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City Learning: Evidence of Policy Information Diffusion from a Survey of U.S. Mayors

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Abstract
Most studies of policy diffusion attempt to infer the processes through which policies spread by observing outputs (policy adoptions). We approach these issues from the other direction by directly analyzing a key policymaking input—information about others' policies. Moreover, we do so by investigating policy diffusion in cities rather than states. Using a survey of U.S. mayors, more specifically, mayors' own lists of cities they look to for ideas, we find evidence that distance, similarity, and capacity all influence the likelihood of a policy maker looking to a particular jurisdiction for policy information. We also consider whether these traits are complements or substitutes and provide some evidence for the latter. Specifically, we find that, at times, mayors eschew similarity and distance to look to highly respected "high capacity" cities but that there is no tradeoff between distance and similarity.

Keywords
policy diffusion, local politics, urban politics, mayors

One of federalism's virtues is the potential for lower levels of government to act as policy laboratories for each other and for their higher-level counterparts. For this experimental approach to policymaking to work, state and local governments must learn from each other. Although a wide array of studies investigates cases of policies diffusing, most of this literature looks at diffusion by focusing on states rather than cities, focusing on policy adoption rather than policy information, and investigating specific policy issues, usually one per study. Previous research offers evidence that a number of mechanisms and/or traits such as geographic proximity (Berry and Berry 1990; Mooney 2001), similarity (Butler et al. 2017; Grossback, Nicholson-Crotty, and Peterson 2004), policy success (Butler et al. 2017; Volden 2006), competition (Baybeck, Berry, and Siegel 2011), and safety in numbers (Glick 2013), along with policy attributes such as salience, observability, and complexity (Boushey 2010; Nicholson-Crotty 2009; Volden and Makse 2011), affect policy diffusion.

We contribute to this literature in several ways. First, we explore a relatively novel locus of study: cities. While several diffusion articles have used cities as their unit of observation (Butler et al. 2017; Shipan and Volden 2008), the bulk of the literature's emphasis on states misses important substantive and methodological advantages that city-level diffusion studies can provide. Substantively, in light of growing partisan polarization at the federal and state levels (Abramowitz 2010; Shor and McCarty 2011), municipalities are increasingly important venues for serious and innovative policymaking. This is especially true for liberals and progressives, whose recent electoral defeats at the state and federal levels may make local government the only realistic avenue for the advancement of policy goals on a wide range of issues including minimum wage (Noguchi 2017), paid parental leave (Hester 2016), and environmental regulations (Biggers 2016). Given their increasing policy salience, it is substantively important to systematically test whether diffusion mechanisms identified at the state level generalize to localities. There are reasons to believe that they may not. Cities are constrained by economic forces and other factors (e.g., Peterson 1981), as well as by higher levels of government, such that the policy areas they address, and the ways they address them, are significantly different from states. Moreover, while recent research has highlighted partisanship in local policy (Einstein and Kogan 2016; Tausanovitch and

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Warshaw 2014), it has traditionally been expected to function differently in cities than in states. Finally, because cities are generally smaller and less professionalized than states, policy diffusion might be less systematic, and the sources of policy migbt be less predictable. Relatedly, it is also possible that the larger number of cities, and the diversity of city governments, induces different mechanisms and correlates of diffusion.

Methodologically, cities offer empirical opportunities that states and nations cannot. First, there are many more of them. Indeed, medium and large U.S. cities have roughly six times as many potential places to learn from than do U.S. states. This larger universe of cities confers value above and beyond increased sample size. It offers greater variation on dimensions key to testing important theories of diffusion. For example, states have at most a few neighbors, while cities will often have a multitude of other cities nearby. Consequently, in many instances, nearby states are fairly similar to each other, making it difficult to parse similarity mechanisms from geographic ones. While nearby cities will often share traits, for any given city, it is also likely that there are richer and poorer, more and less diverse, and bigger and smaller cities nearby and far away.

Our second central contribution is that, instead of studying the spread of specific policies, we look at the pursuit and dissemination of policy information—a step that precedes policy adoption. We ask questions about the systematic (or nonsystematic) search for, and spread of, policy information. Our work, thus, links to others' studies of information in policymaking (e.g., Mooney 1991; Mossberger 2000) and to the small number of other works that study policy diffusion through early-stage inputs rather than outputs (Butler et al. 2017; Karch 2012; Lundin, Oberg, and Josefsson 2015).

To measure cities' sources of policy information, we use a novel survey of mayors, which includes respondents from a wide range of cities, including many of the nation's largest. Among other things, we asked mayors to list the three cities they most recently looked to for policy ideas. We also asked them why they looked to those particular cities. Focusing on the universe of 288 U.S. cities with more than one hundred thousand residents, we construct a dataset with all of the actual named pairs of cities and all of the unnamed, potential pairs. Populating this database with city-level geographic, demographic, and other traits, we evaluate key theories in the policy diffusion literature. Specifically, we investigate whether mayors use geographic proximity, policy success/competence, and/or similarity when evaluating potential sources of policy information. In addition, we evaluate whether these different criteria act as complements or substitutes. These results provide us with new insight into *how* political elites evaluate policy challenges, and offer evidence on how diffusion networks might manifest as America moves into an era of progressive local government policy activism.

Theories of Policy Diffusion

Previous scholarship suggests a variety of mechanisms by which lower levels of government might learn from one another. Prior research contends that political actors are more likely to adopt a policy already implemented by nearby locales (Berry and Berry 1990; Mooney 2001). This mechanism may arise because it is easier to observe what those nearby are doing, because actors compete with their neighbors for resources (Baybeck, Berry, and Siegel 2011), or because neighbors face common challenges. At times, proximity may also be an approximation of similarity (discussed subsequently). Applied to our focus on city policy learning leads to the first hypothesis:

> **Hypothesis 1 (Proximity)**: Policymakers are more likely to look to nearby jurisdictions.

Proximity in the cities context may differ from its application to states. On one hand, cities may have more other cities "close by" to learn from either directly or through regional networks. On the other hand, large cities rarely have other large cities as border neighbors. Frequently, between two cities, one will find small cities, suburbs, exurbs, and/or rural areas.

The second main mechanism is similarity (Grossback, Nicholson-Crotty, and Peterson 2004; Shipan and Volden 2008). At the most general level, the literature suggests that policymakers are more likely to enact policies after similar jurisdictions have done so. General agreement that similarity matters masks important uncertainty and disconsensus. Some focus primarily on political and ideological similarity (Butler et al. 2017; Grossback, Nicholson-Crotty, and Peterson 2004), while others focus more on a broader but less concrete notion of goal similarity (Glick and Myers 2015).

Moreover, disentangling similarity as a mechanism from similar places independently adopting similar policies is challenging (Volden, Ting, and Carpenter 2008). One recent study uses a novel experiment to illustrate the salience of ideological similarity and policy success in policy diffusion (Butler et al. 2017). Likewise, our focus on policy inputs helps avoid some of the challenges that prior scholarship has encountered in attempting to infer similarity using observational data and policy adoption as a dependent variable. Finally, similarity also overlaps with proximity as neighbors tend to be similar. Again, focusing on intentional searches for information, and exploiting the variation in cities, helps address some of these theoretical and empirical challenges. Especially when considering larger cities, their most similar peers may not be geographically proximate. While neighboring states tend to have a lot in common such that many often discuss them as parts of cohesive regions (e.g., New England, the industrial Midwest, the West Coast), larger cities are more likely to face choices between learning from the suburban or satellite cities around them, and learning from their larger analogues in other parts of the country.

Putting the pieces of this discussion together leads to a general similarity hypothesis that is split into two:

Hypothesis 2A (Political Similarity): Policymakers will look to those with similar political traits because what another jurisdiction with similar policy views does will be a good signal for what a similar constituency will want.

