Measuring the Returns of Vote Buying: A Null Effect

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Abstract

Building on Francisco Cantú's 2019 paper "Groceries for Votes: The Electoral Returns of Vote Buying," we reconsider the efficacy of a vote buying scheme in the 2012 Mexican Presidential Elections in which voters were given gift cards in exchange for their support. The author's initial analysis rests on the assumption that the distance between one's precinct and the store where the gift card is valid is exogenous to political beliefs. Here, the author uses distance to a store where one can redeem a gift card a proxy for one's opportunity cost for having their vote bought. We find that this is not the case, as new measures of distance show a correlation between distance and political awareness and beliefs. Further, we find evidence of model dependence, dependent on the metric of distance used. We conclude that it is not possible to leverage distance as a measure of the perceived utility of a vote buying effort. As such, we find that it is not possible to determine whether this 2012 vote buying scheme was effective using the current data.[1]

1 Introduction

In his 2019 paper "Groceries for Votes: The Electoral Returns of Vote Buying," Francisco Cantú argues for the persuasive power and electoral impact of a vote buying scheme in the 2012 Mexican Presidential Election. Cantú's analysis shows a correlation between electoral swings towards the candidate executing the vote-buying scheme (PRI candidate Enrique

[1]All information necessary to replicate the results of this paper is found in: Cayton, Frances; Fu, Chengyu; Hickey, Molly, 2020, "Replication Data for "Measuring the Returns of Vote Buying: A Null Effect"", https://doi.org/10.7910/DVN/T7ZZ0R, Harvard Dataverse.

Peña Nieto), and voters' proximity to a Soriana store, where the gift cards offered as payment could be redeemed. In the following, we examine Cantú's metric for distance, a critical component of his analysis, and the author's subsequent results. Distance and its inverse, proximity, are common independent variables in political science, but they shouldn't be taken as interchangeable.

The alleged vote-buying scheme carried out by the Peña Nieto campaign involved offering voters gift cards to Soriana, a major supermarket chain in Mexico, in exchange for their vote. These gift cards would be activated after the election if Peña Nieto and his PRI party won. Cantú uses proximity to a Soriana store as a proxy for someone's valuation of the gift card, and subsequent willingness to have their vote bought. As a result, proximity to Soriana stores is fundamental to the results of the paper.

The author relies on the assumption that proximity to the stores is uncorrelated with voter preference, and thus sufficiently exogenous as to be a useful proxy for measuring the efficacy of vote buying. Cantú backs up this assumption by showing that the coefficients on a broad array of measures of political behavior and previous electoral results are unrelated to proximity to a Soriana store. He also uses placebo tests to illustrate that similar vote swings are absent in previous elections and that proximity to different retailers are not similarly correlated with vote swings.

Important to note is that when Cantú refers to proximity, it is a measure he defines as the inverse distance between the centroid (geometric center) of a precinct and its closest Soriana store. However, Cantú does not explain the rationale behind choosing the *proximity* of the store to centroids, as opposed to using traditional distance. Proximity offers some advantages over pure distance as a metric, as it is a non-linear manipulation for what is

likely a non-linear variable. For example, while it is clear that there's a difference in the gift card's utility for someone 50 km from a Soriana compared to someone 1 km, it's also likely that the difference in utility is not the same between someone whose distance to a Soriana is 1 km versus 2 km on the one hand, and between 50 km versus 51 km on the other, and as such, we believe the relationship between distance to a Soriana store and gift card utility is non-linear.

However, it is possible that in using proximity as a dependent variable, Cantú is also masking endogenous effects related to measures of urbanity. Here, the author's initial argument rests on the implication that distance is exogenous to one's political views. In turn, the author argues that distance can adequately proxy for one's valuation of the gift card, and subsequent willingness to have your vote bought. We note that if the distance to a Soriana *is* positively correlated with one's political beliefs, this could reflect a potential rural-urban divide in political preferences, with those living closer to Soriana stores simply being more "urban" than those at further distances. This would make it challenging to use distance as a proxy for one's opportunity cost of the gift card.

In the following, we will argue that the decision to use proximity, the inverse distance, as opposed to the traditional distance, is integral to Cantú's results. When we relax the assumption that proximity, as opposed to simple distance, is the correct measure, we find that Cantú's results do not hold. To further examine this point, we also run the author's analysis using coarsened measures of the quantiles of distance and deciles of distance. Here as well the initial results do not hold. If we find the distance to be endogenous to political beliefs, how else might we measure someone's valuation of the gift card? If distance cannot be used as a reliable proxy for someone's willingness to have their vote bought, how do we measure the success of vote buying attempts that follow the model of the PRI vote buying

scheme?

To address these questions, this paper proceeds in the following manner. First, we re-estimate the model using traditional distance and two new measures of distance: coarsened quantiles and deciles. These three measures reduce the assumptions of the original model. Here, we divide distance in a non-linear manner that captures at the simplest level, through these quantile and decile groupings, the degree to which something is "close," "far," and "further." In opening up the distance to be measured in a non-parametric manner, we are able to capture a potential shift in the utility of a gift card at different distance ranges. Re-estimating the author's model for the PRI vote share (Enrique Peña Nieto's party) using these new measures, we find evidence of model dependence.

Further, we find that the author's initial assumptions rest on extrapolations of voter behavior in cases of *far* distances in opposition strongholds with high turnout, to voter behavior in *close* distance to a Soriana store. This suggests that the model requires further re-assessment, as we question whether the political behavior of someone 20 kilometers from a Soriana store is the same as someone who lives down the street from a store.

Understanding that proximity, as utilized in the paper, was a choice inducing a series of model dependence issues, we return to the exogeneity of distance and voter preference. Re-testing this assumption using our new measures of distance, we find that our non-parametric measures of distance are correlated with political attitudes. From this, we conclude that distance to a Soriana store is not exogenous to political beliefs.

We conclude that it is not possible to leverage distance to measure the voter utility of a vote buying effort with the methods and data provided in Cantú's original article. We close with a brief discussion of additional data and methods that would allow us to answer

the question as to whether the Peña Nieto vote buying scheme was successful in Mexico's 2012 Presidential Election.

2 Replication

2.1 Reconsidering Distance

We began our analysis with a re-estimation of the author's initial models. This is in line with the belief that there is likely to be more differences in the utility of the gift cards at a shorter distance than higher distances. Given that the results differ as we change the measures of distance and the model, we hold that the original analysis is model dependent. Our discretized approach allows us to capture this true dispersion of distance between the centroid of a precinct and Soriana stores.

To achieve this, we develop two new, non-linear measures of distance: coarsened quantiles and deciles.[2] The quantile method simply breaks up the distance metrics into four quantiles, while the deciles sort the distance metric into ten decile bins. While the range of distances included in the initial analysis spanned from under 1 km to 100 km away, we found that these decile and quantile bins were skewed toward shorter distances. In fact, the 75th percentile mark was 4.78km. This suggests that the bulk of the population lives within a close distance to a Soriana store.

Notably, once we coarsen distance we run into a problem of collinearity. Here, we

[2]The authors also estimate the models linearly using another transformed distance metric, log distance. The results for this measure closely align with proximity, as both log distance and proximity place higher penalties on further distances. These results are found in appendix part 3 (heading 6.3).

find that in each coarsened model, the regression breaks down for the interaction term between the variables `HighTurnout` and `PRDstr`. `HighTurnout` is a binary variable where `HighTurnout` = 1 if turnout is greater than one standard deviation above the mean. `PRDstr` is also a binary variable, which is equal to 1 if a municipality voted for the PRD candidate by more than 50% in 2009. The fact that `HighTurnout` and `PRDstr` are collinear is substantively interesting, as these two variables are critical to the author's initial hypothesis that the vote buying scheme increased vote share for the PRI in the opposing PRD strongholds (`PRDstr`) where there was a high turnout (`HighTurnout`). For regression to break down here due to the collinearity issue means that we cannot get estimates of these variables.[3]

Tables 1 & 2 show the breakdown of joint `PRDstr` and `HighTurnout` precincts up to the author's initial distance cutoff point of 20 km using quantile and decile coarsening. In each, we see that the coarsened distance finds cases of 0 high turnouts in PRD strongholds for many close-range distances. Further, joint `HighTurnout` and `PRDstr` cases comprise less than 1% of the entire 11,000-observation dataset. Moreover, of these existing cases, we notice that there are only a handful of PRD strongholds with high voter turnout under 5km away.

Critical to the paper is this assumption that a person in a high turnout, PRD stronghold who lives closer to a Soriana store would value the gift card more (and therefore be more willing to cast their vote for a PRI candidate) than someone who lives further away. Yet, only one high turnout stronghold existed under 5 km from a Soriana store (Table 1).

[3]Paying close attention to the measurement of our variables, we consider versions of the model using new thresholds for what qualifies as a "high turnout" district. Here we find that varying the threshold of "high turnout" does not lead to substantive changes in the results of our model. You may find the results of this estimation in part one of the appendix (section 6.1).

