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Shades of inflation targeting: insights from fractional integration

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Abstract

In this paper, we propose a novel approach to classifying inflation-targeting (IT) economies based on fractionally integrated processes. Motivated by the rising prevalence and diversity of IT strategies, we leverage variation in the persistence of inflation rate series to identify four *de facto* IT 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 IT, strict IT, flexible IT, and uncommitted IT categories. This framework sheds light on the differences between declarative and actual monetary policy strategies across 36 advanced and emerging market economies. Notably, we demonstrate that while most economies fall into the flexible IT category, extreme cases, including the uncommitted IT category, occur with marked frequency. Furthermore, we link our IT classification to institutional features of national monetary frameworks using ordinal probit models. The results suggest that differences across IT categories are related to variations in the maturity and stability of IT frameworks, with less pronounced connections to central bank independence and transparency.

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

JEL codes: E52, E58, E31, C22

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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, 2009). 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 targetters 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 & 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 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 given by the practice of central banking. The evolution of institutional setup in recent years gradually pushes the ECB and the Fed in the direction of IT. The example 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 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 covers a diverse group of 36 advanced and emerging market economies between 1999 and 2023. 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 by directly linking it to a range of actual monetary policy strategies. While fractional integration 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 & Miller, 2017a).

[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.'

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). ARFIMA 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.

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 fractional integration 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 fractional integration 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 show 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 fractional integration. 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 focussing 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 fractional integration framework to describe inflation processes. The second one stems from the theoretical analyses of alternative monetary policy strategies, mainly price level targeting and, more recently, average inflation targeting.

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) shows that inflation persistence is an important factor in determining economic outcomes from the perspective of both households and policymakers, but at the same time 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 suggests 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.

While early analyses of fractional integration (FI) go back over four decades (Granger & 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 to suggest that inflation is better described by fractional integration 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 OECD countries 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 & Wolters, 1995), aggregation of heterogeneous firm production (Abadir & Talmain, 2002), persistence in money supply shocks (Scacciavillani, 1994), lack of credibility of the inflation target (Erceg & Levin, 2003), unanchored inflation expectations, and uncertainty about the long-term inflation objective (Orphanides & 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] Ygit (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 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 in 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 & 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 Ygit (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 price level targeting strategy can be found in Ambler (2009) and Hatcher (2011). While early literature on PLT focused on the benefits to long-run price stability at the cost of higher output variability, only after a seminal paper by Svensson (1999, working paper in 1996) the influence of the expectations channel on improving the inflation-output trade-off was fully grasped. Both Ambler (2009) and Hatcher (2011) present the research on the validity of Svensson's 'free lunch', list arguments in favour of 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

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

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 ELB constraint'. In the absence of an effective lower bound (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 (2022) 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).' What this seems to suggest is that the adoption of AIT might have been a communication device aimed at escaping the effective lower bound. 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. 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 fractional integration 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 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 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 the 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, fractional integration 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 fractional integration 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 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 fractional integration 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 fractional integration values that suggest distinct inflationary dynamics, from mean-reverting processes to highly persistent inflation.

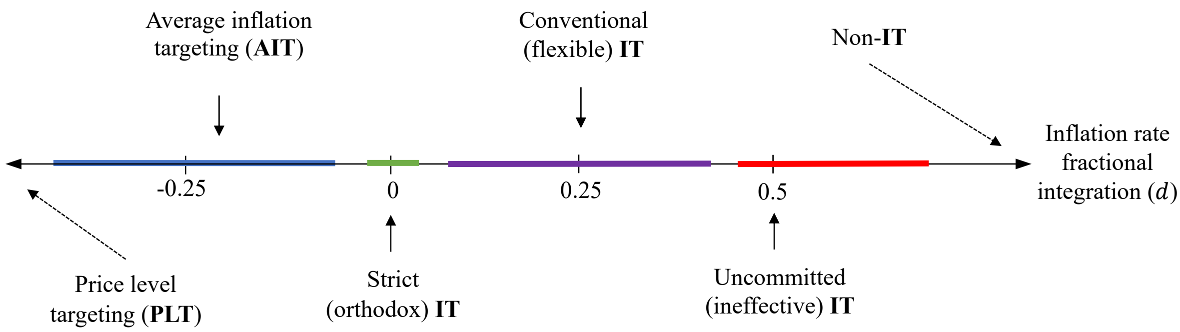

Figure 1: Fractional integration of inflation rates and the classification of monetary policy strategies

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

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.[3] The CPI series are seasonally adjusted using the X-13 ARIMA algorithm. Next, we calculate the simple annualized inflation rates measured as month-to-month changes in the log of the price index:

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

[3] One exception to using the CPI price level is the euro area for which we use the harmonized consumer price index, that also comes from the IFS database. Due to the unavailability of price level data in monthly frequency, the analysis does not cover Australia and New Zealand, for which the price level series are available only in quarterly frequency.

The study covers 36 countries, both advanced and emerging market economies, whose monthly inflation rates are illustrated in Figure A.1 in the Appendix. Our major consideration when selecting this group of economies is their status as inflation targeters, which makes the cross-country comparison of the fractional integration in the inflation rates meaningful. However, countries adopted IT in various years, with relatively few of them introducing this monetary policy strategy in the early 1990s. Numerous economies adopted IT in the late 1990s, the beginning of the 2000s, or later. Hence, we begin our analysis in 2000 and end it in 2019, before the pandemic-induced shock to the world economy and the period of elevated inflation rates.[4] Table A.2 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 (1991 and 1992, respectively), while the most recent one is Moldova (2013).

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.[5] Next, we assess the properties of the selected models. Specifically, we flag cases where (i) the estimated AR(1) coefficient is close to unity, or (ii) the Ljung-Box and Breusch-Pagan diagnostic tests indicate autocorrelation in the residuals, (iii) the confidence bands on the fractional integration parameter are extremely wide.[6] 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 without such 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] A sensitivity check to the baseline results makes use of the extended timespan, covering the post-Covid-19 period. It is discussed in Section 5.
[5] When performing the model selection, we employ the *arfimasoc* module in Stata 18.
[6] Note that we do not remove the ARFIMA models with MA estimated parameters close to unity, because this issues, related to the data overdifferencing, does not create serious estimation problems (Plosser & Schwert, 1977).

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.3 in the Appendix. Table 1 shows the resulting point estimates of the fractional integration 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: it ranges from -0.28 in Norway to 0.49 in Romania indicating substantial differences, lending 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, only in 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 if we take a conservative stand and look at the upper bound of the confidence interval, we can still argue the same but need to admit nonstationarity in ten countries (the bound is 0.5 or more).

To facilitate the discussion of the results, 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.

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 fractional integration 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 & Shukayev, 2011; Diwan et al., 2020). This observation induces us to label this group of countries as following the average IT.

