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Localizing syndemics: A comparative study of hunger, stigma, suffering, and crime exposure in three Haitian communities

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ABSTRACT

Theoretically, disease syndemics are hyper-localized in the forms they take, but little empirical data show how localization manifests. We present a comparison across three sites in Haiti, from data collected in June–august 2017 testing for localizations of risks across three communities: rural farming, border town, and in a high gang-activity urban zone. First, we modeled survey responses collected from heads of 4055 geographically-sampled households via linear regression, considering additive and interaction effects of food insecurity, crime exposure, and discrimination on depression and anxiety levels. Exposure to food insecurity, crime exposure, and discrimination were each associated with more depression and anxiety symptoms. For those living in the urban zone, there was weak evidence of possible interactional risks between the three vulnerabilities, suggesting little meaningful localized syndemic patterning. Second, we conducted thematic and word-based semantic network analysis to identify if people themselves cognitively connected vulnerabilities of hunger/poverty, crime, and suffering/discrimination using 7321 text blocks from 95 semi-structured interviews/focus groups. Network visualization suggested people commonly connect these domains. While the patterns were localized, crime concerns were central to all networks. The domain connections expressed through people's own words were more complexly inter-related than was evident from the modeled survey data, and suggested counter-intuitive influences. The quantitative approach to modeling syndemic interactions suggests no apparent practical benefits to layering or combining local anticrime, anti-hunger, and anti-discrimination programming. However, the qualitative network analysis suggests that programming could none-the-less leverage the perceived connections across domains for more meaningful and effective interventions. For the broader study of syndemics, incorporating novel qualitative approaches clarifies that constituent processes are not just potentially localizing suffering, but are also extremely important in how people cognitively understand and organize their everyday lives.

1. Introduction

Syndemics are, by definition, localized. Singer's original conceptualization defines syndemics as, "the *concentration* and deleterious *interaction* of two or more diseases or other health conditions in a population, especially as a consequence of social inequality and the unjust exercise of power" (Singer, 2009: XV, emphasis ours). These *interactions* are theorized to operate within the health experience of the individual in the context of forms of disadvantage, exploitation, and disempowerment that are historically spatially clustered, culturally-situated, and historically canalized; hence *concentrated* (Mendenhall, 2017; Mendenhall and Singer, 2019; Tsai and Burns, 2015; Tsai and Venkataramani, 2016).

Most syndemic analyses are based on the individual as the locus of concern, in the contexts of population risk, such as how comorbid illnesses or conditions worsen each other; thus, proximate contextual factors are treated as a covariate (Stoicescu et al., 2019; Tomori et al., 2018). However, syndemic *processes* should also cluster and be concentrated in what Rhodes et al. (2005) call syndemic "risk environments," created through the localized processes that Schell (1992, 1997) similarly refers to as "biocultural risk focusing." While exogenous to the individual, these risk environments and risk-focusing processes can be both physical and social. These processes as such define the physical and

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social space ("localization") in which exogenous factors interact with the individual to undermine their health (Rhodes et al., 2005).

Theorizing on such syndemic localization has, ironically, been limited previously because most important prior studies of syndemics, appropriately and out of necessity, focused very specifically on intra-community syndemic dynamics (Carney, 2015; Horton, 2016; *cf.* Marshall, 2013; Mendenhall, 2012). Such ethnographically-oriented work provides solid evidence of predictable additional effects of syndemically interacting factors on worsening physical and mental health (as indices of suffering). And, even as syndemics have been modeled epidemiologically, there is not currently concurrent, robust, comparative evidence around the elements that might help explain *varied* expression of syndemics (Stall et al., 2015; Tsai, 2018; Tsai and Burns, 2015). Moreover, both the ethnographic (lived, observed, understood, given meaning, micro-level) and the epidemiological (counted, modeled, macro-level) approaches to syndemics are rarely integrated. This type of integration is needed to unravel the processes of syndemic risk localization (Littleton et al., 2008).

Here we present a comparative study designed to address directly the question of how "syndemic suffering" (Mendenhall, 2012) locally manifests through risk environments using direct comparison of three very low-resource – but quite different – communities in Haiti. Our analysis focuses on three potential factors that each, in themselves, reflect the consequences of chronic social inequality and drive health disparities: exposure to crime, hunger (food insecurity), and experience of discrimination. Our basic model is that crime exposure, hunger, and discrimination interact within low-resource Haitian communities to create syndemic (additional, interactive) suffering beyond what each contributes alone (Tsai, 2018: Fig. 2, panel 1). But, we also predict that we will observe key interactional differences across sites that reflect specific and identifiable processes of localization in relation to those risk factors for those living there. And we expect that people who live in these risk environments can also reasonably recognize and explain them.

As such, we model data from systematically collected quantitative surveys, using heightened anxiety/depression levels as our marker of negative health effects. All three of our selected health-relevant syndemic risk factors (crime exposure, food insecurity, discrimination) are oft-described as predictive of worse mental health. Living with severe material needs consistently and independently predicts heightened risk of mental illness (Bisung and Elliott, 2017; Lund et al., 2010; Patel and Kleinman, 2003). Food insecurity seems to particularly heighten the risk (Hadley and Patil, 2006). Individual experiences of discrimination from any source are also, in themselves, highly distressing and are associated with worse mental health outcomes (Brewis and Wutich, 2019). Crime exposure is also consistently associated with elevated risk of common mental illnesses (Weisburd et al., 2018). For Haiti specifically, exposures to widespread organized violence has been shown as particularly stressful (Smith-Fawzi et al., 2012).

Identifying what people notice, care about, and place meaning on is another way to capture the signatures of the localization of syndemic suffering. So, we also consider if people themselves identify these syndemic connections. We do this by applying word-based, semantic network analysis of interviews/focus group texts from each of the three sites, supported by thematic analysis to explicate potential *cognitive* localization in how people organize syndemic connections between crime, hunger, and discrimination domains.

So, applying two datasets collected using different epistemological frameworks, the goal is to use comparison across sites and across diverse data forms to consider how syndemics manifests differently across communities that share the same basic cultural understandings and broad structural limitations, i.e., how they *localize*.

1.1. *Study sites*

The three study sites all reflect the broader lived Haitian realities of widespread poverty, hunger, discrimination, and exposure to crime that characterize the lives of those in its most marginalized sectors. The site selection criteria was then to capture maximal contextual variation across the sites.

Site 1: Martissant (population ~280,000), near the capital of Port-au-Prince, is an urban, low-income zone recognized for endemic gang activity and related violent crime. People in Martissant are particularly reliant on the cash economy for access to food and services. With urbanization and an exodus of young people from rural Haiti in recent decades, the population of Port-au-Prince doubled between 1980 and 2012, with the largest increases in population density in the poorest neighborhoods of the capital, including Martissant (Baptiste, 2017).

