Who's Right in the Inflation Targeting Debate in Emerging Markets?

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Abstract

As the inflation targeting (IT) policy spread globally over the last three decades, it produced a large literature examining its effects. The results vary dramatically, with existing estimates of IT's impact on average inflation in emerging economies ranging from -11% to +1%. This paper investigates the sources of this variation and identifies the most reliable estimates. Applying common econometric techniques to 42 emerging markets (1985-2019), I show how methodological choices drive these conflicting conclusions. Monte Carlo simulations evaluate estimation methods in terms of both bias and precision, revealing systematic identification challenges coming from an endogenous choice of IT adoption and mean-reverting inflation dynamics. Importantly, the estimators produce consistently ordered results: two-way fixed effects shows the largest negative impact, serving as the upper bound of IT's inflation-reducing effect, and system GMM yields the smallest effect, providing a lower bound - a pattern that appears in simulations, empirical applications, and previous literature. Under the most credible methods, I find that IT reduced average inflation in emerging markets by approximately 1.2-1.5 percentage points. These results provide a more accurate IT assessment and contribute to the toolkit for evaluating monetary policy frameworks.

Keywords: Inflation targeting, Emerging market economies, Monetary policy, Differences-in-Differences, Propensity score matching, System GMM, Two-way fixed effects, Monte Carlo simulations

JEL No.: C15, E31, E42, E52, E58

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1 Introduction

Introduced in the early 1990s, inflation targeting (IT) quickly became the centerpiece of monetary policy for central banks around the world. The explicit IT regime requires an announced numerical inflation target and a clear commitment and emphasis from the central bank to achieve this objective.[1] Even more than 30 years after its introduction, the IT framework continues to hold a leading position for monetary policy recommendations and is popular among academics and policymakers alike.

Several prominent economists have been among the early supporters of this strategy. For instance, Mishkin (1999) stated that IT countries have "significantly reduced [...] inflation [...] beyond that which would likely have occurred in the absence of inflation targets". He also highlighted that IT reduces "the likelihood that the central bank will fall into the time-inconsistency trap." Similarly, Svensson (1997) claimed that "the central bank's inflation forecast is indeed an ideal intermediate target". Additionally, Bernanke et al. (1999) concluded that "inflation targeting is a highly promising strategy for monetary policy, and [...] it will become the standard approach as more and more central banks and governments come to appreciate its usefulness." The International Monetary Fund (IMF) also includes IT as part of its standard advice and regards it as "becoming the monetary policy framework of choice in a growing number of emerging market and developing countries" (IMF, 2006).

Reflecting the popularity of the framework, IT rapidly expanded from advanced economies to emerging markets. According to the 2020 IMF report on Exchange Arrangements and Exchange Restrictions (AREAER, 2020), a total of 43 countries have formally adopted the inflation targeting regime, with the majority (two-thirds) being emerging markets.[2,3] Figure 1 shows the number of inflation targeting emerging markets each year. Initially, only 6 emerging economies were explicitly following this framework in 2000. However, this number has increased to 29 by April 2020, and the trend continues, with

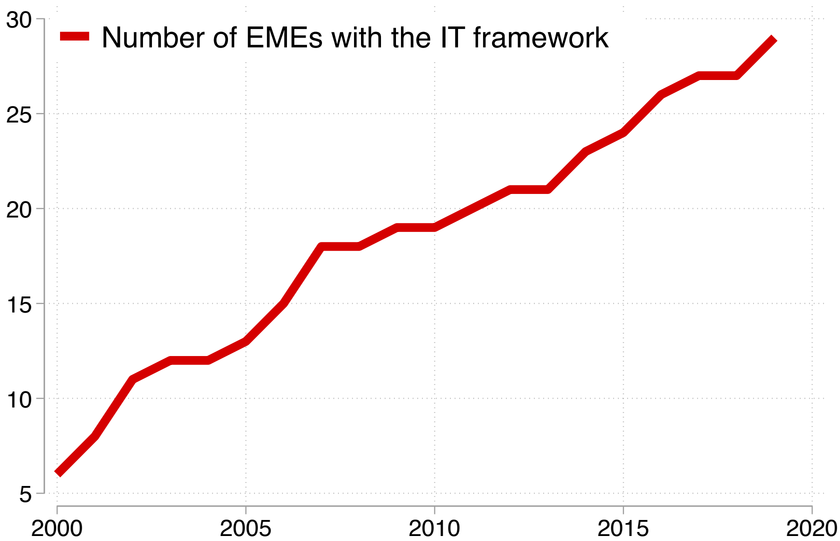
[1] The most commonly used formal definition of inflation targeting by Mishkin (2000) outlines the following conditions for a country to be identified as an inflation targeter: publicly declared numerical targets for inflation; explicit commitment to price stability as the primary goal; a strategy that considers factors beyond monetary aggregates or exchange rates when adjusting policy instruments; enhanced transparency and communication; and accountability mechanisms for meeting targets.

[2] Among these 43 targeting countries, there are 11 advanced economies (AEs), 29 emerging market economies (EMEs) and 3 low-income developing countries (LIDCs). Country classifications follow IMF's definition of advanced economies, emerging market economies and low-income developing countries. AEs: Australia, Canada, Czech Republic, Iceland, Israel, Japan, Korea, New Zealand, Norway, Sweden, and United Kingdom. LIDCs: Ghana, Moldova, and Uganda.

[3] These countries are considered "explicit inflation targeters" because they have formally committed to this framework. According to the IMF report, "the classification system is based on the members' actual, de facto arrangements as identified by the IMF staff, which may differ from their officially announced, de jure arrangements" (AREAER, 2020).

several countries either having adopted IT since then or currently undergoing the transition to this regime.[4] Amidst the backdrop of the COVID-19 pandemic and the resulting inflationary pressures, discussions on the efficacy of various monetary policy strategies have resurfaced, prompting renewed scrutiny of existing frameworks (Duncan et al., 2022).

Figure 1: Evolution of Monetary Policy Frameworks in EMEs



Note. Classifications are obtained from the IMF's Annual Reports on Exchange Arrangements and Exchange Restrictions. All EMEs based on IMF country groupings are considered.

Considering the widespread adoption of IT, it is not surprising that a substantial body of literature has emerged evaluating its effectiveness on macroeconomic performance. This extensive literature examines effects on many aspects of performance, but much of the focus has been on the average level of inflation. The majority of studies evaluating IT have found a statistically significant negative effect on inflation. There are, however, a number of studies that claim otherwise and the quantitative magnitudes of the effects are quite different. Despite the prevalence of studies supporting IT, there are some concerns about a potential publication bias. Some economists, such as Balima et al. (2020), have suggested that this bias tends to favor the results that indicate lower inflation volatility and statistically significant findings.[5]

In this paper, I will explore the significant differences in the findings of previous studies. While multiple factors can influence these results, my analysis will concentrate on a key dis-

[4] Some countries that adopted this policy since 2020 include Uzbekistan (LIDC) and Kenya (LIDC).

[5] The authors conclude that there is some evidence for publication bias. However, they also find that after accounting for it, IT is still associated with lower inflation levels.

tinction: the econometric techniques implemented in the studies. The literature recognizes the identification problem originating from IT endogeneity and has applied various methods to address it. I study the properties of the estimators used and argue that the substantial discrepancies observed in the literature can be linked with econometric differences. Specifically, I undertake the following research questions: (1) What explains the considerable variation in estimates regarding the impact of inflation targeting on the average level of inflation? (2) Which of these estimates are likely to be credible? The answers to these questions rely on the widely different estimation methods used in these earlier studies: differences-in-differences, two-way fixed effects (TWFE), system generalized method of moments (system GMM) and propensity score matching (PSM). Each of these methods has been used by researchers as ways of dealing with the endogeneity of IT adoption.

I begin the paper by reviewing past literature on inflation targeting in emerging markets in section 2. This review highlights the wide range of estimates for IT's effectiveness and sets the stage for the subsequent analysis. Despite the widespread adoption of IT and the well-defined theoretical predictions about its role as the most optimal way of conducting monetary policy, the empirical landscape remains inconclusive. I also describe the broader strands of literature to which this paper belongs.

In section 3, I explain the basic identification problem underlying this research. The data indicates that the concept of IT adoption endogeneity might play a crucial role in evaluating the effectiveness of inflation targeting in reducing inflation in emerging market economies, emphasizing the necessity to adequately control for the possible bias within the empirical methodologies used to assess the causal effects of IT. Specifically, we observe that the dissatisfaction with the past inflation performance increases the likelihood that a country will adopt inflation targeting. Furthermore, since a high inflation performance in the pre-IT period is partly driven by transitory factors, it is also likely that inflation falls in the subsequent periods regardless of adopting the IT framework. Consequently, these findings serve as a confirmation of the possibility of the bias in econometric setups being at play in previous findings. Ball and Sheridan (2005) introduced the concept of regression to the mean in this context, which is important for understanding the challenges in estimating causal effects. Furthermore, the period when IT became popular happened during a time when all countries, whether using IT or not, saw a decline in inflation rates.[6] This makes it difficult to determine if the success of IT countries was actually due to their monetary policy framework or simply reflected broader factors affecting inflation worldwide.

Next, I evaluate the above-described potential bias in commonly used estimators within the IT literature. To do so, I conduct an econometric analysis using Monte Carlo simulations.

[6] See figure 5 in Appendix E.

These simulations are based on inflation processes calibrated to data from emerging market economies. In particular, I examine the relative performance of proposed controls for the identification problem within the empirical methodologies in terms of bias and precision in section 4. Under the main assumptions, I show that as expected, the Ball and Sheridan (2005) method provides an unbiased estimate but relatively low precision. At the same time, TWFE exhibits downward bias, but provides the lowest root mean squared error (RMSE) due to higher precision. Furthermore, system GMM and PSM have an upward bias. This finding suggests the relative ordering of these estimators, which is the key message of the paper.

In section 5, I ask whether the insights from simulations about the role played by the econometric methodologies help uncover the true effect of inflation targeting when applied to real-world data. To isolate the effect of econometric procedures, I apply four different estimation techniques to a carefully selected sample of 42 emerging markets from 1985Q1 to 2019Q4. This common sample approach helps control for other potential sources of variation across studies. Firstly, I provide a supporting evidence within the data for the importance of IT adoption and subsequent mean reversion within my set of countries. Simulation exercises in section 4 are based on these two important assumptions. Applying these methods to my sample, I find that the estimated effect of IT on average inflation ranges from -2.45% using two-way fixed effects to -0.12% with system GMM. These results align perfectly with the insights predicted by the simulated data. Additionally, I conclude that the true effect of IT on average inflation lies around -1.2/-1.5%. This meaningful effect differs from previous estimates that under- or overestimated IT's impact due to methodological issues.

Section 6 returns to the previous studies to check whether my intuition from the simulations and empirics help explain the large heterogeneity within my identified set of papers. I discover two main takeaways. First, when I sort these studies based on the econometric methodology, the ranking of average effect matches with the expected ordering. Although within each method, there is still a large variation of the resulting estimates. Second, my estimated IT effect is consistently smaller than the average within the previous literature under each of the methods. To further provide intuition on different estimates, I also analyze the role of different definitions of IT adoption dates and the targeting countries under consideration. I show that different adoption dates are unlikely to play a major role for the substantial variation in earlier studies. On the contrary, I demonstrate that the earliest wave of emerging market inflation adopters seem to show a different effect in lowering inflation from latest adopter group, when the control countries are kept fixed. While large standard errors prevent me from concluding which group benefited more, this finding suggests that differences between inflation targeting country groups also contribute to conflicting estimates in previous studies.

2 IT Effects: A Wide Range of Estimates

This paper contributes to the extensive literature analyzing the effectiveness of inflation targeting on macroeconomic performance, with a focus on emerging markets where most studies conclude it reduced inflation rates, albeit with substantial disagreement on the magnitude of this effect.

Although some differences of opinion exist regarding the impact of inflation targeting on advanced economies, the literature has largely converged on the view that leading studies indicate negligible effects, suggesting that its impact on the average level of inflation is close to zero (Ball and Sheridan, 2005; Lin and Ye, 2007; Walsh, 2009; Willard, 2012). Among the explanations proposed is the hypothesis that these advanced economies did not experience significant inflation issues prior to the adoption of the IT framework. Moreover, discussions have suggested that advanced economies that are not explicitly classified as inflation targeters may still conduct their monetary policy in some ways similarly to those that do. Hence, it is possible that inflation targeting did not affect advanced economies, but was beneficial to emerging markets. In addition, the credibility of central banks in advanced economies is significantly higher than that of emerging markets. As a result, emerging markets may benefit more from a more structured monetary policy regime, such as inflation targeting.

Many studies have attempted to measure the impact of IT on a number of performance indicators. These indicators include inflation volatility, inflation expectations, output growth, exchange rate stability, interest rates and financial market performance. The average level of inflation is the most common focus, although it has generated considerable disagreement among researchers. I have surveyed this literature and identified 16 studies.[7] Figure 2 provides a brief summary of selected pivotal studies and ranks them based on the estimated magnitude. Results are presented in a way that depicts the estimated effect on average inflation in the main specification, excluding robustness checks. If there are multiple main specifications, the coefficients are averaged.[8] These coefficients are based exclusively on the sample of emerging market economies. Overall, the figure shows a single estimated effect per paper and per econometric approach.

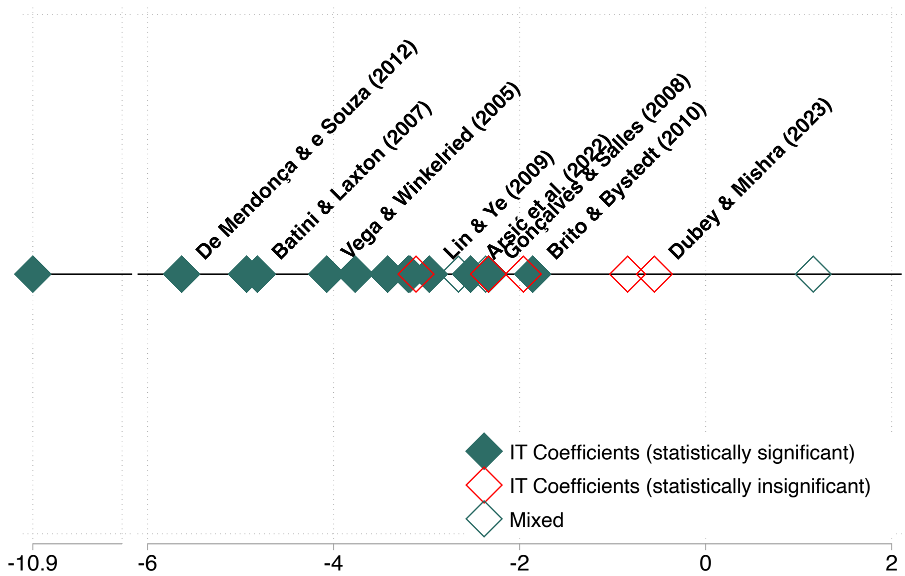
Figure 2 illustrates that a vast majority of studies report a reduction in average

[7] See appendix B for details regarding how the studies were selected.

[8] This explains why some studies are classified as having ”mixed” statistical significance on figure 2. When a coefficient is derived as an average from several coefficients in the main specification, some of which are statistically significant while others are not, it is labeled ”mixed”.

inflation in developing countries, which is often statistically significant (De Mendonça and Guimarães e Souza, 2012; Lin and Ye, 2009; Gonçalves and Salles, 2008; Batini and Laxton, 2007; Brito and Bystedt, 2010; Vega and Winkelried, 2005).[9] However, there are instances in which the effects are insignificant or even reversed (Ardakani et al., 2018). As a result, findings vary widely, with coefficients ranging from close to 1% to as low as -10.9%. Consequently, there is an obvious lack of consensus on how substantial these effects are.

Figure 2: Estimated effects from earlier studies



Note. The figure displays the primary coefficient estimate (or the mean where multiple such estimates exist) for each method and paper in terms of average inflation levels. Filled emerald diamonds indicate estimates that are statistically significant at the 10% significance level, while unfilled red diamonds represent statistically insignificant estimates. Unfilled emerald diamonds denote mixed statistical significance, where the reported estimate is an average of multiple coefficients, some significant and others not. Note that the x-axis includes a gap between -6 and -10.9 to enhance visibility.

The presented estimates reveal considerable variability, even when taken at face value. However, interestingly, there are some reasons to even doubt them. Specifically, some concerns have been raised about the possibility of publication bias in this literature that might warrant attention. Publication bias occurs when the publication of research results depends on their strength and direction of the results. This is a widespread phenomenon in academic publishing, affecting not only literature on IT but any economic research and beyond. Such bias can skew the representation of scientific evidence (Stanley, 2005; Thornton and Lee, 2000; Hedges, 1992). Balima et al. (2020) examined this issue within the IT literature

[9] Statistical significance at the 10% significance level.

specifically, demonstrating that results indicating lower inflation volatility and higher real GDP growth are often favored by researchers. Additionally, coefficients demonstrating statistically significant macroeconomic effects are published more frequently. As a result, the dominant narrative surrounding IT might not even fully be portraying the complexities of its effects on economic performance. In summary, there are some grounds to scrutinize many of these studies, alongside a large disagreements about IT effects.

