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Abstract

Are emerging economies implementing inflation targeting (IT) with a perfectly flexible exchange-rate arrangement, as developed economies do, or have these countries developed their own IT framework? This paper offers a new method for assessing exchange-rate policies that combines the use of "indicator countries", providing an empirical definition of exchange-rate flexibility or rigidity, and clustering through Gaussian mixture estimates in order to identify countries' *de facto* regimes. By applying this method to 19 inflation-targeting emerging economies, I find that the probability of those countries having a perfectly flexible arrangement as developed economies do is 52%, while the probability of having a managed float system, obtained through foreign exchange market intervention, is 28%, and that of having a rigid exchange-rate system (similar to those of pegged currencies) is 20%. The results also provide evidence of two different monetary regimes under inflation targeting: flexible IT when the monetary authorities handle only one tool, the interest rate, prevailing in ten economies, and hybrid IT when the monetary authorities add foreign exchange interventions to their toolbox, prevailing in the remaining nine economies.

Keyword: Inflation-targeting, Foreign Exchange Interventions, Gaussian mixture model.

JEL: E31, E40, E58, F31.

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1 Introduction

Exchange-rate volatility has long been described as the Achilles' heel of inflation-targeting (IT) regimes in emerging economies. Owing to the particularities of emerging economies and the fact that IT was generally intended to go hand in hand with a freely floating exchange rate, it was argued that IT as it is applied in developed economies would not be a panacea for emerging economies[1]. However, since New Zealand first adopted IT in December 1989, this framework has become a standard operating procedure, particularly in emerging economies. Today, of the 29 economies that fulfil the standard criterion that defines IT, 19 are emerging economies (see Hammond 2012). Based on these findings, this paper examines whether emerging economies implement similar IT strategies to developed economies or whether these countries adopt particular policies, especially towards exchange-rate flexibility. Is the exchange rate as flexible in IT emerging economies as in IT developed economies or is it less flexible or perhaps more controlled? Are foreign exchange market interventions more frequent in IT emerging economies than in IT developed economies or is there little difference?

It is generally agreed that the exchange rate plays a greater role - both as a tool and as a target - in monetary policy in emerging economies than in developed economies. This is due to the enhanced role played by exchange-rate channels in emerging economies, which are generally attributed to greater vulnerability to shocks, lower policy credibility and underdeveloped domestic financial markets (see Stone et al. 2009). The prominent role played by the exchange rate in emerging economies" monetary policy is also associated with two phenomena: the "fear of floating" (Calvo & Reinhart 2002) and the "fear of appreciation" (Levy-Yeyati et al. 2013). According to Cavoli2009, the first phenomenon is justified by three factors: the fear of trade contraction due to higher exchange-rate volatility, a higher pass-through from the exchange rate to domestic prices in emerging economies than in developed economies, and balance sheet effects caused by currency mismatches and liability dollarisation. Levy-Yeyati et al. (2013) attribute the second phenomenon to concerns over losing competitiveness. Aghion et al. (2009) also demonstrate that exchange-rate volatility reduces growth in countries with relatively less developed financial sectors.

Therefore, even if they do not set a particular exchange-rate target, the monetary authorities in emerging economies' are more concerned by the exchange rate than their counterparts in developed economies. This idea has been analysed in the literature in such a way so as to suggest that the central banks of emerging economies should give more weight to the exchange rate in their reaction function than developed economies. Hence, on the theoretical side, various models[2] have been developed to explain in which circumstances the central banks of emerging economies are justified in using a Taylor rule augmented by the exchange rate

[1]See Mishkin (2004).

[2]See Batini et al. 2003, Moron & Winkelried 2005, Cavoli & Rajan 2006, Yilmazkuday 2007, Cavoli 2008, Ravenna & Natalucci 2008, Roger et al. 2009, Stone et al. 2009, Bénassy-Quéré & Salins 2010 and Pavasuthipaisit 2010

while, on the empirical side, a large number of papers[3] have estimated such open-economy Taylor rules.

However, those papers in which exchange-rate policy is analysed using the Taylor rule argument only are missing the smoking gun: the most prominent policy is foreign exchange market intervention[4]. Surprisingly, foreign exchange market intervention under inflation targeting has not received much attention in the literature[5]. The main two reasons behind this are, first, macroeconomic models are not well suited to assessing the use of two instruments by one agent (both an interest rate instrument and foreign market intervention) and, second, the channel of foreign exchange market intervention is not yet clearly understood empirically or theoretically. However, the need to address foreign exchange market interventions is growing, as central banking practices increasingly seem to rely on a "two targets, two instruments" principle[6].

This paper aims to fill the gap in the literature: it offers a method for assessing central bank inflation-targeting exchange-rate policy in emerging economies through exchange market interventions, rather than as an augmented Taylor rule. Based on the methodology developed by Levy-Yeyati & Sturzenegger (2005) for classifying exchange-rate arrangements, the degree of flexibility of an exchange rate is defined by the behaviour of both its nominal exchange rate and foreign exchange market interventions. Using a Gaussian mixture model, I compute the probability of any inflation-targeting emerging economy having a floating exchange-rate arrangement, an intermediate system or a fixed exchange-rate system. The definition of each regime is assessed by two pools of "indicator countries", from which data are randomly selected to form a control sample in a bootstrapping loop. My results strongly support the existence of two distinct inflation-targeting regimes: a flexible inflation-targeting regime with a flexible exchange-rate as in developed economies, and a hybrid inflation-targeting regime under which the exchange rate is more controlled and less flexible. However, the share of hybrid inflation-targeters is small: 10 out of 19 inflation-targeting emerging economies (ITEE) have an exchange rate as flexible as that of inflation-targeting developed economies.

This paper is organised as follows: Section 2 presents and discusses the literature on deeds versus words exchange-rate regime classification; Section 3 offers a method for assessing exchange-rate control through foreign exchange market interventions, specifically designed to deal with inflation-targeting emerging economies; Section 4 describes the data; and section 5 presents

[3] See Corbo et al. 2001, Mohanty & Klau 2005, Edwards 2006, Aizenman et al. 2011 and Frömmel et al. 2011.

[4] As emphasized by Stone et al. (2009, page 25) "Foreign exchange interventions (...) is the main exchange-rate policy implementation tool".

[5] With the notable exception of Berganza & Broto (2012) and Chang (2008).

[6] This was described by Ostry et al. (2012, page 13) as follows : "the central bank may opt for an IT regime, subordinating its monetary policy to achieving the inflation objective. If, as the discussion above suggests, emerging markets economies central banks also have available a second instrument (foreign exchange intervention), they can also limit temporary movements of the exchange-rate without prejudicing attainment of their primary target, the inflation rate."

the results. The last section briefly concludes.

2 *Deeds vs words*: the need for *de facto* exchange-rate regimes classification.

Which economies have a floating exchange-rate and which ones have a stickier arrangement? This is a deceptively simple question. The basic and instinctive answer would be to look at monetary authorities' statements on the external value of their currencies. Until 1999, this official information was collected by the IMF and published in its *Annual Report on Exchange-Rate Arrangements and Exchange Restriction.* However, the fear of potential gaps between officially reported exchange-rate regimes and those which actually prevailed led to alternative *de facto* classifications of exchange-rate regimes being constructed in order to test whether the announced policy reflected the actual policy in place. Even if these papers differ in the conclusions reached at the country level, there is a clear consensus that, in practice, many exchange-rate regimes do not function according to the *de jure* rules.

Evidence for this initially involved fixed exchange-rate arrangements. One of the most prominent papers on the topic, Obstfeld & Rogoff (1995), argues that in the post-Bretton Wood environment, the concept of a fixed exchange rate is a "mirage"[7]. The idea was then extended to the floating arrangement when, in a nod to Obstfeld and Rogoff, Reinhart (2000) wrote "The Mirage of Floating Exchange Rates". Using the US dollar, the German deutschemark and the Japanese yen as benchmarks to define flexible exchange-rate arrangements, Reinhart reaches the following conclusions (p65): "Countries that say they allow their exchange-rate to float mostly do not; there seems to be an epidemic case of 'fear of floating'."[8]

Many *de facto* classifications, relying on a wide variety of econometrical and statistical methods, have followed. Therefore, exchange-rate classification methods have almost become a field of research in themselves, as described by Tavlas et al. (2008). The three main results of this literature are presented below.

First of all, the *de jure* classification predicts those classifications built on facts very badly. Table 1, page 5 summarises the correspondence among the official classification and three standard *de jure* classifications: Ghosh et al. (2000) (denoted by GGW), Levy-Yeyati & Sturzenegger (2005) (denoted by LYS) and Reinhart & Rogoff (2004) (denoted by RR). It

[7] Obstfeld & Rogoff (1995) : "aside from some small tourism economies, oil sheikdoms and highly dependent principalities, literally only a handful of countries in the world today have continuously maintained tightly fixed exchange-rates against any currency for five years or more." (p 87) Also, on the determinants of this evolution: "There is little question that the biggest single factor has been the dramatic evolution of world capital markets" and "shifting capital flows". (p77)

[8] She also notes that "The low variability of the nominal exchange-rate is not owing to the absence of real or nominal shocks in these economies." It is "the deliberate result of policy actions to stabilize the exchange-rate." Also "most of the episodes that come under the heading of floating exchange-rates look more like non credible pegs", underlining a credibility problem. Reinhart (2000, page 65)

displays the large discrepancy between the *de jure* regimes and any given *de facto* definition. This result also stresses the need to use a *de facto* classification while studying, for instance, the impact of exchange rate regimes on a macro variable like growth or the determinants of the choice of exchange-rate regime.

