Financial Performance of Mental Health Nonprofit Organizations[1]

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Abstract

Mental illness is a major social problem. In the United States, the vast majority of mental health services and supports are provided through nonprofit organizations. Recent changes in the field of mental health such as the implementation of evidence-based practices, funding cuts, and statewide policy initiatives such as transformation have increased financial pressures on these nonprofits. Yet few dynamic models exist for understanding the impact of these changes on nonprofit mental health organizations and their performance. This paper seeks to address this gap by presenting a model of financial performance of nonprofit mental health organizations. The purpose of this model is to identify some of the key mechanisms driving nonprofit financial performance. The model is based on the longitudinal financial data of 65 nonprofit organizations providing mental health services or supports in a large metropolitan community, and key informant interviews with executive leaders from a subset organizations participating in a three-year longitudinal study. A simulation model is presented along with implications for state policy makers, managers of nonprofit organizations, funders, and organizational scholars.

Keywords: nonprofit organizations, mental health, financial performance

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1. Introduction

Mental illness is a major global disease burden. In market economies, mental illness including suicide represents approximately 15 percent of the overall disease burden; higher than all cancers combined, HIV/AIDS, and substance abuse (Murray and Lopez 1996). In the United States, nearly one in four adults suffer from a diagnosable mental disorder every year, with half of those having one diagnosis suffering another mental illness, and 1 in 17 persons suffering from serious mental illness (Kessler et al. 2005). Total expenditures of mental health and substance abuse treatment in the United States is estimated at $121 billion per year and increasing at an annual rate of approximately 5.6% per year (Mark et al. 2007). This represents 7.5% of the total estimated $1.6 trillion spent on health care services in the United States during 2003 (Mark et al. 2007). Mental health treatment costs accounted for $100 billion while substance abuse treatment totaled $21 billion.

Nonprofit organizations represent a significant portion of the mental health and substance abuse providers in the United States. Nonprofits comprise 65 percent of outpatient mental health and substance abuse centers, 43 percent of psychiatric and substance abuse hospitals, and 66 percent of residential facilities for persons with development disabilities (Burke 2007). Between $85 to $105 billion in Medicaid funding went to nonprofit providers in 2004 (Burke 2007). Increasing dependency of nonprofits on Medicaid funding has both added capacity by introducing more professional medical credentials and led to a more volatile funding base (Burke 2007). With increasing demand for using evidence-based practices and documentation of outcomes, nonprofit providers of mental health services and support face enormous challenges (Mark et al. 2007). Reducing the disease burden of mental illness therefore depends on developing better policies for public financing of services and supports through an improved understanding of nonprofit providers.

Like all organizations, nonprofit human service organizations depend on acquiring resources from their environment and efficiently allocating resources to programs and services in order to fulfill their mission. Levin and Roberts (1976), for example, argue that the organizational life cycle of human service delivery systems can been understood as a dynamic between consumer demand, community support, and the capacity of the organization to provide services. In doing so, Levin and Roberts essentially argue for understanding the dynamics of human service organizations from a resource dependency perspective (Pfeffer and Salancik 1978) where the quality of services follows from a resource driven life cycle of the organization.

Identifying and understanding these resource dynamics, however, is complicated by the diversity of organizations. For example, nonprofit mental health organizations vary greatly in their size, stage of organizational development, training and experience of staff, age, populations served, whether they serve rural or urban areas, organizational form, funding sources, culture and technology just to name a few. This makes it difficult to distinguish the idiosyncrasies of a specific organization from more general underlying feedback mechanisms. Despite this fact, the tendency is still to rely on single case studies of organizations and cross sectional survey research designs for studying and understanding nonprofit organizations. There are, for example, relatively few longitudinal comparative studies that shed light on the variety of behaviors one might expect within a particular set of nonprofit organizations. Ignoring these issues is likely to lead to well intentioned but misguided policies for improving the quality of services, potentially weakening the overall organizational service ecology, and exacerbating disparities in mental health.

This paper seeks to address this gap by presenting a model of financial performance of nonprofit mental health organizations. The purpose of this model is to identify some of the key mechanisms driving nonprofit financial performance, which can then be used to distinguish organizational behavior related to financial variables from other organizational variables such as strategic orientation (Sastry 1997; Tushman and Romanelli 1985; Tushman, Virany, and Romanelli 1985), resistance to change (Samuel and Jacobsen 1997), and managerial commitment (Repenning 2002). This financial performance model is part of a larger system dynamics study focusing on the impact of innovation implementation on organizational performance. Understanding these issues is important to executive leaders of nonprofit providers as they consider strategic questions for their organization, policy makers as they design incentives for increasing the uptake and sustainability of innovations in mental health services and supports, and consumers and other stakeholders as they seek to advocate for more individualized care and better quality.

In focusing on nonprofit financial performance, we argue that 1) any viable model of nonprofit organizational behavior should have as a basis a solid financial model, and 2) the inclusion of additional variables is better justified if it has first been shown that financial variables alone are unable to account for some specific behaviors. Our motivation for this strategy comes from our previous experience modeling organizational theory, and the need to anchor models around common referents. While not without their limitations, financial variables serve this purpose well in addition to being central to decision making of executive leaders and funders.

The remainder of the paper is organized as follows. In section 2, we provide a brief overview of mental health services, nonprofit organizations, and organizational theory. Section 3 describes our sample and data, including our approach to identifying reference modes using grounded theory. Section 4 describes the model, its formulation and the major feedback loops. Section 5 describes the testing and validation. Section 6 concludes with a discussion about implications for state policy makers, managers of nonprofit organizations, and organizational scholars.

2. Mental Health Services and Nonprofit Providers

Operationally, nonprofit organizations are defined within this study as organizations that established a formal relationship with the state through their articles of incorporation as a 501(c) charity. An organization in this sense can have multiple establishments, only some of which may provide mental health services. The U.S. Census Bureau's North American Industry Classification System (NAICS) places mental health services under the category of NAICS Sector 62, Health Care and Social Assistance. The U.S. Census Bureau does not generally draw a distinction between mental health and substance abuse services, but they have historically been distinct types of organizations both due to the more consumer driven movement in addictions that is skeptical of professional providers (e.g., Alcoholics Anonymous) and differences in public funding. The focus in this study is primarily on mental health services and supports.

A large portion of mental health services are not in fact provided by organizations dedicated to mental health services. Doreian and Woodward (1999) point out that approximately 80 percent of mental health services are delivered by organizations that have a different purpose.

We recognize that recovery from mental illness involves more than just treatment to include prevention and supports for families, increasing schooling and employment opportunities for persons with serious mental illness, and improving access to housing in addition to counseling, residential treatment, and psychiatric hospitals (e.g., DHHS 2006). Thus we define nonprofit mental health organizations broadly as those nonprofit organizations providing some type of mental health service or support in order to meet their mission.

