J Bus Psychol (2010) 25:543–554
DOI 10.1007/s10869-010-9183-4

Polynomial Regression with Response Surface Analysis: A Powerful Approach for Examining Moderation and Overcoming Limitations of Difference Scores

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Published online: 6 June 2010

Abstract Polynomial regression with response surface analysis is a sophisticated statistical approach that has become increasingly popular in multisource feedback research (e.g., self-observer rating discrepancy). The approach allows researchers to examine the extent to which combinations of two predictor variables relate to an outcome variable, particularly in the case when the discrepancy (difference) between the two predictor variables is a central consideration. We believe this approach has potential for application to a wide variety of research questions. To enhance interest and use of this technique, we provide ideas for future research directions that might benefit from the application of this analytic tool. We also walk through a step-by-step example of how to conduct polynomial regression and response surface analysis and provide all the tools you will need to do the analyses and graph the results (including SPSS syntax, formulas, and a downloadable Excel spreadsheet). Our example involves how discrepancies in perceived supervisor and organizational support relate to affective commitment. Finally, we discuss how this approach is a better, more informative alternative to difference scores and can be applied to the examination of two-way interactions in moderated regression.

Keywords Polynomial regression · Response surface analysis · Two-way interactions · Job attitudes · Research methods

Introduction

Response surface analysis (e.g., Box and Draper 1987) is an emerging technique that can provide a nuanced view of relationships between combinations of two predictor variables and an outcome variable by graphing the results of polynomial regression analyses in a three-dimensional space (Edwards and Parry 1993). This technique has more explanatory potential than do difference scores or traditional moderated regression analyses, and holds promise for applicability to a wide range of research questions. To date, however, the methodology has been applied mainly to the study of outcomes of self-observer rating discrepancies in multisource feedback (i.e., 360°) instruments (e.g., Atwater et al. 1998; Gentry et al. 2007; Ostroff et al. 2004). Such studies have demonstrated that congruence and discrepancies between self- and other-ratings are meaningfully related to effectiveness (Atwater et al. 1998), managerial derailment potential (Gentry et al. 2007), performance (Atwater et al. 2005; Ostroff et al. 2004), and organizational level (Ostroff et al. 2004).

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Our goal for this paper is to spark interest in, and expand the use of polynomial regression with response surface analysis by: (1) providing some ideas for research questions for which response surface analysis would be appropriate and informative; (2) explaining the basics of the technique in a non-technical way; (3) using an empirical example to describe step-by-step the process a researcher should go through to complete the analysis; (4) supplying the SPSS syntax needed to run the polynomial regression procedures in SPSS; and (5) presenting instructions for creating a three-dimensional response surface graph in Excel and how to interpret the graph. We also point out the benefits of this approach compared to traditional moderated regression, and offer some possible future directions to expand the use of this technique to additional research questions.

What Can be Examined Using Polynomial Regression with Response Surface Analysis?

There are many research questions in the organizational sciences which could benefit from an application of polynomial regression with response surface analysis. This statistical technique should not be limited to the domain of research on multi-rater feedback. Some studies have begun to go beyond the self-awareness domain of interest. For instance, one of the original uses of this technique in the organizational behavior literature was to examine congruence (i.e., fit) questions including how one's actual versus desired levels of job attributes (e.g., variety, autonomy, prestige, span of control, travel, time spent on activities, workload) relate to satisfaction (Edwards 1994, 2002, 2007) and how person-environment fit data, such as actual versus desired job complexity, relate to job dissatisfaction, work load dissatisfaction, boredom, depression, and anxiety (Edwards and Parry 1993). Also, one recent study from the literature on teams examined how similarities and differences in ratings between a leader and his/her team on goal accomplishment and constructive conflict related to team performance (Gibson et al. 2009).

More generally, this technique can be used for any situation in which researchers are interested in how combinations of two predictor variables relate to an outcome. There are, however, a few assumptions that must be met (Edwards 2002). As Edwards explains, the two predictor variables must be commensurate; that is, the predictors must represent the same conceptual domain. That way, any difference in standing on the two predictor variables would be interpretable in a meaningful manner. For example, imagine you are trying to predict compensation from job performance. The conceptual domain of the predictor variables is job performance and the two measured predictor variables might be self and supervisor ratings of job performance. In this case, a discrepancy or difference between a self and a supervisor rating of job performance is meaningful because the measures come from the same conceptual domain. Thus, a discrepancy in the two ratings of performance may be interpretable with respect to the dependent variable, a person's compensation.

The second assumption is that the predictor variables must be measured on the same numeric scale so that their degree of correspondence can be determined (see Edwards 2002 for more detail). For example, both variables might be measured on 5-point Likert-type scale from 1 = *strongly disagree* to 5 = *strongly agree*, or a 7-point frequency scale from 1 = *not at all* to 7 = *to a very great extent*. In addition, if the variables are not measured on the same scale, some researchers have transformed the variables to a standardized scale thereby placing them on a common metric (e.g., see Harris et al. 2008).

Finally, as with any regression technique, all the usual assumptions of multiple regression analysis should also be met (for a listing of these assumptions, see Tabachnick and Fidell 2007). Indeed, polynomial regression may often be used in place of moderated regression and provides information about combinations of variables that goes well beyond the information provided by traditional moderated regression, as you will see throughout the paper. Before we offer specific ideas for research that might benefit from a consideration of this analytic tool, we first define and describe some basic terminology.

Some Basic Terminology

Using polynomial regression and subsequent response surface analysis, one can examine the following:

(1) How does *agreement* between two predictor variables[1] relate to an outcome?
By *agreement* we mean that the levels of the two predictor variables are essentially the same (i.e., within a half standard deviation of each other, we provide more on that in the section called '*Descriptive Information about the Occurrence of Support Discrepancies*'). Using this technique, one can determine how agreement in the level of two predictors (e.g., self- and other-ratings of interpersonal skills) relates to an outcome variable (e.g., performance). For example, for people whose self- and other-rated interpersonal

[1] There are times one would want to examine variables that would predict agreement (i.e., examining agreement as a "dependent" or "outcome" variable). Edwards (1995) discusses how to use multivariate procedures to examine ratings considered jointly as outcome variables. Ostroff et al. (2004), Gentry et al. (2007) and Gentry et al. (in press) give recent empirical examples.

skills are similar (in agreement), does performance increase as their combined level of interpersonal skill ratings increases)?

