Does inflation targeting really make a difference?

--- The other side of the story from developing countries

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Abstract

Previous work by Lin and Ye (2007) shows that inflation targeting has no significant impacts on either inflation or inflation variability in industrial countries. This study evaluates the average treatment effect of inflation targeting in thirteen developing countries that have adopted this policy by the end of 2004. Using of a variety of propensity score matching methods, we show that inflation targeting has large and significant effects on lowering both inflation and inflation variability in these thirteen countries. Our results suggest that the credibility gain from an explicit announcement of inflation targeting is more significant in the developing world.

Keywords: inflation targeting; inflation; propensity score matching, developing countries

JEL classification: E4, E5

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1. Introduction

Although inflation targeting has been widely adopted since the early 1990s, the effectiveness of this policy framework on lowering inflation and inflation variability still remains controversial among researchers and policymakers.[1] Numerous studies in the literature have attempted to empirically evaluate the "treatment effect" of inflation targeting in industrial countries and have found mixed results.[2] A common drawback of these studies, as pointed out in a recent study by Lin and Ye (2007), is that they all ignore the self-selection problem of policy adoption, which can lead to biased estimates in these early studies. Using a variety of propensity matching methods, Lin and Ye (2007) show that, once controlling for self-selectivity, inflation targeting has no significant effects on either inflation or inflation variability in industrial targeting countries.

However, inflation targeting is not a policy just for industrial countries. To date, more than a dozen of developing countries have also officially adopted inflation targeting. Thus, a complete evaluation of the effectiveness of inflation targeting requires further evidence from developing countries.

Can inflation targeting make a difference in developing countries? The main argument in favor of inflation targeting is that an official announcement of an inflation target makes a central bank's policy more credible, which helps to alleviate the dynamic inconsistency problem, and thus should lead to lower (expectations of) inflation and inflation variability.[3] Given the fact that the initial credibility of central banks in developing countries is significantly lower than that in industrial countries, it is

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[1] See Lin and Ye (2007) for a detailed discussion of the debate.
[2] These studies include Ammer and Freeman (1995), Mishkin and Posen (1997), Groenveld (1998), Kuttner and Posen (1999), Johnson (2002), and Ball and Sheridan (2003).
[3] See Bernanke et al. (1999), Svensson (1997), and Mishkin (1999).

reasonable to suspect that the credibility gain from explicitly announcing an inflation target should be much more substantial in developing countries. Therefore, despite its limited effects in industrial targeting countries, inflation targeting may make a large difference in developing countries.

Our study makes the first attempt in the literature to test this hypothesis. We evaluate the average treatment effect of inflation targeting on inflation and inflation variability in thirteen developing countries that have adopted this policy by the end of 2004 using a variety of propensity score matching methods proposed by Lin and Ye (2007). We find strong and robust evidence supporting our speculation: inflation targeting has quantitatively large and statistically significant effects on lowering both inflation and inflation variability in these countries. On average, the adoption of inflation targeting has led to a reduction in the level of inflation by nearly 3 percentage points.

The rest of our study is organized as follows. Section 2 describes our dataset and methodology. Our baseline empirical results are presented in section 3. In section 4, we conduct several robustness checks. Section 5 offers our conclusions.

2. Data and methodology

The dataset for this study includes 52 developing countries examined for the years 1985 to 2005. Most of the data are drawn from the World Bank's World Development Indicator and the IMF's International Financial Statistics.[4]

2.1. The treatment group and the control group

The treatment group includes thirteen developing countries that have adopted inflation targeting by the end of 2004.[5] We obtain their starting years of targeting from

[4] We have also drawn data from Ghosh et al. (2003) (for five-year central bank governor turnover rate), Rose (2006) (for the starting dates of inflation targeting), and Reinhart and Rogoff (2004) (for exchange rate regimes).

Rose (2006), which provides a default starting year and a conservative starting year for each targeting country. Table 1 lists the thirteen targeting countries and their default and conservative starting years of inflation targeting.

To ensure that the treatment group and the control group are reasonably comparable, our control group only includes non-targeting developing countries that have a real GDP per capita at least as large as that of the poorest targeting country and with a population size at least as big as that of the smallest targeting country in our control group. Table 2 lists the 39 non-targeting developing countries that satisfy these criteria.

