Why are Politicians More Likely to Learn From Neighbors? Behavioral Evidence From Three Advanced Democracies

Daniel Cruz* Miguel M. Pereira†

Abstract

Empirical work on policy diffusion has established that policymakers are more likely to learn from the experiences of neighbors. Yet, the underlying mechanism behind spatially clustered policy learning remains unclear. Proximity may signal contextual similarity, leading officials to expect a better policy fit from nearby constituencies. However, proximity may impact policy learning simply due to information exposure. We adjudicate between these mechanisms by repurposing data from two field experiments that delivered information on new policy innovations to local politicians in Germany, the United Kingdom and the United States while varying the constituency of the early adopters. Across studies, issues, and countries, we find no reliable evidence that geographic proximity to early adopters predicts interest in policy learning. The results reveal that proximity effects in studies of policy diffusion likely arise from differential exposure rather than contextual fit and contribute more broadly to our understanding of bounded rationality and elite behavior.[1]

*PhD Fellow, University of Copenhagen, Department of Political Science, daniel.cruz@ifs.ku.dk.

†Associate Professor, European Institute, London School of Economics and Political Science, m.m.pereira@lse.ac.uk.

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We would like to thank Frederik Hjort, Michael Lerner, and Lawrence Ezrow for valuable feedback on earlier versions of the draft.

For decades, academics have sought to explain how policy innovations spread across jurisdictions (Böhmelt et al., 2016; Graham, Shipan and Volden, 2013; Gray, 1973*a*; **?**). Understanding what drives policy diffusion can help us not only grasp the motivations of elected officials in office, but also reform institutions to promote the dissemination of effective policies and to mitigate the reproduction of bad solutions (Shipan and Volden, 2021). A common pattern in the policy diffusion literature is that geographic proximity plays a significant role in shaping policy learning (e.g., Berry and Baybeck, 2005; Curini, Daniele and Stanig, 2025; Dolowitz and Marsh, 2000; Einstein, Glick and Palmer, 2019). Yet, scholars disagree on why distance matters (Shipan and Volden, 2008; Dobbin, Simmons and Garrett, 2007). Nearby constituencies share labor markets, media spheres, and institutional legacies, making external policies both more readily transferable and more accessible (**?**Gilardi, 2010). The exact mechanism underlying this relationship remains an open question (Desmarais, Harden and Boehmke, 2015)

Learning models of diffusion offer two main explanations for why policies disseminate in spatial clusters. On one hand, nearby constituencies tend to share political, economic, and demographic characteristics. Hence, policymakers interested in identifying policy solutions that are feasible and more likely to work in their constituency may be more sensitive to the policy experiences of nearby jurisdictions (e.g., Simmons, Dobbin and Garrett, 2006). On the other hand, politicians may be more likely to learn from geographically closer jurisdictions due to informational constraints. Policymakers operate under severe time and resource constraints (Kingdon, 1989; Zelizer, 2019). In this environment, availability heuristics shape the policy learning process and politicians in any given constituency are more likely to be exposed to nearby policies through regional media, professional associations, or formal and informal networks (**?**Shipan and Volden, 2012; Vis, 2019; Weyland, 2005).

Understanding which mechanism better explains spatially clustered policy learning can shed new light on the policymaking process and the prospects of policy diffusion. While the former mechanism implies that elected officials consciously devote more attention to the experience of nearby constituencies, the informational constraints' mechanism suggests that politicians could

pursue other more suitable policy solutions if only they had the necessary resources to learn about them. This latter mechanism raises concerns about suboptimal policy transfers where ineffective or contextually inappropriate policies may spread simply because they are more easily accessible.

To disentangle these two mechanisms of spatially clustered policy learning, we turn to micro-level evidence and explore the motivations of policymakers to learn about a new policy (Butler et al., 2017; Senninger and Seeberg, 2024). The evidence comes from a reanalysis and extension of two studies with local politicians in Germany, the United Kingdom (UK) and the United States (US) (Pereira, 2022; Pereira et al., 2025). In Study 1 (N = 1,103), German councillors and mayors received an invitation to a real policy webinar on net-zero policies for local governments. The invitation either came from a German local politician or a British counterpart who shared their policy experiences in the workshop. Because the official sending the invitation was randomly assigned in the original study, we can isolate the causal effect of learning about this initiative from a politician in a nearby constituency, relative to a constituency in another country. We find that geographic proximity has no effect on politicians' interest in attending the webinar and learning more about net-zero policies. Observationally, we also find no consistent relationship between geographic proximity to the local governments promoting this policy learning event and interest in attending the workshop among German and British politicians.

In Study 2 (N = 6,713), US local representatives received an identically worded email from a non-governmental organization sharing information about a new immigration reform piloted in Salt Lake County. We calculate the distance from each recipient's constituency to Salt Lake County to estimate the effect of geographic proximity on policy learning. The results, once again, reveal that geographic proximity does not explain interest in policy learning once information availability (by design) is held constant. If anything, US local elected officials further away from Salt Lake County were *more* likely to express interest in learning about the policy. Overall, the results suggest that information availability is the primary mechanism explaining why policy-makers in the study are more likely to learn from office-holders in nearby jurisdictions.

Recent calls for understanding the micro-foundations of policy diffusion have looked at in-

dividual policymakers' decision-making processes directly. A growing body of literature uses surveys of politicians and other individual-level data to probe how decision-makers learn about policy (Butler et al., 2017; Einstein, Glick and Palmer, 2019; Senninger and Seeberg, 2024; Zelizer, 2022). We build on this scholarship to shed light on the underlying mechanisms behind spatially-clustered policy learning. The study also contributes to literature on policy transfers, or how and why policymakers seek ideas from elsewhere (Dolowitz and Marsh, 2000; Rose, 1991). Spatial proximity plays a similar role in this context and we believe our study provides a useful bridge between the study of diffusion – traditionally focused on macro-level processes – and the study of policy transfers.

More broadly, the study sheds new light on why policies spread across jurisdictions. A key implication of the findings is that institutional reforms can help the dissemination of effective policy. If informational exposure rather than rational evaluations shape policy learning, reducing the costs of information acquisition by improving access to diverse sources of policy information may lead to better-informed policy decisions and reduce the risks of pursuing suboptimal solutions.

Spatial Proximity and Policy Learning

The ability of politicians to learn from the experience of others can make policymaking more efficient (Böhmelt et al., 2016; Graham, Shipan and Volden, 2013). Through peer learning, decisions makers can replicate successful policies while avoiding wasting resources on solutions that work less well. The prospect of efficiency gains from peer learning has attracted the interest of scholars and practitioners for decades. Early work framed diffusion as the 'epidemic' spread of innovations (Gray, 1973*b*). Subsequent studies have extensively examined the mechanisms through which dissemination occurs (Shipan and Volden, 2008) and the conditions under which policies spread across jurisdictions (Shipan and Volden, 2012; Simmons, Dobbin and Garrett, 2006). In the context of this study, we focus on learning-based policy diffusion: the process of seeking

solutions that have proven successful elsewhere by early adopters (Berry and Baybeck, 2005).[2]

While scholars have studied several conditions for policy learning, one widely recognized factor is geographic proximity. Early empirical scholarship focused on the experience of US state legislatures and found that proximity predicts policy adoption, with policies more likely to be emulated by nearby states (**?**Boehmke and Witmer, 2004; Elkins and Simmons, 2005; Franzese and Hays, 2008). Similar patterns were observed in different levels of government and different parts of the world (Simmons, Dobbin and Garrett, 2006; Shipan and Volden, 2008; Weyland, 2005).

