“Social Density, Clientelism and Vote Banking”

Jeremy Spater  
jeremy.spater@duke.edu

Erik Wibbels  
ew41@duke.edu

Department of Political Science  
Duke University

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Abstract

We make an analytical distinction between private clientelism, which targets individuals, and “collective” clientelism, which targets neighborhoods. In doing so, we develop an argument that links the centrality of individuals and the social density of neighborhoods to the incidence of both types of clientelism. We test the resulting hypotheses using a combination of original network, experimental and non-experimental survey data collected across 7,452 households in 167 slums across three cities in India. We provide the first survey experimental evidence that collective clientelism is an important phenomenon. We also find that socially central individuals are more likely to be targeted with private clientelism and that more socially dense neighborhoods are more likely to coordinate votes and achieve the legal prerequisites for local public services.
Much research on the politics of the poor has focused on the exchange of individual votes for individual private goods at election time (see, for instance, Levitsky 2003, Calvo and Murillo 2004, Stokes 2005, Kitschelt and Wilkinson 2007, Stokes et al. 2013, Wantchekon 2003). In some cases, this exchange is characterized as “vote buying”, and in others as “turnout buying” (Nichter 2008; Gans-Morse et al. 2014). While traditional models of clientelism emphasize the one-off, individual exchange of private benefits for votes between parties and citizens, a growing body of recent work re-emphasizes older claims (i.e. Lemarchand and Legg 1972) that clientelistic relations are often characterized by persistent problem-solving relations (Calvo and Murillo 2013; Nichter and Peress 2016). We expand on these individual-level arguments by emphasizing neighborhood-level needs and citizen organization as key determinants of political exchanges between poor voters and politicians. In doing so, we build on recent research showing that resource-constrained parties tend to target socially central individuals in communities (Cruz 2013; Schaffer and Baker 2015) where they can efficiently coordinate the votes of coethnics (Ejedmyr et al. 2017) and other groups (Kramon 2017; Gottlieb et al. 2018). We also contribute to recent attempts to understand the conditions under which parties target individuals with private goods versus communities with public goods (Diaz-Cayeros et al. 2016). We advance this literature by showing how neighborhood-level social density and electoral coordination relate to the distributive strategies of parties.

We conceptualize clientelism as an exchange between vote-maximizing, budget-constrained parties and voters in neighborhoods. Parties can deliver private, electioneering benefits to individual voters, and/or local public goods, such as a water
pump, a public toilet, trash pickup, etc. to neighborhoods. Because parties are subject to a budget constraint, they consider both the social or political centrality of individual voters and the social density of neighborhoods when deciding how to distribute benefits. Socially dense neighborhoods are those where relationships exist among voters and informal local leaders that help coordinate neighborhood-level vote banks. Only when neighborhoods can credibly commit to delivering a pool of votes will parties invest in local public goods. We refer to the contingent provision of neighborhood-level votes in exchange for local public goods as “collective clientelism.” Our theoretical distinction between individual and collective clientelism echoes Diaz-Cayeros et al.’s (2016) “portfolio diversification” model of clientelism, but we tie the analytics more precisely to individual social centrality, neighborhoods and their social density.

Consistent with recent work, we hypothesize that socially central individuals are more likely to receive private clientelistic benefits. Our addition of neighborhood social and electoral context provides a novel additional hypothesis, namely that communities with dense social networks are more likely to have the capacity to coordinate in pursuit of community-level benefits. Consistent with our conceptualization of collective clientelism, we expect that communities with higher levels of social density have more centralized leadership, are more likely to share partisan identification and coordinate votes, and achieve eligibility for public services. Our account integrates voter and neighborhood characteristics to provide insight into the incidence of individual- and neighborhood-level political exchanges.
Testing this (indeed, any) argument bearing on clientelism is difficult because the corresponding behaviors are difficult to directly observe, and participants in both private and neighborhood-level clientelistic relations have incentives to under-report the extent of clientelism. We bring to this challenge a rich set of original survey data from more than 7,400 households in 167 slums in three Indian cities – Bangalore, Jaipur and Patna. After a demanding process of finding the settlements, we map their boundaries by sending trained field teams to speak to residents and geocode the borders of the slums, as they are reported and experienced by residents, to ensure that our surveys correspond to the social networks embedded therein.

We then deploy survey experiments to measure the incidence of both private, election day exchange and more coordinated, neighborhood-level exchange. The former mirrors related survey-experimental efforts in Nicaragua, Lebanon and beyond, while the latter is an original attempt to assess neighborhood-level collective clientelism. Together, the two survey experiments provide the first experimental insight into the incidence of both types of clientelism in a single empirical setting. We complement this survey experimental evidence with an original approach to measuring social density, a notoriously slippery concept. We collect full network data from eight slums, which involved a census-like enumeration of every household in each of the eight settlements, including each household’s connections to others within the neighborhood. We use this full network data from the eight-slum subset of our full sample to derive a set of questions that assess individual network degree, to develop a measure of social centrality and density that can then be applied to our sample surveys. The sample surveys also contain data on leadership centralization (i.e. unified community support for an
individual leader), allowing us to assess the relationship between social density, leadership, and the party identification of individuals and neighborhoods. Moreover, we leverage qualitative interviews with 171 informal neighborhood leaders.

The experimental results show for the first time that collective clientelism, or the coordinated delivery of neighborhood votes, is a real phenomenon, and that its incidence is similar to that of individual clientelism. Consistent with our argument, we also find that individuals who are more socially connected are more likely to be influenced by individually targeted clientelistic transfers. Moreover, we show that socially denser neighborhoods tend to be better organized politically: they have more centralized neighborhood leadership, their residents are more unified in their party support, and are more likely to report that their neighborhood is a “vote bank”. These results provide evidence for our hypotheses that more socially connected individuals tend to be the ones targeted for individual transfers, and that neighborhood social density is conducive to collective clientelism. We also find that socially dense neighborhoods are correlated with government recognition of the neighborhood by the local government, which in the context of many Indian states is the main prerequisite for service provision.

In the following section we review the relevant literature. Thereafter, we develop our argument linking voter and neighborhood characteristics to the incidence of individual and collective clientelism. In the third section we describe our extensive original data collection effort and empirical strategy. The fourth section provides results, and the concluding section summarizes our contribution and provides direction for future work.
II. Poor Voters, Clientelism and Social Networks

Studies on clientelism emphasize the direct exchange of material benefits for political support between voters and politicians (Auyero 1999, 2000; Brusco, Nazareno and Stokes 2004; Calvo and Murillo 2004; Chandra 2007; Kitschelt 2000; Kitschelt and Wilkinson 2007; Krishna 2007; Levitsky 2003; Magaloni and Estevez 2007; Nichter 2008; Remmer 2007; Stokes 2005, among many others). Extant work offers insight into which voters will be targeted for clientelistic exchange. Building on Dixit and Londregan (1996), most work posits voters who maximize a joint function of ideological proximity and private, excludable benefits. Due to diminishing returns of consumption, low-income voters are expected to be the principal targets of clientelism because they derive higher marginal utility from handouts. There is now a substantial body of evidence supportive of this claim (Brusco, Nazareno and Stokes 2004; Calvo and Murillo 2004; Remmer 2007; Keefer 2007).