2.2. Propensity score matching methods

As discussed in Lin and Ye (2007), an important econometric issue in evaluating the treatment effects of inflation targeting is non-random selection of policy adoption, which arises when a country's targeting choice is systematically correlated with a set of observable variables that also affect the outcomes (inflation or inflation variability).[6] Following Lin and Ye (2007), we make use of a variety of propensity score matching methods recently developed in the treatment effect literature to address the self-selection problem. In particular, we consider two nearest-neighbor matching estimators with $n = 1$ and $n = 3$, three radius matching estimators with a wide radius ($r = 0.04$), a medium radius ($r = 0.02$), and a tight radius ($r = 0.01$), a kernel matching estimator, and a regression-adjusted local linear matching estimator.[7]

3. Estimating the treatment effects on inflation and its variability

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[5] Indonesia, Romania, Slovak Republic, and Turkey adopted inflation targeting after 2004, but we still treat them as non-targeting countries in this study.

[6] Note that the selectivity problem here is neither selection on unobservables (omitted variables) nor a Heckman-type sample selection problem. See Lin and Ye (2007) for detailed discussions.

[7] See Lin and Ye (2007) for detailed discussions of the propensity score matching methods. The medium radius width (0.02) is set to be roughly equal to the standard deviation of the estimated propensity scores.

This section estimates the treatment effects of inflation targeting on the level of inflation ($CPIG$), defined as the annual growth rate of CPI, and inflation variability ($CPIGSTD$), defined as the standard deviation of a three-year moving average of inflation, in the thirteen targeting countries.

3.1. Estimating the propensity scores

We first estimate the propensity scores using a probit model. The dependent variable is the targeting dummy. Following Lin and Ye (2007), we consider two groups of control variables.[8] The choice of the first group is based on the literature that inflation targeting should be adopted only after some preconditions are met.[9] We choose the following three variables: the lagged inflation rate $(CPIG\_1)$, broad money growth (BMG), and real per capita GDP growth rate $(GDPPCG)$.[10] We expect the first two variables to be negatively correlated with the probability of adopting inflation targeting, and the last one to be positively correlated with the probability. The second group of variables is used to control for the likelihood of choosing exchange rate targeting as an alternative framework for the conduct of monetary policy. We include a fixed exchange rate regime dummy (FIX) and trade to GDP ratio ($OPEN$) as a measure of openness to trade in this group.[11] Since exchange rate targeting is more attractive to countries that have already adopted this policy and to countries that are more open to trade, we expect to see negative coefficients on these variables.

[8] It is important to note that the goal of estimating the propensity score is not to find a best statistical model to explain the probability of policy adoption but to control for variables that can affect the outcomes. Therefore, it is not a problem to exclude variables that systematically affect the targeting probability but do not affect inflation (variability) in the probit regressions.

[9] See, for example, Truman (2003).

[10] Lin and Ye (2007) also include government fiscal balance as a share of GDP and a five-year central bank governor turnover rate in their probit model. Adding these two variables would significant reduce our sample size, especially the targeting observations. However, we do include these two variables later in our probit model as a robustness check.

[11] Our primary data source for de facto exchange rate regimes is Reinhart and Rogoff (2004), which is available till 2001. We use the classifications reported by the IMF, which has switched from reporting de jure classifications to reporting de facto classifications since 1999, after 2001. A fixed regime is defined as either a hard peg or a soft peg.

The results are reported in the first column of Table 3. All estimated coefficients have the expected signs. We find that the lagged inflation rate, broad money growth, openness, and exchange rate regime systematically affect a country's targeting decision. The estimated coefficients on these variables are all negative and significant, indicating that countries with higher previous inflation, higher money growth, higher level of openness to trade, or fixed exchange rate regimes are less likely to adopt inflation targeting. Real GDP per capita growth is insignificant. The overall fit of the regression is reasonable with pseudo R-squares around 0.35.

3.2. Results from matching

Before applying the matching methods, we want to make sure that our treated units and control units share the same support so that they are comparable. We sort all the observations by their estimated propensity scores and then discard all the control units whose estimated propensity scores are lower than the lowest score among the treated units.

The matching results based on the new sample are presented in panel A of Tables 4 and 5.[12] Table 4 reports the estimated average treatment effect on the treated (ATTs) on the level of inflation, and Table 5 reports the estimated ATTs on inflation variability. The first two columns of each table show the results from one-to-one-nearest-neighbor and three-nearest-neighbor matching. The next three columns report the results from radius matching, with radii ranging from 0.01 to 0.04. Local linear regression matching and kernel matching results are shown in the last two columns of each table.