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.

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 & 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 & Panton, 2018), which we dub here strict or orthodox IT.

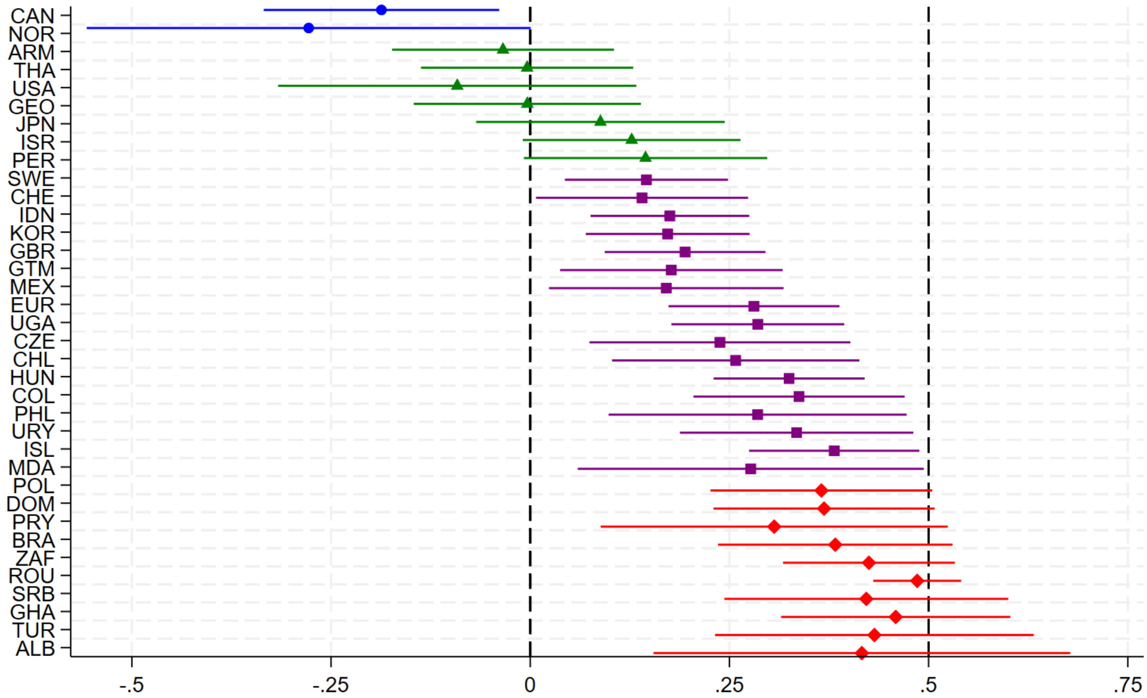

Figure 2: Fractional integration parameters: baseline estimates and confidence intervals

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.

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 advanced economies and Chile and Hungary among emerging market economies, 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 & 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 the ones pursuing 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 emerging market economies often perceived as vulnerable, such as Brazil and South Africa, along with the post-transition Central and Eastern European countries, Romania and Serbia. The fractional integration 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 & 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 fractional integration 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. Noteworthy, the point estimates of d for these countries are smaller than for Iceland, a country classified as pursuing 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 diagrammatical 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.

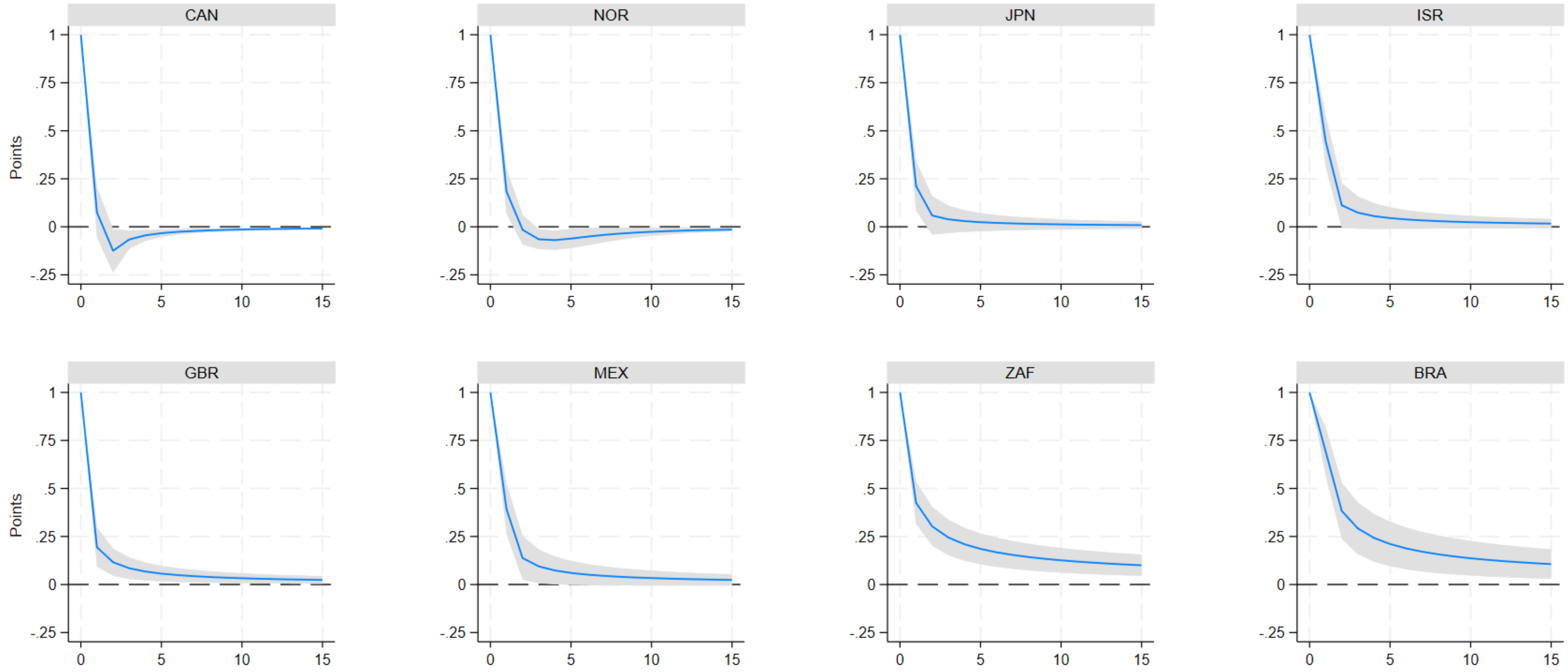

Figure 3: Impulse response functions of inflation rates in ARFIMA models in selected IT economies

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.

