A Reinvestigation of Interest Rate Defense against Speculative Attacks

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Abstract

This paper empirically tests the effectiveness of tight monetary policy against speculative attacks. It is shown that previous empirical studies on this issue suffer a classic sample selection problem by restricting their sample observations to crisis periods only. To correct this selectivity bias, I employ the full information maximum likelihood method to a large unbalanced panel dataset that covers both crisis periods and peaceful periods. I also develop a rare-events-corrected probit model with sample selection that can be used to correct a second bias that is created by the rare events data used to estimate the selection equation. My empirical results show there is no significant statistical relationship between the interest rate and the outcome of a speculative attack.

Key Words: Currency Crises; Interest Rate Defenses; Sample Selection Bias; Rare-Events

JEL Classification: F30, C34.

1. Introduction

Following a new wave of currency crises in the 1990's, there has been growing interest in further understanding the role of interest rate defense against speculative attacks in the literature. According to conventional economic wisdom, a high interest rate helps defend the currency.[1] It makes domestic currency denominated interest-bearing assets more attractive and increase speculators' borrowing cost as well. Furthermore, raising the interest rate before an attack can signal the government's willingness and ability to defend its currency.[2] The contrarian view, however, emphasizes that a high interest would worsen a country's fiscal position, and, therefore, may hasten a speculative attack and make it self-fulfilling.

Theoretical models in the literature often incorporate both views. For example, according to Lahiri and Vegh (2000), raising the interest rate can delay the crisis but only up to a point. Otherwise it may actually hasten the crisis for a higher interest rate increases the government's fiscal liability and imply higher future inflation. The model of Flood and Jeanne (2000) also shows that raising the interest rate makes domestic assets more attractive, but increases public debt service as well. Therefore, if a speculative attack is motivated by underlying fiscal fragility, raising the interest rate can hasten the attack. Drazen (2000) shows that the outcome of an interest rate defense depends on speculators' information about the government's fiscal position. If the fiscal position is known, raising the interest rate may increase the probability of devaluation. Otherwise, it

1 See Kraay (2003) for a more detailed discussion of the conventional view and the contrarian view.
2 See Drazen (1999), Drazen (2001), and Grier and Lin (2004).

can decrease the probability. In Angeletos et al (2003), the government is willing to take a costly policy action only for a small region of moderate fundamentals, and this region shrinks as the information in the market becomes precise. Grier and Lin (2005a) model interest rate defense as a war of attrition game. A high interest rate is not sufficient to guarantee a successful defense. The consensus conclusion one can draw from these models is that an interest rate defense is a double-edged sword. It cuts both ways.

The effectiveness of interest rate defense is ultimately an empirical issue. Empirical evidence in the literature on this issue is mixed. Using daily data, Furman and Stiglitz (1998) find that high interest rates are followed by exchange rate depreciations. Drawing on large sample evidence, Kraay (2003) finds no systematic association between the interest rate and the outcome of a speculative attack. Looking at the same type of data but using simpler statistical methods, Hubrich (2000) finds that different measures of tight monetary policies could have different impacts on the outcome of defenses. Discount rates have an unconventional impact on the exchange rate while domestic credit has conventional results. Drazen and Hubric (2003) find that raising the interest rate strengthens the exchange rate over the short-run but leads to an expected depreciation at a horizon of a year and longer.

The objective of this paper is to empirically test whether raising the interest rate during a speculative attack can help defend the currency peg. This study is distinguished from previous ones in two aspects. First, previous empirical studies on this issue look at sample observations drawn from the crisis periods. As I shall show later, these studies suffer a classic sample selection problem, and their estimation results are, therefore, biased. They confuse the effects of interest rate defenses conditional on speculative attacks with the unconditional effects. To correct this selectivity bias, I employ the full information maximum likelihood method to my sample which contains both the crisis periods and the tranquil periods. The empirical model that I estimate is following that of Van de Ven and Van Praag (1981) and Maddala (1983), in which both the selection equation and the attack outcome equation have binary dependent variables. Second, I develop a rare-events-corrected probit model with sample selection to correct a second bias that is created by the rare events data used to estimate the selection equation. After controlling for other factors, I find empirical evidence that supports neither the conventional nor the contrarian view. Raising the interest rate during speculative attacks does not have significant effect on the outcome of a speculative attack.

