AN EMPIRICAL STUDY OF THE INDUSTRIAL MARKETING MIX

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ABSTRACT

An empirical study is made of how personal selling, advertising and technical service expenditures are associated with industrial products' gross contribution to profit. The implications of a multiplicative model relating the average gross contribution per customer to industrial marketing spending rates are discussed. Robust regression is used to estimate the model's parameters on the basis of a sample of 50 industrial products.

Results indicate that personal selling expenditures are the single most important factor of the industrial marketing mix. They do not support the hypothesis that increasing returns to scale exist in industrial marketing. They also shed some light on the possible substitution between personal selling and industrial communication expenditures.

Introduction

The relationship of industrial marketing activities to a product's contribution to profit has not been well established. Recently, a review appeared of the existing information on the effectiveness of industrial marketing activities, particularly the effectiveness of industrial advertising in terms of sales and profits (see Lilien et al. [1]). The authors concluded that only a limited number of empirical studies were available. They did identify evidence of economies of scale, threshhold effects and interaction effects between industrial communication and personal selling.

This paper investigates on the basis of data collected through the ADVISOR research project [2] how personal selling, advertising and technical service expenditures are related to industrial products' gross contribution to profits.

Our decision to use the gross contribution to profits as a measure to be related to these "budgeted" marketing activities comes from the fact that the gross contribution to profits is made up of three components -- unit price, average total cost, and quantity sold which could all be influenced by the level of these marketing activities.

The relation between a product price and the company's marketing activities has been analyzed by Palda [3]. He considers that any pricing decision must be taken against the background of the firm's total marketing strategy, so that a product price appears more as a dependent variable than as an independent one. Recently, Lambin [4], argued that "consumers exhibit lower price responsiveness in high-intensity advertising markets than they do when the advertising level is low. Companies therefore have the opportunity to charge above-normal prices." Lambin mentions, however, that this opportunity tends to be limited by the use of price controls. The question is: is this comment applicable to industrial markets?

The relation between the quantity of a product sold and the company's marketing activities is one of the basic postulates of marketing theory and often the justification for these expenditures. If we accept this postulate for industrial products, the relation between the firm's marketing activities and the average cost of production is clearer. Usually when the company operates below capacity, an increase in the quantity produced leads to a decrease in the average product cost.

In this paper, we relate the average gross contribution of industrial products, on a customer basis, to the spending rate for personal selling, technical service, and advertising activities. Our results indicate that a substantial part of the variation in industrial products' gross contribution to profit may be explained with these three marketing activities. As a regression model is only descriptive, dealing with measures of association rather than causal relationships [5], a strong interpretation of our results needs the assumption that industrial marketing activities do indeed affect a product's gross contribution to profit.

Interpreted this way, our results underline the importance of personal selling in the industrial marketing mix. They do no support the hypothesis that increasing returns to scale exist in industrial marketing. Finally, they allow us to speculate about substitution between personal selling and advertising expenditures.

Data Collection Procedure

Our analysis has been performed on data received from five out of twelve industrial companies that participate in the ADVISOR research project. Each of these companies was requested to provide information about as many industrial products as it could. No special requirements were set concerning the characteristics of the products to be selected.

Data were collected by questionnaire. The specific information requested arose from a series of personal interviews with industrial marketing managers about the key variables that they take into account in budgeting decisions. More than 190 elements of information were introduced in the questionnaire. The questions were grouped into six broad areas:

- Company characteristics
- Product qualities
- Cost; profit information
- Growth, production and distribution
- Use; customer and competitive characteristics
- Advertising, personal selling and technical service

Due to the confidentiality of some of the requested information, companies were allowed to multiply actual numbers by a "security coefficient." This protection mechanism introduces a small random component in some of the data so that the actual amount is only known with a 10% margin. We expect the effect of this random component on our results is limited due to the way we defined the variables.

Our sample consists of 50 industrial products that range from raw materials and chemicals to more elaborate products such as machinery and equipment. Most are in one of the first three stages in the product life cycle and are associated with oligopolistic markets.

Definition of the Variable Under Study and Preliminary Analysis

Our purpose is to study the relationship between industrial products' gross contribution to profits and the associated level of personal selling, technical service and advertising expenditures. We have attempted to define these variables in such a way that they would have both an operational meaning within the industrial marketing decision making context, and could be estimated on the basis of the available data.