Table 1: `highTURNOUT*PRDstr` within Quantile Bins

(0.0109,1.59]	(1.59,2.57]	(2.57,4.78]	(4.78,20]
0	0	1	47

Table 2: `highTURNOUT*PRDstr` within Decile Bins

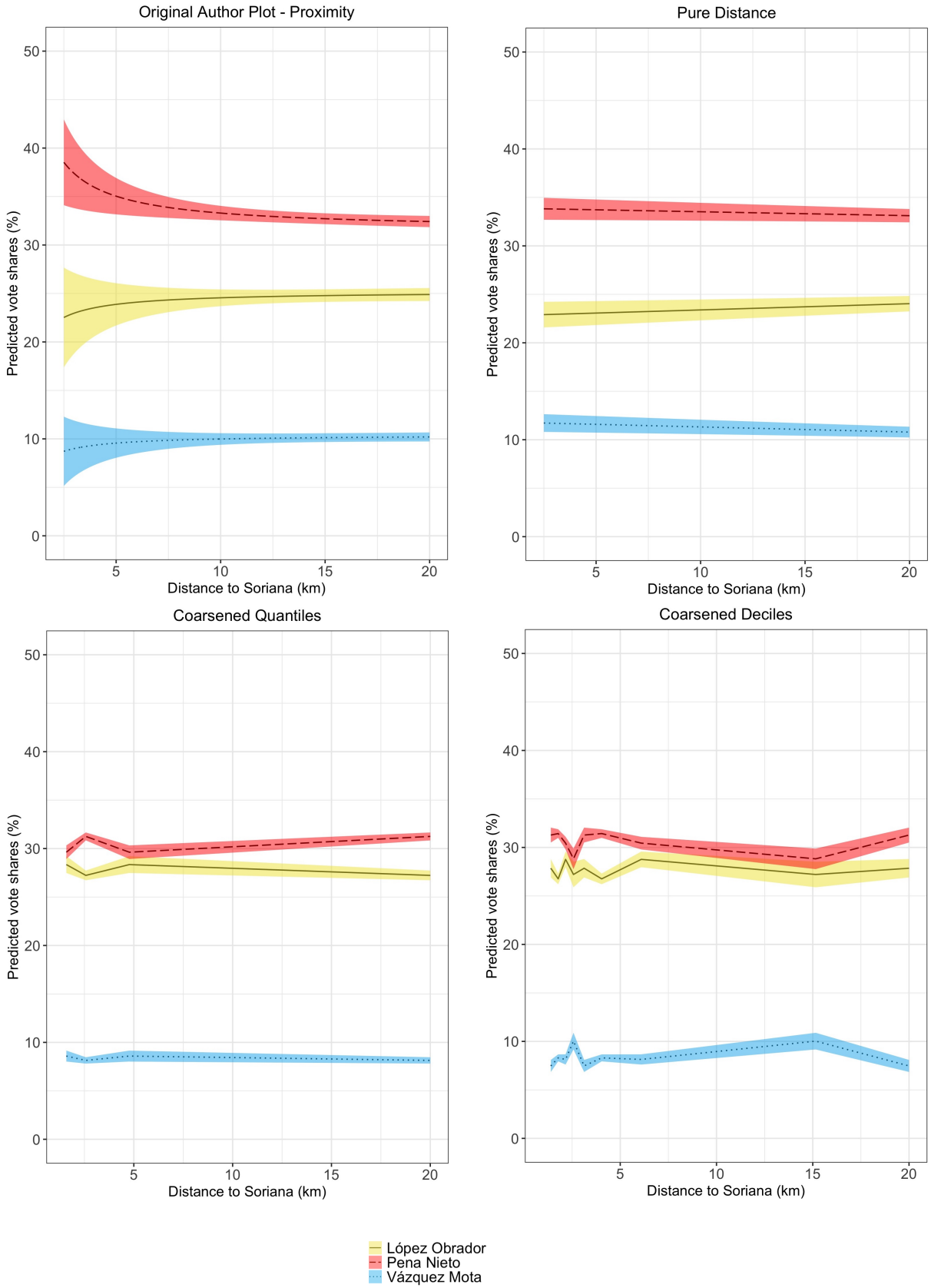
(.0109, .947]	(0.947,1.4]	(1.4,1.78]	(1.78,2.16]	(2.16,2.57]	(2.57,3.12]	(3.12,4.04]	(4.04,6.09]	(6.09,15.2]	(15.2,20]
0	0	0	0	0	1	0	4	31	12

The purported vote shifts in the precincts closest to a Soriana represent some of the most dramatic findings in the initial paper (see Panel 1 of Figure 1). Here, Cantú estimates a high effect of vote buying for those living in high turnout PRD strongholds and under 5km away from a Soriana store. But, given that there is only one such precinct fitting these conditions, we contend that it is difficult to draw these conclusions.

This provides further evidence that the proximity assumption for the distance measure may not be correct, as it allows us to extrapolate the behavior of those living *far* from a Soriana to those living *close by* a store, despite minimal real-world examples of this phenomenon. Here we propose a need to better account for varying utilities at different distances from the store through relaxing our assumptions and adopting a nonparametric approach to distance.

This practical finding has serious substantive implications for the author's model, as it challenges the assumption that we can use distance to Soriana as a proxy for the efficacy of PRI vote buying in PRD strongholds. Put simply, we are extrapolating a rare phenomenon (under 1% of all cases) that occurs at higher distances from a Soriana store to all distance ranges. We contend that because these strongholds are so rare, and for many coarsened bins do not exist, it is not possible to make this extrapolation.

Figure 1: Vote Share Estimates Shift with Distance Measure



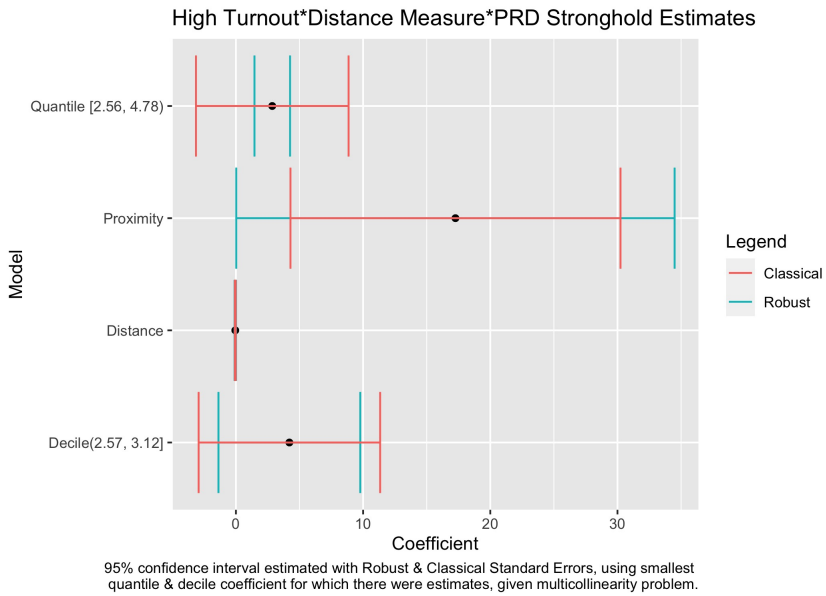
2.2 Relaxed Assumptions Reveal Model Dependence

In addition to the collinearity problem, a shift in the measure of distance changes the results of the model drastically. On page 8 (Figure 1) we present four plots, reflecting candidate vote shares using different measurements of distance. For the plots in which a collinearity problem emerged, we removed the `distance*highTURNOUT*PRDstr` interaction term. Instead, we interact distance solely with `PRDstr` to provide visualizations. A tabular copy of the results of these models is provided in the appendix.

In Figure 1, not only does the initial PRI (Peña Nieto) vote share at the closest-distance drop from the author's initial estimate of 38.5% to as low as 29% in the coarsened quantile model, but this distance-influenced effect on Lopez Obrador vote share goes away entirely or changes in nature through different measures of distance. In the coarsened decile model it appears that, at the shortest distances, one could demonstrate a negative effect of vote buying on Peña Nieto's vote share. If we turn to the coarsened quantile model, the measure of distance suggests a slight vote bump in short (under 5km) ranges though, as demonstrated in Table 1, this is an extrapolation as there are no observations with both high turnout and a PRD stronghold within these short ranges.

Notably, in both of the coarsened models, these confidence intervals of the Lopez Obrador and Peña Nieto vote shares overlap at some points, reflecting the inability to distinguish whether distance to a Soriana is driving a vote difference for each candidate. Still, we note that by relaxing assumptions the confidence intervals drastically shrink in both the coarsened and the traditional distance models. This reflects smaller standard errors and more precise estimates of our quantities of interest under relaxed assumptions.

Figure 2: Improved Estimates with Distance Measure



We also note that the Robust Standard Errors in the original models, using proximity, were nearly twice the size of the Classical Standard Errors, providing further evidence of model dependence (King & Roberts, 2015). Here we find that the pure distance and coarsened models eliminate the discrepancy between robust and classical standard errors. This is visualized in Figure 2, in which it is evident that, of the estimates, the proximity measure appears to produce both biased and inefficient results in comparison to other distance measures.

The findings in Figure 1 & 2 suggest that either a linear pure-distance measure or coarsened decile measure of distance reduces the dissonance between Classical & Robust Standard errors, minimizes bias and the standard errors, and, as such, minimizes model dependence. It is notable that under either of these models there is no clear positive

distance-driven effect of vote buying in high-turnout, PRD strongholds. The estimated 17.25 percentage point increase for this interaction between proximity and these high-turnout, PRD stronghold areas, which is significant in the initial study (though, barely, with the 95% confidence interval ranging from .026 to 34.49), dissolves when we use new measures of distance. Encompassing 0 in almost all cases, thereby suggesting a negative effect of vote buying in these high turnout opposition strongholds, the interacted coefficient actually has a slight (-.049 percentage point) and significant negative effect on Peña Nieto vote share on the pure distance model.

2.3 Exogeneity Questions

Given this extrapolation between long- and short-distance trends, we raise the question of whether the use of distance to a Soriana store as an independent variable is simply a proxy for urban versus rural residence, a division that may be correlated with other political beliefs. In the paper, the author says that he controls for urban or rural residence, but when we examined the regression, this involved controlling at the municipality level. Municipalities in the State of Mexico are quite large, often exceeding 100 square miles.[4]

As a result, it's likely that controlling for municipality does not accurately control for urban versus rural, as a single municipality can contain both urban and rural areas. This means that municipality-level controls cannot account for highly-local trends, such as whether one has a Soriana store within walking distance or 20km away. We investigate this further below, in Figure 3, which examines how distance to a Soriana store also correlates with beliefs, so it cannot be considered as an exogenous variable to measure the impact of

[4]Click here for more information on Mexican municipalities

vote buying.

