JOURNAL OF ECONOMIC DEVELOPMENT 67
Volume 42, Number 2, June 2017

DOES INFLATION TARGETING MATTER FOR FOREIGN PORTFOLIO INVESTMENT: EVIDENCE FROM PROPENSITY SCORE MATCHING

ADEL BOUGHRARA AND ICHRAK DRIDI*

LaREMFiQ Laboratory, High Institute of Commercial Studies (IHEC), University of Sousse, Tunisia

The aim of this paper is twofold. Firstly, it seeks to investigate the nature of the relationship between inflation targeting (hereafter, IT) regime and foreign portfolio investment (hereafter, FPI) inflows. Secondly, it inquires whether IT is able to control for FPI volatility in emerging countries or not. The sample covers the period 1986-2010 and contains 38 emerging countries, of which 13 countries have adopted IT. By addressing the self-selection bias associated to the adoption of IT via a variety of propensity score matching techniques, the paper results show that the adoption of a full-fledged IT increases FPI inflows into emerging countries, but they show no robust results for containing FPI volatility.

Keywords: Inflation Targeting, Propensity Score Matching, Portfolio Investment, Emerging Market Countries
JEL Classification: E52, E58, E42

1. INTRODUCTION

Since the early 1990s, IT regime has been adopted by several central banks as a new monetary policy strategy. Over the years, this monetary policy strategy has become very popular, and many arguments have been forwarded for this trend. Economists and policymakers highlighted the need for central banks to show more discretion and liberty in handling their instruments, along with improving their credibility. They also emphasize that IT does not preclude central banks from having multiple goals for monetary policy. An IT regime can accommodate a goal of output stabilization by

* We wish to warmly thank the anonymous peer referees for their helpful and constructive suggestions, comments and remarks that greatly contribute to improving the quality of the final version of the manuscript. We wish also to thank the JED editor for its generous comments and support during the review process. All errors remain ours.

having wide inflation target bands, long inflation target horizons, and explicit exemptions for supply shocks (Rudebush and Walsh, 2001a, 2001b; Ersel and Özatay, 2008). Thus, IT could be suitable for emerging market countries (EMCs) as it helps them to not focus exclusively on inflation goals over the short-term, which could lead to a highly unstable real economy.

A growing body of literature has brought attention to IT regime performance. Although much of the existing literature on the record of IT has focused on whether inflation and its volatility have been reduced (Meyer, 2001; Neumann and VonHagen, 2002; Lin and Ye, 2007, 2009; De Mendonça and Souza, 2012), and whether other objectives, in particular the volatility of output have been compromised (Mishkin and Posen, 1997; Ball and Sheridan, 2003; Mishkin, 2004; Walsh, 2009; Brito and Bystedt, 2010), a new strand of empirical literature has recently attempted to appraise the effect of IT on other variables. Epstein (2007) suggested shedding light on the relationship between IT and FDI. Indeed, such linkages seem understudied so far. A study like the one of Tapsoba (2012) is an exception. For instance, the latter author finds that IT contributes to attract and enhance foreign direct investment (FDI) inflows into developing countries.

Another body of empirical literature seems to discredit the previous findings regarding the positive effects of IT on economic performances. For instance, Brito and Bystedt (2010) conclude that there is no clear-cut evidence that IT improves economic performance in developing countries when making use of a dynamic panel estimator. Likewise, Ball and Sheridan (2003) find that on average, there is no evidence that IT improves performance and that better performance results from something other than IT regime when applying standard differences in differences approach.

By and large, many methods were used to find out the effect of the adoption of IT on several key economic variables. Lin and Ye (2007, 2009), De Mendonça and Souza (2012) use a variety of propensity score matching (PSM, hereafter) methodology to reveal the effect of the adoption of IT regime on inflation and its volatility. They find out that the average treatment effects of IT on inflation and its volatility are statistically insignificant in industrial countries and statistically significant in developing countries. Brito and Bystedt (2010) apply a dynamic panel estimator on a sample of 46 developing countries; they show that the control of common time effects causes a lower significant effect of IT on inflation and its volatility. Ball and Sheridan (2003) use standard differences in differences approach and they argue that when there is a control for regression to the mean, IT does not have a significant effect on the performance of the country, and the economic outcome does not change.

Against this background, this paper aims at making a contribution to the ongoing debate by investigating whether IT implementation in EMCs boosted FPI inflows and contained FPI volatility or not. To this purpose, this paper uses the best-fitted methodology, namely the PSM methodology. Its main advantage is that it deals with the self-selection problem as compared to other methods. The sample used contains 38 emerging countries, where 13 countries have adopted IT regime and 25 have not adopted

IT regime over the period 1986-2010.

This article is organized as follows: Section 2 summarizes the research in the related literature regarding IT assessment. Section 3 presents the PSM methodology. Section 4 provides a detailed description of the variables used in the PSM and gives an account of the data sources. Section 5 reports the estimates of the PSM models and the results of IT evaluation. Finally, Section 6 reports some policy implications and concludes the article.

2. RELATED LITERATURE REVIEW

We start by reviewing the existing literature to identify how our paper could contribute to this already growing body of empirical studies. We begin by the potential effects of IT regime on countries economic performances. Mishkin (2004) stresses that IT succeeded in promoting macroeconomic stability in a number of EMCs. Some researchers (see for instance Mishkin and Posen, 1997; Neumann and Von Hagen, 2002; Mishkin and Schmidt-Hebbel, 2007; Walsh, 2009) argue that the adoption of IT decreases the inflation rate and its volatility and the volatility persistence (Broto, 2011). Some others (Lin and Ye, 2007, 2009; De Mendonça and Souza, 2012) split the sample into developed and developing nations, and they come to the conclusion that pursuing IT decreases the average inflation rate and its volatility in developing countries and has no significant effect when it comes to developed countries. Vega and Winkelried (2005) reach the same conclusion regarding developing countries. However, when it comes to developed countries, the authors find that IT adoption is associated with lower average inflation.

