Probit Analysis of Non-Ferrous Metals as Leading Indicators: Testing Industrial Metal Prices in a Binary-Response Model of Pre-Crisis Thailand, 1997

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Abstract

There is a large body of scholarship in circulation that has examined the causal relationship between economic factors and output growth leading up to the Asian Financial Crisis of 1997, many of which proposing speculative attacks on the Thai economy as the primary cause. Yet despite its relevance to the study of the pre-crisis Thai economy, there are currently no studies examining the price movements of non-ferrous metals as indicators leading up to the event. This paper examines and compares the metal markets in the semiconductor-dominant Thai market in the mid-90s as an insight into the predictive value of metal prices over the short-, medium- and long-terms. Our study finds that, when assumptions are held, some non-ferrous metals appear to have great value as short- and long-term recession predictors.

1 Introduction

In the run up to the crisis of 1997, Thailands economy posted an average sub-10pct growth year-on year. This was the period of the semiconductor boom, with large multinational companies funnelling large amounts of capital to newly-industrialized nations and their large stocks of cheap labor. One of the beneficiaries of this was Thailand and its nascent semiconductor market. By the late 80s and early 90s, a good part of the Thai economy was propped up by large inflows of investment capital (Basu & Miroshnik, 2000) and along with that the taking off of its equity and real estate market. In quiet, speculative money grew and so did a bubble. Demand for non-ferrous metals used in the production of semiconductors also hit new highs. Yet beneath the veneer of the industrial activity, fragility was still in the bones of the Thai economy - characterized by a floundering export climate through the early and mid 90s and deep current account deficits that Thailand never seemed to pull out off. So when the semiconductor industry began to slump, the Thai economy was essentially left defenseless and vulnerable. In one fell swoop, the broad of speculators that gathered the speculative markets in Thailand, and certainly beyond, was taken out.

While the crisis itself was possibly unpreventable given the exogeneity of circumstances leading up to the event, there are merits in its study. The primary objective of this paper is to determine whether predictors exist, embedded in the pre-crisis metal markets, that could have helped provide a prescience to the circumstance and thereby mitigate the destructive fallout associated with the crisis.

2 Literature Review

The body of literature currently in circulation that deals with modelling leading indicators for impending financial crises often deal with macro-financial data. One of the earlier attempts singularly studied the yield curve as a predictor of US recessions (Estrella & Mishkin, 1996) and provided a strong argument for the usage of the probit method as a useful tool to model event probabilities. Consequently, this method of analysis gained currency over the following years from modelling business cycles to dating (Bamara, 2006; Dopke, 1999; Katsuura & Layton, 2001). Similarly published at the end of the last century in the International Monetary Fund Staff Paper series was a paper studying a more comprehensive array of classical macro-economic indicators, like international reserves, domestic real interest rates, imports and exports (Kaminsky, Lizondo & Reinhart, 1998). This provided one of the first attempts at modelling a generalized warning system via a composite of indicators. Nonetheless, there has never been a paper that has covered an industry-specific approach to a recession.

3 Definitions and Methodology

Since a predictive model necessitates a demarcated timeframe, one of the dicier issues in this study is in regards to the definition of the start and end points of the crisis. There are, in theory, many unofficial definitions of a recession, with different econometric models pursuant to the authors choice of definition. In general, the accepted understanding of a recession is certainly any period of decline in economic activity (Claessens & Kose, 2009). Given the privy, the author of this paper has chosen to define the scope of a recession as at least two consecutive quarters of negative growth. And since this specifies a nominal, binary response, the analysis henceforth is therefore provided by the probit model. The primary merit being the provision of a clean and intuitive interface upon which conclusions may be drawn, the secondary being the long tradition of scholarship devoted to this process. In general, the non-heteroskedastic probit model assumes a given dependent variable characterized by a dichotomous outcome given by a vector I of n independent variables, transformed into a continuous variable and taking on a normal distribution:

$$\begin{aligned} P = pr(Y=1|X) &= \phi[\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + ...\beta_n X_{ni}] \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{I=\sum \beta_i X_i} e^{\frac{t^2}{2}} dt \end{aligned} \tag{1}$$

, where phi provides the restriction on the model that results in a value between zero and 1, and where, by symmetry, when Y=0, the probability is 1-P. The probability of a recession is thus given as the area under the normal distribution from negative infinity to estimated I.

