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. 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 evidence for the latter. Finally, we show that policymakers look to others for a variety of reasons, but report that they most often choose where to look for policy specific reasons.

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. While a wide array of studies investigates cases of policies diffusing, the literature's explications of the mechanisms underlying diffusion, let alone unobserved cases of non-diffusion, remain incomplete (e.g. Dobbin, Simmons, and Garrett 2007; Shipan and Volden 2008). Previous research offers evidence that a number of mechanisms and/or traits such as geographic proximity (Berry and Berry 1990; Mooney 2001), similarity (Grossback, Nicholson-Crotty, and Peterson 2004; Butler et al. 2015), policy success (Volden 2006; Butler et al. 2015), 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 at least some of the time. Nevertheless, the precise details of these mechanisms and how they interact have not been fully explored.

We use novel data collected directly from mayors to investigate where political elites look for policy information, what reasons they give for doing so, and how their information sources align with prominent diffusion theories. Our research distinguishes itself both in its theoretical conceptualization of policy diffusion and in its primary locus of study. Theoretically, we define our dependent variable somewhat differently than most previous studies. Instead of focusing on the spread of specific policies, we look at the pursuit and dissemination of policy information—the step that precedes policy diffusion. We ask questions about the systematic (or non-systematic) 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 (Karch 2012; Butler et al. 2015; Lundin, Oberg, and Josefsson 2015).

In contrast with the literature's focus on state or national governments, we study cities where there is comparatively little research on policy diffusion (though see e.g. Shipan and Volden 2006; Butler et al. 2015; Lundin, Oberg, and Josefsson 2015). The relative lack of diffusion work on cities is surprising for both substantive and methodological reasons. 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 policy making even in spite of the contraints facing local governments (e.g. Peterson 1981). This is especially true for liberals and progressives, whose recent electoral defeats at the state and federal levels may make the local government the only realistic avenue for the advancement of policy goals.

Methodologically, cities offer empirical opportunities that states and nations cannot. There are many more cities than states or countries. Indeed, medium and large US cities have roughly six times as many potential places to learn from than do US 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, one of the central theories in diffusion research posits that policies diffuse to a state from nearby other states. States have at most a few neighbors, while cities will often have a multitude of other cities nearby. This reality not only creates more observations, but more variation. In many instances, nearby states may be 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. This sort of variation, which we exploit, is important for distinguishing different policy diffusion mechanisms.

To measure cities' sources of policy information, we take advantage of a 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 over 100,000 residents, we construct a dataset with all of the actual named pairs of cities and all of 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. We also find that these mechanisms are at times substitutes rather than complements. In other words, when a mayor uses competence to select a source of policy information, she is unlikely to be simultaneously relying on proximity, for example. These results provide us unprecedented 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.

1 Theories of Policy Diffusion

Previous scholarship suggests a variety of mechanisms by which lower levels of government might learn from one another. The first, which has perhaps the longest history in the literature, is proximity. 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 derive from a physical notion of diffusion in which policies literally spread from one space to the next, an informational account in which it is easier to observe what those nearby are doing, and/or a competitive account in which actors compete with their neighbors for resources (Baybeck, Berry, and Siegel 2011). Applying the research on proximity effects to our study of local governments—which is focused more on *sources of policy ideas* rather than observed policy diffusion—leads us to **H1 (Proximity)**: Policymakers are more likely to obtain policy ideas from nearby jurisdictions.

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 learn from "similar" jurisdictions and enact policies after similar jurisdictions have done so. This general agreement that similarity matters masks important uncertainty. Some focus primarily on political and ideological similarity (Grossback, Nicholson-Crotty, and Peterson 2004; Butler et al. 2015) while others focus more on a broader but less concrete notion of goal similarity (Glick and Myers 2014).

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. 2015). Our focus on policy inputs helps similarly 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, and relatedly, similarity also overlaps with geographic proximity as a state or city's neighbors may also be similar to it. Again, focusing on intentional searches for information and exploiting the variation in cities helps address some of these theoretical and empirical challenges. Putting the pieces of this discussion together leads to a general similarity hypothesis **H2** that we split into two pieces: **H2A (Political similarity)** and **H2B (Context similarity)**. H2A asserts that 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. H2B 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.

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 **H3 (Policymaking Capacity)**: jurisdictions that are perceived as better policymakers will, all else equal, be more frequent sources of policy ideas.

These three central ideas—while critically important—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—such as success or similarity—to look further away. This logic leads to **H4A (Distance vs. Capacity)** and **H4B (Distance vs. Similarity)**: policymakers looking to more distant locales as sources of policy information are using another trait—capacity or similarity—as their central criteria. The third combination of two of our three concepts is that involving similarity and capacity. Policymakers may face a tradeoff between learning from high capacity places and learning from similar ones (Glick 2014). While other work has investigated this tradeoff formally and in the lab, observational examinations are lacking. Thus, our third tradeoff hypothesis, **H4C (Similarity vs. Capacity)**, predicts that all else equal, higher capacity sources are less likely to be similar sources.

2 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 general patterns unconnected to a particular policy. 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 by combining survey and objective information to study information diffusion, and, in particular, links between diffusion and successful outcomes.[1] Perhaps most importantly, our work is able to provide insight into *constrained* information preferences. While impressive experimental work on local officials has found that both success and similarity increase interest in a policy (Butler et al. 2015), our work is able to complement these analyses by using constrained 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.