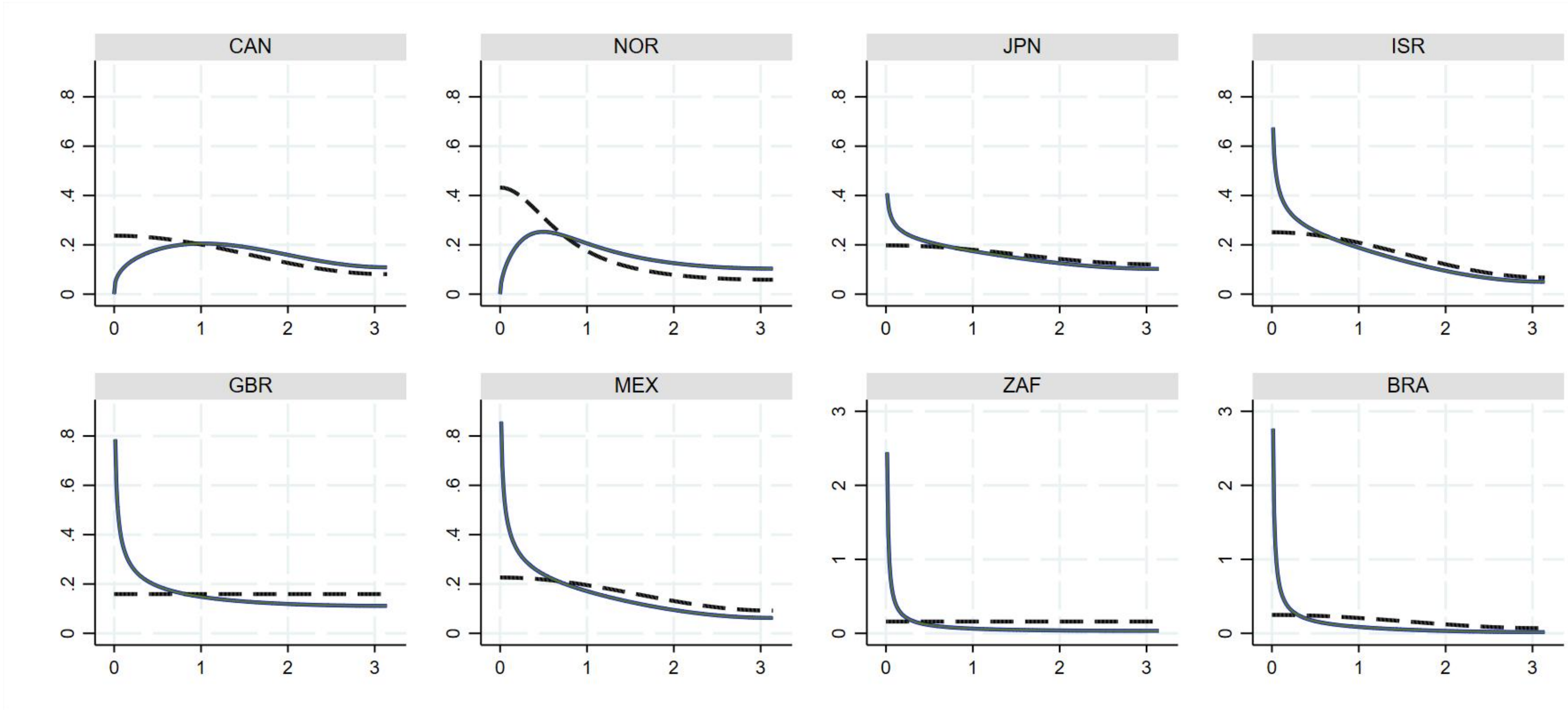

Figure 4: Spectral density plots in selected IT economies

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.

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 look like those in the previous case, but this time shocks dissipate visibly slower, at a hyperbolic rate rather than an exponential decay. Inflation rates in the UK and Mexico are persistent and tend to deviate from their 'equilibrium' levels for longer periods. In other words, contrary to the previous category collecting short-memory processes, this one includes long-memory processes.

The last two countries, Brazil and South Africa, illustrate uncommitted IT. Like in the previous case, the inflation rate is a long-memory process, and its autocorrelation function decays at a slow hyperbolic rate. The main difference is that the response is substantially stretch over time and its confidence band is still 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 coefficient of fractional 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. This 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 & 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 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 analysis

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 fractional integration coefficients with those obtained in the baseline case. In the sensitivity checks based on the ARFIMA models, we use specifications analogous to the baseline.[1] 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 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 the case especially in emerging market economies. The results of this sensitivity check reveal relatively stable estimates compared with the baseline. While the winsorization reduces some of the variance in the fractional integration 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

[1] 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.

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 period 2020M1-2023M12.[2] This extension leads to a noticeable shift in the point estimates, with many countries showing higher fractional integration parameters. This shift likely reflects the persistent inflationary effects brought on by the pandemic and its aftermath, which contributed to the inflation dynamics in both advanced and emerging markets. 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. In most cases, the point estimates shift to the right, indicating increased persistence in inflation rates in the post-Covid era.

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

Finally, we re-estimate the models using the modified log periodogram (MLP) estimator, with a bandwidth parameter of $\alpha = 0.75$, as recommended by Phillips (2007). A key difference in this method is that the MLP estimation does not require an explicit specification of the ARMA part and allows the values of the fractional integration parameter to take a wider range, extending beyond 0.5. The results obtained using the MLP estimator show greater deviations from the baseline, with greater spreads in the fractional integration estimates. In several

[2] Due to the unavailability of the CPI series for ALB from 2023M8 in the IMF IFS database, the remaining observations were sourced from the Albanian Institute of Statistics and suitably transformed.

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 broader, particularly in countries with more complex inflation dynamics, where the MLP estimator captures a wider range of potential values for the fractional integration parameter.