But why are policymakers more likely to be influenced by the policy choices of nearby peers? On one hand, spatial proximity may serve as a proxy for structural similarities between jurisdictions (Gerber, Henry and Lubell, 2013). According to this view, policymakers are more likely to pursue policies that were successfully adopted in nearby areas because these areas share economic, demographic, and institutional characteristics that make policies more applicable and more likely to succeed (Simmons, Dobbin and Garrett, 2006; **?**). Alabama's recent Rural Hospital Tax-Credit Program illustrates this process. State legislators openly cited Georgia's earlier experience, where a matching credit generated hundreds of millions of dollars for rural facilities, as proof that the policy could work in Alabama.[3] Similar examples can be found at the local level. St. Mary's County, Maryland adopted 'Welcome Packs' for jail releases after officials toured Prince George's County's reintegration program and concluded that their similar inmate populations and service gaps made the policy a good fit.[4] In these examples, the argument suggests, policymakers perceived the experience of nearby jurisdictions as more relevant due to shared contextual features. This mechanism can be described as *homophily-based learning* given the emphasis on how shared characteristics attract jurisdictions to each other.

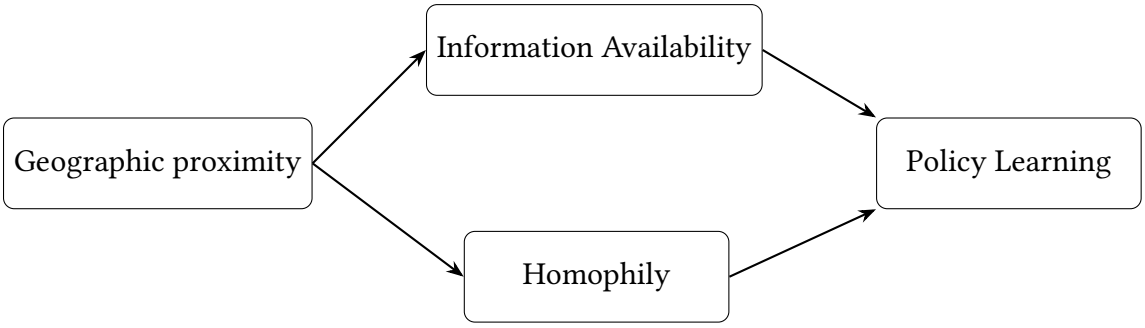
On the other hand, geographic proximity may matter for learning primarily because it affects

[2]Other mechanisms of policy diffusion include coercion, imitation, or competition (e.g., Pacheco, 2012). See Shipan and Volden (2008) for a review.

[3]WTVY, "Challenges for rural hospitals in Alabama continue, but newly passed legislation to support them could help" (May 30, 2025).

[4]The Baynet, "Homeless inmates leaving jail assisted via re-entry program " (April 29, 2016).

Figure 1: How geographic proximity shapes policy learning



the availability of policy-related information (Desmarais, Harden and Boehmke, 2015; Gilardi, 2016). Elected officials face endless demands and strict time constraints, often being forced to make decisions based on incomplete information (Kingdon, 1989; Ramirez-Ruiz and Senninger, 2025). A key part of a decision-maker's job is to decide how to allocate their limited time. In this environment, availability heuristics and other low-effort heuristics may dominate over deliberate reasoning (Tversky and Kahneman, 1974; Vis, 2019; Weyland, 2005). US state legislators, for instance, are more likely to take cues on policy issues from peers seating next to them, particularly at the roll-call voting stage (Masket, 2008; Zelizer, 2019). Research on elite–public cognitive gaps shows that even politicians with ample policy experience often default to frugal heuristics when confronted with information overload (Baekgaard et al., 2019; Pereira, 2021; Stolwijk and Vis, 2021; Walgrave and Dejaeghere, 2017). Under this view, legislators are unlikely to devote sustained effort to vetting every external idea; instead, they skim, rely on staff, and employ simple rules of thumb.

Closer geographical ties make policy success stories more easily accessible (Curini, Daniele and Stanig, 2025; Gilardi, 2010; **?**; Weyland, 2005). Nearby jurisdictions often share media markets that facilitate information transmission (Arceneaux et al., 2016). Politicians' networks – both intra- and inter-party – are also often organized within regions, making peer influence more likely. This is particularly the case in local politics, where administrative boundaries are more porous (Chen and Pope, 2020). Hence, *availability-based learning* describes a process of spatially-clustered policy learning that results from information accessibility, rather than suitability con-

cerns. Existing scholarship on policy learning suggests the plausibility of this mechanism. While studying the dissemination of trade reforms in the Global South, **?** concludes that information availability may play a role in explaining why the experience of Chile and East Asia did not shape trade policy choices in Africa.

Figure 1 illustrates the two mechanisms identified in the literature that can explain the relationship between spatial proximity and policy learning. A key challenge in distinguishing between these mechanisms is the difficulty of inferring underlying mechanisms from macro-level analyses. Spatial-econometric models explaining policy diffusion often reveal spatial interdependence in policy adoption (Elkins and Simmons, 2005; Neumayer and Plümper, 2012). While these models have been well suited to detect different types of policy diffusion, they provided limited insights into *why* these processes occur. A significant spatial-lag coefficient, for instance, tells us if there is diffusion among jurisdictions but not whether this arises from contextual learning or informational exposure.

Understanding which mechanisms better explain how politicians learn from the experience of others has important implications. If politicians are replicating successful policies from nearby constituencies because they recognize them as applicable due to structural similarities, this process can contribute to better governance by ensuring that policies are well-suited to the adopting jurisdiction (Shipan and Volden, 2021). In turn, if politicians are learning from neighbors only due to information availability, high-profile policies – regardless of their suitability or contextual fit – will be more likely to disseminate simply because they are more visible. High-profile policies – whether due to media amplification, political discourse, or public attention – may spread across jurisdictions not because they are effective but because they dominate the informational environment (Baumgartner et al., 2009; Senninger and Hansen, 2025). In such context, policy learning can lead to the spread of ill-fitting policies.

Distinguishing homophily from information availability

To understand why geographic proximity matters for policy learning, we build on existing micro-level scholarship exploring the motivations of politicians to learn. Learning-based policy diffusion ultimately materializes when decision-makers choose to seek out information and pursue an idea previously adopted elsewhere. Hence, tracing those individual-level choices provides a useful complement to macro-level models of policy diffusion.

As described in the previous section, the literature has identified two main mechanisms linking geographic proximity and policy learning: homophily and information availability. Yet the empirical challenge is that geographic proximity predicts both information availability and homophily, making the two mechanisms hard to separate. To overcome this challenge, we study contexts where information about a given policy can be equally accessed by politicians regardless of geographic location. In such context, if politicians use geographic proximity as a heuristic for policy fit, we should expect representatives to devote more attention to information from jurisdictions that are closer by, relative to those that are further away. On the other hand, if information accessibility is the main mechanism underlying the relationship between proximity and policy learning, politicians will pay no greater attention to policies from nearby jurisdictions once exposure to information is held constant.

By equalizing information across jurisdictions, we remove the availability pathway and any remaining impact of geographic proximity on officials' interest in learning should reflect evaluations based on perceived fit (see Figure 1). Empirically, this means that by observing how officials engage with policy information in a context where the information does not depend on geographic proximity, we can adjudicate between homophily-based learning and availability-based learning. This argument rests on the assumption that there is no other relevant mechanism linking proximity and policy learning. We are not familiar with alternative mechanisms of spatially-clustered policy learning in the literature. However, if other mechanisms are at play, the empirical strategy we propose can still allow us to test whether spatially-clustered learning is driven exclusively by information accessibility or some combination of other mechanisms.

Empirical Design

To adjudicate between homophily-based and availability-based learning, we repurposed data from two recent studies on policy learning with local elected officials (Pereira, 2022; Pereira and Öhberg, 2024). In both studies, researchers gave politicians the opportunity to learn about the policy experience of a different local government. The information was provided by non-partisan advocacy groups or local politicians collaborating in the studies and working on immigration and climate policy.[5]In the original studies, the authors experimentally manipulated elements of this communication to understand the motivations of elected officials to learn about these policies. We leverage these natural policy learning environments to adjudicate between the two mechanisms of spatially-clustered policy learning.

