

# Social Fragmentation, Electoral Competition and Public Goods Provision

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## Motivation: Social Structure and Public Goods I

- A broad literature in political economy has studied how social structure influences economic and political outcomes.
- There is an emerging consensus that fragmentation along ethnic, linguistic, caste and religious lines leads to lower public goods provision and worse development outcomes.
- Common channels: heterogeneity in preferences and collective choice (common pool) problems.

## Motivation: Social Structure and Public Goods II

- Conventional explanations focus on bottom-up processes in which communities are responsible for the choice and funding of public goods.
- However, in most developing countries, public goods are provided by elected politicians who rely on transfers from higher levels of government.
- How does social fragmentation shape the incentives of politicians to provide public goods as opposed to targeted or private transfers to some groups of the population?

## Social Fragmentation and Political Competition

- An often overlooked channel through which social structure may shape politician incentives is political competition.
  - When members are concentrated in a relatively small number of groups, leaders of larger groups have high bargaining power and can demand private, targeted, excludable transfers in exchange for the electoral support of its members.
  - Social concentration increases the likelihood of elite capture which can potentially undermine politicians' incentives to provide public goods
- As society becomes more fragmented, the redistributive strategies adopted by politicians to attract voters may shift towards greater – rather than lower – public goods provision.

## In this paper, we

- Study these questions in the Philippines where:
  - public goods provision is the responsibility of elected mayors whose budgets depend mostly on transfers from the central government
  - clans or extended families are the relevant political unit
- Graph full family networks for 15,000+ villages using community detection algorithms to identify clans
- Show how social fragmentation across clans correlates with political competition and public goods provision

## Preview of Findings

- Public goods provision is higher in more fragmented villages.
- We argue that this is partly explained by an increase in electoral competition and a more even distribution of political influence in fragmented villages:
  - Win margins are lower
  - A larger number of individuals run for public office
  - Voters mention a larger set of politically influential individuals in their community

## Related Literature

- **Elite Capture:** Bardhan (2002); Bardhan and Mookherjee (2006); Acemoglu, Reed and Robinson (2014); Anderson, Francois and Kotwal (2015).
- **Family and Kinship Ties:** Padgett and Ansell (1993); Padgett and McLean (2006); Alesina and Giuliano (2013); Bertrand and Schoar (2006); Dal Bo, Dal Bo and Snyder (2009); Moscona, Nunn and Robinson (2017, 2018).
- **Social Networks and Electoral Strategies:** Auyero (2000); Calvo and Murillo (2009); Szwarcberg (2012); Cruz (2013); Larson and Lewis (2017); Cruz, Labonne and Querubin (2017).
- **Ethnic Fragmentation and Favoritism:** Easterly and Levine (1997); Alesina, Baqir and Easterly (1999); Miguel and Gugerty (2005); Montalvo and Reynal-Querol (2005); Burgess et al., (2015) and Munshi and Rosenzweig (2018).
- **Political Competition and Public Goods Provision:** Besley and Burgess (2002); Besley, Persson and Sturm (2010); Crost and Kambhampati (2010); Khemani (2015); and Rosenzweig (2015).

## Outline

- 1 Motivation
- 2 Background
- 3 Network Fragmentation
- 4 Data and Measures
- 5 Results



## Some things you should know about the Philippines...

- Weak parties



## Some things you should know about the Philippines...

- Weak parties
- Political networks matter



## Some things you should know about the Philippines...

- Weak parties
- Political networks matter
- Family is the basic unit of politics



## Clans and Elections I

- Politicians competing in municipal and barangay elections must often seek the support of clans (extended families).
- Families are effective political units:
  - Reputation, loyalties, and alliances are transferable (Fegan, 2009).
  - Behavior regulated by ethics and norms of reciprocity such as **utang na loob** and **hiya** that are not limited to an individual-to-individual relationship but are rather seen as operative from family to family (Corpuz, 1965, Hollsteiner, 1963).

