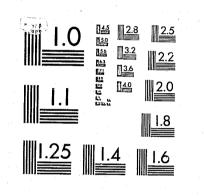
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THE CONTROL OF COLLUSIVE BIDDING IN THE HIGHWAY CONSTRUCTION INDUSTRY

by

Jonathan S. Feinstein Frederick C. Nold Michael K. Block

February 18, 1983

CJRS 7

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Rhodes Associates, 706 Cowper Street, Palo Alto, CA 94301

Executive Summary

Our assessment of the deterrent effect of antitrust enforcement in highway construction has proceeded in three steps: 1) the calculation of contractors' profits as a measure of the prevalence of collusive bidding; 2) the construction of series measuring contractors' perceptions of Department of Justice enforcement efforts; and 3) statistical analysis of the apparent effect of the series on our measure of prevalence.

of a deterrent effect.

The simple ordinary least squares regressions reported suggest a deterrent effect for five of our six elemental antitrust enforcement series. While nothing about the magnitude of the effects can be gleaned from the analysis presented, the consistency of the negative relationship between our indicator of the level of collusion and our enforcement series argues for the presence

Collinearity among the six enforcement series hampered our analysis of how the different aspects of antitrust enforcement measured by the six series interact with one another to affect the level of collusion. Condensing the six to the expected monetary loss facing colluders produced a single measure of enforcement which consistently indicated a deterrent effect for any change or combination of changes in the enforcement series which increased expected loss. A less complete condensation into measures of the severity

of the penalty leveled against colluders and measures of the likelihood of apprehension and conviction yielded mixed results. Only severity appeared to have a consistent negative association with our indicator of the prevalence of collusion. 0

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We took our analysis of severity one step further by breaking that variable into its expected fine and expected jail sentence components. The expected fine was consistently negatively related to our measure of the level of collusion. On the other hand, expected jail sentence was insignificant or showed a positive association. This would seem to suggest that jail sentences are not effective in deterring collusion among highway contractors. However, we noted that average sentences are quite short and may not accurately reflect time served: We reanalyzed the data, substituting the likelihood that a defendent would be jailed for the expected jail sentence. This changed the results substantially, especially in the post 1979 period--a period where we argued that our enforcement series should most closely parallel the threat of antitrust enforcement perceived by construction contractors. The threat of going to jail significantly affected the level of collusion in the post 1979 period, while expected fines appeared relatively unimportant.

Resolving the question of whether jail and fines have a qualitatively different effect on collusive behavior, and sorting out the contributions of the different components

ii

of antitrust enforcement, will require data on a wider variety of situations where the Department of Justice has adopted more diverse enforcement strategies. In addition, our focus has been on federal activities, although states have been active in enforcement efforts. In particular, some states have collected significant damages from those convicted of colluding on highway projects. Nonetheless, this research suggests that increasing antitrust enforcement, especially penalties, is associated with lower levels of collusion amongst highway construction contractors.

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NCJRS APR 15 1965 AGQUISITIONS Introduction

In a previous paper we developed a theoretical model of collusive pricing in the presence of antitrust enforcement.¹ Our model has two major predictions: first, that in most cases increasing antitrust enforcement efforts deters collusion; and second, that increasing the penalties of convicted colluders unambiguously decreases a colluder's optimal markup of price over cost. Our earlier paper tested this model's predictions on the bread baking industry. Recent Department of Justice activity in the highway construction industry provides an opportunity for further testing of our deterrence model. The concentration of federal antitrust efforts on highway construction bid rigging has generated sufficient data for us to pursue a more detailed analysis of separate aspects of antitrust enforcement. In addition, the rather detailed data that is available on highway construction projects from the Federal Highway Administration² provides the basis for our

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²The engineer's estimate of project cost, low bid and identity of low bidder, and other general data about the project were made available to us by the Federal Highway Administration. This data covers roughly 13,000 highway construction projects between 1975 and 1981 and provides the basis for this analysis. The engineer's estimate is compiled by state departments of transportation.

¹See Block, Nold and Sidak, "The Deterrent Effect of Antitrust Enforcement," Journal of Political Economy, June 1981.

measurement of the prevalence of collusion on a project by project basis.

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In the next two sections we discuss how we developed measures of the prevalence of collusive bidding and the levels of antitrust enforcement. We then present our empirical results. An appendix contains our data and some supporting empirical analysis.

Estimating the Prevalence of Collusion in Highway Construction In order to gauge the deterrent effect of antitrust enforcement in highway construction we must first develop a way to accurately assess the prevalence of collusive bidding. Highway construction is an auction market in which state highway agencies collect bids from contractors on a project by project basis, and normally award each project to the lowest bidder. As part of this process, state engineers commonly estimate what a project should cost: we call this estimate the engineer's estimate. A very crude indicator of the prevalence of collusion would be the winning contractor's profit rate on a project calculated as the ratio of lowbid to the engineer's estimate. We call this variable MARKUP. We have used state engineer's cost estimates, rather than developing independent cost functions, because of the variety and complexity of highway construction projects and other empirical problems.³ We corrected MARKUP for the level of economic activity in highway construction, a particularly important correction for this industry, which is notoriously cyclical. The rationale for this correction is that in "good" times profits of all contractors will rise, and hence truly competitive contracts may appear to have inflated profit

³Projects vary from simple resurfacing to complex bridge work, and it is not uncommon for a project to have 100. line items. The empirical problems arise from the fact that the data reflect the operation of auction markets with an unknown incidence of collusive bidding.

margins, and therefore may be incorrectly labeled collusive by a procedure which relies solely on MARKUP. Conversely, in depressed times collusive contracts may have below average markups (which are nonetheless still above depressed competitive markups) and be incorrectly labeled competitive. The correction was achieved by regressing MARKUP against a variable measuring construction activity called CYCLE, and state dummies.^{4,5} The refined measure of profits we use as our indicator of the prevalence of collusion is the residual from this regression, denoted RESID.

