MPRA
Munich Personal RePEc Archive

On the Effectiveness of Inflation Targeting: Evidence from a Semiparametric Approach

Ardakani, Omid and Kishor, Kundan and Song, Suyong

8 January 2015

Online at https://mpra.ub.uni-muenchen.de/75091/
MPRA Paper No. 75091, posted 21 Nov 2016 14:02 UTC

On the Effectiveness of Inflation Targeting: Evidence from a Semiparametric Approach

Omid M. Ardakani [†] N. Kundan Kishor [‡] Suyong Song [§]

Abstract

This paper estimates the treatment effect of inflation targeting for all explicit inflation targeting countries by taking into account the problem of model misspecification and inconsistent estimation of parametric propensity scores by using a semiparametric single index method. In addition, our study uses a broader set of preconditions for inflation targeting and macroeconomic outcome variables than the existing literature. Overall our results suggest no significant difference in level of inflation and inflation volatility in targeters versus non-targeters after the adoption of inflation targeting. Unlike parametric and non-parametric method, we find that inflation targeting leads to a significant decline in the sacrifice ratio and interest rate volatility in developed economies. The results suggest that inflation targeting framework enhances fiscal discipline in both industrial and developing countries.

Keywords: Inflation Targeting, Propensity Score, Treatment Effects, Sieve Estimator, Single Index Model.

JEL Classification: E4, E5, C14, C21.

[†]Department of Economics, Armstrong State University, Savannah, GA 31419 (omid.ardakani@armstrong.edu)
[‡]Department of Economics, University of Wisconsin-Milwaukee, Milwaukee, WI 53211 (kishor@uwm.edu)
[§]Department of Economics, University of Iowa, Iowa City, IA 52242 (suyong-song@uiowa.edu)

1 Introduction

Explicit inflation targeting (IT) has been increasingly adopted as a monetary policy strategy to curb actual inflation over the medium-to-long horizon. Under the IT regime, a central bank publicly announces a target inflation rate and then uses different monetary policy tools to bridge the gap between actual inflation and the target. One of the impressive features of this monetary policy strategy is no country has given up this regime after its adoption. The Reserve Bank of New Zealand became the first central bank to adopt the IT regime in 1990. The increasing popularity of the IT regime has spawned a great deal of academic interest in its effectiveness.

Even though the amount of work on the effectiveness of IT has increased manifold in the last two decades, there is no consensus on the overall impact of this regime on the macroeconomy. One view suggests a significant effect of IT on macroeconomic performance; the opposite suggests that the impact of the IT regime has been mostly insignificant. Several researchers find inflation targeting is successful in reducing inflation and inflation variability (Neumann and von Hagen (2002), Wu (2004), Vega and Winkelried (2005), Mishkin and Schmidt-Hebbel (2007), and Creel and Hubert (2010)). Among them, Mishkin and Schmidt-Hebbel (2001) argue the IT regime not only causes a reduction in inflation and inflation variability, but lessens the sacrifice ratio, output volatility, and inflation expectations. The literature also postulates inflation targeting lowers other economic variables such as exchange rate volatility (Rose (2007) and Lin (2010)),[1] interest rates (Filho (2011)), fiscal indiscipline (Minea and Tapsoba (2014) and Lucotte (2012)), and actual dollarization (Lin and Ye (2013)). However, Johnson (2002) and Angeriz and Arestis (2007) find the IT regime does not reduce the variability of expected inflation. Similar viewpoints have been expressed by Ball and Sheridan (2003), who argue there is no evidence that IT reduces inflation variability, output volatility, and output growth. Lin and Ye (2007) also find IT has no significant effects on either inflation or inflation variability. They suggest both targeters and non-targeters have experienced an unexpected reduction in

[1] Lin (2010) finds inflation targeting lowers real and nominal exchange rate volatility only in industrial economies, but increases them in developing countries.

inflation.

Our study contributes to the existing IT impact literature in several ways. Our econometric approach improves on the treatment effect literature that has been used to estimate the impact of IT. A few methods have been proposed to take into account the self-selection problem that may arise because a central bank's decision to explicitly target inflation is related to the benefits from the adoption of IT. This leads to a biased causal effect. Previous studies (e.g. Lin and Ye (2013) and de Mendonca and de Guimaraes (2012)) have attempted to overcome the selection bias problem by estimating propensity scores and matching treated and control units to mimic a randomized experiment. The parametric approach to estimating the average treatment effect of inflation targeting suffers from model misspecification and provides inconsistent estimates of the propensity scores, when the true data generating process is very different from that based on a pre-specified functional form of the model. The nonparametric approach proposed by Hirano, Imbens and Ridder (2003) could be a possible solution to the issue. The approach, however, suffers from the "curse of dimensionality," which refers to the problem where the high dimension of the variable space due to large number of covariates in their logit series estimation makes the performance of the nonparametric estimator worse. To take into account these econometric problems, we estimate propensity scores by the semiparametric single index method suggested by Klein and Spady (1993). The index estimator can be applied to mitigate the issue of high dimensionality, while the functional form of the propensity score and the distribution of the error terms are still unknown. In fact, Song (2014) shows that conditions of the single index propensity score estimates have no effect on the asymptotic distribution of treatment effects.

Most of the research on the treatment effect of inflation targeting has examined its impact on the level of inflation and inflation volatility. One of the proposed benefits of having a monetary policy regime with a nominal anchor is it enhances the credibility of central banks. As a consequence, the volatility of important macroeconomic variables such as the exchange rate and interest rate may be affected in addition to its impact on the sacrifice ratio. The adoption of IT may also nudge the fiscal policymakers to adopt fiscally responsible policies. Moreover, inflation targeting can be able to bring inflation down at a lower cost. The second contribution of our paper is to examine the effectiveness of the IT regime by not only investigating its impact on inflation and inflation volatility, but also macroeconomic variables such as the level of government debt, the sacrifice ratio, interest rate volatility, and exchange rate volatility.

The propensity score analysis for the IT regime involves estimating the probability of conducting IT in the first stage. Other studies which have adopted the treatment effect approach have ignored the role of financial market development in the probability of adopting inflation targeting, in contrast to the literature that emphasizes the IT preconditions; researchers have strongly opined that financial market development is one of the most important criteria for the adoption and success of the IT regime (Amato and Gerlach (2002) and Bernanke and Woodford (2005)). Our third contribution is that, in addition to the macroeconomic predictors used in the previous studies, we use the central bank assets-GDP ratio and the private credit-GDP ratio as proxies for financial market development in the first stage to estimate the probability of adopting IT.

We find several interesting results from the semiparametric index models. First, we find that there is no significant difference in the impact on inflation and inflation volatility in inflation targeter versus non-inflation targeters in both the developed and developing economies. In contrast, the parametric propensity scores suggest significant decline in inflation volatility in developing countries. Secondly, the adoption of IT leads to significant decline in sacrifice ratio and volatility of interest rate in developed inflation targeters, providing evidence on the credibility hypothesis. However, we do not find a significant impact of IT on the sacrifice ratio and interest rate volatility in developing economies. The adoption of IT leads to an increase in volatility of exchange rates in developed economies, whereas it reduces the exchange rate volatility in developing economies. Our results show that adoption of IT leads to improvement in debt-GDP ratio in both the developed and the developing economies. Overall, our results suggest that IT as a monetary policy strategy seems to have benefited developed economies more than developing economies mainly through the credibility enhancement channel. As a sensitivity analysis, we use conventional covariates, contemporaneous covariates, and a smaller sample period (before the 2008 financial crisis). The estimation results confirm that our approach is robust to various scenarios and the approach to estimating propensity scores in the first stage has significant impacts on the treatment effects.

The remainder of this paper is organized in the following order. Section 2 reviews the IT effectiveness from theoretical and practical points of view. Section 3 describes the data set and country groups. Section 4 examines and compares the impact of IT using single index, nonparametric, and parametric propensity scores and explains the problems associated with the latter two models. Section 5 checks whether the results are robust to the inclusion of different sets of covariates and the use of the pre-crisis sample period. Section 6 gives some concluding remarks.

2 Background

2.1 Theoretical Context

Since the adoption of explicit inflation targeting by the Reserve Bank of New Zealand in 1990, there has been an explosion of interest in the theoretical and empirical work on the effect of inflation targeting. Most of the theoretical work has focused on examining whether inflation targeting is an optimal monetary policy strategy. Central banks adopt explicit inflation targeting by setting an instrument such that the inflation forecast and inflation target become identical. Svensson (1996) interprets inflation targeting as a targeting rule that specifies a target variable and target level to minimize a loss function. Central banks' objective in period t is to choose a sequence of intrest rates to minimize the loss function:

$$\mathbb{E}_t \sum_{\tau=t}^{\infty} \delta^{\tau-t} L(\pi_\tau), \tag{1}$$

where π denotes inflation, $\mathbb{E}_t$ is expectations conditional on information in year t, δ is the discount factor, and $L(\pi_\tau)$ is the loss function which can be written as the following:

$$L_t = \frac{1}{2}[(\pi_t - \hat{\pi})^2 + \lambda y_t^2], \tag{2}$$

where $\hat{\pi}$ denotes the inflation target level, $\lambda \geq 0$ is the relative weight and y_t is the output gap. Thus, the inflation targeting framework is considered as the minimization of a loss function over inflation and output gaps. The first-order condition can be written as $\pi_{t+\tau|t} = \hat{\pi}$, for $\tau \geq T$, where $\pi_{t+\tau|t}$ denotes a conditional forecast of $\pi_{t+\tau}$ and $T \geq 0$ is the shortest horizon at which the instrument has an effect on inflation. In an explicit inflation targeting regime, the central bank commits to minimizing a loss function, such that the target would be equal to the τ-step ahead forecast. The effectiveness of this monetary policy framework can be considered through the two channels of aggregate demand and expectations. In the aggregate demand channel, monetary policy affects aggregate demand and then inflation via the Phillips curve. In the expectations channel, monetary policy affects inflation by anchoring inflation expectations. The latter view suggests the inflation forecast as a target provides better information about central bank actions and therefore influences expectations. This transparency increases the effectiveness of monetary policy (Svensson (1999)). As in Woodford (2005) and Svensson (2005*a*), a higher degree of transparency improves the conduct of monetary policy. The consequences of the transparency of central banks are a reduction in uncertainty about future policy actions and anchoring actual inflation and inflation volatility.

In a theoretical framework, Demertzis and Hallett (2007) show the transparency of central banks has no effect on the level of inflation and output, but decreases the volatility of inflation and the output gap. Morris and Shin (2002) address this issue through the lens of welfare effects. They argue greater transparency does not necessarily improve social welfare. In an economy with highly volatile inflation, the central bank is unlikely to have more information than the private sector, and private information may crowd out the central bank's disclosed information, which leads to a greater volatility. However, Svensson (2005*b*) argues the results of Morris and Shin (2002) are misinterpreted as an "anti-transparency." He shows that the higher degree of transparency increases the social welfare. Recently there has been a surge of interest in the theoretical framework of inflation targeting effectiveness through the channels of expectations, transparency, and the accountability of central banks.The consensus from the theoretical literature suggests that focusing the impact of IT on level of inflation and inflation volatility is not sufficient to measure the effectiveness of IT on macroeconomy. Therefore, this study attempts to examine the impact of IT on not only the conventional macroeconomic outcomes, but also the variables that may be affected due to expectations, credibility and transparency channels.