2.1 Survey of Mayors

Building on a growing body of scholarship that uses surveys of local officials to answer important policy questions (Gerber, Henry, and Lubell 2013; Butler et al. 2015), we asked a nationally representative sample of mayors where they looked to for policy ideas. Our target population was the mayors of large and medium-sized cities. We attempted to recruit

[1] In the US context, our approach is in some respects similar to Glick and Friedland (2014). They tabulated and analyzed the other states mentioned in policy research briefs with an interest in variables such as proximity and innovativeness. Our design offers insight into policy learning across a range of cities nationwide, whereas they only had information about New Hampshire and Vermont. Moreover, our data come directly from senior policymakers (mayors), whereas their access to information sources in state legislators was based on policy briefs prepared by amateur student research teams. Finally, we marshal a wealth of other variables and measures to examine and test the dimensions of key concepts such as similarity, distance, and capacity.

all mayors of cities with 100,000 or more residents.[2] There were 288 such cities in the U.S. 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 participate 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 conferences 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.

Sixty-three mayors of cities over 100,000 people participated. This equates to a 22% response rate from big and medium-city mayors. Due to time and other idiosyncratic reasons, 52 (an 18% response rate) answered the question of interest about policy diffusion. The vast majority of interviews took place either in-person or by phone which guarantees that most (if not all) of our responses came directly from mayors rather than staff. As we show in Table SI1, using 2012 demographic data from the U.S. Census' American Community Survey, the participating cities look a lot like the wider universe of American cities.[3] Moreover (and pertinent in a diffusion study) the cities that comprise our data closely match the national distribution by the four census regions.[4] Our sample skews a very small amount toward

[2]In addition to the benefits of using an observational approach for our analyses outlined above, we also opted not to use an experiment analogous to Butler et al. (2015) because our target population of *large* cities is smaller than the universe of much smaller cities included in Butler et al.'s (2015) sampling frame.

[3]Demographic comparisons use 2012 demographic data from the American Community Survey.

[4]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% respectively vs. 17%,

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 a similar survey we conducted 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. We compare the 2014 data to the broader population in Table SI2.

2.2 Diffusion Measures and Hypothesis Tests

While the survey of mayors covered a variety of topics, this paper only concerns a small subsection about policy information and diffusion. In particular, we rely on the following question as our primary variable of interest in much of the analysis: "Which three cities (either domestic or foreign) have you most recently looked to for policy ideas?" We followed this question by asking why they selected their chosen cities, obtaining results like "Portland for biking" or "Louisville because we have a lot in common." We then coded these explanations into categories (see below) for all instances in which we could match a city to the reason(s) it was mentioned.

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.[5] We use eight census traits (from the 2012 ACS) to measure **trait similarity** and related concepts. These eight traits are pop-

9%, 35%, and 40% nationally.

[5]We were unable to find or calculate city-level Obama vote share for 5 of the 52 naming cities and 19 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.

ulation (logged), population density, poverty rate, unemployment rate, percent minority (black+Hispanic+Asian), percent with bachelors degrees, median house price, and median house price growth (combining 2000 and 2012 census data). This set of city traits capture 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. This use of questions from different years is a virtue in this case since it ensures that mayors' lists of "well-managed cities" and sources of policy ideas are not influenced by one another. 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 to prevent outlying cities that were mentioned more than 4 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.

2.3 Empirical Approach

Our empirical analyses require us to make comparisons between 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 100,000 people, based on the 2012 American Community Survey. 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 100,000 people in the U.S. look to other cities over 100,000 is reasonable. Although there are thousands of smaller cities in the U.S. and thousands more overseas, only 9% of the cities mentioned were *not* U.S. cities over 100,000 people and two thirds of this 9% were large foreign cities such as Paris and

Bogota. In only five instances did mayors of cities over 100,000 people name U.S. cities with fewer than 100,000 people.

Given this universe, we created a dataset with every possible combination of the 52 "naming cities" (the participants) and the 288 potential 'target" cities. There are 14,924 such combinations (excluding the possibility of the 55 cities in our sample naming themselves). Of these combinations, there are 143 named pairs, coded 1, and 14,781 non-pairs, coded 0.[6] 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 non-pairings we would have no baseline for assessing which factors increase the likelihood of being named. Additionally, this approach reflects that by choosing to name three cities, mayors are implicitly choosing *not* to name the others.[7]

Our strategy, however, poses several challenges. First, this approach produces a sparse matrix of named pairs; the probability that a city will name another city is relatively low, and there are far more non-pairings than pairings in the data. The large share of non-matches 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, the survey approach of asking each mayor to name three, and only three, cities introduces the possibilities of false negatives into the data. We cannot distinguish between true negatives, cities that

[6] In addition to the 9% 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.

[7] One possible concern with this approach is that our choice of including all cities with populations greater than 100,000 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 reestimate our models using cutoffs ranging from cities of 50,000 people (773 cities) to 250,000 people (73 cities). These results are reported in Figure SI2. The results are robust to the population cutoff and varying the population cutoff does not substantively affect the results.

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 towards zero, and makes the estimates more noisy. These problems would be alleviated if we could have asked mayors to rank or score all of the potential target cities but, due to the time constraints involved with surveying active mayors, such data collection is not feasible. 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, sometimes figuratively referred to as "distances" (though we have one literal measure of distance as well). We do this by subtracting the value for the naming city from the real or hypothetical target city's value for each metric. For example, *political distance* for a pairing would be the named city's Obama vote share less the target city's Obama vote share. 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. In Figure 3, below, we plot histograms of these raw distances comparing named pairs to unnamed pairs for six measures.[8]

Second, we evaluate similarity by focusing on non-directional (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 stan-

[8]For clarity of presentation, we limit the array of plots to six variations.

dard 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, like New York City, 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.

3 Results

We begin with a descriptive analysis of the cities mayors identified in our survey. We then turn to empirical models where we simultaneously test the hypotheses. We also estimate models on subsets of the data to understand the tradeoffs across factors.

Our ability to directly ask mayors about policy 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 other information sources which we expect to matter in policymaking.[9]

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

[9]See Figure SI1 in the Appendix for the full results.