Our analysis has been limited to mainly seven variables whose definitions follow:

A_t; A_{t-1} refers to the Advertising spending rate per potential customer in 1973 and 1972 respectively.

P_t; P_{t-1} refers to the Personal selling spending rate per potential customer in 1973 and 1972.

S_t; S_{t-1} refers to the technical Service spending rate per actual customer in 1973 and 1972.

G_t refers to the average gross contribution to profit per actual customer in 1973. This amount is obtained by the following relation

$$G_t = (p_t - c_t)\, q_t \,/\, n_t \quad , \quad \text{where}$$

p_t = average unit price for the product in 1973.

c_t = average total cost of production for the product, only excluding marketing costs.

q_t = total quantity sold in 1973.

n_t = actual number of customers in 1973.

In addition to these seven variables, we defined several dummy variables to control for a stage in the life cycle effect and for a company specific effect. These last variables were expected to represent the composite effect of many company-product characteristics not explicitly introduced in the model.

Note that some of these variables were defined on the basis of the actual number of customers while others were on the basis of the potential number of customers. Indeed, it makes more sense to relate industrial advertising and personal selling spendings to the potential number of customers as a large part of these expenditures is aimed at drawing in new customers. On the other hand, the average gross contribution to profits, and technical service expenditures are related to the actual number of customers. In this study, the potential number of customers was considered to be the total number of customers for the industry reported in the questionnaire.

A preliminary statistical analysis of the seven variables of interest was made and is reported in Choffray [6]. Empirical distributions for these variables were found to be highly skewed. Measures of centrality were very sensitive to a few extreme observations and the need for stabilizing transformations was evident. A logarithmic transformation was used, and considerably improved the stability of the various measures of centrality.

A correlation analysis was also performed (see Choffray [6] for details). It was found that the advertising spending rate in 1972 was more strongly related to the average contribution to profit than the advertising spending rate in 1973, suggesting that industrial communication expenditures might have a delayed effect on the product's contribution to profit.

In order to determine if the effect of advertising expenditures on the average contribution to profits was direct or indirect -- with personal selling expenditures as an interviewing variable -- we used a method suggested by Simon [7]. The partial correlation between advertising spending rate and average contribution to profit keeping personal selling expenditures constant appeared to be $\approx .18$. This doesn't allow us to reject the hypothesis that the advertising spending rate has a specific effect on the average gross contribution to profits of industrial products. On the other hand, the partial correlation coefficient between technical service spending rate and average contribution to profit, keeping personal selling expenditures constant, turned out to be $\approx .06$. This indicates that the effect of technical service expenditures on the average gross contribution of industrial products might be deeply intertwined with that of personal selling.

The Model

Assume a relation between the three industrial marketing spending rates under study and the average gross contribution to profit of the following, multiplicative form:

$$G_t = K \prod_J M_J^{\alpha_J},$$

where the M_J's represent the various marketing spending rates.

This model has some important characteristics. It allows for interactions between predictor variables and its interpretation provides interesting insights into the process of how industrial marketing spending rates might affect products' gross contribution to profits. In this respect it can easily be shown that

1 - α_J represents the elasticity of industrial product gross contribution with respect to marketing spending rate M_J.

2 - the nature of returns to scale can be inferred from the simple summation of the model parameters: $\sum_J \alpha_J$.

3 - the rate of substitution of marketing activity M_i for marketing activity M_1 is given by

$$S_{i1} = -\frac{dM_i}{dM_1} = \frac{\alpha_1}{\alpha_i}\frac{M_i}{M_1}$$

In addition, this model is linear in the logarithms. Given the available data, the new dependent variable will be more nearly normal than if the original values had been used. The statistical tests on the parameters of this multiplicative model will then be more meaningful than if a simple linear model relating the original "rates" had been used.

The use of a multiplicative model has important limitations:

- First, it is clear that the model does not allow for a negative average gross contribution to profits as all M_J are always ≥ 0. This does not raise a crucial problem, however, due to the definition we gave of the gross contribution as the difference between sales and total production cost. Indeed, one might reasonably assume that companies discontinue production, when their average production cost is constantly higher than their selling price.
- Second, assuming $\alpha_1 > 0$, the model allows for infinite contribution to profits when infinite amounts are spent on marketing activity M_1. For this reason, it is clear that the model must only be considered as a useful approximation of the true relation within the range of the observed data.