Johnson (2002) assesses, by making use of a panel approach and the difference-in-difference estimator, IT regime performance by emphasizing the expected inflation. The author uses data on five IT countries and six non-targeting countries. He comes to the conclusion that while IT implementation contributes to bring down the expected inflation, it does not necessarily help anchoring the inflation expectation. Likewise, Ball and Sheridan (2003) analyze seven industrialized countries that adopted IT in the early 1990s and thirteen countries that did not. They use cross-section difference-in-difference OLS approach; and, they provide evidence that IT did not improve macroeconomic performance.

Unlike Johnson (2002) and Ball and Sheridan (2003), Gonçalves and Salles (2008) focus specifically on a broad set of emerging economies. They show, by employing the cross-section difference-in-difference OLS estimator approach, that the available evidence lends credence to the belief that IT brings down inflation and growth volatility. However, the authors fail to exhibit a statistically significant effect of IT on the volatility of inflation.

Recently, Brito and Bysteld (2010) examines the impact of IT regime on the level and volatility of emerging countries' inflation and output growth. Unlike Gonçalves and Salles (2008) who use Ball and Sheridan (2003) cross-section difference-in-difference

OLS, they make use of dynamic panel estimators (system-GMM and difference-GMM) which control for simultaneity and omitted variables biases. They conclude to the absence of a clear-cut evidence about the impact of IT, thereby corroborating the results of Gonçales and Salles (2008).

In a nutshell, most of the studies on IT performances were merely focused on the effect of IT on inflation, the volatility of inflation and output. However, IT provoked considerable controversy for amplifying capital flaws swings, especially when it comes to developing and emerging countries (see for instance, Epstein and Yeldan, 2008; Galindo and Ros, 2008; Agénor and Da Silva, 2013). Again, the degree of volatility of capital flows seems to depend to a great extent on both actual and perceived movements in domestic economic fundamentals as well as on external factors such as movements in the world interest rates. Such volatilities may have sizable real effects, especially by putting in motion short-term investments cycles which may deplete economic activities.

Despite the importance of the potential effects of IT regime on capital flows level-whether FDI or FPI and volatility, this issue is under-researched so far. Tapsoba (2012) is an exception. For instance, the latter author finds that IT contributes to attract and enhance FDI inflows into developing countries when using the PSM methodology. As far as we know, studies dealing with the potential effects of IT on FPI inflows and volatility are totally inexistent.[1] Moreover, empirical literature found evidence supporting the idea that FPI boosts the economic growth and fetches a quick development of other markets. For example, Calvo et al. (1996) stress that foreign capital can finance investment and stimulate the economic growth.

By and large, the FPI determinants highlighted in the literature can be broadly divided into internal and external factors and the interactions of both of them. On a large scale, FPI inflows and volatility are believed to shift following some factors such as transparency (see, Goldstein and Razin, 2006) and interest rate alterations (see, Fernandez-Arias, 1996; Taylor and Sarno, 1997). Undoubtedly, exchange rate volatility, inflation rate and economic growth are also considered as influential factors that could impact FPI volatilities and inflows too. Results regarding IT adoption are showing great improvement in macroeconomic fundamentals and institutional environment, which represent fundamental channels that are believed to improve FPI inflows and control for the FPI volatilities. Again, IT countries believe that transparency and credibility are crucial to reach their objectives, and this gives raise to the question of the relationship that exists between IT and FPI inflows and volatility.

[1] IMF (2009) defines the FPI as cross-border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve assets. Portfolio investment differs from other types of investments because it provides a direct way to access financial markets; and thereby it provides liquidity to domestic capital markets and contributes to develop its efficiency and flexibility.

3. THE PROPENSITY SCORE MATCHING METHODOLOGY

Since the article's objective is to evaluate the treatment effect of IT on FPI and its volatility, we consider the adoption of IT by a country as a treatment. We refer to countries having adopted IT as the treated group, whereas non-IT group countries are referred to as the control group. The average treatment effect on treated (hereafter, ATT) is measured as follows:

$$ATT = E(Y_{i1}|IT_i = 1) - E(Y_{i0}|IT_i = 1), \tag{1}$$

where IT_i is the IT dummy variable for country i. It takes 1 if country i adopts IT and 0 otherwise. Y_{i1} is the value of the outcome variable if country i adopts IT regime. Y_{i0} is the value of the outcome variable when the country i is not an IT country. Therefore, $Y_{i0}|IT_i = 1$ is the outcome value that would have been observed if an IT country i had not adopted IT regime, and $Y_{i1}|IT_i = 1$ is the outcome value actually observed on the same IT country i. Eq.(1) gives an unbiased estimate of the ATT of the difference between the outcome value observed in the treatment group and the outcome value observed for the same countries if they had not adopted IT. In practice, the latter outcome cannot be observed, which gives rise to an identification problem. A standard way to circumvent this problem would consist in comparing the FPI and FPI volatility sample mean of the treatment group with that of the control group, which only makes sense if the adoption of IT is random. However, in practice the adoption of IT is far from being random, and it is often dependent on the countries' economic performances and institutional regulations. In short, the IT adoption depends on a set of variables that also affect the outcome of interest, which finally leads to the so-called self-selection bias. This bias could be presented mathematically in this way as stated in Heckman et al. (1998):

$$B(X) = E(Y_{i0}|IT_i = 1, X) - E(Y_{i0}|IT_i = 0, X). \tag{2}$$

The PSM methodology has been advocated to address this issue by mimicking randomized experiments. To this purpose, additional assumptions should be made. It is question of the conditional independence and the overlap condition. These two assumptions are the workhorse of the PSM, which will mitigate the identification and the self-selection bias problem by making sure that only control units similar in term of observable characteristics will be used as a match for treated units. If this is the case, the ATT will be then computed as follows:

$$ATT = E\left(Y_{i1}\middle|IT_i = 1, P(X)\right) - E(Y_{i0}|IT_i = 0, P(X)), \tag{3}$$

where X is a covariate including all the observable characteristics and $P(X)$ is the propensity score or the conditional probability of assignment to a particular treatment given a vector of observed covariates (see Rosenbaum and Rubin, 1983).

$$\mathrm{P(X) = P(IT_i = 1|X)}. \tag{4}$$

To deal well with the nature of the qualitative treatment variable "IT" and to estimate the propensity score, it is necessary to use a probit model. In addition to the importance of the propensity score estimates on the ATT's estimation results quality, matching criterion are considered to be also influential. Using different matching techniques will ensure the robustness of the results. One of the most used matching algorithms is the nearest neighbor that consists in matching each treated individual with one or more untreated individuals that have the closest propensity score. The radius matching is considered to be an extension of the nearest neighbor matching technique by imposing a restriction which is a threshold on the maximum propensity score distance. As for the stratification technique, it consists in dividing the common support into different intervals and determining the effect of the program within each interval. The kernel matching technique works under the principle of comparing the outcome of every treated unit to a weighted average of the outcomes of all non-participants. When using different matching techniques, we take advantage of the extensions in each matching criterion that are expected to overcome the limits of each matching technique. This in turn will give more robust and precise results.