With the understanding that the current estimation of distance induces model dependence, we turn to the central assumption: that distance is exogenous to voter preference. Figure 3 (page 13) is an extension and replication of Figure 1 in the author's original paper, which tests for this potential endogeneity.

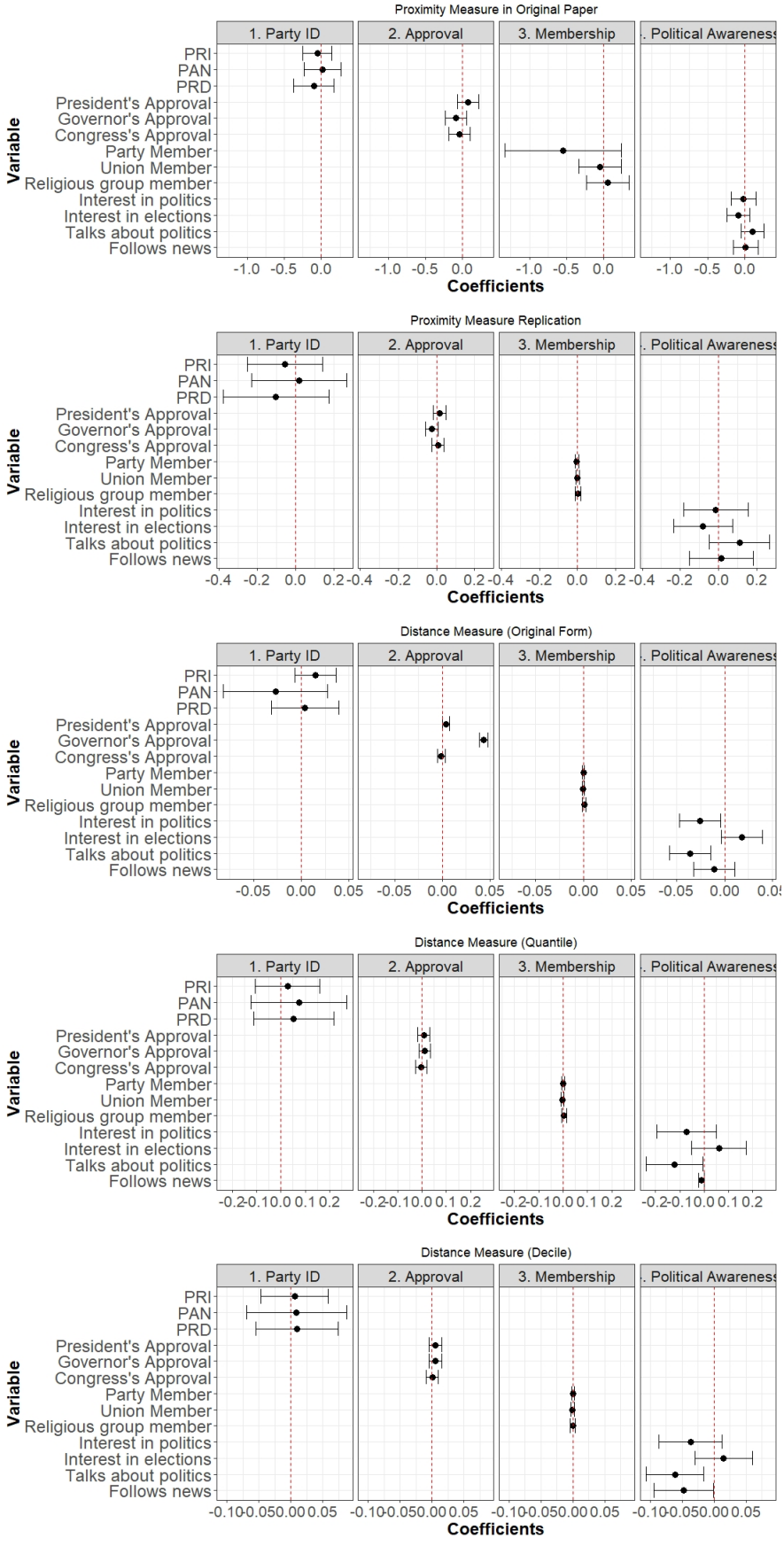
The first row is the original figure, the second is our replicated figure (with no changes in codes or data). Both two rows use proximity as a measurement of gift card values. Notably, here, our replication of the initial figure without changing any of the author's initial assumptions, code, or data finds far smaller confidence intervals for the correlation of distance and party membership, and far wider confidence intervals for the correlation between distance and political awareness.

We believe this variation in results for this exogeneity test is due to the unexplained difference in the number of observations found in the initial and replication data. In the article, the author cites that there are 10,567 observations in the dataset. The replication code provided has 11,644 observations, though there are no hints within the author's initial code as to why and from where these 1000 observations are trimmed.

For rows 3 to 5 of this figure we re-estimate the model with distance, rather than proximity, as a measurement of gift card values. Rows 3 to 5 use pure distance, distance quantiles, and distance deciles for measurement, respectively.

We can see that, in row 3, when replicating the author's initial test with traditional "distance," the finding that proximity is exogenous may not hold. For the pure distance model, distance is positively correlated with approval for the president and the governor.

Figure 3: Correlation between Distance and Political Beliefs, by Distance Measure



It is also negatively correlated with political awareness. Though the results for political approval may not be robust for distance quantile and decile models, we still find that distance is negatively correlated with political awareness, e.g., people's discussion about politics and people's following of political news.

Therefore, the distance to Soriana may not be used as a variable exogenous to political attitudes and political behavior that reflects people's expected value of gift cards (and the ability to have their vote bought).

3 Does vote buying work?

3.1 Additional Substantive Threats to Measuring Vote Buying

Given the challenges in instrumenting distance as a proxy for one's valuation of a vote-buying attempt, and subsequent willingness to have your vote bought, it is important to take a step back and look at the validity of the claims being made in the paper. Activists claimed that Peña Nieto's campaign distributed cards worth between 100 and 1,000 pesos (roughly 8 USD to 80 USD) to 1.8 million voters in Mexico state in the days prior to the election (Nichter & Palmer-Rubin, 2015). In 2019, the average Mexican made 17,595 USD, or around 8.45 USD an hour (OECD, 2017). It's possible to imagine that perhaps a gift card worth, on the lower end, an hour's wage, might not be valuable enough to swing someone's vote, but on the upper end, the gift cards could be worth more than an average day's wage, which would likely be meaningful to most. However, without better data on the gift card's value, it's impossible to be certain to what degree recipients would value the cards, and they likely had a mixed effect among recipients.

Beyond the value of the cards among recipients, there also remains the possibility that recipients might defect and vote for another candidate. In the Mexico 2012 Panel Study, 87 percent of respondents reported believing that their vote choice remains secret (Greene, 2016). If 87 percent of the recipients believed that their votes were secret, even if the value of the gift card was contingent on Peña Nieto's victory, it's reasonable to imagine that some might defect and vote for their favored candidate.

Finally, the use of centroids in the distance calculation plausibly threatens the validity of the results. Because an individual's distance from a Soriana store is measured as the distance from the center of their precinct to the closest Soriana store, there's a possibility of significant variance between the individual's true distance from the store and the recorded centroid distance. Given these contingencies, there are multiple places where the effort to quantify the effect of the vote-buying effort could have broken down, making it difficult to make sense of the Peña Nieto scheme in this analysis.

3.2 Can we estimate the effect of vote buying?

By reducing the assumptions of the author's original model, we have found that we cannot successfully instrument distance to measure the effect of vote buying. This finding, paired with the additional secrecy of the Mexican ballot and lack of data on the gift card's worth, leads us to ask: under what circumstances *could* we measure the effect of PRI candidate Enrique Peña Nieto's vote buying scheme? We agree with Cantú that whether or not this vote buying attempt was successful is a crucial question, with serious substantive implications as to whether politicians in nominally democratic countries can use handouts or rewards to persuade voters.

In order to answer this question, we propose a few routes by which we could definitely measure the effect of vote buying. First, acquiring additional observational data would allow further insight into the success of the Peña Nieto campaign efforts. Here, we would propose working with Soriana to acquire anonymized data of gift card sales and returns. This would allow insight into the number of gift cards typically bought and sold and whether there was a substantive increase in the number of gift cards in circulation at the time of the election. We could eliminate distance to a Soriana store as a proxy for someone's valuation of the gift card, instead, measuring directly how many gift cards, at what value, and which store was redeemed. In turn, we could directly regress change in gift card sales and exchanges against the vote share of a given precinct to see if the PRI and Peña Nieto's vote buying scheme had an effect.

Of course, it may be challenging to acquire this observational data due to potential challenges in gaining Soriana's cooperation. Here, we turn to the tools of game theory, where the literature on vote buying offers some potential mechanisms by which we could answer this question. Notably, Simeon Nichter (2008) argues that, due to the common nature of the secret ballot and subsequent inability to monitor the direct success of a vote buying attempt, vote buying is most effective when parties pursue traditionally low-turnout populations with similar ideological positions. Nichter argues that party machines can measure the success of their efforts by checking to see whether or not the targeted voters choose to vote. Thus, perhaps the success of vote buying is not measured by these high turnout PRD strongholds, as Cantú suggests, but rather by an increase in turnout in low turnout, PRI-strongholds. We note that the interacted coefficient for turnout level and PRI-stronghold is not significant in any of our models,[5] which would offer further support for a theory of no effect of vote buying on these "passive" constituencies.