- Third, the model implies that the "effect" of an additional dollar in any M_J is the same for all industrial companies represented in the sample.

Parameter Estimation

There are several estimation problems related to our data. The first is that the independent variables in our model are subject to error. Indeed, the use of security coefficients resulted in the introduction of a random component in the reported marketing spending amounts.

Regression techniques, used to estimate the model parameters, assume that only the dependent variable -- i.e. the average gross contribution to profits -- is subject to error. When both the dependent and the independent variables are subject to error, least squares regression becomes highly inefficient [8]. In order to estimate our model, we then assume that random fluctuations of the independent variables are negligible.

Another problem is multicollinearity. This is not unexpected as the several spending rates are intercorrelated and further, that for any given marketing activity, say personal selling, the autocorrelcation of its spending rate over time is quite high.

This multicollinearity problem, has two important implications.

- First, ordinary least squares regression usually lead to large standard deviations of the estimated parameters α_J. These coefficients are often large in absolute value, and may even have the wrong sign.
- Second, due to the interdependency among the predictor variables it becomes more difficult to select those which are most meaningful.

For these reasons, we decided to use Ridge regression, an excellent description of which is given by Hoerl and Kennard [9] and [10]. The idea underlying Ridge regression is that we can study the sensitivity of the regression estimates to the multicollinearity problem, by adding a small positive constant k on the diagonal of (X'X), where X denotes the matrix of predictor variables. The important point is that we know that for some value of k, our estimates will be closer to the true value of the parameters than the ordinary least squares estimates.

Our first task is to reduce the original set of six marketing spending rates -- A_{t-1}, A_t, P_{t-1}, P_t, S_t, S_{t-1} -- to be included in the final model. The use of the Ridge Trace [10] as a way to identify the most meaningful subset of prediction variables led to the selection of A_{t-1}, P_t, S_t.

The Ridge Trace for the corresponding model

$$C_t = K A_{t-1}^{\alpha_a} P_t^{\alpha_p} S_t^{\alpha_s}$$

appears in the Appendix, Exhibit I. This Trace is fairly stable. This is specifically true for α_a^*, the standardized coefficient of A_{t-1} and to a lesser extent for α_p^* and α_s^*. The question of deciding whether S_t should be dropped from the model is unclear. The effect of technical service and personal selling spending rates on the average gross contribution to profits are deeply intertwined so that both variables may in fact represent the same basic factor. We decided however to keep S_t in the model on the basis that conceptually we expected the technical spending rate to have a separate effect -- weak perhaps -- on the dependent variable.

The estimated model parameters, evaluated at $k_a = .07$, are given by:

TABLE I

Response Variable n=50	Scale Factor K	Ridge Estimates of the Parameters α_a	α_p	α_s	R^2	CR^2	F(3/46)
G_t	162	.17	.79	-.08	.26	.21	5.29
(t-stat)	(2.7)	(1.29)	(2.49)	(.47)			

The fit that we get is unsatisfactory and the residuals analysis indicates that some extreme observations are present in the original sample.

In order to study how the estimates of the model parameters were sensitive to this problem, we used Robust Regression, a description of which appears in Choffray [6]. Robust Regression provides estimates of the parameters α_J that are not significantly affected when the assumption of normality of the distribution of errors is no longer supported by the data.

Our concern comes from the fact that ordinary L.S. regression associates an important loss to outliers, and clearly, this is not justified when these extreme observations are the result of errors at some stage of the data collection or coding phase.

In our Robust estimation, we use a bounded loss function that associates a constant loss to extreme observations, and so considerably reduces their influence on the estimates.

The Robust Regression, was performed on all 50 observations with the model

$$G_t = K A_{t-1}^{\alpha_a} P_t^{\alpha_p} S_t^{\alpha_s}$$

The Robust Trace for this model is shown in the appendix, Exhibit II. The Trace relates the standardized regression coefficients to the parameter r. When r=1, the Trace reproduces the Least Absolute Residual (LAR) estimates of the parameters, and for r=0, it reproduces the least squares estimates. As r increases, more points are considered as extreme and are set aside.