4. RATIONALE FOR COVARIATES, VARIABLES DESCRIPTION AND DATA SOURCES

Since our objective is to assess the impact of inflation targeting on FPI and its volatility, the selection of the control variables (or covariates) should be done with great circumspection. The literature on statistical matching theory documents that the PSM does not aim to provide the best (statistical) specification that can determine the probability of adopting IT (Lin and Ye, 2007). According to De Mendonça and Souza (2012), "a perfect fit would be destructive for the matching approach". Accordingly, we included in our model the variables that explain IT adoption along with those that drive the outcomes while controlling for the balancing property. Any variable that might cause the failure of this property was discarded.

4.1. The Dependent Variables

The dependent variables is the treatment effect variable, namely the IT full-fledged regime dummy variable (ITF). It takes 1 if country i has adopted IT regime and 0 otherwise. The outcome variables are FPI and its volatility. FPI is foreign portfolio liabilities as a percentage of nominal GDP, and FPI volatility stands for the standard deviation of FPI.

4.2. The Control Variables

In reference to various studies on IT regime determinants (see Lin and Ye,2007, 2009; De Mendonça and Souza, 2012; Tapsoba, 2012; Samarina and De Haan, 2014), we chose some common variables that are deemed to impact on a country decision to adopt IT regime, namely the one year lagged inflation rate (LAGINF) as measured by CPI or GDP deflator, an exchange rate regime indicator[2] (EXREGIME) based on the fine classification of Ilzetzkiet al. (2010); financial openness (FOPEN) as measured by the Chinn and Ito (2008) index, debt ratio (DEBT), trade surplus (TS) measured as the log of exports over imports, corruption index (ICRG) scaling from 6 (highly corrupt) to 0 (highly clean). The motivation and the prima facie expectations are cited in Vega and Winkelried (2005), Lucotte (2010) and De Mendonça and Souza (2012).

The real GDP growth (RGDPG) is included to capture the countries' economic growth. High growth rates allow countries to accumulate more FX reserves, and render them more inclined to adopt fixed exchange rate regimes rather than IT regime to acquire credibility. Thus, real GDP growth is expected to be negatively correlated with the likelihood of IT adoption (see Vega and Winkelried 2005; Batini and Laxton 2007; Gonçalves and Salles, 2008).

To control for the institutional independence, the seigniorage indicator[3] (SEIGNO) is used. As suggested by Berument (1998), countries with higher levels of central bank independence generate less seigniorage revenue. Therefore, this variable should be negatively linked to the probability of adopting IT.

In addition to the above traditional determinants that explain the probability of IT adoption, we have included in the propensity score equation the variables that are deemed to drive FPI and its volatility, and at the same time they affect the probability of adopting IT. It is question of the interest rate spread, the interest rate differentials, an indicator of trade competitiveness and a measure of the exchange rate volatility. Firstly, the interest rate spread (SPREAD) stands for the spread between lending and deposits rates. This variable is often considered as a proxy for the banking system efficiency. High values of this variable tend to indicate that the banking sector is rather poorly developed. Such situation may exhort policymakers to pursue IT to improve their financial system. Secondly, the interest rate differential (IRD) which stands for the difference between domestic and foreign interest rate is considered as the main attractor of FPI in the host country.

Thirdly, as an indicator for trade competitiveness, we considered the real effective exchange rate (REER). An increase in this indicator is a synonym of a loss in the trade competitiveness. Besides, emerging-market countries are highly concerned by exchange rate movements since real appreciation not only makes domestic products less

[2] The Ilzetzkiet al. (2010)'s indicator is based on the fine classification of exchange rate regimes. It takes values between 1 and 15, ranging from least to most flexible exchange rate regimes.

[3] Following Woo et al. (2014), the seigniorage indicator is computed as M2 growth minus the sum of the real GDP growth and the inflation rate.

competitive, but it can bring about large current account deficits. Therefore, it is expected that the effects of an increase in REER on IT adoption is rather negative. Finally, economists agree that exchange rate volatility plays a crucial role in driving FPI volatility. Therefore, as a measure of exchange rate volatility, we considered the nominal effective exchange rate volatility (NEERV).

4.3. Data Sources

Inflation targets as well as IT adoption dates (ITF) are sourced from Rose (2007), Roger (2010), Little and Romano (2009) and Hammond (2012). The FPI variable is extracted from International Monetary Fund-International Financial Statistics (IMF-IFS) database CD-ROM), and FPI volatility is computed by the authors. The control variables data are collected from eight main sources. The macroeconomic variables are retrieved from World Bank's World Development Indicators database (WDI) whereas GDP deflator and interest rates are sourced from IMF-IFS CD-ROM database. Financial openness variable is taken from Chinn and Ito (2008). Data on debt ratio are taken from Abbas et al. (2010). The sources of the effective exchange rate series, the index for the exchange rate flexibility and the corruption index are Darvas (2012a, 2012b and 2012c), Ilzetzki et al. (2010) and the International Country Risk Guide database, respectively. The domestic interest rate for each country is proxied by the Treasury bill rate, the money market rate or the discount rate depending on data availability. However, the foreign rate is proxied by 6-month Libor rate which is sourced from FRED database.

