

Aiming Right at You: Group v. Individual Clientelistic Targeting in Brazil

HÉCTOR BAHAMONDE

*Postdoctoral Fellow • Center For Inter-American Policy & Research • Tulane University

e: hbahamonde@tulane.edu

w: www.hectorbahamonde.com

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Abstract

Do parties target individuals or groups? This is a question fundamental to understanding clientelism, yet the literature does not offer an answer. This paper argues that depending on certain conditions, brokers target individuals when they are identifiable and groups when brokers need to rely on the spillover effects of clientelism. Both identifiability and spillovers depend on individual poverty, group poverty and political competition. Though the theory I outline focuses on targeting, the paper also argues that structural factors, such as the density of the poor, should be considered in the vote-buying literature. Structural factors are one of the few observables upon which brokers can base their decision regarding where to invest in clientelism. Using survey data from Brazil, the paper exploits variations in personal incomes within contexts of differing levels of poverty. I find that political parties engage in segmented or ad-hoc strategies, targeting individuals when identifiability is high, and groups when there are economies of scale. Importantly, non-poor individuals can also be offered clientelism.

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There is no agreement on when, how and why parties choose to aim clientelist practices at individuals or groups. The distributive politics and vote-buying literatures have traditionally pursued one of two approaches. On the one hand, the former has mostly focused on group targeting, usually districts or provinces.¹ In this literature, incumbent parties deliver public-sector jobs or construction projects contingent on the support of *groups* of people. On the other hand, the latter has typically focused on *individuals* and their characteristics, such as their socio-economic or electoral profiles. However, it is not clear when clientelist brokers use one or the other strategy, and why.

Moreover, the decision to investigate group-based and/or individual-based targeting seems to be attributable to distinct research designs and agendas, rather than theory. For example, ethnographers most generally focus on individuals, while others have traditionally focused on groups.²

What is most concerning, however, is that it is relatively assumed or implied that individual and group clientelist targeting strategies are interchangeable, when they are clearly not. Individuals pertaining to groups and individuals by themselves have different incentives to defect to the incumbent. For instance, individuals belonging to larger groups have more incentives to defect,³ while individuals who are personally targeted have less incentives to defect.⁴ Anticipating this, brokers adjust their strategies accordingly. In the first instance, brokers deal with low-informational environments that increase principal-agent problems. In the second instance, brokers knowing their clients better, they are able to leverage this knowledge (by means that are explained later), reducing the probability of defection. Yet, these differences have not been systematized in the literature. In this paper, I propose a framework that explains when is more efficient to target groups or individuals.

Particularly, by focusing on brokers, the paper advances an argument about the decision process regarding who to target. The crux of the argument is that this decision is a function of three factors: individuals' discount factors explained by income levels, the incentives of clientelist brokers to rely on spillover effects caused by the nesting structure of individuals (i.e. whether individuals are nested in poor or non-poor contexts), and brokers' incentives to engage in clientelism explained by higher electoral pressures and political competition. Given the nested structure of the argument and the empirics, I am able to disentangle the effects of "being poor" and "living in a poor area" on clientelist targeting. I share Carlin and Moseley [2015, 14]'s diagnosis, in that "[e]xisting research looks almost *exclusively* at individuals' socio-economic and, specially, electoral profile [and] [y]et our knowledge of who parties target remains incomplete."⁵ The paper seeks to contribute to this

¹See Dixit and Londregan [1996], Khemani [2015] and Calvo and Murillo [2004].

²See for example Scott [1972], Auyero [2000], Szwarcberg [2013] and Weitz-Shapiro [2012] and Gonzalez-Ocantos et al. [2012]. I thank Ezequiel González Ocantos for this suggestion.

³Stokes [2005].

⁴Auyero [2000].

⁵Emphasis is mine.

issue by incorporating structural factors and individual factors that foster clientelism in the same theory. Another important implication of the argument is that I am able to explain why parties which adopt clientelism as a strategy, target their resources to both poor *and* non-poor individuals, an empirical regularity that to the best of my knowledge has been unexplored so far (see [Figure 1](#)).

Perhaps the area in which there is the most agreement among scholars is on the relationship between poverty and vote-buying.⁶ For example, [Brusco et al. \[2004\]](#), [Stokes et al. \[2013\]](#) and [Nazareno et al. \[2008\]](#) explain that since the poor derive more utility from immediate transfers than the uncertain returns associated with future policy packages, clientelist political parties *only* target the poor. In other words, poorer individuals prefer a bag of rice today than waiting for the uncertain benefits of a public policy implemented in the future. In fact, [Weitz-Shapiro \[2014, 12\]](#) explains that “[a]lmost *universally*, scholars of clientelism treat and analyze [this] practice as an exchange between politicians and their poor clients.”⁷

However, this canonical predictor has recently been challenged. [Szwarcberg \[2013\]](#) “challenges the assumption [that brokers] with access to material benefits will always distribute goods to low-income voters in exchange for electoral support,” while [Gonzalez-Ocantos et al. \[2012\]](#) and [Holland and Palmer-Rubin \[2015\]](#) found that income (measured at the individual level) had little or no effect on vote-buying. In fact, the Brazilian case, in [Figure 1](#), also shows that non-poor individuals do receive clientelist offerings. *Why would brokers target non-poor individuals?* And relatedly, *Why is contemporary scholarly work reporting null findings for poverty, traditionally the most important predictor of vote-buying?* I present an argument where individual income *on its own* is not relevant. What matters is how *noticeable* individuals are. Wealthier individuals living in poorer contexts and poor individuals living in poor contexts are very identifiable, increasing their respective probabilities of being targeted. Importantly, in low-information environments, brokers use observables like the degree of visibility to reduce the probability of defection.

One often-considered contextual factor in the literature is the size of the community where clientelism takes place. Large-sized communities impose severe principal-agent problems. If an individual’s vote is bought, he or she may be tempted to accept the benefit and then vote for his or her preferred candidate anyway. [Stokes \[2005, 323\]](#) explains that the “community structure” facilitates (or impedes) monitoring. Large communities make voters more anonymous, increasing their probability of defection. In fact, [Rueda \[2016, 164\]](#) finds that in Colombia, vote buying is more effective in contexts of *small* polling places. Consequently, the incentive to defect increases linearly

⁶See [Calvo and Murillo \[2004\]](#), [Weitz-Shapiro \[2012\]](#), [Kitschelt \[2000\]](#) and Kitschelt and Altamirano in [Carlin et al. \[2015, ch. 10\]](#). Following [Nichter \[2014, 316\]](#), clientelist vote-buying is defined as “the distribution of rewards to individuals or small groups during elections in contingent exchange for vote choices.” This definition is broad enough to encompass the “group” and the “individual” targeting strategies developed on this paper.