2.2 Empirical Background

The existing empirical literature on the effectiveness of inflation targeting suffers from three problems. The first issue is the estimation methodology. Second, the variables used to find the likelihood of adopting inflation targeting ignore the conventional wisdom and extant literature suggesting the role of preconditions in the effectiveness of inflation targeting. Third, most of the work on inflation targeting using the treatment effect methodology has estimated the impact of this regime on the level of inflation and inflation volatility. The literature lacks a comprehensive study on a variety of outcome variables.

The empirical research on the effectiveness of inflation targeting has primarily attempted to examine its impact on the level of inflation and inflation volatility. Initially most of the work focused on examining the effectiveness of the IT regime by performing some form of an event study analysis. This strand of literature compared the behavior of inflation and its volatility before and after the adoption of the IT regime. The event study approach was criticized on the grounds that this methodology does not take into account the changes in the behavior of inflation that would have taken place anyway in the absence of the IT regime. The criticism was based on the global fall in inflation and inflation volatility that took place during the time this regime was in place in different countries.

With reference to the estimation methodology, Ball and Sheridan (2003) find the effect of IT by comparing improvements in targeters to improvements in non-targeters. They apply the difference-in-differences approach. To reduce the bias from the correlation of the outcome before the adoption of IT and the targeting dummy, they add the initial value of the outcome to the differences regression. Ball and Sheridan (2003) argue by including the initial value of the outcome to the differences regression, they control for regression to the mean. They find no evidence inflation targeting improves countries' economic performance. After this study, researchers have attempted to find the causal effect of the IT adoption on macroeconomic performance using the same methodology. Among them, Wu (2004) compares the average change in inflation before and after the IT adoption. He includes the first lag of the outcome variable to consider the persistence of the outcome. He finds that inflation targeters experienced a decrease in average inflation rates after the adoption of IT. One main issue with the differences-in-differences method is that the response in the differences-in-differences estimation, which is the outcome variable such as inflation and inflation variability, is highly serially correlated. Mishkin and Schmidt-Hebbel (2001) address the question of whether there is a causal effect of the adoption of inflation targeting on the macroeconomic outcomes. They argue the adoption of IT is an endogenous choice, and the empirical findings may not imply the causal effect of inflation targeting on economic performance. They control for endogeneity using an instrument set, such as lagged values of inflation, nominal exchange rate depreciation, and the federal funds rate. Their study suggests inflation targeting reduces inflation and output volatilities and adopting IT improves the efficiency of monetary policy.

The problem which arises in estimating the average treatment effect of inflation is the selection problem. Inflation targeting selection is a process that permits central banks to adopt inflation targeting in countries that meet some economic and institutional preconditions. To address the selection problem of the IT adoption, Lin and Ye (2007) estimate average treatment effects using propensity score matching methods. Propensity score analysis allows us to reduce the dimensionality to a one-dimensional score and to balance the differences between targeters and non-targeters. Using the outcome variables, such as inflation, inflation variability, and interest rates, they show inflation targeting has no effect on economic performance. Recently, other studies examine the effectiveness of IT by estimating treatment effects (Lin (2010), Lucotte (2012), de Mendonca and de Guimaraes (2012), Lin and Ye (2013), and Minea and Tapsoba (2014)). One important problem that has been neglected in the literature is the misspecification of propensity scores. Zhao (2008) finds that the results of average treatment effects are sensitive to the specifications of propensity scores. Hirano, Imbens and Ridder (2003) propose a nonparametric series estimator in order to deal with misspecification. The high-dimensionality in the nonparametric model creates other issues. To take into account misspecification caused by the parametric model and the high-dimensionality problem created by the nonparametric approach, we apply a semiparametric methodology in which there is no distributional assumption on the error terms.

The second problem in the inflation targeting effectiveness literature is associated with finding the likelihood of adopting inflation targeting. Most of studies have focused on finding the effect of the macroeconomic variables on the likelihood of the IT adoption. However, a set of preconditions impacts the probability of adopting inflation targeting, especially in emerging market economies. The most important precondition discussed in the literature which has a huge impact on inflation targeting is a healthy financial system (Amato and Gerlach (2002) and Bernanke and Woodford (2005)). Effective monetary policy transmission is guaranteed by a sound banking system and well-developed capital markets. To take into account this criticism of the existing literature, we augment the first stage equation of estimating the probability of adoption of inflation targeting by including the central bank-assets-GDP ratio and the credit-deposit ratio.

The third problem in finding the effectiveness of IT is most of the work on inflation targeting using the treatment effect methodology has estimated the impact of the regime on the level of inflation and inflation volatility. One of the proposed benefits of having a monetary policy regime with a nominal anchor such as inflation targeting is it enhances the credibility of central banks. The higher degree of credibility may influence the volatility of important macroeconomic variables. Moreover, one of the requirements of a successful adoption of the IT regime is the absence of fiscal dominance. Only a few papers (Lucotte (2012) and Minea and Tapsoba (2014)) have looked at the role of the IT regime in disciplining the fiscal behavior of IT countries. Additionally, inflation targeters may experience fewer output losses during disinflations. There are two contrary views on the effect of inflation targeting on the sacrifice ratio (Goncalves and Carvalho (2009) and Brito (2010)). However, the existing studies using the treatment effect methodology have not examined the impact of IT on fiscal discipline and the sacrifice ratio.

3 Data Description

The data set for this study consists of 98 countries for the period from 1990 to 2013 on an annual basis. Data are obtained from the International Monetary Fund's World Development Indicators and International Financial Statistics. Among our full sample, 27 countries are inflation targeters (treated group) and 71 countries are non-targeters (control group). Table A1 in Appendix A presents the list of inflation targeting countries along with the adoption dates, target levels at the adoption date, and their country groups. The lowest target rate at the date of IT adoption belongs to Sweden and Thailand, two percent, and the highest rate is 15 percent for Israel. Seven countries are described as industrial inflation targeters; other 20 targeters are developing countries.[2] Table A2 shows the list of countries used as the control group including 55 developing countries and 16 industrial economies. We impute incomplete multivariate data.

[2]IT industrial countries are: Australia, Canada, Iceland, New Zealand, Norway, Sweden and the United Kingdom.

There are two approaches for the imputation of multivariate data: joint modeling (JM) and Fully Conditional Specification (FCS), also known as Multivariate Imputation by Chained Equations (MICE). We use the MICE method because the MICE algorithm preserves the relationships in the data and retains the uncertainty about these relations (Buuren and Groothuis-Oudshoorn (2011)).

To examine the effectiveness of inflation targeting in emerging market and industrial economies, we divide the sample into developing (DCS) and developed (IND) countries. Table 1 indicates the sample sizes in the propensity score analysis for the full sample, industrial economies and developing countries. The full sample contains all 98 countries. The sample size is 2352, of which 1704 are control and 648 are treated units. After matching, 648 observations are left for the outcome analysis. In the subsample of industrial economies, there are 26 countries, and the total number of observations is 624. The subsample of developing countries includes 72 countries with 1728 observations.

Table 1: Sample sizes in the propensity score analysis for all samples

	FULL		IND		DCS	
	Control	Treated	Control	Treated	Control	Treated
All	1704	648	384	240	1320	408
Matched	648	648	240	240	408	408
Unmatched	1056	0	144	0	912	0
Discarded	0	0	0	0	0	0

FULL: full sample, IND: industrial economies, DCS: developing countries

The dependent variable used in the first stage estimation is the inflation targeting dummy, which has the value one if the country adopts inflation targeting. We choose the following covariates for the propensity score analysis and the estimation of average treatment effects: openness, GDP growth, real money growth, inflation, a pegged exchanged regime dummy, the central bank assets-GDP ratio, and the credit deposit-GDP ratio. Openness is measured as exports plus imports divided by GDP, indicating the total trade as a percentage of GDP. In order to specify pegged exchange regime in each country we follow Ilzetzki, Reinhart and Rogoff (2008).

They provide a classification for exchange rate regimes. They decompose *de facto* exchange regimes into "coarse" and "fine" components. The fine classification narrow the coarse measures down into specific regimes. We focus here on the coarse classification by using code 1, 2, and 3 defined as exchange arrangements with no separate legal tender, currency board arrangements, conventional fixed peg arrangements, crawling pegs, exchange rates within crawling bands, and managed floating with no predetermined path for the exchange rate. This is also based on IMF classification. We use a binary indicator which takes value of one if the country adopts pegged exchange regime according to the above definition. Central bank assets-GDP ratio is used as a measure of financial sophistication. Credit deposit to real sector by deposit money bank is considered as the proxy of financial development.

In the second stage estimation, the outcome variables include inflation, fiscal discipline, the sacrifice ratio, inflation variability, interest rate volatility, and real exchange rate volatility. Following Lin and Ye (2007), we measure inflation variability by the standard deviation of a three-year moving average of inflation. Real exchange volatility is defined as the standard deviation of a three-year moving average of real exchange rates, and interest rate volatility is defined as the standard deviation of a three-year moving average of 10-year government bond interest rates. We consider the government debt-GDP ratio as an inverse proxy of fiscal discipline. The sacrifice ratio is measured by the ratio of the change in output growth to the change in inflation.

4 The Impact of Inflation Targeting

The parameter of interest in estimating the effects of inflation targeting on inflation and inflation variability is the average treatment effects on the treated. In our study, inflation targeting is considered as a treatment indicated by a binary random variable, $T_i \in \{0, 1\}$, where $T_i = 1$ if inflation targeting is adopted and $T_i = 0$, otherwise. The outcome of interest is denoted by Y_i. We specify the inflation rate, the measure of fiscal discipline, the sacrifice ratio, inflation variability, a measure of inflation uncertainty, interest rate volatility, and exchange rate volatility. We find whether Y_i is affected by IT. For each country, there are two potential outcomes; Y_{0i} is the outcome when inflation targeting is not adopted, while Y_{1i} is the potential outcome if this strategy is adopted.

$$\text{potential outcome } = \begin{cases} Y_{1i} & \text{if } T_i = 1 \\ Y_{0i} & \text{if } T_i = 0\ . \end{cases} \tag{3}$$

The causal effect of adopting inflation targeting in country i is the difference between Y_{1i} and Y_{0i}. The difficulty in estimating the causal effect is that we do not observe both Y_{1i} and Y_{0i}, for each country, since each country is either targeter or non-targeter. The observed outcome, Y_i, can be written in terms of potential outcomes as

$$Y_i = T_i Y_{1i} + (1 - T_i) Y_{0i} = Y_{0i} + (Y_{1i} - Y_{0i}) T_i, \tag{4}$$

where $Y_{1i} - Y_{0i}$ is the causal effect of implementing inflation targeting. The average treatment effect on the treated (ATT) is the expected effect of IT on economic outcomes for those countries that actually have adopted an inflation targeting framework. This effect can be written as the following:

$$\tau_{att} = \mathbb{E}[Y_{1i} - Y_{0i} | T_i = 1]. \tag{5}$$

4.1 Impact Evaluation through Propensity Score Analysis

When the treatment is randomized across countries, ATT can be consistently estimated. In our case, however, the randomization of inflation targeting is infeasible. Inflation targeting selection is a process that permits central banks to adopt inflation targeting in countries that meet some economic and institutional preconditions. Selection bias arises when targeters differ from non-targeters for reasons other than the specific monetary policy framework; our observational data lack the randomized assignment of countries into the adoption of IT. One way to overcome the selection problem is to mimic the randomized experiment by utilizing the propensity score analysis. Propensity score analysis is a quasi-experimental design used to estimate causal effect in studies where units are not randomized to treatment. We assume two conditions to estimate τ_{att}: the unconfoundedness assumption which states the treatment is mean independent of the outcomes conditional on the covariates, $E(Y_0|X,T) = E(Y_0|X)$ and $E(Y_1|X,T) = E(Y_1|X)$, and the overlap assumption which states the likelihood that a country adopts inflation targeting is less than one, $\pi(X) < 1$, where $\pi(X) \equiv Pr(T=1|X)$ is the conditional probability of adopting inflation targeting conditional on a vector of observed covariates X (see Rosenbaum and Rubin (1983) for more detailed discussion). As shown in Dehejia and Wahba (2002), given the conditions, ATT is identified as

$$\tau_{att} = \mathbb{E}\left(\mathbb{E}(Y_i|T_i=1,\pi(X_i)) - \mathbb{E}(Y_i|T_i=0,\pi(X_i))|T_i=1\right). \tag{6}$$

The benefits of using propensity score analysis are twofold: to reduce dimensionality to a one-dimensional score and to balance the differences between targeters and non-targeters. Targeters and non-targeters with the same value of the propensity score have the same distribution of the observed covariate. Given the identification, propensity score analysis includes two stages: the first stage estimates the propensity score,which is the conditional probability of adopting IT. The second stage matches each IT country with a non-targeter based on the propensity score and estimates ATT.