Although numerous factors may shape the outcomes of studies on inflation targeting, my focus is on a critical aspect, namely the econometric methods these studies employ. The literature acknowledges the identification challenge, stemming from the likely non-random adoption of inflation targeting, or so-called endogeneity, and has applied various strategies to address this issue. I examine the bias and precision characteristics of the estimators used, proposing that notable differences in findings can be attributed to variations in methodological approaches. Although it should be noted that additional differences still play a role and need further exploration in future research.

2.1 Broader Literature Context

The wide range of estimates for inflation targeting effects discussed in this section illustrates the broader challenges in economic research and policy evaluation. There are several strands of literature that are relevant to this discussion beyond the specific context of inflation targeting.

First of all, this paper is related to the large literature on optimal monetary policy design, specifically, the debate between rules and discretion in policymaking (Kydland and Prescott, 1977; Taylor, 1993; Frankel, 2010). Literature in this field has evolved from the discussion of strict rules versus pure discretion to the examination of intermediate approaches, such as inflation targeting. As a result of the COVID-19 pandemic, this area has received additional interest, as researchers examine the effectiveness and flexibility of various monetary frameworks under unprecedented conditions (Fratzscher et al., 2020; English et al., 2021). The systematic comparison of estimation approaches presented in this paper contributes not only to empirically understanding past IT effectiveness, but also provides timely methodological insights for future research in this field as economists and policymakers are re-evaluating the performance of monetary frameworks in addressing both conventional and unconventional economic challenges.

Second, the differing estimates highlight ongoing debates regarding econometric methodologies for policy evaluation (Imbens and Wooldridge, 2009; Abadie and Cattaneo, 2018; Athey and Imbens, 2017). Methodological approaches used across studies in the IT literature, including differences-in-differences, propensity score matching and dynamic panel methods, have their own strengths and potential biases, particularly in light of policy adoption endogeneity and mean reversion in macroeconomic variables. By critically comparing these approaches, this paper contributes to this methodological discussion.

Third, although the paper is not a formal meta-analysis, its efforts to reconcile differences in estimates from previous studies and explain the heterogeneity of results contribute to the growing body of meta-analytic approaches in economics as well as to the literature on synthesizing economic research findings (Stanley, 2001; Stanley and Doucouliagos, 2012; Thornton and Lee, 2000; Balima et al., 2020).

As a result of the examination of these various IT estimates, this paper makes a valuable contribution not only to the literature on inflation targeting, but also to broader economic debates.

3 Identification problem

One of the main reasons for the different methods used to evaluate inflation targeting is the variety of approaches proposed to address the identification challenge that arises due to the endogenous nature of IT adoption. Before discussing the specific methodologies, it is important to review the fundamental identification challenge that underlies this area of research.

There is a widespread agreement among researchers that to properly assess whether the IT framework is superior and whether the same outcome in terms of inflation rates would have been achieved if inflation targeters had not adopted this framework, one must compare inflation targeting countries with non-targeting countries over time. This approach is necessary because there might be systematic differences between IT and non-IT countries. Additionally, the period when IT gained affluence coincided with improved macroeconomic performance and a declining trend in inflation globally. This fact complicates identifying the true causal effect that came from the success of the monetary policy framework rather than the general factors affecting all countries equally. Therefore, once cannot only consider these targeting countries as a standalone in the pre-IT and IT period, but rather compare them to the emerging markets that follow a different monetary arrangement. For these reasons, researchers typically employ methods similar to differences-in-differences or two-way fixed effects in panel data.

A number of early studies in this strand of literature started out by using simple differences-in-differences (Neumann and Von Hagen, 2002; Landerretche et al., 2001):

$$\bar{\pi}_{i,post} - \bar{\pi}_{i,pre} = \delta + \beta \; IT_i \; + \; \epsilon_i \tag{1}$$

This intuitive method compares the change in average inflation rates before and after IT adoption for both targeting and non-targeting countries. When applied to advanced economies, these studies generally found a statistically significant negative effect of IT on inflation.

Now it is agreed upon that this approach is inappropriate due to the fact that selection into this framework is likely not random. The adoption of IT is endogenous. In particular, it is likely that the dissatisfaction in the pre-IT period with the prevalent inflation rates motivated countries to try a new monetary arrangement (Neumann and Von Hagen, 2002). Specifically, the high inflation or the poor inflation performance in the early part of the sample period induced countries to adopt IT. Furthermore, the elevated initial inflation levels stem partly from transitory factors, suggesting a subsequent decline in inflation regardless of a country's adoption of IT. This phenomenon, known as mean reversion, was initially introduced to this literature by the work of Ball and Sheridan (2005). To reiterate, when countries endogenously choose to adopt IT based on early poor performance and these performances are influenced by transitory effects that naturally revert to the mean, it introduces a bias in the estimated effect of IT. Ball (2010) provides a formal econometric proof of this bias.

Looking at equation (1), a high level of pre-IT average inflation ($\bar{\pi}_{i,pre}$), increases the likelihood that a country will adopt IT ($IT_i = 1$) due to treatment endogeneity.[10] Additionally, because a high value of pre-IT average inflation ($\bar{\pi}_{i,pre}$) reflects partly transitory factors, it also increases the likelihood that inflation (π_i) will fall in subsequent periods. This has a negative effect on the error term, ϵ_i. Treatment endogeneity and mean reversion together suggest that a variation in the pre-IT average inflation ($\bar{\pi}_{i,pre}$) induces a negative correlation between the IT dummy variable and the error term, leading to a downward bias in the estimated β coefficient from equation (1). Section 5.2 will confirm the relevance of endogeneity and mean reversion to the empirical sample of this paper.

This statistical phenomenon of "regression to the mean" is common and can be misinterpreted as the causal effect of a policy in many similar circumstances. A common example of the this problem can be illustrated through a basketball game scenario.[11] Imagine a team

[10] In the context of this paper, I frequently refer to the adoption of IT as the "treatment", following the conventions of causal inference literature.

[11] Another example is the performance of students on the SAT exam. Consider students who perform poorly on their first SAT exam and then take a test preparation course. These students are likely to show more improvement on their second attempt, not necessarily due to the effectiveness of the course, but because of regression to the mean. Test preparation companies often publicize these improvements as evidence of

performing poorly in the first half, missing the majority of their shots. During halftime, the coach "yells" at the players. When the team returns to the court, they perform much better than they did in the first half. If we try to identify the causal effect of the coach's "yelling" on the team's performance, we might conclude that it had a positive effect. However, it is more likely that the team simply regressed to its average performance level, having experienced significant negative transitory shocks in the first half.

4 Simulation Analysis of Inflation Targeting Endogeneity

A wide range of estimators have been used to examine the impact of inflation targeting on the average inflation rate in an attempt to correct for the identification challenge described in section 3. This part of the paper evaluates their relative performance in terms of both bias and precision. In particular, I will develop a process for inflation based on estimates from empirical data. To replicate the conditions of endogeneity and regression to the mean of inflation rates, I will assign inflation targeting to countries in the simulations using a predetermined rule. By applying these estimators from previous studies to the simulated data, I will compare their effectiveness in measuring the impact of inflation targeting.

The Monte Carlo simulations provide a framework to assume the true effect of inflation targeting, allowing for the direct estimation of bias and the root mean squared error (RMSE). Given this setup, I can assess the robustness and sensitivity of the estimators to the underlying bias. Ultimately, the primary objective is to determine how well these estimators correct for the bias introduced by regression to the mean, ensuring more accurate measurement of the actual impact of inflation targeting.

4.1 Design of the Simulation Study

In order to evaluate and compare different approaches, I conduct a Monte Carlo simulation of an economy where inflation dynamics are modeled with a constant country-specific permanent component and a time-varying AR(1) error term. The simulation framework involves assigning inflation targeting to countries, which allows for a detailed analysis of the performance of estimators in this controlled environment.

Inflation process. In my stylized example, I generate data for $N = 40$ countries over

their courses' efficacy, when in fact, the improvement might largely be due to this statistical phenomenon.

$T = 120$-quarter periods. For each country, the data generating process represents inflation as the sum of a constant country effect (α_i) and an AR(1) error term ($\epsilon_{i,t}$):

$$\pi_{i,t} = \alpha_i + \epsilon_{i,t} \tag{2}$$

$$\epsilon_{i,t} = \rho\epsilon_{i,t-1} + \nu_{i,t} \tag{3}$$

where $i = 1, ..., 40$ (countries) and $t = 1, ..., 120$ (quarters). I draw the permanent component once and for all for each of the countries from a normal distribution with parameters $(\mu_\alpha, \sigma_\alpha^2)$ and the white noise component from a normal distribution with $(0, \sigma_\nu^2)$.[12]

To calibrate this model with realistic parameters, I estimate the necessary values from an unbalanced panel sample of 42 emerging economies spanning from 1985Q1 to 2019Q4.[13] The parameters required for the simulations are $\{\mu_\alpha, \sigma_\alpha, \rho, \sigma_\nu\}$.[14,15]

I begin by estimating α_i for each country i as the average of its inflation series. From these estimates, I compute the standard deviation of the set $\{\alpha_1, ..., \alpha_{42}\}$ to obtain σ_α. Next, I estimate the AR(1) coefficient ρ by pooling the inflation residuals $\widehat{\epsilon_{i,t}} = \pi_{i,t} - \widehat{\alpha_i}$ and fitting an AR(1) process to this data. With $\widehat{\rho}$ in hand, I calculate the deviations $\widehat{\nu_{i,t}} = \widehat{\epsilon_{i,t}} - \widehat{\rho\epsilon_{i,t-1}}$ and get the standard deviation of these pooled values to estimate σ_ν.

The resulting parameter estimates are summarized in table 1, which represents the baseline case for my simulations.

Table 1: Parameters (Data Generating Process)

Description	**Parameter value**
Permanent component	$\sigma_\alpha = 2.3783$
	$\mu_\alpha = 5.7399$ (set as 0)
White noise	$\sigma_\nu = 6.3816$
Persistence of transitory shocks	$\rho = 0.34182$
Inflation volatility	$\sigma_\alpha^2 + \sigma_\epsilon^2 = 51.7740$

Note. The table presents the estimated parameters from the empirical sample in section 5.1, which are used to generate inflation series in the simulation exercises. It also shows the implied total inflation volatility based on these parameter values.

[12] Consequently, the mean and variance of the AR(1) error term will equal $\mu_\epsilon = 0$ and $\sigma_\epsilon^2 = \frac{\sigma_\nu^2}{1-\rho^2}$, respectively. To initialize the series for ϵ, the values of $\epsilon_{i,0}$-s are drawn from this distribution.

[13] See section 5.1 for further details about the sample.

[14] Since the specific value of the mean, μ_α, does not affect the main findings, I set it to be 0. This choice has no impact on the magnitude of the bias or the precision.

[15] The estimate of σ_ν will give us the implied value for σ_ϵ.

Determination of inflation targeting. The adoption of inflation targeting is often influenced by a country's historical performance, particularly its high inflation rates before this policy framework was implemented. Many emerging economies adopted IT in response to prior inflationary pressures and dissatisfaction with inflation outcomes. Therefore, in my simulations, it is reasonable to base the assignment of an inflation targeting framework on each country's past inflation data. Specifically, the key issue is that a country is more likely to adopt IT if it experienced high inflation rates before the adoption. I will capture this relationship in a straightforward manner in the simulation exercise.

In my simulations, I first calculate the average inflation rate for each country over the initial 60 quarters. This measure of historical performance is used to determine IT adoption and embodies the concept of treatment endogeneity, where the decision to adopt IT is influenced by past inflation rates. I employ different rules for IT adoption to vary the strength of treatment endogeneity. In the baseline case, I implement a strong form of treatment endogeneity by assigning IT to the top 20 countries with the highest average inflation rates during the initial 60-quarter or pre-IT period. This approach represents the strongest correlation between past inflation and IT adoption. To examine weaker forms of treatment endogeneity, I consider additional scenarios. In the second scenario, IT is assigned to 15 randomly selected countries from the top 20 with the highest pre-IT average inflation rates and to 5 randomly chosen countries from the bottom 20. Consequently, if a country falls in the top 20, it has a 75% chance of being an inflation targeter, while if a country happens to be in the bottom 20, it has a 25% chance. In a similar manner, in the third scenario, IT is assigned to countries in the top 20 with the highest pre-IT inflation rates with a 50% chance of being selected. Therefore, the baseline case demonstrates the strongest treatment endogeneity (and mean reversion), while the subsequent scenarios progressively test weaker forms.[16]

All twenty countries designated as inflation targeters adopt the framework simultaneously starting in quarter 61. This assumption addresses concerns highlighted in recent literature regarding staggered treatment adoption in the TWFE methodology (Borusyak et al. (2021); Callaway and Sant'Anna (2021); Sun and Abraham (2021)).

The final simulated dataset features a balanced panel of 20 countries that adopt inflation targeting and 20 that do not, observed over 120 quarters. The adoption of the framework occurs in quarter 61, resulting in a total of 4,800 observations.

Assumed effect of inflation targeting. One advantage of simulations is that they

[16] The main body of the paper presents the findings for the baseline case, while Appendix C.4 presents those for the second and third scenarios.

allow me to assume a known effect of inflation targeting on the average inflation rate. For this analysis, I assume that the true effect is zero.[17] Hence, once the inflation data is generated and inflation targeters are identified, no subsequent changes are applied to the post-IT period inflation.

The different empirical methodologies are compared in terms of the magnitude of the bias and the correponding root mean squared error (RMSE). The bias is obtained by taking the average of the estimated IT coefficient across the total number of replications. The standard deviation as a measure of precision is computed by taking the standard deviation of these 10,000 coefficient estimates. Similarly, RMSE is calculated as $\sqrt{\frac{\sum_{i=1}^{10,000}\left(\widehat{\beta_{IT}}\right)^2}{10,000}}$ since the true coefficient equals to 0.[18]

4.2 Overview of Selected Estimation Techniques

In this section, I will review the four empirical methodologies which I consider in my analysis and are widely used in the literature on estimating the causal effects of inflation targeting.

Given the data generating process, we observe inflation rates for N countries in periods $1, 2, ..., T$. Countries indexed as $i = \{1, ..., N/2\}$ are "treated", meaning that they formally adopt inflation targeting at period $T/2 + 1$. Therefore, the treatment or IT period spans over $T/2 + 1, ..., T$. The remaining $N/2$ countries ($j = \{N/2 + 1, ..., N\}$) serve as control non-IT countries.

Ball-Sheridan (2005) differences-in-differences. Ball and Sheridan (2005) propose a variation of the standard differences-in-differences approach to address the bias stemming from regression to the mean. Their key innovation is to control for initial inflation levels.

Let $\bar{\pi}_{k,pre} = \frac{1}{T/2}\sum_{t=1}^{T/2}\pi_{k,t}$ be the pre-IT average inflation in country k and $\bar{\pi}_{k,post} = \frac{1}{T/2}\sum_{t=T/2+1}^{T}\pi_{k,t}$ the post-IT adoption average inflation in country k, where $k = 1, ..., N$. The natural equation to estimate is to look at the difference between pre and post-treatment values for a specific macroeconomic indicator and regress it on the inflation targeting dummy variable (equation (4)). However, the resulting β^{BS} coefficient will be biased due to the identification problems stemming from treatment endogeneity and the regression to the mean

[17] Appendix C.1 presents results when true effect > 0.
[18] The RMSE is also equal to the square root of the sum of the squared bias and variance.

within it as described in section 3.[19] This results into a downward bias in the OLS estimate of β^{BS}, increasing the likelihood of finding a negative significant coefficient even if the true effect does not exist.

$$\bar{\pi}_{k,post} - \bar{\pi}_{k,pre} = \delta + \beta^{BS} IT_i \; + \; \epsilon_i \tag{4}$$

$$\bar{\pi}_{k,post} - \bar{\pi}_{k,pre} = \delta + \beta^{BS} IT_i \; + \; \gamma \; \bar{\pi}_{k,pre} + \; \epsilon_i \tag{5}$$

Controlling for initial conditions eliminates the bias because the mean reversion effect disappears and treatment endogeneity while still present no longer results into the correlation between the inflation targeting dummy variable and the error term.[20] Under these conditions, β^{BS} would capture the effect of adopting inflation targeting on $\bar{\pi}$ that is not stemming from initial conditions. However, a question that remains is how precise this estimator is.

Two-way fixed effects (TWFE). Several studies have pointed out that the Ball and Sheridan (2005) method discards a significant amount of data by using averages. To address this limitation, researchers have proposed using two-way fixed effects models that utilize all available observations. This is why there is a separate set of empirical papers that employ dynamic panel methodologies, specifically two-way fixed effects in this context.

