

Captured Labor Markets

Social structure and labor market performance in the Philippines

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Abstract

We study how the structure of social networks shapes the labour market. Using census data on 20 million individuals in 15,000 Filipino villages, we measure the fragmentation of social groups in village-level family networks. We show that occupations in villages with high social fragmentation are disproportionately less likely to be dominated by a single social group. This result is robust to the inclusion of a rich set of controls and to instrumenting current networks with the networks of the older generation. It can be explained by increasing returns to an occupation within a social group, or by an occupation capture model where dominant social groups create barriers to entry in an occupation. Consistently with the second model, we show that workers in villages with high social fragmentation earn higher wages. Overall, these findings point to the existence of a labor market dividend of social diversity.

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1 Introduction

A long-standing idea in the social sciences is that social structure has a profound influence on economic outcomes (Granovetter, 2005; Jackson et al., 2017). For example, homophily can distort the diffusion of innovations; dense social networks can foster cooperation; social segregation may reinforce economic inequality. These hypotheses offer compelling explanations for important economic phenomena. They also suggest that, once the relationship between social structure and economic outcomes is better understood, policy makers may be able to tailor interventions to the specific social fabric of a community. This exciting research program, however, has been hampered by the lack of data on network structure. Existing surveys focus on a limited number of networks (e.g. villages or school) – typically, less than 100 (Banerjee et al., 2013). They have thus enabled researchers to study the effect of individual-level measures of network position, while the impact of network structure has remained empirically uncharted.

In this paper, we investigate the impacts of social fragmentation – an important feature of network structure – on the performance of labor markets in the Philippines. We rely on census data and local naming conventions to measure the social connections that occur between families through marriage. The resulting map of village-level family networks contains an unprecedented level of variation in social structure. In particular, we observe more than 15,000 different family networks. We focus on the social fragmentation of these networks because this dimension parallels the notion of concentration in industrial organisation – a basic indicator of market power and potential distortion of competition. To measure social fragmentation we proceed in two steps. First, we divide families into communities that are closely tied together, using recently developed community-detection algorithms (Girvan and Newman, 2002). Second, we compute the Herfindahl index of the communities in each village.

We hypothesise that social fragmentation fosters competition in the labour market. In socially concentrated villages, powerful communities may be able to stop other communities from entering specific occupations in order to create rents. Capturing an occupation in this way may be harder to do in socially fragmented villages where communities are more evenly sized and hence better able to compete with each other. Importantly, strengthening community competition will have a positive effects on total welfare in the village. Individuals will be able to allocate their talent more effectively and there will be stronger dynamic incentives for innovation and growth.

Our main findings is that social fragmentation significantly reduces occupation capture. In the data, we measure occupation capture as the share of the workforce in an occupation that belongs to the dominant community in that occupation. In villages

with average levels of social fragmentation, mean occupation capture is close to 37 percent. This decreases to 30 percent – a highly significant .25 standard deviations or 23 percent decrease – when social fragmentation increases by one standard deviation. To obtain this result, we control for a large number of village characteristics. Further, we control for village population, the number of communities, and the number of occupations. This restricts our comparison to villages that would have the same expected level of occupation capture if communities had no influence on occupational choice.

This finding is robust to an extensive battery of additional checks. First, we reproduce our main result for a sample that excludes urban areas. This helps us control for endogenous in-migration driven by labor market conditions. Second, we instrument current social fragmentation using the social fragmentation of the family network of the older generation. This provides further evidence against reverse causality (from current labour market conditions to current social structure). Using this IV strategy, we document a significantly larger effect of social fragmentation on occupation capture. Third, we find that our results are not confounded by other types of religious and economic heterogeneity that may be correlated with social fragmentation. Finally, we show robustness to the use of a different community detection algorithm and to dropping geographical areas where naming conventions are not followed as strictly as in the rest of the country.

