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ARTICLE

Shades of inflation targeting: insights from fractional integration

Marek A. Dąbrowski, Jakub Janus, and Krystian Mucha

Department of Macroeconomics, Krakow University of Economics, Kraków, Poland
Corresponding author: Marek A. Dąbrowski; Email: marek.dabrowski@uek.krakow.pl

Abstract

We propose a novel approach to classifying inflation-targeting (IT) economies using fractionally integrated processes. Motivated by the rising prevalence and diversity of IT, we leverage variation in the persistence of inflation rates to identify four de facto strategies, or "shades" of IT. Moving from negative orders of fractional integration, indicating anti-persistent behaviour, to more persistent long-memory processes, often associated with less credible policy frameworks, we classify countries into average, strict, flexible, and uncommitted IT. This framework sheds light on differences between declarative and actual strategies across 36 advanced and emerging economies. Most countries fall into the flexible IT category, though extreme cases, including uncommitted IT, occur quite frequently. Furthermore, we link our classification to institutional features of national frameworks using ordinal probit models. The results suggest differences across categories are related to variations in the maturity and stability of IT frameworks, with weaker connections to central bank independence and transparency.

Keywords: Inflation targeting; monetary policy strategy; central banking; inflation persistence; fractional integration

JEL classifications: E52; E58; E31; C22

1. Introduction

Although inflation targeting (IT) was a monetary policy strategy initially employed exclusively in advanced economies (AEs), it has been gradually adopted by a growing number of emerging market economies (EMEs), making it the monetary strategy of choice of the most important central banks, especially if we include the Fed and the ECB among inflation targeters. Even though the core axioms remain unchanged, the strategy proved flexible enough, serving as a framework, rather than a rule for monetary policy (Bernanke et al. 1999) and being able to accommodate new theoretical developments—such as inflation forecast or unconventional measures—and respond to practical challenges (Mishkin, 2009; Epstein & Yeldan, 2010). While this in many respects confirms that IT has been the most successful monetary policy strategy of the last four decades, this very success means that the number of inflation targeters grew, allowing for increasing diversity within the group and making IT less and less useful as a classification tool for describing monetary policy strategies. The picture became even more complex after the Fed formally adopted average inflation targeting (AIT) in August 2020 (see, e.g., Coulter et al. 2022).

In this paper, we propose a new approach to the classification of inflation targeters. To achieve this goal, we combine two areas of research: the first one dedicated to the analysis of inflation persistence and the second one to alternative monetary policy strategies. We notice that if we interpret IT, AIT, and price level targeting (PLT) as monetary policy strategies set on the same continuum (or as possible variants of IT in a broad sense), the central bank's choice of version of the strategy has important implications for inflation persistence. Conversely, the estimated inflation persistence can show how committed the central bank is, thus making it possible to distinguish between various "subcategories" or "shades" of inflation targeting: average IT, strict IT, flexible IT, and uncommitted IT.

We can see at least four reasons that motivate this line of analysis. First, as mentioned before, the growing popularity of IT (according to the IMF AREAER Database; see also Zhang and Wang, 2022) causes the category to dominate others and become too broad. The common description of inflation targeters lumps together quite a diverse group of monetary policy strategies, treating them as homogeneous. The classification would become more useful if it enabled us to distinguish between different variants or "shades" of IT.

The second reason for the introduction of a new classification is the difference between declarative (*de jure*) inflation targeting typology and the actual (*de facto*) practice of central banks. Some suggestions were offered by other authors. Svensson (1997, 2001) distinguishes between *strict* IT and *flexible* IT, with the former characterised as "completely disregarding the real consequences of monetary policy in the short and medium term and focusing exclusively on controlling inflation at the shortest possible horizon" while the latter being "a somewhat more gradual and more moderate approach to monetary policy, aiming to achieve the inflation target at a somewhat longer horizon (say 2–3 years) than would be technically feasible (perhaps 3–4 quarters)." We argue that the introduction of AIT justifies upgrading this classification into more than two categories. The best-established classification into *full-fledged, eclectic*, and *lite* IT was put forward by Carare and Stone (2003). This proposal is criticised due to its declarative nature, putting more weight towards words rather than deeds of monetary authorities (see, e.g., Truman, 2003). Our approach combines the two: we start with *de jure* classification, using central banks' self-identification as an inflation targeter as a starting point, and then we use the data on inflation persistence to distinguish between various *de facto* subcategories of IT. Because we focus on the second step, we treat the self-identification as given. One could see our classification as conditional on the central banks' declaration.

The third reason is connected to the growing body of theoretical literature on possible variants of IT. Earlier work on optimal monetary policies often contrasted IT and PLT, drawing a strong binary distinction, juxtaposing inflation rate with price level and short-run flexibility with long-run stability (an important contribution breaking this juxtaposition is given by Svensson, 1999; a review of relevant literature is provided by Ambler, 2009 and Hatcher, 2011). The introduction of literature on AIT allows us to interpret IT as a broader category that includes a number of specific strategies depending on the target horizon. IT in a narrow sense is a case where the target is defined as average inflation over one period, while PLT means that the average is over an infinite number of periods; solutions in-between could be called AIT. This formulation means that instead of three separate monetary regimes, we are dealing with a spectrum of potential monetary policy strategies. This suggests that the previous dichotomous understanding is too simplistic and, what is more, we have several intermediate cases that are probably the most interesting ones and cannot be properly described under the old classification. All this further suggests that the group referred to as IT is not a homogeneous category.

The fourth reason is related to the practice of central banking. Investigating the flexibility of inflation-targeting frameworks in the last three decades, Borio and Chavaz (2025) find that central banks have specified numerical targets more strictly, adopted longer horizons for achieving them and placed greater weight on additional objectives such as employment and financial stability. Importantly, these developments are more pronounced in AEs, contributing to growing differences relative to emerging markets. Thus, even though their analysis exploits the time-series dimension, the findings also imply some cross-country differences in inflation-targeting frameworks. For instance, the evolution of institutional setup in recent years has gradually pushed the ECB and the Fed in the direction of IT. The case of the Fed, first moving from the implicit to explicit target (in 2012) and then from IT to AIT (in 2020), shows that "inflation targeter" is

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not a narrow, clear-cut category but a broader, overarching term that seems not only to evolve as a response to the theoretical development described in the previous point, but also informs the research itself. In recent years, such two-way interaction between practice and theory may be exemplified by the shifting interpretation of AIT in the official Federal Reserve (see also Clarida, 2022).[1]

The main objective of the paper is to investigate how self-declared inflation targeters actually conduct their monetary policy. To this end, we construct a novel *de facto* classification of monetary policy strategies based on the properties of inflation rate series in inflation-targeting countries using models of fractionally integrated processes. Specifically, our aim is to map the persistence of the inflation rates, which is, in turn, indicative of central bank credibility and management of expectations, into the description of monetary policy strategies that we dub the "shades" of IT. The analysis encompasses a diverse group of 36 advanced and EMEs, with the core estimation sample spanning from January 2000 to December 2019, and an extended dataset through 2023 to cover the Covid-19 pandemic period. We further aim to characterise the "shades" of IT by linking them with institutional features of monetary policymaking, including strategy maturity, central bank independence, monetary policy transparency, and the potential conflict of stabilisation objectives (the primacy of inflation target).

Our contribution to the literature is threefold. First, we propose a *de facto* classification that is more granular than the one used by the IMF. Our approach combines the advantages of both *de jure* and *de facto* approaches while upgrading the existing classifications to fit the rich and evolving reality of monetary policy conduct. Starting with the differences in the behaviour of inflation rates implied by theoretical distinctions among various monetary policy strategies, we can, using inflation persistence, group all central banks that have officially adopted IT into four groups, or "shades" of IT: average IT, strict IT, flexible IT, and uncommitted IT. Second, we propose a novel economic interpretation of fractional integration (FI) by directly linking it to a range of actual monetary policy strategies. While FI has been employed in the context of monetary policy in previous research, its use was mostly limited to comparison of AEs and EMEs or assessing the effectiveness of IT in inflation expectation management by comparing the periods before and after IT adoption (Yigit, 2010; Canarella and Miller, 2017a). We notice that differences in inflation persistence should be visible in inflation data if a *de jure* homogeneous group of IT is *de facto* heterogeneous, with central banks understanding their mandates in different ways. When formulating its current monetary policy, the central bank might try—or not—to compensate for the effects of past shocks to inflation. For example, strict IT implies short memory (or, theoretically, no memory) in inflation rates. Considering the distinction between stationary and nonstationary processes within a simple I(0) vs I(1) framework seems too restrictive and leads to a distorted view of the dichotomous nature of monetary policy strategies (IT or non-IT). An autoregressive fractionally integrated moving average (ARFIMA) model gives more room for manoeuvre, allowing for different levels of "strictness" within the broader IT group. Third, we contribute to the literature on the institutional setup of monetary policy by looking at the relationship between various institutional features of monetary policy and "shades" of IT. In doing this, we go beyond a standard comparison of advanced and EMEs and investigate alternative factors that may explain cross-country differences in types of IT strategies.

The study leads to several noteworthy findings. Our primary result is that it is possible to solve the difficulties posed by *de jure* classifications, which take central banks' declarations at face value, and the *de facto* classification of the IMF, which is too simplistic. The literature on IT, AIT, and PLT suggests that these strategies, if expressed in terms of inflation rates rather than price levels, can be interpreted on a continuum, as subtypes of IT in a broad sense. The difference between these subcategories depends on the extent to which the central bank wants to compensate for past inflation target misses, as is the case under PLT or AIT, or whether "bygones are bygones," as prescribed by IT in a "narrow" sense. Considering this literature and its implications for the FI of inflation rates, we propose four possible "shades" of IT: average, strict, flexible, and uncommitted.

Second, we find that *de jure* IT economies can, in fact, be assigned to one of four categories. Using a FI parameter, we show that most of them can be classified as flexible IT or strict IT, but cases of more extreme types, like AIT (where the central bank compensates for past mistakes) or uncommitted IT (where not only there is no compensation, but the return to inflation target takes a very long time), are also present. Employing our classification, we can uncover the heterogeneity of IT central banks and assess to what extent their words are consistent with deeds. Third, we demonstrate that the differences between the *de facto* IT strategies, or the "shades" of IT, are related to variations in the maturity and stability of IT frameworks, while central bank independence and monetary policy transparency appear to play a less significant role.

