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Ralph's Pretty Good Grocery Versus Ralph's Super Market: Separating Excellent Agencies from the Good Ones

What makes a public agency perform at a high level? Some agencies are doing extremely well in their environment and it may be because they are lucky enough to have access to plentiful resources, excellent management, and a supportive public. Unfortunately, cases such as these provide little prescriptive evidence for public managers looking to improve their own agency's performance. We apply a new quantitative technique (SWAT) to educational outcome data for 534 school districts in Texas and identify those districts doing extremely well given their fixed and often limited inputs. This approach is useful because the truly superior agencies are those that do more with less, and public managers who lead their organizations to high performance levels despite limited resources provide potential solutions to others.

Charles Goodsell (1983) compares American bureaucracy to a good used car: it is reliable, relatively inexpensive to operate, and generally gives good service. Bureaucracy, in Goodsell's estimation, is the equivalent of Ralph's Pretty Good Grocery in Lake Woebegone. Goodsell's assessment is meant to be an average for American bureaucracy; he recognizes, and others have presented information that American bureaucracies vary a great deal about that average (Meier 1993; Wolf 1997). With the current public philosophy of neoconservative economics (Lan and Rosenbloom 1991; Osborne and Gaebler 1992), being "pretty good" is unlikely to be good enough to meet the expectations of policy makers and the public. Public administrators can no longer be content to simply distinguish the good from the bad and the ugly. What is needed is a way to look at the pretty-good agencies and distinguish from them those that are exceptional, the best organizations that others can emulate to provide more effective performance.

Two general theories explain why the performance of bureaucracy varies. A general set of approaches, best described as open-system theory (Thompson 1967; Rourke 1984), argues that some organizations perform better because they are more highly skilled, possess more useful expertise, or use better-quality leadership to exploit their environments. These agencies are able to do more with less (Downs 1967). But because organizations make decisions by satisficing (Simon 1947), even organizations performing at the highest levels, what they do, and how they do it will vary considerably.

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A second, more provocative theory of organizational variance and survival is that of Herbert Kaufman (1991). Kaufman argues that organizations survive and flourish not because they perform better than other organizations, but because they are lucky. In the Darwinist natural selection of organizations, the survivors are those blessed with favorable and stable environments.[1]

Within the context of either theory, being able to distinguish good (lucky) agencies from better or exceptional (really lucky) agencies is well worthwhile. At the same time, if high performance can be attributed primarily to environmental factors, then Kaufman is likely correct about why some organizations out-perform others;[2] therefore, our attention should shift to the organization's environment and how to structure this environment. If, on the other hand, high performance is the result of using environmental inputs more effectively than other agencies, then the open system's perspective will gain credence.

This article, as a result, has both practical and theoretical ends. It uses recently developed substantively weighted analytical techniques (SWAT[3]) to focus on performance optimization by agencies. The units of analysis are 534 school systems in Texas. School systems are not only the most prevalent public bureaucracies in the United States, they also have some relatively objective measures of outputs that can be used to evaluate performance. First, the article presents a statistical model in which student performance is a function of the school system's environment, policies, and resource allocations. Second, after a brief introduction to SWAT techniques, we modify that approach to distinguish or benchmark excellent districts from those that are merely good. Our benchmark is a relative standard, not an absolute one; we select agencies that do more with less. Third, we examine the agencies using these SWAT techniques, both illustrating how the techniques can be used for this purpose and also addressing the theoretical dispute about how organizations change and adapt. Finally, we discuss additional elements of organizational performance that can be assessed in a similar manner.

Modeling Organizational Performance

An education production function is a model that portrays school districts as economic organizations receiving inputs (resources and students) from their environment and producing outputs (educated students among others). Although this is a seemingly straightforward idea, a vast literature has developed an endless variety of education production functions (Burtless 1996; Smith 1995; Hanushek 1986, 1989,1996). Because our objective is to contribute to the literature on public organizations rather than the education policy literature, our discussion of the models and their possible nuances is brief (for a more elaborate discussion see Burtless 1996). We seek to set up a benchmark for evaluation rather than to resolve substantive issues in education policy.

Our outcome variable— that is, the measure of school system outputs—is based on student scores on standardized tests. Texas requires all school districts to administer exams to students on an annual basis. Our outcome variable is the percentage of students who passed these exams in 1991.