The rest of this paper is organized as follows: Section 2 discusses the empirical models and the methodology. Section 3 addresses data issues. Section 4 provides my empirical results. Section 5 concludes.

2. Empirical Models

A. A Probit Model with Sample Selection

The statistical model can be specified as follows:

$$SF_i^* = \alpha' X_i + U_{1i} \tag{1}$$

$$ATK_i^* = \beta' Z_i + U_{2i} \tag{2}$$

where $U_1 \sim N(0,1)$, $U_2 \sim N(0,1)$, and $corr(U_1, U_2) = \rho$. The first equation regresses the outcome of a speculative attack on a vector of monetary policy variable and other factors affecting the outcome. SF_i^* is an unobserved latent variable. What we observe is an indicator variable SF_i, which equals one if $SF_i^* > 0$ and zero otherwise. In this case, $SF_i^* > 0$ if an attack turns out to be successful and $SF_i^* < 0$ if an attack fails. The second equation is the selection equation. A speculative attack occurs ($ATK_i = 1$) if the underlying latent variable ATK^* is greater than zero. Otherwise, there is no speculative attack ($ATK_i = 0$). Equation (1) and equation (2) are related because one observes SF_i only if $ATK_i = 1$ and the two error terms U_{1i} and U_{2i} are assumed to be jointly normally distributed with correlation coefficient ρ.

Heckman (1979) shows that a direct estimation of equation (1) would produce biased estimate as long as ρ is nonzero. I suspect that this sample selection problem exists in my statistical environment because the unobserved characteristics, which can affect the speculators' attack decision, captured by the error term of equation (2) are also likely to affect the outcome of a speculative attack. After all, rational speculators attack a currency only if they believe that their attack is likely to be successful. Since both equation (1) and equation (2) have binary dependent variables, one can estimate them using either the two-step approach developed by Van de Ven and Van Praag (1981) or the full information maximum likelihood method. Under the assumption that the error terms are jointly normally distributed, the log likelihood function can be written as

$$L = \sum_{ATK=0} \ln[1 - \Phi(\beta' Z_i)] + \sum_{ATK=1}^{SF=1} \ln[\Phi_2(\alpha' X_i, \beta' Z_i, \rho)] + \sum_{ATK=1}^{SF=0} \ln[\Phi_2(-\alpha' X_i, \beta' Z_i, \rho)] \qquad (3)$$

Where $\Phi_2(\ )$ is the cumulative bivariate normal distribution function with zero means and $\Phi(\ )$ is the standard cumulative normal distribution function. The first term in the log likelihood function is the probability of speculators choosing not to attack, the second term is the probability of speculators choosing to attack with success, and the last term is the probability of speculators choosing to attack with failure.

B. Rare Events Corrected Probit Model with Sample Selection

As is known, standard finite sample maximum-likelihood estimates of probit or logit are biased. This bias vanishes as sample size becomes larger. However, King and Zeng (2001 a, b) show that this finite sample bias can be greatly exaggerated when one observed choice occurs rarely in the data. The sample that I used to estimate the selection equation contains 6765 total observations. The dependent variable takes on the value of one in only 96 out of these 6765 total possibilities. Therefore, maximum likelihood estimate of the selection equation can result in a large bias due to the nature of my data. King and Zeng (2001 a, b) develop a method called rare-events-logit to correct the bias. However, their method is not applicable in this study because it would violate the jointly normal assumption of the error terms. [3] To address this problem, I shall develop a rare-events-corrected probit model with sample selection in the following part of this section.

