Supplementary Material

1. The Exponential Random Graph Model (ERGM): model description

When the interest lies in understanding linking structures in a social setting, graph models are the standard way to address it. For a fixed set of *n* nodes (in our application, individuals with varying levels of history of infection), we observe a web of connections (and isolated nodes), **Y**, defined by our proposed affinity formula. The **Y** is the observed configuration (that is, the observed graph structure) denoted by the *n x n* adjacency graph matrix, and can be assessed by an identification function as:

$$Y_{ij} = \begin{cases} 1\ if\ a\ connection\ exists\ between\ i\ and\ j \\ 0\ otherwise \end{cases}$$

For the specific case in this study, a connection exists if any two individuals share at least one standardized evocation in common. Following Pereira (2017), the affinity formula for the existence of a connection (shared representation regarding ZIKV) between individuals *i* and *j* is:

$$\alpha(i,j) = \frac{\sum_{u=1}^{k}\sum_{v=1}^{k}\left[\theta(u,v,k)\times\rho(u,v,k)\times 1_{i_u=j_v}\right]}{k^2\times(k+1)}\times\omega(k)$$
$$\forall\ u,v \geq 1\ and\ u < v \leq k$$

where:

$\rho(u,v,k) = k - |u-v|$ → the distance parameter

$\theta(u,v,k) = [2\times(k+1)] - (u+v)$ → the order parameter

$\omega(k) = \left\{1 - \frac{(K-k)\times(K-k+1)}{K\times(K+1)}\right\}$ → the length penalizer

The affinity measure, $\alpha(i,j)$, is bounded between 0 and 1. Thus, Y_{ij} = 1 if $0 < \alpha(i,j) \leq 1$. The advantage of using the above formula is to transform the identification function into a weighted adjacency matrix, where the connection is weighted by how similar two individuals share representations regarding ZIKV.

Using the formula above, we produce a probabilistic model of **Y** based on the observed network data (the observed connections between individuals regarding ZIKV based on the proposed affinity formula above). The following initial assumptions are imposed to construct our model:

- The connections between individuals are undirected. That is, $Y_{ij} = Y_{ji}$.
- The connections are valued by the affinity coefficient $\alpha(i,j)$
- No self-connection (loop) is modeled. That is, $Y_{ij} = 0\ \forall\ i$.

We include additional information on the attributes of nodes, *n*, which we call them an **X** vector of node attributes. Since we are interested in testing the influence of the history of infection and the diagnostic criterion on the probability of cognitive affinity (the existence of a non-zero Y_{ij}), these are the two attributes of **X** measured directly as a node (ego)'s attribute. We model this structure based on the exponential random graph family of models (ERGM), where the relation between a graph **y** and its probability of occurrence, conditional of a set of nodes attributes, **X**, can be generally expressed as:

$$P_\eta(\boldsymbol{Y}=\boldsymbol{y}) = \frac{\exp\{\sum_{i=1}^{p}\eta_i g_i(\boldsymbol{y},\boldsymbol{X})\}}{\kappa(\boldsymbol{\eta})} = \frac{\exp\{\boldsymbol{\eta}^t\boldsymbol{g}(\boldsymbol{y},\boldsymbol{X})\}}{\kappa(\boldsymbol{\eta})}$$

where **g**(**y**, **X**) will be defined by the modeler as a p-vector of statistics. The parameter vector $\boldsymbol{\eta} \in \boldsymbol{R}^p$ governs the probabilistic configuration of the network structure, while $\kappa(\boldsymbol{\eta})$ is a normalizing parameter to bound the probability within its feasible range (Hunter 2007).