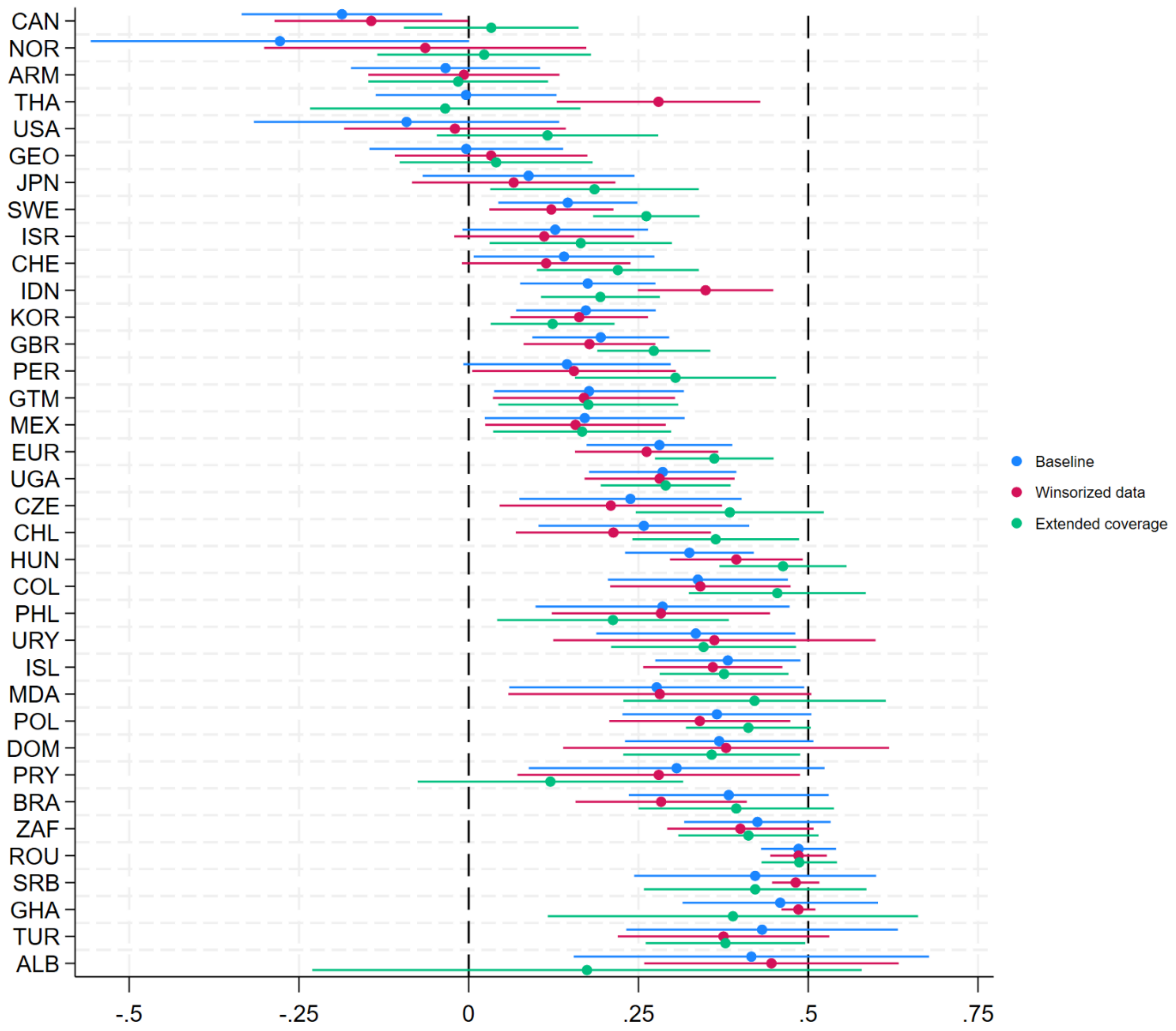

Figure 5: Sensitivity analysis of the baseline fractional integration parameter estimates: Part 1

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.

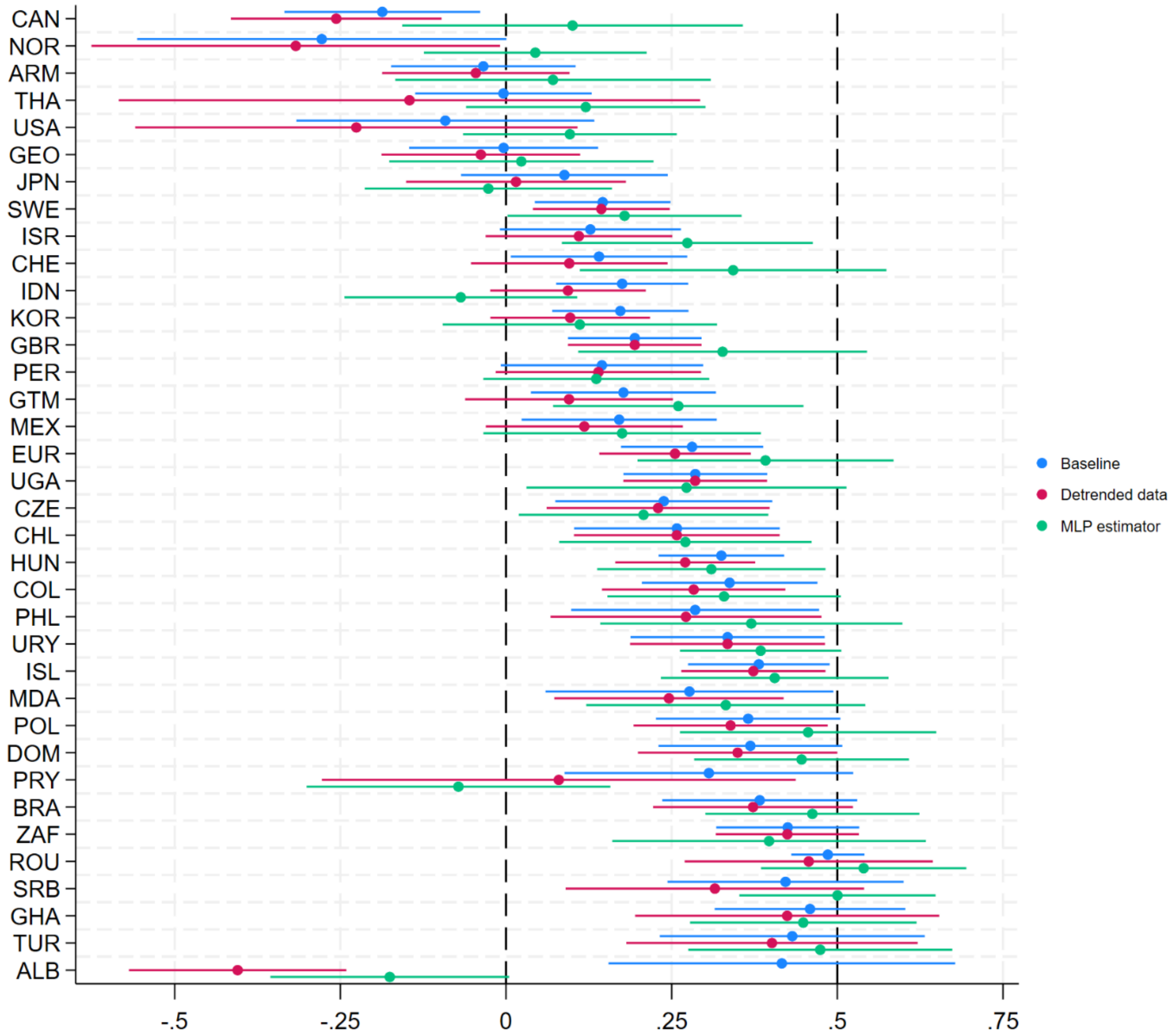

Figure 6: Sensitivity analysis of the baseline fractional integration parameter estimates: Part 2

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 $\alpha = 0.75$.