The rare events corrected probit model with sample selection can be developed

[3] An alternative method would be to apply the rare-events-logit technique to the second equation, and then use the generalized two-step selection bias correction method, which does not require the bivariate normal assumption, introduced by Lee (1982). However, this method requires tedious computation and is much more difficult to apply.

based on traditional two-step approach proposed by Van de Ven and Van Praag (1981), and Maddala (1983). It is a three-step approach. The first step is to estimate the selection equation using probit. The second step is to correct the rare events bias in the probit estimate. McCullagh and Nedler (1989) show that the bias can be estimated by the following weighted least-square expression:

$$b = E[\hat{\beta} - \beta] = (Z'WZ)^{-1} Z'W\xi \qquad (4)$$

where $(Z'WZ)$ is the Fisher information matrix. ξ is a $N \times 1$ vector with $\xi_i = Q_{ii}\eta_i / 2$. Q_{ii} are the diagonal elements of matrix $Q = Z(Z'WZ)^{-1} Z$, and $W = diag\{\phi^2(\beta' Z_i)/[\Phi(\beta' Z_i)\Phi(-\beta' Z_i)]\}$. Thus, the unbiased and consistent estimate, β_u, can be obtained from subtracting the estimated bias from the probit estimate $\hat{\beta}$, $\beta_u = E[\beta] = \hat{\beta} - b$. Also according to McCullagh and Nedler (1989), the variance of β_u can be approximately estimated as $V(\beta_u) = [N/(N+K)]^2 V(\hat{\beta})$ for small β.

The last step corrects the sample selection bias. Maddala (1983) shows that, under the assumption that the error terms are jointly normally distributed, the conditional mean of the error term in equation (1) equals the correlation coefficient ρ times the inverse Mills ratio, λ_i.[4]

$$E[U_{1i} \mid X_i, ATK_i^* > 0] = \rho\lambda_i \qquad (5)$$

where $\lambda_i = \phi(-\beta' Z_i)/\Phi(\beta' Z_i)$ is the inverse Mills ratio, ϕ and Φ are the density and distribution function for a standard normal variable.

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[4] This is only true when the variance of the error term is normalized to one. Otherwise, $E[U_{1i} \mid X_i, ATK_i^* > 0] = \sigma\rho\lambda_i$.

The selectivity-bias-free estimates, therefore, can be obtained by maximizing the following log-likelihood:

$$L(\alpha) = \sum_{ATK=1} [SF_i \ln \pi_i(\alpha) + (1 - SF_i) \ln(1 - \pi_i(\alpha))] \tag{6}$$

where $\pi_i = \Phi[(\alpha' X_i + \rho\lambda_i) / \sqrt{\tau_i^2}\,]$, and

$\tau_i^{\,2} = Var[SF_i \mid X_i, ATK_i > 0] = 1 + \rho^2(-\beta' Z_i \lambda_i - \lambda_i^{\,2})$.

The unbiased estimate β_u will be used to construct the inverse Mill's ratio in equation (6). Notice that a direct estimation of equation (1) with the inverse Mill's ratio as an additional regression using probit is invalid for the new error term is heteroskedastic by construction.

3. DATA

The dataset used in this study is an unbalanced panel comprised of monthly data for 49 countries, both developed and developing, from March 1964 to December 2000.[5] For some countries, there are some time periods excluded from the sample either due to their absence of pegged exchange rate regimes or due to data availability. Much of the data are drawn from Grier and Lin (2005b), including those identified speculative attacks and their outcomes.[6] Table 1 lists all the identified attacks, including 36 successful attacks and 60 failed attacks.

Following Kraay (2003), I consider two measures of monetary policy response in equation (1): a change in central bank discount rate (DIR) and a change in domestic

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[5] I actually started looking at a dataset that include all countries in the world. Those countries that are excluded from the sample are countries that had not had fixed exchange rate during those period or whose data are not available.

