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Keywords: Dynamic Treatment Effect; Emerging Market Economies; Inflation; Inflation Persistence; Inflation Targeting; Inflation Volatility

JEL Code: C21; C22; E52; E31

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This study examines the effects of inflation targeting on inflation levels, its volatility, and its persistence in emerging market economies. To better estimate the dynamic treatment effects of inflation targeting, the study uses a larger set of data, including 59 emerging market economies, an extended sample spanning 1985-2019, and a methodology that takes into account the staggered adoption of inflation targeting by these economies. Traditional models used in the literature failed to account for staggered adoption, resulting in biased estimates. Inflation targeting has been shown to significantly reduce inflation levels in emerging markets, especially when hyperinflationary economies are excluded. Results indicate significant reductions in inflation three to four years after adoption. In comparison, the findings for inflation volatility and persistence are more nuanced. Standard models indicate initial volatility reductions, but models that account for staggered adoption show no significant long-term impact. Moreover, inflation targeting has no significant impact on inflation persistence, even in more stable environments. These findings highlight the effectiveness of using models that account for staggered policy adoption when evaluating long-term policy impacts, and they suggest that, while inflation targeting is a viable tool for reducing inflation in emerging markets, its broader effects on inflation volatility and persistence have been limited.

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1. Introduction

Inflation targeting (IT) has emerged as one of the most prevalent monetary policy frameworks worldwide, particularly since the 1990s. By establishing a publicly announced inflation goal, IT aims to stabilize price levels and enhance central bank accountability, marking a significant shift towards transparency in monetary policy. While early research highlighted that the effect of IT on inflation may be limited for the case of advanced economies (see Lin and Ye (2007); Walsh (2009); Willard (2012); Samarina et al. (2014)), which already had high credibility and lower inflation levels. However, for the case of developing economies, which generally have lower initial credibility and higher inflation levels compared to advanced economies, announcing an explicit inflation target could have a much greater impact on boosting credibility in these regions. This suggests that, although IT might yield limited results in developed economies, it has the potential to significantly influence inflation dynamics in developing economies, as found in several empirical studies (see Lin and Ye (2009); Samarina et al. (2014); Gonçalves and Salles (2008)).[1]

Despite extensive research on IT, a critical gap remains in accounting for the staggered nature of IT adoption, a common characteristic in many emerging markets. Previous studies relied heavily on Difference in Differences (DiD), Propensity Score Matching (PSM), and two-way fixed effects (TWFE) estimators, all of which assumed homogeneous treatment effects of IT across groups and time periods. However, this assumption is problematic when the adoption time varies and the effect is heterogeneous across time and group, as TWFE often includes overlapping comparisons between early and late adopters, leading to distorted results and potentially reversing the policy's apparent effect. Therefore, failure to account for staggered adoption can lead to biased estimates (Imai and Kim, 2019; Imai et al., 2023;

[1]Although, there are few papers that find otherwise (see (Brito and Bystedt, 2010; Stojanovikj and Petrevski, 2021)).

Goodman-Bacon, 2021; Baker et al., 2022), potentially obscuring the true impact of IT on inflation dynamics while questioning the results found in Lin and Ye (2009) and Samarina et al. (2014). To address these issues, this study employs a staggered PSM approach,[2] as recommended in the time series cross section (TSCS) framework [3] by Imai et al. (2023), tailored specifically for TSCS data where staggered adoption is present.

The study examines a sample of 59 emerging economies over the period 1985–2019, with 20 economies implementing IT and 39 following alternative monetary policy frameworks. We estimate the impact of IT on inflation, its volatility and its persistence. We use both the standard PSM approach, which has been used in the existing literature and the staggered PSM approach in order to account for biases that may be present in the standard approach. Finally, to establish the robustness of our results, we conduct a sub-sample analysis focused on relatively stable economies by excluding economies that have experienced episodes of hyperinflation.

Our study contributes to the existing literature in the following ways: First, by implementing a robust staggered PSM framework that addresses the limitations of traditional methods and is consistent with recent calls for more nuanced approaches to staggered policy interventions, this study provides a comprehensive, context-sensitive assessment of IT's dynamic effects on inflation levels, inflation volatility, and inflation persistence.[4] Second, the paper encompasses a comprehensive set of emerging market economies (EMEs), including recent adopters of IT. It also considers an extended time period, from 1985 to 2019, allowing for an analysis that captures both the immediate and long-term effects of IT on these economies.

[2]Here, we refer to staggered PSM approach as methodology suggested in the paper by Imai et al. (2023).

[3]Time-series cross-sectional (TSCS) data involve a substantial number of repeated observations collected for the same units over time. In this type of dataset, units can undergo treatment multiple times, with the timing of each treatment potentially differing across units.

[4]Inflation volatility is the degree of fluctuation in inflation rates over time, reflecting economic instability and uncertainty while inflation persistence describes inflation's tendency to remain high or low for an extended period, showing slow adjustment even after economic shocks.

Third, our analysis encompasses all facets of inflation dynamics, specifically examining inflation levels, its volatility, and its persistence. While existing literature has extensively studied inflation and its volatility, inflation persistence remains relatively unexplored.

Our main findings show that, using both standard and staggered PSM approaches, there is a clear trend of inflation reduction in emerging markets over time following IT adoption, with the effects being most noticeable in economies without a history of hyperinflation. This is in line with the findings of Lin and Ye (2009); Samarina et al. (2014), and Gonçalves and Salles (2008). The staggered PSM results further demonstrate that the reduction in inflation becomes statistically significant only a few years after IT adoption, suggesting a delayed but consistent impact. In the context of inflation volatility, while the standard PSM approach points to initial declines, the staggered PSM method finds no long-term impact, challenging the idea that IT stabilizes inflation variability in the longer run. This contradicts the findings of Lin and Ye (2009), who found a decline in inflation volatility due to IT adoption in developing economies. Moreover, with regards to inflation persistence, the staggered PSM approach shows a slow decline in persistence in more stable inflation environments, though the majority of these effects are statistically insignificant.

To summarize, the findings suggest that, while IT has contributed to lower inflation levels in EMEs, its effectiveness in moderating inflation volatility and persistence has been limited and may be context dependent. The study also emphasizes the importance of using the staggered methodology, which more accurately captures the nuanced, long-term effects of IT on inflation dynamics across different economic conditions. Inflation volatility and inflation persistence are important indicators of the economy's perceived stability, and IT's inability to control them calls into question the success and efficacy of the IT framework in emerging markets.

The rest of the paper is as follows. Section 2 reviews relevant literature around our variable of interest, and Section 3 presents the empirical methodology and describes the data used applied in the paper. Then, Section 4, discusses the paper's results, and ends with a robustness analysis. Finally, Section 5 presents the paper's conclusions, which lead to some implications for economic policy.

2. Literature Review

The question of whether IT makes a difference in reducing inflation has been explored extensively for EMEs. Early studies like Lin and Ye (2009) provide strong evidence that IT has a significant deflationary effect in developing economies. By applying PSM, they found that IT led to substantial reductions in inflation. This was particularly evident in emerging markets, where inflation rates were typically higher before the adoption of the policy. Their findings suggest that IT can be a powerful tool for stabilizing prices in economies with volatile inflation dynamics. Similarly, Gonçalves and Salles (2008) and Samarina et al. (2014) support the notion that IT leads to lower inflation, especially in emerging markets. However, there are papers by Thornton (2016) and Brito and Bystedt (2010) that argues that IT effectiveness may be neutralized by persistent external factors, making volatility reductions inconsistent.

To address the question of the impact of IT, researchers have employed a variety of methodologies. Early studies, such as those by Neumann and von Hagen (2002), used a DiD approach, which compares inflation rates before and after IT adoption between targeting and non-targeting countries. These initial studies found that IT reduced both inflation levels and variance. However, they did not fully account for potential endogeneity, for instance countries with high initial inflation rates may be more likely to adopt IT, which can bias results. Ball and Sheridan (2004) addressed this by including the initial inflation level as an explanatory variable, finding that IT's direct impact was minimal once initial conditions were accounted for. To further manage endogeneity, other researchers have turned to the PSM method, which compares countries with similar initial conditions but different policy choices. For instance, Vega and Winkelried (2005), Lin and Ye (2007, 2009), Gonçalves and Salles (2008), Samarina et al. (2014) and others have applied this method. Finally, there are studies using panel data methods, such as those by Mishkin and Schmidt-Hebbel (2007) and Willard (2012). Table 1 gives exhaustive list of literature related to IT and its effect on inflation dynamics.

However, recent literature (Imai and Kim, 2019; Imai et al., 2023; Baker et al., 2022; Goodman-Bacon, 2021) on impact evaluation emphasizes the importance of accounting for the staggered nature of policy adoption, which is the case for IT. Traditional methods like DiD and panel data methods, while useful, often assume that treatment effects are homogeneous and ignore the complexity introduced by staggered policy adoption. This can result in biases and inconsistent estimates, especially when treatment effects evolve over time or vary across units, as is frequently the case in real-world applications.

Goodman-Bacon (2021) highlights key limitations of traditional DiD methods in the context of staggered policy adoption, particularly due to negative weighting,[5] where early adopters are sometimes used as controls for later adopters and vice versa. This approach can distort estimates, sometimes even reversing the sign of an effect. To address this, staggered methods, such as those using PSM with staggered adoption adjustments, allow for a more refined control selection that aligns better with the timing of treatment, minimizing bias due to heterogeneous timing (Imai and Kim, 2019; Imai et al., 2023).

[5]Negative weights effectively mean that these comparisons contribute the opposite of their expected effect, potentially causing the overall estimate to suggest an effect in the opposite direction of the true treatment effect.