The results are strong and robust. The estimated ATTs in panel A of Tables 4 and 5 are all found to be negative and statistically significant. The average estimated ATT

[12] Matching estimates are obtained by using Stata command PSMATCH2 developed by Leuven and Sianesi (2003).

across different matching methods is large in magnitude, around -2.97 % in terms of annual inflation rate. The evidence from matching suggests that inflation targeting has quantitatively large and statistically significant impacts on both inflation and inflation variability in developing targeting countries.

4. Robustness checks

This section checks the robustness of our empirical results. Since twenty-six countries (including both targeting and non-targeting) in our dataset have experienced hyperinflation (defined as an annual inflation rate of 40% or higher), one may suspect that our results might be driven by those extreme values of inflation. Therefore, our first robustness check is to drop those hyperinflation episodes. The new probit estimates of the propensity scores are shown in the second column of Table 3.The results are very similar to those reported in the first column. $CPIG\_1$, BMG, $OPEN$, and FIX are all negative and significant while $GDPPCG$ is still insignificant. The pseudo R-square of the new regression is about 0.31. The new matching results are reported in Panel B of Tables 4 and 5. Excluding hyperinflation episodes does not change our results. The estimated ATTs on inflation and inflation variability are all negative and significant. The average estimated ATT on inflation across different matching methods is about -2.64% in terms of the annual inflation rate.

Our second robustness check is to examine if our results are sensitive to different starting time of inflation targeting using Rose's (2006) conservative starting years. The new probit estimates of propensity score are shown in the third column of Table 3, and the matching results are presented in panel C of Tables 4 and 5. We obtain very similar results: negative and significant ATTs on inflation and inflation variability with an average ATT on inflation of -2.70%.

Last, we want to check whether our results are robust to different specifications of the probit model. We add two more explanatory variables to our previous probit regression: government fiscal balance as a share of GDP $(CGGDP)$ and a five-year central bank governor turnover rate $(CBTOR5)$ as an inverse proxy of central bank independence. Since large government deficits and low levels of central bank independence often lead to high inflation, we expect to obtain negative coefficients on these variables. Adding these additional variables to the probit regression, however, comes at a large cost. Due to limited data availability, the sample size is reduced almost by half. Although we still have over 400 observations, we now only have 25 targeting observations (which have dependent variables equal to one). The new probit estimates of propensity score are shown in the last column of Table 3. The two additional explanatory variables are both negative and statistically significant at the 1% level while BMG and $OPEN$ now become insignificant. The new pseudo R-square falls to 0.18. The matching results are presented in last panel of Tables 4 and 5. Once again, we find that all the estimated ATTs on inflation and most of the estimated ATTs on inflation variability are negative and significant. But we do obtain a larger average ATT on inflation (about -4.70%).

All in all, the results tell a very consistent story: the adoption of inflation targeting has significant effects on lowering both inflation and inflation variability in these thirteen developing targeting countries.

5. Conclusions

We evaluate the average treatment effect of inflation targeting in thirteen developing countries that have adopted this policy by the end of 2004. Using a variety of propensity score matching methods, we find strong and robust evidence that inflation targeting has quantitatively large and statistically significant effects on lowering inflation and inflation variability in these thirteen countries. On average, the adoption of inflation targeting has led to a fall in the level of inflation by nearly 3 percentage points. Combining our results with those presented in Lin and Ye (2007), we are able to draw a complete conclusion on the effectiveness of inflation targeting: it has very limited effects on lowering inflation and inflation variability in industrial countries but strong and significant effects in developing countries.

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Table 1. Inflation targeting developing countries and starting years

Country	Starting year	
	default starting year	conservative starting year
Brazil	1999	1999
Chile	1991	1999
Colombia	1999	1999
Czech Republic	1998	1998
Hungary	2001	2001
Israel	1992	1997
Korea	1998	1998
Mexico	1999	2001
Peru	2002	2002
Philippines	2002	2002
Poland	1998	1998
South Africa	2000	2000
Thailand	2000	2000

Source: Rose (2006)

Table 2. Control group countries

Algeria	Hong Kong, China	Paraguay
Argentina	Indonesia	Romania
Belarus	Iran	Russia
Bulgaria	Jamaica	Singapore
Cape Verde	Jordan	Slovakia
China	Kazakhstan	Slovenia
Costa Rica	Latvia	Syria
Coratia	Lebanon	Trinidad & Tobago
Dominican Republic	Lithuania	Tunisia
Egypt	Macao, China	Turkey
Estonia	Macedonia	Ukraine
Georgia	Mauritius	Uruguay
Guatemala	Morocco	Venezuela