We provide further evidence for our hypothesised mechanism by studying the effect of social fragmentation on wages. Under our preferred story, occupation capture is the result of barriers to entry which decrease the overall productivity of the occupation. An alternative explanation would be that there are returns to scale for a community in an occupation. For example, this could be because within a community it is easier to share information, labour, and capital that are specific to an occupation. The implication of this alternative mechanism would be that individuals in captured occupations are actually more productive. We use average wages to proxy for the productivity of workers in village labor markets and to disentangle these different explanations.

We find that social fragmentation significantly increases wages. This supports the occupation capture mechanism, and is inconsistent with an explanation based on returns to scale. The size of the effect is meaningful: weekly earnings grow by between 8 to 29 percent, depending on the specification, when social fragmentation increases by one standard deviation. Further, the result is robust to the same battery of additional checks that we performed for the main regression and, crucially, is driven by higher hourly wages (a proxy for productivity) and not by the number of hours worked. Finally, we further corroborate our mechanism by showing that social fragmentation also

increases sectorial and occupation fragmentation. As we fix the number of sectors and occupations, these results are consistent with the idea that captured occupations tend to be unusually small, generating an uneven distribution of workers across occupations.

Our results make three key contributions to the literature. First, we provide original empirical evidence on the effect of network structure on economic outcomes. To our knowledge, we are the first to document the influence of a broad measure of network structure on economic outcomes using data that directly measures offline social connections. As explained above, despite an abundance of theory, empirical analyses of network structure are surprisingly rare. To circumvent the lack of field data on network structure, [Dai et al. \(2018\)](#) proxy network density with population density, [Centola \(2010\)](#) and [Centola \(2011\)](#) study online communities, and a number of researchers explore the effect of social structure in the lab (e.g. see [Charness et al. \(2014\)](#) and [Gallo and Yan \(2015\)](#)). Further, using the same data on family networks that we exploit in this paper, [Cruz et al. \(2018\)](#) investigate the effects of social structure on political outcomes.

Second, we show that social diversity can create economic dividends. Existing work has largely focused on the challenges posed by social diversity. For example, social rivalries can distort production ([Hjort, 2014](#)) and reduce support for redistribution ([Alesina et al., 2018](#)).¹ A smaller literature has documented an association between diversity and productivity, possibly due to skills complementarities ([Ottaviano and Peri, 2006](#); [Alesina et al., 2016](#)). We advance this literature by proposing and providing evidence for a new channel through which social diversity can affect economic performance.

Third, we highlight a novel mechanism that can distort the allocation of talent in labor markets. The recent literature in development economics has devoted much attention to factor misallocation ([Hsieh and Klenow, 2009](#)). Many of the proposed explanations revolve around standard economic forces such as credit constraints and asymmetric information ([Abebe et al., 2017](#); [Bandiera et al., 2017](#); [Bassi and Nansamba, 2017](#); [Dillon and Barrett, 2017](#); [Abebe et al., 2018](#)). In this paper, on the other hand, we show that misallocation can also have social origins. This finding has important policy implications. In particular, it suggests that policy makers may be able to target interventions on the basis of the social structure of communities. In socially fragmented communities, removing credit constraints or providing information may be a viable and effective policy option. On the other hand, when labor markets are captured by powerful social groups, the binding constraints to labor market participation may not be economic in nature. In these contexts, policies that foster entrepreneurship may be more promising options to reduce poverty.

¹[Alesina and Ferrara \(2005\)](#) provide an early review of this literature.

2 Network measures and data

In this section we introduce the algorithm we use to measure social fragmentation and present our various data sources.

2.1 Measuring social fragmentation

Our main empirical challenge is to measure social fragmentation at the village-level. We follow [Cruz et al. \(2018\)](#) and measure how villages are divided into a number of clans. We follow insights from social network analysis to identify those clans and rely on the notion of communities: groups of nodes with dense connections internally (i.e. within the group) and sparser connections between groups ([Jackson, 2010](#)). We can then use community detection algorithms to identify extended clans. We rely on the [Girvan and Newman \(2002\)](#) algorithm which proceeds as follows:²

1. Calculate the betweenness for all edges in the network³
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, select the partition that maximizes network modularity

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

2.2 Network data

We use the non-anonymized version of the National Household Targeting System (NHTS) data collected between 2008 and 2010 by the Department of Social Welfare and Development (DSWD) to select beneficiaries for a large-scale conditional cash transfer (CCT) program ([Fernandez, 2012](#)). We limit our analysis to 20 million observations in the 709 municipalities in which full enumeration took place.