Although many types of endogenous parameters to the graph structure can be modeled in the $\boldsymbol{\eta}$ vector, giving rise to a variety of alternative models, including the curved ERGM, where all the *n-1 k* stars (cliques) of the observed network, $\mathbf{y}$, can be reduced to a single parameter, curving the parameter space to a single estimate (Hunter and Handcook 2006, Snijders et al. 2006), this model is highly instable for most real word social networks (Hunter 2007). In our probabilistic model, we include a single endogenous parameter, the homogenous probability of a connection (edge), valued by the affinity formula, including node attributes: ego's history of infection and diagnostic criterion. We solve the model by maximum likelihood and allow $\mathbf{g}(\mathbf{y}, \mathbf{X})$ to include statistics which depend on both $\mathbf{y}$ and $\mathbf{X}$: 1) main effects of ego's history of infection and diagnostic criterion, and 2) a homophily effect of the diagnostic criterion:

1. The *main effect* of, say, history of infection can be defined as the sum of the value of the history of infection for each endpoint of the existent edge between two pairs of individuals: $\sum_{1\leq i<}\sum_{j\leq n} y_{ij}(infection_i + infection_j)$. That is, every time a new edge is added to the network the effect of history of infection, its main effect if increased by the sum of the infection's attribute value of its two endpoints.
2. The *homophily effect* of the diagnostic criterion, is defined by the number of edges in $\mathbf{y}$ for which both endpoints of the edge have the same value of diagnosis. Thus, if an edge is added to the network, it increases the homophily effect of diagnosis by one if and only if the two endpoints share the same attribute value.

2.1. The Exponential Random Graph Model (ERGM): *model results*

2.1.1. *A note on the data used*

This study used novel data on mental representations of the ZIKV for urban residents of Governador Valadares (GV), Minas Gerais, Brazil. The choice for GV is justified because the city ranks third in the state for the LIRAa index (Assessment of *Aedes aegypti* Infestation Index), and is classified in the very high incidence cluster for Dengue in Brazil (Brasil 2016). The 2017 LIRAa for GV was 8.5%, above the minimum threshold of 3.9% for the high-risk category (PMGV 2017). In 2016 alone, 1,609 cases of Dengue, 115 of Chikungunya, and 3,154 of ZIKV were notified in GV. Key for our study, the city was also hit by contaminated mud from the Samarco dam failure in November 2015 (Felippe 2016). This unprecedented incident created severe water shortage due to the contamination of the city's main river by heavy metals, leading residents to stock water at home. Such massive amount of water stocked has contributed to the proliferation of the *Aedes aegypti* in the region, making the city a key social context for the understanding of the social representation of the ZIKV.

The selection of respondents was based on a baseline probabilistic survey conducted from January 2014 to June 2016 with 1,226 individuals. The baseline survey is part of the research project *Migration, Vulnerability, and Environmental Change in the Rio Doce Valley*. For the present study, we aimed at collecting 150 respondents (Table 1 – Panel A) using the following procedure. We first randomized the 1,226 baseline interviews and separated them into four groups (Female High socioeconomic status – SES; Female Low SES; Male High SES; Male Low SES). The SES assignment was based on a standardized social class scale proposed by the Brazilian Association on Marketing Research (ABEP 2014). We then contacted the first respondent of each group by phone as s/he appeared in the random sequence in order to fill a stratified sample of 50 respondents in each category of infection (past/current ZIKV infection, past/current Dengue or Chikungunya infection but not ZIKV, never infected with any *Aedes aegypti* transmitted disease).

Due to the rarity of the ZIKV event, it was not possible to complete all quotas with the available baseline sample and we ended up filling only 117 cases, which is our analytical sample (Table 1 – Panel B of the manuscript). Infection was based on self-reported answers (Martin et al. 2000). Post-survey weight adjustments were performed based on Dengue, Chikungunya, and ZIKV incidence in GV to balance the group's sizes and avoid biased links between evocations by history of infection.

Although information on infection was self-reported, we performed an initial screening to reduce potential bias. At the first phone contact, respondents were asked how they knew if they were or not infected by Dengue, Chikungunya, or ZIKV. We started by letting them freely suggest the diagnostic criterion. In all cases of self-diagnosis, the interview was interrupted and a new interview was conducted with the next person appearing in the list of random numbers from the baseline survey. For those who said s/he was diagnosed by a health professional, we further asked if they had taken a serological test for detection or if the health professional clinically diagnosed him/her.

2.1.2. Main findings

As pointed by some of the anonymous reviewers of this study, the subjective nature of a self-diagnosis can influence the ways in which individuals perceive an illness and therefore the topology of their cognitive description. In response to this possibility, we include in this supplementary material an inferential analysis using an *Exponential Random Graph Model* (Hunter 2007) to test directly whether the type of diagnosis (clinical or serology) affects the ways individuals signify ZIKV, regardless of their history of infection.

