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

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Abstract

This paper estimates the treatment effect of inflation targeting for 27 explicit inflation targeting countries. Our approach takes into account the problem of model misspecification and inconsistent estimation of parametric propensity scores by using a nonparametric series estimator proposed by Hirano, Imbens and Ridder (2003) and semiparametric single index method suggested by Klein and Spady (1993) and Song (2014). In addition, our paper also examines the impact of inflation targeting regime on a wider set of macroeconomic outcomes. Our findings suggest that results are sensitive to the choice of propensity score estimates based on different methods, and the semiparametric single-index model of propensity score provides the most economically meaningful results. Our findings illustrate that the inflation targeting framework significantly lowers inflation variability and improves fiscal discipline. We find that this monetary policy regime reduces the real exchange rate volatility in developing countries but increases it in developed economies.

Keywords: Inflation Targeting, propensity score, treatment effects, sieve estimator, single index model.

JEL Classification: E4, E5, C14, C21.

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1 Introduction

Explicit inflation targeting 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 makes public a projected, or "target," inflation rate and then attempts to steer actual inflation toward the target through different monetary policy tools. One of the impressive features of the inflation targeting (IT hereafter) regime is that no country has given up this regime after its adoption since the Reserve Bank of New Zealand became the first central bank to adopt the IT regime in 1990. The ever-increasing popularity of the IT regime has also led several other central banks to follow implicit inflation targeting.

The increasing popularity of the IT regime has naturally spawned a great deal of academic interest in its effectiveness. Even though the amount of work on the effectiveness of inflation targeting 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 inflation targeting on macroeconomic performance, whereas another strand of literature suggests that the impact of the IT regime has been mostly insignificant. Several researchers find that 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 that the IT regime not only causes a reduction in inflation and inflation variability, but also lessens the sacrifice ratio, output volatility, and inflation expectations. The literature also identifies inflation targeting with lowering 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 that the IT regime did not reduce the variability of expected inflation. They suggest that targeters and non-targeters have experienced an unexpected reduction in inflation. Similar viewpoints have been expressed by Ball and Sheridan (2003), who argue that there is no evidence that IT reduces inflation variability, output volatility, and output growth. Lin and Ye (2007) also find that IT has no significant effects on either inflation or inflation variability.[2]

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

[2]Taylor (2005) states that 'if central banks continue to focus on price stability and keep inflation low and stable, there is every expectation that the current degree of macroeconomic stability will continue'. On the contrary, Stiglitz (2008) claims that 'inflation targeting is being put to the test and it will almost certainly fail'.

Our study improves on the existing literature on the effectiveness of inflation targeting in three important ways. First, our econometric methodology improves on the existing "treatment effect" literature on impact of inflation targeting that has been proposed to take into account the self-selection problem. Self-selection problem may arise because a central banks' decision to adopt inflation targeting is related to the benefits from the adoption of IT. This may lead to a biased causal effect. The literature (Lin and Ye (2013)); de Mendonca and de Guimaraes (2012)) have attempted to overcome the selection bias problem by estimating propensity score and match treated and control units to mimic a randomized experiment. The parametric approach to estimate the average treatment effect of inflation targeting suffers from model misspecification problem and may also provide us inconsistent estimates of the propensity scores. To take into account these econometric problems, we estimate the propensity scores by a nonparametric series estimator and a semiparametric index model. In particular, we use the nonparametric series estimator proposed by Hirano, Imbens and Ridder (2003) to estimate a consistent propensity score. This estimator can be used when the functional form of the propensity score and the distribution of the error terms are unknown. Even though nonparametric series estimator solves the model misspecification problem, it suffers from the "curse of dimensionality", as the dimension of the variable space increases at the higher power of the logit series estimation. To avoid the curse of dimensionality and to relax the parametric distributional assumption on the error terms, we estimate propensity scores using the semiparametric single index method suggested by Klein and Spady (1993) and Song (2014).

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 nominal anchor like inflation targeting is that it enhances the credibility of central banks and as a consequence volatility of important macroeconomic variables like exchange rate and interest rate may also be affected. Moreover, the adoption of IT regime may also nudge the fiscal policymakers to adopt fiscally responsible policies. 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 important macroeconomic variables like interest rate volatility, exchange rate volatility and fiscal discipline.

The propensity score method for IT regime involves estimating the probability of adoption in the first stage. The extant literature has ignored the role of financial market development in probability of adoption of the IT regime. This is in contrast to the literature that talks about the preconditions for the IT regime, where researchers have strongly opined that financial market development is one of the most important criteria for adoption and the success of the IT regime. Therefore, in addition to the variables like GDP growth, money growth, lagged inflation and openness that have been used in the literature, we also use bank assets-GDP ratio and private credit-GDP ratio as proxies for financial market development in the first step to estimate the probability of adoption of the IT regime.

Our findings suggest that the results of the propensity score weighting using the single index model in the first stage provides a more accurate estimation. We show that the effectiveness of IT and its significance vary among different country groups. In the first stage estimation, we find that institutional characteristics and financial market features, such as private credits and central banks' balance sheets, are crucial to determining the likelihood of the IT adoption. Our results illustrate that the inflation targeting framework significantly lowers inflation variability for all country groups. However, the impact of IT is less in industrial economies than developing countries, implying that developing countries benefit more from adopting inflation targeting. We find that the IT regime significantly improves fiscal discipline for both developing and developed economies and its impact is significantly larger in developing countries. In addition to the significant impact of IT on inflation variability and fiscal discipline, this monetary policy framework reduces the interest rate volatility and the exchange rate variability in the full sample. However, inflation targeting has an asymmetric effect on exchange rate volatility among developing and developed economies. Inflation targeting lowers the real exchange rate volatility in developing countries but increases it in industrial economies. A comparison between parametric propensity score and semiparametric single index model indicate that the absolute value of average treatment effect on the treated is larger and more significant than that of parametric models.

The rest of our study is organized as follows. Section 2 provides the theoretical and empirical background on the inflation targeting effectiveness. Section 3 describes the data set. The lists of inflation targeting countries and non-targeters are presented in Appendix A. Section 4 lays out the impact of inflation targeting on the macroeconomic performance by comparing propensity score matching and weighting models with different estimates of propensity scores. Section 5 offers 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 interest 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 follows:

$$\pi_{t+\tau|t} = \hat{\pi},$$

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, so that the target would be equal to the τ-step ahead forecast. The effectiveness of this monetary policy framework can be considered through two channels of aggregate demand and expectations. In the aggregate demand channel, monetary policy affects aggregate demand, then it affects inflation via the Phillips curve. In the expectations channel, monetary policy affects inflation by anchoring inflation expectations. According to this view, the inflation forecast as a target provides better information about central bank actions and 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 that the transparency of central banks has no effect on the level of inflation and output, but it decreases the volatility of inflation and the output gap. Morris and Shin (2002) address this issue through the lens of welfare effects. They argue that greater transparency does not necessarily improve social welfare. In an economy with high 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 that 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 monetary policy effectiveness through the channels of expectations, transparency, and the accountability of central banks. Nevertheless, many researchers attempt to test monetary policy effectiveness, especially explicit inflation targeting, using different econometric methods. This study attempts to link the theoretical context and empirical framework and addresses issues that occur when estimating the effect of inflation targeting.

2.2 Empirical Background

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 the inflation volatility that took place during the time this regime was in place in different countries. Studies in this strand of literature have borrowed the econometric technique from applied microeconomics to estimate the impact of inflation targeting. However, the existing empirical literature on the effectiveness of inflation targeting suffers from three problems. First issue is the estimation methodology. Second, the variables used to find the likelihood of adopting inflation targeting ignores the conventional wisdom and extant literature that suggests the role of preconditions in the effectiveness of inflation targeting such as a healthy financial system. 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.