The estimates of the model parameters are sensitive to a few individual sample points. Note however that the relative importance of the coefficients does not change. The standardized coefficient α_p^* is the largest of the three, independently of the value of r. The coefficient of A_{t-1}, α_a^* is fairly stable. As expected, the only problem concerns α_s^*, the standardized coefficient of S_t, whose sign changes over the range of r.

The interest of a Robust regression lies in the residuals analysis. Indeed, at r=.175 we know that our estimates are 95% efficient and we would like to know how many points of the original sample have been effectively discarded. For this reason we have included in the appendix, the residuals and weights of the original observations corresponding to r=.175 and r=.238. These values of r correspond approximately to an efficiency of .95, and .80 respectively.

For r = .175, the Robust procedure discards 8 points and gives a weight less than .7 to two other points. The resulting weighted R^2 = .57. For r = .238, 7 additional points receive a weight less than .7 and the resulting weighted R^2 is .64. We will not consider larger values of r, which result in a low efficiency of the estimates and a substantial reduction of the effective sample.

It is interesting to see that at r = .175 and r = .238 the estimates of α_p^* and α_s^* do not change very much. Note that for these values of r, the estimate of α_p, (.48), can be considered as a lower bound on the true value of α_p, as the trace for α_p^* reaches its minimum in the neighborhood of r = .2. So we feel reasonably confident in the estimates of α_a, α_p and K which correspond to r = .175 and are given by

TABLE II

Response Variable	Scale Factor	Robust estimates of the parameters			Weighted	Weighted
n = 50	K	α_a	α_p	α_s	R^2	F (3/46)
G_t	131	.14	.48	.09	.57	20
(t-stat)	(8.83)	(2.64)	(3.72)	(1.28)		

The estimates of K, α_a and α_p are statistically different from zero at the .05 level, while the significance of α_s cannot be established.

Note, that we have lost 5% of efficiency, relative to the usual L.S. estimates. However, we certainly accept this "insurance premium" that guarantees us from the harm that some extreme observations could cause to our estimates.

Two additional Robust Regressions were run to test whether the estimates of α_a, α_p, and α_s would be considerably affected by taking into consideration:

- the product stage in the life cycle, and
- a company factor

In order to introduce these effects into the model, we defined two dummy variables to account for the stage in the life cycle effect -- z_1, z_2 -- and four others -- K_2, K_4, K_9, K_{10} -- to represent the company-specific effect. These variables were introduced in the model so that their coefficient would affect the scale factor. Results are presented in Table III for r=.175.

These results imply a life cycle effect on product contribution to profits. Indeed for a given level of marketing spending rates industrial products that are in stage I of the life cycle have relatively higher average gross contribution (K ≈ \$666) than products that are in stage II (K ≈ \$153), and than products that are in stage III (K ≈ \$138). Note that the explicit consideration of the stage in the life cycle in our model did not improve the fit substantially. Indeed, the weighted R^2 at r = .175, which is now .63, was .57 when only the three marketing variables were considered.

The presence of a company-product effect is especially evident for company number 10. This may suggest that some variables related to industrial products' gross contribution to profits have been omitted from the model and should be introduced in further analysis. When we introduce a company effect, α_s, the coefficient of the technical spending rate becomes statistically different from zero. Note also that the fit is significantly improved, as the weighted R^2 is now .83.

For comparison purposes, we have reproduced in Table IV the main results of our analyses concerning the hypothesized effect of advertising (α_a), personal selling (α_p) and technical service (α_s) spending rates on the average gross contribution to profits of industrial products.

