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ABSTRACT

There is long-standing body of empirical research concerned with the consequences of information technology for organization structure and processes. Several of those studies have reported that the same technology, when implemented in similar organizational settings, can be associated with vastly different, even diametrically opposing, organizational consequences. The seminal study in this stream of research is Barley's (1986) article entitled "Technology as an Occasion for Structuring: Evidence from Observations of CT Scanners and the Social Order of Radiology Departments." That study reported that two similarly-composed radiology departments implemented the same technology yet experienced different structural outcomes, i.e. that the two departments experienced different rates of decentralization and that they evolved through a different number of distinct phases of structuring. This difference in outcomes was attributed to differences between each departments' distribution of relevant expertise and "specific historical processes" (Barley, 1986:107) in which the technology was embedded. My reanalysis of the data uses different and arguably more appropriate research methods and shows that the failure to transform the dependent variable, as well as the exclusion, misspecification, and misinterpretation of several dummy variables, biased the regression estimates and led to erroneous conclusions.

The methodological contribution of this paper is that it underscores problems attendant to not recognizing two of the ways in which dummy variables can be interpreted: as a means for capturing intercept shifts and as a means for controlling for the effects of unobserved heterogeneity. The theoretical contributions relate to how the reanalysis impacts our understanding of the information technology -organizational structure relationship. In short, I conclude that research on the organizational consequences of IT, particularly ethnographic research, may need to (1) exchange the assumption of homogeneity among similarly-constituted organizations for one of heterogeneity (2) take both the observable properties of technology ***and*** its context of use explicitly into account and (3) and make more clear what is meant by "different structural outcomes."

INTRODUCTION

There is long-standing body of empirical research concerned with the consequences of information technology for organization structure and processes (e.g. Lee, 1965; Meyer, 1968; Klatzky, 1970; Whisler, 1970a, 1970b; Blau, 1976; Pfeffer & Leblebici, 1977; Robey, 1981; Carter, 1984; Barley, 1986; Robey & Rodriguez-Diaz, 1989; Zeffane, 1989, 1992; Orlikowski, 1992, 1993; Brynjolfsson, et al., 1994; Leidner & Elam, 1995; Robey & Sahay, 1996; Hitt & Brynjolfsson, 1997). Several of those studies have reported that the same technology, when implemented in similar organizational settings, can be associated with vastly different, even diametrically opposing, organizational consequences (e.g. Barley, 1986; Orlikowski, 1992, 1993; Robey & Sahay, 1996).

Among studies reporting this *same-technology-different-outcome* finding, Barley (1986) stands as the seminal work. Through its examination of changes in the structure of radiological work "occasioned" by the implementation of computerized tomography (CT) scanners, the study sought to challenge the technological and organizational imperatives (Markus & Robey, 1988) which had long dominated the debate on research of the technology-structure relationship. It did so not by taking sides in the “centralization debate” (George & King, 1991). Rather, it sought to explain decades of conflicting predictions by "embracing" divergent outcomes, by accepting contradictory findings "as a matter of course" (Barley, 1986:78), and by applying "alternate theoretical frameworks" such as structuration (Giddens, 1979) and negotiated-order (Strauss, 1978) theories, as well as other perspectives which viewed structure as "patterned action, interaction, behavior, and cognition" (Barley 1986, p.79).

The study’s research methodology (ethnography), quasi-experimental design (comparing the same technology in two highly similar settings), unique conceptualization of technology (as an "occasion for", rather than determinant of structure), strong social science grounding (negotiated-order and structuration), and counter-intuitive finding (that the same technology occasioned different structural outcomes) made it a welcome departure from previous studies of the technology-structure relationship. Not surprisingly, the last 15 years has seen it become perhaps the most cited and influential paper in the literature on the organizational consequences of information technology. A recent (December 2002) *Social Science Citation Index®* search reported over 200 citations for the paper, nearly 12 times the expected level for a publication by a management scholar (Long, Bowers, Barnett, & White, 1998). While over half of these citations appear in research related to the consequences of hospital and managerial information systems or other kinds of technology on organization structure, processes, and performance, it has also been frequently cited by researchers in the areas of jobs, skills, expertise, and careers; theory building and research methods; institutionalization and social behavior in organizations; organizational learning, culture and change; structuration, routines, and sense-making.

The study involved the examination of the implementation of CT scanners by similarly-constituted radiology departments of two community hospitals. It's principal finding was, as follows: (1) "far more" decentralization in one department than the other and (2) a difference between departments in the number of distinct "phases of structuring" through which each "evolved" (ibid, p. 105). This *same-technology-different-outcome* finding is perhaps the most widely cited of the study's conclusions (e.g. Leonard-Barton, 1988; Markus & Robey, 1988; Robey & Rodriguez-Diaz, 1989; Weick, 1990; George & King, 1991; Orlikowski, 1992; Pentland, 1995; Robey & Sahay, 1996; Sahay, 1997; Morrill & Fine, 1997; Anderson & Aydin, 1997; Pinsonneault & Rivard, 1998; Vendelo; 1998; Orlikowski & Barley, 2001). In this paper I have undertaken to determine whether or not the data actually supported that finding. I begin by reanalyzing the data from Barley's (1986) CT Scanner study (hereafter referred to as "the original study"), demonstrating in particular, how the failure to transform the dependent variable and the misspecification, misinterpretation, and exclusion of several dummy variables biased regression estimates and led to erroneous conclusions. Secondly, I remodel the data from the original study using different and arguably more appropriate methods and assumptions. One such difference involves combining the data and introducing a new variable- a dummy variable to control for the presence of unobserved heterogeneity between the two radiology departments. I end the paper with a discussion of the practical and theoretical implications that incorporating the notion of unobserved heterogeneity has on our understanding of the original study, in particular, and of the information technology-organization relationship, more generally.

RESEARCH DESIGN, METHODS, & REPORTED FINDINGS OF ORIGINAL STUDY

The setting for the original study was the radiology department of each of two Massachusetts community hospitals (Urban and Suburban). As their names suggest, the two hospitals differed with respect to physical location but were otherwise considered to be highly similar. Each department employed the same number of radiologists and related staff, performed the same "standard" range of radiological procedures, and purchased and began use of the same model of CT scanner in the same year (Barley, 1986:84). Recall that the original study reported as its major findings: (1) "far more" decentralization in Suburban’s radiology department than in Urban’s and (2) a difference between departments in the number of distinct "phases of structuring" through which each "evolved" (ibid, p. 105).

Table 1, below, provides a description of the eight regression models which were developed in the original study and which are the subject of this analysis. The dependent variable in all models was an index of centralization, operationalized as " the percentage of (nine) decisions made by a radiologist during the course of a scan" (ibid, p.86). The nine decisions were: " (1) when to start a patient (2) where to start scanning (3) how far to scan (4) what techniques to use (5) whether to reposition the patient (6) whether to inject contrast (7) what windows and centers to use (8) whether the radiologist should view the scans and (9) when to end the exam. The import of this measure is that two people were able to make operational decisions concerning the performance of radiological scans, *radiologists*, who were physicians, and technologists, who were not physicians. Because radiologists had higher rank than technologists, the higher the number of the nine operational decisions made by radiologists, the more centralized was the decision-making considered to be.

Insert Table 1 About Here

The independent variables in the models were of two kinds: continuous and categorical (dummy) variables. In the *Suburban-Linear* and Urban-*Linear* models, the only independent variable was the number of days since the start of use of the CT scanner (DAYS). The *Suburban-Quadratic* and *Urban-Quadratic* models had two independent variables: DAYS and a quadratic term, $DAYS^2$. In each of the last four regression models - *Suburban-Suburban, Urban-Urban, Suburban-Combined, and Urban-Combined*- one to three dummy variables were included to represent the number of distinct phases of structuring experienced at each hospital. Phases differed with respect to starting dates and duration and were named according to the nature of the interaction between radiologists, as indicated in Table 2 below.