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. These data show that mayors are citing a wide variety of locations. There is some clustering, with over 10% 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 11 of the 53 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. The figure reveals a few interesting groups of cities. Three mayors identified both New York and Los Angeles, but differed in their third choice of city: Chicago, San Francisco, or Seattle. Two mayors both named Chicago and Austin, and chose somewhat similar third cities: Minneapolis and Pittsburg. However, this figure makes it clear that no one city, or subset of cities, is overwhelmingly influential 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, 35 other cities, including some international ones, were mentioned once.

Figure 2 turns to unpacking why mayors select these cities. While most of our analysis uses objective measures to explore which demographic and institutional traits predict whether a city is named, Figure 2 uses mayors' self-reports. We only include the reasons that we could confidently match to the mention of a particular city. In most cases we coded one reason per city mentioned, though in some, respondents gave more than one reason. 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

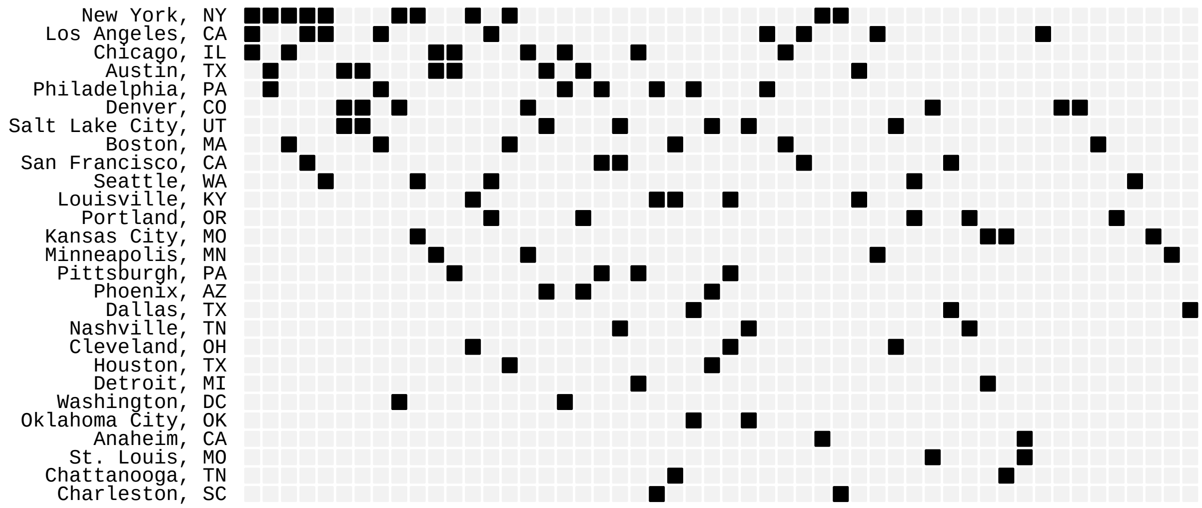


Figure 1: City Mentions

Each row lists a city named more than once, and each column corresponds to a city in our sample. Rows are sorted by naming frequency and city size; columns are sorted by the number of cities over 100,000 people named by the participating mayor and the naming frequency of the named cities. Excludes the 20 cities over 100,000 people that are only named by one city: Abilene, TX; Albuquerque, NM; Carlsbad, CA; Columbus, OH; Des Moines, IA; Eugene, OR; Fargo, ND; Gresham, OR; Lakewood, CO; Las Vegas, NV; Madison, WI; Mesa, AZ; Newark, NJ; Reno, NV; San Antonio, TX; San Jose, CA; Syracuse, NY; Tampa, FL; Tulsa, OK; Westminster, CO.

at them for downtown redevelopment ideas" (or, indeed, any other specific policy arena) 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, for example. 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 (above for example proximity) points to the fact that personal networks and relationships may be under-appreciated as a diffusion mechanism.