⁷Emphasis is mine.

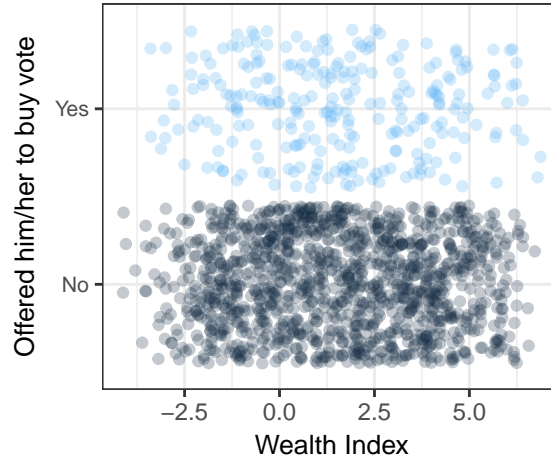


Figure 1: *Individual Wealth and Vote-Buying in Brazil*

with the size of the community where the individual is nested. Several scholars have then argued that brokers prefer smaller groups because individuals nested in small communities should defect less.⁸ Even when brokers might prefer to target small communities (with lesser voters relative to large communities), it is not clear how political parties gain enough electoral returns, especially considering that clientelism is expensive.

Vote-buying is an expensive strategy,⁹ and more so when clients are individually targeted. Stokes [2005, 317] argues that brokers develop skills that allow them to infer whether individual clients in small-sized communities voted for their party by *looking at them in the eyes*. Gay [1993, 1998] documents similar findings for Brazilian case. This strategy requires brokers to sustain close over time relationships with their clients in a personal and individualized way. Knowing the client's needs, delivering him benefits, monitoring his political behavior (and punishing him in case of defection), all in an individualized fashion, makes this strategy an extremely expensive choice. And it gets even more expensive as there are more individuals to target, monitor, reward or punish.

The cost of individual targeting increases linearly with the size of the targeted population. This intuition is important because the brokers' production-possibility frontier cannot be shifted upwards either, i.e. monitoring capacities are bounded. Simply put, at some point party machines run out of enough brokers. Even while individual targeting seems to be extremely expensive given the relatively small number of votes brokers can secure, it is hard to conceive that brokers will stop being clientelist just because the size of the population is large. A priori, it seems a missed opportunity for parties to let go a large amount of votes. Unfortunately, the literature does not explain the mechanics of

⁸Brusco et al. [2004], Kitschelt and Wilkinson [2006, 10] and Magaloni [2008, 67]. Similarly, see Bratton [2008] for Nigeria and Gingerich and Medina [2013, 456] for Brazil.

⁹Zarazaga [2014, 35].

vote-buying in contexts of larger populations, suggesting that in these cases clientelist brokers opt out of clientelism. The article explains that when brokers need to secure large amounts of electoral support, specially when political competition is high, they turn to group-targeting strategies relying on the spillover effects of clientelism. In these contexts, clientelism mobilizes electoral support from *actual* and *potential* beneficiaries, a mechanism that I explain later on in the paper.

Civic associations might help solve some of the challenges large-sized groups present to brokers. As low-information environments prevent brokers from really observing individual electoral behavior,¹⁰ they usually resort to alternative methods that allow them to make safer inferences. For example, Schaffer and Baker [2015] explain that clientelism is “socially multiplied” as party machines target individuals “who are opinion-leading epicenters” in informal situations or “partisan networks,”¹¹ in what has been called “organization buying.”¹² And if parties buy “turnout,”¹³ then they will most probably target associations too, as “citizens immersed in clientelist networks [...] have a higher probability of voting than the rest.”¹⁴ The positive relationship between group-membership and clientelism is acknowledged. However, what has not been explored yet is whether clientelism is explained by association membership itself, or by the fact that poor individuals usually address their problems as a *group*, since otherwise it would be too costly to solve them individually. If this is the case, group *membership* should be spuriously related to clientelism. While I find that group membership does have a positive effect on clientelism, I find that structural contexts that foster group-targeting (the size of the poor people) have even more explanatory power.

In an important paper, Weitz-Shapiro [2012] finds that in several Argentine municipalities, higher levels of political competition, low socioeconomic levels fostered higher levels of clientelism. In her paper, losses are conceptualized in terms of “moral costs.” Evidence for these types of costs has been presented in the literature very recently. For example, Carlin and Moseley [2015] argue that citizens endowed with more democratic values feel more “moral repugnance” to clientelism, Vicente [2014] explains that vote-buying practices have an “immoral/illegal connotation,” and Gonzalez-Ocantos et al. [2012] find that individuals wanting to avoid social stigma usually do not give truthful answers when asked directly about clientelism. Building on this literature, this paper contends that when political competition is high, clientelism will be higher in contexts where poor individuals live in poor economic contexts. Importantly, under certain especial circumstances, non-poor individuals

¹⁰Zarazaga [2014, 35].

¹¹Calvo and Murillo [2013].

¹²Stokes et al. [2013, 250-251]. Holland and Palmer-Rubin [2015, 16] explain that when “parties lack their own brokerage networks [they seek] to capitalize on organizational networks instead.” Similarly, Rueda [2015, 13] argues that parties tend to target very specific civic associations of “seniors and associations of single mothers, organizing trips to recreational centers outside the city where all their expenses are covered.” *Paradoxically*, the stronger the civic society, i.e. the more organized it is, the more clientelism.

¹³Nichter [2008].

¹⁴Carreras and Castaneda-Angarita [2014, 7].

also receive clientelism.¹⁵

WHEN DO PARTIES TARGET INDIVIDUALS AND WHEN GROUPS?

I argue that brokers will have incentives to engage in individual targeting when targets are easier to *identify*. Identifiability not only helps brokers to keep targeted individuals electorally accountable, but also to reduce the net costs of clientelism. Individual targeting is the safest bet a broker can make, but also the most expensive one as it requires brokers to have sustained close relationships with clients. For instance, Zarazaga [2014, 26] explains that “brokers have detailed information about their neighborhood and clients’ needs.” Without question, keeping individual track of every single client (and their respective needs) is an expensive strategy. However, such investment pays off electorally. The same detailed information brokers have about their clients is used to infer (or directly know) the electoral behavior of their respective clientele. Consequently, and to summarize, individual targeting is expensive but safe, relative to group targeting which is (as explained below) cheaper but more uncertain.