[6] See Grier and Lin (2005b) for a detailed description of the identification methodology.

credit growth (DDCG). If the conventional view is correct, one would expect to see negative and significant coefficient on DIR and a positive and significant coefficient on DDCG. In equation (2), I replace a monetary policy variable with a lagged monetary policy variable. Lagged monetary policy variables are used because they are observable to speculators prior to attacks and are expected to have import impacts on speculators' attack decisions.[7]

Four control variables are included in equation (1). The first control variable is a measure of real exchange overvaluation (REROV) constructed as the growth rate of the real CPI weighted exchange rate versus the US in the previous 12 months. The second control variable I consider is a measure of reserves adequacy (RESIMP), which is calculated by dividing a country's total non-gold reserves with its monthly import values. The third control variable is a measure of the point in the business cycle prior to the speculative attack (DGROWTH) defined as deviation of real per capita GDP growth in a country from its average in the five preceding years. The last control variable is a dummy variable for capital control (KAPCON). The control variables I consider in equation (2) include all the above 4 control variables and one additional variable NOA, which is defined as number of attacks occurred in history and is used to capture the historical vulnerability of a currency. Table 2 shows some basic summary statistics of the data. Detailed data sources and variable descriptions are available in the data appendix.

4. Results

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[7] See Grier and Lin (2005b).

A. Results from Simple Probit Regressions

Table 3 reports the results of simple probit regressions of equation (1) without correcting for the selectivity bias. The two panels in Table 3 correspond to my two measures of monetary policy. The two Wald χ^2 statistics are 41.92 and 47.40, indicating that both models are statistically significant at 1% level. Change in discount rate has a negative sign and change in domestic credit growth is positive, neither of which is significant. This evidence suggests that there is no significant statistical relationship between imposing tight monetary policy and the outcome of an attack. In terms of the control variables, DGROWTH, REROV, and KAPCON have expected signs and are statistically significant, meaning that speculative attacks are less likely to be successful in countries that either experience high growth, or have low real exchange rate overvaluation, or impose restrictions on their capital account transactions. RESIMP is insignificant, suggesting that a large reserve does not have the significant impact on the outcome of a speculative attack as one usually believes.

B. Results from Maximum Likelihood

Due to the selectivity bias, previous results of simple probit model cannot be taken seriously. One way to correct the selectivity bias is to jointly estimate both equation (1) and equation (2) using full information maximum likelihood.

The maximum likelihood estimation results are shown in Table 4. The first column of each panel reports the results of the selection equation and the second column of each panel reports the results of the attack outcome regression. The results are quite similar to those reported in Table 3. Even after correcting for selectivity bias, the overall evidence still shows no significant relationship between monetary policy variables and the outcome of a speculative attack. The coefficients on DIR and DDCG are still insignificant. There is also some evidence that lagged monetary policy increases the probability of attacks.[8] In terms of the control variables, NOA is always significant and positive, indicating that countries that have been attacked more are more likely to be attacked in the future. Real exchange rate overvaluation has significant and consistent impacts in both the selection equation and the main equation. A high real overvaluation not only increases the probability of attacks but make these attacks more likely to be successful as well. A large reserve reduces the probability of attacks but does not have significant impact on the outcome of attacks. On the contrary, high economic growth and capital control both help defend the peg though they do not seem to have significant impacts on the probability of attacks. The two estimated correlation coefficients, ρ , are -0.792 and -0.694, both of which are significant. The first Wald χ^2 statistics (with 5 degree of freedom) show that the two statistical models are significant at 1% level. Finally, the second Wald χ^2 statistics (with one degree of freedom) can be used to test the independence of equation (1) and equation (2). For both models, the null hypothesis that these two equations are independent can be rejected at 1% level. Severe sample selection problem does exist in the data.

[8] See Grier and Lin (2005b) for a detailed discussion of this perverse effect of raising the interest rate before attacks.

C. Results from Rare Events Corrected Probit with Sample Selection

As discussed earlier, the finite sample bias of maximum likelihood estimate of the selection equation can be largely exaggerated because of the rare events data used to estimate the selection equation. The three-step approach developed earlier in Section 2 part B can be used to correct both the rare-events bias and the selectivity bias. The first step is to correct the rare-events bias. This can be done by using McCullagh and Nedler's method. The first column and the third column of Table 5 provide the estimation results of equation (2) from the standard probit model and the same columns of Table 6 report the rare-events-corrected probit model. It seems that bias is quite small. These two estimation procedures produce similar coefficients and standard errors, which are also close to the joint maximum likelihood estimators reported in Table 4. The only exception is the coefficients on DDCG. Compared to the simple probit estimate and maximum likelihood estimate, the rare-events-corrected probit model produces a much smaller coefficient on DDCG.