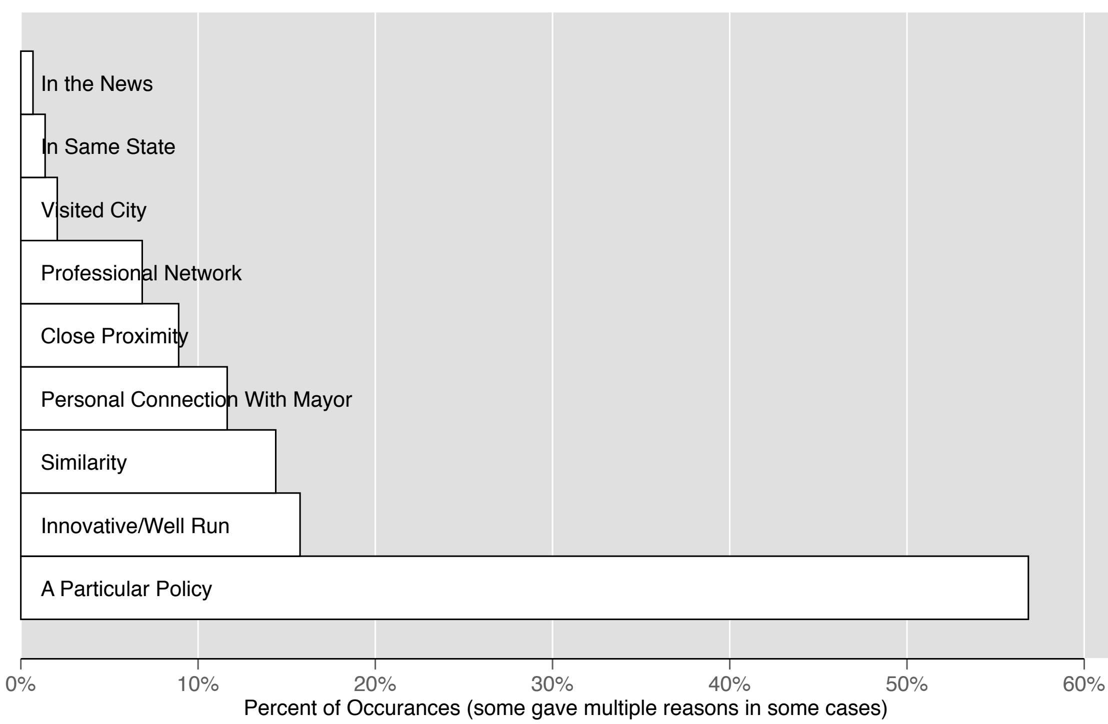


Figure 2: Reasons Given For Looking at Particular Cities

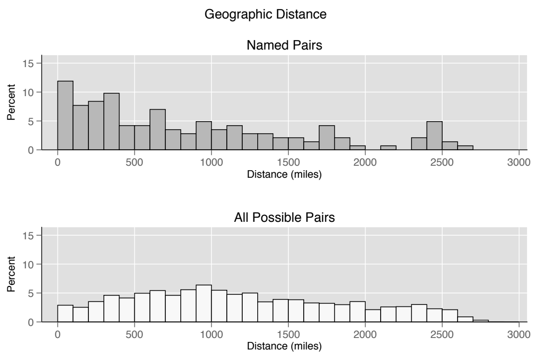
As we noted above, in the core analysis we compare the actual named pairs to the potential unnamed pairs across a range of variables. We first will present raw differences, followed by our similarity analysis and our regression models. We then turn towards a separate set of regression models that assess whether mayors view these different criteria as complements or substitutes.

3.1 Raw Differences

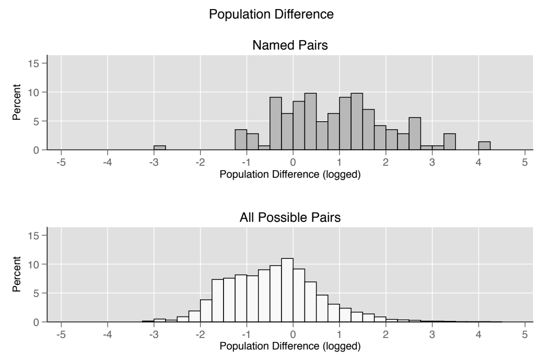
Figure 3 presents histograms comparing the distributions of the differences or "distances" (described above) in the actual dyads (in darker grey) to the full set of cities in the lighter shade. We do so for six pertinent variables: distance between cities, city size (logged), percent Democrat, percent 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, higher housing prices, 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 100 miles apart, and the whole distribution is skewed to the right. 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. 25% of all pairs are more than 1350 miles apart. Thus, while there is a general tendency to look close, mayors frequently look far.[10]

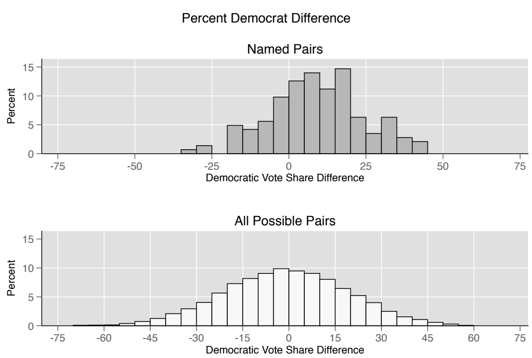
[10]Related to distance, we can also look at the propensity to name cities that are in the same state. Approximately 20% of actual pairs were in the same state compared to only 6%



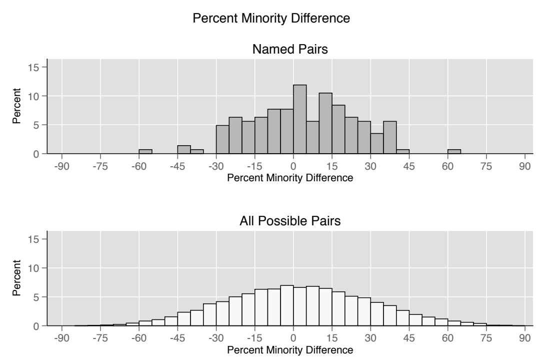
(a) Distance



(b) Population

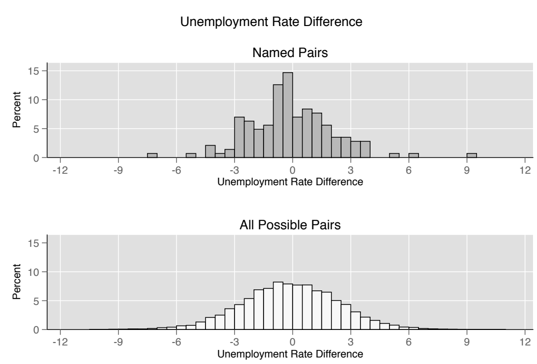


(c) Partisanship



(d) Diversity

(e) Housing Prices



(f) Unemployment

Figure 3: Comparisons of named pairs to all possible pairs

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% 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. These data are consistent with looking at "aspirational" rather than similar cities. One mayor of a mid-sized Midwestern city explicitly cited this aspirational quality when outlining 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 say that ideological similarity was irrelevant. Indeed, one mayor of a small southern city cited Mesa, AZ because it was "a benchmark for conservatives." The named pairs also had marginally significant differences in relative housing prices. That is, compared to 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

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of the non-pairs ($p < .01$). 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."

between the named dyads and all dyads on the unemployment or percent minority metrics.

3.2 Similarity by Trait

We now focus on the standardized similarity measures we introduced above. Figure 4 plots the average dissimilarity 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 in population. Indeed, they are almost two standard deviations less similar than the average of all possible pairings. 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.[11] The other two variables in which mayors named abnormally *dissimilar* cities were population density and percent 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 percent 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.

[11]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 .7 standard deviations less similar than average ($p < .000$). They were still significantly more different when dropping mentions of Los Angeles.

