Why is Brazilian Inflation so high? Inflation persistence in Brazil and other emerging markets[*]

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Abstract*: This paper analyzes inflation persistence in Brazil. Both aggregate and disaggregated inflation persistence are computed. We also compare inflation persistence in Brazil with estimates for other emerging countries with a long history of high inflation. The results indicate that inflation persistence in Brazil is higher than in other emerging markets. Core inflation presents more inflation persistence than headline inflation, particularly due to the exclusion of the low persistence food items. Despite the large persistence in Brazilian inflation, disaggregated data are more sensible to expected inflation than lagged inflation and thus indicates a major role for forward looking behavior.*

Resumo*: Este trabalho estima a persistencia da inflação no Brasil tanto em termos agregados quanto desagregados. O trabalho ainda compara a persistência da inflação no Brasil com a persistência em outros países emergentes. Os resultados indicam que a persistência da inflação no Brasil é maior do que em outros países, mas este resultado não é obtido para todos os metodos de estimação utilizados. A persistência no núcleo da inflação é maior do que na "inflação cheia". Apesar da persistência elevada, nossos resultados indicam que a expectative de inflação é uma variável mais importante na determinação da inflação corrente do que a inflação passada.*

JEL Classification: C11, C22, E31

Keywords: inflation persistence, Phillips curve

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[*] We like to thank Wagner O. Monteiro for his support with several routines/codes used in this paper.

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1 Introduction

After reaching a hyperinflation environment for some years, Brazilian inflation decreased to more normal levels after the introduction of the Real Plan in 1994. Despite the sharp fall in Brazilian inflation and the convergence to the level observed in the emerging market economies, it is still higher than those observed in developed countries.

The aim of this paper is to compare inflation persistence in Brazil with other emerging markets, particularly those with a long history of high inflation. We consider this a first step to better understand what lies beneath the larger inflation in Brazil. Other important differences may be due to larger marginal costs (positive output gaps), larger pass-through of commodity price shocks, larger inflation expectations, among others. All these aspects may be further investigated in future works related to Brazilian inflation. Larger inflation persistence could help explain why Brazilian inflation is higher than in other countries: As the country evolves from a high inflation to a low inflation environment, large persistence rates could make this process slower in some countries.

In this paper we focus on emerging markets inflation, particularly on countries with a history of high inflation in recent years. The question we address is why Brazilian inflation is higher than inflation rates in other emerging markets. We do not exactly aim to answer why inflation is higher in emerging markets. We think this could be an important step towards understanding why some countries reach lower and stable inflation than others.

We do not deal with some aspects of inflation that could explain large inflation in some countries such as the behavior of inflation expectations and the effect of indexation. Indexation mechanisms are related to inflation persistence but they are not the same. The main reason not to deal with these questions is the lack of comparable variables in each country. Therefore, a few countries have data on inflation expectations and usually the methodology varies from country to country; that makes comparisons very difficulty. The characterization of inflation expectations data in each country, its evolution and impacts on current inflation is undoubtedly a subject that should be further investigated. In this paper we use inflation expectation data only for the estimation of the Phillips curve in Brazil. And, as we already mentioned, a deeper analysis of inflation expectations in Brazil and other countries is left for future research.

The countries we include in our sample of emerging markets with a history of high inflation in recent years are: Brazil, Colombia, Peru, Chile and México in Latin America; South Africa in Africa; Czech Republic, Poland and Hungary in Europe and Israel in Asia. All these countries have a history of high or hyperinflation early in the 90's and they have all pursued low inflation through an inflation target regime during the last ten years or more. We do include neither developed countries nor emerging countries in Asia in our sample due to their long history of low inflation.

Table 1: Inflation in Selected Emerging Markets (1980-2010)

	1980 to 1994	1995 to 2010	1995 to 1999	2000 to 2004	2005 to 2010
Brazil	**782,1**	**10,7**	**19,4**	**8,7**	**5,0**
Chile	20,1	4,2	6,0	2,8	3,8
Colombia	24,4	9,7	17,9	7,3	4,7
Czech Republic	n.a.	4,0	7,5	2,6	2,7
Hungary	14,5	10,0	18,9	7,1	5,1
Israel	81,9	4,0	8,2	1,6	2,4
Mexico	51,5	11,2	24,5	6,0	4,4
Peru	856,6	4,4	8,4	2,4	2,6
Poland	91,0	7,5	16,4	4,4	2,6
South Africa	13,9	6,5	7,3	5,5	6,6
Turkey	58,6	40,3	81,0	37,7	8,7
Mean	**199,5**	**10,2**	**19,6**	**7,8**	**4,4**
Median	**55,0**	**7,5**	**16,4**	**5,5**	**4,4**

Source: IMF

Our results indicate that inflation persistence in Brazil between 1995 and 2011 is larger than estimated for other emerging markets in the same period. This result is valid both for headline inflation and core inflation measures and is based in simple autoregressive models. Using the Hansen (1999) method of *median unbiased estimation* the estimated is close to our sample mean of the emerging markets inflation persistence. The inflation persistence in Brazil is also close to persistence estimated for developed countries by other authors.