Study 1 uses evidence from two party-centric systems: Germany and the UK.[6] In the original study, local officials were invited to attend a policy-learning webinar on net-zero solutions for local governments (Pereira et al., 2025). As part of the webinar, local officials collaborating in the project shared their practical experience in this specific domain and gave concrete advice to participants. Crucially, the politician making the invitation was experimentally manipulated. In Germany, the invitation either came from a British councilor or a German local politician, both collaborating in the project. If homophily explains the relationship between geographic proximity and policy learning, we should observe more interest in this policy learning opportunity when the sender is a domestic peer compared to an international counterpart. No relationship between geographic proximity and politicians' interest in the webinar, in turn, would provide evidence consistent with availability-based learning. The study also allows us to explore, both in Germany and the UK, whether officials representing constituencies geographically closer to the politicians sharing their experiences in the webinar (within the same country) expressed more interest in

[5]Email communication is a common and effective way for advocacy groups to disseminate information among policymakers (Bergan, 2009; Ellis and Groll, 2020).

[6]The original study included data from four other countries. However, only German and UK officials received information from peer local officials in their country. Hence, we restrict our analyses to this subset.

attending the webinar.

Study 2 replicates the second part of study 1 in a different policy area and a different country. In the original study, US local officials received an email providing information about a new immigrant integration policy recently implemented in Salt Lake County (Pereira, 2022). The email, sent by a civil society organization as part of an outreach campaign, highlighted the experience of the early policy adopters in Salt Lake County. By tracking recipients' engagement with the information campaign and their exact distance to Salt Lake County, we estimate the effect of proximity on politicians' interest in learning about the policy. If spatial proximity influences policy learning because of perceived policy fit, we should observe higher engagement among representatives located closer to Salt Lake County compared to those farther away.

Germany, UK and the US represent useful cases for this study. On one hand, they offer contrasting institutional and political environments. Differences in electoral systems also influence the type of politicians elected and their incentives to independently learn about new policy solutions (Sellers, Lidström and Bae, 2020). On the other hand, the three countries share relatively high levels of decentralization; contexts where local officials play a significant role in policy adoption. The US, as a large and heterogeneous country with a federal system, provides a most-likely case for homophily-based learning. Germany and the UK, in turn, allow us to test the generalizability of our findings in a context with strong party discipline norms. Moreover, given that Germany is part of the European Union, policymakers are frequently exposed to policies from other member-states, making it a particularly relevant case to assess the role of international diffusion mechanisms (Butler, De Vries and Solaz, 2019; Senninger and Hansen, 2025). Consistent evidence from all three countries will give us confidence that the findings are not an artifact of a specific political system.

Study 1: Net zero policies in German and UK municipalities

In study 1, we explore how geographic proximity shapes politicians' incentives to learn about local climate policy solutions in Germany and the UK. The analyses build on data from Pereira et al. (2025). In April 2021, Oxford NetZero hosted a webinar for local politicians (mayors and councillors) on policy solutions to achieve net-zero climate emissions. The purpose of the webinar was to highlight strategies that local governments could adopt to reduce carbon emission, and to learn about the experiences of local officials in other jurisdictions.

To study the motivations of representatives to attend the webinar and learn about net-zero policies, the original authors experimentally manipulated elements of the invitation sent to local politicians including who sent the invitation. In Germany, subjects were randomly assigned to receive the invitation from either a German local politician or a British councilor collaborating in the project and sharing their experience in the webinar.[7] These local officials can therefore be interpreted as early policy adopters. The authors then tracked engagement with the invitations and registrations to the webinar to measure interest in policy learning.

This setting allows us to study the effects of geographic proximity in two ways. First, we can estimate the differences in engagement with the invitation between German officials invited by a co-national politician or a British councillor. Since the inviter was randomly assigned, this quantity provides a causal estimate of the effect of geographic proximity on politicians' interest in learning about net zero policies. Notably, this setting represents a most-likely case for homophily-based learning. If shared characteristics explain the relationship between geographic proximity and policy learning (see Figure 1), we would expect officials to express significantly more interest in the experience of a conational official, relative to a peer from a different country.

Additionally, we can observationally estimate the effects of proximity to the German and British local politicians who sent the invitation and shared their experiences in the webinar among the subset of officials invited by co-national politicians in each country. To do so, we calculated the distances between the jurisdiction of the policy endorser and the jurisdictions of

[7] In the UK, subjects received invitations either from a British councilor or a climate scientist.

the politicians who received the corresponding invitation.

Measuring policy learning

While policy learning has a well-established conceptual meaning, its empirical measurement presents certain challenges. In this study, we focus on how policymakers engage with policy-related information contained in the email received. For policy learning to take place, it requires policymakers to be aware of a new initiative and to be willing to engage with it. Ultimately, it is the recipient's decision to interact with the information that determines whether a policy spreads to other regions. Our main outcome variables capture officials' expressed interest in learning about the policy experience of their counterparts.

Following the original study, we operationalize interest in policy learning based on whether the recipients of the net zero webinar invitation interacted with the links provided in the email. From this interaction we construct three outcome variables. *Policy interest* is a binary variable that takes the value of 1 if a politician clicked on at least one of the links provided in the invitation, and 0 otherwise. *Policy engagement* measures the total number of links clicked by a given recipient.[8] These measures do not capture learning *per se*. Instead, they provide a behavioral and unobtrusive measure of politicians' motivation to learn. Also following the original study, we include a third outcome *Policy Commitments* capturing whether the official visited the Cities Race to Zero after the webinar, a UN-funded initiative encouraging local governments to make policy commitments to achieve net-zero emissions. This last outcome was measured in a follow-up email 19 days after the original invitation and allows us to capture potential behavioral consequences of policy learning. Since our main interest in this study is to explain what drives policy learning, we treat this outcome as secondary.

By design, the study accounts for information availability. Hence, if we observe a negative relationship between geographical distance and politicians' interest in learning about the policy,

[8]The number of clicks in an online environment is often used as a measure of engagement in digital marketing (Flores, 2013).

the evidence would be consistent with homophily-based learning. On the other hand, if the main mechanism linking geographic proximity and learning is information availability, the sender's location should have no distinguishable effect on politicians' engagement with the policy information provided in the email.

Results

We report our analyses in two steps. First, we leverage the experimental component of the original study to estimate the causal effect of receiving a webinar invitation from a co-national peer politician versus a local official from a different country, among German politicians. We complement this analysis with observational evidence from Germany and the UK on the relationship between geographical proximity to the politician promoting the net zero webinar and policy learning.

Experimental evidence

We begin by exploring the experimental component of the study. This analysis is only possible in Germany, where the origin of the politician sharing their experiences on net zero policies was randomly assigned. The results are summarized in Table 1. The coefficients describe differences in politicians' response to the webinar invitation between German officials contacted by a co-national politician and those contacted by a British local official. Since the source of the invitation was randomly assigned, we treat these differences as average treatment effects of receiving an invitation from a co-national official. The estimates come from simple linear regressions (models 1, 3, and 5) and linear models with covariate adjustment (models 2, 4, 6).