Our results are robust to modifications in the estimation methods of ARFIMA models, different data treatments, and the inclusion of the post-Covid-19 period to the sample, which we validate using several measures of similarity between countries' assignments to the four strategies. Furthermore, to strengthen our analysis of cross-sectional correlates of the inflation targeting classification, we employ an alternative set of covariates capturing institutional features of monetary policymaking, alongside a competing estimation approach.

The remainder of the paper is structured as follows. Section 2 provides an overview of the literature on alternative monetary policy strategies and the measurement of inflation persistence using FI. Section 3 describes the empirical framework, explains the interpretation of a fractional differencing parameter, and presents the data used in the analysis. Section 4 reports and discusses our baseline results. Section 5 discusses a set of sensitivity checks performed on the baseline results, where the ARFMIA models for each country are re-estimated employing a modified sample or a different estimator. Section 6 extends the analysis by focusing on the underlying factors that may explain why different countries are classified as AIT, strict IT, flexible IT, or uncommitted IT. The goal is to explore the institutional features of monetary policymaking that contribute to this variation. Section 7 presents conclusions, policy implications, and areas for future research.

2. Related literature

In our analysis, we expand upon two main strands of literature. The first one comprises empirical work on inflation persistence in (mainly) IT countries, especially the studies that employ the FI framework to describe inflation processes. The second one stems from the theoretical analyses of alternative monetary policy strategies, mainly PLT and, more recently, AIT.

Batini and Nelson (2001) offer three working definitions of inflation persistence: (a) positive serial correlation in inflation; (b) lags between systematic monetary policy actions and their peak effect on inflation; and (c) lagged response of inflation to non-systematic policy actions, i.e., policy shocks. Canarella and Miller (2017b) show that inflation persistence is an important factor in determining economic outcomes from the perspective of both households and policymakers, but, at the same time, it is hard to measure and describe. A thorough overview of different types and classifications of inflation persistence is provided by Fuhrer (2009). The author argues that a policymaker must be able to determine whether or not persistence is structural and thus may be taken as a stable feature of the economic landscape. In order to know this, she must be able to parse the sources of persistence into three types: (1) those generated by the driving process, (2) those that are a part of the inflation process intrinsic to inflation (that is, persistence that is imparted to inflation independent of the driving process), and (3) those that are induced by her own actions or communications. According to Fuhrer (2009, p. 27), the research suggests that "central banks that are more explicit about their inflation goal and act in accordance with that commitment may enjoy less persistence in their nations' inflation rates." This implies that central banks' commitment to IT is a plausible explanation for differences in inflation persistence. Williams (2006) indicates that commitment influences both persistence and overall dynamics of inflation through the expectations channel, by anchoring actors' expectations to the inflation target.

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While early analyses of FI go back over four decades (Granger and Joyeux, 1980; Granger, 1980), there is growing empirical support that economic time series are fractionally integrated (Parke, 1999). Gadea and Mayoral (2006) describe the search for a proper way to model inflation. The sticky price models of Taylor and Calvo do not capture the observed inertia of inflation well enough, nor do their modifications. The authors provide evidence corroborating that inflation is better described by FI than by a simple I(1) or I(0) dichotomy. The impact of price shocks is rarely permanent, as would be in the I(1) case, or has only a short-lasting impact, decaying to zero at an exponential rate, as would be in the I(0) case. The authors argue that even though price shocks are non-permanent, they vanish slowly in a hyperbolic rather than exponential fashion. Zagaglia (2009) shows for 12 member countries of the Organisation for Economic Co-operation and Development (OECD) that CPI series have finite variance and are at least two standard errors below the unit root, thus confirming FI rather than integration of order one. Estimates for some d coefficients are negative, but the uncertainty is too large to draw any definite conclusions. FI is also used for extremely long (8 centuries) time series by Caporale and Gil-Alana (2020). According to them, the main advantage of such a framework is that it requires fewer assumptions than a simple ARMA model and, therefore, is more general.

Gadea and Mayoral (2006) show that the FI behaviour of inflation might result from the aggregation of prices of firms that are heterogeneous in adjusting their prices to costs. Other potential explanations for long memory in inflation are aggregation in price indexes (Hassler and Wolters, 1995), aggregation of heterogeneous firm production (Abadir and Talmain, 2002), persistence in money supply shocks (Scacciavillani, 1994), lack of credibility of the inflation target (Erceg and Levin, 2003), unanchored inflation expectations, and uncertainty about the long-term inflation objective (Orphanides and Williams, 2005). Altissimo et al. (2009) and Paya et al. (2007), among others, suggest a possible connection between inflation persistence and temporal aggregation, with models estimated with higher frequency data showing lower persistence than models estimated with lower frequency data.[2] Yigit (2010) notes that while the empirical work assessing the relative performance of IT usually concentrates on observable variables, such as inflation and output, the true test of IT's effectiveness could be shown by the strategy's influence on inflation expectations. Although direct measurement of expectations is difficult, expensive, and often impossible due to a lack of data, especially before the adoption of IT, the author offers an "indirect methodology" by suggesting the link between inflation persistence and the distribution of inflation expectations. He estimates the FI parameter before and after the adoption of IT and argues that, as the fall in long memory happened exactly at the time of a regime shift, the changed nature of inflation expectations is the best explanation.

The evidence of lower inflation persistence after the adoption of IT is vast and is often used as an argument in favour of adopting the new strategy (Kuttner and Posen, 2001; Levin et al. 2004; Zagaglia, 2009; Bhalla et al. 2023). Canarella and Miller (2017a) analyse shifts in inflation persistence between pre- and post-inflation targeting periods. Unlike Yigit (2010), they use a modified log periodogram (MLP) to estimate inflation persistence, as this semiparametric method does not require the specification of the ARMA model. Authors confirm falling persistence after the adoption of IT. Bhalla et al. (2023) argue that while this argument was clear-cut in the case of early adopters of IT, in countries that switched to the new strategy later, the benefits are not so obvious since there are a number of possible competing explanations for falling levels and persistence of inflation, such as great moderation, also among countries that did not use IT. Contrary to this approach, our goal is to use inflation persistence to show different outcomes within the IT group.

A comprehensive review of the literature on the PLT strategy can be found in Ambler (2009) and Hatcher (2011). While early literature on PLT focused on its contribution to long-run price stability at the cost of higher output variability, only after a seminal paper by Svensson (1999, working paper in 1996) was the influence of the expectations channel on improving the inflation-output trade-off fully grasped. Both Ambler (2009) and Hatcher (2011) present the research on

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the validity of Svensson's "free lunch," list arguments in favour and against switching to PLT, and provide an exhaustive description of relevant institutional issues.

Ruge-Murcia (2014) asks whether IT central banks *de facto* target the price level path and shows that under certain conditions there can be an "observational equivalence between inflation and price-level targeting." They explain that "[t]his equivalence arises from the purposeful policy action of the inflation-targeting central bank, which seeks to deliver average inflation rates close to the target rate in the short run. In principle, this equivalence may also arise as a result of symmetric shocks that take inflation sometimes above, sometimes below, its target."

Although AIT has been present in the theoretical literature since the turn of the century (Nessén & Vestin, 2005), it experienced a surge in popularity following the Fed's announcement. AIT as a viable alternative to both PLT and IT is presented in Svensson (2020), who treats "forecast targeting" as a general (and preferable) monetary policy strategy that could be crystallised as IT, AIT, PLT, temporary PLT, or nominal-GDP targeting and shows that AIT potentially dominates other proposals. Dorich et al. (2021), who analyse alternative strategies as a potential choice for the Bank of Canada, observe that history dependence can lead to better performance in a low neutral rate environment. Since flexible IT, AIT, and PLT "differ only in the degree of history dependence they embed," the authors find that their performance "depends critically on the importance of the effective lower bound (ELB) constraint." In the absence of an ELB, flexible IT dominates the other options, and when the ELB is an important constraint, AIT is the preferred option. Budianto et al. (2023) analyse the role of the expectations channel under AIT and show, under rational expectations, the welfare-improving role of history dependence when facing low interest rates. While, according to the authors, the optimal averaging window is infinitely long, making AIT observationally equivalent to PLT, most of the benefits are to be obtained within a finite but long (e.g. a few years) window. Jia and Wu (2023) analyse the central bank's incentive to deviate from the ex-ante announced AIT. They show that the optimal horizon of AIT is time-dependent and that, provided the central bank is credible, the ex-post switch from AIT back to IT might be welfare-improving.

Clarida (2022) describes the Fed's move to AIT, but his interpretation diverges from a textbook description of AIT. According to him, the Fed's new monetary policy framework has been asymmetric from the very beginning: its goal "is to return inflation to its 2 percent longer-run goal, but not to push inflation below 2 percent." As stated by Clarida (2022, p. 9), "our framework aims ex ante for inflation to average 2 percent over time, but does not make a commitment to achieve ex post inflation outcomes that average 2 percent under any and all circumstances." Therefore, the new strategy could be described as "temporary PLT that reverts to flexible IT (once the conditions for liftoff have been reached)." This seems to suggest that the adoption of AIT might have been a communication device aimed at escaping the ELB. It also means that real-life monetary policy strategies can easily dwell between the theoretical ideal types.