Referring to the first issue, the estimation methodology, Ball and Sheridan (2003) find the effect of targeting by comparing improvements in targeters to improvements in non-targeters. They use a differences-in-differences approach. In their framework, the average of outcome variables before and after the adoption of IT is regressed on a targeting dummy. The coefficient of the targeting dummy measures the effect of targeting on the outcome variables. 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.[3] They find that this method produces an unbiased estimate of the dummy coefficient. In their study, the sample includes seven inflation targeters and 13 non-targeters; outcome variables are inflation, inflation variability, output growth, output volatility, and interest rates. They find no evidence that 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) uses a differences-in-differences approach to compare the average change in inflation. 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 the average inflation rates after the adoption of IT.

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 that the adoption of IT is an endogenous choice, and the empirical findings may not imply the causal effect of inflation targeting on the economic performance. So the OLS results may be biased because of endogeneity of the IT regime to inflation. They control for endogeneity using an instrument set including lagged values of inflation, inflation deviation from the target, inflation targeting dummy, nominal exchange rate depreciation, output gap, and Federal funds rate as well as making use of a panel data IV estimation. Their sample includes 21 developed and developing inflation targeting countries and 13 industrial non-targeters.

[3] Ball and Sheridan (2003) argue that by including the initial value of the outcome to the differences regression, they control for regression to the mean.

The results of panel vector autoregressive model indicate that inflation targeting reduces inflation and output volatilities and adopting IT improves the efficiency of monetary policy.

Another problem that 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. The preconditions include institutional independence of the central bank, and a well-developed technical infrastructure in terms of forecasting, minimal dollarization, a healthy financial system, and well-developed capital markets. Thus, our observational data lack the randomized assignment of countries into the adoption of IT. Researchers must employ statistical procedures to balance the data before assessing treatment effects.

To address the self-selection problem of the IT adoption, Lin and Ye (2007) estimate average treatment effects using propensity score matching methods. They utilize a variety of matching methods to use a control group to mimic a randomized experiment. Their study employs seven industrial inflation targeting countries and 15 non-targeters from the period of 1985 to 1999. They use outcome variables such as inflation, inflation variability, interest rates, and the income velocity of money to show that inflation targeting has no significant effects on economic performance. Recently, other studies examine the effectiveness of inflation targeting using the average treatment effect literature (Lin (2010), Lucotte (2012), de Mendonca and de Guimaraes (2012), Lin and Ye (2013) and Minea and Tapsoba (2014)).

The focus of this paper is on the causal effect of the IT adoption on macroeconomic performance. Ball and Sheridan (2003) and other researchers find this causal effect using a differences-in-differences methodology. However, the estimation of average treatment effect using a differences-in-differences method leads us to a biased estimate. One main issue with this type of estimation is the serial correlation problem. The response in the differences-in-differences estimation, which is the outcome variable such as inflation and inflation variability, is highly serially correlated. This paper compares different methods of estimating the average treatment effects of inflation targeting that have been used in other studies. We explain the drawbacks of those methodologies and attempt to find the inflation targeting effectiveness within an efficient framework.

To find a consistent estimate of the average treatment effect, our methodology must satisfy two assumptions of ignorability and overlap. However, in the inflation targeting literature, ignorability assumption does not hold because of the fact that the randomization of inflation targeting is not feasible. This brings up the problem of selection on observables when central banks' decision of adopting inflation targeting relates to the benefits from the adoption of IT. One way to overcome the selection bias is to estimate propensity score and match treated and control units to mimic a randomized experiment. Using propensity score analysis allows us, first, to reduce the dimensionality to a one-dimensional score and, second, to balance the differences between targeters and non-targeters.

In the propensity score literature, two procedures of matching and weighting are mentioned; propensity score matching model in which the data is balanced through resampling or matching control units to treated ones on probabilities of receiving treatment, i.e., the propensity scores, and propensity score weighting in which the propensity scores are used as sampling weights to perform a weighted outcome analysis. Propensity score weighting has some advantages over the propensity score matching. As in Guo and Fraser (2014), propensity score weighting enhances internal validity rather than external validity. It also does not require a continuous or normally distributed outcome variable. Moreover, propensity score weighting uses the most participants in the outcome analysis without losing observations, as the matching method does.

One important problem that has been neglected in the literature is the misspecification of propensity score. Zhao (2008) finds that under the ignorability assumption, the results of average treatment effects are sensitive to the specifications of propensity scores. Misspecified propensity scores lead us to a biased estimation of average treatment effects. To overcome this problem, we use different estimations of propensity scores as weights to examine the effectiveness of the IT framework. We use a nonparametric series estimator, proposed by Hirano, Imbens and Ridder (2003), to estimate a consistent propensity score. This estimator can be used when the functional form of the propensity score and the distribution of the error terms are unknown. Nonetheless, a nonparametric series estimator suffers from the "curse of dimensionality" problem due to the fact that the dimension of the variable space increases at the higher power of the logit series estimation.[4] To avoid the curse of dimensionality and relax the parametric distributional assumption, we estimate propensity scores using a semiparametric method. This method is useful when a nonparametric series estimator does not perform well because of the high dimension of variable space (Li and Racine (2011)). We consider the semiparametric single index model suggested by Klein and Spady (1993). They introduce this semiparametric model where the response is a binary variable.

[4]The curse of dimensionality refers to the problem where the convergence rate is inversely related to the number of covariates (Li and Racine (2011)).

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—such as GDP growth, lagged inflation, money growth and openness—on the likelihood of the IT adoption. However, a set of preconditions plays a vital role in the probability of adopting inflation targeting, especially in emerging market economies. These preconditions, which are necessary for a monetary policy to be successful, fall into four categories: institutional independence, a well-developed technical infrastructure, economic structure, and a healthy financial system. The most important precondition discussed in the literature that has a huge impact on inflation targeting is a healthy financial system. The banking system should be sound and capital markets well developed to guarantee an effective monetary policy transmission. To examine the role of a healthy financial system for the adoption of inflation targeting, we choose central bank assets-GDP ratio and private credit-GDP ratio along with GDP growth, money growth, lagged inflation and openness. Central bank assets-GDP measures the size of the central bank, while private credit-GDP ratio is used to measure the financial depth.

The third problem in finding the effectiveness of inflation targeting is that 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. One of the proposed benefits of having a monetary policy regime with nominal anchor such as inflation targeting is that it enhances the credibility of central banks and, as a consequence, the volatility of important macroeconomic variables such as exchange rate and interest rate may also be affected. There is no consensus in the literature about how the adoption of the IT regime would affect the volatility of exchange rate and interest rates. It has been suggested that the focus on 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 that a floating exchange rate system is a requirement for a well-functioning inflation targeting regime. The reason for this is that in a world of capital mobility, independent monetary policy cannot coexist with a pegged exchange rate regime; this is the so-called "Impossibility of the Holy Trinity." This 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 that 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. 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 the IT-adopting countries. However, the existing studies using the treatment effect methodology have not examined the impact of IT on fiscal discipline. Therefore, in addition to the level and volatility of inflation, we also look at the effectiveness of the IT regime by examining important macroeconomic variables such as interest rate volatility, exchange rate volatility, and fiscal discipline.

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 is 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 the 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.[5] Table A2 shows the list of countries used as the control group. We impute incomplete multivariate data. 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 using the MICE algorithm preserves the relationships in the data and retains the uncertainty about these relations (Buuren and Groothuis-Oudshoorn (2011)).[6]

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 2 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 2351, of which 1704 are control and 647 are treated units, and, after matching, 647 observations are left for the outcome analysis. In the subsample of industrial economies, there are 26 countries (10 inflation targeters and 16 non-targeters), and the total number of observations is 624. The subsample of developing countries includes 17 targeters and 55

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

[6]For details, see Buuren and Groothuis-Oudshoorn (2011).

non-targeters with 1848 observations.

