

# On the Effectiveness of Inflation Targeting: Evidence from Semi/nonparametric Approach

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March, 2015

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# Inflation Targeting framework

- Inflation targeting (IT) has become one of the most important monetary policy strategies.

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- Inflation targeting (IT) has become one of the most important monetary policy strategies.
- What is Inflation Targeting?

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# Inflation Targeting framework

- Inflation targeting (IT) has become one of the most important monetary policy strategies.
- What is Inflation Targeting?
  - ▶ The public announcement of the target
  - ▶ Achieving the target over a medium to long horizon

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# Inflation Targeting framework

- Inflation targeting (IT) has become one of the most important monetary policy strategies.
- What is Inflation Targeting?
  - ▶ The public announcement of the target
  - ▶ Achieving the target over a medium to long horizon
- The Reserve Bank of New Zealand initiated inflation targeting in 1990.
- Another example of explicit inflation targeting is the United Kingdom.
- Federal Reserve's implicit commitment to inflation targeting.

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# Inflation Targeting framework

- 27 explicit inflation targeting countries in the world.
  - Anchor inflationary expectations
  - Build central banks credibility
  - Avoid business cycle fluctuations
  - Increase transparency
- } IT Goals

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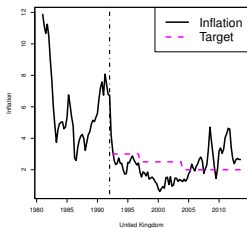
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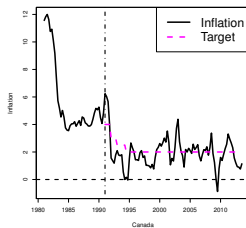
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# Annual inflation rates and targets

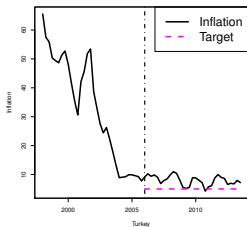
(a) United Kingdom



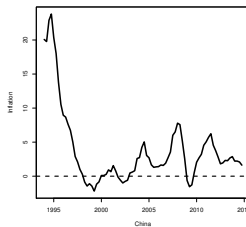
(b) Canada



(c) Turkey



(d) China



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- The effectiveness of inflation targeting
  - Causal effect of Inflation Targeting
    - 1. The IT regime is successful**
      - (Mishkin and Schmidt-Hebbel (2001), Rose (2007), Filho (2011), Lucotte (2010))
    - 2. IT has no effect on the economy**
      - (Johnson (2002), Ball and Sheridan (2003), Lin and Ye (2007))



# Problems with the existing literature

- **Self-selection** problem

*Targeters* and *non-targeters* are different.

Central banks' decision to adopt inflation targeting is related to the benefits from the adoption of IT.

The difference between targeters and non-targeters is due to *selection* and not due to the IT regime.

# Problems with the existing literature

- **Self-selection** problem

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Central banks' decision to adopt inflation targeting is related to the benefits from the adoption of IT.

The difference between targeters and non-targeters is due to *selection* and not due to the IT regime.

- **Random assignment** solves the selection problem.
- Effectiveness can be estimated using simple means between countries.
- Treatment effect: the terminology comes from medicine
- Randomization is **not feasible** in our case.

# Problems with the existing literature

- Two sets of countries are different.
- It is difficult to compare them.
- One solution is **propensity score analysis**

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# Problems with the existing literature

- Two sets of countries are different.
- It is difficult to compare them.
- One solution is **propensity score analysis**
- Propensity score is the probability of adopting IT.
- Propensity score is a scalar variable.
- We can find **countries with similar propensity score**.

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# Problems with the existing literature

- Stages in propensity score analysis
  1. Estimating propensity score  
We **model** the probability of IT using covariates.
  2. Finding the effect of IT  
We compare the difference between matches on the outcome measure of interest.
- What is a **model**? Can we trust our model?
- What if the model is wrong. (Model Misspecification)
- Misspecified propensity score in the first stage leads us to inconsistent results in the second stage.

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# Contribution

1. Estimate the effectiveness of IT taking into account the “*model misspecification*”

- ▶ Nonparametric series propensity score

Overcoming problems with nonparametric estimation.

- ▶ Proposing semiparametric single index propensity score

2. In the first stage we consider the role of preconditions (financial development indicators) along with macroeconomic predictors (such as openness and money growth).
3. Examine the effectiveness of IT on inflation, inflation variability, fiscal discipline, sacrifice ratio, exchange rate volatility and interest rate variability.