(2) How does the *degree of discrepancy* between two predictor variables relate to an outcome?
By *degree of discrepancy* we mean the extent to which the levels of the two predictor variables differ from each other. One can determine the level of the outcome variable as the two predictor variables diverge. For instance, does performance suffer more as the levels of self- and other-ratings of interpersonal skills become increasingly discrepant. The less self-aware one is about one's interpersonal skill, perhaps the worse one's performance.

(3) How does the *direction of the discrepancy* between two predictor variables relate to an outcome?
By *direction of the discrepancy* we mean which predictor is higher than the other. It could be, for example, that self-ratings of interpersonal skill are higher than other-ratings, a situation which has often been referred to as over-rating (e.g., Yammarino and Atwater 1997). Or, it could be that self-ratings of interpersonal skill are lower than other-ratings, a situation referred to as under-rating (e.g., Yammarino and Atwater 1997). Using polynomial regression with response surface analysis one can determine the level of the outcome variable (e.g., performance) when self-ratings of interpersonal skill are higher than other-ratings (when people are over-rating their interpersonal skill), and when self-ratings of interpersonal skill are lower than their observers' ratings (when people are under-rating their interpersonal skill). We'll walk step-by-step through the methods used to understand each of these potential areas to explore, but first here are some examples of research questions in a variety of domains to help spark your ideas.

Some Research Ideas

Justice research is one area that might benefit from this approach. Using polynomial regression with response surface analysis could provide an innovative way to examine the outcomes of discrepancies in procedural justice. To what extent is a discrepancy in procedural justice perceptions (e.g., between oneself and one's supervisor) harmful or beneficial to outcomes such as performance, commitment, or attempts to circumvent the procedure? Does the direction of the discrepancy matter? For example, one could imagine that when subordinate and supervisor procedural justice perceptions are in agreement (at essentially the same level) or the employee's procedural justice is higher than that reported by the supervisor, everything could be fine. However, if the supervisor thinks she is providing more procedural justice than does the subordinate, perhaps the supervisor needs some development and coaching to avoid detriments to commitment, performance or turnover intentions by his or her employees, or the subordinate needs a better understanding of the supervisor's procedures.

A second example of a research area that could benefit from this approach is the support literature. Research on perceived organizational support (POS) is prolific. An example of a POS research question that might be relevant to using polynomial regression with response surface analysis is to examine how discrepancies in anticipated versus post-hire POS affect one's desire to remain in the organization, performance, and other outcomes.

A third example for which response surface methodology may be useful is the goal-setting literature. For example, one could examine the effects of discrepancies in self and other perceptions of goals on performance. Performance may suffer to the extent that goals set by others exceed the goals the employee sets for him or herself.

The Basics: An Overview of the Polynomial Regression with Response Surface Analysis Approach

In the response surface analysis approach, polynomial regression is conducted first. The general form of the equation to test for relationships using polynomial regression is $Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e$, where Z is a dependent variable, X is Predictor 1 (e.g., self-ratings of interpersonal skills), and Y is Predictor 2 (e.g., other-ratings of interpersonal skills). Thus, the outcome variable is regressed on each of two predictor variables (X and Y), the interaction between the two predictor variables (XY), and the squared terms for each of the two predictors (X^2 and Y^2).

Rather than directly interpreting the results from the polynomial regression analysis, the coefficients from the analysis are used to examine what is called the "response surface pattern" (Edwards 1994; Harris et al. 2008) which is graphed to provide a three-dimensional visual representation of the data to aid interpretation (Fig. 1 shows an example graph). The slope and curvature of two lines represent the response surface pattern. The "line of perfect agreement" depicts $X = Y$ (see black line on floor of graph in Fig. 1). When considered in relation to the outcome variable (Z), the slope of the line of perfect agreement represents how *agreement* between two predictor variables relates to an outcome (see Fig. 1). That is, the slope of this line shows the various levels of the outcome variable (e.g., performance) for people whose levels of the two predictor