5. THE EMPIRICAL ASSESSING THE TREATMENT EFFECTS OF IT

We took a quick glance at the mean and standard error of FPI inflows and volatility before running the preliminary regressions. The variables were sorted by treatment, which seems to give rise to interesting outcomes (see Table 1). Indeed, results tend to show that the FPI mean of IT countries is higher than that of non-IT countries. Moreover, the standard deviation of FPI in IT countries is less than that of non-IT countries. These differences could be due to the adoption of IT regime as it could be due too to other characteristics. These results throw lights on a solution for increasing FPI inflows and controlling for its volatility, however an empirical investigation should be carried out to make it lucid.

Table 1. Countries Sorted by Treatment (ITers vs non-ITers)

Variables	Mean		Standard deviation	
	Non-ITers	ITers	Non-ITers	ITers
FPI inflows	0.694	1.355	3.038	1.774

5.1. Estimating the Propensity Scores

Propensity scores equation reduces the bias due to confounding variables that could be found in an estimate of the treatment effect. Consequently, it should include variables related to both treatment and outcomes. One of the implications of the conditional independence assumption on which the PSM methodology relies is that variables omission that has a systematic influence on the IT probability regression equation, but do not affect the outcome variables (FPI inflows and its volatility) has marginal impact of results. To avoid biased estimates, great care should be taken to ensure that variables affect simultaneously the IT probability and the outcomes.

In practice, variables selection is rather guided by the tradeoffs between bias induced by the variables effects (the distance of estimated treatment effect from true effect) and the efficiency (the precision of estimated treatment effect). Besides, PSM confines special attention to the region of common support since ATT is only defined in that region. Hence, an important step is to check the overlap and the region of common support between treatment and control group. In order to identify the variables that should be selected, numerous preliminary regressions were run and only specifications for which the balancing property is satisfied are retained for the remaining analysis.[4] In short, when selecting the covariates, we are guided by the theory and by the balancing tests results rather than by conventional statistical criteria. Therefore, the variables considered for estimating the probability of being selected in the treatment group, are lagged inflation (INFLAG), real GDP growth (RGDPG), debt ratio (DEBT), Seigniorage (SEIGNO), exchange rate regime (EXREGIME), interest rate spread (SPREAD), trade surplus (TS), financial openness (FOPEN). The rationale behind including these variables is that IT should be adopted only after some pre-requirements are fulfilled. We expect the four first variables to be negatively correlated with IT regime dummy and the remaining variables to be positively correlated with IT regime. We included variables that drive FPI dynamics. It is question, in particular, of the differential between domestic and foreign interest rates (IRD), nominal effective exchange rate volatility (NEERV), real effective exchange rate (REER) and corruption index (ICRG).

We start by regressing the dependent dummy variable (ITF) on the entire set of covariates as well as on different subsets of these covariates. Only regressions estimates for which the common support is verified and the balancing property is satisfied are used to assess the average treatment effect of IT on FPI and its volatility. Estimates from the best candidate regression model are reported on the first columns of Table 2. It appears

[4] Several ways for covariates selection are proposed in the literature (see for instance, Heckman, Ichimura and Todd, 1998; and Smith and Todd, 2005). But, the most intuitive and straightforward way is the visual inspection of the density distribution of the propensity scores in both treated and controlled groups. Lechner (2001, p.239) argues that given that the support problem can be spotted by inspecting the propensity score distribution, there is no need to implement a complicated formal estimator.

from these estimates that the coefficients to the covariates bear the expected signs. Countries with flexible exchange regimes, high level of trade surplus, and interest rate spread are more likely to adopt IT while countries with lagged high inflation records, high real GDP, high interest rate differential, high debt ratio, high seigniorage, high corruption index and nominal exchange rate volatility are less likely to choose such monetary policy regime. It is worth noting, however, that although real GDP growth bears the expected sign, it is not statistically significant. Despite the use of common support condition, which reduces the number of observations but improves the matching quality, an important number of individuals remain which ultimately improves the properties of the PSM model. As a matter of fact, the adjustment quality appears quite reasonable ranging from 0.402 to 0.503, which is comparable to what is reported in the PSM literature (see Lin and Ye, 2007, 2009; Tapsoba, 2012; De Mendonça and Souza, 2012). Better, Louviere et al. (2000) argue that a Pseudo R^2 ranging from 0.2 to 0.4 is comparable to an ordinary least squares (OLS) adjusted R^2 ranging from 0.7 to 0.9.

5.2. Average Effect of Treatment on the Treated (ATT)

Once we made it sure that treated and counterfactual individuals are comparable; that is, they share the same support, it becomes therefore possible to undertake the matching process. To this purpose, we sort the individuals according to their estimated propensity scores, and we discard individuals whose estimated scores are lower than the lowest score among the treatment individuals. In a following step and in order to estimate ATTs, we have recourse to matching techniques to choose, among the control group, countries that have almost similar propensity scores to the treatment group. Results are reported in Tables 3 and 4. The first column reports the results from one-to-one nearest neighbor (with replacement), the second column from kernel technique, the third from radius technique and the forth one from stratification technique. The ith raw $(i = 1, \cdots, 4)$ in Table 3 (resp. Table 4) represents the estimated ATTs on FPI inflows (resp. FPI volatility) based on model specification reported in the ith column of Table 2.

As a robustness check, we ran the model in three additional specifications to make sure results are not sensitive to the model specification (see Table 2). By and large, when considering various PSM specifications (Table 2, columns 2 to 4), inference on ATTs do not seem to vary substantially, and the results tend to corroborate on average the baseline model results. Better, in order to show how results are sensitive when estimating with radius matching estimator, we have considered two radius values ($r = 0.05$ and $r = 0.1$). Likewise, when using the kernel matching estimator, we have considered different smoothing parameters (bandwidth=0.01, 0.06, 0.6). Again, results from kernel matching estimator when using the Gaussian kernel function turned out not to be very different from Epanechnikov kernel function. Consequently, only results from the Gaussian kernel function are reported.

By and large, the findings from the baseline model (Table 3, raw 1) show that the average treatment on treated individuals is positive and statistically significant ranging from 0.5 to 0.6. Such finding would indicate that, if a country adopts IT regime, its FPI inflows increase on average by at least 0.5 percent. Put simply, the adoption of IT regime contributes to attract portfolio investments inflow. Such finding lends support to IT proponents who contend that among the prominent benefits of IT are transparency and credibility enhancement, price stability and uncertainty reduction. Furthermore, countries pursuing IT have broader and deeper securities markets when compared to the other non-IT emerging countries.

