Does inflation targeting really make a difference?

--- Evaluating the treatment effect of inflation targeting in seven industrial countries

Shu Lin* and ***Haichun Ye*****

Department of Economics
Florida Atlantic University

Department of Economics
Florida Atlantic University

Abstract

We evaluate the treatment effect of inflation targeting in seven industrial countries that adopted this policy in the 1990s. To address the self-selection problem of policy adoption, we make use of a variety of propensity score matching methods recently developed in the treatment effect literature. Our results show that inflation targeting has no significant effects on either inflation or inflation variability in these seven countries. Further evidence from long-term nominal interest rates and income velocity of money also supports the window-dressing view of inflation targeting.

Keywords: inflation targeting; inflation; propensity score matching

JEL classification: E4, E5

* Shu Lin: Department of Economics, Florida Atlantic Univesity, 777 Glades Road, Boca Raton, FL 33431, USA.
**Haichun Ye: Department of Economics, Florida Atlantic University, 777 Glades Road, Boca Raton, FL 33431, USA.
The authors would like to thank Editor Robert G. King, an anonymous referee, and Kevin Grier for valuable comments. Any remaining errors are ours.

1. Introduction

Inflation targeting has become a popular framework for the conduct of monetary policy since the early 1990s. Compared to other targeting regimes (e.g., monetary or exchange rate targeting), inflation targeting features an explicit target for inflation and greater emphasis on central banks' transparency, credibility, and accountability in conducting monetary policies. Proponents of inflation targeting have claimed many benefits of adopting this policy, chief among which is that it helps to alleviate the dynamic inconsistency problem, and thus should lead to lower (expectations of) inflation and inflation variability.[1] The fact that targeting countries experienced lower inflation and inflation variability after adopting inflation targeting is often used as strong evidence for this framework. On the other hand, opponents argue that inflation targeting is merely conservative window dressing.[2] In their view, what actually led to the lower inflation in these targeting countries was their decision to aim for lower inflation than in earlier periods and their corresponding efforts. They argue that inflation targeting, per se, contributed very little, if anything, to the lower inflation and inflation variability, and point to evidence that non-targeting countries have also experienced lower inflation and inflation variability since the mid-1980s.

This debate is ultimately an empirical issue. Early empirical studies in the literature often apply time series techniques to country case studies and provide mixed results.[3] Recent cross-country studies in the literature include Johnson (2002) and Ball and Sheridan (2003). Johnson (2002) examines the effect of inflation targeting on the behavior of expected inflation in a panel of 11 industrial countries. He finds mixed

[1] See Bernanke et al. (1999), Svensson (1997), and Mishkin (1999).
[2] This argument is due to Anna Schwartz. See Romer (2006), p. 532.
[3] See Ammer and Freeman (1995), Mishkin and Posen (1997), Groenveld (1998), and Kuttner and Posen (1999).

results: the level of expected inflation in targeting countries does fall after the announcement of targeting, but neither the variability of expected inflation nor the average absolute forecast errors fall after targeting. Ball and Sheridan (2003) investigate the influence of inflation targeting on economic performance in 20 industrial countries. Using cross-section regressions, they show that the beneficial effect of inflation targeting is insignificant.

In this study, we use a new dataset and a new methodology to evaluate the treatment effect of inflation targeting in seven industrial countries that adopted this policy in the 1990s. We make two important contributions to the literature. First, our study employs the most comprehensive dataset to examine this issue, covering 22 industrial countries over the period 1985 to 1999. Second, and perhaps more importantly, we make the first attempt in the literature to formally address the self-selection problem of policy adoption by making use of a variety of propensity score matching methods recently developed in the treatment effect literature.

Our main result is that inflation targeting has no significant beneficial effects on targeting countries' inflation or inflation variability. The estimated treatment effects of inflation targeting on long-term nominal interest rates and income velocity of money are also found to be insignificant in targeting countries. The overall evidence lends strong support to the window-dressing view.

The rest of our study is organized as follows. Section 2 describes our dataset. Section 3 discusses the methodology we use to evaluate the treatment effect of inflation targeting. Section 4 reports our empirical results on inflation and inflation variability.

Additional evidence from long-term nominal interest rates and income velocity of money is presented in Section 5. Section 6 offers our conclusions.