The model, which assumes that variance in the error term is constant, ie homoskedastic, was chosen over the heteroskedastic probit, since: (i) each univariate probit regression deals with a single independent variable and how it relates to changes in the probability of our dependent variable over time (as opposed to relating changes in the probability of our dependent variable with different variables cross-sectionally) ,(ii) the heteroskedastic probit model has been found to be fragilely specified (Keele, 2006) and as a consequence is rarely used by researchers studying leading indicators. In sum, the lack of overt heteroskedastic tendencies in our data, and certainly of the form of research undertaken, do not necessitate the unorthodox usage of the modified probit.

4 Data

The data collected for the analysis is as follows: (i) From the second quarter of 1995 to the third quarter of 1997, the quarterly percentage change in GDP data of Thailand; (ii) From the second quarter of 1995 to the third quarter of 1997, the quarterly percentage price changes in the non-ferrous metals(excluding copper and nickel) spot market. From a static evaluation of each individual data point, we obtain a forecast some k quarters ahead (where k=2 for short term, k=4 for medium term and k=8 for long term), and coded for 1=recession and 0=no recession if we witnessed one or the other k quarters from a given point. The choice of data collected for this study is intuitive; we avoided yearly and bi-yearly data due to its diminished precision, and monthly data due to the noise that short-term data often creates. Quarterly data thus ensures minimum noise for as much precision as we need.

A Variance Inflation Factor test was then conducted via least squares on all lagged periods with all variables (Tables 1.1-1.5) to ascertain variable suitability. Since VIF from the regressions of all independent variables on the remaining independent variables are less than 10, the variables selected do not violate the assumption of non-multicollinearity (When the R-squared between any given pair of independent variables is greater than 0.9, the VIF is greater than 10. This provides a common threshold of determining multicollinearity (Kopalle & Mela, 2002)).

What is endeavored to be achieved by this paper is now clear; a post-mortem analysis of the 1997 Asian Financial Crisis from the perspective of the industry (through metal prices as a proxy for industrial demand and supply). This comparison allows us to determine the first movers prior to the crisis and provide a useful reference for future pre-emptive hedges against crises of such nature.

Of course, it is noted that the non-ferrous metal market is not immune to its own speculation, however, with the removal of the more speculative non-ferrous metals - copper and nickel (Papp et al., 2008)- the price movements of the remaining metals are an acceptable proxy for industrial supply and demand. Further it is noted that price data, as opposed to inventory data, is often more accessible to the general public which would allow the results of this study to be referenced by the lay investor in other similar contexts.

5 Estimation

The analysis of estimated indicator performance is based on the z-statistic and the McFadden′s R-squared, the latter being a pseudo R-squared adopted in logistical regressions, given by:

$$R_m^2 = 1 - \frac{\ln(L(M_{full}))}{\ln(L(M_{int}))} \tag{2}$$

Since the log-division component of the equation takes on a value between 0 and 1, the primary characteristic of this parameter is similar to its least squares counterpart, taking on values between zero and 1 as descriptors of how well a model specifies the investigated variable. However, unlike the OLS R-squared, the McFadden′s R-squared accepts lower values as indicators of good fit, with anything between 0.2 and 0.4 considered as an *excellent* fit (McFadden, 1977). In our analysis, we first observe this pseudo R-squared value to determine if the independent variable is a good fit. If so, we then observe its marginal effect on the dependent variable.

In probit modelling, the sign of the coefficient only gives the direction of change and not the actual marginal effect on the dependent variable. To find the actual marginal effect, we assume the properties of the cumulative distribution function and derive the actual marginal effect via the first order condition of (1):

$$\frac{\partial P}{\partial X_i} = \frac{1}{2}[1 + erf\frac{X_i}{\sqrt{2}}]\beta X_i \tag{3}$$

which is the standard normal probability density function (of zero mean and unit variance) evaluated at a given value of an independent variable. Considering the form of our data set, we modified the coefficient of the independent variable from the preceding first order condition by a hundredth so that a one percent change in the independent variable corresponds directly with a one percent change in the dependent variable:

$$ME = \frac{1}{2}[1 + erf\frac{X_i}{\sqrt{2}}](\frac{1}{100})\beta X_i \tag{4}$$

Since there are various x values in a data set, one convention (which shall be applied here) is to take the mean of the marginal effects evaluated at each value of the given independent variable, summed then averaged. Given nine values for each variable in our data set:

$$AME = (\frac{1}{9})\sum_{n=1}^{9}[\frac{1}{2}[1 + erf\frac{X_{in}}{\sqrt{2}}](\frac{1}{100})\beta X_{in}] \tag{5}$$

This provides a closer approximation of the partial effects of an independent variable on the dependent variable vis-a-vis the marginal effect evaluated at the mean (Bartus, 2005). Therefore, we derive a modified average marginal effect (AME) of the independent variable which describes the direction and strength of an independent variable′s relationship with the dichotomous dependent variable.