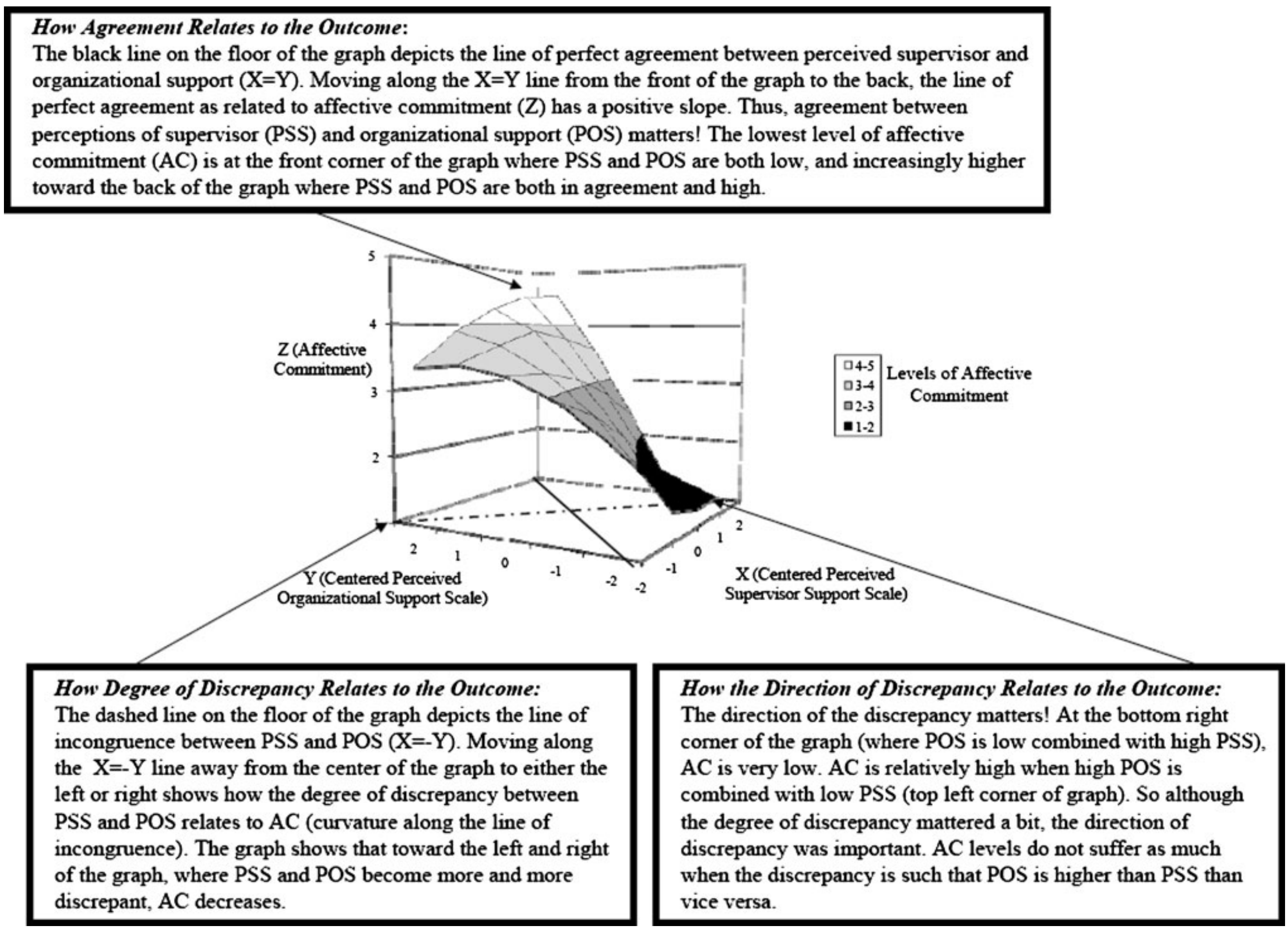


Fig. 1 Affective commitment as predicted by perceived organizational support-perceived supervisor support discrepancy

variables (e.g., self- and other-ratings of interpersonal skills) are essentially the same across the continuum from low ratings on both predictors to high ratings on both predictors. The test for a curvature along the line of perfect agreement (as related to height of the outcome variable) tells us whether the relationship between ratings that are in agreement and the outcome is linear or nonlinear. If this test is significant, the relationship between ratings that are in agreement and the outcome is nonlinear.

The line perpendicular to the line of perfect agreement is often called the "line of incongruence" ($X = -Y$, that is, when the X and Y variables are not in agreement, see dashed line in Fig. 1). Significant curvature along this line (as related to height of the outcome variable) captures how the *degree of discrepancy* between the two predictor variables may influence the outcome variable. For example, significant negative curvature would mean that the outcome variable (e.g., performance) suffers more as the levels of the two predictor variables (e.g., self- and other-ratings of interpersonal skills) diverge (are increasingly discrepant, that is, as we move further away from the line of perfect agreement).

The slope along the line of incongruence as it relates to height in the outcome variable tells us the extent to which the direction of the discrepancy matters, such that the outcome is potentially affected more when the discrepancy is in one direction $X > Y$ (e.g., self-ratings of interpersonal skills are higher than others' ratings of interpersonal skills, indicated by positive significant slope) or the other $X < Y$ (e.g., other's ratings of interpersonal skills are higher than self-ratings of interpersonal skills, indicated by negative significant slope). Let us demonstrate by walking through an example.

Background About Our Example

Our example focuses on an examination of the relationship between two sources of work support and affective commitment (AC). Support in organizations typically comes in two forms, organizational (POS; Eisenberger et al. 1986) and supervisory (perceived supervisor support or PSS; Kottke and Sharafinski 1988), where employees develop global beliefs concerning the extent to which their organizations and supervisors value their contributions and care about their well-being, respectively. Research has linked working in a supportive organization to a variety of positive outcomes including AC, which refers to the employee's emotional attachment to the organization (Meyer and Allen 1997; see Rhoades and Eisenberger 2002, for review of support literature).

POS and PSS lend themselves readily as an example for explaining response surface analysis. Perceived discrepancies between POS and PSS are theoretically important, as it would be difficult to have a strong bond with an organization when one is uncertain whether the supervisor and organization will show consistency in support, including which behaviors they might reward and value (Aselage and Eisenberger 2003). Consistency in support may increase trust-related certainty that the organization is reliable enough to be worthy of an emotional attachment (Aselage and Eisenberger 2003).

In our example PSS is the X variable, POS is the Y variable, and AC is our outcome variable (Z). Because PSS and POS are both positively related to AC (e.g., Rhoades et al. 2001), when PSS and POS are in agreement (i.e., people's perceptions of each form of support are at essentially the same level) we propose a linear relationship such that the higher PSS and POS, the higher AC. Thus, we expect a significant positive slope along the line $X = Y$ (i.e., the line of perfect agreement) as related to AC. We do not expect curvature along this line (i.e., we expect the relationship will be linear).

We also propose that when PSS is greater than POS or vice versa AC will be lower than when the two support variables are in agreement. That is, we expect that levels of AC will decrease as any discrepancy between these two support variables increases. More technically, this proposition corresponds to an expectation of a significant, negative curvature along the line of incongruence (i.e., the $X = -Y$ line) as it relates to AC. Additionally, the direction of discrepancy may differentially influence AC. POS may be more important to maintaining AC because AC represents commitment to the organization, not the supervisor. POS creates a felt obligation to care about the organization's welfare and incorporates organizational membership into employees' social identity (Rhoades et al. 2001). Thus, we propose that when the direction of the discrepancy is such that POS is higher than PSS, the impact of this discrepancy on AC will be less than for the discrepancy created when POS is lower than PSS. Again, expressing this idea more technically with respect to response surface analysis, we expect a significant negative slope for the $X = -Y$ line as it relates to AC.