The next step is to construct the inverse Mills ratio using the unbiased and consistent rare-events corrected probit estimates. Finally, after including the inverse Mills ratio as an additional regressor and taking care of the heteroskedasticity in the error term, equation (6) can be estimated using the probit model. The results are shown in column 2 and column 4 of Table 6 and the results from traditional two-step probit sample selection aer shown in the same columns in Table 5. The results are similar and are also close to those reported in the second column of each panel in Table 4. All control variables remain the same signs. The coefficients on DIR and DDCG are again found to be insignificant, suggesting that imposing tight monetary policies has no significant impact on the outcome of an attack. Furthermore, strong sample selection problem is once again identified in the data. The estimated ρ s are found to be significant in both models.

5. Conclusion

This paper empirically tests the effectiveness of interest rate defense against speculative attacks in a large unbalance panel dataset that covers 49 countries over the time period from March 1964 through December 2000. My empirical evidence shows that there is no significant statistical relation between the interest rate (or domestic credit) and the outcome of a speculative attack.

This paper makes two important contributions to the literature. First, it shows that previous empirical studies suffer a classic sample selection problem that could result in biased estimation results. Severe sample selection problem is identified in the data and is corrected by jointly estimate the equations using full information maximum likelihood. Second, I develop a rare-events-corrected probit model with sample selection that can be used to correct both the rare-events bias and the selectivity bias for datasets in which the selection equation is characterized by rare events.

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Data Appendix

Variable	Source	Description
Nominal Exchange Rate	IFS	local currency units per US dollar
Non-gold Reserves	IFS	in US dollar
Money Market Rate	IFS	
Discount Rate*	IFS	
Domestic Credit	IFS	in local currency units
Monthly Imports	IFS	in US dollar
CPI	IFS	
Real GDP per capita	Penn World Table 6.1	in US dollar
Exchange Regimes	Reinhart and Rogoff (2003)	*de facto* exchange rate regimes
KAPCON	IMF's Annual Report on Exchange Rate Arrangements and Exchange Restrictions	a dummy variable takes on the value one if a country has restrictions on capital account transactions

Notes: I use Bank of England base rate for United Kingdom after February 1981 because its discount rate is not available in IFS since then.

I use Levy-Yeyati and Sturzenegger (2003)'s exchange rate regime classification for Bangladesh, Rwanda and Trinidad and Tobago because they are not available in Reinhart and Rogoff (2003). I treat a regime as hard peg, soft peg, or managed floating if it is classified as fixed, dirty floating/crawling peg, or dirty floating in Levy-Yeyati and Sturzenegger (2003).

Table 1. Identified Successful and Failed Attacks

A. Identified Successful Attacks

Country	Time	Country	Time	Country	Time
Botswana	1992M7	Indonesia	1997M9	Rwanda	1990M11
Brazil	1999M1	Israel	1989M1	Spain	1967M11
Burundi	1983M12	Italy	1992M11	Spain	1982M12
Canada	1992M11	Korea	1974M12	Spain	1995M3
Denmark	1993M8	Korea	1980M1	Sweden	1977M9
Ecuador	1982M5	Korea	1997M11	Sweden	1982M11
Finland	1967M10	Mauritius	1979M11	Sweden	1992M11
Finland	1977M4	Mauritius	1981M10	Thailand	1984M11
Finland	1982M10	Mexico	1994M12	Thailand	1997M7
Finland	1991M11	Peru	1967M8	Trinidad and Tobago	1993M4
Finland	1992M9	Philippines	1970M3	Uruguay	1982M12
Ghana	1967M7	Philippines	1997M8	United Kingdom	1992M9