The capacity brokers have to identify potential clients does not necessarily come from third-party sources (associations), as the “organization buying” proponents explain,¹⁶ but from a few observables brokers have at their disposition. In this paper I focus on how *noticeable* individuals are in their respective contexts. Should brokers engage in individual targeting, they would rather visit highly noticeable *poor* households in largely *non-poor* neighborhoods. As these households stand out in these contexts, it is easy for brokers to notice whether they need construction materials, whether there are wakes to which they could contribute flowers or birthday parties to which they could bring cakes. Borrowing Zarazaga [2014, 26]’s language, higher levels of visibility, in summary, supply brokers with good-quality information about their clients’.

And even when brokers are “reliable neighbors,”¹⁷ that is, members of the same community, brokers have incentives to expand their immediate local networks by colonizing visible targets outside of their own proximate neighborhood. By conceptualizing brokers as active political entrepreneurs who seek new supporters outside of their immediate context, the proposed framework complements other accounts, as presented in Szwarcberg [2013, 32] or Zarazaga [2016, 681], where brokers are neighborhood party agents. Clientelist entrepreneurship can be done directly, or indirectly. For instance, Auyero [2000, 65-66] describes the situation of *Cholo*, a member of the inner circle of one of the brokers in Buenos Aires, Argentina, who visited “other poor neighborhoods of the area adjacent

¹⁵See Figure 1.

¹⁶Holland and Palmer-Rubin [2015], Rueda [2015] and Stokes et al. [2013].

¹⁷Zarazaga [2014, 38].

to" the place where the broker (and himself) lived, to spread news about some government plan, the governor and the Peronist party, but importantly, also *reporting the broker any unattended material needs he might detect*. Consequently, via different channels, brokers also expand their client portfolio outside of their immediate community. This distinction plays an important role in group targeting, which is explained later in the paper.

Importantly, in this framework, income does not play a role by itself. What is more relevant is how individual incomes interact with their respective socio-economic contexts. Thus, individuals will be more noticeable when non-poor individuals are nested in poor areas (quadrant 1) or when poor individuals are nested in non-poor areas (quadrant 4) in Table 1.¹⁸ Importantly, contexts of higher electoral contestation need wider margins of electoral support. While the bulk of it comes from quadrant 2 (which I explain next), under contexts of high electoral competition, votes from non-poor individuals are also bought.

	Non-Poor Individuals	Poor Individuals
High Competition	Poor Areas , <i>identifiable, individual targeting</i>	Poor Areas , <i>spillover effects, group targeting, cheap vote-buying</i>
Low Competition	Non-Poor Areas , <i>group targeting, expensive vote-buying, lack of checks and balances, embezzlement</i>	Non-Poor Areas , <i>identifiable, individual targeting</i>

Table 1: *Strategy Set: Group v. Individual Targeting*

When poor individuals are nested in poor areas, or vice-versa, individual targeting is no longer efficient. Identifiability makes receivers more prone to cooperate, rising the costs of defection. Since individuals are masked by their environments, identifiability is hard to achieve, increasing the cost of this strategy. In these circumstances, depicted in quadrants 2 and 3 in Table 1, group targeting is more efficient as it relies on the *spillover* effects provided by larger concentrations of individuals. Group targeting works because it also mobilizes electoral support from *potential* clients, that is, those who have not received benefits yet. Auyero [2000, 65] describes the case of *Alfonsina* in Argentina. *Alfonsina* was part of the brokers' inner circle and got a job as a cleaning lady in a public school. As the broker explained to her before getting the job, *Alfonsina* had to be *patient* because as a member of "the circle," she was in the pool of potential beneficiaries; it was only a "matter of time" until she could get the job. Building on this intuition, my argument presents two ideal types: *actual* and *potential* beneficiaries. The former receive particularistic benefits "today" and vote for the

¹⁸Importantly, poor households need not be close to each other, but *visible* enough for brokers to detect their needs.

more development, Each quadrant of Table 1 probably deserves its own paragraph, Addressing the party, the broker and the client's costs and benefits and strategies

broker's candidate "tomorrow," while the latter do not receive benefits "today" (in the expectation of receiving them in the future) but *still* vote for the broker's candidate.¹⁹ Actual beneficiaries want to remain actual beneficiaries; thus, they keep supporting the broker's candidate. Potential beneficiaries want to become actual beneficiaries, but are uncertain when that might happen; as a result, they keep supporting the broker's candidate. This mechanism requires the broker's ability to not allow the transaction costs of switching strategies to be lower than what it costs clients to wait to be benefited. In other words, brokers need to take care of their reputation and, eventually, deliver the benefits, an insight that goes in line with Zarazaga [2014, 14], who explains that brokers and voters' interests are aligned. In particular, voters know that the flow of resources is dependent on the brokers' electoral success. Also, voters do not know whether new brokers might have access to fewer resources, or distribute them to other people. Consequently, the equilibrium for the voters is to support the current broker. Moreover, no matter what type an individual is, both actual and potential beneficiaries keep voting for the broker's party. Relatedly, given that the poor are risk-averse, potential beneficiaries are better-off waiting (and voting for the broker's party) than defecting.²⁰ Hence, the cost of switching brokers (or defecting) is very high since it also involves building from scratch relationships of confidence with the new broker. Also reputation costs keep clients disciplined; brokers exploit these self-enforced compliance dynamics.

Vote-buying is also targeted to non-poor groups individuals nested in poor groups (quadrant expand here 3). On the one hand, vote-buying has decreasing returns to scale in non-poor individuals. That is, wealthier individuals derive less advantages from a bag of rice relative to poorer individuals. Candidates, anticipating this, will not offer the same benefits to wealthy individuals, segmenting the type of offerings they make to the better-off. To be attractive, these goodies should be relatively more expensive. Consequently, buying votes from non-poor individuals gets more expensive as income increases. Low levels of political contestation give local politicians more "room to move," allowing them to divert local resources into more expensive means of targeting (embezzlement).

CASE SELECTION, RESEARCH DESIGN AND DATA ANALYSES

This paper tests the effects of individual income, the effects of being nested in *communities* with different poverty structures (a variable which I call **density of the poor**), and the effect of being exposed to different levels of political competition, on receiving clientelist benefits. Brazil is a good

¹⁹The idea of expectations or "hope" is important. Auyero [2000, 65] explains that "The *hope* of a job serves as important glue within the inner circle. Although not everyone is employed at the municipality, the fact that someone gets [a] job has an important *demonstration* effect." Emphases are mine.