Insert Table 2 About Here

In the Suburban-*Suburban* model, the independent variable was a single dummy representing the first of that hospital's two phases. The Urban-*Urban* model utilized three dummy variables, one for each of the first three of Urban's four hypothesized phases of structuring. The two "combined" models each had *four* dummy variables representing the three phases of structuring at Urban *and* the single phase at Suburban.

Figure 1 below is a reproduction of the original study's "Figure 3" which contained plots of the centralization index for each hospital (ibid, p.103). The data indicate that for each hospital the proportion of the nine operational decisions made by radiologists decreased significantly as the days since the scanner's first use (DAYS) increased.

Insert Figure 1 About Here

Table 3 is a reproduction of "Table 1" from the original study and shows results of the regression analyses for the first four models (ibid, p.104). The significance of the regression coefficients for the independent variable (DAYS) in the *Suburban-Linear* (b_1 = -0.001, t = -4.20, p < 0.001) and *Urban-Linear (*b_1 = *-0.002)* models (p < 0.01, t = -3.60, p < 0.001) was taken to indicate that centralization decreased significantly at both hospitals.

Insert Table 3 About Here

The *Suburban-Quadratic* and *Urban-Quadratic* models were intended to test for the presence of "quadratic trends" in the data. It was reported that "the addition of the quadratic term to the linear model significantly increase(d) the proportion of explained variance only for Suburban's data" (ibid, p.104). Thus, it was concluded that centralization decreased at "different rates" at each hospital, i.e. "geometrically declining" at Suburban and "gradually, in a linear fashion" at Urban (ibid, p.104). It was upon this finding that the claims of differential rates of decentralization was based.

Table 4 is a reproduction of the original study's "Table 2" and contains the results of the latter four regression models, those intended to assess the differences in the number of phases of structuring that each department experienced (ibid, p.105). The positive and statistically significant (b_1 = 0.50, t = 9.93, p < 0.001) value of the regression coefficient for the single dummy variable in the *Suburban-Suburban* model was interpreted as indicating that its first phase of structuring had higher levels of centralization than did its second phase, the period extending from about the 22nd day onward.

Insert Table 4 About Here

The *Urban-Urban* model tested for differences in centralization across the four phases hypothesized for Urban. It was reported that the regression coefficients for the dummy variables representing the first and third phases were highly significant ($b_1 = 0.36$, $t = 4.77$, $p < 0.001$; $b_3 = 0.22$, $t = 2.90$, $p < 0.01$) but that the coefficient for the second phase was not ($b_2 = -0.04$, $t = 0.39$, $p > 0.10$). These results were interpreted to indicate that phases 1 and 3 had significantly higher levels of centralization than did phase 4 but that phase 2 did not.

Finally, the two "combined" models, *Suburban-Combined* and *Urban-Combined,* each contained four dummy variables- one from Suburban and three from Urban. For these models it was reported that "in neither case did the combined model substantially increase the proportion of variance explained by the hospital's own model" (ibid, p.105). In other words, the *Suburban*- and *Urban-Combined* model did not explain a significantly greater proportion of the variance than the *Suburban-Suburban* and *Urban-Urban* models, respectively. Based upon the results of these four models, it was concluded that the data were "consistent" with the claim that Suburban experienced two phases of structuring but that Urban experienced four such phases.

Thus, the first four models were used to establish that the *rate* of decentralization differed in each hospital while the last four models were intended to show that the two hospitals experienced a different *number* of distinct phases of structuring.

METHODOLOGICAL CRITIQUE

As noted above, the original study examined the appropriation of CT scanners in radiology departments of two community hospitals and reported that they experienced different structural outcomes: "far more" decentralization in one department than the other and (2) a difference between departments in the number of distinct "phases of structuring" through which each "evolved" (ibid, p. 105). This section of the paper divides its investigation of the claim of different structural outcomes into two parts. The first examines whether there is support for the findings of "far more decentralization" being experienced at Suburban (ibid, p.105). The second considers whether Urban's radiology department evolved through a greater number of phases of structuring.

The Data

All analyses in this section were performed with data which taken directly from the graphs of the decision proportions (centralization index) appearing in *Figure 3* (ibid, p.103) of the original study, Figure 1 of this study. It is observed that the plot for Suburban contained forty-five (45) observations while that for Urban had forty-two (42). The positions of each of the 87 observations along the two coordinate axes were estimated by this author and by a research assistant. The average value of the two sets of estimates was used for all subsequent regression analyses.

To determine how faithfully the estimated data represented the original data, estimated proportions were regressed on estimated days and compared to the results of the same regression shown in *Table 1* of the original study. As can be seen in Table 5 below, the estimated and the original values of the intercept (b_0), the sole regression coefficient (b_1), and the coefficient of determination (R^2) are almost identical.

Insert Table 5 About Here

Transformation of the Dependent Variable

The first area for concern relates to the need for the transformation of the original study's dependent variable- the proportion of the nine operational decisions made by radiologists. As a rule, transformations of independent or dependent variables are employed to correct for any of the following violations of the requirements of regression models: (1) non- linearity among variables (2) heteroscedasticity or instability of error variance and (3) non-normality of the distribution (Hair, et al., 1995). There are several transformations that correct for each violation and some correct for more than one. Distributions based on proportions or percentages are especially susceptible to being guilty of the all three violations (Cohen & Cohen, 1983: 266) and their need for transformation has been long recognized (e.g. Bliss, 1937; Bartlett, 1937; Fisher & Yates, 1938).[1]

The arcsine transformation can be employed to correct for both the heteroscedasticity (Bartlett, 1947; Snedecor & Cohran, 1967; Winer, 1970; von Eye & Schuster, 1998) and the non-normality violations (Hair, et al, 1995). It is defined as twice the angle (A) whose sine equals the square root of the percentage (*p*) being transformed or

$A = 2 \sin^{-1} (p)^{1/2}$. If the percentage, *p*, is equal to 0.0 or to 1.0 then a different transformation is used: $A_0 = 2 \arcsin (1/4d)^{1/2}$ and $A_1 = 3.1416 - A_0$ where *d* equals the denominator of the fraction which generated the percentage (Walker and Lev, 1953; Owen, 1962; Cohen & Cohen, 1983; Snedecor & Cochran, 1967). In our case, d = 9.

The results of analyses performed with data subjected to an arcsine transformation are not necessarily different than those obtained with untransformed percentages, however (Hair, et al**.,** 1995). When “nearly” (Snedecor & Cochran, 1967:328) or "almost" (Cohen & Cohen 1983: 266) all of the observations lie *within* the range between 0.25-0.75, the

[1] While there is widespread agreement in statistical and research methods literatures as to how and why these transformations should be performed, many widely-used textbooks on statistical methods contain no discussion of data transformation in general, or of the transformation of percentages, in particular. Of those that do discuss transformation, the discussion is often limited to the more common ones, e.g. the "power" transformations. My review of several dozen introductory and advanced statistics textbooks whose publication dates ranged from the 1950's to 1990's discovered that data transformation was discussed in less than half of them. When it was discussed, the topic of the transformation of percentages was more frequently excluded than included.

arcsine transformation produces little or no noticeable change in the results of statistical analyses and is not needed. If, however, a large number observations lie outside this range, estimated regression coefficients are unreliable and likely to be invalid, i.e. biased.

A sizeable portion of the data for both hospitals lies outside the prescribed (25-75%) range. Almost 70% (31/45) of Suburban's observations lie outside of it, with eight (8) of them being equal to zero. For Urban, 43% (18/42) lie outside of the range, with five being equal to 1.0. The resulting distributions are, thus, highly skewed. Figure 2 provides a frequency distribution of both the raw and the arcsin-transformation of the centralization index for Suburban. It is evident that the effect of the arcsine transformation is to make the distribution of the index more nearly normal. The same effect was observed for Urban's data as well.