The basic TWFE specification is written in equation (6), where $\pi_{i,t}$ is the inflation rate in country i in quarter t, θ_t are time fixed effects and ω_i are country fixed effects. The same concern about a negative correlation between the IT dummy and the error term, leading to a downward bias in the estimated effect of IT, still holds. To control for potential bias from mean reversion, many studies include lagged inflation as in specification (7). Brito and Bystedt (2010) and Alpanda and Honig (2014) suggest that controlling for lagged inflation addresses the regression to the mean phenomenon in a manner similar to the cross-sectional differences-in-differences specification. They argue that "the lagged inflation is included to capture mean-reverting dynamics". While this approach uses more information and likely provides higher precision, it has not been proven by previous work whether this method actually reduces or eliminates the bias associated with IT adoption endogeneity.

$$\pi_{i,t} = \beta^{TWFE} IT_{i,t} + \theta_t + \omega_i + \epsilon_{i,t} \tag{6}$$

$$\pi_{i,t} = \beta^{TWFE} IT_{i,t} + \gamma \pi_{i,t-1} + \theta_t + \omega_i + \epsilon_{i,t} \tag{7}$$

[19] Comment on notation: The superscripts denote different estimation methods used to estimate the same underlying population parameter β. While the notation differs, all estimators aim to recover the same population parameter.

[20] Ball (2010) formally derives conditions under which this estimator is unbiased.

Two-step system-GMM. There are concerns that even if we assume the TWFE equation is the true model, estimating it using OLS does not establish causation and may be biased. Specifically, the fixed-effects transformation, which demeans variables, can introduce correlation between the demeaned IT variable and error term, violating a key OLS assumption. This is particularly concerning since IT adoption decisions are likely influenced by past inflation performance, which is reflected in the error term. While controlling for lagged inflation helps account for historical performance that might influence IT adoption, it may not capture all relevant time-varying factors affecting the adoption decision. To address this, some papers use a system GMM approach. This method uses regressors as instruments to handle endogeneity (Arellano and Bover, 1995; Blundell and Bond, 1998). These papers use a system GMM approach to isolate the effect of adopting inflation targeting from other factors, such as common time-varying effects, country fixed effects, and endogeneity.

It is important to note that GMM itself does not address endogeneity; rather, it is the specific modeling approach within system GMM that handles this issue. The system GMM consists of two equations: the original equation and the first-differenced equation, which eliminates fixed effects. In this method, the original (level) equation employs past differences as instruments, while the differenced equation uses lagged values as instruments. Equations (8) and (9) show moment conditions. Regressors are internally instrumented by their lags ($z_{i,t} = (\pi_{i,t-1}, IT_{i,t})$).

$$E\left[z_{i,t-s} \cdot \Delta\epsilon_{i,t}\right] = 0 \text{ for } \begin{cases} s \geq 1, t = 2, \ldots, T, & \text{if } z_{i,t} \text{ is predetermined} \\ s \geq 2, t = 3, \ldots, T, & \text{if } z_{i,t} \text{ is endogenous} \end{cases} \tag{8}$$

$$E\left[\Delta z_{i,t-s} \cdot (\omega_i + \epsilon_{i,t})\right] = 0 \text{ for } \begin{cases} s = 0, t = 2, \ldots, T, & \text{if } z_{i,t} \text{ is predetermined} \\ s = 1, t = 3, \ldots, T, & \text{if } z_{i,t} \text{ is endogenous} \end{cases} \tag{9}$$

In the estimation procedure, the IT variable can be treated as either predetermined or endogenous. Treating IT as predetermined means that inflation influences IT adoption only with a lag, so current inflation does not affect IT adoption, although past inflation might. On the other hand, treating IT as endogenous implies that inflation affects IT adoption contemporaneously, or that an omitted variable is influencing both inflation and IT adoption. GMM estimation is generally more appropriate for micro data, particularly in situations where the number of periods (T) is smaller than the number of countries (N). To manage the number of instruments, these studies mostly work with an annual data and take 3-year averages. They consider this averaging approach suitable because it allows sufficient time for a variable to respond, while also distinguishing the effects of IT treatment from those of other events occurring nearby (Brito and Bystedt, 2010).

Propensity Score Matching (PSM). Another widely used method in this literature is propensity score matching. There is a specific reason why some studies choose this approach: it is intended to address the self-selection problem (Rosenbaum and Rubin, 1983). This method aims to generate comparable observations for the treated and control groups. Propensity score matching tries to mimic randomization and generate the counterfactual inflation that would have been observed for the inflation targeting country in the absence of the formal IT adoption. The intuition is to "match" inflation observations for IT countries with control inflation rate observations from non-IT control countries. Therefore, it uses observations that come from the similar group as the IT country as counterfactual. By matching, we are able to say that the two groups are the same on average.

For each country in each period, I estimate the probability of adopting IT based on a set of observable characteristics (X). This probability is called the propensity score. Typically, this is done using a logit or probit model as in equation (10). The two observations that have the same perceived probability of adopting inflation targeting are matched with each other, where it just so happened that one adopted it and the other did not. Their outcomes are compared to measure the causal effect.

$$\hat{p}\left(X_{i,t}\right) = P\left(IT_{i,t} = 1 \mid X_{i,t}\right) \tag{10}$$

Papers in the IT literature began to include the lagged inflation rate to control for mean reversion (De Mendonça and Guimarães e Souza, 2012; Lin and Ye, 2009). Typically, we match observations using many variables and not just one. However, given that in the simulation, I exactly know the data generating process, for my purposes of testing how the PSM would perform in terms of the mean reversion bias if lagged inflation is used as one of the variables, I will only consider the lagged inflation. To calculate the propensity score, I use probit regression of the IT dummy on a constant and lagged inflation. Based on the estimated coefficients, the predicted IT value will be the probability of adopting IT conditional on the lagged inflation. Once we have propensity scores, there are different ways to proceed with matching.

4.3 Monte Carlo Results

Monte Carlo simulations involve 10,000 replications. For each replication, I apply the different estimation methods and compute their respective coefficient estimates. The average of these estimates across all simulations provides a measure of bias, while their standard deviation indicates precision. I also calculate the Root Mean Squared Error (RMSE) to assess overall performance. Table 2 summarizes sample characteristics across these replications in terms of permanent, transitory and overall inflation for targeting and non-targeting countries in pre- and post-IT periods.

Table 2: Summary Statistics of the sample in consideration

	IT	**Non-IT**		**IT**	**Non-IT**
pre-IT α_i	1.6556	-1.6511	post-IT α_i	1.6556	-1.6511
pre-IT ϵ_{it}	0.4479	-0.4514	post-IT ϵ_{it}	0.0035	-0.0049
pre-IT π_{it}	2.1035	-2.1026	post-IT π_{it}	1.6591	-1.6560

Note. The table shows the average values of the permanent country effect, the transitory component, and overall inflation for IT and non-IT countries in the pre- and post-IT periods, based on 10,000 replications.

Table 3 presents the results of these simulations, showing the magnitude of the bias, standard deviation of the estimated coefficient, and RMSE for each method.[21] For some methods, I consider several variations.

First, I find that the Ball and Sheridan (2005) method without initial inflation conditions shows a downward bias of -0.89%. However, once initial conditions are controlled, the bias disappears, as expected given past theoretical work (Ball, 2010). This confirms the effectiveness of their approach in addressing the regression to the mean problem under the reasonable assumptions in the simulation setup.

Regarding the TWFE estimator, I observe that it exhibits the same magnitude of downward bias as Ball-Sheridan if lagged inflation is not controlled for.[22] Controlling for lagged inflation reduces the size of the downward bias from -0.89% to -0.60%, but does not eliminate it entirely. Interestingly, controlling for a 4-quarter moving average of inflation further reduces the bias to -0.01%. This further confirms that the inclusion of a single lag of inflation is not enough to fully capture the mean reversion dynamics. Not surprisingly,

[21] Since the true effect is 0, the magnitude of the bias corresponds to the average coefficient estimate across these replications.

[22] The two methods give the same exact estimated coefficient due to the design of IT adoption. In particular, all countries are assumed to switch to the IT framework at the same time. Given that this is not true in the real-world cases, it should not be expected that the two are equal to each other in the empirical sample. However, they will still be close to each other.

given the greater number of observations used, the TWFE approach provides much more precision. As a result, it achieves a lower RMSE compared to Ball-Sheridan, particularly when using both lagged inflation and the 4-quarter moving average. Hence, I observe that careful selection of the lagged variable can significantly improve overall performance in terms of both bias and precision under this method.

Table 3: DGP - A constant country effect plus an AR(1) error term

Method	Bias	Std. Dev.	RMSE
Ball-Sheridan (2005)			
w/o initial inflation	-0.8909	0.5319	1.0376
w/ initial inflation	0.0094	0.8850	0.8850
Two-way Fixed Effects			
w/o lagged inflation	-0.8909	0.5319	1.0376
w/ lagged inflation	-0.6026	0.3621	0.7030
w/ 4-quarter moving average	-0.0985	0.1125	0.1495
Two-step system GMM			
IT Predetermined	2.43	0.55	2.49
IT Endogenous	2.47	0.55	2.53
Propensity Score Matching			
NN (n = 1)	1.3045	0.3349	1.3468
NN (n = 3)	1.3051	0.2944	1.3379
RM (r = 0.04)	1.4055	0.2511	1.4278
RM (r = 0.02)	1.2945	0.2634	1.3210
RM (r = 0.01)	1.2347	0.2663	1.2631
Kernel (Epanechnikov, band = 0.06)	1.4512	0.2488	1.4723

Note. The table presents the main results of the simulation analysis, where the true IT effect is 0. It displays the bias and precision of various estimators, along with their RMSE.

Surprisingly, both the two-step system GMM and propensity score matching methods show an upward bias. The system GMM demonstrates a similar upward bias of 2.4% to 2.5%, regardless of whether IT is treated as predetermined or endogenous. PSM also shows similar coefficients across different matching methods, with an average upward bias of around 1.3%.

The potential upward bias in system GMM estimates can be explained by considering how different components of inflation interact with the method's key assumptions. System GMM relies on the assumption that lagged changes in inflation are uncorrelated with country fixed effects. However, this assumption may be violated in the context of inflation targeting adoption, leading to bias. Inflation consists of both permanent and transitory components. The decision to adopt IT is based on total inflation, not distinguishing between its components. However, changes in inflation depend on the split between permanent and transitory components. Even though the country fixed effect (α_i) is constant over time, it can still be correlated with $\Delta\pi_{i,t}$ due to how it interacts with the transitory component. If IT adoption was mainly due to high permanent inflation (large α_i), $\Delta\pi$ will likely be small, as most inflation persists. If IT adoption was mainly due to high transitory inflation (large $\epsilon_{i,t}$), $\Delta\pi$ will likely be large and negative due to mean reversion. In both cases, the change in inflation is correlated with the fixed effect, violating the key assumption of system GMM. The upward bias occurs because the method fails to properly account for these different inflation dynamics.

The upward bias in PSM can be attributed to how it matches countries based on their perceived likelihood of adopting inflation targeting. When comparing two countries with high perceived likelihoods of adopting inflation targeting, but only one actually adopts, what might cause this mismatch? A plausible explanation lies in how propensity score matching estimates adoption probabilities. Consider a country that PSM assigns a high IT adoption probability, but which does not actually adopt it. This likely occurs because PSM is overstating the true adoption probability. The country might have experienced high inflation for a brief period, perhaps just one quarter. Based on this short-term data, the propensity score model calculates a high chance of adopting IT. However, the actual decision to adopt IT typically depends on longer-term inflation trends, such as the average inflation over the first half of the sample period. Despite its temporarily high inflation, this country did not actually have persistent inflation problems warranting IT adoption. Subsequently, this country's inflation naturally reverts to its mean level in the next period. From the perspective of PSM, it appears as if a "high-probability" country didn't adopt IT, yet its inflation decreased anyway. This creates the illusion that IT is less effective than it actually is. In essence, a country that PSM thinks had a high IT adoption probability, but did not adopt, likely never had a truly high adoption probability in the first place. PSM's reliance on short-term data led to an overestimation of the adoption likelihood, failing to capture the longer-term inflation dynamics that truly drive IT adoption decisions.

To reiterate, the upward bias in PSM stems from its inability to distinguish between permanent and transitory components of inflation. PSM matches countries based on their total inflation, which can lead to misleading comparisons. An IT-adopting country might have high permanent inflation but low transitory shocks in period $t-1$. This country could be matched with a non-IT country observation that has low permanent inflation but high transitory shocks in period $t-1$. In the subsequent period t, the non-IT country's inflation is likely to decrease more significantly due to mean reversion of its transitory component. Meanwhile, the IT country's inflation may show less dramatic change as its high inflation is more persistent. Consequently, this leads to an upward bias in PSM estimates, potentially understating the true effect of inflation targeting.

In conclusion, the interaction between permanent and transitory inflation components can lead to violated assumptions in system GMM and PSM, resulting in biased estimates of the inflation targeting effect. If inflation only included one of these components, the estimated coefficient would be unbiased.

Summary. My analysis reveals that the cross-sectional differences-in-differences method with pre-IT average inflation remains unbiased, while other methods show varying degrees of bias under the assumptions of endogeneity and mean reversion. This suggests that the proposed approaches in these alternative estimators do not fully account for potential biases. The simulation exercise highlights a sequential pattern in the estimated treatment effect across different methods: $\widehat{\beta_{1lag}^{TWFE}} \leq \widehat{\beta_{4QMA}^{TWFE}} \leq \widehat{\beta^{BS}} \leq \widehat{\beta^{PSM}} \leq \widehat{\beta^{s-GMM}}$, where TWFE represents two-way fixed effects, BS refers to Ball and Sheridan (2005) cross-sectional differences-in-differences with initial conditions, PSM stands for propensity score matching and s-GMM for two-step system GMM. The ordering shows the methods that define the lower and upper bounds of the IT effect. Notably, the two-way fixed effect method with lagged inflation emerges as the most desirable due to its optimal combination of bias and precision, resulting in the smallest root mean squared error. These findings underscore the importance of carefully considering each method's assumptions and mechanics when applying them to inflation targeting studies. While some approaches effectively address certain biases, they may introduce others or perform unexpectedly when both permanent and transitory inflation components are present.

4.4 Sensitivity of Results

While the previous section presents findings based on parameter estimates from real-world data, it is important to examine how sensitive these findings are to different parameter values, given that these can vary depending on the countries and time periods under consideration. The key parameters in the current data generating process are the ratio of the standard deviation of permanent and transitory components, and the persistence of shocks. This section explores the sensitivity of our earlier findings to variations in these parameters.

Transitory & Permanent Shocks. To conduct the exercise, I will fix the overall variability of the inflation and change the relative variance of the permanent and transitory components. The total variance of inflation is fixed at the value presented in table 1, $\sigma_\alpha^2+\sigma_\epsilon^2 = 51.7740$. The variance of the transitory shocks, ϵ, depend on both the persistence parameter (ρ) and the variance of white noise (σ_ν^2). Therefore, I do the following sensitivity analysis. First, I fix the value of ρ and change the ratio of the two standard deviations, $\frac{\sigma_\alpha}{\sigma_\epsilon}$. An increase in the ratio implies an increased importance of cross-country permanent differences. Second, I fix the the ratio of the two standard deviations, $\frac{\sigma_\alpha}{\sigma_\epsilon}$ and change the value of persistence, ρ. Figures in appendix C.2 and C.3 show my findings.

I find that my earlier findings in table 3 regarding the TWFE and BS (2005) are robust to changing parameter values within my data generating process. Across all exercises, BS (2005) remains unbiased, while TWFE exhibits a downward bias. TWFE is also unbiased together with BS (2005) when the treatment endogeneity is mostly driven by permanent country differences.

The PSM and system GMM methods for the baseline parameters shows an upward bias on average across all of matching methods. In the case of sensitivity analysis, the extreme cases show an unbiased estimate of PSM and system GMM. The extreme cases are $\sigma_\alpha = 0$ (everything is driven by transitory shocks and there are no permanent differences) and $\sigma_\alpha = 7.22$ (everything is driven by permanent differences and there are no (very small) transitory shocks. Therefore, no role for mean reversion). Hence, this reaffirms intuition explained earlier that for these methods to have a biased estimate of the IT effect, there must be both transitory and permanent differences across targeters and non-targeters.

In terms of persistence, as the persistence goes up, the upward bias in PSM approaches 0. This again makes sense because persistence partly controls the speed of mean reversion and a higher persistence means a lower speed for mean reversion. Therefore, matching on lagged inflation does not result into as much bias as when the mean reversion is immediate.

Sensitivity of Results to the Strength of Treatment Endogeneity. The benchmark results consider the case where the top 20 countries with the highest pre-IT average inflation adopt inflation targeting. This represents an extreme scenario with the strongest IT adoption endogeneity. Appendix C.4 illustrates the impact on these coefficients as the strength of this endogeneity weakens. As we would expect intuitively, as the correlation between pre-IT average inflation and IT adoption decreases, so does the bias in these estimators. In the other extreme scenario, where only 10 out of the top 20 countries are selected as targeters, we observe that all estimators become unbiased. This further demonstrates that the ordering of the estimators in the main results depends on the presence of IT adoption endogeneity within the sample of countries under consideration.