B. Identified Failed Attacks

Country	Time	Country	Time	Country	Time
Brazil	1997M11	France	1969M10	Pakistan	1991M3
Brazil	1998M9	France	1979M9	Philippines	1990M1
Canada	1976M3	Greece	1988M3	Portugal	1985M1
Canada	1978M2	Greece	1989M5	Portugal	1990M10
Canada	1981M7	Greece	1997M10	Spain	1987M5
Canada	1982M2	Hong Kong	1998M8	Sweden	1976M4
Canada	1984M6	Indonesia	1991M3	Sweden	1976M10
Canada	1990M5	Ireland	1997M4	Sweden	1980M2
Costa Rica	1979M8	Italy	1986M1	Sweden	1988M5
Denmark	1980M2	Italy	1990M12	Sweden	1990M2
Denmark	1984M12	Korea	1980M6	Sweden	1991M11
Denmark	1987M2	Korea	1983M1	Thailand	1978M2
Denmark	1993M2	Korea	1986M1	Thailand	1984M1
Finland	1976M2	Korea	1989M11	Thailand	1985M3
Finland	1979M11	Korea	1996M8	Thailand	1990M9
Finland	1980M11	Mauritius	1976M8	Thailand	1992M9
Finland	1986M8	Mexico	1994M5	Thailand	1994M6
Finland	1990M11	Netherlands	1976M7	Trinidad and Tobago	1988M1
Finland	1991M5	Netherlands	1979M12	Tunisia	1991M4
France	1968M10	Netherlands	1981M8	Uruguay	1998M9

Table 2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ATK	6765	0.014	0.118	0	1
SF	96	0.375	0.487	0	1
DIR	6765	-0.117	3.803	-231.400	21.940
DIRt-1	6765	-0.070	2.510	-84.200	95.000
DDCG	6765	0.004	10.504	-106.099	90.263
DDCGt-1	6765	-0.158	11.179	-146.237	90.263
DGROWTH	6765	-0.034	4.829	-34.723	52.245
REROV	6765	0.057	2.865	-35.305	82.784
RESIMP	6765	4.045	4.644	0.007	46.556
KAPCON	6765	0.736	0.441	0	1
NOA	6765	1.660	2.129	0	11

Table 3. Results From Simple Probit Regressions

	DMP=DIR	DMP=DDCG
CONSTANT	-1.193* (0.631)	-1.171* (0.615)
DMP	-0.070 (0.094) [-0.018]	0.014 (0.011) [0.004]
DGROWTH	-0.213** (0.093) [-0.054]	-0.220** (0.090) [-0.053]
REROV	0.428*** (0.097) [0.109]	0.439*** (0.099) [0.106]
RESIMP	0.013 (0.129) [0.003]	-0.023 (0.104) [-0.006]
KAPCON	-0.816** (0.379) [-0.171]	-0.829** (0.342) [-0.164]
LOG-LIKELIHOOD	-19.659	-19.772
Wald $\chi^2(5)$	41.92***	47.40***
TOTAL OBS	96	96

Notes: DMP denotes a certain measure of policy change. Cluster adjusted robust standard errors and estimated marginal effects are in parenthesis and brackets, respectively. $^{*}p<0.10$. $^{**}p<0.05$. $^{***}p<0.01$.

Table 4. Results from Full Information Maximum Likelihood

	DMP=DIR		DMP=DDCG	
	ATK	SF	ATK	SF
CONSTANT	-2.357*** (0.089)	1.272*** (0.501)	-2.357*** (0.089)	0.904* (0.499)
DMP		-0.034 (0.058)		0.012 (0.008)
DMPt-1	0.026** (0.012)		0.001 (0.023)	
NOA	0.077*** (0.014)		0.077*** (0.014)	
DGROWTH	-0.010 (0.009)	-0.115* (0.060)	-0.010 (0.009)	-0.145*** (0.052)
REROV	0.093*** (0.021)	0.211** (0.090)	0.092*** (0.021)	0.270*** (0.075)
RESIMP	-0.040** (0.019)	0.017 (0.084)	-0.040** (0.019)	-0.002 (0.085)
KAPCON	0.038 (0.074)	-0.610* (0.320)	0.042 (0.073)	-0.676** (0.335)
RHO	-0.792*** (0.102)		-0.694*** (0.156)	
Log-Likelihood	-445.962		-447.43	
Wald $\chi^2(5)$	12.72**		17.67***	
Wald $\chi^2(1)$	15.34***		8.11***	
TOTAL OBS	6765	96	6765	96