Table 2. Probit Estimates of Propensity Scores

	(1)	(2)	(3)	(4)
LAGINF	-0.057***	-0.062***	-0.058***	-0.060***
	(0.017)	(0.014)	(0.014)	(0.012)
RGDPG	-0.002	-0.013	-0.004	-0.014
	(0.024)	(0.024)	(0.023)	(0.020)
IRD	-0.024	-0.047**	-0.043**	-0.022**
	(0.022)	(0.019)	(0.018)	(0.010)
EXREGIME	0.373***	0.314***	0.320***	0.323***
	(0.041)	(0.036)	(0.034)	(0.032)
DEBT	-0.029***	-0.028***	-0.028***	-0.018***
	(0.005)	(0.005)	(0.004)	(0.003)
SPREAD	0.049***	0.054***	0.054***	
	(0.011)	(0.010)	(0.010)	
SEIGNO	-0.032***	-0.031***	-0.030***	
	(0.009)	(0.007)	(0.007)	
TS	0.052	-0.442	-0.288	
	(0.503)	(0.428)	(0.409)	
ICRG	-0.293***			
	(0.093)			
NEERV	-0.035**			
	(0.017)			
REER		-0.016***		
		(0.005)		
FOPEN				0.142**
				(0.058)
Constant	-1.463***	-0.249	-2.050***	-2.420***
	(0.494)	(0.725)	(0.389)	(0.387)
Pseudo-R^2	0.503	0.459	0.443	0.402
Log likelihood	-142.175	-160.551	-165.334	-198.792
Blocks number	5	6	5	7
Common support	[0.020, 0.914]	[0.009, 0.975]	[0.006, 0.951]	[0.007, 0.824]
AIC	0.515	0.526	0.538	0.508
BIC	-3446.568	-3809.238	-3806.146	4980.134
Observations	595	648	648	810

Note: The results reported on the first column (1) are obtained for the baseline model. Pseudo-R^2 is the McFadden's R^2, AIC denotes the Akaike information Criterion and BIC is the Bayesian information Criterion. The balancing property is satisfied for all four models. ***, ** and * denote significance level at 1%, 5% and 10%, respectively. Standard errors are in parentheses.

In addition, they have also an attracting investment climate thanks to their liberalized capital account, which in turn make private and institutional investors more willing to invest in IT countries. Better, IT regime creates an investors' confidence-enhancing macroeconomic environment in domestic policies and in countries' institutions as well.

When it comes to FPI volatility, the results are less clear-cut than the previous ones, and therefore deserve a close inspection. Firstly, and on the basis of the baseline model (specification (1) in Table 2), all the matching estimators provide non-statistically significant ATTs, except the kernel matching estimator (bandwidth=0.6) which exhibits a positive ATT. Secondly and more importantly, when using the same matching estimator, namely kernel estimator with (bandwidth=0.6), we obtain almost the same value of ATT whatever the PSM specification used. Such estimates are positive and statistically significant, and they range from 0.3 to 0.34. Thirdly, the radius estimator and the NN matching estimator permit to almost get the same results on the basis of specifications 3 and 4, respectively.

In sum, the results regarding FPI volatility show that IT regime adoption may increase investment volatility. The results suggest that such an increase in volatility amounts on average to almost 0.3 per cent. While such an increase is not very high, it constitutes nonetheless a serious warning to central bankers and policymakers to be ready to take the required preemptive measures to mitigate the harmful effects of volatility.

Table 3. ATT using Different Matching Techniques for FPI Inflows

	NN matching	Kernel matching			Radius matching		Stratification
		0.01	0.06	0.6	0.05	0.1	
ATT1	0.541	0.671*	0.553*	0.602***	0.638***	0.585**	0.352
	(0.415)	(0.354)	(0.310)	(0.230)	(0.234)	(0.255)	(0.403)
Treated Obs.	111	111	111	111	111	111	111
Untreated Obs.	42	173	173	173	173	173	173
ATT2	1.332***	0.984***	0.859***	0.631***	0.755***	0.701***	0.868***
	(0.339)	(0.280)	(0.267)	(0.207)	(0.222)	(0.231)	(0.272)
Treated Obs.	111	111	111	111	110	111	111
Untreated Obs.	53	252	252	252	252	252	252
ATT3	0.895**	0.743**	0.685**	0.662***	0.636***	0.654***	0.743***
	(0.361)	(0.294)	(0.285)	(0.193)	(0.213)	(0.227)	(0.270)
Treated Obs.	111	111	111	111	111	111	111
Untreated Obs.	57	283	283	283	283	283	283
ATT4	0.362	0.544**	0.611**	0.690***	0.681***	0.678***	0.533**
	(0.351)	(0.252)	(0.241)	(0.201)	(0.197)	(0.208)	(0.241)
Treated Obs.	116	116	116	116	116	116	115
Untreated Obs.	64	394	394	394	394	394	395

Note: Standard errors are in parentheses. ***, ** and * denote significance level at 1%, 5% and 10%, respectively. N-N matching refers to the nearest neighbor matching technique. All matching techniques are based on 500 replications.

Table 4. ATT using Different Matching Techniques for FPI Volatility

	NN matching	Kernel matching			Radius matching		Stratification
		0.01	0.06	0.6	0.05	0.1	
ATT1	0.165 (0.331)	0.000 (0.259)	0.077 (0.195)	0.303* (0.171)	0.249 (0.166)	0.211 (0.174)	0.016 (0.176)
Treated Obs.	111	111	111	111	111	111	111
Untreated Obs.	42	173	173	173	173	173	173
ATT2	0.005 (0.283)	0.135 (0.214)	0.160 (0.191)	0.331** (0.149)	0.085 (0.170)	-0.140 (0.208)	0.138 (0.193)
Treated Obs.	111	111	111	111	56	18	111
Untreated Obs.	51	252	252	252	232	247	252
ATT3	0.255 (0.254)	0.255 (0.189)	0.208 (0.196)	0.348** (0.137)	0.322* (0.176)	0.413** (0.188)	0.206 (0.168)
Treated Obs.	111	111	111	111	78	66	111
Untreated Obs.	53	283	283	283	260	275	283
ATT4	0.372** (0.190)	0.214 (0.155)	0.147 (0.163)	0.345*** (0.131)	0.185 (0.175)	-0.073 (0.166)	0.172 (0.155)
Treated Obs.	116	116	116	116	55	24	115
Untreated Obs.	62	394	394	394	315	378	395

Note: Standard errors are in parentheses. ***, ** and * denote significance level at 1%, 5% and 10%, respectively. N-N matching refers to the nearest neighbor matching technique. All matching techniques are based on 500 replications.