Table 1: Empirical studies and their results

Study	Outcomes Considered	Duration	economies	Methodology	Results
Lin and Ye (2009)	Inflation, Inflation Volatility	1985-2005	Developing economies	Propensity Score Matching	IT has significant effects on lowering both inflation and inflation variability.
Gonçalves and Salles (2008)	Inflation, Inflation Volatility	1980-2005	Emerging Market Economies	Difference-in-Differences	IT reduces inflation but have insignificant effect on inflation volatility in EMEs.
Brito and Bystedt (2010)	Inflation, Inflation Volatility	1980-2005	Emerging Economies	Panel Data, GMM	IT reduces inflation but not consistently associated with reduced inflation volatility.
Ardakani et al. (2018)	Inflation, Inflation Persistence	1998-2013	Advanced and Developing	Propensity Score Matching	No significant difference in the impact on inflation and inflation volatility in inflation targeter versus non-inflation targeters.
Ball and Sheridan (2004)	Inflation, Inflation Volatility, Persistence	1985-2001	Advanced Economies	Difference-in-Differences	IT does not outperform non-targeting economies in inflation performance.
Samarina et al. (2014)	Inflation	1985-2011	Advanced & Developing Economies	Difference-in-Differences, Propensity Score Matching	No effect of IT for advanced economies, whereas the results suggest a significant negative effect on inflation in emerging and developing economies. Effects are more pronounced after excluding hyperinflation economies.
Vega and Winkelried (2005)	Inflation, Inflation Volatility, Inflation Persistence	1990-2004	Advanced and Emerging Markets	Propensity Score Matching	IT reduces inflation and inflation volatility in both advanced and emerging economies. Ambiguous effect on inflation persistence.
Levin et al. (2004)	Inflation, Inflation Persistence	1990-2003	Advanced Economies	Structural VAR	IT anchors inflation expectations but has mixed effects on persistence.
Fraga et al. (2003)	Inflation, Inflation Volatility	1990s	Emerging Market Economies	Case Study	IT successful in controlling inflation but mixed outcomes for inflation volatility.
Mishkin and Schmidt-Hebbel (2007)	Inflation, Inflation Volatility	1989-2004	Advanced and Emerging Economies	Difference-in-Differences, Panel Estimations	No effect for advanced economies, negative effect for emerging economies.
de Mendonça and de Guimarães e Souza (2012)	Inflation, Inflation Volatility	1990-2007	Advanced and Developing Economies	Propensity Score Matching	No effect for advanced economies, negative effect for developing economies.
Neumann and von Hagen (2002)	Inflation, Inflation Volatility	1978-2001	Advanced Economies	Difference-in-Differences	Negative effect on inflation but cannot confirm the superiority of IT over other monetary policy strategies geared at price stability,
Willard (2012)	Inflation, Inflation Volatility	1985-2002	Advanced Economies	Panel Estimations	No effect of IT on inflation and inflation volatility.
Ball (2010)	Inflation, Inflation Volatility, Persistence	1985-2007	Advanced Economies	Difference-in-Differences	Very small effect on inflation outcomes and persistence.
Batini and Laxton (2007)	Inflation, Inflation Volatility	1985-2004	Emerging Markets	Difference-in-Differences	IT significantly reduces inflation and volatility in emerging markets.
Lin and Ye (2007)	Inflation, Inflation Volatility	1985-1999	Advanced Economies	Propensity Score Matching	IT has no significant effect on inflation outcomes in advanced economies.
Gemayel et al. (2011)	Inflation, Inflation Volatility	1990-2008	Low-Income Economies	Difference-in-Differences, Panel Estimations	Negative effect of IT on inflation and volatility in low-income economies.
Stojanovikj and Petrevski (2021)	Inflation, Inflation Volatility, Persistence	1990-2017	Emerging Markets	Panel Data Method	IT significantly reduces inflation and persistence, while volatility results are insignificant.
Arsić et al. (2022)	Inflation, Inflation Volatility, Inflation Persistence	1997–2019	European & Asian Emerging Economies	Dynamic panel modeling and propensity score matching	IT improves inflation control and reduces volatility. IT policy did not affect inflation persistence.

3. Methodology and data

3.1. Methodology

The empirical strategy for this study begins with a review of PSM, which is a commonly used method for estimating causal effects in observational studies. PSM helps to mimic the conditions of a randomized experiment by selecting control observations that are similar to treated observations in terms of observable characteristics, ensuring that the treatment variable is independent of confounders. This method offers intuitive diagnostics for assessing the quality of the matches, such as covariate balance checks (Rubin (2006); Stuart (2010)). In our study, we have used multiple matching methods, these are kernel matching, inverse probability weighting, nearest neighbor matching and radius matching. Through these diagnostics, PSM reduces model dependence and enhances the validity of causal inference (Ho et al. (2007)). Finally, the DiD method is used to estimate the average treatment effect of the treated.

In scenarios involving multiple units and time periods, the regression-based DiD framework is typically modeled using a TWFE specification (Baker et al., 2022). This approach incorporates unit-specific fixed effects to control for time-invariant characteristics of each unit and time-specific fixed effects to account for period-specific shocks or trends that are uniform across units. The TWFE structure facilitates isolating the treatment effect by accounting for both cross-sectional and temporal heterogeneity, ensuring a robust identification of the causal impact of an intervention or policy change.

The base model for evaluating the effect of IT on the dependent variable Y is a DiD framework with fixed effects for country (λ_i) and time (λ_t). The equation can be represented as follows:

$$Y_{it} = \beta_0 + \beta_1 IT_{it} + \beta_2 X_{it} + \lambda_i + \lambda_t + \epsilon_{it} \tag{1}$$

Where:

- Y_{it} could be inflation, inflation volatility or inflation persistence for country i at time t.
- IT_{it} is the treatment indicator for IT.
- X_{it} is a vector of control variables
- λ_i and λ_t are country and time fixed effects.
- ϵ_{it} is the error term.

However, while standard PSM is widely applied in observational studies, it faces challenges when used in TSCS data, where treatment timing can vary across units Imai et al. (2023). For instance, in the case of IT policies, economies often adopt IT at different points in time. The standard PSM method assumes simultaneous treatment, which can lead to biased estimates if treatment is staggered across units. Most social scientists working with TSCS data rely on linear regression models with fixed effects to address this issue (Angrist and Pischke (2009)). These TWFE models control for unit and time fixed effects, but they heavily depend on parametric assumptions and lack diagnostic tools to verify covariate balance or control for unobserved treatment dynamics.

3.1.1. Limitations of the TWFE Estimator in Staggered Settings

In staggered treatment settings, such as IT where different economies adopt the policy at different times, the TWFE estimator is frequently used. However, as recent research has shown, TWFE computes a weighted average of all 2×2 DiD estimates in the data, with weights depending on group size and variation in treatment timing (Goodman-Bacon, 2021). In some cases, the TWFE estimator compares treated groups before they receive treatment with later-treated groups, using earlier-treated groups as controls after they have already been treated.

The key issue arises when treatment effects are heterogeneous i.e. varying either over time or between treated cohorts. In these cases, the TWFE estimator can produce biased estimates because some of the 2×2 estimates used in the weighted average may enter with negative weights. Negative weights occur when the ”control group” is treated in both time periods, leading to the treatment effect being differenced out in one of the periods. These negative weights are problematic as they can cause the overall treatment effect estimate to have the opposite sign of the true average treatment effect of the treated (ATET). Given these limitations, traditional two-period DiD designs, which assume treatment is binary and fixed at a particular time, are often ill-suited for staggered treatment settings. They fail to capture dynamic treatment effects, i.e., how the treatment effect evolves over time as different groups adopt the treatment at different points in time. The failure to account for this dynamic nature of treatment can result in biased estimates that do not accurately reflect the true effects of the policy.

To address these challenges, we apply a more sophisticated approach: staggered PSM. This method builds on the strengths of standard PSM but incorporates weights to handle the staggered adoption of treatment. Developed by Imai et al. (2023), this method combines matching with a DiD estimator, offering a more robust solution for estimating causal effects in TSCS data. Unlike the traditional methods, the staggered PSM approach accounts for both time variation in treatment and heterogeneous treatment effects across groups, avoiding the pitfalls of negative weights and biased estimates.

3.1.2. Introducing staggered PSM and its advantages

In the staggered PSM approach, for each treated observation, we first select a set of control observations from units in the same time period that share similar pre-treatment covariate histories and an identical treatment history over a pre-specified time span. By doing this, we ensure that both treated and control units have comparable characteristics not only in a single time period but over an extended period before treatment. This process reduces bias by ensuring the comparison is made between units with similar observable histories.

After constructing this matched control group, we refine the matches further using weighting methods. These weights ensure that the control group resembles the treated group as closely as possible in terms of both covariate history and timing of treatment. The matching process creates a synthetic control group that closely resembles the treated units, providing a more valid basis for causal inference. In order to substantiate our claims, we have used various refinement methods, these are covariate balancing propensity score (CBPS) weighting, Mahalanobis distance matching (MDM) and propensity score weighting (PS weight).

Given the refined matched sets, following Imai et al. (2023), the DiD estimator with matching is expressed as follows:

$$\delta(F,L) = \frac{1}{\sum_{i=1}^{N}\sum_{t=L+1}^{T-F} D_{it}} \sum_{i=1}^{N}\sum_{t=L+1}^{T-F} D_{it}\left[\left(Y_{i,t+F} - Y_{i,t-1}\right) - \sum_{j\in M_{it}} w_{ij}\left(Y_{j,t+F} - Y_{j,t-1}\right)\right], \tag{2}$$

where:

- $\delta(F,L)$ is the estimated ATET for F leads and L lags. We have considered F=4 and L=2 for our analysis.
- $Y_{i,t}$ represents the outcome variable for treated unit i at time t.

- D_{it} is the treatment indicator, which equals 1 if unit i is treated at time t, and 0 otherwise.