Although an improvement over MARKUP, RESID suffers from a number of problems as an accurate measure of highway contractors' profits. The most important of these arises when engineers' estimates are based on bids for previous contracts. In this case, when collusion has occurred in the past, past jobs will contain inflated profit margins which will tend to inflate the engineer's estimate above a project's true competitive cost.⁶ Thus

⁴Several different series could be used as measures of economic activity. The series we chose is employment in the construction industry by state. This series is a compilation of several Bureau of Labor Statistics publications, and is monthly employed (by state and industry) divided by the annual average labor force (state and industry). ()

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⁵The approach we used is described in greater detail in the companion report, "The Identification of Collusive Bidding in the Highway Construction Industry."

⁶One very attractive alternative measure of prevalence is to use results from our work on identification to impute a proability that a particular project reflected collusive bidding. Unfortunately, we need more data than was available from the Federal Highway Administration to develop this enhanced measure of prevalence. RESID may systematically understate contractors' profits, and so may less accurately indicate collusion. Another difficulty with RESID is the heteroscedasticity which might arise if engineer's estimates vary in accuracy across states. We have not been able to devise a way to correct for these potential errors in the RESID variable.⁷

⁷Development of reliable and independent cost estimation techniques would seem to be the best approach for solving this problem. While we adopted this approach in our study of collusion in the bread and ready-mix concrete industries, resources were not available to undertake this expensive approach for the highway construction industry.

Variables that Measure Federal Antitrust Enforcement Efforts

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We must develop variables which reflect contractors' perceptions of antitrust enforcement efforts in order to test the deterrence hypothesis in highway construction. Our measures are designed to capture several aspects of DOJ antitrust enforcement: the probability of apprehension, the probability of conviction given apprehension, and the relative use of fines and jail sentences as sanctions.

The most difficult variable to construct is the probability of a colluding contractor being apprehended, because for this variable we must estimate the number of colluding contractors in highway construction. In particular, the probability of a colluding contractor being apprehended is defined as: the number of contractors indicted by the Department of Justice in a given month divided by the number of contractors colluding.⁸ Since the primary objective of a cartel is extraordinary profits, we expect the incidence of collusion to be related to the incidence of abnormally high markups. Therefore to approximate the number of contractors likely to be colluding we have calculated the fraction of contracts in a given year

 8 In our earlier work in the bread industry we finessed this issue by focusing on changes in the prevalence of collusion, which we assumed to be proportional to changes in profit level.

particular month was used as numerator, to produce an

⁹It has been noted that this approach to constructing an apprehension rate can produce a bias towards finding a deterrent effect. This potential bias may prejudice our empirical work towards finding a deterrent effect for PCHARGE or any variable which has the same denominator as PCHARGE.

¹¹AVEFINE includes fines to both firms and individuals. AVEJAIL includes jail sentences to individuals. We do not know how much time individuals actually spend in jail. None of these variables reflect fines, jail sentences, or damage recoveries imposed by state governments.

with a positive RESID value, which indicates excess profits, and multiplied this fraction by the number of active contractors in the specified year. This indicator of collusive bidding was then used as the denominator, and the number of contractors named in Department of Justice actions in a

estimate of the probability that a colluder might be indicted. We denote this variable PCHARGE. 9

Along with PCHARGE, we were able to develop a relatively full complement of monthly measures of the level of DOJ antitrust enforcement. The elemental measures that we developed were: CPCONVICT, the conditional probability that a highway construction contractor charged with an antitrust violation will be found guilty; CCPFINE, the conditional probability that a charged contractor will be fined if convicted; CCPJAIL, the conditional probability that an individual charged and convicted will be sentenced to jail; and AVEFINE and AVEJAIL, the average fines and jail sentences levied by the Department of Justice for those fined and/or jailed. 11

¹⁰ Fines and jail sentences are not mutually exclusive. Both penalties are used guite often.

While these monthly series provide us with a rare opportunity to evaluate the response of colluders to several different aspects of federal antitrust enforcement, our series suffer from three difficulties, each of which complicates the extrapolation from actual enforcement levels to contractors' perceptions of enforcement levels.

The first problem relates to the relative scarcity of cases in highway construction over the period 1975-79, as opposed to the large number of cases from 1980 on. As a result of this disparity, our monthly series are missing values for the majority of months prior to 1980. We have assigned zeroes to enforcement variables in months when there was no federal enforcement activity, but we do not believe this is entirely satisfactory. Presumably contractors' perceptions of enforcement probabilities do not fall all the way to zero in months of federal inactivity, particularly when antitrust actions have occurred in months immediately preceding the federal inactivity. This is particularly true of certain aspects of antitrust enforcement. For example, the probability of conviction given apprehension for antitrust violations is generally regarded to be near one.