The dependent variable used in the first stage estimation is the inflation targeting dummy, which has the value 1 if the country adopts inflation targeting. We choose the following covariates for the propensity score analysis and the estimation of average treatment effects: the lagged inflation rate; real money growth; GDP growth; openness which is measured as exports plus imports divided by GDP, indicating the total trade as a percentage of GDP; central bank assets-GDP ratio as a measure of financial sophistication; and credit deposit to real sector by deposit money bank, which is the proxy of financial development. In the second stage estimation, the outcome variables include inflation, fiscal discipline, 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. We consider government debt-GDP ratio as an inverse proxy of fiscal discipline, with real exchange volatility defined as the standard deviation of a three-year moving average of real exchange rates and interest rate volatility defined as the standard deviation of a three-year moving average of 10-year government bond interest rates.

4 The Impact of Inflation Targeting

To find the impact of inflation targeting on macroeconomic performance, we use propensity score analysis. Propensity score analysis is a quasi-experimental design used to estimate causal effects in observational studies, i.e., studies where units are not randomized to treatment. In the propensity score literature, two procedures of matching and weighting are mentioned. In propensity score matching, we are concerned with adjusting for selection bias, and we model inflation targeting using observed variables. With estimated propensity scores, matches are created for evaluating the impact of IT.

4.1 Impact Evaluation through a Propensity Score Matching Model

Most approaches to estimating the effects of inflation targeting on inflation and inflation variability fall into estimating average treatment effects. In our study, inflation targeting is considered as a treatment indicating by a binary random variable, $T_i = \{0, 1\}$. The outcome of interest is denoted by Y_i. We specify inflation rate, the measure of fiscal discipline, inflation variability, interest rate volatility, and exchange rate volatility as the outcome variables. We attempt to find whether Y_i is affected by the inflation targeting framework. 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.

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

We would like to know the causal effect of the adoption of inflation targeting in country i, which is the difference between Y_{1i} and Y_{0i}.[7] The observed outcome, Y_i, can be written in terms of potential outcomes as:

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

where $Y_{1i} - Y_{0i}$ is the causal effect of implementing inflation targeting. The average treatment effect (ATE) can be expressed by the average treatment effect on the treated and selection bias.

$$\begin{aligned} \tau_{ate} = \mathbb{E}[Y_i|T_i = 1] - \mathbb{E}[Y_i|T_i = 0] =& \mathbb{E}[Y_{1i}|T_i = 1] - \mathbb{E}[Y_{0i}|T_i = 1] \\ &+ \mathbb{E}[Y_{0i}|T_i = 1] - \mathbb{E}[Y_{0i}|T_i = 0], \end{aligned} \tag{5}$$

where $\mathbb{E}[Y_{1i}|T_i = 1] - \mathbb{E}[Y_{0i}|T_i = 1]$ is the average treatment effect on the treated and $\mathbb{E}[Y_{0i}|T_i = 1] - \mathbb{E}[Y_{0i}|T_i = 0]$ is the selection bias. Equation (5) provides the average causal effect of inflation, fiscal discipline, inflation variability, interest rate, and exchange volatility on targeters, which is the expected effect of IT on a randomly drawn country from our sample. The other quantity of interest is the average treatment effect on the treated (ATT), which is the mean effect for those countries that actually have adopted an inflation targeting framework. This effect can be written as the following:

$$\tau_{att} = \mathbb{E}[Y_{1i} - Y_{0i}|T_i = 1]. \tag{6}$$

We consider two assumptions to estimate τ_{ate} and τ_{att}. First, the treatment must be

[7] We do not observe both Y_{1i} and Y_{0i}, since each country is either targeter or non-targeter. This is called 'missing data problem' introduced by Rosenbaum and Rubin (1983).

randomized across countries, the "unconfoundedness assumption." [8] Second, the likelihood that a country adopts inflation targeting lies between zero and one, the overlap assumption.[9] In our case, the randomization of inflation targeting is infeasible. A central banks' decision is based on whether it adopts IT, and its decision relates to the benefits from that treatment, $Y_{i1} - Y_{i0}$. Therefore, there is self-selection into adopting inflation targeting.

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 selection problem is to randomize the assignment, because in a random assignment T_i is independent of potential outcomes. Researchers employ statistical procedures to balance the data before assessing treatment effects. There are four methods of estimating average treatment effect when the unconfoundedness assumption does not hold: Heckman's sample selection model, matching estimators (Abadie and Imbens (2006)), propensity score analysis (Rosenbaum and Rubin (1983)), and the bayesian approach to the estimation of ATE. Propensity score analysis is a quasi-experimental design used to estimate the causal effect when countries are not randomized to adopting inflation targeting. The benefits of using propensity score analysis are as follows. First, this method reduces dimensionality to a one-dimensional score. Second, propensity scores balance the differences between inflation targeting countries and non-targeters.[10]

The propensity score is the "conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum and Rubin (1983), p. 41). The probability of being treated can be written as the following:

$$\pi(X_i) \equiv Pr(T_i = 1|X_i). \tag{7}$$

The balancing property under exogeneity suggests that:

[8] Unconfoundedness or ignorability assumption states that $(Y_{1i}, Y_{0i}) \perp\!\!\!\perp T_i|X_i$ for all X_i.

[9] Overlap assumption declates that $0 < \pi(X_i) < 1$. The combination of both 'ignorability' and 'overlap' assumptions is called 'strong ignorability assumption' (Rosenbaum and Rubin (1983)).

[10] Targeters and non-targeters with the same value of the propensity score have the same distribution of the observed covariate.

$$T_i \perp\!\!\!\perp X_i | \pi(X_i). \tag{8}$$

Thus, the ignorability assumption with the propensity score can be written as follows:

$$(Y_{1i}, Y_{0i}) \perp\!\!\!\perp T_i | \pi(X_i). \tag{9}$$

In the matching stage, each IT country is matched with a non-targeter based on the set of covariates. After defining a distance measure, we choose the matching algorithm. We report the results of estimating the average treatment on the treated using nearest neighbor matching.[11] Nearest neighbor matching selects the r best non-targeter matches for each inflation targeting country.

In the first stage of propensity score matching, we use a binary logistic regression to estimate the propensity scores. Thus, we define the conditional probability of receiving treatment as follows:

$$\pi(X_i) = \mathbb{E}(T_i \mid X_i) = \frac{e^{X_i \beta_i}}{1 + e^{X_i \beta_i}}. \tag{10}$$

This is a nonlinear model; however, by using a logit function, we can express the model as a generalized linear model:

$$\log\left(\frac{\pi}{1-\pi}\right) = X_i \beta_i, \tag{11}$$

where π denotes $Pr(T_i = 1 | X_i)$. β is selected to maximize the logistic log-likelihood:

$$\mathscr{L}(\beta) = \frac{1}{N} \sum_{i=1}^{N} T_i \beta' x_i - \log(1 + \exp(\beta' x_i)). \tag{12}$$

Equation (12) is estimated with the maximum likelihood estimator. After propensity scores are estimated, we match targeters to non-targeters based on the estimated propensity scores.

[11] The results of nearest neighbor matching is reported. However, we perform the matching procedure using full, optimal and genetic matching and we find the similar results for all other matching methods.

If T_i and X_i are dependent, we need to preprocess the data to eliminate the relationship between T_i and X_i.

4.1.1 Preconditions for the IT Adoption

In the first stage estimation of treatment effects, we examine the role of institutional characteristics and macroeconomic performance on the likelihood of adopting IT. The results of the logit model are presented in Table 1.[12] We find a 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. Our findings show that the real money growth is significant and positively associated with the probability of adopting IT. Money growth has an inflationary pressure, and it increases the likelihood of adopting inflation targeting. Moreover, GDP growth as an indicator of the level of economic development is inversely correlated with the probability of the IT adoption. Our results are consistent with Lucotte (2012) and Samarina, Terpstra and De Haan (2013).