6. MAIN FINDINGS, POLICY IMPLICATION AND CONCLUDING REMARKS

Despite the growing number of studies in IT effects on macroeconomic variables, there are still some unexplored issues. This paper attempts to shed some light on one of the still under-searched issues in IT literature, namely the potential effects of IT on capital inflows and their volatility in the emerging countries. More specifically, this study assesses quantitatively the impact of adopting IT regime on FPI inflows and their volatility by making use of a relevant econometric methodology, namely a variant of the simulation techniques of a quasi-natural experiment, called the non-parametric PSM methodology while controlling for a set of macroeconomic and institutional variables.

The paper's results show that the enhancement effects of IT on FPI inflows are substantial and statistically significant, whatever the matching technique used. This would indicate that IT adoption is beneficial for emerging countries since it has permitted to attract more FPI inflows. On another front, these results tend to indicate that IT is rather contributing to amplifying portfolio investment volatility, albeit such finding is far from being robust and depends on the model specification and the matching technique. The character of "easily reversible" is always assigned to FPI flows, making these flows risky and able to be a disturbing factor for financial and economic stability.

Therefore, the positive ATTs values regarding FPI volatility, albeit not statistically significant, should be considered by emerging-countries policymakers as a warning flag. Perusing IT is not a free lunch. It rather requires a close watching of all potential sources of volatility, including those that might trigger or amplify FPI volatility. There is a wide agreement among economists that exchange rate fluctuations, stock market returns decline or volatility and inflation pressure are (among) the main factors that drive FPI volatility.

Therefore, under the hypothesis that IT regime is effective in bringing down inflation and its volatility, it remains however for emerging-countries policymakers to monitor exchange rate and stock market dynamics. As far as the exchange rate is concerned, instead of implementing a pure inflation targeting regime as recommended by theory, emerging-countries policymakers should pursue a pragmatic inflation targeting by focusing not only on a single anchor (i.e, inflation) but also on managing the exchange rate as long as the two targets do not conflict. By doing so, they may limit exchange rate fluctuations, and thereby mitigating the FPI volatility.

Besides, the conduct and the stance of the monetary policy is not defined so much by the current central bank (short-term) policy rate, it is also and to a great extent what market operators expect regarding the future path of the interest rates and their potential effects on financial markets and finally on the real economy. Setting the policy rate by the central bank during the official board meetings is only a step in the formulation of the central bank policy. The other step consists in the releasing of the information that might shape the market's expectations operators. In this context, transparency plays a fundamental role not only in enhancing the effectiveness of the monetary policy, including IT but also in reducing uncertainty and thereby lowering volatility in various financial markets, including the stock market. Low volatility is a synonym of low risk premium which may boost the investment and ultimately enhance the economic growth. Better, low risk premiums lead ipso facto to high asset prices which may in turn lessen FPI volatility.

This study did not seek to criticize other monetary regimes nor did it outline IT regime as the best monetary policy. It rather aims at finding out whether pursuing IT contributes to attract more FPI inflows and control for FPI volatility or not. As such, the study's results may be useful in guiding policymakers towards widening the scope of IT regime to encompass financial stability in addition to price stability.

APPENDIX

A1. Control and Treatment Groups

Treatment Group	Control group
Brazil, Chile, Colombia, Guatemala, Indonesia, Mexico, Peru, Philippines, Poland, Romania South Africa, Thailand, Turkey.	Argentina, Bolivia, , Bulgaria, Cameroon , China H.K, Croatia, Costa Rica, Egypt , El Salvador, India, Jamaica, Kazakhstan, Kenya, Latvia, , Lithuania, Mali, Malaysia, Mauritius, Morocco, Nigeria, Tunisia, Pakistan, Sri Lanka, Ukraine, Venezuela.

A2. The Matching Estimators

The PSM analysis consists in choosing for each IT country its counterfactual. To this end several matching techniques were proposed. We present some of these techniques below.[5]

A2.1. The Stratification Matching

The stratification technique consists in splitting the common support into different strata, and calculates the impact of the program (the treatment) within each strata by taking the mean difference in outcomes between treated and non-treated units. The ATT by the stratification technique is the average of ATTs of each interval weighted by the distribution of the treated individuals between the intervals. Formally, if we design by T the treated group, C the control group, and Y_i^TandY_i^C, the observed outcomes for the treated and control groups, ATTs are therefore estimated over each strata by:

$$\tau_q^S = \frac{1}{N^T} \sum_{i \in I(q)} Y_i^T - \sum_{i \in I(q)} Y_j^C, \tag{a1}$$

where q is the index of intervals; $I(q)$ is the group of individuals in the interval q; $N_q^T$and N_{q}^C are the number of treated and control individuals in the interval q. Finally, the estimation of ATT is calculated as follows:

$$\tau^S = \sum_{q=1}^{Q} \tau_q^S \frac{\sum_{i \in (q)} D_i}{\sum_{\forall_i} D_i}, \tag{a2}$$

where Q is the number of intervals and the weights of each interval is given by the share of corresponding treated individuals. Assuming the independence of results across the individuals and the fixed weights, the variance of the estimator τ^S can be expressed as:

[5] This appendix is based on Becker and Ichino (2002) and De Mendonça and Souza (2012).

$$Var(\tau^S) = \frac{1}{N^T}\left\{Var(Y_i^T) + \sum_{q=1}^{Q} \frac{N_q^T N_q^T}{N^T N_q^C} Var(Y_j^C)\right\}. \quad \text{(a3)}$$

Consequently, the standard errors can be achieved either by (b3) or by bootstrapping.