A second problem closely related to the first is the erratic behavior of our series prior to 1980. We expect contractors' perceptions to be much less erratic than the actual series. Thus we have smoothed our enforcement series

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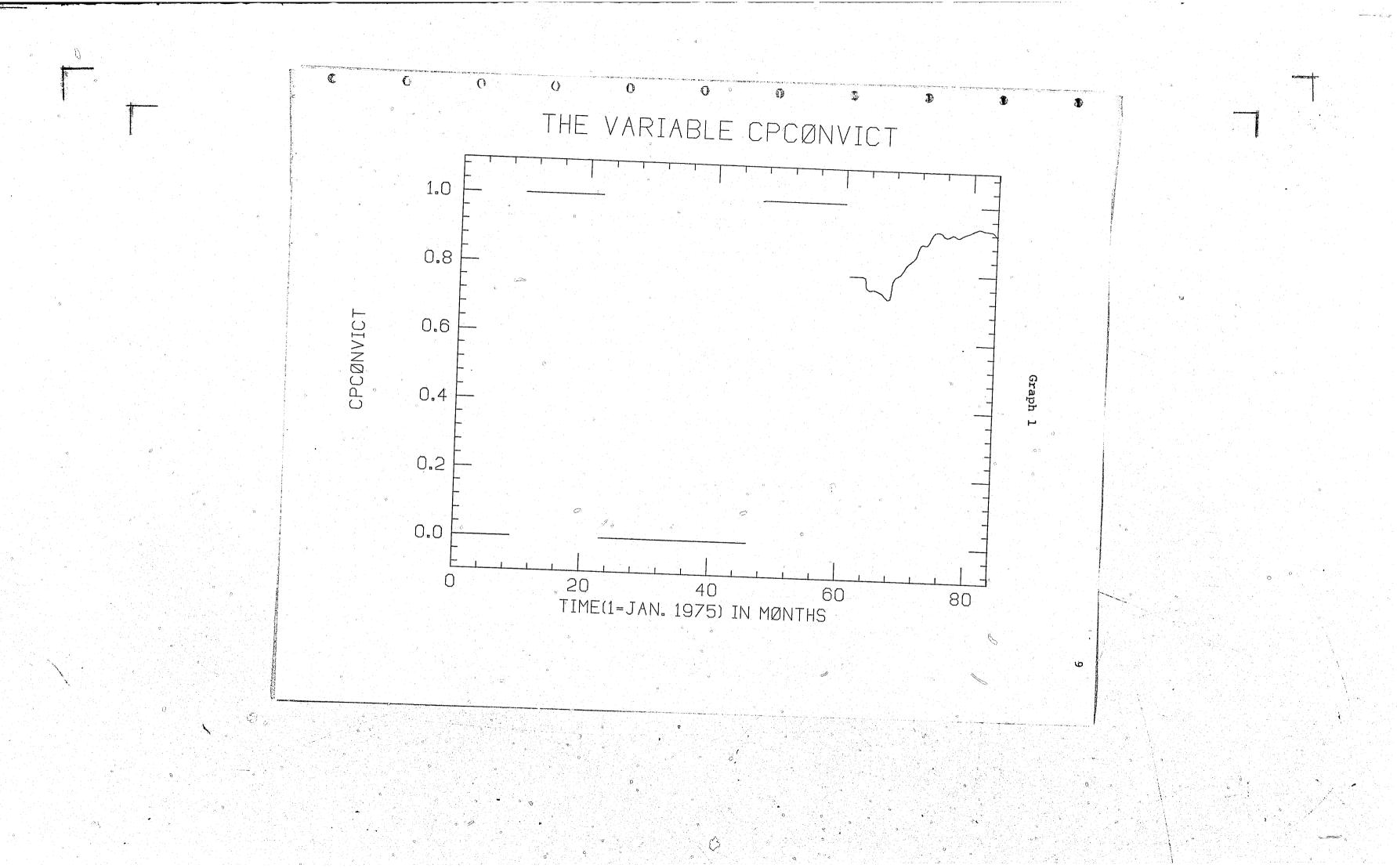
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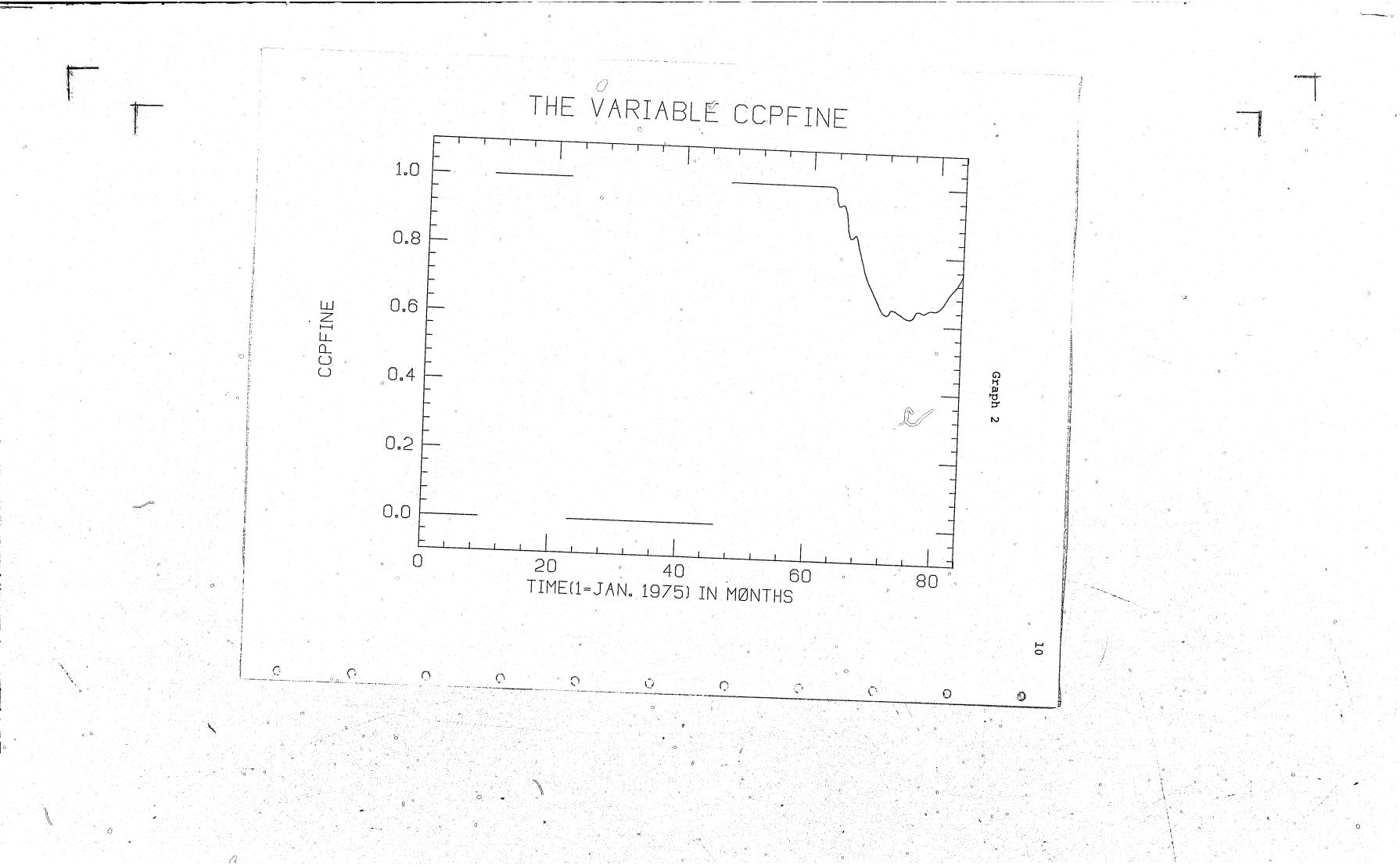
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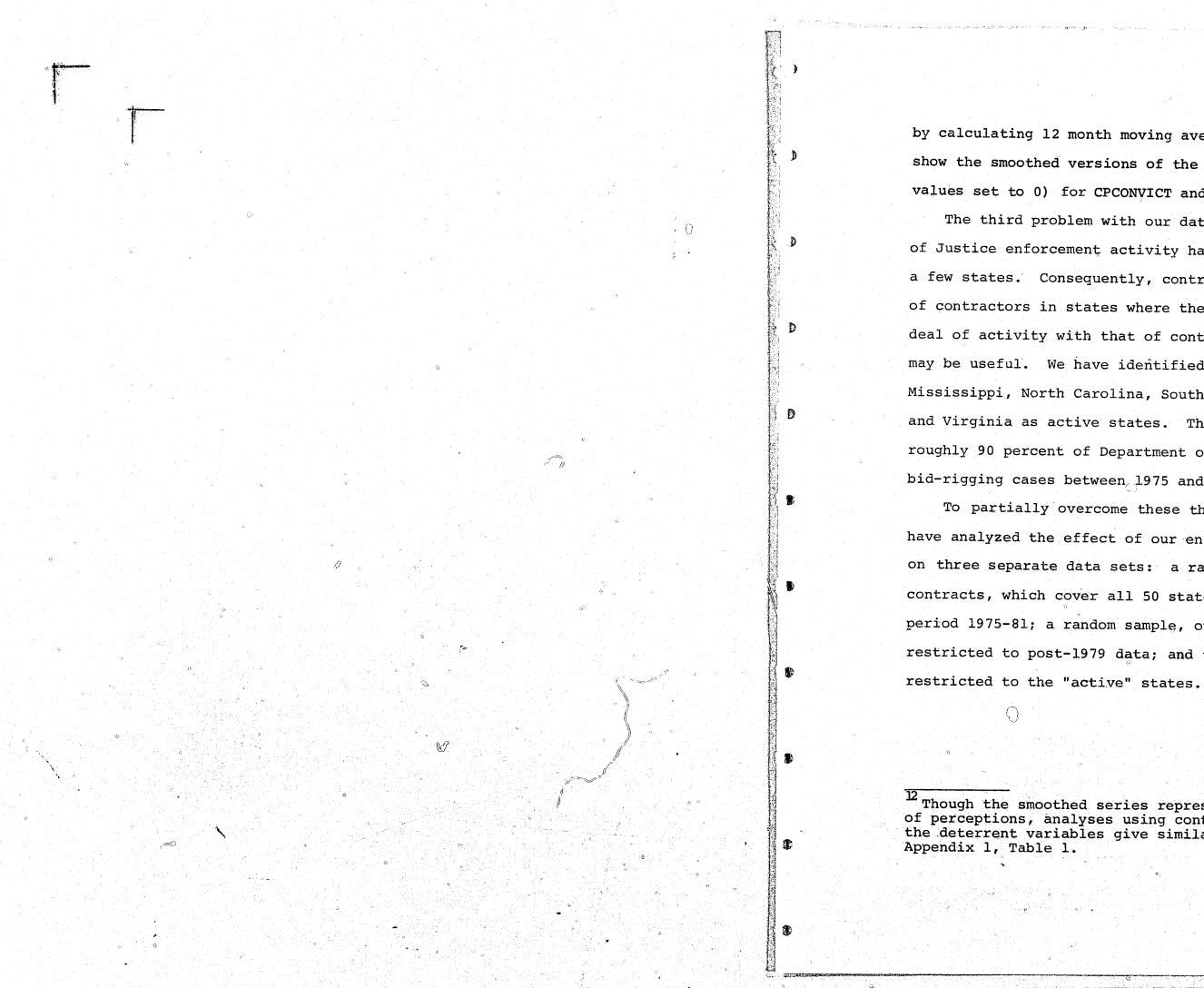
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by calculating 12 month moving averages. Graphs 1 and 2 show the smoothed versions of the variables (with missing values set to 0) for CPCONVICT and CCPFINE.¹² The third problem with our data is that Department of Justice enforcement activity has been concentrated in a few states. Consequently, contrasting the behavior of contractors in states where there has been a great deal of activity with that of contractors in other states may be useful. We have identified Georgia, Illinois, Mississippi, North Carolina, South Carolina, Tennessee, and Virginia as active states. They account for roughly 90 percent of Department of Justice highway bid-rigging cases between 1975 and the end of 1981. To partially overcome these three difficulties we have analyzed the effect of our enforcement series on three separate data sets: a random sample of all our contracts, which cover all 50 states, over the time period 1975-81; a random sample, over all 50 states, restricted to post-1979 data; and the post-1979 data