Summary of Simulation Resuts. Previous sections demonstrate that the methodology from Ball and Sheridan (2005) has the smallest magnitude of bias. However, precision is also an important factor to consider. In terms of precision, the TWFE estimator shows the smallest standard deviations. The combination of these two factors is summarized using the RMSE, displayed for all methods in Figure 4. It can be seen that under all sensitivity analyses and different parameter values, TWFE with 4-quarter moving average inflation shows the smallest RMSE (except for the extreme persistence values). This suggests that with this method, the benefit of greater precision outweighs the slightly larger bias. It should also be emphasized that these properties of estimators are relying on the assumptions made regarding the IT adoption and mean reversion in the inflation rates.

5 Empirical Analysis of Inflation Targeting Endogeneity

The simulation exercises highlight how effectively four primary estimators used in the inflation targeting literature address the bias associated with IT adoption endogeneity. These exercises predict the expected ranking of these methods when applied to real-world data, assuming a constant sample. In this section, I present empirical evidence demonstrating how different econometric methodologies identify varying magnitudes of the effect of inflation targeting on the average level of inflation, corroborating the rankings predicted by the simulations. Furthermore, using the intuition regarding the expected direction of bias, I can identify which of these magnitudes are likely to reflect the true impact of adopting the IT framework on emerging market economies.

5.1 Sample Selection Nuances

Evaluating the causal effects of inflation targeting on macroeconomic performance is complicated by its heterogeneous implementation across different countries. To determine its superiority over other monetary frameworks, it is essential to compare the relative performance of both targeting and non-targeting countries, rather than only considering the performance of targeting countries. In the existing literature, two primary challenges stand out: accurately pinpointing the dates of adoption and selecting appropriate countries for both targeting and control groups.

5.1.1 Country Selection

This paper considers all the inflation targeters that are included within 2020 Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER, 2020). In it, the definition of inflation targeting framework is similar to that of Mishkin (2000). However, it appears that one of the decisive factors in identifying a country as an inflation targeter is whether the country self-identifies as such[23]. For example, Argentina was classified as an inflation targeter by the IMF for a brief period (2016) because it declared itself as one.[24] To the best of my knowledge, all papers empirically evaluating the macroeconomic effects of inflation targeting focus on countries that have formally announced its adoption, despite differences in its design and execution. Specifically, as defined by Truman (2003), these studies use the benchmark of "self-description". Given that one of the main objectives of this paper is to understand the range of estimates in the literature, I will follow previous papers in this regard.[25] Hence, the goal is to discern the effects stemming from the "explicit" adoption of inflation targeting, referring in this context to a central bank that formally announces adoption of the framework.

Furthermore, to identify emerging market economies (EMEs), I follow IMF's fiscal monitor classification of country groupings.[26] The control group comprises of all the remaining non-inflation targeting emerging markets with the population above 1 million and available CPI data in the IMF's International Financial Statistics.[27] I impose a restriction

[23] Examining the impacts of inflation targeting presents a challenge due to the complexity of categorizing countries into targeters and non-targeters, partly due to differing definitions of the regime. Some countries may self-identify as inflation targeters but may not adhere closely enough to the framework. Conversely, there can be others not explicitly acknowledging themselves as inflation targeters but effectively exhibiting all essential aspects of inflation targeting, often called as "implicit" targeters. This paper is currently concerned with the impact that comes from the central bank officially revealing itself as an inflation targeter and abstracts from the discussion of so-called "implicit" and "bad" targeters. The IMF also has insights into the specifics of the countries in the classification.

[24] In particular, Argentina was officially listed as an inflation targeter only in 2016. According to the 2017 IMF report on Exchange Arrangements and Exchange Restrictions, the central bank of Argentina formally adopted this regime on September 26, 2016. However, in the 2018 IMF report, it is stated that Argentina transitioned from the inflation targeting regime to a monetary aggregate target in October 2018.

[25] Some papers consider some subsets of inflation targeters, such as "fully-fledged" versus "lite" (Carare and Stone (2006)). However, I do not differentiate between the two.

[26] It's important to note that the IMF's fiscal monitor offers a less restrictive EME classification compared to other classifications like Morgan Stanley's (MSCI) Emerging Market Index. The MSCI index identifies only 24 countries as EMEs: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Kuwait, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. For a robustness check, I will utilize this narrower definition. Additionally, it's worth mentioning that four countries listed as EMEs by the MSCI are classified as advanced economies (AEs) by the IMF (Czech Republic, Greece, Korea, and Taiwan). Since I adhere to the IMF's classifications, these countries are excluded from my sample.

[27] Countries of a very small size confront a unique set of options when it comes to deciding on monetary policy frameworks.

on high inflation rates by beginning the sample period for each country after the exact inflation over four quarters no longer goes above 30%.[28] I only include a country in my sample if its data

Table 4: Benchmark Sample of Countries and Time Periods

IT EMEs (20)	Start Date	End Date	Non-IT EMEs (22)	Start Date	End Date
Albania	1998q2	2019q4	Algeria	1995q3	2019q4
Armenia, Rep. of	1996q2	2019q4	Azerbaijan, Rep. of	1996q2	2019q4
Brazil	1995q3	2019q4	Bolivia	1987q1	2019q4
Chile	1985q4	2019q4	Botswana	1985q1	2019q4
Colombia	1991q4	2019q4	Bulgaria	1998q2	2019q4
Costa Rica	1991q3	2019q4	China, P.R.: Mainland	1987q1	2019q4
Georgia	1996q4	2019q4	El Salvador	1987q1	2019q4
Guatemala	1991q3	2019q4	Equatorial Guinea, Rep. of	1995q1	2019q4
Hungary	1995q3	2019q4	Eswatini, Kingdom of	1985q1	2019q3
India	1985q1	2019q4	Gabon	1995q1	2019q4
Jamaica	1996q3	2019q4	Jordan	1989q4	2019q4
Kazakhstan, Rep. of	1997q1	2019q3	Kuwait	1992q3	2019q4
Mexico	1996q4	2019q4	Malaysia	1985q1	2019q4
Paraguay	1991q2	2019q4	Mauritius	1985q1	2019q4
Peru	1994q2	2019q4	Morocco	1985q1	2019q4
Philippines	1985q3	2019q4	North Macedonia, Republic of	1995q1	2019q4
Poland, Rep. of	1995q3	2019q4	Pakistan	1985q1	2019q4
South Africa	1985q1	2019q4	Panama	1985q1	2019q4
Thailand	1985q1	2019q4	Saudi Arabia	1985q1	2019q4
Uruguay	1996q2	2019q4	Sri Lanka	1985q1	2019q1
			Trinidad and Tobago	1985q1	2019q3
			Tunisia	1988q3	2019q4

Note. The table shows the start and end dates of the period for each country included in the empirical sample, after applying the inflation rate restriction of not exceeding the 30% cutoff.

starts no later than 1998Q1[29] and goes through the end of the sample period (2019Q4). Therefore, I exclude countries with missing data in the middle of the sample period or the ones for which the inflation rate might surpass the high inflation threshold not only at the beginning of the sample period but also at later dates (before 2019Q4). Table 4 presents the list of countries and corresponding periods in the benchmark sample.[30] The benchmark

[28] The selection of a 30% cutoff, while seemingly arbitrary, is grounded in previous literature. It draws from the inflation categorizations by Dornbusch and Fischer (1993), who classify moderate inflation as average year over year rates of 15-30% sustained over at least three years, and from Bruno and Easterly (1998), who define inflation crises as instances where annual December to December CPI inflation exceeds 40% for two consecutive years, excluding one-year inflation crises. These criteria are closely related, with the former providing a slightly smoothed definition of inflation and a lower benchmark. To minimize the effect of outliers in my analysis and to concentrate on inflationary scenarios relevant to inflation targeting, I limit my dataset to periods where the inflation rate, calculated as the year-over-year change for the same quarter, remains below 30% at all times.

[29] The mean initial announcement date for early adopters is 1998Q2.

[30] Uruguay was categorized under the monetary aggregate target in the IMF annual reports of 2014 and

sample is an unbalanced panel of 42 countries over the period 1985Q1 - 2019Q4.

5.1.2 IT Adoption Dates

Depending on the underlying rationale guiding our understanding of the functioning of inflation targeting and formation of inflation expectations, different interpretations of the appropriate IT adoption dates can emerge. It is important to ensure consistency in applying the chosen criteria uniformly across all countries. Many of the earlier studies rely on adoption dates from Roger (2009) and Hammond (2012). These previous studies may combine adoption dates from different sources or incorporate data from countries not contained in those initial works. Consequently, the specific criteria employed to determine the effective adoption date of inflation targeting may become mixed. Motivated by this consideration, I independently identify three sets of dates: (1) Initial Announcement Date, (2) Explicit Adoption Date, and (3) Target Enforcement Date. The effectiveness of inflation targeting often relies on the expectations channel, suggesting that the anticipated benefits of this framework are dependent on how agents form their expectations regarding it. In my baseline scenario, I rely on the target enforcement dates, where fully informed agents recognize that they are currently operating within the inflation targeting regime, following the dating suggested by Ball and Sheridan (2005). Additionally, I acknowledge the possibility that economic agents may adjust their inflation expectations upon anticipating the central bank's shift to inflation targeting in the near future. Hence, I identify two additional sets of dates:

1. Initial Announcement Date: The first quarter in which there is a clear indication from the central bank that it has begun the gradual process of transitioning to the IT framework in the near future. The signal may include discussions with the IMF, requests for technical assistance regarding the path to IT, and/or indications of the possibility in the central bank meeting minutes and inflation reports.

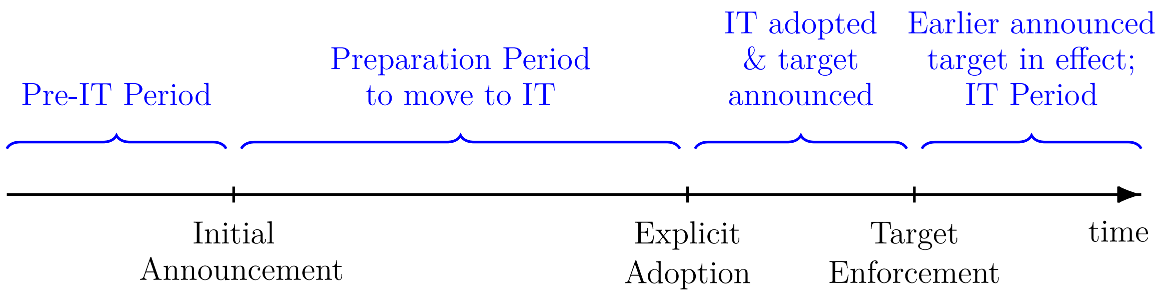
2. Explicit Adoption Date: The quarter in which the central bank explicitly announced it had switched to the IT framework and announced the target. Therefore, the bank begins to refer to itself as following the IT monetary policy.

3. Target Enforcement Date: The first full quarter during which a particular inflation

2015. Nevertheless, the 2016 annual report reclassified Uruguay as an inflation targeter, indicating that "the monetary policy framework was reclassified retroactively, overriding a previously published classification." Therefore, I also identify Uruguay as an inflation targeter for these two years.

target was effective, preceded by the central bank's earlier announcement of the IT framework adoption and the corresponding target (Ball and Sheridan (2005)).

Figure 3: Timing of Inflation Targeting Adoption Dates



Note. The figure shows how the three different adoption dates align on the timeline.

To illustrate the timing of the three sets of adoption dates, Figure 3 presents the timeline. Typically, central banks undergo a preparatory period before officially declaring themselves as inflation targeters, during which they may need to enact legislative changes, establish monetary policy committees, and enhance communication strategies. Furthermore, once they explicitly adopt inflation targeting, the announced target might be implemented at a later date. It is important to note that the initial announcement and explicit adoption dates can coincide. For example, the Bank of Thailand announced its inflation targeting framework on May 23, 2000, following a reassessment post-IMF program, which concluded that inflation targeting would be more effective than money supply targeting. Until this time, there was no mention of inflation targeting in any of central bank communications and IMF country reports. Therefore, I set 2000Q2 as both the initial announcement and explicit adoption dates.

Having three sets of adoption dates allows me to assess the implications of the different dates used in earlier studies on the corresponding effects on the average level of inflation. Table 5 presents information on the compiled dates for inflation targeting countries in the sample.[31] Taking the case of South Africa, in 1998, the country began considering the adoption of an explicit inflation targeting regime for its monetary policy, as discussed in the IMF country report approved on June 30, 1998. Thus, 1998Q2 is set as the initial announcement date. Subsequently, in February 2000, it officially implemented this strategy, setting a CPIX inflation target range of 3-6 percent for 2002 and 2003. Therefore, 2000Q1 corresponds to the explicit adoption date. Since 2002 was the first year in which the South

[31] Appendix A provides additional information and sources used to identify these dates.

African Reserve Bank was supposed to achieve an explicit target, 2002Q1 is identified as the target enforcement date.

Table 5: IT Dates

Country	**Initial Announcement**	**Explicit Adoption**	**Target Enforcement**
Poland	1998Q1	1998Q3	1999Q1
Brazil	1999Q1	1999Q2	1999Q3
Chile	1990Q3	1999Q3	2000Q1
Thailand	2000Q2	2000Q2	2000Q3
Colombia	1995Q1	1999Q3	2001Q1
Mexico	1998Q1	2001Q1	2001Q2
Hungary	2001Q2	2001Q2	2001Q4
South Africa	1998Q2	2000Q1	2002Q1
Philippines	2000Q1	2002Q1	2002Q2
Peru	2001Q4	2002Q1	2002Q4
Guatemala	2002Q1	2005Q1	2005Q4
Uruguay	2004Q3	2007Q3	2007Q4
Armenia	2004Q1	2006Q1	2007Q1
Albania	2002Q4	2008Q4	2009Q1
Georgia	2006Q1	2008Q4	2009Q1
Paraguay	2004Q2	2011Q2	2011Q3
Kazakhstan	2004Q2	2015Q3	2015Q4
India	2015Q1	2016Q3	2016Q4
Jamaica	2013Q1	2017Q3	2018Q2
Costa Rica	2006Q3	2018Q1	2018Q2

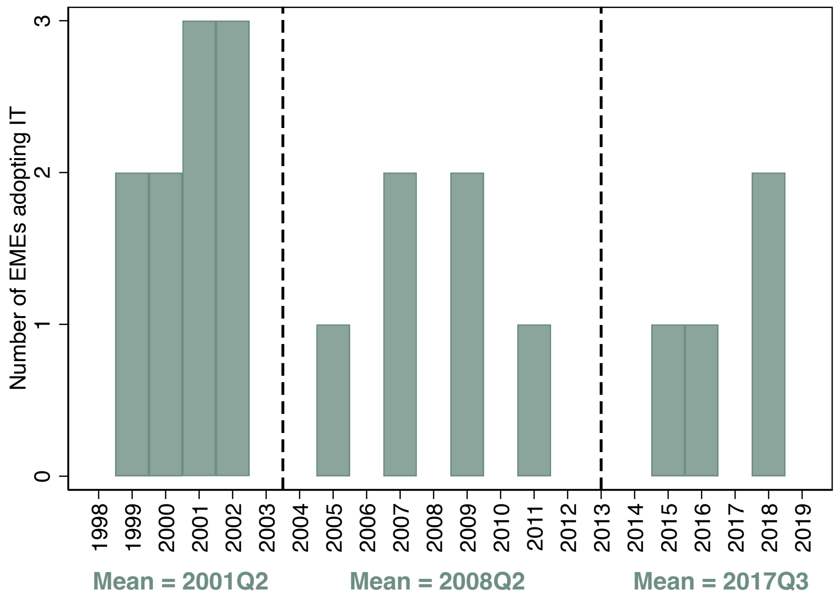
Source: IMF Staff Country Reports and Central Bank Websites

Note. The figure presents the inflation targeting adoption dates identified based on three different definitions. The "Target Enforcement" date is used in the main analysis.

Three waves of IT adopters. In contrast to the simulations and the case for advanced economies, the adoption of the inflation targeting framework in emerging markets spreads over three decades. Hence, I find it logical to divide the entire cohort of EME adopters into three groups according to the wave of adoptions during which they declared themselves as explicit targeters. To identify, a natural split of inflation targeting emerging markets into separate groups, I provide a graphical illustration on figure 4 that shows the number of emerging markets adopting inflation targeting regime each year based on target enforcement dates.[32] As it appears, inflation targeting emerging markets can be subdivided into three groups: early adopters which include 10 countries adopting inflation targeting before 2003, middle adopters which include 6 countries adopting inflation targeting between 2005 and 2011, and late adopters which consist of 4 countries adopting the framework after 2014.