6 Results and Discussion

Salient findings are detailed in table 3, distilled from the probit regression results detailed in tables 2.1-2.13: Based on our findings, we observe that Tin is a fair short-term indicator, with a 1 percentage increase in the price of Tin resulting in a more than 2.4 percent decrease in the probability of a recession seen two quarters from that change, while Aluminium is an appropriate medium-term indicator, with a 1 percentage increase in the price of aluminium resulting in a more than 8 percent increase in the probability of a recession seen four quarters from that change.

We also observe that Lead and Zinc perform extremely well as long-term indicators, with a 1 percentage increase in the price of lead resulting in a 10.5 percent increase in the probability of a recession seen eight quarters from that change and a 1 percentage increase in the price of Zinc resulting in an approximately 8.9 percent decrease in the probability of a recession seen eight quarters from that change We note that while there is, in theory, no upper or lower bound to the percentage changes in prices, the changes in probability of a recession are moving within the bounds of 0 and 1 given by the density function, therefore an eight to ten percent change should be interpreted significantly. Immediate conclusions, however, cannot be drawn from the above.

We assume that, *a priori*, all four metals each have exclusive (non-substitutable) functions in the semiconductor industry and low trading volatility, yet we observe contradictory movements in metal prices and their recession predictions: Aluminium and Lead being positive indicators and Tin and Zinc being negative. Taking the derivative of recession probability with regard to price change, p, the following holds:

$$\frac{\partial P}{\partial p(DD_{al})}, \frac{\partial P}{\partial p(DD_{lead})} > 0; \frac{\partial P}{\partial p(DD_{tin})}, \frac{\partial P}{\partial p(DD_{zinc})} < 0 \quad (6)$$

Where price is some positive function of demand. Given *a priori* assumptions, we further postulate that demand for all four metals and their recession predictions should move in tandem, ceteris paribus. Specifically, if price movements are antecedent to the recession, recession probability should be a negative function of price change, or simply:

$$P = -\alpha(p) \tag{7}$$

Some observations from our probit model however indicate otherwise.

Two (divergent) possibilities may be drawn: (i) price movements of the primary semiconductor metals in the industry is not evidenced to be indicative of the recession in 1997, but only appear to be leading indicators by incident; (ii) Both metals of the Tin-Zinc pair are leading indicators, with each having a substitutable function and thus a substitute metal within the pair. Assuming substitutability, we observe the following cross-price elasticity:

$$\frac{\partial DD_{m1}}{\partial p_{m2}} * \frac{p_{m2}}{DD_{m1}} > 0 \tag{8}$$

For equation (8) and thus conclusion (ii) to hold, metals, M1 and M2, when chosen, must be from a single pair of metals that moved in tandem with the change in recession probability (given by our probit), either Tin-Zinc or Aluminium-Lead. However, as established earlier, only Tin-Zinc moved in our postulated direction given by (7), therefore metals, M1 and M2, must individually be one from the tin-zinc pair. A theoretical consideration, however, is that, as substitutes, a runaway inflationary scenario exists, where an increase in the price of M1 leads to an increase in the demand for M2 and thus the price for M2 and thus the demand for M1, since it must hold that the cross price elasticities of M1 vis-a-vis M2 and M2 vis-a-vis M1 are simultaneously greater than zero. This is nonetheless mitigated by the inelastic and ponderous nature of physical stock contracts. Accordingly, from our results, zinc prices moved first as the leading indicator k=8 quarters ahead of the recession, with tin prices lagging as the short term leading indicator k=2 quarters ahead. Therefore, the condensed form of conclusions (i) and (ii) is that if Tin-Zinc substitutability exists, then both from the Tin-Zinc pair of metals are true leading indicators, otherwise there are none.