¹² Though the smoothed series represent a more stable set of perceptions, analyses using contemporaneous values for the deterrent variables give similar results. See

Empirical Results

Table 1 contains six sets of simple ordinary least squares regressions, one set for each of our elementary enforcement variables; in all cases the dependent variable is RESID, our indicator of collusion. In each set three distinct regressions are reported, corresponding to our three different subsamples of the data: a 25 percent random sample of all the contracts in our dataset, covering all states and the period 1975-81; the subset of this random sample which is post-1979; and the subset of the random sample post-1979 restricted to our "active" states. None of the intercepts are given for the sake of brevity. Nearly all of the regressions demonstrate a negative relationship between our indicator of collusion, RESID, and the 12 month moving averages of our enforcement variables, lending strong support to the deterrence hypothesis.

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¹³It should be noted that, using the model we developed for the bread industry study, enforcement and collusion are part of a simultaneous system. Nevertheless, while we cannot draw conclusions about the magnitude of deterrent effects associated with the enforcement variables, the sign of the estimated coefficients can reasonably be argued to reflect the direction of effect. For a detailed discussion of this point, the reader is referred to footnotes 22 and 27 of Block, Nold, and Sidak, op.cit.

¹⁴Comparable regressions using the contemporaneous values of the monthly series are reported in Appendix 1, Table 1.

Table 1

Bivariate Regression Results

Dependent Variable RESID

Independent Variable

ndependent Variable	Random Sample, All States, Post 1975	All States, Post 1979	Active States, Post 1979
PCHARGE	227	082	123
	$(12.0)^{1}$	(2.93)	(2.07)
CPCONVICT	055	134	192
	(9.94)	(2.50)	(1.73)
CCPFINE	043	.152	.198
	(7.57)	(4.71)	(2.93)
CCPJAIL	168	193	270
	(12.6)	(4.50)	(3.02)
AVEFINE ²	052	026	042
	(13.7)	(3.72)	(2.87)
AVEJAIL	001	003	0002
	(11.2)	(2.50)	(1.17)
NUMBER OF OBSERVATION	3544 IS	1263	238

¹The t-ratio, in parentheses, is signed identically to its associated coefficient.

²Per \$100,000 of fines.

Only one enforcement variable, CCPFINE, fails to have a negative association with RESID, that being for the post-1979 and post-1979 active states samples. We believe that this occurs because the government changed the relative use of fines as penalties for convicted colluders towards the end of our sample period. Graph 2 displays this trend in the use of fines.

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In fact, comparison of Graphs 1 and 2 reveals a confluence of the smoothed series for CPCONVICT and CCPFINE. The simple correlation between the two series is .96. Unfortunately, the other series show the same behavior, generating a serious multicolinearity problem.¹⁵ Apparently the Department of Justice antitrust enforcement efforts did not produce an experiment where individuals were exposed to independent variation in different aspects of enforcement. The six series we have developed can each be used individually in a multiple regression or can be combined to form variables which are summaries of different aspects of enforcement activity. The most radical condensation is to produce a single enforcement series.