Site 2: Ouanaminthe (population ~100,000), located in the North-east Department, is a market town, its hinterland near the Dominican Republic with a mix of rural and urban households. It is a site of crime and other economic and social tensions related to its border with the Dominican Republic.

Site 3: Cornillon (population ~60,000) municipality is a rural area of smallholder farming and charcoal production, low literacy levels, and very low household incomes, but relatively lower levels of violent crime.

2. Methods

The study employed a combination of geographically sampled surveys with household heads alongside qualitative data collection with purposefully selected respondents in these three sites (Table 1). Data collection was conducted as part of the multi-year Haiti Justice Sector Strengthening Project (JSSP): full details of the study design are available elsewhere (Diagnostic & Development Group [DDG], 2017). All data collection applied informed consent, with oversight provided by Arizona State University. All protocols were extensively piloted in Haitian Kreyòl, with repeated back translations to English. Piloting and training took place in April–May 2017 and data collection took place in June–August 2017.

2.1. *Quantitative (survey) data*

2.1.1. *Survey sampling and data collection*

Sampling was based on the most recent national representative *Haiti échantillon-maître* census framework constructed in July 2011 by the Institut Haïtien de Statistique et d'Informatique [IHSI]), and used a two-stage cluster sampling approach to select households. In the first stage, Dissemination Areas (DAs: the smallest census territory), were stratified by four levels of access to core services and central markets located in the main town or village: inaccessible, barely accessible, accessible, and highly accessible. Using the technique of probability proportional to size, an approximately self-weighting approach, a random sample of DAs was then selected at each access level (157 of 389 DAs in all three sites). In the second stage, 25–26 households within each DA were selected using a randomly generated sequence. Appendix Table S1 shows that the population estimates and targets are well reflected in the analyzed data. Survey interviews were conducted with either a male or female household head representing a single household (final sample, 52.2% female).

Table 1
Data source by format and site.

	Quantitative Dataset	*Qualitative Dataset*		
	Household Head Surveys (n)	Focus Groups (n)	One on one interviews (n)	Key informant interviews (n)
Martissant	1678	8	16	6
Ouanaminthe	1586	8	16	8
Cornillon	791	8	16	9
Total	**4055**	**24**	**48**	**23**

2.1.2. Variable construction

2.1.2.1. Outcomes. Depression/Anxiety Levels: Our outcome variables, levels of common mental disorder symptoms, are based on individual responses to locally adapted and validated depression and anxiety inventories. The Zanmi Lasante Depression Symptom Inventory (ZLDSI) assesses a combination of 13 culturally adapted items from standard depression screeners and local idioms of distress (Rasmussen et al., 2015). Scoring is based on a Likert scale response for each item from "not at all" (0), "almost every day" (3), to "within the last two weeks" (possible range, 0 to 39). For anxiety levels, we use a version of the Beck Anxiety Inventory (BAI) previously culturally adapted for Haiti (Kaiser et al., 2013); it presents 20 anxiety symptoms scored from "not at all" (0) to "severe" (3), yielding a possible score range from 0 to 60. Both outcome variables are the square root transformed to take into account left skewed distributions. We note that the decision to transform some of the variables may have made the resulting marginal plots harder to interpret.

2.1.2.2. Potential syndemic factors. Exposure to Crime: We asked the household head if any household member had been the victim of any of ten serious crimes within the last 12 months: unarmed robbery with no assault or physical threats; unarmed robbery with assault or physical threats; armed robbery; assault but not robbery; rape or sexual assault; kidnapping; vandalism; burglary of your land; burglary of your home; extortion. A score of 10 means that someone in the household had experienced all these, a score of 0 meant no one in the household had.

Food Insecurity: We use the widely-applied Household Hunger Scale (HHS), as our means to estimate food insecurity. This scale asks whether, "in the last 4 weeks, (a) was there ever no food to eat because of lack of resources to get food, (b) did you or any household member go to sleep hungry because not enough food, (c) did you or any household member go a whole day or night without food?" (Ballard et al., 2011). Item responses are tallied as never = 0, rarely = 1, often = 2 and always = 3. These are then summed, with a score of 9 reflecting extreme household food insecurity, and 0 reflecting complete food security. We additionally tested a comprehensive household material wealth index (Lachaud et al., 2019) as a different measure of extreme material need/poverty; it added nothing to the models beyond the influence already accounted for by food insecurity, so we excluded it from the final models.

Discrimination: We asked each respondent if they had been discriminated against ("treated worse than other people") or humiliated [*imilyasyon*] within the last 12 months, in a) government offices of agencies, b) public places like on the street, or c) by family, friends, or neighbors. A response of never is scored as 0, rarely as 1, often as 2, always as 3 for each location, then summed to create a score out of 9. In all three sites the modal response of the main reason for being treated poorly is "because of being poor or having no money" (63.7% Port-au-Prince, 50.3% Ouanaminthe, 31.3% Cornillon). The second most frequent reason in Martissant is "being a woman" or "not having enough food" (both 6%). It is "being a farmer" in Ouanaminthe (22.3%) and Cornillon (20.4%).

Respondent gender: Gender is also included as a covariate in models; it is widely recognized as a key predictor of depression and anxiety levels, with women typically at significantly elevated risk compared to men (Culbertson, 1997).

2.2. Statistical analysis

Given the primacy that syndemic theory places on how factors *interact* to compound risk, we selected a maximally saturated regression model (Tsai and Venkataramani, 2016). Our approach to testing for syndemic patterns within systematically sampled survey data thus focuses on identifying the influence of all potential interaction effects (i.e., saturation) for the factors that were our epidemiological focus (crime exposure, discrimination, food insecurity) on common mental illness symptoms (depression, anxiety). Linear regression modeling was conducted in R using the *svyglm* function (R Development Core Team, 2008) that takes into account the sampling design, with each outcome modeled separately. Given our particular focus on localization of syndemic interactions, we conducted all the analyses site-by-site rather than combine them in a nested/hierarchical model. This allows clearer identification of which interactions mattered to suffering *within* each site. Our model was saturated for all the key variables, but not fully saturated because we did not test the four way interactions that included gender; this would have made model interpretation extremely difficult.

Cases with any missing variables were removed from analyses: this was 144 (9.4%) for Martissant, 81 (5.4%) for Ouanaminthe, and 20 (2.6%) for Cornillon. As can be seen in Appendix Table S2, these case removals do not have any discernible impact on the Martissant or Cornillion analyses. For Ouanaminthe, missing cases suggest a −2.3 difference for depression and −3.8 difference for anxiety; this could potentially bias (underestimate) results for this particular site.