3. Empirical framework and data

This section outlines the empirical framework used in the study and describes the dataset.[3] Our main task at hand is to investigate the persistence of inflation rates at the country level. We next use this property to classify the monetary policy strategies into several categories or "shades" of inflation targeting. The empirical setting of the study relies on fractionally integrated processes. Specifically, we utilise ARFIMA models. The major feature of such models is that they encompass standard autoregressive and moving average (ARMA) components while allowing for non-integer (fractional) orders of integration in time series. One significant advantage of FI is that it breaks the dichotomous distinction between stationary (mean-reverting, I(0)) processes and nonstationary (unit-root, I(1)) processes, providing a more nuanced understanding of various degrees of persistence in inflation rates. As we discuss below, this approach adds more complexity to the modelling of inflation rates by accommodating the so-called long-memory properties of time series or the ability of the series to exhibit significant autocorrelation at long lags. Unlike models of I(0) and

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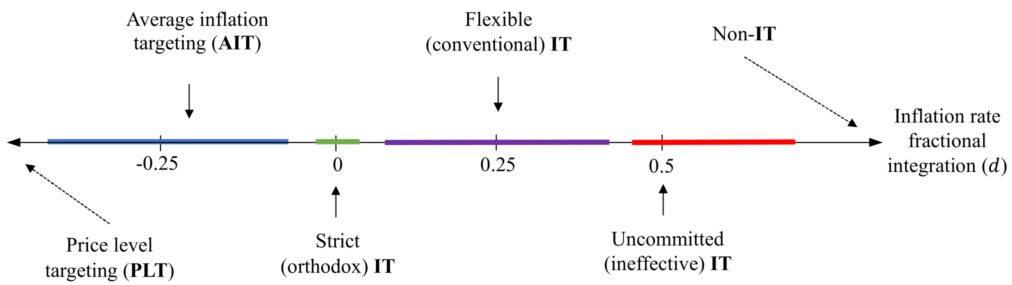

Figure 1. Fractional integration of inflation rates and the classification of monetary policy strategies.
Notes: The figure shows a schematic relationship between the fractional integration of inflation rates (parameter d in the ARFIMA models) and monetary policy strategies.

I(1) processes, ARFIMA models can capture intermediate levels of persistence, reflecting both short-term fluctuations and long-term dependencies. This flexibility allows ARFIMA models to represent the gradual decay of shocks' effects over time, offering a richer depiction of the dynamics underlying the inflation rates.

A general ARFIMA(p, d, q) process of the inflation rate series, π_t, may be expressed as:

$$\phi\ (L)\ (1-L)^{d}\ \pi_t = \theta\ (L)\ \varepsilon_t, \tag{1}$$

where $\phi(L)$ is the autoregressive lag polynomial, $\theta(L)$ denotes the moving average lag polynomial, while ε_t is the white noise error term. Our main object of interest is the fractional differencing parameter d. Notice that when $d = 0$, the process in Equation (1) collapses to a standard stationary ARMA process, and the inflation rates are integrated of order zero. However, an ARFIMA process involves a range of intermediate cases.

As d increases and approaches 0.5, the process remains stationary but exhibits long-term dependence, or "long memory." In such an instance, the autocorrelation function decays more slowly over time, meaning that the effects of shocks to the inflation rate persist for a longer period than in a regular I(0) case. The higher the value of d, the more pronounced the long-term dependence, indicating that it takes a considerable amount of time for the inflation rate to revert to its mean. On the other hand, when d falls between -0.5 and 0, the process demonstrates negative long-term dependence, which implies a strong mean-reverting behaviour. This type of process is often referred to as "intermediate memory" or "antipersistent." For inflation rates, this means that after experiencing a shock, the process overcompensates during its reversion to the mean, often resulting in a negative adjustment following a positive shock, and *vice versa*.

We argue that the properties of fractionally integrated processes in inflation rates provide a valuable framework for analysing actual monetary policy strategies across countries. Our key premise is that while inflation targeting (IT) regimes are typically associated with stationary inflation rates, the degree of long-term dependence (or long memory) in inflation may vary across different inflation targets. Hence, we advance the ideas put forward by Yigit (2010) and Canarella and Miller (2017b) that monetary policy strategies can be investigated indirectly by scrutinising the effects of monetary policy credibility and the effectiveness of expectations management embedded in the inflation series. This approach allows for an evaluation of how well central banks establish credibility and anchor inflation expectations. Moreover, FI of inflation rates offers insights not only into the relative effectiveness of IT (in a narrow sense) as opposed to its alternatives, but also into alternative formulations of the IT frameworks in a broad sense, where some of the formulations are "observationally equivalent" to strategies conventionally treated as separate (such as AIT or PLT).

Figure 1 presents a schematic representation of the relationship between FI of inflation rates and different types of monetary policy strategies. The figure distinguishes between four main possibilities, corresponding to different values of d. Around $d = 0$, we identify what we refer to as

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a "strict" or "orthodox" inflation-targeting regime. In this regime, inflation exhibits only short-term memory, meaning that the central bank's interventions quickly stabilise inflation around the target without significant persistence or long-term effects.

As d increases toward 0.5, the process remains stationary but exhibits longer-term dependencies, meaning that inflation shocks take longer to dissipate. This region represents a more "conventional" or "flexible" inflation-targeting regime. In this framework, the central bank allows for more flexibility in inflation management, tolerating some degree of persistence in inflationary shocks. When d approaches or exceeds 0.5, inflation exhibits significant long-term dependence, implying an "uncommitted" or "ineffective" inflation-targeting regime, where central banks struggle to anchor inflation expectations effectively. Shocks to inflation are highly persistent, suggesting either weak policy interventions or a lack of credibility in the central bank's ability to manage inflation. Conversely, moving to the left of $d = 0$, the figure shows negative values of the FI parameter, which indicate mean-reverting behaviour with negative long-term dependence. This region we link with the "average" inflation-targeting (AIT) regime. It tolerates temporary deviations from the inflation target but aims to bring the average inflation rate back to a specified level over time. Two extreme cases close the spectrum of monetary policy frameworks. Under PLT, the central bank targets a stable price level, allowing inflation to fluctuate but ensuring that the price level is corrected over time. When the inflation rate is allowed to be an I(1) process, the regime can no longer be treated as IT (non-IT). Table A.1 in the Appendix summarises the inflation persistence properties across IT regimes, highlighting a range of FI values that suggest distinct inflationary dynamics, from mean-reverting processes to highly persistent inflation.

The underlying series on the CPI price level are sourced from the IMF International Financial Statistics. The restriction we face here is the availability of monthly CPI price level data.[4] The CPI series are seasonally adjusted using the X-13 ARIMA-SEATS algorithm. Next, we calculate the continuously compounded, annualised inflation rates measured as month-to-month changes in the logarithm of the price index:

$$\pi_t = 12 \times 100[\log(P_t) - \log(P_{t-1})]. \tag{2}$$

This transformation is consistent with earlier applications of FI to inflation data (e.g., Canarella and Miller, 2017a). The resulting monthly inflation rates form the basis for our long-memory estimates and are constructed uniformly for all countries over the common estimation window.

The study covers 36 countries, both advanced and EMEs, whose monthly inflation rates are illustrated in Figure A.1 in the Appendix. Table A.2 in the Appendix reports detailed descriptive statistics of these series, which suggest a wide range of average inflation levels and volatility across countries. Our major consideration when selecting this group of economies is their status as inflation targeters, which makes the cross-country comparison of the FI in inflation rates meaningful. However, countries adopted IT at different points in time, with relatively few of them introducing this monetary policy strategy in the early 1990s. Numerous economies adopted IT in the late 1990s, at the beginning of the 2000s, or later. Hence, we begin our analysis in 2000 and end it in 2019, before the pandemic-induced global shock and the period of elevated inflation rates.[5] Table A.3 in the Appendix lists all the countries included in the study. The average year of IT adoption is approximately 2003 with a standard deviation of about 5.6 years, and the median year is 2001. The earliest IT adopters are Canada and the UK (in 1991 and 1992, respectively), while the most recent one is Moldova (in 2013).

Including both the Federal Reserve and the European Central Bank may be considered contentious, as their classification as inflation-targeting central banks remains ambiguous. Both institutions, however, are often characterised as *de facto*, rather than *de jure*, inflation targeters. Goodfriend (2004, p. 334) writes well before 2012, when the Fed officially adopted the IT, that "the Greenspan Fed practices inflation targeting implicitly," arguing that "the Fed should continue to utilise the inflation-targeting procedures developed and employed implicitly by the Greenspan Fed after Chairman Greenspan retires." Similar statements can be found in numerous authors

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describing both the Fed and the ECB. For example, Carare and Stone (2003, p. 7) treat the US as an inflation-targeting country "without a clear commitment" whereas Alichi et al. (2015) argue that the Fed is "functionally very close to flexible inflation targeting [. . .] as the basis for monetary policy, although official statements of the Federal Reserve carefully avoid using such terminology." On the other hand, despite the changes introduced in 2012 and 2020, the IMF continues to classify the US under the "other monetary framework" category rather than the "inflation-targeting framework" (see the IMF's AREAER online database). We believe that our classification, being a *de facto* classification, provides a good enough reason to include both central banks in the analysis.

The selection of ARFIMA(p, d, q) models for each country's inflation rate series follows a systematic procedure to ensure the best-fitting specifications. In the first step, we estimate a range of ARFIMA models, where the autoregressive (AR) and moving average (MA) lag lengths are chosen, and the ARFIMA parameters, including the fractional differencing parameter, are estimated. The models are selected by minimising the Akaike Information Criterion (AIC), with p and q restricted to a maximum value of one.[6] Next, we assess the properties of the selected models. Specifically, we flag cases where (i) the estimated AR(1) coefficient is close to unity, (ii) the Ljung-Box and Breusch-Pagan diagnostic tests indicate autocorrelation in the residuals, or (iii) the confidence bands on the FI parameter are extremely wide.[7] If either of these issues arises, we repeat the model search with p and q still limited to a maximum value of 1. For models not affected by these issues, we re-evaluate the specifications to confirm their suitability. In the rare cases where satisfactory models cannot be identified, we expand the search to explore alternative combinations of lags. Whenever possible, we estimate the ARFIMA models using the maximum modified profile likelihood estimator, which has been shown to reduce bias in the presence of exogenous variables (including constants) in small samples. Only if the estimation algorithm fails to converge, we resort to the standard maximum likelihood estimator with robust standard errors.

4. Baseline results and discussion

This section presents and discusses our baseline results. The first step of our model selection procedure proved sufficient to select plausible ARFIMA specifications for 31 out of 36 countries. Hence, only a handful of cases required searching for alternative lag structures or using the maximum likelihood estimator. Full details on the estimated models are provided in Table A.4 in the Appendix. Table 1 shows the resulting point estimates of the FI parameter of the inflation rates, along with the 95-percent confidence intervals. We first notice that the point estimate of d reveals substantial variation across countries, ranging from −0.28 in Norway to 0.49 in Romania, which lends support to the conjecture that there exists more than a single *de facto* IT regime. Second, the precision of estimates is not uniform: for countries like Hungary and Romania, the confidence interval is relatively narrow, whereas at the other end of the spectrum, e.g. in Albania and Norway, it is five times wider. Fortunately, classifying the latter countries is rather unambiguous, except for several cases, which we discuss below. Third, in only seven out of 36 countries do the confidence intervals include the integer d. For other countries, the confidence intervals cover only non-integer numbers, indicating that no conventional ARMA model would be capable of correctly mirroring the dynamics of inflation. Fourth, the point estimates of d reveal that in all countries the inflation rate is not only mean-reverting but also stationary. Even taking a conservative stand and looking at the upper bound of the confidence interval, we can still argue the same, but we need to admit nonstationarity in ten countries (the bound is 0.5 or more).