Insert Figure 2 Here

Table 6 contains the results of the reanalysis of the first four regression models of the original study using the arcsine transformed proportions. The results share some important similarities to those reported in *Table 1* of the original study (Table 3 of this study) where untransformed proportions were the dependent variable.[2] First of all, the slope coefficient for the variable DAYS is negative and highly significant in both department's linear models ($b_{1\ SUBURBAN}$ = -3.61E-03, t = -4.04, p < 0.001; $b_{1\ URBAN}$ = -3.55E –03; t = -3.53, p < 0.001). This indicates that each hospital experienced significant decentralization as the days of the use of the CT scanners increased.

2 The difference in degrees of freedom between the results shown in Tables 3 and 6 are attributable to differences in the number of data points considered. The original study's analysis appears to have been based upon 49 observations for Suburban and 42 for Urban. However, the plots of the centralization index for the two hospitals, as shown in Figure 1, contain only 45 data points for Suburban. Also note that the degrees of freedom in the original study were incorrectly reported as (1,46) for *Suburban-Quadratic and* (1,39) for *Urban-Quadratic.* The number of degrees of freedom of the regression is given by the number of estimated coefficients (including the constant) minus one. For the degrees for the residual it is equal to the sample size minus the number of estimated

Insert Table 6 Here

Recall that in the original study, the coefficients of the quadratic term, $DAYS^{2,}$ was highly significant ($t = 2.88$; $p < 0.01$) for Suburban, but only marginally so for URBAN ($t = 1.83$, $p < 0.10$). This was taken to indicate that centralization decreased at "different rates" in the two radiology departments, i.e. "geometrically declining" at Suburban and "gradually, in a linear fashion" at Urban (ibid, p.104). Transforming the data reveals that this finding still holds, albeit less strongly. Now, the quadratic term for Suburban is less highly significant ($b = 5.07E-05$; $t = 2.58$, $p < 0.05$) while the significance level for Urban is unchanged ($b = 3.11E-05$; $t= 1.86$, $p < 0.10$). Thus, the *rates* of decentralization do still differ across the two sites, provided we rely upon the results of separate quadratic models as our indicator.

There are, however, important reasons to reconsider a reliance on the quadratic models to indicate differences in rates in decentralization. First of all, the quadratic model does not closely parallel the unfolding pattern of interaction between radiologists and technicians described in the study. Specifically, neither narrative associated with the two radiology departments described a dynamic between radiologists and technicians that would have seen centralization beginning to increase about 2/3 of the way through the implementation and returning to its starting levels just 3-6 months after the end of the observation period. This is, however, what the quadratic models predict. When the model's estimates are used to predict the level of centralization beyond the end of the observation period, we find that that for Urban, the model predicts that after 170 days centralization began to *increase* and that by 384 days, barely 6 more months after the end of the observation period, the level of centralization would have returned to its original levels. The same holds for Suburban. Its quadratic regression predicts that centralization would begin to increase after only 150 days into the implementation and would return to its initial level by day 349. That's a mere

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coefficients (again including the constant). Since three coefficients were calculated in each *Quadratic* model (constant, DAYS, and $DAYS^2$) the degrees should have been reported as (2, 46) and (2, 39) for Suburban and Urban, respectively.

100 days after the end of the observation period for this hospital. These are hardly results that the original study would have us believe could have been the case a few short months after the end of the technology's appropriation.

By way of contrast, a power model ($y = b_0 * x^{b1} + e$) would seem to be a better choice. As shown in Figure 3, below, a power model more closely parallels the pattern of interaction between radiologists and technicians that the original study described: it predicts that centralization declined rapidly and then stabilized. From the results contained in the third and sixth rows of Table 6, it can also be observed that the power models fit the observed data much better, capturing as they do, the very rapid decline of centralization that we are told both departments experienced in the first 20-30 days after the CT scanners' introduction. Recall that Suburban's & Urban's first phases were each between 21-28 days. Not surprisingly, then, the power models explain an additional 4-5% of the variance in structure than the quadratic models do. That said, the results still somewhat support the thesis of the original study: even though the slope coefficient for DAYS associated with both sites is negative and highly significant, the magnitude of Suburban's slope coefficient ($b_1 = -0.274$, $t = -5.34$, $p < 0.001$) is double of that for Urban ($b_1 = -0.141$, $t = -4.24$, $p < 0.001$).

Insert Figure 3 Here

This apparent difference in slopes may not actually be an indicator that each department decentralized at different rates, however. A careful examination of Figure 3 reveals, among other things, that the values of centralization for Suburban run consistently below those for Urban throughout most of the observation period. Although such a test was not performed in the original study, it can be readily determined whether the mean level of the centralization index is in fact higher for Urban than for Suburban. After determining that the two hospitals did not have different variances in their centralization scores ($F = 1.21$, $p = 0.27$) , a two-sample t-test assuming equal variances was performed. It indicated that the mean levels (of the arcsine transformed measure) of centralization for Suburban (1.05) and Urban (1.92) were significantly different ($t= 7.09$, $p < 0.001$). Figure 4, below, displays the regression lines for two power models: the same one for Urban that is shown in Figure 3, plus another for Suburban but with a constant value of 0.867, the difference between the mean level for Urban and Suburban, added to it. And although it is hard to tell, Figure 4 does contain two plots of regressions lines. What we see is that when the mean difference is accounted for, the two regression lines appear to be one. The slope coefficients are almost identical: the intercept and slope coefficient for Urban are 3.221 and –0.149, respectively, while those for Suburban are 3.212 and –0.147. The only appreciable difference between the two power models that remains is that Urban's model explains a smaller proportion of the variance (30.4%) than does Suburban's (45.2%).

Insert Figure 4 Here

This result raises doubts about whether there is reliable evidence to support the finding of differential rates of decentralization. The most direct way to address this question is to combine the data, and regress centralization on DAYS, a dummy variable to capture the difference in the mean levels of the two sites' centralization, and an interaction terms between the dummy and DAYS. This analysis is discussed in a later section of this paper. First, I attend to the question of the difference in the number of phases of structuring, the other of the two major claims of the original study.

Phases of Structuring

Whereas the preceding section of the analysis has shown that there was no reliable evidence of differential rates of decentralization experienced by the two sites, this section examines the other reported finding of the original study: that the two hospitals experienced a different number of "phases of structuring." Suburban, it was argued, evolved through two distinct phases whereas Urban had four. In the study, four regression models with dummy variables representing the distinct stages of structuring were developed and tested. The primary difference between the first and second section of the analysis is that the focus is now on the independent variables, particularly with their specification and interpretation.

In the top two rows of Table 7 are found the results of the re-analysis of the two regression models from *Table 2* of the original study, *Suburban-Suburban* and *Urban-Urban*. In the former model, one dummy variable was defined to represent the first of that site's two hypothesized phases. The significant and positive slope coefficient for that variable indicates that centralization was significantly higher in the first phase of Suburban's structuring than in the second. This is consistent with the finding of the original analysis (Barley, 1986:105).

The *Urban-Urban* model utilized three dummy variables, one for each of the first three of Urban's four hypothesized phases of structuring. The coefficients for the dummy variables representing phases 1 and 3 were highly significant ($p < .001$ and $p < 0.01$, respectively) but that for Phase 2 was not. This result also is consistent with the results reported in the original study but does not confirm the existence of four distinct phases, however, since Phase 2 did not differ from phase 4. Thus, it is clear that Urban experienced three, rather than four, phases while Suburban experienced only two.

Insert Table 7 Here

In order to demonstrate that Urban did experience four phases, two additional "combined" regression models were also tested in the original analysis. The justification for these models that was provided is as follows:

> Since Suburban was said to have experienced two phases and Urban four, Suburban's data were regressed on one dummy variable representing the first phase of structuring while Urban's data were regressed on

> three variables representing Urban's first three phases. Each site's data were then regressed on *all four dummy variables* in a combined analysis. If each site's phasing was adequately defined then the combined model should predict radiologists' involvement no better than the model constructed to depict the site's own phases of restructuring (Barley, 1986:105, *emphasis added*).