Let us now walk you through the steps needed to complete the test of our proposed relationships. We use the term "predictor variable" for ease of understanding. However, in our example all variables were collected at the same time point and from the same source (the employee).

Step 1: Descriptive Information About the Occurrence of Support Discrepancies

Before conducting the polynomial regression analyses, it is important to inspect how many participants would be considered to have discrepancies between the two predictors so that you have an idea of the base rate of discrepancies in your sample. Without this information, you have no idea whether there are discrepancies that even exist in your sample, how many, and in what direction. If it turns out that very few participants have discrepant values (e.g., POS higher than PSS or PSS higher than POS) the practical value of exploring how discrepancies affect an outcome variable would be small.

A good source to follow is the procedure conducted in Fleenor et al. (1996). Standardize the scores for each predictor variable (PSS and POS). Any participant with a standardized score on one predictor variable that is half a standard deviation above or below the standardized score on the other predictor variable is considered to have discrepant values. Determine the percentages of "in agreement" values and the percentages of discrepant values in either direction. We provide a sample table (Table 1) to report this descriptive information based on our example. As you can see in Table 1, nearly half our sample has values of PSS and POS that are different from each other in one direction or the other. Based on our data, we can conclude that exploring how discrepancies between these sources of support relate to commitment makes practical sense.

Step 2: Run Polynomial Regression in SPSS and Calculate the Surface Values

Once you are satisfied that discrepant values exist in your sample, proceed with conducting the polynomial regression

Table 1 Frequencies of PSS levels over, under, and in-agreement with POS levels needed for Step 1

Agreement groups	Percentage	Mean PSS	Mean POS
PSS more than POS	23.9	4.31	3.03
In agreement	55.4	3.77	3.62
PSS less than POS	20.7	2.93	3.83

Note: $N = 173$

PSS perceived supervisor support, *POS* perceived organizational support analysis. We followed the procedure outlined by Atwater et al. (2005). First, center the predictors (POS and PSS) around the midpoint of their respective scales (Edwards 1994). We subtracted three (3) from each score because PSS and POS were measured on a 5-point Likert-type scale with 1 = *strongly disagree* and 5 = *strongly agree* (see the first two compute statements in the SPSS syntax in Appendix 1). Centering aids interpretation and reduces the potential for multicollinearity (Aiken and West 1991). As Aiken and West note, there are a variety of ways to center data depending on your research questions and interpretation needs (around the mean, around the midpoint of the scale, etc.). Note that centering around the midpoint of the scale is recommended for this type of analysis (Edwards 1994).

Then, make three new variables: (a) the square of the centered PSS variable; (b) the cross-product of the centered PSS and POS variable; and (c) the square of the centered POS variable (represented in the remaining three compute statements in the SPSS syntax in Appendix 1). Next, run the polynomial regression analysis. You do this by regressing the outcome variable (AC) on the centered predictor variables (PSS and POS), the product of centered PSS and POS, the centered PSS squared, and the centered POS squared terms into the regression equation (see the regression statement syntax in the Appendix 1).

Rather than examining the regression coefficients as would be done in a common regression analysis, if the R^2 (variance in the outcome variable explained by the regression equation) is significantly different from zero (Edwards 2002), the results of the polynomial regression are evaluated with regard to four surface test values: a_1, a_2, a_3, and a_4. The slope of the line of perfect agreement (PSS = POS) as related to AC is given by $a_1 = (b_1 + b_2)$, where b_1 is the unstandardized beta coefficient for the centered PSS variable and b_2 is the unstandardized beta coefficient for the centered POS variable. Curvature along the line of perfect agreement as related to AC is assessed by calculating $a_2 = (b_3 + b_4 + b_5)$, where b_3 is the unstandardized beta coefficient for the centered PSS squared, b_4 is the unstandardized beta coefficient for the cross-product of the centered PSS and centered POS, and b_5 is the beta coefficient for the centered POS squared. The curvature of the line of incongruence as related to AC, indicating the degree of discrepancy between PSS, POS, and the outcome, is assessed by calculating $a_4 = (b_3 - b_4 + b_5)$. The slope of the line of incongruence as related to AC, indicating the direction of the discrepancy (PSS higher than POS or vice versa), is assessed by calculating $a_3 = (b_1 - b_2)$. The results for the example data are shown in Table 2. The formulas to determine the significance of each surface value are contained in Appendix 1 and a helpful Excel spreadsheet to help you calculate each surface value and its significance is shown in Appendix 2 and can be downloaded for your use.

Table 2 Organization-supervisor support discrepancy as predictor of affective commitment

	Affective commitment
Variable	*b* (se)
Constant	3.10 (.07)**
Perceived supervisor support	−.23 (.12)
Perceived organizational support	.77 (.12)**
Perceived supervisor support squared	−.07 (.11)
Perceived supervisor support × perceived organizational support	.27 (.17)
Perceived organizational support squared	−.10 (.09)
R^2	.53**
Surface tests	
a_1	.54**
a_2	.10
a_3	−1.00**
a_4	−.44*

Note: $N = 173$

$a_1 = (b_1 + b_2)$, where b_1 is beta coefficient for perceived supervisor support (PSS) and b_2 is beta coefficient for perceived organizational support (POS). $a_2 = (b_3 + b_4 + b_5)$, where b_3 is beta coefficient for PSS squared, b_4 is beta coefficient for the cross-product of PSS and POS, and b_5 is beta coefficient for POS squared. $a_3 = (b_1 - b_2)$. $a_4 = (b_3 - b_4 + b_5)$

b unstandardized regression coefficient, *se* standard error. Significance depends in part on standard errors, thus a values of equivalent magnitude may not both be significant

* $p < .05$, ** $p < .01$

Step 3: Graph the Results in Excel

To aid and enhance interpretation of the results, plot the three-dimensional response surface and examine its features (see Fig. 1 for an example). One good method to achieve this is to use the graphing function in Excel. Appendix 2 walks you through how to create the graph in Excel and can be downloaded for your use.