To facilitate the discussion of the results, Table 2 assigns each country to one of four types of IT, while Figure 2 shows a coefficient plot, ordered from lowest to highest upper bound of the 95-percent confidence interval within the IT groups imposed. Using the time series properties of the inflation rate implied by the estimates of the fractional differencing parameter, we classify inflation-targeting countries into four categories discussed in the previous sections.

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Table 1. Baseline estimates of fractional integration parameters of inflation rates in IT economies

Country	$\hat{d}$	CI $\hat{d}$	Country	$\hat{d}$	CI $\hat{d}$
ALB	0.416***	(0.155; 0.677)	JPN	0.088	(−0.068; 0.244)
ARM	−0.034	(−0.174; 0.105)	KOR	0.173***	(0.07; 0.276)
BRA	0.383***	(0.236; 0.53)	MDA	0.277**	(0.059; 0.495)
CAN	−0.187**	(−0.335; −0.039)	MEX	0.171**	(0.024; 0.318)
CHE	0.14**	(0.007; 0.273)	NOR	−0.278*	(−0.556; 0)
CHL	0.258***	(0.103; 0.413)	PER	0.145*	(−0.008; 0.298)
COL	0.337***	(0.205; 0.469)	PHL	0.285***	(0.098; 0.472)
CZE	0.238***	(0.074; 0.402)	POL	0.365***	(0.226; 0.504)
DOM	0.369***	(0.23; 0.508)	PRY	0.306***	(0.088; 0.524)
EUR	0.281***	(0.174; 0.388)	ROU	0.486***	(0.431; 0.541)
GBR	0.194***	(0.093; 0.295)	SRB	0.422***	(0.244; 0.6)
GEO	−0.004	(−0.146; 0.139)	SWE	0.146***	(0.044; 0.248)
GHA	0.459***	(0.315; 0.603)	THA	−0.004	(−0.137; 0.129)
GTM	0.177**	(0.037; 0.317)	TUR	0.432***	(0.232; 0.632)
HUN	0.325***	(0.23; 0.42)	UGA	0.286***	(0.178; 0.394)
IDN	0.175***	(0.075; 0.275)	URY	0.334***	(0.188; 0.48)
ISL	0.382***	(0.275; 0.489)	USA	−0.092	(−0.317; 0.134)
ISR	0.127*	(−0.01; 0.264)	ZAF	0.425***	(0.317; 0.533)

Notes: The table displays the country codes, along with the point estimates and 95-percent confidence intervals of the fractional integration parameter of inflation rates obtained using ARFIMA (p, d, q) models.

Table 2. "Shades" of inflation targeting across countries: baseline estimates

Average IT	Strict IT (Orthodox IT)	Flexible IT (Conventional IT)	Uncommitted IT (Ineffective IT)
Canada	Armenia	Chile	Albania
Norway	Georgia	Colombia	Brazil
	Israel	Czechia	Dominican Rep.
	Japan	Euro area	Ghana
	Peru	Guatemala	Paraguay
	Thailand	Hungary	Poland
	United States	Iceland	Romania
		Indonesia	Serbia
		Korea	South Africa
		Mexico	Turkey
		Moldova	
		Philippines	
		Sweden	
		Switzerland	
		Uganda	
		United Kingdom	
		Uruguay	

Notes: The table assigns one type of IT to each country, according to the baseline estimates.

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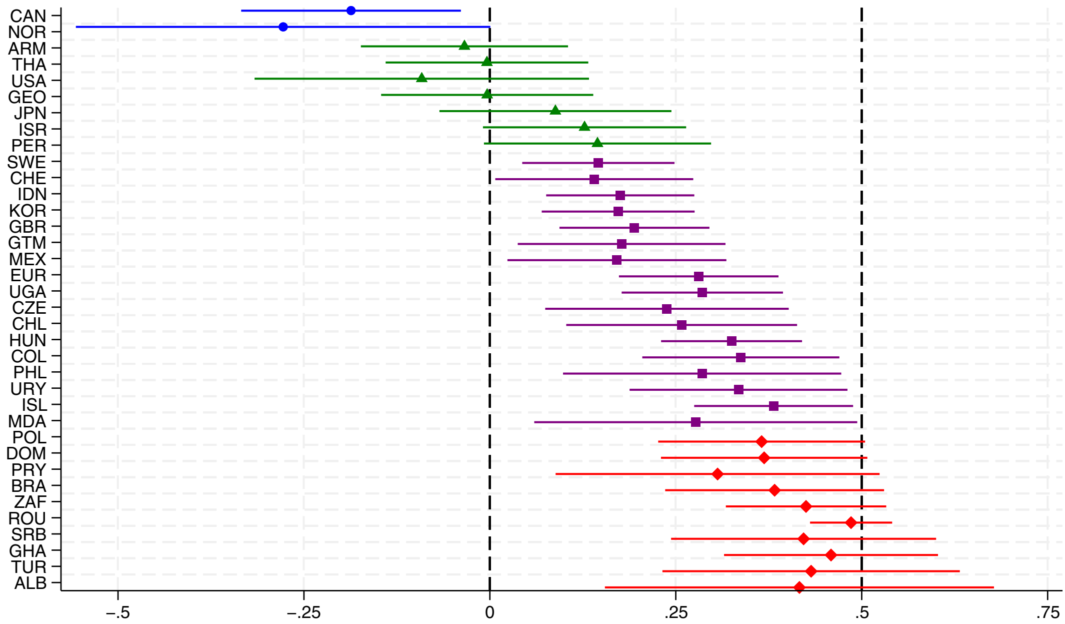

Figure 2. Fractional integration parameters: baseline estimates and confidence intervals.
Notes: The figure displays 95-percent confidence of the fractional integration parameters based on the ARFIMA models. The countries are sorted into four "shades" of IT, depicted by coloured bars. See Figure 1 and the main text for a further discussion of the classification.

Starting with the first category of IT regimes, we find only two countries in the sample to display anti-persistence in the inflation rates, Norway and Canada. The negative values of FI imply that the autocorrelations (for lags greater than 0) of the inflation rate are negative, so the mean reversion is faster than that of the white noise. Importantly, the negative dependencies in the inflation rate alleviate or even wipe out the long-term impact of shocks on the price level, contributing to maintaining it on or close to the initial trajectory (see, e.g., Masson and Shukayev, 2011; Diwan et al. 2020). This observation prompts us to label this group of countries as following the average IT.

The second category includes seven countries, in which the inflation rate displays short memory. Among them, we have Israel, an early adopter of IT, Japan and the United States, which have been long considered as pursuing an eclectic IT (Carare and Stone, 2003), and somewhat surprisingly, countries like Armenia, Georgia, Thailand, and Peru with relatively less transparent monetary policy (Dincer et al. 2022; Niedźwiedzińska, 2022; Stone, 2003). The estimate of the d parameter is statistically insignificant, implying that inflation can be thought of as an I(0) process. The long-range dependencies captured by the fractional-integration parameter are non-existent, so the inflation rate reverts relatively quickly to its mean or target. Even though shocks produce no long-lasting effects on inflation, they shift the price level path, making it non-trend stationary. Letting the "bygones be bygones" is a prominent characteristic of standard IT strategy (see, e.g., Bernanke et al. 1999; McKibbin and Panton, 2018), which we dub here strict or orthodox IT.

The largest group encompasses 17 countries with a positive estimate of d with the upper bound clearly below 0.5, i.e. in the range of stationarity. The typical examples of inflation targeters, such as Sweden and the United Kingdom among AEs and Chile and Hungary among EMEs, fall into this category. Some less obvious candidates are Colombia, Guatemala, and Uganda with relatively non-transparent monetary policies (Dincer et al. 2022; Niedźwiedzińska, 2022). Unlike the previous category, under this one, the inflation rate has a long memory and is persistent, meaning that shocks in the distant past still exhibit some influence on the dynamics of the process (Canarella

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and Miller, 2017b). Even though their effects decay slowly, at a hyperbolic rate, they dissipate fast enough to keep the variance of the inflation rate finite. The non-negligible role of long-range dependencies in the inflation rate gives rise to the conjecture that monetary authorities follow their IT strategy more flexibly than those pursuing the strict IT. For this reason, we call this type of IT flexible or conventional.

The last group, which we dub the uncommitted IT, is populated by ten EMEs often perceived as vulnerable, such as Brazil and South Africa, along with the post-transition Central and Eastern European countries, Romania and Serbia. The FI coefficient is positive and lies close to the region of nonstationarity: the upper bound of the confidence interval is at least 0.5. The effects of shocks disappear even more slowly than in the previous group of countries, making the inflation rate highly persistent. At a 5% significance level, we cannot rule out that the d coefficient is 0.5 or greater. Even though the inflation rate has infinite variance in such a case, it remains a mean-reverting process (since the upper bound is well below 1) (Granger and Joyeux, 1980). High persistence of inflation coupled with lengthy mean-reversion is likely to signal the ineffectively pursued IT strategy and induce us to label it as uncommitted or ineffective.

We realise that the classification is not perfect, given the variation in the precision of estimates of the FI coefficient. The issue, however, seems to be of secondary importance, since it is limited to five cases. The first two are Israel and Peru, classified into the strict IT category despite the fractional coefficient being well above 0, at the level characteristic of countries like Sweden and Switzerland, which are in the flexible IT group. Admittedly, the issue here is that the estimation is not precise enough, and the lower bound of the confidence interval is marginally below 0. Employing a 90% confidence interval would shift Israel and Peru to flexible IT (see Figure A.2 in the Appendix). The remaining three cases, the Dominican Republic, Poland, and Paraguay, fall into the uncommitted IT type due to the relatively wide confidence intervals. It is worth noting that the point estimates of d for these countries are smaller than for Iceland, a country classified as following the flexible IT. Thus, marginally more precise estimates would shift these countries, enlarging the conventional IT category. Let us emphasise that, rather than jeopardising our approach, potential deficiencies in our classification encourage us to interpret the borderline cases with caution, the caveat relevant for any classification. The robustness of our results will be discussed in further detail in the section on sensitivity analyses.