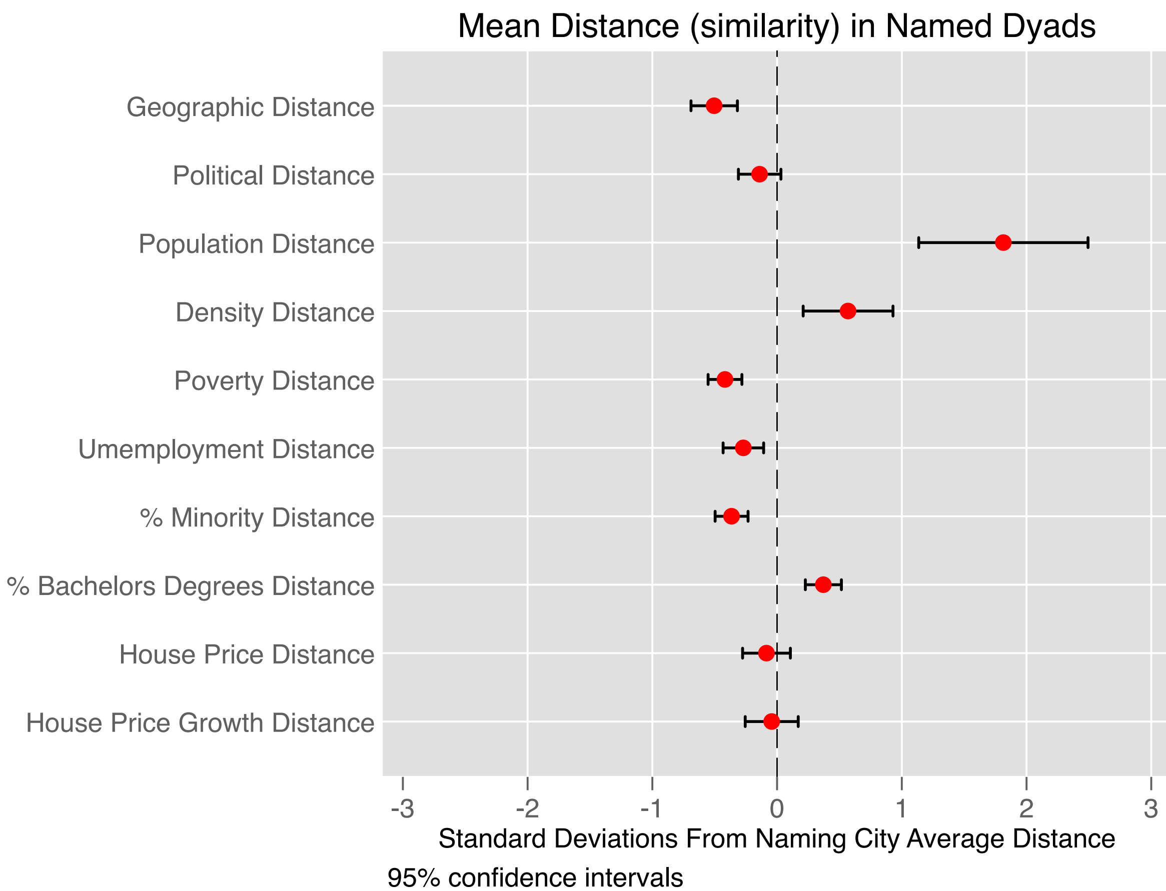

Figure 4: Standardized dissimilarity scores for named dyads. The zero line indicates average dissimilarity. Negative values indicate above average similarity.

3.3 Regression Models

To more rigorously test hypotheses H1 (Proximity), H2A (Political similarity), H2B (Context similarity), and H3 (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 above).

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[12] except for the political and population ones (which are included separately).[13] *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 equally small and large deviations as the same—these dummy variables allow us to examine if 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.

Table 1 presents the results.[14] Models 1, 2, and 3 estimate the probability of a city being

[12]These measures are: poverty, unemployment, minority %, bachelors degree %, housing prices, housing price growth, and density

[13]These variables seem to pick up on intuitive (but non obvious) similar and dissimilar cities. Take Milwaukee for example. Its five most similar cities demographically using our index are Springfield MA, Allentown PA, St. Louis MO, Rochester NY, Buffalo NY. Its five least similar cities are Carlsbad CA, Cambridge MA, New York City, Arlington VA, and San Francisco. Madison, the nearest city over 100K people is actually quite dissimilar to Milwaukee on our index.

[14]To check for robustness, we also estimate the model using using rare-events logit and ordinary least squares (Table SI3). 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

targeted using the corresponding variables for hypotheses H1, H2, and H3, respectively, and Model 4 pools all three sets of variables. 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 falls just short of significance at the .05 level. On trait similarity, we find a significant negative relationships 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* in Model 2, but not Model 4. 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 H3.

Finally, and more explicitly focused on H3, we find strong evidence in favor of the policy-making 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.

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presented in the paper, and display the alternative model results in the appendix.

Table 1: Base Models

VARIABLES	(1) named_pair	(2) named_pair	(3) named_pair	(4) named_pair
Same State	0.8363**			1.1804**
	(0.2366)			(0.2759)
Standardized Distance	-0.4032**			-0.3454**
	(0.1283)			(0.1291)
Std. Poltical Similarity		-0.0951		-0.1523
		(0.1122)		(0.1017)
Std. Population Similarity		0.2855**		0.1457**
		(0.0319)		(0.0327)
Std. Similarity Index		-0.8563**		-0.6916**
		(0.2417)		(0.2205)
Bigger City		1.8236**		1.2728**
		(0.2212)		(0.2224)
Higher Housing Prices		0.5080*		0.3758
		(0.2301)		(0.2147)
Well-Managed City			1.1330**	0.9777**
			(0.0537)	(0.0753)
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
** $p<0.01$, * $p<0.05$
Standard errors clustered by naming city.