	GGW	LYS	RR
IMF *de jure*	0.60	0.28	0.33

Table 1: *De jure* and *de facto* correlations.
Source: Frankel & Wei (2008b)

Second, building an exchange rate classification relying only on facts is not an easy task. Only very few classifications do not rely on any *de jure* component and, moreover, the various *de facto* regimes barely correspond any more closely to one another than to the official regime.

Finally, the definition of an exchange rate is relative. It is almost impossible to define an exchange-rate regime as fixed or floating by applying a threshold or ex ante criterion on exchange-rate volatility or, indeed, on any other variable. The variables that define a policy have to be analysed jointly and carefully. *De facto* regimes also rarely correspond to the ideal view but are more likely to result from a negative inference: for example, a country does not have a flexible arrangement because its central bank never intervenes in the foreign exchange market, but rather because the central bank intervenes relatively less frequently than other central banks. The approach developed by Levy-Yeyati & Sturzenegger (2005) is, in this way, quite accurate. They propose a purely statistical classification methodology, which does not rely on any *de jure* component coming from an official source or any threshold left to the author's discretion. Economies are only ranked or classified in relation to their characteristics.

Among the various methods developed in the literature that of LYS distinguishes itself in that the number of currencies used to define a country's exchange rate is flexible. In the general case, one reference currency (the main trade and finance partner) is used, but where there is no such immediate reference currency, or where a basket peg is known, a weighted exchange-rate can also be used. The exchange-rate series considered are the official ones and not those from the parallel or black markets as in Reinhart & Rogoff (2004). As long as the classification is not used to study bilateral trade, this seems to be fair (see Shambaugh 2004). Both the exchange rate and some exchange-rate control instruments are used to define a regime, unlike in hard peg regime studies such as Frankel et al. (2001), Bénassy-Quéré & Coeuré (2002) and Bénassy-Quéré et al. (2006). LYS use foreign exchange reserves to measure foreign exchange interventions, as in Edwards & Savastano (1999), Reinhart (2000) and Edwards (2002). Their measure is a close substitute for the exchange market pressure proposed by Girton & Roper (1977) and used by Frankel & Wei (2008a), Frankel & Xie (2009) and Frankel & Xie (2010). The method adopted by LYS is purely statistical, as in Frankel &

Wei (2008a) and Frankel & Xie (2010), and thus does not rely on any *de jure* information, contrary to Ghosh et al. (1997), Eichengreen & Leblang (2003) and Dubas et al. (2005), nor does it rely on the researcher's judgment, contrary to Bubula & Atker (2002).

LYS classification main features. LYS classify exchange-rate regimes according to the behaviour of three variables: interventions in the foreign exchange market, the volatility of the nominal exchange rate and the volatility of nominal exchange-rate changes. Interventions in the exchange markets are measured through the volatility of central banks' foreign reserves. Idiosyncratic shocks may explain some of the nominal exchange-rate changes; therefore, a currency's stability has to be measured according to the volatility of its exchange rate relative to that of its reserves. The volatility of nominal exchange-rate changes is taken into account in order to consider policies with a medium-term exchange-rate target, achieved via short-term objective. In such a procedure, known as a crawling peg, a currency's exchange rate is periodically adjusted, but the exchange rate may remain fixed between one adjustment and the next. Therefore, exchange-rate volatility does not imply volatility of nominal exchange-rate changes, as opposed to what is observed with a freely floating exchange rate.

Every variable is expressed as a yearly average of monthly data, thus any observation is a three-dimensional object (one dimension for each variable), related to a given country and a given year. LYS then apply the K-means partitioning algorithm[9] to their dataset in order to group similar observations into clusters. Once the data have been grouped, each cluster is associated with an exchange-rate regime.

	$\sigma(e)$	$\sigma(\Delta e)$	$\sigma(r)$
Flexible	High	High	Low
Crawling Peg	High	Low	High
Fixed	Low	Low	High
Dirty float	High	High	High
Inconclusive	Low	Low	Low

Table 2: LYS classification criteria

To identify the policy regime, LYS assume "the cluster with high volatility of reserves and low volatility in the nominal exchange-rate identifies the group of fixers. Conversely, the cluster with low volatility in international reserves and substantial volatility in the nominal exchange-rate corresponds to countries with flexible arrangements" (LYS 2005, p 1605). The group with high volatility in the nominal exchange rate and international reserves but low volatility in nominal exchange-rate changes is made up of those countries with a "crawling peg". They add a fourth group, "dirty float", which "should be associated to the case in which volatility is relatively high across all variables, with intervention only partially smoothing

[9] This method, based on nearest centroid sorting, assigned individual cases to the cluster with the smallest distance between the case and the center of the cluster.

exchange-rate fluctuations." (LYS 2005, p 1606). Last, the cluster in which every variable has low values is labelled "inconclusive". This group does not match up with any obvious regime and, therefore, is treated as a special case.

Strengths and weaknesses. The LYS classification method has three main advantages when compared with other methods. First, exchange-rate movements and foreign exchange interventions are both considered simultaneously. Second, it is a purely *de facto* classification; it does not rely on any *de jure* component from an official source or any component left to the author's discretion. Third, the LYS classification is based on relative definitions, as opposed to absolute definitions based on thresholds or specific *ex ante* measurements. Given that the message delivered by the literature on the "fear of floating" (Reinhart and others) is precisely that there is no right threshold to define a regime, this is a major factor to be taken into account when properly defining exchange-rate systems.

Though the LYS regimes classification has become a standard in exchange-rate policy studies, there are, nevertheless, some limitations that must be taken into account.

Firstly, the classification ends in 2005 and thus does not cover the years of IT sufficiently. Secondly, and more importantly, the LYS way of dealing with the "inconclusive" cluster is not convincing. This cluster contains 1,798 out of 2,860 observations. Therefore, more than 60% of the observations are not associated with a policy regime and are passed by in the initial classification. To resolve this issue, LYS proceed to a second classification: they apply the same method used for the whole sample during the first round on the single inconclusive group. However, there is no convincing argument suggesting that the observations labelled in the first round (for instance, "dirty float") are similar to those that were given the same label in the second round. This can be seen clearly when looking at the clusters' boundaries in the two rounds. Are the classifications produced from the two rounds really referring to the same policy realities? This is a major concern. In addition, even after the second round, a large number of observations (698) still remain in the "inconclusive" cluster. Hence, 25% of the initial dataset is simply left aside and is not associated with a policy regime[10].

Last, even though the K-means algorithm used by LYS to cluster the data has become a standard in the partitioning literature, it is also known to have several drawbacks. First, the number of clusters, k, is an input parameter that has to be defined ex ante. Therefore, it is not exact to say that "cluster analysis has the advantage of avoiding any discretion from the researcher"[11]; the researcher has to choose how many groups are to be found in the data.

[10] Despite the limitations of the method, it seems that the high number of "inconclusive" cases is due to the partitioning algorithm and to the extremely large time period and country coverage chosen by the authors. Their dataset covers any country included in the IMF statistic from 1973 to 2005. Hence, it covers a wide variety of realities and includes a large number of outliers, most notably among the "inconclusive" observations. On the other hand, even though they left out less than one in four observations, with such a large coverage they obtain an interesting and useful classification, seen as a standard in the literature.

[11] Full quote: "cluster analysis has the advantage of avoiding any discretion from the researcher beyond that

Furthermore, LYS do not provide any information about the goodness-of-fit of the number of groups (k) or of the grouping itself. Another limitation of the partitioning algorithm is that the results are sensitive to data composition. In the case of LYS, removing only a few observations may modify the entire classification, which may explain why the inconclusive countries are not considered as outliers and are excluded from the sample[12]. Last, clusters formed by the K-means algorithm have a constrained variance-covariance matrix which gives them a spherical shape and a similar size (see Hennig 2011). This particularity may explain the large number of intermediate regimes they obtain.

3 An original method for assessing exchange-rate control

3.1 The approach.

My purpose is to examine whether emerging economies implement similar IT strategies to developed economies or adopt particular policies, especially with regard to exchange-rate control through foreign exchange intervention. Therefore, I propose a new classification method, specifically designed to assess the degree of flexibility of the currencies of inflation-targeting emerging economies (ITEE).

Two control samples. I consider that two fundamental elements of the LYS method are good and are to be retained when developing my own approach: first, the use of exchange rate volatility, the volatility of exchange-rate changes and interventions in the exchange market to characterise a policy and, second, a partitioning procedure to group the observations into consistent policy group. I focus on ITEE; therefore, these countries will constitute the core of my data sample. However, a good classification of exchange-rate arrangements has to be a relative classification[13]. Therefore, in order to access the exchange rate arrangement of ITEE, I must analyse their exchange-rate flexibility relative to that of some other economies. These control samples are hereafter referred to as "indicator countries" and constitute the counterfactual economies. However, I require two control samples, one for each polar policy: flexible and rigid arrangements. The flexible arrangement control sample is made up of developed IT economies; these economies act as the benchmark for inflation-targeting frameworks associated with a flexible exchange-rate regime. Hence, the sample shows whether the exchange rates of ITEE are as flexible as those of IT developed economies. The fixed arrangement control sample is made up of economies that have rigid regimes. Finally, my database is the sum of the ITEE observations, and the flexible and rigid indicator country samples.

required to determine the classifying variables and to assign clusters to different exchange-rate regimes, once they are identified by the procedure." Levy-Yeyati & Sturzenegger (2005, page 1610)

[12]Similarly, k-means may converge to a local minimum, and thus their results are sensible to the initialization parameters.