The explanatory variables fall into four categories—environmental constraints, financial resources, teacher qualifications, and district policies. Environmental constraints are factors that restrict agency performance; in the case of education, the key constraint is how difficult it is to educate students. The three measures of constraint, all correlated with poverty, are the percentage of low-income students (defined as those eligible for free school lunches), the percentage of black students, and the percentage of Latino students. Each should be negatively related to organizational performance.

Financial resources are the raw materials of any organization's attempt to meet its goals. Three measures of financial resources are included—per-student instructional funds, average teacher's salary, and percentage of funds received via state aid. These measures represent the total resources devoted to education, the attractiveness of teaching positions in a competitive marketplace, and state efforts to overcome the unequal distribution of local financial resources. All relationships should be positive.

Teacher qualification is measured by the percentage of teachers who hold a temporary certification in a subject specialty (as opposed to a permanent certification) and the average number of years of experience. The relationship for noncertification should be negative, but the predicted relationship for experience is ambiguous (see Meier, Gill, and Waller 1999).

Finally, the education production function contains three policy measures—the percentage of students taking gifted classes, class size, and student attendance (percentage attending on an average day). Performance should be positively related to gifted classes, and attendance should be negatively related to class size.

Texas has a large number of school districts; many are very small or comprise a homogeneous student body. In an effort to analyze a set of organizations relatively similar in the tasks that they perform, we have restricted our analysis to 534 school districts that have at least 500 students and between 10 and 90 percent Anglo students.

SWAT Approaches to Analysis

The SWAT approach to analysis begins with the assumption that organizations vary in their ability to use resources in pursuit of goals. Rather than using regression diagnostics to eliminate unusual organizations (that is, outliers) and generalize to the average case, SWAT exploits the information in outlying cases to determine how agencies that perform better than average differ from those that are just average.

The SWAT approach begins as a statistical procedure (linear regression), but it is actually a *qualitative investigative technique*. The focus is not on parameter estimation or statistical reliability; instead, SWAT highlights *relative* differences in the way that outlying cases (organizations) use explanatory variables (resources). This distinction is important: Using SWAT to produce exact parameter estimates for the purpose of prediction could lead to unreliable results. Using SWAT to isolate and focus on cases with particularly successful outcomes, however, is a qualitatively informed method. Prescriptive advice can be found by highlighting the use and mix of resources that allow organizations to perform better than expected.

In their original study, Meier and Keiser (1996) proposed using jackknifed residuals[4] (see box, "The Mechanics of SWAT") of greater than 0.7 (from a regression of organizational performance) to select high-performing cases. Agencies that failed to meet this criterion were gradually downweighted in a series of regressions to reveal how high-performing agencies differ from average ones. Meier and Gill (2000, ch. 3) relates this selection criterion to the F-distribution and shows that a jackknifed residual of greater than 0.7 will select about 20 percent of the cases for most distributions. In short, it will select the "pretty-good" agencies rather than the "super-star" agencies.

This article applies SWAT techniques in a somewhat different manner. Rather than substantively weighting the above-average cases, it will gradually change the definition of an above-average agency so that it encompasses fewer and fewer agencies. These smaller and smaller subsets of better-performing agencies will be considered the supermarkets of agencies.

Findings

The ordinary least squares results from the statistical model for all school districts are reported in table 1. These results should be considered the base regression and should serve as a standard for comparison.[5] The general predictions of the model are borne out rather well. Student pass rates are negatively associated with all three environmental factors—percentages of low-income, black, and Latino students. Financial resources do not fare as well; only teachers' salaries are significantly related to student performance, although the other two measures are in the predicted direction. The teacher qualification measures are disappoint-

Table 1
Education Production Function: OLS, All Districts

Dependent variable = exam pass rate

Explanatory variable	Value	Std. Error	*t* value	P
Intercept	–35.7455	29.2202	–1.22	0.2218
Environment				
Percent low-income	–0.2931	0.0374	–7.84	0.0000
Percent black	–0.2307	0.0346	–6.67	0.0000
Percent Latino	–0.1146	0.0262	–4.37	0.0000
Financial				
Instructional funds	0.3534*	1.7715	0.20	0.8421
Teachers' salary	1.2444*	0.3568	3.49	0.0005
Percent state aid	0.0303	0.0246	1.23	0.2184
Policy				
Attendance	0.9187	0.2934	3.13	0.0018
Gifted classes	0.1985	0.0996	1.99	0.0468
Class size	–0.9083	0.3370	–2.70	0.0073
Teachers				
Percent noncertified	–0.1256	0.0699	–1.80	0.0728
Experience	–0.0006	0.2267	–0.00	0.9978

Residual standard error: 7.153 on 522 degrees of freedom.
Multiple R-squared: 0.59.
F-statistic: 69.33 on 11 and 522 degrees of freedom; the *p*-value is 0.
*Explanatory variable in thousands of dollars.