²We also implement the *walktrap* algorithm developed by [Pons and Latapy \(2006\)](#). Intuitively, the algorithm relies on the idea that random walks on a graph tend to get “trapped” into densely connected parts corresponding to communities. The algorithm thus generates a large number of random walks and groups together nodes that are tied together through those walks. See [Pons and Latapy \(2006\)](#) for more details.

³This centrality measure captures the extent to which the edge serves as a link between different groups. It is calculated using the number of shortest paths between nodes in the network that pass through that edge ([Freeman, 1977](#)).

We use information on family names to measure family connections through marriage. This approach takes advantage of unique features of Filipino naming conventions:⁴ (i) within a municipality, a shared family name implies family connections; (ii) each individual carries two family names, which establishes that a marriage took place between members of those two families; (iii) names are difficult to change.⁵

Names used in the Philippines were imposed by Spanish colonial officials in the mid-19th century. One of the stated objective was to distinguish families at the municipal level to facilitate census-taking and tax collection. Last names were selected from the *Catalogo alfabetico de apellidos*, a list of Spanish names. They do not reflect pre-existing family ties. In each municipality a name was only given to one nuclear family. As a result, there is a lot of heterogeneity in names used at the local level, reducing concerns that names capture a similar ethnic background or other social grouping. Names are transmitted across generations according to well-established rules. Specifically, each individual has two family names: a last name and a middle name. A man’s last name is his father’s last name and his middle name is his mother’s last name. Similar conventions apply to unmarried women. A married woman has her husband’s last name and her middle name is her maiden name, *i.e.*, her father’s last name.

The full names of all individuals in each village provides us with complete information on all marriages between families. We are thus able to reconstruct the full marriage network - with each name being a node - in each village and to implement the Girvan-Newman algorithm. Our main measure of fragmentation (SF) is a standard Herfindahl-Hirschman index:

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

where s_c is the share of nodes in each community c . The total number of communities is C . To simplify interpretation we normalise SF to be mean zero and standard deviation 1.

We’re also interested in how communities are able to capture occupation. To proxy for that we compute the share of the largest community in each occupation.

2.3 Labor market data

We use LFS data collected by the Philippine Statistics Authority (PSA). The surveys are conducted four times a year (January, April, July and October), and we have access

⁴It has been used by [Fafchamps and Labonne \(2017a\)](#), [Cruz et al. \(2017\)](#), [Fafchamps and Labonne \(2017b\)](#) and [Cruz et al. \(2018\)](#).

⁵As indicated by [Fafchamps and Labonne \(2017a\)](#), there are strict legal constraints on name changes in the Philippines which reduce concerns about strategic name changes.

to all 26 surveys in the period July 2003 to October 2009.⁶ We only use working-age individuals (above 15) and build a yearly (unbalanced) panel of 1,112 villages for which the NHTS data is available. More details are available in [Franklin and Labonne \(2019\)](#).

Respondents provide three important pieces of data that allow us to compute the following outcomes: (i) Daily earnings; (ii) Average # hours worked per day during the past seven days and; (iii) Total # hours worked during the past seven days.⁷ We combine them to compute hourly wage (Daily earnings / Average # hours worked per day during the past 7 days) and weekly earnings (Hourly wage * Total # hours worked during the past 7 days).⁸ We then average those variable at the village*year level.

Respondents also provide information on their occupation and sector of employment. We compute the share of individuals in each occupation and sector and generate the corresponding Herfindhal indices of fragmentation. The NHTS data also include information on occupation and we are thus able to compute occupation fragmentation for a larger sample of villages. As above, to simplify interpretation we normalise the fragmentation measures to be mean zero and standard deviation 1.