Since mental health services and supports often depend on other organizations, it is important to consider organizations within an overall service network or organizational ecology. For example, several studies have noted the high comorbidity of physical health and mental health issues for persons with severe mental illness, which can combine to shorten life expectancy by an average of 25 years than the general population (National Association of State Mental Health Program Directors 2006). Contributing factors include side effects from medications that increase obesity, higher rates of smoking and heart disease, and lack of access quality medical care due to a diagnosis of mental illness where providers may discount patients' physical distress as psychosomatic as opposed to indicators of disease. However, to effectively meet both sets of needs, providers need to rely on supports such as transportation or family members who can play an integral role in recovery. Lack of coordination and funding combined with high levels of stigma and geographically dispersed services can pose formidable barriers to meeting these needs, creating cracks in the service network. Moreover, cuts in publicly funded services or events such as natural disasters can have major ripple effects on the availability and quality of services, creating new needs.

These gaps also create opportunities for new organizations. Specifically, nonprofits can find and exploit new resource niches either through expansion of existing programs, mergers, or the creation of new organizations (Chambré and Fatt 2002). Nonprofit organizations generally do not start the same way as for-profit organizations, usually beginning with little or no capital under the assumption of volunteerism and altruism (Fernandez 2007). This contributes to significant uncertainty and potentially high failure rates. Previous studies on organizational ecology have often ignored the importance financial resources (Fernandez 2007). Despite the recent trend of increasing size in nonprofit human service organizations, many new nonprofits continue to be founded (Tucker and Sommerfeld 2006). These issues are critical to understand from a dynamic perspective that ultimately addresses both issues related to resource dependency and legitimacy within organizational ecology. Cho and Gillespie (2006) argue for a dynamic resource theory that addresses some of the limitations of traditional resource dependence. They focus on how quality changes over time with an emphasis on service reliability, which they define as the "probability that a service will be delivered in a dependable and consistent manner with minimal variation over time or across service recipients" (p. 499). The focus of this paper is therefore on understanding the financial dynamics as they relate to reliability and quality of mental health services and supports within an organizational ecology.

3. Sample and Data

Data sources for this model include the IRS 990 returns for the 65 organizations in our sampling frame from a metropolitan area, notes from the 32 organizations we interviewed in our initial meetings and have agreed to participate in our study, agency documents (e.g., pamphlets, websites describing mission and services), and the Secretary of State's list of business entities with the founding dates. This section describes the sample, its construction, and the construction of the reference modes identifying different patterns of organizational change.

3.1. Sample

The primary sample used for the analysis and modeling described here comes from a systematic search using GuideStar to identify nonprofit organizations providing mental health services in a Midwestern metropolitan statistical area of approximately 2.5 million people. The initial sampling frame was constructed from a GuideStar search joining the results from a keyword search using the terms “family services” and “mental health”. This yielded 167 organizations. Of these 167 organizations, 106 did not have complete financial information or reported annual revenue of less than $100,000 per year, leaving a sample of 61 organizations. Comparing this list against a list of Department Mental Health providers list added 4 more organizations to our sample for a total of 65 organizations.

The median age of the organizations in our sample was 13 years, consistent with the recent growth in the number of nonprofit human service organizations in the United States, which has been especially steep in recent years as a consequence of privatization of the welfare state (Chambré and Fatt 2002). Total revenue for our sample in 2005, the most recent complete year of data, was $183 million with median revenue of $1.7 million (see Table 1). The sample reflects the large number of relatively small nonprofits in a given community, with over half the organizations representing less than 1% of the total revenue. The mean revenue was $2.9 million and increased by approximately 3% per year, although this variation was statistically insignificant when compared with within organization variation for any given year ($R^2 = 0.0018, F(1,455), p = 0.18$).

Table 2 shows the distribution of program expenses along with the average program expense ratio. The overall average of program expenses was $2.4 million per year. The overall mean program expense ratio (PER) was 0.79, which did not differ ($t(451) = -0.8857, p = 0.3763$) from a national average of 0.80 for human service organization (Center on Nonprofits and Philanthropy & Center on Philanthropy August 2004).

From this sample of 65 organizations, we purposefully selected a subset of 33 organizations for key informant interviews and more in-depth data collection using several criteria.[2] First, we wanted to include organizations that politically important such as providers for the department of mental health and organizations that were already involved with research projects with our university. After selecting these organizations, we then randomly sampled selected organizations to balance our research design by their level of funding and program expense ratio.

Members of the research team sent initial approach letters with basic study information, followed up by a call by the organizational liaison coordinator to answer initial questions and schedule a meeting with the principal investigator and other team members. Agency visits were then conducted to discuss the study and seek the organization’s participation and nomination of a key informant, and followed up with a thank you email and template letter of agreement. Of the 37 organizations approached, 3 declined to participate over the phone citing reasons such as already being involved in another evaluation or research study and being overwhelmed by other demands. One declined to participate after the initial meetings citing questions about the direct

[2] Recruitment continued after the results from this paper and the study now includes 43 organizations.

benefit of participation to the organization, leaving 33 organizations in our sample. Nonetheless, a participation rate of 89% is considered high in this area of research.

Table 1 Revenue by fiscal year

		Revenue ($/Year)				
Fiscal year	N	Total	Mean	Median	Min	Max
1996	2	2,281,511	1,140,755	1,140,755	44,720	2,236,791
1997	25	50,789,945	2,031,598	1,227,833	88,817	5,870,217
1998	35	86,422,287	2,469,208	1,728,184	66,652	9,117,519
1999	50	154,268,077	3,085,362	1,384,285	36,403	22,687,001
2000	52	144,337,417	2,775,720	1,315,869	35,819	26,386,983
2001	52	140,447,226	2,700,908	1,396,131	34,325	11,002,084
2002	55	176,864,534	3,215,719	1,716,933	49,860	29,215,539
2003	60	170,581,717	2,843,029	1,356,192	42,324	14,650,531
2004	57	182,531,148	3,202,301	1,333,366	259	14,656,581
2005	50	183,203,847	3,664,077	1,763,698	66,844	14,190,971
2006	19	52,861,069	2,782,162	1,126,171	172,801	14,814,957

Table 2 Program expenses by fiscal year

		Program expenses ($/Year)			
Fiscal year	N	Total	Mean	Median	Program Expense Ratio
1996	2	1,696,297	848,148	848,148	0.74
1997	25	41,907,217	1,676,289	1,112,334	0.83
1998	35	66,783,640	1,908,104	1,036,596	0.77
1999	50	122,735,034	2,504,797	1,117,143	0.80
2000	52	115,915,747	2,229,149	1,057,768	0.80
2001	52	114,631,041	2,247,668	1,251,740	0.82
2002	55	150,069,946	2,728,545	1,171,054	0.85
2003	60	136,046,630	2,267,444	1,006,917	0.80
2004	57	152,561,732	2,676,522	1,142,541	0.84
2005	50	144,492,540	2,889,851	1,230,979	0.79
2006	19	44,080,171	2,320,009	989,229	0.83

3.2. Data Sources

We draw on two data sources for our model building: financial data from IRS 990 returns and key informant interviews. Financial data are commonly used to compare organizations and trends within an organization (Finkler 1994). Both program revenue and program expenses are reported on the IRS 990 forms, which all nonprofits with average annual revenues of $25,000 or more are required to file. Within the last 10 years or so, these forms and the data they contain have become increasingly available through the National Center for Charitable Statistics and

GuideStar, and led to a proliferation of nonprofit rating schemes based on financial measures alone.