3.4 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, as outlined in our hypotheses concerning similarity vs. capacity, similarity vs. distance, and capacity vs. distance.

To measure the relative importance of distance, similarity, and capacity, we repeat the logit analysis above with subsamples of the data. Table 2 reports the results of this analysis. In Model 1 we restrict the sample of possible named cities to low capacity cities (cities that are not mentioned as well-managed), and in Model 2 we restrict the sample to high capacity cities. Doing so allows us to see how the other variables' impact on city choices changes when looking at high and low capacity places. When mayors name lower capacity cities they are naming cities that are significantly bigger (and more size dissimilar) cities but geographically closer away. There is some suggestive evidence that they are naming more politically dissimilar places, but this difference in estimates is not significant ($p = .13$). None of the other differences approach significance. All in all, we find little evidence (with the possible exception of politics) to support the hypothesized tradeoff between similarity and capacity.

Models 3 and 4 of Table 2 split the sample by distance and enable us to look at the distance vs. similarity and distance vs. capacity tradeoffs. Model 3 includes potential pairs that are closer than average to the naming city, and Model 4 potential pairs that are farther away. These models do provide support for the distance vs. capacity tradeoff. When mayors name cities that are farther away they are selecting cities that are significantly more likely to be described as well-managed cities by other mayors ($p = .04$). In contrast, closer cities are significantly more similar in terms of traits (similarity index, $p = .02$). Again, there is some suggestive but not significant evidence that further places are more politically similar ($p = .19$ for the difference in coefficients).

In the last analysis, our evidence on tradeoffs is mixed. We find strong support for the distance vs. capacity tradeoff, and mixed evidence on tradeoffs between distance vs. similarity and similarity vs. capacity. One potential explanation is that cities do not necessarily face the stark tradeoffs that states and countries do. Because there a large number of cities mayors may not always face tough choices between, for example, similarity and capacity. The rich set of options that city leaders face relative to governors for instance may be an

Table 2: Subsample Models

	(1)	(2)	(3)	(4)
	Mentions		Distance	
	Mentions=0	Mentions>0	dist< avg	dist> avg
VARIABLES	named_pair	named_pair	named_pair	named_pair
Same State	0.8295*	1.1494*		
	(0.3562)	(0.4865)		
Bigger City	1.5583**	-0.2685	1.4513**	0.7109
	(0.3066)	(0.2554)	(0.2487)	(0.4331)
Higher Housing Prices	-0.5267*	1.0174*	0.5315*	-0.2172
	(0.2376)	(0.4020)	(0.2352)	(0.5076)
Standardized Distance	-0.7935**	-0.1005		
	(0.2007)	(0.1649)		
Std. Population Similarity	0.7843**	0.0797*	0.2206**	0.1274**
	(0.0881)	(0.0335)	(0.0516)	(0.0412)
Std. Poltical Similarity	-0.0539	-0.3669**	-0.0583	-0.3753*
	(0.1503)	(0.1180)	(0.1364)	(0.1887)
Std. Similarity Index	-0.8051*	-0.2767	-1.3867**	-0.2456
	(0.3788)	(0.2296)	(0.2920)	(0.3510)
Well-Managed City			0.8186**	1.2004**
			(0.0924)	(0.1414)
Constant	-6.5137**	-3.4179**	-6.5092**	-6.8541**
	(0.3443)	(0.5068)	(0.3954)	(0.6627)
Observations	14,153	771	7,772	7,152
Named Pairs	64	79	97	46

Robust standard errors in parentheses

** p<0.01, * p<0.05

Standard errors clustered by naming city.

important and under-explored source of variation in diffusion studies.

4 Conclusion

The data we introduce and analyze offer unprecedented insight into how political elites acquire policy information, and just as importantly, the tradeoffs they make when selecting information sources. Indeed, we find evidence that mayors obtain policy information from similar, proximal, and high-capacity cities. What's more, they are not using all of these criteria simultaneously. In particular, when they seek ideas from a high-capacity city, they tend to be looking farther away.

This insight is important. It suggests that mayors are looking to different kinds of cities depending upon 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, 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 provide more generalizable conclusions about the underlying factors driving policy diffusion. In addition to the statistical evidence presented above 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 open-ended 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. In many cases mayors' views of, or connections to, each other appear to matter more than systematic city-level traits. 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 diffusion mechanisms in a movement towards broader, more generalizable studies of the spread of policy ideas.

Finally, we believe that mayors' emphasis on success and capacity in particular—and their willingness to trade off proximity to look to high capacity cities—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.

Future research might begin to unpack whether cities who look to distant, high capacity places for their policy ideas are more likely to promulgate successful policies. Even more broadly, these thoughtfully governed cities might be high achieving across a variety of dimensions because of the care with which they select policies; they might be more rapidly growing and/or more attractive to businesses and highly skilled 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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Appendix

Sample traits comparison for the main survey (2015) described in the text are found in Table SI1. A similar comparison of the 2014 survey traits are found in Table SI2. This survey provides the questions about well-managed cities and policy information sources more generally. 72 mayors from 30 different states and all regions of the country participated in the survey. Unfortunately, only 56 of 72 mayors completed the entire survey meaning we have fewer responses to the diffusion questions, which came near the end. Because we over-recruited big cities, we split the demographic comparison into "big cities" and "small cities" using 400,000 as our cut-point. Using self reported partisan identification (irrespective of partisan election rules) and Google searches where necessary, we assessed the proportion of our sample that was Democratic and this number matched the national share reported in Gerber and Hopkins (2011). The two-party split in our data (65% Democrat) is virtually identical to that in Gerber and Hopkins (2011) (67%). We also use data about mass partisanship to see how the constituents of the mayors in our sample look compared to the country as a whole.[15] The average 2008 Democratic vote share (Einstein and Kogan 2016) in our sample aligns with that of cities as a whole (exact numbers available in Table SI2). Moreover, the distribution of the vote share is remarkably similar, suggesting that our sample is neither more nor less extreme than the country as a whole: the percentages Democrat at the 25^{th} and 75^{th} percentiles of our data do not differ from the national equivalents by more than three percentage points.