Income aside, there are important theoretical disagreements as to the role of ideology. While Dixit and Londregan (1996) and Stokes (2005) suggests that ideologically indifferent voters represent the best investments in private benefits, Cox and McCubbins (1986) suggest that core supporters should receive the most benefits, and Nichter (2010) echoes that argument with the suggestion that election campaigns are primarily aimed at motivating turnout amongst the like-minded rather than convincing the swing voter. Despite some evidence to the contrary (Lindbeck and Weibull, 1987; Stokes, 2005), the
weight of evidence is generally supportive of the core voter hypothesis (Hsieh et al. 2011; Calvo and Murillo 2004; Bickers and Stein 2000).

One of the biggest analytical challenges has been understanding the conditions under which clientelism is time consistent. Early research in anthropology and sociology posited clientelism as a “durable, face-to-face, hierarchical and thus asymmetrical exchange relation . . . supported by a normative framework” (Kitschelt and Wilkinson 2007; see also Piliavsky, 2014), a practice characterized as “lopsided friendship” (Wolf 1966, p. 16). Early work in political science understood clientelism as “complementary role relationships rooted in expectations of reciprocal rights and obligations” (Lemarchand and Legg 1972, p. 152). However, beginning with Scott (1972), researchers began to conceptualize clientelistic exchange as an instrumental-rational practice of “market corruption,” consisting of single-shot exchanges on a spot market. The contingency of benefits on voting behavior necessitates a mechanism by which parties can be sure that voters keep their side of the exchange. As it became clear that any one-off clientelistic exchange suffered from dynamic inconsistency, work has modeled clientelism as a repeated game in which voters provide political support and participation in rallies in exchange for handouts, access to subsidies, welfare programs, etc. These linkages are part of a problem-solving network, and the ongoing nature of the relationship serves to resolve crucial information problems inherent to clientelistic exchange (Calvo and Murillo 2013; Lemarchand and Legg 1972). In this account, clientelistic relations are ongoing and “relational” (Nichter 2010). As summarized by Björkman (2014: pg 618), clientelistic gifts “work much like any other gifted good in producing relations of debt
and obligation” and are “constitutive of enduring networks of trust, sociality, and accountability.”

Recent work has identified three mechanisms through which networks facilitate clientelism. The first mechanism is monitoring. In contexts characterized by a secret ballot, it is necessary for parties to have some assurance that the individual votes as desired. In Stokes et al. (2013) local brokers serve as key nodes in partisan networks and serve to monitor voters. Alternatively, social networks provide a means for voters to monitor each other. Well-connected individuals are easier to monitor: by virtue of having more social contact, their vote choice is more likely to be known and diffused through the network. This is the reason Cruz (2013: 5) cites when noting that “having a large social network makes it more likely that others will know how the individual voted.”

Second, individuals embedded in dense social networks might be more disposed to intrinsic reciprocity (Finan and Schechter 2012), the tendency to repay a good turn even at personal expense. Reciprocators are good targets for clientelism, because they tend to uphold a bargain even in the face of time inconsistency. They can be trusted (more so than non-reciprocators) to faithfully vote for the party offering benefits, in appreciation for the gifts they have received. This echoes the logic in Cruz, Labonne, and Querubin (2017), who argue that individual social centrality facilitates individual clientelism because “personal links make it more likely that an individual will reciprocate with electoral support” (p. 3009).
Third, social networks provide a means for clientelistic exchanges to persuade voters to vote for parties. According to Schaffer and Baker (2015: 1094), parties “target citizens who are opinion-leading epicenters in informal conversation networks,” calling this phenomenon a “social multiplier effect” whereby the party can influence the preferences even of voters who do not themselves receive direct benefits.¹ Unlike monitoring, which relies on an implicit threat of social censure or worse, persuasion implies that individuals believe the persuader has their best interests in mind and can help them select the right candidate.² This mechanism implies that parties should target socially-connected individuals, whose embeddedness in social networks allows them to exercise persuasion.

Together, these mechanisms suggest that dense networks of social interaction “tie voters together and bring them into contingent exchange relationships with political parties” (Holland and Palmer-Rubin 2015: pg 1204) and serve as crucial glue for sustaining clientelism over time. There is, however, scant empirical work testing the relationship between the properties of social networks and clientelism. Indeed, to the extent such tests exist, they have focused on the hypothesis that socially central individuals will be targets of the excludable benefits that define traditional notions of clientelism. Cruz (2014), for instance, finds that individuals with many network connections tend to be disproportionately targeted, and Shaffer and Baker (2015) find evidence that “persuasive” individuals (those who converse with neighbors about politics with the aim of changing their views) are more likely to be targeted. Moreover, Cruz, Labonne, and Querubin

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¹ The same logic can be found in Downs (1957, pg 140), who writes that “some [people] are more important than others politically, because they can influence more votes than they themselves cast. Since it takes scarce resources to provide information to hesitant citizens, [people] who command such resources are able to wield more than proportional political influence.”
² See Björkman (2014, page 623) for an excellent ethnographic example.
(2017) argue that socially central politicians are better able to make use of clientelistic linkages with voters.

We build on this growing attention to the social centrality of individuals in two ways. First, we emphasize that voters, and particularly poor voters, tend to live in geographically-defined neighborhoods that define social networks. This echoes recent work on how the geographic concentration of ethnic and other groups can facilitate partisan targeting (Ejdeemyr et al. 2017; Kramon 2017; Gottlieb et al. 2018) and promote ethnic violence (Kasara 2017). Because social networks have a spatial component, the social aspects of clientelism tie into a well-developed literature on the effects of neighborhood context on voting behavior (Huckfeldt and Sprague 1991, Pattie and Johnson 2000). Second, the problems that voters want politicians to solve are oftentimes collective in nature and can be addressed by local public goods. Whereas traditional models of clientelism emphasize private transfers, we echo Diaz-Cayeros et al. (2016) in suggesting that neighborhood benefits – be they a water pump, a local clinic, or a public toilet – are also subject to explicit political exchange. Understanding these exchanges, however, requires shifting the analysis from individual voters to the social and political characteristics of whole neighborhoods.

III. Social Density and Clientelism: The Argument

We begin with the observation that poor voters tend to be clustered together in neighborhoods, and this simple fact has important implications for how politics operates. We conceptualize neighborhoods as social networks comprising voters and local political...
brokers (Huckfeldt 1983). That clientelism is embedded in a neighborhood context means that important dynamics operate at the neighborhood level rather than as a series of aspatial, individual-level exchanges: an entire neighborhood receives water, electricity or a public toilet at the same time; no individuals can be rewarded by receiving them earlier. If we understand neighborhoods as social networks, their political and social organization is very relevant for the study of clientelism and has important implications for who among the poor will receive access to basic public services.

We elaborate on the definition of clientelism from Holland and Palmer-Rubin (2013: pg 1188) as “any distribution of particularistic or club goods conditioned on the political behavior of an individual or group” to distinguish between two types of clientelism, as defined below:

**Individual clientelism**: the contingent exchange of an individual vote in return for material goods to be consumed by that individual’s household.

**Collective clientelism**: the provision of a club good or local public good to the inhabitants of a neighborhood, conditional on the aggregate voting behavior of the neighborhood’s inhabitants.

This definition of collective clientelism is subtly, but importantly, distinct from pork barrel spending. Evans 2011 (p. 316) defines pork barrel projects as “discrete, highly divisible benefits targeted to specific populations such as states and congressional districts”. Pork barrel spending implies that incumbents will deliver club goods or local
public goods if they keep winning elections; the incumbent does not distinguish between supporting and opposing voters, since the goal is to bring benefits to the district as a whole, and the spending results from legislative bargaining. The definition of pork hinges on the geographical concentration of the benefits, rather than on the contingency of their provision on individual or community voting behavior. Collective clientelism, on the other hand, implies that benefits will only come to a group of voters if they vote for the clientelistic politician. Thus while pork barrel spending is contingent on *election outcomes*, collective clientelism is contingent on the *voting behavior* of neighborhoods. Pork barrel spending benefits all voters within an electoral constituency, and is therefore *not* contingent upon voting behavior. By contrast, collective clientelism is targeted to *particular* vote banks within an electoral constituency, and is contingent upon the coordinated voting behavior of those groups.