7 Conclusion

Based on our in-sample probit analysis, we may tentatively conclude that, where assumptions are held, tin and zinc do appear to have value as short- and long-term indicators respectively. This model may be extended upon further investigations made to determine the substitutability of tin and zinc in the semiconductor industry. Lastly, similar tests of substitutability may then be conducted on various input pairs for all out-of-sample, binary-specified, pre-crisis economies to investigate the extendibility of this model.

8 Appendix

Table 1.1

Variance Inflation Factors
Date: 05/10/15 Time: 12:25
Sample: 1995Q3 1997Q3
Included observations: 9

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.000933	7.049139	NA
TIN	0.170870	2.222556	2.024090
LEAD	0.104771	4.667676	4.632852
ZINC	0.031309	2.312666	1.649993
SET	0.079650	9.371834	5.009581

Table 1.2

Variance Inflation Factors
Date: 05/10/15 Time: 12:32
Sample: 1995Q3 1997Q3
Included observations: 9

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.000317	4.844807	NA
ALUMINIUM	0.041817	2.279522	2.233146
ZINC	0.015410	2.300958	1.641640
LEAD	0.046491	4.186833	4.155596
SET	0.025402	6.041743	3.229528

Table 1.3

Variance Inflation Factors
Date: 05/10/15 Time: 12:32
Sample: 1995Q3 1997Q3
Included observations: 9

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.001224	4.341502	NA
ALUMINIUM	0.141944	1.797726	1.761152
TIN	0.285475	1.743927	1.588201
LEAD	0.206347	4.317509	4.285298
SET	0.135809	7.504821	4.011596

Table 1.4

Variance Inflation Factors
Date: 05/10/15 Time: 12:33
Sample: 1995Q3 1997Q3
Included observations: 9

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.001980	6.270089	NA
ALUMINIUM	0.596150	6.739556	6.602443
TIN	1.080928	5.894205	5.367873
ZINC	0.258978	8.019609	5.721666
SET	0.082911	4.089707	2.186095

Table 1.5

Variance Inflation Factors
Date: 05/10/15 Time: 12:34
Sample: 1995Q3 1997Q3
Included observations: 9

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.000820	2.329714	NA
ALUMINIUM	0.563737	5.714328	5.598072
ZINC	0.212015	5.886677	4.199906
TIN	0.734633	3.591797	3.271063
LEAD	0.103130	1.727039	1.714154

Table 2.1

Dependent Variable: KTHAI2
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:36
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.449662	0.441672	-1.018091	0.3086
ALUMINIUM	-1.849731	7.659237	-0.241503	0.8092

McFadden R-squared	0.005173	Mean dependent var	0.333333
S.D. dependent var	0.500000	S.E. of regression	0.533188
Akaike info criterion	1.710887	Sum squared resid	1.990027
Schwarz criterion	1.754715	Log likelihood	-5.698991
Hannan-Quinn criter.	1.616307	Deviance	11.39798
Restr. deviance	11.45726	Restr. log likelihood	-5.728628
LR statistic	0.059273	Avg. log likelihood	-0.633221
Prob(LR statistic)	0.807649		
Obs with Dep=0	6	Total obs	9
Obs with Dep=1	3		

Table 2.2

Dependent Variable: KTHAI4
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:37
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.361367	0.512257	0.705440	0.4805
ALUMINIUM	16.36667	11.76689	1.390909	0.1643

McFadden R-squared	0.242226	Mean dependent var	0.555556
S.D. dependent var	0.527046	S.E. of regression	0.480900
Akaike info criterion	1.485567	Sum squared resid	1.618857
Schwarz criterion	1.529395	Log likelihood	-4.685053
Hannan-Quinn criter.	1.390987	Deviance	9.370107
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	2.995201	Avg. log likelihood	-0.520561
Prob(LR statistic)	0.083512		
Obs with Dep=0	4	Total obs	9
Obs with Dep=1	5		

Table 2.3

Dependent Variable: KTHAI2
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:38
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.484841	0.476577	-1.017341	0.3090
LEAD	-8.012578	6.992303	-1.145914	0.2518

McFadden R-squared	0.134740	Mean dependent var	0.333333
S.D. dependent var	0.500000	S.E. of regression	0.502035
Akaike info criterion	1.545945	Sum squared resid	1.764276
Schwarz criterion	1.589773	Log likelihood	-4.956753
Hannan-Quinn criter.	1.451365	Deviance	9.913506
Restr. deviance	11.45726	Restr. log likelihood	-5.728628
LR statistic	1.543749	Avg. log likelihood	-0.550750
Prob(LR statistic)	0.214061		
Obs with Dep=0	6	Total obs	9
Obs with Dep=1	3		