To illustrate the differences among the four categories of IT regimes, in Figure 3, we plot impulse response functions (IRFs) of inflation rates to a one-point shock implied by the ARFIMA models. The diagrammatic exposition includes two representative examples of each IT type.

The IRFs share a similar shape: after an initial rise, the inflation rate decreases and returns to its long-term level. It is in line with the mean-reverting property of the inflation rate, without which the monetary policy framework could not be considered any *de facto* IT.

The notable difference between IRFs is in the pace at which the effect of a shock peters out. The response under the AIT regime quickly becomes significantly negative and then gradually approaches zero, offsetting the initial rise in inflation. The implication is that some portion of an increase in the price level is reversed. Both in Canada and Norway, the inflation rate displays symptoms of anti-persistence.

The next two countries, Japan and Israel, belong to the strict IT group. The effect of shocks is short-lived, and there is a quick reversion to zero, which takes place just after several months. Even though the IRF does not move outside a positive territory, the response of inflation decays exponentially, in a way characteristic of non-persistent I(0) processes. Accordingly, the shock has no longer-term effects on the inflation rate, albeit the price level rises permanently.

The responses of countries in the flexible IT group resemble those in the previous case, albeit this time, shocks dissipate visibly slower, at a hyperbolic rate rather than an exponential decay. Inflation rates in the UK and Mexico exhibit greater persistence and tend to remain away from their “equilibrium” levels for extended periods. In other words, unlike the previous category, which captures short-memory processes, this one is characterised by long-memory processes.

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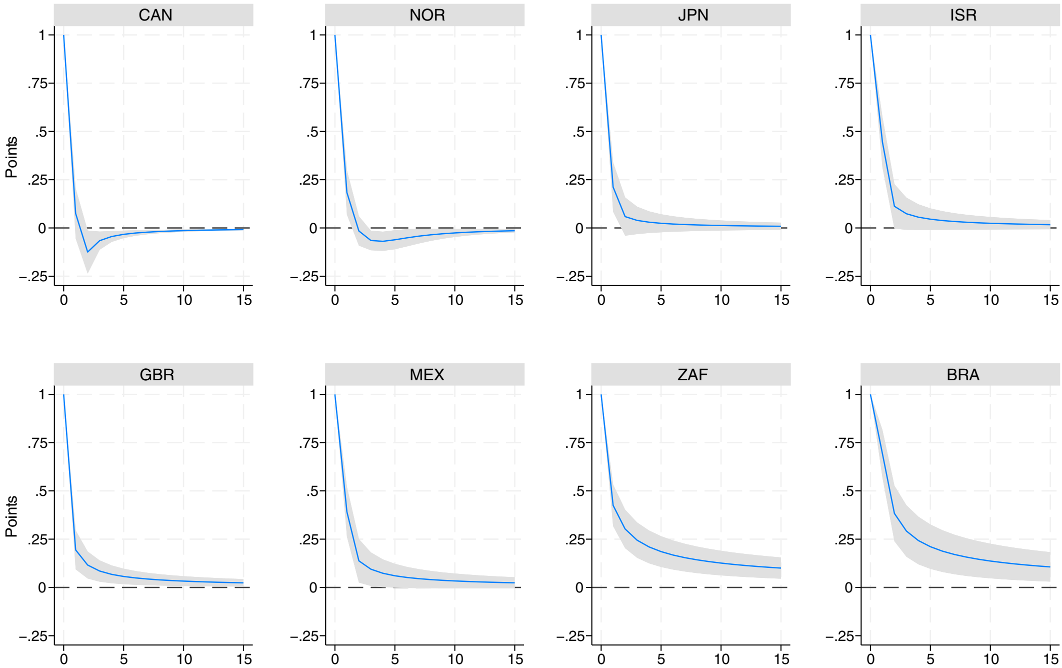

Figure 3. Impulse response functions of inflation rates in ARFIMA models in selected IT economies.
Notes: The figure displays impulse response functions of the inflation rate to a one-unit shock, based on the estimated ARFIMA models for selected economies. Two representative economies are shown for each IT category. The shaded bands show 95-percent confidence intervals around the base estimates.

The last two countries, Brazil and South Africa, illustrate the uncommitted IT. Similarly to the previous case, the inflation rate is a long-memory process, and its autocorrelation function decays at a slow hyperbolic rate. The main difference, however, is that the response is substantially stretched over time, and its confidence band remains above zero 15 months after the shock. This case is the only one in which the inflation rate is nonstationary, albeit it is mean-reverting.

Another way to show the difference between the IT types is by exploiting the frequency domain. The spectral density describes the relative contribution of periodic components at different frequencies to the variance of the process. Figure 4 illustrates the long-memory and short-memory spectral densities across the alternative IT categories. The former density describes the fractionally integrated series, whereas the latter portrays the fractionally differenced series.

In theory, when the process has a short memory ($d = 0$), there is no difference between these spectra. This is the case of Japan and Israel, or more generally, the group of strict IT, which includes countries with the fractional coefficient close to 0.

The picture for the other groups of IT is different: the two spectra diverge at low frequencies because the inflation rate has a long memory. It aligns with the observation that the usual ARMA model can closely approximate the spectrum of the process with fractional d "at all frequencies *except* those near zero" (Granger and Joyeux, 1980). In flexible IT countries like the United Kingdom and Mexico, a part of the spectrum at low frequencies substantially contributes to the variance, signalling the persistence of the inflation rate that cannot be captured well by the conventional ARMA model with the integer d. The uncommitted IT, as exemplified by the South African and Brazilian cases, is marked by the dominance of (a pole on) a low-frequency part of the spectral density. The contribution of short-term cyclical components to the variance is almost non-existent, which is in line with uncovering the elevated persistence of the inflation rate in this IT category. Long-memory and short-memory spectra are also different in the group

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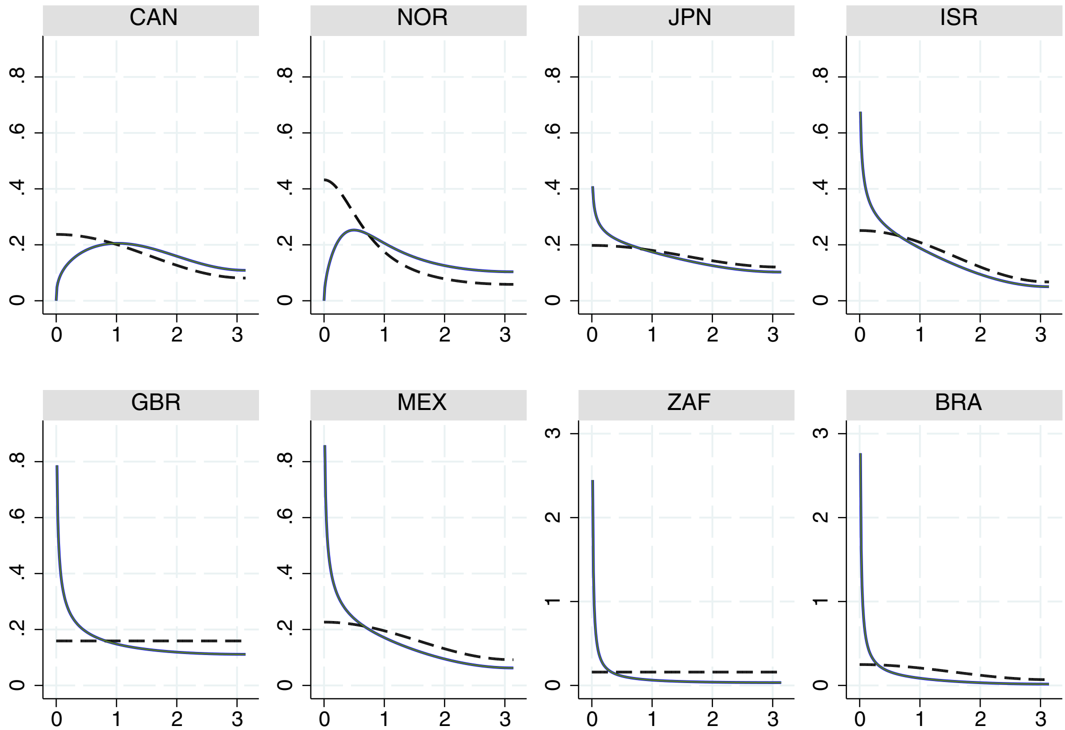

Figure 4. Spectral density plots in selected IT economies.

Notes: The figure displays the spectral density plots of the estimated ARFIMA processes of the inflation rates in selected economies. Two representative economies are shown for each IT category. Horizontal axes represent the frequency of the inflation rate series. Solid lines denote the long-memory components, while dashed lines show the short-memory spectral density. Note that the scale on the vertical axes for BRA and ZAF differ from the remaining cases.

of average IT, as exemplified by Canada and Norway. This time, however, the cyclical components at a frequency close to 0 have a negligible contribution to the variance, enabling the shocks to dissipate faster than for a short-memory process. Being anti-persistent, inflation quickly "forgets" the shocks and secures the price level stability.

5. Sensitivity analyses

This section discusses a set of sensitivity checks performed on the baseline results. We put forward four sensitivity checks. In each case, we re-estimate the ARFMIA models for each country, employing a modified sample or a different estimator, and compare FI coefficients with those obtained in the baseline case. In the sensitivity checks based on the ARFIMA models, we use specifications analogous to the baseline.[8] Next, we compare the alternative IT classifications with the baseline using three conventional similarity measures, i.e. accuracy, the adjusted Rand index, and Cohen's kappa.

First, we re-estimate the ARFIMA models using the winsorized inflation rate series. We trim and replace the extreme observations at the 5 and 95 percentiles for each economy to investigate whether our estimates are not driven by outliers, which may be especially problematic in EMEs. Even though winsorization is a mechanical procedure, it mitigates two issues. First, extreme monthly inflation values, often reflecting data anomalies, can bias persistence estimates by introducing artificial long-range dependence. Second, ARFIMA estimators can be sensitive to tail behaviour (for example, low inflation rates during the Global Financial Crisis), and small-sample distortions from rare inflation spikes may affect the estimated order of integration.