The recognition that many clientelistic exchanges involve local public goods accommodates the fact that the most pressing needs of the poor are often for a public toilet, clean water, or a solution to open sewage. Indeed, our interviews with 171 neighborhood leaders across more than 80 slums showed that the vast majority identify these basic public goods as their most important goals and achievements, and nearly all of them emphasize the importance of trading slum votes for achieving these ends. This

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3 It bears noting that contingency does not imply anything about temporal sequencing; the goods could be delivered before or after the election. If the neighborhood “vote bank” failed to deliver, then the work might not be completed, or service could be shut off, or the neighborhood could be shut out from further service provision in the future.

4 In a related line of argumentation, Kitschelt and Wilkinson (2007: pg 12) note that club goods can be distributed either programmatically or clientelistically.

5 Stokes et al (2013) separate pork from clientelism by characterizing the latter by contingency on *individual* voting behavior, and characterize pork as a particular type of “non-contingent partisan bias.” By contrast, we allow for the possibility of benefits being contingent upon *group* voting behavior.
more social characterization of clientelism also overcomes some of the technical problems that characterize one-off exchanges of private benefits for votes. Notably, parties need not observe individual vote choice in the face of time inconsistency problems, as they can easily and legally observe neighborhood-level voting outcomes at the booth or precinct level (Chandra 2007; Hale 2007; Kitschelt and Wilkinson 2007; Levitsky 2007; Scheiner 2007; Smith and Bueno De Mesquita 2012; Rueda 2015).

Our conception of collective clientelism overlaps with a phenomenon known as “vote banking” in the Indian context (Srinivas 1955). Vote banking is the practice of coordinating votes within a slum (Breeding 2011, Auerbach 2016). Collective clientelism, meanwhile, is a relationship between parties and voters, mediated by local leaders or party brokers, in which voters take part in a “vote bank” in a contingent exchange for neighborhood-level public goods. Our conceptualization situates vote banking as a constituent component of collective clientelism: the former is a means on the part of slum-dwellers, while the latter is an overarching concept that links voters participating in a vote bank to parties through leaders and brokers. As such, the incidence of neighborhood-level collective clientelism can be estimated by the self-reported incidence of vote banking, accompanied by the organization of a slum around local, informal leaders, and by unified support around a single political party. We conceptualize collective clientelism as a distinct form of clientelism, characterized by vote banking on the part of the neighborhood with neighborhood-level service provision as one of its primary goals.
Our interviews with neighborhood focus groups across 167 slums and 171 individual leaders provide qualitative evidence that our conception of collective clientelism is familiar to the individuals in our sample (described below), and that neighborhood services are the main objective. The interviews emphasize neighborhood unity, support for a particular party, and coordination through local organizations. For illustrative purposes, we present focus-group responses, as paraphrased by our local enumeration teams, to the question “Why is your neighborhood an effective vote bank?” Here are some representative responses: “If we vote for the same person and win, he will provide us the government facilities.” “We want to be united.” “For development.” “Better services.” “For notification and we want to be united.”6 “They are provide [sic] facility, e.g. health and water facility.” “We can receive facilities only if we vote collectively.” These interviews demonstrate that vote banking is understood to involve collective voting in contingent exchange for neighborhood-level services, and that coordination is a necessary ingredient.

But why would particular individuals and neighborhoods be targeted with individual and/or collective clientelism? Political parties face a budget constraint; they cannot offer unlimited clientelistic benefits to all potential voters. They must decide how best to disburse their limited budget, and in particular which voters should be offered private benefits and which voters to target with neighborhood-level public goods.

6 “Notification” refers to a status conveyed by city and/or state officials which provides residents with assurance that their settlement is legal and, therefore, qualifies for public services.
We argue below that parties base their targeting decisions in part on *individual social connectedness* and *neighborhood social density*. Drawing on Putnam (2007), we define individual social connectedness as the extent to which an individual is embedded in intra-neighborhood social networks and is bound by the associated norms of reciprocity and trustworthiness. Neighborhood social density is a neighborhood-level aggregation of individual social connectedness, reflecting the degree to which a neighborhood is characterized by tight networks of social interaction. We operationalize neighborhood social density as the neighborhood-level mean of individual social connectedness. A socially connected *individual* is closely tied to many other individuals; a socially dense *neighborhood* has many such individuals.

Consistent with the arguments outlined above, we claim that parties and brokers tend to target individual clientelism to voters who are socially connected. This policy is sensible for the three reasons noted above: first, because social connections make these voters’ intentions and activities an open book to neighbors (and to party operatives working in the neighborhood), socially central individuals are easy to monitor; second, because of their tendencies toward intrinsic reciprocity such voters are more likely to spontaneously comply with their agreement to vote for a patron’s party; and third, these socially connected individuals are likely to be Downsian “persuaders” with the capacity and inclination to bring other voters (who may or may not have also received individual-clientelistic benefits\(^7\)) into the fold.

\(^7\) Another possible mechanism is that socially connected voters who receive clientelistic benefits are instrumental in enforcing the individual-clientelist bargain that *others* have entered into. They might do this by appealing to norms of reciprocity and trustworthiness, or by other means.
Meanwhile, because local public goods are expensive and not excludable to those in the neighborhood who support a certain party, their provision in exchange for votes only makes sense if a high proportion of the neighborhood’s residents can be relied upon to vote “correctly.” Parties should therefore only provide them when they can be sure of consistently gathering a large share of support from any given neighborhood. Our claim here is distinct from Díaz-Cayeros et. al (2016), who argue that parties should target swing districts with public goods as they are an efficient tool for convincing swing voters. We think otherwise, largely because we are operating in an urban context where single member electoral districts (in the Indian context, these elect ward leaders) include many different neighborhoods, and expenditure decisions result from bargaining within the dominant city-wide party. Since needs greatly outstrip available budgets, we expect politicians to target expensive, scarce local public goods to those neighborhoods that provide the most votes. Indeed, this is consistent with a large body of work on core targeting in the Indian case (Bohlken 2018; Auerbach 2016). Yet even should neighbors want to, serving as a neighborhood-level vote bank for a party represents a collective action problem from the point of view of individual residents.

