

# Understanding the Factors behind Inflation Targeting: A Panel Logit Approach

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## Abstract

We use a Panel Logit Regression Model to identify the factors that determine the adoption of Inflation-Targeting policy by countries around the world. We show that most of the explanatory variables that we use provide expected sign in the regression which leads to the correct direction in which they effect the Inflation Targeting decision. We conduct Pooled, Fixed effect and Random Effect regressions and compare their results. The fixed effect model provides the best fit. Finally we test the presence of Country specific Fixed effect. We find evidence in favour of Fixed effect

## 1 Introduction

The adoption of explicit inflation targeting (EIT hereafter) as a framework for monetary policy in a number of countries constitutes arguably the most important change in the way in which central banks conduct policy since the introduction of generalized floating exchange rates in the early 1970s. EIT has in the last decade been adopted in Australia, Canada, Finland, New Zealand, Spain, Sweden and the United Kingdom. Reflecting this fact, a large literature has developed addressing a number of aspects of EIT. Somewhat surprisingly, however, this literature has not yet systematically addressed the question of which factors may have influenced countries' choice of this policy strategy.

While the empirical work suggests that the past history of inflation predicts the adoption of EIT, this finding is incomplete in that both the monetary policy framework and the inflation record are endogenous variables that are determined by deeper structural features of the economy. Thus, the observation that countries may have adopted EIT in reaction to high past inflation merely raises the question what factors caused them to have high inflation. Furthermore, focusing solely on inflation as triggering the switch to EIT fails to explain why Canada, Finland and Sweden introduced EIT, while Denmark and Ireland did not, despite their similar inflation record.

In this paper, we undertake a Panel Logit regression approach to find whether there is any country specific fixed effect in the EIT adoption decision. Using a Panel of 24 countries with data from 1980 to 2004, we show that there is indeed fixed effect present. We also carry out Pooled Logit and Random effect logit regression to compare our results with previous works. Our results are consistent with previous findings. We are also able to make improvements in explaining the factors that determine inflation targeting.

The paper is organized as follows. In section 2, we provide a brief overview of the existing literature. In section 3 we explain the model specification and also the Econometric Methodology that I will use. Different subsections will discuss the motivation, the nature of the data, the

specific model used, the regression results and hypothesis testing. Finally, we will discuss the limitation of our study. In section 4, we conclude

## 2 Literature Review

This paper draws experience of inflation analysis from several previous works. We will very closely follow Gerlach(1999). He conducted a Multivariate Probit Regression to find out the factors that motivated inflation targeting for the EIT countries. He included both EIT and non-EIT countries to analyze whether there is any structural differences between them. We will also draw on three more earlier works. *First*, in the last few years, several countries have adopted EIT. In order to include them in our analysis and learn about factors that motivated them to switch to EIT, we will follow Schmidt-Hebbel and Tapia(2002). They conducted an actual survey where they interviewed Central Banks around the world. They asked these central banks what monetary policy they currently follow(Fixed exchange rate, EIT, floating exchange rate and so on), and also what factors motivated them to decide their monetary policy regime. *Secondly*, Bernanke, Laubach, Mishkin and Posen(1999) Published a very influential book where they provided an in-depth look at the issue if Inflation targeting. Without any formal econometric treatment, they outlined factors behind the choice of EIT regime for countries before 1999. *Thirdly*, Svensson(1995) summarizes an earlier experience of EIT countries.

## 3 Model Specification and Econometric Methodology

### 3.1 Motivation

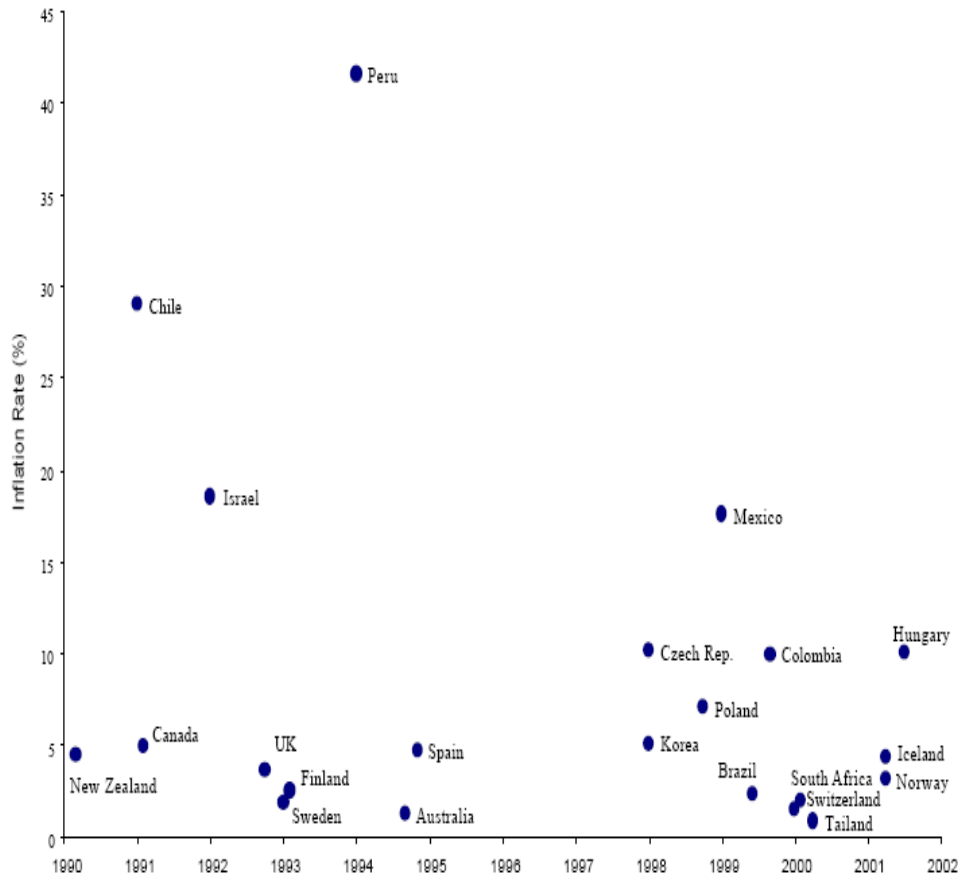
We will use a Panel of 24 countries for time period of 24 years. The motivation for using a Panel Logit regression approach is three fold. *First*, we do not want to identify the factors that determine Inflation Targeting decision. Rather, we will take a set of explanatory variables which have been generally accepted as important determinants of Inflation Targeting. We will then look at how changes in those explanatory variables effect the probability of Inflation Targeting which we assume to be a binary choice variable. *Second*, the Logit model will help us interpret the regression coefficients more closely to the changes in the probability of Inflation Targeting. *Third*, a Panel data structure will allow us obtain better precision(Hsiao, 2002). It will also allow us to focus on a very important issue. As Bernanke, Laubach, Mishkin and Posen(1999) pointed out, the decision of Inflation Targeting often entails no theoretical basis. It sometimes becomes a "Discretion rather than a Rule". Empirical analysis of each of the EIT countries have lead to inconsistency in terms of finding the factors effecting the targeting decision. One hypothesis would be that there might some unobserved heterogeneity present in the decision making process which might be quite important. Therefore, *country specific fixed factor* might lead to inflation targeting.