- M_{it} denotes the set of control units j matched to the treated unit i at time t, ensuring valid comparisons.

- w_{ij} are the weights assigned to control units j, based on their similarity to treated unit i in terms of covariates.

- $Y_{i,t+F} - Y_{i,t-1}$ measures the observed change in the outcome for treated units between the pre-treatment period $(t-1)$ and the post-treatment period $(t+F)$.

- $\sum_{j \in M_{it}} w_{ij} \left(Y_{j,t+F} - Y_{j,t-1}\right)$ computes the weighted average change in outcomes for matched control units j, which are used as a counterfactual for treated units i.

- j refers to control units that are not treated at time t and are matched to treated unit i. These units provide a baseline comparison for estimating the causal effect of treatment.

The staggered PSM allows for dynamic adjustment of treatment effects and controls for unit and time fixed effects in a more flexible manner than the TWFE estimator.

3.1.3. Robustness of the Staggered PSM Approach

The staggered PSM method offers several advantages over the traditional methods used for the case of multiple . First, it is more robust to model misspecification. As noted above, traditional methods like the TWFE model assume constant treatment effects and can suffer from substantial bias when treatment effects are heterogeneous across time and groups. In contrast, the staggered PSM approach does not rely on strong parametric assumptions and provides a flexible method for accounting for the dynamic nature of treatment.

Moreover, the staggered PSM approach includes intuitive diagnostics, such as covariate balance checks, which allow researchers to evaluate how well the matching procedure balances covariates across treated and control units. These diagnostic tools ensure that any differences in outcomes between treated and control units are attributable to the treatment rather than differences in pretreatment characteristics, improving the credibility of the results.

Additionally, the staggered PSM approach is well suited for panel data with a limited number of time periods, a common scenario in TSCS data. By matching pretreatment covariate histories and treatment histories, this method provides reliable causal estimates even when time variation is limited. It also generates asymptotic confidence intervals with reasonable coverage, reflecting the uncertainty of the estimates in a more accurate manner.

3.2. Data

Our data set includes 59 developing nations observed during the period 1985 to 2019. In addition, we have considered subsample that remove hyperinflation economies.[6] The majority of the data originate from the World Bank's World Development Indicators and the International Monetary Fund's International Financial Statistics. Drawing on earlier research examining the likelihood of adopting IT and its impact on inflation (see Lin and Ye (2007, 2009); de Mendonça and de Guimarães e Souza (2012) ; Samarina et al. (2014)), we select several key variables that could influence a country's decision to adopt IT. These include: (1) the Consumer Price Index (CPI) inflation rate, lagged by one year (CPIG_1); (2) GDP per capita growth rate (GDPPCG) ; (3) growth in broad money (BMG);(4) fiscal balance as a percentage of GDP(FIS_BAL);(5) an exchange rate regime measure (ERR), where higher values (from 1 to 15) indicate greater exchange rate flexibility; (6) trade openness (OPEN), defined as the sum of exports and imports as a percentage of GDP; (7) financial openness (KA_OPEN), based on the Chinn-Ito index of capital account liberalization and (8) central

[6] We have considered hyperinflation countries as mentioned in Samarina et al. (2014).

bank independence index (CBI) based on Jacome and Vazquez (2008).[7] Moreover we calculate the inflation volatility as the standard deviation of a 5-year rolling window of the annual inflation rate, whereas we estimate inflation persistence as AR(1) autoregressive coefficient of inflation using rolling regression of the past five years.[8]

3.2.1. The treatment group and the control group

The treatment group includes 20 IT economies listed in Table 2 while list of 39 control group economies is given in Table 3.

Table 2: IT Developing economies

IT economies	Adoption Date
Albania	2009
Brazil[a]	1999
Chile	2001
Colombia	1999
Dominican Republic	2012
Georgia	2009
Guatemala	2005
Hungary	2001
Indonesia	2006
India	2016
Mexico	2001
Peru[a]	2002
Philippines	2002
Poland[a]	1999
Paraguay	2013
Romania[a]	2005
Russian Federation[a]	2014
Thailand	2000
Turkiye[a]	2006
South Africa	2001

Note: [a]Countries with hyperinflation.

[7]Updated dataset for this is available at the following website https://cbidata.org/.

[8]Similar approach for measuring persistence has been used in Diana and Sidiropoulos (2004); Geronikolaou et al. (2016, 2020).

Table 3: Control Group Developing Economies

Angola[a]	Kazakhstan[a]
Antigua and Barbuda	Kuwait
Azerbaijan[a]	Libya
Bulgaria[a]	Sri Lanka
Bahrain	Morocco
Bahamas, The	North Macedonia
Belarus[a]	Mongolia[a]
Bolivia	Mauritius
Botswana	Malaysia
China	Namibia
Costa Rica	Oman
Dominica[a]	Pakistan
Algeria	Panama
Ecuador[a]	Qatar
Egypt, Arab Rep.	Saudi Arabia
Gabon	Seychelles
Equatorial Guinea	Tunisia
Iran, Islamic Rep.	Ukraine[a]
Jamaica	Uruguay[a]
Jordan	

Note: [a]Countries with hyperinflation.

4. Results

4.1. Results

Table 4 presents the result of the impact of IT on inflation. The full sample results, considering standard PSM suggests a reduction in inflation due to IT across most of the matching methods. For example, the nearest neighbor matching for the one-to-one matching (N = 1) shows an ATET of -2.16 with a significant t-statistic of -2.71 (p-value < 0.1), indicating a statistically significant reduction in inflation. Similarly, the nearest neighbor matching (for N= 3 and N= 5) provides ATET values of -2.24 and -2.53, both with significant t-statistics (-3.38 and -4.14, respectively), confirming that IT has a significant deflationary effect in the full sample. Other methods, including kernel matching and inverse probability weighting, although provide negative estimates, but they are statistically insignificant, indicating caution in drawing firm conclusions.

Further analysis using the staggered PSM approach, which is more robust approach as argued in the methodology section suggests that the adoption of IT has largely led to the decline in inflation. For example, after the adoption of IT, the CBPS method yields an ATET of -2.31 with a p-value of 0.026, showing a statistically significant effect. Moreover, the impact becomes stronger over time, and by t+3, the CBPS and MDM methods show ATETs of -2.98 and -2.50, with p-values of 0.0171 and 0.0404, respectively, confirming that IT leads to a more substantial reduction in inflation over time.

In the sample excluding hyperinflation economies, the results are clearer, with more statistically significant findings across both methods. For instance in the standard PSM approach we find that the coefficients are negative and significant across all the matching methods used, furthermore, using staggered approach suggests the same showing that the reduction in inflation grows over time but it only happens after a few years of adoption, for instance, we find that by t+4, the ATET reaches around -3.8 for all the matching methods for the staggered adoption approach, showing that IT continues to reduce inflation substantially several years after adoption. Both standard PSM and staggered PSM results confirm that IT significantly reduces inflation, with stronger and more consistent effects observed when hyperinflation economies are excluded. The staggered PSM approach shows that the effect deepens over time, particularly around t+3 and t+4, making this a more reliable method for assessing the long-term impact.

Now, we consider the case of the impact of IT on inflation volatility. In the full sample, the standard PSM results for inflation volatility show mixed findings. As shown in Table 5, nearest neighbor matching and inverse probability weighting yields significant reductions in inflation volatility, confirming that IT can reduce volatility in the short term. However, the staggered PSM results in the full sample do not show statistically significant effects on volatility over time. Despite large negative ATET values (around -43.2), the p-values remain above 0.3 across all time periods, indicating no robust dynamic impact on volatility.

In the sample excluding hyperinflation economies, the standard PSM results are more consistent, most of the matching methods show a significant reduction in volatility. However, the staggered PSM results show no significant reduction in volatility over time. Across all time periods, the p-values remain above 0.1, indicating that the dynamic effects of IT on inflation volatility are not statistically significant when hyperinflation economies are excluded. Although standard PSM results suggest a significant reduction in inflation volatility, particularly when hyperinflation economies are excluded, the more reliable staggered PSM approach shows no significant dynamic effect over time. This question, the findings of the paper by Lin and Ye (2009) and Samarina et al. (2014) where they found a significant effect of IT in reducing inflation volatility.

Table 4: Impact of IT on inflation

Impact on inflation considering full sample

Dependent variable:		Standard PSM Approach						
		Kernel Matching	Nearest Neighbor Matching			Inverse Probability Weighting	Radius Matching	
			N=1	N=3	N=5		R= 0.01	R= 0.03
Inflation	ATET	-2.50684528	-2.16162016	-2.24192144	-2.52899551	-4.851842	-2.1925898	-2.68266106
	tstat	-0.14	-2.71	-3.38	-4.14	-1.82	-3.82	-0.14

	Staggered PSM Approach		
	CBPS	MDM	PS weight
t	-2.31	-0.795	-2.2
p-value	0.026	0.324	0.0308
t+1	-2.61	-0.918	-2.39
p-value	0.0923	0.388	0.103
t+2	-2.21	-1.92	-1.9
p-value	0.0527	0.0482	0.111
t+3	-2.98	-2.5	-2.59
p-value	0.0171	0.0404	0.0358
t+4	-2.56	-2.01	-2.18
p-value	0.0772	0.147	0.138

Impact on inflation considering samples after removing hyperinflation economies

Dependent variable:		Standard PSM						
		Kernel Matching	Nearest Neighbor Matching			Inverse Probability Weighting	Radius Matching	
			N=1	N=3	N=5		R= 0.01	R= 0.03
Inflation	ATET	-2.61240945	-3.88730322	-2.61709348	-2.34429976	-2.393134	-2.21220638	-2.75349018
	tstat	-3.13	-3.36	-3.23	-3.12	-2.44	-3.72	-3.14