[5]See the full results of our models in the Appendix, section 6.3.

Notably, Nichter also suggests the need for a mixed-method approach to estimate whether vote buying and turnout buying schemes are effective. In order to concretely ascertain whether a vote buying scheme may have an effect, we suggest that conducting interviews or a survey with Mexican voters may provide the clear qualitative counterpoint necessary to triangulate the effect of vote buying.

In fact, this discrepancy between the insight that a quantitative and qualitative study of vote buying yields is the subject of a 2012 *American Journal of Political Science* article by Gonzalez-Ocantos, et. al., in which the authors attempt to resolve this divergence through a survey-based list experiment. In turn, they find support for the efficacy of vote buying, despite a strong social desirability bias in a respondent's willingness to acknowledge participating in a vote buying scheme in Nicaragua. While only 2% of respondents acknowledged having their vote bought when asked directly, 24% of respondents recognized participating in vote buying through a list experiment. Through conducting a similar experiment in the Mexican context, we consider whether we may be better able to measure the utility of vote buying in the 2012 election.

4 Conclusion

Through solely relaxing the initial assumptions as to how we measure distance, we found that we cannot scientifically measure the effect of vote buying in the Mexican context. From our tests, we argue that one must take a careful approach to distance when using it as a proxy for one's political beliefs. As our final tests demonstrate, distances may not be truly exogenous to political beliefs. If we take either the less biased and more efficient pure distance or coarsened quantile models, we note that distance could be correlated with

politician approval (Figure 3, Row 3) and negatively correlated with political awareness (Figure 3, rows 3 and 4). We conclude that it is not possible to leverage distance to a 'point of redemption' as a measure of the voter-level utility of a vote buying effort.

A successful model for proving vote-buying based on distance ought to achieve two benchmarks: first, it must prove that distance is exogenous to voting behavior, and second, that vote swings towards the candidate in question are related to the voter's distance from a Soriana store. As illustrated above, the analysis does not meet the first benchmark. We found that the author's assumption that distance is exogenous to political beliefs does not hold when we applied other metrics of distance. Second, we did not find a convincing argument for the existence of vote-buying, given the dependence of the model's findings on the measure of distance it used. We believe that the shortfalls in the analysis are due to the insufficiency of the data currently available to answer this question. The varying values of the gift cards, the potential for voters to defect, and the inherent uncertainty of the centroid as a measure all work together to make it difficult to ascertain the precise effect of a vote-buying effort. As noted above, with additional qualitative and quantitative data, there exists a potential to answer this question, but not given the current information available.

5 Sources cited

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6 Appendix

6.1 Stronghold Indicator

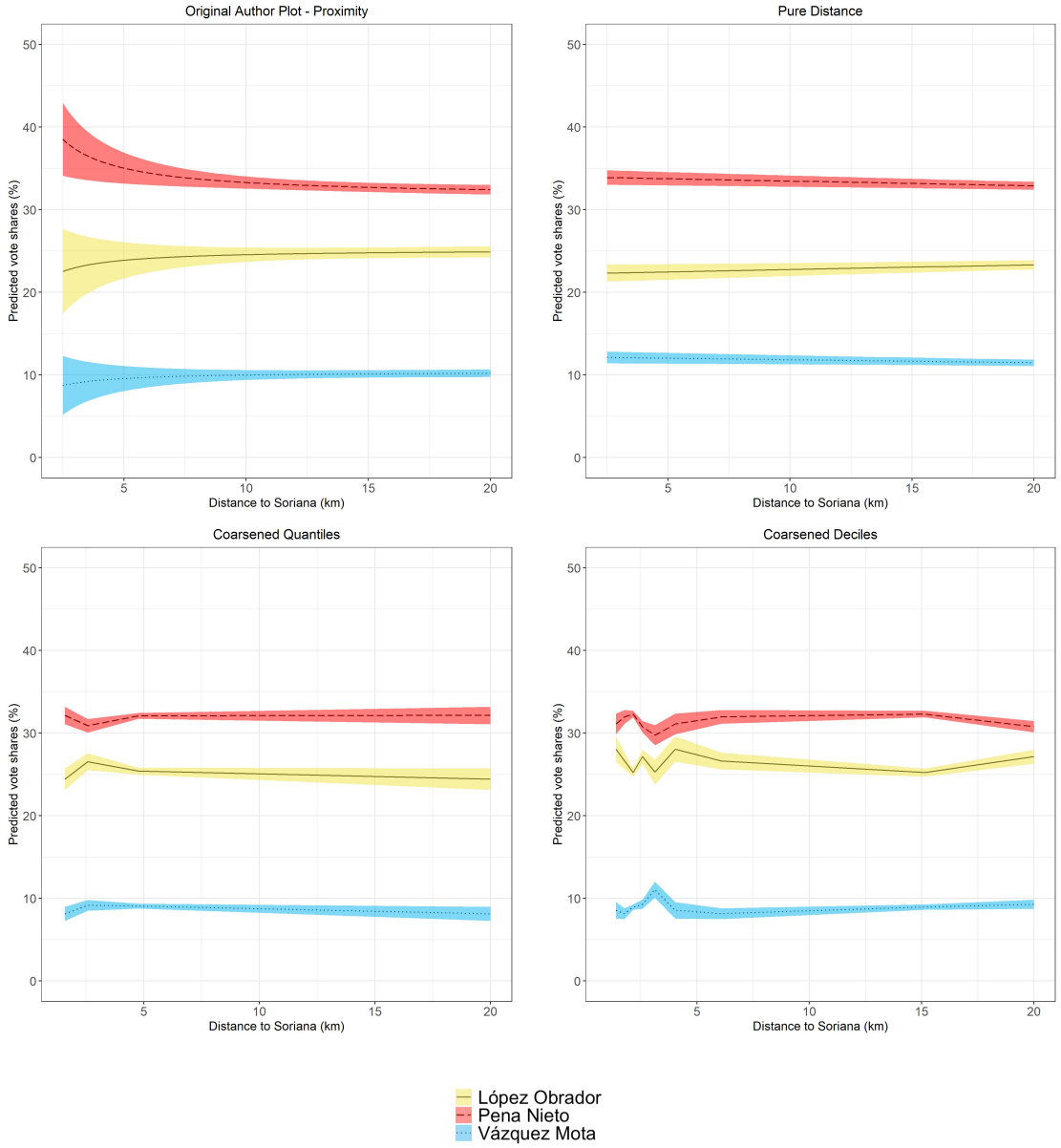
In the original paper, Cantú uses taking up a majority of votes (i.e., more than 50% of the vote share) as an indicator of one party's stronghold in a precinct. This strategy, however, may underestimate the number of strongholds because, in a multi-party system, it is hard for parties to maintain a majority of votes even in precincts where they face few challenges. As a robustness check, here we relax the requirement for strongholds: We code a precinct as stronghold if one party receives 10 more percentage points of the vote share than any other party.

Table 3 presents the comparison of stronghold shares among all precincts for each party before and after changing the threshold. We can see that the stronghold proportions increase hugely after we change the criteria to a 10 percent margin. However, in Figure 4, we replicate Figure 1 by using the new stronghold variables. The results turn out to be similar across graphs, which indicates that the measurement of strongholds may not affect main identification results too much.

Table 3: Stronghold Shares Before and After Changing Thresholds

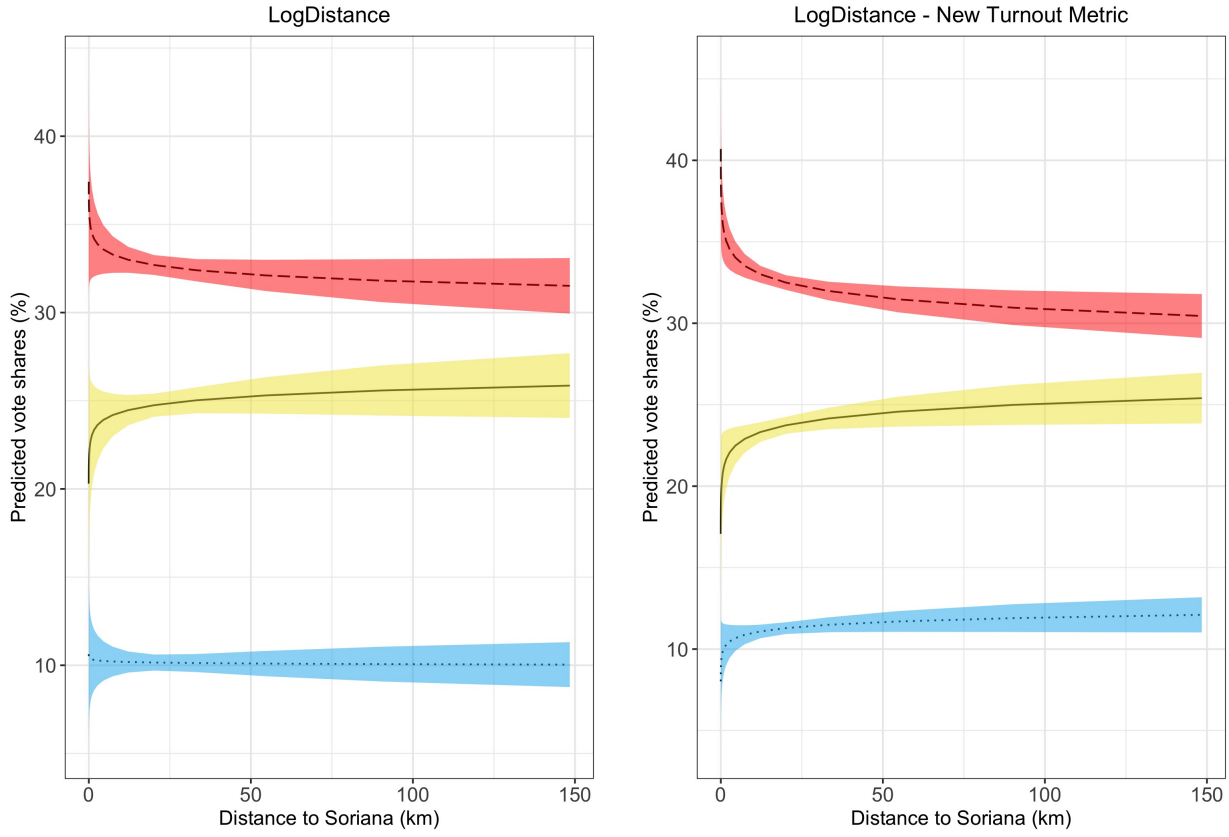
	PRI Stronghold	PRD Stronghold	PAN Stronghold
Original (Majority)	0.15	0.08	0.03
New (10% Margin)	0.30	0.27	0.09