²⁰In the same vein but in a slightly different subject, Magaloni [2008, 20] explains that The Mexican PRI lasted as long as it did not because of electoral fraud but because voters supported the "known devil."

case because its poverty structure is such that it is possible to find low-income individuals nested in non-poor areas (and vice versa). This case is also interesting from an institutional perspective. The Brazilian electoral system *incentivizes* clientelism. Several factors such as multimember districts with open lists and the institution of the *candidato nato*,²¹ “clearly [makes] Brazil one of the most personalistic systems of democratic governance.”²² In fact, [Gingerich \[2014, 290\]](#) finds that vote-buying drastically changed electoral results, concluding that “[v]ote brokerage can still pay electoral dividends in contemporary Brazil.”

To test this hypothesis, I use survey data from 2010 from [the Latin American Public Opinion Project \[LAPOP\]](#).²³ Though the LAPOP survey provides a question for income, people who are somewhat better off than their neighbors but live in poor areas may not “feel” poor. If this is the case, this could confound the results. Additionally, when answering the questioner, individuals might not want to reveal their true incomes (either because it is too low or too high). Following the advice of [Córdova \[2008\]](#) and [Córdova and Seligson \[2009, 2010\]](#), a relative wealth index (RWI) was constructed.²⁴ Using principal component analyses, the index measures wealth based on actual assets weighted by how common these assets are. Different indexes were constructed for urban and rural contexts. [Figure 1](#) plots the distribution of the combined index separated by clientelism. To measure the density of the poor, I followed a strategy similar to that of [Weitz-Shapiro \[2012\]](#), measuring the degree of poverty at the municipal level. Using information from the 2010 Brazilian census,²⁵ a variable was constructed that measures the percentage of individuals who live on less than half of the minimum wage in a given municipality (**density of the poor**). Given that the municipality of residence for each individual in the LAPOP survey is recorded, I was able to merge the census percentage with the LAPOP dataset. The **density of the poor** serves as a good proxy to capture the size of the poor group. It is important to stress that the unit of analysis is the individual, and that this variable captures the economic context in which each individual lives. And just like other scholars in the past have tested the effect of being nested in rural areas,²⁶ this paper focuses on another class of contextual variable. Although the **density of the poor** group was originally a semi-continuous variable,²⁷ it had to be dichotomized at the median (29%) to be able

²¹ “[R]ule that removed parties’ control over the nominations process and let an electoral legislator decide to run on any party ticket.” See [Carlin et al. \[2015, Chapter?\]](#).

²² [Carlin et al. \[2015, Chapter?\]](#).

²³ “I thank the Latin American Public Opinion Project (LAPOP) and its major supporters (the United States Agency for International Development, the United Nations Development Program, the Inter-American Development Bank, and Vanderbilt University) for making the data available.” The sample consists of five strata representing the five main geographical regions of Brazil. Each stratum was further sub-stratified by urban and rural areas.

²⁴ See also [Santos and Villatoro \[2016\]](#).

²⁵ Official data comes from the Bureau of Statistics of Brazil [IBGE](#).

²⁶ See for example [Brusco et al. \[2004\]](#) and [Stokes \[2005\]](#). Both of them use the log of population, which is a proxy for urban/rural.

²⁷ I.e., a percentage.

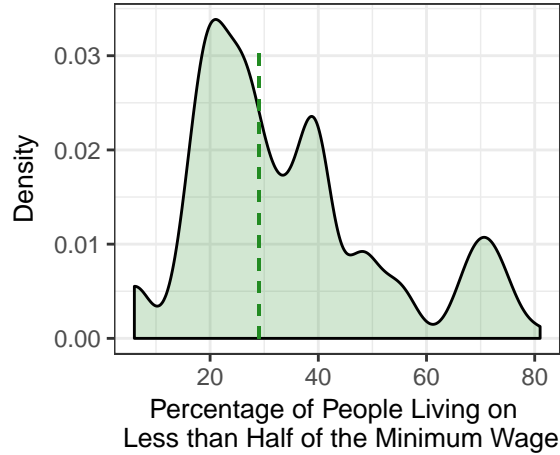


Figure 2: *Distribution of the Density of the Poor*

to construct a matched sample, which I justify and explain below. **Figure 2** shows the continuous distribution dichotomized at the median (dashed line). Finally, to measure political competition, the paper follows **Weitz-Shapiro [2012]**. Using official electoral data from the 2008 municipal elections,²⁸ a variable was constructed that measures the percentage of seats that are not controlled by the mayor's party in a given municipal council.

There is a built-in lack of relationship between “being poor” and “living in a poor municipality,” confirming that Brazil is in fact a good case to test this theory. **Figure A1** in the Appendix shows that the unmatched/raw dataset had already embedded low levels of correlation between these two variables (0.44).²⁹ Using matching methods, I am able to further break this relationship. Matching is a two-stage process. In the first stage the analysts preprocesses the data, seeking to break any systematic relationship between, in this case, the **density of the poor** and the wealth index (RWI).³⁰ Matching does so by deleting observations for which matches cannot be found.³¹ The idea is to obtain a good covariate balance as in **Figure OA2** (in the Online Appendix), to then estimate any appropriated statistical model.³² From a statistical standpoint, preprocessed datasets are less model-dependent³³ and prevent analysts from making extreme counterfactuals.³⁴ **Table A2** and

²⁸Data from the *Tribunal Superior Eleitoral*.

²⁹The figure shows that for both the matched and raw datasets, “being poor” and “living in a poor municipality” are not confounded, as it is possible to find poor individuals living in non-poor areas, and viceversa.

³⁰**King et al. [2011]**

³¹The final procedure matched 761 individuals living in the low-density poverty condition with 676 individuals living in the high-density poverty condition.

³²The idea is that the propensity of being exposed to the “high” *density of the poor* condition (the ‘propensity score’) has a similar distribution in both ‘treated’ and ‘control’ groups. It is important to say that, despite the language, I do not claim any causal relationship in this paper.

³³See **Ho et al. [2007]**.

³⁴**King and Zeng [2005]**. The matching routine used was the full matching routine (see **Hansen [2004]** and **Rosenbaum [2010]**), via the **MatchIt** R package (see **King et al. [2011]**).

Table A1 in the Appendix provide summary statistics for both the matched and raw datasets.³⁵ The preprocessed data used in the matching approach has 54 municipalities while the raw data used in the generalized propensity score (GPS) approach (which I explain below) has 54 too. **Figure 3** lists the municipalities and shows which ones are considered “high” or “low” in terms of the **density of the poor** after the dichotomization process. The figure also shows that there exists considerable variance in income/RWI in both high and low poverty density conditions (bubbles).³⁶

It could be argued that dichotomizing the **density of the poor** variable at the median is an arbitrary decision. While there have been theoretical advances regarding general treatment effects regimes for continuous or semi-continuous response doses,³⁷ algorithms with the ability to match on continuous treatment variables are not common. In order to obtain covariate balance in a non-parametric way (as matching does) but *without* dichotomizing the **density of the poor**, I also use the original (i.e. *continuous*) **density of the poor** variable to construct a generalized propensity score (GPS).³⁸ The score is used to *weight* each observation in the model. Besides matching on and weighting by income, I also included the following variables to match on/weighting by: municipal opposition, municipal population and individual involvement in civic associations.