This has been met with considerable criticism. Program expenses need not correlate with actual consumer outcomes (Hagar and Greenlee 2003). IRS 990 returns are also limited in that there are effectively no audits nor any real accountability in the accuracy of the information, and variations in reporting between and within organizations are an issue (Froelich, Knoepfle, and Pollak 2000; Hagar and Greenlee 2003). This has led many to raise caution about the use of these measures (Center on Nonprofits and Philanthropy & Center on Philanthropy August 2004; Froelich, Knoepfle, and Pollak 2000).

To assess some of these concerns, Froelich, Knoepfle, and Pollak (2000) compared the IRS 990 returns and audited financial statements for a variety of nonprofit organizations. For human service organizations, they found that total revenue was the most reliably reported on IRS 990 returns with a correlation of 0.91 between the IRS 990 returns and budges for total revenue, 0.86 for program expenses, and 0.69 for program expense ratios. We deem these reliabilities adequate for this study given that we are 1) only relying on them for qualitative descriptions of behavior over time as opposed to statistical analysis, 2) also involving executive leaders in key informant interviews to understand the organizational dynamics, and 3) using simulation modeling as a means of triangulating the financial data with the interviews. We discuss some proposals for further assessing the impact of reliability issues at the end of this paper.

In addition to the IRS 990 data, which were available for all 65 organizations in our sample, we also drew on key informant interviews with members of executive teams from a subset of organizations. Executive directors were asked to identify someone in their organization who was familiar with the delivery of mental health services and supports, implementation of innovations, and the strategic choices of the organization. Some identified themselves as the most appropriate key informant while others identified several key informants within their organization (e.g., VP for children's services and VP for adult services).

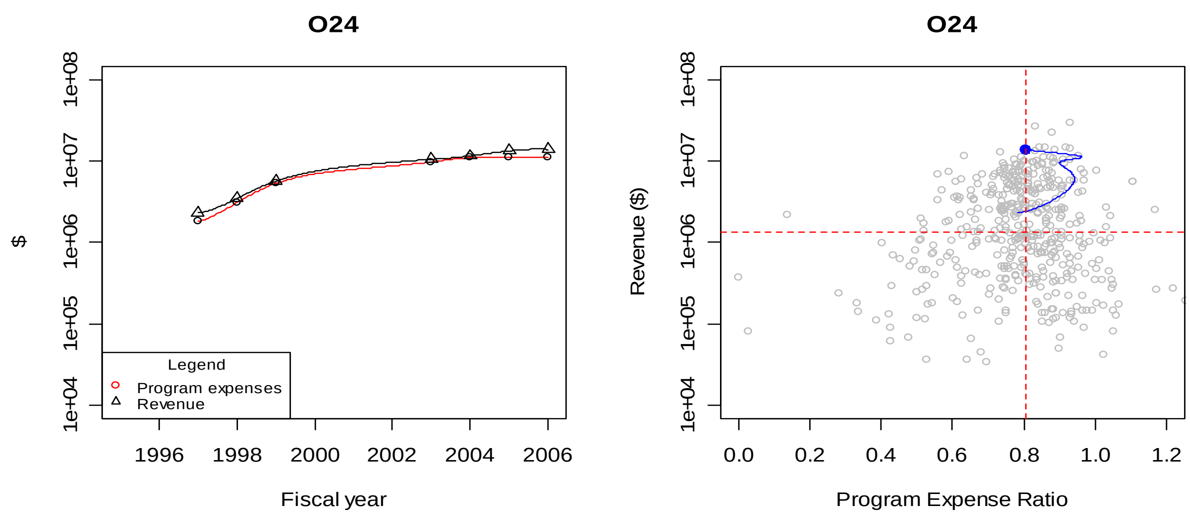
3.3. Dynamics

We constructed pairs of graphs to characterize the behavior over time of financial variables (total revenue, program expenses, and program expense ratios) for each of the 65 organizations in our sample. Figure 1 shows the behavior over time graphs for organization O24. Both graphs have revenue on the vertical axis. In order to make it easier to discern differences between small organizations, revenue is plotted on a log base 10 scale. The left graph shows program expenses and revenue over time with revenue and program expenses increasing steadily. Both reported values are averaged rates in units of dollars/year. Splines were constructed to provide smooth interpolations between observations.

The right graph is a parametric plot of revenue versus program expense ratio (program expenses/revenue) as a blue line with the most recent data indicated by the solid blue disk. These were based on the smooth splines constructed for the left graph (see supporting materials for the actual code). The gray circles denote all other observed points in the sample over the entire period of observation, which provides a sense for the overall range of realistic values for this set of organizations. The dashed red lines indicate the overall median revenue and program expense ratios.

The right graph in Figure 1 shows the organization increase in revenue along a path that initially involves increasing the program expense ratio and then decreasing the program expense ratio as increases in revenue begin to slow. It is important to keep in mind that because the revenue is on a log base 10 scale the vertical difference shown here reflects nearly a ten-fold increase in revenue over a period of 10 years.

Figure 1 **Sample of graph pairs used to identify reference modes**



3.4. Reference Modes

A good robust model should be able to describe the dynamics over a range of situations (Forrester 2007). Saeed (1998) has made the point that defining reference modes when considering empirical data is often an iterative process and that one needs to consider how system behavior may be compositions of multiple underlying processes. Yet most models rely on only a single set of multiple time series. This is a practice that both Saeed and Forrester (2007) have warned against.

Part of this has to do with a tendency to focus system dynamics studies on a single case, as opposed to considering multiple cases over a wide range of conditions. In this study, we selected our organizations for maximum variation within a particular sector of services. This increases our chances of identifying behavior modes of nonprofits organizations than either single case studies or studies that focus rely on cross sectional surveys.

Decomposing reference modes can be done through visual inspection or more formally through spectral decomposition techniques such as Fourier analysis (e.g., Saeed 1994). The relatively short number observations limit the applicability of quantitative methods given the number and complexity of the behavior patterns. So we approached the task of identifying reference modes working inductively using qualitative techniques, specifically taking a grounded theory approach (Strauss and Corbin 1998, 1994).