### 3.2 Countries and Time period of Analysis

We will use data for a group of 24 countries, Australia, Brazil, Canada , Chile , Colombia ,Czech Republic, Finland, Germany, Hungary, Iceland, Israel, Korea, Mexico, New Zealand, Norway, Peru, Poland, South Africa, Spain, Sweden, Switzerland, Thailand, United Kingdom, United States. Except for USA, Austria and Germany, all the other countries are EIT. We will include them in our analysis because we will also like to find out the structural differences between the EIT and the non-EIT countries. Many people believe that USA have been pursuing an Explicit

**Figure 1**

**Annual Inflation at Adoption of Inflation Targeting Framework in 22 Countries (1)**



(1) Inflation attained one quarter before adopting IT.

EIT policy for a long time but has not yet made any formal announcement. There is a similar ambiguity about Germany. Finally, Australia will be included because they had a very similar situation as New Zealand when the latter adopted EIT but the former did not. Figure 1 from Schmidt-Hebbel and Tapia(2002) shows the timing of EIT for various countries. The figure also provides the first

motivation for using a panel data approach. We will use a panel data set of 1980-2004 although the first reported EIT came in 1989 from New Zealand. The reason for including the pre 1989 period is to find whether there was any structural changes made to all the countries before and after the EIT .We will first experiment with the full sample of 24 countries. Then we will also report our experiment results for the only EIT countries.

### 3.3 Variables Used and Sources of Data

We will use a Panel Logit Model where the dependent variable is Inflation Targeting(IT) which takes a value of 1 if a certain country has adopted EIT and zero for otherwise. The set of explanatory variables will be same as Gerlach(1999) and are as follows. *First*, we will use Inflation rate(IR) which is the inflation rate measured by percentage change in the CPI. *Second*, we will use

trade Three indicators of trade patterns were used to measure the degree to which an economy is exposed to external shocks. Since exporting a broad range of goods is likely to provide some diversification benefits, an index of the commodity concentration of trade (CONC) published by UNCTAD was used. Countries that export a narrow group of goods have a high value of this index. Since they may experience relatively large external shocks, we hypothesis that it may be difficult for them to maintain a fixed exchange rate. We therefore expect this variable to increase the probability that they adopt an EIT regime, and thus to have a positive parameter in the probit regressions. We also use an index of the diversification of trade (DIVER) published by the same source. This index essentially measures to what extent a country's exports differ from that of the average country. A country exporting few goods will have a high value of this index, so that it is also expected to enter the Logit regressions with a positive parameter. The third structural variable we use is a measure of commodity composition of exports (COMM), which is defined as the fraction of exports that are related to the exploitation of natural resources. The reason for employing this variable is that many resource-based goods {defined here as metals, fish, forest products and fuels } experience large price swings in response to international business cycle developments. One would therefore expect that economies in which such goods play an important role will tend to experience large external disturbances and be more inclined to operate with an EIT regime rather than with fixed exchange rates. *Thirdly*, we will use some variables to measure External shocks. Two measures of the importance of external shocks were used in the empirical analysis: the percentage change in the Real Exchange rate from year to year (RER) and the percentage change of the year-to-year changes of the terms-of-trade (TOT). We expect these variables to enter with a positive sign in the Logit regressions. We start the estimation in 1980 to avoid the period of oil-price shocks in the 1970s. *Fourth*, there would be a variable to measure Openness. This is defined as export/GDP ratio (OPEN) which proxies for the degree of openness of the economy. The intuition for including this variable is straightforward. Since unanticipated monetary expansions lead to real exchange rate depreciation, which is more harmful the more open the economy is, policy makers in open economies have greater disincentives to inflate. One would therefore expect the advantages of adopting EIT to be smaller the more open the economy is. Finally, we will include two dummy variables, one for the EU membership(eu\_dum) and the other one for European countries(Europe\_Dum). We would expect both this variables should have positive sign in the regressions because more and more European and EU members countries have been adopting EIT. All the above variables have been collected from the UN Statistics Division's Common database.

### 3.4 Descriptive Statistics

Table 2 provides a descriptive summary of the data. We also report the correlation between the different independent variables in our regression analysis in the appendix along with the stata output. We also report the correlation between the different independent variables in our regression analysis in the appendix along with the stata output. For both full sample and the EIT sample. We notice that the EU dummy and the Europe Dummy are correlated with each other. The EU dummy is not correlated with IR, the inflation variable. CONC and DIVER are strongly correlated. EU dummy and DIVER has somewhat strong negative correlation. DIVER is also strongly correlated with COMM. All the results are consistent with Gerlach(1999).