To summarise the results of the sensitivity analysis, 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 to the total number of countries. The results are reported in Table 2. Either winsorizing or detrending data do not change the classification much: less than ten countries are classified in a different category than in the baseline, and the accuracy metric is 75% or higher. The accuracy of classification derived under the extended sample is a bit lower, 67%, which can be expected, given the large shocks in the early 2020s. 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. Indeed, when we checked the agreement with the classification obtained on the detrended data, the accuracy metric increased to 61% (see Table A.4 in the Appendix).

Table 2: 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.4 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 & van der Hoef, 2022). In our hypothetical example that 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.4 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 2 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 & 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.[3] 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.4 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.

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

In the previous sections, we documented substantial cross-country heterogeneity in the fractional integration parameters of inflation rates, which enabled us to classify economies into four distinct monetary policy strategy categories: AIT, strict IT, flexible IT, and uncommitted

[3] 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).

IT. This section extends the analysis by focusing on the underlying factors that may explain why different countries are classified into these categories. The goal is to explore the institutional features of monetary policymaking that contribute to this variation. By examining these factors, we aim to understand what drives certain economies to demonstrate higher or lower persistence in inflation, and why they align with one of the four identified monetary policy strategies. Investigation of those elements provides 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 fractional integration of inflation rates, we first consider the overall level of economic development, proxied by GDP per capita in purchasing power parity (PPP) and sourced from the World Bank WDI database. Given the scope of the study, we focus primarily on institutional features of monetary policymaking, particularly those related to inflation targeting. 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.

In addition to the level of development, 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[4]; 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 IMF classification. Note that these variables are designed to reflect characteristics typically associated with more effective inflation control, corresponding to countries classified into categories with lower values of the fractional integration parameter d.

Figure 7 presents the correlation matrix between types of monetary policy strategy, fractional integration 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

[4] 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).

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).

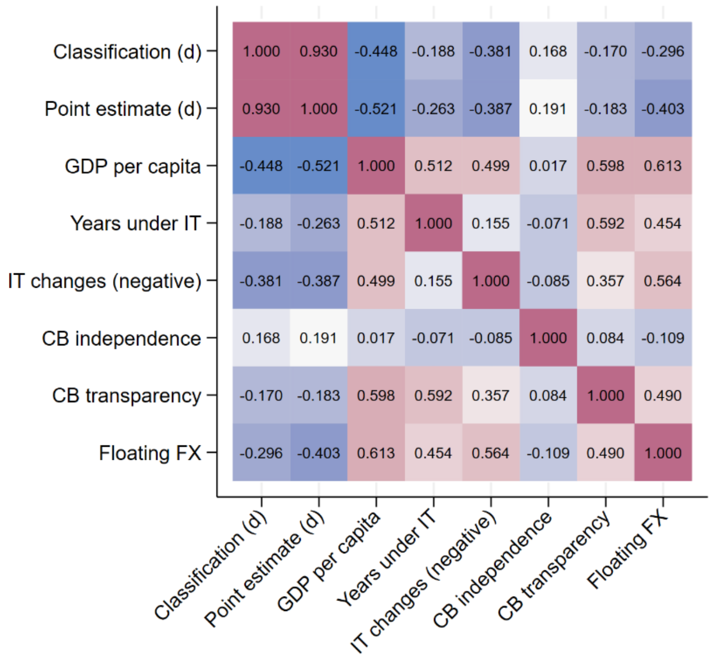

Figure 7: Correlation matrix of variants of inflation targeting, fractional integration of inflation rates, and country-level covariates

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.

The ordinal probit model is employed to estimate 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 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. By utilizing the ordinal probit approach, we capture how institutional and economic factors influence the probability of a country being classified into one of the four categories.

Table 3 reports the baseline results of the ordinal probit regression. 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 lead to less persistent inflation. From an institutional perspective, this implies 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 suggest that countries with more advanced economic frameworks are better equipped to handle inflationary pressures. The pseudo R-squared values suggest that while the model explains part of the variation in monetary policy classifications, it is likely that other variables, such as external shocks or specific country policies, also influence inflation persistence. The significant roles of target stability and transparency highlight the importance of consistent and clear policy frameworks in reducing inflation persistence. In contrast, central bank independence, though theoretically important, does not show a significant impact, suggesting that *de jure* independence may not translate directly into effective inflation control without accompanying operational measures.

Table 3: 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 0.15, 0.1, and 0.05 levels, respectively.

In Table 4, alternative definitions of the country-level covariates are explored. We use the log values of GDP per capita and years under IT to account for potential nonlinearities. The standard deviation of IT 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, Masciandaro, and Tabellini (1991) classification, updated by Romelli (2022). Central bank transparency is sourced from Niedźwiedzińska (2022), and the exchange-rate regime is captured by the classification from Dąbrowski, Papież, and Śmiech (2020), which defines the share of years during which a country is classified as 'float'. The results remain consistent with the baseline findings: GDP per capita and years under IT continue to show significant negative relationships with the parameter d and IT categories. These alternative measures reinforce the idea that economic development and stability in monetary frameworks contribute to lower inflation persistence, while transparency continues to be a key factor in effective inflation control.

Table 4: 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 st. dev. (negative)			-0.646*			
			(0.370)			
CB independence (alt)				0.0376		
				(0.776)		
CB transparency (alt)					-0.220*	
					(0.113)	
Floating FX (alt)						-1.520**
						(0.750)
Intercept (1)	-6.456**	-4.147**	-1.341**	-1.526**	-2.967**	-2.885**
	(2.022)	(1.556)	(0.386)	(0.518)	(0.970)	(0.768)
Intercept (2)	-5.445**	-3.186*	-0.374	-0.776	-2.025**	-1.953**
	(2.111)	(1.628)	(0.278)	(0.546)	(0.819)	(0.694)
Intercept (3)	-4.098*	-1.871	0.967**	0.628	-0.676	-0.608
	(2.119)	(1.590)	(0.308)	(0.552)	(0.757)	(0.638)
Observations	36	36	36	33	34	36
Pseudo R-squared	0.0505	0.0356	0.0464	2.89e-05	0.0387	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 0.15, 0.1, and 0.05 levels, respectively.

Finally, Table A.5 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 fractional integration estimation. 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.3 in the Appendix shows scatterplots and the fitted regression lines. The outcome of the WLS estimations supports our results. The relationships between GDP per capita, IT maturity, and floating exchange rates with inflation persistence 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 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 ITs are also quite frequent. Unsurprisingly, given the relatively short time span since its inception, the AIT is found to be present only in two advanced economies. 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 shows, 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 stimulate 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 after the post-Covid inflation surge, and among the less mature inflation targeters, such as emerging market economies. 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 emerging market economies, 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 we 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.