¹⁵The multiple correlation coefficients between each of the enforcement series and the remaining five over the whole time period are respectively: .96 for PCHARGE; .99 for CPCONVICT; .99 for CCPFINE; .97 for CCPJAIL; .98 for AVEFINE, and .96 for AVEJAIL. These high correlations are generated in part by our insertion of zero values for months when there was no antitrust activity in highway construction. However, multiple correlation coefficients for the post 1979 period were: .97 for PCHARGE; .95 for CPCONVICT; .98 for CCFINE; .99 for CCPJAIL; .98 for AVEFINE; and .87 for AVEJALL.

with antitrust enforcement according to be presumably, of collusion. unambiguous deterrent effect.

¹⁶ Simple regressions similar to those presented in Table 1 are given in Appendix 1, Table 2.

In order to accomplish such a reduction we must monetize the jail sentences used as sanctions. Any monetary value selected for a day in jail is arbitrary--we chose \$137 per day which translates to \$50,000 a year. We then defined the variable ELOSS, the expected monetary loss associated

ELOSS=PCHARGE · CPCONVICT · (CCPFINE · AVEFINE + CCPJAIL · AVEJAIL · \$137). Results for this condensed measure of Department of Justice antitrust enforcement are given in the first row of Table 2. The estimated coefficient is negative and significant for all three subsets of data, indicating that increases in ELOSS are associated with lower levels of RESID and,

A less dramatic reduction would be to use PCHARGE, CPCONVICT, and the term in parenthesis in our definition of ELOSS, which we call SEVERITY in a multiple regression.¹⁶ SEVERITY comes through consistently with a negative and significant coefficient. This is interesting because SEVERITY measures the one aspect of enforcement which our model of collusive behavior predicted to have an

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	Multiple Regression Results	•
	Dependent Variable RESID	
	Random Sample All	Active
Independent Variable	All States, States, <u>Post 1975</u> <u>Post 1979</u>	States, Post 1979
ELOSS R ²	$188^{1}(11.5)^{2}$ $055(2.46)$.036.0048	086 (1.86) .015
PCHARGE CPCONVICT SEVERITY R ²	.040 (.615) 025 (3.75) 070 (3.70) .056 .076 (.702) .099 (.734) 078 (2.27) .011	.169 (.673) .070 (.264) 122 (1.66) .030
PCHARGE CPCONVICT CCLFINE CCLJAIL R ²	003 (.046) .075 (.693) 037 (5.15) .099 (.734) 156 (5.84)083 (1.86) .002 (4.34)000 (.013) .061 .011	.159 (.635) .030 (.111) 208 (2.23) .002 (1.36) .039
PCHARGE CPCONVICT CCLFINE CCPJAIL R ²	106 (1.58) 035 (4.62) 130 (4.79) .108 (2.78) .061 .011 061 (.54) .420 (2.68) 007 (.168) .380 (3.91) .011	.064 (.210) .425 (1.12) 052 (.54) 411 (1.72) .039
PCHARGE CPCONVICT CCPFINE CCPJAIL AVEFINE AVEJAIL R ²	$\begin{array}{cccccccccccccccccccccccccccccccccccc$.107 (.384) .525 (1.70) 220 (.635) 442 (.695) 139 (1.85) .001 (1.40) .068

¹Per \$100,000.

²The t-ratio, in parentheses, is signed identically to its associated coefficient.

In the next set of results we split SEVERITY into CCLJAIL and CCLFINE, expected jail and expected fine conditional upon conviction, respectively. We can dispense with monetizing the jail sentence, since that adjustment was adopted only to allow aggregation of the penalties.¹⁷ These and the next set of regression results shed some light on the jail versus fine controversy. The conditional expected loss through fine variable, CCLFINE, has a negative and significant coefficient for all three subsets of the data. The performance of the conditional expected jail sentence suggests jail sentences might not be too important. However, we pointed out above that AVEJAIL may not be a very accurate measure of actual time served. In addition, the average length of sentences 18 is relatively short. We conjectured that it may not be the length of sentence but merely the fact that an individual is going to serve some time in prison that matters. The next set of results explores this possibility by

using CCPJAIL; the conditional probability that an individual is sentenced to a jail term. This set of results contrasts sharply with the previous set in that the chances of being sentenced to jail appear to be a more important determinant of collusion than expected fines in the post 1979 period.

¹⁷CCLFINE is the product of CCPFINE and AVEFINE and so gives the expected loss given that a firm is charged and convicted. The variable CCLJAIL is the product of CCPJAIL and AVEJAIL and gives the expected jail sentence for an individual given he was charged and convicted.

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¹⁸The average value for AVEJAIL in the post 1979 period is

Although we did not collect data for 1982, analysis of that data along with the post 1979 data might provide a more definitive test of the efficacy of jail sentences versus fines as a sanction for collusion. 18

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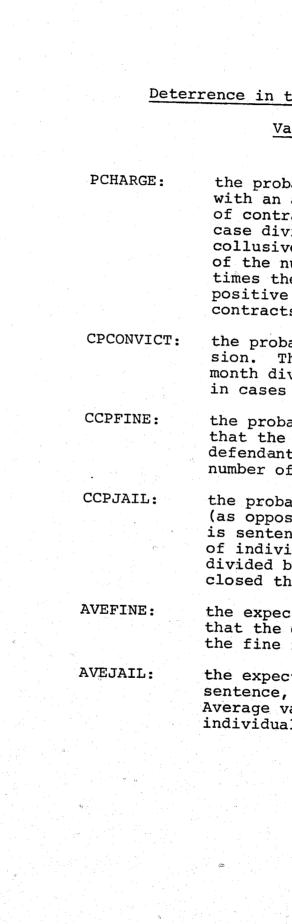
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Finally, regression results and the six elemental enforcement series are given. There are no consistent indications of deterrent effects to discuss, with the possible exception of the negative coefficients on AVEFINE. In fact, CPCONVICT has a relatively strong positive association. As we have noted, that series is highly correlated with CCPFINE.