For two of the three outcomes in the simple linear regression models, the coefficient is positive – suggesting more interest in the policy learning opportunity after receiving an invitation from a German peer. However, the differences are small and indistinguishable from zero. The estimated effect sizes are 11.2% of a standard deviation for Policy Interest (p = 0.07), and 7.3% of a standard deviation for Policy Engagement (p = 0.20). Models with covariate adjustment render the same

Table 1: The effects of receiving an invitation from a co-national peer politician (relative to a UK politician) on policy learning

	Policy interest		Policy engagement		Policy commitments	
	(1)	(2)	(3)	(4)	(5)	(6)
German politician (baseline = UK politician)	0.033 (0.018)	0.029 (0.019)	0.031 (0.026)	0.028 (0.029)	−0.001 (0.010)	0.001 (0.011)
Covariate adjustment	No	Yes	No	Yes	No	Yes
Observations	1,103	940	1,103	940	1,103	940

Note: Estimates from linear models of the causal effect of receiving an invitation from a German politician (relative to a UK politician) on interest in attending the net zero webinar (columns 1-4) and making policy commitments on net zero policies (columns 5-6). Models 2, 4, and 6 include covariate adjustment. Full model specifications in Appendix Table B.1. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.01$

substantive conclusions despite the potential increase in precision (Gerber and Green, 2012). We cannot rule out small positive effects of receiving an invitation from a co-national politician. The final outcome captures politicians' interest in making policy commitments to achieve net-zero emissions after the webinar. Here, we find a precisely estimated null effect (−0.001; s.e. = 0.010). Whatever small effect on interest in policy learning the original contact generated, it did not translate into more meaningful action from the officials in the study. Taken together, the results suggest that proximity to the politicians sharing their experience on net-zero policies had negligible to small effects on officials' expressed interest in learning. This result provides no evidence for homophily-based policy learning. Once information availability is held constant (by design), we find no evidence that politicians are more interested in learning from peers in their country, relative to peers in a different country.

We believe this result is particularly relevant since it reflects a most-likely case for detecting homophily effects. If geographic proximity matters due to shared policy environments or policy fit, we should have seen larger differences between treatment groups. Yet, the evidence overwhelmingly points to no meaningful effects of proximity.

Observational evidence

We now turn to the observational results on the relationship between spatial proximity and policy learning. While the inviter's country of origin varied only in Germany, both German and UK local officials in the study received invitations from co-national local officials collaborating in the study. This setting allows us to analyze observationally whether local officials in both countries are more likely to express interest in learning about net-zero policies when exposed to the policy experience of peers from nearby constituencies.

To measure geographic proximity, we calculated the distance between the jurisdiction of the politician collaborating in the project in each country and the jurisdiction of all the local officials contacted in that same country. We rely on the same three outcomes used above to predict politicians' interest in learning about the experiences of the officials promoting the event. The models account for features of the subjects' constituency and for partisan alignment between the inviter and the invitee. More specifically, we account for population size and the local vote share of the green party locally, which may be associated with both proximity to the inviter and politicians' interest in net-zero policy solutions. All models include country fixed effects. Finally, since proximity effects may operate differently at a smaller scale, we estimate effects for the full sample as well as for the subset of municipalities within 200km (≈ 125 miles) of the inviters' constituency. The results remain substantively unchanged with different cuttoffs (see table B.2).

Table 2 presents the main results of this analysis. We find that distance to the local politicians sharing their policy experience in the webinar is not reliably associated with policy learning. For the full sample (models 1, 3, and 5), the point estimates for distance are positive. The coefficients for policy interest and policy commitments are $\beta = .001$ ($p = 0.91$) and $\beta = 0.007$ ($p = 0.05$), respectively. Only policy engagement (model 3) yields a statistically significant effect, ($\beta = 0.009$, $p < .001$), but the sign is *positive* suggesting that politicians further away from the politician collaborating in the project were more likely to engage with the email invitation. These results run counter to the expectation that geographically closer politicians would express more interest in learning about the experience of nearby constituencies due to shared interests and policy fit

Table 2: Geographic proximity and policy learning in German and British local governments

	Policy Interest		Policy Engagement		Policy Commitments	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (100km)	0.001	−0.096	0.095***	−0.362***	0.007	−0.004
	(0.010)	(0.051)	(0.025)	(0.103)	(0.004)	(0.014)
Population (log)	0.026	0.026	0.056	−0.071	0.009	−0.001
	(0.017)	(0.042)	(0.044)	(0.084)	(0.007)	(0.011)
Green party (%)	0.009***	0.011***	0.029***	0.024***	0.0004	0.00004
	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)
Copartisan	0.024	0.036	0.098	0.052	0.006	0.003
	(0.032)	(0.048)	(0.082)	(0.097)	(0.012)	(0.013)
Constant	−0.224	−0.098	−0.801	1.371	−0.097	0.033
	(0.223)	(0.549)	(0.575)	(1.114)	(0.085)	(0.152)
Sample	Full	$\leq$ 200km	Full	$\leq$ 200km	Full	$\leq$ 200km
Observations	765	392	765	392	765	392

Note: Linear models on the relationship between geographic proximity (Distance) and policy learning. Models 1, 3 and 5 include the full sample in Germany and the UK. Models 2, 4, and 6 are based on a subset of officials from constituencies within 200km of the politician sending the invitation. All models include country FEs. *p<0.05; **p<0.01; ***p<0.001

considerations.

For the analyses subsetting to nearby local governments (models 2, 4, and 6), the results are more in line with homophily-based learning. The coefficients for distance are negative, suggesting less interest in policy learning among public officials further away from the official promoting the event. However, the effects are small and indistinguishable from zero for two of the three outcomes. The exception is policy engagement (-0.362; s.e. = 0.107; $p < 0.01$). According to model 4, a 276km (≈ 171 miles) increase in distance to the official promoting the net-zero webinar was associated with one fewer click in the various links provided in the email invitation.[9] This result, while substantively small and not robust across outcomes, suggests that officials closer to the early adopters promoting the policy were more likely to engage with the policy learning opportunity. A similar pattern emerges in bivariate models exploring the relationship between distance

[9]Since the variable distance is measured in 100km: 100/0.362 $\approx$ 276km

and policy interest (see table B.3).

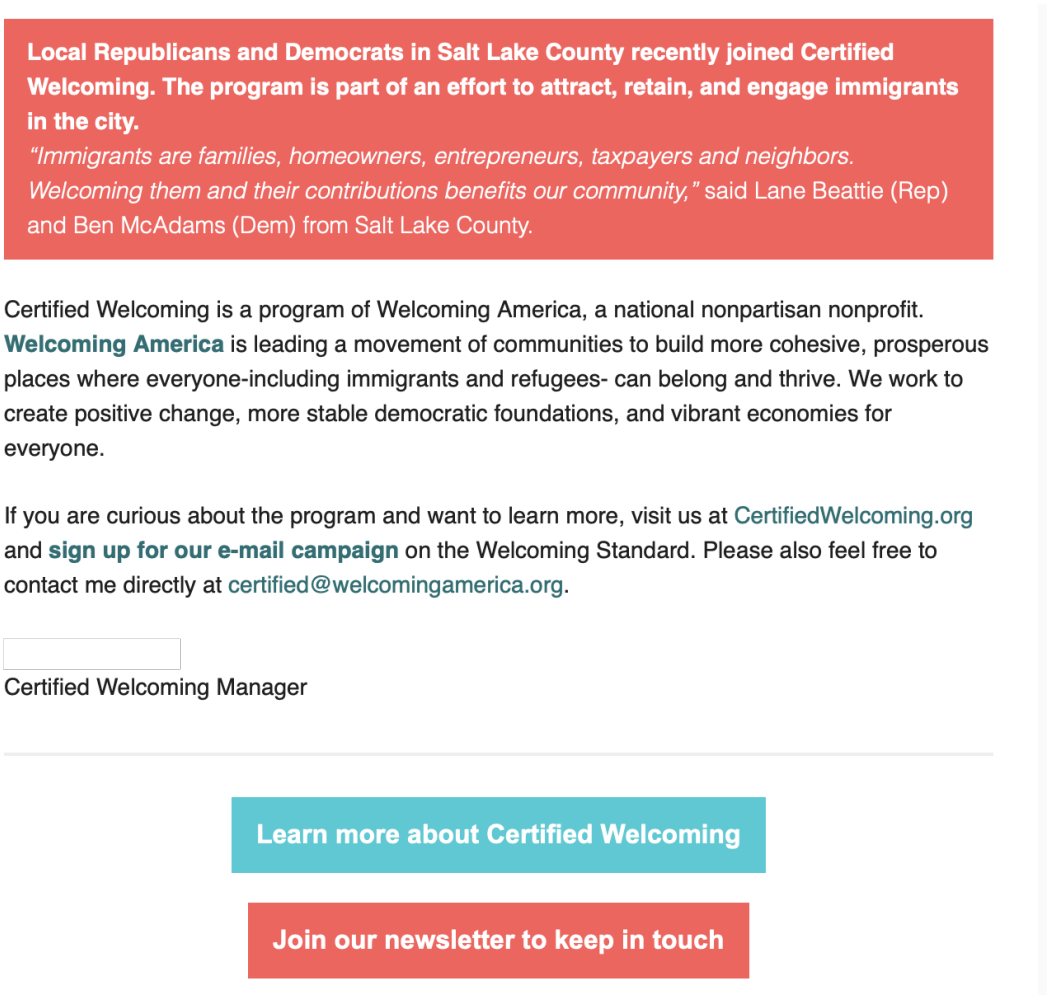
The observational results should be interpreted with caution given the inability of the design to account for all possible confounders. Still, taken together with the experimental findings reported above, they point to a consistent conclusion: geographical proximity does not robustly predict interest in learning from early policy adopters. We find no robust evidence for the homophily-based policy learning mechanism among local politicians in Germany and the UK. The only exception arises in a more geographically constrained subsample: when restricting the analysis to proximate municipalities, distance is negatively associated with officials' interest in the webinar. Yet given the small effects and the sample size, these observational result must be interpreted carefully. Study two, based on a different policy area and a different political context, allows us to assess the robustness of this pattern.