Table 3. Probit estimates of propensity scores

	Baseline model	Excluding hyperinflation episodes	Using conservative inflation targeting years	Adding more explanatory variables
CPIG_1	-8.484***	-8.463***	-14.497***	-2.667***
	(1.492)	(1.499)	(2.057)	(0.813)
OPEN	-0.007***	-0.007***	-0.007***	-0.003
	(0.001)	(0.001)	(0.002)	(0.003)
BMG	-1.763*	-1.704*	-1.926*	-0.717
	(1.003)	(1.007)	(1.148)	(0.745)
FIX	-1.635***	-1.634***	-2.020***	-0.966***
	(0.169)	(0.168)	(0.195)	(0.229)
GDPPCG	2.616	2.460	-0.241	-0.325
	(1.772)	(1.830)	(1.840)	(2.195)
CGGDP				-15.224***
				(5.407)
CBTOR5				-1.030***
				(0.466)
No. of Obs.	831	723	831	439
Pseudo-R^2	0.35	0.31	0.44	0.18

Notes: Constant terms are included but not reported. Robust standard errors are reported in parenthesis. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

Table 4. Matching estimates of treatment effect on the level of inflation

Panel A	Baseline model						
	Nearest Neighbor Matching	3-Nearest Neighbor Matching	Radius Matching r=0.04	r=0.02	r=0.01	Local Linear Regression Matching	Kernel Matching
ATT	-0.030** (0.012)	-0.032**** (0.010)	-0.028*** (0.007)	-0.031*** (0.008)	-0.033*** (0.009)	-0.026*** (0.008)	-0.028*** (0.007)
Panel B	**Excluding hyperinflation episodes**						
	Nearest Neighbor Matching	3-Nearest Neighbor Matching	Radius Matching r=0.04	r=0.02	r=0.01	Local Linear Regression Matching	Kernel Matching
ATT	-0.024** (0.011)	-0.027*** (0.010)	-0.027*** (0.007)	-0.029*** (0.007)	-0.030*** (0.009)	-0.022*** (0.008)	-0.026*** (0.007)
Panel C	**Using conservative inflation targeting years**						
	Nearest Neighbor Matching	3-Nearest Neighbor Matching	Radius Matching r=0.04	r=0.02	r=0.01	Local Linear Regression Matching	Kernel Matching
ATT	-0.022* (0.013)	-0.027** (0.012)	-0.024** (0.010)	-0.032*** (0.010)	-0.036*** (0.012)	-0.025** (0.010)	-0.023** (0.010)
Panel D	**Using alternative probit model**						
	Nearest Neighbor Matching	3-Nearest Neighbor Matching	Radius Matching r=0.04	r=0.02	r=0.01	Local Linear Regression Matching	Kernel Matching
ATT	-0.080** (0.033)	-0.072*** (0.025)	-0.038*** (0.014)	-0.034** (0.015)	-0.034** (0.018)	-0.042** (0.020)	-0.037*** (0.012)

Notes: A 0.06 fixed bandwidth and an Epanechnikov kernel are used for kernel and local linear regression matching. Bootstrapped standard errors are reported in parenthesis. They are based on 500 replications of the data. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

Table 5. Matching estimates of treatment effect on inflation variability

	Nearest Neighbor Matching	3-Nearest Neighbor Matching	Radius Matching r=0.04	Radius Matching r=0.02	Radius Matching r=0.01	Local Linear Regression Matching	Kernel Matching
Panel A	Baseline model						
ATT	-0.020**	-0.027***	-0.024***	-0.027***	-0.021***	-0.023***	-0.024***
	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Panel B	Excluding hyperinflation episodes						
ATT	-0.021**	-0.027***	-0.023***	-0.025***	-0.021***	-0.022***	-0.023***
	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Panel C	Using conservative inflation targeting years						
ATT	-0.032***	-0.027***	-0.026***	-0.025***	-0.026***	-0.024***	-0.026***
	(0.010)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Panel D	Using alternative probit model						
ATT	-0.015	-0.018*	-0.021***	-0.019***	-0.019***	-0.015	-0.021***
	(0.016)	(0.011)	(0.006)	(0.007)	(0.009)	(0.009)	(0.006)

Notes: A 0.06 fixed bandwidth and an Epanechnikov kernel are used for kernel and local linear regression matching. Bootstrapped standard errors are reported in parenthesis. They are based on 500 replications of the data. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.