Our result indicates that core inflation is more persistent than headline inflation. This result arises as a consequence of the exclusion of food products from core inflation. Regarding the determinants of inflation persistence, our results are inconclusive as the persistence of most variables used in our Phillips Curves estimation is very close to each other.

Despite the relatively large inflation persistence in Brazil, our proxy for expected inflation is more important for inflation determination than lagged inflation. This result is more pronounced when we use disaggregated than aggregated data. Our results indicate that disaggregated inflation persistence is much lower than aggregated inflation persistence. This result is also reported by other author's estimation of disaggregated inflation persistence for other countries (mainly developed countries). This can be a result of common factors present at aggregated data but not identifiable in disaggregated data as indicated by Granger (1987). In such cases, inflation expectations may capture only this common factor which could explain our results. We let this question as an issue for future research.

2 Phases in Brazilian Inflation after the Real Plan

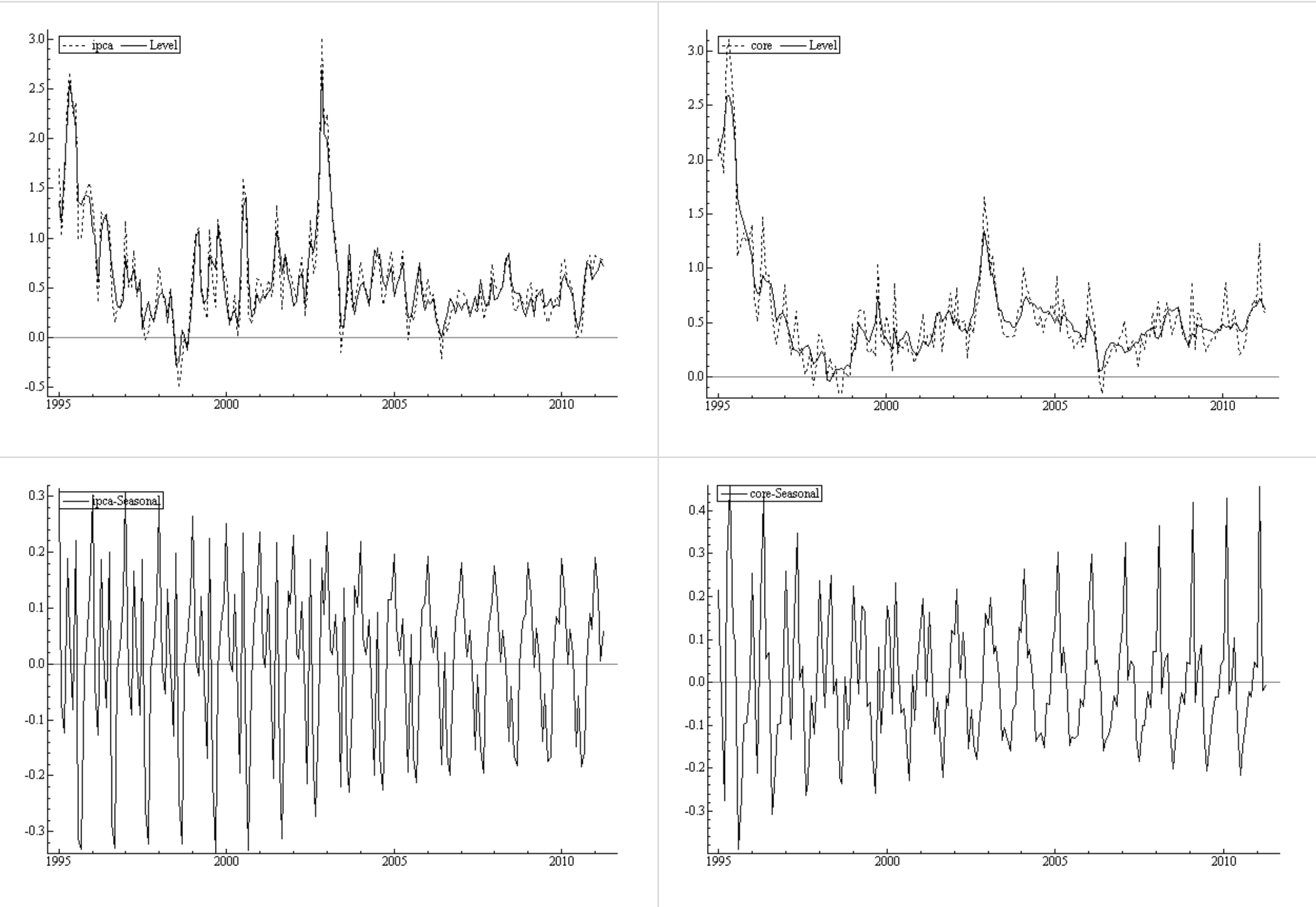
In this section we use an unobserved components model of inflation to explain the evolution of Brazilian inflation since the Real Plan by using monthly data since 1995. Many authors have already described the evolution of Brazilian inflation using small sample periods such as Minela *et al* (2008). In general, authors recognize at least two different periods in Brazilian inflation after the Real Plan: a) the first years after the introduction of the Plan when inflation was still high but tending downwards (in the 10-year period before the Real Plan inflation was higher than 100% per year on average) and b) the following years, when the Real Plan was already consolidated and inflation remained low for some time. There are also some interesting episodes during these periods, e.g. the introduction of the Inflation Targeting Regime in 1999 and the confidence crisis of 2002.