The dependent variable is clientelism. To measure it, I use the question that asks if *a candidate or someone from a political party offered [the respondent] something, like a favor, food, or any other benefit or thing in return for [her/his] vote or support*. Subjects could answer that this had happened *often*, *sometimes* or *never*. Carreras and Irepoglu [2013] and Holland and Palmer-Rubin [2015] use the same dataset and outcome variable. As they explain, the question did not ask whether respondents *took* the offer, hence it should not be an important source of social desirability bias. For statistical and substantive reasons, I dichotomized this variable, combining the alternatives *often* (n = 91) and *sometimes* (n = 150), leaving *never* (n = 1196) unchanged.³⁹

The following control variables were considered. *Perception of corruption* was included to hold constant the effect of respondents who declared clientelist activity when in reality they were referring to corruption scandals.⁴⁰ Brokers usually target civic associations. Following Holland and Palmer-Rubin [2015, 28], who use the same dataset/year, an additive index to measure civic participation (*Political Involvement*) was created.⁴¹ Some have also found group size to be important.⁴² Using

³⁵Tables generated using the **stargazer** R package (Hlavac [2015]).

³⁶**Figure OA1** in the Online Appendix shows the frequency of individuals by municipality in both raw and matched datasets.

³⁷See Imai and van Dyk [2004] and Hirano and Imbens [2004].

³⁸See Imbens [2004], Guardabascio and Ventura [2014] and Imai and Ratkovic [2014]. To generate the weighting vector, I used the CBPS R package (see Fong et al. [2014]).

³⁹These numbers come from the matched dataset.

⁴⁰I thank Cesar Zucco for this suggestion.

⁴¹This variable was constructed by adding the frequency of attendance at religious meetings, community improvement meetings and political party meetings (variables *cp6*, *cp8* and *cp13*, respectively).

⁴²Stokes et al. [2013].

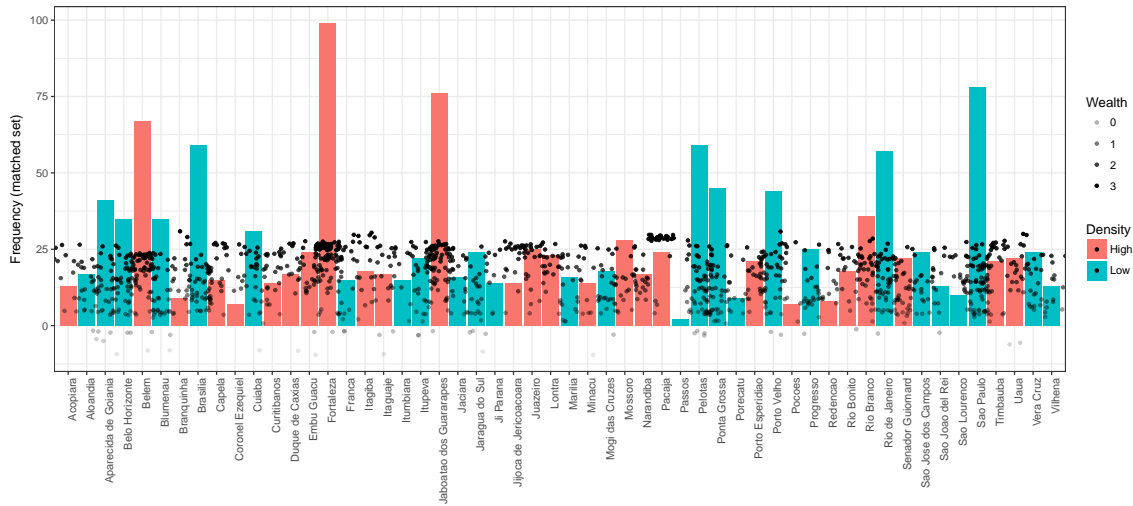


Figure 3: *Distribution of Observations by Municipality, Wealth Index and Density of the Poor*

Brazilian census data, a variable to measure *population size* at the municipal level was constructed. Following the convention in statistical studies of clientelism, an *urban/rural* dummy was also included. Some have argued that parties target their own supporters,⁴³ moderate opposers⁴⁴ or unmobilized supporters.⁴⁵ To keep these constant, a variable to capture party identification (*Political Id.*) was included. Higher levels of democratic support should be negatively associated with clientelism. To control for that, a variable measuring *democratic support* was included. [Gonzalez-Ocantos et al. \[2014\]](#) find that schooling plays a negative role on clientelism; hence, I control for *education* too.

Observations are clustered on a number of important factors such as levels of municipal political competition, municipal poverty and municipal population size. In order to account for these clustering effects, I use a generalized estimating equations approach. GEE were introduced by [Liang and Zeger \[1986\]](#) to fit clustered, repeated (i.e. correlated) and panel data. This method is especially efficient when the data are binary.⁴⁶ GEE models are similar to random effects models⁴⁷ in that they allow observations to be nested in hierarchical structures. This method requires analysts to parameterize the working correlation matrix. Though [Hedeker and Gibbons \[2006, 139\]](#) explain that “the GEE is robust to misspecification of the correlation structure,”⁴⁸ [Hardin and Hilbe \[2013, 166\]](#) point out that “[i]f the observations are clustered (not collected over time), then [...] the exchangeable

⁴³Dixit and Londregan [1996] and Cox and McCubbins [1986].

⁴⁴Stokes [2005].

⁴⁵Nichter [2008].

⁴⁶Hanley et al. [2003].

⁴⁷Gardiner et al. [2009].

⁴⁸Carlin et al. [2001, 402] argue that “[r]elatively minor differences in estimates may arise depending on how the estimating equations are weighted, in particular within the generalized estimating equation (GEE) framework.” Westgate and Burchett [2016] and Gardiner et al. [2009, 227] make the same point.

correlation structure" is the most appropriate working correlation matrix. Given that the data do not follow a panel but rather a clustered structure, the exchangeable correlation matrix was specified in all models.