Hypothesis 2B (Context Similarity): This hypothesis substitutes attributes such as size and economic factors for politics under the logic that the policies most likely to fit and work well in a city are those enacted in a similar policymaking context.

Similarity mechanisms may differ between cities and states. The ideological distribution of cities is very different than that of states. Moreover, at least some of what cities do may be less ideological such that political similarity matters less, or at least differently. In addition, since cities deal with different issues and constraints, the key dimensions of similarity could be different. For example, housing market similarity may matter relatively more to cities than states.

The third and final concept we focus on is capacity and effectiveness. Some cities may simply be better places to look to for policy ideas because they are well run, have unusual resources, and/or achieve good outcomes. While "capacity" for good policymaking is intuitive, the details are a bit murkier. Prior scholarship suggests that higher capacity locales are more likely to make good policies and be more professional (Volden 2006), attentive (Shipan and Volden 2008), and innovative (Boehmke and Skinner 2012). This idea is also related to learning from successful policies (Volden 2006) but with a focus on the policy's source rather than the policy itself. This brings us to the third hypothesis:

Hypothesis 3 (Policymaking Capacity): Mayors will look to jurisdictions that they believe to be better, or more innovative, policymakers.

Although both states and cities comprise tremendous variation in resources and professionalism, the potential for capacity variation in cities with more than ten thousand people is noteworthy. The resources in the New York or Los Angeles mayor's office would obviously dwarf those available in even mid-sized cities.

These three central ideas are well-trod in diffusion scholarship. In contrast, there has been comparatively less consideration of whether political elites are required to make tradeoffs when weighing the use of these different criteria. Given geographic proximity's long history in the diffusion literature, we begin with the presumption that looking close is the default behavior and that policymakers need a reason to look further away. This logic leads us to consider, for example, whether policymakers looking to more distant locales as sources of policy information are using another trait—capacity or similarity—as their central criteria. This would lead to an inverse relationship between distance and each of the other traits. A few cities may be lucky enough to have high-capacity (and/or similar) neighbors, but since only a fraction of cities can be the highest capacity ones, they may be far away from most other cities. Similarly, policymakers may face a tradeoff between learning from high-capacity places and learning from similar ones (Glick 2014). After testing each mechanism separately, we investigate whether mayors are able to find learning targets that offer proximity, similarity, and capacity simultaneously, or whether they make tradeoffs among the three.

Data and Methods

In contrast with most work in the literature, we focus on *sources of policy ideas rather* than the spread of one particular policy or a set of specific policies. While studying the adoption of policies with event history analysis has yielded many important insights, focusing on the adoption of particular policies also comes with inherent limits (Fransese and Hays 2007). By centering our analysis on sources of information, we capture patterns unconnected to any one particular policy. This is not to say that where mayors look does not vary by issue (in fact, their comments suggest that for some it does). Because we asked the question, in general, we are capturing their responses across whatever issues they happened to be thinking about. Moreover, by illuminating the inputs into policy diffusion, we obtain new leverage for understanding mechanisms. The most similar approach to our own comes from Lundin, Oberg, and Josefsson (2015) who study diffusion in municipalities in Sweden. Our approach pools across policy areas rather than specific policies like Desmarais, Harden, and Boehmke (2015) do for state policies.[1]

Perhaps most importantly, our work is able to provide insight into *constrained* information preferences. That is, each data point (a named city) comes at the expense of the opportunity cost of other cities not being named. Our subjects neither got to list all of the criteria that might matter to them, nor all of the cities they might learn from. Assuming that there are not too many cities that are close, similar, and high capacity, listing just three cities imposes constraints. While impressive experimental work on local officials has found that both success and similarity increase interest in a policy (Butler et al. 2017), our work is able to complement these analyses by using constrained (i.e., the set of places to learn from is limited) preferences to better understand tradeoffs. Their work shows that, all else equal, success and ideological similarity matter. Our approach sacrifices experimental tidiness for the ability to see how different attributes stack up next to each other.

Survey of Mayors

Building on a growing body of scholarship that uses surveys of local officials to answer important policy questions (Butler et al. 2017; Gerber, Henry, and Lubell 2013), we asked a nationally representative sample of mayors where they looked to for policy ideas (Einstein and Glick 2016). Our target population was the mayors of large and medium-sized cities. We attempted to recruit all mayors of cities with one hundred thousand or more residents. There were 288 such cities in the United States according to the 2012 American Community Survey. In the weeks before the 2015 summer meeting of the U.S. Conference of Mayors (USCM), we sent personalized email invitations to all mayors in this population that were planning on attending the conference. We then followed up on all invitations that did not receive an initial response via email and/or phone. There was also an announcement from the podium at one of the conference's plenary sessions reminding the mayors about the survey. All interviews that took place at the USCM meeting were conducted in person directly with the mayor. After the conference, we conducted similar outreach to mayors in the target population that did not attend, and conducted phone interviews throughout the summer. Importantly, the survey was pitched as a general survey covering issues and leadership. Only about one quarter of respondents participated in person at the conference, and the rest participated throughout the summer. Thus, mayors did not select into participating based on their enthusiasm to talk about policy learning, nor does the survey reflect these views of an overly "networked" set of conference attendees.

Sixty-three mayors of cities of more than one hundred thousand people participated. This equates to a 22 percent response rate from big and medium-city mayors. Due to time and other idiosyncratic reasons, fifty-two (an 18 percent response rate) answered the question of interest about policy diffusion. As we show in Table A1, the participating cities look a lot like the wider universe of American cities.[2] While our sample skews toward larger cities, the traits of the participating cities align with the population of interest in important ways that might affect policy. The average participating city is very similar to the average city of over one hundred thousand residents in terms of population density and racial demographics. It is also virtually identical economically as measured by housing prices, income, poverty, and unemployment. These residential and demographic traits are the types of variables that affect cities' policy needs, preferences, and constraints. Moreover, 66 percent of the participating mayors are Democrats (per our manual web searches and coding). This number matches the estimate for larger cities reported in Gerber and Hopkins (2011). Because of its connection to policy priorities and city similarity, this representativeness in terms of party affiliation is also important. Moreover (and pertinent in a diffusion study), the cities that comprise our data closely match the national distribution by the four census regions.[3] Our sample skews slightly toward larger cities, which is, if anything, preferable; large cities most naturally generalize to states and other large political entities. We supplement this 2015 survey with two items from similar survey we conducted with mayors in 2014. That survey included items concerning (1) sources of information generally and (2) cities that mayors considered to be "well-managed." We incorporate these items into our analysis in a couple of places. This survey included seventy-three respondents from across the range of U.S. cities. Similar to the survey that provides most of the variables, it was a general survey of mayors that included an array of questions about policy priorities, challenges, and city leadership. As with the 2015 survey, responses came directly from mayors either in person at a conference or on the phone. We compare the 2014 data to the broader population in Table A2.

Diffusion Measures and Hypothesis Tests

We focus on a small subsection of the broader survey by utilizing responses to the following question as our primary variable of interest: "Which three cities (either domestic or foreign) have you most recently looked to for policy ideas?" We followed this question by asking mayors why they selected their chosen cities. We obtained results like "Portland for biking" or "Louisville because we have a lot in common." While the search for information about a particular policy or policy area underlies each observation, the question did not prompt mayors to think about anything in particular. We are, therefore, pooling across a variety of issues and policies rather than reporting responses to a question such as "where do you generally get information?" We then coded these explanations into categories (see the following) for all instances in which we could match a city to the reason(s) it was mentioned. This design choice has the benefit of not generalizing from a pre-selected policy area. On the other hand, it means our results, and the predictions they imply, may miss issue-specific variation and other interactions between the general mechanisms we focus on and specific policy contexts or attributes. We chose to ask about "the three most recent" rather than "most common" sources of information to prompt the mayors to think of specific instances. We hoped this would mitigate against them answering based on who has a good reputation or which cities seem like the best places to look. While this approach risks some recency bias, the fact that the interviews occurred throughout the summer should ameliorate these concerns and reduce the chances that the responses are dominated by one temporarily salient issue.