2.2.1. Qualitative data

2.2.1.1. Text data collection. Purposeful respondent recruitment for qualitative data collection was achieved through varied local contacts, with a goal to construct adult focus groups (N = 24, 10 women only, 8 mixed gender, 6 men only), identify key informants from religious, justice, NGO, or other service sectors who knew the communities well and were identified as leaders (N = 23), and a diversity of local residents for one-on-one interviews (N = 48, half women): see Table 1. The number of semi-structured interviews well exceeds the minimum required for site-specific theme identification (Guest et al., 2006) and the total number of qualitative observations exceeds the minimum needed for multisited metathematic analysis (Hagaman and Wutich, 2017). All qualitative data collection was conducted by the same two trained social scientists, one male and one female. At each site, they used the same set of predefined questions to guide data collection (e.g., "*what are the most important problems related to crime in this community?*"). Recordings in original Kreyòl were then transcribed verbatim and imported into MAXQDA for text management and analysis in the original language.

2.2.1.2. Defining thematic domains. In an epidemiological analysis we can separate out the effects of "household poverty" from "food insecurity" using a material asset inventory versus a validated food insecurity scale completed by respondents in surveys. In analyzing text derived in extended interviews, this distinction is impossible to impose because people often talk about these two things inter-changeably. So, we apply "poverty-hunger" as a single analytic construct for text analysis. Similarly, in word-based analysis varied constructs of suffering (misery, sickness) tend to be entwined with emotional terms like humiliation [*imilyasyon*]. Ethnographically then, if not epidemiologically, such compression into a domain of "suffering/discrimination" makes sense. This means we test the connections between three slightly different configured domains in the text analysis: crime, poverty/hunger, and suffering/discrimination.

2.2.1.3. Text data analysis. The purpose of the following analytic design is to show the nuance, context, and local embeddedness of core themes as they emerged from respondents' own words in Martissant, Ouanaminthe, and Cornillon. The textual data corpus contains 221,258 total words and 7321 text blocks and yields 9576 unique words. For individual interviews, the text block is the answer to one of the defined questions; thus each speaker contributed roughly the same number of responses (text blocks) to the same elicitations. For focus groups, each text block is based on each different speaker in answer to pre-specified questions (i.e., speaker turns in answer to a single elicitation).

Using semantic network analysis (Bernard et al., 2016), we identified word connections between the focal syndemic domains (crime, poverty-hunger, suffering-discrimination) in each text block. To begin, we created word domains, listing *a priori* all high-frequency words that pertained to the three focal syndemic factors from the total corpus of unique words. We then performed a frequency analysis for words occurring in response segments elicited at each site and for all sites combined. Like other creole languages, debates about proper orthography in Haitian Kreyòl have led to a system where words can have a variety of spellings (Ottenheimer, 2009). We combined multiple Kreyòl spellings for each word into a single analytic unit for the frequency analysis. Then, we identified the five most frequent Kreyòl words from each subdomain based on plot analysis (Bernard et al., 2016), and these were the basis for the semantic network analysis (shown in Table 2).

For semantic network analysis, we used MAXQDA software to extract from the textual dataset a word-by-observation profile matrix (Bernard et al., 2016), in which each row contained the number of occurrences of each word in each data observation (e.g., one interview). Next, we imported the profile matrices into UCINET and dichotomized them. The purpose of dichotomization is to transform word counts into nominal (presence/absence) data (Bernard et al., 2016). Next, we produced a word-by-word similarity matrix using Jaccard matches in UCINET's similarity function (Borgatti et al., 2002), in which each cell represents the degree to which a pair of words co-occurs within each observation across the dataset being analyzed (Bernard et al., 2016). We performed this process for each site, creating a word-by-word similarity matrix for textual data collected for each.

For the semantic network analysis, we performed three analytic routines: degree centrality in UCINET, categorical core/periphery network analysis in UCINET, and network visualization in NETDRAW. The degree centrality analysis reveals which words are most highly linked in each site's semantic network, as well as any isolate words that are completely unlinked from other words in the dataset. In this analysis, we chose *a priori* to examine the five most degree-central words in each site. The categorical core/periphery network analysis yields the set of words that produce the most highly-linked subset of words in the semantic networks. The size of the core network is determined by the analysis, and cannot be set *a priori*. The network visualization displays semantic networks by: (1) word category (black nodes are words in the "crime" domain, grey nodes are words in the "poverty" domain, and white nodes are words in the "suffering" domain), (2) each word's degree centrality (larger nodes are more degree central), (3) strength of co-occurrence between each pair of words (thicker ties indicate greater co-occurrence). The results of these analyses enable us to characterize the most common semantic networks emerging from the analysis of the interview transcripts from each site.

Table 2
Fifteen highest-frequency Kreyòl words in three analytic domains that form the basis of the semantic network analysis.

Domain 1: Crime words	
konfli	Conflict
lapolis	Police
avoka	Lawyer
zam	Guns/weapons
Bat	Beat up
Domain 2: Poverty-hunger words	
manje	Food
malere	Poor person
grangou	Hungry
pov	Poor
geto	Ghetto
Domain 3: Suffering-discrimination words	
soufri	Suffer
kolè	Angry
mizè	Misery
malad	Sick
vilnerab	Vulnerable

In addition to the semantic network analyses, we also performed a conventional thematic analysis (Ryan and Bernard, 2003). For each of the three textual datasets, we reviewed data based on their relevance to the three key analytic domains: crime, poverty-hunger, and suffering-discrimination. Then, we selected typical exemplars for key themes from each of the sites, based on their representativeness of the textual data collected in each site, and finally translated them from the original Kreyòl.

3. Results

3.1. Descriptive results from survey data

Mean depression and anxiety levels differ across the sites and are highest in Martissant and lowest in Cornillon. Food insecurity is highest in Cornillon. Reported experience of discrimination is highest in Martissant and lowest in Ouanaminthe. Reported exposure to crime is highest in Martissant and lowest in Cornillon (Table 3). All the mean differences across sites in scores are significantly different based on ANOVA ($p < 0.05$), except for no difference between Martissant and Ouanaminthe in mean food insecurity scores.

3.2. Modeling interaction effects from survey data

3.2.1. Depression levels

Women have significantly heightened depression scores [square root] compared to men in Martissant and Ouanaminthe, but not Cornillon (Table 4). Exposure to crime, food insecurity, and experiences of discrimination all independently contribute to elevated depression levels in Martissant and Ouanaminthe; in Cornillon, food insecurity and discrimination also contributes but crime exposure does not (noting it is the site with least crime).