TABLE III

Model I: $LnG_t = LnK + C_1 Z_1 + C_2 Z_2 + \alpha_a LnA_{t-1} + \alpha_p LnP_t + \alpha_s LnS_t$

Coefficient	Robust Estimates of the Parameters (t-stat)	Fit
LnK	4.9295 (9.27)*	
C_1	1.5729 (2.54)*	weighted R^2 = .63
C_2	0.0983 (.29)	weighted F(5/44) = 14.7
α_a	0.2109 (3.65)*	
α_p	0.4286 (3.33)*	
α_s	0.0619 (.86)	

Model II: $LnG_t = LnK + C_2 K_2 + C_4 K_4 + C_9 K_9 + C_{10} + K_{10} + \alpha_a LnP_{t-1} + \alpha_p LnP_t + \alpha_s LnS_t$

Coefficient	Robust Estimates of the Model Parameters	Fit
LnK	3.6941 (5.30)*	
C_2	0.6767 (1.68)	weighted R^2 = .83
C_4	0.8611 (1.28)	weighted F(7/42) = 30.48
C_9	-0.3631 (.76)	
C_{10}	7.9782 (11.26)*	
α_a	0.1217 (2.07)*	
α_p	0.3710 (2.76)*	
α_s	0.3705 (4.13)*	

* means that the corresponding estimates are statistically different from

The scale factor, K, has not been introduced in this table as:

- the value of K depends on the stage in the product life cycle and on the company under consideration.
- the value of K does not affect the analysis of the results of our study.

TABLE IV

Robust Estimates of the Parameters

r = .175

model parameters	simple Model	"Life Cycle" Effect Added	"Company" Effect Added
α_a	.139 *	.210 *	.121 *
α_p	.482 *	.428 *	.371 *
α_s	.095	.062	.370 *

* means that these estimates are significantly different from zero at the .05 level.

Discussion of Results

We will eliminate technical service from our discussion of results as the estimate of α_s has been found quite unstable, and strongly influenced by the company factor. A larger data base, however, might help dissociate the specific effect of technical service expenditures from the effect of personal selling.

The results of this study do not allow us to reject the hypothesis that higher gross contribution to profits are supported by larger personal selling and communication spending rates. Indeed, the results imply that those industrial products for which more is spent in personal selling and advertising per potential customer tend to be those realizing the largest gross contribution to profits on a customer basis.

The best model to relate industrial products' contribution to profits to marketing spending rates was found to include A_{t-1}, P_t and S_t. The results, however, were not changed fundamentally when A_t was used instead of A_{t-1}. It is then delicate to make inferences concerning the lagged effect of communication expenditures, although the results seem to indicate that advertising could have a lagged effect.

The relative importance of these two elements of the industrial marketing mix is interesting to consider. The personal selling spending rate has been consistently found to be the most important element of the marketing mix in terms of its association with the average gross contribution to profits. Indeed, the elasticity of the average gross contribution to profit, with respect to the personal selling spending rate was found to be approximately between two and three times larger than the elasticity of this same measure with respect to the advertising spending rate. If we were to make the (strong) assumption of causality, the model then implies that the budget should be allocated in such a way that the ratio of the communication spending rate to the personal selling spending rate equals the ratio of the elasticity of the average gross contribution with respect to both of them. I.e., $A/P = \alpha_a/\alpha_p$, where α_a/α_p was found to lie in the interval [.33, .50]. As these two marketing spending rates are both defined with respect to the number of potential customers, our data indicate that the overall industrial advertising budget should represent between 1/3 and 1/2 of the total personal selling budget! This contrasts with the median ratio (≃ .11) found in our sample.

The substitution between personal selling and communication expenditures is also interesting to discuss. The rate of substitution of communication for personal selling is given by

$$S_{a,p} = -\frac{dA}{dP} = \frac{\alpha_p}{\alpha_a} \cdot \frac{A}{P}$$

As the ratio α_p/α_a varies approximately in the interval [2,3] we can get an estimate of the upper and lower bounds on $S_{a,p}$ when we know the current level of both A and P. On the basis of the observed data it appears that a reasonable estimate of A/P is 1/6.* So, if we assume that the estimated relation is indeed true, the bounds on $S_{a,p}$ are:

$$S_{a,p}^{(upper)} = .5$$

$$S_{a,p}^{(lower)} = .33$$

*This estimate is based on the ratio of the average spending rate for advertising and personal selling in 1973.

Again, a causal interpretation of our model could lead to more spending (on the average) for advertising at the expense of personal selling in our sample.

As far as the nature of returns to scale is concerned, the results indicate that the sum of α_a, α_p, and α_s is consistently less than 1. So, these results do not support the hypothesis that increasing returns to scale, in terms of products' gross contribution to profits exist in industrial marketing.