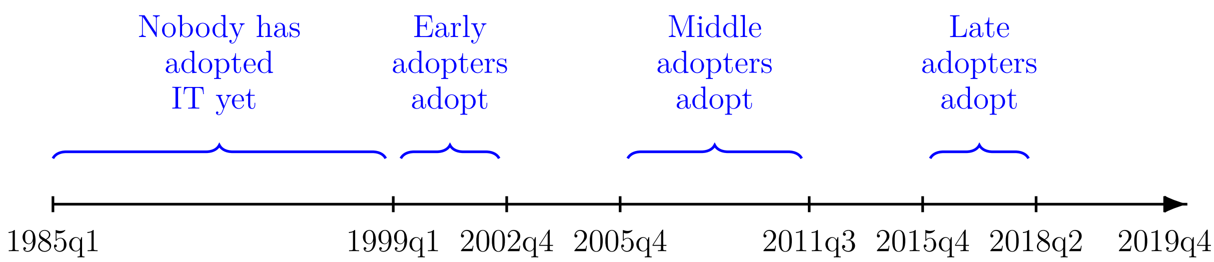
[32] Figure 5 shows the timeline.

Figure 4: Number of EMEs Adopting IT each year (Target Enforcement Dates)



Note. The figure shows the number of countries that adopted inflation targeting each year. It aims to examine the timing of the natural split between adoption waves, based on periods when multiple countries were actively transitioning to the framework versus periods when no country had transitioned.

Figure 5: Four Sample Periods (Target Enforcement Dates)



Note. The figure conveys a similar message to figure 4. However, to better illustrate the time periods during which early, middle, and late adoptions occurred, it presents a timeline.

5.2 IT Endogeneity & Mean Reversion Patterns in Data

This section illustrates the importance of the endogeneity of IT adoption and the mean reversion of inflation rates within the group of emerging market countries examined in this paper. It is important to provide evidence of the two in the empirical data because the insights from simulations rest on these two key assumptions.

Table 6: Determinant of $P(IT_i = 1)$ - Probit estimates

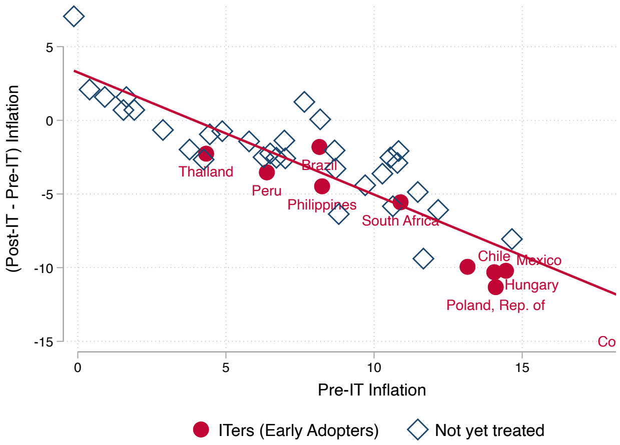
	(1) IT_i	(2) IT_i	(3) IT_i	(4) IT_i	(5) IT_i
$\overline{\pi}_{i,pre}$	**0.18*****	**0.20****	**0.35****	**0.14*****	**0.16****
	(0.06)	(0.09)	(0.17)	(0.04)	(0.06)
D_t^2					0.80
					(0.87)
D_t^3					-0.78
					(1.25)
$D_t^2 \times \overline{\pi}_{i,pre}$					-0.09
					(0.11)
$D_t^3 \times \overline{\pi}_{i,pre}$					0.19
					(0.18)
Observations	42	32	26	100	100
Early Adopters	✓			✓	✓
Middle Adopters	✓	✓		✓	✓
Late Adopters	✓	✓	✓	✓	✓
Non-ITers	✓	✓	✓	✓	✓
Pseudo R^2	0.20	0.15	0.25	0.12	0.15

* p<0.10, ** p<0.05, *** p<0.01
Includes a constant term
$\overline{\pi}_{i,pre}$ is calculated since the last decision point

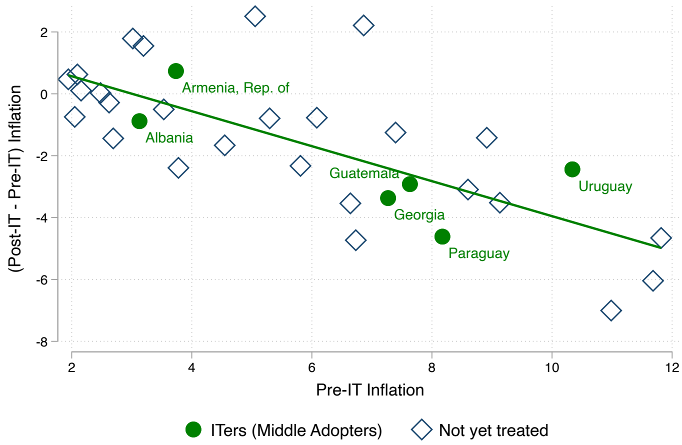
Note. The table shows coefficient estimates from the probit regression, demonstrating that high average pre-IT inflation increases the likelihood of a country adopting IT. Columns (1)-(3) present this relationship separately for each adoption wave, considering the average pre-IT inflation since the last decision point. Column (4) combines all countries, so the number of observations is the sum of those in the previous columns. Column (5) allows for different effects based on decision points.

First, to demonstrate that the decision to adopt inflation targeting depends on dissatisfaction with past inflation performance, I run probit regressions. These regressions capture the idea that the decision is influenced by the average level of inflation a country experiences since its last decision window. The last decision window refers to the division of the entire group of targeters into three subgroups, as discussed in section 5.1.2. Specifically, regressions (1)-(3) in table 6 report probit estimates for these groups separately. For early adopters, I calculate the pre-IT average inflation starting from 1985Q1 (or the first available value). For middle adopters, the starting point is 2001Q2. For late adopters, it is 2008Q2. Thus, I test whether emerging markets are more likely to adopt the IT framework within the adoption window if they experienced higher average inflation in the period preceding the decision point. Column (4) puts all the groups together. Column (5) allows for different coefficients based on the sample period. All of the coefficients are statistically significant and positive, indicating that pre-IT inflation performance is indeed an important factor influencing emerging countries' choice to adopt the framework.

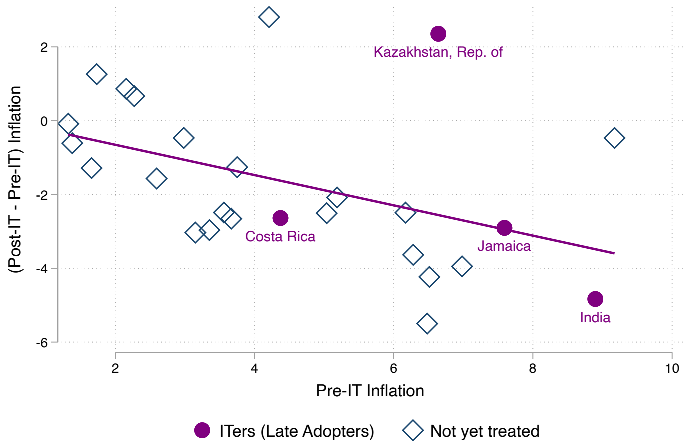
Figure 6: Regression to the Mean



(a) Early Adopters



(b) Middle Adopters



(c) Late Adopters

Note. The figure shows the pre-IT average inflation against the change in average inflation between the post-IT and pre-IT periods. It does so separately for early, middle, and late adopters, as well as the "not yet treated" group in each case.

Second, to demonstrate that these countries also experience mean reversion in inflation rates, influenced by transitory shocks, I plot pre-IT average inflation rates against the difference between post-IT and pre-IT averages. I show separate figures for each of the adopter group in figure 6. The control group consists of countries that have "not yet been treated." For example, when plotting the figure for early adopters, the control group includes non-ITers as well as middle and late adopters, since they have not yet adopted the framework.

A downward-sloping line illustrates that countries with high pre-IT inflation tend to experience larger decreases in their inflation rates in the post-IT period, supporting the concept of regression to the mean.

Overall, figures 5 and 6 together support the validity of two key assumptions in the setup of the simulation analysis.

5.3 Results

Guided by insights from simulation exercises, I will present findings on the effect of adopting inflation targeting on the average level of inflation in emerging market economies using the commonly employed estimators in this literature on a common sample. The use of a common empirical sample allows the isolation of the effects arising only due to different estimation methods.

I begin by considering Ball and Sheridan (2005) methodology. One of the important parts in the analysis is splitting the sample time period in pre- and post-treatment periods. The separation is natural for the targeting countries and will happen at the inflation targeting adoption date. However, the split is arbitrary for non-targeting countries and will occur at the average start date of adopters. As discussed earlier, the wave of adoptions spread across three decades in the case of emerging market economies. Therefore, subdividing the sample period into two parts: pre- and post-treatment is unlikely to be sufficient.[33] Instead, I will consider four sample periods corresponding to the discussions in figures 4 and 5. To summarize, I compare two policy regimes: IT and non-IT, and also four time periods which is natural given the observed timing of regime shifts. In this case, the specification follows Ball (2010) and becomes

$$\begin{aligned}\overline{\pi}_{i,t} - \overline{\pi}_{i,t-1} &= aD_t^2 + bD_t^3 + cD_t^4 + \mathbf{eIT_{i,t}} + f(\overline{\pi}_{i,t-1} \times D_t^2) + \\ &+ g(\overline{\pi}_{i,t-1} \times D_t^3) + h(\overline{\pi}_{i,t-1} \times D_t^4) + \epsilon_{i,t} \qquad (11)\end{aligned}$$

$$t = 2, 3, 4$$

$$D_t^2, D_t^3, D_t^4 : \text{dummy variables for periods 2, 3, and 4}$$

$$IT_{i,t} : \text{changes in regime from period } t-1 \text{ to period } t$$

[33] Although, to the best of my knowledge, all papers in the literature that build onto this method and investigate emerging markets, only considers two subperiods: pre- and post-IT.

Table 7: Ball and Sheridan (2005) Regression: 1985Q1 - 2019Q4

	(1)	(2)
	$\overline{\pi}_{i,t}$	$\overline{\pi}_{i,t}$
D_t^2	-1.693^{***}	3.296^{***}
	(0.442)	(0.633)
D_t^3	-0.744^{*}	1.746^{**}
	(0.424)	(0.678)
D_t^4	-1.090^{**}	0.151
	(0.418)	(0.710)
$IT_{i,t}$	**-3.050*** **	**-1.244** **
	(0.662)	(0.521)
$\overline{\pi}_{i,t-1} \times D_t^2$		-0.684^{***}
		(0.0732)
$\overline{\pi}_{i,t-1} \times D_t^3$		-0.499^{***}
		(0.111)
$\overline{\pi}_{i,t-1} \times D_t^4$		-0.327^{**}
		(0.150)
Observations	126	126
R^2	0.380	0.674

Standard errors in parenthesis
* p<0.10, ** p<0.05, *** p<0.01

Different time period dummy variables allow constant in the regression to differ across time periods. Similarly, separate interaction terms also allow regression to the mean to differ across time periods. The coefficient of interest is e, which captures the effect of a change in regime from period $t-1$ to period t. $IT_{i,t}$ is equal to 1 if country i switched from traditional or non-IT regime to IT in period t and 0 otherwise. For instance, for an early adopter country, $IT_{i,t}$ will equal to 1 in period 2 but will equal to 0 in periods 3 and 4. We have three observations per country: the dependent variable as a change in inflation from period 1 to period 2, from period 2 to period 3, and period 3 to peroid 4.

Table 7 presents the findings using this estimator. It indicates that once we adjust for initial conditions, the estimated effect of IT changes from -3.05% to -1.244%. Consequently, the effect becomes 2.5 times smaller. Nevertheless, it is also important that even after accounting for the possible bias, the coefficient retains its statistically significance. Therefore, while the smaller coefficient indicates the presence of bias in column (1), it also signifies that the adoption of IT had an impact on the average inflation level beyond mere regression to the mean. Moreover, drawing from insights gained from simulations and the proof of unbiasedness of this estimator by Ball (2010), we regard the effect of -1.244% as capturing the true causal effect in an unbiased manner.

Table 8: TWFE Regression: 1985Q1 - 2019Q4

	(1)	(2)	(3)	(4)
	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$
$IT_{i,t}$	**-3.379*** **	**-2.448*** **	**-1.475*** **	**-1.28*** **
	(0.556)	(0.396)	(0.382)	(0.34)
$\pi_{i,t-1}$		0.249***		
		(0.0318)		
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$			0.441***	0.38***
			(0.0443)	(0.04)
Observations	4,930	4,888	4,762	4,493
Time FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Controls				✓
R^2	0.293	0.336	0.334	0.38
R^2 (within)	0.02	0.08	0.08	0.14

Driscoll-Kraay Standard errors in parenthesis
* p<0.10, ** p<0.05, *** p<0.01

In Table 8, I employed the two-way fixed effects (TWFE) estimator on the same sample of countries and time periods. Several key observations emerge. Firstly, the coefficient of -3.38% in column (1) without lagged inflation closely matches the coefficient in column (1) of Table 7 when initial conditions are not considered. However, the coefficients diverge when we incorporate one lag of inflation and initial conditions. Under TWFE in column (2), the effect is -2.45%, which is twice as large as the estimate of -1.2%. This reinforces the intuition from simulations that a single lag of inflation may not adequately control for bias. Secondly, it's important to note that the standard error under TWFE is smaller compared to the one in Table 7, further supporting earlier insights. Lastly, instead of a single lag of inflation, employing a moving average of inflation from the last four quarters yields a coefficient of -1.48%, much closer to an unbiased estimate of -1.2%.

Table 9 displays the estimates of the IT effect using propensity score matching across various matching methods. It's important to note that propensity scores are typically generated using a range of different variables. However, in this study, the focus is on demonstrating the impact of including lagged inflation among those variables. Therefore, only lagged inflation is used to generate propensity scores. Intuitively, this is equivalent to solely matching on lagged inflation. As we learned from simulations, matching on lagged inflation introduces a bias in the estimator, particularly an upward bias. Consequently, under this method, we are likely to observe an IT effect on the inflation level that is smaller than the true effect. Across different matching methods, the observed average effect is

-0.79%, which is smaller than the -1.2% reported in table 7. This once again validates the anticipated effect from simulations and indicates a 0.4% smaller effect under this estimator, corresponding to an upward bias.

Table 9: Propensity Score Matching: 1985Q1 - 2019Q4

	Nearest Neighbor (nn = 1)	Nearest Neighbor (nn = 3)	Radius (r = 0.04)	Radius (r = 0.02)	Radius (r = 0.01)	Kernel Epanechnikov (bandwidth = 0.06)
Baseline model	**-0.61***** (0.29)	**-0.76***** (.23)	**-0.87***** (0.20)	**-0.81***** (0.20)	**-0.79***** (0.20)	**-0.89***** (0.20)
Observations	4,888	4,888	4,888	4,888	4,888	4,888

* p<0.10, ** p<0.05, *** p<0.01

Table 10: Two-step system GMM: 1985Q1 - 2019Q4

	$\pi_{i,t}$ IT endogenous
$IT_{i,t}$	**-0.12**
	(0.31)
$\pi_{i,t-1}$	0.54***
	(0.10)
Observations	396
# of Countries	42
# of Instruments	30
AR(2) test	0.730
Hansen J-test	0.132

* p<0.10, ** p<0.05, *** p<0.01

Lastly, let's turn to the fourth estimator considered in this paper, which is a two-step system GMM. Based on simulations, we anticipate this estimator to exhibit an upward bias. Moreover, it's expected to have a larger upward bias compared to the propensity score matching estimator. Table 10 uncovers an estimate of -0.12% when IT is treated as endogenous under this method. Notably, this value is not only much smaller than the one reported in table 7, but it's also smaller than the average effect of -0.79% observed under propensity score matching. Furthermore, the effect here is not statistically significant, suggesting that not only is the effect of adopting the framework on the average level of inflation very small, but it's also statistically indistinguishable from zero.

Summary. To reiterate, we identified a specific ordering of the estimators considered within the simulation setup. In this sequence, $\widehat{\beta^{BS}}$ is unbiased, while $\widehat{\beta_{1lag}^{TWFE}}$ shows a downward bias, and both $\widehat{\beta^{PSM}}$ and $\widehat{\beta^{s-GMM}}$ exhibit an upward bias.

$$\underline{\text{Simulations:}} \quad \widehat{\beta_{1lag}^{TWFE}} \leq \widehat{\beta_{4QMA}^{TWFE}} \leq \widehat{\beta^{BS}} \leq \widehat{\beta^{PSM}} \leq \widehat{\beta^{s-GMM}}$$

In this section of a paper, we further provided evidence that the same ordering is found when we apply these estimators on a common sample of real-world data.

$$\underline{\text{Empirics:}} \quad -2.45 \leq -1.47 \leq -1.24 \leq -0.79 \leq -0.12$$

5.4 Robustness Exercises

Given that the TWFE exhibits the lowest RMSE, I conduct a few robustness exercises using this particular method.