In Martissant, we observe a positive, but weak, three-way interaction between food insecurity, discrimination, and crime exposure, suggesting that exposure to all three had additional depressive effects. This 3-way interaction effect is not observed in the other two sites.

We also observe significant two-way interactions in Martissant between crime*discrimination, and for food insecurity*discrimination in Ouanaminthe. However, these observed two-way interactional effects of depression are all negative, suggesting that when these co-occur that depression may be buffered in some manner (rather than magnified). Indeed, the magnitude of the 3-way interaction (0.008) is substantially smaller than the significant negative 2-term interactions (−0.062 and −0.023). The negative interactions may thus be absorbing the small positive effect of the 3-way interaction.

However, examining the marginal effects across different levels of the variable suggests there is no discernible buffering or reversed interactional effect, so we interpret most of the two-way negative interaction effects as a non-finding (see Appendix). The only exception is for the negative interaction of crime*discrimination for Martissant, which we identify on the basis of the marginal effects as a meaningful interaction (Fig. 1). That is, for people in Martissant reporting with low levels of discrimination (e.g., score 0 or 1), their household crime exposure is positively associated with depression level; for people who report very high discrimination levels (score 12), their predicted level of depression is negatively associated with household crime exposure.

3.2.2. Anxiety Levels

The analysis of anxiety levels (Table 5) provides generally similar results. Women have heightened risk of anxiety symptoms [square root] compared to men in Martissant and Ouanaminthe, but not Cornillon. All three key factors – crime exposure, hunger/food insecurity, and discrimination – contribute to anxiety levels in Martissant and Ouanaminthe; in Cornillon (noting it is the lower-crime, rural site) discrimination and food insecurity both contribute but crime does not. Similarly to the depression model, Martissant shows an additional positive, three-

Table 3
: Descriptives by study site.

		Martissant Urban (n = 1678)		Ouanaminthe Border town (n = 1586)		Cornillon Rural (n = 791)		Total (N = 4055)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Mean	Depression Level	13.11	9.21	11.6	8.69	9.5	11.5	11.8	9.8
	Anxiety Level	13.84	11.16	11.6	9.41	7.3	8.8	11.7	10.3
	Crime Exposure	1.3	2.1	1.2	2.2	0.5	1.1	1.1	2.0
	Food insecurity	2.4[a]	2.8	2.1[a]	2.8	2.7	3.0	2.3	2.8
	Experienced Discrimination	1.7	2.6	1.0	1.9	1.3	2.6	1.4	2.4
Percentage	Female respondents	49.3%		56.7%		49.3%			
	Female-headed household	43.1%		45.1%		42.4%			
	Rural location of household	0.0%		33.5%		100%			
	Very low household income (<18000 HTG/month)	59.2%		69.2%		90.8%			
	Food insecure household (score >0)	55.2%		47.4%		52.9%			
	Experienced any discrimination	42.9%		32.3%		27.1%			

[a] All mean scores are significantly different by site ($p < 0.05$), except for between Martissant and Ouanaminthe in food insecurity.

way interaction between food insecurity, discrimination, and crime exposure, suggesting that exposure to all three has additional depressive effects. The other sites do not.

Table 4
Saturated model for the three key variables predicting level of depression symptoms. Results shown are coefficients (with SE), t values and significance.

	DEPRESSION LEVELS		
	Martissant urban	Ouanaminthe border town	Cornillon Rural
	(1)	(2)	(3)
Male gender	−0.189 (0.072) t = −2.600[a]	−0.232 (0.083) t = −2.790***	−0.059 (0.071) t = −0.833
Crime exposure	0.125 (0.026) t = 4.804***	0.074 (0.0258) t = −2.912***	−0.007 (0.049) t = −0.133
Food insecurity	0.111 (0.017) t = 6.538***	0.192 (0.024) t = 7.871***	0.199 (0.036) t = 5.555***
Discrimination	0.243 (0.026) t = 9.353***	0.215 (0.038) t = 5.668***	0.286 (0.053) t = 5.356***
Crime[b]Food insecurity	−0.012 (0.009) t = −1.236	−0.001 (0.006) t = −0.171	0.001 (0.042) t = 0.014
Food insecurity[b]Discrimination	−0.009 (0.005) t = −1.567	−0.023 (0.087) t = −2.763***	0.003 (0.008) t = 0.425
Crime[b]Discrimination	−0.062 (0.009) t = −6.860***	−0.008 (0.009) t = −0.866	0.001 (0.022) t = 0.053
Crime[b]Food insecurity[b] Discrimination	0.008 (0.002) t = 3.603***	0.001 (0.002) t = 0.602	0.001 (0.007) t = 0.197
Constant	2.981 (0.089) t = 33.365***	2.750 (0.129) t = 21.222***	1.907 (0.111) t = 17.242***
N	1530	1499	768
R^2	0.243	0.224	0.548
Adjusted R^2	0.239	0.220	0.544
Residual Std. Error	1.124 (df = 1521)	1.145 (df = 1490)	1.083 (df = 759)
F Statistic	61.075*** (df = 8; 1521)	53.834*** (df = 8; 1490)	115.164*** (df = 8; 759)

Notes: ***Significant at the 1 percent level.
[a] Significant at the 5 percent level.
[b] Significant at the 10 percent level.

There is also a very small positive interaction effect in Cornillon for crime*discrimination for anxiety, if not for depression. Significant and negative two-way interactions are also observed for crime exposure*food insecurity and crime exposure*discrimination in Martissant, and food insecurity*discrimination in both Ouanaminthe and Cornillon. Yet

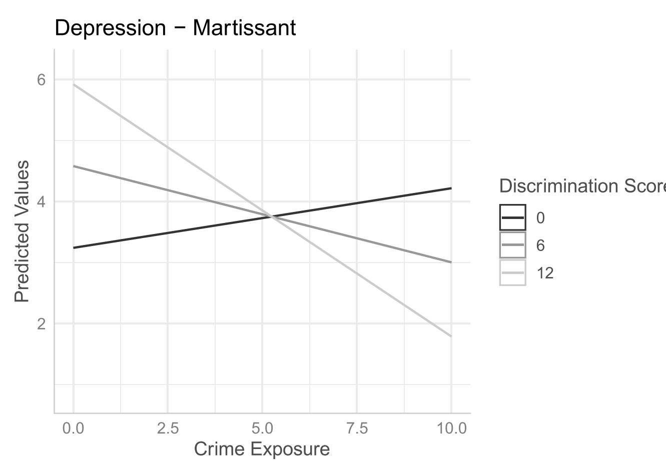

Fig. 1. Marginal effect plot for low (0), medium (6) and high (12) levels of discrimination by household crime exposure on depression, for Martissant site.