[13]As opposed to an absolute classification, which would be based on thresholds or specific measurements.

Partitioning algorithm. I apply a partitioning algorithm to this database in order to split the whole set of observations into consistent groups. I show, in the next section, the advantage of using a Gaussian mixture approach over the K-means algorithm used by LYS. Data are split according to the likelihood that they belong to a given Gaussian distribution. All the observations belonging to a Gaussian form one cluster (or one group). Each distribution is then assumed to be produced by a unique process, which, in turn, is assumed to be a given exchange-rate regime. The optimal number of clusters and the cluster composition are defined by statistical criteria and each cluster is then associated with an exchange-rate policy.

Labeling policies. The indicator countries are used to label the groups, so as to associate a cluster to a monetary policy. For instance, in the case that there are two resulting clusters, all observations in the group which includes the majority of floating exchange-rate indicator countries are labelled as *de facto* floating. Hence, any observation from an IT emerging economy included in this group will be considered as *de facto* floating. As there are generally more than two groups, an "intermediate" regime also has to be considered. The Gaussian model estimation gives the probability that any given observation belongs to any given cluster; this is therefore the probability that a given country on a given date has a given policy. Hence, as opposed to other classifications found in the literature, the aim of my classification scheme is not to state that a certain country has a certain arrangement: my final result shows the precise probabilities that a country has a flexible arrangement, a fixed system and a "dirty float".

Robustness. An important drawback of partitioning algorithms is their sensitivity to data composition: a slight change in the data can have a large impact on the results. This is particularly true in the presence of outliers. To address this issue and ensure the results' stability, I propose a bootstrapping approach with random sampling. At each iteration the observations for the ITEE remain in the dataset but the two sets of indicator countries change. The sets of indicator countries used for a given partition are randomly selected from all the control observations including both fixed and floating indicator countries. Therefore, the partition is made over a set of observations consisting in the ITEE, some randomly selected fixed indicator countries and some randomly selected floating indicator countries. At any iteration I compute the probability that an ITEE observation belongs to any given policy. My final result is the average of the probabilities of all iterations, that is, the average of the results of more than 50,000 partitions; in this way I ensure stability.

3.2 Partitioning through Gaussian mixtures

In order to cluster the observations into consistent group, I estimate a Gaussian mixture model.

Gaussian mixture definition. Let's think of the k policy groups obtained with the k-means clustering method by LYS. One can suppose that there is a Gaussian centered at any group' s mean. Thus each cluster can be characterized by a density function, and the overall dataset can be described by a mixture of all these density functions (plus the probability for a given observation to belong to one of them). This analysis of a dataset can be done through a Gaussian mixture model.

The univariate Gaussian distribution is given by

$$p(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) \tag{1}$$

where the mean $\mu \in \mathbb{R}$ and the variance $\sigma \in \mathbb{R}^+$ are the parameters of the distribution.

In my case I have three variables per observations (the nominal exchange-rate volatility, the interventions in the foreign exchange market and the volatility of nominal exchange-rate changes). Hence this is a "trivariate" case. When the Gaussian distribution is extended to more than one distribution, it is given by:

$$p(x|\mu,\Sigma) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)\right) \tag{2}$$

where d (equals 3) is the number of distributions. In the multivariate case the mean is a vector, $\mu \in \mathbb{R}^d$, and the covariance is a positive definite matrix, $\Sigma \in \mathbb{S}^d$.

For a given set of m observations, $x = \{x_1, ..., x_M\}$ that are assumed i.i.d and drawn from a multivariate Gaussian, the distribution's log-likelihood is:

$$p(x|\mu,\Sigma) = -\frac{Md}{2}log(2\pi) - \frac{M}{2}log|\Sigma| - \frac{1}{2}\sum_{m=1}^{M}(x_m-\mu)^\top \Sigma^{-1}(x_m-\mu) \tag{3}$$

By definition a Gaussian distribution is unimodal. If assuming k groups in the dataset, a combination of k Gaussians into a Gaussian Mixture Model is to be considered. With a mixing coefficient denoted by $\pi \in \mathbb{R}^K$ and satisfying any $\pi_k \geq 0$ and $\sum_{k=1}^{K}\pi_k = 1$, the Gaussian mixture model is then given by:

$$p(x|\pi,\mu,\Sigma) = \sum_{k=1}^{K}\pi_k \mathcal{N}(x|\mu_k,\Sigma_k) \tag{4}$$

where $\mu = \{\mu_1, ..., \mu_K\}$ and $\Sigma = \{\Sigma_1, ..., \Sigma_K\}$ are the mean and variance of the respective Gaussian distributions ($\mathcal{N}$, as in equation (2)). [14]

The log-likelihood associated to this model (for m points, assuming independance) can be

[14] Since the observations are assumed to be independently distributed, equation (4) may be written as: $p(x|\pi,\mu,\Sigma) = \prod_{m=1}^{M}\sum_{k=1}^{K}\pi_k \mathcal{N}(x_m|\mu_k,\Sigma_k)$

written as

$$log \quad p(X|\pi,\mu,\Sigma) = \sum_{m=1}^{M} log \sum_{k=1}^{K} \pi_k \mathcal{N}(x_m|\mu_k,\Sigma_k) \tag{5}$$

Once the parameters estimates have been obtained, the *a posteriori* probability that an observation m belongs to the group k can be deduced:

$$\pi_{m,k} = \frac{\pi_k \mathcal{N}(x_m|\mu_k,\Sigma_k)}{\sum_{k'} \pi_{k'} \mathcal{N}(x_m|\mu_{k'},\Sigma_{k'})} \tag{6}$$

In this paper, $\pi_{m,k}$ is the probability that an observation m, for example Brazil in 2010, belongs to a group k, for example free floating exchange-rate group. Also, the sum of $\pi_{m,k}$ and $\pi_{m,k'}$ equals 1. In that example, k' stands for fixed and intermediate exchange-rate groups.

Variance decomposition. This general expression of the Gaussian mixture model allows some sophistications. In particular, the covariance matrix can be decomposed into different variables on which a large set of constraints can be applied.

Following Banfield & Raftery (1993) a spectral decomposition of the covariance matrix is given by:

$$\Sigma_k = \lambda_k D_k A_k D_k^{\top} \tag{7}$$

for $k = 1, ..., K$ and where

- $(\lambda_{k1}, ..., \lambda_{kd})$ are the matrix eigenvalues with $\lambda = \Pi_{m=1}^{d}(\lambda_{mk})^{1/d}$.
- D_k is the matrice of eigenvectors .
- A_k is a diagonal matrix whose elements are proportional to the eigenvalues, that is $A_k = \frac{1}{\lambda_k}$ diag$(\lambda_{k1}, ..., \lambda_{kd})$ and det$A_k = 1$.

This decomposition of Σ_k allows to characterize the distribution: D_k gives the orientation of the covariance matrix, A_k specifies the shape of the density contours and λ_k determines the volume of the corresponding ellipsoid (or hypervolume). These three characteristics (orientation, volume and shape) can be estimated from the data, and can be allowed to vary between clusters, or constrained to be the same for all clusters can vary between clusters, or be constrained as the same for all clusters.

Celeux & Govaert (1995) have discribed the different model that can be obtained by constraining the orientation, volume and shape of the covariance matrix. They also provide details on the EM algorithm for the maximum likelihood estimation of these models. Fraley et al. (2012) (see also Fraley & Raftery 2007) proposed a computational methodology for some of them. In this paper I focus on the multidimensional case considering three options : to be equal among clusters, to vary among clusters, to be given by the identity matrix. Also I use Fraley et al. (2012) denomination system: a 3 letters code, with 1 letter for each of the 3 characteristics (volume, shape and orientation)[15]. The different model of the covariance matrix for which a computational method is known are summarized in Table 3 and I keep referring to this name system in the section dedicated to the results, in particular see Graph 2 page 17.

A criteria to choose the number of clusters. The choice of the number of components has to be done according to the quality of the fit of the estimated density and the detection of distinct groups. A particularly simple and viable method consists in choosing the value of K which minimizes the Bayesian Information Criterion (BIC), as difined by Schwarz (1978).

$$BIC = -2\ \widehat{l} + w\ log\ n \tag{8}$$

where $\widehat{l}$ is the estimated log-likelihood, n is the number of observations, and the term w corresponds to the number of parameters to be estimated ($w = 3K - 1$) in the bivariate case.

From k-means to Gaussian mixture. In the Appendix B page 33, I show how the Gaussian mixture differs from the K-means algorithm used by Levy-Yeyati & Sturzenegger (2005). Indeed, the K-means used by LYS is similar to the Gaussian distribution, but there

[15]For example EVI denotes a model in which the volumes of all clusters are equal (E), the shapes of the clusters may vary (V), and the orientation is the identity (I). Clusters in this model have diagonal covariances with orientation parallel to the coordinate axes.

