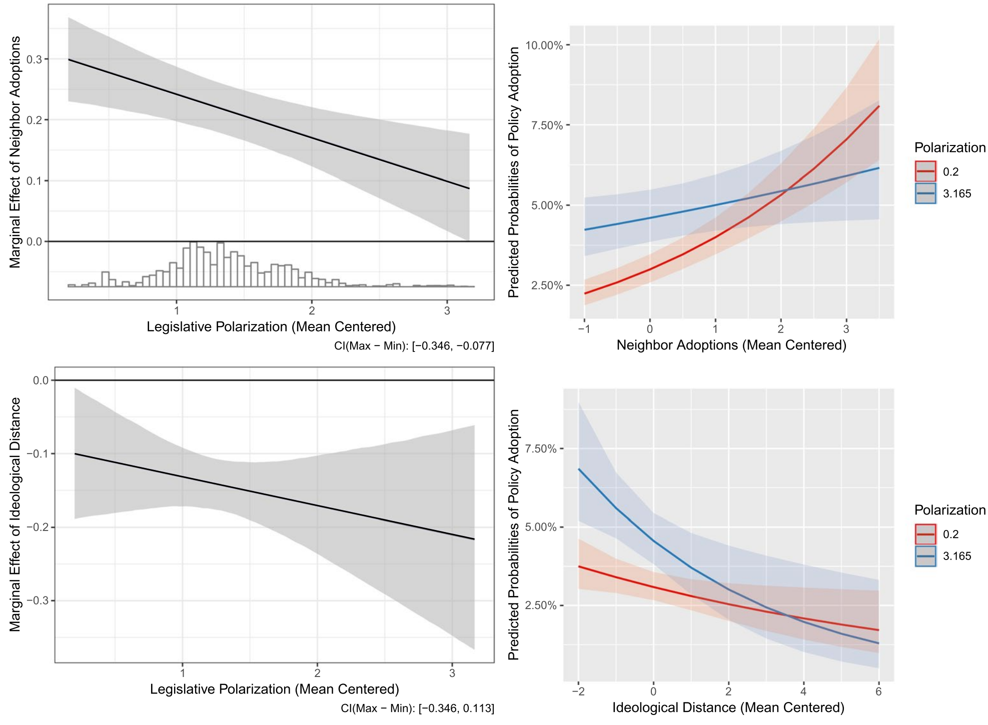

Figure 4. Marginal Effects and Predicted Probabilities of Neighbor Adoptions and Ideological Distance, Conditional on Legislative Polarization. [Colour figure can be viewed at wileyonlinelibrary.com]

least polarized. Again, at roughly the mean ideological distance and above, the two effects are statistically indistinguishable. Adoption is simply less likely for both.

Discussion and Conclusion

Studying policy diffusion patterns in the United States helps us to better understand how ideas emerge, are legitimized, spread, and sometimes fizzle in American politics. Though single-policy diffusion studies either explicitly or implicitly test aspects of Berry and Berry's (2018) model that unifies internal and external predictors, even the most important variables yield inconsistent results across studies. This study sought to address one important inconsistency, the fact that not all innovations are subject to the influence of neighbor state adoption cues. Ideological "neighbors" also often serve as source states of policy innovations. Furthermore, it appears that the relative influence of policy and political cues have shifted over time and there is evidence to suggest that polarization plays a role in that shift. This study does not exhaustively test all potential explanations for why diffusion patterns are changing. But it does confirm in the modern era an observation that Jack Walker made in 1969 that the correlates of state innovation do in fact change over time. This has important implications for how we understand and study American federalism.

Perhaps the most important implication of these findings is the decline of neighbor adoption cues and a concomitant increasing in the relative importance of ideological cues. The question arises as to why this transition occurred. Political polarization is one culprit that receives a great deal of attention among political scientists. The above suggests that polarization and gridlock in Congress may not only be shifting policymaking to the states, but is also affecting how, when, and what policies states adopt. This has normative importance for the good governance image of the states as laboratories of democracy. The underlying assumption of the laboratories frame is that the states are experimenting for the purpose of finding the best policy solutions. Ideas that do not work can be discarded without much damage and those that do can either diffuse widely or are nationalized. Ideological learning, however, may violate this assumption if it fosters the spread of policies falling closer to the ideological fringe. Of course, this raises a jointly normative and empirical question of whether policies spreading in traditional diffusion patterns are in some sense "better" than those that are driven by ideology. It is unlikely that organizations like ALEC and SIX will shrink in importance in an age of overabundant information. Thus, the increased relevance of ideological diffusion should result in greater scholarly attention to these organizations and particularly their role in policy diffusion.

Beyond the shifting influence of contiguity and ideology, these results corroborate that policy attributes belong in the general model of diffusion alongside internal and external predictors (Makse & Volden, 2011); ideological cues are not conditioned by the salience or complexity of a policy. Much like Berry and Berry's (1990) fusion of internal and external predictors, innovation attributes should be included in any study of policy diffusion at the macro level. There are many avenues for advancing our understanding of how these attributes condition the likelihood and speed of policy adoption. Measurement should be one major area of focus. The broader theory of innovation adoption outlines five common attributes: relative advantage, observability, compatibility, complexity, and trialability (Rogers, 2003). Given that these attributes are identified "in the eye of the beholder," the most internally valid method for measuring them requires surveys of political elites (Makse & Volden, 2011). This approach, however, is highly resource-intensive and thus difficult to scale up in a way that allows us to examine their effect in a macro-level model. Therefore, additional effort is required to develop archetypes of these attributes that can be measured, and thus compared, across policies.