Step 4: Interpret the Surface Values and Graph

Next, interpret the graph and calculated surface values. There are three things to interpret from our example. First, how does agreement in PSS and POS relate to AC? Second, how does the degree of discrepancy between PSS and POS relate to AC? Third, how does the direction of the discrepancy between PSS and POS relate to AC? As we walk you through the interpretation of the graph, you may follow along by looking at Fig. 1, which contains the graph and a summary of the information presented in the next few paragraphs about how to interpret the graph.

First, response surface analysis allowed us to examine how agreement in the two sources of support related to AC. If there is a linear (additive) relationship along the line of perfect agreement as it relates to AC, a_1 will be significant but a_2 will not. If a_1 is positive, the outcome variable (e.g., AC) increases as PSS and POS increase. If a_1 is negative, the outcome variable decreases as both PSS and POS increase. In this example, the surface tests resulted in a significant positive a_1 value with a non-significant a_2 value (see Table 2). This indicates that when PSS and POS were in agreement, AC increased as PSS and POS increased. In Fig. 1, the highest level of AC is at the back corner of the graph where PSS and POS are both high, and lowest at the front of the graph where PSS and POS are both low. This finding indicates an additive model of support, wherein AC is enhanced by both forms of support in combination.

For most of our research questions, we anticipate a linear relationship between variables, thus we do not expect a significant a_2. A significant a_2 indicates a non-linear slope of the line of perfect agreement (agreement in the two predictor variables relates to the outcome in a non-linear way). If a_2 had been significant and positive, it would have suggested that the line of perfect agreement as it relates to AC is positive and a convex surface (upward curving); a significant and negative a_2 value would indicate a concave surface (downward curving) along the line of perfect agreement (i.e., outcomes could increase or decrease more sharply as both PSS and POS become lower or higher from some point).

Second, interpret how the degree of discrepancy between PSS and POS relates to the outcome variable AC, by assessing the curvature along the line of incongruence ($X = -Y$) as it relates to AC with a_4. A significant negative a_4 indicates a concave surface, that is, AC decreases more sharply as the degree of discrepancy increases. The a_4 value in our example was negative and significant, indicating that as the discrepancy between POS and PSS increased, AC decreased. Figure 1 depicts the results of degree of discrepancy. The graph shows that toward the left and right of the graph, where PSS and POS become more and more discrepant, AC decreases. A significant positive a_4 would have indicated a convex surface, that is, outcomes would increase more sharply as the degree of discrepancy increases (see Fig. 2 for how a graph of our results might have looked in the case of a significant positive a_4).

Finally, consider how the direction of the discrepancy is related to the outcome, as indicated by the slope of the $X = -Y$ line (line of incongruence) as it relates to AC, assessed with a_3. A significant negative a_3 here (see Table 2) indicates that AC is higher when the discrepancy is such that POS is higher than PSS than vice versa.

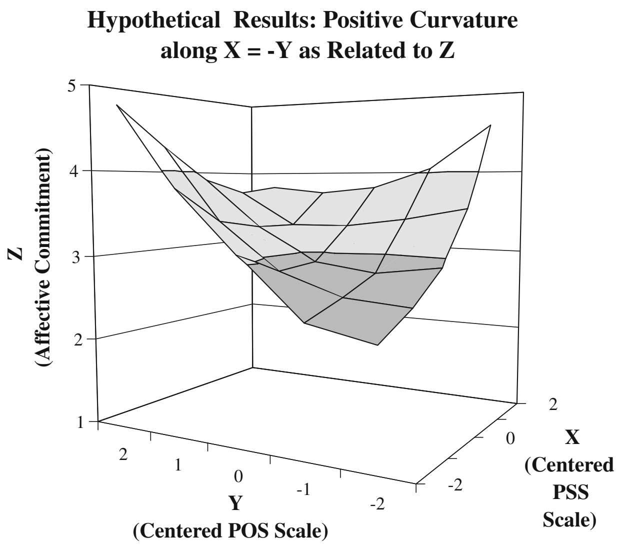


Fig. 2 In this hypothetical graph, unlike in our example, the test of the degree of discrepancy (a_3) would be significant and positive (indicating positive curvature along the line of incongruence ($X = -Y$) as related to affective commitment. That is, affective commitment would be relatively low when perceived supervisor support (PSS) and perceived organizational support (POS) are in agreement, and increase as the degree of discrepancy between PSS and POS increases

Figure 1 depicts these results, showing that at the left corner of the graph where POS is high combined with low PSS, AC is still relatively high, whereas at the right corner of the graph where POS is low combined with high PSS, AC is very low. AC levels decreased less when the discrepancy was such that POS was higher than PSS than when PSS was higher than POS. If we had a significant positive a_3 it would indicate AC is higher when the direction of the discrepancy is such that PSS is higher than POS than vice versa (imagine PSS on the Y-axis and POS on the X-axis with the same results). We include Fig. 3 showing what our results might look like if direction of discrepancy did not matter as much. That is, the graph shows the situation where AC is similarly decreased by dips in both PSS and POS.