We argue that neighborhoods that are characterized by high levels of social density\(^8\) are more likely to overcome this collective action problem. Consistent with theorizing on networks (Huckfeldt 1983; Ward et al. 2011), dense networks enable three mechanisms

\(^8\) Our theory connecting network attributes to collective action concerns edge or link density, rather than centralization or hierarchy. This is because our main sample data set (167 neighborhoods) contains a proxy for individual network degree, which we verify using a subset (8 neighborhoods) in which full network census data was collected. The estimated network edge density of the neighborhoods in the sample data are calculated from the estimated degree of the individuals in each neighborhood. The small number of neighborhoods for which we have full network census data gives us insufficient power to test theories about network attributes that cannot be directly estimated from individual degree, such as the amount of centralization or clustering.
for coordinating collective action. First, they provide a social technology that transmits information on how other members of the neighborhood network behave. While it is nearly impossible for formal parties and other outsiders to know how individuals vote, tightly-knit neighbors and local leaders who live in those communities are usually aware of voting behavior. In short, a dense neighborhood network internalizes the cost of monitoring clientelistic exchanges; it does this, in part, because residents know they will not receive the local public good if the neighborhood as a whole does not deliver the votes. Second, dense neighborhood networks provide a mechanism for sanctioning community members who deviate from socially expected behavior, i.e. voting for the machine. In the context of neighborhood politics, this might involve an inability to draw on local, informal social insurance (Nichter and Peress 2017) or extract household benefits from neighborhood leaders. Third, dense networks facilitate coordination around a common neighborhood leader. The literature on brokers (Stokes et al. 2013; Auerbach 2016; Auerbach and Thachil 2017), emphasizes the role of informal social ties in maintaining reciprocal relationships between a political broker and her constituents. Individual citizens are better able to assess the effectiveness and responsiveness of a broker when they or others in their network have had dealings with that broker and can vouch for her. Thus, when the neighborhood is tightly knit together by social ties, a leader’s “catchment area” – the group of people who have personal knowledge of that leader, or whose friends have – is larger. Together, the augmented capacities to monitor and sanction fellow citizens and coordinate on a leader provide dense neighborhood networks the tools to overcome collective action problems and coordinate votes for the sake of collective clientelistic benefits.
Thus, we hypothesize that collective clientelism will be targeted at socially dense neighborhoods. In summary, we have two hypotheses:

H1. Individuals with high social connectedness are more likely to be targets of individual clientelism.

H2. Neighborhoods with high social density are more likely to be targets of collective clientelism.

Ours is the first research that analytically distinguishes neighborhood social density from individual social centrality, links them to collective clientelism and individual clientelism, and brings the appropriate data to bear to test the relationships among these variables.

Our argument echoes several threads in recent work on clientelism. Auerbach (2016) shows that denser slum-level partisan networks provide a means for the poor to successfully articulate their demands vis-a-vis government. While he is focused on how parties organize slums, we focus on how social relationships among voters condition the capacity of communities to bargain with parties. Similarly, Rueda (2015) finds that smaller polling stations invite more clientelism because they allow for aggregate monitoring that overcomes the challenge of monitoring individual voters. We specify how that aggregate monitoring might take place and link it to different kinds of clientelism. Likewise, we build on recent work on the impact of geographically concentrated groups on targeting (Ejedmyr et al. 2017; Kramon 2017; Gottlieb et al. 2018) by providing more extensive development of the concept of collective clientelism.
Finally, Holland and Palmer-Rubin (2015) find that participation in civic organizations is the primary determinant of clientelistic targeting; our own conceptualization of social density provides insight into where such organizations are most likely to emerge and emphasizes that they are often neighborhood-based.9

IV. Empirical Setting and Approach

To test our argument we draw on original household and neighborhood data collected in 2015-16 in Jaipur, Rajasthan; Patna, Bihar; and Bengaluru, Karnataka. These cities provide a sample frame that reflects the diversity of Indian conurbations. The three cities are located at the three corners of India’s land mass, with Bengaluru in the south, Patna in the northeast and Jaipur in the northwest. They span the range of development outcomes; Bengaluru is considered the epicenter of India’s IT revolution (Nair 2005) and is among the richest India cities, while Patna is among the poorest, with Jaipur in between.

Given the clear evidence linking poverty to clientelism, within each city we enumerated slum areas. In the absence of accurate government lists of slums, we went through an onerous identification process that included satellite imagery, field teams, government lists and NGO-generated lists. This process produced a non-exhaustive list of 517 slums (273 for Jaipur, 132 for Bangalore, and 112 for Patna). To ensure a cross-section of slum conditions, we sampled across slum “types” which we defined with reference to the quality of housing, availability of services and the haphazardness of the layout. We then

9 Holland and Palmer-Rubin emphasize the importance of functional organization, such as street vending organizations, whereas we emphasize neighborhood organization.
randomly selected 40 slums per survey wave (one wave each in Patna and Jaipur and two in Bangalore)\textsuperscript{10} to preserve the distribution across slum types. We then sent teams to each neighborhood in the sample to map the borders of the slum, \textit{as perceived by residents living there}, to ensure that the boundaries of the slums from which we sampled households for interviews reflected the underlying human geography. We conducted household interviews and neighborhood focus groups in 167 slums; we also conducted 171 interviews with informal slum leaders in the 80 Jaipur and Patna settlements.

From each neighborhood, we randomly sampled between 30 and 60 households. The total number of household respondents across cities and slums is 7,452. The interviews lasted approximately 45 minutes, and took place in or near the respondents’ homes. The interviews were collected on tablet computers running the Open Data Kit (ODK) platform, and contained questions including basic demographic information, such as age, caste, and religion; economic information, such as education, employment, incomes, and expenditures; and political attitudes, including political engagement, party support, and neighborhood leadership.

We complemented these sample surveys with a full network survey (i.e. the enumeration and interview of each household) in 8 slums, and neighborhood surveys that gathered key information on housing and public goods characteristics; below we use the network survey to calibrate a set of individual social centrality questions and our neighborhood social density measure.

\textsuperscript{10} Surveys were conducted in 167 slums (83 in Bengaluru, 45 in Jaipur, and 39 in Patna) for reasons of accessibility and representativeness.
Our initial slice at the evidence relies on a list experiment to measure the incidence of clientelism among our respondents. List experiments are a survey method to measure sensitive behaviors or attitudes that survey respondents might be reluctant to admit to if asked directly. Respondents are randomly assigned to control or treatment group(s). Those in the control group are shown a list with a few (e.g. 3) items, while those in the treatment group are shown the same list, but with one additional, sensitive item that is of particular interest to the researcher. Both groups were asked how many of the items apply to them. The difference in means between treatment and control groups estimates the aggregate incidence of the sensitive attitude or behavior in the sample (Blair and Imai 2012).

Consistent with research showing a social desirability bias in responses to questions about vote buying (Gonzalez-Ocantos et al. 2012; Corstange 2018), we treat clientelism as a sensitive item. We randomly assign respondents to the control group or to one of two treatment groups. Echoing similar list experiments, respondents are asked, “People decide who to vote for based on many different considerations. I will read you some of the reasons people have told us. Please tell me how many of these influence your vote choice. Don’t tell me which ones, just tell me how many.” The control group is shown the list of un-bolded points, while the treatment group is shown the un-bolded points plus the bolded treatment, which measures the incidence of coordinated voting:

- Party took me at Delhi party office.
- Listening to radio coverage of the campaign.
- Discussing the election with friends or family.
• The suggestions of your neighborhood leader because he/she has made arrangements with a political party.

We recognize that neighborhood-level vote coordination can happen without a neighborhood leader and that our approach likely underreports the incidence of collective clientelism. In emphasizing them, our design relies on the crucial role of local vote brokers (Stokes et al. 2013), particularly amongst the urban poor in India (Auerbach 2016; Auerbach and Thachil 2017). To the extent there are other ways to coordinate neighborhood voting, this list experiment represents a hard test, since it only captures that done by local leaders on behalf of a party.

To assess individual-level clientelism, we include the sensitive item:

• One party promising more favors, such as clothes or food, to you or your family.