Supplementary Table 1 shows results from our probabilistic ERGM. We first note the importance of the network density (edges coefficient) in helping to explain the observed configuration. That is, the density of shared thoughts is important to explain the construction of a social representation beyond random collection of isolate, individual representation of the ZIKV in this context, expressing an operative and functional mechanism of cognitive sharing and learning through communication. It also suggests that those who reported having been tested for the disease (Dengue, Chikungunya, or Zika) were less likely (OR = 0.718) to share common meanings of ZIKV with the rest of the surveyed population than those with a clinical diagnosis by a health professional. This result holds, *regardless* of the history of infection (columns "Endogenous + Covariates") and the density of the network (the edges coefficient). Interestingly, those individuals who share the same type of diagnostic criterion are statistically more likely to have similar representations of the ZIKV (OR = 1.377) than those who share some representations, $\alpha(i,j) > 0$, but with different type of diagnosis.

Supplementary Table 1: Estimated Odd-Ratios for the Probability of Cognitive Affinity regarding ZIKV – Exponential Random Graph Model, Governador Valadares, Minas Gerais, Brazil, 2016

Parameters	**Endogenous**	**Endogenous + Covariates**	**Endogenous + Covariates + Homophily**
Endogenous			
Edges	**1.099*** **	**1.106*** **	**0.809** **
Exogenous			
Node Attributes			
Ego' Reported Infection (base = none)			
Dengue or Chikungunya		**1.237*** **	**1.212*** **
Zika (regardless of others)		**0.901***	**0.880***
Diagnostic Criterion (base = clinical)			
Serological		**0.718*** **	
Node Homophily			
Diagnostic Criterion			**1.377*** **
Anova	-8758.4***	-8704.3***	-8709.1***
Goodness of fit			
AIC	8760	8712	8717
BIC	8767	8739	8744
Observations			
Nodes	113	113	113
Edges	3313	3313	3313

Source: Authors' elaboration based on primary survey data (Governador Valadares, Brazil, 2016)
Note: Estimates based on our "wordevok" R package along with the following packages: "igraph" and "ergm". P-values are represented by stars in their critical values: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01

Due to the significant results indicating a difference, we opted to re-run our network models with the goal of comparing the webs by individuals' diagnostic criteria. This analysis was performed for those infected with ZIKV, as shown in Figure 2 of the manuscript. The differences are revealing. Those who were tested for ZIKV had a much closer representation of the disease as described by the symptoms commonly associated with virus. CDC (2016), for instance, reports *Fever*, *Rash*, *Headache*, *Joint and Muscle Pain* as the most common ZIKV symptoms. The list of symptoms is also similar to the one released by the Brazilian Ministry of Health, which comprises *fever, rash (with itch), joint pain/swelling, conjunctivitis (red eyes; conjunctival hyperemia), muscle pain, and headache*. The same symptoms are not observed in the network for those diagnosed with ZIKV by a health professional without a serological test. On the other hand, the representation of the ZIVK in the network of clinical diagnosis goes hand in hand with the protocol utilized by the Brazilian Ministry of Health, which recommended that only more severe cases of the disease needed to undergo serology to discard Dengue or Chikungunya infection (the one they were more concerned about due to its higher mortality). Thus, in case of non-severity of symptoms, most clinical diagnoses of ZIKV could have been defined solely based on the presence of "itch". Note that besides "pain", "itch" is the only other specific symptom to appear in their network, highlighting the quality of the data we are collecting.