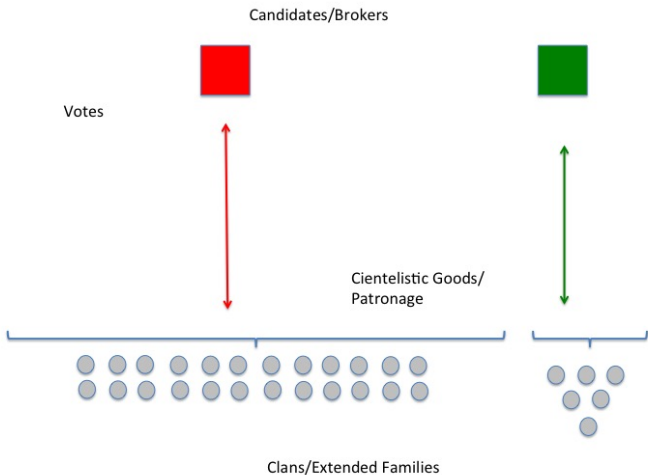
## Clans and Elections II

- Politicians can often secure a large number of votes by brokering deals with the heads of clans who can commit to deliver the votes of all clan members in exchange for access to private transfers and services including:
  - Money
  - Jobs
  - Medical, educational and funeral expenses
  - Construction materials
  - Preferential access to government programs
  - Business and building permits.
- These private transfers often come at the expense of the provision of public goods that would benefit all village residents equally.

## Electoral Strategies and Social Fragmentation I

- In villages in which the population is concentrated, clientelistic transactions between politicians and clan heads become more likely.
- Bargaining power of each individual clan head increases as they can deliver the votes of a relatively large number of village residents.
- Candidates also favor these strategies since the concentration of voters in a relatively small number of clans decrease the transaction and monitoring costs involved in the distribution of private transfers.

## High Concentration

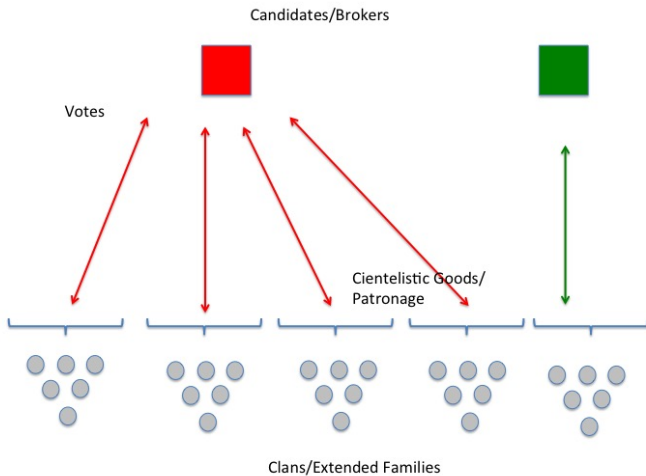


## Electoral Strategies and Social Fragmentation II

- In highly fragmented villages the provision of targeted transfers becomes relatively less attractive as clan leaders control relatively small numbers of voters and enforcing several individual transactions becomes infeasible.
- Politicians may thus opt for adopting policies with more diffuse benefits and provide more public goods in order to attract the electoral support of a large number of voters.



## Low Concentration



1 Motivation

2 Background

**3 Network Fragmentation**

4 Data and Measures

5 Results

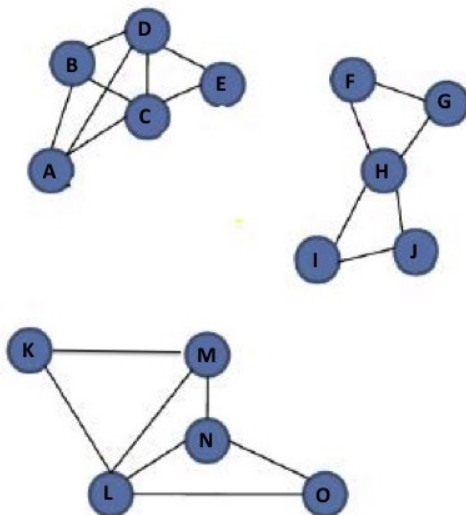
## Measuring Social Fragmentation I

- Empirical challenge: identifying the different clans or extended families in every village since boundaries are hard to define.
- A clan is a set of families:
  - Connected to each other by marriage
  - Where mutual norms of cooperation and reciprocity are enforced by all its members
- An enumeration of every clan in every village based on survey data is unfeasible so we propose to use network analysis to address this issue.