Table 3: Possible parameterizations of the covariance matrix Σ_j for multidimensional data.

Model name	Form	Distribution	Volume	Shape	Orientation
EII	λI	Spherical	Equal	Equal	NA
VII	$\lambda_j I$	Spherical	Variable	Equal	NA
EEI	λA	Diagonal	Equal	Equal	Coordinate axes
VEI	$\lambda_j A$	Diagonal	Variable	Equal	Coordinate axes
EVI	λA_j	Diagonal	Equal	Variable	Coordinate axes
VVI	$\lambda_j A_j$	Diagonal	Variable	Variable	Coordinate axes
EEE	λDAD^T	Ellipsoidal	Equal	Equal	Equal
EEV	$\lambda D_j A D_j^T$	Ellipsoidal	Equal	Equal	Variable
VEV	$\lambda_j D_j A D_j^T$	Ellipsoidal	Variable	Equal	Variable
VVV	$\lambda_j D_j A_j D_j^T$	Ellipsoidal	Variable	Variable	Variable

Source: Fraley & Raftery (2007, page 8).

are two limitations: the covariance matrix is constrained and the probability of belonging to a given group is not computed. The covariance matrix constraint gives the clusters their spherical shape and all clusters are of a similar size; this may be a problem because it also creates policy groups of a similar size. Therefore, it can be argued that intermediate regimes are as important as polar regimes. This may be right; however, the algorithm used by LYS creates an important bias towards that result. Also, when adopting their approach, the probability of an observation belonging to a certain group is not computed. An observation either belongs to a group or it does not, whereas, in my approach, the clusters' shape is flexible and the precise probability of belonging to a group is computed. This avoids stating that a country has a fixed or floating arrangement and instead gives the probability that a country has a fixed or floating arrangement. All in all, the Gaussian mixture approach seems to be more flexible and robust than the K-means approach.

4 Data

4.1 Data coverage.

My dataset is made up of 75 countries, including 28 IT countries, of which 19 are emerging economies and 9 are developed economies. I use the list of IT countries produced by the Bank of England (BoE) in a paper based on a broad set of indicators, which is very well documented (see Hammond 2012. Also related are Mishkin 2004 and Roger 2009, among others). The essential elements that define an inflation-targeting regime are:

- Price stability is explicitly recognised as the main goal of monetary policy;
- There is a public announcement of a quantitative target for inflation;
- Monetary policy is based on a wide set of information including an inflation forecast;
- Transparency;
- Accountability mechanisms.

To define the rigid regime indicator countries, I follow the IMF classification (see "Classification of Exchange Rate Arrangements and Monetary Policy Frameworks", IMF website). I consider two items: "currency board arrangements" and "other conventional fixed peg arrangements against a single currency"[16]. I obtain 47 indicator countries for the fixed exchange-rate benchmark. Information about the dataset is summarised in the Appendix A page 31. The

[16]There are plenty of different rigid exchange rates families. My fixed exchange rates control sample takes a broad definition. It includes a lot of countries having various degrees of rigidity. Therefore, the robustness and stability of my result is insured through the boot-strapping estimation method.

number of floating indicators and rigid indicators is balanced through the bootstrapping method, which selects similar subsamples.

I use monthly data from the IMF's International Financial Statistics over the period 1990-2012. This is the widest range possible since the first country which adopted IT, New Zealand, did so in December 1989. For every country, I only consider the years after IT was implemented. The starting dates of IT come from the BoE's Handbook on IT (Hammond 2012) and correspond, by and large, to the date declared by the central banks, also known as the "default starting dates" in Rose (2007)'s terminology. I follow Levy-Yeyati & Sturzenegger (2003) and Levy-Yeyati & Sturzenegger (2005) for the definition and computation of the three variables:

- Exchange-rate volatility (σe), measured as the average of the absolute monthly log changes in the nominal exchange rate relative to the relevant anchor currency over the year.
- The volatility of exchange-rate changes ($\sigma_{\Delta e}$), measured as the standard deviation of the monthly log change in the exchange rate.
- Interventions in the exchange markets, measured as central banks' foreign reserve volatility (σr), that is, the average of the absolute monthly log change in dollar-denominated international reserves relative to the log change in the value of the monetary base.

Each variable is expressed as a yearly average (of monthly data), thus an observation is a three dimensional object related to a given country and a given year in the (σe , $\sigma_{\Delta e}$, σr) space.

Random sampling. After computing the three variables, I discarded an observation where I lacked data for at least one of the classifying variables. I obtain 1,035 country-year data points: 154 for floating exchange-rate indicator countries, 603 for fixed exchange-rate indicator countries and 278 for the inflation-targeting emerging economies.

The difference in size of the two control sample does not pose any problems because it will be corrected by a repetitive random sampling process. This approach consists in estimating the Gaussian mixture model multiple times, each time with a different counterfactual sample composed of observations randomly selected from the two indicator countries' datasets. Hence, the Gaussian mixture model is estimated using a sample made up of all points for inflation-targeting emerging economies, and $2x$ points for indicator countries, among which x points are randomly chosen from observations for floating exchange-rate indicator countries and x points are randomly chosen from those for fixed exchange-rate indicator countries. The variable x takes any value from 100 to the size of the smallest indicator country's sample. The process is complete after more than 50,000 iterations. In other words, the Gaussian mixture model is estimated with more than 50,000 different data samples.

4.2 Partitionning loop.

The classification process is based on the following loop:

- **Step 1:** Random composition of the control sample. A given number of observations are randomly selected among the two sets of indicator countries in order to create the control sample. When added to the ITEE observations, they make up the dataset for one iteration (see Graph 1 page 16).
- **Step 2:** Gaussian mixture model estimation. The Gaussian mixture model is estimated. The BIC criterion maximisation gives the best variance-covariance decomposition model and the optimal number of Gaussians that are mixed into the model (see Graph 2 and Graph 3 page 17). Only the optimal distribution is taken into account. The probability of any ITEE observation belonging to any Gaussian is computed.
- **Step 3:** Exchange-rate arrangement classification. All observations belonging to one Gaussian are assumed to form one group (or cluster). That cluster is then assigned to an exchange-rate regime according to the indicator countries' position (see Graph 4 page 18). The probability of any ITEE observation belonging to any Gaussian can now be read as the probability of having a monetary regime.

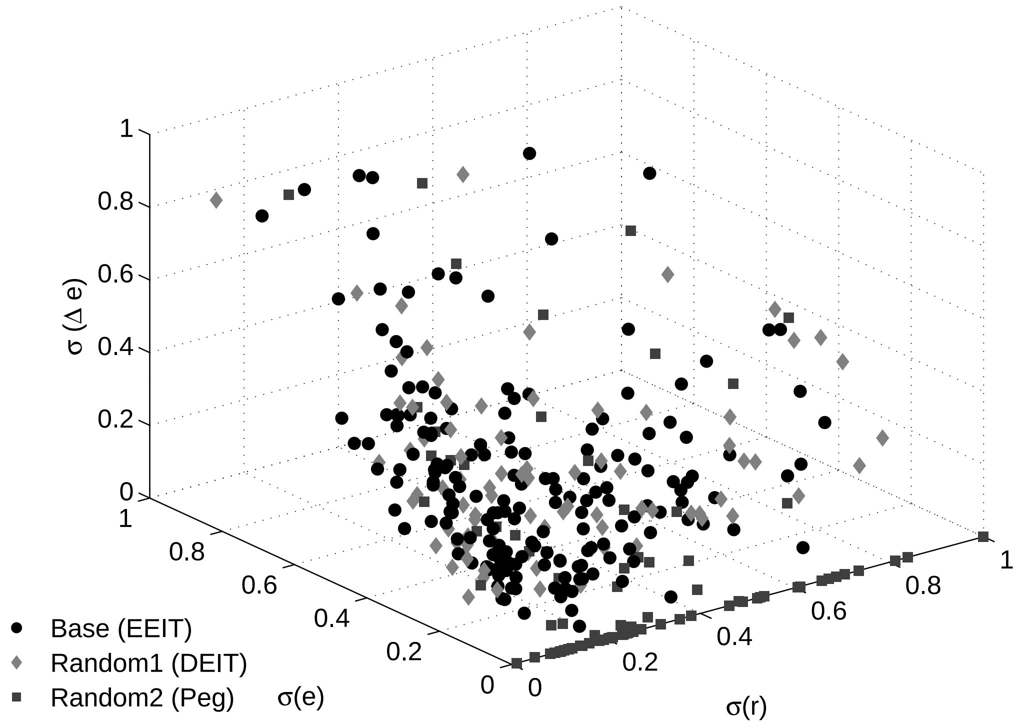

Figure 1: Random composition of the data sample (Step 1).

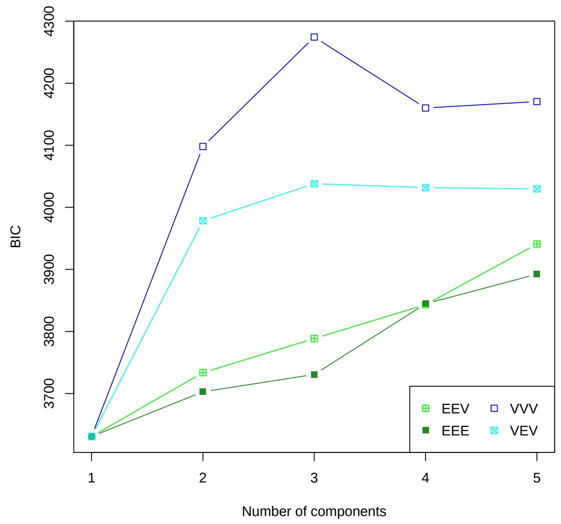

Figure 2: Identification of the optimal model and number of Gaussians (Step 2).