Preconditions play a crucial role in the inflation targeting literature, especially in emerging market economies. The preconditions are necessary for a monetary policy to be successful. These preconditions fall into four categories: institutional independence, well-developed technical infrastructure, economic structure, and a healthy financial system. The most important precondition discussed in the literature that has a huge impact on inflation targeting is a healthy financial system. The banking system should be sound and capital markets well developed to guarantee an effective monetary policy transmission. To examine the role of a healthy financial system for the adoption of inflation targeting we choose central bank assets-GDP ratio and private credit-GDP ratio. Central bank assets-GDP measures the size of the central bank. We find that as central banks' balance sheets expand the probability of the IT adoption rises in developing countries. However, higher central bank assets-GDP ratio lowers the likelihood of adopting IT in industrial economies. Thus, the balance sheets of central banks matter in the monetary authorities' decision. In industrial economies, the expansion of central banks' balance sheets as a share of GDP causes a loss in their credibility

[12] We also estimate the propensity score using a probit model. The results are similar to the logit estimation.

and decreases the probability of adopting IT. Private credit-GDP ratio is used to measure the financial depth. Our results show that it significantly affects the likelihood of adopting IT, meaning that more financially developed countries are more likely to adopt IT. This result is consistent with Lucotte (2012). Our findings indicate that countries that meet some financial and capital market preconditions are more likely to adopt inflation targeting.

4.1.2 Treatment Effects of Inflation Targeting

After estimating the propensity scores, the next step is matching the non-targeters to the targeters using selected matching algorithm. Our sample size for the full sample is 2351, but after matching, 647 observations are left for the outcome analysis. Figure 1 illustrates the kernel density of the estimated propensity scores for the full sample, developing countries and industrial economies. The kernel densities of propensity scores for the control and treated units are shown in the dashed lines and solid lines, respectively. We find little difference in the kernel density of propensity scores for countries that did and did not adopt inflation targeting in the full sample. However, the kernel densities for the industrial economies in the treated and control groups are quite different. This indicates that matching would improve the results of the estimation for the industrial subsample. Figure 2 plots the histograms of the estimated logit propensity scores in the original treated and control groups and histograms of the logit propensity scores in the matched treated and control groups for the full sample. The spread of the estimated propensity scores before and after matching are illustrated in the left and right graphs, respectively. As shown, 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 3–5 for all samples. 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 figures, matching would not improve the empirical distribution for central bank assets-GDP, private credit-GDP and real money growth.

The results from matching using logit propensity scores are presented in Table 3. For the full sample including both developed and developing economies, ATT on inflation is negative and statistically significant. Its magnitude is about -1.01, implying that on average, inflation in IT countries has been lower. Our findings indicate that treatment effects in developing countries and industrial economies separately is not significant. We also find that the ATT on debt is significant and negative for all samples. Thus, adopting inflation targeting positively affects fiscal discipline in both developing and industrial economies. The average treatment on the treated on inflation variability is negative across the samples. Interestingly, IT has a larger negative effect on the inflation variability in developing countries than developed economies. The average treatment on the treated on interest rate volatility is negative and significant for the full sample. It has been argued in the literature that less variable interest rates is a sign of more credible central banks. Chadha and Nolan (2001) provide a theoretical model to link transparency and interest rates volatility. They argue that information flows increase the volatility of interest rates. Our results show that the IT regime reduces interest rates volatility. We also examine the relationship between inflation targeting and exchange rate volatility. Our findings suggest that IT significantly reduces exchange rate volatility in developing countries. Nonetheless, it significantly increases the volatility of real exchange rates in industrial economies.

4.2 Evaluation of IT through a Propensity Score Weighting Model

Even though, studies on the effectiveness of inflation targeting have used the propensity score matching model, this methodology has some drawbacks. One disadvantage of this method is that it only accounts for observed covariates. Covariates that are not observed would not be accounted for in the matching. In the propensity score matching model, hidden bias remains after matching because the procedure only takes into account the observed covariates. In hidden bias, countries are not comparable in a way that was not measured. The second disadvantage of the propensity score matching is that nearest-neighbor matching has a small bias, especially when the outcome is not predictable. Thus, using matching methods can lead us to the worst covariate balance (Busso, DiNardo and McCrary (2011)). As shown in Figure 3– 5, matching does not improve the distributions of central bank assets-GDP, private credit-GDP, and real money growth and the distributions of propensity score are still different for these covariates.

To overcome these problems, researchers use bias-corrected matching or propensity score weighting, where the bias will be reduced, especially when the model is properly specified. Busso, DiNardo and McCrary (2011) argue that the weighting method performs well in terms of both bias and variance when the overlap assumption is satisfied. In comparison to bias-corrected matching, weighting has lower variance. To make sure that our results are robust and overcome the above-mentioned problems in the matching procedure, we use propensity score weighting in which the inverse probability of treatment is used as a weight. Propensity score weighting has some advantages over propensity score matching. As Guo and Fraser (2014) emphasize, propensity score weighting enhances internal validity rather than external validity. It also does not require a continuous or normally distributed outcome variable. Moreover, propensity score weighting uses the most participants in the outcome analysis without losing observations as matching method does. Considering propensity scores as weights, the population ATE and ATT can be written as the following weighting algorithm:

$$\begin{aligned}\tau_{treated} &= \mathbb{E}[Y(1)-Y(0)|T=1] = \mathbb{E}[\mathbb{E}[Y(1)-Y(0)|X,T=1]|T=1] \\ &= \mathbb{E}[\mathbb{E}[Y(1)-Y(0)|X]|T=1] = \mathbb{E}[\tau(X)|T=1], \end{aligned} \tag{13}$$

where

$$\begin{aligned}\mathbb{E}[\tau(X)|T=1] &= \int \tau(x)dF(x|T=1) \\ &= \int \tau(x)\pi(x)dF(x) / \int \pi(x)dF(x). \end{aligned} \tag{14}$$

Therefore, the moment equation can be written as:

$$\psi(y,t,x,\tau_{treated},\pi(x)) = \pi(x)\cdot\left(\frac{y\cdot t}{\pi(x)} - \frac{y\cdot(1-t)}{1-\pi(x)} - \tau_{treated}\right). \tag{15}$$

The solution to the following equation is the ATT estimator:

$$0 = \sum_{i=1}^{N}\pi(x)\cdot\left(\frac{y\cdot t}{\hat{\pi}(x)} - \frac{y\cdot(1-t)}{1-\hat{\pi}(x)} - \tau_{treated}\right), \tag{16}$$

where $\hat{\pi}(X_i)$ is the estimated propensity score.

For estimating ATE and ATT, weights will be different. In the estimation of ATE, we use the following weights:

$$\omega(T,x) = \frac{T}{\hat{\pi}(x)} + \frac{1-T}{(1-\hat{\pi}(x))}. \tag{17}$$

When $T=1$, $\omega(T=1,x) = 1/\hat{\pi}(x)$, and when $T=0$, $\omega(T=0,x) = 1/(1-\hat{\pi}(x))$. On the other hand, for estimating ATT the weights will be as follows:

$$\omega(T,x) = T + (1-T)\frac{\hat{\pi}(x)}{(1-\hat{\pi}(x))}. \tag{18}$$

Therefore, when $T = 1$, $\omega(T = 1, x) = 1$, and when $T = 0$, $\omega(T = 0, x) = \hat{\pi}(x)/(1-\hat{\pi}(x))$.

We use different estimates of propensity score to examine the effect of the IT framework on a variety of outcome variables by estimating the average treatment effect on the treated. First, we use Equation (10) to estimate logit propensity score, the mostly used method. Then, we estimate the propensity score using the nonparametric estimation proposed by (Hirano, Imbens and Ridder (2003)) and a semiparametric single index method. To estimate the average treatment on the treated for different outcome variables, we apply Equations (16) and (18).