	Staggered PSM Approach		
	CBPS	MDM	PS weight
t	-1.72	-1.51	-1.67
p-value	0.148	0.202	0.15
t+1	-2.13	-1.98	-2.1
p-value	0.158	0.14	0.175
t+2	-2.15	-2.26	-2.04
p-value	0.0434	0.0501	0.0506
t+3	-2.92	-3.37	-2.82
p-value	0.113	0.0692	0.102
t+4	-3.83	-3.98	-3.8
p-value	0.0426	0.0207	0.0361

Note: CBPS refers to Covariate Balancing Propensity Score, MDM refers to Mahalanobis Distance Matching and PS Weight refers to Propensity Score Weighting

Table 5: Impact of IT on inflation volatility

Impact on inflation volatility considering full sample

		Standard PSM Approach						
		Kernel Matching	Nearest Neighbor Matching			Inverse Probability Weighting	Radius Matching	
Dependent variable:			N=1	N=3	N=5		R= 0.01	R= 0.03
Inflation	ATET	-3.7116	-3.72725	-3.71533	-3.33965	-14.4723	-2.52395	-3.44466
	tstat	-0.2	-4.78	-4.07	-3.95	-1.87	-0.6	-0.17

	Staggered PSM Approach		
	CBPS	MDM	PS weight
t	-43.2	-42.7	-43.2
p-value	0.289	0.303	0.305
t+1	-42.9	-43.1	-43
p-value	0.305	0.311	0.32
t+2	-41.9	-43.2	-42
p-value	0.319	0.311	0.334
t+3	-41.3	-43.2	-41.4
p-value	0.326	0.311	0.342
t+4	-41.4	-43.3	-41.4
p-value	0.324	0.309	0.34

Impact on inflation volatility considering samples after removing hyperinflation economies

		Standard PSM						
		Kernel Matching	Nearest Neighbor Matching			Inverse Probability Weighting	Radius Matching	
Dependent variable:			N=1	N=3	N=5		R= 0.01	R= 0.03
Inflation	ATET	-4.82893	-5.53658	-3.79786	-3.35725	-15.7404	-2.7795	-4.59466
	tstat	-5.43	-3.64	-4.12	-3.66	-1.65	-5.08	-4.92

	Staggered PSM Approach		
	CBPS	MDM	PS weight
t	0.797	0.703	0.787
p-value	0.325	0.334	0.399
t+1	1.8	0.77	1.81
p-value	0.19	0.357	0.234
t+2	3.41	1.11	3.62
p-value	0.169	0.254	0.179
t+3	3.7	1.09	4
p-value	0.226	0.425	0.232
t+4	3.5	0.795	3.86
p-value	0.271	0.573	0.269

Note: CBPS refers to Covariate Balancing Propensity Score, MDM refers to Mahalanobis Distance Matching and PS Weight refers to Propensity Score Weighting

Finally, we consider the impact of IT on inflation persistence as shown in Table 6. In the full sample, the standard PSM results show no significant effect of IT on inflation persistence across various matching methods. The estimates remain small and statistically insignificant, suggesting that IT is unable to significantly alter inflation persistence when hyperinflation economies are included. This is likely due to the fact that inflation in hyperinflation economies is driven by deep-rooted structural issues, making it difficult for monetary policy alone to have a meaningful impact on persistence.

The staggered PSM approach, which is more reliable for assessing the dynamic effects of IT, similarly reveals no strong evidence of a significant reduction in inflation persistence in the early years following adoption. While there are marginal signs of a potential reduction around t+2, the effects are largely insignificant until t+4, where some borderline significance emerges. However, even at this point, the evidence is not strong enough to draw definitive conclusions. This suggests that in hyperinflation environments, IT struggles to reduce persistence, likely because of the extreme nature of inflationary pressures and underlying economic instability.

In the sample excluding hyperinflation economies, the impact of IT on inflation persistence is more promising. Although the standard PSM results also show no significant reductions in persistence in the immediate aftermath of adopting IT, the staggered PSM results indicate that the policy that while the effects becomes negative overtime, however, it is not significant for most of the refinement method (except for the case of PS weight where there is evidence that inflation persistence starts to decline, with marginal significance at 10 percent level by t+4). This suggests that the effect of IT on inflation persistence is largely insignificant, in contrast to the finding of Vega and Winkelried (2005).

Table 6: Impact of IT on inflation persistence

Impact on inflation persistence considering full sample

		Standard PSM Approach						
		Kernel Matching	Nearest Neighbor Matching			Inverse Probability Weighting	Radius Matching	
Dependent variable:			N=1	N=3	N=5		R= 0.01	R= 0.03
Inflation	ATET	-0.0677	-0.09442	-0.09508	-0.08224	-0.02521	-0.04979	-0.05822
	tstat	-1.49	-1.54	-1.88	-1.7	-0.27	-1.03	-1.23

	Staggered PSM Approach		
	CBPS	MDM	PS weight
t	-0.104	-0.0776	-0.107
p-value	0.353	0.47	0.362
t+1	-0.143	-0.133	-0.15
p-value	0.28	0.328	0.25
t+2	-0.143	-0.207	-0.152
p-value	0.133	0.0756	0.0875
t+3	-0.138	-0.158	-0.15
p-value	0.258	0.284	0.203
t+4	-0.19	-0.24	-0.203
p-value	0.18	0.111	0.147

Impact on inflation persistence considering samples after removing hyperinflation economies

		Standard PSM						
		Kernel Matching	Nearest Neighbor Matching			Inverse Probability Weighting	Radius Matching	
Dependent variable:			N=1	N=3	N=5		R= 0.01	R= 0.03
Inflation	ATET	0.038618	0.075604	0.046679	0.028054	-0.01046	0.034979	0.03854
	tstat	0.64	1	0.74	0.45	-0.17	0.61	0.62

	Staggered PSM Approach		
	CBPS	MDM	PS weight
t	0.0475	0.0689	0.0286
p-value	0.797	0.679	0.877
t+1	-0.0349	-0.0332	-0.0877
p-value	0.875	0.869	0.697
t+2	-0.115	-0.0657	-0.121
p-value	0.35	0.665	0.329
t+3	-0.151	-0.102	-0.18
p-value	0.324	0.52	0.233
t+4	-0.317	-0.227	-0.333
p-value	0.1	0.253	0.0937

Note: CBPS refers to Covariate Balancing Propensity Score, MDM refers to Mahalanobis Distance Matching and PS Weight refers to Propensity Score Weighting

4.2. Robustness analysis

To assess the quality of matching in the standard PSM approach, we examine the balancing properties post-matching. Table A1 and Table A2 indicate that after matching, the mean differences between treatment and control groups are statistically insignificant in both samples, suggesting that effective balance has been achieved. Building on the frameworks by Imai et al. (2023) and Franchino (2024), we further assess covariance balance through a three-refinement method in the staggered PSM approach. Figure B1 to Figure B6 illustrate that balancing improves after refinement for inflation, inflation persistence, and inflation volatility, with points below the 45-degree line indicating reductions in standardized mean differences. This pattern suggests that the mean difference post-refinement is lower than the initial difference, underscoring enhanced balance. As illustrated in Figure B1, the CBPS weight refinement method places the majority of points below the 45-degree line, indicating an improvement in balance post-refinement. Moreover, we see that CBPS weighting refinement produces the best improvement in covariance balance for the case of all EMEs while MDM for the case of EMEs without hyperinflation.

Further following Franchino (2024), Hope and Limberg (2022) and Berman and Israeli (2022), we also consider the improvement of covariance balance due to matching over the two years prior to the administration of the treatment at t-1, it helps us evaluate the appropriateness of the parallel trend assumption used to justify the proposed DiD estimator, as shown in Figure B7 to Figure B12, we find that the standardized mean differences for the lagged, represented by the black lines, we see improved balancing with respect to before matching and it stay relatively constant over the pre-treatment period being largely close to zero (indicated by dotted line), lending support for the appropriateness of the parallel trend assumption. For instance, in Figure B7 for the case MDM, the minimal deviation of the black line from the zero line suggests that the differences are negligible and statistically insignificant. This supports the notion that matching has effectively achieved balance and that the parallel trends assumption remains valid for the pre-treatment period. .

5. Conclusion

In conclusion, this study finds that IT has a clear impact on reducing inflation levels in EMEs over time, especially when hyperinflationary cases are excluded. Using both standard and staggered PSM approaches, we observe that while the standard PSM method indicates significant effects across inflation, volatility, and persistence, these results may be biased due to the failure to account for staggered IT adoption. By applying the staggered PSM method, we gain a more accurate understanding of IT's effects, demonstrating that IT primarily reduces inflation levels in the long run yet has a limited impact on inflation volatility and persistence. This suggests that IT's effectiveness in stabilizing inflation dynamics may be more modest and context-dependent than initially thought, reinforcing the importance of country-specific economic conditions and institutional stability.

From a policy standpoint, these findings stress the need for carefully tailored IT frameworks in EMEs. Although IT can be an effective tool for reducing inflation, the results indicate that additional measures may be required to address inflation volatility and persistence, particularly in diverse economic settings where IT alone may not suffice. Policymakers should consider complementary structural reforms and improvements to institutional quality to enhance IT's effectiveness. The study's application of staggered PSM highlights its importance in capturing long-term, dynamic policy effects, underscoring the need for nuanced evaluation techniques to assess IT's role in emerging markets.

References

Angrist, J. D. and Pischke, J.-S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Ardakani, O. M., Kishor, N. K., and Song, S. (2018). Re-evaluating the effectiveness of inflation targeting. Journal of Economic Dynamics and Control, 90:76–97.

Arsić, M., Mladenović, Z., and Nojković, A. (2022). Macroeconomic performance of inflation targeting in European and Asian emerging economies. Journal of Policy Modeling, 44(3):675–700.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? Journal of Financial Economics, 144(2):370–395.