## Measuring Social Fragmentation II

- Consider a social network in which a node is a family (identified with a unique family name) and edges between nodes imply that a marriage has occurred between members of these families.
- One intuitive approach would be to identify each different clan with the different components in the marriage network.
- This approach, while appealing, can be quite restrictive in practice since family networks in real life (and in our Filipino context, in particular) rarely feature neatly distinct components.

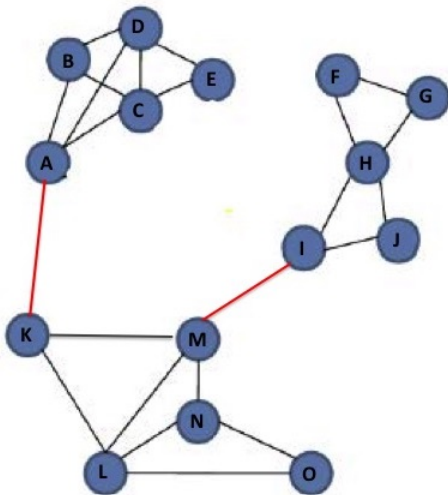
## Clans as Components



## Measuring Social Fragmentation III

- An alternative is the concept of *communities*.
- In a social network, communities are groups of nodes with dense connections internally (i.e. within the group) and sparser connections between groups (Jackson, 2010).
- We associate different clans with the different communities detected in the social networks.
- The community structure in a network is a latent feature that needs to be uncovered.

## Clans as Communities



## Girvan-Newman Algorithm I

- Girvan and Newman (2002) developed a powerful algorithm to detect communities.
- If two groups of nodes are only loosely connected with each other, removing links between those two groups will generate components in the restricted networks.
- Edges with high *betweenness* centrality are precisely the ones that we expect to connect communities.

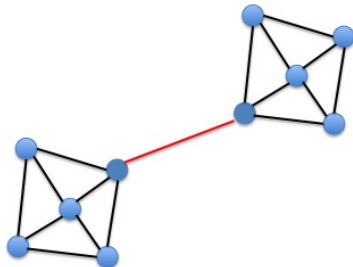


## Edge Betweenness

### Edge Betweenness

Extent to which the edge serves as a link between different groups.

Calculated using the number of shortest paths between nodes in the network that pass through that edge



## Girvan-Newman Algorithm II

The Girvan-Newman algorithm proceeds as follows:

- 1 Calculate the betweenness for all edges in the network.
- 2 Remove the edge with the highest betweenness
- 3 Recalculate betweenness for all edges affected by the removal.
- 4 Repeat from step 2 until no edges remain
- 5 From resulting dendrogram, pick partition that maximizes network modularity.

For robustness we also implement the walktrap algorithm (Pons and Latapy 2005)

## Community Fragmentation

The algorithm delivers a partition of  $C$  communities (indexed by  $c = 1, \dots, C$ ), each containing a share  $s_c$  of nodes.

Once we've identified communities we compute social fragmentation with a standard Herfindahl-Hirschman index:

$$SF = 1 - \sum_{c=1}^C s_c^2 \quad (1)$$

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## Our data

- Survey data for 20 million individuals (700+ municipalities, 15,000+ villages)
  - Demographic information
  - Full names: important because of naming conventions
- Census data (2010) on public goods available in every village, as well as shares of different ethnic and religious groups.
- Detailed household survey data for 2013 ( $n = 3,408$ ) and 2016 ( $n = 3,476$ ) in two provinces: influential individuals, public goods preferences, collective action
- Precinct-level results for the 2010 municipal elections and 2010 and 2013 village elections

## Family Names Data

Three convenient features of Philippine naming conventions:

- 1 names are difficult to change
- 2 each individual carries two family names

firstname midname lastname

- firstname: given first name
  - midname: mother's maiden name (father for married women)
  - lastname: father's surname (husband for married women)
- 3 within a municipality, a shared family name implies family connections