Most of this paper, however, uses more objective measures to infer the reasons for information diffusion choices. We use two variables to measure the importance of *proximity*: (1) a continuous measure of the distance (in miles) between city pairs and (2) a binary measure of whether two cities are in the same state. We use one variable to measure *political similarity*: city-level Obama vote share in 2008.[4] We use eight census traits (from the 2012 American Community Survey [ACS]) to measure *trait similarity* and related concepts. These eight traits are population (logged), population density, poverty rate, unemployment rate, percentage minority (black + Hispanic + Asian), percentage with bachelors degrees, median house price, and median house price growth (combining 2000 and 2012 census data). This set of city traits captures a broad portrait of a city's people and economy. Finally, to approximate *policymaking capacity*, we use the following question: "Which three cities (either domestic or foreign) do you think are the best managed?" from our 2014 survey of mayors (Einstein, Glick, and Lusk 2014). Thus, we are focused on perceived capacity (skill at policy making) rather than actual resources. Among other things, this allows for the possibility that some smaller cities with moderate resources are considered among the best policy makers. This use of a question from a different year is a virtue. It ensures that mayors' lists of "well-managed cities" and sources of policy ideas are not influenced by one another. A mayor in the 2015 survey has no ability to influence the capacity measure (collected in 2014) and, thus, cannot, among other things, use capacity as a justification after naming a city. We use a count of *well-managed mentions* for each city as an indicator of mayors' perceptions of its policymaking capacity/efficacy (we tally these mentions into categories of 0, 1, 2, 3, and 4 (or more) to prevent outlying cities that were mentioned more than four times from driving our results). In the regression analyses, we also include indicators for bigger cities and those with higher housing prices, both of which may be associated with capacity and/or success.

Empirical Approach

Our empirical analyses require us to make comparisons between the places mayors said they looked to for ideas to those they did not mention. Finding that the cities mayors targeted were on average x miles apart is interesting but ultimately not terribly informative. In contrast, knowing that the average "targeted city" was x miles from the "naming city" is much more illuminating when we know that the average "non-targeted city" was y miles away. To derive this valuable comparison group, we defined our universe as the 288 U.S. cities over one hundred thousand people, based on the 2012 ACS. This provides a reasonable and bounded universe of cities that those in our sample could have named. The data suggest that the underlying assumption that cities over one hundred thousand people in the United States look to other cities over one hundred thousand is reasonable. Although there are thousands of smaller cities in the United States, and thousands more overseas, only 9 percent of the cities mentioned were *not* U.S. cities over a hundred thousand people, and two-thirds of this 9 percent were large foreign cities such as Paris and Bogota. In only five instances did mayors of cities over a hundred thousand people name U.S. cities with fewer than hundred thousand people.

Given this universe, we created a dataset with every possible combination of the fifty-two "naming cities" (the participants) and the 288 potential "target" cities. There are 14,924 such combinations (excluding the possibility of the fifty-two cities in our sample naming themselves). Of these combinations, there are 143 named pairs, coded 1, and 14,781 nonpairs, coded 0. That is, 99 percent of the observations are zeros.[5] We can then compare the real dyads to the potential (or the unnamed) "non-pairings."

Including the entire set of large cities is critical to the analysis. Without the full set of all of the nonpairings, we would have no baseline for assessing which factors increase the likelihood of being named. In addition, this approach reflects the fact that by choosing to name three cities, mayors are implicitly choosing *not* to name the others. To some extent, the large number of zeros is driven by our decision to extend the universe down to cities over one hundred thousand residents. If we restricted it to cities over four hundred thousand, then 95 percent of the observations would be zeros. If we defined it as all cities that were named by someone, we would be left with 94 percent zeros. While smaller cities were named enough to mandate including them in the universe of possibilities, many were not named at all. Overall, 16 percent of cities were named at least once. Only 6 percent of cities with between a hundred and two hundred thousand residents were named by someone. In contrast, more than half of the cities with over four hundred thousand residents were named.[6]

Our strategy, however, poses several challenges. One is the sparse matrix of named pairs with far more nonpairings than pairings in the data. The large share of nonmatches reduces our ability to make predictions about the cities that each mayor would name (for the cities in our survey sample and those not in the sample). Second, asking each mayor to name three, and only three, cities introduces the possibility of false negatives into the data. We cannot distinguish between true negatives, cities that a mayor would never name, and false negatives, cities that would be named if the mayor were allowed to name more than three cities. This limitation, therefore, biases the results toward zero, and makes the estimates noisier. However, we believe our empirical approach, despite its limitations, offers the best framework for analyzing how cities identify other cities from which to learn. Among other things, it avoids the selection bias inherent in only looking at actual instances of policy learning or diffusion. Moreover, by only asking for three cities, we constrained our respondents such that the cities they did name should be meaningful.

Using these comparison groups, we analyze the key independent variables of interest in three ways. First, we calculate raw differences or "distances." We do this by subtracting the value for the naming city from the real or hypothetical target city's value for each metric. The exception is the actual distance in miles measure, which is simply the geographic distance between pairs such that large values indicate less proximate cities.

Second, we evaluate similarity by focusing on nondirectional (magnitude only), standardized versions of all of our trait variables. We begin with the absolute value of the raw "distance" measures to capture the magnitude of the difference between a named and a naming city. This approach is similar to that in the network analysis in Gerber, Henry, and Lubell (2013). We then standardize these variables around the mean difference by naming city. That is, we take the magnitude of each difference, subtract the naming city's average difference (across the 287 possible named cities) for each variable, and divide by the standard deviation at the naming city level. The end result is a set of variables, one for each demographic trait, in which a value of zero indicates an observation in which a city was paired with one that was exactly the average distance (of the 287 possible pairings) away from itself, negative values indicate similarity, and positive values indicate dissimilarity.

Creating these scores has two important advantages. First, it accounts for variations in the opportunity to name similar cities (and in the magnitude of similarity) based on a naming city's own traits. For example, for cities in the densest part of the distribution, there are many possible cities to cite with similar demographic traits. In contrast, cities at the tail of the demographic distribution have few options (or even none). Second, they allow us to compare similarity across variables that are on very different scales such as unemployment rate, population, and housing prices.

Following this descriptive analysis, we estimate logit models to simultaneously test the hypotheses. Alongside these models (and at length in the online appendix), we also we estimate exponential random graph model (ERGM) network models (e.g., Cranmer and Desmarais 2010). In both sets of models, we include city- and pair-level traits to test for distance, similarity, and capacity effects. After testing the three main hypotheses, we explore, primarily descriptively, potential tradeoffs between them.

