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Loop Analysis of Causal Feedback in Epidemiology: An Illustration Relating To Urban Neighborhoods and Resident Depressive Experiences

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Abstract

The causal feedback implied by urban neighborhood conditions that shape human health experiences, that in turn shape neighborhood conditions through a complex causal web, raises a challenge for traditional epidemiological causal analyses. This article introduces the loop analysis method, and builds off of a core loop model linking neighborhood property vacancy rate, resident depressive symptoms, rate of neighborhood death, and rate of neighborhood exit in a feedback network. I justify and apply loop analysis to the specific example of depressive symptoms and abandoned urban residential property to show how inquiries into the behavior of causal systems can answer different kinds of hypotheses, and thereby compliment those of causal modeling using statistical models. Neighborhood physical conditions that are only indirectly influenced by depressive symptoms may nevertheless manifest in the mental health experiences of their residents; conversely, neighborhood physical conditions may be a significant mental health risk for the population of neighborhood residents. I find that participatory greenspace programs are likely to produce adaptive responses in depressive symptoms and different neighborhood conditions, which are different in character to non-participatory greenspace interventions.

Keywords

USA; loop analysis; causal feedback; urban neighborhoods; depression; abandoned property

Introduction

Does urban property abandonment contribute to depressive symptoms? Can so-called greenspace programs address such health effects? The question of whether abandoned urban property—including vacant buildings and empty lots—affects the depressive experiences of local residents raises questions of causal feedback. Abandoned property results from the rate of occupant exit, which is a function of occupant death, occupant out-migration and in-migration. But if mortality is a function of depressive experience, and if residential relocation is a response to a “depressing environment,” then our research may best be served by understanding both depressive experiences and abandoned property as both causes *and* effects of the urban environment.

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This conceptual frame describes human experiences and environmental phenomena as a dynamic system where each system variable directly or indirectly influences and is influenced by every other system variable. What is the nature of change in depressive experience and environmental change in such a system? What opportunities exist for intervention? To answer these questions I introduce loop analysis (Levins, 1974) of the system behavior entailed in causal feedback, articulate the specific kinds of hypotheses it answers, and describe how to interpret results in light of the hypotheses. This article deemphasizes the mathematical theory of loop analysis published elsewhere (Levins, 1974; Puccia and Levins, 1986; Dambacher, et al., 2002; Justus, 2005), and instead guides readers into its application and interpretation.

This research is informed by results of an unpublished analysis (manuscript, Dinno, et al.) of observed depressive symptomatology over a course of 13 years in a population of 2812 individuals aged 65 and older in New Haven, Connecticut, (Berkman et al., 1986) which were related to spatially detailed representations of building vacancy produced by the annual New Haven Fire Department vacant building census and the New Haven City Plan's GIS database of real property. Neighborhood vacancy was found to strongly explain variation in depressive symptom scores, after controlling for individual factors including economic impoverishment and individual proximity to vacant buildings.

This study builds on these findings by detailing how neighborhood greenspace programs may provide a locus for population intervention for depressive experiences. There is actual on-the-ground interest in New Haven (and other post-industrial Midwestern and Eastern U.S. cities) in the question of whether participatory greening programs give better environmental and social results than externally imposed approaches to environmental change. (Murphy-Dunning, C., personal communications, Summer, 2000) Loop analysis facilitates direct comparisons of system behavior in different models, such as models with different system compositions or causal assumptions. We can thus characterize neighborhood resident/environment experiences in loop models with and without greenspace programs. Comparing loop models with both greenspace program approaches provides answers to questions about differences in the behavior of systems defined by either one.

Justification of the Approach

It is important to distinguish between the analytic properties of a loop analysis of causes as compared with those of more conventional epidemiologic analytic methods. Inquiry characterizing statistical analysis of causality answers questions equivalent to the form 'does a precise change in X directly or indirectly cause a precise change Y absent causal feedback among model variables?' I use the word 'feedback' here in place of alternatives like 'endogeneity' or 'autocorrelation' because causal feedback is the ontological motivator of analytic interest, whereas the other terms are descriptors of a class of violations to statistical analytic methods. By contrast an inquiry characterizing loop analysis of causality attempts to answer questions of the form 'what can we understand about the behavior of objects in a system defined by causal feedback?' Causal feedback presents difficulties in ascertaining causal contributions of one object to another; the operative verbs in statistical analyses of causation are 'to control' or 'to account' for causal feedback, for example, by using instrumental variable methods. (Angrist, 1991; Angrist and Krueger, 2001) By contrast, loop analysis concerns the characterization of causal feedback among a system of interrelated objects as being itself an object of substantive interest, and therefore permits meaningful inquiry into models that might be considered too complex for other analytic modalities.