2. Data

The dataset for this study includes 22 major industrial countries examined for the years 1985 to 1999.[4] It contains 321 observations.[5] Most of the data are drawn from the International Monetary Fund's World Economic Outlook and International Financial Statistics.[6]

Seven countries–Australia, Canada, Finland, New Zealand, Spain, Sweden, and the United Kingdom–adopted inflation targeting during our sample period.[7] Following the identification strategy employed by Ball and Sheridan (2003), we define each country's starting time of inflation targeting as the first year in which a specific target or target range was in effect.[8] Similarly, following Ball and Sheridan (2003), we define the starting time of constant inflation targeting as the first year in which a country had an unchanging target or target range. This is a more restrictive definition of inflation targeting, which we will use to check the robustness of our results. To avoid confusion, throughout the article we will call the first definition of inflation targeting non-constant inflation targeting. Table 1 lists the seven targeting countries and their starting years.

---

[4] These countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, New Zealand, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States.

[5] There are nine missing values in year 1999 for some variables in our dataset, which is why we do not have a total of 330 observations.

[6] We have also drawn data from OECD Main Economic Indicators (for M1 money stock), Ghosh et al. (2003) (for five-year central bank governor turnover rate), Ball and Sheridan (2003) (for the starting dates of inflation targeting), and Reinhart and Rogoff (2004) (for exchange rate regimes).

[7] Two of the targeters, Finland and Spain, adopted the euro in 1999. We still treat them as targeters in year 1999, for targeting may still have some lagged effect in this short period. Changing them to non-targeters only makes our results stronger. Switzerland adopted inflation targeting in 1999, but we still consider it a non-targeter in that year, following Ball and Sheridan (2003).

[8] Since Ball and Sheridan (2003) use quarterly data, they define the starting time of targeting as the first quarter in which a specific target or target range was in effect and the target had been announced publicly at some earlier time.

According to the definition of non-constant (constant) inflation targeting, we identify 45 (41) targeting observations and 276 (280) non-targeting observations in our dataset.

3. Methodology

We turn now to the discussions of our empirical methodology.

3.1. Treatment effect and selection bias

Our objective is to evaluate the treatment effect of inflation targeting in targeting countries. To estimate this average treatment effect on the treated (ATT), we consider the following equation:

$$ATT = E[Y_{i1} \mid D_i = 1] - E[Y_{i0} \mid D_i = 1] \quad (1)$$

where D is the targeting dummy. $Y_{i0} \mid D_i = 1$ is the value of the outcome that would have been observed if a targeting country had not adopted inflation targeting policy and $Y_{i1} \mid D_i = 1$ the outcome value actually observed in the same country. The fundamental difficulty in estimating the ATT is that the second term on the right-hand side ($E[Y_{i0} \mid D_i = 1]$) is not observable. We cannot observe the inflation rate or inflation variability of a targeting country had it not adopted such a policy. If a country's targeting choice is random, one can easily obtain the ATT by comparing the sample mean of the treatment group (targeters) with that of the control group (non-targeters). However, this method would generate biased estimates if the targeting decision is not random. In particular, if the targeting choice is systematically correlated with a set of observable variables that also affect the outcomes, then we will have the "selection on observables" problem, which makes traditional linear regression an unreliable method.[9]

3.2. Matching on propensity scores

[9] See Dehejia and Wahba (2002) and Heckman et al. (1998) for detailed discussions. Also, note that the selectivity problem here is neither selection on unobservables (omitted variables) nor a Heckman-type sample selection problem.

To address the “selection on observables” problem, we make use of a variety of propensity score matching methods recently developed in the treatment effect literature. The central idea of matching is to use a control group to mimic a randomized experiment. The key assumption needed to apply the matching method is the conditional independence assumption ($Y_0, Y_1 \perp D \mid X$), which requires that, conditional on X, the outcomes be independent of the targeting dummy.[10] Under this assumption, equation (1) can be rewritten as

$$ATT = E[Y_{i1} \mid D_i = 1, X_i] - E[Y_{i0} \mid D_i = 0, X_i] \tag{2}$$

where we have replaced $E[Y_{i0} \mid D_i = 1, X_i]$ with $E[Y_{i0} \mid D_i = 0, X_i]$, which is observable.