Figure 4: Vote Share Estimates Shift with Distance Measure (New Stronghold Measures)



6.2 Log Distance Results

As noted in footnote 1, the authors also estimate the models linearly using another transformed distance metric, log distance. The results for this measure closely align with proximity, as both log distance and proximity place higher penalties on further distances. This reinforces our initial argument that, under certain assumptions on the nature of distance, we could find evidence of the vote buying scheme and therefore this finding is model dependent on our measure of distance.



6.3 Full Regression Results- Extension of Table 1 in Original Paper

	Model				
	Proximity	Distance	Quantile	Decile	Log
proximity	0.001				
	(0.017)				
distance		−0.059*			
		(0.025)			
Quantile(1.59,2.57]			−0.033		
			(0.101)		
Quantile(2.57,4.78]			−0.124		
			(0.129)		
Quantile(4.78,20]			−0.623*		
			(0.263)		
Decile(0.947,1.4]				0.007	
				(0.108)	
Decile(1.4,1.78]				0.041	
				(0.135)	
Decile(1.78,2.16]				0.022	
				(0.137)	
Decile(2.16,2.57]				−0.033	
				(0.155)	
Decile(2.57,3.12]				−0.014	
				(0.169)	
Decile(3.12,4.04]				−0.114	
				(0.203)	
Decile(4.04,6.09]				−0.474*	
				(0.209)	
Decile(6.09,15.2]				−0.285	
				(0.351)	