Questions about system behavior answered by loop analysis include: what is the direction of change in any component variable of the system given a 'press perturbation' (i.e. a sustained external signal; for example in-migration of middle-class families to a city or region might

produce a negative press perturbation on the rate at which individual residents exit a neighborhood) at a specific system variable? Does press perturbation tend to spread across a system's components, or sink into only a few? Is the system stable? (That is, do variables tend to remain within recognizable ranges when the system is perturbed, or do they tend to vary wildly?) Does the behavior of the system hinge upon specific causal linkages (for example how does system behavior change given non-linear causal relationships, the breaking of specific links, the addition of new links, or even the insertion of new objects into the causal system)? (Puccia and Levins, 1985) This is akin to the notion of statistical model robustness where the stability of estimates and inferences is described for specific variations in the composition, scaling or functional expression of the variables in the model. Recent extensions to loop analysis answer the question what is the predicted change in life expectancy (or expected half-life) of the phenomena represented by the variables in the system given a perturbation? (Dambacher, et al., 2005)

Statistical models produce numerically precise analyses that include real-world data and real world-causal schemes, but which suffer from a lack of generality—in the sense that the inferences from particular statistical models do not apply to *all* models that are members of the same class. Generality should not to be conflated with the desirable property of generalizability of inferences from valid statistical models to larger populations! (Levins, 1993) By contrast, loop analysis provides valuable insights about models that are both realistic in that the models need not sacrifice particular variables (for example, if they are unmeasured) or relationships between variables (for example, causal feedback relationships), and general in that the results of a specific loop model apply to all systems sharing the same compositional and causal structure. Because of the sacrifice of precision, the core loop analysis method can be quite inexpensive: it requires for data only *qualitatively specified direct causal relationships* (meaning causally increases, causally decreases or has no direct causal effect) among phenomena that have turnover rates within approximately an order of magnitude (inverse half-lives or inverse residence times that are within a factor of ten). (Levins, 1974; Puccia and Levins, 1985) Thus loop analysis makes deductive inferences from the causal assumptions that go into a model independently of data, by taking those assumptions as given. By contrast with statistical model fitting (which determines most parsimonious and valid representation of observed data), empirical validation of loop models is thus a means of evaluating the validity of insights from a conceptual model (or model ensemble as will be discussed later).

Loop analysis can thus make predictions derived from empirical evidence from other studies. However, the method can also use described system behaviors to create testable hypotheses that may then be validated or invalidated by direct empirical observation; predictions from competing loop models can be evaluated for correspondence with bivariate model predictions of change in observed data. However, insights can be drawn from evidence ranging from direct observation to causal speculation, so loop analysis can easily accommodate and integrate competing hypotheses, and new knowledge. Indeed, that might be considered the point of conducting it.

With respect to elderly depressive experiences and building vacancy in a neighborhood context (where neighborhood is taken as the block of the street upon which one lives), the motivation arises because building vacancy and depression produce a causal feedback as illustrated in Figure 1: neighborhood vacancies are directly caused only by occupancy and vacation rates; but vacation rates are only caused by either the death of the occupant, or by his moving residential address. To the extent that residents of a neighborhood experience the neighborhood as an integrated whole, neighborhood death and exit events may also cause experiences of depression among neighbors. But death and moving may be caused by depressive experiences (a resident may be inclined to move away particularly if she associates depressive experience

with the locale). Yet it is plausible that depressive experience may itself be caused by neighborhood vacancy.

Aims

This paper attempts to answer the following questions about the system in Figure 1: How might press perturbations in vacancy be expected to affect depression? How does system behavior change if we incorporate hypothetical pathways for social isolation?

What are the predicted effects of hypothetical pathways for greenspace projects? What happens to system behavior if greenspace projects are modeled as part of the system?

Methods

A Brief Introduction to Loop Analysis

I provide here a brief introduction to causal signed digraphs, community matrices, and community effect matrices. The ‘signed digraph’ organizes and communicates the assumptions defining a system of causal feedback, and the ‘community matrix’ is the corresponding algebraic representation of the signed digraph. (Both terms are defined in Figure 2) The ‘community effect matrix’ for a signed digraph results from applying the community effect formula (Levins, 1974; Puccia and Levins, 1985) to the community matrix (see Figure 2). I will attend primarily to interpreting these objects, and will not provide a formal treatment of the theory underlying the method, which has been addressed elsewhere (Puccia and Levins, 1985)

Loop analysis was devised to explore the behavior of systems of causal feedback. Although predominantly applied in population biology and ecology, extensions and variants have been applied in such fields as physical geography (Phillips, 1993), electrical engineering (Flake, 1980), chemical and biochemical engineering (Iri, 1981; Tarifa and Scenna, 1997), and nuclear chemistry. (Park and Seong, 1994) The core method proceeds in three steps: (1) graphic and algebraic representation of a causal system using the signed digraph and community matrix; (2) computation of the relative direction of change in each variable (object) of the system given an external perturbation for each variable to produce the community effect matrix; and (3) interpretation of the community effect matrix.

A community effect matrix (CEM), such as the one in Figure 2, answers a few kinds of questions about the behavior of the system described in Figure 2. First, each element answers the question “what is the expected direction of change in a variable (column) given an increase in another (row)?” For example, given an increase in neighborhood vacancies, the neighborhood exit rate will decrease (illustrating the difference between direct and indirect effects). All CEMs in this paper were produced using LoopAnalyst 1.1-2 for R. The software is freely available for download from <http://cran.r-project.org/src/contrib/PACKAGES.html> and includes documentation with sample community matrices with interface improvements planned.