## Tracing Relatives Using Family Names

- In 1849 Governor Narciso Claveria y Zaldua became frustrated with the arbitrary naming conventions in the Philippines and the difficulties for administrative purposes (especially tax collection)
- Created a catalog with a list of 61,000 official Spanish surnames and ordered local officials to assign different surnames to each family within municipalities
- As a result a shared last name is a strong indicator of a family tie, even for relatively common last names

▶ [List of Names](#)

## Measuring family networks

- Each node is a **family**
- Ties are **intermarriages** with other families, and established whenever we observe a marriage between two families



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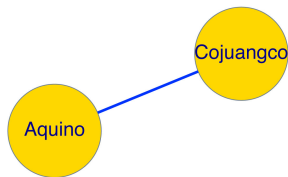
NoyNoy  
Cojuangco  
Aquino

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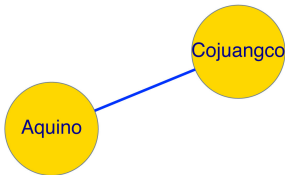


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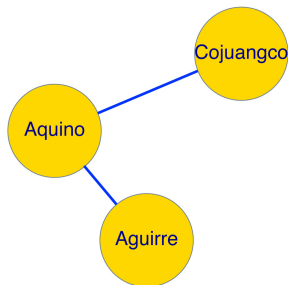
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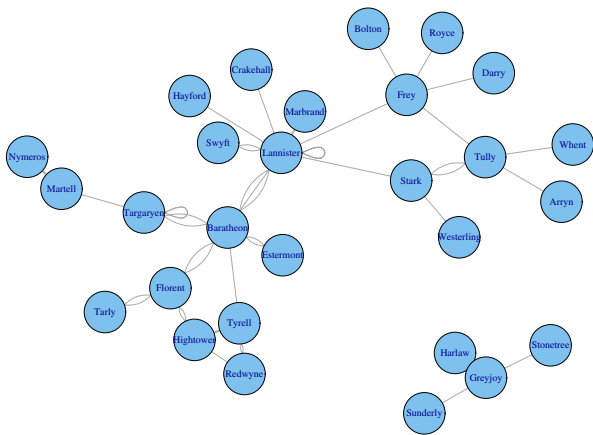


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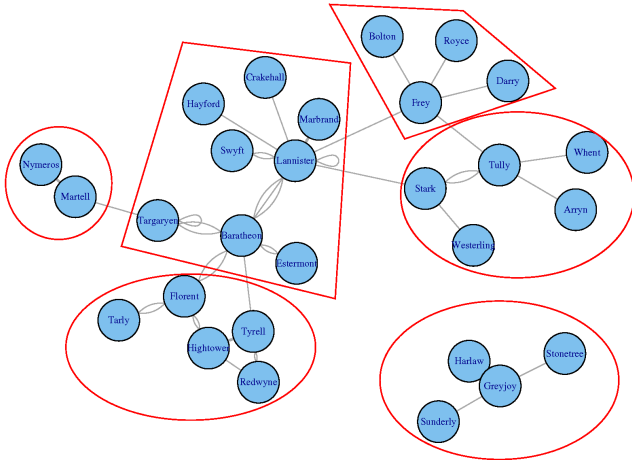


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## GOT: An Example I



## GOT: An Example II



1 Motivation

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## Empirical Strategy

Our analysis is based on cross-sectional regressions of the form:

$$y_{vm} = \alpha + \beta SF_{vm} + \gamma X_{vm} + \delta_m + \epsilon_{vm}$$

$y_{vm}$  is the outcome variable in village  $v$  in municipality  $m$  (public goods provision and political competition)

$SF_{vm}$  is our measure of social (family) fragmentation

$\delta_m$  is a full set of municipality fixed-effects (important given mayor's decision)



## Results: Public Goods

Fragmentation is **positively** correlated with public goods provision, even when controlling for a wide range of village characteristics:

- Age
- Length of stay in the village
- Gender ratio
- Population
- Number of distinct families
- Rural dummy
- Population in each of 17 educational and 11 occupational categories
- Per capita income
- Poverty incidence