3 Results

3.1 Specification

We study the relationship between social fragmentation and labour market outcomes with models of the following form:

$$\text{outcome}_{im} = \beta_0 + \beta_1 \cdot \text{fragmentation}_{im} + X_{im} \cdot \kappa + u_{im}. \quad (1)$$

The unit of observation i is the village, the village-year, or the village-occupation. $\text{fragmentation}_{im}$ is the Herfindhal index of social fragmentation discussed above, normalised to have mean zero and standard deviation one; X_i is a vector of controls. We cluster standard errors at the level of the municipality m . For every regression, we offer five types of robustness checks. First, we exclude urban areas from the analysis. This helps us address concerns related to selective in-migration, as most migration is from rural areas to urban areas. Second, we exclude ARMM areas, as the naming conventions we exploit are

⁶More information on the survey design is available at: http://www.census.gov.ph/data/technotes/notelfs_new.htm visited on 26 March 2012.

⁷The measure of daily earnings is derived differently according to how someone is paid. For workers who are paid on an hourly basis, the daily rate is computed as their hourly rate multiplied by average working hours (per day) over the past week. For workers who are paid monthly, the daily rate is computed as their monthly wage divided by the number of working days per month.

⁸Our main measures of earnings are at the weekly level because the reference period for earnings and hours worked in the survey is over the last seven days.

followed less strictly in these areas. Third, we show results that use the Latapy/Pons algorithm to detect communities. This helps us establish robustness to different ways of categorising communities. Fourth, we control for indicators of economic inequality, and religious and ethnic heterogeneity. This helps us rule out that our estimates of the effect of social fragmentation are not confounded by other types of heterogeneity in the community. Finally, we use the social fragmentation in the networks of people above 45 to instrument for current total social fragmentation. This strategy again addresses concerns about endogenous contemporaneous changes in social structure.

3.2 Main result

Our main result is that social fragmentation reduces occupation capture. For every occupation in every village in our sample, we measure capture by the share of the workforce in that occupation that belongs to the dominant community.⁹ In all regressions, we control for the population, the number of communities and the number of occupations in the village. These variables determine the expected share of the average community in an occupation. For example, for a given population and number of occupations, increasing the number of communities will mechanically decrease the expected share of the average community in each occupation. Our controls absorb this variation and enable us to focus on non-mechanical changes in occupation capture. We report our results in Table 1.

We find that a one standard deviation increase in social fragmentation is associated with a significant reduction of .25 of a standard deviation in our measure of occupation capture. The concentration of communities within occupations is surprisingly large. Occupations in villages with average levels of social fragmentation have a mean of 37 percent of the workforce that belongs to the dominant community. This goes down to about 30 percent when social fragmentation increases by one standard deviation – a 23 percent decrease.

This result passes all of our robustness tests. When we exclude urban areas and when we control for other types of heterogeneity, we obtain a very similar coefficient to our main specification. When we change the community detection algorithm, the coefficient drops somewhat, but remains statistically significant at the 1 percent level. When we drop ARMM areas or use the IV estimator, we obtain a significantly larger coefficient. In particular, our IV estimates imply that a one standard deviation increase in social fragmentation reduces occupation capture by .32 of a standard deviation. This

⁹To do this, we first calculate the share of each community in the workforce of a given occupation. We then take the maximum share.

may reflect attenuation bias due to measurement error. Alternatively, current social fragmentation may be correlated with unobserved factors that increase occupation capture.

< Table 1 here. >

3.3 Returns to scale or barriers to entry?

A community may come to dominate an occupation for two different reasons. First, to exploit economies of scale. Sharing a community link may make it easier for people in the same occupation to pool capital, labour and information (Munshi, 2011; Dai et al., 2018). The benefits of this community support are likely to grow with community size. As a result, communities may naturally tend to become dominant in specific occupations – a process which would be presumably more visible in socially concentrated villages where a few large communities are well-positioned to take over key occupations. Alternatively, communities become dominant in order to create barriers to entry in an occupation and share the resulting rents. For example, once a community secures a dominant position, it can reduce the profitability of other communities in that occupation by restricting access to labour and physical inputs.¹⁰ Dominance may also allow the community to reduce competition through predatory pricing or by generating the power to lobby local politicians for favorable treatment. These barriers to entry, while statically rational from the point of view of the individual community, will create dynamic losses to the local economy through reduced innovation and growth.