Results

Our ability to directly ask mayors about policy information diffusion provides important descriptive evidence that helps us understand the magnitude of policy diffusion across cities and how mayors choose cities from which to learn. Indeed, the diffusion literature's preponderance of studies of one policy at a time cannot tell us how common diffusion actually is. In 2014, when we asked mayors how often they used a variety of entities—including other cities/mayors—as sources of policy information, "other cities" ranked second only to "your mayoral staff," and ahead of other information sources, which we expect to matter in policymaking.[7]

Figure 1 illustrates which target cities mayors identified. Each row of the figure lists a named target city, and each column corresponds to a city in our survey (names excluded to preserve anonymity). For example, the first column of the figure shows that one mayor named New York, Los Angeles, and Chicago, the three largest cities in the United States. We include all cities named more than once in the figure. These data show that mayors are citing a wide variety of locations. There is some clustering, with more than 10 percent of mayors mentioning New York, Chicago, Philadelphia, Los Angeles, Denver, Austin, Salt Lake City, and Boston. On the other hand, there is impressive range. Many cities appear on at least two lists, and even the most commonly cited cities are only cited by a moderate fraction of respondents. For example, New York, the most commonly named city, is only named by eleven of the fifty-three mayors. There is only one repeated triad of cities: Austin, Denver, and Salt Lake City are named by two different mayors. In all other cases, mayors select a unique set of cities. This figure makes it clear that, while there is some clustering, no one city, or subset of cities, is overwhelmingly influential

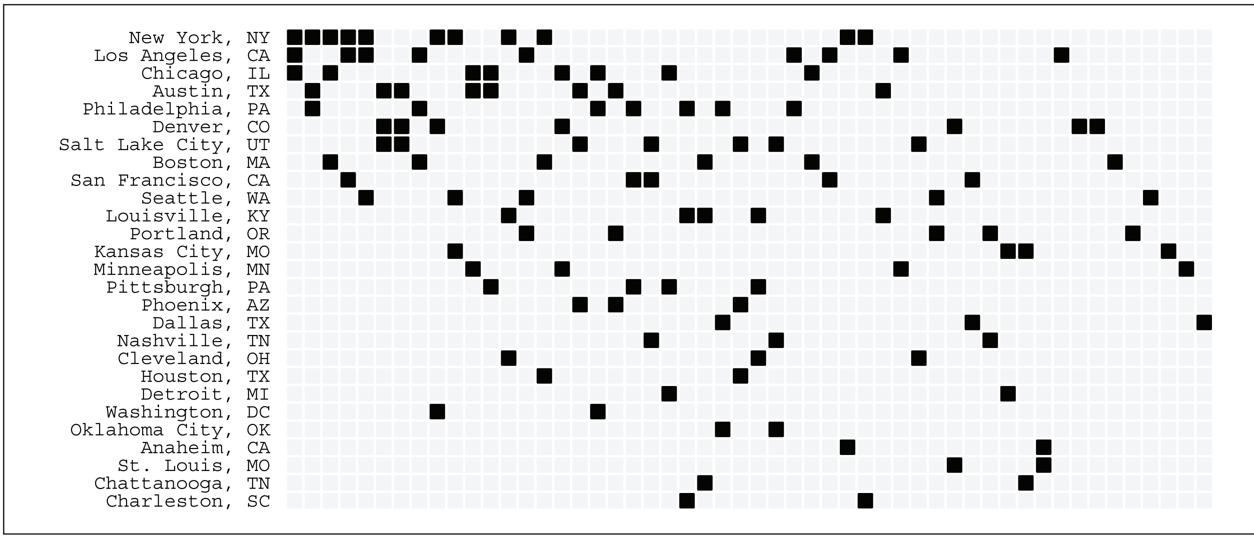

Figure 1. City mentions.
Each row lists a city named more than once, and each column corresponds to a city in our sample. The twenty cities over hundred thousand people that are only named by one city are excluded.

across the mayors in our sample. In most cases, when two mayors choose the same city, their other two choices are very different. For example, among the four cities targeting Pittsburgh, the other selected cities are Chicago and Austin, Philadelphia and San Francisco, Chicago and Detroit, and Louisville and Cleveland; only Chicago is targeted twice. Consistent with this breadth, thirty-five other cities, including some international ones, were mentioned once.

Figure 2 turns to unpacking why mayors select these cities using their self-reports. We only include the reasons that we could confidently match to the mention of a particular city. By far, the most common response was the "policy specific" category, which meant that mayors were guided to select a city by a particular policy. For example, if a mayor said, "we looked at them for downtown redevelopment ideas" we coded it as a "policy specific" reason. The prevalence of this category provides suggestive evidence that specific policy challenges often drive policy diffusion. In many instances, the mayors looked to other cities that they perceived as effective in a particular area. One mayor of a medium-sized West Coast city succinctly described his efforts to find best practices. When asked why he looked to a particular set of cities, he said, "[B]ecause we heard about a best practice . . . that 'Oh, they found out a way to deal with that. Let's scratch off Philadelphia and write in [City X] and adopt that ordinance." This search for policy-specific expertise provides some support for our hypothesis on capacity and expertise, and likely explains why mayors looked to such a wide range of cities, rather than a small subset of dominant cities.

The next two most commonly cited reasons align with two of our hypotheses: similarity and capacity/innovativeness. Any mentions of a selected city having a "lot in common," "similar demographics," or "the same challenges" (for example) fell into the similarity category. Reasons such as "they are innovative" or "they do a lot of good things" fell into the innovative/well-run category. The next most common reason is also worth noting because it is less prominent in the literature. In many instances, mayors focused more on the mayor of the city they mentioned than on the city's particular traits or policies. That is, they cited being friends with the mayor, having conversations with the mayor, or attending conferences with the mayor. Visits to mayors and their cities were also influential. A large West-Coast city mayor noted, "I was just out in Minneapolis and . . . was a fan . . . of what they're doing on trails and bike infrastructure. I used those opportunities to expand our secondary transit." While overlapping with the other mechanisms, the relative frequency of this reason (mentioned more than "proximity," for example) points to the fact that personal networks and relationships may be under-appreciated as a diffusion mechanism.

Raw Differences

Figure 3 presents histograms comparing the distributions of the differences or "distances" (described earlier) in the actual dyads (in darker grey) to the full set of cities in the lighter shade. We do so for six pertinent variables: distance between cities, city size (logged), percentage Democrat,

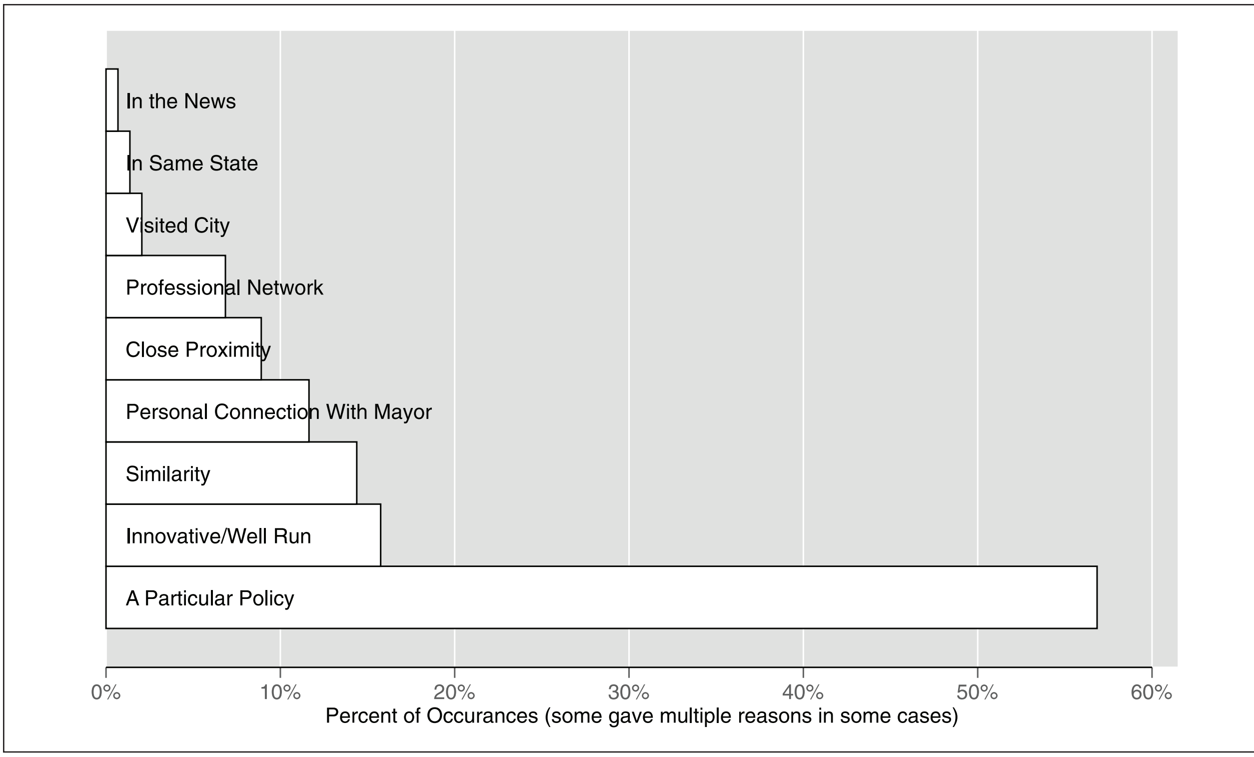

Figure 2. Reasons given for looking at particular cities.

percentage minority, median housing price, and unemployment rate. For all but the straightforward distance measure, positive values indicate that the named city (real or "potential") had a larger value (larger population, more unemployment) than the city that named it. Observations close to zero indicate pairings in which the two cities were similar. These plots provide a full and transparent accounting of our key data, and allow one to easily compare the traits of the cities that mayors said they looked at to all of those they could have mentioned but did not.