Staggered Adoption. Recently, a large body of literature has emerged on staggered adoption in settings where treatments are implemented at different times across units. The papers voice concerns about estimating causal effects under staggered treatment timing due to problematic assumptions common in traditional differences-in-differences methods. Other related papers build on these ideas by refining methods to account for heterogeneous treatment effects and spillovers in staggered designs (Borusyak et al., 2021; Sun and Abraham, 2021). In appendix D, I apply the proposed solutions to my data to see whether the main insight of TWFE holds up to these criticisms.

More Restrictive Classification of EMEs. It's important to note that the IMF's fiscal monitor offers a less restrictive EME classification compared to other classifications like Morgan Stanley's (MSCI) Emerging Market Index. The MSCI index identifies only 24 countries as EMEs: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Kuwait, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. For a robustness check, I will utilize this narrower definition. Additionally, it's worth mentioning that four countries listed as EMEs by the MSCI are classified as advanced economies (AEs) by the IMF (Czech Republic, Greece, Korea, and Taiwan). Since I adhere to the IMF's classifications, these countries are excluded from my sample. Of the

24 countries classified as EMEs under the MSCI index, my benchmark sample includes only 15. This sample excludes the Czech Republic, Egypt, Greece, Indonesia, Korea, Qatar, Taiwan, Turkey, and the United Arab Emirates. Among these 15 EMEs, only 4 (China, Kuwait, Malaysia, and Saudi Arabia) were not inflation targeters by the end of 2019. Although this robustness analysis results in a very small control group, there is still some variation in the adoption dates among the countries. Appendix D shows TWFE estimates under a more restrictive EME classification than that used in the IMF's fiscal monitor.

Exclusion of Hard Peggers. I classify a country's exchange rate regime based on the criteria set forth by Ilzetzki et al. (2019). The coarse classification includes six categories. Based on this classification, categories 1 and 2 would likely correspond to a fixed exchange rate and category 1 to hard peggers. Out of the 42 countries in my benchmark sample, only 17 never had a hard peg during the specified sample period. Among the countries that adopted the IT framework by the end of 2019, 7 had a hard peg at some point within this period. I have retained these 17 countries for analysis. Among them, 4 countries (Botswana, Tunisia, Algeria, and Pakistan) are not inflation targeters. The remaining 13 countries (Chile, Jamaica, Paraguay, Brazil, South Africa, Guatemala, Kazakhstan, Georgia, Peru, Poland, Mexico, Hungary, and Colombia) are inflation targeters. Appendix D shows TWFE estimates in this case.

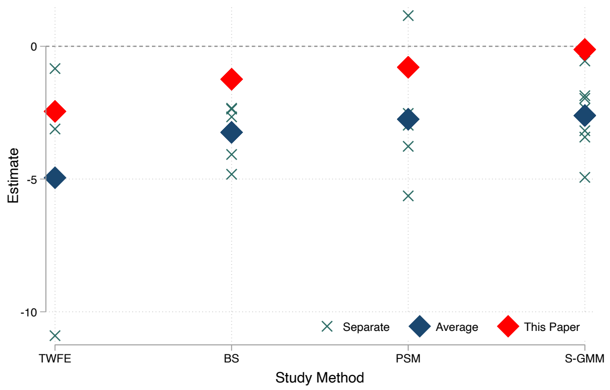
6 Reconciling literature

This paper began by presenting various estimates from the existing literature. Given the significance of the inflation targeting framework and the lack of consensus regarding its effects, the primary objective was to explore how the heterogeneity of econometric estimators contributes to the differing magnitudes of the causal effect of inflation targeting reported across studies. Throughout, we have established the expected ordering of different estimators based on various econometric methodologies when addressing IT adoption endogeneity and mean reversion in inflation rates. A logical next step is to assess whether the ranking identified through simulation exercises and my empirical analysis aligns with the patterns observed in previous studies. To this end, figure 7 arranges these coefficient estimates (previously shown in figure 2) by econometric methodology and includes results from my carefully selected empirical sample as well.

There are two main takeaways: (1) A similar pattern of ordering is observed when averaging estimates across studies within each methodology. (2) My estimates are notably smaller than the average.

While the ordering of average estimates from earlier studies aligns with the ordering demonstrated in my simulation and empirical exercises, significant heterogeneity exists within each method. Additionally, outliers have a substantial impact on the ordering. This suggests that methodological differences contribute to the variations across studies, but they are not the sole factor. My consistently smaller estimates might be due to several factors, including the fact that many earlier studies do not cover data beyond 2019, control variables or the possibility of publication bias.

Figure 7: Estimates from Previous Studies by Methodologies



Note. The x's in the figure represent the same coefficients as those depicted in figure 2 in the introduction. However, they are sorted by the estimation method used. The blue diamond represents the average of these coefficients under each method, while the red diamond corresponds to the coefficient estimates from the empirical sample introduced in section 5.3.

Several additional factors may explain differences across studies, including variations in the definitions of IT adoption dates and the sample of IT countries under consideration. To investigate whether these factors contribute to the observed variability within each method, I examine these aspects in more detail. Tables 11 and 12 illustrate the potential impact of these factors.

Table 11 examines the impact of using different definitions for IT adoption dates. In my main analysis, I defined the start of inflation targeting as the target enforcement date. However, some previous studies use the initial announcement or explicit adoption date as the starting point. This table explores how results might differ with these alternative definitions.[34]

[34] Details about these date definitions were discussed in section 5.1.2.

Table 11: Definition of IT Adoption Dates

	(1)	(2)	(3)
	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$
$IT_{i,t}$	-1.63^{***}	-1.53^{***}	-1.47^{***}
	(0.37)	(0.40)	(0.38)
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$	0.44^{***}	0.44^{***}	0.44^{***}
	(0.04)	(0.04)	(0.04)
Observations	4,762	4,762	4,762
Time FE	✓	✓	✓
Country FE	✓	✓	✓
R^2	0.33	0.33	0.33
R^2 (within)	0.08	0.08	0.08
Initial announcement	✓		
Explicit adoption		✓	
Target enforcement			✓

Driscoll-Kraay Standard errors in parenthesis

* p<0.10, ** p<0.05, *** p<0.01

To conduct this exercise, I use only the TWFE methodology with a four-quarter moving average of inflation. This allows me to isolate the impact of different definitions of adoption dates. Table 11 shows that the results remain consistent across different adoption dates, with only minor variations in magnitude. Therefore, I conclude that differences in adoption dates are unlikely to be a major contributor to the substantial variation observed in earlier studies.

Lastly, not all previous studies account for all explicit inflation targeters up to 2019, which may lead to differences in results within the same econometric methodology due to varying definitions of the targeter group.

Table 12 fixes the control group of non-IT emerging markets and separately examines IT adopters classified into early, middle, and late adoption groups. It shows that emerging market economies adopting IT in the earliest wave show the largest coefficient, while those adopting it later experienced the smallest effects on lowering inflation. While due to large standard errors, I cannot say which group benefited the most, it shows that studies focusing on countries in the early adoption group compared to late are likely to observe different effects from inflation targeting.

Overall, while the emphasis on early, middle, or late adopters in previous studies may influence the wide range of estimates regarding the effect of IT, differences in adoption dates do not seem to have the same impact.

Table 12: Waves of ID Adopters

	(1)	(2)	(3)
	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$
$IT_{i,t}$	-2.04^{***}	-1.19^{*}	-0.18
	(0.49)	(0.64)	(1.24)
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$	0.49^{***}	0.35^{***}	0.41^{***}
	(0.05)	(0.05)	(0.05)
Observations	3,763	3,220	3,069
Time FE	✓	✓	✓
Country FE	✓	✓	✓
R^2	0.39	0.31	0.34
R^2 (within)	0.12	0.04	0.06
Early adopters	✓		
Middle adopters		✓	
Late adopters			✓
Non-IT	✓	✓	✓

Driscoll-Kraay Standard errors in parenthesis

* p<0.10, ** p<0.05, *** p<0.01

7 Conclusion

This paper set out to address two key questions regarding the impact of inflation targeting in emerging markets: (1) What factors contribute to the significant variation in estimates found in previous studies regarding the impact of explicit adoption of the inflation targeting framework on average inflation levels? (2) Which estimates can be considered credible? Through a combination of Monte Carlo simulations and empirical analysis using a carefully constructed panel of 42 emerging markets from 1985Q1 to 2019Q4, this study provides several important insights.

First, the choice of econometric methodology plays a crucial role in explaining the wide range of estimates in the literature. Different estimators, including two-way fixed effects (TWFE), Ball and Sheridan (2005)'s differences-in-differences, propensity score matching (PSM), and system generalized method of moments (GMM), exhibit varying degrees of bias when dealing with the endogeneity of IT adoption and mean reversion in inflation rates. Specifically, TWFE tends to show a downward bias, while PSM and system GMM demonstrate an upward bias. The Ball and Sheridan method, when properly specified, appears to be unbiased.

Second, precision varies substantially across methods. TWFE offers the highest precision, due to its utilization of all available data points. In contrast, the Ball and Sheridan (2005) method, while unbiased, exhibits lower precision as it relies on averaged data. PSM and system GMM fall between these extremes in terms of precision.

Third, when considering both bias and precision together through the root mean squared error, TWFE emerges as the preferred estimator. This suggests that in the trade-off between bias and precision, the gains in precision from TWFE outweigh its slight bias, particularly when using a 4-quarter moving average of inflation.

Fourth, applying these insights to real-world data, I find that inflation targeting lowered average inflation in emerging markets by 1.2-1.5 percentage points. This effect is more modest than the previous literature. However, this is a meaningful effect that has been either under- or overestimated in many previous studies.

Fifth, beyond econometric methodology, differences in inflation targeting country samples also contribute to the variation in estimates. Early IT adopters appear to have a larger coefficient estimate compared to later adopters, which may explain some of the higher estimates in earlier studies focused on the first wave of IT countries.

These findings have several important implications. For researchers, they underscore the need to carefully consider the trade-offs between bias and precision when selecting estimation methods. While unbiasedness is a desirable property, it should not come at the cost of excessively low precision. The results also highlight the importance of sensitivity analysis across different econometric approaches.

For policymakers, the more modest effect of IT identified in this study does not weaken the case for its adoption. The magnitude of the observed impact still indicates that IT can serve as an effective tool for controlling inflation. Furthermore, the average inflation rate is just one dimension of macroeconomic performance. Even if the effect on this particular variable is less pronounced, IT may have exerted a more substantial influence on other key indicators, such as inflation expectations. Moreover, understanding how different estimators behave is crucial for policymakers when assessing the effectiveness of IT. Being aware of potential biases and precision issues in various econometric approaches allows policymakers to more accurately interpret and weigh evidence on IT's impact. This knowledge can lead to more informed decision-making about whether to adopt IT and how to set realistic goals for its performance. Policymakers armed with this methodological insight can better distinguish between robust findings and potentially misleading results, ultimately leading to more effective monetary policy strategies.

Several important areas warrant further research. First, as many countries are currently transitioning to or will soon adopt inflation targeting, studying these cases could provide further insights into its specific effects on average inflation levels. Second, when classifying countries as inflation targeters or non-targeters, it's important to consider the practical implementation of the framework. Some emerging markets may officially declare themselves as inflation targeters but do not fully adhere to the framework's principles, while others may not officially identify as such but follow similar policies. It is interesting to examine these nuances and evaluate countries based on their actual policy behavior rather than just their formal declarations for future work.

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Appendix

A Adoption Dates

Table 1: Inflation Targeting Adoption Dates

Country	Rationale
Poland	The Poland's Monetary Policy Council (RPP) was formed in February 1998. Subsequently, in September of the same year, the council officially declared its intention to adopt an inflation targeting framework starting in 1999, with the objective of reducing inflation to below 4% by 2003. The council set the one-year target for 1999 within the range of 8% to 8.5%, with a focus on evaluating the consumer price index.
Brazil	The Brazilian authorities signaled their intent to implement a formal inflation targeting framework following the adoption of a floating exchange rate regime in mid-January 1999. The President issued a decree in June 1999 formally adopting inflation targeting, with specific inflation targets and tolerance intervals established by the National Monetary Council. The decree emphasized that inflation targets for 1999, 2000, and 2001 would be set no later than June 30, 1999. Specific inflation targets and tolerance intervals were established, with targets for 1999 set at 6-8%, 2000 at 4-8%, and 2001 at 2-6%.
Chile	Chile announced its intent to adopt an inflation targeting framework in September 1990, starting to use an explicit annual inflation target for the subsequent year. However, the full adoption of IT coupled with a floating exchange rate regime was announced in September 1999. The target for CPI inflation was set at 3.5% for the 12-month change at year-end 2000, followed by a target range of 2 to 4% starting in 2001.
Thailand	The Bank of Thailand announced its inflation targeting framework on May 23, 2000. This decision followed a reassessment post-IMF program, concluding that inflation targeting would be more effective than money supply targeting. The Monetary Policy Board was first appointed on 5 April 2000. A target range of 0-3.5 percent for the quarterly-average of core inflation was deemed appropriate by the committee.
Colombia	The initial steps towards adopting an inflation targeting strategy in Colombia began in 1995, with the development of inflation forecasting models and the introduction of a monthly internal Inflation Report. The Central Bank of Colombia officially adopted inflation targeting with a floating exchange rate in September 1999. Subsequently, in November 2000, the central bank announced inflation targets for 2001 and 2002, set at 8 percent and 6 percent, respectively.
Mexico	In 1998, Banco de México signaled a move towards a restrictive monetary policy stance, addressing crisis challenges and initiating a gradual shift towards an inflation targeting framework. By 2000, an inflation target of 3% for 2003 was established, along with intermediate targets of 6.5% and 4.5% for 2001 and 2002, respectively. The full adoption of an inflation targeting regime was announced on Jan. 31, 2001, with the Bank of Mexico abandoning its previous approach to managing monetary aggregates. This transition was officially communicated in the Bank of Mexico's Inflation Report for Q3 2000, establishing a permanent 3% target for the annual CPI.
Hungary	Hungary announced its inflation targeting regime in June 2001, setting a long-term inflation objective of two percent. Intermediate targets included achieving 7 percent by December 2001, transitioning to 4.5 percent by the end of 2002, and subsequently lowering to 3.5 percent by the end of 2003. These targets are determined based on the 12-month increase in the Consumer Price Index (CPI) at the end of December.

Source: IMF Staff Country Reports and Central Bank Websites

Country	Rationale
South Africa	In 1998, South Africa began considering the adoption of an explicit inflation targeting regime for its monetary policy. Subsequently, in February 2000, it officially implemented this strategy, setting a CPIX inflation target range of 3-6 percent for 2002 and 2003, and adjusting it to 3-5 percent for 2004 and 2005. 2002 was the first year in which the South African Reserve Bank was supposed to achieve an explicit target.
Philippines	On January 24, 2000, the Monetary Board of the Central Bank of Philippines approved the transition to inflation targeting as the framework for monetary policy. The formal adoption of this framework in January 2002 aimed to assist in achieving this goal, with the government setting a target range for annual headline inflation at 4.5-5.5 percent for the years 2002 and 2003.
Peru	Before formally adopting inflation targeting, the Central Reserve Bank of Peru had been announcing target bands since 1994 as part of a gradual transition to this framework, with the aim of reducing inflation to international levels. In December 2001, the central bank initiated formal procedures for adopting an IT framework. Subsequently, in January 2002, the authorities announced the implementation of an inflation-targeting framework for monetary policy, with the Board setting a medium-term inflation target range of 2.5% plus/minus 1% by end of December.
Guatemala	The Banco de Guatemala initiated a gradual transition to a monetary scheme with explicit inflation targets following the passage of a new law in 2002. Although reforms began in 2002, it wasn't until 2005 that an inflation-targeting monetary scheme was formally adopted. For December 2005 and January-December 2006, a target range of 4% to 6% were established.
Indonesia	The formal adoption of the inflation targeting framework in Indonesia occurred on July 1, 2005, following detailed documentation provided by the central bank in late June. The government, in consultation with the central bank, set the inflation target at 6% plus/minus 1% in 2005, 5.5% plus/minus 1% in 2006, and 5% plus/minus 1% in 2007. While the implementation of monetary policy in Indonesia aimed to achieve target inflation since at least 2000, the official adoption of inflation targeting occurred in 2005, with prior announcements facilitating a learning process for the central bank towards a more formal inflation targeting approach.
Uruguay	In the latter half of 2004, Uruguay operated within an inflation-targeting regime, although the central bank did not officially acknowledge it, establishing a public inflation target without commitment to monetary aggregates. By November 2004, a targeted inflation range of 6 to 8 percent was announced for September 2005. Subsequently, in 2005, the central bank shifted focus solely to inflation targeting, abandoning the monetary base target. Uruguay formally adopted inflation targeting in September 2007, with a target inflation range of 4-6%, utilizing the policy inflation rate as the primary intermediate instrument and the interest rate as the main monetary policy instrument.
Armenia	Discussions on pursuing inflation targeting with the IMF began in 2004, as evidenced by a technical assistance mission held between January 26 and February 6 of that year. Since 2006, the Central Bank of Armenia has initiated the transition to a comprehensive inflation targeting strategy as outlined in the CBA monetary policy program of 2006. The Central Bank Board, approving the monetary policy program for 2007 on December 11th, 2006, established inflation targets for a 12-month period. These targets were defined as 4 percent for 2007 and 3 percent for 2008, with a tolerance band of 1.5 percent.
Albania	During discussions with the IMF in October 2002, authorities acknowledged that the move to formal inflation targeting was not feasible in the next few years but stressed the intention to eventually do so. In 2008, the Bank of Albania announced a new monetary strategy to the public, setting the inflation target at 3% with a tolerance band of plus/minus 1%.