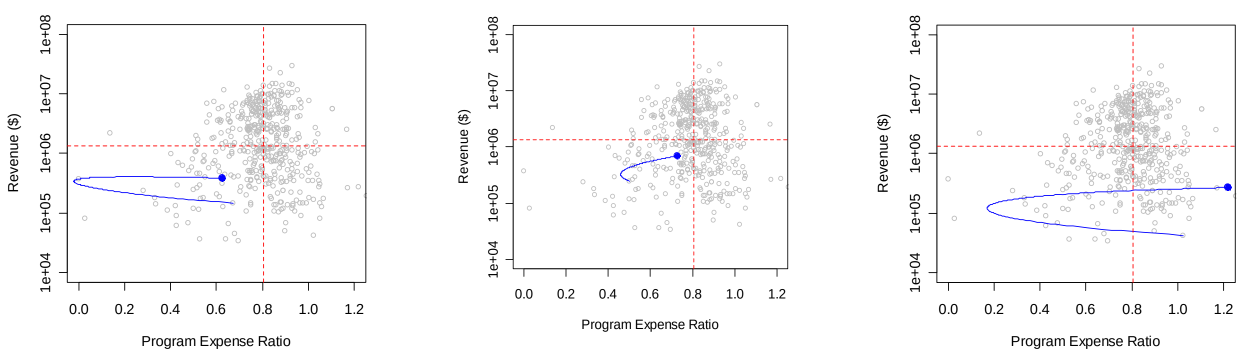
While qualitative techniques and grounded theory have been discussed as methods for analyzing qualitative data in system dynamics (e.g., Luna-Reyes and Andersen 2003), they can also be applied to discerning patterns in behavior over time graphs. Strauss and Corbin (1994) point out the iterative nature of induction and deduction in grounded theory, and the emphasis on grounding theories in data. Both aspects are echoed in system dynamics through the process of understanding and basing models in reference modes, and the iterative nature of simulation modeling (e.g., Homer 1983, 1997; Saeed 1998).

We followed standard techniques in grounded theory (Strauss and Corbin 1998), beginning with open coding the 65 pairs of behavior over time graphs. In grounded theory, coders approach data without a preset list of codes; instead an open coding process is utilized where data is examined and concepts and themes emerge organically. Two members of the research team independently coded the trajectories in the graphs and compared notes on the coding method, structure, and themes that emerged. There was consistency in the method of grouping the graphs and identifying themes: both coders adopted a modified pile-sort method to separate the graphs by a variety of features. This process led to the identification of codes which were also similar across both coders. For example, we classified trajectories by the amount ("small", "medium", "large", or "very large") and intensity ("smooth" or "erratic") of the changes. The direction of the change was also coded where trajectories that moved horizontally represented dominant changes in program expense ratios, and trajectories that moved vertically represented dominant changes in revenue. We then coded all the graphs using these codes. The codes associated with the various features were then compared and refined through discussions with the research team, additional comparisons, and selective coding.

We observed that some organizations followed the similar trajectories. For example, Figures 2a, 2b, and 2c appeared to be part of the same C-shaped trajectory. Based on meetings with these agencies, we learned that they serve similar populations, which increased our confidence in the use of the graphs.

Figure 2 Example of three graphs of behavior over time with similar "C" trajectories

(a) O63 (b) O64 (c) O62



We also noticed, for example, how some trajectories seemed rare or absent from our sample. Sometimes, this was a direct consequence of creating a code for one feature (e.g., crossing the program expense ratio median) and then wondering if the alternative was present (e.g., crossing the revenue median).

As pile-sorting and coding continued, the coders picked up on relationships between the codes, in particular the direction and the intensity of changes in the trajectories. When trends in an organization's program expenses mirrored the revenue trends, the changes in the trajectories were less intense and appeared as smooth curves that moved vertically along the revenue axis. However, when revenue and program expenses did not change consistently (creating fluctuations in the program expense ratio) the trajectories changed intensely and appeared as erratic z-shapes that moved horizontally along the program expense ratio axis.

Figure 3 Low inertia and high momentum

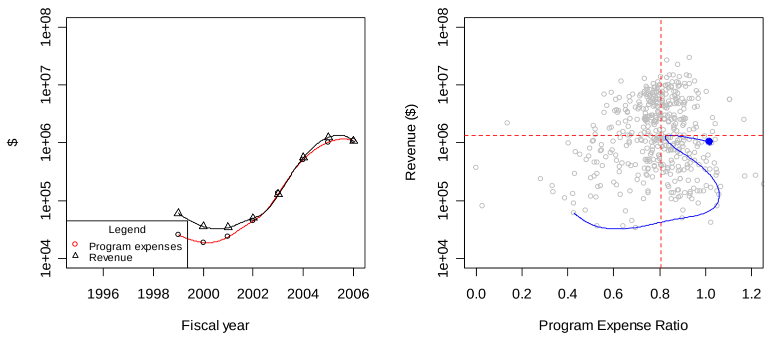


Figure 4 Low inertia and low momentum

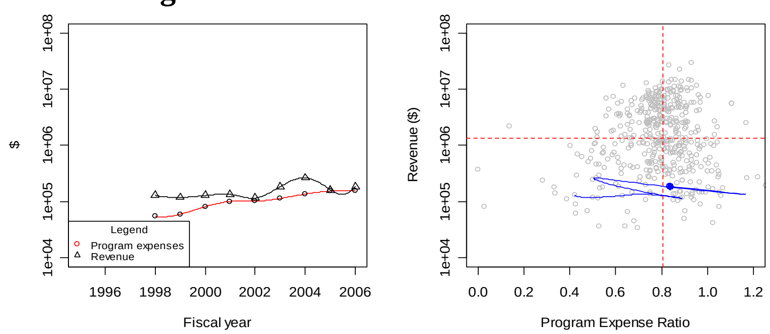
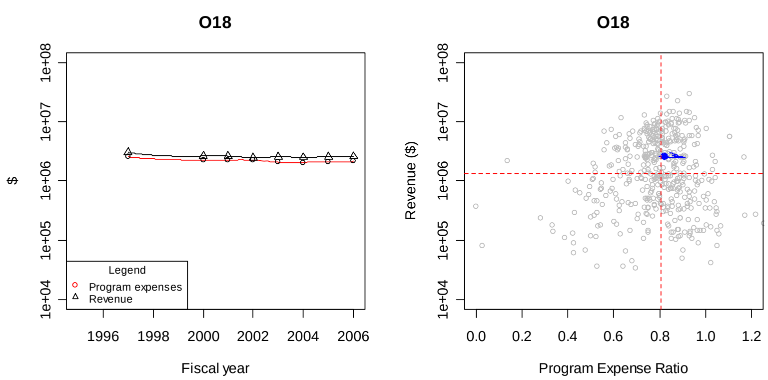