These answers may also include no effect (typically indicated by a zero in the CEM), and ambiguous effect (i.e. for a given press perturbation, we cannot know whether a given variable will increase, decrease or remain the same without more information; ambiguous predictions are typically indicated by “?” or “+/- ” in the CEM). An ambiguous effect implies that the relative strengths of feedback loops or pathways will determine the direction of change.

Ambiguous effects are not necessarily totally uninformative because ambiguity arises as a specific property of specific parts of any given system. Ambiguity can arise because the

direction of effect for one path to variable i from variable j is opposite to the direction arising from a different path to i from j . However, it can also be true that on a single path to i from j the feedback of the complementary subsystem is itself ambiguous. Sometimes different variables and pathways may share the same complementary subsystem (for example, in a system of five variables a , b , c , d , and e , the complementary subsystem of a single direct path to a from b is the same as the complementary subsystem of a single direct path to b from a , namely the subsystem comprised of c , d , and e). In this case an ambiguous result does not imply complete unpredictability of system behavior because we know that both paths (a to b , and b to a) share identical complimentary feedback, which multiplies the effect of each path, so the direction of predicted change will be the same and unknown if the paths are of the same sign, and in opposite though unknown directions if the paths are of opposite signs.

Predicted change—i.e. the effects of press perturbations to the system given time to percolate through it—can also provide insight into inputs entering at multiple points. In the example from Figure 2, predictions may indicate effects that are: (a) ambiguous (e.g. the effect on neighborhood exit rate of simultaneous perturbations to exit rate and vacancies); (b) irrelevant (e.g. the effect on depressive experience of simultaneous perturbations to depressive experience and exit rate) or (c) that support one another (e.g. the effect on depressive experience of simultaneous positive perturbations to exit rate and vacancies).

The CEM also answers questions about the nature of perturbations to the whole system such as “does perturbation percolate across the system?” (I.e. for a perturbation to a given variable, there are non-zero values for all or most of the system variables in the corresponding row of the CEM). Or conversely, “does perturbation sink into only a few variables?” A related kind of question is whether “any variables are resistant to perturbation?” (I.e. the variable's column contains many zeros in the CEM) In the system described by Figure 2, all variables of the system are sensitive to perturbation to neighborhood exit rate. By contrast, vacancy acts as a sink for perturbations to depressive experience.

A major strength of loop analysis lies in the ability to inexpensively contrast competing hypotheses, and thereby ask how sensitive system behavior or understanding of system behavior is to specific causal relationships. This makes it possible to assess system behavior in the face of: competing claims about:

- a specific relationship (e.g. “number of neighborhood abandoned properties is/is not self-damping.”);
- resolving model ambiguity (e.g. “assume the self-damping of exit rate is stronger than the self-damping of depressive experience”);
- system composition (e.g. “there is an omitted variable *individual social isolation* which relates to depressive experience, neighborhood exit rate, and vacancies thus...”)
- and non-linear or stochastically varying causal-relationships (e.g. “vacancies only increase depressive experience up to a certain threshold value of vacancies, and neither increases nor decreases depressive experience beyond that threshold,” or “a specific direct effect of varies randomly between no effect and causal decrease.”).

The degree to which system behavior changes in the face of such analyses indicates how sensitive both system behavior and *knowledge* of system behavior are to particular relationships. Conversely, the degree to which the predictions in the CEM remain consonant suggests that the understanding generated by the modeling process is robust to that body of differing assumptions.

Finally, loop analysis can be applied to empirical observation of a subset of the modeled variables, because a CEM can be used to produce predictions of bivariate correlation for any two variables given a perturbation to any system variable. (Puccia and Levins, 1985, Chapter 3: Predicting Change) Predicted correlation is calculated by multiplying the signs of the predicted direction of change in the two variables for a perturbation to a given variable. Thus a model can be partly empirically validated for cases where data is available for some, but not all variables in the system.

Objects of Study

Several assumptions are made about systems modeled by loop analysis. First is the compositional assumption that a direct or indirect causal path leads from each variable to every other system variable. Also, variables in the signed digraph represent values at any given time. Therefore arrows linking each variable represent past, present and future states, and thus the feedback, of the whole system.

Another assumption about the system is that the objects of interest have rates of change within an order of magnitude of one another. For example, if a social behavior in a feedback system changes over time periods of the order of weeks or months, then this group behavior phenomenon functions as a constant parameter with regard to the feedback dynamics of individual serum norepinephrine and social-anxiety responses, that change over periods of the order of minutes or hours. Similarly, phenomena with rates much greater than other objects of a feedback system are assumed to reach equilibrium independently of the slower objects in the system. (Levins, 1974, p 130; Puccia and Levins, 1985, p 13) This point is underscored by the word “aggregation” appearing in Figure 1 next to the links from individual depressive experience to neighborhood death and exit rates. An individual's depressive experiences will vary far more often than individual death rates (i.e. one event per lifetime) or residential moves (taking place over periods of the order of years). But the frequency of deaths in a neighborhood increases with the aggregate of all residents' duration of residence in the neighborhood, and is of the same order as rates of change in individual depressive experiences. This property of aggregation also holds for individual versus neighborhood rates of moving from one residence to another.