This design closely echoes that in Gonzalez-Ocantos et al. (2012), which emphasizes excludable individual or household benefits. Ours is more demanding in the sense that it assesses the role of private benefits in actual voting behavior, rather than whether or not the respondent was simply offered a gift irrespective of whether this affected her vote. The outcomes from the list experiments are shown in Table 1, which summarizes the responses from each group (control and two treatments).
We designed the list experiment to minimize ceiling effects and floor effects, which can occur if all or none, respectively, of the non-sensitive items are applicable to the respondent. This would lead the respondent to not count the sensitive item, because doing so would break the respondent’s anonymity. Table B1 in Appendix B shows the results of balance tests between the control group and the two treatment groups in the list experiment. The tests show that the treatment group is balanced on observables with respect to the control group, with the exception of neighborhood social density (see below), which is slightly lower in the treatment group for individual clientelism. Because the imbalance is the wrong sign to produce our hypothesized result (we expect that lower neighborhood social density should decrease the rate of clientelism), this does not undermine our identification strategy.

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11 We estimate the proportion of respondents affected by ceiling and floor effects using a generalized linear model (Blair and Imai 2012). This yields estimated proportions of 0 and 1%, respectively, demonstrating that ceiling and floor effects are unlikely to affect our results. We also assess ceiling or floor effects by checking the proportion of respondents in the control group who respond with the maximum (3) and minimum (0) number of items, respectively. In our sample, approximately 11% of the control group responded with 3 items, and 8% with zero items, indicating that the prevalence of ceiling and floor effects is relatively low.
To test our hypotheses about the relationship between individual connectedness, neighborhood social density and clientelism, we construct indices out of several questions in the household survey. Measuring social connectedness is difficult in a sample survey (Handcock and Gile 2010). A common approach is to ask respondents how much they interact with others or engage in political speech with others (Schaffer and Baker 2015). It is hard to validate these self-reports, and relying on single questions could be problematic. Thus, we take a different approach, which validates the capacity of a series of survey questions to capture individual social centrality by examining them in the context of a full network survey of 2,581 residents in 8 slums. Our operationalization of individual social connectedness, which we define in the preceding section, is based on a principal component analysis (PCA) of responses to the three survey questions that are common across survey waves. They are as follows: “Suppose that 10 of your neighbors were invited to help in community work, such as a community water project, cleaning of gutters, or weeding on the side of the road. How many do you think would show up?”; “How often are there serious disagreements among people who live in this neighborhood?”; and “Have you attended a community meeting in your neighborhood in the past 12 months?” The details of the PCA are shown in Appendix A. Of course, some of these measures ask respondents about others in the settlement and thus do not seem to reflect the social centrality of the respondent in the settlement. But as we show below, responses to these questions do reflect the social centrality of respondents.

12 The reported frequency of disagreements loads positively on the social density metric, because neighborhoods with little contact between residents are unlikely to have disagreements. We also constructed an alternative social connectedness metric without this question, discussed below, with substantively similar results.
In order to validate our approach, we draw on a parallel network survey that maps the social networks of all households in 8 slums in Jaipur and Patna. In collecting these data we completed a demanding process of, first, conducting a census of all residents of the community, gathering the names of residents, and programming those names for subsequent use; and second, asking respondents from every household a set of 23 questions bearing on social, political and economic ties with individuals in their settlement; these questions asked respondents to provide the names of individuals they socialized with, talked politics with, would go to with problems, who helped them find jobs, etc. This process resulted in 2581 respondents (one per household) in the 8 settlements and allows us to map their full social and political networks. Figure 1 shows the social network graphs\(^{13}\) of the eight neighborhoods in the network sample. To assess the relationship between our individual-connectedness questions and the social network density of respondents, we regress the network attributes of individuals, including their in-degree, out-degree, and total degree\(^ {14}\) on responses to each of the three questions that constitute our individual connectedness measure (Appendix C). The results indicate that the three questions in our sample survey are doing a good job of capturing individual network degree, reflecting social connectedness.

---

\(^{13}\) The social network graphs are constructed from three questions on the network survey that reflect social ties: “If you suddenly needed to borrow Rs. 1000 [about $14] for a day, is there someone in the slum who you could ask? If yes, who?”; “Who in the settlement would come to you if they needed to borrow Rs. 1000?”; and “In your free time, whose house do you visit in this neighborhood?”

\(^{14}\)An individual’s in-degree refers to the number of respondents who name that individual as a connection. Out-degree refers to the number of other respondents whom that individual names as a connection. Total degree is the sum of in-degree and out-degree.
Figure 2 shows the distribution of our individual connectedness metric. The modal respondent among respondents at least one standard deviation above (below) the mean responded that 10 (5) out of 10 neighbors would respond to a call for community work; that there are sometimes (never) disagreements among people living in the neighborhood; and that they themselves have (have not) attended a neighborhood meeting in the past year.
Our operationalization of neighborhood social density, as defined in the previous section, is the average individual connectedness score for all the respondents in each neighborhood. This provides an estimate of the edge density of the full network. A socially dense neighborhood is one where there are many socially connected individuals. Figure 3 shows the distribution (with neighborhoods as the unit of analysis) of our neighborhood social density metric. The modal respondent of a neighborhood at least one standard deviation above (below) the mean reported that 10 (5) out of 10 neighbors would turn out for community work, and that disagreements sometimes (never) occur within the neighborhood, while 22% (7%) report having attended a community meeting in the last year.
The empirical implication of Hypothesis 1 is that individuals with higher social connectedness scores should be more likely to participate in individual clientelism, as measured in the list experiment, than individuals with lower social connectedness. This implies a positive interaction term between the individual-clientelism treatment and individual social connectedness, reflecting a greater difference in the number of list items indicated between the treatment and control groups for connected individuals relative to less-connected individuals.
We test Hypothesis 2 at the level of the neighborhood.\textsuperscript{15} We expect that neighborhoods with higher social density should evince a higher degree of coordinated political mobilization, as reflected by more agreement regarding which neighborhood leader and which political party are supported by individuals in the neighborhood, and a higher proportion of individuals reporting that the neighborhood is a vote bank. Moreover, we expect that this coordinated mobilization should in turn be positively correlated with neighborhood notification (described in greater detail below), which is the key prerequisite for the official provision of services by local governments.

V. Results

V.1 Incidence of Individual and Collective Clientelism

Table 2 shows the basic result of our list experiment. The treatment effect of the list item “The suggestions of your neighborhood leader . . .”, which we term the collective clientelism treatment, corresponds to 9.6% of our sample being influenced by collective clientelism. The treatment effect of the list item “One party promising more favors . . .” corresponds to 8.4% of our sample’s vote being influenced by individual clientelism. This is the first experimental evidence showing the incidence of a key ingredient of collective clientelism, namely the coordination of votes at the neighborhood level. This evidence supports our notion that most research on clientelism has underappreciated the importance of neighborhood-level dynamics for political exchange.

\textsuperscript{15} We do not have adequate power to use the list experiment to test the relationship between social density and collective clientelism. Because social density varies only at the neighborhood level, there is substantial intra-cluster correlation, causing the standard errors to become large when they are made robust to intra-cluster correlation. As a result, the effective number of observations is closer to the number of neighborhoods (167) than to the number of individuals surveyed (7,452).
V.2 Social Connectedness and Individual Clientelism

Our first hypothesis is that individuals with higher social connectedness are more likely to be targeted for individual clientelism. We test this hypothesis by interacting the individual clientelism treatment in the list experiment with the individual connectedness score. Our hypothesis implies that the coefficient on this interaction term should be positive. The results are shown in Table 3. The left-hand column shows the results for a basic specification with no demographic controls, while the right-hand column includes controls (age, gender, assets, education, migrant status, caste, mother-tongue\(^{16}\), and religion; full results in Appendix D).\(^{17}\) Results are estimated using OLS, with standard errors clustered at the neighborhood level. For both specifications, the interaction term between the individual clientelism treatment and individual connectedness is positive and statistically significant.