APPENDIX I

Deterrence in the Highway Construction Industry

Variable Definitions

the probability a contractor will be charged with an antitrust violation. It is the number of contractors apprehended by open date of the case divided by an indicator of the number of collusive firms. The indicator is the product of the number of active highway contractors times the number of contracts that month with a positive RESID divided by the total number of contracts let that month.

the probability of conviction, given apprehension. The number of contractors convicted that month divided by the total number of defendants in cases closed that month.

the probability a defendant will be fined, given that the defendant is convicted. Number of defendants fined that month divided by total number of defendants in cases closed that month.

the probability a defendant who is an individual (as opposed to a firm, which cannot go to jail) is sentenced to jail, given conviction. Number of individuals sentenced to jail that month divided by total number of individuals in cases closed that month.

the expected value of a defendant's fine, given that the defendant is fined. Average value of the fine for all defendants fined that month.

the expected value of an individual's jail sentence, given that the individual is jailed. Average value of the jail sentence for all individuals jailed that month.

Appendix 1, Table 1

Bivariate Regression Results (contemporaneous)

Dependent Variable RESID

Independent Variable	Random Sample, All States, Post 1975	All States Post 1979	Active States, Post 1979	
PCHARGE	090 (10.1)	039 (3.51)	.015 (.614)	
CPCONVICT	070 (12.3)	036 (2.89)	058 (2.32)	
CCPFINE	065 (10.2)	014 (1.30)	040 (1.79)	
CCPJAIL	063 (10.7)	006 (.605)	033 (1.76)	0
AVEFINE ²	028 (11.4)	008 (2.45)	009 (1.39)	
AVEJAIL	0001 (4.06)	.0001 (1.95)	0001 (1.44)	
NUMBER OF OBSERVATIONS	3544	1263	238	0

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The t-ratio, in parenthesis, is signed identically to its associated coefficient.

²Per \$100,000 of fines.

Independent Variable SEVERITY CCLFINE CCLJAIL - N PCHARGE CPCONVICT CCPFINE CCPJAIL AVEFINE AVEJAIL - 4 43

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Appendix 1, Table 2

Dependent Variable RESID

Random Sample, All States, <u>Post 1975</u>	All States, Post 1979	Active States, Post 1979
070	035	^a 053
(13.7)	(3.46)	(2.47)
075	038	057
(13.7)	(3.46)	(2.52)
001	00062	00073
(12.6)	(3.19)	(1.82)

Appendix 1, Table 3

All Years

Post 1979

Mean	Standard Deviation	Mean	Standard Deviation
.092	.127	.213	,142
.587	.454	.862	.068
.554	.440	.761	.125
.15	.180	.379	.091
42417.	69246.	124501.	65207.
3.3	53.3	104.	41.7

Appendix 1, Table 4

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Elemental Enforcement Series