Conclusions

The results of this study allowed us to give tentative answers to some important questions faced by industrial marketers. Specifically, our results indicate that:

- the hypothesis according to which industrial marketing activities support larger contribution to profits cannot be rejected.
- personal selling expenditures are the most important element of the industrial marketing mix in terms of its association with products' gross contribution to profit.
- the hypothesis according to which industrial marketing activities produce decreasing returns to scale is supported by the available data.

Finally, if our model is given a causal interpretation, then companies represented in the sample could be overspending on personal selling.

By using personal selling, communication and technical service spending rates, we were able to "explain" 57% of the total variation in industrial products' contribution to profits. As noted earlier, the importance of the company effect confirms that some important product-market characteristics were omitted from the model. Future research should concentrate on the identification of these characteristics and on their integration in a model.

Many problems we encountered in this study were associated with the use of cross-sectional data to estimate a model of response to industrial marketing activities. From a methodological point of view, the use of cross-sectional data to estimate such a model presents serious weaknesses that have been discussed by Quandt [11].

Despite these weaknesses, the study provides some indications about how industrial marketing activities might work. The use of time series data could allow us to dig deeper into the industrial marketing mix problem.

APPENDIX

EXHIBIT I. RIDGE TRACE

Model $G_t = K\, A_{t-1}^{\alpha_a}\, P_t^{\alpha_p}\, S_t^{\alpha_s}$

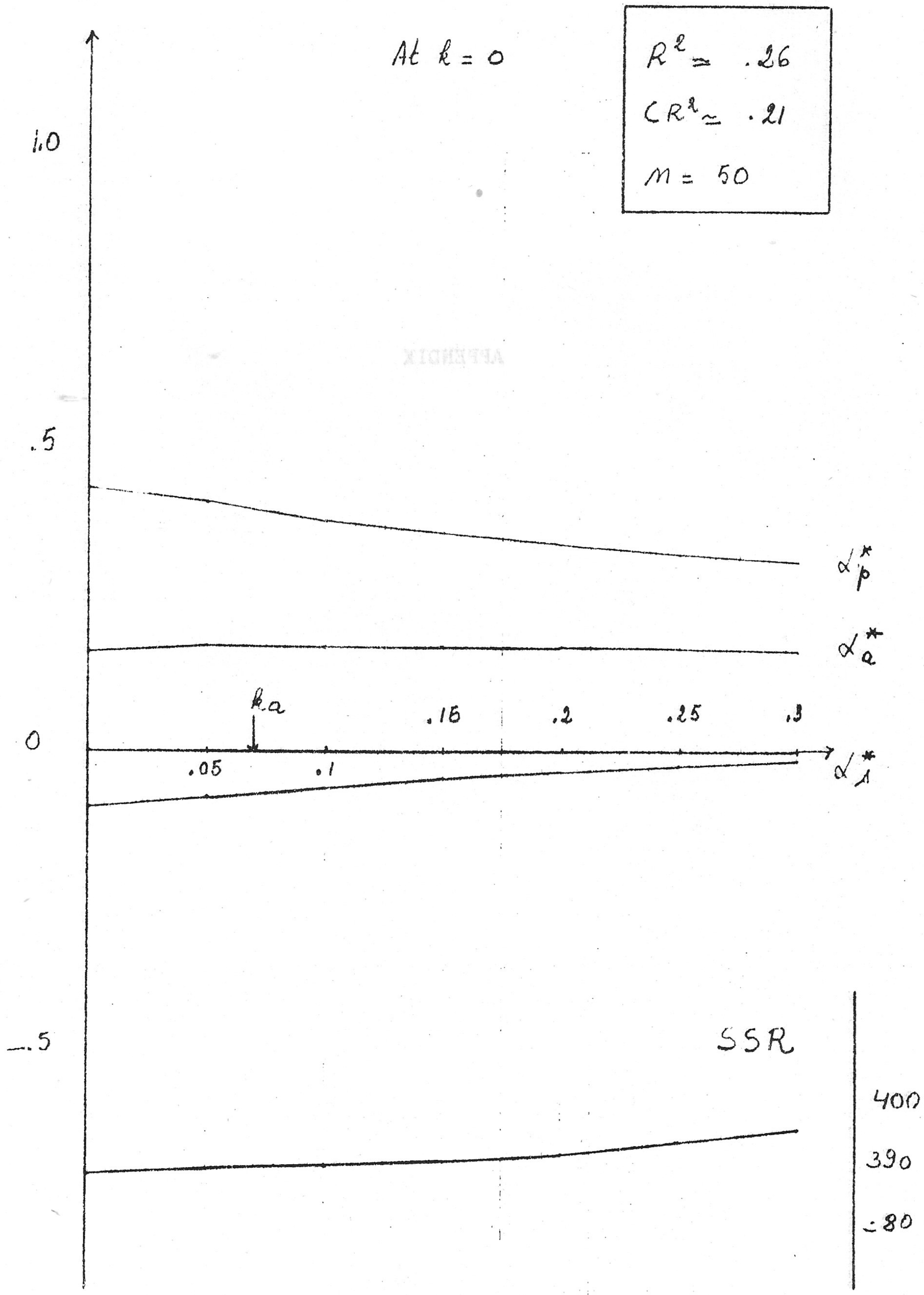
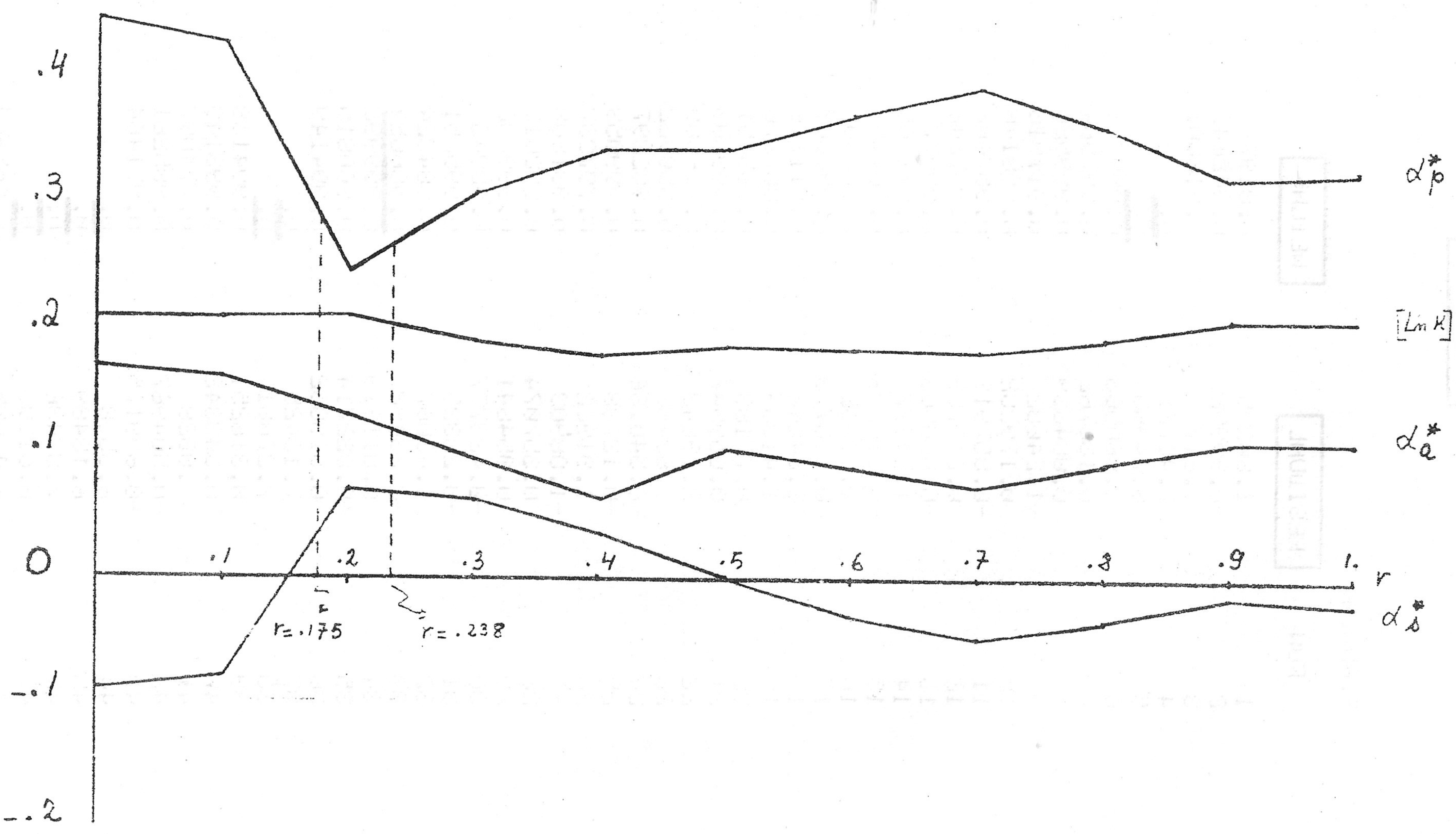