\(^{16}\) Mother tongue is included as a “local language” dummy that takes a value of 1 for native speakers of the locally dominant languages (Kannada in Bangalore, Hindi and Marwari in Jaipur, and Hindi and Bihari in Patna).

\(^{17}\) In Appendix E, we show results for individual clientelism versus neighborhood social density. The interaction term between the treatment and neighborhood social density is close to zero, indicating that individual clientelism does not seem to be less prevalent in socially denser neighborhoods.
Figure 4 shows a marginal effects plot of the individual-clientelism treatment effect as a function of individual connectedness. The marginal effects plot shows that the treatment effect (i.e. the incidence of individual clientelism) is close to zero for the least socially connected individuals, but increases to nearly 15% for the most socially connected individuals. Measuring social connectedness in a sample survey is not easy, but robustness checks suggest that these results are broadly consistent with alternative measures.\textsuperscript{18}

\begin{table}[h]
\centering
\caption{List experiment: Individual social connectedness and individual clientelism}
\begin{tabular}{lcc}
\hline
 & (1) & (2) \\
\hline
Individual Favors Treatment & 0.093*** & -0.102 \\
 & (0.024) & (0.182) \\
Individual Social Connectedness & -0.066*** & -0.058*** \\
 & (0.021) & (0.021) \\
Treatment * Connectedness & 0.050** & 0.055** \\
 & (0.025) & (0.026) \\
Demographic Controls & No & Yes \\
N & 4523 & 4498 \\
$R^2$ & 0.006 & 0.047 \\
\hline
\end{tabular}
\textsuperscript{Note:} *p<0.1; **p<0.05; ***p<0.01
\end{table}

\textsuperscript{18} The alternate measure of social density omits the question about disagreements in the neighborhood, and includes only the two questions about neighborhood work and neighborhood meetings. The result of using this alternate measure is that the estimated interaction term between the treatment and social connectedness is slightly smaller and noisier, and thus is no longer quite statistically significant at conventional levels.
V.3 Social Density and Collective Clientelism

Our second hypothesis is that collective clientelism should increase with neighborhood-level social density. We test this using survey data bearing on mobilization practices associated with collective clientelism, namely, leader fractionalization, party fractionalization, and reported vote banking. Having established the relationship between social density and collective political mobilization, we then show that these mobilization strategies are in turn associated with government recognition of the legality of a neighborhood by the local government, which is a key prerequisite for service provision.
We first examine the relationship between social density and centralized leadership. As discussed above, informal leaders serve as the crucial political intermediary between slum citizens and formal government, and their influence is increasing in the number of votes they can deliver. Our survey instrument in the Bangalore 2015 and 2016 survey waves asked respondents to name the most important leader in their neighborhood. This allows us to construct an index for each neighborhood’s leadership fractionalization:

\[ F = 1 - \sum_{i=1}^{n} s_i^2 \]

where \( F \) is the fractionalization score; \( n \) is the number of leaders in one neighborhood; and \( s \) is the proportion of respondents in the neighborhood naming each leader. The score goes from 0 to 1, with 0 corresponding to everyone naming one leader. Low values indicate neighborhood agreement on the most important leader, which indicates a higher level of political coordination. High levels of political coordination by neighborhood leaders is consistent with accounts of neighborhood vote banking.

The variation in leadership centralization among slums is demonstrated by Figure 5, which shows network graphs from four slums in our household sample; each arrow indicates a node being named as a leader. Some slums have many respondents who do not name a leader; some have several leaders; and some have one dominant leader.

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19 Identifying and harmonizing leader names was not trivial. We, the field managers and the enumerators developed a system for harmonizing the spelling of leader names the morning after field work in each settlement.

20 This is a distinct concept from individual social centrality. Leadership centralization is a neighborhood-level attribute measuring the extent to which the neighborhood has united around a single leader.
Table 4 shows the results of an OLS regression of leadership centralization on neighborhood-level social density, with the right-hand column controlling for average assets of neighborhood respondents. These results show a significantly higher level of leadership centralization (lower fractionalization) in socially denser neighborhoods. When units are normalized, the coefficient in Column 2 indicates that a one-standard deviation increase in neighborhood social density is correlated with a ~0.3 standard deviation decrease in leadership fractionalization. Separate analysis confirms these results with an alternative dependent variable, namely the proportion of neighborhood respondents who named the top leader.
Next we turn to shared party identification within slums. Insofar as collective clientelism relies on vote banking, residents should identify with one party. Harmonized responses could reflect the efforts of local leaders, neighborhood social norms, or overlap in citizen attitudes and preferences. Table 5 shows the results of fractionalization analysis based on the question “In your opinion, which party is doing good?” As with the evidence above on leadership centrality, party centrality is positively and significantly correlated with neighborhood-level social density. When units are normalized, the coefficient in Column 2 reflects that a one standard deviation increase in neighborhood social density is correlated with a ~0.25 standard deviation decrease in party fractionalization.

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21 In the Indian context, this is equivalent to the standard party ID question in the U.S. and beyond. The wording was chosen after consultation with field staff and field testing.
Next, we turn to voting itself. To the extent social density contributes to the community’s political coordination capacity, it should result in successful vote banking. We asked respondents: “Do you think your neighborhood is an effective vote bank?” The responses provide another indication of slum-level political coordination. Table 6 shows the relationship between neighborhood-level social density and the proportion of respondents claiming an effective vote bank. Once again, social density is positively and significantly correlated with neighborhood-level political coordination. To the extent vote banking is a crucial tool for attracting attention from parties and government, this finding shows that socially dense neighborhoods have important advantages in organizing it. When units are normalized, the coefficient in Column 2 reflects that a one-standard deviation increase in
neighborhood social density is correlated with a ~0.27 standard deviation (four-percentage-point) increase in reported vote banking.

Finally, we consider the relationship between neighborhood political coordination, in the form of unified party support and vote banking, on the likelihood of neighborhoods being “notified”. “Notification” refers to a status conveyed by city and/or state officials which provides residents with assurance that their settlement is legal and, therefore, qualifies for public services. Spater et al (2019) show that notification, while nominally subject to legal definition, is in fact highly mediated by neighborhood politics. On one hand, legal definitions are amenable to alternative interpretations and shifting administrative
priorities. On the other hand, state and city officials who manage notification suffer from an excess of demands and report that prioritization of cases is responsive to political pressure from elected ward leaders and members of legislative assemblies. Cities cannot legally provide services to settlements that are illegal, so notification is an important precursor to accessing piped water, sewage, a public toilet, garbage pickup and the like.

Table 7 shows the results of regressions at the neighborhood level, where the dependent variable slum notification. Assessing notification status is not as straightforward as it sounds. Given the value of notification to residents, many politicians provide “papers” to local residents that actually have no legal status, generating confusion. We operationalize notification as the proportion of respondents who report that the slum has been notified, though separate analysis on the basis of (incomplete) government lists provides similar results. The independent variables of interest are leader fractionalization, party fractionalization, and reported vote banking. These results show that neighborhoods with more unified (i.e. less fractionalized) party support, and with a higher proportion of residents reporting that the neighborhood is a vote bank, also tend to have the legal status that makes them eligible for government services. Subsequently attaining services is itself politically mediated, but official notification is an important step in receiving them.