Another assumption built into my model has to do with frame of reference. In this case the neighborhood frame, or street block, identifies the population experiencing the modeled system dynamics. So predictions about, say, depressive experience, in Figure 1 are for individuals remaining within the neighborhood, not for those who exit it. Likewise, the model reflects the “experiences” of a specific neighborhood, the flow of causal effects through it, and does not describe what happens in other neighborhoods when some of its residents migrate to or from them. If models like the one in Figure 1 validly depict reality, they may prove to be quite general: most residents of New Haven, CT live on street blocks conforming to the neighborhood concept described above.

Consideration of frame and turnover in the model in Figure 1 also suggests one boundary of the system's behavior: size. If very few people reside on a street block, then the turnover rate for that neighborhood's experience of death and exit may drop below the order of magnitude threshold, diminishing the systemic behavior of the identified phenomena, and invalidating the analysis.

Loop model predictions also entail analytic assumptions. One is the assumption of the local stability of the system, which is reflected in the idea that for a press perturbation, the feedback of the whole system is negative. Another analytic assumption is that a conditional or unconditional stable equilibrium exists for the system. Finally, predictions of system response

to press perturbations assume enough time for the system to reach the neighborhood of a new stable equilibrium. (Levins, 1974; Justus; 2006)

Causal Conjectures and Competing Models

The core model in Figure 1 contains four phenomena—individual depressive experience, neighborhood death rate, neighborhood exit rate, and neighborhood vacancies—linked by eleven qualitatively specified and non-zero causal relationships (that is, the relationships are specified only in terms of the sign and presence, and not magnitude of their effects). Depressive experience is modeled as a negative function of prior depressive experience (meaning that such experiences “decay” towards some level over time), a positive function of neighborhood vacancy (vacancies are chronic low grade stressors), a positive function of neighborhood exit rate (loss of neighboring relationships is a stressor), and a positive function of neighborhood death rate (neighbors dying is a stressor); Vacancy is a function determined entirely by neighborhood exit and neighborhood death (by definition); neighborhood exit is conjectured to be a positive function of depressive experience (if depressive experience arises from the neighborhood environment, this may prompt a residential move), death (the death of a family member may sponsor a move), and prior exit (the net exit rate tends towards an assumed stable level determined by unmodeled factors, for example city-wide housing demand, city or regional economic opportunity, etc.); neighborhood death rate is modeled as a function of depressive experience (depression and stress are understood to be major contributors of major causes of mortality), and prior death rate (assume death rate tends to a stable level determined by factors outside the model).

Analysis of Model 1

This model predicts increased depression as a response to increased vacancy. Predictions from the community effect matrix for the core model in Figure 1 have been presented in Table 1, along with the predictions from all other models in this paper. This model predicts depressive experience, neighborhood exit rate, and neighborhood death rate as sensitive to neighborhood vacancies, exit rate and death rate. Neighborhood vacancy reflects sensitivity to aggregate depressive experience, but the model is ambiguous in its predictions of vacancy's sensitivity to perturbations in vacancy, exit rate and death rate. The effect of an increase in vacancy on itself is ambiguous, due to the instability of its complimentary subsystem, which has both negative and positive feedback. However, because the levels of feedback are predominantly of one sign, and because the model does not distinguish between relative strengths of the linkages, we should expect that the effect of vacancy upon itself is negative using *weighted feedback*: a method used to resolve ambiguity in loop model predictions. (See Dambacher et al., 2003) By contrast, the ambiguity of the effect of neighborhood exit rate upon vacancy results from negative feedback on the path from exit to depressive experience to death to vacancy, but positive feedback on the direct path from exit rate to vacancy. The predicted effect of neighborhood death rate on vacancy is uncertain for similar reasons, but weighted feedback indicates a positive expectation. Model 1 describes vacancy as a sink for aggregate depressive experience. This pattern holds across all subsequent models, because the path through depressive experience is the only one for variation in vacancy to influence any variable in the system.

Description and Analysis of Model 2

We can extend Model 1 by including individual experience of social isolation in the core system (Figure 3). Social isolation is modeled as a function of individual depressive experience (assume depressive experiences inhibit social isolation), neighborhood exit rate (loss of neighbors decreases opportunities for social interaction with neighbors), and is self-limiting (factors external to this model are assumed to stabilize individual experience of isolation around

some level). In addition, the direct effect of social isolation on depressive experience replaces the direct effect of neighborhood exit rate on depressive experience.

Depressive experience is increased by increased social isolation and neighborhood exit, and is ambiguously affected by death as well as vacancy; increases to individual social isolation are predicted to increase vacancy, and the converse is true as well. However, predictions from Model 2 are more ambiguous than Model 1. Specifically, the effects of all variables on vacancy, and the effect of vacancy on all variables but neighborhood exit are ambiguous, although weighted feedback indicates increases to both depressive experience and social isolation increase neighborhood vacancy.