### 3.5 Model Specification

Following Cameron and Trivadi(2005), we will specify a Binomial Panel Logit model with individual specific effects where the dependent variable,  $IT_{it} = 1$  if EIT is adopted and 0 otherwise. Thus:

**Table\_2: Summary of the DATA**

<b>Full sample</b>						
Variable	Obs	Mean	Std. Dev.	Min	Max	
id	600	12.5	6.927962	1	24	
year	600	1992	7.217119	1980	2004	
Country	0					
IT	600	.345	.4757649	0	1	
COMM	600	.6101135	1.624336	0	10.81284	
CONC	600	.1777667	.1161372	.045	.58	
DIVER	600	.4885667	.1304924	.224	.786	
IR	555	26.34803	150.5877	-88.96089	2076.684	
OPEN	600	.34205	.9763451	.0156324	11.7846	
RER	595	10.84736	115.2354	-51.7969	2006.675	
TOT	530	-.2623205	13.82194	-100	230.6748	
eu_dum	600	.1533333	.3606091	0	1	
countrydum	600	12.5	6.927962	1	24	
Europe_Dum	600	.4583333	.4986766	0	1	

<b>Only EIT Sample</b>						
Variable	Obs	Mean	Std. Dev.	Min	Max	
id	525	12.71429	6.421449	2	23	
year	525	1992	7.21798	1980	2004	
Country	0					
IT	525	.3085714	.4623443	0	1	
COMM	525	.6746538	1.725028	0	10.81284	
CONC	525	.1880533	.1197404	.045	.58	
DIVER	525	.4994533	.1251292	.224	.786	
IR	492	29.2113	159.7273	-88.96089	2076.684	
OPEN	525	.2700907	.3956338	.0156324	4.485842	
RER	520	8.712733	86.44621	-26.09473	1678.897	
TOT	480	-.2835428	14.43625	-100	230.6748	
eu_dum	525	.127619	.3339834	0	1	
countrydum	525	12.71429	6.421449	2	23	
Europe_Dum	525	.4761905	.4999091	0	1	

<b>Table1: Regression results: Full Sample</b>			
<b>Dependent Variable: IT</b>			
<b>Independendent Variable</b>	<b>Pooled Panel Logit</b>	<b>Fixed Effect Panel Logit</b>	<b>Random Effect Panel Logit</b>
COMM	0.3435	-3.106	0.182
(se)	0.111	1.65	0.1665
CONC	0.6694	-1.022	0.0377
(se)	1.817	4.409	3.45
DIVER	-4.4	-40.703	-14.899
(se)	1.739	7.975	3.051
IR	-0.1859	-0.2199	-0.25301
(se)	0.0754637	0.0410024	0.0382424
OPEN	0.53244	4.2195	1.1415
(se)	0.2007013	1.483	0.48246
RER	-0.0055	-0.0052	-0.0101
(se)	0.00627	0.01036	0.0106
TOT	0.0345	0.01147	0.02329
(se)	0.0175	0.0284	0.023
EU_Dummy	0.81143	2.335	1.774
(se)	0.4525	0.9043	0.6942
Europe_Dummy	-1.6978		-4.358
(se)	0.32478		0.879
Constant	2.921		9.3
(se)	0.98205		1.38
R_Square	0.2957		
Log Likelihood	-218.0073	-102.9398	-185.4739

$$\Pr [y_{it} = 1|x_{it}, \beta, \alpha_i] = \Lambda(\alpha_i + x'_{it}\beta)$$

Where,  $\Lambda(\cdot)$  is the logistic cdf,  $Y_{it} = IT_{it}$ ,  $X = [\text{IR CONC DIVER COMM RER TOT OPEN eu\_dum Europe\_Dum}]$

We will conduct three kinds of regression analysis. First, we will do a Pooled Logit Regression analysis based on the above set of explanatory variables. Second, we will conduct our main regression analysis, a panel logit Fixed effect regression. Finally, we will do a random effect Panel logit regression too. But the main purpose of that exercise would be to compare the results with the fixed effect model. We will do regressions first by taking the he full sample of countries, three of which are not explicit inflation targeters. Then we will take only the subsample of EIT countries and carry out the regression exercise.

## 3.6 Results and Discussion

### 3.6.1 Regression results

Table1 summarizes the results from the Pooled, Fixed effect and Random effect regressions for the full sample.

We will first report for the full sample. Lets analyze the pooled regression results first. This will help us to compare our results with Gerlach(1999). As hypothesized, the sign of the regression coefficient for TOT, EU Dummy, COMM, CONC are positive which contradicts Gerlach(1999). The Europe Dummy has a negative sign which matches with Gerlach(1999). We get negative

**Table 3: Marginal effects after logit: Full Sample**

$$y = \text{Pr}(\text{IT}) (\text{predict})$$

$$= .00721151$$

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
COMM	.0024595	.00409	0.60	0.547	-.005553	.010472		.554436
CONC	.0047928	.01001	0.48	0.632	-.014826	.024412		.17301
DIVER	-.0315125	.05121	-0.62	0.538	-.131892	.068867		.482096
IR	-.0013312	.00184	-0.72	0.470	-.004945	.002283		29.696
OPEN	.003812	.007	0.54	0.586	-.009905	.017529		.363771
RER	-.0000395	.00008	-0.51	0.608	-.00019	.000111		8.70045
TOT	.000247	.0004	0.61	0.540	-.000544	.001038		-.746671
eu_dum*	.0077773	.0176	0.44	0.659	-.026724	.042279		.166667
Europe~m*	-.0125089	.02205	-0.57	0.571	-.055733	.030715		.45

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

sign for RER and DIVER. These results again contradict our hypothesis but supports Gerlach's findings. But our and OPEN has positive sign which contradicts both our hypothesis and Gerlach(1999) as well. The only explanation we can provide for this result is that the countries that have adopted inflation targeting might have undermined the adverse effect of real exchange rate depreciation and therefore ignored the effect of Openness. This perverse behavior might be the first evidence that there might country specific fixed factors that might have prompted the countries to adopt EIT. But the most important result of our pooled regression is the negative sign of the IR variable. We interpret this as a clear sign of *reverse causality*, which was warned by Gerlach(1999) and prompted him not to use this variable in his Probit regression. We also report the marginal effect results for the pooled regression in table 3. Results indicate very small changes in the

in the probability of EIT adoption for changes in the independent variables, except for some significant effect for the DIVER variable. Next we focus on the fixed effect panel Logit regression results. As expected the Europe Dummy drops out. All variables except CONC and COMM retain there usual sign. The EU dummy now has a much larger coefficient. The coefficient for DIVER is unusually large. We do not have any explanation for this. Finally, we report the results for the random effect panel logit regression for completeness. The results are now more comparable to the pooled regression. Turning back to the goodness of fit measures, the fixed effect logit model has the largest Log-likelihood. This means that the fixed effect model provides the best fir of the data.