[15]We rely on mass partisanship, rather than ideological scaling data (Tausanovitch and Warshaw 2014) to maximize the available number of observations; the mass partisanship data in (Einstein and Kogan 2016) contain almost eight times the number of cities.

Table SI1: 2015 Survey: Primary data source

Variable	All U.S. Cities Over 100,000	Participating Cities Over 100,000
Population		
Population	298,885	395,544
Population Density	4,224	4,338
Race		
% White	48.7%	50.1%
% Black	16.8%	15.6%
% Hispanic	24.2%	23.3%
Socioeconomic		
Median Household Income	$52,898	$50,620
% Poverty	17.8%	18.7%
% Unemployed	6.8%	6.8%
Median House Price	$232,755	$231,178
Number of Responses	288	63

Notes: 1)Some numbers are rounded. 2) The first column reports demographics for those who provided city lists for the key diffusion question. 3) All data are from the 2012 American Community Survey and the Office of Management and Budget (we use the OMB's 2013 list of principal cities for classification).

Table SI2: 2014 Survey: Used for "Well-Managed" mentions data and for importance of learning from others in general result. Comparison of average traits of cities in our sample to all cities.

	Under 400,000 People		Over 400,000 People	
Variable	**In Sample**	**All Cities**	**In Sample**	**All Cities**
Population				
Population	94,200	74,300	777,200	1,015,300
Population Density	3,200	3,800	4,800	5,300
Race				
% White	63%	58%	49%	43%
% Black	13%	12%	21%	22%
% Hispanic	14%	20%	18%	25%
Socioeconomic				
Median Household Income	$57,600	$58,400	$49,200	$48,800
% Poverty	16%	15%	19%	20%
% Unemployed	6%	6%	7%	7%
% Owner Occupied	53%	56%	46%	45%
Political				
% 2008 Obama Vote	60%	59%	65%	65%
Mayoral Traits				
Average Age	57.5	56.1	53.9	57.0
Attended 2015 Conference	37%	34%	88%	73%
Bachelors Degree	41%	36%	21%	37%
Law Degree	28%	19%	36%	34%
Other Advanced Deg	28%	44%	43%	27%
Prior Lawyers	22%	15%	31%	28%
Prior Businessmen	26%	15%	50%	35%
Number of Responses	57		16	

Notes: 1)Some numbers are rounded. 2)Not all mayors answered all questions. We included all mayors that completed the open-ended priorities and challenges section of the survey in these demographics. All data are from the 2012 American Community Survey and the Office of Management and Budget (we use the OMB's 2013 list of principal cities for classification). Cities under 30,000 people are excluded. (Our smallest is approximately 28,000 people)

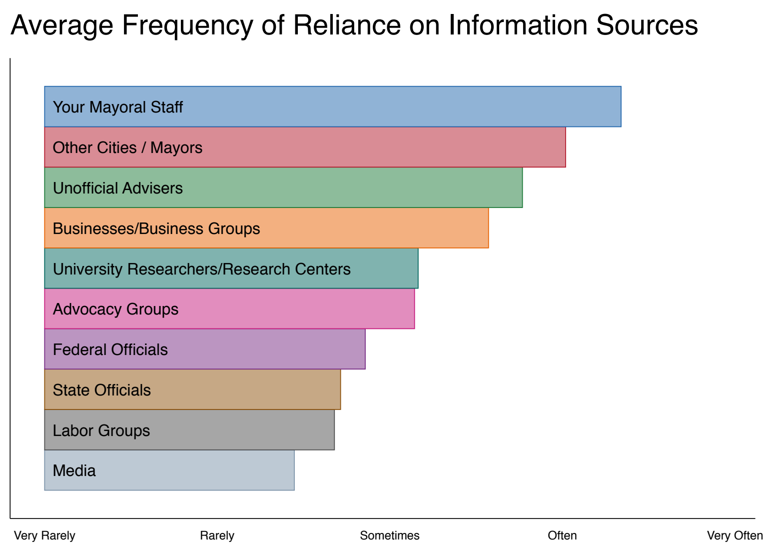


Figure SI1: Mayors' top sources of policy information showing the importance of learning from other cities. (from 2014 survey)

Table SI3: Alternative Regression Models

VARIABLES	(1) logit	(2) firth	(3) ols
Same State	1.1804**	1.1871**	0.0198**
	(0.2759)	(0.2897)	(0.0064)
Standardized Distance	-0.3454**	-0.3409**	-0.0028**
	(0.1291)	(0.1092)	(0.0009)
Std. Poltical Similarity	-0.1523	-0.1494	-0.0016*
	(0.1017)	(0.0998)	(0.0007)
Std. Population Similarity	0.1457**	0.1439**	0.0111**
	(0.0327)	(0.0307)	(0.0034)
Std. Similarity Index	-0.6916**	-0.6788**	-0.0055**
	(0.2205)	(0.1970)	(0.0019)
Bigger City	1.2728**	1.2633**	0.0067**
	(0.2224)	(0.2237)	(0.0015)
Higher Housing Prices	0.3758	0.3723	0.0031
	(0.2147)	(0.2038)	(0.0018)
Well-Managed City	0.9777**	0.9734**	0.0311**
	(0.0753)	(0.0730)	(0.0035)
Constant	-6.7273**	-6.6668**	-0.0007
	(0.3254)	(0.3275)	(0.0019)
Observations	14,924	14,924	14,924
R-squared			0.0705

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$

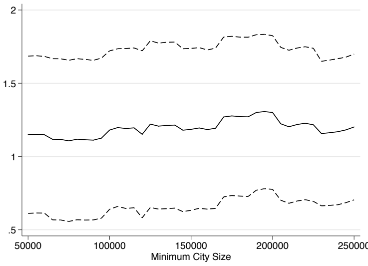
Standard errors clustered by naming city in the logit and OLS models.