Table 2.4

Dependent Variable: KTHAI4
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:39
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.245561	0.466436	0.526463	0.5986
LEAD	-9.055339	6.472955	-1.398950	0.1618

McFadden R-squared	0.181036	Mean dependent var	0.555556
S.D. dependent var	0.527046	S.E. of regression	0.499758
Akaike info criterion	1.569638	Sum squared resid	1.748309
Schwarz criterion	1.613465	Log likelihood	-5.063369
Hannan-Quinn criter.	1.475058	Deviance	10.12674
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	2.238570	Avg. log likelihood	-0.562597
Prob(LR statistic)	0.134605		

Obs with Dep=0	4	Total obs	9
Obs with Dep=1	5		

Table 2.5

Dependent Variable: KTHAI8
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:41
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.291496	0.585618	-0.497758	0.6187
LEAD	20.98002	12.63783	1.660097	0.0969

McFadden R-squared	0.517059	Mean dependent var	0.444444
S.D. dependent var	0.527046	S.E. of regression	0.383789
Akaike info criterion	1.107968	Sum squared resid	1.031058
Schwarz criterion	1.151796	Log likelihood	-2.985857
Hannan-Quinn criter.	1.013388	Deviance	5.971714
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	6.393594	Avg. log likelihood	-0.331762
Prob(LR statistic)	0.011453		

Obs with Dep=0	5	Total obs	9
Obs with Dep=1	4		

Table 2.6

Dependent Variable: KTHAI2
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:41
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.154925	1.000050	-1.154867	0.2481
TIN	-29.53373	27.59637	-1.070204	0.2845

McFadden R-squared	0.203049	Mean dependent var	0.333333
S.D. dependent var	0.500000	S.E. of regression	0.483610
Akaike info criterion	1.458986	Sum squared resid	1.637154
Schwarz criterion	1.502813	Log likelihood	-4.565435
Hannan-Quinn criter.	1.364406	Deviance	9.130870
Restr. deviance	11.45726	Restr. log likelihood	-5.728628
LR statistic	2.326385	Avg. log likelihood	-0.507271
Prob(LR statistic)	0.127197		

Obs with Dep=0	6	Total obs	9
Obs with Dep=1	3		

Table 2.7

Dependent Variable: KTHAI4
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:42
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.070441	0.506177	-0.139163	0.8893
TIN	-14.13409	13.23688	-1.067781	0.2856

McFadden R-squared	0.114303	Mean dependent var	0.555556
S.D. dependent var	0.527046	S.E. of regression	0.520791
Akaike info criterion	1.661324	Sum squared resid	1.898561
Schwarz criterion	1.705151	Log likelihood	-5.475956
Hannan-Quinn criter.	1.566744	Deviance	10.95191
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	1.413396	Avg. log likelihood	-0.608440
Prob(LR statistic)	0.234493		

Obs with Dep=0	4	Total obs	9
Obs with Dep=1	5		

Table 2.8

Dependent Variable: KTHAI8
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:43
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.208191	0.454062	-0.458509	0.6466
TIN	-5.039239	11.47074	-0.439313	0.6604

McFadden R-squared	0.016434	Mean dependent var	0.444444
S.D. dependent var	0.527046	S.E. of regression	0.558175
Akaike info criterion	1.795788	Sum squared resid	2.180916
Schwarz criterion	1.839616	Log likelihood	-6.081048
Hannan-Quinn criter.	1.701208	Deviance	12.16210
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	0.203213	Avg. log likelihood	-0.675672
Prob(LR statistic)	0.652140		
Obs with Dep=0	5	Total obs	9
Obs with Dep=1	4		

Table 2.9

Dependent Variable: KTHAI2
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:43
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.824082	0.554226	-1.486906	0.1370
ZINC	6.880069	5.605508	1.227377	0.2197

McFadden R-squared	0.145962	Mean dependent var	0.333333
S.D. dependent var	0.500000	S.E. of regression	0.476748
Akaike info criterion	1.531659	Sum squared resid	1.591022
Schwarz criterion	1.575486	Log likelihood	-4.892463
Hannan-Quinn criter.	1.437079	Deviance	9.784927
Restr. deviance	11.45726	Restr. log likelihood	-5.728628
LR statistic	1.672328	Avg. log likelihood	-0.543607
Prob(LR statistic)	0.195947		
Obs with Dep=0	6	Total obs	9
Obs with Dep=1	3		