We begin with proximity. The upper left corner of Figure 3 provides strong initial support for Hypothesis 1. This plot makes clear that policymakers look to cities that are more proximate to their own than they would if selecting at random. The modal real pair was less than a hundred miles apart, and the whole distribution is skewed relative to the full set of possibilities. The average distance between actual named pairs was 341 miles closer than the mean for all of the other plausible pairs ($p < .01$). Despite these strong results, it is also important to note that in many instances, mayors are *not* looking to their neighbors (or even their extended neighbors). The mean distance between a named and a naming city is still 862 miles, and the median is 650. In all, 25 percent of all pairs are more than 1,350 miles apart. Thus, while there is a general tendency to look close, mayors frequently look far.[8]

The other five plots in Figure 3 turn to the similarity and capacity hypotheses. The mayors clearly named bigger cities than they would have if choosing at random from the available options ($p < .000$). The real distribution is heavily concentrated to the right of zero, with more than 75 percent of the real dyads including named cities that are larger than the naming city. This works against the similarity hypothesis but offers suggestive support for the capacity one. One reason for focusing on bigger cities is that they have more resources to devote to making and implementing policy. One mayor of a midsized Midwestern city explicitly cited "aspirational" cities while explaning his reasons for selecting Minneapolis, Chicago, and Austin:

> They're three progressive cities . . . in each case larger than [my city], but [excellent at] addressing issues around attracting and retaining young talent, millennials with education. [For] bicycle infrastructure, Minneapolis is just a great city to look for that. Arts and culture, Chicago and Austin stand out in my mind.

Consistent with naming bigger cities, the mayors also named cities that were more Democratic than their own. In real pairs, the named city was about 10 points more Democratic than the naming city compared with essential parity in the overall distribution ($p < .000$). This is not to

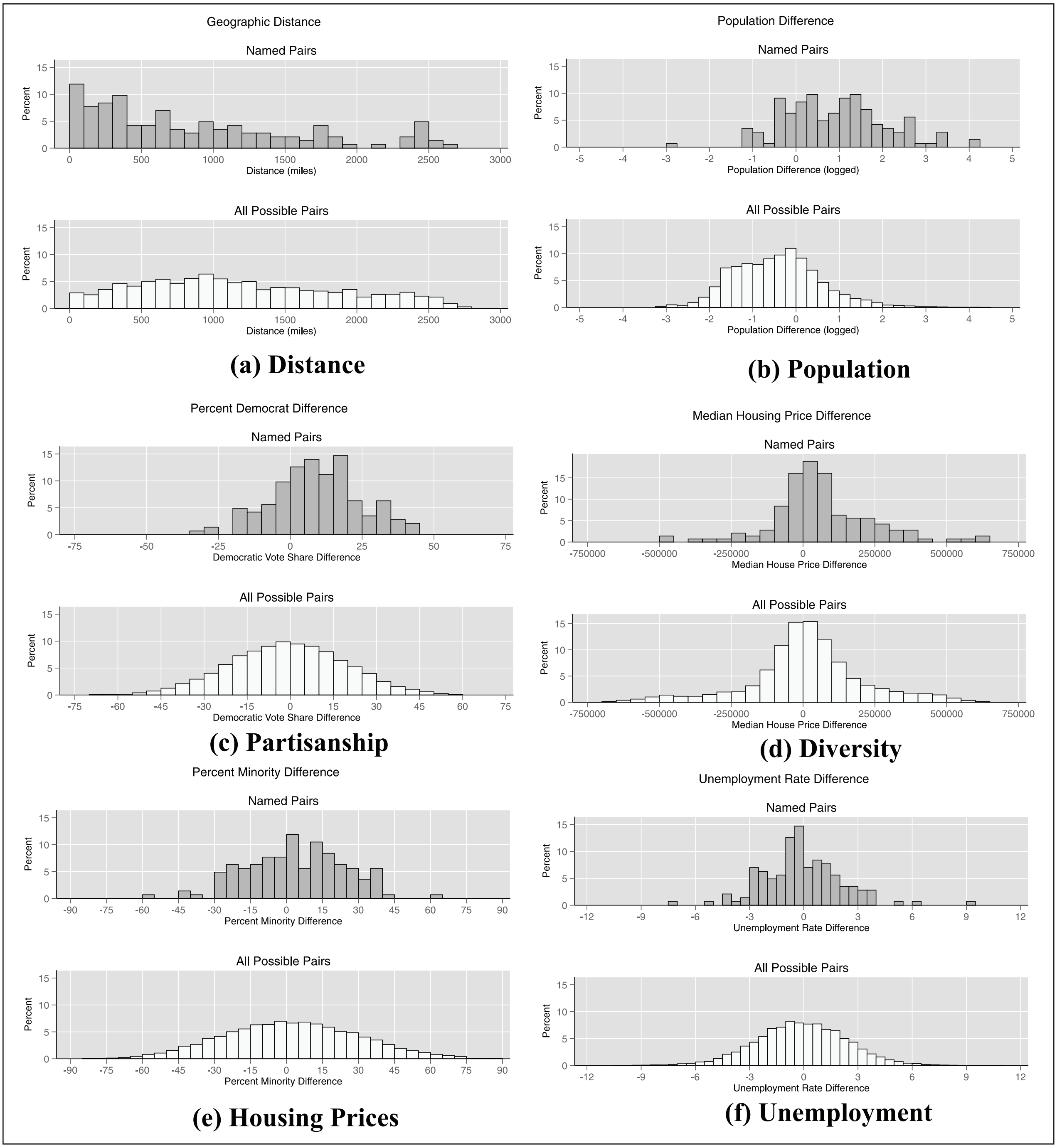

Figure 3. Comparisons of named pairs to all possible pairs.

say that ideological similarity was irrelevant. Indeed, one mayor of a small southern city cited Mesa, Arizona because it was "a benchmark for conservatives." The named pairs also had marginally significant differences in relative housing prices. That is, compared with the overall distribution, the actual cities mayors mentioned had higher median property values relative to their own (p = .07). On the other hand, consistent with the plots, there were no discernable average differences between the named dyads and all dyads on the unemployment or percentage minority metrics.