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Decile(15.2,20]				−1.269	
				(0.809)	
logdist					−0.149
					(0.089)
PRIstr	−0.903**	−0.887***	−0.513*	−0.433	−0.758**
	(0.300)	(0.253)	(0.260)	(0.304)	(0.270)
highTURNOUT	−0.021	−0.759	−1.252*	−1.330*	−1.363**
	(0.388)	(0.393)	(0.524)	(0.635)	(0.418)
PRDstr	−1.151***	−0.926***	−0.449	−0.474	−0.634*
	(0.277)	(0.245)	(0.324)	(0.288)	(0.295)
PANstr	2.038***	0.986	−0.690	−0.588	0.068
	(0.560)	(0.666)	(0.477)	(0.771)	(0.463)
PRI09a	0.626***	0.632***	0.615***	0.611***	0.619***
	(0.037)	(0.037)	(0.040)	(0.040)	(0.037)
PRD09a	−0.043	−0.040	−0.082*	−0.083*	−0.049
	(0.036)	(0.035)	(0.035)	(0.034)	(0.035)
PAN09a	0.064	0.069	0.075*	0.077*	0.053
	(0.040)	(0.039)	(0.036)	(0.035)	(0.038)
PART09	−0.009	−0.013	−0.016	−0.016	−0.006
	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)
lnpop	−0.239	−0.244	−0.160	−0.173	−0.239
	(0.134)	(0.132)	(0.111)	(0.110)	(0.128)
P18	2.532	2.804	1.531	1.559	2.313
	(2.489)	(2.442)	(2.291)	(2.244)	(2.461)
P65	12.219***	11.170***	9.134***	8.849***	12.570***
	(2.736)	(2.639)	(2.342)	(2.240)	(2.696)
area	0.046*	0.048**	0.065***	0.064**	0.045*
	(0.018)	(0.019)	(0.019)	(0.020)	(0.018)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
density	−0.00000	−0.00000	−0.00000	−0.00000	−0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
INDIGENOUS	−2.308*	−2.196*	−4.757	−3.898	−2.327*
	(1.138)	(1.105)	(4.106)	(3.870)	(1.105)
CATHOLIC	−1.560	−1.513	−1.977	−1.794	−1.453
	(2.128)	(2.148)	(2.427)	(2.414)	(2.127)
NONRELIGIOUS	−10.357*	−10.208*	−10.203*	−9.826*	−10.338**
	(4.050)	(4.068)	(4.100)	(3.952)	(3.985)
EDUCATION	0.479*	0.473*	0.382*	0.363	0.479*
	(0.201)	(0.201)	(0.194)	(0.196)	(0.198)
POSTEDUC	−10.532***	−10.486***	−8.951***	−8.745***	−10.321***
	(1.974)	(1.992)	(1.788)	(1.799)	(1.946)
ILLITERACY	−6.958	−4.632	2.417	2.772	−5.729
	(3.985)	(3.768)	(5.850)	(5.960)	(3.784)
PROM_HNV	0.341	0.474	1.333***	1.364***	0.417
	(0.502)	(0.475)	(0.379)	(0.370)	(0.480)
PEAprop	5.244*	4.940*	3.056	2.960	5.031*
	(2.372)	(2.407)	(2.047)	(2.053)	(2.415)
PEAfemale	−2.102	−1.961	−0.576	−0.810	−1.995
	(2.556)	(2.581)	(2.140)	(2.166)	(2.612)
NOINSURANCE	0.861	1.121	1.063	1.000	1.162
	(1.001)	(0.977)	(0.895)	(0.899)	(0.973)
FEMALEJEFA	2.830*	2.820*	3.473**	3.465**	2.827*
	(1.109)	(1.123)	(1.096)	(1.100)	(1.109)
PERROOM	−0.293	−0.529	−1.847*	−1.916*	−0.363
	(0.956)	(0.922)	(0.840)	(0.849)	(0.920)
DIRTFLOOR	−2.391	−2.517	−1.572	−1.300	−2.389
	(2.362)	(2.379)	(2.637)	(2.642)	(2.452)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
SERVICES	−0.424	−0.371	−1.198	−1.124	−0.376
	(0.650)	(0.643)	(0.683)	(0.673)	(0.638)
NO_SERVICES	−0.755	−1.672	−4.767	−4.094	−1.202
	(2.372)	(2.283)	(4.227)	(3.951)	(2.325)
CAR	0.242	0.383	0.041	−0.044	0.397
	(1.039)	(0.990)	(0.966)	(0.976)	(0.998)
CELULAR	0.581	0.477	−0.245	0.015	0.605
	(1.605)	(1.545)	(0.952)	(0.914)	(1.565)
INTERNET	2.031	2.037	1.919	1.903	2.051
	(1.134)	(1.132)	(1.033)	(1.016)	(1.134)
ACOLMAN	−0.524	−0.620			−0.082
	(1.044)	(1.568)			(1.064)
ACULCO	3.122***	2.890***	5.267***	5.003***	2.927***
	(0.646)	(0.815)	(0.848)	(1.036)	(0.652)
ALMOLOYA DE ALQUISIRAS	3.541***	1.925			2.079***
	(0.542)	(1.783)			(0.606)
ALMOLOYA DE JUAREZ	9.076***	8.853***	8.436***	8.338***	9.451***
	(0.791)	(1.321)	(0.550)	(0.706)	(0.824)
ALMOLOYA DEL RIO	10.665***	10.563***	10.592***	10.358***	10.946***
	(0.936)	(1.356)	(0.576)	(0.604)	(0.915)
AMANALCO	−1.202*	−1.458	−0.520	−0.672	−1.143
	(0.575)	(0.985)	(0.798)	(0.817)	(0.597)
AMATEPEC	0.045	0.906			−0.104
	(1.174)	(1.112)			(1.141)
AMECAMECA	−1.609	−1.471	−0.273	0.330	−1.425
	(1.031)	(1.375)	(0.301)	(0.653)	(1.037)
APAXCO	2.487***	2.403*	2.106***	2.194***	2.639***
	(0.647)	(1.087)	(0.476)	(0.634)	(0.640)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
ATENCO	−3.469**	−3.720*	−2.945***	−2.970***	−2.906*
	(1.109)	(1.686)	(0.350)	(0.404)	(1.168)
ATIZAPAN	6.764***	6.676***	6.437***	6.184***	7.189***
	(0.833)	(1.277)	(0.608)	(0.649)	(0.807)
ATIZAPAN DE ZARAGOZA	−5.324***	−5.969***	−5.925***	−5.934***	−4.913***
	(0.835)	(1.481)	(0.520)	(0.503)	(0.916)
ATLACOMULCO	7.154***	7.156***			7.235***
	(0.477)	(0.664)			(0.475)
ATLAUTLA	−3.666***	−3.205**			−3.326***
	(0.886)	(1.138)			(0.921)
AXAPUSCO	8.898***	8.772***	11.334***	12.247***	8.748***
	(0.882)	(1.123)	(0.965)	(1.192)	(0.897)
AYAPANGO	3.271***	3.261*	3.897***	4.301***	3.409***
	(0.976)	(1.366)	(0.384)	(0.656)	(0.955)
CALIMAYA	5.849***	5.711***	5.519***	5.459***	6.305***
	(0.733)	(1.285)	(0.459)	(0.462)	(0.762)
CAPULHUAC	3.248***	2.932*	3.430***	3.338***	3.810***
	(0.889)	(1.417)	(0.476)	(0.497)	(0.946)
CHALCO	−2.481*	−2.984	−2.300***	−2.321***	−1.953
	(1.068)	(1.638)	(0.437)	(0.451)	(1.119)
CHAPA DE MOTA	−0.873	−1.070			−1.007
	(0.544)	(0.788)			(0.615)
CHAPULTEPEC	1.384	1.455	2.443***	3.178***	2.171**
	(0.743)	(1.343)	(0.443)	(0.461)	(0.796)
CHIAUTLA	2.655*	2.541	3.473***	3.272***	3.143**
	(1.139)	(1.654)	(0.299)	(0.342)	(1.137)
CHICOLOAPAN	−1.577	−2.176	−1.347**	−1.328**	−1.142
	(1.054)	(1.673)	(0.414)	(0.462)	(1.130)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
CHICONCUAC	-6.658^{***}	-6.796^{***}	-5.919^{***}	-6.037^{***}	-6.081^{***}
	(1.039)	(1.580)	(0.376)	(0.414)	(1.057)
CHIMALHUACAN	-3.461^{***}	-4.119^{*}	-3.726^{***}	-3.688^{***}	-3.111^{**}
	(1.021)	(1.657)	(0.634)	(0.643)	(1.117)
COACALCO DE BERRIOZABAL	-4.429^{***}	-5.062^{**}	-4.662^{***}	-4.691^{***}	-4.036^{***}
	(0.915)	(1.585)	(0.481)	(0.465)	(1.024)
COATEPEC HARINAS	1.368^{*}	1.522			1.253
	(0.643)	(0.787)			(0.742)
COCOTITLAN	-0.911	-0.959	-0.161	-0.624	-0.106
	(0.921)	(1.492)	(0.418)	(0.548)	(0.952)
COYOTEPEC	-4.855^{***}	-5.219^{***}	-5.039^{***}	-5.290^{***}	-4.251^{***}
	(0.861)	(1.453)	(0.355)	(0.411)	(0.927)
CUAUTITLAN	-4.048^{***}	-4.611^{**}	-4.310^{***}	-4.254^{***}	-3.406^{***}
	(0.855)	(1.531)	(0.470)	(0.480)	(0.979)
CUAUTITLAN IZCALLI	-7.184^{***}	-7.790^{***}	-7.575^{***}	-7.558^{***}	-6.619^{***}
	(0.832)	(1.507)	(0.523)	(0.519)	(0.933)
DONATO GUERRA	6.445^{***}	6.117^{***}			6.302^{***}
	(0.876)	(0.968)			(0.819)
ECATEPEC DE MORELOS	-3.394^{***}	-4.063^{**}	-3.730^{***}	-3.718^{***}	-3.022^{**}
	(0.904)	(1.560)	(0.499)	(0.496)	(0.982)
ECATZINGO	5.718^{***}	5.668^{***}			5.444^{***}
	(1.029)	(1.241)			(1.076)
EL ORO	1.886^{***}	1.605^{**}			1.445^{***}
	(0.279)	(0.490)			(0.351)
HUEHUETOCA	-0.124	-0.570	-0.208	-0.237	0.676
	(0.770)	(1.430)	(0.527)	(0.565)	(0.868)
HUEYPOXTLA	6.933^{***}	6.652^{***}	6.636^{***}	6.608^{***}	7.159^{***}
	(0.903)	(1.345)	(0.648)	(0.690)	(0.928)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
HUIXQUILUCAN	-3.974^{***}	-4.270^{**}	-4.344^{***}	-4.543^{***}	-3.637^{***}
	(0.835)	(1.389)	(0.365)	(0.380)	(0.878)
ISIDRO FABELA	9.532^{***}	9.452^{***}	9.893^{***}	9.631^{***}	9.813^{***}
	(0.960)	(1.420)	(0.517)	(0.716)	(0.952)
IXTAPALUCA	-4.694^{***}	-5.266^{**}	-4.740^{***}	-4.759^{***}	-4.235^{***}
	(0.974)	(1.618)	(0.468)	(0.454)	(1.037)
IXTAPAN DE LA SAL	-4.855^{***}	-4.892^{***}			-5.161^{***}
	(0.709)	(0.708)			(0.696)
IXTAPAN DEL ORO	0.615	0.447			0.308
	(0.753)	(0.805)			(0.732)
IXTLAHUACA	11.509^{***}	11.109^{***}	10.619^{***}	10.371^{***}	12.152^{***}
	(0.587)	(1.139)	(0.733)	(0.787)	(0.680)
JALTENCO	2.045^{*}	1.550	1.852^{***}	1.787^{***}	2.470^{**}
	(0.818)	(1.452)	(0.381)	(0.368)	(0.887)
JILOTEPEC	1.312	1.202	-3.101^{***}	-2.114^{**}	1.173
	(0.846)	(1.054)	(0.322)	(0.740)	(0.832)
JILOTZINGO	4.292^{***}	4.132^{**}	4.468^{***}	4.618^{***}	4.576^{***}
	(0.973)	(1.443)	(0.414)	(0.492)	(0.969)
JIQUIPILCO	8.009^{***}	7.759^{***}	7.646^{***}	7.264^{***}	8.244^{***}
	(0.693)	(1.169)	(0.516)	(0.588)	(0.719)
JOCOTITLAN	6.344^{***}	6.268^{***}	5.881^{***}	5.887^{***}	6.620^{***}
	(0.505)	(0.893)	(0.601)	(0.699)	(0.524)
JOQUICINGO	6.600^{***}	6.340^{***}	13.864^{***}	14.874^{***}	6.572^{***}
	(0.788)	(1.035)	(0.809)	(1.040)	(0.740)
JUCHITEPEC	-0.203	-0.307	0.030	0.614	-0.088
	(0.932)	(1.325)	(0.491)	(0.751)	(0.938)
LA PAZ	-4.511^{***}	-5.106^{**}	-4.395^{***}	-4.406^{***}	-4.049^{***}
	(0.924)	(1.560)	(0.437)	(0.439)	(0.995)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
LERMA	2.469**	2.304	2.355***	2.431***	2.867***
	(0.750)	(1.267)	(0.319)	(0.367)	(0.778)
LUVIANOS	−4.817***	−3.244**			−4.608***
	(1.138)	(1.051)			(1.209)
MALINALCO	1.543***	1.359			1.367**
	(0.434)	(0.723)			(0.467)
MELCHOR OCAMPO	0.036	0.090	0.945*	0.276	0.835
	(0.887)	(1.493)	(0.423)	(0.485)	(0.941)
METEPEC	−0.418	−0.673	−0.284	−0.251	0.706
	(0.796)	(1.495)	(0.544)	(0.525)	(0.982)
MEXICALTZINGO	0.421	0.343	0.704*	1.265*	1.103
	(0.840)	(1.454)	(0.333)	(0.578)	(0.881)
MORELOS	5.619***	5.362***	4.079***	3.787***	5.590***
	(0.611)	(0.881)	(0.780)	(0.996)	(0.632)
NAUCALPAN DE JUAREZ	−5.010***	−5.652***	−5.267***	−5.270***	−4.464***
	(0.912)	(1.537)	(0.662)	(0.636)	(0.986)
NEXTLALPAN	6.807***	6.612***	6.945***	6.759***	7.313***
	(0.968)	(1.483)	(0.463)	(0.480)	(0.999)
NEZAHUALCOYOTL	−3.551***	−4.190**	−3.808***	−3.787***	−3.173**
	(0.998)	(1.610)	(0.504)	(0.494)	(1.065)
NICOLAS ROMERO	−4.223***	−4.830***	−4.641***	−4.662***	−3.786***
	(0.808)	(1.459)	(0.425)	(0.438)	(0.894)
NOPALTEPEC	1.522*	1.368			1.399
	(0.776)	(1.042)			(0.763)
OCOYOACAC	7.545***	7.411***	7.910***	7.702***	8.114***
	(0.903)	(1.444)	(0.466)	(0.488)	(0.940)
OCUILAN	−3.792***	−4.064***	−3.753***	−3.544***	−3.815***
	(0.762)	(1.104)	(0.875)	(0.971)	(0.761)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
OTUMBA	1.370	1.271	1.754*	2.681**	1.346
	(0.956)	(1.248)	(0.737)	(0.951)	(0.971)
OTZOLOAPAN	2.542**	2.032*			1.892*
	(0.913)	(1.030)			(0.935)
OTZOLOTEPEC	3.185***	3.130*	2.848***	2.749***	3.469***
	(0.831)	(1.258)	(0.360)	(0.437)	(0.849)
OZUMBA	−0.370	0.145			0.134
	(0.843)	(1.142)			(0.876)
PAPALOTLA	−0.320	−0.411	0.007	0.051	0.274
	(0.873)	(1.444)	(0.388)	(0.375)	(0.894)
POLOTITLAN	11.667***	11.510***	14.043***	12.896***	11.649***
	(0.743)	(0.989)	(0.646)	(0.965)	(0.715)
RAYON	10.045***	9.961***	10.105***	9.845***	10.300***
	(0.840)	(1.281)	(0.413)	(0.440)	(0.824)
SAN ANTONIO LA ISLA	1.841	1.834	2.049***	1.754***	2.241*
	(0.969)	(1.437)	(0.443)	(0.457)	(0.946)
SAN FELIPE DEL PROGRESO	7.168***	6.945***	4.833***	4.682***	7.132***
	(0.311)	(0.569)	(1.300)	(1.286)	(0.363)
SAN JOSE DEL RINCON	4.684***	4.629***			4.545***
	(0.374)	(0.536)			(0.420)
SAN MARTIN DE LAS PIRAMIDES	−3.331***	−3.407*	−3.336***	−2.639***	−3.245***
	(0.957)	(1.336)	(0.358)	(0.656)	(0.958)
SAN MATEO ATENCO	6.404***	5.857***	6.021***	5.981***	7.208***
	(0.725)	(1.383)	(0.550)	(0.581)	(0.835)
SAN SIMON DE GUERRERO	9.406***	9.299***			9.106***
	(1.324)	(1.279)			(1.298)
SANTO TOMAS	−0.733	−0.760			−1.068
	(0.696)	(0.671)			(0.675)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
SOYANIQUILPAN DE JUAREZ	−0.189	−0.141	0.439	1.721	0.061
	(0.643)	(1.035)	(1.141)	(1.518)	(0.681)
SULTEPEC	−1.382	−2.151			−2.122*
	(0.771)	(1.147)			(0.824)
TECAMAC	−2.854***	−3.013*	−3.278***	−3.584***	−2.206**
	(0.725)	(1.324)	(0.454)	(0.479)	(0.780)
TEJUPILCO	−1.211	−0.147			−1.109
	(0.975)	(0.820)			(0.967)
TEMAMATLA	−2.348*	−2.391	−1.512***	−1.774***	−1.644
	(1.091)	(1.651)	(0.309)	(0.365)	(1.120)
TEMASCALAPA	−1.608*	−1.754	−2.119***	−2.051***	−1.234
	(0.761)	(1.264)	(0.564)	(0.566)	(0.784)
TEMASCALCINGO	4.770***	4.843***			4.695***
	(0.368)	(0.374)			(0.378)
TEMASCALTEPEC	0.325	0.126			0.098
	(0.579)	(0.729)			(0.611)
TEMOAYA	1.181*	1.122	2.514***	2.487***	1.482*
	(0.556)	(0.923)	(0.639)	(0.738)	(0.588)
TENANCINGO	−4.090***	−3.385***			−3.439***
	(0.667)	(0.901)			(0.696)
TENANGO DEL AIRE	0.505	0.525	1.457***	1.530***	0.867
	(1.019)	(1.497)	(0.407)	(0.396)	(1.017)
TENANGO DEL VALLE	0.431	0.407	2.581***	3.059***	0.885
	(0.760)	(1.171)	(0.420)	(0.621)	(0.802)
TEOLOYUCAN	−4.039***	−4.232**	−4.046***	−4.290***	−3.538***
	(0.930)	(1.492)	(0.236)	(0.264)	(0.973)
TEOTIHUACAN	−2.428**	−2.448	−2.416***	−2.154***	−2.156*
	(0.923)	(1.374)	(0.266)	(0.352)	(0.938)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
TEPETLAOXTOC	1.856	1.667	2.251***	2.344***	2.103*
	(0.998)	(1.525)	(0.480)	(0.610)	(1.016)
TEPETLIXPA	−3.990***	−3.682***			−3.559***
	(0.858)	(1.086)			(0.858)
TEPOTZOTLAN	−5.506***	−5.867***	−5.985***	−6.089***	−4.816***
	(0.689)	(1.338)	(0.453)	(0.529)	(0.764)
TEQUIXQUIAC	−2.720***	−2.855*	−3.501***	−4.006***	−2.317***
	(0.671)	(1.186)	(0.627)	(0.722)	(0.698)
TEXCALTITLAN	4.514***	4.383***			4.115***
	(0.578)	(0.782)			(0.702)
TEXCALYACAC	7.463***	7.422***	7.625***	7.997***	7.659***
	(0.862)	(1.262)	(0.495)	(0.585)	(0.841)
TEXCOCO	−9.577***	−10.070***	−9.340***	−9.305***	−9.057***
	(0.989)	(1.592)	(0.322)	(0.351)	(1.056)
TEZOYUCA	−1.041	−1.244	−0.565*	−0.785**	−0.508
	(1.135)	(1.671)	(0.229)	(0.276)	(1.184)
TIANGUISTENCO	2.041**	1.960	1.902***	1.872***	2.403***
	(0.656)	(1.138)	(0.516)	(0.514)	(0.663)
TIMILPAN	5.514***	5.222***			5.315***
	(0.359)	(0.554)			(0.374)
TLALMANALCO	1.412	1.461	1.652***	1.746***	2.031*
	(0.909)	(1.374)	(0.335)	(0.379)	(0.965)
TLALNEPANTLA DE BAZ	−4.202***	−4.826**	−4.653***	−4.659***	−3.719***
	(0.879)	(1.517)	(0.653)	(0.650)	(0.962)
TLATLAYA	−1.618	−1.068			−1.892
	(1.159)	(1.086)			(1.135)
TOLUCA	−1.921*	−2.247	−2.202***	−2.145***	−1.185
	(0.755)	(1.376)	(0.552)	(0.547)	(0.858)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
TONANITLA	2.354*	4.127*	4.918***	2.477**	4.490***
	(1.174)	(1.685)	(0.531)	(0.902)	(1.107)
TONATICO	2.697***	2.626**			2.240**
	(0.739)	(0.878)			(0.829)
TULTEPEC	0.374	−0.241	0.586	0.755	0.833
	(0.941)	(1.572)	(0.409)	(0.437)	(1.024)
TULTITLAN	−2.160*	−2.834	−2.377***	−2.373***	−1.783
	(0.999)	(1.650)	(0.656)	(0.656)	(1.085)
VALLE DE BRAVO	−3.940***	−3.773***			−4.042***
	(0.922)	(1.103)			(0.965)
VALLE DE CHALCO SOLIDARIDAD	−2.812**	−3.478*	−2.702***	−2.650***	−2.455*
	(1.022)	(1.653)	(0.512)	(0.533)	(1.105)
VILLA DE ALLENDE	7.689***	7.416***	3.896***	3.890***	7.562***
	(0.764)	(1.025)	(0.753)	(0.879)	(0.769)
VILLA DEL CARBON	1.840**	1.626	4.069***	3.886***	1.870**
	(0.647)	(0.997)	(0.843)	(1.034)	(0.659)
VILLA GUERRERO	9.458***	9.468***			9.329***
	(0.656)	(0.824)			(0.694)
VILLA VICTORIA	3.273***	3.045**	1.351	1.378	3.588***
	(0.404)	(0.955)	(0.847)	(0.855)	(0.488)
XALATLACO	0.277	0.127	−2.610***	−2.995**	0.746
	(0.652)	(0.974)	(0.721)	(1.022)	(0.654)
XONACATLAN	−3.797***	−3.913**	−3.958***	−4.110***	−3.611***
	(0.784)	(1.209)	(0.358)	(0.465)	(0.775)
ZACAZONAPAN	2.208	2.071*			1.890
	(1.138)	(1.035)			(1.101)
ZACUALPAN	0.251	0.419			0.036
	(0.925)	(0.987)			(0.985)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
ZINACANTEPEC	11.445***	11.234***	10.299***	10.104***	11.885***
	(0.614)	(1.134)	(0.515)	(0.542)	(0.665)
ZUMPAHUACAN	3.071***	2.813***			2.708***
	(0.561)	(0.813)			(0.680)
ZUMPANGO	0.921	0.724	−0.016	0.099	1.254
	(0.707)	(1.275)	(0.525)	(0.547)	(0.758)
ALVARO OBREGON	−5.842***	−6.394***	−6.038***	−6.081***	−5.502***
	(1.089)	(1.659)	(0.571)	(0.560)	(1.147)
AZCAPOTZALCO	−5.208***	−5.820***	−5.397***	−5.424***	−4.869***
	(1.039)	(1.638)	(0.593)	(0.575)	(1.110)
BENITO JUAREZ	−4.542***	−5.160**	−4.676***	−4.692***	−4.152***
	(1.064)	(1.633)	(0.636)	(0.625)	(1.128)
COYOACAN	−5.251***	−5.855***	−5.424***	−5.446***	−4.945***
	(1.252)	(1.763)	(0.876)	(0.860)	(1.317)
CUAJIMALPA DE MORELOS	−0.615	−1.003	−0.559	−0.670	−0.072
	(0.978)	(1.513)	(0.526)	(0.527)	(1.031)
CUAUHTEMOC	−3.894***	−4.468**	−4.054***	−4.078***	−3.542**
	(1.098)	(1.678)	(0.637)	(0.617)	(1.159)
GUSTAVO A. MADERO	−4.953***	−5.531***	−5.136***	−5.122***	−4.574***
	(1.072)	(1.640)	(0.663)	(0.649)	(1.131)
IZTACALCO	−5.093***	−5.676***	−5.290***	−5.292***	−4.743***
	(1.082)	(1.671)	(0.575)	(0.556)	(1.147)
IZTAPALAPA	−5.114***	−5.733***	−5.277***	−5.277***	−4.810***
	(1.100)	(1.686)	(0.626)	(0.614)	(1.170)
LA MAGDALENA CONTRERAS	−4.760***	−5.173**	−4.549***	−4.662***	−4.259***
	(1.062)	(1.602)	(0.551)	(0.550)	(1.122)
MIGUEL HIDALGO	−2.958**	−3.532*	−3.027***	−3.063***	−2.534*
	(1.052)	(1.625)	(0.560)	(0.547)	(1.103)