## Community Fragmentation and Public Goods

	(1)	(2)	(3)	(4)
	Elem. School	High School	Market	Health Centre
Panel A: No Controls				
Fragmentation	0.01** (0.01)	0.08*** (0.01)	0.06*** (0.01)	0.06*** (0.01)
Observations	15,449	15,449	15,449	15,449
R-squared	0.001	0.027	0.020	0.014
Mean Dep. Var.	0.806	0.209	0.190	0.639
Panel B: Full Controls				
Fragmentation	0.03*** (0.01)	0.02*** (0.01)	0.02*** (0.00)	0.03*** (0.01)
Observations	15,432	15,432	15,432	15,432
R-squared	0.075	0.172	0.139	0.049
Mean Dep. Var.	0.806	0.209	0.190	0.639

## Reverse Causality: Restricted Network

- Public goods provision may also influence network structure
- Results are similar when we construct village networks based on individuals 45 or older, or use this as instrument for the whole network

## Community Fragmentation and Public Goods: Over 45

	(1)	(2)	(3)	(4)
	Elem. School	High School	Market	Health Centre
Panel A: OLS				
Fragmentation (over 45)	0.01** (0.01)	0.08*** (0.01)	0.06*** (0.01)	0.06*** (0.01)
Observations	15,449	15,449	15,449	15,449
R-squared	0.001	0.027	0.020	0.014
Mean Dep. Var.	0.806	0.209	0.190	0.639
Panel B: IV				
Fragmentation	0.06*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	0.08*** (0.01)
Observations	15,428	15,428	15,428	15,428
Mean Dep. Var.	0.806	0.209	0.190	0.641

## Robustness Tests

Our estimates are robust to:

- Weighting edges by family size or using alternative community detection algorithms [▶ Weighted](#)
- Dropping outliers: villages with network fragmentation in the bottom 1, 5 and 10% [▶ Outliers](#)
- Dropping villages in ARMM
- Controlling for characteristics of the incumbent and challengers' families in the village [▶ Cand. Chars](#)
- Controlling for Ethnic and Religious Fragmentation

## Ruling Out Traditional Channels

- Our results contrast with previous findings that show a *negative* correlation between ethnic and religious fragmentation and public goods provision.
- A key difference in our setting is that politicians and not communities are responsible for providing public goods.
- Moreover, fragmentation across clans (as opposed to across ethnic or religious groups) may not have the same implications for preference heterogeneity and collective action documented by previous studies.

## Results: Preference Heterogeneity and Collective Action

- Social fragmentation is not robustly associated with more or less heterogeneous preferences over public goods
- No major differences in collective action (social capital) either

## Heterogeneity in Public Goods Preferences

Dependent variable is standard deviation of % of budget that respondents would allocate to:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Health	Education	Emergencies	Water	Road	ComFaci	EconProg	Agriculture	Peace	Festivals
Panel A: No Controls										
Fragmentation	-0.05 (0.53)	-0.29 (0.35)	-0.21 (0.30)	-0.50** (0.22)	-0.00 (0.25)	0.15* (0.07)	0.19 (0.32)	-0.33 (0.30)	-0.14 (0.13)	-0.04 (0.10)
Observations	283	283	283	283	283	283	283	283	283	283
R-squared	0.000	0.002	0.002	0.020	0.000	0.005	0.001	0.002	0.004	0.000
Mean Dep. Var.	11.19	11.19	8.285	7.425	6.836	5.526	7.798	15.14	5.855	4.064
Panel B: Full Controls										
Fragmentation	0.05 (0.51)	-0.20 (0.35)	-0.09 (0.30)	-0.51** (0.22)	-0.03 (0.27)	0.12 (0.07)	0.28 (0.29)	-0.29 (0.32)	-0.12 (0.11)	-0.03 (0.09)
Observations	283	283	283	283	283	283	283	283	283	283
R-squared	0.082	0.066	0.118	0.057	0.023	0.043	0.065	0.071	0.049	0.011
Mean Dep. Var.	11.19	11.19	8.285	7.425	6.836	5.526	7.798	15.14	5.855	4.064