Figure 5 High inertia and low momentum



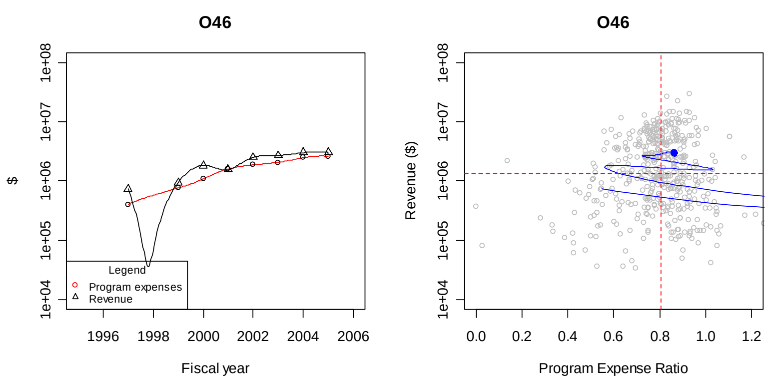
Distinctions were also seen between what is often discussed as organizational inertia and momentum. Organizational inertia represents existing monetary and psychological investments by the organization—sunk costs in the current direction of an organization (Hannan and Freeman 1984). Organizational inertia is seen as essential for reliably producing outputs, as reliability depends on institutionalization and enactment of standardized routines (Hannan and Freeman 1984). However, some confusion exists over whether inertia and momentum refer to the same or different concepts. Tushman and Romanelli (1985) see the terms as interchangeable, while others such as Miller and Friesen (1980) draw a distinction between inertia and momentum by defining momentum as the tendency to continue in a direction of change. Likewise, for Kelly and Amburgey (1991) the concept of organizational momentum is distinguished from organizational inertia by pointing out that organizations can develop routines for change that keep them changing; examples include an organization that is in a pattern of making acquisitions. The problem that scholars of organizational change focus on is not that organizations are not changing (the always are), but a change in the direction of change and the tendency to go past extrapolated trends and overshoot (Miller and Friesen 1980).

While we were not searching for evidence of this distinction, it became apparent through comparisons of behavior over time graphs. For example, Figures 3 and 4 both show organizations that are demonstrating considerable variability relative to the other 63 organizations in the sample and thus point to low inertia. Yet they differ in their momentum. Figure 3 illustrates rapid change but over a relatively smooth and stable arc, while Figure 4 seems to be both rapid and erratic. In contrast to the large movements shown in Figures 3 and 4, Figure 5 illustrates an organization that is not moving, displaying high levels of inertia.

Based on these types of comparisons and insights using grounded theory, we were able to identify a family of discrete behavior patterns that we thought were salient to our model of financial performance.

Initially, we tended to focus on discrete features or segments of behavior discussed previously. As we proceeded through analysis, however, we began to see similarities between patterns that would otherwise appear to be quite distinct. For example, the C patterns discussed earlier were seen as separate from a reversed C pattern, and both of these were seen as different from cycles, flat trajectories, and the serpentine pattern shown in Figure 6. Further examination, however, led to seeing the serpentine pattern in Figure 6 as the more general trajectory from which the others might be derived. This led us to consider two features as especially significant—the tendency of organizations to be on a vertical trajectory that followed a serpentine path as shown in Figure 6. This was in contrast to the fact that no organizations displayed a similar but rotated pattern.

Figure 6 Serpentine trajectory



4. Model Formulation

The purpose of the nonprofit financial performance model is to provide a means of understanding and comparing nonprofit financial behavior over time in order to subsequently be able to distinguish financial aspects of nonprofit performance from other aspects of organizational behavior and dynamics. We want to know, to what extent we can account for the observed trajectories using financial variables alone and gain insights into the types of questions and additional data that we might want to collect from organizations? We begin with the assumption that the model is in a dynamic equilibrium and start by defining some of the key boundary conditions of the equations. Model equations are then derived along with their initial conditions.

4.1. Key Boundary Conditions

We want to start the model in equilibrium in order to see the effects of changes to funding, caseloads, etc. Although there are a number of parameters in this model, most have no effect on the initial conditions and either have unique solutions based on conditions of the model being in a dynamic equilibrium or are free in the sense that they can take on any arbitrary value. However, since these models are generally underdetermined, some assumptions or key parameters need to be defined at the outset in order to determine the initial conditions for some stocks.

Initial effectiveness and initial quality of services are largely unknown from financial data alone and difficult to adequately measure across organizations providing diverse set of services. Rather than focus on absolute values of effectiveness and quality of services then, we focus on effectiveness and quality of services relative to a baseline equilibrium condition, which we define as value of 1. Thus an effectiveness of 1.25 would mean an increase of 25% over baseline. Initial effectiveness and quality are "fixed" as a condition of the model being in a dynamic equilibrium.

Table 3 Key Parameters Defining Boundary Conditions

Parameter	**Description**	**Value**	**Units**
Initial quality of services	Average quality of service, fixed	1.0	Dimensionless
Initial effectiveness	Quality of services times number of clients served, fixed	1.0	Dimensionless
Initial PER	Program expense ratio, free	0.80	Dimensionless
Initial caseload	Number of clients, free	140	Clients
Initial revenue	Total revenue per year, free	$2.9 million	dollars/year
True program cost per client	True cost of services per client to achieve maximum results, free	$34,000	dollars/year/client

Four other parameters define the state of the system when it is in a dynamic equilibrium: initial program expense ratio, initial caseload, initial revenue, and true program cost per client. These have to be specified by the user but are "free" in the sense that the user can choose what value to specify. The default values are based on the sample of organizations in our study. Initial program expense ratio is given a default value of 0.80 based on the mean value within our sample. Initial caseload is assigned a default value of 140 clients at any given time. This value will in actuality vary considerably from organization to organization depending on the type of service they provide. For example, a crisis call center may serve upwards of 1,400 calls per month or close to 17,000 clients per year, whereas a residential treatment facility may have as few as 10 clients at any given time. The actual value, however, has no effect on the dynamic behavior of the system. Similarly, the initial revenue is free and set to a default value of \$2.9 million per year based on our sample of organizations. True program cost per client is also free, and more difficult to estimate empirically since it depends on having extensive data on the relationship between cost and quality of services. As a default value, we assumed based on our experience working with nonprofits that the true cost of services for maximum benefit was twice the revenue, so that the true program cost per client under default conditions would be 2 x \$2.4 million/140 or \$34,000 per client per year. Table 3 provides a summary of the key parameters defining the boundary conditions. These are used in the remainder of the description of model formulation to define the initial conditions of stocks.

4.2. Effectiveness

Effectiveness refers to the perception of the organization in the community. To simplify the equations, we assume that the initial effectiveness is 1 so that an effectiveness of 1.25 means that the organization's reputation increased by 25% over its initial starting point, and 0.80 means that the organizations reputation in the community is 20% less than the initial starting point. Effectiveness is a function of caseload and the average quality of service per client or consumer, and doubling the number of clients being served should double effectiveness if quality remains the same, while doubling the quality of services and caseload being the same should have a similar effect. To represent this relationship, we write effectiveness as the product of quality and the ratio of the current caseload to the initial caseload,

$$Effectiveness(t) = Quality(t) \cdot \frac{Caseload(t)}{Caseload(0)}.$$

Effectiveness is not perceived immediately, but instead is information that diffuses through a network of consumers and providers often described as an S-shaped diffusion. So we represent this using a third order smooth where

$$Perceived\ effectiveness(t) = SMOOTH3I(Effectiveness, TC, 1)$$

and *SMOOTH3I* is a third order information delay of *TC* and with an initial value of 1.