There is a problem with this logic. As a rule, dummy variables are used to render information on membership in one of *k* mutually-exclusive and cumulatively-exhaustive categories (Hair, et al., 1995). This is accomplished by defining *k-1* dichotomous variables. For example, since Suburban had two (k=2) phases it was represented by one (k -1 =1) dummy variable. Urban, with its four (k =4) hypothesized phases, was represented by three (k -1= 3) dummy variables.

The *k* phases through which *each hospital* was believed to have evolved constitute a mutually-exclusive and cumulatively-exhaustive set *for that hospital only.* Each of the *k-1* dummy variables for each hospital expresses one, and only one, meaningful aspect of group membership: for example, Phase 1 **or** Phase 2 in the case of Suburban; Phase 1 or Phase 2 or Phase 3 in the case of Urban. In a regression model, the interpretation of any of the *k-1* dummy variables is always in relation to the (undefined) k*th* category- the reference category. For example, in the *Urban-Urban* model the positive and statistically significant slope coefficient for dummy variable *Urban_Phase 3* is interpreted as indicating that Phase 3 has a higher level of centralization than Phase 4, the reference category.

The two combined models each have a total of four dummy variables representing Urban's Phases 1, 2, and 3, and Suburban's Phase 1. However, combining both Suburban's single and Urban's three dummy variables into the same model violates the requirements of exhaustiveness and exclusivity. In such a model no interpretation of any of the dummy variables is possible and, neither of the combined models can be construed as supporting the existence of four phases of structuring for Suburban. What can be done, however, is to determine whether or not modeling four phases for Urban provided the best fit of the data. The rows beneath the top two in Table 7 contain the results of a series of regressions of all remaining combinations of Urban's four phases. Two obvious trends emerge from this analysis. The first is that the best fit (adj-R^2 = 40%) is provided by a model with variables for phases 1 and 3. The positive sign of their coefficients suggests that, as was the case with the original study, these two phases experienced much higher centralization than phases 2 and 4. This is further supported by observing the sign and significance of the coefficients in the model containing dummies for phases 1,3, and 4. Again, the coefficients for phases 1 and 3 are significant and positive while that for phase 4 is positive but not significant. The second important observation is that all models containing three phases explain a nearly identical proportion of the variance. This would be the case because either phase 2 or phase 4 must be included as a dummy variable or the comparison category in all such models. Thus, while there was evidence to support the claim that Urban and Suburban evolved through a different number of phases, the support is weaker than originally reported: Urban had three distinct phases and Suburban had two; each departments one's first phase lasted about 25 days in length and the majority of the decentralization occurred within those first 3-4 weeks.

Summary

My reanalysis suggests that the central conclusion of the original study- that the *same technology* led to *different (structural) outcomes*- does not possess the level of support which was claimed for it. Rather, it seems that the same technology was associated with quite similar structural outcomes: both hospitals decentralized significantly and did so at seemingly the same rate; one evolved through at least two phases of structuring while the other experienced three. There was, however, a noticeable difference in the mean level of centralization at the two hospitals The next section of the paper discusses why accounting for that variation is important.

AN ALTERNATE APPROACH

As noted above, the data for the two sites appear to be separated by a constant difference over the entire observation period (see Figure 3). This suggests the presence of an "intercept shift" , a difference which can be captured statistically by the addition in a regression model of *N-1* dummy variables representing the *N* categories into which observations can be classified. In the case under consideration, capturing the intercept shift would have required adding a single dummy variable for hospital to a regression model that utilized observations pooled from both sites, as shown in Equation 1, below.

$$Y_i = b_0 * b_1 * \text{DAYS} + b_2 \text{ HOSPITAL} + e \qquad (1)$$

Where HOSPITAL is a dummy variable coded 1 for Urban and 0 otherwise. Thus, for Urban, the model is: $Y_i = b_0 * b_1 * \text{DAYS} + b_2 * 1 + e = b_0 * b_1 * \text{DAYS} + b_2 + e$, and for Suburban is: $Y_i = b_0 * b_1 * \text{DAYS} + b_2 * 0 + e = b_0 * b_1 * \text{DAYS} + e$

Employing such a model would have afforded at least two important benefits over separate regressions. More generally, it would have made it possible to simultaneously assess the impact of both classes of explanations for the variation in structure- the technological and the contextual. More specifically, by adding an interaction term between hospital and the days in use, one could test for the existence of differential rates of decentralization at the two sites. Further, it would have been possible to assess whether one factor mediated the other; whether one factor provided a stronger explanation of variation in structure than the other; and whether the two factors together explained more of the variation in the structure than it left unexplained.

Summary of Results of Regressions with Pooled Data

Table 8 below presents the results of four power model regressions of centralization on several combinations of the two independent measures: on the technological measure, DAYS, alone (Model 1); on the contextual measure, HOSPITAL, alone (Model 2); on the both DAYS & HOSPITAL (Model 3); and, finally, on DAYS, HOSPITAL, and the interaction of the two, DAYS*HOSP (Model 4).

Insert Table 8 Here

Models 1, 3, and 4 indicate that the standardized slope coefficient for the technological variable, DAYS, is both negative and highly significant ($-0.572 < b_1 < -0.527$; $-8.30 < t < -5.71$; $p < 0.001$) thereby indicating that the locus of decision-making regarding scans declined significantly as the number of days the CT Scanner was in use increased.

Models 2, 3 and 4 indicate that the standardized regression coefficients for the dummy variable, HOSPITAL, are significant and positive ($0.605 < b < 0.867$; $3.33 < t < 9.40$; $p < 0.001$), indicating that a greater number of decisions were made by the radiologists in Urban's radiology department that than in Suburban's. Finally, the significance of the interaction term DAYSHOSP contained in Model 4 is not statistically significant (standardized $b_2 = -0.160$, $t = -0.687$) indicating that the rates of centralization did not differ across sites.

Interpretation of Results of Regressions with Pooled Data

Recall that a major motivation for the original study was to challenge the technological imperative, i.e. that the organizational consequences of information technology are attributable to measurable, material, or otherwise objective properties of the technology (Markus & Robey, 1988). The significance of the dummy variable for hospital in Models 3 indicates that we can readily reject the strongest form of the technological imperative, i.e. technology is the *only* determinant of structure. Clearly both the measure of technology and of context explained a significant proportion of the variation in structure.

Furthermore, the results of Model 3 also permit the rejection a more “relativistic” form of technological imperative, i.e. one that asserts that technology impact on structure is *stronger* than that attributable to its “context of use”. As the results indicate, the magnitude of the standardized coefficient for the number of days in use ($-0.572 < b_{DAYS} < -0.527$; $-8.31 < t < -5.71$) is much smaller than that for the hospital ($0.605 < b_{HOSPITAL} < 0.867$; $3.33 < t < 9.40$). Both are highly significant predictors of structure, but the latter is clearly much more so.

The results of Models 1 and 3 could also be interpreted as a test of a “context as mediator” hypothesis, i.e. that the effects attributable to technology are either wholly absent (strongest form) or are significantly diminished (weaker form) when the context of the technology’s use is controlled. The data indicate that the impact of the days in use remains as strong when hospital is controlled as when it is not. Thus, neither form of a “context as mediator” hypothesis is supported by the results of the original study.

Similarly, the insignificant value of the coefficient for the interaction term between HOSPITAL and DAY ($b_{DAYSHOSP} = -0.160$, $p = 0.687$) in Model 4 indicates there is also no support for a “context as moderator” hypothesis, i.e. that there were differences in outcomes between the two departments, particularly differential rates of decentralization. Thus, there is no reliable evidence to support such a claim.