12-Month Moving Averages

1	-				· · · ·				
YR MONTH	PCHARGE	CPCONVICT	CCPFINE	CCPJAIL	AVEFINE	AVEJAIL			
75 1	0.0	0.000	0.000	0.000	0.0	0.0			
75 2	0.0	0.000	0.000	0.000	0.0	9.0	. A		·* *
75 3	0.0	0.000	0.000	0.000 -	0.0	0.0			
75 4	0.007	0.000	0.000	0.000	0.0	0.0			
75 5	0.007	0.000	0.000	0.000	0.0	0.0			
75 6	0.007	0.000	0.000	0.000	0.0	0.0			
75 7	0.007	0.000	0.000	0.000	0.0	0.0			
75 8	0.007	0.000	0.000	0.000	0.0	0.0			
75 9	0.007	0.000	0.000	0.000	0.0	0.0			
75 10	0.007	1.000	1.000	0.000					
75 11	0.007	1.000	1.000	0.000	1111.1	0.0			
75 12	0.007	1.000	1.000	0.000					
76 1	0.0165	1.000	1.000	0.000	1111.1	0.0			
76 2	0.0167	1.000	1.000	0.000	1111.1	0.0			
76 3	0.0171	÷			1111.1	0.0			
76 4	0.0172	1.000	. 1.000	0.000	1111.1	0.0			
76 5			1.000	0.000	1111.1	0.0			
	0.0000	1.000	1.000	0.000	1111.1	0.0		•.	(
	0.0000	1.000	1.000	0.000	1111.1	0.0			
76 7 76 9	0.0000	1.000	1.000	0.000	1111.1	0.0			
76 8	0.0000	1.000	1.000	0.000	1111.1	0.0			
76 9	0.0000	1.000	1.000	0.000	1111.1	0.0			
76 10	0.0000	1.000	1.000	0.000	1111.1	0.0			
76 11	0.0000	0.000	0.000	0.000	0.0	0.0			
76 12	0.0000	0.000	0.000	0.000	0.0	0.0			
77 1	0.0000	0.000	0.000	0.000	0.0	C.J	25		()
77 2	0.0912	0.000	0.000	0.000	0.0	0.0			
77 3	0.0849	0.000	0.000	0.000	0.0	0.0			
77 4	0.0782	0.000	0.000	0.000	0.0	0.0			
77 5	0.0664	0.000	0.000	0.000	0.0	0.0			
77 6	0.0607	0.000	0.000	0.000	0.0	0.0			
77 7	0.0615	0.000	0.000	0.000	0.0	0.0			
77 8	0.0604	0.000	0.000	0.000	0.0	0.0			-
77 9	0.0611	0.000	0.000	0.000	0.0	0.0	· · ·		()
77 10	0.0614	0.000	6.000	0.000	0.0	0.0			
77 11	0.0585	0.000	0.000	0.000	0.0	. 0.0	n pe		
77 12	0.0589	0.000	0.000	0.000	0.0	0.0	. A .		
78 1	0.0552	0.000	0.000	0.000	0.0	0.0	(3)		
78 2	0.0551	0.000	0.000	0.000	0.0	0.0	1.1		
78 3	0.0000	0,000	0.000	0.000	0.0	0.0			
78 4	0.0000	0.000	0.000	0.000	0.0	0.0			
78 5	0.0000	0.000	0.000	0.000	0.0	0.0	4 ¹		C
78 6	0.0064	0.000	0.000	0.000	0.0	0.0	· ·		
78 7	0.0076	0.000	0.000	0.000	0.0	0.0	s .		
78 8	0.0089	0.000	0.000	0.000	0.0	0.0			c ·
78 9	0.0087	0.000	0.000	0.000	0.0	0.0			
78 10	0.0087	0.000	0.000	0.000	0.0	0.0			
78 11	0.0086	0.999	0.999	0.000	1666.7	0.0			
78 12	0.0085	1.000	1.000	0.200	5101.9	60.0			
79 1	0.0084	1.000	1.000	0.200	5101.9	60.0		,	()
79 2	0.0085	1.000	1.000	0.200	5101.9	60.0		1 . W	• •
79 3	0.0086	1.000	1.000	0.200	5101.9	60.0			
79 4	0.0085	1.000	1.000	C.200	5101.9	60.0			
79 5	0.0128	1.000	1.000	0.200	5101.9	60.0	· · · ·		
79 6	0.0132	1.000	1.000	0.200	5101.9	60.0			
79 7	0.0120	1.000	1.000	0.200	5101.9	60.0			
79 8	0.0123	1.000	1.000	0.200	5101.9	60.0	and the second second		
79 9	0.0094	1.000	1.000	0.200	5101.9	60.0	9		C
79 10	0.0110	1.000	1.000	0.200	5101.9	60.0			
79 11	0.0096	1.000	1.000	0.182	5958.0	60.0			
			,		# F # 4 7 5 W			1. C.	
1									

79 12	0.0097
80 1	0.0162
80 2	0.0182
80 3	0.0273
80 4	0.0277
80 5	0.0454
80 6	0.0512
80 7	0.0676
80 8	0.0752
80 9	0.0866
80 10	0.1024
80 11	0.1252
80 12	0.1744
81 1	0.2011
81 2	0.2723
81 3	0.3173
81 4	0.3083
81 5	0.3033
81 6	0.2980
81 7	0.3262
81 8	0.3233
81 9	0.3197
81 10	0.3455
81 11	0.4206
81 12	0.3970
82 1	0.3507
82 2	0.3899
82 3	0.3714
82 4	•
82 5	•
82 6	•
82 7	•

YR MONTH PCHARGE

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Appendix 1, Table 4 (continued)

CPCONVICT	CCPFINE	CCPJAIL	AVEFINE	AVEJAIL
1.000	1.000	0.200	4291.4	60.0
0.789	1.000	0.200	23284.7	50.0
0.789	1.000	0.200	23284.7	50.0
0.789	1.000	0.200	23284.7	50.0
0.750	0.944	0.222	29326.4	52.5
0.750	0.944	0.222 ,	29326.4	52.5
0.741	0.850	0.300	29326.4	60.0
0.724	0.857	0.286	58493.1	60.0
0.787	0.784	0.324	74705.2	74.2
0.800	0.725	0.375	74705.2	80.9
0.828	0.687	0.396	86371.9	87.7
0.844	0.648	0.426	113455.2	91.5/
0.836	0.628	0.423	128682.4	100.5
0.888	0.644	0.402	141718.1	106.7
0.921	0.634	0.462	124279.7	66.1
0.925	0.622	0.459	142196.4	72.3
0.911	0.619	0.460	163029.7	77.3
0.918	0.642	0.472	171442.6	88.7
0.912	0.637	0.476	171442.6	103.7
0.922	0.646	0.469	176859.2	143.7
0.929	0.646	0.469	160192.6	143.7
0.938	0.664	0.451	148235.7	129.5
0.934	0.695	0.430	156829.4	126.6
0.932	0.718	0.427	158183.6	142.3
0.913	0.754	0.397	144173.2	146.1
0.899	0.776	0.402	141978.7	145.4
0,906	0.774	0.434	161095.8	148.7
0.91/1	0.775	0.412	173992.5	169.5
0.868	0.815	0.391	242534.2	170.2
0.881	0.846	0.404	232648.5	167.6
0.863	0.842	0.376	229943.9	162.0
4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1	• .	•	•	•