The Mechanics of SWAT

We use the elementary form of SWAT in this analysis, SWLS (substantively weighted least squares). SWLS is based on a simple weighted multivariate linear regression that is run 20 consecutive times on the same data (although users are free to vary this parameter). The first iteration weights all data points equal to one (that is, unweighted OLS regression), followed by regressions that consecutively downweight by 0.05 each case with a jackknifed residual less than 0.70. The i^{th} jackknifed residual (also called an externally studentized residual) is the normal residual, weighted inversely proportional to the estimate of the regression standard error, *leaving out the* i^{th} *case*. The idea is to measure the influence of one particular case on the OLS calculations.

Virtually any statistical software package can perform weighted least squares and thus SWAT.

After 20 iterations, high-performing cases will have weights at 1.0, and low-performing cases will have weights at 0.05. At this point, variables with regression coefficients that are different from OLS slopes are identified as factors which have a different effect on higher-performing cases. SWAT, therefore, identifies cases that perform well above expectation (high jackknifed residual) given their allotted resources—not just high performers due to resource richness.

Why is this distinction between high-performing cases and highly advantaged cases important? First consider the problem of defining high-performing cases without a specific methodology. Clearly, highly advantaged cases benefit from more resources (that is, the corresponding high levels of explanatory variables). To find a high-performing case, that is, one doing well *given* a specific mix of levels, requires the analyst to look at the corresponding residual. Conversely, a highly disadvantaged case may be performing extremely well relative to similarly affected cases, but not relative to advantaged cases. In both scenarios, we are interested in residual outliers with all model-specified explanations included.

ing; both relationships are negative, but neither meets traditional levels of significance. Policy measures hold up rather well, with performance being positively related to attendance, and gifted classes being negatively related to class size.

Pretty-Good Agencies

The most basic version of SWAT, substantively weighted least squares (SWLS), takes the jackknifed residuals from this equation and runs a series of weighted least squares regressions, downweighting those cases that do not exceed 0.7. In this case, a series of 19 additional regressions were run and each iteration downweighted the average cases by 0.05, leaving the high-performing cases weighted at 1.0. This iterative process continued until the final regression had respective weights of 0.05 and 1.0.[6]

Table 2 presents the final weighted regression from the SWLS analysis. Because our selection criterion for above-average agencies was 0.7, this regression essentially shows how the pretty-good agencies differ from the average agencies. One way to compare these two regressions is to use a multiregression barplot (see figure 1). Several findings jump out from this graphic: First, student performance is now positively and significantly related to instructional monies and percentage of state aid. Second, student performance in the above-average agencies is also negatively related to noncertified teachers. Third, the positive rela-