While this method is very flexible, GEE estimates remain uninterpretable in practice,⁴⁹ making regression tables useless from a substantive standpoint. In this case, the problem is even more severe due to the interactive hypotheses being tested in this paper. The main hypothesis is tested by fitting a parameter for the multiplicative term between the variables **wealth index**, **political competition** and **high density**. Methodologists agree on "not interpret[ing] the coefficients on the constitutive terms," as they lack substantive meaning.⁵⁰ These problems get more complex when it comes to generalized models as a series of challenges arise. As **Ai and Norton [2003]** explain, *(1) the interaction effect could be nonzero, even when the estimation says it is zero, (2) the statistical significance of the interaction effect cannot be tested with a simple t-test on the coefficient of the interaction term, (3) the interaction effect is conditional on the independent variables, [...] and (4) the interaction effect may have different signs for different values of covariates.* **Brambor et al. [2005, 74]** offer the same advice, namely "one cannot determine whether a model should include an interaction term simply by looking at the significance of the coefficient on the interaction term." Given that cross-partial derivatives are not advisable either, simulation methods are required.⁵¹ Particularly, I follow the simulation approach introduced in **King et al. [2000]**. This procedure samples via simulation from the point estimates, generating a new and larger distribution. That is, taking the single estimated parameters (the regression coefficients), I construct a distribution of estimated values for each coefficient. Relying on the central limit theorem, with enough sampling draws, the new simulated distribution is a transformation that approximates with a great degree of precision the (uninterpretable) coefficients. Subsequently, means and uncertainty measures can be constructed for each of these distributions. From a substantive standpoint, simulation methods also allow for sampling new distributions at different values of the independent variables. This will be important in simulating the expected value of clientelism for different "profiles," such as *non-poor* individuals nested in *high-poor* dense municipalities in contexts of *high* political competition, etc.

Since it is "impossible to evaluate conditional hypotheses using only the information provided in traditional results tables,"⁵² I focus instead on the substantive results from the simulation methods. However, I still present the raw results in **Table A3** in the Appendix.⁵³ Analogous to **Table 1**,

⁴⁹**Carlin et al. [2001]**.

⁵⁰**Brambor et al. [2005, 77]**.

⁵¹**Zelner [2009]**.

⁵²**Brambor et al. [2005, 76]**.

⁵³Table generated via the **texreg** R package. The first column shows the estimates for the matched dataset while the second column shows the results for the GPS wighted model. Virtually all coefficients have the same size and sign.

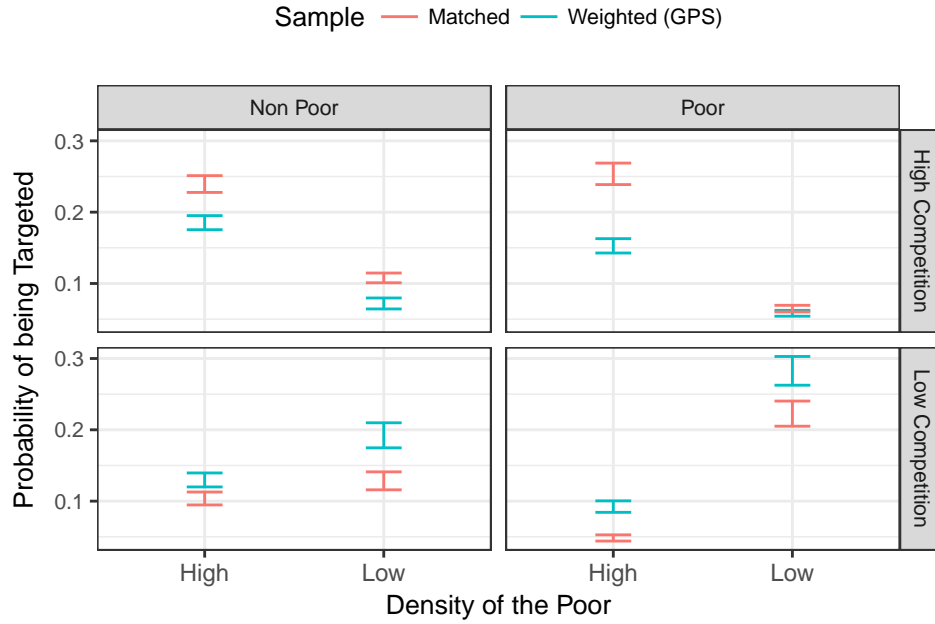


Figure 4: *Simulated Expected Values of Clientelism*

in Figure 4 I simulate the predicted probabilities of being targeted using both the matched and weighted/GPS models. The horizontal panel depicts simulations for the upper (“non-poor,” 75%) and lower (“poor,” 25%) quartiles of the continuous **wealth index** variable. In turn, the vertical panel shows the simulated values for the maximum (100%) and minimum (43%) values of the **municipal opposition index**. Each quadrant shows simulations for individuals nested in poor municipalities (*high density of the poor*) and non-poor municipalities (*low density of the poor*). Each profile shows two simulated probability distributions (with 95% confidence intervals), one for the matched sample and one for the weighted/GPS model.⁵⁴

Figure 4 suggests that brokers engage in *individual* targeting when individuals are identifiable. That is, when individuals are poor *but* nested in low-poor density municipalities (quadrant 4, with a probability of being targeted 22%)⁵⁵ and when individuals are not poor but nested in high-poor density municipalities (quadrant 1, with a probability of being targeted 24%). This suggests that political competition incentivizes motivated brokers to engage in vote-buying regardless of personal income when political competition is high. *Group* targeting is more efficient in quadrant 2, supporting the spillover effects hypothesis. When municipal mayors are politically challenged, brokers target

⁵⁴In the case of the weighted/GPS model which does not use the dichotomized variable, I use the continuous version of the size of the poor variable, where “low density” represents the lower quartile while “high density” the upper quartile.

⁵⁵Matched sample.