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22 See, for instance, p. 8 of the 1973 Karnataka Slum Act and note how open to interpretation the statute is: [http://ksdb.kar.nic.in/docs/Board_Docs/Karnataka%20Slum%20Development%20Act.pdf](http://ksdb.kar.nic.in/docs/Board_Docs/Karnataka%20Slum%20Development%20Act.pdf)

23 The significance of leadership fractionalization is not robust to the inclusion of controls. This is consistent with the finding from Auerbach (2016) that the presence of multiple party operatives in a neighborhood is associated with better services, but only if the operatives all belong to the same party. Thus party fractionalization, rather than leader fractionalization, is robustly associated with notification.
These results indicate that socially dense neighborhoods are better able to coordinate votes. Given the cross-sectional nature of our data, we are unable to investigate the relationship between vote banking and the delivery of collective clientelistic benefits, because social density likely responds to the potential gains from organization. Thus, social density and vote banking might well decline once desired services are achieved. Nevertheless, our qualitative work in these cities strongly suggests that vote banking is a crucial ingredient for achieving local services.

**Conclusion**
Building on a massive data collection effort, we provide evidence for the practice of individual and collective clientelism among the urban poor in India. The practice of collective clientelism reflects the demands of the urban poor for key, neighborhood-level benefits and the prevalence of vote banking in urban slums. Collective clientelism also overcomes the observability challenge inherent in monitoring private exchanges, since parties can observe how neighborhoods vote by looking at booth-level returns. We argue that social density further ameliorates the clientelistic technical challenges because it outsources monitoring and coordinating of voters to neighbors and their leaders. In also showing that socially central individuals are more likely to be targeted with private clientelism, we are the first to provide direct evidence on the incidence of both types of clientelism. Many scholars (e.g. Stokes 2005) underscore the exploitative aspect of the asymmetric relationship between voters and politicians, while Auyero (1999) and Nichter and Peress (2017) have drawn attention to the mutually beneficial side of clientelism. Here we have shown that clientelism is consistent with both individual exploitation and neighborhood-wide benefits.

These findings point to two challenges for future research. First, while we show evidence of a link between vote banking and slum notification, the available data is insufficient to bring the evidence all the way to public services themselves. Several obstacles must be overcome to test this relationship. First, we do not have an exhaustive census of neighborhood services, and the services ostensibly supplied by city and state governments vary across time, city and state. Even more challenging is that vote banking is likely to be endogenous to service quality. A high level of services today might reflect
the outcome of successful organizing in years past, and extensive vote banking today
might reflect the absence of services today and a hope for getting them soon. To resolve
the relationship between political coordination and neighborhood-level service provision,
one would need panel data rather than the cross-sectional data at our disposal. Given the
effort involved in gathering the cross-section we have, this is not a trivial task.

Second and relatedly, we face the challenge that bedevils most work on social networks
and social capital, namely that we do not know from whence dense networks and social
cooperation emerge. Do dense political leadership networks and successful vote banking
emerge from some ideal, primordial social conditions early in a slum’s history? Or do
good leaders, i.e. successful political entrepreneurs, produce densely organized
communities and vote banks by dint of organizing, constituency service, and the
continuous application of hard work?

Furthermore, how does network structure condition the capacity for collective action?
The present work finds that edge density facilitates collective clientelism, but cannot
address the effects of network hierarchy and centralization. Network experiments (Mason
and Watts 2012) have shown that “flatter,” less centralized networks are more efficient in
solving certain types of problems. However it may be that collective clientelism places a
higher premium on coordination and therefore on centralization. We surmise that
networks with high centralization and low clustering are the most conducive to collective
mobilization in pursuit of public goods, because a centralized neighborhood structure
reflects unified political leadership of the slum, and a single point of contact between the
slum and outside political actors. Moreover, we expect that a high degree of clustering is detrimental to this type of collective action, because it could reflect the presence of political disunity or rival partisan networks, which often undermine collective mobilization for local public goods (Auerbach 2016). However, testing the relationship between more complex network structures and collective clientelism requires the collection of detailed network data from a large number of slums.

A closely related issue for any work on neighborhood effects is that individuals, to some extent, self-select into neighborhoods, and it is difficult to distinguish the effect of self-selection from that of places on individuals. In separate work, we find limited evidence of residential sorting on social capital, but considerable research on ethnic and religious heterogeneity suggests that caste and religious diversity should condition the collective action capacity of local communities. Again, in separate analysis we do not even find correlational evidence supportive of such a notion in our 167 slums. Nevertheless, progress on this front will require sustained analytical engagement with an emergent (mostly formal) work on leadership, sustained panel data collection on a large number of slums, and substantial sociological work reconstructing the histories of those communities. Given the growing evidence on the social nature of clientelism and its role in mediating the poor’s access to government, such efforts strike us as important.
References


Appendix A: Construction of Social Connectedness Metric

To test our hypothesis about the relationship between social capital and clientelism, we construct indices to measure social capital at the individual and neighborhood level. Our individual measure, which we call individual connectedness, is based on a principal component analysis (PCA) of individual responses to the three survey questions that are common across our survey waves that address social capital. They are as follows: “Suppose that 10 of your neighbors were invited to help in community work, such as a community water project, cleaning of gutters, or weeding on the side of the road. How many do you think would show up?”; “How often are there serious disagreements among people who live in this neighborhood?”; and “Have you attended a community meeting in your neighborhood in the past 12 months?”

First, we drop from the analysis any individuals living in neighborhoods from whom fewer than 20 respondents were surveyed. We also drop respondents whose neighborhood is unknown, due to geolocation errors. This cleaning step reduces our sample from 7452 to 7258 observations.

We then create a social connectedness metric by performing a primary component analysis (PCA) on individual responses to the three questions listed above. The responses are scaled, so that the difference in scales across questions, and differing levels of variation in responses across questions, does not affect the result.
Table A1 shows the proportions of variance captured by the three components of the PCA. Based on a common rule of thumb, we retain the components corresponding to eigenvalues (square of standard deviation) higher than 1; in this case, this means retaining only the first component.

Table A1: PCA summary: importance of components.

<table>
<thead>
<tr>
<th></th>
<th>First</th>
<th>Second</th>
<th>Third</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation</td>
<td>1.046</td>
<td>0.9935</td>
<td>0.9581</td>
</tr>
<tr>
<td>Proportion of variation</td>
<td>0.365</td>
<td>0.329</td>
<td>0.306</td>
</tr>
<tr>
<td>Cumulative Proportion</td>
<td>0.365</td>
<td>0.694</td>
<td>1</td>
</tr>
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</table>

Figure A1 shows a scree plot of the three PCA components.
Appendix B: Balance Tables for List Experiment

Table B1: Balance table: Individual Clientelism Treatment

<table>
<thead>
<tr>
<th></th>
<th>Mean (Control)</th>
<th>Mean (Favors Treatment)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>39.34</td>
<td>39.71</td>
<td>0.33</td>
</tr>
<tr>
<td>Male</td>
<td>0.46</td>
<td>0.46</td>
<td>0.96</td>
</tr>
<tr>
<td>Assets</td>
<td>9.67</td>
<td>9.61</td>
<td>0.63</td>
</tr>
<tr>
<td>Education</td>
<td>4.21</td>
<td>4.27</td>
<td>0.61</td>
</tr>
<tr>
<td>Permanent Resident</td>
<td>0.74</td>
<td>0.72</td>
<td>0.15</td>
</tr>
<tr>
<td>General Caste</td>
<td>0.13</td>
<td>0.13</td>
<td>0.47</td>
</tr>
<tr>
<td>Hindu</td>
<td>0.81</td>
<td>0.80</td>
<td>0.37</td>
</tr>
<tr>
<td>Connectedness</td>
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<td>-0.02</td>
<td>0.27</td>
</tr>
<tr>
<td>Neigh. Density</td>
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<td>-0.02</td>
<td>0.02</td>
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<td>N</td>
<td>2,404</td>
<td>2,458</td>
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Table B2: Balance table: Collective Clientelism Treatment