Benefits of Polynomial Regression Compared to Difference Scores

Polynomial regression with response surface analysis came about as a solution for the problems associated with using difference scores to analyzing discrepancies in ratings (Edwards 1994, 1995, 2002). Difference scores are the algebraic, squared, or absolute difference between two scores or the absolute or squared difference among a profile of scores. The use of polynomial regression has many

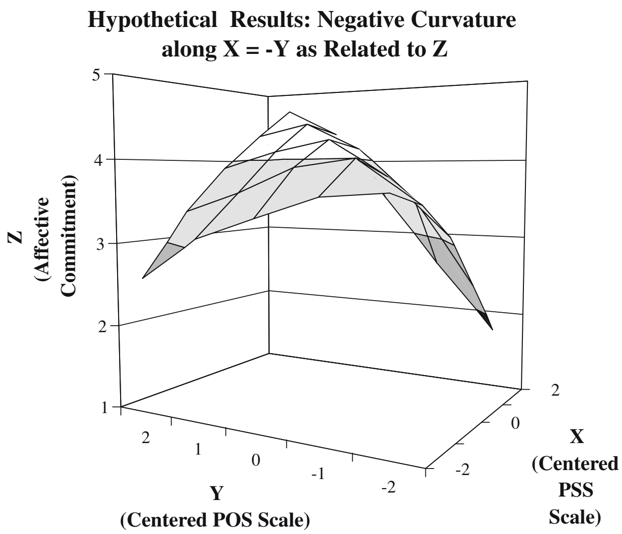


Fig. 3 In this hypothetical graph, as in our example, the test of the degree of discrepancy (a_3) would be significant and negative (indicating negative curvature along the line of incongruence ($X = -Y$) as related to affective commitment. However, unlike in our example, in this case the direction of discrepancy does not matter much (a_4 would likely be nonsignificant, that is, moving away from the center of the graph, affective commitment decreases similarly as the discrepancy between perceived supervisor support (PSS) and perceived organizational support (POS) increases in either direction (PSS high or POS high)

advantages over traditional difference scores, a few of which we highlight here. First, by combining distinct measures into one score, difference scores confound the effects of each of the component measures on the outcome. Difference scores do not tell us the extent to which each of the component measures contribute to the outcome variable. For example, using a difference score, we would not be able to tell whether PSS or POS contributed more to an outcome such as AC. Similarly, we would not be able to tell whether it was better (or worse) for AC to have more PSS than POS or vice versa. Using polynomial regression however, the independent effect of each component measure is retained. This makes it possible to examine the extent to which each component measure contributes to variance in the outcome, helping to overcome problems with ambiguous interpretation and confounded effects. Congruence between PSS and POS ratings, for example, would be represented by a point instead of by the line produced by graphing the results of response surface analysis (see the line of perfect agreement in Fig. 1). By reducing our model to two dimensions, we lose valuable information that aids in the interpretation of our results.

An excellent resource for understanding all the advantages of polynomial regression over difference scores is Edwards (2002). As well, you might consult Atwater et al. (2005) for additional discussion of the topic including empirical examples.

Benefits of Response Surface Analysis Compared to Traditional Moderated Regression

Less attention has been paid to the benefits of polynomial regression with response surface analysis over traditional moderated regression. Traditional regression analyses of interactions provide a *two-dimensional* view of the relationship between combinations of two predictor variables (e.g., PSS and POS) and an outcome variable (e.g., AC, see Fig. 4). Response surface methodology, however, allows for a *three-dimensional* examination of this relationship (see Fig. 1).

To show these benefits of response surface analysis, we present a test of the relationships among PSS, POS, and AC from our example data using a more traditional moderated regression approach. Namely, we conducted hierarchical regression analysis to test the role of PSS as a moderator of the relationship between POS and AC. Following recommendations by Aiken and West (1991), we mean-centered the predictor variables (POS and PSS) to aid in interpretation and to reduce multicollinearity. In Step 1, we entered POS and PSS. In Step 2, we entered the POS–PSS interaction term. Both POS and PSS predicted AC. The interaction term was significant, suggesting that the relationship between POS and AC may depend in part upon PSS. We plotted the relationships between POS and AC at different levels of PSS (i.e., at one standard deviation above and below the mean, cf. Cohen et al. 2003) in Fig. 4. We also conducted simple

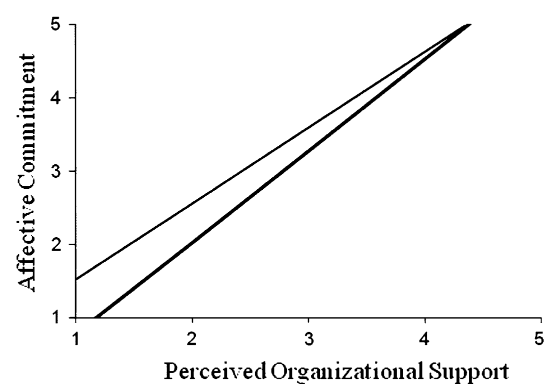


Fig. 4 The *bottom, bolded line* represents the relationship between perceived organizational support (POS) and affective commitment when perceived supervisor support (PSS) was 1 standard deviation above the mean; the *upper line* represents the relationship between POS and affective commitment when PSS was 1 standard deviation below the mean. $N = 173$

effects tests (Aiken and West 1991), which indicated significant positive relationships between POS and AC when PSS was both one standard deviation above, $t(169) = 10.28$, $p < .001$, and one standard deviation below, $t(169) = 8.86$, $p < .001$, the mean PSS score. The slope of the line representing the relationship between POS and AC was steeper when PSS was high than when PSS was low, $t(169) = 2.00$, $p < .001$. If we were to have conducted traditional moderated regression analysis only, we may have concluded that the relationship between POS and AC depends in part upon PSS and that POS is more important to high AC than PSS. This is valuable and accurate; however, as discussed below, response surface analysis provides much more information about how combinations of the two support variables may affect AC.

Figure 1 shows the response surface graph of the results from our example. Figure 4 shows a traditional graph of the two-way interaction between PSS and POS using moderated regression. The traditional graph gives only a snapshot of information compared to the response surface graph. For example, on the response surface graph, moving along the line of perfect agreement from low to high, one can see the level of the outcome variable (AC) when PSS and POS are in agreement but low. One can also see the level of AC when PSS and POS are in agreement but increasingly higher all the way up to the level of AC when PSS and POS are in agreement and high. Traditional moderated regression does not provide such a nuanced assessment of the level of AC when PSS and POS are in agreement.