We propose to disentangle between these two views by studying average wages in the village. The intuition behind this test is that, under the first view, occupation capture makes individuals in socially concentrated villages more productive through economies of scale; under the second view, on the other hand, occupation capture stifles competition and innovation and thus ultimately makes individual less productive. These changes in productivity should be reflected in wages.

We find that wages are significantly higher in socially fragmented villages. This supports the explanation of occupation capture as a source of barriers to entry. In Table 2 we report regressions for weekly wages, hourly wages, and total hours worked. We find that individuals in socially fragmented villages earn more and that this driven by higher hourly wages and not by hours worked. Weekly earnings increase by between

¹⁰For example, if most plumbers belong to a community and are unwilling to work for firms that belong to a different community, this will make it hard for new firms to contest the market for plumbing services.

8 to 29 percent, depending on the specification. Further, in Table 3, we report our standard battery of robustness tests and show that the result survives all of them: different definitions of the sample, a different community detection algorithm, controls for other types of heterogeneity, and the IV strategy.

< Table 2 here. >

We also find that social fragmentation is significantly associated with occupation and sectoral fragmentation. We measure these dependent variables by calculating the Herfindhal index of occupations and sectors in a village, using in turn the LFS and NHTS data. We find consistently large and significant effects of social fragmentation on fragmentation of occupations and sectors (Table 4), which are robust to the usual set of test (Table 5). This result suggests that highly dominated occupations or sectors tend to be smaller than the average occupation and sector. As social fragmentation decreases barriers to entry, workers flow to these occupations and sectors, moderating concentration in the allocation of workers across economic activities.

< Table 4 here. >

4 Discussion

Two aspects of our results deserve further discussion. First, what explains the large variation in social structure that we observe in the data? Recent work has suggested that some individuals form social networks following rules of thumb such as always linking to the most popular node (Caria and Fafchamps, 2017). If this were the case in this context, and if individuals are randomly exposed to a subset of all nodes at the time of forming a link (Chandrasekhar et al. 2018), then the families that are randomly given the opportunity to form more links at the beginning of the network formation process would reinforce this central position over time. Variation in social structure would emerge as a function of the number of families that gain early social prominence. The higher the number of families that achieve early prominence, the less concentrated the steady state social structure.

Second, are there any policy leads that emerge from our findings? One novel insight is that the government may decide to target social policy on the basis of the underlying social structure of the targeted community. For example, active labor market policies may be ineffective in environments where individuals face barriers to entry in desirable occupations. In these contexts, cash and asset transfer programs that favor entrepreneurship may be more effective to lift people out of poverty. On the contrary,

in communities where the labour market is easier to access, employment programs may be a useful policy option to pursue.

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Table 1: Social Fragmentation and Captured Occupations

		Exclude:		Other	Alternative	
		ARMM	Urban	Diversity	Algorithm	IV
Fragmentation	-0.069*** (0.00)	-0.074*** (0.00)	-0.065*** (0.00)	-0.066*** (0.00)		-0.084*** (0.01)
Fragmentation (walktrap)					-0.041*** (0.00)	
Observations	118860	99183	103636	116717	118860	118856
R^2	0.37	0.38	0.38	0.38	0.35	

Notes: Results from occupation*village-level regressions with occupation and municipal fixed-effects. The dependent variable is the share of the largest community in each occupation (mean: 0.37; std. dev.: 0.26). Regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural as well as the number of individuals in each occupation. In Column 2, all villages in ARMM are excluded from the sample. In Column 3, all areas classified as urban are excluded from the sample. In Column 4, regressions control for gini as well as ethnic and religious fragmentation. In Column 5, the measure of fragmentation is computed using communities identified with the Latapy/Pons algorithm. In Column 6, we instrument the fragmentation measure with the fragmentation obtained on the sample of individuals older than 45. Standard errors, clustered by municipality, in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2: Social Fragmentation and Labour Market Outcomes