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Appendix

The appendix contains additional tables and figures, referenced in the main text.

Table A.1: Inflation properties across IT regimes and the non-IT regime with an I(1) process

Time series properties	Average IT	Strict IT	Flexible IT	Uncommitted IT	Non-IT
	$-0.5 < d < 0$	$d = 0$	$0 < d < 0.5$	$0 \ll d < 1$	$d = 1$
Mean-reversion	yes	yes	yes	yes	no
Stationarity	yes	yes	yes	yes/no	no
Memory	intermediate*	short	long	long	permanent
Autocorrelation function decay	hyperbolic**	exponential	hyperbolic	hyperbolic	negligible***
Persistence	anti	no	low	high	infinite

Notes: * Some authors consider processes with a negative d as having long memory (e.g. Box et al., 2016) and some as having short-memory (Baillie, 1996). ** All autocorrelations are negative (except at lag zero). *** For the process with the initial condition in period $t - N$, when t goes to infinity, the ACF converges to 1 (for the process without the initial condition, the ACF does not exist).

Table A.2: List of countries covered in the study and the year of inflation targeting adoption

Country	Country code	IT adoption	Country	Country code	IT adoption
Albania	ALB	2009	Japan	JPN	2012
Armenia	ARM	2006	Korea	KOR	1998
Brazil	BRA	1999	Moldova	MDA	2013
Canada	CAN	1991	Mexico	MEX	2001
Switzerland	CHE	2000	Norway	NOR	2001
Chile	CHL	2000	Peru	PER	2002
Colombia	COL	1999	Philippines	PHL	2002
Czechia	CZE	1998	Poland	POL	1999
Dominican Republic	DOM	2012	Paraguay	PRY	2011
Euro area	EUR	1999	Romania	ROU	2005
United Kingdom	GBR	1992	Serbia	SRB	2009
Georgia	GEO	2009	Sweden	SWE	1995
Ghana	GHA	2007	Thailand	THA	2000
Guatemala	GTM	2005	Turkey	TUR	2006
Hungary	HUN	2001	Uganda	UGA	2011
Indonesia	IDN	2005	Uruguay	URY	2007
Iceland	ISL	2001	United States	USA	2000
Israel	ISR	1997	South Africa	ZAF	2002

Notes: The table provides the full list of countries included in the study. The year of the inflation targeting adoption is based on information obtained from the respective central bank documents and websites.

Table A.3: ARFIMA models: estimates of fractional integration parameters, and residual tests

Country	Selected ARFIMA	Estimator	$\hat{d}$	$se(\hat{d})$	LB(10) – stat	LB(10) – p-value	BG(4) – stat	BG(4) – p-value
ALB	(0, d, 2)	MLE	0.416***	0.133	17.400	0.066	5.513	0.239
ARM	(0, d, 1)	MPL	-0.034	0.071	4.978	0.893	1.964	0.742
BRA	(0, d, 1)	MPL	0.383***	0.075	11.900	0.292	3.271	0.514
CAN	(0, d, 1)	MPL	-0.187**	0.075	5.401	0.863	0.667	0.955
CHE	(1, d, 1)	MPL	0.14**	0.068	11.110	0.349	0.673	0.955
CHL	(1, d, 1)	MPL	0.258***	0.079	18.660	0.045	1.746	0.782
COL	(0, d, 1)	MPL	0.337***	0.068	7.473	0.680	4.197	0.380
CZE	(1, d, 0)	MPL	0.238***	0.084	15.860	0.104	2.732	0.604
DOM	(1, d, 1)	MPL	0.369***	0.071	15.520	0.114	2.428	0.658
EUR	(0, d, 0)	MPL	0.281***	0.055	5.712	0.839	1.436	0.838
GBR	(0, d, 0)	MPL	0.194***	0.051	3.020	0.981	1.892	0.756
GEO	(0, d, 1)	MPL	-0.004	0.073	4.588	0.917	0.773	0.942
GHA	(0, d,1)	MLE	0.459***	0.073	17.390	0.066	5.784	0.216
GTM	(0, d, 1)	MPL	0.177**	0.071	5.174	0.879	0.343	0.987
HUN	(0, d, 0)	MPL	0.325***	0.048	12.170	0.274	1.655	0.799
IDN	(0, d, 0)	MPL	0.175***	0.051	14.370	0.157	3.335	0.503
ISL	(0, d, 0)	MPL	0.382***	0.055	9.962	0.444	3.817	0.431
ISR	(0, d, 1)	MPL	0.127*	0.070	14.080	0.169	2.531	0.639
JPN	(0, d, 1)	MPL	0.088	0.080	9.639	0.473	0.305	0.990
KOR	(0, d, 0)	MPL	0.173***	0.053	16.860	0.078	5.491	0.241
MDA	(1, d, 0)	MPL	0.277**	0.111	7.047	0.721	2.727	0.605
MEX	(0, d, 1)	MPL	0.171**	0.075	11.280	0.336	2.898	0.575
NOR	(1, d, 0)	MPL	-0.278*	0.142	8.426	0.587	2.486	0.647
PER	(0, d,1)	MPL	0.145*	0.078	17.460	0.065	4.281	0.369
PHL	(0, d, 1)	MLE	0.285***	0.096	5.925	0.822	2.984	0.561
POL	(1, d, 1)	MPL	0.365***	0.071	8.877	0.544	2.661	0.616
PRY	(4, d, 0)	MPL	0.306***	0.111	18.610	0.046	1.184	0.881
ROU	(0, d, 1)	MLE	0.486***	0.028	14.260	0.161	7.117	0.130
SRB	(1, d, 0)	MPL	0.422***	0.091	29.330	0.001	6.853	0.144
SWE	(0, d, 0)	MPL	0.146***	0.052	10.370	0.409	3.428	0.489
THA	(1, d, 1)	MPL	-0.004	0.068	10.510	0.397	4.960	0.291
TUR	(1, d, 1)	MLE	0.432***	0.102	5.583	0.849	2.262	0.688
UGA	(0, d, 0)	MPL	0.286***	0.055	8.052	0.624	0.936	0.919
URY	(0, d, 1)	MPL	0.334***	0.075	4.079	0.944	0.273	0.991
USA	(1, d, 1)	MPL	-0.092	0.115	3.315	0.973	1.249	0.870
ZAF	(0, d, 0)	MPL	0.425***	0.055	10.360	0.409	3.610	0.461

Notes: The table contains details on the estimation of the baseline ARFIMA(p, d, q) specification for 36 economies. Symbols ***, **, and * denote statistical significance of the fractional integration parameter estimates at the 0.1, 0.5, and 0.01 levels, respectively. LB(10) denotes the Ljung-Box test statistics for autocorrelation of residuals up to 10 lags, while BG(4) shows the Breusch-Godfrey test statistics up to 4 lags.