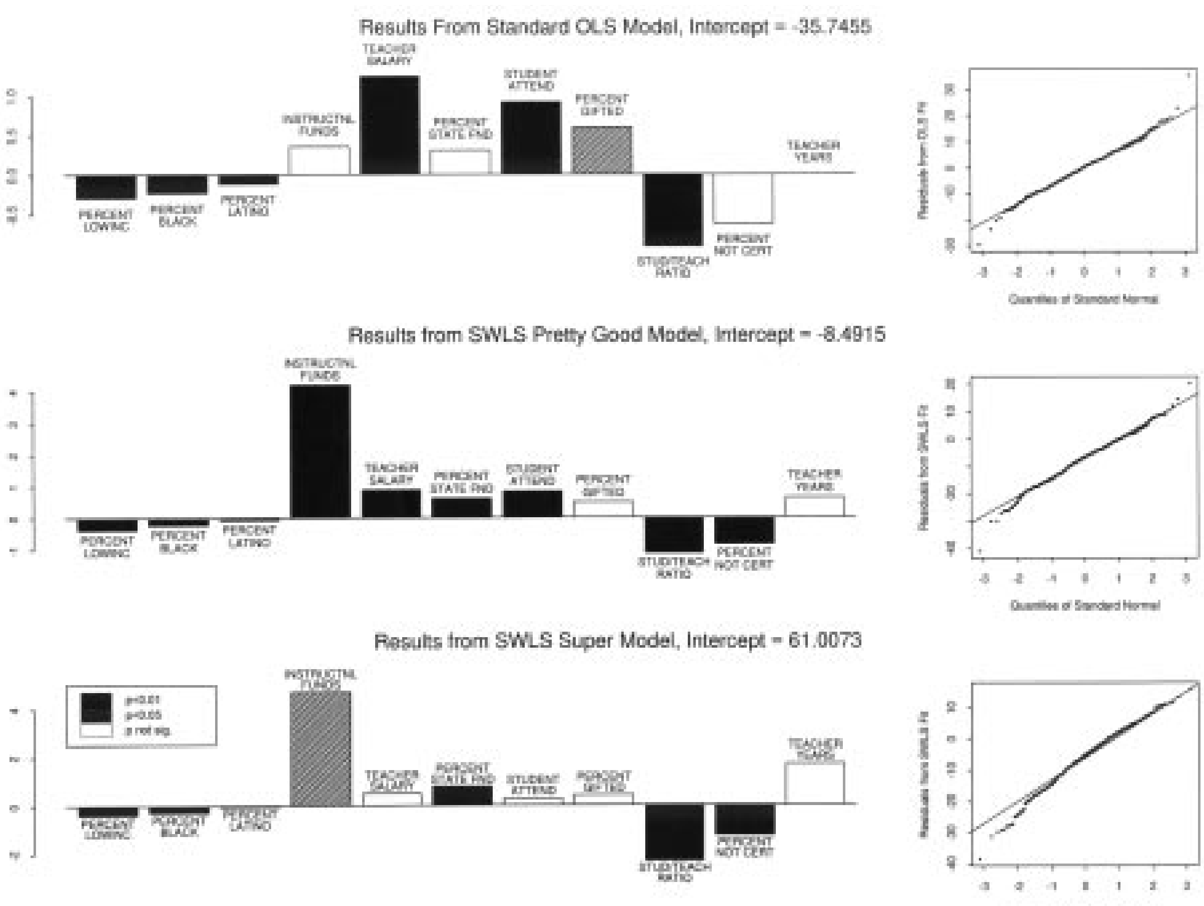
Table 2 Pretty-Good Agencies: SWLS

Dependent variable = exam pass rate

Explanatory variable	Value	Std. Error	*t* value	P
Intercept	–8.4915	20.3821	–0.43	0.6700
Environment				
Percent low-income	–0.3778	0.0323	–11.71	0.0000
Percent black	–0.2198	0.0287	–7.65	0.0000
Percent Latino	–0.0683	0.0235	–2.91	0.0036
Financial				
Instructional funds	4.3350*	1.6056	2.70	0.0069
Teachers' salary	0.8696*	0.3011	2.89	0.0039
Percent state aid	0.0601	0.0207	2.90	0.0037
Policy				
Attendance	0.7616	0.1913	3.98	0.0001
Gifted classes	0.1297	0.0943	1.37	0.1692
Class size	–1.1558	0.2839	–4.07	0.0000
Teachers				
Percent noncertified	–0.1643	0.0545	–3.02	0.0025
Experience	0.0598	0.1808	0.33	0.7409

Residual standard error: 3.030 on 522 degrees of freedom.
Multiple R-squared: 0.72.
F-statistic: 122.06 on 11 and 522 degrees of freedom; the *p*-value is 0.
*Explanatory variable in thousands of dollars.

Figure 1: SWLS, Multiregression Barplot



tionship between gifted classes and student performance disappears. Quite clearly, the relationships for the above-average agencies differ from those for the average agency. figure 1 also provides normal-quantile plots of the residuals from each model. This diagnostic indicates whether heteroscedasticity has been introduced during the SWAT procedure. The absence of deviance from the line indicates homoscedasticity, approximately normally distributed residuals for all models.

A more precise view of the difference between average agencies and pretty-good ones is shown in table 3, which compares the slopes for the two sets of regressions. In addition to the striking findings in figure 1, there are a variety of incremental differences between the sets of agencies. All other things being equal, the relationships for the above-average agencies are 29 percent larger for the percentage of low-income students, 5 percent smaller for black students, and a fairly large 40 percent smaller for Latino students.[7] The relationship for teachers' salaries is 30 percent smaller in the pretty-good districts, suggesting that salaries per se are not as important in these districts; at the same time, instructional funds (now significant) and state aid (98 percent) are far more important.[8] The relationship for teacher certification is 31 percent larger for the pretty-good districts. In terms of policies, the pretty-good agencies have a 35 percent smaller relationship for gifted classes, 17 percent smaller for attendance, and 27 percent larger for class size.