Source: IMF Staff Country Reports and Central Bank Websites

Country	Rationale
India	India announced its intention to move to an inflation targeting framework on February 20th, 2015, formalizing it as the prime objective of the central bank with the signing of a monetary policy framework agreement between the Ministry of Finance and the RBI. The adoption was completed with the formation of the Monetary Policy Committee and amendments to the RBI Act in September 2016, announcing the target of 4 percent CPI inflation with a symmetrical band of 2 percent for a five-year period on August 5th, 2016.

Source: IMF Staff Country Reports and Central Bank Websites

B Comparison Studies

Selection criteria. Comparison studies were selected using Google Scholar (the most recent check was conducted in June 2024). I focused on papers published after 2000 to allow sufficient time for countries to have explicitly implemented the inflation targeting framework before research studies could conduct a relevant analysis.

As a first step, a broad search was carried out for all papers containing ”Inflation Targeting” or ”Inflation Targeter” in the title. Afterward, a refined search was performed utilizing the following keywords anywhere within the paper: (”Inflation Targeting” OR ”Inflation Targeters”) AND (”Emerging” or ”Developing”) AND (”Propensity Score Matching” or ”Fixed Effect” or ”Dynamic Panel” or ”Synthetic Control” or ”DID” or ”Difference” or ”Difference-in-Difference” or ”Differences-in-Differences” or ”GMM”).[35]

I included the studies if they contained empirical work comparing countries with and without inflation targeting, examined the level of inflation as at least one of the measures of macroeconomic performance in emerging market economies and utilized specified econometric methods. Among the ones with results for both advanced and developing economies, only those with separate results for developing countries were selected.

Additionally, I applied a minimum citation restriction. For papers published prior to 2019, I required 30 citations, while for more recent studies I did not have such a restriction. For each query, the search was limited to the first 20 pages of results and case studies were excluded.

[35] The synthetic control method has been employed in three studies that meet the selection criteria (Lee, 2011; Brito and Bystedt, 2010; Duncan et al. (2022)). However, I have decided to exclude this method from the analysis for several reasons. Primarily, the data-driven nature of the method often necessitates the inclusion of a large number of countries in the donor pool to generate an appropriate pre-treatment fit. This requirement frequently leads to the mixing of countries at different stages of economic development. This study aims to focus specifically on emerging market economies, maintaining a homogeneous sample to ensure comparability and relevance of results. The need for a diverse donor pool conflicts with this objective. I found it difficult to obtain desirable pre-treatment fits for many countries within the restricted sample of emerging economies.

As a result of the systematic selection process, I compiled studies objectively rather than subjectively. This is important to create a relevant and unbiased set of comparative studies on inflation targeting in emerging markets.

B.1 Adoption Dates Across Studies

Country	**Abo-Zaid and Tuzemen (2012)**	**Alpanda and Honig (2014); Brito and Bystedt (2010)**	**Ardakani et al. (2018)**	**Ayres et al. (2014)**	**Batini and Laxton (2007)**	**Dubey and Mishra (2022)**
Albania						2009
Argentina						2016 - 18
Armenia			2006Q1			2006
Brazil	1999	1999	1999Q2	1999Q3	1999Q2	1999
Chile	1991	1999	1999Q3	1991Q1	1999Q3	1999
Colombia	1999	1999	1999Q3	1999Q4	1999Q3	1999
Czech Rep.	1998	1998	AE	1998Q1	1998Q1	AE
Dominican Rep.						2012
Georgia						2009
Ghana			2002Q1			2007
Guatemala			2005Q1			2005
Hungary	2001	2001	2001Q2	2001Q3	2001Q3	2001
India						2016
Indonesia			2005Q3	2005Q3		2005
Israel	1992	1997	AE	1992Q1	1997Q2	AE
Jamaica						2017
Kazakhstan						2015
Mexico	1999	2002	2001Q1	1999Q1	2002Q1	2001
Moldova						2013
Paraguay						2011
Peru	1993	2002	2002Q1	2002Q1	2002Q1	2002
Philippines	2002	2002	2002Q1	2002Q1	2002Q1	2002
Poland	1998	1999	1998Q1	1998Q4	1999Q1	1998
Romania			2005Q3	2005Q3		2005
Russia						2015
Serbia			2006Q3			2009
Slovakia				2005Q1		
South Africa	2000	2000	2000Q1	2000Q1	2000Q1	2000
South Korea	AE	1998	AE	1998Q2	1998Q2	AE
Thailand	2000	2000	2000Q2	2000Q2	2000Q2	2000
Turkey			2006Q1	2002Q1		2006
Uganda						
Ukraine						2017
Uruguay						2007

Note. The table presents adoption dates used in previous studies.

Country	de Mendonça and de Guimarães e Souze (2012)		Gonçalves and Salles (2008)	Lin and Ye (2009)		Thornton (2016)
	Initial	Conservative		Default	Conservative	
Albania						
Argentina						
Armenia						2006
Brazil	1999	1999	1999	1999	1999	1999
Chile	1991	2000	1991	1991	1999	1999
Colombia	2000	2000	2000	1999	1999	
Czech Rep.	1998	1998	1998	1998	1998	
Dominican Rep.						
Georgia						
Ghana	2003	2007				2007
Guatemala	2005	2006				2005
Hungary	2001	2001	2001	2001	2001	2001
India						
Indonesia	2005	2006				2005
Israel	AE		1992	1992	1997	
Jamaica						
Kazakhstan						
Mexico	1995	2001	1999	1999	2001	2001
Moldova						
Paraguay						
Peru	1994	2002	1994	2002	2002	2002
Philippines	2002	2002	2002	2002	2002	2005
Poland	1999	1999	1999	1998	1998	
Romania	2005	2006				2000
Russia						
Serbia						
Slovakia	2005	2005				
South Africa	2000	2000	2000	2000	2000	2000
South Korea	AE		1998	1998	1998	
Thailand	2000	2000	2000	2000	2000	2000
Turkey	2002	2006				2006
Uganda						
Ukraine						
Uruguay						

Note. The table presents adoption dates used in previous studies.

Country	Ouyang and Ramkishen (2019)		Samarina et al. (2014)		Vega and Winkelried (2005)	
	Initial	Conservative	Loose	Strict	Classification 1	Classification 2
Albania	2009	2009	1999Q1	1999Q3		
Argentina						
Armenia	2006	2006				
Brazil	1999	1999			1999	1999
Chile	1991	2000	1991Q1	2001Q1	1991	1999
Colombia	2000	2000	1991Q1	1999Q4	1995	1999
Czech Rep.	1998	1998	1998Q1	1998Q1	1998	1998
Dominican Rep.	2012	2012				
Georgia	2009	2009				
Ghana	2003	2007	2007Q2	2007Q2		
Guatemala	2005	2006	2005Q1	2005Q1		
Hungary	2001	2001	2001Q1	2001Q3	2001	2001
India	2015	2015				
Indonesia	2005	2006	2005Q1	2006Q1		
Israel	1992	1997	AE		1992	1997
Jamaica						
Kazakhstan						
Mexico	1995	2001	1999Q1	2001Q1	1995	1999
Moldova	2010	2010				
Paraguay	2013	2013				
Peru	1994	2002	1994Q1	2002Q1	1994	2002
Philippines	2002	2002	2001Q1	2002Q1	1995	2002
Poland	1999	1999	1998Q1	1999Q1	1998	1998
Romania	2005	2006	2005Q3	2005Q3		
Russia	2014	2014				
Serbia	2006	2006				
Slovakia	2005	2005	2005Q1	2005Q1		
South Africa	2000	2000	2000Q1	2001Q1	2000	2000
South Korea	1998	2001	AE		1998	1998
Thailand	2000	2000	2000Q1	2000Q2	2000	2000
Turkey	2002	2006	2000Q1	2002Q2		
Uganda	2012	2012				
Ukraine						
Uruguay	2007	2007				

Note. The table presents adoption dates used in previous studies.

B.2 Methodological and Statistical Details

The table below shows details regarding the coefficient estimates depicted on figures 2 and figures 7.

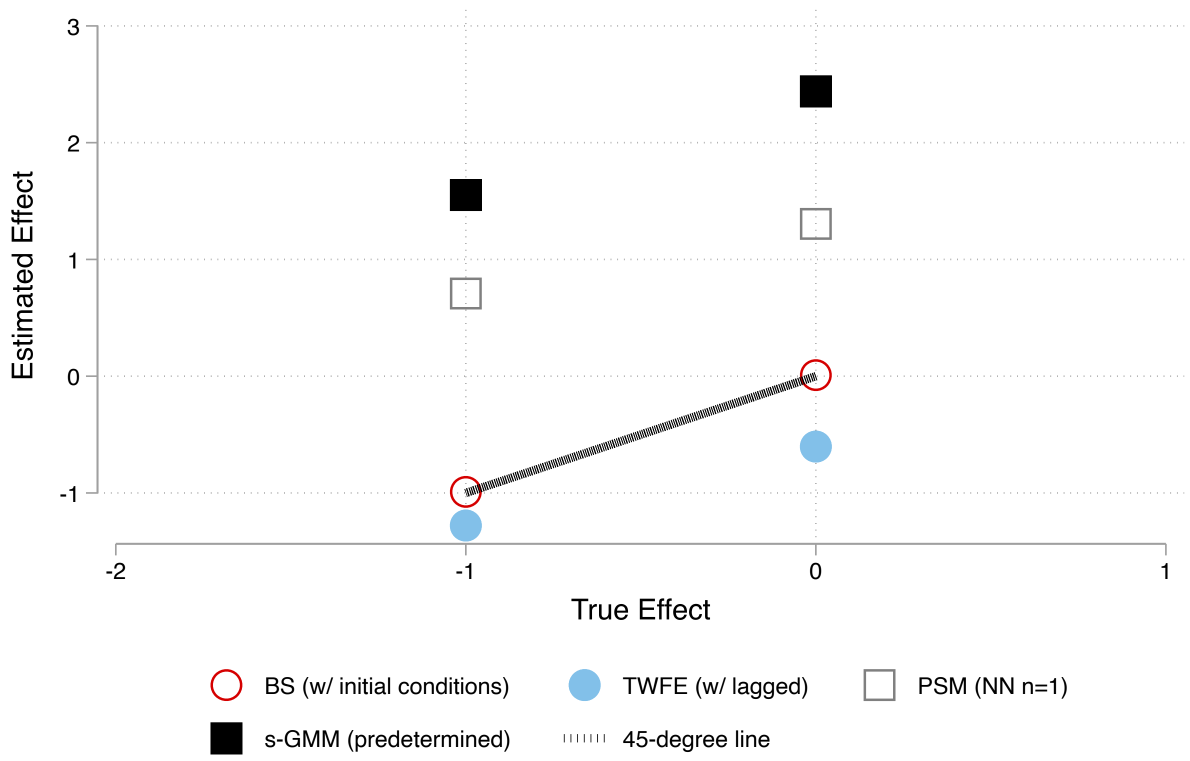
Paper	Method	Coefficient (Average Level of) Inflation)	Statistical Significance	ITers	Non-ITers	Time Period
Abo-Zaid and Tezemen (2012)	BS DID	-3.197%	Yes	12	17	1980 - 2007
Alpanda and Honig (2014)	s-GMM P s-GMM E	-3.42% -1.96%	Yes No	13	31	1980 - 2006
Ardakani et al. (2018)	PSM	1.157%	Mixed	17	55	1990 - 2013
Arsić et al. (2022)	s-GMM PSM	-2.336% -2.528%	No Yes	12	14	1997 - 2019
Ayres et al. (2014)	TWFE	-0.839%	No	17	34	1985 - 2010
Batini and Laxton (2007)	BS DID	-4.82%	Yes	13	29	1985 - 2004
Brito and Bystedt (2010)	TWFE s-GMM P s-GMM E	-10.9% -1.86% -3.18%	Yes Yes Yes	13	33	1980 - 2006
de Mendonça and de Guimarães e Souza (2012)	PSM	-5.634%	Yes	17	133	1990 - 2007
Dubey and Mishra (2022)	s-GMM	-0.552%	No	28	38	1991 - 2018
Duong (2022)	TWFE	-3.114%	Yes	15	39	2002 - 2010
Gonçalves and Salles (2008)	BS DID	-2.333%	Yes	13	23	1980 - 2005
Lin and Ye (2009)	PSM	-2.971%	Yes	13	39	1985 - 2005
Ouyang and Ramkishen (2019)	s-GMM P	-4.936%	Yes	30	24	1980 - 2015
Samarina et al. (2014)	BS DID PSM	-2.365% -3.768%	Mixed Yes	17	42	1990 - 2011
Thornton (2016)	BS DID	-2.658%	Mixed	14	58	1990 - 2013
Vega and Winkelried (2005)	PSM + BS DID	-4.075%	Yes	13	86	1985 - 2004

C Sensitivity of Simulation Findings

C.1 The Effect of IT > 0

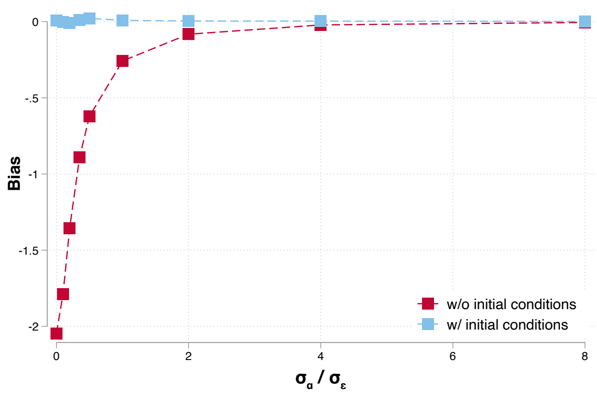
The main simulation exercise assumes that there is no true effect of switching to the IT framework. It is also useful to see whether the main insights and the ordering of the estimators hold if we had assumed a particular effect of IT on the level of inflation instead. Given the empirical findings, I now assumed that the adoption of IT lowers average level of inflation by 1%. To do so, I subtract 1 from the permanent country component for all countries that are identified as inflation targets in the post-IT period. As shown in Figure 1, the direction of biases and the relative ordering still holds in this case.