EXHIBIT II

ROBUST TRACE FOR $G_t = K A_{t-1}^{\alpha_a} P_t^{\alpha_p} S_t^{\alpha_s}$



ROBUST REGRESSION RESIDUALS

$r = .175$

R.AND.W

ROW	RESIDUAL	WEIGHT
1	1.80295	0.81979
2	-0.999527	0.942642
3	1.217	0.916801
4	7.46721	0.
5	6.74965	0.
6	-0.068563	0.999773
7	0.188762	0.997964
8	-0.064659	0.999566
9	-1.24882	0.911916
10	0.179282	0.998146
11	-0.657919	0.957402
12	0.217759	0.997242
13	-0.068563	0.999773
14	1.84277	0.811965
15	-0.816286	0.961559
16	-1.09052	0.902505
17	-0.138173	0.998869
18	-1.24244	0.911716
19	1.41339	0.887276
20	-0.77183	0.965451
21	0.059547	0.999803
22	2.29843	0.716609
23	1.63463	0.850922
24	-0.540186	0.982897
25	-0.12738	0.999053
26	1.91922	0.797837
27	-1.08903	0.931808
28	0.357074	0.992013
29	0.054641	0.999832
30	-0.423777	0.98943
31	-0.28325	0.995251
32	1.43067	0.884324
33	-2.83492	0.388624
34	0.011819	0.999992
35	-0.822714	0.960815
36	0.318832	0.994149
37	7.13425	0.
38	7.27681	0.
39	0.316251	0.994138
40	0.343342	0.993149
41	2.0328	0.774097
42	-0.504967	0.985261
43	-0.699175	0.971464
44	6.3558	0.
45	6.18489	0.
46	7.87436	0.
47	6.61303	0.
48	-2.49689	0.669424
49	-0.327788	0.993782
50	0.648643	0.975675

ROBUST REGRESSION RESIDUALS

$\boxed{r = .238}$

R.AND.W

ROW	RESIDUAL	WEIGHT
1	1.60035	0.686699
2	-1.00913	0.867556
3	1.25931	0.806647
4	7.44029	0.
5	8.75689	0.
6	-0.112694	0.998273
7	0.165708	0.996291
8	-0.062361	0.999404
9	-1.24487	0.801132
10	0.240766	0.992555
11	-0.767	0.920006
12	0.200036	0.994831
13	-0.112694	0.998273
14	1.83527	0.598474
15	-0.852968	0.944444
16	-1.92152	0.565235
17	-0.101961	0.995462
18	-1.16697	0.822364
19	1.43095	0.745378
20	-0.711973	0.955564
21	0.168169	0.978551
22	2.38689	0.554427
23	1.7035	0.651236
24	-0.476191	0.985879
25	-0.120501	0.997991
26	2.00588	0.535921
27	-1.03681	0.858571
28	0.321241	0.981108
29	-0.061208	0.999413
30	-0.332146	0.982523
31	-0.215812	0.993295
32	1.44865	0.738198
33	-2.80889	0.219606
34	0.043176	0.999785
35	-0.771363	0.920513
36	0.42296	0.977033
37	7.16263	0.
38	7.23151	0.
39	0.252135	0.991168
40	0.330934	0.985367
41	2.15355	0.404944
42	-0.465482	0.968573
43	-0.656072	0.944162
44	6.41082	0.
45	6.22667	0.
46	7.89978	0.
47	6.61033	0.
48	-2.50708	0.322888
49	-0.383571	0.980685
50	0.684423	0.953792

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