One matching method would be to match the treated units to the control units with similar values of X. As the number of covariates in X increases, however, this method would be hard to apply in practice. To overcome this high-dimension problem, Rosenbaum and Rubin (1983) propose that one can match the treated units and control units on their propensity scores, which are the probabilities of policy adoption conditional on X and can be estimated using simple probit or logit models. A further assumption needed to apply propensity score matching is the common support assumption ($p(X_i) < 1$), which requires the existence of some comparable control units for each treated unit.[11] Using propensity score matching, the ATT now can be estimated as:

$$ATT = E[Y_{i1} \mid D_i = 1, p(X_i)] - E[Y_{i0} \mid D_i = 0, p(X_i)] \tag{3}$$

[10] Under the conditional independence assumption, the average treatment effect (ATE) equals the average treatment effect on the treated (ATT). According to Heckman et al. (1998), the ATT can actually be estimated consistently under a weaker mean independence assumption ($E[Y_{i0} \mid D_i = 1, X_i] = E[Y_{i0} \mid D_i = 0, X_i]$), which only requires that the outcomes in non-targeting countries be independent of the targeting decision, conditioning on the observed covariates. Under this weaker assumption, ATE and ATT are generally different.

[11] Estimating ATE requires a stronger common support condition ($0 < p(X_i) < 1$), which requires the existence of both comparable treated units for each control unit and comparable control units for each treated unit.

We consider a variety of commonly used propensity score matching methods. The first method is nearest-neighbor matching with replacement, which matches each treated unit to the n control units that have the closest propensity scores. We use two nearest-neighbor matching estimators: $n = 1$ and $n = 3$. The second method is radius matching, which matches a treated unit to the control units with estimated propensity scores falling within radius r. We use a wide radius ($r = 0.03$), a medium radius ($r = 0.01$), and a tight radius ($r = 0.005$). The third method is kernel matching, which matches a treated unit to all control units weighted in proportion to the closeness between the treated unit and the control unit. The last method is the regression-adjusted local linear matching developed by Heckman et al. (1998).

4. Estimating the treatment effects on inflation and its variability

This section estimates the treatment effects of inflation targeting (non-constant or constant) 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 seven targeting countries. Figure 1 illustrates the average inflation and inflation variability in targeting countries and non-targeting countries from 1985 to 1999. There is a clear downward trend in inflation (variability) during this period in both country groups. Therefore, a naive comparison of pre-targeting inflation (variability) and post-targeting inflation (variability) in targeting countries can lead to the false conclusion that inflation targeting matters. Indeed, by looking at the figures, one can reasonably suspect that the low inflation (variability) might be caused by some common uncontrolled factors that affect both targeting and non-targeting countries.

In the rest of this section, we will use propensity score matching methods to estimate the treatment effects on the treated.

4.1. Estimating the propensity scores

We first estimate the propensity scores using a probit model. The dependent variable is the targeting (either non-constant targeting $(NCIT)$ or constant targeting (CIT)) dummy. We consider two groups of control variables.[12] The choice of the first group is based on the literature that inflation targeting should be adopted only after some preconditions are met.[13] We choose the following five variables: the lagged inflation rate $(CPIG\_1)$, broad money growth (BMG), government fiscal balance as a share of GDP $(CGGDP)$, a five-year central bank governor turnover rate $(CBTOR5)$ as an inverse proxy of central bank independence, and real per capita GDP growth rate $(GDPPCG)$. We expect the first four 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.[14] 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.

[12] 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. According to the conditional independence assumption, it is not a problem to exclude variables that systematically affect the targeting probability but do not affect inflation (variability) in the probit regressions. See Persson (2001) for detailed discussions.

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

[14] We use the de facto exchange rate classification proposed by Reinhart and Rogoff (2004). Reinhart and Rogoff classify exchange rate regimes into five broad categories: hard peg, soft peg, managed floating, freely floating, and freely falling. We consider the first two categories as fixed regimes. A regime is classified as freely falling if the annual inflation rate is higher than 40%. However, in our sample, no country experienced such high inflation. Therefore, the omitted category contains only managed floating and freely floating regimes.

The results are reported in Table 2. The two columns in Table 2 correspond to our two targeting dummies $NCIT$ and CIT. Most estimated coefficients have the expected signs. We find that the lagged inflation rate, broad money growth, central bank governor turnover rate, and fixed exchange rate regime dummy systematically affect a country's targeting decision. The estimated coefficients on these variables are all negative and significant, meaning that countries with higher previous inflation, higher money growth, lower levels of central bank independence, or fixed exchange rate regimes are less likely to adopt inflation targeting. Other variables are not significant. The overall fit of these two regressions is reasonable with pseudo R-squares around 0.22.[15]

4.2. 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.[16] Thus, 78 out of 276 control units are discarded when we use non-constant inflation targeting, and 93 out of 280 control units are discarded when we use constant inflation targeting.