4.2 A Semiparametric Propensity Score Matching Model

Since estimating the propensity score correctly is crucial, propensity score analysis could be sensitive to the model specifications of the propensity score. We must take into consideration the model specification of the first stage estimator for two reasons: the coefficients of the propensity score are poorly estimated in the misspecified propensity score and using the parametric propensity score sacrifices the efficiency of the estimator. The misspecified propensity score has an influence on the estimated ATT (Zhao (2008)). The following example illustrates how misspecified propensity scores given a vector of covariates x leads to biased results. Let y be a continuous response, t be the treatment, τ be the treatment effect, and β is a vector of parameters relating the covariates x to the response in the model $E(y|x,t) = g(x;\beta) + \delta t$. Assume $E_x|g(x;\beta)| < \infty$. Let $\bar{y}_i$ denotes the sample averages of treated and control units and, similarly, $\bar{y}_{i,\pi(x)}$ denotes the average response at the propensity score $\pi(x)$. In an observational study $\hat{\tau} = \bar{y}_{1,\pi(x)} - \bar{y}_{0,\pi(x)}$ is an unbiased estimator of treatment effect (Rosenbaum and Rubin (1983)). Suppose that $\pi(x)$ is not known and misspecified to be some function $\phi(x)$. Then, $E[\bar{y}_1 - \bar{y}_0|\phi(x)] = \tau + E_x[g(x;\beta)|t = 1, \phi(x)] - E_x[g(x;\beta)|t = 0, \phi(x)]$ and $\bar{y}_{1,\phi(x)} - \bar{y}_{0,\phi(x)}$ is not unbiased for τ. We propose to use the semiparametric methods to deal with model misspecification.

We apply a semiparametric single index model in the first stage estimation to examine the effect of IT and compare the results with their nonparametric and parametric counterparts. Among all the approaches for estimating propensity scores, the semiparametric single index model provides the most accurate results. Applying a misspecified parametric propensity score such as a probit model, $\pi(X_i) = Pr(T_i|X_i) = (2\pi)^{-1/2}exp[-(X_i\beta_i)^2/2]$, leads us to an inconsistent estimate of average treatment effects. Hirano, Imbens and Ridder (2003) suggest a nonparametric propensity score to deal with the misspecification problem. They estimate propensity scores in a sieve approach by the series logit estimator; nonetheless, the nonparametric estimator suffers from the "curse of dimensionality." The curse of dimensionality refers to a poor performance of the nonparametric series method for multivariate data. The behavior of nonparametric estimators deteriorates as the dimension of the observed covariates increases because of the sparseness of multidimensional data (Stone (1980)).[3] To break the curse of dimensionality, we apply the semiparametric single index model for estimating propensity scores. The semiparametric single index model is an alternative approach to mitigate bias arising from the curse of dimensionality. It also avoids the problem of error distribution misspecification. The single index model for the binary response is suggested by Klein and Spady (1993). The index model is given by:

$$T = g(X'\beta_0) + u, \tag{7}$$

where T is the binary dependent variable, $X \in \mathbb{R}^d$ is the vector of explanatory variables, and the functional form of $g(\cdot)$ is unknown. Klein and Spady (1993) suggest estimating the parameters by the maximum likelihood method:

$$\mathscr{L}(\beta, h) = \sum_i (1 - T_i)\ln(1 - \hat{g}_{-i}(X_i'\beta)) + \sum_i T_i \ln(\hat{g}_{-i}(X_i'\beta)), \tag{8}$$

where $\mathscr{L}(\cdot)$ is the log-likelihood function and $\hat{g}_{-i}(X_i'\beta)$ is the leave-one-out estimator. We apply the estimated index propensity scores to estimate the ATT. There are some identifiability conditions for estimating semiparametric single index models. X_i must contain at least one continuous random variable and cannot contain a constant. X_i does not include a constant term, because β_0 cannot contain the location parameter which is known as the location normalization condition (See Hayfield and Racine (2008) for more details on how to apply this normalization). The first component of X_i also has a unit coefficient which is known as the scale normalization condition. We set the lagged openness coefficient to one. We report the results of estimating the

[3]In other words, the speed of convergence decreases, when the observations are sparsely distributed. The optimal bandwidth converges at $\mathcal{O}(\mathcal{N}^{\frac{-2}{4+d}})$, where d is the dimension. The curse of dimensionality refers to the problem where the convergence rate is inversely related to the number of covariates (Li and Racine (2011)).

average treatment effect on the treated using nearest neighbor matching.[4] Nearest neighbor matching selects the r best non-targeter matches for each inflation targeting country. Finally, we use the matched sample for the outcome analysis.

Certain preconditions are necessary for IT to be successful. These preconditions fall into four categories: institutional independence, well-developed technical infrastructure, economic structure, and a healthy financial system. Among them, a healthy financial system is one of the important pre-requisites for inflation targeting as a monetary policy strategy. We need a sound banking system and well-developed capital markets to guarantee an effective monetary policy transmission. We use central bank assets-GDP and private credit-GDP ratios as proxies for financial system development. Our results of the single index model for central bank assets are different among country groups; the higher central bank assets-GDP ratio increases the likelihood of adopting IT in industrial countries and lowers it in developing countries. This implies that the expansion of central banks' balance sheets as a share of GDP causes a loss in their credibility and decreases the probability of adopting IT. We also use the private credit-GDP ratio to measure financial depth. Financial depth indicates the financial resources, such as loans and non-equity securities, available to the private sector. Figure 1 shows the scatter plot and kernel densities of the estimated semiparametric propensity scores. The scatter plot shows the spread of propensity scores. As shown in the plot, propensity scores are scattered between zero and one. The kernel densities of propensity scores for the control and treated units are shown in the solid lines and dashed lines, respectively. We find that the densities of propensity scores for countries that did and did not adopt inflation targeting in the full sample, industrial economies, and developing countries are different, indicating that matching would improve the results of the estimation.

Table 2 presents the results of semiparametric single index models for the full, industrial, and developing samples. Our findings suggest that GDP growth as an indicator of the level of economic development is inversely correlated with the probability of the IT adoption in the

[4] Although we perform the matching procedure by full, optimal, and genetic matching. We find the similar results to those presented in this paper.

full sample, developing countries, and developed economies. Our results are consistent with Lucotte (2012) and Samarina, Terpstra and De Haan (2013), who argue that countries with poor performance are more likely to adopt inflation targeting. Furthermore, real money growth is negatively associated with the probability of adopting IT in all country groups.

Table 2: Single index models for all samples

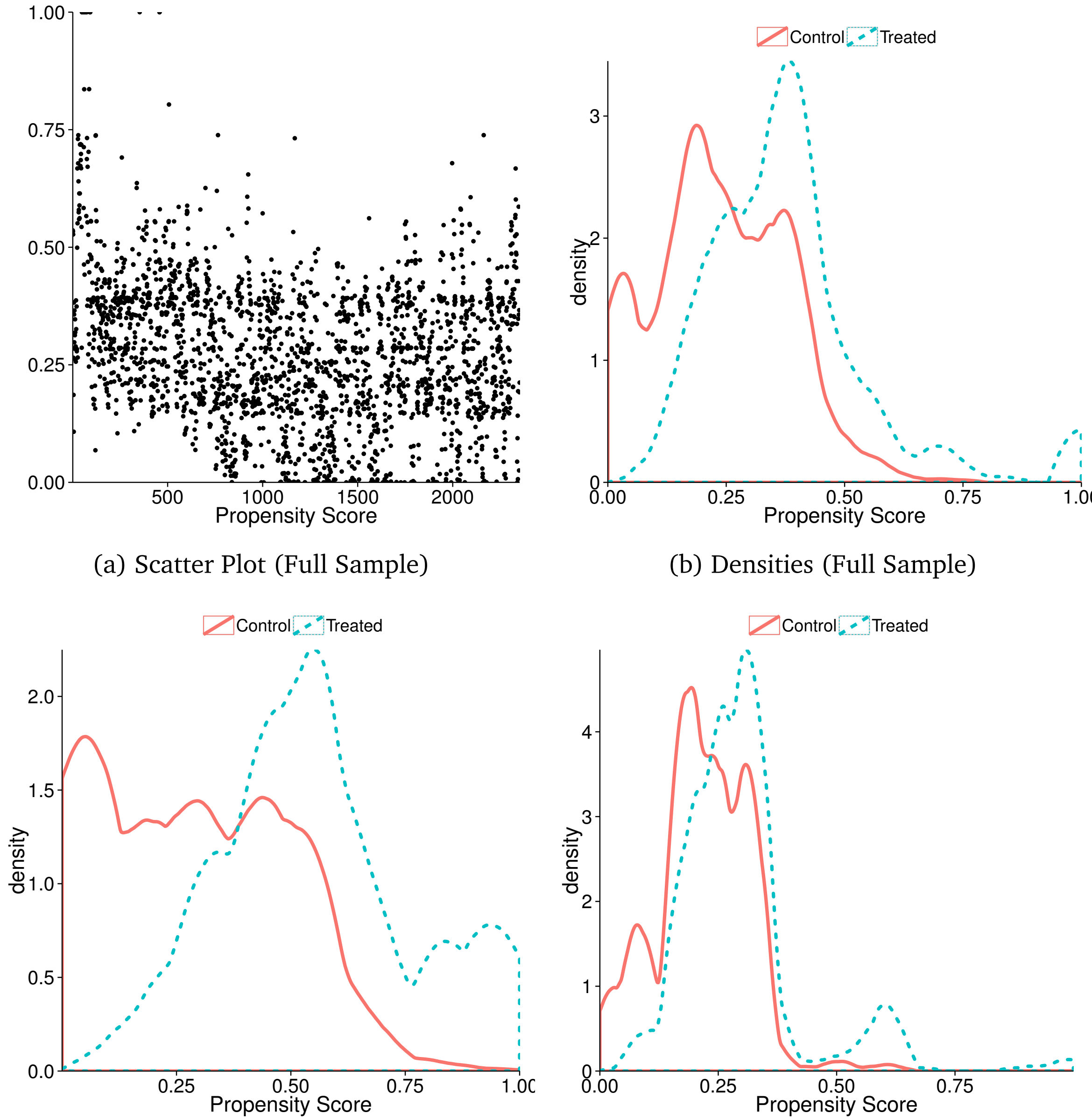
	FULL	IND	DCS
Lagged GDP Growth	-0.18***	-2.63***	-0.13***
	(0.012)	(0.967)	(0.026)
Lagged Money Growth	-0.15***	-0.97***	-0.02**
	(0.004)	(0.083)	(0.003)
Lagged Inflation	-0.06***	-0.67***	-0.21***
	(0.007)	(0.108)	(0.014)
Pegged Exchange Regime	-0.30***	-0.19	-2.21***
	(0.170)	(1.153)	(0.563)
Lagged CB Assets	0.17***	0.79***	-0.21***
	(0.019)	(0.119)	(0.030)
Lagged Credit Deposit	-0.23***	-0.19***	-0.05***
	(0.003)	(0.018)	(0.019)

The dependent variable is the targeting dummy, which has the value 1 if the country adopts inflation targeting.
The lagged openness coefficient is normalized to one.
*p<0.1; **p<0.05; ***p<0.01.