Next we report our results for the EIT sample only in table 4. The results are very similar to the full sample. We can therefore reach a strong conclusion that there is basically no significant difference between countries that have adopted

Inflation targeting and countries that could have adopted EIT. We therefore do not report the marginal effect analysis in the paper but include it in the appendix.

### 3.6.2 Hypothesis Testing

In the appendix, We report a set of hypothesis tests that were carried out to have a better understanding of the experiment. First,we report the test for individual specific effects in case of the pooled regression. Here we will try to test the presence of individual country specific random effects against the null hypothesis assumption of iid errors. This will be done using the pooled regression. Our Stata output reports Wald test which basically tests the same thing. The results indicate that we reject the null hypothesis of iid errors.

**Table 4: Regression results: EIT Sample**  
**Dependent Variable: IT**

<b>Independent Variable</b>	<b>Pooled Panel Logit</b>	<b>Fixed Effect Panel Logit</b>	<b>Random Effect Panel Logit</b>
COMM	0.316	-2.41	0.152
(se)	0.108	1.54	0.168
CONC	0.354	-0.74	-0.0814
(se)	1.807	4.395	3.37
DIVER	-3.36	-39.99	-13.14
(se)	1.77	8.568	3.17
IR	-0.17	-0.2104	-0.234
(se)	0.071	0.0406	0.038
OPEN	0.544	4.168	1.161
(se)	0.217	1.47	0.4834
RER	-0.004	-0.0042	-0.0085
(se)	0.0048	0.0096	0.0105
TOT	0.025	0.0036	0.0106
(se)	0.0159	0.029	0.024
EU_Dummy	-1.622	2.365	1.754
(se)	0.45	0.9	0.698
Europe_Dummy	-1.62		-4.25
(se)	0.32		0.899
Constant	2.354		8.38
(se)	0.951		1.44
R_Square	0.2716		
Log Likelihood	-202.1259	-98.40997	-174.3615



Now we report the result of the most important test of our project. We would like to test whether there are fixed effects. This will be done by a hausman test. A large value of the Hausman test statistics will lead to rejection of the null hypothesis that the individual -specific effects are uncorrelated with the regressors. So the conclusion would be that there is fixed effects present in the model. The results indicate that we reject the null hypothesis<sup>1</sup>. For the EIT sample, we get similar test statistics.

### 3.7 Limitations of the study

We will highlight some of the limitations of the study which were identified by Gerlach(1999). The first limitation of the study is the *size of the data*. EIT has been adopted only for the last 16 years. We need more data to have concrete conclusions about the probability of Inflation targeting. This limitation cannot be overcome even by using a Panel data. Since it seems likely that many factors play a role in influencing the choice of policy framework, the small sample size suggests the empirical analysis can at best only identify the most important factors. The second limitation is related to the *classification of policy regimes*. The fact that countries adopt an EIT regime by a public announcement of a target (band or point) for the inflation rate, etc., implies that there is no doubt about what central banks operate with explicit inflation targets. However, Finland and Spain in 1997 each had an EIT and were members of the ERM, raising the issue of how they should be classified. They are classified below as having an EIT, under the presumption that the adoption of  $\pm 15\%$  broad ERM exchange rate bands in 1993 effectively meant that monetary policy was no longer directly geared to the exchange rate. However, this classification could be disputed. A further problem is that relying on formal announcements in order to classify a country as having an EIT regime may be inappropriate. For instance, academic economists have argued that the Bundesbank gears monetary policy to the near-term inflation outlook, and that there is little evidence that it responds to deviations of M3 from target, implicitly suggesting that the Bundesbank targets inflation. The Federal Reserve has also been interpreted by some observers as conducting a policy of implicit inflation targeting. Since both these central banks may feel that the public knows that they de fact gear policy to maintaining low inflation, they may have little reason to announce this and will thus not be classified as having an EIT. The next limitation is the *Suboptimal policy frameworks*. This problem arises from the fact that some central banks may conduct monetary policy using a framework that they believe to be suboptimal but are unable to change. A particular issue for central banks that would like to introduce EIT is that doing so entails moving from a fixed to a floating exchange rate regime, which typically requires the consent of the government. This agreement may be difficult to obtain, particularly in countries with large and politically powerful export industries where the government may shy away from the increase in real exchange rate volatility that may follow if EIT is adopted. The last limitation is the *Missing variables problems*. Some of the variables influencing the choice of policy framework are difficult to measure. For instance, political considerations may have influenced the choice of a "fixed exchange rates regime among many European countries. While the dummy for members of the European Union may capture this effect, it would be desirable with a better measure of such political considerations. Furthermore, the dummy for European countries may not appropriately capture the fact that some countries have a "natural" foreign currency to peg to.

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<sup>1</sup>If the P value is insignificant (Prob>chi2 larger than .05) then it is safe to use random effects model. If you get a significant P-value, however, you should use fixed effects. For more information, please go to: [http://dss.princeton.edu/online\\_help/analysis/panel.htm#choice](http://dss.princeton.edu/online_help/analysis/panel.htm#choice)

## 4 Conclusion

In this paper we made a novel attempt to address three issues related to Inflation Targeting. Using a larger set of Panel data, we attempted to analyze how a set of potentially important variables change or influence the probability of adopting Inflation targeting. We were quite successful in finding out the direction in which our set of explanatory variables change the probability of inflation targeting. Second, we were able to show that with a larger set of panel setup, one can reconcile some of the ambiguity related to the sign of some of the explanatory variables in changing the EIT adoption encountered by previous works. Finally, we attempted to test whether there is any fixed effect present in the analysis of EIT adoption decision, because previous empirical works point to this. We were able to prove that there might be fixed country effect. For future work, a Multinomial Panel Logit model might be more appropriate where choice between different monetary policy regime can be analyzed.