What is really interesting in these differences is that the differences *matter* to policy makers. Environmental forces are fixed and cannot be changed by managers. The good news, however, is that the pretty-good agencies have identifiable resource decisions that not only matter, but also differ from the average case. This is where SWAT analysis is most useful: pretty-good agencies should not necessarily heed prescriptive advice from an analysis that focuses on the average agency. In this case, the OLS results would indicate that spending limited resources to decrease the number of noncertified teachers is not an effective way to increase exam pass rates. For the pretty-good agencies, however, the opposite is true.

Class size is another interesting case. In both models, class size is important, but for the pretty-good agencies the predicted effect is 27 percent greater. Therefore, if allocative decisions are being made at pretty-good schools, the advice would be to decrease class size to produce a higher payoff. Similarly, gifted classes only matter for average districts; those in the above-average group are unlikely to make any gains by increasing gifted classes.

Table 3 Average Agencies versus the Pretty-Good Ones: A Comparison of Slopes

Dependent variable = exam pass rate

Explanatory variable	All agencies (OLS)	Pretty-good agencies (SWLS)	Ratio
Environment			
Percent low-income	–0.2931	–0.3778	1.29
Percent black	–0.2307	–0.2198	0.95
Percent Latino	–0.1146	–0.0683	0.60
Financial			
Instructional funds	0.3530	4.3350	*
Teachers' salary	1.2444	0.8696	0.70
Percent state aid	0.0303	0.0601	1.98
Policy			
Attendance	0.9187	0.7616	0.83
Gifted classes	0.1985	0.1297	0.65
Class size	–0.9083	–1.5578	1.27
Teachers			
Percent noncertified	–0.1256	–0.1643	1.31
Experience	–0.0006	0.0598	**

*The OLS instructional funds coefficient is essentially 0, rendering the ratio meaningless.

**Neither coefficient significant.

Super-Agencies

While the contrast between the average districts and the pretty-good agencies is valuable, our interest here is the best agencies, those that do a great deal better than even the pretty-good agencies. To provide leverage on this problem, we repeated the above analysis, but changed the benchmark from 0.7 to 0.8. We continued this approach by increasing the jackknifed residual selection parameter by 0.1 eight additional times until the last SWLS regression procedure used a jackknifed residual of 1.6.

Table 4 shows how this process focused on fewer and fewer agencies that performed better and better. The pretty-good regression, as noted above, was not particularly selective, with some 123 of 534 districts qualifying. The pretty-good districts still had a significantly higher mean pass rate (65.0) than did all districts (55.6). The number of districts in the top category continued to drop as the jackknifed residual increased, until only 21 agencies (less than four percent of the total) remained in the high-performing category.

What Super-Agencies Do Differently

Table 5 presents the final SWLS results for the best-agencies regression (R > +1.6). The slopes in this regression are compared, in relative terms, to those for all agen-

Table 4 Number of Agencies and Average Pass Rate

Jackknifed residual	N	Mean	Standard deviation
0.7	123	65.0	10.1
0.8	112	65.6	9.9
0.9	93	66.4	9.5
1.0	73	67.1	10.0
1.1	59	70.7	9.0
1.2	50	68.3	9.2
1.3	39	69.6	9.7
1.4	34	70.8	9.5
1.5	24	73.9	6.7
1.6	21	73.8	6.8

Table 5 The Excellent Agencies: SWLS

Dependent variable = exam pass rate				
Explanatory variable	**Value**	**Std. Error**	***t* value**	**P**
Intercept	61.0072	25.9944	2.35	0.0189
Environment				
Percent low-income	–0.3916	0.0525	–7.45	0.0000
Percent black	–0.2814	0.0479	–5.88	0.0000
Percent Latino	–0.0632	0.0366	–1.73	0.0842
Financial				
Instructional funds	4.6992*	2.3335	2.01	0.0440
Teachers' salary	0.4992*	0.4729	1.06	0.2912
Percent state aid	0.0766	0.0291	2.63	0.0086
Policy				
Attendance	0.2760	0.2423	1.14	0.2545
Gifted classes	0.1392	0.1444	0.96	0.2939
Class size	–2.3293	0.4591	–5.07	0.0000
Teachers				
Percent noncertified	–0.2533	0.0833	–3.04	0.0024
Experience	0.3409	0.3034	1.12	0.2611

Residual standard error: 2.793 on 522 degrees of freedom.
Multiple R-squared: 0.49.
F-statistic: 45.63 on 11 and 522 degrees of freedom; the *p*-value is 0.
*Explanatory variable in thousands of dollars.