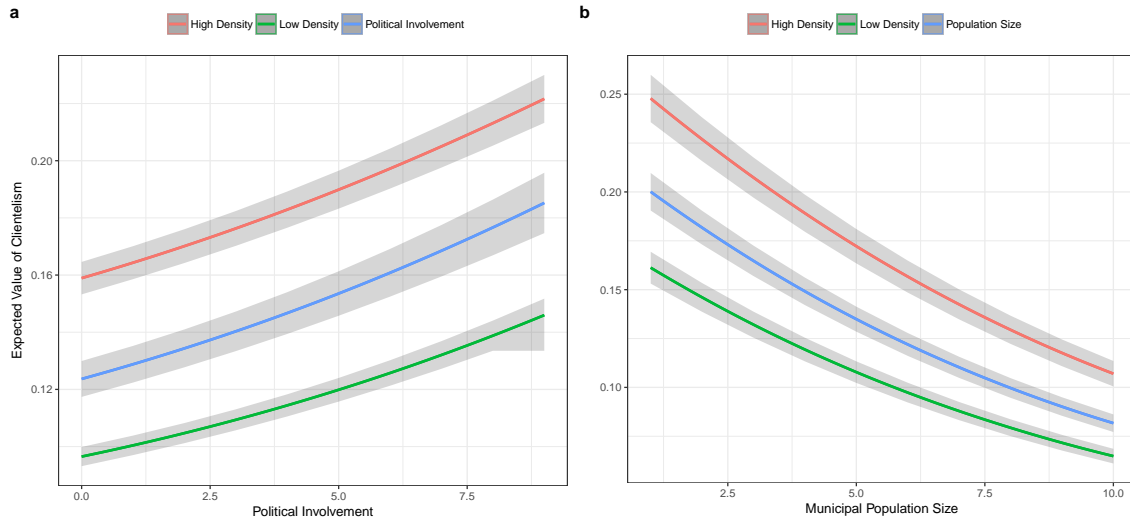


Figure 5: *Simulated Expected Probability of being Targeted: Political Involvement and Population Size*

groups of poor individuals in poor municipalities (quadrant 2, 25%). I argue that brokers take advantage of the spillover effects of clientelism based on the incentives both *potential* and *actual* beneficiaries have to support the broker's candidate. Non-poor individuals nested in low-poor density municipalities but exposed to lower levels of political competition (quadrant 3) are still offered some vote-buying. In these contexts there are less political competition and less checks and balances, having incumbents more "room to move." I argue that even when politicians are not in need of more electoral support, they still engage in this expensive form of vote-buying which is sustained by lowly challenged electoral actors.

Figure 5 shows a plot divided in two panels. Panel **a** shows the simulated expected probabilities (with 95% confidence intervals) of being targeted at different levels of political involvement. As the blue lines suggests, individuals who participate in civic associations have higher probabilities of being targeted. This is in line with findings in previous research.⁵⁶ However, once I decompose these effects, being nested in high-poor density areas contributes substantially more to the model. These differences are statistically significant. Panel **b** shows the probability (with 95% confidence intervals) of being targeted at different increments of the size of the population. In line with the literature, I also see that this relationship is negative.⁵⁷ However, the effect of being nested in high-poor density municipalities outperforms the effect of population size, suggesting spillover effects.

⁵⁶Schaffer and Baker [2015], Carreras and Castaneda-Angarita [2014, 7], Calvo and Murillo [2013], Holland and Palmer-Rubin [2015, 16] and Rueda [2015].

⁵⁷Stokes [2005, 323], Kitschelt and Wilkinson [2006, 10], Magaloni [2008, 67], Rueda [2016], Bratton [2008] and Gingerich and Medina [2013, 456].

Discussion

Incentives to offer or take clientelist offerings are not guided by structure or individual factors only. This paper has suggested that both are necessary to better understand how clientelism happens. Clearly, pressures to incur in this expensive and uncertain strategy rise as political competition rises as well. However, the execution of this strategy largely differs depending on whether brokers face homogeneous or heterogeneous groups of individuals. Each one provides a different cost-and-benefit structure to either defect or cooperate. When poor individuals live in poor areas, brokers engage in group targeting relying on the spillover effects of clientelism. Given that the poor are risk-averse, even the ones who do not receive benefits support the broker's candidate, while the ones who did receive benefits, support him to keep receiving more benefits. In this sense, clientelism propagates easily when the poor live among the poor. However, in heterogeneous areas brokers adapt their strategy and execute clientelism in a different way, relying on how identifiable individuals are. Identifiability makes receivers more prone to cooperate, rising the costs of defection. Finally, the paper hopes that the literature considers that groups and individuals provide different incentives to both brokers and individuals, and hence, this distinction should be incorporated to better understand clientelism.

APPENDIX

Table A1: *Summary Statistics: Raw Sample*

Statistic	N	Mean	St. Dev.	Min	Max
Clientelism	1,483	0.171	0.376	0	1
Wealth Index	1,483	1.543	0.846	-0.899	3.050
Municipal Opposition	1,483	81.761	11.821	43	100
Density of the Poor	1,483	2.435	1.120	1	4
Municipal Population	1,483	5.393	2.841	1	10
Urban	1,483	0.860	0.347	0	1
Political Involvement Index	1,483	1.792	1.619	0	9
Support for Democracy	1,483	5.426	1.682	1	7
Party Id.	1,483	5.939	1.150	1	12
Perception of Corruption	1,483	2.027	1.003	0	3
Years of Education	1,483	9.398	3.857	1	18

Table A2: *Summary Statistics: Matched Sample*

Statistic	N	Mean	St. Dev.	Min	Max
Clientelism	1,437	0.168	0.374	0	1
Wealth Index	1,437	1.557	0.811	-0.899	3.050
Municipal Opposition	1,437	81.912	11.749	43	100
High Density of the Poor	1,437	0.470	0.499	0	1
Municipal Population	1,437	5.384	2.792	1	10
Urban	1,437	0.860	0.347	0	1
Political Involvement Index	1,437	1.784	1.613	0	9
Support for Democracy	1,437	5.417	1.684	1	7
Party Id.	1,437	5.934	1.160	1	12
Perception of Corruption	1,437	2.029	1.000	0	3
Years of Education	1,437	9.359	3.843	1	18

	Matched Data	Weighted Data
(Intercept)	1.404 (1.968)	2.958 (2.691)
Wealth Index	-1.374 (0.990)	-1.320 (1.209)
Municipal Opposition	-0.040 (0.025)	-0.061 (0.032)
High Poor Density	-6.550** (2.399)	
Municipal Population	-0.115* (0.048)	-0.101 (0.053)
Urban	-0.091 (0.401)	-0.077 (0.416)
Political Involvement	0.046 (0.055)	0.047 (0.055)
Support for Democracy	-0.056 (0.046)	-0.051 (0.048)
Party Id.	-0.082 (0.053)	-0.087 (0.052)
Perception of Corruption	0.240** (0.088)	0.267** (0.089)
Years of Education	0.051* (0.021)	0.054** (0.020)
Wealth Index * Municipal Opposition	0.018 (0.013)	0.013 (0.015)
Wealth Index * High Poor Density	2.509 (1.319)	
Municipal Opposition * High Poor Density	0.085** (0.030)	
Wealth Index * Municipal Opposition * High Poor Density	-0.029 (0.016)	
Density of the Poor		-1.992* (0.921)
Wealth Index * Density of the Poor		0.555 (0.372)
Municipal Opposition * Density of the Poor		0.024* (0.011)
Wealth Index * Municipal Opposition * Density of the Poor		-0.005 (0.004)
Num. obs.	1437	1483
Num. clust.	54	54

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Clustered standard errors at the municipality level.