Although we observe differences by type of self-reported diagnostic criterion, some key points must be considered. *First*, the stratification by diagnostic criterion is not able to completely rule out the bias caused by self-reported infection, although Figure 2 of the manuscript is revealing of a more consistent representation of the ZIKV infection among those identified as infected based on self-reported serological tests. *Second*, the networks of meanings are not restricted to symptoms, as individuals identify words clearly related to the disorder of local care, social chaos, limited control of breeding sites, and other public and personal causes for the existence and consequence of the epidemics. This is the very richness of this type of analysis based on lay thinking, as advocated by many studies on collective meanings on health (Walter et al. 2004; Bachrach and Morgan 2013). *Third,* because the diagnostic criterion is self-reported, false positives and negatives are more likely to occur. This was a point raised by two anonymous reviewers, which we acknowledge next. False positives are more likely to occur among those with associated morbidities, since there is still confusion by the population regarding differences across the diseases transmitted by the mosquito. False negatives, on the other hand, are more likely among those who reported not having an illness associated with the *Aedes aegypti*, since many cases of ZIKV can be symptomless. *Forth*, the persistence of symptoms not related to the specific infection may reflect the consequences of associated morbidities. In our analysis, we included individuals identified as infected by ZIKV, regardless of also having been infected by Dengue or Chikungunya. This was necessary due to the small sample size of those who had Zika but no other infections transmitted by the mosquito. *Finally,* the web of meanings in the clinical diagnosis subsample (Figure 2 of the manuscript) also shows *Itching* for those with Zika. Although this could be interpreted as a symptom not directly associated with ZIKV (indicating a reliability issue with the web of meaning for those clinically diagnosed), some diagnostic protocols in Brazil may help us understand this case as discussed above.

2. Association between Representations of Symptoms and Symptoms based on the Medical Literature regarding ZIKV, Chikungunya, and Dengue

In February 2015, the *Secretaria de Vigilância em Saúde* of the Ministry of Health started to monitor the occurrence of an "undetermined exanthematous syndrome" in Northeast Brazil. The most common symptom was indeed the exanthema (known as skin rash), with intensive itch, low fever if present, conjunctivitis, and joint pain. Following, one of the first bulletins released by the Brazilian Ministry of Health about Zika brings a list of the most common symptoms possibly linked to ZIKV infection. This list was comprised of fever, rash (with itch), joint pain/swelling, conjunctivitis (red eyes; conjunctival hyperemia), muscle pain, and headache (Supplementary Table 2). These symptoms were then utilized for clinical diagnoses of patients in the public health service nationwide. Due to the existence of other arbovirus (Dengue and Chikungunya) in the same geographic regions and the fact that these diseases share common symptoms with ZIKV, the clinical criterion for diagnosing ZIKV became challenging even for health professionals. Thus, in case of non-severity of symptoms, which could possibly signal a Dengue diagnosis (the one they were more concerned about due to its higher mortality), most diagnosis of ZIKV were defined based on the presence of exanthema with itch and conjunctivitis, fewer alterations in white blood cells, and thrombocytes (FEBRASGO 2017, FIOCRUZ 2016). The protocol for ZIKV in the State of Minas Gerais suggests that the presence of rash with itch (*exantema máculopapular pruriginoso*, in Portuguese) with at least two other symptoms of the disease were already considered a condition for ZIKV notification and clinical diagnosis (PMGV 2017).

Because of this protocol, it is possible that patients presenting itch were automatically diagnosed as ZIKV even without serological testing. Patients with other symptoms could have been led to perform blood tests. In Brazil, the mandatory serological testing was implemented only for pregnant women with exanthema, patients with severe symptoms or neurological manifestations, children with microcephaly, and in case of suspected death. Unfortunately, since the symptoms may also overlap, the true diagnosis of the ZIKV can only be done by serological tests that can differentiate the arbovirus. However, the recommendation was that only the first autochthonous cases were to be confirmed by serological tests and the following ones by clinical criteria (FEBRASGO 2017). Therefore, even with data on actual diagnosis in hand, it is likely that false negative among those clinically diagnosed would remain.

Supplementary Table 2: Comparison of the Main Symptoms Caused by Dengue, Chikungunya, or Zika Virus Infection

Symptom	Dengue	Chikungunya	Zika	Measels
Fever	++++	+++	+++	++++
Myalgia/Arthralgia	+++	++++	++	0
Edema	0	0	++	0
Maculopapular rash	++	++	+++	++++[b]
Retroorbital stabbing pain	++	+	++	0
Conjunctival Hyperemia	0	+	+++[a]	++++[c]
Lymphadenopathy	++	++	+	+
Hepatomegaly	0	+++	0	+
Leukopenia/Thrombocytopenia	+++	+++	0	+++
Bleeding	+	0	0	0[d]
Productive cough	0	0	0	+++

a Not showing prurigo or exudation

b Craniocaudal evolution

c Showing photophobia

d It can happen in the aggravation

Note: + represents the severity of the symptom, varying from 0 (absence of symptom) to ++++, which represents the maximum severity.