## Collective Action

	(1)	(2)	(3)	(4)
	Bayanihan		Group	
Fragmentation	0.09*	0.08	-0.05	-0.05
	(0.05)	(0.05)	(0.04)	(0.05)
Controls	No	Yes	No	Yes
Observations	283	283	283	283
R-squared	0.008	0.092	0.002	0.128
Mean Dep. Var.	0.751	0.751	0.658	0.658

## Political Competition and Concentration of Political Influence

- Social fragmentation across clans may trigger greater political competition and shift politicians towards the provision of public (as opposed to private) goods.
- We explore the correlation between social fragmentation and standard measures of political competition.
- Social fragmentation undermines the ability of a handful of clan leaders to exercise disproportionate influence on the political choices of village residents.
- We also consider a non-electoral measure of political competition defined as the number of politically influential individuals mentioned by village respondents in our 2013 survey.

## Results: Concentration of Political Influence

- More fragmented villages exhibit a higher number of individuals running in village elections
- Village and municipal elections are also more competitive in more fragmented villages
- Survey evidence confirms leadership less concentrated in more fragmented villages

▶ Robustness Checks

## Number of Candidates and Political Competition in Village Elections I

	(1)	(2)	(3)	(4)	(5)
	# Candidates	Bgy. Cpt.	Golosov	Win Margin	# Candidates
	Raw	Laakso	Golosov	Margin	Bgy. Councilors
Panel A: No Controls					
Fragmentation	0.06*** (0.01)	0.04*** (0.01)	0.03*** (0.00)	-1.73*** (0.28)	0.72*** (0.09)
Observations	31,344	30,985	31,344	30,593	31,344
R-squared	0.004	0.003	0.002	0.002	0.012
Mean Dep. Var.	2.175	1.875	1.667	36.89	16.84
Panel B: Full Controls					
Fragmentation	0.05*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	-1.68*** (0.32)	0.59*** (0.08)
Observations	31,306	30,947	31,306	30,555	31,306
R-squared	0.012	0.009	0.008	0.007	0.054
Mean Dep. Var.	2.175	1.875	1.667	36.89	16.84

## Political Competition in Municipal Elections

	(1)	(2)
	Win Margin	
Fragmentation	-1.94*** (0.35)	-0.63* (0.33)
Controls	No	Yes
Observations	17,023	17,021
R-squared	0.006	0.021
Mean Dep. Var.	33.60	33.60

## Survey Evidence: Number of Influential Individuals

	(1)	(2)	(3)
	# Influential Individuals		
	Raw	Laakso	Golosov
Panel A: No Controls			
Fragmentation	0.74*** (0.24)	0.47** (0.16)	0.45** (0.15)
Observations	269	269	269
R-squared	0.017	0.014	0.014
Mean Dep. Var.	9.137	5.900	5.157
Panel B: Full Controls			
Fragmentation	0.80** (0.27)	0.54*** (0.16)	0.53*** (0.14)
Observations	269	269	269
R-squared	0.054	0.073	0.075
Mean Dep. Var.	9.137	5.900	5.157

## Conclusion

- Our correlations should be interpreted cautiously – biases from unobserved village characteristics are a concern.
- We do not question the relevance of previous work on ethnic and religious heterogeneity and public goods provision: rather, we highlight ways that social fragmentation may have different economic and political consequences, depending on the institutional context.
- Clans and norms of reciprocity are important in many other societies (see, for example, Finan and Schechter, 2012 and Acemoglu, Reed and Robinson, 2014).
- Important to understand how a community's social structure shapes elite capture, electoral competition and the incentives of politicians to provide public goods.