	Log(Weekly Income)		Log(Hourly Wage)		Weekly Hours	
Fragmentation	0.29*** (0.04)	0.074*** (0.02)	0.24*** (0.03)	0.054*** (0.02)	2.65*** (0.56)	0.38 (0.38)
Controls	No	Yes	No	Yes	No	Yes
Observations	5937	5931	5945	5939	6297	6290
R^2	0.08	0.27	0.09	0.30	0.04	0.15

Notes: Results from year*village-level regressions with municipal fixed-effects. The dependent variable is log weekly labour income (Columns 1-2), log hourly wage (Columns 3-4) and weekly working hours (Column 5-6). Regressions control for survey year. In Columns 2, 4 and 6 regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural, as well as variables from the LFS surveys: education levels, number of male and female in the sample, number of male and female age 15-30 in the sample. Standard errors, clustered by municipality, in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: Social Fragmentation and Labour Market Outcomes: Robustness Checks

	Exclude:		Other	Alternative	
	ARMM	Urban	Diversity	Algorithm	IV
Fragmentation	0.069*** (0.02)	0.061** (0.03)	0.071*** (0.02)		0.13* (0.07)
Fragmentation (walktrap)				0.058** (0.02)	
Observations	5345	4627	5931	5931	5931
R^2	0.31	0.21	0.27	0.27	

Notes: Results from year*village-level regressions with municipal fixed-effects. The dependent variable is log weekly labour income. Regressions control for survey year and for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural, as well as variables from the LFS surveys: education levels, number of male and female in the sample, number of male and female age 15-30 in the sample. In Column 1, all villages in ARMM are excluded from the sample. In Column 2, all areas classified as urban are excluded from the sample. In Column 3, regressions control for gini as well as ethnic and religious fragmentation. In Column 4, the measure of fragmentation is computed using communities identified with the Latapy/Pons algorithm. In Column 5, we instrument the fragmentation measure with the fragmentation obtained on the sample of individuals older than 45. Standard errors, clustered by municipality, in parentheses.
 * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: Social Fragmentation and Fragmented Occupation

<i>Source:</i>	Occupation Fragmentation				Sectoral Fragmentation	
	NHTS		LFS		LFS	
Fragmentation	0.25*** (0.02)	0.20*** (0.03)	0.53*** (0.08)	0.16*** (0.05)	0.54*** (0.08)	0.17*** (0.05)
Observations	12957	12935	6297	6290	6297	6290
R^2	0.08	0.10	0.10	0.33	0.11	0.37

Notes: Results from village-level regressions (Columns 1-2) and year*village-level regressions (Columns 3-6) with municipal fixed-effects. The dependent variable is a measure of occupation fragmentation computed with the NHTS data (Columns 1-2), computed with the LFS data (Columns 3-4) and a measure of sectoral fragmentation computed with the LFS data (Columns 5-6). Regressions control for survey year and for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural, as well as variables from the LFS surveys: education levels, number of male and female in the sample, number of male and female age 15-30 in the sample. Standard errors, clustered by municipality, in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Social Fragmentation and Fragmented Occupation

	Exclude:		Other	Alternative	
	ARMM	Urban	Diversity	Algorithm	IV
Fragmentation	0.24***	0.21***	0.15***		0.27***
	(0.04)	(0.02)	(0.02)		(0.05)
Fragmentation (walktrap)				0.18***	
				(0.02)	
Observations	10657	11464	12721	12935	12933
R^2	0.14	0.08	0.17	0.10	

Notes: Results from village-level regressions with municipal fixed-effects. The dependent variable is the measure of occupation fragmentation computed on the NHTS sample. Regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural. In Column 1, all villages in ARMM are excluded from the sample. In Column 2, all areas classified as urban are excluded from the sample. In Column 3, regressions control for gini as well as ethnic and religious fragmentation. In Column 4, the measure of fragmentation is computed using communities identified with the Latapy/Pons algorithm. In Column 5, we instrument the fragmentation measure with the fragmentation obtained on the sample of individuals older than 45. Standard errors, clustered by municipality, in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$