A2.2. The Nearest Neighbor Matching

It is the most renowned matching technique. With the nearest neighbor matching, each treated unit is matched to its closest control unit (or units) in term of propensity score, and this is done either with or without replacement. For the latter case - with replacement-, a control unit can serve as a counterfactual for more than one treated unit.

If we design by $C(i)$ the set of the counterfactual units for each treated individual i with a propensity score p_i; the set $C(i)$ can therefore be expressed as: $C(i) = \min_j \|p_i - p_j\|$. The ATT is then measured as follows:

$$\tau^M = \frac{1}{N^T}\sum_{i\in T} Y_i^T - \frac{1}{N^T}\sum_{j\in C} \omega_j Y_j^C, \quad \text{(a4)}$$

where $\omega_j = \sum_i \omega_{ij}$ represents the weights.

Under the assumption of independence across individuals and assuming that the weights are fixed, the variance of the estimator τ^M is:

$$Var(\tau^M) = \frac{1}{N^T} Var(Y_i^T) + \frac{1}{(N^T)^2}\sum_{j\in C}(\omega_j)^2 Var(Y_j^C). \quad \text{(a5)}$$

The standard errors can be achieved either analytically by (b5) or by the bootstrapping technique.

A.2.3. The Radius Matching

The radius matching technique has an additional option when compared to the nearest neighbor technique. This option consists in imposing a radius. All control units that fall within the radius are used as counterfactuals for treated units. It is measured as follows

$$C(i) = \{p_j \; such\, that \; \|p_i - p_j\| < r\}, \quad \text{(a6)}$$

All control units with propensity scores distance less than radius r for p_i are matched with the treated units i.

A2.4. The Kernel matching

This matching technique paired each treated unit with all control units with an assigned weight that is inversely proportional to the distance between the propensity scores of treated and control units. The kernel matching estimator is given by:

$$\tau^k = \frac{1}{N^T}\sum_{i \in T}\left\{Y_i^T - \frac{\sum_{j \in C} Y_j^C F\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{j \in C} F\left(\frac{p_j - p_i}{h_n}\right)}\right\}, \tag{a7}$$

where $F(\cdot)$ is a kernel function (Gaussian or Epanechnikov) and h_n is the smoothing parameter that specifies the bandwidth. Hence, a consistent estimator for the counterfactual outcome Y_{0i} is given by:

$$\frac{\sum_{j \in C} Y_j^C F\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{j \in C} F\left(\frac{p_j - p_i}{h_n}\right)}. \tag{a8}$$

The standard errors are estimated exclusively by bootstrapping.

A3. Countries that have adopted the full-fledged IT regime

Country	Current inflation target (%)	Full-fledged IT date
Chile	3 (+/-1)	August 1999
Czech Republic	3(+/- 1)	January 1998
Israel	2 (+/- 1)	June 1997
Poland	2.5 (+/- 1)	September 1998
Mexico	3 (+/- 1)	January 2001
Brazil	4.5 (+/- 1)	June 1999
Colombia	2-4	October 1999
Philippines	4 (+/- 1)	January 2002
South Africa	3-6	February 2000
Thailand	0.5-3	May 2000
Hungary	3(+/- 1)	August 2001
Peru	2(+/- 1)	January 2002
Guatemala	5(+/- 1)	January 2005
Indonesia	5(+/- 1)	July 2005
Romania	3 (+/- 1)	August 2005
Turkey	5.5(+/- 2)	January 2006
Serbia	4-8	September 2006
Ghana	8.5(+/- 2)	January 2007
Korea	3 (+/- 1)	April, 1998
New Zealand	1-3	March, 1990
Canada	2 (+/- 1)	January, 1992
United Kingdom	2	October, 1992
Sweden	2	January, 1995
Australia	2-3	September, 1994
Iceland	2.5 (+/- 1.5)	March, 2001
Norway	2.5 (+/- 1)	March, 2001
Armenia	4.5 (+/- 1.5)	January 2006
Albania	3 (+/- 1)	2009

Source: Rose (2007), Little and Romano (2009), Roger (2010), Hammond (2012).

REFERENCES

Abbas, S.M., N. Belhocine, A. A. E. Ganainy and M. Horton (2010), "A historical Public Debt Database," IMF Working Paper, 10/245.

Agénor, P.R. and L.A.P. Da Silva (2013), "Inflation Targeting and Financial Stability: A Perspective from the Developing World," Working Papers Series 324, Central Bank of Brazil, Research Department.

Batini, N., and D. Laxton (2007), "Under what Conditions can Inflation Targeting be Adopted? The Experience of Emerging Markets," *Central Banking, Analysis, and Economic Policies Book Series*, 11, 467-506.

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

Becker, S.O. and A. Ichino (2002), "Estimation of Average Treatment Effects based on Propensity Scores," *Stata Journal*, 2(4), 358-377.

Berument, H. (1998), "Central Bank Independence and Financing Government Spending," *Journal of Macroeconomics*, 20(1), 133-152.

Brito, R. and B. Bystedt (2010), "Inflation Targeting in Emerging Economies: Panel Evidence," *Journal of Development Economics*, 91(2), 198-210.

Broto, C. (2011), "Inflation Targeting in Latin America: Empirical Analysis using GARCH models," *Economic Modelling*, 28(3), 1424-1434.

Calvo, G.A., L. Leiderman and C.M. Reinhart (1996), "Inflows of Capital to Developing Countries in the 1990s," *Journal of Economic Perspectives*, 10(2), 123-139.

Chinn, M., and H. Ito (2008), "A New Measure of Financial Openness," *Journal of ComparativePolicy Analysis: Research and Practice*, 10(3), 309-322.

Darvas, Z. (2012a), "Real Effective Exchange Rates for 178 Countries: A New Database," Bruegel Working Paper, 2012/06, March.

_____ (2012b), "Compositional Effects on Productivity, Labor Cost and Export Adjustment," Bruegel Working Paper, 2012/11, June.

_____ (2012c), "Productivity, Labor Cost and Export Adjustment: Detailed Results for 24 EU Countries," Bruegel Working Paper #2012/11, July.