The matching results based on these new samples are presented in Tables 3 and 4.[17] Table 3 reports the estimated ATTs on the level of inflation, and Table 4 reports the estimated ATTs on inflation variability. The upper panel of each table shows the ATTs of non-constant inflation targeting, while the bottom panel shows those of constant inflation

[15] A pseudo R-square around 0.2 is comparable to an ordinary least squares (OLS) adjusted R-square of 0.7. See Louviere et al. (2000) for detailed discussions.
[16] See Persson (2001). Keeping these observations does not change our results.
[17] Matching estimates are obtained by using Stata command PSMATCH2 developed by Leuven and Sianesi (2003).

targeting. 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 0.5% to 3%. 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 Table 3 are all found to be quantitatively small and statistically insignificant. The average estimated ATT across different matching methods and definitions of targeting is only about -0.17% in terms of the annual inflation rate.[18] The results on inflation variability are similar. The estimated ATTs are all quantitatively small, and some of them are even positive. Almost all of them are insignificant. The only exception is the estimated ATT of constant inflation targeting on inflation variability using kernel matching. However, it is only marginally significant at the 10% level and quantitatively small. Overall, the evidence from matching suggests that inflation targeting has no significant impact on either inflation or inflation variability.[19]

5. Additional evidence from nominal interest rates and velocity

In this section, we employ the same propensity score matching methods to evaluate the treatment effects of inflation targeting on long-term nominal interest rates and income velocity of money.[20] Long-term nominal interest rates are often used by policymakers as an indicator of inflation expectations.[21] Empirical studies in the literature have also shown that real interest rates are fairly stable at long horizons, and that most of the

[18] For radius matching with medium radius and tight radius, a small number of treated units are discarded, for no controls can be found within these radii. Other matching methods have employed all the treated units.
[19] In fact, all the estimated ATTs on inflation and most of the estimated ATTs on inflation variability are insignificant even at the 20% level.
[20] We would like to thank an anonymous referee for this suggestion.
[21] See Goodfriend (1993), Goodfriend (1998), Goodfriend and King (2005).

movements of long-term nominal interest rates are due to changes in expected inflation.[22] If inflation targeting can effectively lower the public's expectations about inflation and inflation variability, then both the level and variability of long-term nominal interest rates should fall. The income velocity of money has also long been of interest to monetary policymakers. The breakdown of monetarism in the 1980s was largely caused by volatile velocity, which made targeting monetary aggregates an unreliable framework for conducting monetary policy. Investigating the variability of velocity thus can help to shed light on the window-dressing view. If inflation targeting is merely window dressing, it should not affect velocity variability.

Figure 2 illustrates the averages of long-term nominal government bond rates, bond rate variability (defined as the standard deviation of a three-year moving average of bond rates), and velocity variability (defined as the standard deviation of a three-year moving average of the ratio of nominal GDP to M1) in targeting countries and non-targeting countries from 1985 to 1999. There is a clear downward trend in long-term nominal government bond rates in both country groups, while the downward trends in the two variability series are less obvious. However, we can again observe that the movements in each one of these series follow a very similar pattern in both country groups.

Formal empirical results from matching are presented in Tables 5 through 7.[23] Tables 5 and 6 report estimated ATTs on the level and variability of long-term nominal government bond rates. The results are striking: all estimated ATTs in Tables 5 and 6 are positive. There is even some evidence, though it is very weak, that inflation targeting

[22] See, for example, Barr and Campbell (1997).
[23] These matching results are based on the same estimated propensity scores used in Section 4. Again, control units whose estimated propensity scores are lower than the lowest score among the treated units are discarded to ensure comparability.

actually leads to higher and more volatile long-term nominal interest rates. Unless one is willing to believe that there have been dramatic increases in the level and variability of long-term real interest rates in the targeting group, the above evidence implies that inflation targeting has not significantly lowered the public's expectations of inflation and inflation variability. Similar results can be found when we apply matching methods to velocity variability. A majority of the estimated ATTs are positive and no single ATT is statistically significant in Table 7. There is no evidence that inflation targeting leads to more stable money demand in targeting countries.

6. Conclusions

We evaluate the average treatment effect of inflation targeting in seven industrial countries that adopted this policy in the 1990s. We carefully address the self-selection problem ignored in previous empirical studies. Using propensity score matching methods, we find that the average treatment effects of inflation targeting on inflation and inflation variability are quantitatively small and statistically insignificant in these seven countries. The treatment effects on long-term nominal interest rates and income velocity of money are also found to be insignificant.