Finally, the results of the first three models taken a group provide strong support for one other hypothesis that could have been tested with pooled data: one that asserts that co-consideration of and its context of its use provides a better explanation of the observed variation in structure than either does alone. The data suggest that this hypothesis is supported by the data in both and absolute and a relative sense. In relative terms, we note that the adjusted-R^2 of Model 3 (64.3%) one that includes both the number of days in use (DAYS) and a variable representing the context (HOSPITAL), is much higher than the R^2 for Models 1 (26.9%) and 2 (35.8%). This is a clear indication that the joint consideration of both technology and its context provide a superior explanation of the observed variation in structure than either variable does alone. In absolute terms we can note that the R^2 of the combined model (64.3%) is well in excess of 50%. This indicates that the proportion of variance explained by the model which jointly considers technology and its context (Model 3) is greater that the proportion of variance left unexplained.

Another Word about Dummy Variables

There are two interpretations of the coefficient of the dummy variable HOSPITAL in Models 2-4 above, each of which deserves careful consideration. First, there is our understanding of it in strictly statistical terms, i.e. as the estimate of the slope coefficient for HOSPITAL as an intercept shift, as the expected difference in centralization across the two sites. This is confirmed by observing that in Model 3 the non-standardized value of the coefficient for the dummy variable, HOSPITAL, took on a value of 0.867, the amount that I earlier showed was the difference between the mean levels of centralization and Urban and Suburban. This value translates into a difference of about 1.4 additional decisions being made by radiologists at Urban versus radiologists at Suburban. What the value of coefficient of the dummy variable for hospital in the pooled regressions does not and can not tell us, however, is *why* such a difference existed. That issue is addressed by our second interpretation, one which treats dummy variables as controls for unobserved heterogeneity, i.e. for the presence of unobserved factors that could be expected to affect the outcome variable. Properly accounting for unobserved heterogeneity is required in order to preclude the possibility of misinterpreting results attributable to observable characteristics (Heckman, 1981; Heckman & Singer, 1984; Heckman, Holtz, & Walker, 1985). Controlling for unobserved heterogeneity through the specification of dummy variables is a very common practice in quantitative empirical research in management and others social sciences.

Examples of entities for which unobserved heterogeneity has been shown to exist include industries, firms, strategic business units, test subjects and sites, schools, and patent classes. They are invariably are found to be significant sources of variation in the dependent measure (Heckman & Singer, 1984).

The “fixed effects” method of controlling for unobserved heterogeneity associated with *N* categories involves specifying *N-1* dummy variables (Hsiao, 1986). In our case, the factor of interest is the hospital wherein the technology was deployed. Since there were only two (N) hospitals, then only one (N-1) dummy variables was required to control for unobserved heterogeneity. What we observed in Models 3 and 4 was that the dummy variable HOSPITAL was positive and highly significant, indicating thereby that a substantial proportion of the observed variation in centralization was attributable to site-specific factors, to possibly long-lived sources of unobserved heterogeneity across the two departments. This point relates directly to an important contribution of the original study- and others like it- which heretofore has gone unrecognized.

Imagine for a moment that the data from the original study been obtained by way of survey methods or other secondary sources. Imagine further that the author never visited the either of the two radiology department; never observed scans taking place; never witnessed the patterns of interaction between radiologists and technicians. Had this been the case, it would have been quite difficult to know *why* there were differences in the mean level of centralization across the two sites. The statistics would have revealed that the difference did exist, but it would have been left to conjecture as to what it could be attributed. Fortunately for us, this is not how the data was collected. Rather, it was gathered in such a way that make it more easy to ascertain the sources of variation between the two sites, sources that would have otherwise remained unobserved. These were, as we now know, each site’s "specific historical processes" in which the technology was embedded and the "relative distributions of expertise." The detail that was the by-product of the ethnographic approach which Barley took provided valuable insight as to why a dummy variable for hospital *would* have been highly significant - *had the data been pooled and that variable been included.* The error, as I see it, was in attributing (what seemed to be) differences in rates of decentralization to differences across sites in processes and expertise. As we have seen, unobserved, or at least unmeasured, differences across sites explained the mean level of centralization rather than *rate* of decentralization.

CONCLUSION

Recall that the original study concluded that the same technology occasioned different structural outcomes, in particular different *rates* of decentralization and numbers of phases of structuring. These different outcomes were attributed to differences in technology's context-of-use at each site rather than to the observable properties of the technology itself. In this study I have shown:

(1) That while there was no reliable evidence of differential *rates* of decentralization between the hospitals, but there was reliable evidence of differences in their mean *level* of centralization;
(2) That there was no reliable evidence that the differences in organizational processes and expertise account for *rates* of decentralization, but there was reliable evidence that they accounted for the difference in the *mean level* of centralization;
(3) That there was no reliable evidence of a (statistical) interaction between context and technology, but there was reliable evidence that the two variables taken together provide a better explanation of the variation in structure than either one does alone.

The implications of these findings for the understanding of the IT-organization relationship are several. The first is this: the findings present a direct challenge to the "contextual imperative", i.e. the notion that technology is socially-constructed, that it is not a determinant of structure, and that its organizational consequences are attributable to its context-of-use rather than to its material or observable properties (Robey & Sahay, 1996; Weick, 1990; Orlikowski, 1992, 1993). A typical example of this perspective to the technology-structure relationship is provided in the quote below. It comes from a study of the consequences of implementation of a geographical information system (GIS) by two adjacent county government organizations which reported "radically different" experiences with and consequences associated with the GIS but provided no measures of them:

> "Thus, we concur with Barley (1986) that technology is an occasion for, not a determinant of, organizational change. Similar technologies may be introduced in different organizations to support similar kinds of work, but the social processes and contexts surrounding their implementation may be so different as to occasion divergent outcomes" (Robey & Sahay, 1996:108).

Even without my analysis of Barley (1986) it is unclear why the evidence supporting technology's role as, at the very least, a co-determinant of structure is so forcefully denied, or why it appears necessary to emphasize context's undoubted importance at technology's expense. Several quantitative empirical studies of the IT-structure relationship which treat IT as a determinant of structure have found decentralization to increase with increases in measures like the number of tasks or functions to which computers are applied (Carter, 1984; Zeffane, 1989), the frequency and length of time of use (Leidner and Elam, 1995), the number of computers (Klatzky, 1970; Hitt and Brynjolfsson, 1997), size of the IT department (Pfeffer and Leblebici, 1977) and the processing capacity of IT resources (Hitt and Brynjolfsson, 1997) and length of time in use (Leidner & Elam, 1995). The only exception among this list is Leidner & Elam (1995) who's test of Huber's (1990) hypothesis that increased frequency and length of use of IT would be associated with *centralization* was *not* supported. As we can see, original study's measure, the days since first use, and the results, greater decentralization, square nicely with the results of these other studies, the kinds of studies and results Barley had set out to challenge.

One problem may be that because the above studies, as well as others like them, typically *control* for contextual factors, such as size, environment, ownership, and industry when explaining technology's impact on structure, they may have been construed as supporting the technological imperative or of downplaying the importance of technology's context of use. If so, that would be an unfortunate misunderstanding. Implicit in the act of controlling for context is the recognition that it may explain variation in structure. That said, it is worth noting that a few of the aforementioned quantitative studies have gone beyond controlling for contextual variables to testing for significant statistical interactions between technology and contextual variables such as environmental complexity, size, ownership, and level in the organizational hierarchy of the user (e.g. Pfeffer & Leblebici, 1977; Zeffane, 1989, 1992; Leidner & Elam, 1995). What is lacking, however, is any theoretical guidance about which elements of context are determinants of structure in their own right or which influence structure by way of their interaction with technology. A greater understanding of the technology-structure interaction would likely result if more ethnographies followed the lead of the original study and measured structure, context, and technology.