Table 6 Comparing Excellent Agencies to All Others

Dependent variable = exam pass rate		
Explanatory variable	**All agencies**	**Ratio of excellent slope to pretty-good slope**
Environment		
Percent low-income	1.34	1.04
Percent black	1.22	1.28
Percent Latino	0.55	0.92
Financial		
Instructional funds	*	1.08
Teachers' salary	0.40	0.57
Percent state aid	2.52	1.27
Policy		
Attendance	0.30	0.36
Gifted classes	0.70	1.08
Class Size	2.56	2.02
Teachers		
Percent noncertified	2.02	1.54

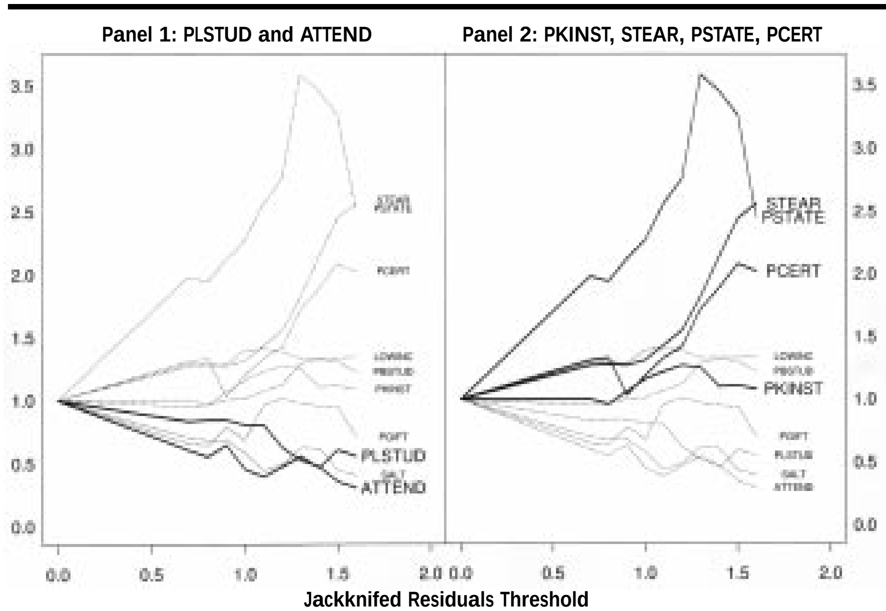
*Variable not significant in OLS equation.

cies and to those for the pretty-good agency regression in table 6 and in figure 1. Table 5 suggests that the best agencies are affected by far fewer forces in their environments. Latino students are no longer significant, a striking finding suggesting that in these districts Latino students do about as well on achievement tests as Anglo students.[9] Two other variables that are significant for both all districts and the pretty-good regression—attendance and teacher salaries—also drop to insignificance. The very best districts do not appear restricted either by their absenteeism rates or by the inability to pay higher salaries (teachers' salaries do not differ between the two groups in table 7). The super-district regression also repeats the pattern of the pretty-good regression that gifted classes do not matter.

For three variables, the relationships for excellent agencies look similar to those for the pretty-good districts—low-income students, black students, and instructional funding. In the latter case, both the pretty-good and the best regression show a significant relationship, but the all-agencies regression does not. What distinguishes the best from the pretty-good regression are the other three relationships—class size, teacher certification, and state aid. The best districts get twice the impact of reducing class size as the pretty-good districts get. The best districts also get about 54 percent more from better teacher qualifications and 27 percent more from increases in state aid. If one were to focus on a single variable that appears to distinguish the best districts from the pretty-good ones, it would be what these districts do as they reduce the size of their classes.