Figure 3: Correspondance between the optimal number of Gaussians and the number of modes appearing on the join density.

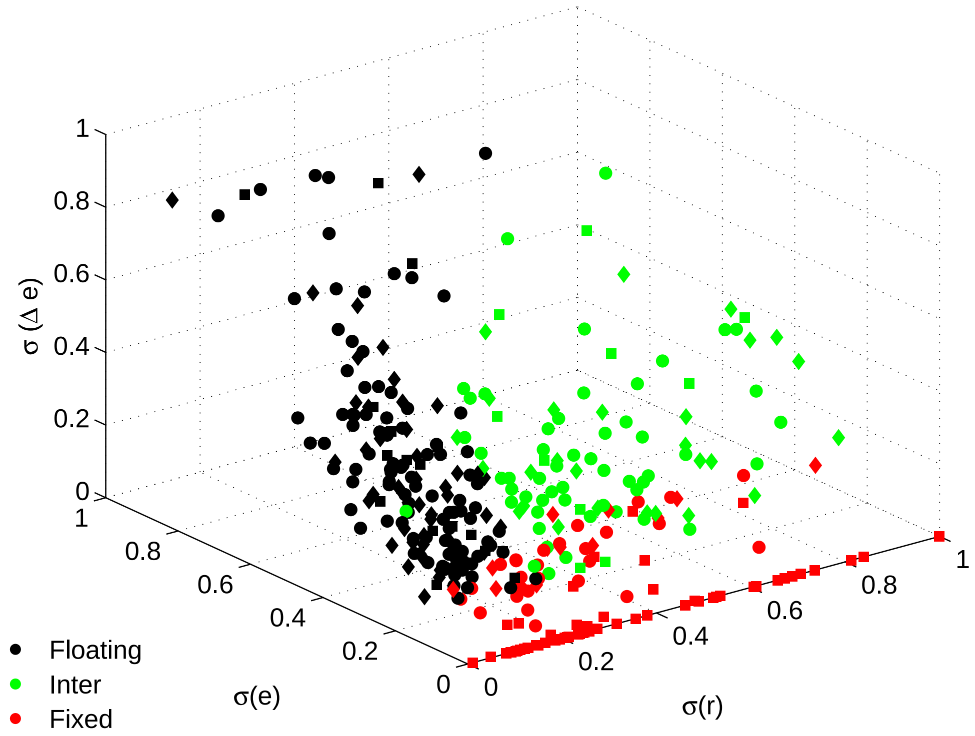

Figure 4: Labelling clusters as *de facto* regimes (Step 3).

5 Results

5.1 Three exchange-rate flexibility degrees: floating, intermediate and fixed.

When the Gaussian mixture model is estimated in step 2, it gives the optimal number of partitions (generally three). Therefore, three degrees of exchange-rate flexibility are to be considered in step 3 when labelling the clusters as fixed, floating or intermediate exchange-rate arrangements. The procedure is the following: if the majority of a Gaussian's elements come from the floating exchange-rate indicator countries, the Gaussian label is "*de facto* floating exchange-rate arrangement", and the probability of any observation belonging to that Gaussian is seen as the probability of having a *de facto* floating exchange-rate arrangement. The same reasoning holds for fixed exchange-rate arrangements. If there is a third group, it is labelled as "*de facto* intermediate exchange-rate arrangement". As we will see below, this group stands for managed floating or "dirty float" regimes. The process described above is repeated thousands of times with different, randomly composed, indicator country samples and the final result (shown below) is, for any observation, the average probability of each iteration.

Table 4: Classification: summary statistics

	Fixed		
	$\sigma(e)$	$\sigma(\Delta e)$	$\sigma(r)$
min	0.2	0.2	0.2
mean	1.0	1.0	1.0
max	1.7	1.7	2.1
std	1.0	1.0	1.0
	Intermediate		
	$\sigma(e)$	$\sigma(\Delta e)$	$\sigma(r)$
min	0.1	0.1	1.4
mean	1.9	1.9	2.4
max	3.8	3.9	4.6
std	2.1	2.3	1.7
	Floating		
	$\sigma(e)$	$\sigma(\Delta e)$	$\sigma(r)$
min	0.5	0.1	0.2
mean	3.4	3.1	1.2
max	8.8	9.6	4.4
std	4.2	4.5	2.2

Values are expressed relatively to the mean
and std of the fixed exchange rate arrangement group.

Table 4 summarises the main statistics that characterise the three policy groups. Values are expressed relative to the mean (and standard deviation) of the fixed exchange-rate arrangement group for each variable. For example, looking at the means in first column, we can see that the nominal exchange-rate volatility, $\sigma(e)$, in the intermediate group is, on average, 90% greater than in the rigid exchange rate group, whereas it is 3.5 times higher in the floating group than in the rigid exchange-rate group. The standard deviation captures the average distance between the observations of a cluster and the cluster's centroid (or centre). The fixed exchange rate arrangement group displays the lowest standard deviation value for $\sigma(e)$, which means that countries in this group have similar nominal exchange rate volatilities. On the other side, the floating arrangement cluster has a large standard deviation for $\sigma(e)$, meaning that exchange-rate volatilities in this group are much more heterogeneous.

The second column shows the values for the volatility of exchange-rate changes, $\sigma_{(\Delta e)}$. The ranking and values are quite similar to those in the first column, which indicates the possibility of a strong correlation between the two variables. The absence of a cluster with large $\sigma(e)$, and $\sigma(r)$, and low $\sigma_{(\Delta e)}$) (as in Table 2 page 6) indicates that there is no such behaviour as a crawling peg. This also supports the argument that the intermediate group should be seen as a "dirty-float" or "managed-float" system, or, in other words, a floating system with frequent interventions in the foreign exchange market.

This idea is confirmed by the figures in the third column, dedicated to $\sigma(r)$, the intervention in the foreign exchange market. The mean values for the floating and fixed arrangement groups are almost the same, while the mean of the intermediate group is very large. Once again, this indicates that the intermediate group matches up with a managed float strategy where there are large-scale exchange market interventions.

5.2 Results at the country level

The results for individual countries are given in the Appendix C page 37. For instance, in 1999, there is a 98% probability of Chile having a floating exchange rate according to Table C.11 (page 39). Consistently, there is a 2% probability of it having an intermediate exchange-rate arrangement (page 38) and a null probability (0%) of it having a fixed exchange rate (page 37). In other words, the probability of Chile's exchange rate being as flexible as that of developed IT economies in 1999 was 98%, while the probability of it being as controlled as that of fixed exchange-rate economies was null. This does not mean that Chile never tried to control its exchange rate or that foreign exchange market interventions never happened in Chile. Chile's monetary authorities may have intervened in the foreign exchange market, but the results seem to indicate that if they did, they did it to a similar extent as IT developed central banks. Another example is given by the same country seven years later. In 2006, the probability of Chile having a fixed exchange rate arrangement was still very low: 2%. Therefore, Chile's exchange rate policy was, by no comparison, similar to that of the monetary authorities of the pegged currencies. However, the most probable arrangement is no longer the same: the probability of having a floating system has decreased to below one third (27%), while the probability of having an intermediate exchange-rate arrangement has risen to 71%. This does not mean that Chile had a controlled exchange rate in 2006, but rather it indicates that there is strong evidence to show that Chile's exchange market interventions were carried out on a broader scale than in developed countries.

An overview of the results at the country level is presented in Table 6 page 23 and Table 5 page 22.

Table 6 gives, for any country, the average probabilities of the three degrees of exchange-rate flexibility (for all years since the country adopted IT). The most probable exchange rate arrangement is a floating system. As can be seen in the last row of the table, the probability of an inflation-targeting emerging economy having a floating exchange rate is 52%. This figure may appear quite balanced. However, looking at the country level clearly indicates that the most probable degree of flexibility is that of having a floating arrangement: across the 19 ITEE, the probability of having a floating arrangement is the highest for 14 countries. Only three countries are most likely to have a fixed exchange rate arrangement: Albania, Guatemala and Peru (with an overall probability of 20%). Finally, Brazil and Hungary are most likely associated with an intermediate system (with an overall probability of 28%).

The finding that most observations show a floating exchange rate was to be expected. Theoretically, the definition of inflation-targeting implies that the focus is only on price stability and, therefore, the exchange rate is allowed to float. The finding that 28% of the observations are associated with an intermediate arrangement is also not surprising: a large body of literature has shown that monetary authorities try to reduce exchange rate volatility, most notably in emerging economies. This is the well-known "fear of floating" phenomenon. However, the share of the most rigid arrangements, 20%, is unexpectedly high. One in five ITEE exchange-rate observations is most probably as rigid as an exchange rate with a peg. Theoretically speaking, the issue of inflation-targeting under such circumstances should be questioned.

Focusing on the highest probability for each year, Table 5 page 22 summarises the number of years associated with each degree of flexibility for all countries. The table portrays the same phenomenon as the previous one: a floating system appears to be the most probable arrangement. It is associated with approximately half of the sample: 101 observations out of 197. This result is emphasised at the country level; floating arrangements occur most often in 12 out of 19 countries.