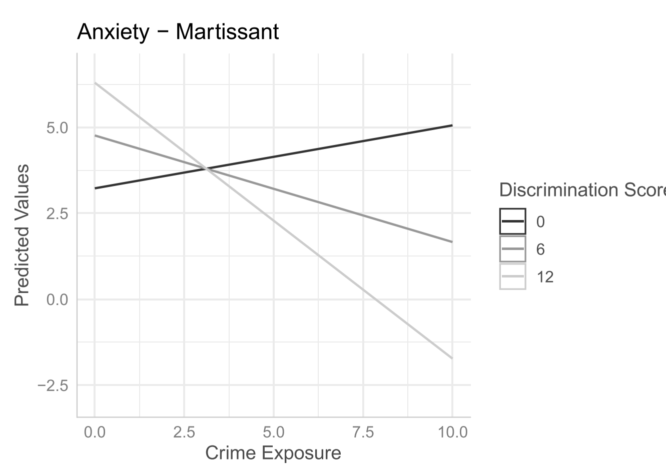

Fig. 2. Marginal effect plot for low (0), medium (6) and high (12) levels of discrimination by household crime exposure on anxiety, for Martissant site.

Table 5
Saturated model for the three key variables predicting level of anxiety symptoms. Results shown are coefficients (SE), t values and significance.

	ANXIETY LEVELS		
	Martissant urban	Ouanaminthe border town	Cornillon Rural
	(1)	(2)	(3)
Male gender	−0.284	−0.217	−0.103
	(0.082)	(0.104)	(0.111)
	t = −3.476[c]	t = −2.073[a]	t = −927
Crime exposure	0.236	0.078	−0.053
	(0.063)	(0.030)	(0.045)
	t = 3.691[c]	t = 2.555[a]	t = −1.182
Food insecurity	0.039	0.147	0.171
	(0.022)	(0.035)	(0.046)
	t = 1.791[b]	t = 2.208[c]	t = 3.692[c]
Discrimination	0.252	0.229	0.276
	(0.031)	(0.042)	(0.026)
	t = 8.064[c]	t = 5.497[c]	t = 10.006[c]
Crime[b]Food insecurity	−0.023	0.002	−0.018
	(0.014)	(0.007)	(0.020)
	t = −1.586	t = 0.240	t = −0.912
Food insecurity[b]Discrimination	0.002	−0.026	−0.019
	(0.014)	(0.010)	(0.006)
	t = 0.265	t = −2.521[a]	t = −2.772[a]
Crime[b]Discrimination	−0.108	−0.003	0.031
	(0.016)	(0.010)	(0.016)
	t = −6.902[c]	t = −0.331	t = 1.949[b]
Crime[b]Food insecurity[b] Discrimination	0.011	0.0001	−0.002
	(0.003)	(0.002)	(0.004)
	t = 3.146[c]	t = 0.038	t = −0.511
Constant	3.136	2.762	1.885
	(0.104)	(0.142)	(0.127)
	t = 30.203[c]	t = 19.397[c]	t = 14.842[c]
N	1533	1500	769
R^2	0.185	0.150	0.331
Adjusted R^2	0.180	0.145	0.323
Residual Std. Error	1.390 (df = 1524)	1.281 (df = 1491)	1.147 (df = 760)
F Statistic	43.101[c] (df = 8; 1524)	32.888[c] (df = 8; 1491)	46.906[c] (df = 8; 760)

[a] Significant at the 5 percent level.
[b] Significant at the 10 percent level.
[c] Significant at the 1 percent level.

again, the magnitude of the 3-way interaction (0.011) in Martissant is smaller than the observed negative 2-term significant interactions (−0.023, −0.026, and −0.019); accordingly – while significant – it should be interpreted with caution. Examining the marginal effects across different levels of each variable suggests there is no clearly suggested buffering or reversed effect, and these should thus be interpreted as non-findings in all but one case (Appendix). Again, the only exception is for the negative interaction of crime and discrimination in Martissant, which we interpret as a meaningful finding (see Fig. 2). For people in Martissant reporting with low or no discrimination, their household crime exposure is positively associated with anxiety level; for people who report high discrimination levels their predicted level of anxiety is negatively associated with household crime exposure.

3.3. Semantic network and thematic analysis

3.3.1. Urban martissant

The semantic network in Martissant (Fig. 3), derived from analysis of what people said, reveals that the five most degree-central (highly linked) words all came from the crime domain and, to a lesser extent, the poverty-hunger domain. The only isolate, *kolè* (angry), is from the suffering-discrimination domain. The core/periphery network analysis shows that the Martissant core network contained six words: *konfli* (conflict), *lapolis* (police), *avoka* (lawyer), *zam* (guns/weapons), *bat* (beat up), and *manje* (food). The words in the core network are all from the crime and the poverty-hunger domains.Fig. 3 here.

Typical exemplars from Martissant suggest people understand crime and poverty-hunger as complexly related in ways pivotal to shaping potential suffering. Relationships between domains are clearly expressed as co-occurring.

In a country with no jobs, people are dying of starvation … as the idiom says, "a hungry dog is not kind." Whatever they need to do, they will do.

Once the man has no money to take care of the family, the wife always accuses him of having side chicks and the man retorts, then the conflict grows, lots of discussions, and so on. So, the source of these conflicts is the money problems.

There was an incident while people from Gran Ravine were in conflict with people from Tibwa. A young street vendor who was selling tomtom was on his way back to Gran Ravine, where he lived, when he met people from Tibwa who asked him where he was from and then shot him.

Because these folks don't have power to make decisions. They can't afford a lawyer to defend them, they don't have money, so they suffer.