Given the cogent summary that the final regressions provide of the difference between excellent and pretty-good agencies, one might ask, was it worthwhile going through the iterative process? Why not simply jump to the final results (assuming that one would not jump too far and not have any districts remaining)? The iterative process contains a great deal of useful information, illustrated in figure 2. Panel 1 of figure 2 charts the change in relationships for the percentage of Latino students and the percentage attendance as the set of districts became more exclusive (that is, performed better). For Latino students, there is a gap between all districts and the pretty-good districts. Even though the best districts' slope for Latinos is insignificant

Figure 2 Change in Slopes from Good to Excellent Organizations: Latino Students and Attendance



and the pretty-good slope is significant, in substantive terms they are about the same size. The gains achieved by the best districts, therefore, are already apparent in the pretty-good districts. Attendance shows a different pattern: Pretty-good districts do not overcome attendance problems with nearly the skill that the best districts do.

Panel 2 of figure 2 presents the relationship-change graphs for state aid, class size, teacher noncertification, and instructional funding. Instructional funding shows a major jump from all districts (where it is nonsignificant) to the pretty-good districts. The best districts really do not get much more out of additional instructional funds than the pretty-good districts do, suggesting that the process for doing so is fairly well known to districts with above-average talents. Certification and class size form a different pattern, with the best districts doing much better than the pretty good ones. The real differences appear at jackknifed residuals of 1.0 and higher, suggesting that a fairly high level of skill is needed to maximize return from such resources. Finally, the state-aid curve shows what appears to be an eventual diminishing marginal return. The impact of state aid, while higher among the best agencies than among the pretty-good ones, actually peaks at a jackknifed residual of 1.3.

Lucky or Good?

A key theoretical question concerning the difference between the super-agencies and the pretty-good agencies is, are they actually better or just lucky? One view of quality versus luck is to determine if some agencies have more favorable environments than the other agencies. If the super-agencies have more favorable inputs, then the argument that they are lucky rather than good gains some credence. If the inputs are relatively equal, then the difference is in what the agencies do with their inputs. Translating inputs into higher levels of outputs requires some skill rather than just luck.[10]

Table 7 compares the means for the explanatory variables for the super-agencies and the other agencies. Despite the 19-point difference in pass rates, the means of the explanatory variables are relatively similar. In only two cases are the differences statistically significant at the .05 level—class size and per capita instructional funds. The super-agencies have a mean class size of 14.2 (compared to 15.4) and spend $165 more per pupil in instructional monies. These are relatively modest differences and can account for no more than two percentage points of the 19-percentage-point difference between the two groups. Kaufman's theory that organizations survive because they are lucky does not appear to hold for these agencies. The super-agencies differ from the average agencies, not because the super-agencies are lucky, but because they are better at turning their relatively scarce inputs into valued outputs.

Table 7 Super-Agencies and the Also-Rans

Explanatory variable	Mean Values: Super-Agencies	Mean Values: Others	*t* value	P
Environment				
Percent low-income	39.6	40.6	0.25	0.81
Percent black	9.3	11.5	0.77	0.44
Percent Latino	28.8	31.2	0.38	0.70
Financial				
Instructional funds	2411.5	2246.7	1.98	0.0073
Teachers' salary	25785.1	25878.0	0.24	0.81
Percent state aid	47.8	48.0	0.05	0.96
Policy				
Attendance	96.0	96.1	0.41	0.69
Gifted classes	6.4	6.7	0.41	0.68
Class size	14.2	15.4	3.08	0.0021
Teachers				
Percent noncertified	5.3	5.2	0.14	0.89
Experience	12.1	11.4	1.83	0.67
Dependent variable				
Student pass rates	73.8	54.8	8.14	0

Other Applications

This study was designed to distinguish public agencies that are "pretty good" at their jobs from those that are even better. The process used, a SWAT technique altered to focus on better and better performance, can be used in a wide variety of public policy and public management situations.

First, while the focus here was on the best performers, quite clearly the emphasis could also be on the worst performers (see Meier, Gill, and Waller 1999). One interesting situation might be a case where public agencies are interested in preventing the worst-case scenario. In environmental protection, for example, the nature of risk assessment is such that policy makers are concerned with the most extreme cases. If adequate models of environmental quality could be constructed, then SWAT techniques could focus on environmental cases with negative residuals and with those further and further below the regression line.

Second, the process could also be used to study regulatory compliance. In all areas of regulation, some firms comply quickly with the law, while others are more reticent and some resist compliance with every resource at their disposal. With a measure of compliance, SWAT can be used to construct models of the most resistant to compliance (all other things being equal) and to focus on how those firms make decisions different from the average firm.[11]

Third, additional work needs to focus on situations where the number of exceptional cases is too small to provide any meaningful information. Clearly, the selection criteria can be increased so that fewer and fewer programs will qualify. The benefit of having fewer programs is that these are more likely to be the elite programs. The disadvantage is that there might be so few of these programs that their activities and processes cannot be generalized (or serve as role models) to other public organizations.