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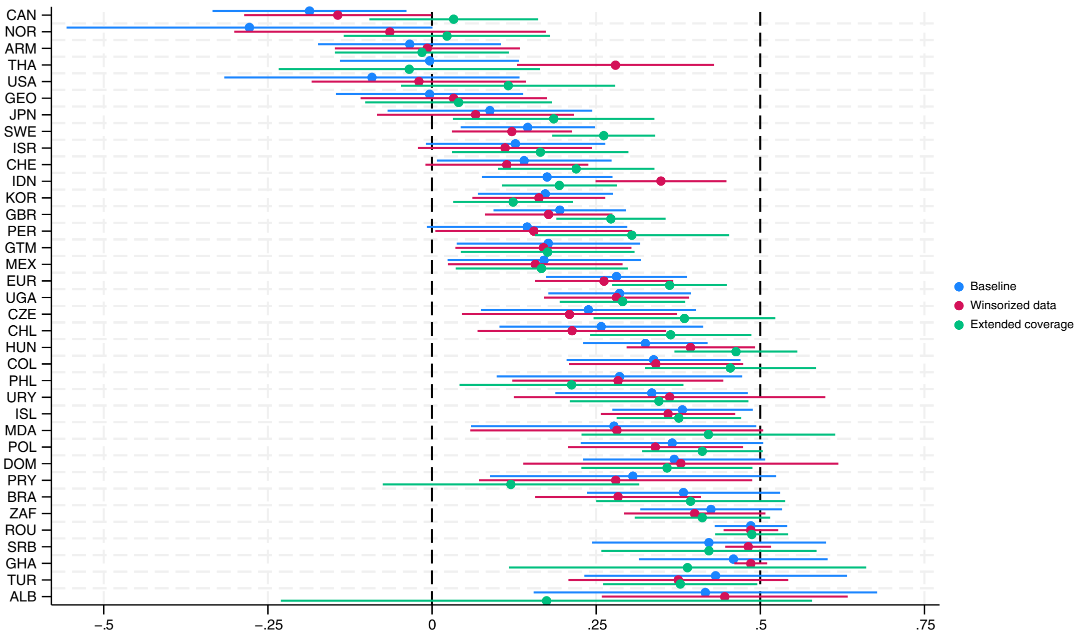

Figure 5. Sensitivity analysis of the baseline fractional integration parameter estimates: Part 1.
Notes: The figure displays 95-percent confidence intervals around the point estimates of the fractional integration parameters for the "Baseline" specification (as described in Section 4) and two sensitivity checks. "Winsorized data" shows the results for the CPI inflation series winsorized at the 5 and 95 percentiles. "Extended time coverage" denotes the results based on the ARFIMA models estimated on the sample that includes the post-Covid-19 period, 2000M1–2023M12.

The results of this sensitivity check reveal relatively stable estimates compared with the baseline, suggesting our findings are robust to such anomalies. While the winsorization reduces some of the variance in the FI estimates, particularly in emerging markets where inflation volatility is higher, the point estimates themselves remain close to the baseline. This confirms that outliers do not substantially distort the estimates, although their presence slightly inflates the confidence intervals (CIs) in the baseline. With winsorized data, the CIs for several countries narrow, particularly in economies with more volatile inflation, indicating that removing extreme values reduces the estimation uncertainty.

Second, we extend the data coverage of the inflation rates to include the post-Covid-19 period and estimate the ARFIMA model for the timespan 2000M1–2023M12.[9] This extension enables us to assess the stability of the classification in the presence of a major structural shift in inflation rates. The updated estimates show a noticeable increase in the FI parameters for many countries, likely reflecting the persistent inflationary effects triggered by the pandemic and its aftermath, which affected both advanced and EMEs. The inclusion of the post-Covid period also widens the confidence intervals in several cases, reflecting the heightened uncertainty during this time. The broader CIs suggest that inflation persistence during the pandemic period was more difficult to estimate precisely, particularly in economies that experienced severe shocks.

Third, we test an alternative series preparation by detrending the inflation rate series. The inflation rates used in the benchmark estimation are detrended and demeaned with a linear trend. In this sensitivity check, the point estimates remain quite close to the baseline, indicating that inflation persistence is not significantly affected by long-term trends in the data. The detrending process appears to have a minimal impact on the overall dynamics captured by the ARFIMA models. The confidence intervals are generally comparable to the baseline, with some slight narrowing in countries with stable inflation rates. It suggests that while some trends may be present in the data, they do not drive the core persistence patterns of inflation. The results confirm that

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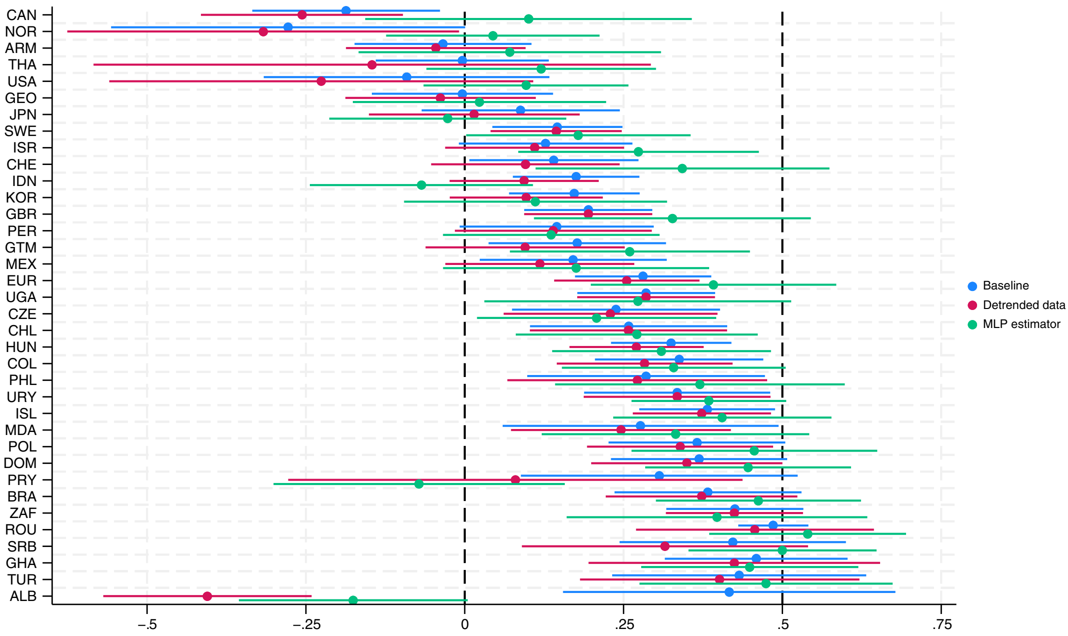

Figure 6. Sensitivity analysis of the baseline fractional integration parameter estimates: Part 2.
Notes: The figure displays 95-percent confidence intervals around the point estimates of the fractional integration parameters for the "Baseline" specification (as described in Section 4) and two sensitivity checks. "Detrended data" shows the results based on the ARFIMA models estimated on the CPI the inflation rates with the removed linear trend. "MLP estimator" indicates the fractional integration estimates using the modified log periodogram estimator with the power of the bandwidth T^{α} of $\alpha = 0.75$.

short- and medium-term dynamics are more critical to understanding inflation persistence than long-term trends.

Finally, we re-estimate the models using the MLP estimator, with a bandwidth parameter of $\alpha = 0.75$, as recommended by Phillips (2007). A key distinction from the estimator used to obtain the baseline results is that the MLP estimation does not require an explicit specification of the ARMA part and accommodates a broader range of values for the FI parameter, including those exceeding 0.5. The results obtained using the MLP estimator show greater deviations from the baseline, with greater spreads in the FI estimates. In several countries, MLP estimates indicate higher levels of persistence than the baseline results, suggesting that the MLP method captures longer memory processes that are not fully reflected in the ARMA-based specification. The confidence intervals are also wider, particularly in countries with more complex inflation dynamics, where the MLP estimator captures a broader range of potential values for the FI parameter.

To summarise the results of the sensitivity analyses, we weigh the classification obtained in each check against the baseline. The straightforward way to do this is to use the accuracy metric. It is a simple measure of agreement defined as the number of countries classified in the same category as in the baseline case divided by the total number of countries. The results are reported in Table 3. Neither winsorizing nor detrending data substantially alters the classification much: fewer than ten countries are reassigned to a different category compared to the baseline, and the accuracy metric remains at 75% or higher. The accuracy of the classification derived under the extended sample is somewhat lower, at 67%. Still, the consistency with the baseline results remains solid, especially given that the extended period includes the post-Covid-19 years, which introduced a major inflation shock and potential structural breaks in inflation dynamics. The classification derived by the MLP estimator has the lowest accuracy, which, however, is well above 50%. A part of the disagreement likely stems from the fact that the MLP estimator employs detrended data.

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Table 3. Sensitivity analysis: comparison of monetary policy regime classifications against the baseline

Classification obtained under	Accuracy	Adjusted Rand index	Kappa (no weights)	Kappa (equal weights)
Winsorized data	0.750	0.377	0.611	0.699
Extended coverage	0.667	0.297	0.480	0.558
Detrended data	0.778	0.457	0.683	0.684
MLP estimator	0.556	0.146	0.378	0.480

Notes: The table displays the pairwise comparison between classifications obtained in the baseline case and four sensitivity checks using four metrics. All kappa statistics have p-values smaller or equal than 0.01. See also Table A.5 in the Appendix.

Indeed, when we checked the agreement with the classification obtained on the detrended data, the accuracy metric increased to 61% (see Table A.5 in the Appendix).

One of the weaknesses of the accuracy metric is that it masks imbalances between categories. If, for example, we arbitrarily assigned all countries to the conventional IT, i.e., the category which dominates in the baseline classification, the accuracy would be 47%. To avoid this issue, we calculate the adjusted Rand index. It is a measure of agreement based on counting pairs of objects. In general, the index lies between 0, indicating a random agreement, and 1, denoting a perfect agreement (see, e.g., Warrens and van der Hoef, 2022). In our hypothetical example, which assigns all countries into a single class, the adjusted Rand index is 0.