Table 5: Exchange-rate arrangements occurrences

	Number of years with			Years Covered
	Fix	Intermediate	Float	
ALBANIA	3	1	0	4
ARMENIA	0	1	6	7
BRAZIL	0	6	8	14
CHILE	0	4	10	14
COLOMBIA	2	2	10	14
CZECH REPUBLIC	3	2	9	14
GHANA	2	1	3	6
GUATEMALA	6	2	0	8
HUNGARY	0	9	3	12
INDONESIA	1	3	4	8
MEXICO	1	5	6	12
PERU	7	2	2	11
PHILIPPINES	5	4	2	11
POLAND	0	4	10	14
ROMANIA	4	1	3	8
SERBIA, REPUBLIC OF	1	3	3	7
SOUTH AFRICA	0	1	12	13
THAILAND	6	4	3	13
TURKEY	0	0	7	7
Total	41	55	101	197

Exchange-rate flexibility degree based on the most probable regime.

5.3 From flexibility degrees to IT regimes

While looking at the main results on the three degrees of flexibility, it may appear paradoxical that the overall probability of having a floating system is approximately one half, while it is the most probable arrangement for three-quarters of the countries considered. To reconcile these two dimensions, I propose to focus on the monetary regime implied by exchange-rate flexibility. The sample is made up of countries that fulfil the standard criterion defining IT: explicitly committing to a publicly announced inflation target. Therefore, the main question to be asked in order to define the monetary regime of these countries is: do these countries have only one target, price stability, or do they also target exchange-rate stability?

To answer this question, I will consider two inflation-targeting regimes, distinguished by the role played by the exchange rate: flexible inflation-targeting and hybrid inflation-targeting.

Flexible inflation-targeting corresponds to the standard definition: a monetary framework in which price stability is explicitly recognised as the main goal of monetary policy. Within this framework, the Tinbergen's principle holds: the central bank has one objective and only one instrument, the interest rate. Although "flexible" inflation-targeting refers to Svensson's well-known IT definition[17], in the context of this paper, "flexible" also refers to the degree of

[17] "Flexible inflation-targeting means that monetary policy aims at stabilizing *both* inflation around the

flexibility.

Proposition: Under *hybrid inflation-targeting*, aside from the goal of price stability and the tool with which to achieve this goal, interest rate setting, the central bank aims to manage the exchange rate through exchange market interventions.

Table 6: Inflation-targeting regime based on exchange-rate flexibility degree.

	Arrangement probability			IT regime
	Fix	Intermediate	Float	
ALBANIA	0.59	0.28	0.13	Hybrid IT
ARMENIA	0.04	0.29	0.67	Flexible IT
BRAZIL	0.04	0.51	0.45	Hybrid IT
CHILE	0.04	0.32	0.64	Flexible IT
COLOMBIA	0.13	0.17	0.70	Flexible IT
CZECH REPUBLIC	0.28	0.17	0.55	Flexible IT
GHANA	0.32	0.28	0.41	Hybrid IT
GUATEMALA	0.62	0.21	0.16	Hybrid IT
HUNGARY	0.10	0.51	0.39	Hybrid IT
INDONESIA	0.19	0.25	0.56	Flexible IT
MEXICO	0.20	0.29	0.51	Flexible IT
PERU	0.56	0.20	0.24	Hybrid IT
PHILIPPINES	0.35	0.29	0.37	Hybrid IT
POLAND	0.05	0.27	0.68	Flexible IT
ROMANIA	0.38	0.21	0.42	Hybrid IT
SERBIA, REPUBLIC OF	0.11	0.33	0.56	Flexible IT
SOUTH AFRICA	0.03	0.21	0.76	Flexible IT
THAILAND	0.32	0.26	0.42	Hybrid IT
TURKEY	0.02	0.22	0.76	Flexible IT
All countries	0.20	0.28	0.52	

To distinguish countries under the flexible IT regime from those under hybrid IT[18], the following rule is assumed: if the probability of having a flexible system is higher than the sum of the probabilities of all other systems, the country has a flexible inflation-targeting regime; otherwise, it has a hybrid IT regime.

The results are given in the last column of Table 6 page 23. Ten countries are found to have a flexible inflation-targeting regime: Armenia, Chile, Colombia, the Czech Republic, Indonesia, Mexico Poland, Serbia, South Africa and Turkey. The remaining nine have a hybrid IT

inflation target and the real economy, whereas strict inflation-targeting aims at stabilizing inflation *only*, without regard to the stability of the real economy, what Mervyn King (1997) has described as being an "inflation nutter". " in Svensson (2010, page 1).

[18]"Hybrid inflation-targeting regimes" is also the title of a paper by Roger et al. (2009). In this paper, the authors examine whether including the exchange rate explicitly in the central bank's reaction function can improve macroeconomic performance using a DSGE model. They call hybrid inflation-targeting regimes those in which the central bank reacts to the exchange rate or controls the exchange rate, as opposed to "plain vanilla IT".

regime: Albania, Brazil, Ghana, Guatemala, Hungary, Peru, the Philippines, Romania and Thailand.

The large number of hybrid IT regimes confirms that inflation-targeting cannot be implemented in emerging economies in the same way as it is implemented in developed countries. Countries with a hybrid IT regime have adapted IT to suit their specific requirements. However, the large number of flexible IT regimes confirms the theoretical views on inflation-targeting: IT may lead to greater exchange-rate flexibility than that generally seen in emerging economies.

6 Conclusion

In this paper, I ask whether emerging economies implement a “flexible” inflation-targeting strategy, with one goal (price stability) and one tool (short interest rate), or a “hybrid” IT strategy, mixing two goals (price stability and exchange rate stability) and two instruments (short interest rate and foreign exchange market interventions).

In answer to this question, this paper offers a new exchange-rate regime classification method, which relies on three variables: the nominal exchange-rate volatility, the volatility of nominal exchange-rate change and interventions in the foreign exchange markets.

This method shows a clear improvement on the existing one and on that proposed by Levy-Yeyati & Sturzenegger (2005). I show that the LYS method is a constrained form of the algorithm I use. This constraint creates a bias towards intermediate regimes in the LYS paper, whereas my approach is more flexible and relies on an explicit criterion to define the quality of fit and the number of policy groups observed in the data.

The stability and robustness of my results is ensured through a bootstrapping loop using a random sample composition process. Move from statistical characteristics to policy behaviour, I use two control samples: one with IT developed countries and flexible exchange rates and another with countries with controlled exchange rates. A Gaussian mixture model is estimated to cluster the data into consistent groups and the control samples are used to label the different groups of IT emerging economies.

Across the 19 emerging economies that have adopted inflation targeting, I find clear evidence that 12 have an exchange rate which is as flexible as that of the IT developed economies. This does not mean that these countries never intervene in the foreign exchange market, but rather that if they do ever intervene, the impact on their exchange rate is similar to that on the rate in developed economies. Among the remainders, three have a managed float arrangement while the remaining four have an exchange-rate system as rigid as the standard peg currencies.

The probability of a country having a perfectly flexible arrangement is 52%, while the probability of having a managed float system obtained through foreign exchange market intervention is 28%, and that of having a rigid exchange-rate system (similar to those of pegged currencies) is 20%.

The results can also been sumarized by seeing evidence of two different monetary regimes under inflation targeting: flexible IT when the monetary authorities handle only one tool, the interest rate, and hybrid IT when the monetary authorities add foreign exchange interventions to their toolbox. Finally, flexible inflation-targeting prevails in ten countries and appears to be the main strategy.

Last, the probability of the exchange rate regime computed for the emerging economies that target inflation and presented in this paper can be used for many other purposes. For example, the database created for this paper can be used to test the relevance of the currency mismatches hypothesis (see Eichengreen et al. 2007 and Hausmann & Panizza 2011) as a determinant of exchange rate regime choice in emerging economies. Also, the probability of having a floating exchange rate can be seen as one of the Trilemma variables, that goes along Chinn & Ito (2008) capital openness index and Aizenman et al. (2010) monetary independence index.

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A Data Appendix

Data set

The currency of reference of each country is used as numeraire to express the nominal exchange rate value. It is either the US dollar or the Euro. The list of inflation targeting countries consists of emerging economies (Status = emerging) and developed economies (Status = developed). Developed economies are used in the control sample as indicator of flexible exchange-rates policies while we assess emerging economies exchange-rate arrangement. Fix exchange-rate countries are the counterpart of developed IT countries: they are used in the control sample as indicator of fix exchange-rates policies (and they display how flexible can be an exchange rate arrangement in an IT country).