Our results should be interpreted carefully. First, although no non-targeter in our sample has publicly announced any inflation targets, some of them do have policies very similar to those of the targeters. For example, the United States is often considered an "implicit targeter." Therefore, it cannot be concluded from our results that efforts made by central banks to reduce inflation are unimportant. Rather, our results imply that central banks' deeds matter more than their words. The additional explicit announcement of a specific inflation target seems to have very little effect on the outcomes. Second, as many emerging market economies and transition economies have adopted inflation targeting recently, it would be interesting to investigate the treatment effects in these countries. Our results may not necessarily apply to these countries, for their economic and social structures are very different from those of industrial countries. Finally, as Ball and Sheridan (2003) correctly point out, an insignificant treatment effect cannot be used as evidence against inflation targeting as long as no harmful effect is found. Inflation targeting may have other benefits not investigated in our study.

References

Ammer, J., Freeman, R.T., 1995. Inflation targeting in the 1990s: The experiences of New Zealand, Canada, and the United Kingdom. Journal of Economics and Business 47(2), 165-192.

Ball, L., Sheridan, N., 2003. Does inflation targeting matter? NBER Working Paper 9577.

Barr, D., Campbell, J., 1997. Inflation, real interest rates, and the bond market: A study of UK nominal and index-linked government bond prices. Journal of Monetary Economics 39, 361-383.

Bernanke, B.S., Launach, T., Mishkin, F.S., Posen, A.S., 1999. Inflation targeting: Lessons from the international experience. Princeton University Press, Princeton, NJ.

Dehejia, R.H., Wahba, S., 1999. Causal effects in non-experimental studies: Re-evaluating the evaluation of training programs. Journal of the American Statistical Association 94, 1053-1062.

Dehejia, R.H., Wahba, S., 2002. Propensity score-matching methods for nonexperimental causal studies. Review of Economics and Statistics 84(1), 151-161.

Ghosh, A., Gulde, A., Wolf, H., 2003. Exchange rate regimes: Choice and consequences. MIT Press, Cambridge, MA.

Goodfriend, M., 1993. Interest rate policy and the inflation scare problem: 1979-1992. Federal Reserve Bank of Richmond Economic Quarterly 79(1), 1-23.

Goodfriend, M., 1998. Using the term structure of interest rates for monetary policy. Federal Reserve Bank of Richmond Economic Quarterly 84(3), 13-30.

Goodfriend, M., King, R.G., 2005. The incredible Volker disinflation. Journal of Monetary Economics 52(5), 981-1015.

Groenveld, J.M., 1998. Inflation patterns and monetary policy: Lessons for the European central bank. Edward Elgar, Cheltenham.

Heckman, J., Ichimura, H., Todd, E., 1998. Matching as an econometric evaluation estimator. Review of Economic Studies 65, 261-294.

Johnson, D., 2002. The effect of inflation targeting on the behavior of expected inflation: Evidence from an 11 country panel. Journal of Monetary Economics 49, 1521-1538.

Kuttner, K.N., Posen, A.S., 1999. Does talk matter after all? Inflation targeting and central bank behavior. Federal Reserve Bank of New York Staff Report 88.

Leuven, E., Sianesi B., 2003. PSMATCH2: Stata module to perform full mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. http://ideas.repec.org/c/boc/bocode/s432001.html. Version 3.0.0.

Louviere, J.J., Hensher, D., Swait, D., 2000. Stated choice methods: Analysis and application. Cambridge University Press.

Mishkin, F.S., 1999. International experiences with different monetary policy regimes. Journal of Monetary Economics 43, 579-605.

Mishkin, F.S., Posen, A.S., 1997. Inflation targeting: Lessons from four countries. Federal Reserve Bank of New York Economic Policy Review, 9-110.

Persson, T., 2001. Currency union and trade: How large is the treatment effect? Economic Policy 33, 433-448.

Rosenbaum, R., Rubin, B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41-55.

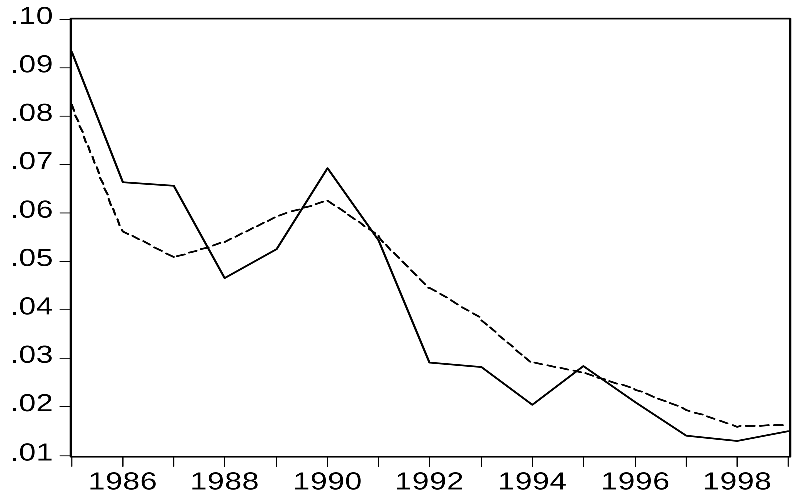
Reinhart, C., Rogoff, K., 2004. The modern history of exchange rate arrangements: A reinterpretation. Quarterly Journal of Economics 119, 1-48.