We apply the results of the semiparametric single index model to estimate the average treatment effect on the treated. Song (2014) finds that, in propensity score analysis, the conditions of single index propensity score estimates do not affect the asymptotic distribution of treatment effects even when the single index propensity score is cube-root consistent.

Table 3 presents the ATTs using the single index estimate of propensity score. Our findings are summarized as follows:

1. The results from the index model show that there is no significant impact on the level of



(a) Scatter Plot (Full Sample)

(b) Densities (Full Sample)

(c) Densities (Industrial Economies)

(d) Densities (Developing Countries)

Figure 1: Scatter plot and kernel densities of the estimated semiparametric propensity scores

Table 3: Average treatment effect on the treated, single index propensity scores

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	-0.31	-14.35***	-0.17	-1.05*	-0.94**	-1.58*
	(0.92)	(2.02)	(0.15)	(0.64)	(0.33)	(0.61)
IND	0.05	-36.62***	-0.93***	-0.06	-0.48**	2.17**
	(0.21)	(3.05)	(0.28)	(0.10)	(0.24)	(0.51)
DCS	1.65	-8.51***	0.01	-0.22	0.14	-1.07*
	(1.31)	(2.66)	(0.18)	(0.86)	(0.42)	(0.85)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

inflation in IT economies as compared to a non-targeter. For inflation volatility, we find a decline for the full-sample at the 10 percent significance level, though this disappears when we break the sample into developing and developed economies. This result is consistent with Lin and Ye (2007) who also find no significant effect on either inflation or inflation variability. Overall the decline in inflation and inflation volatility observed during this time period in inflation targeters may have also been experienced by non inflation targeters.

2. The ATTs on the government debt-GDP ratio for the full sample, developed economies, and developing countries are -14.35, -36.62, and -8.51, respectively. The statistically significant negative estimates have two implications: inflation targeting improves fiscal discipline and the impact of IT on fiscal discipline in industrial countries is significantly larger than that of in developing economies. IT adoption encourages fiscal authorities to improve fiscal discipline to support central banks to build up their credibility. Most of developing countries that have adopted inflation targeting did not meet the preconditions

of the IT adoption. Accordingly, they enhance fiscal discipline in order to convince the private sector of their commitment to price stability. Adopting IT helps the governments in industrial economies to reduce the level of their debt. They implement fiscal policies at the same time to anchor the price level. One of the consequences is lowering debt and improving fiscal discipline. Minea and Tapsoba (2014) indicate that inflation targeting improves fiscal discipline only in developing countries.

3. The comparison of the effect of IT on the sacrifice ratio among all subsamples implies that industrial targeters were able to reduce inflation at a lower cost than developing targeters. The ATT for industrial economies is -0.93, which is statistically significant at the one percent significance level.

4. The ATTs on interest rate volatility are negative and statistically significant for the full sample and industrial economies. Less volatile interest rate is a sign of more credible central banks. Chadha and Nolan (2001) provide a theoretical model to link transparency and interest rate volatility. They argue that information flows lead to a reduction in the volatility of interest rates.

5. There is no consensus in the literature about how the adoption of the IT regime would affect the volatility of exchange rates. Inflation targeting may move the focus of central banks, especially in emerging markets, away from foreign exchange markets. Mishkin and Savastano (2001), for example, suggest a floating exchange rate system is a requirement for a well-functioning inflation targeting regime which is the idea behind the "Impossibility of the Holy Trinity." The Impossibility of the Holy Trinity suggests independent monetary policy cannot coexist with a pegged exchange rate regime. The connection between inflation targeting and floating exchange rates has led some analysts to argue that one of the costs of IT is the increase in exchange rate volatility. However, Gregorio, Tokman and Valdés (2005) discuss this issue in the Chilean context and show in Chile nominal exchange rate volatility has not been higher than in other countries with floating exchange

rates. Similarly, Edwards (2006) argues that a credible monetary policy can reduce the exchange rate volatility. We examine the relationship between inflation targeting and exchange rate volatility using our propensity score matching analysis. We find IT reduces exchange rate volatility in developing countries (ATT = -1.07), but increases it in industrial economies (ATT = 2.17). Lin (2010) also shows that inflation targeting has different impacts on exchange rate volatility in different country groups. He argues that the IT regime significantly lowers the volatility of exchange rates in industrial economies and increases them in developing countries. Rose (2007) also finds that inflation targeters experienced lower real exchange rate volatility than non-targeters.[5]

Overall, our results from the semiparametric index model suggests that developed economies seem to benefit more from the IT regime as these countries witness a relative decline in the sacrifice ratio and interest rate volatility. The decline in the sacrifice ratio and interest rate volatility suggests that developed countries adopting the IT regime build higher credibility and as a result inflation could be reduced at a lower output loss and also lower interest rate volatility. With regard to an increase in volatility of exchange rates for developed economies and reduction for the developing economies, it can be argued that stabilizing exchange rates is not one of the foremost objectives of the central banks in developed economies. However, the central banks in developing economies do take into account exchange rate volatility and in some scenarios their ability to control the inflation rate may also be dependent on a stable exchange rate regime.

4.3 Nonparametric Series Propensity Scores

Another way of dealing with the model misspecification problem is to use a nonparametric method. We apply the nonparametric series estimator proposed by Hirano, Imbens and Ridder (2003) to estimate consistent propensity scores in a matching framework. The nonparametric

[5]The above propensity score estimates are based on the normalization of the lagged openness coefficient. As a robustness check, we estimate the treatment effects using different normalized coefficients in the first stage and find consistent results.

series estimator can be used when the functional form of the propensity score and the distribution of the error terms are unknown. Hirano, Imbens and Ridder (2003) estimate $\pi(x)$ in a sieve approach by the series logit estimator (SLE). Suppose $R^K(x) = (r_{1K}(x), r_{2K}(x), \ldots, r_{kK}(x))'$ be a K-vector of functions where $K = 1, 2, \ldots$. The SLE is defined by $\hat{\pi}(x) = \Lambda(R^k(x)'\hat{\pi}_K)$, where $\Lambda(a) = \exp(a)/(1+\exp(a))$ is the logistic distribution function. $\hat{\pi}_k$ is estimated as the following:

$$\hat{\pi}_K = \underset{\pi}{\operatorname{argmax}} \sum_{i=1}^{N} (T_i \cdot \ln(\Lambda(R^k(x)'\pi)) + (1 - T_i) \cdot \ln(1 - \Lambda(R^k(x)'\pi)). \tag{9}$$

Table B1 summarizes the nonparametric series estimates where power series functions are adopted to approximate the unknown function. The nonparametric model consists of 35 covariates including the second powers and their interaction terms. The estimation is stopped at the second power, because standard errors become very large, causing instability in the estimates of the coefficients as the order of power series increases due to the curse of dimensionality. Table 4 shows the ATTs using the nonparametric series propensity scores. The average treatment effect on the treated for debt, the inverse measure of fiscal discipline, is statistically significant and negative across all samples. The magnitude is larger for industrial countries than for developing economies. We find the similar results for the fiscal discipline outcome using single index and nonparametric propensity scores. We find real exchange rate volatility increased in developed countries and decreased in developing countries. The findings for other outcomes of interest are mostly different between the two methods. In the full sample, IT reduces the sacrifice ratio and the impact is statistically significant at the one percent level. As mentioned before, however, we need to be cautious in interpreting the estimation results, since the nonparametric approach is unstable given that the number of covariates is large.

Table 4: Average treatment effect on the treated, nonparametric propensity scores

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	1.91**	-27.37***	-1.62***	-1.47**	-0.28	0.01
	(0.81)	(2.2)	(0.18)	(0.69)	(0.33)	(0.56)
IND	-0.19	-23.65***	-0.36	-0.07	0.31**	2.61***
	(0.13)	(2.72)	(0.28)	(0.13)	(0.13)	(0.39)
DCS	2.54**	-15.36***	0.12	1.23*	-0.83*	-0.17
	(1.14)	(2.8)	(0.18)	(0.72)	(0.46)	(0.74)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