## References

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Appendix-1

```
-----
log: F:\Fall_06\Microeconometrics\My Project\Fine data\project.log
log type: text
opened on: 18 Dec 2006, 00:43:14
```

```
. reshape long IT COMM CONC DIVER IR OPEN RER TOT eu_dum , i(id) j(year)
(note: j = 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004)
```

```
Data                                wide  ->  long
-----
Number of obs.                      24    ->   600
Number of variables                  227   ->   12
j variable (25 values)              ->   year
xij variables:
      IT1980 IT1981 ... IT2004      ->   IT
      COMM1980 COMM1981 ... COMM2004 ->   COMM
      CONC1980 CONC1981 ... CONC2004 ->   CONC
      DIVER1980 DIVER1981 ... DIVER2004 ->   DIVER
      IR1980 IR1981 ... IR2004      ->   IR
      OPEN1980 OPEN1981 ... OPEN2004 ->   OPEN
      RER1980 RER1981 ... RER2004   ->   RER
      TOT1980 TOT1981 ... TOT2004   ->   TOT
      eu_dum1980 eu_dum1981 ... eu_dum2004 ->   eu_dum
-----
```

```
. tsset id year, yearly
      panel variable: id, 1 to 24
      time variable: year, 1980 to 2004
```

```
. *** Summary of the Data***
. sum
```

Variable	Obs	Mean	Std. Dev.	Min	Max
id	600	12.5	6.927962	1	24
year	600	1992	7.217119	1980	2004
Country	0				
IT	600	.345	.4757649	0	1
COMM	600	.6101135	1.624336	0	10.81284
CONC	600	.1777667	.1161372	.045	.58
DIVER	600	.4885667	.1304924	.224	.786
IR	555	26.34803	150.5877	-88.96089	2076.684
OPEN	600	.34205	.9763451	.0156324	11.7846
RER	595	10.84736	115.2354	-51.7969	2006.675
TOT	530	-.2623205	13.82194	-100	230.6748
eu_dum	600	.1533333	.3606091	0	1
countrydum	600	12.5	6.927962	1	24
Europe_Dum	600	.4583333	.4986766	0	

\*\*\* Descriptive Statistics\*\*\*

. global X COMM CONC DIVER IR OPEN RER TOT eu\_dum Europe\_Dum

.  
. correlate \$X  
(obs=480)

COMM	CONC	DIVER	IR	OPEN	RER	TOT	eu_dum	Europe~m
COMM		1.0000						
CONC		0.2494	1.0000					
DIVER		0.4257	0.6353	1.0000				
IR		-0.0224	-0.0495	0.0133	1.0000			
OPEN		-0.0668	-0.0897	-0.2258	-0.0349	1.0000		
RER		-0.0276	-0.0408	0.0198	-0.0086	-0.0125	1.0000	
TOT		0.0520	-0.1689	-0.1134	-0.0672	0.0065	-0.0246	1.0000
eu_dum		-0.1429	-0.2220	-0.5620	-0.0729	0.2173	-0.0419	0.0327
1.0000								
Europe_Dum		-0.1901	-0.2611	-0.5671	-0.0939	0.1770	0.0785	0.0150
0.4944	1.0000							

```

. *** Pooled Binary Logit with full sample***
. logit IT COMM CONC DIVER IR OPEN RER TOT eu_dum Europe_Dum , robust
Iteration 0: log pseudolikelihood = -309.51796
Iteration 1: log pseudolikelihood = -268.79456
Iteration 2: log pseudolikelihood = -261.85887
Iteration 3: log pseudolikelihood = -251.90656
Iteration 4: log pseudolikelihood = -235.9383
Iteration 5: log pseudolikelihood = -222.8439
Iteration 6: log pseudolikelihood = -218.37658
Iteration 7: log pseudolikelihood = -218.01013
Iteration 8: log pseudolikelihood = -218.00728
Iteration 9: log pseudolikelihood = -218.00728

```

```

Logistic regression                                Number of obs =          480
                                                    Wald chi2(9)  =          60.73
                                                    Prob > chi2   =          0.0000
Log pseudolikelihood = -218.00728                Pseudo R2     =          0.2957

```

IT	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
COMM	.3435284	.1114302	3.08	0.002	.1251292	.5619276
CONC	.669433	1.817114	0.37	0.713	-2.892046	4.230912
DIVER	-4.401496	1.739639	-2.53	0.011	-7.811126	-.9918663
IR	-.1859362	.0754637	-2.46	0.014	-.3338422	-.0380301
OPEN	.532444	.2007013	2.65	0.008	.1390767	.9258114
RER	-.0055171	.0062704	-0.88	0.379	-.0178068	.0067726
TOT	.0345044	.0175121	1.97	0.049	.0001814	.0688275
eu_dum	.8114306	.452545	1.79	0.073	-.0755412	1.698402
Europe_Dum	-1.697893	.3247823	-5.23	0.000	-2.334454	-1.061331
_cons	2.921267	.9820599	2.97	0.003	.9964649	4.846069

Note: 16 failures and 0 successes completely determined.

```

. *** Marginal effect in the pooled regression with full sample***
. mfx
Marginal effects after logit
y = Pr(IT) (predict)
= .00721151