Ball, L. and Sheridan, N. (2004). 6. Does Inflation Targeting Matter?, pages 249–282. University of Chicago Press, Chicago.

Ball, L. M. (2010). The Performance of Alternative Monetary Regimes. Technical report, National Bureau of Economic Research, Inc.

Batini, N. and Laxton, D. (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.

Berman, R. and Israeli, A. (2022). The value of descriptive analytics: Evidence from online retailers. Marketing Science, 41(6):1074–1096.

Brito, R. D. and Bystedt, B. (2010). Inflation targeting in emerging economies: Panel evidence. Journal of Development Economics, 91(2):198–210.

de Mendonça, H. F. and de Guimarães e Souza, G. J. (2012). Is inflation targeting a good remedy to control inflation? Journal of Development Economics, 98(2):178–191.

Diana, G. and Sidiropoulos, M. (2004). Central bank independence, speed of disinflation and the sacrifice ratio. Open Economies Review, 15:385–402.

Fraga, A., Goldfajn, I., and Minella, A. (2003). Inflation Targeting in Emerging Market Economies. NBER Macroeconomics Annual, 18:365–400.

Franchino, F. (2024). International oversight of fiscal discipline. European Journal of Political Research, 63(1):281–302.

Gemayel, M. E. R., Jahan, M. S., and Born, M. A. (2011). What can low-income countries expect from adopting inflation targeting? International Monetary Fund.

Geronikolaou, G., Spyromitros, E., and Tsintzos, P. (2016). Inflation persistence: The path of labor market structural reforms. Economic Modelling, 58:317–322.

Geronikolaou, G., Spyromitros, E., and Tsintzos, P. (2020). Progressive taxation and human capital as determinants of inflation persistence. Economic Modelling, 88:82–97.

Gonçalves, C. E. S. and Salles, J. M. (2008). Inflation targeting in emerging economies: What do the data say? Journal of Development Economics, 85(1-2):312–318.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. Journal of Econometrics, 225(2):254–277.

Ho, D. E., Imai, K., King, G., and Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Political Analysis, 15(3):199–236.

Hope, D. and Limberg, J. (2022). The economic consequences of major tax cuts for the rich. Socio-Economic Review, 20(2):539–559.

Imai, K. and Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? American Journal of Political Science, 63(2):467–490.

Imai, K., Kim, I. S., and Wang, E. H. (2023). Matching methods for causal inference with time-series cross-sectional data. American Journal of Political Science, 67(3):587–605.

Levin, A. T., Natalucci, F. M., Piger, J. M., et al. (2004). The macroeconomic effects of inflation targeting. Review-Federal Reserve Bank of Saint Louis, 86(4):51–8.

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

Lin, S. and Ye, H. (2009). Does inflation targeting make a difference in developing countries? Journal of Development Economics, 89(1):118–123.

Mishkin, F. S. and Schmidt-Hebbel, K. (2007). Does inflation targeting make a difference? Working Paper 12876, National Bureau of Economic Research.

Neumann, M. J. and von Hagen, J. (2002). Does inflation targeting matter? Federal Reserve Bank of St. Louis Review, 84(Jul):127–148.

Rubin, D. B. (2006). Matched sampling for causal effects. Cambridge University Press.

Samarina, A., Terpstra, M., and De Haan, J. (2014). Inflation targeting and inflation performance: a comparative analysis. Applied Economics, 46(1):41–56.

Stojanovikj, M. and Petrevski, G. (2021). Macroeconomic effects of inflation targeting in emerging market economies. Empirical Economics, 61(5):2539–2585.

Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. Statistical Science, 25(1):1–21.

Thornton, J. (2016). Inflation targeting in developing countries revisited. Finance Research Letters, 16:145–153.

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

Walsh, C. E. (2009). Inflation targeting: what have we learned? International Finance, 12(2):195–233.

Willard, L. B. (2012). Does inflation targeting matter? A reassessment. Applied Economics, 44(17):2231–2244.

Appendices

Appendix A

We assess post-matching balancing properties for standard PSM approach in Tables A1 and A2. Results indicate that after matching, mean differences between the treatment and control groups are statistically insignificant in both samples, signaling that matching has achieved effective balance. This balance ensures that observed differences are minimized, improving the comparability between groups and enhancing the robustness of the causal estimates obtained.

Table A1: Test of the balancing properties for all EMEs for the case of standard PSM approach

Variable	Mean		t test	
	Treated	Control	t stat	p-value
CPIG_1	4.5545	5.1283	-0.46	0.646
GDPPCG	2.8627	2.8253	0.1	0.921
BMG	11.203	10.962	0.21	0.837
FIS_BAL	-2.3031	-2.1845	-0.33	0.742
ERR	10.211	10.45	-1.13	0.26
OPEN	68.677	72.909	-1.56	0.119
CBI	0.65509	0.65069	0.27	0.787
KA_OPEN	0.5825	0.59289	-0.4	0.689

Table A2: Test of the balancing properties for EMEs without hyperinflation economies for the case of standard PSM approach

Variable	Mean		t test	
	Treated	Control	t stat	p-value
CPIG_1	4.4442	4.9905	-1.52	0.13
GDPPCG	2.6439	2.7003	-0.13	0.9
BMG	10.91	11.048	-0.15	0.883
FIS_BAL	-1.933	-1.84	-0.2	0.84
ERR	10.283	10.391	-0.45	0.653
OPEN	75.782	79.097	-0.84	0.399
CBI	0.58946	0.60669	-0.77	0.441
KA_OPEN	0.56577	0.57339	-0.25	0.806

Appendix B

This section looks at covariate balancing for the case of staggered PSM approach. Figures B1 to B6 demonstrate improved balance after applying refinement techniques, specifically for inflation, its persistence, and its volatility. The points falling below the 45-degree line indicate that the standardized mean differences are smaller post-refinement, signaling a better match between the treatment and control groups. This improved covariance balance reflects that the refinement process effectively reduces initial disparities.

To assess the parallel trend assumption underlying the Difference-in-Differences (DiD) estimator, we also examine the improvement in covariance balance over the two years preceding treatment, specifically at $t-1$. This evaluation helps to verify that the treated and control groups followed similar trends prior to the intervention. Figures B7 to B12 illustrate this balance for lagged covariates, shown as black lines, with results indicating improved balance following matching. Additionally, the standardized mean differences remain relatively stable and close to zero throughout the pre-treatment period, which supports the validity of the parallel trend assumption necessary for the DiD approach. This stability suggests that matched groups were comparable in their pre-treatment trajectories, thereby strengthening the reliability of the DiD results.

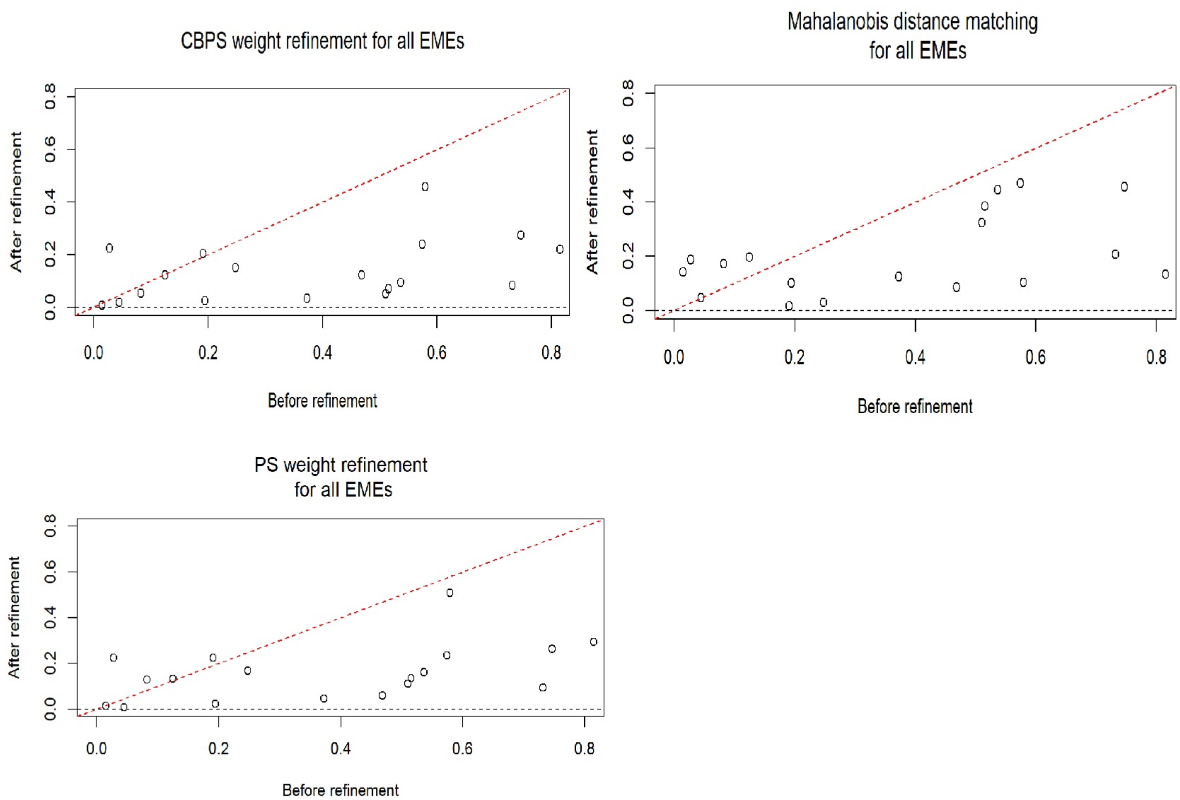

Figure B1: Improved Covariate Balance for inflation due to the Refinement of Matched Sets for all EMEs