Table 2.10

Dependent Variable: KTHAI8
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:44
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.373384	0.526360	0.709370	0.4781
ZINC	-16.99772	12.56831	-1.352426	0.1762

McFadden R-squared	0.343597	Mean dependent var	0.444444
S.D. dependent var	0.527046	S.E. of regression	0.446190
Akaike info criterion	1.346292	Sum squared resid	1.393602
Schwarz criterion	1.390120	Log likelihood	-4.058314
Hannan-Quinn criter.	1.251712	Deviance	8.116627
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	4.248681	Avg. log likelihood	-0.450924
Prob(LR statistic)	0.039281		
Obs with Dep=0	5	Total obs	9
Obs with Dep=1	4		

Table 2.11

Dependent Variable: KTHAI2
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:45
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.940924	0.703930	-1.336673	0.1813
SET	-5.357046	5.338137	-1.003542	0.3156

McFadden R-squared	0.096266	Mean dependent var	0.333333
S.D. dependent var	0.500000	S.E. of regression	0.503882
Akaike info criterion	1.594924	Sum squared resid	1.777276
Schwarz criterion	1.638751	Log likelihood	-5.177156
Hannan-Quinn criter.	1.500344	Deviance	10.35431
Restr. deviance	11.45726	Restr. log likelihood	-5.728628
LR statistic	1.102943	Avg. log likelihood	-0.575240
Prob(LR statistic)	0.293621		
Obs with Dep=0	6	Total obs	9
Obs with Dep=1	3		

Table 2.12

Dependent Variable: KTHAI4
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:45
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.102582	0.560933	-0.182877	0.8549
SET	-2.983791	4.686595	-0.636665	0.5243

McFadden R-squared	0.033044	Mean dependent var	0.555556
S.D. dependent var	0.527046	S.E. of regression	0.551614
Akaike info criterion	1.772967	Sum squared resid	2.129945
Schwarz criterion	1.816795	Log likelihood	-5.978352
Hannan-Quinn criter.	1.678387	Deviance	11.95670
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	0.408604	Avg. log likelihood	-0.664261
Prob(LR statistic)	0.522679		

Obs with Dep=0	4	Total obs	9
Obs with Dep=1	5		

Table 2.13

Dependent Variable: KTHAI8
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 05/10/15 Time: 12:47
Sample: 1995Q3 1997Q3
Included observations: 9
Convergence achieved after 2 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.344964	0.603746	0.571373	0.5677
SET	5.956997	5.204483	1.144590	0.2524

McFadden R-squared	0.116776	Mean dependent var	0.444444
S.D. dependent var	0.527046	S.E. of regression	0.523797
Akaike info criterion	1.657926	Sum squared resid	1.920540
Schwarz criterion	1.701754	Log likelihood	-5.460667
Hannan-Quinn criter.	1.563346	Deviance	10.92133
Restr. deviance	12.36531	Restr. log likelihood	-6.182654
LR statistic	1.443975	Avg. log likelihood	-0.606741
Prob(LR statistic)	0.229497		

Obs with Dep=0	5	Total obs	9
Obs with Dep=1	4		

Table 3.	*K=2*	*K=4*	*K=8*
Aluminium			
McFadden's R-Squared	0.005173	0.242226	*
Average Marginal Effect	***	0.08128	*
z-statistic	-0.241503	1.390909	*
Lead			
McFadden's R-Squared	0.134740	0.181036	0.517059
Average Marginal Effect	***	***	0.10545
z-statistic	-1.145914	-1.398950	1. 660097
Tin			
McFadden's R-Squared	0.203049	0.114303	0.016434
Average Marginal Effect	-0.02427	***	***
z-statistic	-1.070204	-1.067781	-0.439313
Zinc			
McFadden's R-Squared	0.145962	**	0.343597
Average Marginal Effect	***	**	-0.08856
z-statistic	1.227377	**	-1.352426

* Perfectly predicts binary response failure

** Perfectly predicts binary response success

*** Average Marginal Effect not needed since variable does not satisfy the criteria of a good fit based on McFadden's R-squared

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