4.2.1 Parametric Propensity Score

Table 4 presents information on the pre-treatment covariates before and after weighting using the logit propensity scores. The second and third columns, $E(Y1|T = 1)$ and $E(Y0|T = 1)$, show the treatment and control means for each covariate. The last column, $E(Y0|T = 0)$, shows the unweighted means. The forth column, KS, is the p-value of the Kolmogorov-Smirnov test. Kolmogorov-Smirnov test is used to show a significant difference across entire distributions. The null hypothesis is that the samples are drawn from the same distribution. The results indicate that the average treatment on the treated is sensitive to the choice of covariates. Panel (a) in Figure 6 illustrates the standardized effect size of pre-treatment variables. It checks balance and compares the effect of weights on the magnitude of difference between weighted control group and unweighted treatment group on each pre-treatment covariate.[13] The left graph shows absolute standard difference using effect size, whereas, the right graph indicates the absolute standard difference using the Kolmogrov-Smirnov statistics. In panel (a), substantial reductions in effect sizes are observed for real money growth and private credit-GDP ratios (blue lines), two variables, openness and GDP growth increase in effect size (dashed red line and red line). Closed red circles show a statistically significant difference. Panel (b) in Figure 6 indicates p-values for the Kolmogorov-Smirnov test. The Q-Q plot compares the quantiles of the observed p-values to the quantiles of the uniform distribution, showing whether group differences observed

[13] It is shown by the mean of the covariate balance metrics 'mean' or the maximum of the balance metrics 'max'.

before and after weighting are consistent with what we expect to see in a random assignment. Before weighting (closed circles), the groups have statistically significant differences on many covariates.[14] After weighting (open circles), the p-values are generally above the 45-degree line. This indicates that the p-values are larger than would be expected in a randomized study.

Table 7 summarizes the results of the average treatment effect on the treated using propensity score weighting with the logit estimate of propensity score.[15] We find that the IT regime significantly affects inflation, government debt-GDP ratio, inflation variability, interest rate volatility and real exchange rate volatility.[16] Our results illustrate that inflation targeting framework lowers not only inflation and inflation variability, but improves fiscal discipline and significantly reduces interest rate volatility and exchange rate variability. We find that the IT regime significantly affects inflation variability in developing countries, while this effect is not significant for industrial economies. Moreover, exchange rate volatility had decreased after the adoption of IT in developing countries. However, it had increased in industrial economies. This indicates the asymmetric effect of inflation targeting on the exchange rate volatility for developing and developed economies.

4.2.2 Nonparametric Propensity Score

It has been argued that propensity score analysis is sensitive to the specifications of the propensity score. We must take into consideration the specification of the first stage estimator for the following reasons. First, the coefficients of the propensity score are poorly estimated in the misspecified propensity score, and this has an influence on the estimated ATT (Zhao (2008)). Second, using the parametric propensity score sacrifices the efficiency of the estimator (Heckman and Ichimura (1998)), even if it removes all biases (Rosenbaum and Rubin (1983)). The following example illustrates how misspecification of propensity score given a vector of covariates x ($\pi(x)$) leads to biased results. Let y be a continuous response, t be the treatment, and τ be the treatment effect, and β is a vector of parameters relating the covariates x to the response in the model $E(y \mid x, t) = g(x; \beta) + \delta t$. Assume $E_x \mid g(x; \beta) \mid < \infty$. Let $\bar{y}_1$ and $\bar{y}_0$ denote the sample averages of treated and control units. In a randomized study, $\hat{\tau} = \bar{y}_1 - \bar{y}_0$ is an unbiased estimator of τ. Similarly, if we denote the average response in treatment group i at $\pi(x)$ by $\bar{y}_{i,\pi(x)}$, then in an observational study $\tilde{\tau} = \bar{y}_{1,\pi(x)} - \bar{y}_{0,\pi(x)}$

[14] i.e. p-values are near zero.

[15] We perform conditional permutation test using a matched sample to find whether treatment is effective or not (we test if $ATT = 0$).

[16] The magnitudes of ATT for inflation, government debt-GDP ratio, inflation variability, interest rate volatility and real exchange rate volatility outcomes are -1.054, -19.03, -1.81, -0.66 and -1.412, respectively.

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, $E[\bar{y}_1 - \bar{y}_0 \mid \phi(x)] = \tau + E_x[g(x;\beta) \mid t = 1, \phi(x)] - E_x[g(x;\beta) \mid t = 0, \phi(x)]$ and $\bar{y}_{1,\phi(x)} - \bar{y}_{0,\phi(x)}$ is not unbiased for τ. To solve these problems, Hirano, Imbens and Ridder (2003) introduce an estimation of the average treatment effect by weighting the inverse of a nonparametric estimate of the propensity score. We use the nonparametric series estimator proposed by Hirano, Imbens and Ridder (2003) to estimate a consistent propensity score. This estimator can be used when the functional form of the propensity score and the distribution of the error terms are unknown. They 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 $K = 1, 2, \ldots$. Denote the logistic cdf by $\Lambda(a) = \exp(a)/(1 + \exp(a))$, the SLE is defined by $\hat{\pi}(x) = \Lambda(R^k(x)'\hat{\pi}_K)$ where,

$$\hat{\pi}_K = \underset{\pi}{\operatorname{argmax}} \sum_{i=1}^{N} (T_i \cdot \ln(\Lambda(R^k(x)'\pi)) + (1 - T_i) \cdot \ln(1 - \Lambda(R^k(x)'\pi)). \tag{19}$$

After estimating $\pi(x)$ using this method, we can estimate the average treatment on the treated. Table 8 shows the results of the ATT nonparametric series estimation of propensity score in the weighting analysis. The average treatment on the treated for all outcomes in the full sample is significant at the five percent level or higher. In our full sample, we find that inflation targeting significantly reduces inflation variability, interest rate volatility, and real exchange rate volatility and improves fiscal discipline. Our results show that real exchange rate volatility had significantly increased in developing countries.

4.2.3 Semiparametric Propensity Score

One problem with nonparametric series estimator is that it suffers from the "curse of dimensionality." The curse of dimensionality refers to the poor performance of the nonparametric series method for multivariate data. The behavior of nonparametric estimators deteriorates as the dimension increases because of the sparseness of multidimensional data (Stone (1980)). To break the curse of dimensionality, we use the semiparametric single index model for estimating propensity score. The semiparametric single index model is an alternative approach to mitigate bias arising from the curse of dimensionality. It also can avoid the problem of error distribution misspecification. The single index model is suggested by Klein and Spady (1993). They introduce this semiparametric model where the response is a binary variable. A semiparametric single index model is given by:

$$T = g(X'\beta_0) + u, \tag{20}$$

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

$$\mathscr{L}(\beta, h) = \sum_i (1 - T_i)\ln(1 - \hat{g}_{-i}(X_i'\beta)) + \sum_i T_i \ln(\hat{g}_{-i}(X_i'\beta)), \tag{21}$$

where $\hat{g}_{-i}(X_i'\beta)$ is the leave-one-out estimator. After estimating propensity scores using this method, we use them as weights to estimate ATE and ATT. Song (2014) finds that in propensity score analysis, the conditions of the single index propensity score estimate do not affect the asymptotic distribution of treatment effects. This condition holds even when the single index propensity score is cube-root consistent. To assess the accuracy of our single index estimate, we compare the confusion matrices of the logit and single index models. A confusion matrix shows the actual outcomes versus the predicted outcomes estimated by a model. The confusion matrices are presented in Table 9. It can be seen that the single index model correctly classifies 75% of the treatment, while the parametric logit model correctly classifies 71%. It can be seen that semiparametric single index model does better than logit model when modeling inflation targeting.

Table 10 indicates the results of ATT using the semiparametric single index estimate of propensity score. Our findings show that IT significantly reduces inflation variability. The ATT for the full sample is -.996, for the industrial subsample is -.38, and for developing countries is -1.045. However, the impact of IT is less in industrial economies than developing countries, implying that developing countries benefit more from adopting inflation targeting in terms of a reduction in inflation uncertainty. The average treatment effect on the treated for the government debt-GDP ratio for the full sample, developed economies, and developing countries are -15.624, -31.186 and -12.57, respectively. These results show two features: first, inflation targeting significantly improves fiscal discipline; second, the impact of IT on fiscal discipline in developing countries is significantly larger than that of in industrial 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 more than developed countries in order to convince the private sector of their commitment to price stability. This is consistent with the literature that emphasizes the impact of inflation targeting on the fiscal discipline. Minea and Tapsoba (2014) indicate that inflation targeting improves fiscal discipline only in developing countries.