Study 2: Local immigration policy in the United States

To complement the results from study 1, we use data from a different study conducted in the United States with a similar research design. Study 2 was embedded in an outreach campaign led by Welcoming America, an organization that promotes immigrant inclusion policies in local and state governments (Pereira, 2022). In February 2018, 18,741 local representatives across the country received an email from Welcoming America containing information about a new program successfully adopted by the Salt Lake County government. Figure 2 provides an excerpt from the message sent by the organization partnering in the study. All the emails highlighted information about the early adopter and their experience with the policy. The email included several hyperlinks providing further details about the policy: a connection to the program's website labeled "Learn more about Certified Welcoming", a link to subscribe to the organization's newsletter, and links to the organization's social media accounts.

The email subject – "Introducing a New Certification Program for Local Governments" – did not provide information about the endorsers or the content of the policy. Hence, following the

Figure 2: Excerpt of email sent to U.S. local officials



Source: Pereira (2022)

original study the analyses focus on those officials who opened the email (N = 6,713) (Coppock, 2019). As in study 1, we measure interest in the new certification program based on whether the recipients interacted with the links provided in the email. *Policy interest* is a binary variable that takes the value of 1 if a recipient clicked on at least one of the links provided in the email, and 0 otherwise. *Policy engagement* measures the total number of links clicked by a given recipient. Our main predictor, once again, is the distance between the early policy adopters (Salt Lake County) and the officials receiving the email.

As in study 1, the research design keeps information availability constant. All officials in the study receive the same policy-relevant information. Hence, a negative relationship between

distance to the early adopters and politicians' interest in learning about the program would be consistent with homophily-based learning. If the main mechanism linking geographic proximity and learning is information availability, distance to Salt Lake County should have no distinguishable effect on politicians' engagement with the policy information provided in the email.

To adjudicate between the two mechanisms, we estimate the effect of distance to the early adopter (Salt Lake County) on policy interest and engagement. In the models, we account for observables that may confound the effect of distance to the policy endorser. While the email sent in the original study is exogenous to different considerations of the local officials at the time, the propensity to be interested in the certification program is likely shaped by different characteristics of the officials receiving the email and the context in which they operate. First, policymakers in larger jurisdictions may face similar policy challenges to Salt Lake County, which could lead them to devote more attention to the certification program. Therefore, we account for the log of county population. Second, because the policy concerns immigration, representatives from counties with larger immigrant populations may be more interested in the topic. We therefore account for the share of foreign-born citizens in the recipient's county. Third, ideology is a strong predictor of policy preferences on immigration in the US (Homola, 2021). Hence, we control for county-level Democratic vote share in the previous election.[10] Finally, as in study 1, we estimate the same models for the nation-wide sample of local politicians and for a small subset of politicians in contiguous states. This latter specification is meant to capture more fine-grained proximity effects that may not be observable in a nation-wide analysis.

[10]The original study included an experimental manipulation in the email sent by the partner organization. The email highlighted either the support of Democrats, Republicans, or members of both parties in the local government. By design, this intervention is orthogonal to distance and therefore cannot confound the relationship between our main predictor of interest and politicians' interest in the program. Still, for the sake of completeness we replicate the main analyses accounting for treatment assignment in Table C.5 (Appendix). As expected, the results remain substantively unchanged.

Results

Table 3 summarizes the main results from study 2. Models 1 and 3 report findings for the full sample of local officials who opened the email with information about the certification program adopted in Salt Lake County, while models 2 and 4 subset the analyses to officials from Utah and contiguous states. The findings indicate that geographic proximity to the early adopters (Salt Lake County) is not associated with politicians' likelihood of engaging with the information.

For the full sample (models 1 and 3), the effect of distance is small and indistinguishable from zero. According to Model 1, a 500km ($\approx$ 310 miles) increase in distance to Salt Lake County is associated with a 0.2 percentage point *increase* in the probability of clicking in one of the links providing information about the policy (p-value = 0.65). The effect size is trivial, corresponding to 0.4% of a standard deviation. The effect size on the number of clicks (model 3) is also negligible (1% of a standard deviation) suggesting a tightly estimated null effect. Finally, the estimated coefficients for the full sample are positive ($\beta = 0.002$ and $\beta = 0.010$ respectively), suggesting that – if anything – geographic proximity reduces the likelihood of politicians expressing interest in and engaging with the policy information.

If geographic distance matters for policy learning in this context, we may expect the effects to be more discernible closer to the early policy adopter. Theories of spatially clustered policy learning tend to focus on the interactions between nearby communities. To explore this possibility, we replicate the main analyses in models 2 and 4 after restricting the analysis to officials in Utah and contiguous states. The results remain substantively unchanged. The effects of geographic proximity (distance) to Salt Lake County remains small and indistinguishable from zero (Model 2 $\beta = 0.018$; s.e. = 0.033; Model 4 $\beta = 0.012$; s.e. 0.056).

These results are robust to different model specifications. First, as these variables could also drive homophily, we estimate a bivariate model that omits population size, immigrant share, and vote preferences. The distance coefficient remains statistically indistinguishable from zero (see Table C.1). Second, we introduce state fixed effects to account for unobserved state-level factors. The within-state estimates mirror those in the baseline model, again showing no meaningful role

Table 3: Geographic proximity and policy learning among US local officials

	Policy Interest		Policy Engagement	
	(1)	(2)	(3)	(4)
Distance (500km)	0.002	0.018	0.010	0.012
	(0.004)	(0.033)	(0.007)	(0.056)
Population (log)	0.010	0.015	0.011	0.027
	(0.005)	(0.011)	(0.011)	(0.020)
% Foreign-born citizens	−0.040	−0.910*	0.147	−1.249
	(0.120)	(0.409)	(0.243)	(0.744)
Democratic vote share	0.214***	−0.228	0.473***	−0.585
	(0.056)	(0.182)	(0.117)	(0.322)
Constant	0.172***	0.255	0.306***	0.496*
	(0.053)	(0.133)	(0.106)	(0.250)
Sample	Full	Contiguous States	Full	Contiguous States
Observations	6,274	403	6,274	403
R^2	0.007	0.027	0.008	0.026

Note: Linear models on the relationship between geographic proximity (Distance) and policy learning. Policy interest takes the value of 1 if officials clicked on links in the email; 0 otherwise. Policy engagement captures the number of clicks. Robust standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001

for distance (see Table C.2). Third, introducing a quadratic distance term to capture possible non-linearities does not improve fit nor the results (Table C.3). Finally, zero-inflated and negative-binomial models that address excess zeros and over-dispersion in the count data again return null distance coefficients (Table C.4). Taken together, these alternative specifications relax the linearity, distributional, and measurement assumptions of the baseline OLS, and converge on the same conclusion: geographic proximity does not meaningfully increase politicians' interest in learning once information availability is held constant. This result questions the notion that spatially clustered patterns of policy learning are driven by politicians perceiving the experience of nearby jurisdictions as more relevant due to shared contextual characteristics (homophily-based learning).