Greenspace Intervention: An Initial Model

Greenspace interventions in New Haven, CT and in other old industrial Eastern cities tend to involve social organization of neighbors around specific projects such as vegetable gardens, play areas, or even the conversion of simple eyesore properties into a refuse-free area with overgrowth of plants kept in check. Such projects are supported by a variety of local institutions including community foundations, city agencies, local and national non-profit organizations and academic institutions, and incorporate varying degrees of participatory and community lead approaches. The validity of the remainder of this analysis rests on an important caveat in that it assumes that the relationships between vacant properties and other system variables also hold for empty properties (these are property parcels without buildings on them because they were never built, decayed, were intentionally demolished or destroyed by fire or some disaster) as part of a general category of the urban landscape commonly called *abandoned land*. In New Haven, empty lots are more likely to be used for greenspace programs due to legal contingencies pertaining to whether ownership has reverted to the city, or to a city contracted holding agency, and to legal liability for residents voluntarily working in or about possibly dangerous empty structures.

The initial pass, then, is to assess greenspace programs as a signal input to abandonment, and exit rate using the predictions from Model 1 (Figure 4). The conjecture that greenspace programs “decrease abandonment” comes about because a property that visibly manifests the collective social engagement of its adjacent community ceases to be socially abandoned property, even though it may still be privately and publicly abandoned property. Personal communication with prospective renters and buyers viewing neighboring greenspaces on empty lots in New Haven suggests that visible community led greenspace programs make a block more attractive, supporting the conjecture that greenspace decreases exit rate. This input applied to Model 1 combines to give a decrease in both depressive experiences and death, while ambiguous effects are obtained for abandonment and exit. (Although it does not resolve this example, weighted feedback may resolve ambiguous predictions for more inputs at more than one variable by summing corresponding adjoint values multiplied by the direction of change at each variable and dividing by the summed total feedback, as per Dambacher et al., 2002.)

Applying the same reasoning (i.e. decreasing abandonment and neighborhood exit) to Model 2 yields ambiguous results for all variables, although the weighted feedback method indicates an expectation of decreased exit and social isolation. Further, assuming that greenspace programs decrease social isolation (the prevailing model for greenspace programs is participatory), weighted feedback indicates a decrease in depression and exit rate, but an ambiguous effect on property abandonment, death rate, and social isolation.

Description and Analysis of Model 3

Greenspace projects both self-perpetuate—they may survive several annual cycles of organization, planning and implementation—and cease. By considering them as part of the system, the input assumptions on greenspace programs above produce the model in Figure 5, where neighborhood exit is modeled as decreasing greenspace programs (assuming that population exit decreases collective efficacy in the neighborhood), and greenspace programs are modeled as self-limiting (assuming greenspace programs tend towards a stable level as a function of unmodeled variables—notably foundation funding, program outreach for different NGOs, city resources, etc.).

The incorporation of greenspace programs is somewhat vague: what is meant by an increase in greenspace program rate? Without delving too deeply, I note that such projects vary in the extent of neighbor involvement, physical area covered, amount of resources applied, and number of abandoned properties attended to, or nature of socio-physical change (c.f. the Environmental Expression on Abandoned Lots Scale, Dinno 2001), and submit that the concept could be measured and defined in some fashion making it appropriate for loop analysis.

Model 3 predicts a decrease in depressive experience and death associated with increasing input to greenspace programs. As with Models 1 and 2, predicted effects on and effects of abandonment (previously vacancy) tend to ambiguity. Abandonment still serves as a sink for aggregate depressive experience, with weighted feedback indicating an increase in abandonment with increased depressive experience. Increased abandonment results in increased neighborhood exit and decreased greenspace program rates. Depressive experience is ambiguously sensitive to changes in the rate of death, but weighted feedback indicates a positive relationship. The ambiguity of increased greenspace program rate is explained, as with many of the ambiguities in this model series, by complimentary subsystems of self-damping variables embedded in positive feedback loops with one another.

Description and Analysis of Model 4

Model 4 merges Models 3 and 2 by removing the direct link between neighborhood exit rate and greenspace programs, and by linking (aggregated) individual social isolation and greenspace programs as mutually antagonistic. (Figure 6) Model 4 represents neighborhoods with both changing rates of property abandonment and changing presence of greenspace programs.

Output for Model 4 is highly ambiguous, which is not surprising, given its size and connectivity. The same pattern of abandonment as (ambiguous) sink for depressive experience holds. Social isolation shows the most definite effects, including a counter-intuitive increase in greenspace programs resulting from increasing aggregate social isolation experiences. Increases to greenspace programs are all ambiguous, but weighted feedback indicates that increases to greenspace produce decreases in depressive experience and death and subsequent reduction in greenspace programs. Abandonment has totally ambiguous effects on subsequent abandonment, and neighborhood exit, but weighted feedback resolves ambiguity into an inverse relationship for both depressive experience and neighborhood death rate. This inverse relationship with depressive experience is a new result compared to the other models presented here. Increased abandonment decreases greenspace programs and increases social isolation.