De Mendonça, F.H. and G. Souza (2012), "Is Inflation Targeting a Good Remedy to Control Inflation?" *Journal of Development Economics*, 98(2), 178-191.

Epstein, G. (2007), *Central Banks as Agents of Employment Creation, paper presented to UN-DESA conference on employment and Decent Work*, New York: UN.

Epstein, G. and E. Yeldan (2008), "Inflation Targeting, Employment Creation and Economic Development: Assessing the Impacts and Policy Alternatives," *International Review of Applied Economics*, 22(2), 131-144.

Ersel, H. and F. Özatay (2008), "Fiscal Dominance and Inflation Targeting: Lessons from Turkey," *Emerging Markets Finance and Trade*, 44(6), 38-51.

Fernandez-Arias, E. (1996), "The New Wave of Private Capital Inflows: Push or Pull?" *Journal of Development Economics*, 48(2), 389-418.

Galindo, L.M. and J. Ros (2008), "Alternatives to Inflation Targeting in Mexico," *International Review of Applied Economics*, 22(2), 201-214.

Goldstein, I. and A. Razin (2006), "An Information-based Tradeoff between Foreign Direct Investment and Foreign Portfolio Investment," *Journal of International Economics*, 70(1), 271-295.

Gonçalves, C.E.S. and J.M. Salles (2008), "Inflation Targeting in Emerging Economies: What do the Data Say?" *Journal of Development Economics*, 85(1), 312-318.

Hammond, G. (2012), *State of the Art of Inflation Targeting*, London: Bank of England.

Heckman, J.J., H. Ichimura and P. Todd (1998), "Matching as an Econometric Evaluation Estimator," *Review of Economic Studies*, 65(2), 261-294.

Ilzetzki, E., C.M. Reinhart and K. Rogoff (2010), "Exchange Rate Arrangements Entering the 21st Century: Which Anchor Will Hold?" Maryland University and Harvard University, Mimeo.

IMF (2009), *Balance of Payments and International Investment Position Manual 6th eds*, Washington, D.C: International Monetary Fund.

Johnson, D. (2002), "The Effect of Inflation Targeting on the Behavior of Expected Inflation: Evidence from an 11 Country Panel," *Journal of Monetary Economics*, 49(8), 1521-1538.

Lechner, M. (2001), "A Note on the Common Support Problem in Applied Evaluation Studies,"*Annales d'Economie et de Statistique*, 91/92, 219-239.

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.

_____ (2009), "Does Inflation Targeting Make a Difference in Developing Countries?" *Journal of Development Economics*, 89, 118-123.

Little, J.S. and T.F. Romano (2009), "Inflation Targeting-Central Bank Practice Overseas," FRB of Boston Public Policy Briefs, 08/1.

Louviere, J.J., D.A. Hensher and J.D. Swait (2000), *Stated Choice Methods: Analysis and Applications*, Cambridge University Press.

Lucotte, Y. (2010), "The Choice of Adopting Inflation Targeting in Emerging Market Economies: Do Institutions Matter?" MPRA Paper, 2-34.

Meyer, L. (2001), "Inflation Targets and Inflation Targeting," *Federal Reserve Bank of St Louis Review*, 83(6), 1-13.

Mishkin, F.S. (2004), "Can Inflation Targeting Work in Emerging Market Countries," NBER Working Paper #10646.

Mishkin, F.S. and A. Posen (1997), "Inflation Targeting: Lessons from Four Countries," Federal Reserve Bank of New York Economic Policy Review, 3(3), 9-110.

Mishkin, F.S. and K. Schmidt-Hebbel (2007), "Does Inflation Targeting Make a Difference?" NBER Working Paper, 12876.

Neumann, M.J. and J. Von Hagen (2002), "Does Inflation Targeting Matter?" Federal Reserve Bank of St Louis Review, July/August, 127-148.

Roger, S. (2010), "Inflation Targeting Turns 20," *Finance and Development*, 47(1), 46-49.

Rose, A. (2007), "A Stable International Monetary System Emerges: Inflation Targeting is Bretton Woods Reserved," *Journal of International Money and Finance*, 26(5), 663-681.

Rosenbaum, P. and D. Rubin (1983), "The Central Role of Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70(1), 41-55.

Rudebush, G.D. and Walsh, C.F. (2001a), "Central Banks Inflation Targeting," in Rabin,A.A., and G.L. Stevens, eds., *Handbook of Monetary and Fiscal Policy*, CRC Press.

_____ (2001b), "US Inflation Targeting: Pro and Con," in Rabin,A.A., and G.L. Stevens, eds., *Handbook of Monetary and Fiscal Policy*, CRC Press.

Samarina, A. and J. De Haan (2014), "Right on Target: Exploring the Factors Leading to Inflation Targeting Adoption," *Contemporary Economic Policy*, 32(2), 372-389.

Smith, J.A. and P.E. Todd (2005), "Does Matching Overcome La Londe's Critique of Non- experimental Estimators?" *Journal of Econometrics*, 125(1/2), 305-353.

Tapsoba, R. (2012), "Does Inflation Targeting Matter for Attracting Foreign Direct Investment into Developing Countries?" CERDI Working Paper, E2012/03.

Taylor, M. and L. Sarno (1997), "Capital Flows to Developing Countries: Long- and Short-term Determinants," *World Bank Economic Review*, 11(3), 451-470.

Vega, M. and D. Winkelried (2005), "Inflation Targeting and Inflation Behavior: A Successful Story?" *International Journal of Central Banking*, 1(3), 153-175.

Walsh, C. (2009), "Inflation Targeting: What Have We Learned?" *International Finance*, 12(2), 195-233.

Woo, W.T., Y. Pan, J.D. Sachs and J. Quian (2014), *Financial Systems at the Crossroads, Lessons for China*, London: Imperial College Press.

Mailing Address: IHEC, Route Hzamia Sahloul 3 – BP 40, 4054 Sousse, Tunisia. Email: adel.boughrara@fdseps.rnu.tn, ichrak.dridi.ihec@gmail.com

Received February 4, 2016, Revised March 5, 2017, Accepted May 11, 2017.