4.3. Caseload

Caseload refers to how many clients are currently being served by organization. Caseload has units of clients where clients can be individuals, couples, families, etc. Caseload increases through new referrals and decreases through termination or completion of services, both in units of clients/year. The model is formulated so that the user specifies the current number of clients since this is usually known along with the average length of services, and then the initial referral rate is calculated as initial caseload/length of service where caseload will be in a dynamic equilibrium. So caseload is written as,

$$Caseload(t) = \int_0^t Referrals(u) - Completions(u)du + Caseload(0),$$

where

$$Completions(t) = Caseload(t) \,/\, Length\,of\;service\,.$$

To then increase the referral rate, we multiple the initial referral rate by factors that increase or decrease the referral rate. In this initial model, we are mainly concerned with how effectiveness might increase referrals. The simplest assumption is that doubling the effectiveness would double the referral rate. This obviously ignores the fact that 1) the relationship might not be linear, and 2) there would be a delay between when the perceived effectiveness increased and its effect on referrals. For the moment, however, we assume the simpler case where

$$Referrals(t) = \max(Initial\ Referrals \cdot Perceived\ Effectiveness(t), 0)$$

and

$$Initial\ Referrals = Initial\,Caseload \,/\, Length\,of\;service\,.$$

The use of the maximum function reflects the assumption that clients will not be referred to the organization if their perceived effectiveness is negative, i.e. they are perceived to be harming clients. This might not be accurate and it is something that will need to be considered in future interviews with key informants. The current referral rate is then some multiple of the initial referral rate, in this case effectiveness. So an organization that is twice as effective doubles its referral rate.

4.4. Quality of Service

Quality of service, *Q(t)*, refers to how well each client or consumer is served. Quality of service is initially defined as 1 in manner similar to effectiveness. Quality is treated as a function of how well programs are funded and how much human and physical is available to provide those services. To represent this, we write quality of service as the product of the fraction of program expenses funded and the fraction of needed capital that is available. Since we assume that quality of service is 1 at the start of the simulation, we normalize this product by dividing by its initial value of this product. Hence,

$$Quality(t) = \frac{Fraction\,of\;program\,expense\;funded(t) \cdot Fraction\,of\;needed\;capital\;available(t)}{Fraction\,of\;program\,expense\;funded(0) \cdot Fraction\,of\;needed\;capital\;available(0)}\,.$$

In future work, this can also be extended by multiplying funding of program and capital by other factors such as effect size or reliability. At present, however, we assume that the only constraint on quality of services is adequacy of funding programs and services and capital.

4.5. Program Expense Ratio

The program expense ratio is defined as program expenses divided by total revenue. It represents the allocation of revenue to programs and services that directly fulfill the mission of the organization. We treat the program expense ratio essentially like a budget fraction for allocating resources within the organization.

In this model, we simplify the financial picture to focus on two key production factors: program expenses and capital. Program expenses such as labor of therapists, drivers, nurses, assessment instruments. Capital refers to the means of production and includes such things as the building or facility that services where services are provided, vans for transporting, and human capital that results from training and development of therapists, nurses, house parents and so on. Program expenses are immediate expenditures (dollars/year) whereas capital is represented as a stock (dollars) that accumulates through capital investments and depreciates.

For simplicity, revenue is allocated to either direct program expenses or capital investments via the current value of the program expense ratio. The program expense ratio reflects the day to day budget allocation of revenue and is treated as a stock. Our interest in this model is with understanding to what extent we can explain the observed dynamics as adjustments to the allocation of resources between capital investments and programs. Thus we are interested in understanding how the program expenses ratio is adjusted via increases to the program expense ratio (PER) and decreases to PER.

We reason that organizations face pressures to increase the PER when 1) program expenses fall below what is needed given the current caseload, or 2) when organizations have more capital than they need and begin to reallocate their spending from capital investments to program expenses. Similarly, we argue that organizations face pressures to decrease the PER when 1) program expenses are above what is needed given the current caseload, or 2) organizations lack the needed human, physical, and financial capital relative to what they need. These is represented with,

$$Program\,expense\,ratio(t) = \int_0^t Increase\,PER(u) - Decrease\,PER(u)du + Initial\,PER\,,$$

where *Initial PER* is a boundary condition at set at a value of 0.80, the average value for human service organizations. The increase in PER is written as fraction of needed program expenses not being being met,

$$Increase\,PER(t) = \frac{1 - Fraction\,of\;\,program\,expenses\;\,funded(t)}{Time\,to\,increase\,PER}$$

and the decrease in PER is written as the fraction of the capital that needed:

$$Decrease\,PER(t) = \frac{1 - Fraction\,of\;\,needed\;capital\;available(t)}{Time\,to\,decrease\,PER}\,.$$

4.6. Program Expenses

Program expenses represent expenditures on direct services in units of dollars per year. Within the model, the focus is on the allocation of program expenses relative to what is required to maintain a given level of service. This is represented as the faction of program expenses funded,

$$\textit{Fraction program expenses funded(t)} = \frac{\textit{Progam expenses(t)}}{\textit{Program expenses needed(t)}}$$

where

$$\textit{Program expenses(t)} = \textit{Revenue(t)} \cdot \textit{Program expense ratio(t)} .$$

4.7. Capital

Capital and refers to the organization's combined human, fiscal, and physical capital. Capital is a stock and monetized in dollars. Similar to program expenses, the focus is on the available capital relative to the capital needed to provide a given level of services. This is represented as the fraction of needed capital that is available,

$$\textit{Fraction needed capital available(t)} = \frac{\textit{Capital(t)}}{\textit{Needed capital(t)}} ,$$

where

$$\textit{Capital(t)} = \int_0^t \textit{Capital investments(u)} - \textit{Depreciation}(u)du + \textit{Initial capital} .$$

Capital investments refers to purchasing buildings, equipment, transportation, training for developing human resources, and others resources or infrastructure that may be required to deliver services. Capital investments is defined as,

$$\textit{Capital investments}(t) = \left(1 - \textit{Program expense ratio}(t)\right) \cdot \textit{Revenue(t)} .$$

Capital depreciates as equipments is used, buildings decline, and skills acquired from training become obsolete. Depreciation is defined as,

$$\textit{Capital depreciation}(t) = \textit{Capital}(t) \,/\, \textit{Time to depreciate capital} .$$

Under equilibrium conditions,

$$\textit{Capital investment}(t) = \textit{Capital depreciation}(t) ,$$

so,

$$\left(1 - \textit{Program expense ratio}(t)\right) \cdot \textit{Revenue}(t) = \frac{\textit{Capital}(t)}{\textit{Time to depreciate capital}}$$

which implies that under equilibrium conditions,

$$Capital(t) = \left(1 - Program\,expense\,ratio(t)\right) \cdot Revenue(t) \cdot Time\,to\,depreciate\,capital\ .$$