We also examine the relationship between inflation targeting and exchange rate volatility using propensity score weighting with the single index propensity score estimate. Our findings suggest that IT significantly reduces exchange rate volatility in developing countries but increases it in industrial economies. The ATT on real exchange volatility for the full sample is -1.817. Our results from the logit and nonparametric models are -1.412 and -0.876, respectively. Therefore, the absolute value of average treatment effect on the treated for the full sample is larger than that of logit and nonparametric models.

This holds for developing countries and industrial economies. Lin (2010) shows that inflation targeting has different impacts on exchange rate volatility. She argues that the IT regime significantly lowers the volatility of exchange rate 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. Interestingly, we find that the absolute value of the ATT magnitudes for different outcome variables are higher than the logit estimation and nonparametric series estimator. We find that the choice of propensity scores, especially the single index model, has a considerable impact on the treatment effect estimates. As a result, within the framework of a semiparametric single index model, the impact of inflation targeting is larger and more significant. The results are supported by our estimation. 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 Concluding Remarks

The purpose of this paper is to examine the causal effect of the IT adoption on macroeconomic performance. To do so, we compare different methods of estimating the average treatment effects of inflation targeting and attempt to find its effectiveness within an efficient framework. We use propensity score matching and weighting models to perform an outcome analysis. Since misspecification of the propensity score leads us to a biased estimate, we use a nonparametric series estimator proposed by Hirano, Imbens and Ridder (2003). However, this model suffers from the curse of dimensionality. We avoid the curse of dimensionality by using a semiparametric single index model. This study also considers the prominent role of preconditions in IT adoption. One of the necessary preconditions before adopting inflation targeting is a sound financial system and a developed capital market. To find the role of these preconditions, we choose central bank assets-GDP ratio and private credit-GDP ratio in the first stage estimations. We examine the effectiveness of inflation targeting in our outcome analysis by considering inflation, inflation variability, fiscal discipline, interest rate volatility, and real exchange variability.

The results from a propensity score matching model using a logit estimate indicate that inflation targeting lowers inflation and improves fiscal discipline in both developing and developed countries. We find that the IT regime negatively affects interest rates volatility. Our findings based on the semiparametric estimate show that IT significantly reduces inflation variability, and this reduction is larger in developing countries. We find that fiscal authorities in developing countries enhance fiscal discipline more than developed countries as a sign of their commitment to price stability. We also examine that the inflation targeting regime significantly reduces the exchange rate volatility in developing countries. However, industrial economies experienced higher exchange rate variability after the adoption of IT. Our comparison among different models and estimates 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.

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Appendix A

This Appendix provides the list of inflation targeting countries along with the adoption dates, target level at the adoption date and their country groups. It also presents the control units with their country groups.

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.

Table 1: Logit models for the full sample, industrial economies and developing countries

	FULL (1)	IND (2)	DCS (3)
Intercept	-0.0899	0.7940***	-0.2825**
	(0.0708)	(0.1516)	(0.0872)
CB Assets	0.0016	-0.0311**	0.0056*
	(0.0022)	(0.0102)	(0.0023)
Credit Deposit	0.0083***	0.0015	0.0048***
	(0.0007)	(0.0013)	(0.0010)
GDP Growth	-0.0801***	-0.0976**	-0.0653***
	(0.0129)	(0.0339)	(0.0136)
Money Growth	0.0001*	0.0015**	0.0001*
	(0.0000)	(0.0005)	(0.0000)
Lagged Inflation	-0.0007	-0.0075	0.0009
	(0.0016)	(0.0167)	(0.0016)
Openness	-0.0114***	-0.0112***	-0.0096***
	(0.0008)	(0.0013)	(0.0011)

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

Table 2: Sample sizes in propensity score analysis for all samples

	FULL		IND		DCS	
	Control	Treated	Control	Treated	Control	Treated
All	1704	648	384	240	1440	408
Matched	648	648	240	240	408	408
Unmatched	1056	0	144	0	1032	0
Discarded	0	0	0	0	0	0

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

Table 3: Average treatment on the treated using propensity score matching, logit propensity score

	π	$debt$	σ_π	σ_i	σ_s
FULL	-1.019*	-18.194***	-1.3	-0.67**	-1.538**
	(0.55)	(1.88)	(0.441)	(0.291)	(0.612)
IND	0.049	-28.553***	-0.136	-0.172	1.643***
	(0.162)	(3.255)	(0.12)	(0.171)	(0.476)
DCS	0.366	-15.709***	-1.599**	-0.126	-1.54*
	(0.731)	(2.519)	(0.605)	(0.416)	(0.877)

[a] Outcomes are inflation (π), government debt-GDP ratio ($debt$), inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s).
[b] FULL: full sample, IND: industrial economies, DCS: developing countries.
[c] *p<0.1; **p<0.05; ***p<0.01.

Table 4: Balance of the treatment and comparison groups, logit model

	E(Y1|T=1)	E(Y0|T=1)	KS	E(Y0|T=0)
CB Assets	8.18	7.55	0.18	6.99
Credit Deposit	57.34	47.20	0.16	45.60
GDP Growth	0.05	0.41	0.65	32.67
Money Growth	231.79	78.39	0.12	50.30
Lagged Inflation	6.86	6.53	0.04	6.02
Openness	62.36	77.39	0.18	92.14

Table 5: Balance of the treatment and comparison groups, nonparametric series estimator

	E(Y1|T=1)	E(Y0|T=1)	KS	E(Y0|T=0)
CB Assets	8.77	7.29	0.18	6.99
Credit Deposit	55.58	48.68	0.12	45.60
GDP Growth	0.03	0.45	0.64	32.67
Money Growth	301.25	27.48	0.15	50.30
Lagged Inflation	7.74	5.54	0.04	6.02
Openness	61.70	79.61	0.20	92.14

Table 6: Balance of the treatment and comparison groups, semiparametric single index model

	E(Y1|T=1)	E(Y0|T=1)	KS	E(Y0|T=0)
CB Assets	13.35	5.17	0.16	6.99
Credit Deposit	50.17	44.38	0.14	45.60
GDP Growth	0.08	24.78	0.70	32.67
Money Growth	291.45	45.41	0.11	50.30
Lagged Inflation	7.88	5.94	0.07	6.02
Openness	64.41	92.23	0.26	92.14

Table 7: Average treatment on the treated using propensity score weighting, logit estimate

	π	$debt$	σ_π	σ_i	σ_s
FULL	-1.054**	-19.030***	-1.819***	-0.665**	-1.412***
	(0.53)	(1.763)	(0.524)	(0.257)	(0.502)
IND	0.021	-29.348***	-0.164	-0.099	2.255***
	(0.178)	(3.042)	(0.140)	(0.176)	(0.506)
DCS	-0.945	-16.65***	-1.872**	-0.137	-1.023
	(0.699)	(2.007)	(0.650)	(0.360)	(0.669)

[a] Outcomes are inflation (π), government debt-GDP ratio ($debt$), inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s).
[b] FULL: full sample, IND: industrial economies, DCS: developing countries.
[c] *p<0.1; **p<0.05; ***p<0.01.

Table 8: Average treatment on the treated using propensity score weighting, nonparametric estimate

	π	$debt$	σ_π	σ_i	σ_s
FULL	-0.925	-17.780***	-0.88**	-0.556**	-0.876*
	(0.646)	(1.808)	(0.381)	(0.253)	(0.518)
IND	0.039	-26.726***	-0.227	-0.032	2.135***
	(0.195)	(2.758)	(0.185)	(0.187)	(0.484)
DCS	-0.803	-15.323***	-0.873*	-0.12	-0.469
	(0.819)	(2.122)	(0.511)	(0.353)	(0.690)

[a] Outcomes are inflation (π), government debt-GDP ratio ($debt$), inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s).
[b] FULL: full sample, IND: industrial economies, DCS: developing countries.
[c] *p<0.1; **p<0.05; ***p<0.01.