I am the principal of the school, if a person has a problem with me I will just call my lawyer and a judge and then I can say: "look at this man he can't even eat a corn meal at his house, he has no right to be against me." Then I will say, "here is two hundred dollars, here is three hundred dollars, dismiss

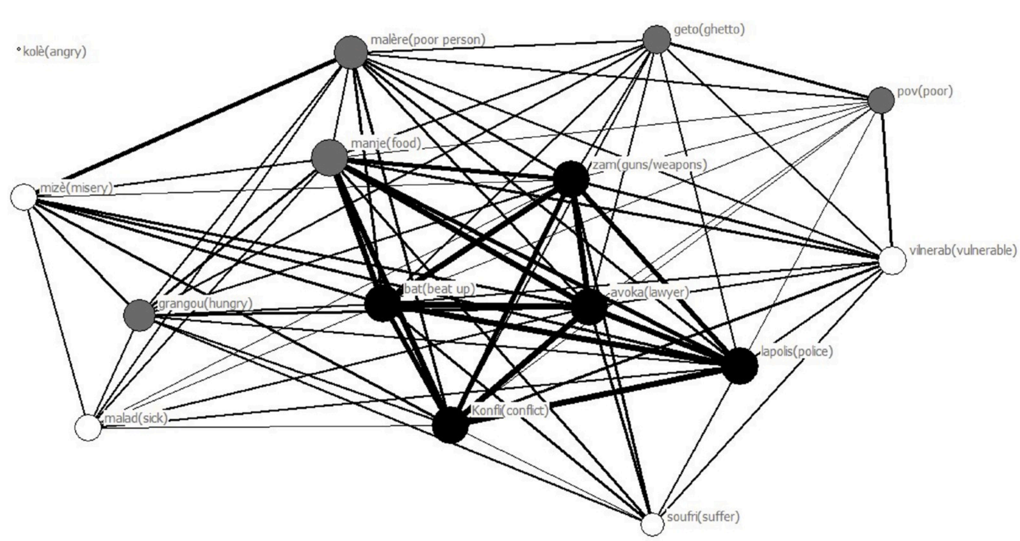

Fig. 3. Visualization of the Martissant semantic network, focusing on the most frequent words across crime (black), hunger-poverty (grey), and suffering-discrimination (white) domains.

this case." Here it is the money that gives you justice [in the courts], but it's not a fair justice.

First of all, something happened in front of me. It's not something I heard, it's what I experienced, and it made me cry. A guy was sleeping in his house, then he got up and went downstairs with two gallons to go to get some water to bathe. The police car encountered him and asked him to get in the car. He got in, and this year will be his tenth year in jail for nothing.

Let's take for example, a child with a bright future, her parents spend money to send her to school … if she gets raped it's like she lost everything, lost her value.

But the connections are also bi-directional in ways not normally anticipated in epidemiological risk analyses. That is, crime is also expressed as a means to cope with or manage poverty-hunger.

Why should I not be allowed to tell my wife what to do, or whip my children, just because I am just a street water vendor? *You can't tell me what to do, because you don't help me in any way.*

Not only should the rapist get punished, but the rape victim must have something to help her in return. Something that can help her.…So justice would be to not only punish the rapist, but the rapist should pay money to compensate the raped.

3.3.2. Border town Ouanaminthe

The semantic network in Ouanaminthe (Fig. 4) reveals that the most degree-central, or highly linked words all come from the crime domain and, in one case, the poverty-hunger domain (Table 6). However, there are no isolate words. The core/periphery network analysis shows that the Ouanaminthe core network contains seven words: *konfli* (conflict), *lapolis* (police), *avoka* (lawyer), *zam* (guns/weapons), *bat* (beat up), *malere* (poor person), and *soufri* (suffer). In the case of Ouanaminthe, the words in the core network are from all three analytic domains (crime, poverty-hunger, suffering-discrimination).

The thematic analysis of typical exemplars from Ouanaminthe reveals how suffering-discrimination is tightly interwoven with experiences of both crime and poverty-hunger. In addition to discrimination of poor Haitians by those with means, there is also significant discussion of discrimination by Dominicans, as Ouanaminthe sits at the border crossing with the wealthier Dominican Republic.

He could have gone to a judge. But firstly, he needs to have money for a taxi, secondly when he gets to court, he must have money to pay the register. But he doesn't have this money, so he just sits at home.

If I am poor and I have a problem with someone rich, they [authorities] will certainly judge my appearance, my poor clothes and shoes. The rich person will get "justice" instead of me even if I was innocent.

Table 6
Most linked (or "degree central") and unlinked ("isolate") words at each site.

Word Rank	Site		
	Martissant	Ouanaminthe	Cornillon
1	*avoka* (lawyer)	*konfli* (conflict)	*manje* (food)
2	*bat* (beat up)	*avoka* (lawyer)	*avoka* (lawyer)
3	*konfli* (conflict)	*zam* (guns/weapons)	*konfli* (conflict)
4	*manje* (food)	*bat* (beat up)	*zam* (guns/weapons)
5	*lapolis* (police)	*manje* (food)	*lapolis* (police)
Isolated words	*kolè* (angry)	<none>	*geto* (ghetto)

Sometimes, you might go to court … but the other party has more money than you, if they know that you have filed a complaint against them and if they know which judge is handling the case, they can reach out to the judge, then they give bribes to the judge … you may do whatever you want, you won't find justice.

I'm just a woman in from the countryside, but I was in conflict with someone pretty rich. I didn't get justice because he has more money. I was actually right, but when we went to trial, I got no justice because he had money.

For example, if I'm a friend of a senator and when I do something not too severe do you think the senator will let them put me in jail? This means that the people in high places are not impartial, and what happens to you depends on those you surround yourself with. But those who deserve justice can't do anything to get it because they do not have any powerful people behind them.

When you go to the police the first thing they tell you is, "you need to put three hundred dollars [∼USD5] *of fuel in the car for us to go investigate." That means if I'm seeking justice and I don't have the money they won't help me. Also, to have a warrant, you need to have the money for the warrant and I am broke. I must just accept and suffer in silence, other people all day are making fun of me. I can't do anything about that. In this case I keep quiet and do nothing.*

For example, my dad has land and another guy let his cows into my dad's garden and they destroyed his garden. A judge came to check and he decided my dad was guilty in this situation. He made fun of my dad just because the [other] man had more money than my dad. There is no justice in this situation.

Dominicans can do whatever they want to us … they may steal something right out of your hand while looking at you right in the eyes, without you being able to do or say anything about it.