## Family Names Example

<b>name</b>	<b>nickname</b>	<b>province</b>	<b>municipality</b>	<b>office</b>
FABELLON, ALBERTO FANER	ALBERT	ROMBLON	BANTON	COUNCILOR
FABELLON, PERSHING FABROA	PERSHING	ROMBLON	BANTON	COUNCILOR
FABIALA, ISMAEL FESALBON	MAING	ROMBLON	BANTON	COUNCILOR
FABRERO, BERNADETH FETALCO	NADETTTE	ROMBLON	BANTON	COUNCILOR
FADRI, ISMAEL FADALLAN	MAENG	ROMBLON	BANTON	COUNCILOR
FAIGAO, ABNER FADRI	DUTCHIE	ROMBLON	BANTON	COUNCILOR
FAINSAN, ROLO FONTANOSA	ROLLY	ROMBLON	BANTON	COUNCILOR
FAJILAN, CHERRY FETALVERO	CHERRY	ROMBLON	BANTON	COUNCILOR
FAMILARA, RICARDO FERRANCO	BARON	ROMBLON	BANTON	COUNCILOR
FEDELIN, CHRISTOPHER FEGAL	IPE	ROMBLON	BANTON	COUNCILOR
FEGALAN, LOI JORGE FEGALQUIN	LOI	ROMBLON	BANTON	COUNCILOR
FETALCORIN, FELICITO FORTU	FLECIT	ROMBLON	BANTON	COUNCILOR
FETIZANAN, CRESENCIANO FESALBON	CANONG	ROMBLON	BANTON	COUNCILOR
FIECAS, JIMMY FONTE	JIM	ROMBLON	BANTON	COUNCILOR
FIECAS, LEONARDO FADERON	NARDING	ROMBLON	BANTON	COUNCILOR
FIETAS, AGUINALDO FADERAN	GUINAL	ROMBLON	BANTON	COUNCILOR
FLORES, PATRICIO FABROA	PAT	ROMBLON	BANTON	COUNCILOR
FONTE, BEMBOY MAGSINO	EMBOY	ROMBLON	BANTON	COUNCILOR
FRUELDA, PERLA FABICON	PING	ROMBLON	BANTON	COUNCILOR

## Robustness: Weighting Edges and Using Walktrap Algorithm

	(1)	(2)	(3)	(4)
	Elem. School	High School	Market	Health Centre
Panel A: Edge removal, weighted by family size				
Fragmentation	0.03*** (0.01)	0.02*** (0.00)	0.02*** (0.00)	0.03*** (0.01)
Observations	15,432	15,432	15,432	15,432
R-squared	0.076	0.172	0.139	0.049
Panel B: Walktrap algorithm				
Fragmentation	0.03*** (0.01)	0.02*** (0.00)	0.02*** (0.00)	0.04*** (0.00)
Observations	15,432	15,432	15,432	15,432
R-squared	0.077	0.172	0.139	0.051

## Robustness: Dropping Outliers and ARMM

	(1)	(2)	(3)	(4)
	Elem. School	High School	Market	Health Centre
Panel A: Remove bottom 1 percent				
Fragmentation	0.03*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	0.06*** (0.01)
Observations	15,287	15,287	15,287	15,287
R-squared	0.076	0.174	0.140	0.050
Panel B: Remove bottom 5 percent				
Fragmentation	0.03*** (0.01)	0.06*** (0.01)	0.04*** (0.01)	0.07*** (0.01)
Observations	14,669	14,669	14,669	14,669
R-squared	0.077	0.176	0.141	0.047
Panel C: Remove bottom 10 percent				
Fragmentation	0.02** (0.01)	0.07*** (0.01)	0.05*** (0.01)	0.08*** (0.01)
Observations	13,897	13,897	13,897	13,897
R-squared	0.080	0.174	0.143	0.045
Panel D: Remove ARMM				
Fragmentation	0.04*** (0.01)	0.03*** (0.01)	0.02*** (0.00)	0.05*** (0.01)
Observations	13,147	13,147	13,147	13,147
R-squared	0.095	0.180	0.148	0.053

## Robustness: Controlling for Candidate Characteristics

	(1)	(2)	(3)	(4)
	Elem. School	High School	Market	Health Centre
Panel A: Controlling for Incumbent Characteristics				
Fragmentation	0.03*** (0.01)	0.02*** (0.01)	0.02*** (0.01)	0.03*** (0.01)
Observations	9,697	9,697	9,697	9,697
R-squared	0.078	0.179	0.149	0.054
Panel B: Controlling for Incumbent and Challenger Characteristics				
Fragmentation	0.03*** (0.01)	0.02*** (0.01)	0.02*** (0.01)	0.03*** (0.01)
Observations	8,739	8,739	8,739	8,739
R-squared	0.091	0.184	0.153	0.061
Panel C: Controlling for Ethnic and Religious Fragmentation				
Fragmentation	0.03*** (0.01)	0.02*** (0.01)	0.02*** (0.00)	0.04*** (0.01)
Observations	15,432	15,432	15,432	15,432
R-squared	0.076	0.175	0.139	0.050