Table 9: Confusion matrices for the full sample

	Predicted	
Actual	0	1
0	1615	89
1	572	76

(a) Logit Model

	Predicted	
Actual	0	1
0	1698	6
1	584	64

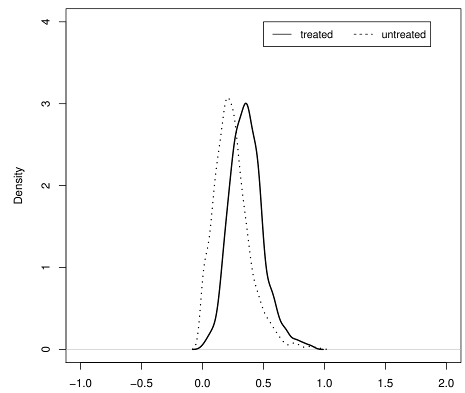
(b) Single Index Model

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

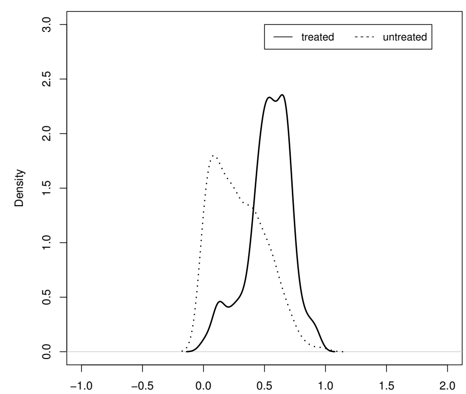
Table 10: Average treatment on the treated using propensity score weighting, semiparametric single index estimate

	π	$debt$	σ_π	σ_i	σ_s
FULL	-0.305	-15.624***	-0.996***	-0.172	-1.817***
	(0.447)	(1.756)	(0.339)	(0.270)	(0.487)
IND	-0.021	-31.186***	-0.38**	0.122	2.274***
	(0.265)	(3.322)	(0.184)	(0.182)	(0.438)
DCS	-0.075	-12.57***	-1.045**	0.39	-1.862***
	(0.612)	(2.059)	(0.462)	(0.370)	(0.638)

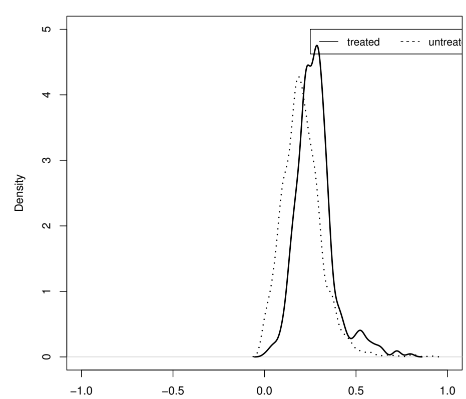
[a] Outcomes are inflation (π), government debt-GDP ratio ($debt$), inflation variability (σ_π), interest rate volatility (σ_i), and exchange rate volatility (σ_s).
[b] FULL: full sample, IND: industrial economies, DCS: developing countries.
[c] *p<0.1; **p<0.05; ***p<0.01.



(a) Full Sample



(b) Industrial Economies



(c) Developing Countries

Figure 1: Kernel density of the estimated logit propensity scores

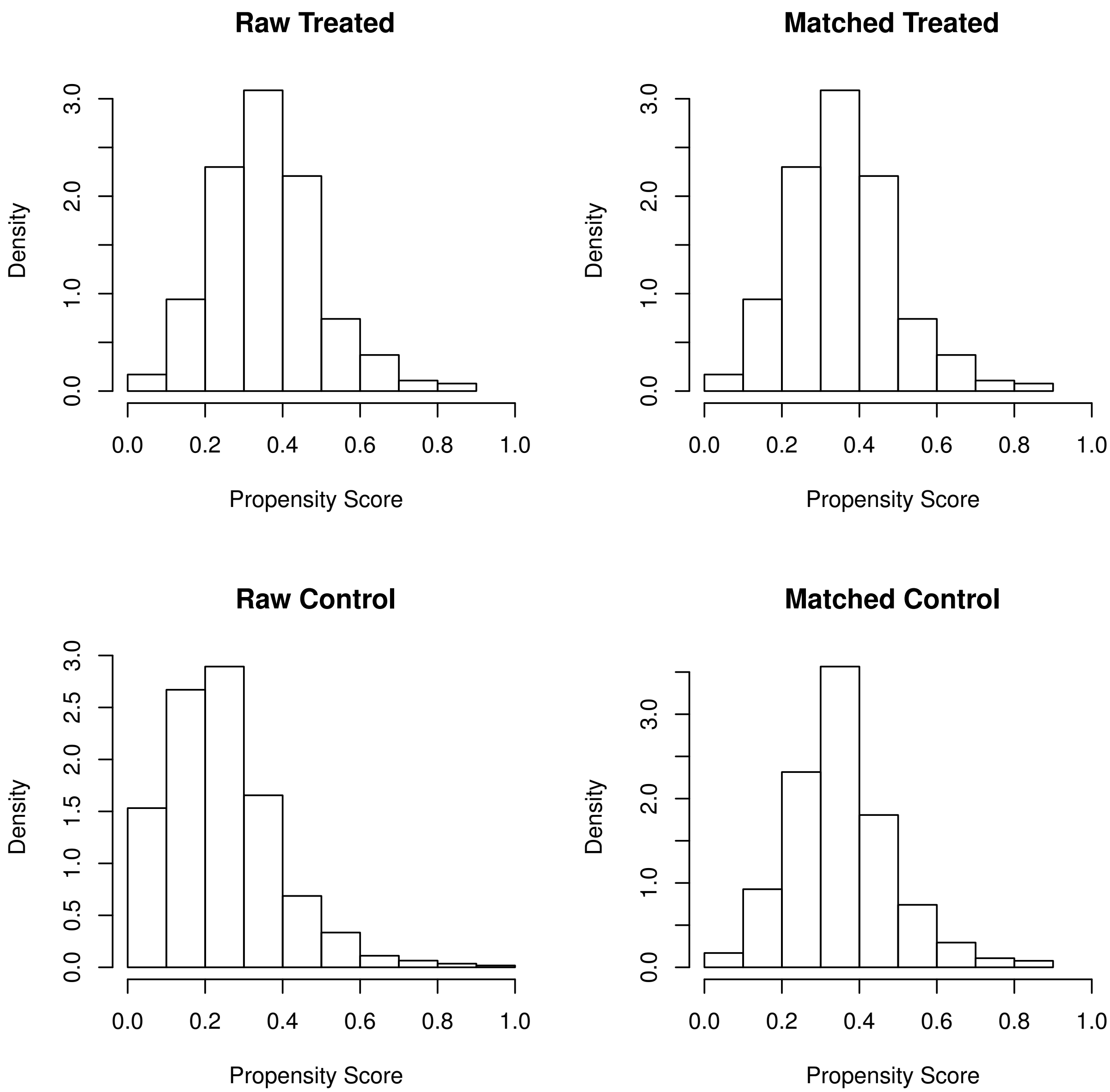
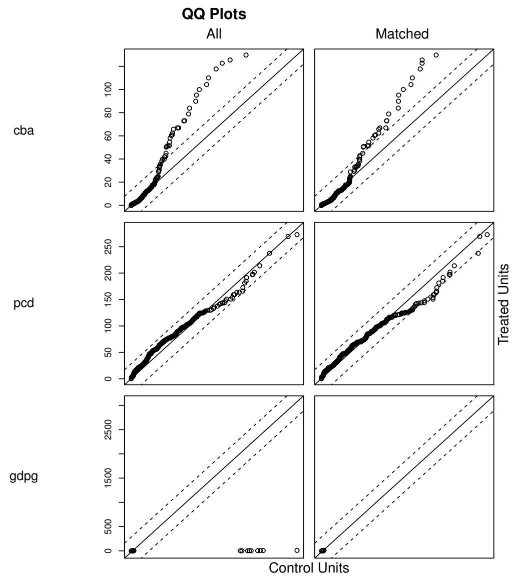
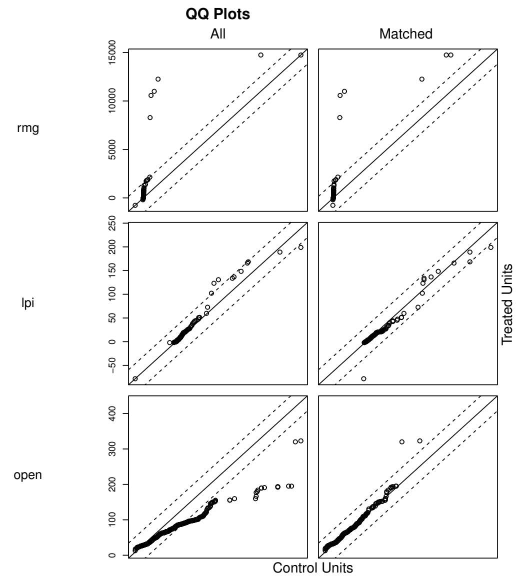