Similarity by Trait

We now focus on the standardized similarity measures we introduced above. Figure 4 plots the average dissimilarity

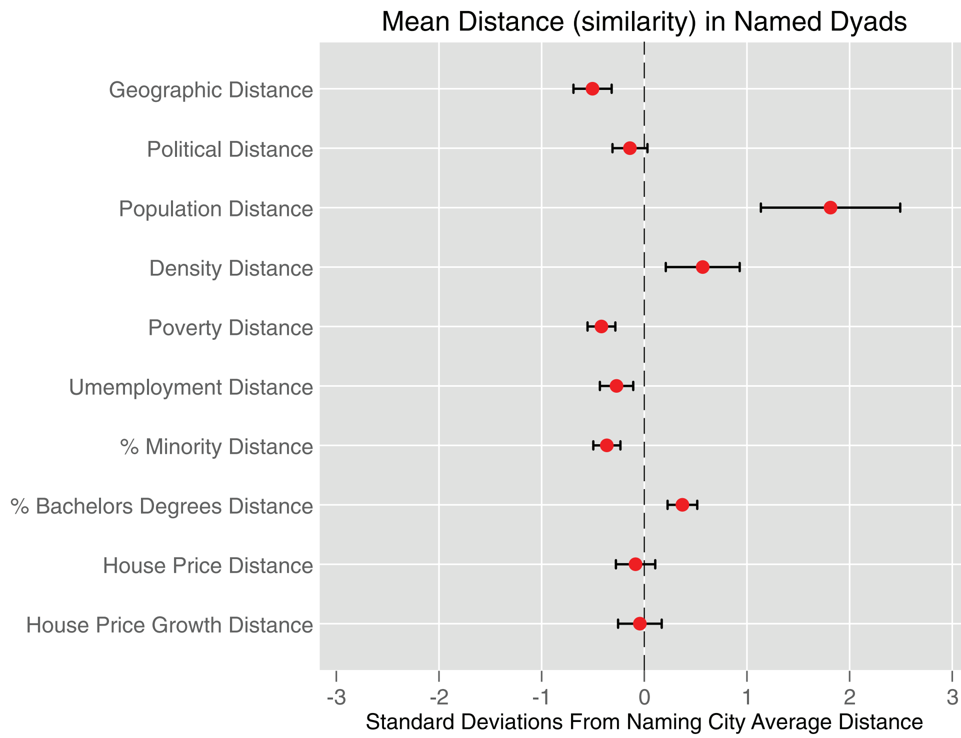

Figure 4. Standardized dissimilarity scores for named dyads.
The zero line indicates average dissimilarity. Negative values indicate above-average similarity.

scores for the *actual named dyads* across a variety of variables. A score of "1" indicates a pairing in which the named city was 1 standard deviation less similar than average and a score of "–1" indicates a city that was 1 standard deviation more similar than average. The 0 line does *not* indicate perfect alignment; it shows average dissimilarity. These measures are symmetrical. A city that is 10 points more Democratic would receive the same similarity score as one that is 10 points less Democratic.

Consistent with the skew toward larger cities noted above, the real pairings are significantly dissimilar (two standard deviations) in population. Given the findings above, most if not all, of this dissimilarity is driven by cities naming others that are larger than their own rather than smaller ones.[9] The other two variables in which mayors named abnormally *dissimilar* cities were population density and percentage bachelors degree.

In addition to being closer than average in literal distance (top row of the plot), the named cities were significantly more similar than average across a handful of demographic traits: political difference, poverty rate, unemployment rate, and percentage minority. The only two variables in which named cities were not significantly more or less similar than if chosen at random were housing prices and housing price growth.

Regression Models

To more rigorously test Hypotheses 1 (Proximity), 2A (Political Similarity), 2B (Context Similarity), and 3 (Policymaking Capacity), we use simple logit models to estimate the likelihood of a named pair. The dependent variable in these models is a binary indicator of actual named pairs. The models include two proximity measures: *Same State* and *Standardized Distance* (outlined earlier).

We also incorporate five variables to assess our similarity hypotheses. For all of the following standardized similarity variables, higher values indicate greater *dissimilarity. Standardized Population Similarity* measures the difference in population between the surveyed city and potential matches. *Standardized Similarity Index* captures overall city trait similarity. It is the mean of all of the standardized similarity measures[10] except for the political and population ones (which are included separately).[11] *Standardized Political Similarity* measures political similarity. Finally, we include two dummy variables, *Bigger City*, which is coded as 1 if the named city has a larger population than the surveyed city, and *Higher Housing Prices*, which is coded as 1 if the named city has higher average housing prices than the surveyed city. Unlike the population and political similarity measures and the similarity index—which treat

Table 1. Base Models.

	(1)	(2)	(3)	(4)	(5)
	Logit	Logit	Logit	Logit	ERGM
Same State	0.8363**			1.1804**	1.357***
	(0.2366)			(0.2759)	(–0.352)
Standardized Distance	−0.4032**			−0.3454**	−0.346***
	(0.1283)			(0.1291)	(–0.132)
Standardized Political Similarity		−0.0951		−0.1523	−0.131
		(0.1122)		(0.1017)	(–0.112)
Standardized Population Similarity		0.2855**		0.1457**	0.127***
		(0.0319)		(0.0327)	(–0.034)
Standardized Similarity Index		−0.8563**		−0.6916**	−0.566**
		(0.2417)		(0.2205)	(–0.223)
Bigger City		1.8236**		1.2728**	1.610***
		(0.2212)		(0.2224)	(–0.276)
Higher Housing Prices		0.5080*		0.3758	0.397*
		(0.2301)		(0.2147)	(–0.237)
Well-Managed City			1.1330**	0.9777**	0.866***
			(0.0537)	(0.0753)	(–0.091)
Constant	−4.7634**	−6.5388**	−5.3577**	−6.7273**	
	(0.0712)	(0.3565)	(0.0877)	(0.3254)	
Observations	14,924	14,924	14,924	14,924	

Robust standard errors in parentheses. Standard errors clustered by naming city. *Edges* and *Mutual* terms omitted from model 5. See Online Appendix Table B1. ERGM = exponential random graph model.
$^{*}p < .0$. $^{**}p < .01$,

equally small and large deviations as the same—these dummy variables allow us to examine whether bigger or wealthier cities are more likely to be named. Finally, to test the policymaking capacity hypothesis, we rely on the *Well-Managed City* variable. We also include regional fixed effects (based on census region) to account for regional differences across surveyed cities. Since each naming city selects three different cities (and implicitly declines to choose the 284 other cities as one of their top three), observations are not independent at the naming city level. As a result, we cluster the standard errors by naming city.

In addition to the logit models, we also model the relationship as a network using ERGMs to estimate the likelihood of a named pair. We construct a directional network where each node is one of the 288 possible target cities. For each of the fifty-two naming cities in the sample, we add a directed edge to each of the target cities that the mayors identified. These models have become increasingly popular in political science and policy studies (e.g., Box-Steffensmeier and Christenson 2014, 2015; Cranmer and Desmarais 2010; Leifeld and Schneider 2012; Lubell et al. 2012). They have been used to make inferences about observations rather than whole networks (e.g., Desmarais and Cranmer 2012), to model policy diffusion (e.g., Desmarais, Harden, and Boehmke 2015), and to infer the effects of similarity (e.g., Gerber, Henry, and Lubell 2013). These models, allow us to explicitly incorporate the constraint that each naming city could only give identify three target cities. They should also ameliorate some potential concerns about the sparse matrix of pairs because they can account for the zeros (nonexistent edges), and they allow us to include a mutual dependence term.

Table 1 presents the results.[12] Models 1, 2, and 3 estimate the probability of a city being targeted using the corresponding variables for Hypotheses 1, 2, and 3, respectively. Model 4 pools all three sets of variables, and model 5 incorporates model 4's covariates using an ERGM. The results in models 4 and 5 are nearly identical, indicating that the constraint of three target cities for each respondent, which is included in model 5 but not in model 4, is not biasing our primary results. We provide more information (including diagnostics) about, and results from, the ERGM in the online appendix.

While the coefficient sizes vary, the direction and statistical significance of the variables are consistent across the models. We find significant evidence supporting the proximity hypothesis. The positive coefficient on *Same State* is substantively large and statistically significant; cities are more likely to target another city in their state than cities in other states. The coefficient on *Standard Distance* is likewise significant but negative. As the distance between cities increases, they are less likely to be targeted.