Fourth, SWAT techniques are clearly applicable to a wide variety of private-sector activities. In any situation where goals are relatively clear and a production function can be set up, the technique can provide a wealth of useful information. Nothing in the public–private distinction prevents the application of this technique in the private sector.

Conclusion

This article had both methodological and substantive goals. Methodologically, we used SWAT techniques to single out elite agencies. The best agencies differed not only from the average agencies but also from the above-average agencies. This article provides some guidance for those seeking to reform government by transferring the techniques from the best agencies to all other agencies. The designation of the best agencies should rely on systematic methods that combine quantitative analysis with qualitative assessments, rather than anecdotes.

The approach is useful both for theoretical reasons, as presented in this article, and practical management purposes. SWAT can assist managers to both focus on the best-performing agencies and isolate those factors that contribute to performance. At that point, detailed management analysis can focus on these agencies to determine if what they do can be transferred to other agencies.

Substantively, this article addressed why some agencies perform at higher levels than others. Two theories have very different conclusions about why some agencies succeed and some fail. The open-systems theory holds that agencies succeed because they have better leadership, more skills, more adaptable technology, and other factors internal to the organization. Kaufman, on the other hand, feels that success is a function of a favorable environment. In short, while the open-system theory contends that organizations succeed because they are good, Kaufman would contend that success if more a matter of luck.

While a supportive environment is always preferable, this study found that the best agencies do more with less, transforming inputs into outputs at a much higher rate. If anything, the best agencies are less restricted by their environments than the average agency. Agencies that succeed may or may not be lucky, but they are clearly good.

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Notes

1. The logical extension of Kaufman's argument is Chubb and Moe's (1989) suggestion that we should focus on organizational environments and structure them in such a way that they do not make a large number of contradictory demands on the organization. In their study of school choice, Chubb and Moe argue that suburban and private schools perform better because they exist in homogeneous environments.
2. Kaufman could still be wrong if the key organizational skill that is operating is the ability to placate one's environment. As open systems, bureaucracies both respond to their environment and shape the nature of that environment. What might appear to be a highly favorable environment might actually reflect exceptional political and managerial skills. For example, J. Edgar Hoover was able to define the FBI's role in such a way to be able to deal with cases that were highly visible yet easy to solve (bank robbery, kidnapping) and avoid cases that were difficult to solve or corrupting (prohibition, drug abuse); see Poveda (1990). The result of this strategy was a great deal of organizational autonomy and ample resources.
3. Software for a variety of platforms can be obtained free on our Web site. See *http://web.clas.ufl.edu/~jgill*. We also provide additional documentation on the technical background and various diagnostic techniques that SWAT practitioners may be interested in reading.
4. A jackknifed residual is a measure of how far above or below the regression line a given data point falls. Jackknifed residuals are based on standardized distances from a regression line, with the point in question excluded from the calculations made for that line.
5. Note: *p*-values are provided for consistency with the literature in this area. See Gill (1999) for a discussion of the problems associated with p-values and "stars" in social science literatures.
6. The analyst can vary these weights either by increasing the size of the incremental change and decreasing the number of iterations, or by decreasing the size of the incremental change and increasing the number of iterations.
7. Substantively, this means the pretty-good agencies are more affected by low-income students but less affected by minority students. More directly stated, minority students' pass rates are higher in the pretty-good districts.
8. Why might state aid be so important to these school districts? In organizational terms, one must remember that

major state aid for education is a relatively recent phenomenon in Texas. Many school districts are like organizations that have been on severe financial diets for many years. The best of these organizations have many ideas for improvement, but lack the money necessary to implement them. State aid essentially provides new monies and taps this reservoir of built-up reforms.

9. In substantive terms, this is a remarkable finding suggesting that the super districts have found a way to achieve equity in test scores between Anglos and Latinos. Exactly what the districts are doing needs to be probed by a series of in-depth case studies.

10. We are overstating the case somewhat. That is, an agency could try something and by luck get better performance by some quirk of fate. The true test to distinguish between those agencies that are lucky and those that are good requires a longer-term assessment. An agency that out-performs its peers with the same inputs year after year cannot be considered lucky.

11. The method likely has some application in the area of deviant behavior. Because we are concerned with how organizations deal with their environments, we have left these issues for others to address.

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