Table A.4: Sensitivity analysis: comparison of monetary policy regime classifications: the full list of cases

Classification	Accuracy	Adjusted Rand index	Kappa (no weights)	Kappa (equal weights)	Kappa (quadratic weights)
Baseline – Winsorized data	0.750	0.377	0.611	0.699	0.800
Baseline – Extended coverage	0.667	0.297	0.480	0.558	0.653
Baseline – Detrended data	0.778	0.457	0.683	0.684	0.663
Baseline – MLP estimator	0.556	0.146	0.378	0.480	0.594
Winsorized data – Extended coverage	0.611	0.145	0.375	0.489	0.632
Winsorized data – Detrended data	0.667	0.301	0.516	0.579	0.615
Winsorized data – MLP estimator	0.528	0.068	0.341	0.428	0.531
Extended coverage – Detrended data	0.500	0.162	0.275	0.403	0.506
Extended coverage – MLP estimator	0.500	0.120	0.282	0.409	0.547
Detrended – MLP estimator	0.611	0.332	0.455	0.597	0.730

Notes: The table shows pairwise comparisons between the classifications obtained in the baseline case and four sensitivity checks. All kappa statistics have p-values smaller than or equal to 0.01.

Table A.5: Covariates of the inflation rate fractional integration parameters: weighted least squares regressions

	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita	-0.0250*					
	(0.0139)					
Years under IT		-0.0104*				
		(0.00548)				
IT changes (negative)			-0.0221**			
			(0.0107)			
CB independence				0.222		
				(0.178)		
CB transparency					-0.0101	
					(0.0107)	
Floating FX						-0.202**
						(0.0845)
Intercept	0.336**	0.449**	0.174**	0.126	0.353**	0.343**
	(0.0606)	(0.118)	(0.0423)	(0.111)	(0.124)	(0.0539)
Observations	36	36	36	33	32	36
R-squared	0.075	0.104	0.177	0.054	0.016	0.201

Notes: The table shows the baseline estimation results using weighted least squares. Dependent variable: point estimates of the fractional integration parameter d of inflation rates in ARFIMA models. Weights are equal to the inverse of standard errors of estimates. See the main text for the definitions of explanatory variables. Robust standard errors are given in parentheses. †, *, and ** denote statistical significance at 0.15, 0.1, and 0.05 levels, respectively.

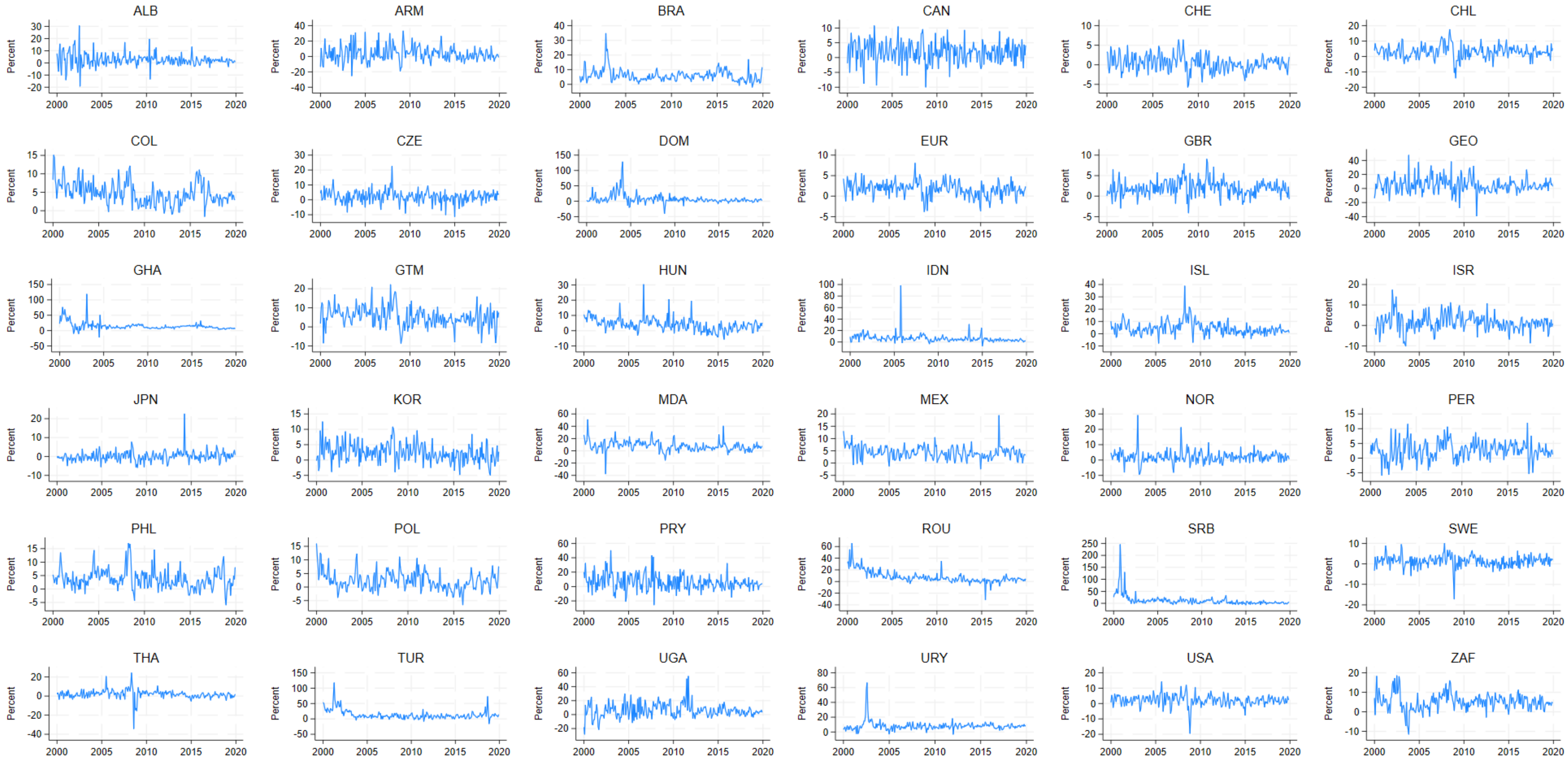

Figure A.1: Inflation rate series used in the study

Notes: The figure displays annualized inflation rates, in monthly frequency, for IT countries covered in the study. The series are calculated using the price level data from the IMF's International Financial Statistics.