Description and Analysis of Models 5 and 6

As discussed above the concept of abandoned property includes empty lots in addition to vacant buildings. If the housing stock in a neighborhood is changing (i.e. properties with buildings are becoming empty lots, or new buildings are constructed), then signals to the system (for example, through the real estate market) may impact abandoned property directly. For this

reason models 3 and 4 have been extended by the addition of a self-damping term to abandoned property.

Model 5 adds a damping 'self-effect' to abandonment in Model 3 (Figure 5). Over half the predicted effects of press perturbation for Model 5 are ambiguous, although five ambiguous effects resolve using the weighted feedback. For perturbations at depressive experiences, Model 5 makes ambiguous predictions for effects on depressive experience (ambiguous complimentary feedback), and neighborhood death rate (ambiguous complementary feedback). This contrasts with unambiguous predictions for previous models, which do not include this self-damping term. Analysis of Model 5 predicts increased abandonment (using weighted feedback), increased neighborhood exit rate, and decreased neighborhood greenspace programs. Inputs to abandoned property are predicted to have decreasing effects on abandonment (using weighted feedback), increasing effects on exit, and decreasing effects on greenspace programs, with other effects being ambiguous (arising in the feedback from different levels of the complementary subsystems). In Model 5 perturbations to greenspace predict decreased depressive experience, neighborhood death rates and greenspace programs.

Model 6 is Model 4 with self-damping added to abandoned property. As for model 4 there is ambiguity in its predictions, one third of which are resolved using weighted feedback (Figure 6). In model 6 all predicted effects upon abandonment and neighborhood exit rate are ambiguous. This is because the complementary feedback from the subsystem comprised of depressive experience and death rate is ambiguous, so is the complementary feedback from the subsystem comprised by exit rate and greenspace program. Since every path to property abandonment and every path to neighborhood exit must entail one of these two subsystems, ambiguous prediction is unavoidable. As with Model 4, this model predicts a decrease in depressive experience with perturbations entering the system at abandoned property. As with Models 3, 4 and 5 increases to greenspace programs predict decreased depressive experiences, and neighborhood death rates, however the predicted effect on greenspace programs is ambiguous (arising from ambiguous complimentary feedback).

Empirical Analysis

Models serve as formal statements about different assumptions of the researchers, and their utility is contingent upon the validity of the models. Validation of loop models can take different forms. The degree to which direct causal linkages are uncontested is one form of validation. For example, it is difficult to conceive of vacancy resulting from anything other than the net number of people moving out of/into a neighborhood plus the rate at which neighborhood residents die.

Another kind of validation is by empirical observation of system behavior that corresponds to predicted effects. Levins (1966) tells us that because all formal models are in some sense false, scientists must adopt strategies to find the truth in "the intersections of independent lies." This plays out in empirical model testing and inference for loop models as follows: for each model's community effect matrix, there are associated tables of predicted correlation between variables (the product of predictions for two variables given an experimental or observed perturbation to a given variable); when different reasonable models (i.e. different causal assumptions) share a correspondence between predicted and observed pair-wise correlations between modeled variables, we can say that the behavior described is robust to these assumptions.

Lamentably, the secondary nature of the available data and the quality of the study design producing the data make individual depression, individual social isolation, and neighborhood vacancy the only variables for which we have observations in the EPESE dataset produced by Berkman, et al. (1986). Moreover, the timing of data collection weakens the validity of inferences made: an ideal interval between waves would be on the order of four to six months

or even shorter intervals, whereas human measurements were made every three to six years, and vacancy measurements were made annually and not matched to a particular individual's date of interview.

Discussion

Significance of Findings

These findings have several implications. First, neighborhood environments can reflect the health of their residents. Collective depressive experience will, in theory, become manifest in the physical features of the environment, because the indirect effects of perturbation to depressive experiences 'sink' into change in neighborhood vacancies/property abandonment in all models analyzed. Modeling the individual causal relationships together in a feedback system makes apparent and analytically explicit the indirect sensitivity of environment to human experience.

Conversely, vacant buildings and abandoned property may be a mental health risk, and not merely an incentive for residents to move to a new neighborhood. Depressive experiences are sensitive to perturbations at vacant/abandoned properties for all models, albeit with consistent ambiguity.

In all four participatory greenspace models, perturbations to greenspace decrease depressive experience. This contrasts with the model of greenspace program as an external perturbation, which gave a decrease in depression in the Model 1, but ambiguous results for Model 2.

Greenspace programs from the first take following a non-participatory model (for example, a short lived greenspace program on abandoned lands that amounted to workers entering a street with almost no resident consultation) may decrease depressive experience, however the nature of individual/neighborhood interactions makes this finding uncertain. By contrast, participatory programs appear to reduce both depressive experiences and death rate, and also to recast the significance of abandoned property within a neighborhood. The self-limiting effect of participatory greenspace programs may be interpreted as a community response to abandoned property (and perhaps social isolation); participatory greenspace programs may be seen as adaptive responses that mitigate the effects of property abandonment upon depressive experience and death.