```

variable	dy/dx	Std. Err.	z	P> z	[ 95% C.I. ]		X
COMM	.0024595	.00409	0.60	0.547	-.005553	.010472	.554436
CONC	.0047928	.01001	0.48	0.632	-.014826	.024412	.17301
DIVER	-.0315125	.05121	-0.62	0.538	-.131892	.068867	.482096
IR	-.0013312	.00184	-0.72	0.470	-.004945	.002283	29.696
OPEN	.003812	.007	0.54	0.586	-.009905	.017529	.363771
RER	-.0000395	.00008	-0.51	0.608	-.00019	.000111	8.70045
TOT	.000247	.0004	0.61	0.540	-.000544	.001038	-.746671
eu_dum*	.0077773	.0176	0.44	0.659	-.026724	.042279	.166667
Europe~m*	-.0125089	.02205	-0.57	0.571	-.055733	.030715	.45

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

. \*\*\* Random Effects Logit with observations grouped by time with full sample  
\*\*\*\*

. xtlogit IT COMM CONC DIVER IR OPEN RER TOT eu\_dum Europe\_Dum , i(id) re

Fitting comparison model:

Iteration 0: log likelihood = -309.51796  
 Iteration 1: log likelihood = -268.79456  
 Iteration 2: log likelihood = -261.85887  
 Iteration 3: log likelihood = -251.90656  
 Iteration 4: log likelihood = -235.9383  
 Iteration 5: log likelihood = -222.8439  
 Iteration 6: log likelihood = -218.37658  
 Iteration 7: log likelihood = -218.01013  
 Iteration 8: log likelihood = -218.00728  
 Iteration 9: log likelihood = -218.00728

Fitting full model:

tau = 0.0 log likelihood = -218.00728  
 tau = 0.1 log likelihood = -210.11806  
 tau = 0.2 log likelihood = -205.68089  
 tau = 0.3 log likelihood = -202.99829  
 tau = 0.4 log likelihood = -201.42679  
 tau = 0.5 log likelihood = -200.7351  
 tau = 0.6 log likelihood = -201.01949  
 Iteration 0: log likelihood = -200.6924  
 Iteration 1: log likelihood = -186.24709  
 Iteration 2: log likelihood = -185.48145  
 Iteration 3: log likelihood = -185.47394  
 Iteration 4: log likelihood = -185.47394

Random-effects logistic regression Number of obs = 480  
 Group variable (i): id Number of groups = 22

Random effects u\_i ~ Gaussian Obs per group: min = 11  
 avg = 21.8  
 max = 25  
 Wald chi2(9) = 103.83  
 Prob > chi2 = 0.0000  
 Log likelihood = -185.47394

IT	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
COMM	.1823552	.1665544	1.09	0.274	-.1440855	.5087959
CONC	.0377001	3.4515	0.01	0.991	-6.727116	6.802516
DIVER	-14.89971	3.051564	-4.88	0.000	-20.88067	-8.918758
IR	-.2530133	.0382424	-6.62	0.000	-.3279669	-.1780596
OPEN	1.141503	.4824649	2.37	0.018	.1958889	2.087116
RER	-.0101763	.010665	-0.95	0.340	-.0310793	.0107267
TOT	.0232958	.0234384	0.99	0.320	-.0226426	.0692343
eu_dum	1.774147	.6942364	2.56	0.011	.4134686	3.134825
Europe_Dum	-4.358717	.8790293	-4.96	0.000	-6.081583	-2.635851
_cons	9.303301	1.381526	6.73	0.000	6.595561	12.01104
/lnsig2u	1.414374	.3715676			.6861149	2.142633
sigma_u	2.028278	.3768211			1.40925	2.91922
rho	.5556501	.0917412			.3764291	.7214741

Likelihood-ratio test of rho=0: chibar2(01) = 65.07 Prob >= chibar2 = 0.000

```

. *** Fixed Effects Logit with observations grouped by time with full sample***
. xtlogit IT COMM CONC DIVER IR OPEN RER TOT eu_dum Europe_Dum , i(id) fe
note: multiple positive outcomes within groups encountered.
note: 3 groups (43 obs) dropped due to all positive or
      all negative outcomes.
note: Europe_Dum omitted due to no within-group variance.

```

```

Iteration 0:   log likelihood = -155.84294
Iteration 1:   log likelihood = -108.32822
Iteration 2:   log likelihood = -103.46643
Iteration 3:   log likelihood = -102.95526
Iteration 4:   log likelihood = -102.93982
Iteration 5:   log likelihood = -102.93976
Iteration 6:   log likelihood = -102.93976

```

```

Conditional fixed-effects logistic regression      Number of obs      =      437
Group variable (i): id                          Number of groups   =      19

                                                Obs per group: min =      13
                                                avg               =     23.0
                                                max               =      25

                                                LR chi2(8)        =     237.80
Log likelihood = -102.93976                    Prob > chi2       =      0.0000

```

IT	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
COMM	-3.105978	1.649865	-1.88	0.060	-6.339653 .1276973
CONC	-1.022045	4.409356	-0.23	0.817	-9.664223 7.620133
DIVER	-40.70258	7.97538	-5.10	0.000	-56.33403 -25.07112
IR	-.2199304	.0410024	-5.36	0.000	-.3002937 -.1395671
OPEN	4.219582	1.483616	2.84	0.004	1.311748 7.127416
RER	-.0052802	.0103631	-0.51	0.610	-.0255915 .0150311
TOT	.0114784	.0284996	0.40	0.687	-.0443797 .0673366
eu_dum	2.335021	.9043233	2.58	0.010	.56258 4.107462

```

. est store fixed

```





```
. *** Hausman Test of Hypotheis with full sample****
. hausman fixed
```

	---- Coefficients ----			
	(b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
COMM	-3.105978	.1823552	-3.288333	1.641436
CONC	-1.022045	.0377001	-1.059745	2.744005
DIVER	-40.70258	-14.89971	-25.80286	7.36849
IR	-.2199304	-.2530133	.0330829	.0147892
OPEN	4.219582	1.141503	3.078079	1.402977
RER	-.0052802	-.0101763	.0048961	.
TOT	.0114784	.0232958	-.0118174	.0162132
eu_dum	2.335021	1.774147	.5608741	.5795139

```
-----
b = consistent under Ho and Ha; obtained from xtlogit
B = inconsistent under Ha, efficient under Ho; obtained from xtlogit
```

```
Test: Ho: difference in coefficients not systematic
```

```
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
          = 54.60
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)
```

```
.
.
end of do-file

. edit
- preserve

. exit, clear
```