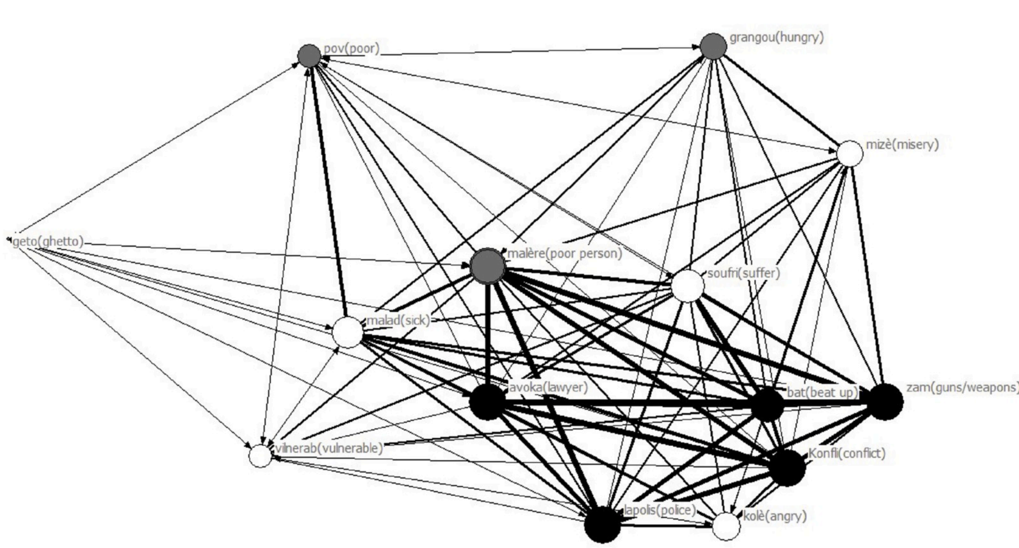

Fig. 4. Visualization of the Ouanaminthe semantic network, focusing on the most frequent words across crime (black), hunger-poverty (grey), and suffering-discrimination (white) domains.

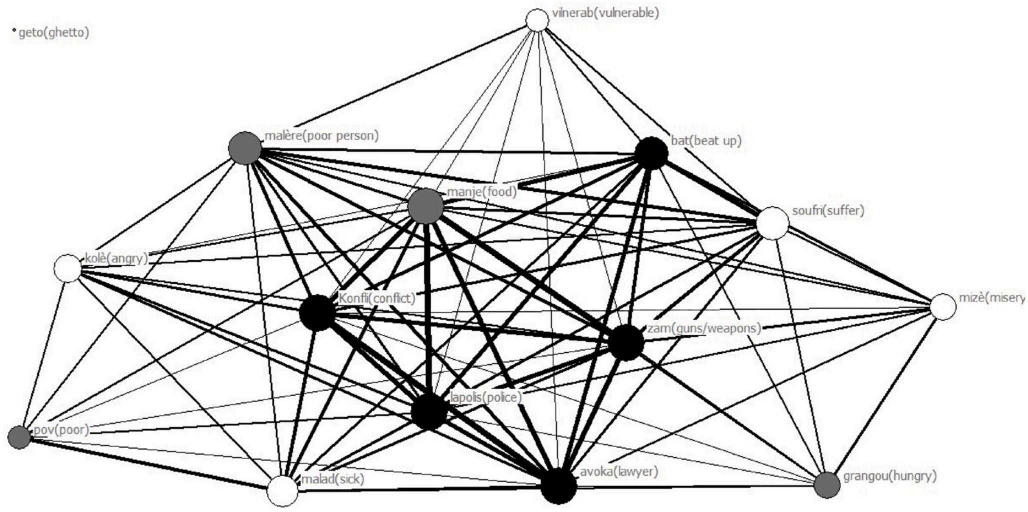

Fig. 5. Visualization of the Cornillon semantic network, focusing on the most frequent words across crime (black), hunger-poverty (grey), and suffering-discrimination (white) domains.

3.4. Rural Cornillon

The semantic network in Cornillon (Fig. 5) reveals that the most degree-central, or highly linked, words all came from the conflict domain and poverty-hunger domains (Table 6). The only isolate, *geto* (ghetto), refers to a form of urban poverty that is not highly relevant to understanding the rural environment of Cornillon. The core/periphery network analysis showed that Cornillon's core network, like that of the Martissant, contains six words: *konfli* (conflict), *lapolis* (police), *avoka* (lawyer), *zam* (guns/weapons), *bat* (beat up), and *manje* (food). Here, too, the words in the core network are all from the conflict and the poverty-hunger domains.

A more in-depth analysis of typical exemplars from Cornillon shows how these dynamics uniquely manifest in this rural site. Crime is low, people say, because people just don't have much. But animals, crops, and land, material assets that produce food, then become the major source of conflict and crime and in complex ways; not just stealing, but selling them to pay a lawyer, or destroying others' food sources as retribution. Having nothing or being hungry too, here, are seen as the basis for not just enacting but also (falsely) reporting crime. These complex dynamics help explain why Cornillon was the only site in which a word from the poverty-hunger domain, *manje* (food), was the most linked (degree central) word in the semantic network.

People steal chickens or goats sometimes – this cause problems with the law but it's not too serious.

In the community, sometimes, they steal our turkeys and our goats, but we don't have a lot.

If I begin to present you all the cases I deal with it could take all afternoon but when it is not family conflict, it is land conflicts here.

Most of the conflicts happen between farmers, as for example a farmer letting his animal in the garden of another farmer. There are also minor conflicts, but they occur within families.

That's the biggest problem … sometimes you had to rent out a piece of land or sell a cow to pay the judge if you don't want them to lock you up.

There are a lot of family-based conflicts … Sometimes these are conflicts that are money-related where one borrowed money from another, and when he doesn't get paid back he goes into the yard and cuts off one of the animal's heads.

Sometimes there are people that pretend in the court that their child was a victim of rape. They are just pretending it. They say instead of punishing the offender, they would rather the person pay them money.

3.5. Cross-site comparison

Degree Centrality*:* Table 6 shows the most linked (or "degree central") words in each site across all the three focus domains based on network analysis of the transcribed interview and focus group text. In semantic networks for Martissant, Ouanaminthe, and Cornillon, words from two analytic domains—crime (e.g., *konfli,* or conflict) and poverty-hunger (e.g., *manje*, or food)—are highly linked. Yet some core differences emerge across the three sites. Violent crime words, such as *bat* (beat up) and *zam* (guns/weapons), are among the highly-linked words in the Martissant and Ouanaminthe semantic networks but are less highly-linked in the Cornillon semantic network. In contrast, *manje* (food), a word from the poverty-hunger domain, is the most highly-linked only in the rural site of Cornillon. Although salient in our thematic analysis, no word from the suffering-discrimination are among the most highly-linked degree central words in any site.

Core/periphery network: The categorical core/periphery network analysis reveals key similarities across all three sites. The core networks all contain five crime words (*konfli*/conflict, *lapolis*/police, *avoka*/lawyer, *zam*/guns-weapons, *bat*/beat up), as well as one poverty-hunger word. Yet there are also some important differences in the core networks across sites. The semantic networks for Martissant and Cornillon both contain a key poverty-hunger word: *manje* (food). In contrast, the semantic network in Ouanaminthe is the only one that includes a word from the suffering-discrimination domain: *soufri* (suffer). In addition, the Ouanaminthe core network contains one unique word from the poverty-hunger domain (*malere*/poor person).