The classifications obtained under sensitivity checks are much more similar to the baseline than the uniform assignment. Using this metric, we see that classifications based on detrended or winsorized data are the least different from the baseline. When we employ the extended sample or the MLP estimator, the index deteriorates to 0.30 and 0.15, respectively. Interestingly, the low value of the index in the latter case seems to be driven by detrending data under the MLP estimator. When we compare this classification with the one based on the detrended sample, the index goes up to 0.33 (Table A.5 in the Appendix). Overall, the picture is not that different from the one based on the crude accuracy measure.

The drawback of the adjusted Rand index in our context is that it neglects the labels attached to the categories. If, for example, we arbitrarily reclassified each country one category up, i.e., from AIT to strict IT, from strict IT to conventional IT, and so on, and compared this classification with the baseline, the adjusted Rand index would be 1. Thus, to sort out this problem, we turn to Cohen's kappa. Being the measure of the degree of agreement between two classifications, it seems well fitted to our comparisons. Cohen's kappa values range from -1 to 1. The value of 0 indicates a random agreement between the classifications, and negative (positive) values denote less (more) agreement than random chance. For example, Cohen's kappa for the arbitrary reclassification of all countries to the conventional IT category is -0.33.

Table 3 also reports two kappa coefficients, unweighted and weighted. The former is suitable for the case with classes corresponding to a nominal variable, whereas the latter is relevant when classes can be ordered (Sim and Wright, 2005). The unweighted kappas obtained under four sensitivity checks tell the same story as the two other similarity metrics, although in a more reliable way. The weighted kappas are better suited to our IT classifications because they account for the ordering of categories. The kappa coefficients of more than 0.6 for the classifications under winsorized or detrended data indicate substantial agreement with the baseline.[10] For the other two classifications, the agreement is moderate. Noteworthily, the agreement between classifications derived under the MLP estimator and the detrended data is much higher, with Cohen's kappa of almost 0.6, and is at the border of being substantial. Moreover, in Table A.5 in the Appendix, we report kappas under quadratic weighting, which strongly penalises larger discrepancies between classifications. All coefficients indicate substantial agreement with the baseline, except for the classification obtained with the MPL estimator, where the kappa value is marginally below 0.6.

In general, sensitivity checks confirm the robustness of the baseline classification while highlighting the impact of methodological variations.

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6. Institutional monetary policy features and the inflation targeting classification: a cross-sectional analysis

In the previous sections, we document substantial cross-country heterogeneity in the FI parameters of inflation rates, which enables us to classify economies into four distinct monetary policy strategy categories: AIT, strict IT, flexible IT, and uncommitted IT. This section extends the analysis by focusing on the underlying factors that may explain why different countries are classified into these categories. Our main goal is to explore the institutional features of monetary policy-making that contribute to this variation. By examining these factors, we aim to understand what influences certain economies to demonstrate higher or lower persistence in inflation, and why they align with one of the four identified monetary policy strategies. This part of the analysis should also provide insights into the broader frameworks that shape a central bank's ability to anchor inflation and respond to inflationary shocks.

Among the potential factors explaining the variation in FI of inflation rates, we first consider the overall level of economic development, proxied by GDP per capita in purchasing power parity and sourced from the World Bank WDI database. The level of development is often linked to more advanced monetary policy institutions and central bank capabilities, which may influence differences in the persistence of inflation rates across economies. Next, we consider five key factors related to the institutional monetary policy design: (i) the maturity of the IT regime, measured as the total number of years under IT until 2019, (ii) the stability of the inflation target definition, represented as the negative of the number of changes in the target during the study period, (iii) central bank independence, based on the *de jure* independence indices from Romelli (2022), (iv) central bank transparency, based on the Dincer and Eichengreen (2014) index, which draws from various central bank documents (see also Dincer et al. 2022),[11] and (v) the dual objective of internal price stability versus external exchange-rate stabilisation, measured as the share of years under a "floating" or "free floating" exchange rate regime for each economy, using the IMF classification. Note that these variables are designed to reflect characteristics typically associated with more effective inflation control, corresponding to countries classified into IT categories with lower values of the FI parameter d.

Table A.6 in the Appendix summarises the baseline and alternative sets of covariates, including their definitions, sources, and major instances of missing data. Descriptive statistics for all variables are reported in Table A.7, while Figure A.3 provides boxplots illustrating their distribution. Figure 7 presents the correlation matrix between types of monetary policy strategy, FI parameters of inflation rates, and country-level variables. The results highlight several key relationships. GDP per capita shows a strong negative correlation with the type of monetary policy strategy and the parameter d, suggesting that higher levels of development are associated with less persistent inflation and "lower" categories of IT (e.g., AIT or strict IT). Additionally, GDP per capita is positively correlated with institutional features of central banks, such as transparency and stability in policy targets, which further explains why more developed economies tend to exhibit lower inflation persistence. In contrast, frequent changes in the IT target are positively correlated with higher d values, indicating more persistent inflation and "higher" IT categories (e.g., flexible or uncommitted IT).

The ordinal probit model is employed to examine the relationships between country-level variables and the "shades" of IT, with heteroscedasticity-robust standard errors used to correct for non-constant variance in residuals. This model treats the dependent variable, our four types of IT, as an ordinal variable, where lower values (AIT, strict IT) are associated with better inflation control, and higher values (flexible, uncommitted IT) correspond to greater inflation persistence. The classification reflects a degree of policy commitment to inflation targeting, but without assuming that the distances between categories are equal. The ordered probit model is thus well suited to this setting, as it captures the ordinal nature of the outcome while avoiding unjustified cardinal assumptions. It allows us to show how institutional and economic factors affect the probability of a country being classified into one of the four IT categories.

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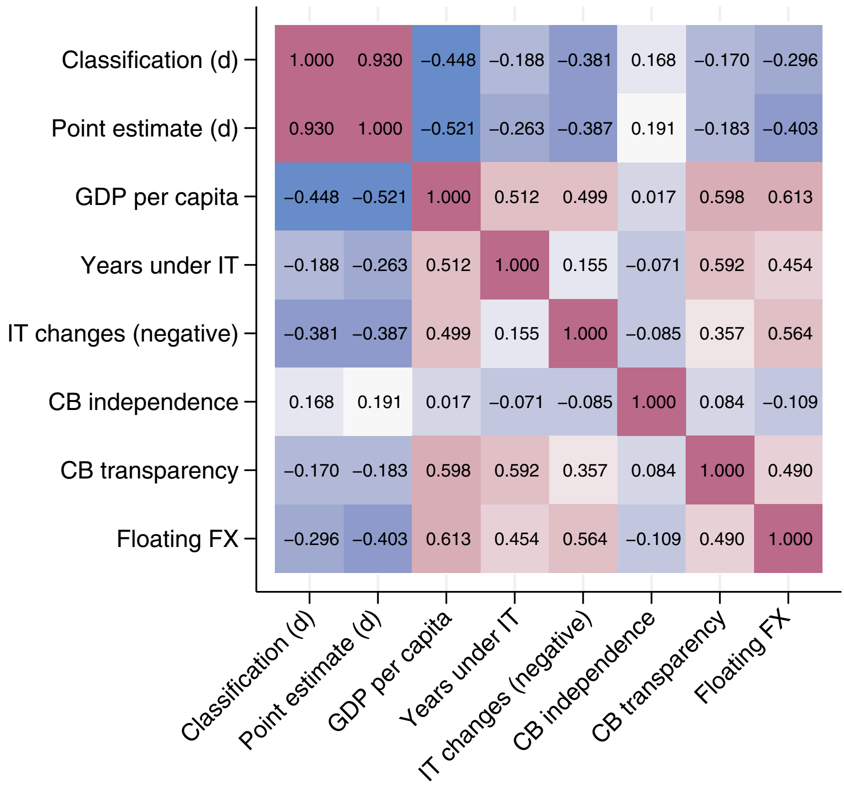

Figure 7. Correlation matrix of variants of inflation targeting, fractional integration of inflation rates, and country-level covariates.
Notes: The figure plots the correlation matrix between the baseline classification of monetary policy strategies or "shades" of IT, the fractional integration parameter *d*, and a set of country-level variables. For the definitions and sources of variables, see the discussion in Section 6.

Table 4 reports the baseline results of the ordinal probit regressions. A key finding is the significant negative relationships between GDP per capita and years under IT with inflation persistence, confirming that higher levels of development and longer experience with IT are associated with a higher probability of moving from uncommitted to conventional and strict IT. From an institutional perspective, this suggests that wealthier economies tend to have stronger monetary institutions that can more effectively anchor inflation expectations and manage shocks. Longer IT maturity further reflects institutional credibility, as sustained inflation targeting builds trust in the central bank's policies. Economically, these findings indicate that countries with more advanced economic frameworks are better equipped to contain inflationary pressures. The significant coefficient estimates on the number of changes in inflation targets and exchange-rate arrangements highlight the importance of consistent policy objectives in explaining variation in monetary policy strategies. In contrast, central bank independence, though theoretically important, does not reveal a significant relationship with the "shade" of IT, suggesting that *de jure* independence alone may not translate directly into effective inflation control. We similarly find no significant association between monetary policy transparency and the classification of monetary policy strategies.