Source: http://portalarquivos.saude.gov.br/images/pdf/2015/agosto/26/2015-020-publica----o.pdf. English translation from original table.

3. Categorization of the qualitative data used as representations of the ZIKV

Categorization of qualitative data is essentially subjective. Many steps were used in this study to minimize the researcher's classification bias. Evocations were coded according to their meaning, a procedure described in Bradley, Curry and Devers (2007). Although 240 unique words or expressions were originally evoked, the standardization (grouping them into common concepts) resulted in only 66 categories of meaning. As suggested by Bradley, Curry and Devers (2007), we applied inductive reasoning when defining preliminary codes in order to reflect the participant's meanings. Qualitative codes in public health research might refer to specific behavior, incidents, values, emotions, or what Saldana (2009) calls methodological elements, which refer to the interviewer's impression about the person (e.g., the interviewee doesn't seem to know what s/he is talking about).

These codes also had the intention of reducing the amount of variation to the analysis without losing their unique meaning. For example, the expressions "accumulated trash" and "pollution" were reclassified into the category "Trash". We recognize that this process is entirely subjective to their coder interpretation, but a rigorous process of "constant comparison" and code structure guarantees the quality of subsequent analysis (Miles and Huberman 1994 in Bradley, Curry and Devers (2007). In this process, data are reviewed line by line in detail and as a concept becomes apparent, a code is assigned. Upon further review of data, the analyst continues to assign codes that reflect the emerging concepts, highlighting and coding lines, paragraphs, or segments that illustrate the chosen concept. As more data are reviewed, the specifications of codes are developed and refined to fit the data. To ascertain whether a code is appropriately assigned, the analyst compares text segments to segments that have been previously assigned the same code and decides whether they reflect the same concept (Glaser and Strauss 1967 in Bradley, Curry and Devers 2007). When the word was too vague for proper classification, the researcher read the answers to question #3 from the instrument for data collection (You mentioned that expression '"FILL IN" was the most important for you. What does it mean to you? *[Open question*]) searching for an explanation that would satisfy the meaning given to the vague word. In case it would not fit any code already existent, a new one would be created (i.e., bed, mutation).

The second step in our qualitative analysis was to group common codes into themes, which are "recurrent unifying concepts or statements about the subject of inquiry" (Boyatzis 1998 in Bradley, Curry and Devers 2007). Nine major themes were recognized and they represent the underlying meaning behind the codes (see Supplementary Table 3):

a) Symptoms
b) Consequences
c) Vector
d) Public Health
e) Lack of Social Responsibility
f) Contagious
g) Treatment/Prevention
h) Chaos
i) Lack of Personal Responsibility

Supplementary Table 3: List of codes by themes – Data on Representations of Zika Virus, Governador Valadares, Minas Gerais, Brazil, 2016

Symptoms	Consequences	Vector	Public Health	Lack of Social Responsibility	Contagious	Treatment or Prevention	Chaos	Lack of Personal Responsibility
Bed	Abortion	Dengue	Empty lot	Badly treated at the clinic	Contagious	Can be eradicated	Calamity	Awareness
Bloated	Death	Disease	Public Health	Cost of treatment	Epidemics	Curable	Chaos	Lack of prevention
Depression	Disability	Rain	Sanitation	Lack of commitment	Transmission	Health	Danger	Population's fault
Fever	Microcephaly	Forest	Trash	Lack of treatment	Virus	Hospital	Fear	Populations
Headache	Family	Mosquito	Vulnerable population	Law	Proliferation	Medicine	Problem	
Itching	Pregnancy	Mosquito bite	Standing water	Search for health care		Prevention	Something bad	
Joint pain		Mutation		Olympics		Treatment	Doesn't know if has a solution	

Lack of appetite						Vaccine	Doesn't make sense	
Malaise						Well treated at the clinic		
Medical leave								
Nausea								
Pain								
Rash								
Suffering								
Symptoms								
Weakness								
Weight loss								

Source: Author's elaboration based on primary survey data (Governador Valadares, 2016).