A second implication of my findings is that they highlight why research on the organizational consequences of IT must make more clear what is meant by "different structural outcomes." The standard implied by the original study – a difference in rates of decentralization, in particular- is not one which other studies would be advised to emulate given that it is possibly the lowest possible threshold for establishing differences. In theory, the claim of different structural outcomes would have been most strongly supported if Barley had observed significant changes in opposite directions, e.g. one site centralized and the other decentralized. The next strongest level of support for the claim of differential rates would be if one site changed significantly (in either direction) while the other did not. The lowest threshold, the one implied by the original study, would be if both changed, did so in the same direction, but did so at different rates. To give credit where it's due, the original study is the only of its genre that offered data on its dependent measures. While other published ethnographic studies of technology's like computer-aided software engineering (CASE) tools (Orlikowski, 1992, 1993) and geographical information systems (GIS) (Robey & Sahay, 1996) have reported diametrically opposing outcomes, none have quantified those differences in ways that are amenable to the kind of analysis that the original study attempted. Without data of that kind, the matter of what constitutes different outcomes will prove difficult to resolve.

A third implication of these findings is that they highlight the need for a greater recognition of the role of unobserved heterogeneity in explaining variation in structure, especially in similarly-constituted organizations. To date, the notion that variation in dependent measures can depend as much on variation in the unobserved measures as on observable ones is not universally accepted by researchers at the intersection of technology and institutions. Neglecting to control for unobserved heterogeneity when investigating the impacts of technology on similarly-constituted organizations increases the chance of biasing regression estimates and reaching erroneous conclusions about the absolute and relative influence of technology and context.

Replacing the current "homogeneity assumption", i.e. that similarly-constituted organizations should *not* exhibit variation in outcomes associated with technology, with one cognizant of unobserved heterogeneity will require that researchers now assume (1) that no matter how similar two organizations may be in observed ways, there will also be unobserved differences among them and (2) that unobserved differences may account for variation in structure both independently of technology, as well as through an interaction with it. This set of assumptions dovetails quite nicely with recent calls for more "interaction" and "cross-fertilization" between the fields of information technology and organization studies" (Orlikowski & Barley, 2001:145). More specifically, they have argued that "organization studies can benefit… by.. taking material properties of technologies into account." It is hard to deny that the "fields" of IS and organization studies would greatly benefit from the type of "cross-fertilization" Barley, Orlikowski, Robey[3] and presumably many others have in mind. The question that remains is what form that "cross-fertilization" and "interaction" takes. If the "cross-fertilization" between IS and organization studies is translated into considering technology and context as co-determinants of technology, then much stands to be gained. If the "interaction" they recommend extends not only to the paradigmatic level, but to the measurement level as well, even greater will be the benefits. If scholars of the technology-organization relationship combine their recommendations with the ones put forth here concerning unobserved heterogeneity and operationalizing "different structural outcomes", the result could be a bumper crop.

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[3] This paper appeared in Management Information Systems Quarterly (MISQ), a top journal in the IS field. The Senior Editor on this paper was Daniel Robey. Along with Barley's CT scanner study, Orlikowski 's ethnography of CASE tools (1992, 1993) and Robey's study of GIS (Robey & Sahay, 1996) are very frequently cited as examples of the *same-technology-different-outcome* finding.

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Table 1 Names and Independent Variables of Regression Models Developed and Tested in Original Study

Model Name	Independent Variable(s)
SUBURBAN-Linear	DAYS
URBAN-Linear	DAYS
SUBURBAN-Quadratic	DAYS + $DAYS^2$
URBAN-Quadratic	DAYS + $DAYS^2$
SUBURBAN-Suburban	SUBURBAN_PHASE1
URBAN-Urban	URBAN_PHASE1 + URBAN_PHASE2 + URBAN_PHASE3
SUBURBAN-Combined	SUBURBAN_PHASE1 + URBAN_PHASE1 + URBAN_PHASE2 + URBAN_PHASE3
URBAN-Combined	SUBURBAN_PHASE1 + URBAN_PHASE1 + URBAN_PHASE2 + URBAN_PHASE3

Table 2 Name and Duration of Distinct Phases of Structuring for Suburban and Urban Hospitals

Hospital (Phase)	Name	Days Since Start	Duration
Suburban (1)	Negotiation of Discretion	0-21	21
Suburban (2)	Usurping Autonomy	21-250	230
Urban (1)	Negotiating Dependence	0-28	28
Urban (2)	Constructing Ineptitude	29-42	13
Urban (3)	Ensuring Ineptitude	43-105	62
Urban (4)	Toward Independence	106-235	129

Table 3 Reproduction of *Table 1: Linear & Quadratic Trends in the Proportion of Operational Decisions Involving Radiologists*

Hospital	Model	Intercept	Day	Day^2	R^2	df	F
Suburban	**Linear**	.40 (9.14)**	-.001 (-4.20)**		.27**		
	Quadratic	.53 (8.94)**	-.006 (-3.67)**	2.15(10-5) (2.88)**	.38**	(1,46)	8.36**
Urban	**Linear**	.77 (17.29)**	-.002 (-3.60)**		.24**		
	Quadratic	.86 (13.38)**	-.005 (-2.63)**	1.41(10-5) (1.83)	.30**	(1,39)	3.33

*p< 0.05, ** p<.01, (Numbers appearing in parentheses are *t*-tests for corresponding parameters).

Table 4 Reproduction of *Table 2*: *Adequacy of Each Department's Own Model of Structuring for Predicting the Proportion of Operational Decisions Involving Radiologists*

Hospital	Model	Intercept	Suburban Phase 1	Urban Phase 1	Urban Phase 2	Urban Phase 3	R^2	df	*F*
Suburban	**Suburban**	.17 (7.46)**	.50 (9.96)**				.67		
	Combined	.13 (3.99)**	.53 (6.91)	.01 (0.21)	.07 (1.31)	.14 (2.12)*	.71	(3,44)	1.43
Urban	**Urban**	.47 (8.20)**		.36 (4.77)**	-.04 (0.39)	.22 (2.90)**	.45**		
	Combined	.47 (8.66)**	.22 (2.34)*	.21 (2.19)*	-.04 (0.41)	.22 (3.06)**	.52	(3.37)	1.54

* p< 0.05, ** p<.01 (Numbers appearing underneath parameters are *t*-statistics).

Table 5 **Comparison of Intercept, Regression Coefficient, and Coefficient of Determination Using Original and Estimated Data**

Hospital	**Data**	**Intercept (b_0)**	**Regression Coefficient (b_1)**	**Coefficient of Determination (R^2)**
Suburban	Original	.40	-0.001	.27
Suburban	Estimated	.41	-.0015	.28
Urban	Original	.77	-0.002	.24
Urban	Estimated	.76	-.0015	.23

Table 6 Results of Re-Analysis of Models Appearing in *Table 1* of Original Study using Arcsine Transformed Data

Hospital	Model	Intercept	Day	Day^2	Adj. R^2	df	F
Suburban	**Linear**	1.377*** (12.29)	-3.61 E-03 *** (-4.04)		0.26	(1,43)	16.29***
Suburban	**Quadratic**	1.641*** (11.15)	-1.54 E-02** (-3.31)	5.07 E-05* (2.58)	0.34	(2,42)	12.54***
Suburban	**Power**	2.531*** (4.799)	-0.274*** (-5.338)		0.39	(1,43)	28.49***
Urban	**Linear**	2.183*** (20.64)	-3.55 E-03 *** (3.52)		0.22	(1,40)	12.41***
Urban	**Quadratic**	2.384*** (13.96)	-1.08 E-02 ** (-2.42)	3.10 E-05 # (1.69)	0.25	(2,39)	7.87***
Urban	**Power**	3.221*** (7.234)	-0.149*** (-4.243)		0.29	(1, 40)	18.00***

Unstandardized Coefficients. (Numbers appearing underneath parameters are *t*-statistics). # $p < 0.10$, * $p< 0.05$, ** $p < 0.01$, *** $p < 0.001$, 2-tailed test.