4. Discussion

This study employed two very different forms of data to test for the hyper-localization of syndemic interactions. Based on the linear regression modeling of survey data, more household exposure to crime, more frequent discrimination, and more food insecurity is associated with higher depression and anxiety levels for those living in urban Martissant and border-town Ouanaminthe. In rural Cornillon, where overall depression and anxiety levels and crime exposures are lowest, only discrimination and food insecurity are associated with heightened depression and anxiety levels. For Ouanaminthe and Cornillon, possible two and three way interactions between crime exposure, food insecurity, and discrimination, appear to have no meaningful influence on anxiety and depression levels. That is, syndemic effects are not locally apparent.

Martissant results are distinctive. There is an additional, and positive three-way interaction between food insecurity, discrimination, and crime exposure that we conclude could be meaningful, in that exposure to all three has additional depressive and anxiety-provoking effects for those living in the urban zone. This suggests some possible localized syndemic effects, i.e., risks beyond those provided by each factor alone. However, that the positive three-way interaction effect is smaller than that of the negative two-way interaction effects suggests the finding should be treated as suggestive at best.

The stronger negative interaction between crime and discrimination in Martissant that remains after review of the marginal effects requires additional explanation, as it is the opposite of what a syndemic analysis might predict. This suggests rather than amplification, that there is a buffering of the effects of each on depression/anxiety when the two factors co-occur. It could be, for example, that people in Martissant report more household exposure to crime when they are more centrally involved in gang activities. Armed groups, originally created to defend the local population, have transformed into armed urban gangs over the last twenty years (Martissant, 2008). Comprised mostly of younger men, they are known for engaging in organized violence, extortion, and drug sales. These groups also can provide protection against external forces perceived as a threat to those in the controlled territories, and can provide some basic social services and "policing" for residents (Martissant, 2008). Greater engagement in this very particular setting of highly evident organized crime/protection could then potentially buffer against some of the negative mental health effects of experiencing discrimination, especially if gang involvement increases social status or prestige with a local community. This proposition generally fits with the proposition that mental illness is considerably worsened when people not only experience but also *internalize* discrimination or stigma (Brewis and Wutich, 2019); in-group membership or other forms of belonging can be very protective in this regard even in groups discriminated against more widely because it builds and reinforces self-esteem (Umaña-Taylor and Updegraff, 2007). It also fits with some statements made in interviews. But we did not ask people specifically about this point, so we cannot confirm this.

The word-based network analysis provides a different perspective on the localization of syndemics, indicating they have meanings for people even in the sites where significant interactions were not observed based on survey data. A reading of the exemplars also reinforces that people fully grasp the many ways violent crime exposure, poverty-hunger, and discrimination interact to shape suffering within their communities. People consistently emphasize connections between poverty-hunger and violent crime in particular in all three sites (e.g., guns/weapons, beating), not just Martissant. They also often highlight the role of discrimination in relation to suffering, particularly along the lines of being poor, rural, or Haitian. Within the network analysis, this concern stands more alone, less integrated with others in how people connect aspects of their struggles.

While the two analytic approaches (quantitative-survey and qualitative-text) necessarily use different constructs to identify the general domains of interest, by combining these two approaches with cross-site comparison, we are then able to clarify that it is *crime exposure* that is most central (i.e., what matters most to other things*)* to people's syndemic – interconnected, amplified – experiences of suffering in their everyday lives (see Table 6).

Thematic analysis, considered in the context of the exemplar quotes, also reveals some complex forms of interactions among domains in ways that could mask their associations within the quantitative analysis. Going to the food market to buy or sell puts you at risk of violent crime, at least in Martissant, because of inter-gang conflicts. In rural Cornillon, in contrast, material poverty may also conversely reduce opportunity for exposure to crime because there is nothing that can be stolen. Lack of money is also described as a major exclusionary factor in the wake of experiencing crime in all three sites, because of judicial corruption, further complicating how poverty, crime, and discrimination connect. For example, corruption can amplify the negative effects of experiencing crime in the rural areas when it means one must liquidate food-producing assets to pay for justice. Similarly, hunger is given in multiple cases as a reason to falsely report crime, in the hope of the compensation will help feed the family. People who feel discriminated against might engage in crime to assert authority, or those who engage in gang-related crime may be less vulnerable to discrimination because it affords its own social status. What is revealed by the qualitative analysis is, thus, not straight-forward. But it clearly indicates the limits of how we can examine syndemic localization on the basis of modeling population-representative data.

5. Conclusion

Many people living in low-resource, under-served communities in Haiti struggle daily with exposures to hunger, discrimination, and crime. Based on text analysis, we can observe that people across all three sites recognize and explicate key connections between these core risk factors, placing primacy in their cognitive models on exposure to crime as a central factor interacting with and worsening other risk factors. In modeling survey data, we also observe that anxiety and depression levels appear to worsen with reported exposure to hunger, discrimination, and crime. In border-town Ouanaminthe and rural Cornillon, the effects appear additive. But residents of urban Martissant – in a particularly violent zone of informal settlement – those who are triple-burdened by hunger, crime, and discrimination perhaps suffer even more, with additionally elevated risks for expression of depression and anxiety above those added by each factor alone. The cognitive connections observed through people's own words are more complexly inter-related than is evident from the modeled survey data, and also suggests key bi-directional influences (e.g., crime engagement mitigates hunger).

Of course, the findings of the quantitative versus qualitative data sets are more complementary than directly comparable because of issues with epistemological bases and with construct equivalence. But the use of multi-method comparison between sites, a novel point of our study, points to the potential for multi-sited studies to reveal patterns of risk that might be crucial in mapping, understanding, and alleviating syndemic conditions of suffering. This also moves the study of syndemics from the study of interactions of diseases and conditions of the individual to consider how key dimensions of people's everyday physical and social spaces might interact to localize risk. Connecting micro and macro approaches further clarifies that syndemic risk processes are not just localizing ill-health, but are also extremely important in how people cognitively understand and organize their everyday lives.

Finally, these differing results have implications for anti-crime, anti-hunger, and anti-discrimination programming. The quantitative (survey-modeling) analyses suggest no apparent additional benefit to their integration as they appear to be additive to suffering rather than sydemic. By contrast, the qualitative (interview-network) analyses suggests localized programming that expressly integrates across these domains will be meaningful and relevant in some – but not all – communities.

Author contributions

AB designed the overall study with assistance from AW and JL; JL designed and managed the sampling; AB managed cleaning and checking of all datasets prior to analysis; AB and JL designed and conducted the quantitative analysis; AW and MB designed the qualitative analysis; AW conducted the qualitative analysis; AB drafted the first draft of the manuscript; all authors contributed to, revised, and checked additional and final drafts.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2020.113031.

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