Strengths and Limitations of the Loop Analysis Method

In undertaking these analyses I have endeavored to provide a justification and example of an alternative approach to modeling causality than that employed in either conventional statistical approaches, or in more sophisticated causal Bayesian network approaches. This analysis illustrates the utility of loop models for making qualitative predictions of changes in response to system perturbations, contrasting interventions defined by system perturbation with those defined by altering system composition, and evaluating a number of related models, rather than selecting a "best" model.

Loop models are general in that their results extend beyond any particular data set or specific set of system variables to all systems with comparable compositions, and realistic in that they do not need to sacrifice any variables that are believed to make up a real-world system nor make overly simplistic assumptions about causal relationships (for example, that endogeneity is 'controlled for' in the analysis). Loop analysis provides deductive insights, but also supports inductive inference.

To achieve its aims, the method sacrifices precision, description of magnitude (even relative magnitude), and description of rates of stabilization following perturbation, providing instead

qualitative descriptors of indirect effects. This distancing from precision permits analysis without precise quantification, using qualitatively specified causal hypotheses that are very inexpensive to produce. The inexpensiveness of specifying alternate models, and the comparability of predictions from competing or complementing models, means that we can incorporate all of what we know in a loop analysis.

For small systems, CEMs can be quickly computed. For systems of the size of the models presented here, computation time is negligible. For systems of about a dozen or more variables computing time starts to become an issue. For a maximally connected matrix, the addition of a new variable will increase the computation time of the former system, by a multiple approximately equal to the number of variables in the system. Moreover, the usefulness of the method generally diminishes with system size, because the findings are much more likely to be ambiguous when more variables or more causal links between them are added to a system. (May, 1973; Dambacher, 2003)

Because the mechanics of loop analysis pinpoint precisely where ambiguous results arise, the method can be used to identify where further information can be injected into the analysis to resolve such ambiguities. (Puccia and Levins, 1985; Justus, 2006) For example, an ambiguity arising from opposite signs for two different paths, if we can say we are certain that the magnitude of one of the paths is greater than the other.

Loop analysis facilitates direct comparison of competing models, and accommodates different relationships and different sets of model variables, including ones that have not or cannot be observed. There is an important difference between analysis of related loop models and analysis of competing statistical models: instead of accepting or rejecting a specific model as the best available representation of the truth, related loop models with community effect predictions that correspond well with observed data may each be taken as different generalizations about the state of nature from which we can draw valid and useful conclusions. This emphasis in differences between statistical and loop-modeling methods follows from the current scarcity of statistical model ensemble methods in epidemiology. Agreement among such an ensemble of models indicates a generality of findings, while disagreement indicates sensitivity to the specific contingencies modeled.

These models have been deductively analyzed independently of observed data. However, these findings would be better validated by more research supporting individual links between variables, and by validation of models' predictions against empirical observations. Accepting these findings without further validation poses a risk of relying on analytically appealing models that may be invalid. Empirical validation is relatively cheap compared to large population samples for statistical models. While attention needs to be paid to timing, and, where possible, to experimental manipulation, the sample size for validating loop models needs to be large enough only to comfortably test the sign or absence of bivariate correlations. (Puccia and Levins, 1985)

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Figure 1.
Model 1: the core loop model of individual depressive experience, neighborhood vacancies, neighborhood resident exit rate, and neighborhood death rate.

1. Example Signed Digraph

2. Key Definitions

Direct Effects A pointed arrowhead indicates direct causal increase (+) from cause to effect, a circular arrowhead indicates a direct causal decrease (−) from cause to effect, and the absence of an arrow indicates no direct causal effect (0).

Self Effects A direct effect of a variable upon itself. The presence of a negative self loop (termed “self-damping”) indicates that, absent any direct or indirect effects of other variables in the system, the variable tends to stabilize towards some equilibrium level. A positive self-effect (termed “auto-catalysis”) indicates that, absent any direct or indirect effects of other variables in the system, the variable tends to diverge (either in a negative or positive direction).

Path A path starts at one system variable, enters any subsequent system variable on the path exactly once and terminates in another system variable. In the example digraph, there are two paths from individual depressive experience to neighborhood vacancies: one direct path, and an indirect one that traverses first through neighborhood exit rate. A variable is the only path from and to itself.

Complementary Subsystem All variables and the direct effects among them that do not lie on a specific path. The complimentary subsystem of the path from individual depressive experience to itself comprises neighborhood exit rate and vacancies, the self-damping of neighborhood exit rate and the direct effect of exit on vacancies.

Loop Like a path in which every variable is entered and exited exactly once. In the example signed digraph neighborhood exit rate and individual depressive experience form one of five loops in the system. All self-effects are loops.

3. Key Assumptions of Model Composition

Time Variables represent values at any given time. Therefore the arrows linking each variable represent past, present and future states, and thus feedback, of the whole system.

Rates of Change System variables are assumed to all be changing at about the same rate; they are assumed to have rates of turnover that are within an order of magnitude of one another.

Connectance There is at least one path to each variable of a system from every other variable in the system. The system is not fully connected.