Table 7 Re-Analysis & Extension of Regression Models Appearing in *Table 2* of Original Study

Model	Intercept	Suburban Phase 1	Urban Phase 1	Urban Phase 2	Urban Phase 3	Urban Phase 4	df	Adj. R^2	F
Suburban – Suburban	**0.793***** (12.660)	**0.798***** (8.698)					(1,43)	0.63	75.71***
Urban – Urban	**1.496***** (11.117)		**0.713***** (4.59)	**-0.034** (-0.243)	**0.440**** (2.84)		(3, 38)	0.38	9.46***
Urban – Phase 1	**1.722***** (19.394)		**0.513***** (3.784)				(1, 40)	0.25	14.43***
Urban – Phase 2	**1.980***** (23.291)			**-0.328*** (-2.196)			(1, 40)	0.09	4.79*
Urban – Phase 3	**1.876***** (18.569)				**0.111** (0.708)		(1, 40)	-0.01	0.50
Urban – Phase 4	**2.047***** (23.550)					**-0.441**** (-3.095)	(1, 40)	0.17	9.58**
Urban – Phases 1, 2	**1.783***** (18.493)		**0.459**** (3.320)	**-0.209** (-1.508)			(2, 39)	0.30	8.52***
Urban – Phases 1, 3	**1.477***** (13.610)		**0.730***** (5.295)		**0.457**** (3.314)		(2, 39)	0.40	14.41***
Urban – Phases 1, 4	**1.848***** (17.271)		**0.403**** (2.821)			**-0.280#** (1.966)	(2, 39)	0.30	9.60***
Urban – Phases 2, 3	**1.967***** (18.409)			**-0.320*** (-2.052)	**0.032** (0.208)		(2, 39)	0.06	2.38
Urban – Phases 2, 4	**2.160***** (25.623)			**-0.437**** (-3.379)		**-0.529***** (-4.096)	(2, 39)	0.34	11.75***
Urban – Phases 3, 4	**2.076***** (18.210)				**-0.062** (-0.400)	**-0.463**** (-2.990)	(2, 39)	0.16	4.77*
Urban – Phases 1, 2, 4	**2.005***** (16.989)		**0.264#** (1.826)	**-0.343*** (-2.526)		**-0.406**** (-2.844)	(3, 38)	0.38	9.41***
Urban – Phases 1, 3, 4	**1.439***** **(7.564)**		**0.763***** (3.901)		**0.489***** (2.526)	**0.045** (0.243)	(3, 38)	0.38	9.41***
Urban – Phases 2, 3, 4	**2.304***** (20.261)			**-0.524***** (-3.901)	**-0.259#** (-1.826)	**-0.644***** (-4.587)	(3, 38)	0.38	9.41***

Standardized Coefficients. (Numbers appearing underneath parameters are *t*-statistics). # $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, 2-tailed test.

Table 8 **Results of "Pooled" Regressions Predicting the Proportion of Operational Decisions Involving Radiologists**

Model	DAYS	HOSPITAL	DAYS*HOSP	df	Adj. R^2	F
1	-0.527*** (-5.710)			(1, 85)	0.27	32.60***
2		0.605*** (7.00)		(1, 85)	0.36	48.95***
3	-0.535*** (-8.301)	0.867*** (9.398)		(2, 84)	0.64	78.48***
4	-0.572*** (-6.779)	0.755*** (3.327)	-0.160 (-0.687)	(3, 83)	0.64	52.15***

Standardized Coefficients (Numbers appearing underneath parameters are *t*-statistics). # p < 0.10, * p< 0.05, ** p < 0.01, *** p < 0.001, 2-tailed test.

Figure 1 Reproduction of *Figure 3* : *Proportion of operational decisions made by radiologists at Suburban and Urban hospitals*

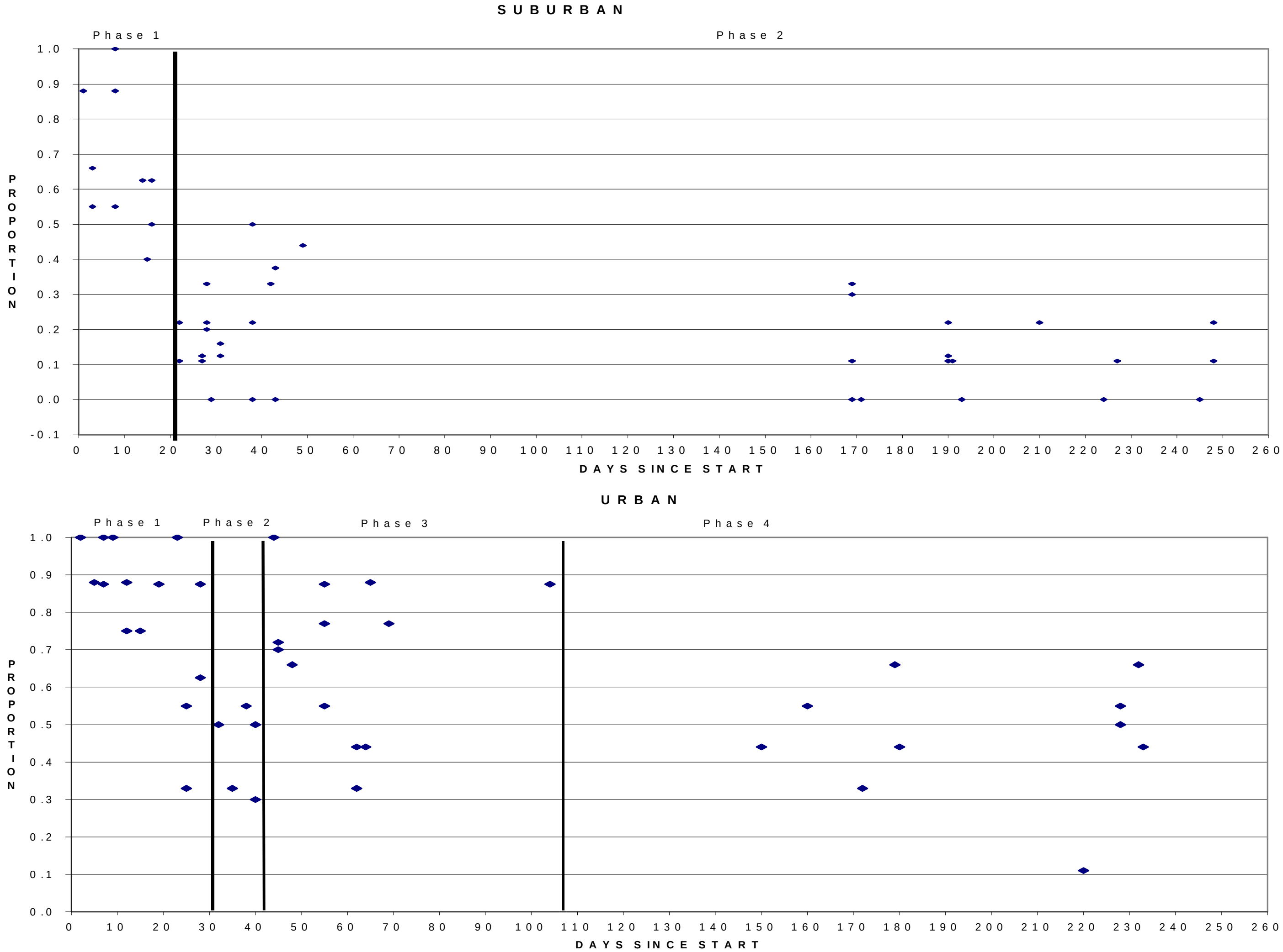
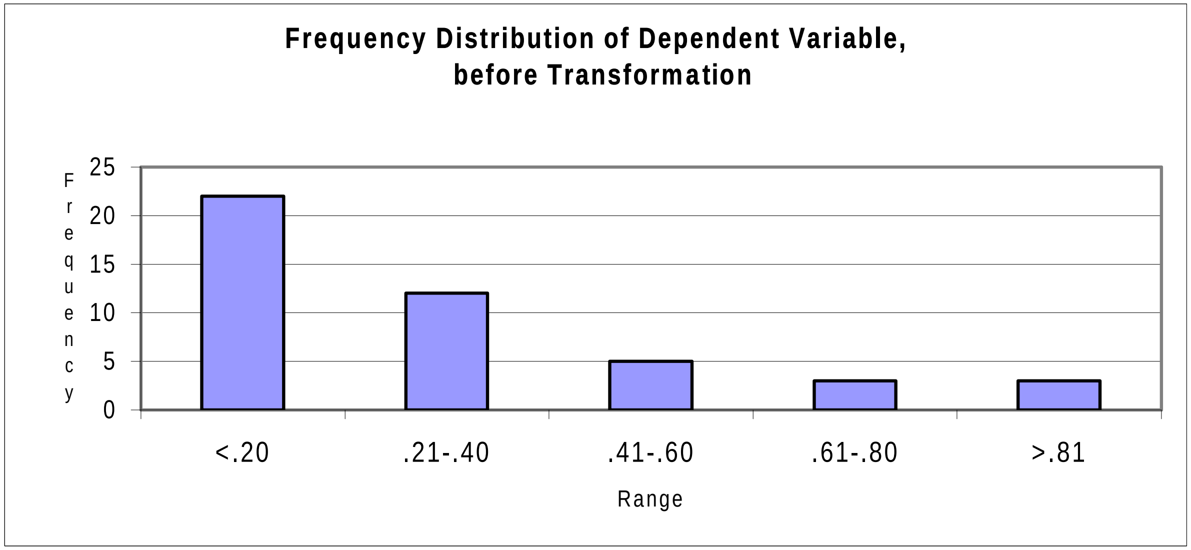