The pseudo R-squared values for the baseline specifications suggest that the covariates explain part of the variation in monetary policy classifications, while leaving room for other influences, such as external shocks, institutional nuance, or country-specific policy setups. Model specifications that include multiple covariates do not substantially improve explanatory power and raise concerns about collinearity, particularly among institution-related variables. Hence, we opted for

Table 4. Covariates of the monetary policy regime classification: baseline ordinal probit regressions

	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita	−0.255**					
	(0.0878)					
Years under IT		−0.0664*				
		(0.0364)				
IT changes (negative)			−0.142**			
			(0.0543)			
CB independence				1.115		
				(1.118)		
CB transparency					−0.0794	
					(0.0580)	
Floating FX						−1.108**
						(0.518)
Intercept (1)	−2.533**	−2.822**	−1.199**	−0.859	−2.288**	−2.210**
	(0.364)	(0.685)	(0.408)	(0.791)	(0.508)	(0.343)
Intercept (2)	−1.439**	−1.845**	−0.204	−0.0840	−1.316**	−1.194**
	(0.384)	(0.726)	(0.322)	(0.780)	(0.559)	(0.342)
Intercept (3)	−0.0383	−0.516	1.175**	1.347*	0.0562	0.149
	(0.345)	(0.682)	(0.326)	(0.814)	(0.607)	(0.307)
Observations	36	36	36	33	32	36
Pseudo R-squared	0.0877	0.0453	0.0593	0.0127	0.0100	0.0531

Notes: The table shows the baseline estimation results of the ordinal probit models. Dependent variable: the IT variant under the baseline monetary policy strategy classification derived from the ARFIMA models of inflation rates. See the main text for the definitions of explanatory variables. Heteroscedasticity-robust standard errors are given in brackets. * and ** denote statistical significance at 0.1 and 0.05 levels, respectively.

a simpler strategy based on individual regressions, which maximises sample size and enhances the interpretability of individual covariate effects. However, to complement the baseline results, we provide additional results using alternative covariates and different estimators that employ a continuous dependent variable based directly on the FI estimates.

In Table 5, we explore alternative definitions of the country-level variables introduced in the ordered probit models. We use the log values of GDP per capita and years under IT to account for potential nonlinearities. The standard deviation of target changes replaces the number of changes to better capture the volatility of the inflation target. The measure of central bank independence is now based on the Grilli et al. (1991) classification, updated by Romelli (2022).[12] Central bank transparency is sourced from Niedźwiedzińska (2022), and the exchange-rate regime is captured by the classification from Dąbrowski et al. (2020), which defines the share of years during which a country is classified as "float." The results remain consistent with the baseline findings. Specifically, GDP per capita, variability of inflation targets, and the adoption of floating exchange rates continue to show significant negative relationships with the IT categories. These alternative measures reinforce the idea that economic development, stability in monetary frameworks, and consistent policy objectives0 are associated with more committed strategies. Evidence on the role of years under IT is somewhat weaker than in the baseline, but the coefficient estimate on the log of IT year is only marginally insignificant at the 0.1 level. Interestingly, we find a significant coefficient on the alternative monetary policy transparency variable, pointing to a relationship between this dimension of policymaking and stricter IT strategies.[13]

Finally, Table A.8 in the Appendix presents the weighted least squares (WLS) results, where the weights are the inverse of the standard errors of the d parameter from the FI estimation.[14]

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Table 5. Covariates of the monetary policy regime classification: ordinal probit results using alternative explanatory variables

	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita (log)	−0.476**					
	(0.209)					
Years under IT (log)		−0.894				
		(0.557)				
IT std. dev. (negative)			−0.646∗			
			(0.370)			
CB independence (alt)				0.0376		
				(0.776)		
CB transparency (alt)					−0.308***	
					(0.093)	
Floating FX (alt)						−1.520**
						(0.750)
Intercept (1)	−6.456**	−4.147**	−1.341**	−1.526**	−3.582**	−2.885**
	(2.022)	(1.556)	(0.386)	(0.518)	(0.737)	(0.768)
Intercept (2)	−5.445**	−3.186∗	−0.374	−0.776	−2.602**	−1.953**
	(2.111)	(1.628)	(0.278)	(0.546)	(0.674)	(0.694)
Intercept (3)	−4.098∗	−1.871	0.967**	0.628	−1.242	−0.608
	(2.119)	(1.590)	(0.308)	(0.552)	(0.634)	(0.638)
Observations	36	36	36	33	35	36
Pseudo R-squared	0.0505	0.0356	0.0464	0.0000	0.0694	0.0445

Notes: The table shows the estimation results of the ordinal probit using the alternative set of explanatory variables. Dependent variable: the IT variant under the baseline monetary policy strategy classification derived from the ARFIMA models of inflation rates. See the main text for the definitions of explanatory variables. Heteroscedasticity-robust standard errors are given in brackets. ∗ and ** denote statistical significance at 0.1 and 0.05 levels, respectively.

The WLS regression uses the estimated d values as the dependent variable, with weights based on the error variance from the ARFIMA model, and Figure A.4 in the Appendix shows the corresponding scatterplots and the fitted regression lines. The outcome of the WLS estimations supports our results. The relationships between GDP per capita, IT maturity and stability, and floating exchange-rate regimes with IT strategies remain significantly negative, although the explanatory power of each of these factors is limited. Importantly, as shown in the scatterplots, the findings are not driven by outliers, adding confidence to the robustness of these institutional and economic factors in explaining inflation persistence across countries.

7. Conclusions

This paper explores how self-declared inflation targeters actually conduct their monetary policy and uses these insights to construct a novel and granular *de facto* classification of inflation targeting strategies. Our classification, on the one hand, overcomes the declarative nature of a popular 20-year-old *de jure* classification by Carare and Stone (2003), which divides inflation targeting into full-fledged, eclectic, and lite regimes, and, on the other hand, refines the IMF's classification of *de facto* monetary policy frameworks by decomposing the IT category into its shades or variants. Employing models of fractionally integrated processes to map the persistence of inflation, the paper identifies four shades of IT, including average, strict, flexible, and uncommitted IT. Furthermore, it investigates whether institutional features of the monetary policy setup, such as

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IT maturity, central bank independence, monetary policy transparency, and the primacy of price stability, can be linked to these shades of IT.

Our main findings can be summarised as follows. First, the group of 36 inflation targeters is not homogenous in terms of actual monetary policy strategy, and we find empirical counterparts of each of the shades of IT. Second, even though flexible IT is a dominant shade with almost half of central banks classified as following it, the other shades, i.e., uncommitted and strict IT, are also quite frequent. Unsurprisingly, given the relatively short time span since its inception, the AIT is found to be present only in two AEs. Third, examining the institutional characteristics of the monetary policy framework that indicate a more effective control of inflation, we observe that differences between the IT shades are associated with maturity and stability of the IT strategy and its uncompromised orientation toward price stability, while the links to central bank independence and monetary policy transparency are relatively weak.

Our classification confirms, in line with intuition, that rather than being a uniform framework, IT encompasses a set of strategies. Distinguishing shades of *de facto* IT, especially when included in the IMF's classification of monetary policy frameworks, can encourage central banks to elevate their strategies, better communicate their choices, and care more about consistency between words and deeds. These improvements can contribute to better policymaking, particularly in periods of disinflation like the one following the post-Covid inflation surge, and among less mature inflation targeters, such as EMEs. Further on the policy front, the results suggest that inflation targeting is not a silver bullet, and its adoption as a *de jure* monetary policy framework should not be regarded as an ultimate goal. This is particularly true for EMEs, where simply joining the inflation-targeting "club" may not automatically lead to the same benefits typically observed in mature inflation-targeters.

We emphasise that the classification put forward in the paper is not set in stone but rather shows the current state of affairs to be revised and updated in the future. An important limitation of our research arises from recent dates of IT adoption by some of the analysed economies. While we start our analysis in 2000, some of the central banks of the countries we cover in the study introduced IT after that date. With time, we will be able to eliminate unequal samples for economies that introduced IT in various years, which can lead to improvements in the classification. Relatedly, other explanations of cross-sectional differences in the IT strategy classification proposed in this paper may emerge as all economies become more "mature" inflation targeters.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/S1365100525100539. The data and replication folder is available at https://doi.org/10.58116/UEK/KI15DF.

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Notes

1 This change regarding the average inflation targeting is demonstrated best in the official communication of the Fed. During the FOMC press conference on 16 September 2020, less than a month after the introduction of AIT, Jerome Powell stated that the Fed serves the economy "(. . .) best if we can actually achieve average 2 percent inflation, we believe. And that's why we changed our framework." Four years later, at the FOMC press conference on 7 November 2024, Chair Powell was asked whether after a period of higher inflation it would be appropriate for the Fed to undershoot for a while on its inflation goal under the average inflation targeting. His answer seemed clear: "No, that's not the way our framework works. We‘re aiming for inflation at two percent. (. . .) we did not think it would be appropriate to deliberately undershoot."

2 We come back to the issue of data frequency in Section 3.

3 The data and replication folder is available at https://doi.org/10.58116/UEK/KI15DF.

4 One exception to using the CPI price level is the euro area, for which we use the harmonised consumer price index sourced from the IFS database. Due to the unavailability of price level data at monthly frequency, the analysis does not cover Australia and New Zealand, for which the price level series are available only in quarterly frequency.

5 A sensitivity check of the baseline results makes use of the extended timespan, covering the post-Covid-19 period. It is discussed in Section 5.
6 When performing the model selection, we employ the *arfimasoc* module in Stata 18.
7 Note that we do not remove the ARFIMA models with MA estimated parameters close to unity, because this issue, related to the data overdifferencing, does not create serious estimation problems (Plosser and Schwert, 1977).
8 There are just three cases across all the sensitivity checks in which we introduce modifications to the baseline specifications to ensure that the estimation algorithm converges or to shorten extremely wide confidence intervals of the fractional integration estimates.
9 Due to the unavailability of the CPI series for Albania from 2023M8 in the IMF IFS database, the remaining observations were sourced from the Albanian Institute of Statistics and suitably transformed.
10 Landis and Koch (1977) provide a set of benchmarks to describe the relative strength of agreement (the upper bound for kappa in parentheses): poor (0), slight (0.2), fair (0.4), moderate (0.6), substantial (0.8), almost perfect (1.0).
11 Note that the central bank independence indices are unavailable for three economies (Armenia, Israel, and Serbia), while the transparency indices do not cover four economies (Dominican Republic, Paraguay, Serbia, and Uruguay).
12 We also replace the overall index of central bank independence with Romelli's (2022) sub-index capturing the "objectives" dimension of the monetary policy authority, which reflects whether price stability is legally designated as its primary goal. The results remain consistent with the baseline specifications. We thank the anonymous reviewer for this useful suggestion.
13 Note that the country coverage of the baseline and alternative measures of monetary policy transparency does not fully overlap (see Table A.6). After excluding countries for which either indicator is unavailable, the estimate for the alternative measure remains statistically significant at the 0.05 level.
14 For completeness, we also estimate OLS regressions using the same dependent variable (d) and covariates. Results reported in Table A.9 in the Appendix further confirm the ordered probit and WLS specifications.

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