Figure 1: IT Effect (the average level of inflation) of 0% vs -1%

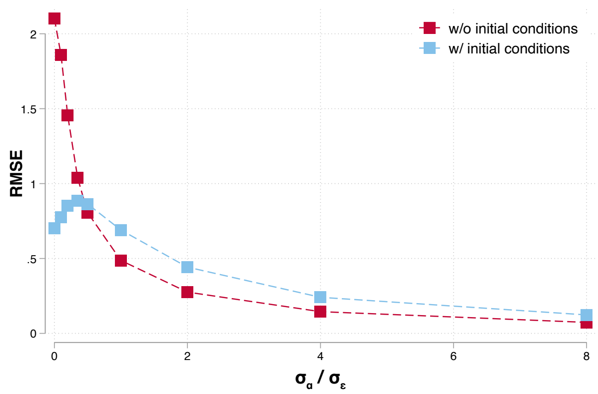


C.2 Ratio of variances

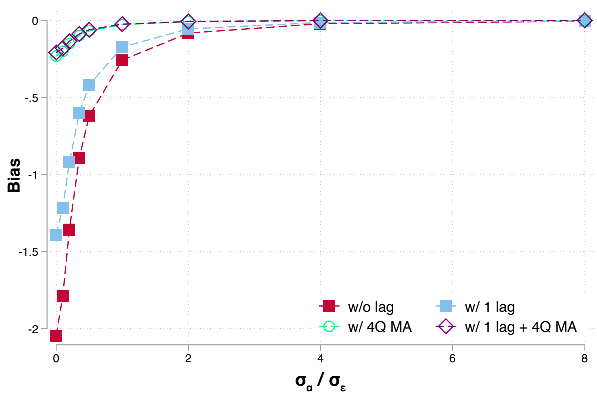
Figure 2: Sensitivity to $\sigma_\alpha/\sigma_\epsilon$ (relative importance of transitory and permanent differences)



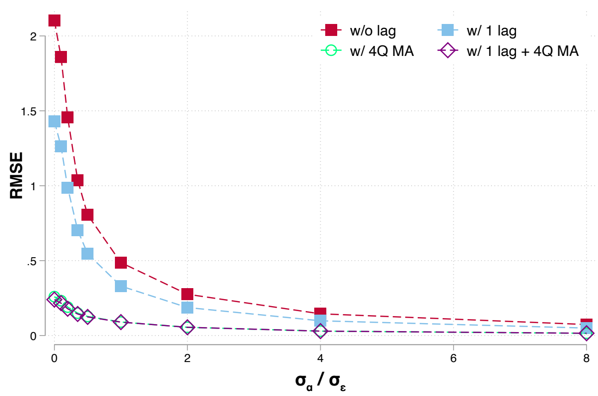
(a) Coefficient - BS (2005)



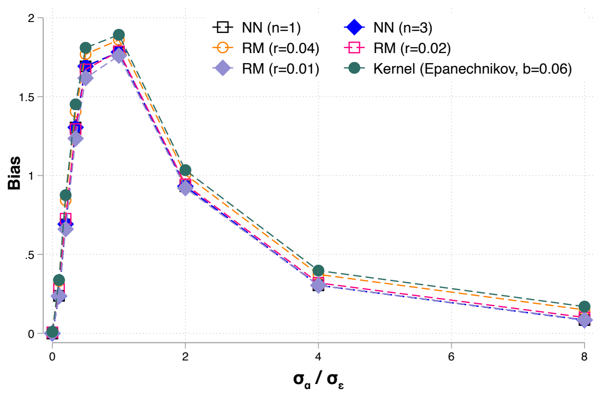
(b) RMSE - BS (2005)



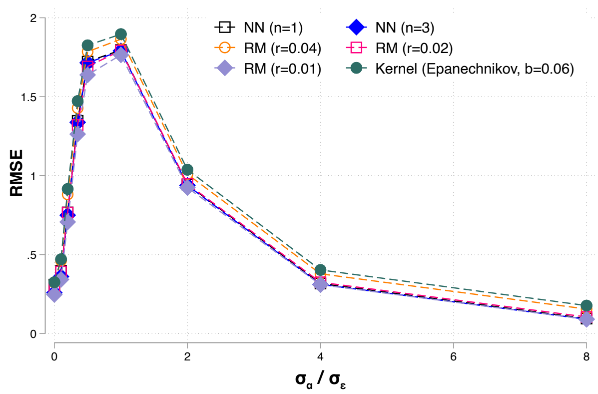
(c) Coefficient - TWFE



(d) RMSE - TWFE



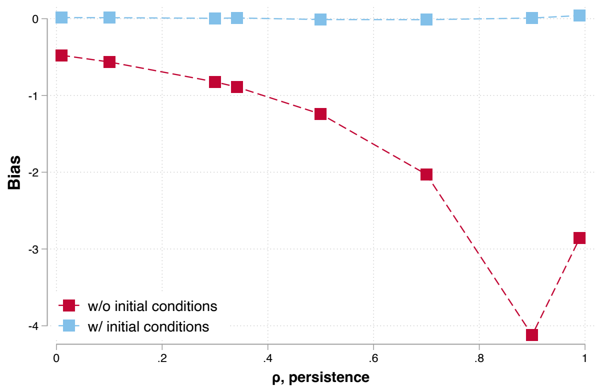
(e) Coefficient - PSM



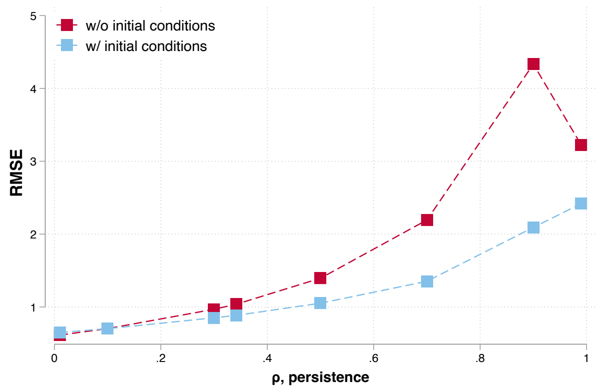
(f) RMSE - PSM

C.3 Persistence

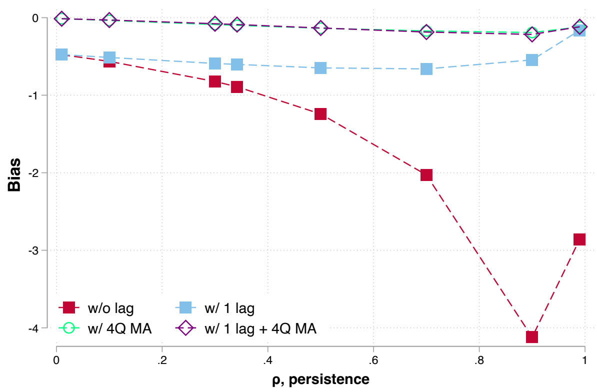
Figure 3: Sensitivity to ρ (persistence)



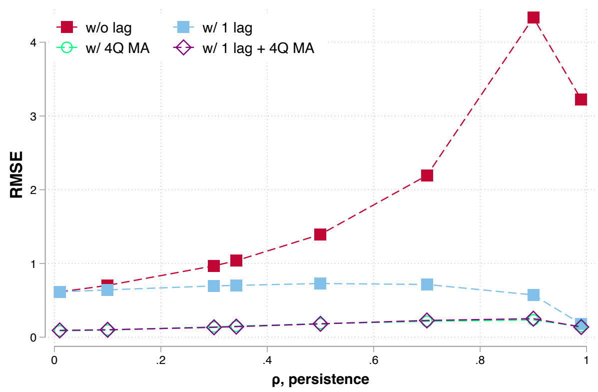
(a) Coefficient - BS (2005)



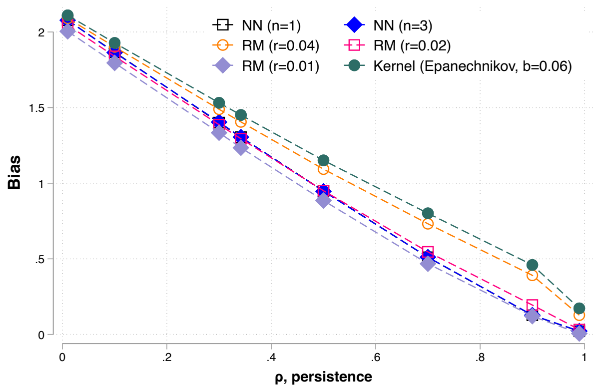
(b) RMSE - BS (2005)



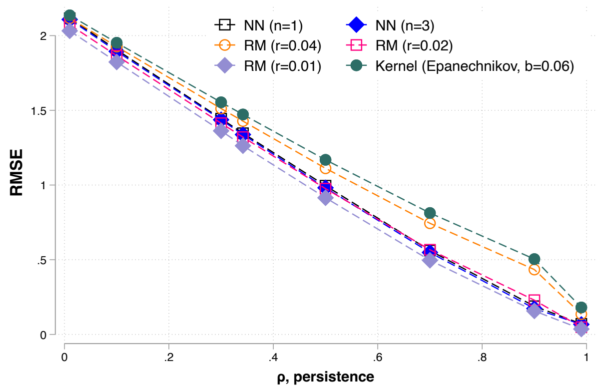
(c) Coefficient - TWFE



(d) RMSE - TWFE



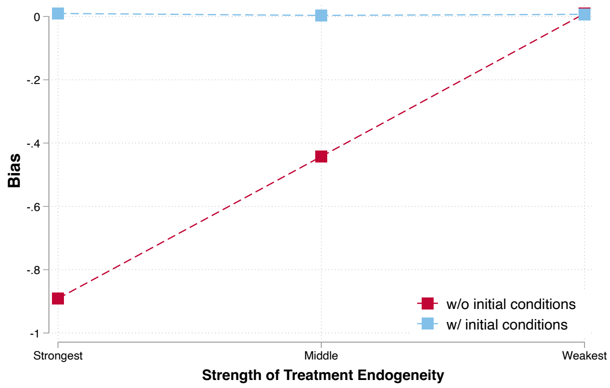
(e) Coefficient - PSM



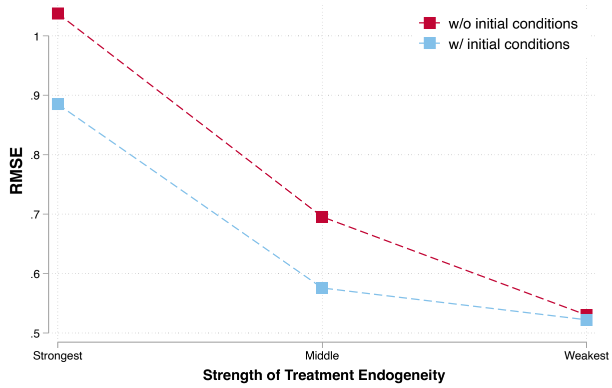
(f) RMSE - PSM

C.4 Strength of Endogeneity

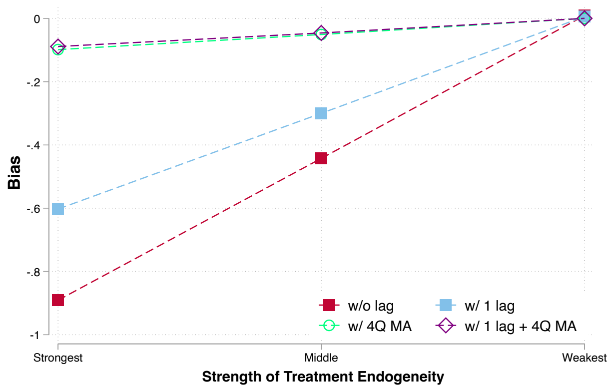
Figure 4: Sensitivity to the Strength of Treatment Endogeneity



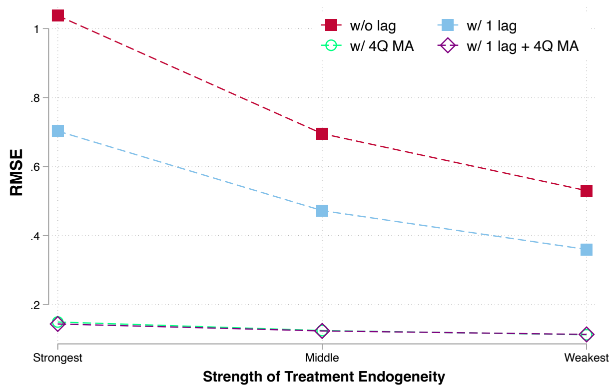
(a) Coefficient - BS (2005)



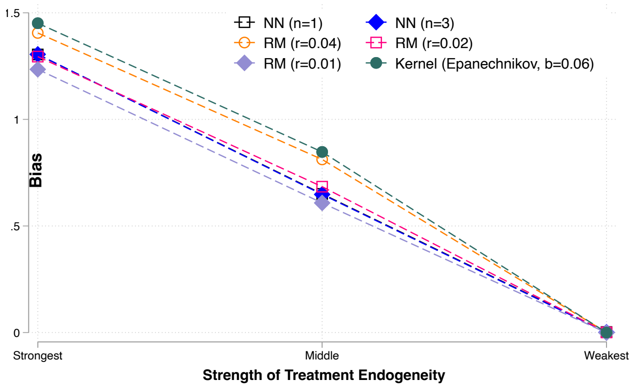
(b) RMSE - BS (2005)



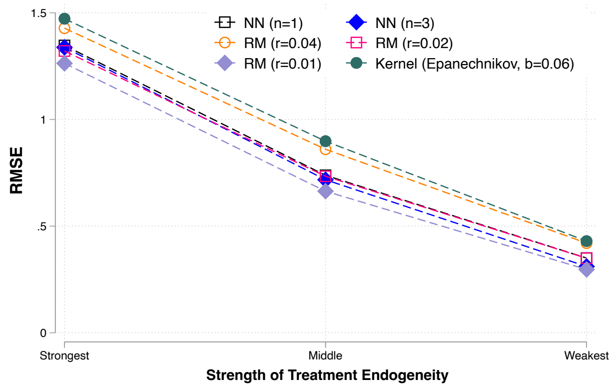
(c) Coefficient - TWFE



(d) RMSE - TWFE



(e) Coefficient - PSM



(f) RMSE - PSM

D Robustness of Empirical Findings

Table 2: Robustness - Staggered TWFE

	(1)	(2)	(3)	(4)
	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$
PANEL (a) - Borusyak et al. (2021)				
$IT_{i,t}$	**-4.462*****	**-3.347*****	**-2.067*****	**-2.090*****
	(0.462)	(0.384)	(0.362)	(0.357)
$\pi_{i,t-1}$		0.229***		0.146***
		(0.0386)		(0.0307)
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$			0.392***	0.257***
			(0.0637)	(0.0608)
PANEL (b) - Sun and Abraham (2021)				
$IT_{i,t}$	**-3.172****	**-2.586****	**-1.301**	**-1.532**
	(1.318)	(1.160)	(1.001)	(1.001)
$\pi_{i,t-1}$		0.213***		0.122**
		(0.0698)		(0.0531)
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$			0.387***	0.273***
			(0.103)	(0.0897)
Observations	4,930	4,888	4,762	4,762
Time FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01

Note. The table shows coefficient estimates from Borusyak et al. (2021) and Sun and Abraham (2021), which were introduced to correct for potential biases arising from staggered adoption dates (treatment) in the new literature on two-way fixed effects.

Table 3: More Restrictive Classification of EMEs - Morgan Stanley EME index

	(1)	(2)	(3)
	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$
$IT_{i,t}$	**-5.06*****	**-2.66*****	**-0.87**
	(0.92)	(0.57)	(0.62)
$\pi_{i,t-1}$		0.43***	
		(0.03)	
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$			0.68***
			(0.05)
Observations	1,820	1,805	1,760
Time FE	✓	✓	✓
Country FE	✓	✓	✓
R^2	0.40	0.51	0.53
R^2 (within)	0.06	0.24	0.27

Driscoll-Kraay Standard errors in parenthesis
* p<0.10, ** p<0.05, *** p<0.01

Note. The table shows coefficient estimates under two-way fixed effect if the paper had used Morgan Stanley EME index to identify emerging markets instead of IMF's fiscal monitor.

Table 4: Exclude Hard Pegs

	(1)	(2)	(3)
	$\pi_{i,t}$	$\pi_{i,t}$	$\pi_{i,t}$
$IT_{i,t}$	**-4.41*****	**-2.74*****	**-1.80*****
	(0.70)	(0.48)	(0.52)
$\pi_{i,t-1}$		0.35***	
		(0.03)	
$\frac{1}{4}\sum_{k=1}^{4}\pi_{i,t-1}$			0.50***
			(0.08)
Observations	1,892	1,875	1,824
Time FE	✓	✓	✓
Country FE	✓	✓	✓
R^2	0.05	0.165	0.137

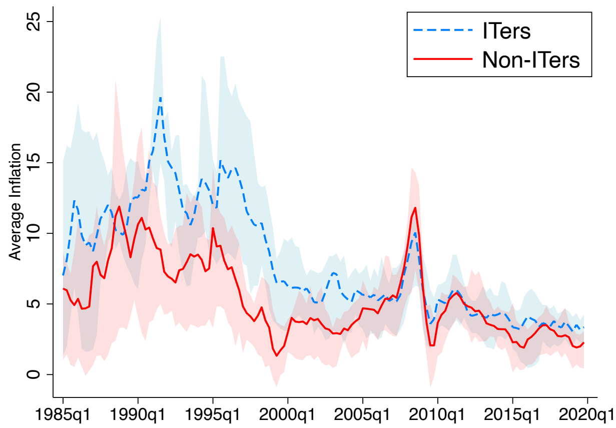
Driscoll-Kraay Standard errors in parenthesis
* p<0.10, ** p<0.05, *** p<0.01

Note. The table shows coefficient estimates under two-way fixed effect if the countries that had a hard peg at any time during the sample period had been excluded from the sample of countries.

E Miscellaneous

Figure 5 shows a declining trend in inflation rates across both IT and non-IT emerging markets since the 1990s, which also marked the onset of the growing dominance of the IT framework. It is important to note that this figure consider ITers and non-ITers in a specific quarter. This means that a country adopting the framework in a later quarter will be considered a non-ITer in the current quarter. It demonstrates that both IT and non-IT economies have experienced disinflation, though average inflation within the IT group initially started higher and remains slightly elevated compared to non-IT counterparts. The two groups of countries have mostly coverged close to each other in terms of average inflation rates. However, the observation of declining trends in both groups at the time of increased IT popularity complicates the task of uncovering the true role played by the specific framework in driving better performance in IT countries than it would have been under any other reasonable framework.

Figure 5: Inflation Trends in EMEs



Note. Inflation rates are calculated as % year-over-year changes. Only EMEs within the baseline sample of this paper (42 EMEs) are considered.