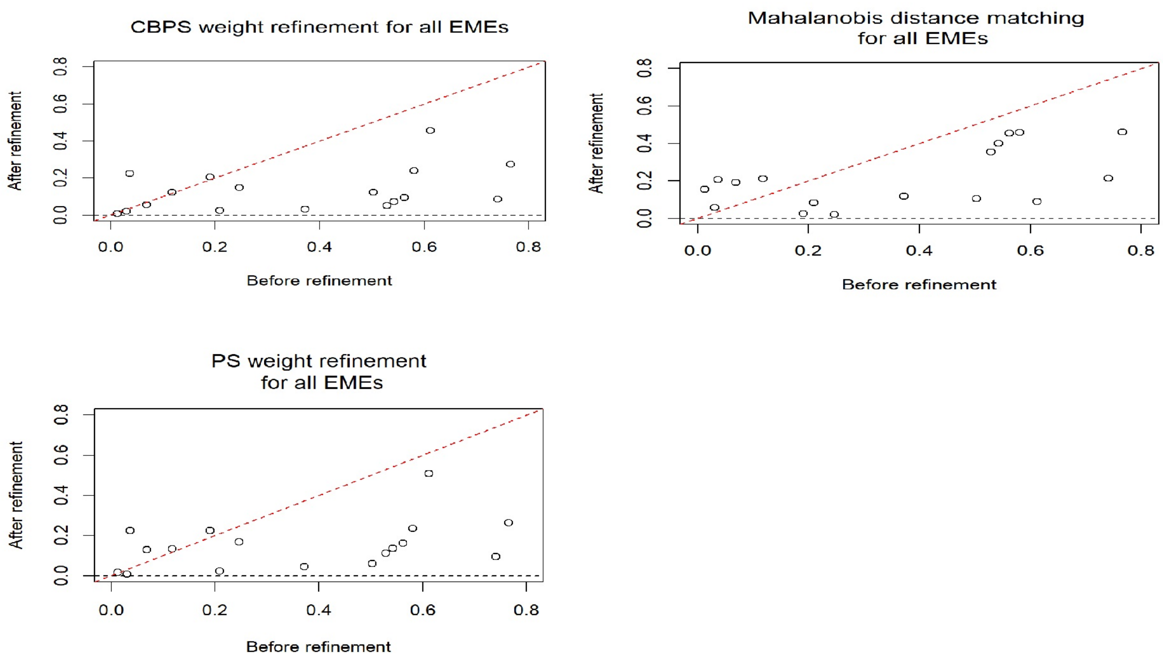

Figure B2: Improved Covariate Balance for inflation persistence due to the Refinement of Matched Sets for all EMEs

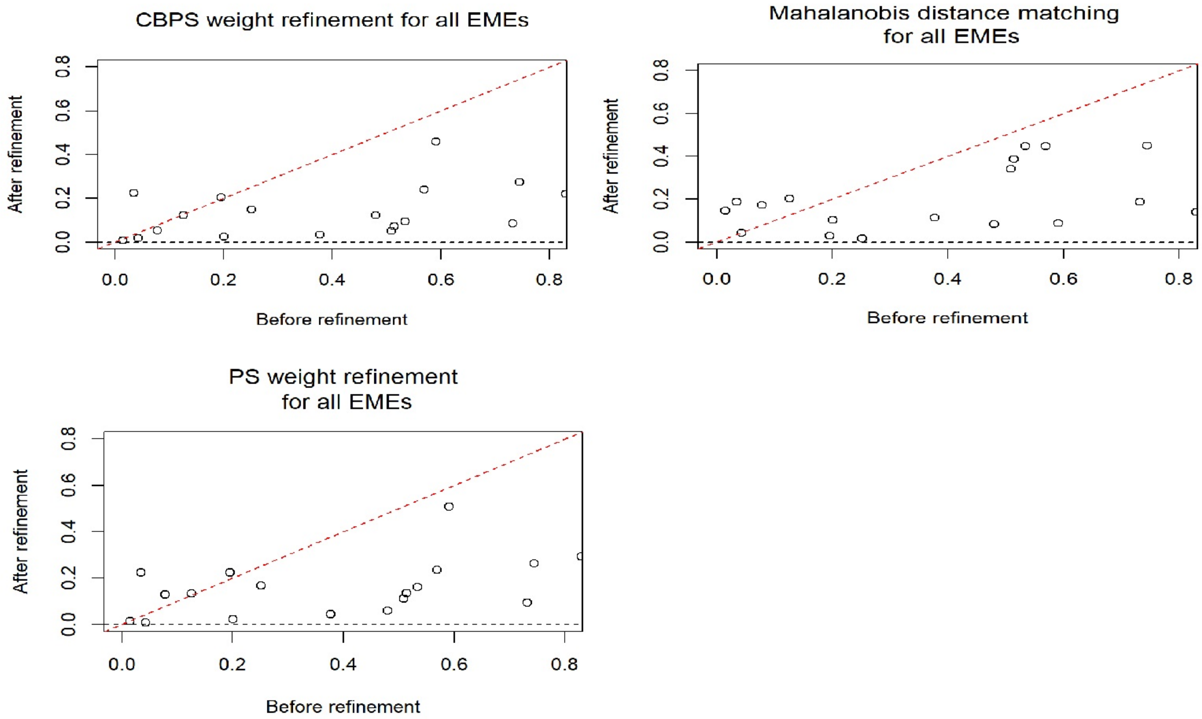

Figure B3: Improved Covariate Balance for inflation volatility due to the Refinement of Matched Sets for all EMEs

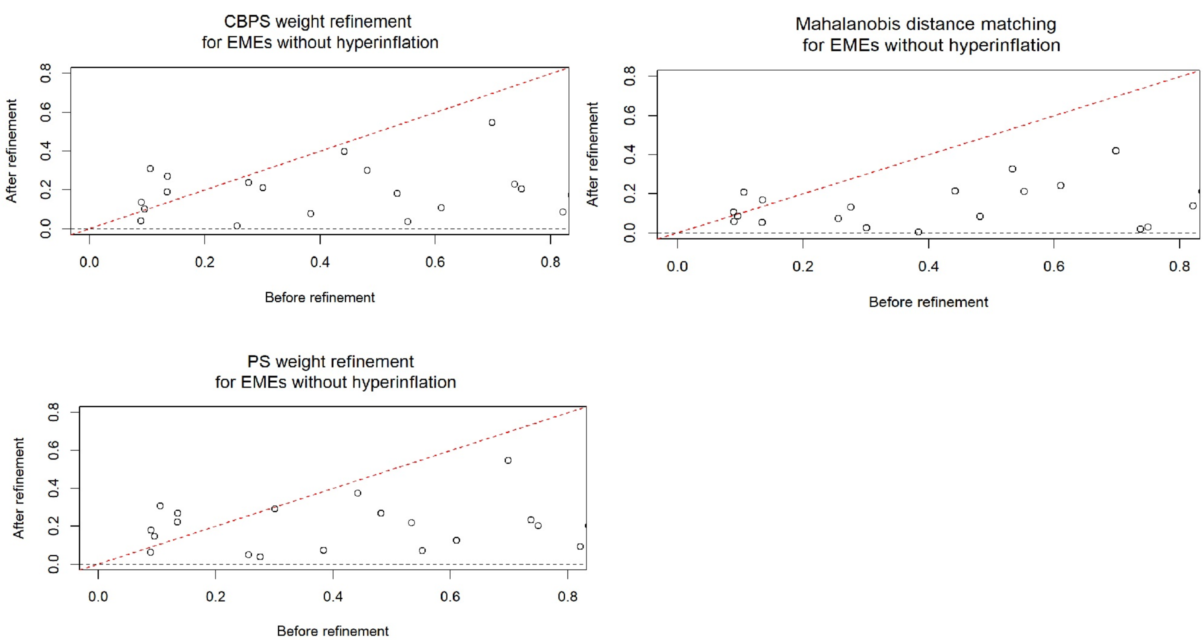

Figure B4: Improved Covariate Balance for inflation due to the Refinement of Matched Sets for EMEs without hyperinflation economies

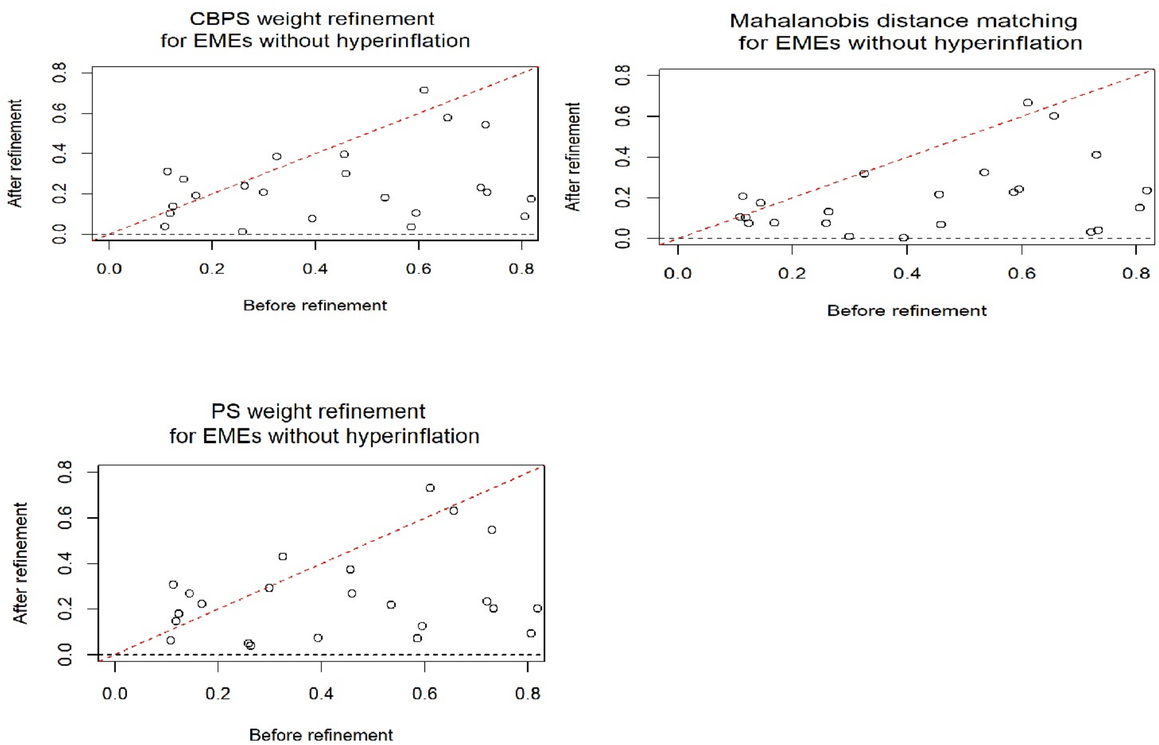

Figure B5: Improved Covariate Balance for inflation persistence due to the Refinement of Matched Sets for EMEs without hyperinflation economies