The Policy Relevance of Immigration

To further probe our results, we explore how issue salience moderates the relationship between distance and politician's interest in the certification program. While immigration has been a

salient issue in the US for several years, the relevance of the issue varies considerably across municipalities (Kustov, 2023). Local jurisdictions in the US vary in exposure to foreign-born populations and it is possible that geographic proximity in this specific context only matters for politicians from communities with either larger immigrant communities or rates similar to those found in Salt Lake County (around 10%).

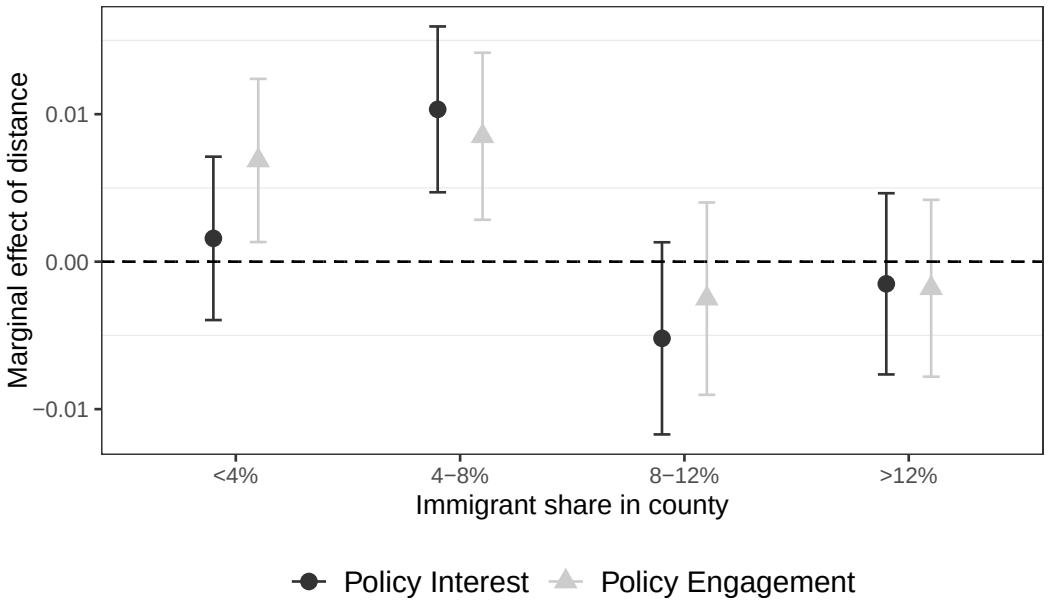
To explore this version of homophily-based learning, we estimate the effects of geographic proximity for local officials with different levels of exposure to foreign-born communities. Figure 3 is a marginal effect plot by binned immigration population. With this method, we avoid making assumptions about the functional form of the relationship of interest. The results suggest that geographic proximity remains an unreliable predictor of politicians interest in the certification program, regardless of the levels of immigration in a given constituency. Once the immigrant population reaches roughly eight percent of a local jurisdictions, the confidence intervals for distance straddles zero for both outcomes. In other words, the positive effect of distance observed in the main analyses is likely driven by officials in low-immigration constituencies (< 8%). In more diverse counties, the effect of distance, while in the expected direction according to the homophily mechanism, is small and indistinguishable from zero.

These findings reinforce the conclusion that information availability, not homophily, is the main mechanism underlying spatially clustered policy learning. Even when focusing on counties where an immigration policy should carry the greatest substantive relevance – those with the highest shares of foreign-born residents – representatives located closer to the policy source are no more likely to engage with the information than their distant counterparts.

Conclusion

Understanding which mechanism explains why policies disseminate in geographic clusters has important implications. If politicians are learning from nearby constituencies main due to information availability, salient policies – regardless of their suitability or contextual fit – will also

Figure 3: Distance effect by share of immigrants



be more likely to diffuse simply because they are more visible. High-profile policies, whether due to media amplification, political discourse, or public attention, may spread across jurisdictions not because they are effective but because they dominate the informational environment (Baumgartner et al., 2009; Weyland, 2005).

In this article, we have provided evidence to support the idea that availability, rather than homophily, is the more likely mechanism driving spatially clustered policy learning. Our results indicate that when availability is held constant, distance is not a reliable predictor of office holders' engagement with new environmental or immigration policy.

Our results are normatively relevant. If proximity effects are largely an artifact of unequal information exposure, then well-resourced jurisdictions – more professionalized public officials, or with access to broader networks – will continue to enjoy a better access to well-suited policies. In the meantime, smaller and peripheral communities risk being limited to copying whatever policy is salient, not what would be best for them. Leveling the informational field should therefore should improve the decision-making process.

Despite our the efforts to combine observational and experimental evidence from different policy issues and three established democracies with different local political institutions, a number of questions remain open. First, the patterns uncovered here are specific to one type of learning environment – politicians passively exposed to policy information from advocacy groups. While this process of policy learning is common (Ellis and Groll, 2020; Hall and Deardorff, 2006; Willems, Maes and Walgrave, 2024), it is possible that more active forms of information seeking are driven by different mechanisms (Einstein, Glick and Palmer, 2019). Our findings cannot speak to these and other forms of policy learning or to what policymakers decide to do with the information received at later stages. Second, our outcomes are proxies for policy learning. They capture behavioral intentions to learn rather than actual learning or adoption. Future scholarship can study learning in different forms by adapting the research designs developed in the studies reported here. Third, we only offer evidence for relatively new environmental and immigration reforms. Politicians may engage differently with other policy issues. For less novel issues, for instance, politicians may already know what peers in nearby communities are doing, changing how proximity shapes policy learning. Future work can build on the findings reported here by studying different forms of policy learning and less salient policies.

The study makes several contributions the study of how politicians acquire information and more broadly to the literature on policy diffusion. First, we supply rare micro-level evidence to a literature dominated by macro data and models. Second, we offer evidence for specific mechanisms underlying policy diffusion processes. Third, by combining data from two vastly different contexts, we add external validity to our results. This is a relevant addition to a field that has disproportionately relied on evidence from the United States. Finally, we identify an often overlooked distinction between passive and active exposure to policy information that can lead to different processes of policy learning and deserves further inquiry.

Conflicting Interests

The authors declare no competing nor conflicting interests.

This research complies with the journal's ethical standards and the original data collection received ethical approval regarding research involving human participants.

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Online Appendix (Supporting Information) for "Why are Politicians More Likely to Learn From Neighbors? Behavioral Evidence From Three Advanced Democracies"

Table of Content

- **Table C.2**: Geographic proximity and policy learning among US officials with state fixed effects
- **Table C.3**: Geographic proximity and policy learning among US officials. Quadratic model
- **Table C.4**: Geographic proximity and policy learning among US officials. Poisson and zero inflated models

Appendix A: Survey descriptives and treatments

Study 1

Descriptives

The invitation was sent to 4,578 German politicians in the original study. Here, we are only interested in those who were treated with either the German or British politician (a scientific source was also used). Excluding those treated with the scientist source as treatment, the message was sent to 2,714 local politicians in Germany. Of those, 1,101 opened the email. Table A.1 below summarizes the opening rate per treatment. Notably, differences between opening rates are non significant between treatment groups.