Hence,

$$Initial\ capital = \left(1 - Initial\ PER\right) \cdot Initial\,revenue \cdot Time\,to\,depreciate\,capital\ .$$

4.8. Needed Capital and Needed Program Expenses

In a dynamic equilibrium, the program expense ratio is constant, so

$$Increase\,in\,PER(t) = Decrease\,in\,PER(t)\ ,$$

which implies

$$\frac{1 - \dfrac{Capital(t)}{Needed\ capital(t)}}{Time\,to\,decrease\,PER} = \frac{1 - \dfrac{Program\,expenses(t)}{Program\,expenses\,needed(t)}}{Time\,to\,increase\,PER}\ .$$

Capital, program expenses, time to decrease PER and time to increase PER are all fixed when the model is in a dynamic equilibrium. Thus, we can solve for either needed capital or program expenses needed. Of these two, it is easiest to empirically estimate needed program expenses and then derive a needed capital. Solving for the needed capital,

$$\begin{aligned}
&Needed\ capital(t) = \\
&\quad (Capital(t) \cdot Needed\ \ program\,expenses(t) \cdot Time\,to\,increase\,PER)\ / \\
&\quad (Program\,expenses(t) \cdot Time\,to\,decrease\,PER + \\
&\quad Needed\ \ program\,expenses(t) \cdot Time\,to\,increase\,PER - \\
&\quad Needed\ \ program\,expenses(t) \cdot Time\,to\,decrease\,PER)
\end{aligned}\ .$$

At the start of the simulation, this implies that

$$\begin{aligned}
&Initial\,needed\,capital = \\
&\quad (Initial\,capital \cdot Needed\ \ program\,expenses(0) \cdot Time\,to\,increase\,PER)\ / \\
&\quad (Program\,expenses(0) \cdot Time\,to\,decrease\,PER + \\
&\quad Needed\ \ program\,expenses(0) \cdot Time\,to\,increase\,PER - \\
&\quad Needed\ \ program\,expenses(0) \cdot Time\,to\,decrease\,PER)
\end{aligned}\ .$$

4.9. Revenue

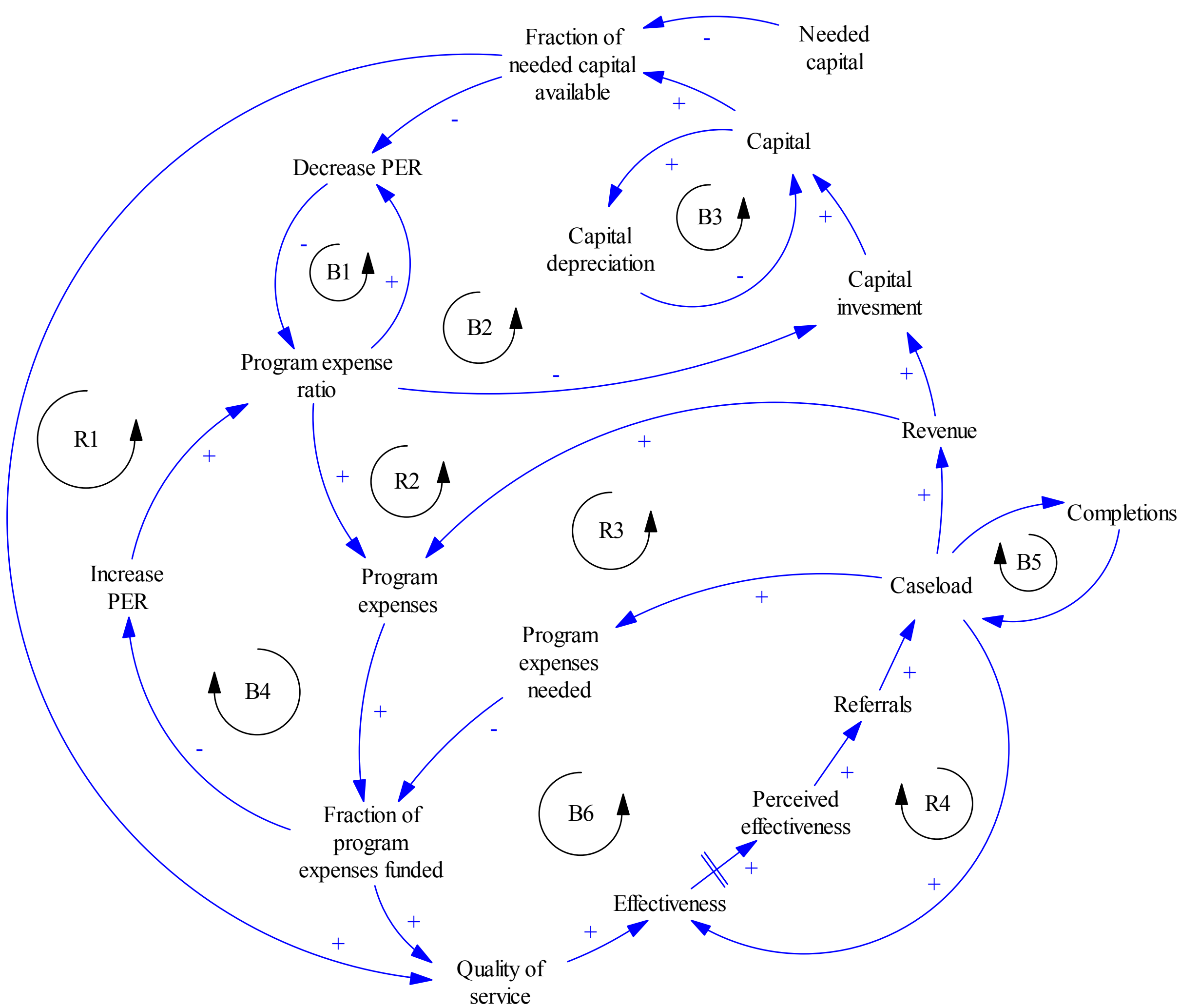
Revenue is treated in this model as a function of the number of clients such that doubling the number of clients relative to the initial number of clients doubles revenue. This is represented by,

$$Revenue(t) = Initial\ revenue \cdot \frac{Caseload(t)}{Initial\ caseload}.$$

4.10. Main Feedback Mechanisms

The model consists of 53 variables including 6 stocks, 18 auxiliary variables, and 14 constants. The complete simulation model is included with the supplemental materials. Figure 7 provides an overview of the model and main balancing and reinforcing feedback mechanisms. Table 4 provides a description of each mechanism along with its path. Reinforcing mechanisms are identified with an 'R' prefix and balancing mechanisms with a 'B' prefix.

Figure 7 Causal loop diagram of nonprofit financial performance



There are three reinforcing mechanisms for improving quality: improving quality through capital investments (R1), improving quality by increasing program expenditures through capital investments that meet capital needs (R2), and improving quality through increases in program expenditures (R3). Each of these three mechanisms will—if influential—increase the quality for each client and thereby contribute to increasing effectiveness and perceived effectiveness. Alternatively, R4 increases effectiveness not by improving quality but through increasing the number of clients served. Thus the more clients an agency serves, the greater its effectiveness, the more clients are referred to the agency.