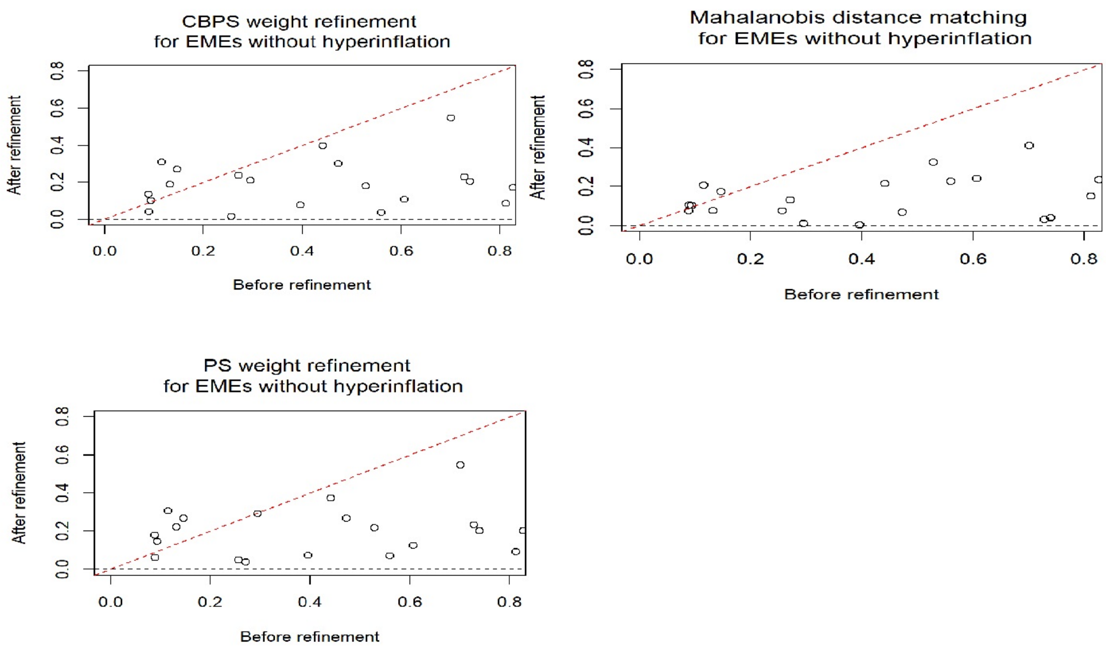

Figure B6: Improved Covariate Balance for inflation volatility due to the Refinement of Matched Sets for EMEs without hyperinflation economies

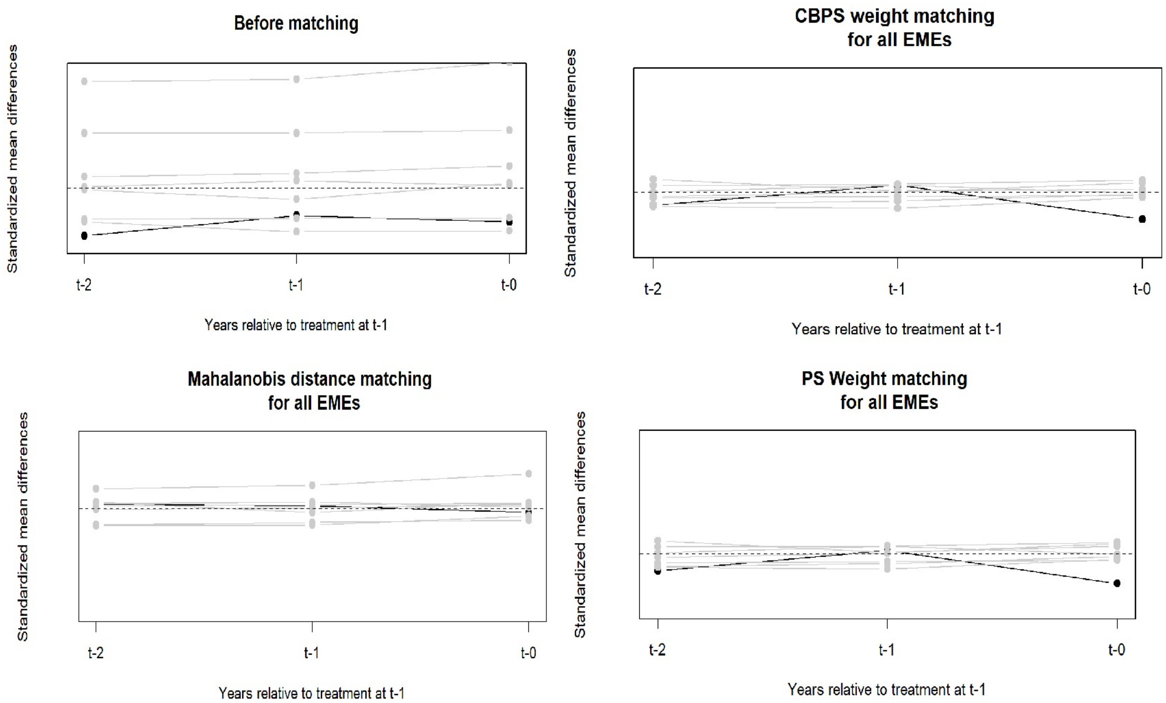

Figure B7: Improved Covariance Balance for inflation due to Matching over the Pre-treatment Period for all EMEs

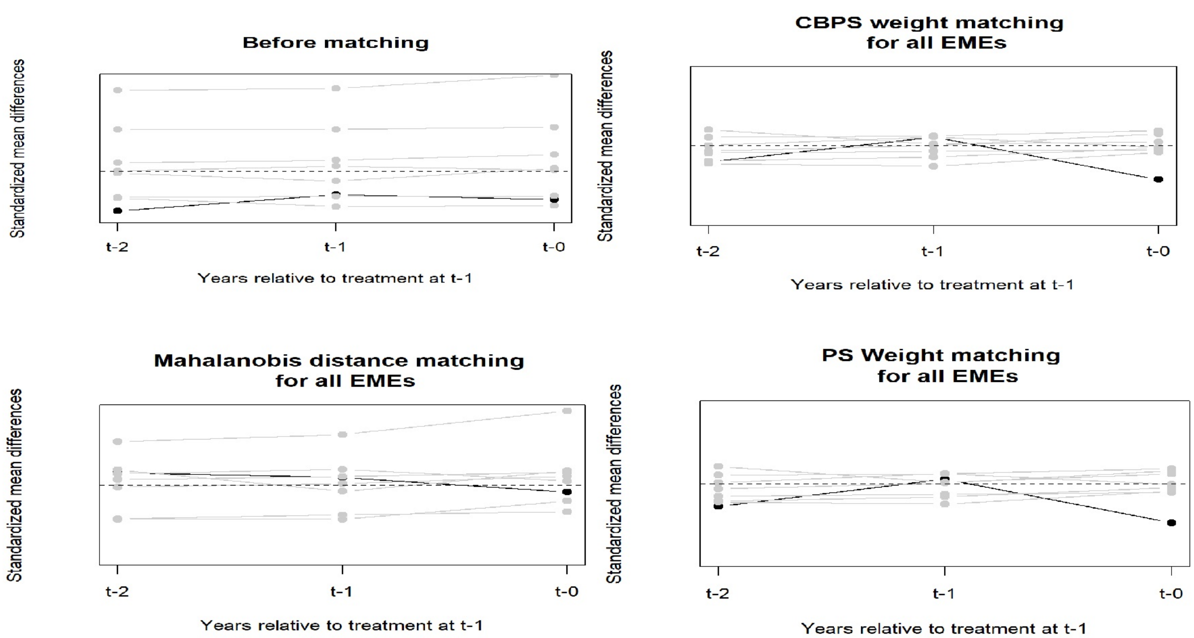

Figure B8: Improved Covariance Balance for inflation persistence due to Matching over the Pre-treatment Period for all EMEs