# Theoretical framework

- Transparency increases the effectiveness of monetary policy (Svensson (1999) and Woodford (2005)).
- The effectiveness of IT is considered through **aggregate demand** channel and **inflation expectation** channel.

Monetary policy  $\rightarrow$  aggregate demand  $\rightarrow$  inflation

Monetary policy  $\rightarrow$  inflation expectations  $\rightarrow$  inflation

# The empirical setup

- Consists of 98 countries from 1990 to 2013.
- Includes 27 targeters and 71 non-targeters.
- We impute missing data.
- Divide it into developing and developed countries.
- First stage estimation:
  - ▶ Response: the targeting dummy
  - ▶ Covariates:  $\pi_{t-1}$ ,  $M_g$ ,  $GDP_g$ , Openness, CBA, and PC
- Second stage estimation:
  - ▶ Outcomes:  $\pi$ ,  $debt$ ,  $SR$ ,  $\sigma_\pi$ ,  $\sigma_i$ ,  $\sigma_s$



# Macroeconomic outcomes

- **Volatilities** are measured by the standard deviation of a three-year moving average.
- **Interest rates** are 10-year government bond rates.
- **Fiscal discipline** is proxied by the inverse of government debt-GDP ratio.
- **Sacrifice ratio** is measured by the ratio of the change in output growth to the change in inflation.

# Treatment effects of inflation targeting

- To estimate the effects of inflation targeting on macroeconomic performance, we estimate the average treatment effect on the treated.
- **Inflation targeting selection** is a process that permits central banks to adopt IT if they meet economic and **institutional preconditions**.
- One way of estimating *ATT* to overcome self-selection is **Propensity Score Analysis**.

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# Propensity Score Analysis

- Propensity Score Analysis used to estimate causal effects in observational studies.
- We define a model to estimate propensity score.

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# Propensity Score Analysis

- Propensity Score Analysis used to estimate causal effects in observational studies.
- We define a model to estimate propensity score.
- Match targeters to non-targeters based on the estimated propensity scores.
- Use propensity scores as weights to find the effectiveness.

# First stage estimation results

	FULL (1)	IND (2)	DCS (3)
GDP Growth	-0.0801*** (0.0129)	-0.0976** (0.0339)	-0.0653*** (0.0136)
Money Growth	0.0001* (0.0000)	0.0015** (0.0005)	0.0001* (0.0000)
Lagged Inflation	-0.0007 (0.0016)	-0.0075 (0.0167)	0.0009 (0.0016)
Openness	-0.0114*** (0.0008)	-0.0112*** (0.0013)	-0.0096*** (0.0011)
Credit Deposit	0.0083*** (0.0007)	0.0015 (0.0013)	0.0048*** (0.0010)
CB Assets	0.0016 (0.0022)	-0.0311** (0.0102)	0.0056* (0.0023)

Dependent variable is the targeting dummy.

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

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# First stage estimation results

1. More developed economies are less likely to adopt IT.
2. The real money growth is positively associated with the probability of adopting IT (inflationary pressure).
3. A higher degree of openness lowers the probability of adopting IT (Romer (1993)).
4. Preconditions play a crucial role, especially in emerging market economies.
5. Higher private credit-GDP ratio (financial depth) increases the probability of adopting IT in DCS.
6. Higher size of central banks' balance sheets increases the probability of the IT adoption in DCS.

# Propensity Score Weighting

- Propensity scores may be used without matching.
- Inverse probability of adopting IT as a weight.
- Perform a weighted outcome analysis.
- Take a differential amount of information from each country.

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- Inverse probability of adopting IT as a weight.
- Perform a weighted outcome analysis.
- Take a differential amount of information from each country.

## Benefits:

- ▶ Enhance internal validity rather than external validity.
- ▶ Outcome shouldn't be continuous or normally distributed.
- ▶ Retain most countries in the outcome analysis.

# Treatment Effects of Inflation Targeting

Table: Average treatment on the treated using propensity score weighting, logit estimate

	$\pi$	<i>debt</i>	<i>SR</i>	$\sigma_{\pi}$	$\sigma_i$	$\sigma_s$
FULL	-1.05** (0.53)	-19.03*** (1.76)	-0.2 (0.13)	-1.81*** (0.52)	-0.66*** (0.25)	-1.41*** (0.50)
IND	0.02 (0.17)	-29.34*** (3.04)	-0.45 (0.33)	-0.16 (0.14)	-0.09 (0.17)	2.25*** (0.50)
DCS	-1.12 (0.80)	-13.28*** (2.01)	-0.07 (0.13)	-2.19*** (0.70)	-0.29 (0.36)	-1.76** (0.69)

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ .

# Nonparametric Propensity Scores

- Results are sensitive to the specification.
- We estimate the causal effect by weighting the inverse of a nonparametric estimate of the propensity score.
- The model and the distribution of error terms are unknown.

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# Nonparametric Propensity Scores

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A **problem** with this estimate is the “*curse of dimensionality*”

In higher dimensions the observations are sparsely distributed.

Table 10: Average treatment on the treated using propensity score weighting, nonparametric estimate

	$\pi$	<i>debt</i>	<i>SR</i>	$\sigma_\pi$	$\sigma_i$	$\sigma_s$
FULL	-0.92 (0.64)	-17.78*** (1.80)	-0.32** (0.13)	-0.88** (0.38)	-0.55** (0.25)	-0.87* (0.51)
IND	0.03 (0.19)	-26.72*** (2.75)	-0.77** (0.33)	-0.22 (0.18)	-0.03 (0.18)	2.13*** (0.48)
DCS	-0.95 (0.98)	-12.64*** (2.18)	-0.14 (0.14)	-0.99* (0.57)	-0.25 (0.36)	-1.18 (0.72)

<sup>a</sup> Outcomes are inflation ( $\pi$ ), government debt-GDP ratio (*debt*), sacrifice ratio (*SR*), inflation variability ( $\sigma_\pi$ ), interest rate volatility ( $\sigma_i$ ), and exchange rate volatility ( $\sigma_s$ ).

<sup>b</sup> FULL: full sample, IND: industrial economies, DCS: developing countries.

<sup>c</sup> \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

Table 11: Confusion matrices for the full sample

Actual	Predicted	
	0	1
0	1615	89
1	572	76

(a) Logit Model

Actual	Predicted	
	0	1
0	1698	6
1	584	64

(b) Single Index Model

The diagonal elements contain correctly predicted outcomes, while the off-diagonal ones contain incorrectly predicted (confused) outcomes.

# Semiparametric Single Index Model

- To break the curse of dimensionality, we use the semiparametric single index model.

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- $x'\beta$  is scalar single index.
- The nonparametric part is the unknown function  $g(\cdot)$ .
- Give us estimates of values no matter what probability distribution the errors have.

# Treatment Effects of Inflation Targeting

**Table:** Average treatment on the treated using propensity score weighting, semiparametric single index estimate

	$\pi$	<i>debt</i>	<i>SR</i>	$\sigma_{\pi}$	$\sigma_i$	$\sigma_s$
FULL	-0.3 (0.44)	-15.55*** (1.75)	-0.17 (0.13)	-0.99*** (0.33)	-0.17 (0.27)	-1.82*** (0.48)
IND	-0.02 (0.26)	-31.18*** (3.32)	-0.13 (0.34)	-0.38** (0.18)	0.12 (0.18)	2.27*** (0.43)
DCS	-0.02 (0.65)	-9.64*** (2.09)	-0.14 (0.13)	-1.04** (0.50)	0.27 (0.37)	-2.39*** (0.65)

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ .

# Treatment Effects of Inflation Targeting

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1. IT significantly improves fiscal discipline (as a sign of their commitment to price stability).
  - ▶ This reduction is larger in industrial countries.
2. Our finding show that IT significantly reduces inflation variability.
  - ▶ the impact of IT is less in industrial economies than developing countries.
3. IT has a significant effect on exchange variability.
  - ▶ significantly reduces exchange rate volatility in developing countries but increases it in industrial economies.

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# Treatment Effects of Inflation Targeting

1. The choice of propensity scores especially single index model has a considerable impact on the treatment effect estimates.
2. Within the framework of a semiparametric single index model, the impact of inflation targeting is larger and more significant.
3. The single index coefficient regression model in conjunction with the proposed estimation method could be useful in propensity score analysis.

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# Conclusion

- Our findings based on the semiparametric estimate show that IT significantly reduces inflation variability and this reduction is larger in developing countries.
- We examine that the inflation targeting regime significantly reduces the exchange rate volatility in developing countries. However, industrial economies experienced a higher exchange rate variability after the adoption of IT.
- We show that the choice of propensity scores has a considerable impact on the treatment effect estimates. Consequently, a semiparametric single index estimate of propensity scores provides the most meaningful results.