Romer, D., 2006. Advanced macroeconomics. McGraw-Hill/Irwin, New York.

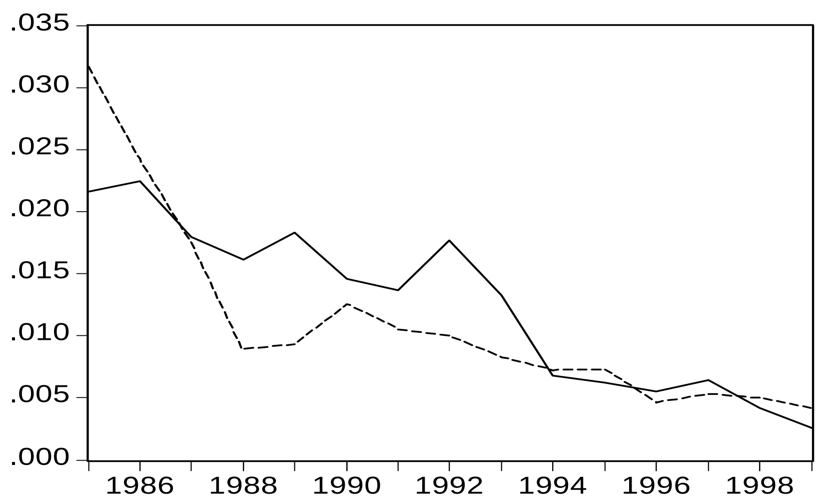
Svensson, L., 1997. Inflation forecast targeting: Implementing and monitoring inflation targets. European Economic Review 41, 1111-1146.

Truman, E., 2003. Inflation targeting in the world economy. Institute for International Economics, Washington, DC.

Figure 1. Average inflation and inflation variability in targeting countries and non-targeting countries



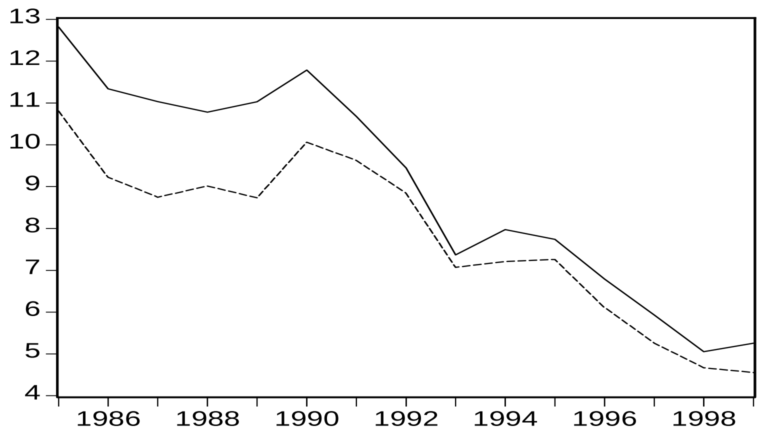
(A) Inflation



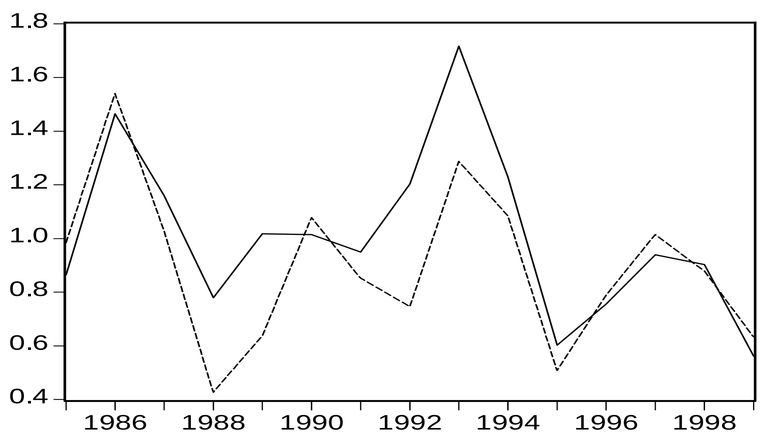
(B) Inflation variability

Notes: Solid line indicates targeting countries. Dash line indicates non-targeting countries.