4. List of Evocations Weighted Degree by History of Infection and Diagnostic Criterion

Supplementary Table (ST) 4 presents the list of evocations based on their descriptive importance in the web of meanings, which supports Figures 1 and 2 of the manuscript. The node (evocation) degree is based is defined as the number of other evocations connected to the evocation for which the degree is attributed. The weight is given by the edge weights formula defined in the methods section of the manuscript. The 10 most important words (in terms of weighted degree) are highlighted in bold in ST 4.

Supplementary Table 4: List of Evocations Weighed Degree by History of Infection and Diagnosis Criterion, Governador Valadares, Minas Gerais, Brazil, 2016

Terms	History of Infection						
	Never infected	Infected by Dengue or Chikungunya			Infected by Zika		
		Clinical Diagnosis	Serological Test	All	Clinical Diagnosis	Serological Test	All
Abortion		0.69		0.69			
Awareness	2.35	0.05		0.05			
Badly treated at the clinic	1.50						
Bed	0.77					0.35	0.35
Bloated						**0.69**	0.69
Calamity	0.88	0.15		0.15			
Can be eradicated	3.28	0.81		0.81		0.35	0.35
Chaos	1.28	0.47		0.47		**0.38**	0.38
Contagious	1.19	0.05		0.05			
Cost of treatment	1.20						
Curable	0.15	0.05		0.05			
Danger	**5.34**	**1.88**		**1.88**			
Death	3.13	0.77	0.68	**1.44**	0.68		0.68
Dengue	1.31		**0.77**	0.77			

Depression	0.15					0.15	0.15
Disabilities	2.09				0.74		0.74
Disease	**14.55**	**7.89**	0.56	**8.45**	**1.81**	**0.69**	**2.50**
Doesn't know if has a solution		0.05		0.05			
Doesn't make sense	0.05						
Empty lot	0.15						
Epidemics	3.65	0.69	**1.43**	**2.12**			
Family			0.05	0.05			
Fear	3.08	**1.97**	0.33	**2.30**	0.05		0.05
Fever	3.15	**1.18**	**0.69**	**1.87**		0.35	0.35
Forest	1.45						
Headache	1.20	0.05		0.05		**0.69**	0.69
Health	2.03	0.81		0.81	0.05		0.05
Hospital	0.33						
Itching	0.35	0.74	0.15	0.88	0.74		0.74
Joint pain						**0.35**	0.35
Lack of appetite	0.35						
Lack of commitment	**6.21**	0.83	0.50	1.33	**1.78**	**0.77**	**2.54**
Lack of prevention	**4.96**	0.15	0.05	0.19	**1.10**	**0.69**	**1.88**
Lack of treatment	1.02	0.35		0.35			
Law	0.69		0.15	0.15			
Malaise	2.81	0.88	**0.69**	**1.57**	0.15	0.05	0.19
Medical leave	0.15				0.11	0.05	0.16
Medicine	0.83	0.15	**0.77**	0.91	0.35		0.35
Microcephaly	**4.69**	**1.69**	**1.43**	**3.12**	**1.46**		**1.46**
Mosquito	**9.15**	**3.16**	**0.84**	**4.00**	**1.66**		**1.66**
Mosquito bite					**1.00**		**1.00**
Mutation		0.35		0.35			
Nausea						0.15	0.15
Pain	**5.56**	0.66	0.11	0.77	**2.72**	**2.33**	**5.05**
Population's fault	2.83	0.91	0.35	1.26	0.15	0.15	0.29
Populations					0.11		0.11
Pregnancy	2.49	0.77		0.77			
Prevention	**9.21**		0.35	0.35			
Problem	0.35	0.35		0.35			
Proliferation					0.25		0.25
Public health	2.30	**1.04**		1.04			
Rain					0.35		0.35
Rash	0.74	0.05	**1.09**	1.14	0.33	**0.81**	**1.14**
Sanitation	0.05						
Search for health care	0.83						
Something bad	1.18	**1.17**		1.17	0.11		0.11