Table A.1: Opening rates - German experiment (study 1)

Treatment Group	Opened	Open-Rate	Dif (p-value)
UK Politician	586	39.7	
DE Politician	515	41.6	-1.9 (p = 0.32)
Total	1,101	41.1	

Tables REF show the distribution of the data on observables like gender, party and region.

Table A.2: Descriptives - Germany

Variable	Level	N	%
Bundesland	Nordrhein-Westfalen	159	31.3
	Baden-Württemberg	105	20.7
	Bayern	86	16.9
	Hessen	36	7.1
	Rheinland-Pfalz	31	6.1
	Niedersachsen	30	5.9
	Brandenburg	22	4.3
	Schleswig-Holstein	19	3.7
	Berlin	10	2.0
	Sachsen	4	0.8
	Hamburg	2	0.4
	Saarland	2	0.4
	Mecklenburg-Vorpommern	1	0.2
	Sachsen-Anhalt	1	0.2
Gender	Male	341	66.2
	Female	174	33.8
Party	SPD	131	26.3
	CDU	103	20.6
	Grünen	88	17.6
	Linke	34	6.8
	CSU	23	4.6
	FDP	2	0.4
	Other	118	23.6

Table A.3: Descriptives - UK

Variable	Level	N	%
Party	Conservative	111	33.1
	Labour	66	19.7
	Liberal Democrats	45	13.4
	Independent	25	7.5
	Plaid Cymru	5	1.5
	Green Party	4	1.2
	SNP	3	0.9
	Ukip	1	0.3
	NR/Other	75	22.4
Area	England	293	87.7
	Wales	24	7.2
	Scotland	17	5.1
Gender	female	214	63.9
	male	121	36.1

Treatments

The electronic invitation on the original study randomized the person from whom the message was sent. The invitation read:

On behalf of Councillor [UK Name / German Name]. Dear [title, last name of local official], I write you as a fellow local representative with an invitation to a webinar on setting and achieving net zero climate emissions at the local level

The email concluded with the name and title of the local official sending the invitation, as well as a link to their institutional website.

Table A.4 summarizes the balances test on observables between treatment groups using t.tests. Both groups are balanced in all but two variables: population and share of votes for the green party. However, the differences are substantively small and likely to have emerged by chance. The difference in population sizes (12.280 vs 12.142) is only about 1%. In turn, the difference in the vote share for the Green party is 1 percentage point.

Table A.4: Covariate balance across treatment arms

	Means		
Variable	Control mean (UK sender)	Treatment mean (DE sender)	p-value
female	0.364	0.338	0.365
pop_log	12.280	12.142	0.037
left	0.474	0.472	0.930
right	0.168	0.190	0.345
CDU_share	0.346	0.349	0.555
green_share	0.184	0.194	0.017
copartisan	0.203	0.176	0.270

Study 2

Descriptives

The information about the policy was sent to 18,741 valid emails, with an open rate of 35.8%. Similar to the original study, here we focus on those who opened the emails (N = 6,713) as all the policy information was contained in the body of the message and not the subject.

Table A.5 compares the characteristics of subjects who opened the email and took part in the study, and those who chose not to open the email. For the descriptive variables available, the differences across groups are substantively small. As an example, the average county-level Democratic vote share in the 2012 presidential election was 47.2% among subjects who did not open the email, and 48.0% among subjects who took part in the study. The difference (0.8 percentage points) is statistically significant due to the large sample sizes. Finally, the geographic distribution of local politicians in the original study is summarized in Table A.6.

Table A.5: Descriptives. Not-opened vs opened samples

	Did not opened	Opened	p-value
Dem. vote share	0.47	0.48	<0.01
Population (log)	11.67	11.83	<0.01
N° elected officials	8.10	8.26	0.11
Republican (partisan races)	0.17	0.19	<0.01
Democrat (partisan races)	0.13	0.14	0.10
N	14,679	6,214	-

Note: Table replicated from original article.

Table A.6: Study participants by state

State	N	%	State	N	%	State	N	%	State	N	%
AK	22	0.30	IL	385	5.70	NC	185	2.80	SC	120	1.80
AL	74	1.10	IN	67	1.00	ND	9	0.10	SD	29	0.40
AR	26	0.40	KS	87	1.30	NE	28	0.40	TN	75	1.10
AZ	185	2.80	KY	55	0.80	NH	20	0.30	TX	176	2.60
CA	212	3.20	LA	72	1.10	NJ	143	2.10	UT	66	1.00
CO	86	1.30	MA	60	0.90	NM	32	0.50	VA	200	3.00
CT	33	0.50	MD	66	1.00	NV	34	0.50	VT	2	0.00
DC	5	0.10	ME	38	0.60	NY	418	6.20	WA	116	1.70
DE	21	0.30	MI	381	5.70	OH	201	3.00	WI	181	2.70
FL	146	2.20	MN	125	1.90	OK	46	0.70	WV	12	0.20
GA	165	2.50	MO	75	1.10	OR	405	6.00	WY	31	0.50
IA	661	9.80	MS	25	0.40	PA	1019	15.20	–	–	–
ID	26	0.40	MT	44	0.70	RI	23	0.30	–	–	–

Note. Entries are the number and share of local officials in the study, by state.

Appendix B: Robustness checks - Study 1

Complete results of the main models described in the article can be found below in Table B.1. table B.2, in turn, reports results from observational analyses in nearby communities, based on different distance cutoff points.

We also estimated bivariate versions of our main models to assess whether our full specifications might be 'overcontrolling'. The results, presented in Table B.3, summarize these analyses. We also estimated the models separately by country (see Table **??**). The results are inconsistent across specifications and overall substantively small. For instance, our distance coefficient in the case of policy interest in Germany (−0.032 pp per 100 km) is roughly two orders of magnitude smaller than the benchmark estimate in Einstein, Glick and Palmer (2019). Converting their logit coefficient (−0.403 per mile) to a marginal probability effect yields ˘5 to ˘9 percentage points per 100 km (depending on the baseline probability), i.e. ≈ 150x our estimate.

We also run models with FE at the state level in both countries. We cluster the errors at the municipal level. The results are consistent with our main models: either we see small effects indistinguishable from zero in the expected direction (for interest and engagement) or effects that are in the opposite direction. Results are summarized in Table B.5.

Table B.1: The effects of receiving an invitation from a co-national peer politician (relative to a UK politician) on policy learning. Complement to Table 1

	Policy interest		Policy engagement		Policy commitments	
	(1)	(2)	(3)	(4)	(5)	(6)
German politician	0.033	0.029	0.031	0.028	−0.001	0.001
(baseline = UK politician)	(0.018)	(0.019)	(0.026)	(0.029)	(0.010)	(0.011)
Long-term		0.023		0.043		0.002
		(0.020)		(0.029)		(0.011)
Green party (%)		0.049		0.050		0.101
		(0.165)		(0.244)		(0.094)
Co-partisan		0.028		0.051		0.0002
		(0.024)		(0.036)		(0.014)
Population (logged		0.011		0.019		−0.008
		(0.013)		(0.019)		(0.007)
Constant	0.080***	−0.086	0.109***	−0.162	0.031***	0.108
	(0.012)	(0.151)	(0.018)	(0.223)	(0.007)	(0.086)
Observations	1,103	940	1,103	940	1,103	940

Note: *p<0.05; **p<0.01; ***p<0.01

Table B.2: Geographical proximity and policy interest in nearby constituencies, by distance cutoff