Table A3: Generalized Estimating Logistic Equations: Clientelism

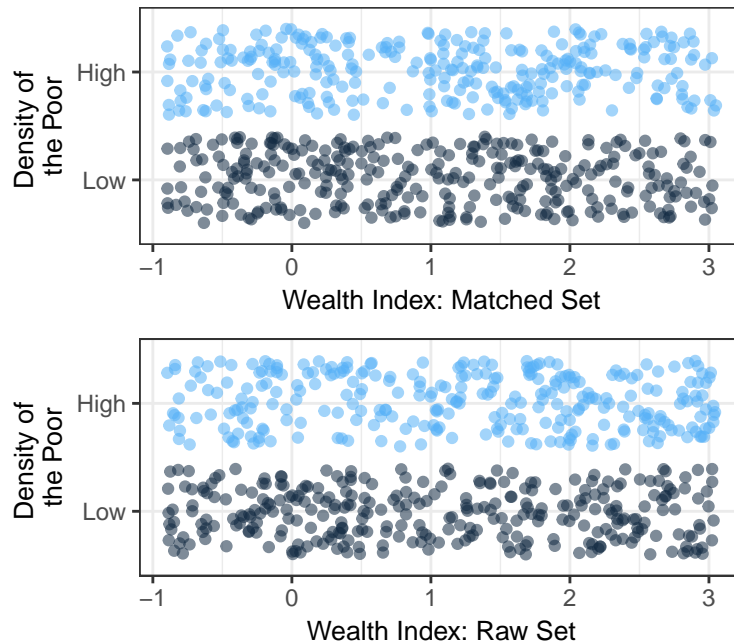


Figure A1: Distribution of Pre and Post Matching Observations by Wealth Index and Density of the Poor

I. ONLINE APPENDIX

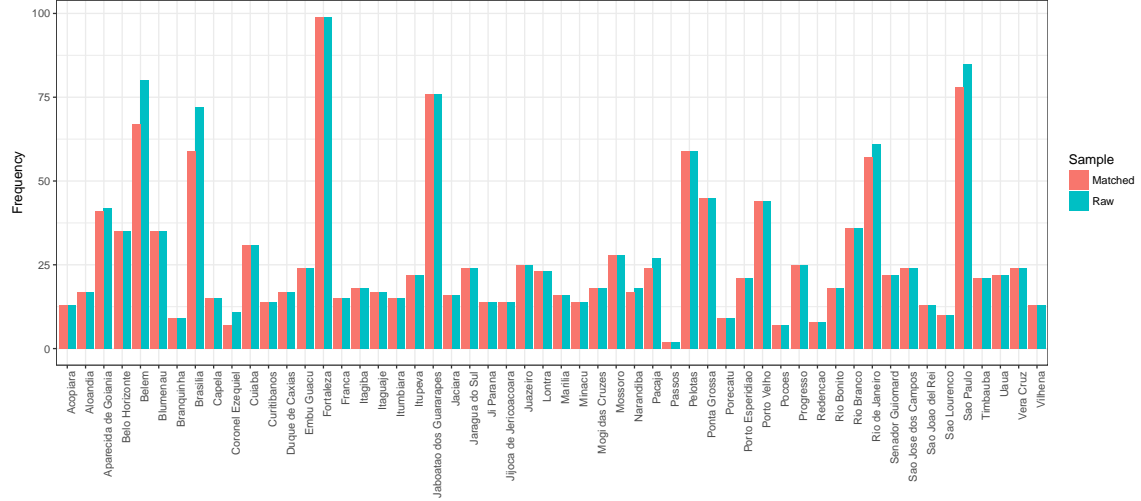


Figure OA1: *Frequency of Individuals by Municipality, Pre and Post Matching Deletion*

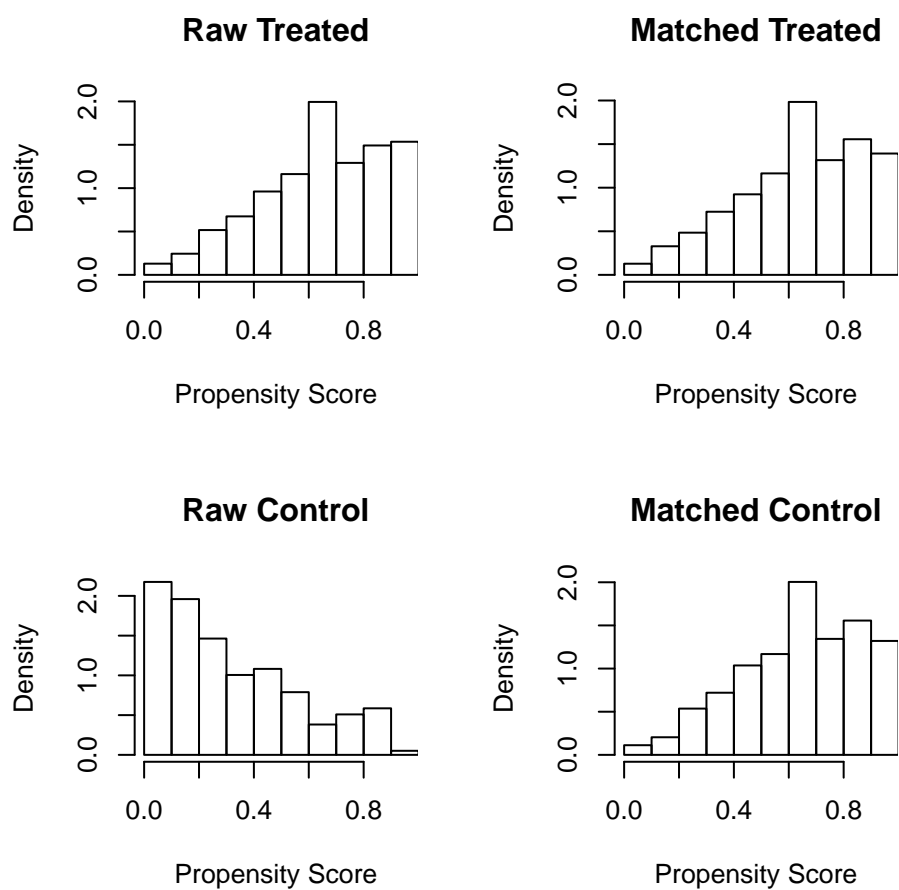


Figure OA2: *Pre and Post Matching Balance: Distribution of Propensity Scores*

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