With traditional moderated regression, one also cannot assess whether there is a non-linearity along the line of perfect agreement as related to AC (e.g., maybe similar levels of support from both sources is good for AC to a point, with diminishing returns once both types of support reach a certain level). Also, response surface analysis tests for and depicts how an increasing degree of discrepancy between predictor variables (PSS and POS) relates to the outcome (AC). The farther away from the line of perfect agreement in either direction, the greater the degree of discrepancy between the predictor variables, and the graph shows the continuum of how the degree of discrepancy between PSS and POS may affect AC. This cannot be seen on a two-dimensional interaction graph, which only shows PSS and POS as discrepant at finite points of PSS (low and high; POS is on a continuum but PSS is not).

Conclusion

In summary, to conduct polynomial regression with response surface analysis you need to:

(1) Determine whether your research design is appropriate for this technique. Are you interested in how the combination of two predictor variables relates to an outcome? Are the variables measured on the same numeric scale, share a conceptual domain and meet the assumptions of multiple regression analysis?
(2) Examine how many discrepancies between the two predictor variables exist in your data set. Is there a sufficient percentage of discrepant ratings on the two variables in your data set (e.g., about 10% or more) to warrant further examination of the relationships of degree and direction of discrepancy on an outcome variable?
(3) Run the polynomial regression analysis and calculate the surface values. Use the syntax (if using SPSS) and formulas in Appendix 1 as well as our description of this step in the text to guide you.
(4) Graph the results in Excel. Use Appendix 2 to guide you.
(5) Interpret the surface values and the graph. Figure 1 shows a response surface graph with visual aids to help you learn how to interpret the graph. We also provide two additional graphs (Figs. 2, 3) that show examples of how other results might look.

Our goal was to offer a highly detailed and accessible explanation of what polynomial regression with response surface analysis is all about from "soup to nuts," that is, from considering the possible uses for it all the way through how to create and interpret the graph that results from it. For the first time to our knowledge in the organizational science literature we provide the syntax in SPSS and how to use Excel to create response surface graphs; we have walked through an empirical example of how to conduct the analyses, we provide a sample table and process to go along with each step, describe the importance of determining whether you have enough discrepancies in your sample to pursue this analysis, and provide very detailed instructions on how to interpret the graph if you have enough discrepancies in your sample to ask such research questions. We hope this paper has piqued your interest in pursuing research questions using polynomial regression with response surface analysis that will push the limits of our current theoretical knowledge.

Acknowledgment This research was supported, in part, by funds from the University of North Carolina at Charlotte.

Appendix 1

See Tables 3 and 4.

Table 3 SPSS syntax and significance test formulas for Step 2 (run the polynomial regression analysis and calculate the surface values): Polynomial regression syntax using variables from illustrative example

Notes	Syntax
Midpoint centering PSS and POS	Compute psscntr = pss – 3
Note we subtracted 3 because it is the midpoint on the 1–5 Likert-type scale on which these variables were measured	Compute poscntr = pos − 3 Execute
Compute the squared PSS and POS terms and the product term of PSS and POS	COMPUTE xsquared = psscntr * psscntr COMPUTE xy = psscntr * poscntr COMPUTE ysquared = poscntr* poscntr Execute
Polynomial regression analysis; AC = affective commitment	REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS BCOV R ANOVA /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT AC /METHOD=ENTER psscntr poscntr xy xsquared ysquared

Note: Asking for BCOV in the syntax will give the covariance matrix in the output necessary for the significance-testing formulas for a_1 through a_4. We chose the /MISSING LISTWISE subcommand consistent with Tabachnick and Fidell's (2007) recommendations to deal with missing data through deletion, mean substitution or another missing value imputation method before running one's main analyses

Table 4 Formulas for calculating the significance tests of the surface values (a_1 through a_4)

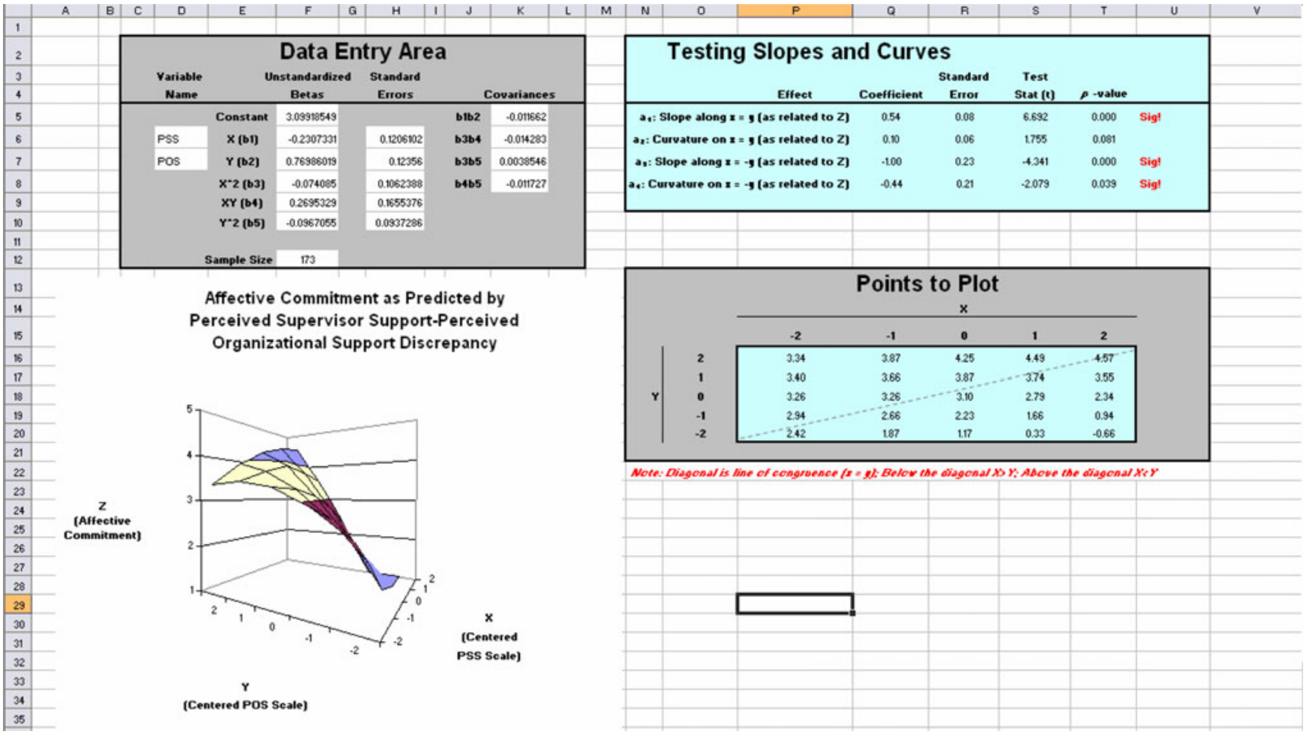
Variable	Equation
a_1	$t = \frac{a_1}{\sqrt{(\mathrm{SE}^2 b_1 + \mathrm{SE}^2 b_2) + 2\mathrm{cov}\, b_1 b_2}}$
a_2	$t = \frac{a_2}{\sqrt{(\mathrm{SE}^2 b_3 + \mathrm{SE}^2 b_4 + \mathrm{SE}^2 b_5) + 2\mathrm{cov}\, b_3 b_4 + 2\mathrm{cov}\, b_4 b_5 + 2\mathrm{cov}\, b_3 b_5}}$
a_3	$t = \frac{a_3}{\sqrt{(\mathrm{SE}^2 b_1 + \mathrm{SE}^2 b_2) - 2\mathrm{cov}\, b_1 b_2}}$
a_4	$t = \frac{a_4}{\sqrt{(\mathrm{SE}^2 b_3 + \mathrm{SE}^2 b_4 + \mathrm{SE}^2 b_5) - 2\mathrm{cov}\, b_3 b_4 + 2\mathrm{cov}\, b_4 b_5 - 2\mathrm{cov}\, b_3 b_5}}$