Standing water	**6.27**	**1.21**	**0.69**	**1.90**	**1.44**		**1.44**
Suffering	3.32	0.11		0.11			
Symptoms	0.15				**1.38**		**1.38**
Transmission	0.98	**1.04**		1.04			
Trash	**4.30**	0.74	0.05	0.78		**0.74**	0.74
Treatment	1.15				**0.77**		0.77
Vaccine			**0.69**	0.69			
Virus	0.35	0.15	0.68	0.82	0.60		0.60
Vulnerable population	0.10	0.35		0.35			
Weakness	2.96					0.15	0.15
Weight loss	0.35						
Well treated at the clinic	0.69						

Note: Ten terms with the highest weighted vertex degree highlighted in bold.
Source: Author's elaboration based on primary survey data (Governador Valadares, 2016).

References

ABEP. Critério de classificação econômica Brasil. (2014). Assoc Bras Empres Pesqui Available Httpwwwabeporgcriterio-Bras. 2014.

Bachrach, CA, Morgan, SP. (2013). A cognitive–social model of fertility intentions. *Population and Development Review* 39(3): 459-85.

Bradley EH, Curry LA, Devers KJ. (2007). Qualitative Data Analysis for Health Services Research: Developing Taxonomy, Themes, and Theory. *Health Serv Res., 42*(4), 1758–72.

Brasil. Ministério da Saúde. Levantamento Rápido de Índices para Aedes aegypti (LIRAa). Resultados por municípios. [Internet]. 2015 [citado 8 de dezembro de 2016]. Available at: http://portalsaude.saude.gov.br/images/pdf/2015/novembro/24/LIRAa-2015-municipios.pdf

CDC – Center for Disease Control and Prevention. Symptoms, Testing, & Treatment (Zika Virus Home). [Internet]. 2016. [citado 20 de maio de 2017]. Available at: https://www.cdc.gov/zika/symptoms/symptoms.html

FEBRASGO. Orientações e recomendações da FEBRASGO sobre a infecção pelo vírus Zika em gestantes e microcefalia [Internet]. São Paulo, SP: Federação Brasileira das Associações de Ginecologia e Obstetrícia; 2016 [citado 25 de março de 2017]. Available at: http://www.febrasgo.org.br/site/wp-content/uploads/2016/05/Virus-Zika-em-gestantes-e-microcefalia.pdf

Felippe MF, Costa A, Franco R, Matos R. (2016). A Tragédia Do Rio Doce: A Lama, O Povo e a Água. Relatório de Campo e Interpretações Preliminares Sobre as Consequências do Rompimento da Barragem de Rejeitos de Fundão (Samarco/Vale/Bhp). Geografias. 2016; Belo Horizonte-Edição Especial-Vale do Rio Doce: formação geo-histórica e questões atuais.

FIOCRUZ. ZIka: Abordagem clínica na atenção básica. UFMS/FIOCRUZ-MS/UNA-SUS/SVS/SAS/Ministério da Saúde; 2016.

Hunter, DR, Handcock, MS. (2006). Inference in curved exponential family models for networks. *Journal of Computational and Graphical Statistics*, 15, 565–583.

Hunter, DR. (2007). Curved exponential family models for social networks. *Social networks*, *29*(2), 216-230.

Martin LM, Leff M, Calonge N, Garrett C, Nelson DE. (2000). Validation of self-reported chronic conditions and health services in a managed care population. *Am J Prev Med.*, *18*(3).

PMGV - Prefeitura Municipal de Governador Valadares. Dengue: 1º LIRAa de 2017 aponta aumento no número de focos do mosquito [Internet]. Prefeitura Municipal de Governador Valadares. 2017. Available at: http://www.valadares.mg.gov.br/detalhe-da-materia/info/dengue-1o-liraa-de-2017-aponta-aumento-no-numero-de-focos-do-mosquito/53160

Saldaña J. (2009). *The coding manual for qualitative researchers*. London: Sage.

Snijders, TA, Pattison, PE, Robins, GL, Handcock, MS. (2006). New specifications for exponential random graph models. *Sociological methodology*, *36*(1), 99-153.

Walter, FM, Emery, J, Braithwaite, D, Marteau, TM. (2004). Lay understanding of familial risk of common chronic diseases: a systematic review and synthesis of qualitative research. *The Annals of Family Medicine*, *2*(6), 583-594.