## Robustness: Weighting Edges and Using Walktrap Algorithm

	(1)	(2)	(3)	(4)	(5)
	# Candidates Raw	Bgy. Cpt. Laakso	Cpt. Golosov	Win Margin	# Candidates Bgy. Councilors
Panel A: Edge removal, weighted by family size					
Fragmentation (over 45)	0.04*** (0.01)	0.03*** (0.01)	0.03*** (0.00)	-1.38*** (0.31)	0.51*** (0.07)
Observations	31,306	30,947	31,306	30,555	31,306
R-squared	0.012	0.009	0.008	0.007	0.052
Panel B: Walktrap algorithm					
Fragmentation	0.04*** (0.01)	0.03*** (0.01)	0.02*** (0.01)	-1.46*** (0.32)	0.53*** (0.06)
Observations	31,306	30,947	31,306	30,555	31,306
R-squared	0.011	0.009	0.008	0.007	0.054

## Robustness: Dropping Outliers and ARMM

	(1)	(2)	(3)	(4)	(5)
	# Candidates Raw	Bgy. Cpt. Laakso	Golosov	Win Margin	# Candidates Bgy. Councilors
Panel A: Remove bottom 1 percent					
Fragmentation	0.07*** (0.01)	0.05*** (0.01)	0.04*** (0.01)	-2.08*** (0.45)	0.84*** (0.10)
Observations	31,011	30,661	31,011	30,280	31,011
R-squared	0.012	0.009	0.008	0.007	0.054
Panel B: Remove bottom 5 percent					
Fragmentation	0.09*** (0.02)	0.06*** (0.01)	0.05*** (0.01)	-1.95*** (0.56)	1.03*** (0.13)
Observations	29,760	29,436	29,760	29,079	29,760
R-squared	0.012	0.009	0.008	0.007	0.055
Panel C: Remove bottom 10 percent					
Fragmentation	0.10*** (0.02)	0.06*** (0.01)	0.05*** (0.01)	-1.42** (0.68)	1.15*** (0.15)
Observations	28,193	27,904	28,193	27,561	28,193
R-squared	0.011	0.008	0.008	0.007	0.055
Panel D: Remove ARMM					
Fragmentation	0.06*** (0.01)	0.05*** (0.01)	0.04*** (0.01)	-2.28*** (0.36)	0.72*** (0.07)
Observations	27,267	27,185	27,267	26,864	27,267
R-squared	0.019	0.012	0.011	0.009	0.071

## Robustness: Controlling for Candidate Characteristics

	(1)	(2)	(3)	(4)	(5)
	# Candidates	Bgy. Cpt.	Win	Win	# Candidates
	Raw	Laakso	Golosov	Margin	Bgy. Councilors
Panel A: Controlling for Incumbent Characteristics					
Fragmentation	0.05*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	-2.11*** (0.39)	0.51*** (0.09)
Observations	19,703	19,440	19,703	19,197	19,703
R-squared	0.025	0.018	0.016	0.015	0.077
Panel B: Controlling for Incumbent and Challenger Characteristics					
Fragmentation	0.05*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	-1.99*** (0.40)	0.50*** (0.09)
Observations	17,777	17,543	17,777	17,330	17,777
R-squared	0.032	0.025	0.022	0.023	0.084
Panel C: Controlling for Ethnic and Religious Fragmentation					
Fragmentation	0.05*** (0.01)	0.03*** (0.01)	0.03*** (0.00)	-1.75*** (0.32)	0.53*** (0.08)
Observations	31,306	30,947	31,306	30,553	31,306
R-squared	0.014	0.011	0.009	0.008	0.062