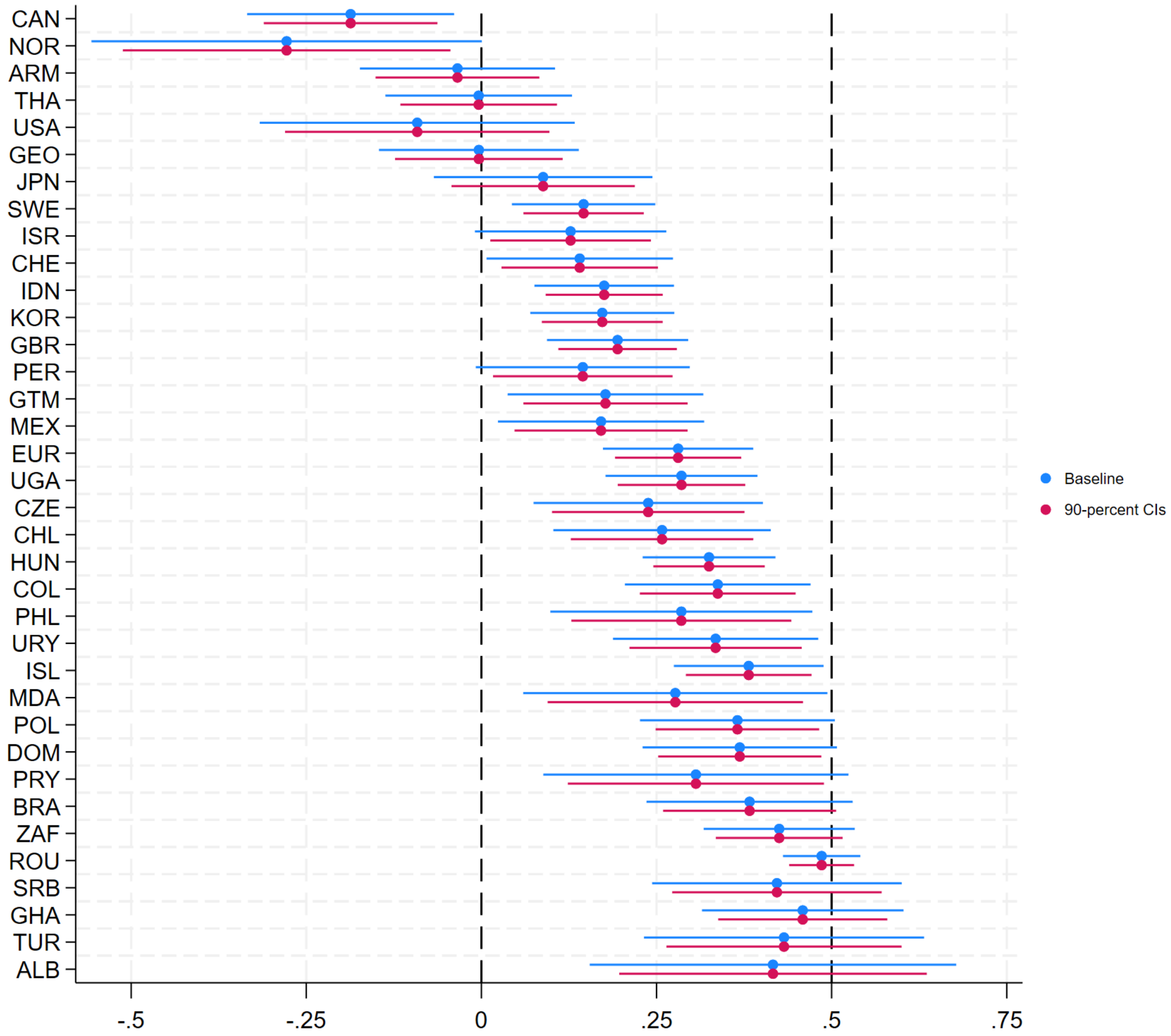

Figure A.2: Baseline fractional integration parameter estimates: 95-percent and 90-percent confidence intervals

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), along with the '90-percent CIs' results which show the corresponding 90-percent confidence intervals.

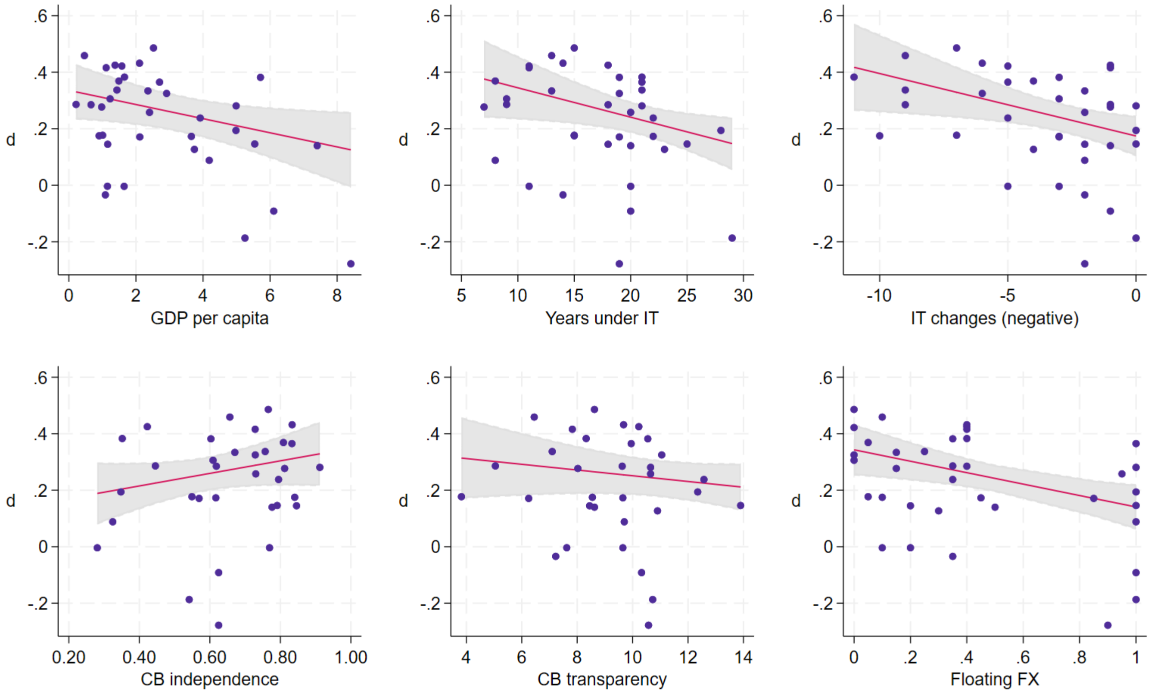

Figure A.3: Bi-variate regression plots of estimated fractional integration parameters and country-specific variables

Notes: The figures display scatterplots for the estimates of fractional integration parameters and a set of country-specific variables. Simple regressions are fitted using the weighted least squares (WLS) estimator with weights equal to the inverse of standard errors of the estimates of fractional integration parameters (d) of inflation rates. Shaded areas represent 95-percent confidence intervals constructed using heteroscedasticity-robust standard errors.