Table A.7: Inflation targeting countries

Country	IT adoption	Status	Numeraire
Albania	2009	emerging	EUR
Armenia	2006	emerging	EUR
Australia	1993	developed	USD
Brazil	1999	emerging	USD
Canada	1991	developed	USD
Chile	1999	emerging	USD
Colombia	1999	emerging	USD
Czech Rep.	1998	emerging	EUR
Ghana	2007	emerging	USD
Guatemala	2005	emerging	USD
Hungary	2001	emerging	EUR
Iceland	2001	developed	EUR
Indonesia	2005	emerging	USD
Israel	1997	developed	USD
Korea	2001	developed	USD
Mexico	2001	emerging	USD
New Zealand	1990	developed	USD
Norway	2001	developed	EUR
Peru	2002	emerging	USD
Philippines	2002	emerging	USD
Poland	1998	emerging	EUR
Romania	2005	emerging	EUR
Serbia	2006	emerging	EUR
South Africa	2000	emerging	USD
Sweden	1993	developed	EUR
Thailand	2000	emerging	USD
Turkey	2006	emerging	USD
United Kingdom	1992	developed	EUR

Table A.8: Fix exchange-rate countries

Country	Numeraire	Country	Numeraire
Aruba	USD	Lesotho	USD
Bahamas, The	USD	Lithuania	EUR
Bahrain, Kingdom of	USD	Macedonia, FYR	EUR
Barbados	USD	Malaysia	USD
Belize	USD	Maldives	USD
Bhutan	USD	Namibia	USD
Bolivia	USD	Nepal	USD
Bosnia & Herz.	EUR	Netherlands Antilles	USD
Brunei Dar.	USD	Oman	USD
Bulgaria	EUR	Qatar	USD
Cape Verde	USD	Saudi Arabia	USD
China	USD	Seychelles	USD
Comoros	USD	Slovenia	EUR
Croatia	EUR	Suriname	USD
Djibouti	USD	Swaziland	USD
Eritrea	USD	Syrian Arab Rep.	USD
Estonia	EUR	Tanzania	USD
Guinea	USD	Turkmenistan	USD
Hong Kong	USD	Ukraine	USD
Iraq	USD	United Arab Emirates	USD
Jordan	USD	Venezuela, Rep.	USD
Kazakhstan	USD	WAEMU	EUR
Kuwait	USD	Zimbabwe	USD
Lebanon	USD		

B Methodological Appendix

In this methodological appendix, I show how the Gaussian mixture model used in this paper differ from the K-means alogorithm used by Levy-Yeyati & Sturzenegger (2005). LYS' k-means is closed to the Gaussian approach, but it assumes two technical limitations that may have a large impact on the final results and on their interpretations.

Technically, the covariance matrix is constrained and the probability of belonging to a group is led to a binary variable. This constraint on the covariance matrix gives to their clusters a circular shape, and all clusters are being of similar size. This may create an important bias for their results. In particular, because all groups are large and of similar size, they can only conclude that the intermediate group is as big as the other groups, and reject the bipolar theory. In my approach the clusters' shape is flexible and therefore it avoids constraining the groups to be of similar size

Also, in LYS approach, a country is for example either floating or pegging[19]. In my classification scheme, a precise probability to belong to a group is computed. Therefore, a country is not either floating or pegging, but it has a probability of being floating and a probability of being pegging. All in all, the Gaussian mixture approach I propose is more flexible and robust than those with k-means.

K-means cluster analysis

The K-means algorithm is a clustering method, which is used to divide a set of objects into groups, called clusters, such that objects within a group tend to be more similar, or closed, to one another as compare to objects belonging to different goups. As simply said by Wu & Kumar (2010, page 21) "clustering algorithms place similar points in the same cluster while placing dissimilar points in different clusters". It was independently discovered by Steinhaus (1956) and Lloyd (1982) (Unpublished Bell Lab. Note of 1957, see Jain (2010) for a wider historical perspective).

Let $X = x_1, x_2, ..., x_M$ be a set of M d-dimensional points, to be clustered into a set of K clusters, denoted by $C = c_1, c_2, ..., c_K$. K-means algorithm finds a partition such that the within-cluster sum of squares is minimized. Let μ_k be the mean of cluster c_k. The default measure of closeness is the Euclidean distance. Thus, the squared error between μ_k and the points in cluster c_k is given by:

$$J(c_K) = \sum_{x_m \in c_k} ||x_m - \mu_k||^2 \tag{9}$$

[19]There are more precisely 4 alternative policies in LYS approach.

The K-means algorithm minimizes the within-cluster sum of squares over all K clusters:

$$arg\ min \sum_{k=1}^{K} \sum_{x_m \in c_k} ||x_m - \mu_k||^2 \tag{10}$$

The cluster means, μ_k with $k = 1, 2..., K$, also called cluster centroids, allow to represents each of the k clusters by a single point in $\mathcal{R}^d$ As described by Levy-Yeyati & Sturzenegger (2005, page 8), "K cases in the data file, where K is the number of clusters requested, are selected as temporary centers. As subsequent cases are processed, a case replaces a center if the smallest distance to a center is greater than the distance between the two closest centers. The center that is closer to the case is replaced. A case also replaces a center if the smallest distance from the case to a center is larger than the smallest distance between the center and all other centers. Again, it replaces the center closest to it. The procedure continues until all cases are classified."

The K-means algorithm clusters in an iterative fashion, alternating between reassigning the cluster of all points, and updating the empirical mean of each cluster. The main steps of K-means algorithm are as follows (see Jain & Dubes 1988)

- Select an initial partition with K clusters,
- Assignment step: generate a new partition by assigning each observation to the cluster with the closest mean

  $$C_k^{(t)} = \{x_m : ||x_m - \mu_k|| \leq ||x_m - \mu_{k*}^{(t)}|| \tag{11}$$

  where (t) represents the iterative step, for all $k^* = 1, ..., K$
- Update step: Calculate the new means to be the centroid of the observations in the cluster.

  $$\mu_k^{(t+1)} = \frac{1}{c_k^{(t)}} \sum_{x_m \in c_k^{(t)}} x_m \tag{12}$$

- Repeat assignment and update steps until cluster membership stabilizes.

The algorithm converges when the assignments, and hence the centroids values, no longer change. One can show that the objective function defined in equation (10) will decrease whenever there is a change in the assignment or the relocation steps, and convergence is guaranteed in a finite number of iterations.

From k-means to Gaussian mixture

The k-means are similar to the Gaussian mixture model, but it supposed a constained covariance matrix and a bi-modal probability of belonging to a group.

Following Vishwanathan (2011), let assume that the covariances of the mixture components are given by $\Sigma_m = \epsilon Id$, where $\epsilon > 0$ and Id denotes the identity matrix. In this case the univariate Gaussian distribution given by equation (1) reduces to

$$\mathcal{N}(x|\mu, \epsilon I) = \frac{1}{\sqrt{2\pi\epsilon}} exp\left(-\frac{1}{2\epsilon}||x-\mu||^2\right) \tag{13}$$

Then, equation (6) can be written as :

$$\pi_{m,k} = \frac{\pi_k \ exp\left(-\frac{1}{2\epsilon}||x_m - \mu_k||^2\right)}{\sum_{k'} \pi_{k'} \ exp\left(-\frac{1}{2\epsilon}||x_m - \mu_{k'}||^2\right)} \tag{14}$$

Let $\mu_{k'}$ denotes the μ that minimizes $||x_m - \mu||$ (that is $\mu_{k'}$ is the closest μ to x_m. If one assume $\epsilon \to 0$ then $\pi_{m,k} \to 0$ for all k except for k', and $\pi_{m,k'} \to 1$ for j' .

Let $r_{m,k}$ be defined as:

$$\pi_{m,k} = \begin{cases} 1 & \text{if} k = argmin_{k'}||x_m - \mu_{k'}||^2 \\ 0 & \text{otherwise} \end{cases}$$

Then, we can rewrite equation (9) which minimizes within-cluster sum of square over all cluster k, in term of Gaussian mixture model's equation (4), as:

$$J(\pi, \mu) = \sum_{m=1}^{m} \sum_{k=1}^{K} \pi_{m,k}||x_m - \mu k||^2 \tag{15}$$

This is equivalent to add a binary parameter in the minimizing within-cluster sum of squares, as defined by equation (9) and (10) and thus, this is equivalent to the K-means algorithm .

To resume, I have express the k-means algorithm as a form of Gaussian mixture model. This was done by assuming that the covariance matrice of the mixture components was constrained, with equal variance among the groups. This is equivalent to the model EII in Table 3. Therefore, I can consider that the k-means problem as defined by Levy-Yeyati & Sturzenegger (2005) for grouping monetary regimes, is a particular case of the more general gaussian mixture problem I handle here. Futhermore classifying exchange-rate regimes using the Gaussian mixture model approach, gives, first, a criterium to determine the number of clusters, and then, the best fit among various model. In particular it allows my clusters to be ellipsoidal and not constraint to circles like in LYS. To illustrate this outcome, I plot on

Graph B.5 page 36 the clusters obtained with LYS approach, using exactly the same sample as in Section 4, Graph 4 page 18