Figure 2: Histograms of the estimated logit propensity scores before and after matching

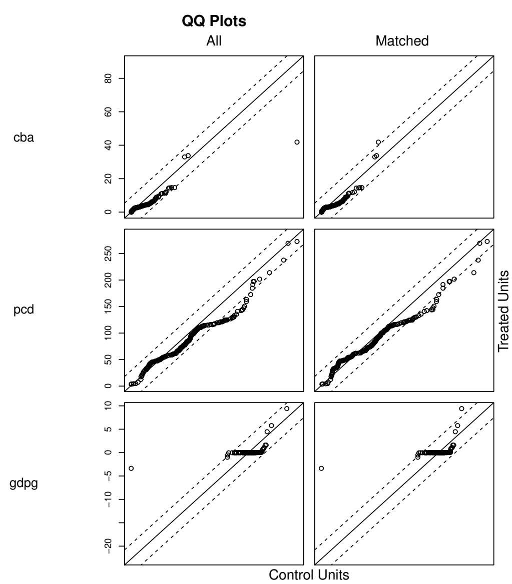


(a)

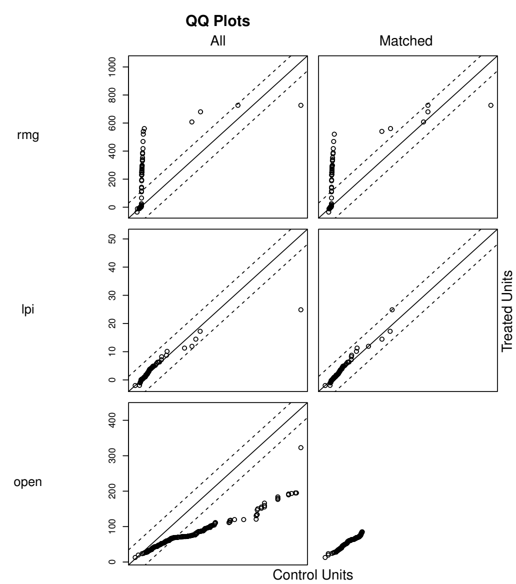


(b)

Figure 3: QQ plots for all covariates, Full Sample

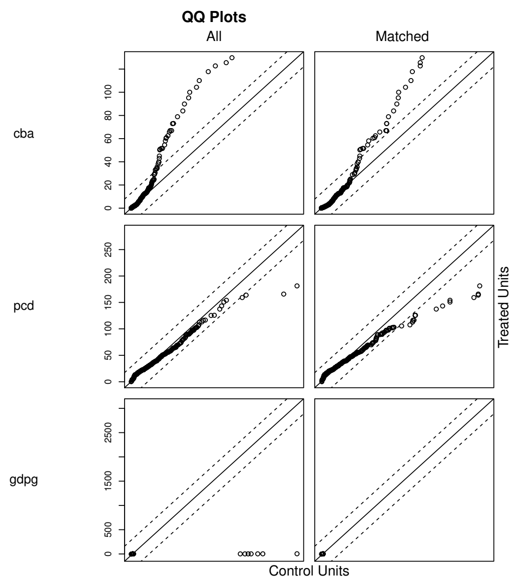


(a)

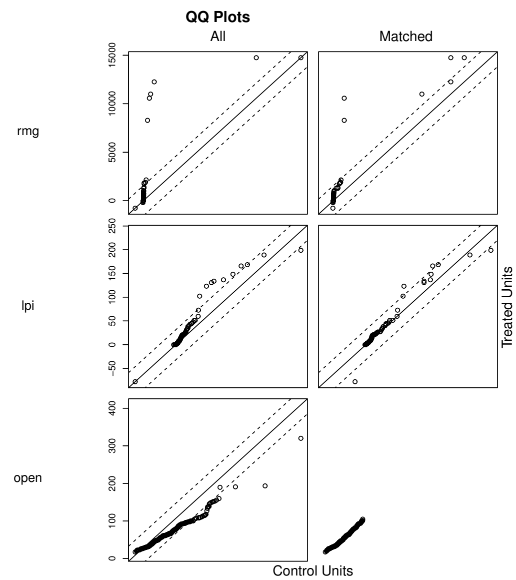


(b)

Figure 4: QQ plots for all covariates, Industrial Economies

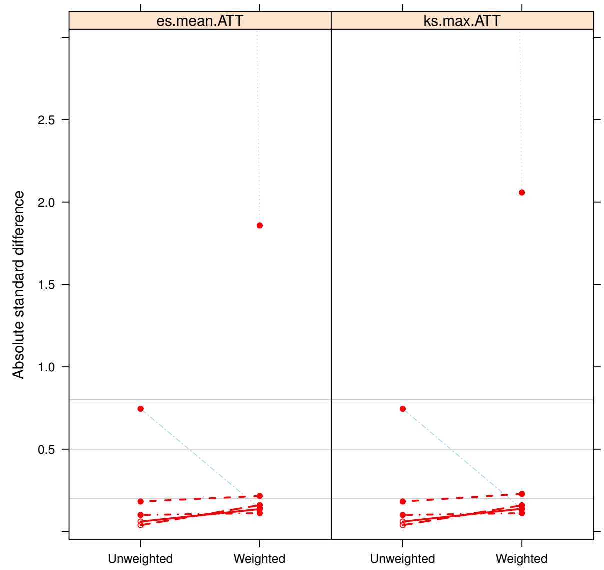


(a)

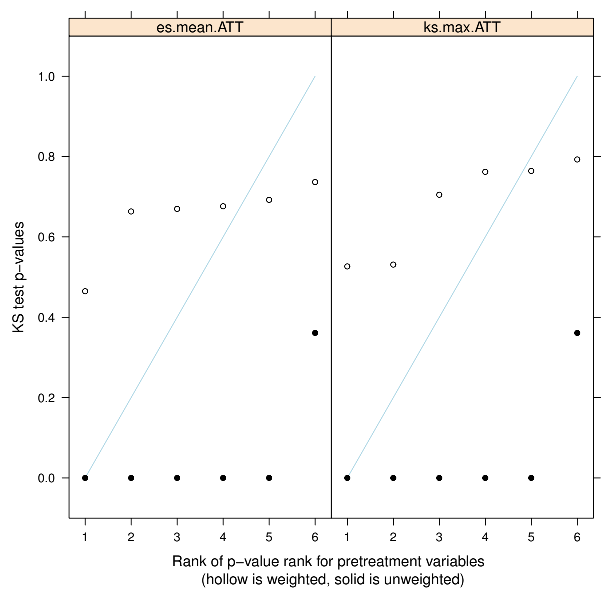


(b)

Figure 5: QQ plots for all covariates, Developing countries



(a) Standardized effect size of pretreatment variables



(b) Kolmogorov-Smirnov *p*-values for weighted variables

Figure 6: Density estimation of the estimated logit propensity scores

ES and KS specify the method for summarizing across balance metrics. 'es.mean' uses the effect size or the absolute standardized bias and summarizes across variables with the mean and the 'ks.max' uses the Kolmogorove-Smirnov statistics to assess balances and summarizes using the maximum across variables.