	Model:				
	Proximity	Distance	Quantile	Decile	Log
MILPA ALTA	-5.788^{***}	-5.920^{***}	-5.345^{***}	-5.542^{***}	-5.147^{***}
	(0.992)	(1.474)	(0.511)	(0.490)	(1.058)
TLAHUAC	-4.227^{***}	-4.624^{**}	-4.106^{***}	-4.348^{***}	-3.729^{***}
	(1.029)	(1.572)	(0.537)	(0.522)	(1.093)
TLALPAN	-5.790^{***}	-6.321^{***}	-5.855^{***}	-5.928^{***}	-5.403^{***}
	(1.101)	(1.653)	(0.546)	(0.530)	(1.156)
VENUSTIANO CARRANZA	-3.103^{**}	-3.664^{*}	-3.247^{***}	-3.199^{***}	-2.735^{*}
	(1.158)	(1.714)	(0.666)	(0.620)	(1.208)
XOCHIMILCO	-4.451^{***}	-4.927^{**}	-4.405^{***}	-4.530^{***}	-4.006^{***}
	(1.096)	(1.639)	(0.595)	(0.579)	(1.161)
proximity:PRIstr	0.177				
	(0.180)				
proximity:highTURNOUT	-0.214				
	(0.272)				
distance:PRIstr		0.017			
		(0.022)			
distance:highTURNOUT		0.056^{**}			
		(0.022)			
Quantile(1.59,2.57]:PRIstr			-0.282		
			(0.300)		
Quantile(2.57,4.78]:PRIstr			-0.519		
			(0.421)		
Quantile(4.78,20]:PRIstr			-0.080		
			(0.467)		
Quantile(1.59,2.57]:highTURNOUT			-0.174		
			(0.526)		
Quantile(2.57,4.78]:highTURNOUT			-0.139		
			(0.815)		