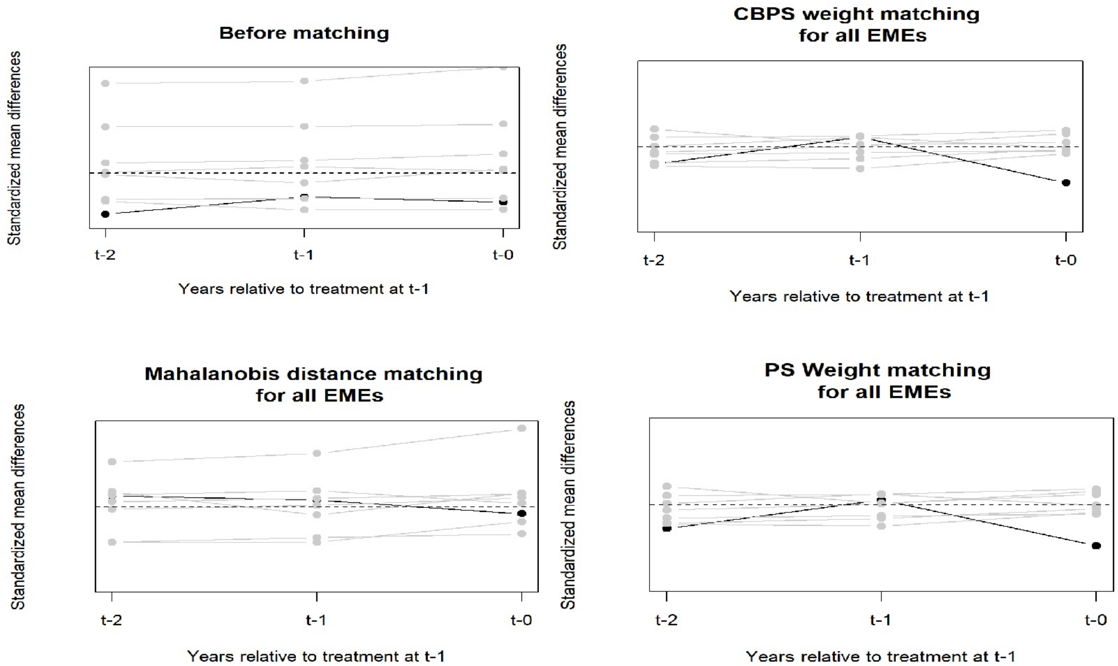

Figure B9: Improved Covariance Balance for inflation volatility due to Matching over the Pre-treatment Period for all EMEs

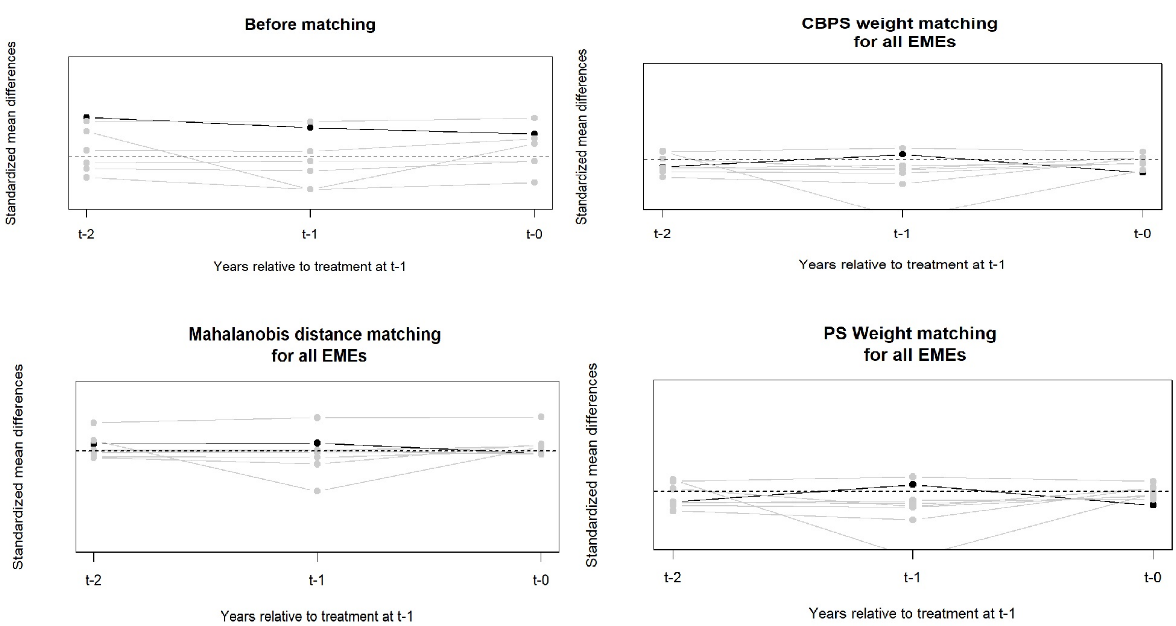

Figure B10: Improved Covariance Balance for inflation due to Matching over the Pre-treatment Period for EMEs without hyperinflation economies

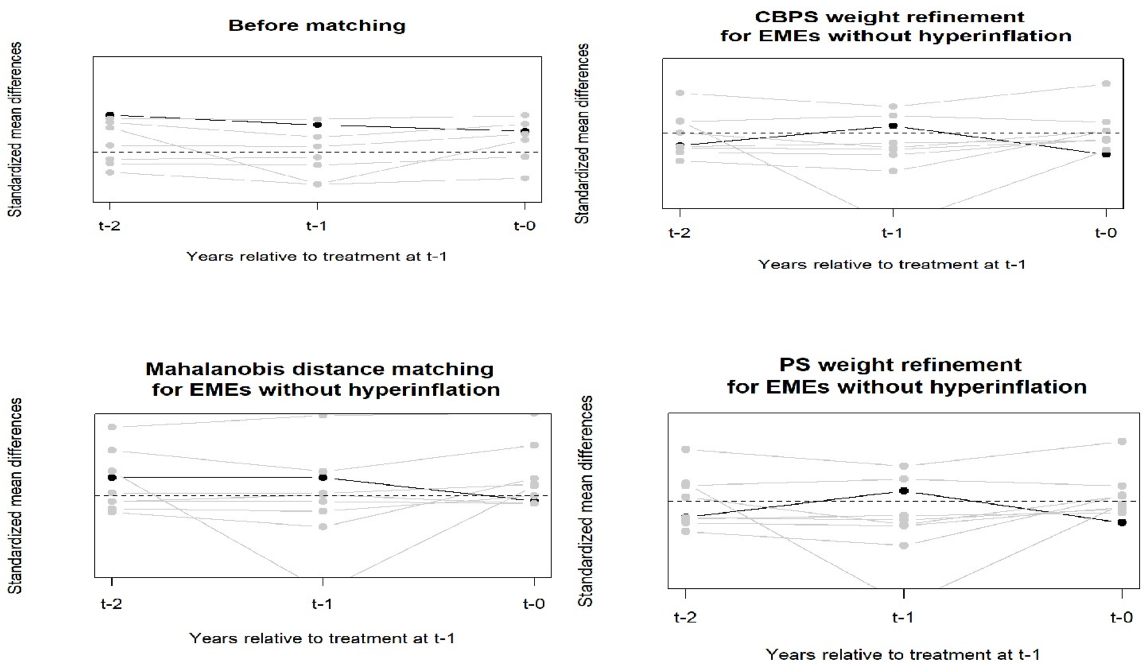

Figure B11: Improved Covariance Balance for inflation persistence due to Matching over the Pre-treatment Period for EMEs without hyperinflation economies

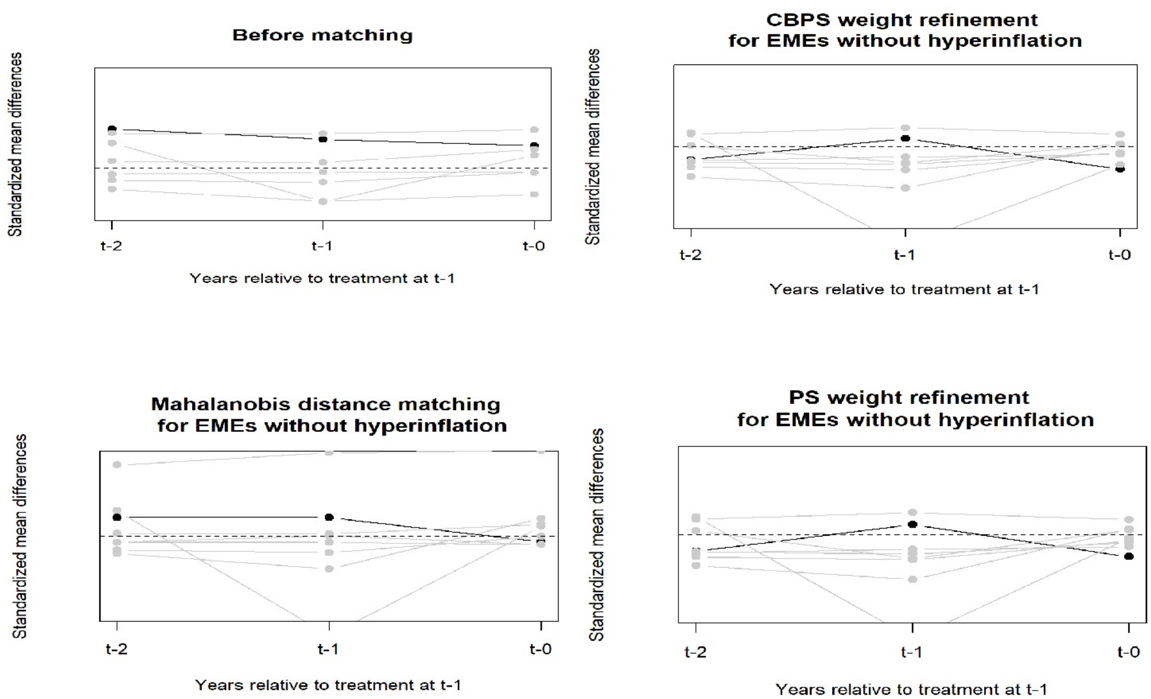

Figure B12: Improved Covariance Balance for inflation volatility due to Matching over the Pre-treatment Period for EMEs without hyperinflation economies