Note: The Stata package for rare-events logit does not allow for clustering standard errors. In the logit and OLS models, clustering the standard errors has a negligible impact on the results.

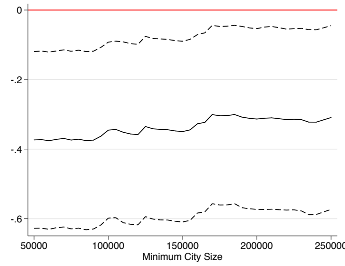
Table SI4: Base Models with Components of Similarity Index

VARIABLES	(1) logit	(2) firth	(3) ols
Same State	1.1634**	1.1730**	0.0199**
	(0.2965)	(0.2938)	(0.0036)
Std Geo Dist	-0.3233**	-0.3164**	-0.0026**
	(0.1117)	(0.1109)	(0.0009)
Std Pop Dist	0.2236**	0.2194**	0.0117**
	(0.0480)	(0.0477)	(0.0009)
Std Pov Dist	-0.1974	-0.1902	-0.0007
	(0.1274)	(0.1268)	(0.0008)
Std Unemp Dist	-0.0033	0.0009	0.0003
	(0.1216)	(0.1212)	(0.0008)
Std Minority Dist	-0.2110	-0.2055	-0.0014
	(0.1140)	(0.1133)	(0.0008)
Std Bachdeg Dist	0.1841	0.1857	0.0004
	(0.1194)	(0.1190)	(0.0009)
Std Housing Dist	0.1824	0.1820	0.0017
	(0.2107)	(0.2121)	(0.0018)
Std Housegrowth Dist	-0.3478	-0.3412	-0.0038*
	(0.2131)	(0.2143)	(0.0018)
Std Density Dist	-0.2143*	-0.2095*	-0.0018
	(0.0944)	(0.0939)	(0.0009)
Std Pol Dist	-0.1316	-0.1280	-0.0017*
	(0.1032)	(0.1025)	(0.0008)
Bigger City	1.2315**	1.2188**	0.0065**
	(0.2279)	(0.2262)	(0.0018)
Higher Housing Prices	0.2347	0.2311	0.0031
	(0.2276)	(0.2260)	(0.0018)
Well-Managed City	0.9396**	0.9309**	0.0314**
	(0.0820)	(0.0814)	(0.0015)
Constant	-6.6335**	-6.5396**	-0.0009
	(0.3389)	(0.3345)	(0.0024)
Observations	14,717	14,717	14,717
R-squared			0.0706

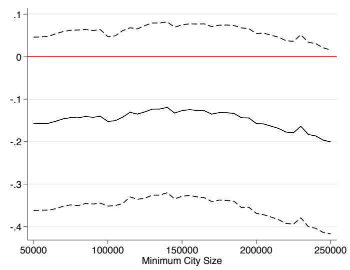
Standard errors in parentheses
** p<0.01, * p<0.05



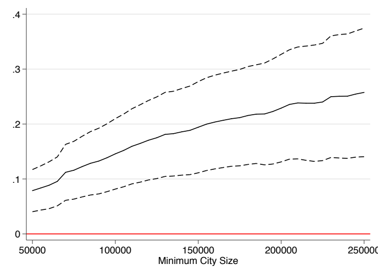
(a) Same State



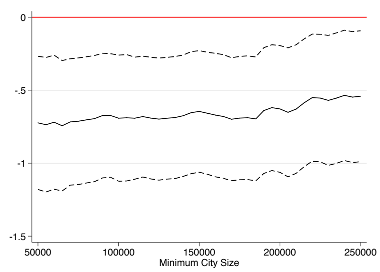
(b) Distance



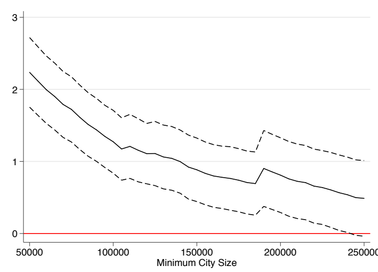
(c) Political Similarity



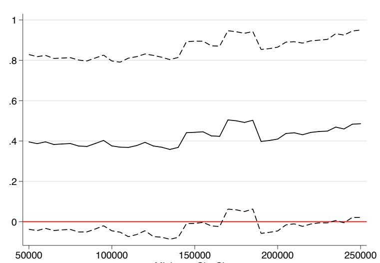
(d) Population Similarity



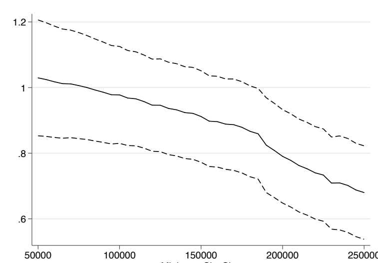
(e) Similarity Index



(f) Bigger City



(g) Higher Housing Prices



(h) Well-Managed City

Figure SI2: Logistic Regression Coefficients with Different Minimum City Sizes: To check that our results to robust to different sets of possible named pairs, we repeated the regression used in Table 1, Model 4, with different minimum city sizes. Using minimum city sizes ranging from 50,000 people (773 cities) to 250,000 people (73) cities, the results are not substantively different. For Bigger City and Well-Managed City, we see substantial reduction of the effect sizes as the cutoff increases because the population minimum reduces the number of potential target cities that are not larger than the naming city or that are not well-managed.