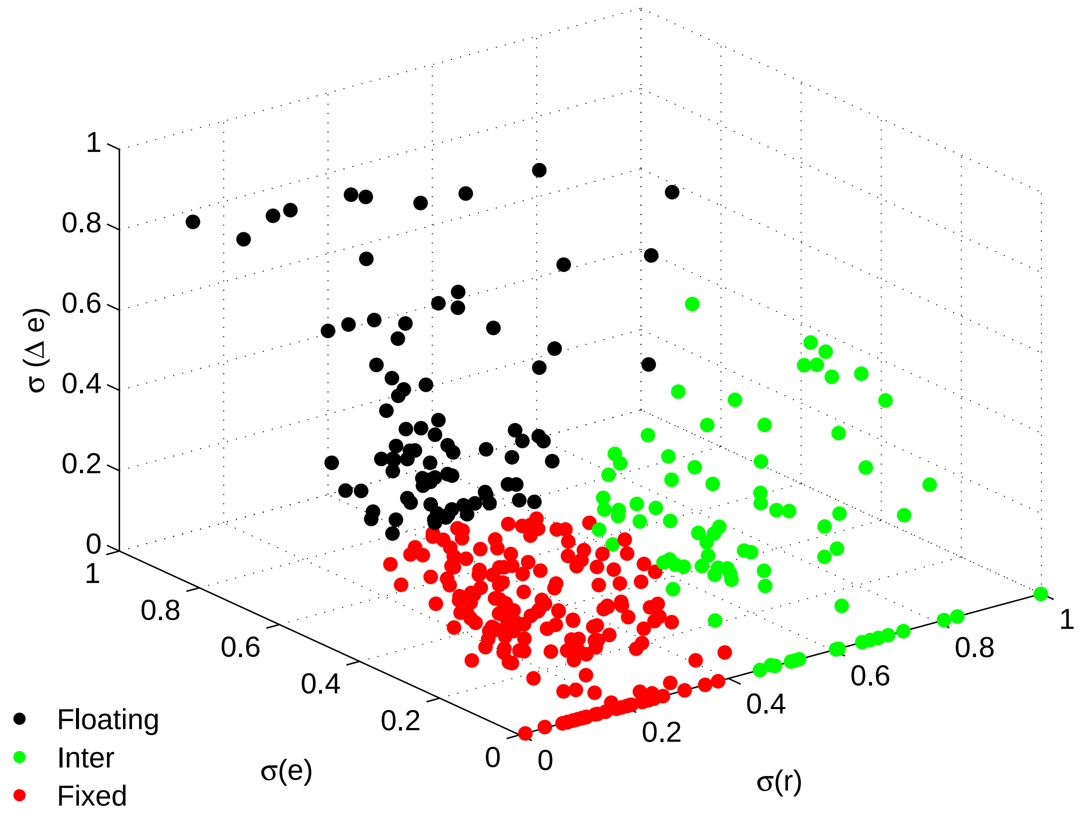

Figure B.5: Step 3 following Levy-Yeyati & Sturzenegger (2005) approach.

C Results Appendix

Table C.9: Probability of having a fix exchange-rate arrangement

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA											0	90	58	90
ARMENIA								1	1	2	5	2	0	19
BRAZIL	0	9	4	5	4	0	3	9	0	5	5	9	3	2
CHILE	0	5	0	12	0	0	13	2	14	5	1	1	8	2
COLOMBIA	0	0	56	0	27	0	88	2	0	4	0	0	3	1
CZECH REPUBLIC	1	23	17	12	76	100	43	11	20	1	0	43	19	32
GHANA									100	4	2	0	79	4
GUATEMALA							88	96	100	43	17	12	53	88
HUNGARY			8	24	10	16	17	3	17	0	2	14	0	6
INDONESIA							2	18	9	5	0	31	53	35
MEXICO			9	100	0	26	30	11	36	5	0	15	2	6
PERU				76	84	100	17	71	5	0	7	92	65	100
PHILIPPINES				61	12	18	61	0	0	2	53	21	74	79
POLAND	1	0	1	0	2	1	18	12	15	3	0	2	2	11
ROMANIA							0	66	9	1	1	76	67	81
SERBIA, REPUBLIC OF								44	17	1	1	0	16	0
SOUTH AFRICA		0	0	1	5	5	1	5	8	5	5	0	0	1
THAILAND		0	15	48	40	2	51	1	79	21	78	14	17	54
TURKEY								2	3	5	0	0	4	0

De facto regime probability, such that for a country and for a year, the probability of having a fixed + an intermediate + a floating arrangement = 1. Period displayed: after IT adoption.

Table C.10: Probability of having an intermediate exchange-rate arrangement

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA											100	1	7	2
ARMENIA								7	6	13	37	14	100	23
BRAZIL	0	64	41	36	40	100	46	64	100	36	34	49	47	56
CHILE	2	8	3	61	100	5	18	71	60	35	6	29	40	7
COLOMBIA	4	2	5	5	10	1	2	51	5	43	0	3	69	36
CZECH REPUBLIC	16	52	57	34	2	0	16	6	11	15	6	7	9	8
GHANA									0	43	55	15	10	43
GUATEMALA							1	1	0	32	43	62	29	3
HUNGARY			65	9	64	58	57	8	57	6	62	60	100	67
INDONESIA							5	49	12	36	4	45	5	42
MEXICO			16	0	3	47	6	63	37	36	5	60	18	59
PERU				7	10	0	26	3	52	100	12	1	3	0
PHILIPPINES				4	62	59	5	2	100	8	11	53	11	2
POLAND	6	3	10	5	49	64	52	10	59	48	0	8	8	62
ROMANIA							100	4	32	10	8	2	4	5
SERBIA, REPUBLIC OF								33	58	12	65	1	58	4
SOUTH AFRICA		4	0	11	36	35	6	38	63	36	36	4	3	7
THAILAND		1	59	18	37	7	11	68	6	49	4	61	7	6
TURKEY								16	46	35	6	3	41	7

De facto regime probability, such that for a country and for a year, the probability of having a fixed + an intermediate + a floating arrangement = 1. Period displayed: after IT adoption.

Table C.11: Probability of having a floating exchange-rate arrangement

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA											0	9	35	8
ARMENIA								92	92	85	58	85	0	58
BRAZIL	100	27	54	59	56	0	51	26	0	59	61	42	50	42
CHILE	98	87	97	27	0	94	68	27	26	59	93	71	52	91
COLOMBIA	96	98	39	95	63	99	10	47	94	53	100	97	28	63
CZECH REPUBLIC	83	25	26	54	22	0	41	83	69	84	94	50	72	60
GHANA									0	54	43	85	10	54
GUATEMALA							11	3	0	25	40	26	18	8
HUNGARY			27	67	27	26	26	89	26	93	36	26	0	27
INDONESIA							93	32	78	59	96	24	41	23
MEXICO			75	0	96	27	64	26	27	59	95	26	80	35
PERU				17	6	0	57	26	42	0	81	7	32	0
PHILIPPINES				34	26	23	34	98	0	90	36	26	15	19
POLAND	93	97	89	95	49	35	30	78	26	49	100	90	90	27
ROMANIA							0	30	58	90	91	21	29	14
SERBIA, REPUBLIC OF								23	26	87	34	99	26	95
SOUTH AFRICA		96	100	88	59	59	93	57	29	59	59	96	97	93
THAILAND		99	26	34	23	91	38	31	15	30	18	25	76	41
TURKEY								82	51	59	93	96	55	93

De facto regime probability, such that for a country and for a year, the probability of having a fixed + an intermediate + a floating arrangement = 1. Period displayed: after IT adoption.

Table C.12: Inflation Targeting Regime

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA											Hybrid	Hybrid	Hybrid	Hybrid
ARMENIA								Flexible	Flexible	Flexible	Flexible	Flexible	Hybrid	Flexible
BRAZIL	Flexible	Hybrid	Flexible	Flexible	Flexible	Hybrid	Flexible	Hybrid	Hybrid	Flexible	Flexible	Hybrid	Flexible	Hybrid
CHILE	Flexible	Flexible	Flexible	Hybrid	Hybrid	Flexible	Flexible	Hybrid	Hybrid	Flexible	Flexible	Flexible	Flexible	Flexible
COLOMBIA	Flexible	Flexible	Hybrid	Flexible	Flexible	Flexible	Hybrid	Hybrid	Flexible	Flexible	Flexible	Flexible	Hybrid	Flexible
CZECH REPUBLIC	Flexible	Hybrid	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Flexible
GHANA									Hybrid	Flexible	Hybrid	Flexible	Hybrid	Flexible
GUATEMALA							Hybrid	Hybrid	Hybrid	Hybrid	Hybrid	Hybrid	Hybrid	Hybrid
HUNGARY			Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Flexible	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Hybrid
INDONESIA							Flexible	Hybrid	Flexible	Flexible	Flexible	Hybrid	Hybrid	Hybrid
MEXICO			Flexible	Hybrid	Flexible	Hybrid	Flexible	Hybrid	Hybrid	Flexible	Flexible	Hybrid	Flexible	Hybrid
PERU				Hybrid	Hybrid	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Flexible	Hybrid	Hybrid	Hybrid
PHILIPPINES				Hybrid	Hybrid	Hybrid	Hybrid	Flexible	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Hybrid
POLAND	Flexible	Flexible	Flexible	Flexible	Flexible	Hybrid	Hybrid	Flexible	Hybrid	Flexible	Flexible	Flexible	Flexible	Hybrid
ROMANIA							Hybrid	Hybrid	Flexible	Flexible	Flexible	Hybrid	Hybrid	Hybrid
SERBIA, REPUBLIC OF								Hybrid	Hybrid	Flexible	Hybrid	Flexible	Hybrid	Flexible
SOUTH AFRICA		Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Hybrid	Flexible	Flexible	Flexible	Flexible	Flexible
THAILAND		Flexible	Hybrid	Hybrid	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Hybrid	Hybrid	Hybrid	Flexible	Hybrid
TURKEY								Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Flexible

De facto regime based on highest probability for three possible arrangements: "Float" for perfectly floating exchange-rates, "Inter" for intermediate or managed float exchange-rate arrangements and "Fix" for rigid systems.