Notes: DMP denotes a certain measure of policy change. Cluster adjusted robust standard errors are in parenthesis. $^{*}p<0.10$. $^{**}p<0.05$. $^{***}p<0.01$. Equations are jointly estimated using STATA heckprob command.

Table 5. Two-Step Probit with Sample Selection

	DMP=DIR		DMP=DDCG	
	ATK	SF	ATK	SF
CONSTANT	-2.356*** (0.089)	1.499*** (0.545)	-2.355*** (0.089)	1.138** (0.555)
DMP		-0.030 (0.038)		0.011 (0.036)
DMPt-1	0.024** (0.011)		0.001 (0.002)	
NOA	0.077*** (0.014)		0.076*** (0.014)	
DGROWTH	-0.010 (0.009)	-0.103 (0.079)	-0.010 (0.009)	-0.133*** (0.080)
REROV	0.093*** (0.021)	0.183*** (0.040)	0.092*** (0.021)	0.243*** (0.041)
RESIMP	-0.040** (0.019)	0.016 (0.047)	-0.040** (0.019)	0.0003 (0.047)
KAPCON	0.039 (0.074)	-0.569 (0.392)	0.042 (0.074)	-0.637 (0.402)
RHO		-0.851*** (0.161)		-0.760*** (0.162)
LOG-LIKELIHOOD	-426.944	-18.943	-428.025	-19.363
TOTAL OBS	6765	96	6765	96

Notes: DMP denotes a certain measure of policy change. The Huber/White robust standard errors are reported in parenthesis for the main equation. Cluster adjusted robust standard errors are reported for the selection equations. $^{*}p<0.10$. $^{**}p<0.05$. $^{***}p<0.01$. The Huber/White robust standard error are estimated using the SAS IML. The maximum likelihood estimates of the main equations are estimated using Eviews. Codes are available upon request.

Table 6. Rare-Events-Corrected Two-Step Probit with Sample Selection

	DMP=DIR		DMP=DDCG	
	ATK	SF	ATK	SF
CONSTANT	-2.352*** (0.089)	1.533*** (0.538)	-2.351*** (0.089)	1.538** (0.547)
DMP		-0.028 (0.038)		-0.029 (0.036)
DMPt-1	0.027*** (0.011)		0.0005 (0.011)	
NOA	0.076*** (0.014)		0.076*** (0.014)	
DGROWTH	-0.011 (0.009)	-0.100 (0.079)	-0.010 (0.009)	-0.100*** (0.081)
REROV	0.092*** (0.021)	0.177*** (0.039)	0.091*** (0.021)	0.177*** (0.040)
RESIMP	-0.036* (0.019)	0.013 (0.048)	-0.037* (0.019)	0.013 (0.047)
KAPCON	0.036 (0.074)	-0.559 (0.392)	0.042 (0.074)	-0.557 (0.401)
RHO		-0.861*** (0.157)		-0.862*** (0.158)
LOG-LIKELIHOOD	---	-18.895	---	-19.363
TOTAL OBS	6765	96	6765	96

Notes: DMP denotes a certain measure of policy change. The Huber/White robust standard errors are reported in parenthesis for the main equation. Cluster adjusted robust standard errors are reported for the selection equations. *p<0.10. **p<0.05. ***p<0.01. The unbiased rare-events-corrected probit estimates and the Huber/White robust standard error are estimated using the SAS IML. The maximum likelihood estimates of the main equations are estimated using Eviews. Codes are available upon request.