On our two similarity hypotheses, we find mixed results. The coefficient on *political similarity* is negative, as expected, but not significant. On *trait similarity*, we find a significant negative relationship on the *similarity index*, indicating that more similar cities are more likely to be targeted. However, our models also reveal significant positive relationships on dummy variables for *Bigger City* and *Population Similarity*. Cities are more likely to target larger cities, not similarly sized cities. We also find a positive and weakly significant coefficient on *Higher Housing Prices*. Thus, the empirical evidence on similarity is inconsistent. Cities are more likely to look to larger and more expensive cities, but also prefer cities with similar characteristics on other dimensions. One possibility is that city size and housing prices are picking up on capacity/success rather than similarity, suggesting some support for Hypothesis 3.

Finally, and more explicitly focused on Hypothesis 3, we find strong evidence in favor of the policymaking capacity hypothesis. The coefficient on the *Well-Managed City* variable, our proxy for policymaking capacity, is large, positive, and statistically significant. Mayors are choosing to target cities that are seen by other mayors as well-managed. Interestingly, the effect of capacity does not appear to vary in either direction with the capacity of the naming city. Overall, cities that at least two other mayors named as high-capacity cities named another high-capacity city about 65 percent of the time compared with 50 percent of the time for low-capacity-naming cities. Much of this difference appears to be driven by the fact that the high-capacity cities tend to be larger and name other larger cities. If we focus only on cities over three hundred thousand residents, cities that are and are not frequently named as "well-managed" name well-managed cities at almost identical rates. This analysis is very tentative, and the cells are very small, but it at least suggests that a city's own capacity does not affect where it searches for information.

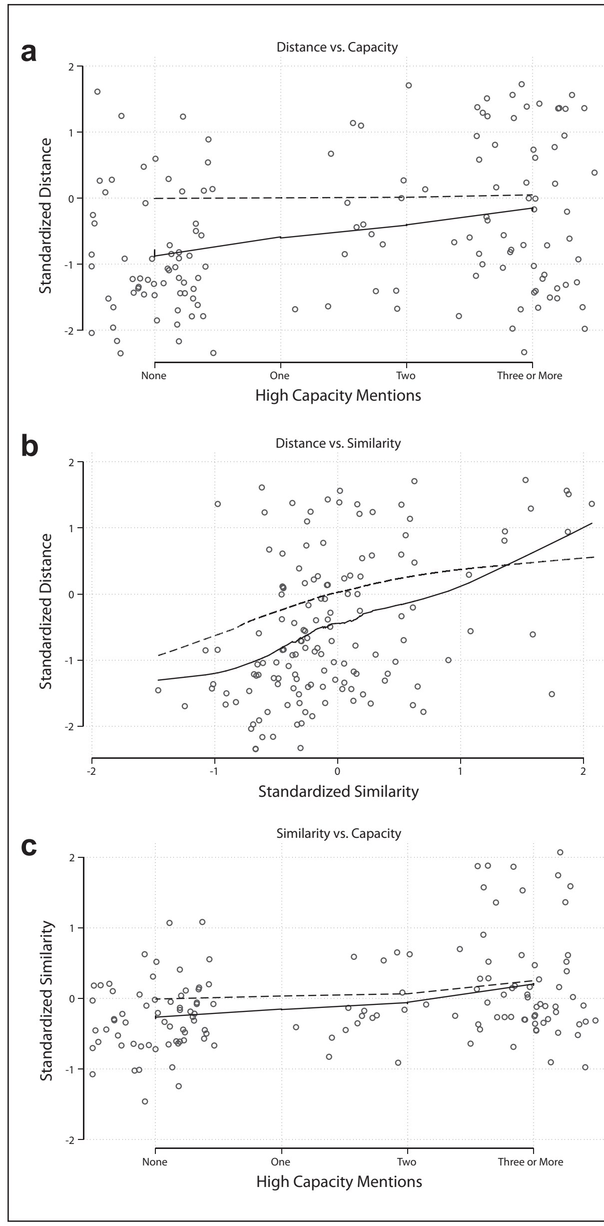

Figure 5. Two way tradeoffs (raw data) between distance, similarity, and capacity for named pairs. Solid line = actual pairs. Dashed line = all possible pairs.

Tradeoffs between Mechanisms

Thus far, we have shown that distance, similarity, and success/capacity are all associated with the places mayors look to for policy ideas, but that each of the three can only contribute to explanations of some of the data points. The most likely explanation for these mixed findings is that (1) there is not one dominant mechanism and (2) the three are often incompatible. This means that there are potentially important tradeoffs between the different diffusion mechanisms.

To begin assessing the possibility of tradeoffs, we investigate bivariate relationships (distance vs. capacity, distance vs. similarity, and similarity vs. capacity) using our standardized geographical distance, similarity index, and well-managed mentions variables. Our interest is the strength and direction of the relationship between each pair of variables for the actual named pairs in the data. In short, seeing an inverse relationship between two variables in the actual city pairs that is not manifest in the underlying distribution of all possible pairs suggest mayors are making an implicit or explicit tradeoff.

In Figure 5, we plot the data for all named pairs for each of three tradeoffs. We also plot Lowess lines for (1) the named pairs (solid line) and (2) all possible pairs (dashed line). As the plots show, the strongest ostensible tradeoff is between distance and capacity. There is no relationship in the full set of possible pairs. However, when mayors name higher capacity cities, they tend to name those that are further away, and they very rarely name lower capacity cities that are also distant. In contrast, there is no evidence whatsoever of a tradeoff between distance and similarity. The plot through the actual pairs and the plot through all possible pairs are parallel. More importantly, they show a positive rather than an inverse relationship. Sometimes, mayors look at far away and dissimilar cities, and other times, they look at proximate and similar targets. Rarely do they look to distant and similar, or near and dissimilar, cities. Finally, the plot of the relationship between capacity and proximity provides tentative evidence of a more modest tradeoff. When mayors look to high-capacity cities, they tend to look to those that are less similar. This makes sense because many of the cities cited for their policy making capacity are very large and may have less in common with smaller cities that look to them. Finally, while not in the text, we note that we find little evidence of a tradeoff between political similarity and distance or capacity.

Because of the modest number of observations and the quantitative and qualitative insight we have into the variety of considerations between each mayor's choices, we interpret these bivariate relationships cautiously. To bolster the visual analysis, we estimated models to test for similar effects in the online appendix. These models, which include controls for political similarity, whether the named city was bigger, and whether the named city had higher housing prices, comport with the bivariate plots here. Indeed, if anything, they provide stronger evidence for a tradeoff between capacity and similarity than does the descriptive plot. Nevertheless, we emphasize the more cautious interpretations and plots presented above.

In sum, the data at least suggest that mayors face, and make, tradeoffs between capacity and each of the other two variables. When mayors look to close and/or similar cities, they are looking at places other mayors are less likely to name as high-capacity cities. In contrast, we find evidence contrary to a tradeoff between similarity and distance. Both in the universe of cities and in the set of actual pairs, they move in tandem. Closer cities tend to be more similar, and mayors often look to cities that meet both criteria. When they look further away, presumably for capacity reasons, they tend to give up both proximity and similarity. As with the main results above, these findings are consistent with multiple diffusion mechanisms and calculations. At times, mayors prioritize "fit" (e.g., similarity and distance) and at others, they prioritize expertise.

Conclusion

The data we introduce and analyze offer unprecedented direct insight into how local political elites acquire policy information, and how this contributes to the diffusion of policies. Indeed, we find evidence that mayors obtain policy information from similar, proximal, and high-capacity cities. In short, we find that previously identified diffusion mechanisms and systematic policy learning generalize to (1) the information gathering stage, (2) U.S. cities, and (3) new data and empirical approaches. Cities and mayors are taking on complicated and, at times, ideological policy issues. When they do so, they are gleaning ideas and identifying workable innovations in a similar manner to states. When asked for three cities they recently looked to for ideas, mayors neither produced a random list nor did they all say "New York" or the closest big city to their own. Their responses indicate systematic and intentioned learning that matters both as a new empirical test in the literature, and because what cities do is so consequential for their residents, businesses, and visitors.