This analysis does not overcome the challenges of convenience sampling that plague policy diffusion data. It is quite possible that the nonrandom selection of these policies affects the results. To be sure, this is a broader challenge for all diffusion studies (Nicholson-Crotty, Woods, Bowman, & Karch, 2014; Rogers, 2003). There is no proper sampling frame from which to draw innovations to study. The accumulation of studies, and now datasets of policies, is an encouraging advancement. Richer and broader datasets of innovations, like SPID, are still ultimately convenience samples, but their greater coverage of time and policy domain will add to the confidence we have in the generalizability of our results. It is encouraging that advances in technology and interest by a committed community of scholars are rapidly advancing our understanding of how innovation occurs in the American federal system.

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Notes

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1. Though the pace of constitutional change slowed greatly by the 1980s (Cain & Noll, 2009).
2. The 556 policies represent 21 different major policy topics, with the most represented being Law (29 percent), Civil Rights and Liberties (17 percent), Finance (13 percent), and Health (10 percent). An important limitation to note is that SPID remains a convenience sample of policies, meaning we cannot know its representativeness of policies under consideration by the states during that time frame. This is a thorny problem that is well noted within the study of policy diffusion (Nicholson-Crotty, Woods, Bowman, & Karch, 2014). Section I of the Supplemental Information uses the Pennsylvania Policy Agendas Project (McLaughlin et al., 2010) as a rough benchmark showing that the Law category is likely the most over-represented. Section III of the Supplemental Information, however, demonstrates that adding a fixed effect for the Law category is not statistically significant and does not alter the main results. As past researchers have argued, the diversity and broadness of a diffusion dataset's policy topic coverage increases its external validity (Miller, Nicholson-Crotty, & Nicholson-Crotty, 2018) and the SPID data are the broadest available. That said, the limitation of convenience sampling remains.
3. Reproduction data and analysis scripts are available at: https://doi.org/10.7910/DVN/O7HHKB.
4. For the first year of adoption, I use the distance between each state and the average ideology of all 50 states. This gives a sense of how distant the first adopter(s) was from the rest of the states and then each subsequent year measures the distance of an adopting state from the cluster of previous adopters.
5. This is drawn from the Comparative Agendas Project. https://www.comparativeagendas.net/.
6. http://www.iandrinstitute.org/states.cfm.
7. Since Squire's measure is only calculated in 1979, 1986, 1996, 2003, 2009, and 2015, I use linear interpolation to fill in missing values between each measured year and copy the first (1979) and last (2015) measured values back and forward, respectively (Zileis & Grothendieck, 2005).
8. Shor and McCarty also include a polarization measure for Nebraska's unicameral legislature based on Seth Masket's work, thus Nebraska is still included in this analysis.
9. Makse and Volden (2011) measured all five attributes offered by diffusion theory, but had to rely on surveys of legislators to do so. This is impossible to implement for such a large set of policies and long time span.
10. Both are drawn from the Comparative Agendas Project. https://www.comparativeagendas.net/.
11. Presently, there is no other measure of complexity for these policies, such as bill length (Gerber & Teske, 2000), lexical complexity, or citation complexity (Bommarito & Katz, 2010, Katz & Bommarito, 2014).
12. Section II of the Supplemental Information assesses whether a logit, probit, or cloglog link is more appropriate for the data. Beck, Katz, and Tucker (1998) argue that there is little difference between the results using a logit and cloglog link when the probability of an event is small. This is indeed the case for this data and there is little difference in the results and the loglikelihood of both models. Thus, I use the more familiar logit link.
13. Random slopes were also initially included for ideological distance, but there is little variation across the slopes and thus it was removed to simplify the model.

14. While a spline of time fit the data the best, I have no theoretical basis for establishing knots. This is a good reason to consider including a polynomial of time (Carter & Signorino, 2010), a log of time was an improvement over both a count of time and a polynomial (see Section III of the Supplemental Information).

15. All continuous independent variables were standardized with a mean of 0 and standard deviation of 1. This was done to avoid convergence issues in lme4 with variables measured on different scales. This means that the coefficients in Table 1 represent the resulting change in the odds of a 1 standard deviation change in a continuous measure.

16. One cannot fully understand the statistical significance of interaction effects from the magnitude of significance of the beta coefficients (Brambor, Clark, & Golder, 2006). To assess this, I first plot marginal effects with confidence intervals that help us understand the region of significance for the conditional effect (Berry, DeMeritt, & Esarey, 2010; Berry, Golder, & Milton, 2012). The marginal effects plots make appropriate corrections for the false discovery rate (Esarey & Sumner, 2018). Second, plots of meaningful quantities, particularly the predicted probabilities, are included to better understand the substantive significance of the interactions (Hanmer & Ozan Kalkan, 2013). This process is replicated in all reported interactions. Marginal effects are plotted using Interplot (Solt & Hu, 2015) and predicted probabilities are plotted using sjPlot (Lüdecke, 2018) in R. Note that the minimum value for MIP is −0.67 and the maximum observed value is 7.80. Thus, though sparse, there are MIP observations between 3 and 3.8, though they are not visible on the *x*-axis histogram.

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Supporting Information

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