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Quantile(4.78,20]:highTURNOUT			1.818*		
			(0.706)		
Decile(0.947,1.4]:PRIstr				−0.177	
				(0.285)	
Decile(1.4,1.78]:PRIstr				−0.101	
				(0.337)	
Decile(1.78,2.16]:PRIstr				0.012	
				(0.302)	
Decile(2.16,2.57]:PRIstr				−0.639	
				(0.510)	
Decile(2.57,3.12]:PRIstr				−0.729	
				(0.609)	
Decile(3.12,4.04]:PRIstr				−0.570	
				(0.481)	
Decile(4.04,6.09]:PRIstr				−0.113	
				(0.349)	
Decile(6.09,15.2]:PRIstr				−0.675	
				(0.677)	
Decile(15.2,20]:PRIstr				1.403	
				(1.228)	
Decile(0.947,1.4]:highTURNOUT				0.299	
				(0.807)	
Decile(1.4,1.78]:highTURNOUT				0.448	
				(0.748)	
Decile(1.78,2.16]:highTURNOUT				0.166	
				(0.680)	
Decile(2.16,2.57]:highTURNOUT				−1.059	
				(0.933)	

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Decile(2.57,3.12]:highTURNOUT				−0.895	
				(1.021)	
Decile(3.12,4.04]:highTURNOUT				0.313	
				(1.225)	
Decile(4.04,6.09]:highTURNOUT				1.888	
				(1.034)	
Decile(6.09,15.2]:highTURNOUT				1.918*	
				(0.869)	
Decile(15.2,20]:highTURNOUT				1.648	
				(1.061)	
logdist:PRIstr					−0.045
					(0.218)
logdist:highTURNOUT					0.728***
					(0.203)
PRIstr:highTURNOUT	0.014	−0.208	0.088	−0.969	−0.142
	(0.433)	(0.458)	(0.777)	(1.200)	(0.698)
proximity:PRDstr	0.405*				
	(0.204)				
distance:PRDstr		0.012			
		(0.009)			
Quantile(1.59,2.57]:PRDstr			−0.254		
			(0.166)		
Quantile(2.57,4.78]:PRDstr			−0.175		
			(0.389)		
Quantile(4.78,20]:PRDstr			−0.594		
			(0.411)		
Decile(0.947,1.4]:PRDstr				0.326	
				(0.482)	

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Decile(1.4,1.78]:PRDstr				−0.328	
				(0.471)	
Decile(1.78,2.16]:PRDstr				−0.582	
				(0.341)	
Decile(2.16,2.57]:PRDstr				0.149	
				(0.310)	
Decile(2.57,3.12]:PRDstr				0.355	
				(0.289)	
Decile(3.12,4.04]:PRDstr				−0.131	
				(0.384)	
Decile(4.04,6.09]:PRDstr				−0.706	
				(0.364)	
Decile(6.09,15.2]:PRDstr				−0.507	
				(0.477)	
Decile(15.2,20]:PRDstr				−0.459	
				(2.287)	
logdist:PRDstr					−0.212
					(0.174)
highTURNOUT:PRDstr	1.765	3.655***	2.906***	4.325	5.697***
	(1.007)	(0.865)	(0.666)	(2.813)	(1.336)
proximity:PANstr	−0.872***				
	(0.256)				
distance:PANstr		0.146			
		(0.132)			
Quantile(1.59,2.57]:PANstr			0.843		
			(0.693)		
Quantile(2.57,4.78]:PANstr			2.881***		
			(0.796)		

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Quantile(4.78,20]:PANstr			4.703***		
			(0.977)		
Decile(0.947,1.4]:PANstr				−0.102	
				(0.748)	
Decile(1.4,1.78]:PANstr				−0.466	
				(0.723)	
Decile(1.78,2.16]:PANstr				0.458	
				(0.860)	
Decile(2.16,2.57]:PANstr				1.527	
				(1.076)	
Decile(2.57,3.12]:PANstr				1.336	
				(1.044)	
Decile(3.12,4.04]:PANstr				3.199**	
				(1.108)	
Decile(4.04,6.09]:PANstr				4.917***	
				(0.892)	
Decile(6.09,15.2]:PANstr				2.539*	
				(1.235)	
Decile(15.2,20]:PANstr				1.412	
				(2.755)	
logdist:PANstr					1.686***
					(0.351)
highTURNOUT:PANstr	−0.499	−1.465	0.126	−0.571	−1.062
	(0.913)	(1.183)	(1.344)	(2.071)	(1.182)
proximity:PRIstr:highTURNOUT	−0.130				
	(0.361)				
proximity:highTURNOUT:PRDstr	17.259*				
	(8.243)				

	Model:				
	Proximity	Distance	Quantile	Decile	Log
proximity:highTURNOUT:PANstr	−2.593				
	(1.611)				
distance:PRIstr:highTURNOUT		−0.008			
		(0.021)			
distance:highTURNOUT:PRDstr		−0.050*			
		(0.022)			
distance:highTURNOUT:PANstr		−0.087			
		(0.120)			
Quantile(1.59,2.57]:PRIstr:highTURNOUT			1.190		
			(0.907)		
Quantile(2.57,4.78]:PRIstr:highTURNOUT			1.205		
			(1.026)		
Quantile(4.78,20]:PRIstr:highTURNOUT			−1.453		
			(1.102)		
Quantile(2.57,4.78]:highTURNOUT:PRDstr			2.855***		
			(0.646)		
Quantile(1.59,2.57]:highTURNOUT:PANstr			−2.660		
			(1.743)		
Quantile(2.57,4.78]:highTURNOUT:PANstr			0.559		
			(2.550)		
Quantile(4.78,20]:highTURNOUT:PANstr			−2.905		
			(1.817)		
Decile(0.947,1.4]:PRIstr:highTURNOUT				2.340	
				(1.613)	
Decile(1.4,1.78]:PRIstr:highTURNOUT				1.008	
				(1.163)	
Decile(1.78,2.16]:PRIstr:highTURNOUT				1.549	
				(1.428)	

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Decile(2.16,2.57]:PRIstr:highTURNOUT				3.235	
				(1.786)	
Decile(2.57,3.12]:PRIstr:highTURNOUT				4.468**	
				(1.690)	
Decile(3.12,4.04]:PRIstr:highTURNOUT				1.688	
				(1.209)	
Decile(4.04,6.09]:PRIstr:highTURNOUT				−1.625	
				(1.401)	
Decile(6.09,15.2]:PRIstr:highTURNOUT				−0.446	
				(1.625)	
Decile(15.2,20]:PRIstr:highTURNOUT				0.218	
				(2.122)	
Decile(2.57,3.12]:highTURNOUT:PRDstr				4.203	
				(3.068)	
Decile(4.04,6.09]:highTURNOUT:PRDstr				2.024	
				(3.137)	
Decile(6.09,15.2]:highTURNOUT:PRDstr				−2.191	
				(3.385)	
Decile(0.947,1.4]:highTURNOUT:PANstr				2.028	
				(2.264)	
Decile(1.4,1.78]:highTURNOUT:PANstr				−1.556	
				(2.249)	
Decile(1.78,2.16]:highTURNOUT:PANstr				−2.615	
				(2.624)	
Decile(2.16,2.57]:highTURNOUT:PANstr				0.157	
				(2.467)	
Decile(3.12,4.04]:highTURNOUT:PANstr				0.352	
				(3.071)	

	Model:				
	Proximity	Distance	Quantile	Decile	Log
Decile(4.04,6.09]:highTURNOUT:PANstr				2.254	
				(2.117)	
Decile(6.09,15.2]:highTURNOUT:PANstr				−0.708	
				(2.357)	
logdist:PRIstr:highTURNOUT					0.031
					(0.333)
logdist:highTURNOUT:PRDstr					−0.957*
					(0.434)
logdist:highTURNOUT:PANstr					−0.861
					(0.487)
Constant	13.134**	13.739**	16.465***	16.419***	12.681**
	(4.472)	(4.724)	(4.394)	(4.456)	(4.505)
Adjusted R-Squared	.875	.875	.873	.874	.876

Note: Robust standard errors in parentheses *p<0.05; **p<0.01; ***p<0.001