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<tr>
<th></th>
<th>Mean (Control)</th>
<th>Mean (Leader Treatment)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>39.34</td>
<td>39.09</td>
<td>0.51</td>
</tr>
<tr>
<td>Male</td>
<td>0.46</td>
<td>0.47</td>
<td>0.56</td>
</tr>
<tr>
<td>Assets</td>
<td>9.67</td>
<td>9.76</td>
<td>0.45</td>
</tr>
<tr>
<td>Education</td>
<td>4.21</td>
<td>4.37</td>
<td>0.23</td>
</tr>
<tr>
<td>Permanent Resident</td>
<td>0.74</td>
<td>0.75</td>
<td>0.19</td>
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<tr>
<td>General Caste</td>
<td>0.13</td>
<td>0.13</td>
<td>0.81</td>
</tr>
<tr>
<td>Hindu</td>
<td>0.81</td>
<td>0.83</td>
<td>0.13</td>
</tr>
<tr>
<td>Connectedness</td>
<td>0.01</td>
<td>0.01</td>
<td>0.87</td>
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<td>Neigh. Density</td>
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<td>0.94</td>
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<td>2,374</td>
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Appendix C: Regression Tables from Network Data

Table C1

<table>
<thead>
<tr>
<th></th>
<th>In-degree</th>
<th></th>
<th>Out-degree</th>
<th></th>
<th>Total-degree</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>Community Work</td>
<td>0.217***</td>
<td>0.233***</td>
<td>0.067***</td>
<td>0.079***</td>
<td>0.284***</td>
<td>0.312***</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.080)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.078)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.534***</td>
<td>2.305***</td>
<td>3.753***</td>
<td>3.546***</td>
<td>6.288***</td>
<td>5.851***</td>
</tr>
<tr>
<td></td>
<td>(0.551)</td>
<td>(0.710)</td>
<td>(0.083)</td>
<td>(0.103)</td>
<td>(0.559)</td>
<td>(0.719)</td>
</tr>
<tr>
<td>Neighborhood dummies?</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,581</td>
<td>2,581</td>
<td>2,581</td>
<td>2,581</td>
<td>2,581</td>
<td>2,581</td>
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<tr>
<td>R²</td>
<td>0.003</td>
<td>0.005</td>
<td>0.013</td>
<td>0.079</td>
<td>0.005</td>
<td>0.011</td>
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<tr>
<td>Adjusted R²</td>
<td>0.003</td>
<td>0.002</td>
<td>0.012</td>
<td>0.076</td>
<td>0.005</td>
<td>0.008</td>
</tr>
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</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Table C1 shows that individuals who give higher responses to the question “Suppose that 10 of your neighbors were invited to help in community work, such as a community water project, cleaning of gutters, or weeding on the side of the road. How many do you think would show up?” tend to have significantly higher numbers of social contacts (in-degree, out-degree, and total-degree) in our network data set.
Table C2 shows that individuals who give higher responses to the question “How often are there serious disagreements among people who live in this neighborhood?” (where numerically higher responses correspond to more frequent disagreements) tend to have significantly higher numbers of out-degree social contacts in our network data set.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>In-degree</th>
<th>Out-degree</th>
<th>Total-degree</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Neighborhood Disagreements</td>
<td>0.209</td>
<td>0.123</td>
<td>0.205**</td>
</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.213)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.535***</td>
<td>3.454***</td>
<td>3.739***</td>
</tr>
<tr>
<td></td>
<td>(0.503)</td>
<td>(0.662)</td>
<td>(0.074)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neighborhood dummies?</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>2,546</td>
<td>2,546</td>
<td>2,546</td>
<td>2,546</td>
<td>2,546</td>
<td>2,546</td>
</tr>
<tr>
<td>R²</td>
<td>0.0004</td>
<td>0.002</td>
<td>0.019</td>
<td>0.071</td>
<td>0.002</td>
<td>0.006</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.00004</td>
<td>−0.001</td>
<td>0.018</td>
<td>0.068</td>
<td>0.001</td>
<td>0.003</td>
</tr>
</tbody>
</table>

*p<0.1; **p<0.05; ***p<0.01
Table C3

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>In-degree</th>
<th>Out-degree</th>
<th>Total-degree</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Neighborhood Meeting</td>
<td>2.909***</td>
<td>2.886***</td>
<td>0.975***</td>
</tr>
<tr>
<td></td>
<td>(0.878)</td>
<td>(0.963)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.893***</td>
<td>3.629***</td>
<td>4.142***</td>
</tr>
<tr>
<td></td>
<td>(0.230)</td>
<td>(0.614)</td>
<td>(0.032)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neighborhood dummies?</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>2,359</td>
<td>2,359</td>
<td>2,359</td>
<td>2,359</td>
<td>2,359</td>
<td>2,359</td>
</tr>
<tr>
<td>R²</td>
<td>0.005</td>
<td>0.006</td>
<td>0.026</td>
<td>0.093</td>
<td>0.008</td>
<td>0.013</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.004</td>
<td>0.003</td>
<td>0.025</td>
<td>0.090</td>
<td>0.008</td>
<td>0.010</td>
</tr>
</tbody>
</table>

*Note: *p<0.1; **p<0.05; ***p<0.01

Table C3 shows that individuals who respond affirmatively to “Have you attended a community meeting in your neighborhood in the past 12 months?” tend to have significantly higher numbers of social contacts (in-degree, out-degree, and total-degree) in our network data set.
Appendix D. Individual connectedness and individual clientelism, with controls included

Table D1: List experiment: Individual social connectedness and individual clientelism

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Individual Favors Treatment</strong></td>
<td>0.093***</td>
<td>−0.102</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.182)</td>
</tr>
<tr>
<td><strong>Individual Social Connectedness</strong></td>
<td>−0.066***</td>
<td>−0.058***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>0.004***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td></td>
<td>−0.079**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.035)</td>
</tr>
<tr>
<td><strong>Assets</strong></td>
<td>0.012**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td><strong>Permanent Resident</strong></td>
<td></td>
<td>0.079*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.042)</td>
</tr>
<tr>
<td><strong>Treatment * Connectedness</strong></td>
<td>0.050**</td>
<td>0.055**</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.026)</td>
</tr>
<tr>
<td><strong>Treatment * Age</strong></td>
<td></td>
<td>−0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td><strong>Treatment * Male</strong></td>
<td></td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.049)</td>
</tr>
<tr>
<td><strong>Treatment * Assets</strong></td>
<td></td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Treatment * Education</strong></td>
<td></td>
<td>−0.00003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Treatment * Perm. Res.</strong></td>
<td></td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.059)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Caste, Religion, and Language</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>4523</td>
<td>4498</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.006</td>
<td>0.047</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01
Appendix E. Neighborhood social density and individual clientelism

Table E1: List experiment: Individual social connectedness and neighborhood density

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual Favors Treatment</td>
<td>0.078***</td>
<td>0.060</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.520)</td>
</tr>
<tr>
<td>Neighborhood Social Density</td>
<td>-0.242***</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>Treatment * Density</td>
<td>-0.008</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.103)</td>
</tr>
</tbody>
</table>

Demographic Controls No Yes
N 4862 4838

Note: *p<0.1; **p<0.05; ***p<0.01