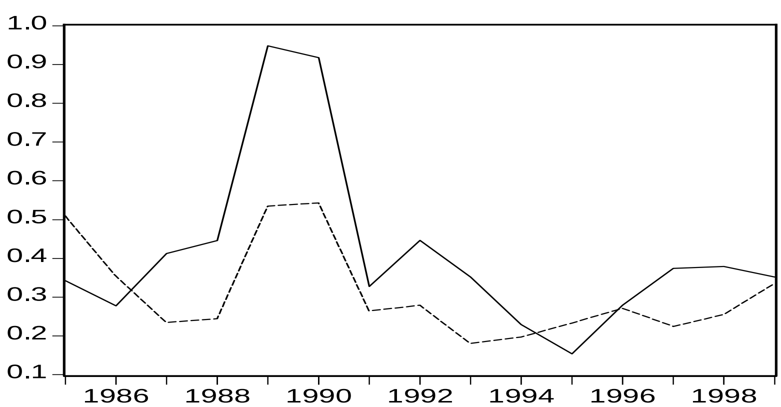
Figure 2. Average long-term nominal interest rates, interest rate variability and velocity variability in targeting countries and non-targeting countries



(A) Long-term nominal interest rates



(B) Long-term nominal interest rate variability



(C) Velocity variability

Notes: Solid line indicates targeting countries. Dash line indicates non-targeting countries.

Table 1. Starting year of inflation targeting in industrial countries

Country	Starting year	
	non-constant inflation targeting	constant inflation targeting
Australia	1994	1994
Canada	1992	1994
Finland	1994	1994
New Zealand	1990	1993
Spain	1995	1994
Sweden	1995	1995
United Kingdom	1993	1993

Table 2. Probit estimates of propensity scores

	Dependent variable	
	NCIT	CIT
CPIG_1	-18.798***	-19.768***
	(5.695)	(5.486)
OPEN	-0.011	-0.198
	(0.315)	(0.327)
BMG	-3.911**	-3.117*
	(1.823)	(1.793)
CBTOR5	-2.426***	-2.445***
	(0.792)	(0.818)
GDPPCG	2.896	6.137
	(2.964)	(3.805)
CGGDP	0.430	1.398
	(2.959)	(3.214)
FIX	-0.665***	-0.515**
	(0.258)	(0.267)
No. of Obs.	321	321
Pseudo-R^2	0.22	0.22

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 3. Matching estimates of treatment effect on the level of inflation

Panel A	Treatment effect of non-constant inflation targeting on the level of inflation						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	r=0.01	r=0.005	local linear regression matching	kernel matching
ATT	-0.0034 (0.0038)	-0.0018 (0.0034)	-0.0013 (0.0025)	-0.0012 (0.0031)	-0.0027 (0.0038)	-0.0014 (0.0352)	-0.0015 (0.0026)
No. of Treated	45	45	45	44	40	45	45
No. of Controls	31	75	198	166	108	198	198
No. of Obs. Used	76	120	243	210	148	243	243

Panel B	Treatment effect of constant inflation targeting on the level of inflation						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	r=0.01	r=0.005	local linear regression matching	kernel matching
ATT	-0.0020 (0.0039)	-0.0010 (0.0031)	-0.0017 (0.0026)	-0.0010 (0.0032)	-0.0011 (0.0038)	-0.0018 (0.2201)	-0.0018 (0.0024)
No. of Treated	41	41	41	40	37	41	41
No. of Controls	32	76	185	153	113	187	187
No. of Obs. Used	73	117	226	193	150	228	228

Notes: A 0.06 fixed bandwidth and a biweight kernel are used for kernel and local linear regression matching. Bootstrapped standard errors for ATT 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 4. Matching estimates of treatment effect on inflation variability

Panel A	Treatment effect of non-constant inflation targeting on inflation variability						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	radius matching r=0.01	radius matching r=0.005	local linear regression matching	kernel matching
ATT	0.0009 (0.0016)	-0.00004 (0.0014)	0.0006 (0.0012)	0.0005 (0.0015)	0.0008 (0.0018)	0.0007 (0.0038)	0.0007 (0.0012)
No. of Treated	45	45	45	44	40	45	45
No. of Controls	31	75	198	166	108	198	198
No. of Obs. Used	76	120	243	210	148	243	243