## Appendix-2

```
-----
log: F:\Fall_06\Microeconometrics\My Project\Fine data\project_2.log
log type: text
opened on: 18 Dec 2006, 00:49:39
```

```
. reshape long IT COMM CONC DIVER IR OPEN RER TOT eu_dum, i(id) j(year)
(note: j = 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004)
```

```
Data                wide  ->  long
-----
Number of obs.             21  ->   525
Number of variables        227  ->   12
j variable (25 values)     ->  year
xij variables:
      IT1980 IT1981 ... IT2004  ->  IT
      COMM1980 COMM1981 ... COMM2004  ->  COMM
      CONC1980 CONC1981 ... CONC2004  ->  CONC
      DIVER1980 DIVER1981 ... DIVER2004  ->  DIVER
      IR1980 IR1981 ... IR2004  ->  IR
      OPEN1980 OPEN1981 ... OPEN2004  ->  OPEN
      RER1980 RER1981 ... RER2004  ->  RER
      TOT1980 TOT1981 ... TOT2004  ->  TOT
      eu_dum1980 eu_dum1981 ... eu_dum2004  ->  eu_dum
-----
```

```
. gen countrydum = 0
. gen Europe_Dum = 0
. tsset id year, yearly
      panel variable:  id, 2 to 23
      time variable:  year, 1980 to 2004
```

```
. . *** Summary of the Data: EIT sample***
. sum
```

Variable	Obs	Mean	Std. Dev.	Min	Max
id	525	12.71429	6.421449	2	23
year	525	1992	7.21798	1980	2004
Country	0				
IT	525	.3085714	.4623443	0	1
COMM	525	.6746538	1.725028	0	10.81284
CONC	525	.1880533	.1197404	.045	.58
DIVER	525	.4994533	.1251292	.224	.786
IR	492	29.2113	159.7273	-88.96089	2076.684
OPEN	525	.2700907	.3956338	.0156324	4.485842
RER	520	8.712733	86.44621	-26.09473	1678.897
TOT	480	-.2835428	14.43625	-100	230.6748
eu_dum	525	.127619	.3339834	0	1
countrydum	525	12.71429	6.421449	2	23
Europe_Dum	525	.4761905	.4999091	0	1

\*\*\* Descriptive Statistics\*\*\*

. global X COMM CONC DIVER IR OPEN RER TOT eu\_dum Europe\_Dum

.  
 . correlate \$X  
 (obs=442)

	COMM	CONC	DIVER	IR	OPEN	RER	TOT
eu_dum	-0.1309	-0.1993	-0.5076	-0.0711	0.0135	-0.0378	0.0313
Europe_Dum	-0.1902	-0.2606	-0.5271	-0.1002	0.1895	0.0822	0.0152
COMM	1.0000						
CONC	0.2434	1.0000					
DIVER	0.4407	0.6556	1.0000				
IR	-0.0252	-0.0551	0.0134	1.0000			
OPEN	-0.0835	-0.0929	-0.1785	-0.0527	1.0000		
RER	-0.0297	-0.0447	0.0186	-0.0100	0.0047	1.0000	
TOT	0.0554	-0.1703	-0.1201	-0.0672	0.0034	-0.0244	1.0000
eu_dum	1.0000						
Europe_Dum	0.4586	1.0000					

```
. *** Pooled Binary Logit with EIT sample***
.
. logit IT COMM CONC DIVER IR OPEN RER TOT eu_dum Europe_Dum , robust
```

```
Iteration 0: log pseudolikelihood = -277.49678
Iteration 1: log pseudolikelihood = -246.66803
Iteration 2: log pseudolikelihood = -241.392
Iteration 3: log pseudolikelihood = -232.08285
Iteration 4: log pseudolikelihood = -217.38814
Iteration 5: log pseudolikelihood = -206.03895
Iteration 6: log pseudolikelihood = -202.40018
Iteration 7: log pseudolikelihood = -202.1277
Iteration 8: log pseudolikelihood = -202.12591
Iteration 9: log pseudolikelihood = -202.12591
```

```
Logistic regression                                Number of obs =          442
                                                    Wald chi2(9) =          54.89
                                                    Prob > chi2 =          0.0000
Log pseudolikelihood = -202.12591                Pseudo R2 =          0.2716
```

IT	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
COMM	.3157926	.1082835	2.92	0.004	.1035609	.5280244
CONC	.3539385	1.807096	0.20	0.845	-3.187905	3.895782
DIVER	-3.362829	1.770859	-1.90	0.058	-6.83365	.1079913
IR	-.1715387	.0713563	-2.40	0.016	-.3113945	-.0316828
OPEN	.5439069	.2168425	2.51	0.012	.1189033	.9689104
RER	-.0043981	.0048046	-0.92	0.360	-.0138151	.0050188
TOT	.0254293	.0159139	1.60	0.110	-.0057615	.0566201
eu_dum	.7558862	.4525439	1.67	0.095	-.1310836	1.642856
Europe_Dum	-1.621896	.3208604	-5.05	0.000	-2.250771	-.9930208
_cons	2.353934	.9510977	2.47	0.013	.4898167	4.218051

Note: 15 failures and 0 successes completely determined.

```
. *** Marginal effect in the pooled regression with EIT sample***
. mfx
Marginal effects after logit
y = Pr(IT) (predict)
= .0064298
```

variable	dy/dx	Std. Err.	z	P> z	[ 95% C.I. ]		X
COMM	.0020174	.00344	0.59	0.558	-.004726	.008761	.576892
CONC	.0022611	.00947	0.24	0.811	-.016309	.020832	.176337
DIVER	-.0214833	.03565	-0.60	0.547	-.09135	.048384	.481932
IR	-.0010959	.00155	-0.71	0.479	-.004129	.001938	31.903
OPEN	.0034747	.00653	0.53	0.594	-.009316	.016265	.269091
RER	-.0000281	.00005	-0.51	0.609	-.000136	.00008	9.45952
TOT	.0001625	.00028	0.59	0.558	-.000382	.000707	-.789086
eu_dum*	.0064021	.01485	0.43	0.666	-.022701	.035505	.151584
Europe-m*	-.0107619	.01941	-0.55	0.579	-.048813	.027289	.459276