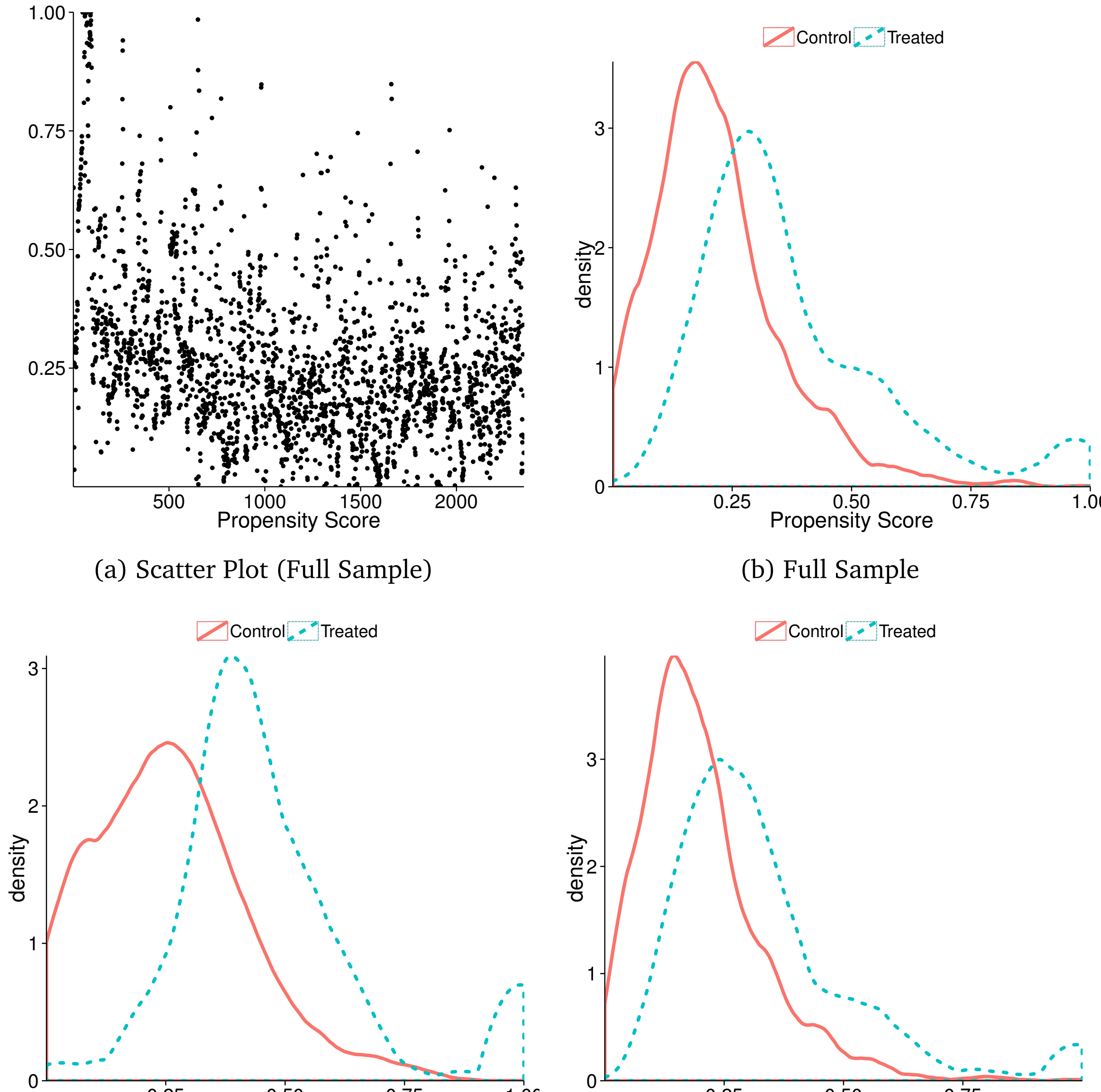
4.4 Parametric Propensity Scores

In addition to applying semiparametric single index and nonparametric models, we use the conventional parametric propensity scores to estimate treatment effects and compare the findings with its counterparts. The existing literature on the treatment effect of IT has mainly used parametric methods. The conditional probability of adopting inflation targeting, $\pi(X_i) = Pr(T_i = 1|X_i)$, can be estimated by a probit model, $\pi(X_i) = \mathbb{E}(T_i|X_i) = (2\pi)^{-1/2} exp[-(X_i\beta_i)^2/2]$, or a logit model, $\pi(X_i) = (1 + e^{-X_i\beta_i})^{-1}$. The results of the probit model are presented in Table B2. We also estimate the propensity score using a logit model. The estimates are similar to the probit, so we omit them for brevity. The response variable is the targeting dummy and takes the value of 1 if the country adopts inflation targeting. In the first stage estimation of treatment effects, we include both institutional characteristics and macroeconomic predictors to estimate the likelihood of adopting IT. We find different results for the single index and parametric models. For example, the signs of lagged credit deposit-GDP coefficients are opposite among all samples. It holds true for the lagged central bank assets-GDP and lagged money growth coefficients. We also capture these differences by comparing Figure 1 and Figure 2. Figure 2 plots kernel densities of the estimated probit propensity scores. The densities of index estimates differ from those of parametric estimates for both treated and control units.

After propensity scores are estimated, we match targeters to non-targeters based on the estimated propensity scores. Figure 2 illustrates that the distributions between control and treated groups are quite different among all samples. Thus, we expect that matching improves the results of treatment effects. Figure 3 plots the histograms of the estimated probit propensity scores before (left graphs) and after (right graphs) matching for the full sample. The distribution of the propensity scores for non-targeters changes after applying the nearest-neighbor matching and it is close to the distribution of the propensity scores for targeters. We examine the balance of each covariate graphically in Figure 4 for all samples. The covariates are $lcba$, the lagged central bank assets-GDP ratio, $lpcd$, the lagged credit deposit-GDP ratio, $lgdpg$, lagged GDP growth, $lrmg$, lagged money growth, lpi, lagged inflation, and $lopen$, lagged openness. If the empirical distributions are the same for targeters and non-targeters, the points in the Q-Q plots lie on the 45 degree line. Deviations from it imply differences in the empirical distribution. As shown in these plots, matching would improve the empirical distribution for lagged openness and lagged GDP growth in the full sample.

The results of average treatment effect on the treated using parametric propensity scores are presented in Table 5. In all samples, the ATTs on inflation is negative, but not statistically significant. The ATT estimates using the parametric model are different than those estimated by the semiparametric model. The contrary signifies the impact of propensity score misspecification on the ATTs. Other results supporting our view are the estimates on the sacrifice ratio, inflation variability, and interest rate volatility. The average treatment effect on the treated on inflation variability is negative across different country groups and coefficients are statistically significant in the full sample and developing subsamples.

The sign of treatment effects on fiscal discipline and exchange rate volatility are similar



(a) Scatter Plot (Full Sample)

(b) Full Sample

(c) Industrial Economies

(d) Developing Countries

Figure 2: Scatter plot and kernel densities of the estimated probit propensity scores

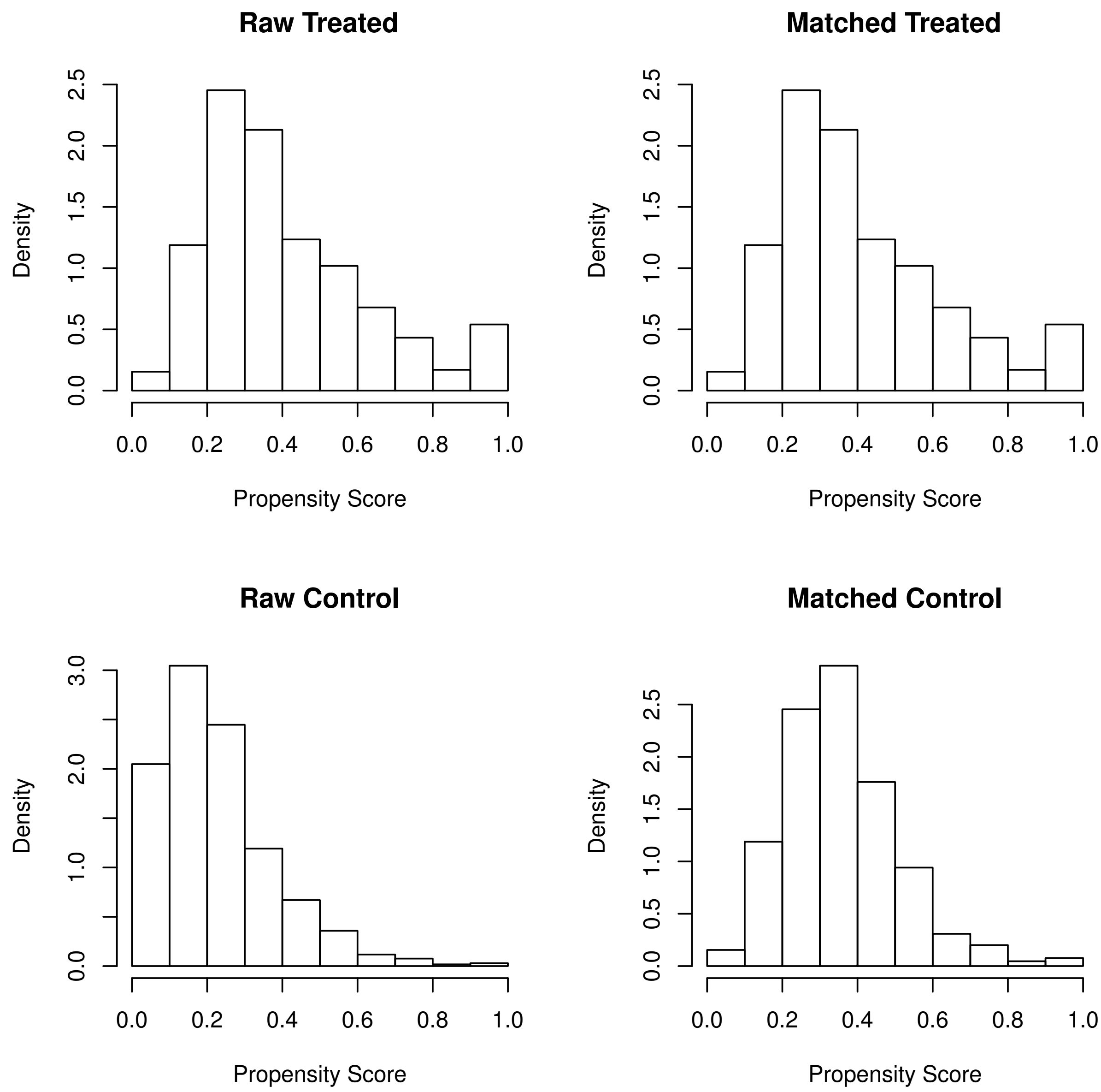
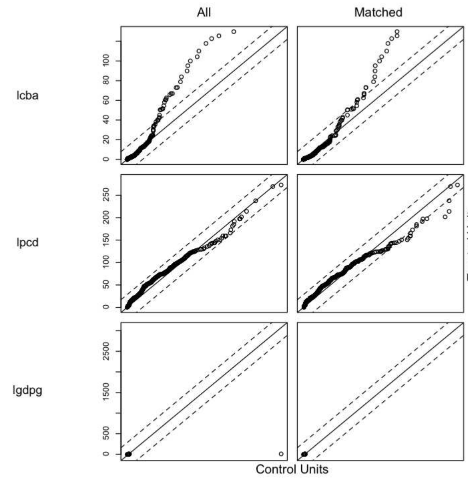
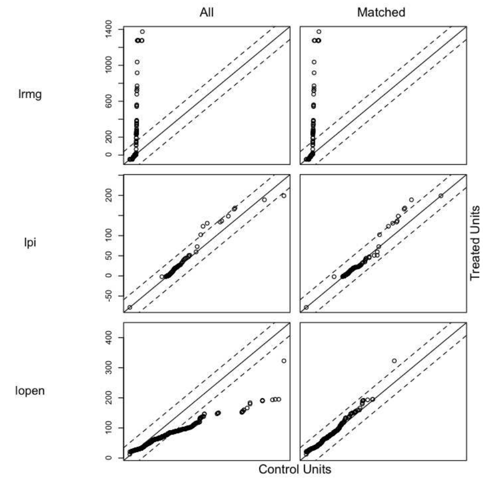


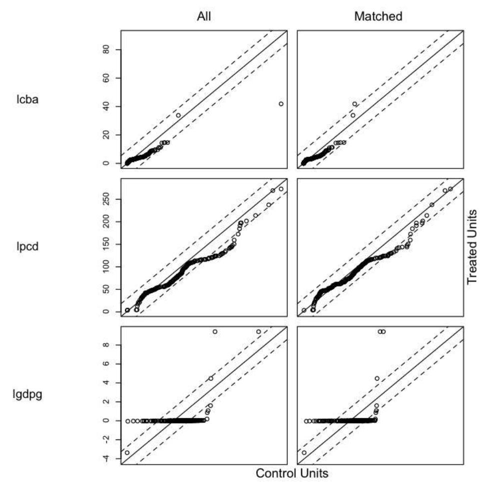
Figure 3: Histograms of the estimated propensity scores before and after matching



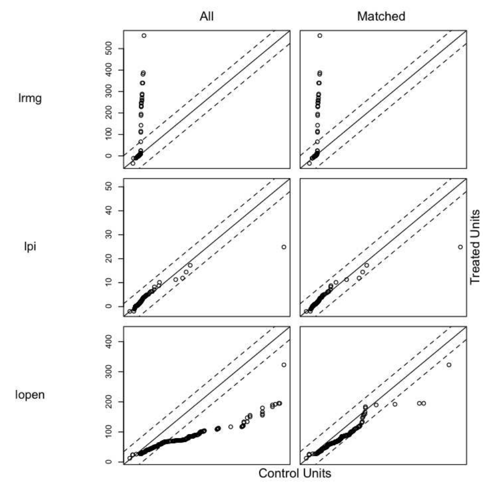
(a) Full Sample



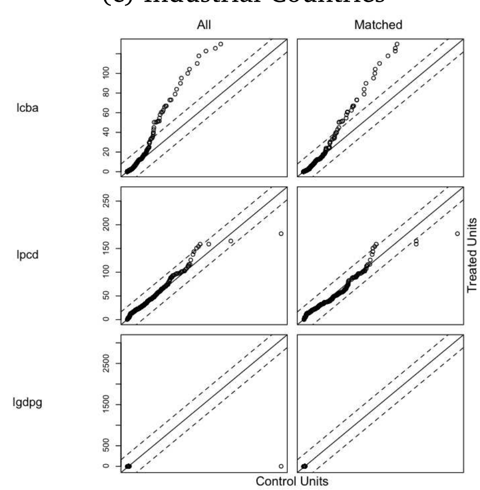
(b) Full Sample



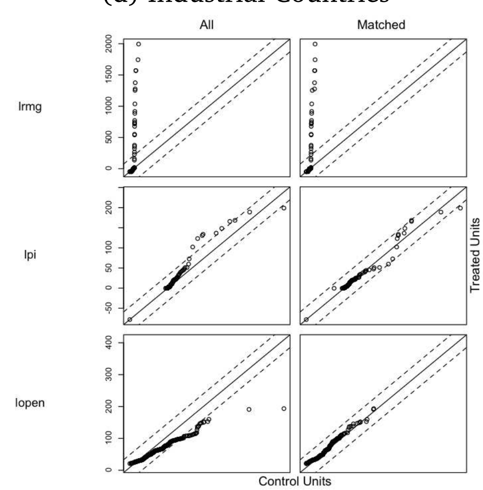
(c) Industrial Countries



(d) Industrial Countries



(e) Developing Countries



(f) Developing Countries

Figure 4: QQ plots for all covariates

The covariates are $lcba$, the lagged central bank assets-GDP ratio, $lpcd$, the lagged credit deposit-GDP ratio, $lgdpg$, lagged GDP growth, $lrmg$, lagged money growth, lpi, lagged inflation, and $lopen$, lagged openness.