Panel B	Treatment effect of constant inflation targeting on inflation variability						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	radius matching r=0.01	radius matching r=0.005	local linear regression matching	kernel matching
ATT	-0.0003 (0.0016)	-0.0013 (0.0014)	-0.0018 (0.0012)	-0.0016 (0.0012)	-0.0015 (0.0015)	-0.0017 (0.0016)	-0.0018* (0.0011)
No. of Treated	41	41	41	40	37	41	41
No. of Controls	32	76	185	153	113	187	187
No. of Obs. Used	73	117	226	193	150	228	228

Notes: A 0.06 fixed bandwidth and a biweight kernel are used for kernel and local linear regression matching. Bootstrapped standard errors for ATT 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 the level of long-term nominal interest rates

Panel A	Treatment effect of non-constant inflation targeting on the level of long-term nominal interest rates						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	r=0.01	r=0.005	local linear regression matching	kernel matching
ATT	0.3881 (0.6033)	0.5846 (0.4759)	0.7776** (0.3852)	0.6898 (0.4846)	0.3175 (0.5703)	0.7439 (0.8443)	0.7392* (0.3826)
No. of Treated	45	45	45	44	38	45	45
No. of Controls	36	80	197	169	105	197	197
No. of Obs. Used	81	125	242	213	143	242	242

Panel B	Treatment effect of constant inflation targeting on the level of long-term nominal interest rates						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	r=0.01	r=0.005	local linear regression matching	kernel matching
ATT	1.1461* (0.6070)	0.9098* (0.5043)	0.7554* (0.4171)	0.7985 (0.4989)	0.8382 (0.5940)	0.7713 (0.8045)	0.6680* (0.3908)
No. of Treated	41	41	41	39	35	41	41
No. of Controls	33	74	184	150	115	186	186
No. of Obs. Used	74	115	225	189	150	227	227

Notes: A 0.06 fixed bandwidth and a biweight kernel are used for kernel and local linear regression matching. Bootstrapped standard errors for ATT 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 6. Matching estimates of treatment effect on long-term nominal interest rate variability

Panel A	Treatment effect of non-constant inflation targeting on long-term nominal interest rate variability						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	r=0.01	r=0.005	local linear regression matching	kernel matching
ATT	0.1537 (0.1395)	0.1957 (0.1158)	0.2070** (0.1002)	0.1850 (0.1330)	0.2246 (0.1581)	0.1960 (0.1617)	0.1886* (0.0975)
No. of Treated	45	45	45	44	39	45	45
No. of Controls	34	82	196	168	103	196	196
No. of Obs. Used	79	127	241	212	142	241	241

Panel B	Treatment effect of constant inflation targeting on long-tem nominal interest rate variability						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	r=0.01	r=0.005	local linear regression matching	kernel matching
ATT	0.1019 (0.1500)	0.1750 (0.1334)	0.1699 (0.1167)	0.1797 (0.1363)	0.0426 (0.1624)	0.1782 (0.1665)	0.1674 (0.1098)
No. of Treated	41	41	41	40	35	41	41
No. of Controls	71	74	183	147	111	185	185
No. of Obs. Used	30	115	224	187	146	226	226

Notes: A 0.06 fixed bandwidth and a biweight kernel are used for kernel and local linear regression matching. Bootstrapped standard errors for ATT 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 7. Matching estimates of treatment effect on velocity variability

Panel A	Treatment effect of non-constant inflation targeting on velocity variability					
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	radius matching r=0.01	radius matching r=0.005	local linear regression matching	kernel matching
ATT	0.1032 (0.0865)	0.0627 (0.4759)	0.0743 (0.0631)	0.0990 (0.0711)	0.1124 (0.0907)	0.0675 (0.0844)	0.0687 (0.0597)
No. of Treated	45	45	45	43	36	45	45
No. of Controls	36	82	196	160	113	196	196
No. of Obs. Used	81	127	241	203	149	241	241

Panel B	Treatment effect of constant inflation targeting on velocity variability						
	nearest-neighbor matching	3-nearest-neighbor matching	radius matching r=0.03	radius matching r=0.01	radius matching r=0.005	local linear regression matching	kernel matching
ATT	-0.0059 (0.0957)	0.0091 (0.0761)	0.0234 (0.0659)	-0.0092 (0.0748)	-0.0382 (0.1103)	0.0186 (0.0541)	0.0222 (0.0605)
No. of Treated	41	41	41	39	36	41	41
No. of Controls	32	72	183	161	114	185	185
No. of Obs. Used	73	113	224	200	150	226	226

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