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

```
. *** Fixed Effects Logit with observations grouped by time with EIT sample***
. xtlogit IT COMM CONC DIVER IR OPEN RER TOT eu_dum Europe_Dum , i(id) fe
note: multiple positive outcomes within groups encountered.
note: 2 groups (30 obs) dropped due to all positive or
      all negative outcomes.
note: Europe_Dum omitted due to no within-group variance.
```

```
Iteration 0:   log likelihood = -145.72951
Iteration 1:   log likelihood = -104.08561
Iteration 2:   log likelihood = -98.894056
Iteration 3:   log likelihood = -98.478609
Iteration 4:   log likelihood = -98.414296
Iteration 5:   log likelihood = -98.409976
Iteration 6:   log likelihood = -98.40997
```

```
Conditional fixed-effects logistic regression   Number of obs   =       412
Group variable (i): id                       Number of groups =        18

                                             Obs per group: min =        13
                                             avg =           22.9
                                             max =           25

LR chi2(8) = 216.24
Prob > chi2 = 0.0000

Log likelihood = -98.40997
```

IT	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
COMM	-2.408533	1.536647	-1.57	0.117	-5.420307	.6032399
CONC	-.7401676	4.395011	-0.17	0.866	-9.354231	7.873896
DIVER	-39.99411	8.568209	-4.67	0.000	-56.78749	-23.20073
IR	-.2104023	.0406102	-5.18	0.000	-.2899969	-.1308078
OPEN	4.168052	1.472044	2.83	0.005	1.282899	7.053205
RER	-.0042219	.0095577	-0.44	0.659	-.0229545	.0145108
TOT	-.0036896	.0294998	-0.13	0.900	-.0615081	.054129
eu_dum	2.365162	.9003358	2.63	0.009	.6005359	4.129787

```
. est store fixed
```

```
. *** Random Effects Logit with observations grouped by time with EIT sample
. xtlogit IT COMM CONC DIVER IR OPEN RER TOT eu_dum Europe_Dum , i(id) re
```

Fitting comparison model:

```
Iteration 0: log likelihood = -277.49678
Iteration 1: log likelihood = -246.66803
Iteration 2: log likelihood = -241.392
Iteration 3: log likelihood = -232.08285
Iteration 4: log likelihood = -217.38814
Iteration 5: log likelihood = -206.03895
Iteration 6: log likelihood = -202.40018
Iteration 7: log likelihood = -202.1277
Iteration 8: log likelihood = -202.12591
Iteration 9: log likelihood = -202.12591
```

Fitting full model:

```
tau = 0.0 log likelihood = -202.12591
tau = 0.1 log likelihood = -195.1164
tau = 0.2 log likelihood = -191.26826
tau = 0.3 log likelihood = -189.03132
tau = 0.4 log likelihood = -187.83408
tau = 0.5 log likelihood = -187.4874
tau = 0.6 log likelihood = -188.04028
Iteration 0: log likelihood = -187.37332
Iteration 1: log likelihood = -174.98802
Iteration 2: log likelihood = -174.37358
Iteration 3: log likelihood = -174.36147
Iteration 4: log likelihood = -174.36145
```

Random-effects logistic regression  
Group variable (i): id

```
Number of obs = 442
Number of groups = 20
```

Random effects u\_i ~ Gaussian

```
Obs per group: min = 11
                avg = 22.1
                max = 25
```

Log likelihood = -174.36145

```
Wald chi2(9) = 89.14
Prob > chi2 = 0.0000
```

IT	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
COMM	.1516105	.1680315	0.90	0.367	-.1777252	.4809462
CONC	-.0814127	3.372163	-0.02	0.981	-6.690731	6.527906
DIVER	-13.13944	3.179693	-4.13	0.000	-19.37153	-6.907361
IR	-.2397803	.0379757	-6.31	0.000	-.3142112	-.1653494
OPEN	1.161265	.483445	2.40	0.016	.2137302	2.1088
RER	-.0085145	.0105395	-0.81	0.419	-.0291715	.0121424
TOT	.010653	.0238616	0.45	0.655	-.0361149	.0574209
eu_dum	1.754185	.6981227	2.51	0.012	.3858894	3.12248
Europe_Dum	-4.249881	.8993645	-4.73	0.000	-6.012603	-2.487159
_cons	8.358165	1.447165	5.78	0.000	5.521773	11.19456
/lnsig2u	1.382081	.3935475			.6107424	2.15342
sigma_u	1.995791	.3927194			1.357129	2.935008
rho	.5476633	.0974928			.3589084	.7236366

Likelihood-ratio test of rho=0: chibar2(01) = 55.53 Prob >= chibar2 = 0.000

```
. *** Hausman Test of Hypotheis with EIT sample***
. hausman fixed
```

	---- Coefficients ----		(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
	(b) fixed	(B) .		
COMM	-2.408533	.1516105	-2.560144	1.527433
CONC	-.7401676	-.0814127	-.6587549	2.818623
DIVER	-39.99411	-13.13944	-26.85467	7.956365
IR	-.2104023	-.2397803	.0293779	.0143888
OPEN	4.168052	1.161265	3.006787	1.390394
RER	-.0042219	-.0085145	.0042927	.
TOT	-.0036896	.010653	-.0143425	.0173454
eu_dum	2.365162	1.754185	.6109769	.5685325

```
-----
b = consistent under Ho and Ha; obtained from xtlogit
B = inconsistent under Ha, efficient under Ho; obtained from xtlogit
```

```
Test: Ho: difference in coefficients not systematic
```

```
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
          = 49.06
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)
```

```
.
.
end of do-file

. exit, clear
```