Table 5: Average treatment effect on the treated, probit propensity scores

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	-0.70	-21.29***	-0.06	-1.88***	-1.22***	-1.53***
	(0.97)	(2.23)	(0.15)	(0.67)	(0.34)	(0.6)
IND	-0.05	-33.9***	-0.2	-0.16	-0.06	1.77***
	(0.23)	(3.49)	(0.3)	(0.14)	(0.19)	(0.48)
DCS	-0.72	-11.68***	-0.02	-1.93**	-0.68	-2.01**
	(1.51)	(2.78)	(0.18)	(0.98)	(0.47)	(0.81)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

compared to the index results, but the magnitudes are different. The effects of IT on inflation, inflation variability, the sacrifice ratio, and interest rate volatility are inconsistent. The results suggest that the choice of propensity scores has a considerable impact on the treatment effect estimates. The semiparametric single index framework provides more accurate effect estimates. Our empirical study suggests that the single index coefficient regression model in conjunction with the proposed estimation method could be useful in propensity score analysis.

5 Sensitivity Analysis

A vast literature uses parametric propensity score matching to examine the effectiveness of inflation targeting. The sensitivity analysis determines whether the results from our proposed semiparametric approach are robust to various scenarios. As a robustness check, we report the results of the first and second stages when the conventional covariates are used. Conventional covariates are macroeconomic predictors in which the preconditions are not included. We also compare the ATTs when the contemporaneous variables are used in the first stage. Our last comparison involves propensity score models for the pre-crisis period.

5.1 Conventional Covariates

One of the contributions of this paper is to include preconditions in the estimation of propensity scores. Existing studies such as Lin and Ye (2007) estimate propensity scores based only upon macroeconomic predictors. In the previous sections, we show how preconditions affect the likelihood of the IT adoption. We compare our results to the literature by estimating propensity scores with conventional covariates. Tables 6 and 7 include treatment effects of IT using the single index and probit propensity scores. The comparison of Table 6 with Table 3 implies the ATTs on inflation using the conventional covariates in the first stage differs from the results using all the variables. This holds true for the sacrifice ratio in the full and developing samples, inflation variability for the full sample, and interest rate volatility in the developing sample. The findings in this section signify the role of preconditions.

Table 6: Average treatment on the treated, index propensity scores with conventional covariates

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	0.27	-13.92***	0.04	-0.34	-1.05***	-2.36***
	(0.85)	(2.13)	(0.15)	(0.54)	(0.32)	(0.64)
IND	-0.23	-29.41***	-1.44***	-0.14	-0.74***	1.13**
	(0.19)	(2.85)	(0.29)	(0.13)	(0.29)	(0.55)
DCS	-0.11	-9.98***	-0.04	-0.72	-0.61	-1.67*
	(1.56)	(2.65)	(0.17)	(0.92)	(0.46)	(0.86)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

Table 7: Average treatment on the treated, probit propensity scores with conventional covariates

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	-0.88	-15.92***	-0.08	-1.33**	-1.81***	-2.47***
	(0.88)	(2.03)	(0.16)	(0.59)	(0.34)	(0.61)
IND	-0.02	-34.85***	0.01	0.02	-0.32	1.75***
	(0.16)	(3.45)	(0.29)	(0.11)	(0.24)	(0.51)
DCS	-1.11	-13.96***	-0.04	-1.45*	-1.18**	-2.32***
	(1.53)	(2.58)	(0.18)	(0.87)	(0.47)	(0.82)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

5.2 Lagged vs. Contemporaneous Covariates

The literature on treatment effects of IT lacks a rigorous explanation of endogeneity. Gertler (2005) points to the endogeneity problem in examining whether IT is effective. He explains the difficulties of identifying its effects have been raised by Ball and Sheridan (2003) and Mishkin and Schmidt-Hebbel (2007). We note there is a lag period in response to the inflation targeting framework. In order to consider the lag in the effect IT, we model the likelihood of IT using lagged covariates. However, some studies estimate the propensity score using contemporaneous variables. This section shows the robustness of our findings compared to those which include covariates at level.

Table B4 summarizes the first stage estimations using the single index model with contemporaneous variables. Tables 8 and 9 present the average treatment effect on the treated using corresponding variables and methods. The treatment effects on all variables considering contemporaneous variables are similar to the treatment effects from the baseline model suggesting the robustness of our results to the use of conventional covariates. The point estimates, however, are different. For example, as compared to the baseline model we find that IT leads to reduction in inflation, inflation volatility and interest rate volatility, though these effects are insignificant for the developing economies. Comparing Table 9 with Table 5 shows that the treatment effects are not sensitive to the choice of variables in case of parametric specification except interest rate volatility where the effect is significantly negative in the case of conventional covariates. Consistent with the comparison of the semiparametric model with the parametric model in the case of the baseline model, we also find differences in the results when we use conventional variables. For example, using parametric propensity score, we find that the treatment effect on inflation volatility is significantly negative.

Table 8: Average treatment on the treated, index propensity scores with the contemporaneous covariates

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	0.77	-15.34***	0.01	-0.6	-0.82***	-2.06***
	(0.81)	(2.11)	(0.15)	(0.55)	(0.32)	(0.61)
IND	-0.13	-39.69***	-0.78***	-0.1	-0.31	0.96**
	(0.21)	(3.25)	(0.31)	(0.13)	(0.23)	(0.48)
DCS	1.43	0.26	0.07	0.35	-0.18	-1.73**
	(1.29)	(2.53)	(0.17)	(0.79)	(0.45)	(0.83)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

5.3 Pre-crisis Period

The empirical work on the IT effectiveness has considered a sample period before the global financial crisis (Ball and Sheridan (2003), Lin and Ye (2007), Lucotte (2012), and Lin and Ye (2013)). Our sample period of 1990–2013 includes years after the crisis. In this section we consider whether our results are sensitive to the inclusion of the crisis and the post-crisis time periods by estimating the model for the pre-crisis period (1990–2007). Table B5 summarizes

Table 9: Average treatment on the treated, probit propensity scores with contemporaneous variables

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	0.39	-17.68***	-0.09	-1.13**	-1.2***	-1.37**
	(0.88)	(2.14)	(0.16)	(0.56)	(0.33)	(0.58)
IND	-0.04	-32.71***	-0.37	-0.16	0.01	2.07**
	(0.22)	(3.27)	(0.33)	(0.15)	(0.18)	(0.47)
DCS	-0.2	-12.42***	0.07	-1.71	-0.55	-1.85**
	(1.51)	(2.72)	(0.18)	(1.00)	(0.48)	(0.81)

Outcomes are inflation (π), the debt-GDP ratio ($debt$) as a proxy for fiscal discipline, the sacrifice ratio (SR) measured by the change in output to the change in inflation, inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s). Volatilities are measured by the standard deviation of a three-year moving average.
FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

the results of the first stage using conventional variables for the pre-crisis period. We exclude the lagged central bank assets ratio and the lagged credit deposit-GDP ratio. The findings of the second stage estimation, Table 10, indicate the effect of IT on fiscal discipline remains unchanged prior to the crisis which is consistent with our previous findings. We interpret these robust results as evidence for the causal role of inflation targeting per se on fiscal discipline. Inflation variability has decreased in all targeters in the pre-crisis period. However, the coefficient is not statistically significant. The treatment effects on interest rate volatility remain the same before the crisis. The findings presented in Table 10 and the comparison with the full sample period (Table 3) determine our main findings are not sensitive to the post-crisis period.

Lin and Ye (2007) also referred to the selection problem, but their approach is estimating the propensity scores parametrically. They use a sample of 22 industrial countries over the period 1985–1999. Our Table 11 presents the results most comparable to those of Lin and Ye (2007).[6] Their ATTs on inflation for the constant and non-constant inflation targeting frameworks are -.002 and -0.0034. The ATTs are not statistically significant. We find the ATT on inflation

[6]See Tables 3 and 4 in P. 2528 of Lin and Ye (2007).

for industrial countries -0.88 which is statistically significant at the one percent level. Their treatment effects on inflation variability are -.0003 and .0009 and are not statistically significant. Our treatment effect on inflation variability is -2.93 and statistically significant at the one percent level. One reason for the huge difference is the choice of misspecified parametric propensity scores versus the semiparametric counterpart.

Table 10: Average treatment on the treated, single index propensity scores with conventional covariates (pre-crisis periods)

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	-0.10	-14.94***	0.08	-0.94	-0.63*	-2.37***
	(1.26)	(2.4)	(0.16)	(0.80)	(0.37)	(0.76)
IND	-0.49**	-33.72***	-1.26***	-0.11	-1.26***	-0.27
	(0.21)	(3.65)	(0.32)	(0.14)	(0.36)	(0.84)
DCS	0.94	-5.60*	0.10	-0.91	0.20	-0.95
	(1.86)	(3.25)	(0.18)	(1.23)	(0.50)	(1.02)

FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

Table 11 summarizes the average treatment on the treated, index propensity scores with contemporaneous covariates for the pre-crisis periods. Fiscal discipline is robust to the contemporaneous variables.

Table 11: Average treatment on the treated, single index propensity scores with contemporaneous covariates (pre-crisis periods)

	π	$debt$	SR	σ_π	σ_i	σ_s
FULL	1.72	-15.6***	0.06	0.32	-0.37	-0.88
	(1.08)	(2.46)	(0.15)	(0.66)	(0.37)	(0.72)
IND	-0.88***	-21.72***	-1.15***	-2.93***	-0.51*	2.71***
	(0.25)	(3.00)	(0.28)	(0.47)	(0.29)	(0.57)
DCS	3.41**	-4.11	-0.21	0.07	0.37	-1.32
	(1.65)	(3.38)	(0.18)	(1.10)	(0.51)	(0.89)

FULL: the full sample, IND: industrial economies, DCS: developing countries.
*p<0.1; **p<0.05; ***p<0.01.