4. The Community Matrix

The statements of direct causal relationship (+, −, or 0) in a model amount to saying “the value of a variable depends generally upon the (signed) prior values of its causal predecessors.” In the example signed digraph depressive experience at time t is modeled as some generic function of prior (t) negative depressive experience, neighborhood exit rate and neighborhood vacancies:

$$\text{Depressive experiences}^t = f(-\text{Depressive experiences}^{t-1}, \text{Vacancies}^{t-1}, \text{Exit Rate}^{t-1})$$

The signs from the right-side of a generic function for each variable in a system can be assembled into a corresponding community matrix. Zeros represent variables not appearing in the right side of a given function in the community matrix. At right is the community matrix corresponding to the example system graphed above.

	Dep	Vac	Exit
Dep	−	+	+
Vac	+	0	+
Exit	+	0	−

5. The Community Effect Matrix

Predictions The community effect matrix is a table of predicted indirect effects on one variable of a system (column) given a press perturbation at some variable in the system (row). Applying the community effect formula to the community matrix produces the community effect matrix.

Sinks Some perturbations sink into only one or a few variables, others diffuse across the whole system. In the example system, perturbations to depressive experience sink into neighborhood vacancies.

Ambiguity Some predictions are ambiguous. Without more information (such as relative strength of causal relationships, or even full quantitative specification), we cannot know whether the variable will increase, decrease or stay the same given a perturbation. For example a perturbation to vacancies has an ambiguous effect on vacancies.

Correlations The community effect matrix indicates correlations between variables following a press perturbation at a given point in the product of the two predicted effects for a perturbed variable. In the example system, the analysis predicts a positive correlation between depressive experience and neighborhood vacancies given a perturbation at neighborhood exit rate, but a negative correlation between exit rate and depressive experience.

	Dep	Vac	Exit
Dep	0	+	0
Vac	+	?	+
Exit	+	+	−

Figure 2. Introduction to loop analysis including signed digraphs, key definitions, key assumptions community matrices, and community effect matrices.

Figure 3.

Model 2: extending the core loop model of individual depressive experience, neighborhood vacancies, neighborhood exit rate, and neighborhood death rate by adding individual social isolation.

Figure 4.
Interpreting greenspace projects as inputs to neighborhood vacancies and neighborhood exit rate in the core loop model

Figure 5.

Model 3 (without the dashed self-effect): extends the core loop model of individual depressive experience, neighborhood abandoned property, neighborhood exit rate, and, neighborhood death rate by incorporating greenspace programs as part of the system. Model 5: the same as Model 3, but including a self-effect for neighborhood abandoned property (dashed line).

Figure 6.

Model 4 (without the dashed self-effect): extends Model 2 which includes individual depressive experience, neighborhood abandoned property, neighborhood exit rate, neighborhood death rate, and individual social isolation by incorporating greenspace programs as part of the system. Model 6: the same as Model 4, but including a self-effect for neighborhood abandoned property (dashed line).

Predicted direction of change in system variables for a press perturbation to the indicated variable

Table 1

Predicted Direction of Effect on					
Individual Depressive Experience	Neighborhood Vacant (Abandoned) Properties	Neighborhood Exit Rate	Neighborhood Death Rate	Individual Social Isolation	Neighborhood Greenspace Program
Effects for:					
For a Press Perturbation Entering at Individual Depressive Experience					
Model 1	0	+	0		
Model 2	0	(+)	0	0	0
Model 3	0	(+)	0		0
Model 4	0	?	0	0	0
Model 5	?	(+)	+	?	-
Model 6	(-)	?	?	+	-
Effects for:					
For a Press Perturbation Entering at Neighborhood Vacant (Abandoned) Parcels					
Model 1	+	(-)	+	+	
Model 2	?	?	?	?	-
Model 3	?	?	+		-
Model 4	(-)	?	?	+	-
Model 5	?	(-)	+	?	-
Model 6	(-)	?	?	+	-
Effects for:					
For a Press Perturbation Entering at Neighborhood Exit Rate					
Model 1	+	?	+	?	+
Model 2	+	-	+		?
Model 3	+	?	+		?
Model 4	?	?	?	?	?
Model 5	+	?	+		?
Model 6	(+)	?	?	?	?
Effects for:					
For a Press Perturbation Entering at Neighborhood Death Rate					
Model 1	+	(+)	+	-	
Model 2	?	?	+	-	
Model 3	(+)	?	+		-
Model 4	?	?	?	(-)	-
Model 5	(+)	?	+	(-)	-
Model 6	?	?	?	(-)	-
Effects for:					
For a Press Perturbation Entering at Individual Social Isolation					
Model 2	+	(+)	+	-	+
Model 4	+	?	?	-	(+)
Model 6	+	?	?	+	
Effects for:					
For a Press Perturbation Entering at Neighborhood Greenspace Program					
Model 3	-	?	?	-	-
Model 4	(-)	?	?	(-)	(-)
Model 5	-	?	?	-	(-)
Model 6	(-)	?	?	(-)	(-)

Predicted Direction of Effect on					
Individual Depressive Experience	Neighborhood Vacant (Abandoned) Properties	Neighborhood Exit Rate	Neighborhood Death Rate	Individual Social Isolation	Neighborhood Greenspace Program