	Interest (1)	Engagement (2)	Commit (3)	Interest (4)	Engagement (5)	Commit (6)
Dist (100km)	0.016	-0.417^{*}	0.010	-0.049	-0.164^{***}	-0.006
	(0.086)	(0.177)	(0.024)	(0.030)	(0.059)	(0.008)
Pop(log)	0.041	-0.050	-0.008	0.042	-0.006	0.004
	(0.052)	(0.107)	(0.015)	(0.033)	(0.064)	(0.008)
Green/Labour Share	0.011^{***}	0.026^{***}	-0.0002	0.010^{***}	0.019^{***}	0.0001
	(0.002)	(0.005)	(0.001)	(0.002)	(0.004)	(0.0005)
Copartisan	0.021	0.046	0.003	0.035	0.033	0.003
	(0.056)	(0.114)	(0.016)	(0.041)	(0.080)	(0.010)
UK	-0.503^{***}	-1.039^{***}	-0.029	-0.431^{***}	-0.805^{***}	-0.019
	(0.113)	(0.231)	(0.032)	(0.087)	(0.172)	(0.023)
Constant	-0.361	1.128	0.119	-0.331	0.429	-0.020
	(0.689)	(1.412)	(0.193)	(0.428)	(0.842)	(0.110)
Distance Cutoff	150km	150km	150km	250km	250km	250km
Observations	335	335	335	499	499	499
R^2	0.079	0.116	0.017	0.079	0.104	0.014

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table B.3: Geographic proximity and policy learning in German and British local governments. Bivariate models

	Policy Interest (1)	Policy Engagement (2)	Policy Commitments (3)
Dist (100km)	-0.023^{***}	0.007	0.006
	(0.009)	(0.022)	(0.003)
Constant	0.186^{***}	0.261^{***}	0.006
	(0.022)	(0.055)	(0.008)
Observations	842	842	842
R^2	0.008	0.0001	0.004
Note:			*p<0.05; **p<0.01; ***p<0.01

Table B.4: Geographic proximity and policy learning, by country

	United Kingdom			Germany		
	Interest	Engagement	Commitment	Interest	Engagement	Commitment
Distance (100kms)	0.064***	0.334***	0.000	−0.032***	−0.045***	0.011
	(0.018)	(0.060)	(0.000)	(0.012)	(0.016)	(0.006)
Pop (log)	0.102*	0.335*	0.000	0.019	0.027	0.010
	(0.046)	(0.149)	(0.000)	(0.020)	(0.028)	(0.011)
Green/Labour share	1.174***	3.916***	0.000	0.008	0.056	−0.002
	(0.170)	(0.554)	(0.000)	(0.268)	(0.375)	(0.143)
Constant	−1.707***	−5.946***	0.000	−0.054	−0.109	−0.115
	(0.608)	(1.982)	(0.000)	(0.233)	(0.327)	(0.124)
Observations	334	334	334	444	444	444
R^2	0.133	0.158		0.023	0.023	0.008

Note: *p<0.05; **p<0.01; ***p<0.01

Table B.5: Geographic proximity and policy learning in German and British local governments. Models with region FE

	Interest	Engagement	Commit
Distance (100km)	−0.024 (0.014)	−0.033 (0.026)	0.029 (0.006)***
Copartisan	0.037 (0.041)	0.042 (0.058)	0.008 (0.023)
Population(log)	0.029 (0.014)*	0.052 (0.023)*	0.023 (0.008)**
Vote Share(Green/Labor Party)	−0.084 (0.111)	−0.057 (0.173)	0.075 (0.086)
Total N	431	431	431
SE clusters	by: municipality	by: municipality	by: municipality

Appendix C: Robustness checks - Study 2

To avoid potentially blocking causal paths between distance and the outcomes in study 2, Table C.1 reports bivariate versions of the main models. The results are consistent with the findings reported in the main text. We also run models with fixed effects at the state level. The results are depicted in Table C.2. Turning distance into a quadratic term doesn't improve fitness either. The coefficients remain insignificant and close to 0, as depicted in Table C.3.

We re-estimate the U.S. models with a zero-inflated Poisson, allowing a separate 'always-zero' process for officials that never clicked. The distance coefficient in the count part is similar to the Poisson estimates and to our main results, confirming that zero inflation does not drive the results. The results are depicted in Table C.4. In the Poisson component the coefficient on distance is effectively null for both outcomes ($p = 0.98$ and $p = 0.15$, respectively). In the zero-inflation part, distance again fails to predict membership in the never-click group ($p > 0.3$ in both models).

Finally, in Table B.3 we present the main results accounting for the treatment conditions assigned in the original study. In the model, the Treat variable captures effects of receiving information from an out-partisan or co-partisan having a bi-partisan endorsement as the baseline. Our variable of interest (distance) remains insignificant.

Table C.1: Geographic proximity and policy learning among US officials. Bivariate models

	Policy Interest	Policy Engagement
	(1)	(2)
Distance (500 kms)	0.003	0.013
	(0.003)	(0.007)
Constant	0.368***	0.638***
	(0.017)	(0.034)
Observations	6,713	6,713
R^2	0.0001	0.001
Note:		*p<0.05; **p<0.01; ***p<0.01

Table C.2: Geographic proximity and policy learning among US officials with state fixed effects

	Policy Interest	Policy Engagement
Distance (100km)	−0.038 (0.041)	−0.058 (0.077)
Population(log)	0.013 (0.012)	0.012 (0.024)
% Foreign-born citizens	−0.099 (0.304)	−0.153 (0.582)
Democratic vote share	0.086 (0.123)	0.274 (0.252)
Total N	6274	6274
SE clusters	by: County	by: County
FE: State	X	X
Note:		*p<0.05; **p<0.01; ***p<0.01

Table C.3: Geographic proximity and policy learning among US officials. Quadratic model

	Policy Interest	Policy Engagement
	(1)	(2)
Distance (500kms)	0.0001	0.001
	(0.0004)	(0.001)
Population (log)	0.010	0.011
	(0.005)	(0.011)
% Foreigners	−0.045	0.125
	(0.119)	(0.241)
Democratic vote share	0.214***	0.475***
	(0.056)	(0.117)
Constant	0.175***	0.321***
	(0.053)	(0.106)
Observations	6,274	6,274
R^2	0.007	0.008
Note:		*p<0.05; **p<0.01; ***p<0.01

Table C.4: Geographic proximity and policy learning among US officials. Poisson and zero inflated models

	Policy Interest		Engagement Level	
	Poisson	Zero Inf.	Poisson	Zero Inf.
Distance (500 kms)	0.0003	−58.40	0.017	0.001
	(0.188)	(61.57)	(0.012)	(0.023)
Population (log)	0.020	-21.44	−0.021	−0.079
	(0.019)	(61.57)	(0.022)	(0.041)
% Foreigners	−0.091	−161.1	0.474	0.670
	(0.379)	(165.99)	(0.348)	(0.705)
Democratic vote share	0.538***	−19.84	0.277	−0.861
	(0.185)	(74.51)	(0.200)	(0.377)
Constant	−1.418***	248.1	0.295	1.14
	(0.188)	(264.5)	(0.228)	(0.403)
Observations	6,274	6,274	6,274	6,274

Note: *p<0.05; **p<0.01; ***p<0.01

Table C.5: Geographic proximity and policy learning among US officials, controlling for original treatment assignation

	Policy interest		
	(1)	(2)	(3)
Distance (500 kms)	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)
Treat (copartisan)	0.006	0.006	0.006
	(0.015)	(0.015)	(0.015)
Treat (outpartisan)	0.015	0.015	0.015
	(0.015)	(0.015)	(0.015)
Population (log)	0.010	0.010	0.010
	(0.005)	(0.005)	(0.005)
% Foreigners	−0.037	−0.037	−0.037
	(0.120)	(0.120)	(0.120)
Democratic vote share	0.212***	0.212***	0.212***
	(0.056)	(0.056)	(0.056)
Constant	0.166***	0.166***	0.166***
	(0.054)	(0.054)	(0.054)
Observations	6,274	6,274	6,274
R^2	0.007	0.007	0.007
Note:		*p<0.05; **p<0.01; ***p<0.01	