6 Concluding Remarks

The purpose of this paper is to examine the causal effect of the IT adoption on macroeconomic performance using a semiparametric index model. The semiparametric index model takes into account the inconsistent estimation of propensity scores and the 'curse of dimensionality" problem associated with the nonparametric model. We also consider the prominent role of preconditions in IT adoption by including the central bank assets-GDP ratio and the private credit-GDP ratio in the first stage estimations of the probability of adoption of IT. In addition to examining the impact on level of inflation and inflation volatility, we also estimate the treatment effect on volatility of interest rate and exchange rate, sacrifice ratio and the debt-GDP ratio. This provides us a measure of the indirect effect of IT.

We find that the treatment effect on inflation and inflation volatility is insignificant for both the developed and the developing economies. This result is in contrast to the parametric propensity scores that suggest significant decline in inflation volatility in developing countries. The results from the semiparametric model also suggest a decline in sacrifice ratio and interest rate volatility for the developed country inflation targeters, whereas the impact is insignificant in case of developing economies. The adoption of IT leads to an increase in volatility of exchange rate in developed economies, whereas it reduces the exchange rate volatility in developing economies. Our results show that adoption of IT leads to improvement in debt-GDP ratio in both the developed and the developing economies. Overall, our findings present mixed results and have differential impact on various variables in developed and developing economies. As a sensitivity analysis, we use a smaller sample period (pre-crisis) with conventional and contemporaneous covariates to compare our results with Lin and Ye (2007) who use the parametric propensity scores. We find the approach to estimate propensity scores in the first stage has significant impacts on the treatment effects.

References

Amato, J. D., and S. Gerlach. 2002. "Inflation targeting in emerging market and transition economies: Lessons after a decade." *European Economic Review*, 46(4-5): 781–790.

Angeriz, A., and P. Arestis. 2007. "Assessing the performance of 'inflation targeting lite' countries." *The World Economy*, 30(11): 1621–1645.

Ball, L., and N. Sheridan. 2003. "Does inflation targeting matter?" *The Inflation Targeting Debate. University of Chicago Press*.

Bernanke, B., and M. Woodford. 2005. *The Inflation-Targeting debate.* Vol. 32, Chicago and London:University of Chicago Press.

Brito, R. 2010. "Inflation targeting does not matter: another look at OECD sacrifice ratios." *Journal of Money, Credit, and Banking*, 42(8): 1679–1688.

Buuren, S., and K. Groothuis-Oudshoorn. 2011. "MICE: Multivariate imputation by chained equations in R." *Journal of Statistical Software*, 45(3).

Chadha, J. S., and C. Nolan. 2001. "Inflation targeting, transparency and interest rate volatility: ditching 'monetary mystique' in the UK." *Journal of Macroeconomics*, 23: 349–366.

Creel, J., and P. Hubert. 2010. "Has inflation targeting changed the conduct of monetary policy?" *Macroeconomic Dynamics*, FirstView: 1–21.

Dehejia, R. H., and S. Wahba. 2002. "Propensity score-matching methods for nonexperimental causal studies." *The Review of Economics and Statistics*, 84: 151–161.

de Mendonca, H. F., and G. J. de Guimaraes. 2012. "Is inflation targeting a good remedy to control inflation?" *Journal of Development Economics*, 98(2): 178–191.

Demertzis, M., and A. H. Hallett. 2007. "Central bank transparency in theory and practice." *Journal of Macroeconomics*, 29(4): 760–789.

Edwards, S. 2006. "The relatioship between exchange rates and inflation targeting revisited." *National Bureau of Economic Research*.

Filho, I. 2011. "28 months later: how inflation targeters outperformed their peers in the great recession." *The BE Journal of Macroeconomics*, 11(1).

Gertler, M. 2005. "Comment on 'Does Inflation Targeting Matter?'." *The Inflation Targeting Debate*, 276–281.

Goncalves, C. E., and A. Carvalho. 2009. "Inflation targeting matters: evidence from OECD economies' Sacrifice Ratios." *Journal of Money, Credit, and Banking*, 41(1): 233–243.

Gregorio, J., A. Tokman, and R. Valdés. 2005. "Flexible exchange rate with inflation targeting in Chile: Experience and issues." *Working Paper, Inter-American Development Bank, Research Department*.

Hayfield, T., and J. S. Racine. 2008. "Nonparametric econometrics: The np package." *Journal of Statistical Software*, 27(5): 1–32.

Hirano, K., G. W. Imbens, and G. Ridder. 2003. "Efficient estimation of average treatment effects using the estimated propensity score." *Econometrica*, 71(4): 1161–1189.

Ilzetzki, E., C. M. Reinhart, and K. S. Rogoff. 2008. "Exchange rate arrangements entering the 21st century: Which anchor will hold?" *University of Maryland and Harvard University*.

Johnson, D. R. 2002. "The effect of inflation targeting on the behavior of expected inflation: evidence from an 11 country panel." *Journal of Monetary Economics*, 49(8): 1521–1538.

Klein, R. W., and R. H. Spady. 1993. "An efficient semiparametric estimator for binary response models." *Econometrica*, 61: 387–421.

Lin, S. 2010. "On the international effects of inflation targeting." *The Review of Economics and Statistics*, 92(1): 195–199.

Lin, S., and H. Ye. 2007. "Does inflation targeting really make a difference? Evaluating the treatment effect of inflation targeting in seven industrial countries." *Journal of Monetary Economics*, 54(8): 2521–2533.

Lin, S., and H. Ye. 2013. "Does Inflation Targeting Help Reduce Financial Dollarization?" *Journal of Money, Credit and Banking*, 45(7): 1253–1274.

Li, Q., and J. S. Racine. 2011. *Nonparametric econometrics: Theory and practice.* Princeton University Press.

Lucotte, Y. 2012. "Adoption of inflation targeting and tax revenue performance in emerging market economies: An empirical investigation." *Economic Systems*, 36(4): 609–628.

Minea, A., and R. Tapsoba. 2014. "Does inflation targeting improve fiscal discipline?" *Journal of International Money and Finance*, 40: 185–203.

Mishkin, F. S., and K. Schmidt-Hebbel. 2001. "One decade of inflation targeting in the world: What do we know and what do we need to know?" *National Bureau of Economic Research*.

Mishkin, F. S., and K. Schmidt-Hebbel. 2007. "Does inflation targeting make a difference?" *National Bureau of Economic Research*.

Mishkin, F. S., and M. A. Savastano. 2001. "Monetary policy strategies for Latin America." *Journal of Development Economics*, 66(2): 415–444.

Morris, S., and H. S. Shin. 2002. "Social value of public information." *The American Economic Review*, 92(5): 1521–1534.

Neumann, M. J., and J. von Hagen. 2002. "Does inflation targeting matter?" *ZEI Working Paper*.

Romer, D. 1993. "Openness and inflation: Theory and evidence." *Quarterly Journal of Economics*, 108(4): 869–903.

Rose, A. K. 2007. "A stable international monetary system emerges: Inflation targeting is Bretton Woods, reversed." *Journal of International Money and Finance*, 26(5): 663–681.

Rosenbaum, P. R., and D. B. Rubin. 1983. "The central role of the propensity score in observational studies for causal effects." *Biometrika*, 70(1): 41–55.

Samarina, A., M. Terpstra, and J. De Haan. 2013. "Inflation targeting and inflation performance: a comparative analysis." *Applied Economics*, 46(1): 41–56.

Song, K. 2014. "Semiparametric models with single-index nuisance parameters." *Journal of Econometrics*, 178: 471–483.

Stone, C. J. 1980. "Optimal rates of convergence for nonparametric estimators." *The annals of Statistics*, 8(6): 1348–1360.

Svensson, L. E. 1996. "Inflation forecast targeting: Implementing and monitoring inflation targets." *European Economic Review*, 41(6): 1111–1146.

Svensson, L. E. 1999. "Inflation targeting as a monetary policy rule." *Journal of Monetary Economics*, 43(3): 607–654.

Svensson, L. E. 2005*a*. "Optimal inflation targeting: Further developments of inflation targeting." *Sveriges Riksbank Conference,'Inflation Targeting: Implementation, Communication, and Effectiveness'*.

Svensson, L. E. 2005*b*. "Social value of public information: Morris and Shin (2002) is actually pro-transparency, not con." *National Bureau of Economic Research*.

Vega, M., and D. Winkelried. 2005. "Inflation targeting and inflation behavior: a successful story?" *International Journal of Central Banking*, 1(3): 153–175.

Woodford, M. 2005. "Central bank communication and policy effectiveness." *National Bureau of Economic Research*.

Wu, T. Y. 2004. "Does inflation targeting reduce? inflation? An analysis for the OECD industrial countries." *Working Paper Series*.

Zhao, Z. 2008. "Sensitivity of propensity score methods to the specifications." *Economics Letters*, 98(3): 309–319.

Appendix A

Table A1 provides the list of inflation targeting countries along with the adoption dates, target level at the adoption date and their country groups, whether the country is developed or developing. Table A2 presents the control units and their country groups. The first country that has adopted explicit inflation targeting is New Zealand with the target rate of 4 percent at the adoption date and the last one is Serbia with the target rate of 8 percent in 2006Q3.

Table A1: Treated group (targeters): adoption date, target level at the adoption date, and country group

Countries	Adoption Date	Target	Group
Armenia	2006Q1	4	DCS
Australia	1993Q2	3	IND
Brazil	1999Q2	8	DCS
Canada	1991Q1	4	IND
Chile	1999Q3	3	DCS
Colombia	1999Q3	5	DCS
Czech	1997Q4	6	DCS
Ghana	2002Q1	12	DCS
Guatemala	2005Q1	5	DCS
Hungary	2001Q2	7	DCS
Iceland	2001Q1	4	IND
Indonesia	2005Q3	5	DCS
Israel	1992Q1	15	DCS
Mexico	2001Q1	5	DCS
New Zealand	1989Q4	4	IND
Norway	2001Q1	3	IND
Peru	2002Q1	3	DCS
Philippines	2002Q1	5	DCS
Poland	1998Q1	8	DCS
Romania	2005Q3	8	DCS
Serbia	2006Q3	8	DCS
South Africa	2000Q1	3	DCS
South Korea	1998Q2	9	DCS
Sweden	1993Q1	2	IND
Thailand	2000Q2	2	DCS
Turkey	2006Q1	5	DCS
UK	1992Q3	3	IND

DCS denotes developing countries and IND indicates industrial economies.

Table A2: Control group (non-targeters)

Countries	Group	Countries	Group
Albania	DCS	Madagascar	DCS
Algeria	DCS	Malawi	DCS
Argentina	DCS	Malaysia	DCS
Armenia	DCS	Maldives	DCS
Austria	IND	Mali	DCS
Azerbaijan	DCS	Malta	IND
Belarus	DCS	Moldova	DCS
Belgium	DCS	Morocco	DCS
Belize	DCS	Mozambique	DCS
Bolivia	DCS	Myanmar	DCS
Bulgaria	DCS	Nepal	DCS
China	DCS	Netherlands	IND
Costa Rica	DCS	Nicaragua	DCS
Cyprus	IND	Niger	DCS
Denmark	IND	Saudi Arabia	DCS
Ecuador	DCS	Senegal	DCS
Egypt	DCS	Singapore	IND
El Salvador	DCS	Slovenia	IND
Estonia	DCS	Spain	IND
Fiji	DCS	Sri Lanka	DCS
France	IND	Sudan	DCS
Germany	IND	Swaziland	DCS
Greece	IND	Tanzania	DCS
India	DCS	Tunisia	DCS
Iran	DCS	Uganda	DCS
Ireland	IND	Ukraine	DCS
Italy	IND	United Arab Emirates	DCS
Jamaica	DCS	United States	IND
Japan	IND	Uruguay	DCS
Jordan	DCS	Vanuatu	DCS
Kazakhstan	DCS	Venezuela	DCS
Kenya	DCS	Vietnam	DCS
Lebanon	DCS	Yemen	DCS
Libya	DCS	Zambia	DCS
Luxembourg	IND	Zimbabwe	DCS
Macedonia	DCS		

DCS denotes developing countries and IND indicates industrial economies.