Figure 2 Frequency Distribution of Dependent Variable for Suburban Hospital, before and after Arcsine Transformation



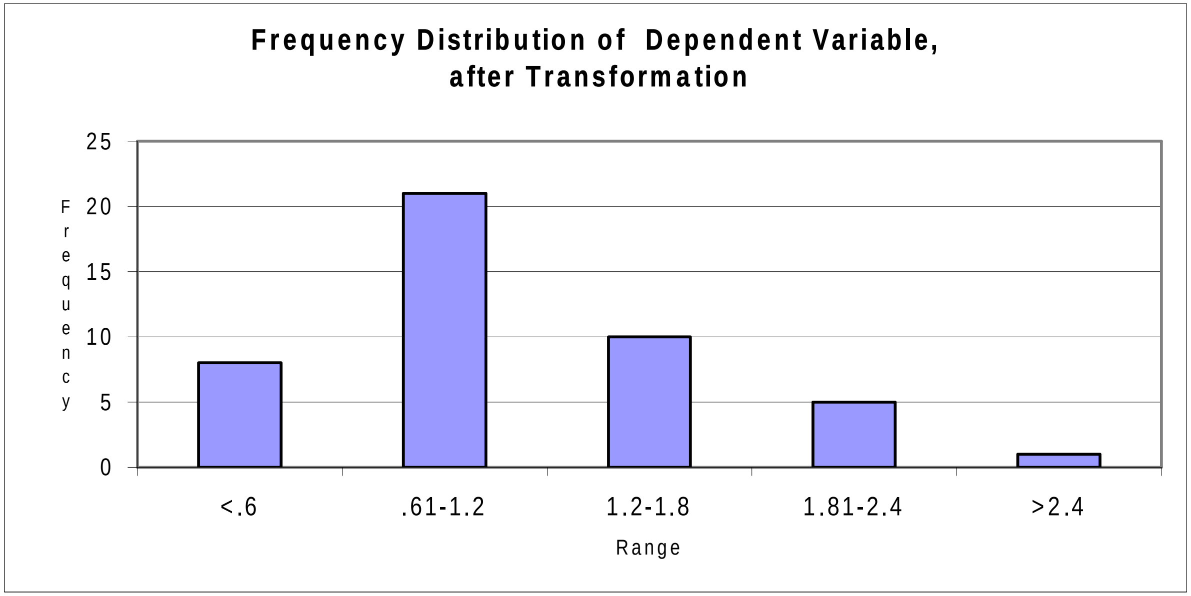


Figure 3: Centralization at Suburban & Urban Regressed Separately on Days in Use: Power vs. Quadratic Model

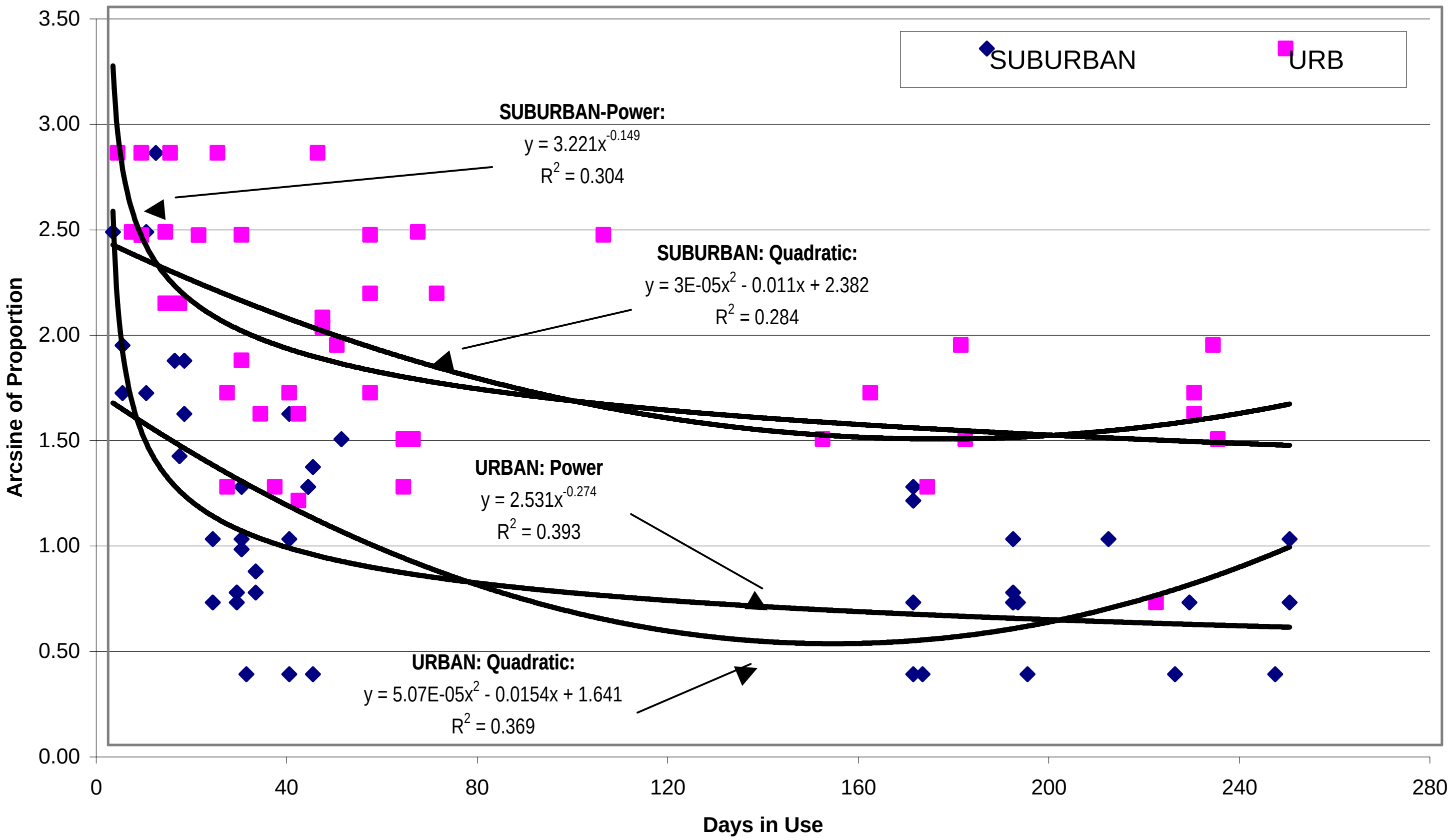


Figure 4: Centralization (Absent Mean Differences) at Suburban & Urban Regressed Separately Upon Days in Use