On the other hand, mayors' responses also included hints of intriguing differences between policy learning in cities and states. While currently untestable because comparable data do not exist for governors, these hints speak to future research questions and to the potential for important variations in the mechanisms and manifestations of diffusion. For instance, of all of the traits we looked at in the similarity index, the ones on which naming and target cities were most similar were those related to the housing market (e.g., median price). This is especially noteworthy because we also know that some of the most commonly cited cities, often for capacity reasons, were extreme outliers in terms of housing prices suggesting that the other pairs stuck very close to their peers on this dimension. This housing similarity makes perfect sense for cities because of the links between housing prices and urban tax base, and because housing and development are so central to urban policy and constraints on it. This at least tentatively suggests the need to delve into "similarity" in more depth. Are policy makers targeting their sources of information in nuanced enough ways that different similarity parameters drive diffusion at different levels of government? Are other factors such as size, or density, or ideology relatively more important when states learn from each other? We also find indirect quantitative, and very direct qualitative, evidence that mayors are not relying on all of the key attributes at once. This finding is important. It suggests that mayors are looking to different kinds of cities depending on the type of concern. Perhaps certain kinds of policy issues drive mayors to seek information from different types of cites. Policy-specific concerns appear to motivate mayors to look farther afield, while an emphasis on similarity unsurprisingly spurs mayors to search for ideas from similar communities. Future research focused on multiple policy arenas, rather than the single-issue analyses typical in the diffusion literature, might begin to outline what kinds of policy initiatives lend themselves to high-capacity versus similar versus proximal cities.

More generally, and methodologically, our results militate in favor of studies that focus directly on political elites. By analyzing elites and information—rather than a single policy—our findings allow us to speak somewhat generally about the underlying factors driving policy diffusion. In addition to the statistical evidence from closed-ended survey responses, we also were able to obtain rich open-ended responses from mayors that further illuminate the elite processes undergirding policy diffusion. These responses augment the statistical findings by adding depth to the mayors' considerations of factors such as similarity. They also, however, demonstrate that these variables and other theories in the literature can only partly explain diffusion. Indeed, some of the responses point to more idiosyncratic and personalized patterns of information sharing.

This qualitative evidence points to another intriguing potential difference between city and state diffusion, and more generally, to a harder to observe but important diffusion channel. Specifically, some of the qualitative evidence speaks to the importance of variables and mechanisms beyond the three we provide systematic evidence of. For example, at least some of the mayors spoke more in terms of another mayors' qualities and expertise rather than his or her city's. In many cases, mayors' views of, or individual connections to, each other appear to matter more than systematic city-level traits. That is, assessments of individual mayors, and the network of mayors, may be driving capacity diffusion mechanisms. The same city could be considered "high capacity" under one mayor's leadership but not her successor's. Relatedly, the open-ended explanations also speak to the depth of variables like success and capacity. They captured mayors citing conference presentations, grant competitions, and lobbying networks that informed them about the ostensibly innovative and effective cities, and initiatives from which they wanted to learn. In light of cities' growing policy salience, we hope that future scholarship will incorporate these more novel, and less quantifiable, diffusion mechanisms that require a mix of methods and continued focus beyond policy choices. Perhaps states, which tend to have more professionalized and permanent executive and legislative resources behave differently. Perhaps they behave similarly, and other states are learning as much from Governor Brown as they are from California. This discussion is very speculative but speaks both to the importance of future work and to the value of qualitative methods in the study of diffusion.

Finally, we believe that mayors' emphasis on success and capacity in particular—and their willingness to trade off proximity and similarity to look to high-capacity cities (or mayors)—may be important beyond simply understanding the sources of mayoral policy ideas. Our qualitative interviews with mayors—and the policy-specific reasons they provided when asked why they looked to a particular city—suggest that, when mayors look far afield for policy ideas, they are doing so thoughtfully. We could imagine, then, that these carefully selected policy ideas are more likely to be successful than initiatives chosen haphazardly and quickly.

We hope that future scholars take these results as a starting point to investigate the impact of these policy-making decisions. Do cities that look farther for policy ideas actually implement better policy? Are these thoughtfully governed cities high achieving across a variety of dimensions because of the care with which their leaders select policies? They might grow more rapidly and/or attract businesses and high quality employees, for example. Cities face many challenges. Those that address their challenges most effectively likely have mayors that actively seek out policy innovations and learn from a wide variety of other cities, both near and far. New approaches and carefully refined best practices should not be confined to the places that develop them; by learning from each other, cities can avoid pitfalls and achieve greater success than they could on their own.

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Notes

1. In the U.S. context, our approach is in some respects similar to Glick and Friedland (2015), which tabulated and analyzed the other states mentioned in policy research briefs prepared in two states. Our design comprises a range of city and insight into information sources direct from senior policymakers (mayors).
2. Demographic comparisons use 2012 demographic data from the American Community Survey.

3. In our sample, the proportion of cities (that answered the diffusion question) located in the Midwest, Northeast, South, and West are 18, 9, 36, and 36 percent, respectively versus 17, 9, 35, and 40 percent nationally.
4. We were unable to find or calculate city-level Obama vote share for five of the fifty-two naming cities and nineteen of the 288 potential target cities. For these cities, we used 2008 county-level vote share in place of city-level vote share. Excluding the cities where city-level vote share is missing does not substantively affect the results.
5. In addition to the 9 percent that named smaller or foreign cities, a few mayors did not name a full set of three cities such that we have 143 instead of 156 named pairs.
6. One possible concern with this approach is that our choice of including all cities with populations greater than hundred thousand people may bias our results. That is, if we were to set the cutoff lower and include more cities, or set the cutoff higher and exclude potential targets, the results might change. To address this concern, we estimate logit models using cutoffs ranging from cities of fifty thouand people (773 cities) to 250,000 people (seventy-three cities). These results are reported in Figure C3. Varying the population cutoff does not substantively affect the results.
7. See Figure A1 in the online appendix for the full results.
8. Related to distance, we can also look at the propensity to name cities that are in the same state. Approximately 20 percent of actual pairs were in the same state compared with only 6 percent of the nonpairs ($p < .01$). What is less clear at this point is whether doing so is evidence for a proximity mechanism or a similarity one. Cities in the same state will naturally have important traits in common, most notably, the same state laws and state government. Indeed, one mid-sized southern mayor's explanation for his cited cities seems to point to the latter. He named one of his three cities, which was located in the same state as his city, because "we have the same state legislature to deal with."
9. Importantly, this finding is not solely driven by mayors naming New York, the most commonly named city. Even dropping all observations involving New York, named cities were more than 0.7 standard deviations less similar than average ($p < .000$). They were still significantly more different when dropping mentions of Los Angeles.
10. These measures are as follows: poverty, unemployment, minority percentage, bachelors degree percentage, housing prices, housing price growth, and density.
11. These variables seem to pick up on intuitive (but non-obvious) similar and dissimilar cities. For example, Milwaukee's five most similar cities using our index are Springfield, Massachusetts; Allentown, Pennsylvania; St. Louis, Missouri; Rochester, New York; Buffalo, New York. Madison, the nearest city over 100K people is actually quite dissimilar to Milwaukee on our index.
12. To check for robustness, we also estimate the model using rare-events logit and ordinary least squares (Table C1). Given the similarity of the logit and rare-events logit models, and the consistency of the results across models, we use standard logit for the results presented in the paper, and display the alternative model results in the online appendix.

Supplemental Material

Supplemental materials for this article are available with the manuscript on the *Political Research Quarterly* (*PRQ*) website. Due to institutional review board (IRB) restrictions and anonymity issues, for replication data questions, please contact David Glick.

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