Appendix B

Appendix B summarizes the first stage estimates.

Nonparametric Propensity Scores

Table B1 includes the results of the nonparametric series estimates proposed by Hirano, Imbens and Ridder (2003). The variables in Table B1 are defined as follows: X_1 is lagged openness. X_2 is lagged GDP growth. X_3 indicates lagged real money growth. X_4 is lagged inflation. X_5 denotes the pegged exchange regime dummy. X_6 and X_7 represent lagged CB assets-GDP and lagged private credit-GDP, respectively. Our model consists of 35 covariates including the second powers and their interaction terms. The estimation is stopped at the second power, because standard errors become very large, causing instability in the estimates of the coefficients.

Parametric Propensity Scores

The results of the probit model are presented in Table B2. We also estimate the propensity score using a logit model. The estimates are similar to probit. The response variable is the targeting dummy and takes the value of 1 if the country adopts inflation targeting. In the first stage estimation of treatment effects, we include both institutional characteristics and macroeconomic predictors to estimate the likelihood of adopting IT. We find a statistically significant and negative relation between openness and the likelihood of adopting IT for the full sample, industrial economies and developing countries. A higher degree of openness lowers the probability of adopting IT. As pointed out by Romer (1993), more open economies are less likely to adopt inflation targeting. Under monetary expansion, the real exchange rate depreciates. Since the harms of real depreciation are greater in more open economies, the degree of openness and the benefits of expansion are inversely related. Moreover, GDP growth lowers the probability of the IT adoption.

Table B1: Nonparametric series models for the full, industrial, and developing samples

Covariates	FULL	IND	DCS	Covariates	FULL	IND	DCS
X_1	-0.018^{***}	-0.021^{***}	-0.023^{***}	X_4X_5	0.009	0.056	0.023^{**}
	(0.004)	(0.007)	(0.005)		(0.006)	(0.142)	(0.009)
X_1^2	-0.00002	-0.00004	0.00005^{***}	X_5^2	0.0003	0.001	0.004
	(0.00002)	(0.00003)	(0.00002)		(0.0002)	(0.01)	(0.003)
X_2	-0.293^{***}	-0.245	-0.308	X_6	-0.060^{***}	-0.145^{**}	-0.046^{***}
	(0.065)	(0.244)	(0.271)		(0.013)	(0.057)	(0.016)
X_1X_2	-0.0001	-0.0004	0.008^{***}	X_1X_6	0.0002	-0.00005	0.0002^{*}
	(0.001)	(0.002)	(0.003)		(0.0001)	(0.0004)	(0.0001)
X_2^2	-0.057^{***}	0.020	-0.958^{***}	X_2X_6	0.005^{**}	0.016	-0.008
	(0.007)	(0.017)	(0.097)		(0.002)	(0.010)	(0.007)
X_3	-0.020	0.091^{*}	-0.040^{*}	X_3X_6	-0.0001	-0.005	-0.0002
	(0.014)	(0.047)	(0.023)		(0.001)	(0.003)	(0.001)
X_1X_3	0.00005	-0.001^{*}	0.001^{**}	X_4X_6	-0.0002	0.001	0.0001
	(0.0002)	(0.0005)	(0.0003)		(0.0004)	(0.005)	(0.001)
X_2X_3	-0.005^{*}	-0.029	-0.025^{**}	X_5X_6	0.019^{***}	0.058	0.017^{**}
	(0.003)	(0.019)	(0.012)		(0.006)	(0.040)	(0.007)
X_3^2	0.0002^{*}	0.0002	0.0001	X_6^2	0.001^{***}	0.002^{*}	0.001^{***}
	(0.0001)	(0.0002)	(0.0001)		(0.0001)	(0.001)	(0.0001)
X_4	-0.014	-0.084	-0.027^{**}	X_7	0.018^{***}	-0.005	0.024^{***}
	(0.010)	(0.161)	(0.014)		(0.003)	(0.007)	(0.007)
X_1X_4	0.0001	-0.003^{*}	0.0001	X_1X_7	0.0001^{***}	0.0001^{**}	0.00002
	(0.0001)	(0.001)	(0.0001)		(0.00003)	(0.00005)	(0.00005)
X_2X_4	0.004^{***}	-0.029	0.009	X_2X_7	-0.0001	0.0002	-0.017^{***}
	(0.001)	(0.029)	(0.007)		(0.001)	(0.002)	(0.003)
X_3X_4	-0.00001	-0.004	-0.0001	X_3X_7	0.0002	0.0001	-0.00001
	(0.0001)	(0.004)	(0.0003)		(0.0001)	(0.0004)	(0.0003)
X_4^2	0.0001	-0.002	0.0002^{**}	X_4X_7	-0.0001	0.004^{***}	-0.0003^{***}
	(0.00004)	(0.002)	(0.0001)		(0.0001)	(0.001)	(0.0001)
X_5	-0.740^{***}	-1.600^{***}	-0.390	X_5X_7	-0.005^{***}	-0.007^{*}	-0.010^{**}
	(0.178)	(0.522)	(0.298)		(0.002)	(0.004)	(0.005)
X_1X_5	0.004	0.014^{***}	-0.004	X_6X_7	-0.0002	0.0004	-0.001^{**}
	(0.002)	(0.005)	(0.004)		(0.0001)	(0.0004)	(0.0002)
X_2X_5	0.087	0.003	0.013	X_7^2	-0.0001^{***}	-0.00004	-0.00001
	(0.055)	(0.165)	(0.202)		(0.00002)	(0.00003)	(0.0001)
X_3X_5	-0.004	0.031	0.010				
	(0.011)	(0.035)	(0.018)				
Observations	2,352	624	1,728				
Log Likelihood	-993.626	-263.836	-487.513				
Akaike Inf. Crit.	2,057.253	597.673	1,045.027				

X_1: lagged openness, X_2: lagged GDP growth, X_3: lagged real money growth, X_4: lagged inflation, X_5: pegged exchange regime dummy, X_6: lagged CB asset to GDP, X_7: lagged private credit to GDP.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table B2: Probit models for the full sample, industrial, and developing countries

	FULL	IND	DCS
Lagged Openness	-0.010^{***}	-0.008^{***}	-0.010^{***}
	(0.001)	(0.001)	(0.001)
Lagged GDP Growth	-0.090^{***}	-0.168^{***}	-0.082^{***}
	(0.015)	(0.055)	(0.016)
Lagged Money Growth	0.006^{***}	0.023^{**}	0.004^{***}
	(0.001)	(0.011)	(0.001)
Lagged Inflation	-0.003^{*}	0.022	-0.003^{*}
	(0.002)	(0.017)	(0.002)
Pegged Exchange Regime	-0.402^{***}	−0.159	-0.472^{***}
	(0.056)	(0.114)	(0.068)
Lagged CB Assets	0.002	−0.015	0.004^{*}
	(0.002)	(0.009)	(0.002)
Lagged Credit Deposit	0.008^{***}	0.005^{***}	0.009^{***}
	(0.001)	(0.001)	(0.001)
Observations	2,352	624	1,728
Log Likelihood	−1,165.593	−328.671	−821.601
Akaike Inf. Crit.	2,345.186	671.342	1,657.201

The dependent variable is the targeting dummy, which has the value 1 if the country adopts inflation targeting.

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

Index Propensity Scores with Conventional and Contemporaneous Covariates

Tables B3 presents the findings of the first stage using the single index model when the lagged openness coefficients are normalized to one. The sign of lagged GDP growth, lagged inflation, and pegged exchange regime coefficients are similar to the main results in Table 2. Higher GDP growth lowers the probability of the IT adoption. Also, it is less likely that the country with a pegged exchange rate regime adopts inflation targeting. However, using the conventional covariates provides different results on the real money growth. We find the higher the real money growth the higher the likelihood of the IT adoption. The finding contrasts with the results in Table 2.

Table B3: Single index models with the conventional variables

	FULL	IND	DCS
Lagged GDP Growth	-0.698***	-1.413***	-0.437***
	(0.214)	(0.424)	(0.082)
Lagged Money Growth	0.016***	0.188***	0.126***
	(0.007)	(0.012)	(0.002)
Lagged Inflation	-0.137***	-0.927***	-0.201***
	(0.012)	(0.233)	(0.012)
Pegged Exchange Regime	-0.172	0.47	-0.439***
	(0.342)	(0.427)	(0.150)

The dependent variable is the targeting dummy, which has the value 1 if the country adopts inflation targeting.
Lagged openness is normalized to one for the identification in the single index model.
*p<0.1; **p<0.05; ***p<0.01.

Table B4 summarizes the first stage estimations using the single index model with contemporaneous variables.

Table B4: Single index models with the contemporaneous covariates

	FULL	IND	DCS
GDP Growth	0.052	0.093	-0.508***
	(0.094)	(0.939)	(0.049)
Money Growth	-0.066***	-0.239***	0.013***
	(0.002)	(0.03)	(0.003)
Lagged Inflation	0.149***	-0.578	-0.189***
	(0.017)	(0.651)	(0.006)
Pegged Exchange Regime	-0.99*	-2.512	-0.735**
	(0.579)	(2.517)	(0.337)
Credit Deposit	0.098***	-0.182***	0.055***
	(0.006)	(0.018)	(0.006)
CB Assets	0.201***	0.971***	-0.04***
	(0.029)	(0.174)	(0.012)

The dependent variable is the targeting dummy, which has the value 1 if the country adopts inflation targeting.
The lagged openness coefficient is normalized to one.
*p<0.1; **p<0.05; ***p<0.01.

The Pre-Crisis Period

Table B5 summarizes the results of the first stage using conventional and contemporaneous variables for the pre-crisis period. We exclude the lagged central bank assets ratio and the lagged credit deposit-GDP ratio.

Table B5: Single index models with the conventional and contemporaneous covariates, (pre-crisis periods)

	FULL	IND	DCS	FULL	IND	DCS
Lagged GDP Growth	-1.752***	-0.987	-0.48**	-2.558***	-0.247**	-0.364***
	(0.357)	(1.029)	(0.201)	(0.204)	(0.129)	(0.128)
Lagged Money Growth	0.053***	-0.872***	0.029***	0.03***	-0.004	-0.046***
	(0.01)	(0.132)	(0.009)	(0.009)	(0.003)	(0.005)
Lagged Inflation	0.101***	-0.916***	-0.373***	0.019	0.005	-0.001
	(0.047)	(0.276)	(0.023)	(0.033)	(0.045)	(0.019)
Pegged Exchange Regime	-1.973***	0.141	-1.911***	-0.66	-0.783***	-1.211***
	(0.566)	(0.753)	(0.402)	(0.592)	(0.168)	(0.409)
Lagged CB Assets				0.047***	-0.042***	-0.16***
				(0.012)	(0.003)	(0.001)
Lagged Credit Deposit				0.072	-0.008	-0.175***
				(0.045)	(0.026)	(0.001)

The dependent variable is the targeting dummy, which has the value 1 if the country adopts inflation targeting.
The lagged openness coefficient is normalized to one.
*p<0.1; **p<0.05; ***p<0.01.