Note: For the formulas listed above, recall from Table 2 that $a_1 = (b_1 + b_2)$, where b_1 is beta coefficient for perceived supervisor support (PSS) and b_2 is beta coefficient for perceived organizational support (POS). $a_2 = (b_3 + b_4 + b_5)$, where b_3 is beta coefficient for PSS squared, b_4 is cross-product of PSS and POS, and b_5 is beta coefficient for POS squared. $a_3 = (b_1 - b_2)$. $a_4 = (b_3 - b_4 + b_5)$. Also recall that the BCOV subcommand in the SPSS syntax will provide the covariances needed for the "2cov" (two times the covariance) terms listed above

Appendix 2: Sample Excel Screen Shot for Step 3 (Graphing the Results)

Instructions to go with the Excel spreadsheet

1. To download a copy of the Excel spreadsheet for your use, please visit: www.springer.com/psychology/community+psychology/journal/10869.
2. Enter the unstandardized regression coefficients and their associated standard errors from your polynomial regression run in SPSS into the 'Data Entry Area' at the top left of the spreadsheet. Also enter the sample size of your data set in the space provided.
3. Enter the covariances for your regression coefficients in the righthand column of the 'Data Entry Area'. You will get these from your SPSS output from the polynomial regression run (remember, as Table 3 in Appendix 1 indicates, you will include the 'bcov' subcommand in SPSS so that you will get the covariance matrix of regression coefficients).
4. The 'Testing Slopes and Curves' box to the right of the spreadsheet calculates the surface values a_1 through a_4 and assesses their significance. These calculations will occur automatically once you have entered your data into the 'Data Entry Area'. The formulas for calculating a_1 through a_4 also appear in Table 4 in Appendix 1 in case you want to calculate them by hand or choose not to download this Excel spreadsheet.
5. The 'Points to Plot' box shows the predicted values of the outcome variable (affective commitment) for each combination of the two predictor variables based on the polynomial regression equation and associated unstandardized beta weights. The values −2 to 2 in the gray area represent the points along the *X*- and *Y*-axes and are based on centered-scores of a 5-point Likert-type scale ranging from 1 to 5 (you can change these values to fit the parameters of your measures, keeping within the 5-point framework, e.g., if you have a 7-point scale you could use −4, −2, 0, 2, and 4 as your



values). Values are dependent upon the original metric of the scale. PSS values are across the top, POS values are down the left-hand side.

The polynomial regression formula from our data was:

$$\begin{aligned} \mathrm{AC} = {} & (3.10) + -.23(\mathrm{PSS}) + .77(\mathrm{POS}) \\ & + -.07\left(\mathrm{PSS}^2\right) + .27(\mathrm{PSS} * \mathrm{POS}) \\ & + -.10\left(\mathrm{POS}^2\right). \end{aligned}$$

The Excel sheet calculates the predicted values of AC in the ‘Points to Plot’ box automatically, but as an example, to create the predicted value for the cell −2 PSS and 2 POS, plug −2 and 2 into the polynomial regression formula as follows:

$$\begin{aligned} & 3.10 + -.23(-2) + .77(2) + -.07\left(-2^2\right) \\ & \quad + .27(-2 * 2) + -.10\left(2^2\right) \\ & \quad = 3.34. \end{aligned}$$

6. The Excel spreadsheet automatically creates the graph. But if you want to do this on your own, you would create a table like the ‘Points to Plot’ table. Then highlight the table including the −2 to 2 values on both sides, choose “insert chart,” then choose “surface chart.” If using the table set up as shown above, choose “series in columns” and continue with the chart wizard. The minimum and maximum on the *Z*-axis (the axis for the outcome variable, in our case, AC) should span the minimum and maximum values of the scale of the original outcome variable (in our case, 1 is the minimum and 5 is the maximum). Values on the diagonal represent the line of perfect agreement. Values below the diagonal represents when PSS > POS. Values above the diagonal represents when PSS < POS.

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