There are a number of balancing mechanisms that can limit the increase. Balancing feedback mechanisms B2 and B4 represent the process of trying to close the gap between what is needed and what is available, with B2 decreasing the program expense ratio to increase capital, and B4 increase the program expense ratio to increase program expenses.

Table 4 Main Feedback Mechanisms

Label	**Description**	**Path**
R1	Quality improvement cycle through increasing capital investments	*Quality of service → Effectiveness → Perceived effectiveness → Referrals → Caseload → Revenue → Capital investment → Capital → Fraction of needed capital available → Quality of service*
R2	Quality improvement cycle through increasing program expenses made possible by meeting capital needs	*Program expense ratio → Program expenses → Fraction of program expenses funded → Quality of service → Effectiveness → Perceived effectiveness → Referrals → Caseload → Revenue → Capital investment → Capital → Fraction of needed capital available → Decrease PER → Program expense ratio*
R3	Quality improvement cycle through increasing program expenses	*Program expenses → Fraction of program expense funded → Quality of service → Effectiveness → Referrals → Caseload → Revenue → Program expenses*
R4	Increasing perceived effectiveness by serving more clients	*Effectiveness → Perceived effectiveness → Referrals → Caseload → Effectiveness*
B1	Limits decrease in PER since program expense ratio cannot be decreased below zero	*Decrease PER → Program expense ratio → Decrease PER*
B2	Increasing capital investment to meet capital needs	*Program expense ratio → Capital investment → Capital → Fraction of needed capital available → Decrease PER → Program expense ratio*
B3	Depreciating capital	*Capital → Capital depreciation → Capital*
B4	Increasing program expenses to meet program expense needs	*Program expense ratio → Program expenses → Fraction of program expenses funded → Increase PER → Program expense ratio*
B5	Clients completing services	*Caseload → Completions → Caseload*
B6	Increasing caseloads increases needed program expenses and limits quality	*Caseload → Program expenses needed → Fraction of program expenses funded → Quality of service → Effectiveness → Perceived effectiveness → Referrals → Caseload*

There is also a limit to increasing caseloads that is similar to Levin and Robert's (1976) point about human service delivery systems reaching a dynamic equilibrium or quasi-equilibrium with caseloads. Specifically, as the caseload increases program expenses also increases, which can reduce fraction of services funded and lead to lower quality. As a consequence, there may be fewer referrals, and limits the growth of caseloads. This is represented by the balancing feedback mechanism B6.

There are also a number of minor balancing mechanisms. For example, when the program expense ratio approaches zero, there is less to remove from program expenses, which is represented by the balancing feedback mechanism B1. Similarly, while depreciation removes capital, it cannot remove capital that does not exist, which is represented by the balancing mechanism B3. Lastly, clients complete services, and clients can only leave services if there are clients in services. This constraint is represented by balancing feedback loop B5.

5. Testing and Validation

The model was developed and tested using multiple data sources, including key informant interviews, secondary financial data from Internal Revenue Services (IRS) 990 tax returns, and knowledge of the organizations. In addition to passing standard confidence building tests as outlined by Sterman (2000) such as dimensional consistency and extreme conditions test, the model was also able to reproduce a wide range of the behaviors described earlier, and was able to reveal the potential underlying relationships between otherwise dissimilar behavior patterns. For example, the model was able to produce both an inverted C (Figure 8) and upward serpentine (Figure 9) as shown below. Moreover, these trajectories were also shown to be closely related with the inverted C becoming a serpentine with a longer length of service and time to perceive effectiveness. That is, one could create the serpentine pattern by increasing the length of service or time to perceive effectiveness. When we then compared this with what we knew about the two organizations representing each case, we noticed that the two organizations differed on these characteristics. The organization shown in Figure 8 provided residential treatment with long delays between clients completing services and anticipated outcomes, while the organization shown in Figure 9 corresponded to the an organization that provided short-term crisis intervention and assessment with a relatively quick impact on clients and stakeholders.

Figure 8 Reverse C trajectory

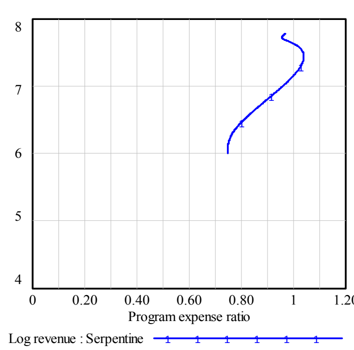
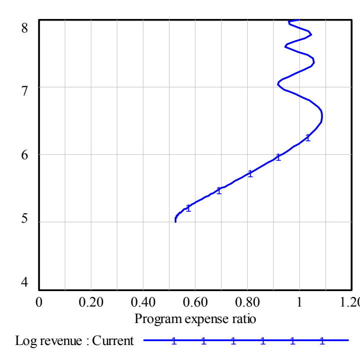


Figure 9 Upward serpentine trajectory



6. Discussion

Analysis of the model helped us both see and demonstrate the underlying similarity between different behavior patterns and gain insight into nonprofit financial performance. For example, simulations showed us how the relationship between time to increase the program expense ratio and time to decrease the program expense ratio was an important feature of oscillatory program expense ratios, which focused our questions with key informants about how quickly they might respond to various kinds of financial challenges.

Length of service and time to perceive effectiveness turned out to be important determinants of organizational behavior. This has important implications when considering the impact of policies and changes in the organizational environment since nonprofit providers of mental health services vary greatly in both dimensions. Call centers have contacts with clients that may be as short as several minutes whereas residential treatment facilities for children with severe emotional disturbances or independent living centers may provide services and supports to a client for many years. Likewise, the length of time before people notice changes can vary significantly by the type of service they provide and their position in a service network since organizations. One would expect organizations that are well connected to be also better known (for better or worse), while organizations that are more isolated would likely have a harder time getting the word out about their services.

Although the diversity of organizations providing mental health services is widely acknowledged, very little has been said or studied in a systematic way as to which characteristics may be more important to understand than others. Size is often discussed as an important feature of the organization, but in this model of financial performance at least, size has less relevance than some of the characteristics just discussed. This highlights the importance of developing better understanding of financial and organizational behavior as part of assessing and arguing for better alternative policies. Blindly implementing policies without such consideration is likely to risk the performance of some nonprofit providers and undermine efforts to improve the overall access and quality of mental health care and supports.

While all models remain works in progress, developing this early simulation model of nonprofit financial performance has proved invaluable to us as a research team in sensitizing us to key concepts in key informant interview. Work continues on developing this model as part of the main study. Recruitment of organizations and key informants has continued with an emphasis on developing a better understanding of how executive management teams think about nonprofit financial performance in relation to implementing innovations such as evidence based practice and organizational performance. Such models will be essential to advancing the organizational theory and ultimately improving the quality of mental health services in the United States.

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