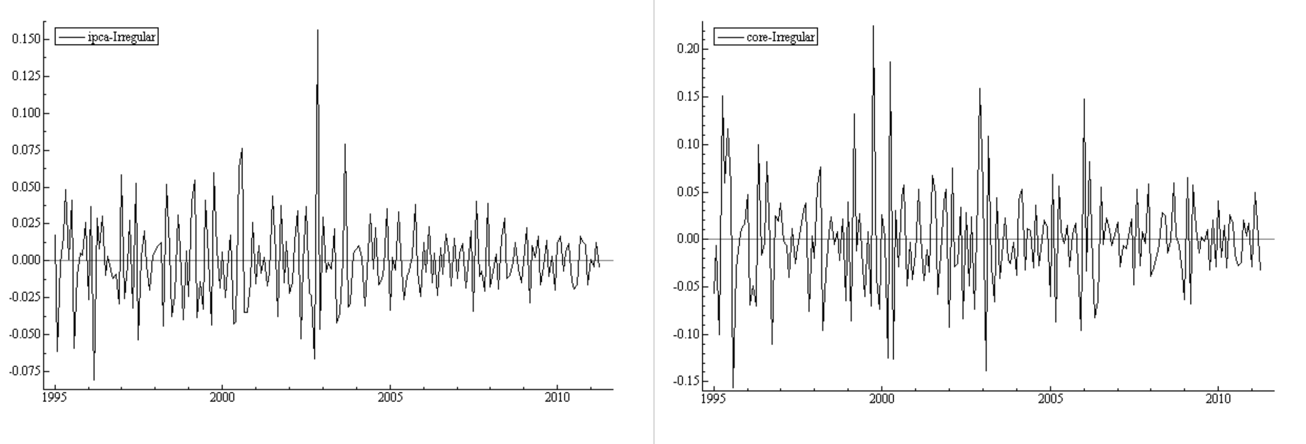
Figure 1 shows the evolution of the underlying level of Brazilian inflation estimated by using an unobserved components model. It is clear that inflation diminished in the years that followed the introduction of the Real Plan in 1994 and increased after the exchange rate devaluation in the beginning of 1999. Another increase in inflation occurred in the confidence crisis of 2002. After 2003, inflation had remained between 1% and 2% per quarter.

The figures indicates that Brazilian inflation present a clear seasonal pattern: inflation is higher at year end and also at the beginning of each year. The seasonal pattern is more pronounced in the second half of our sample.

We did not test for structural breaks in Brazilian inflation data. We will include a time trend for the first half of our sample (up to 4Q98) in our estimations of the Phillips curve whenever this is possible. We will also include seasonal dummy variables or AR(4) models as our preferred specification due to the seasonality of inflation in Brazil.

Figure 1: Inflation Decomposition - Structural Time Series Model (1995-2010)





Note: Structural Time Series (STM) model for Brazilian inflation. The left column presents the estimated components of headline inflation while the right column presents the core inflation. Inflation components are Level (first row), Seasonal component (second row) and Irregular component (third row).

3 Inflation Persistence in Brazil: Aggregated Data

3.1 Introduction

Inflation persistence has been widely studied in developed countries but not so much in developing countries. Levin and Piger (2004) and O'Reilly and Whelan (2005) are good references for the study of inflation persistence in advanced economies. Gerlach (2008) studies inflation persistence in Asian countries. In Brazil, there are some studies of inflation persistence by using long memory (ARFIMA) models like Figueiredo and Marques (2009) and Rebelo *et al* (2009) and also by using autoregressive models without long memory and structural models (Phillips curve) like Oliveira and Petrassi (2010).

A useful way to study inflation persistence is by estimating a simple autoregressive model and computing the sum of coefficients on lagged inflation:

$$\pi_t = a + \sum_{i=1}^{p} \lambda_i \pi_{t-i} + e_t \tag{1}$$

Where π_t is the quarterly inflation rate. Another specification that is useful to analyze inflation persistence is rewriting the inflation process as:

$$\pi_t = a + \rho \pi_{t-1} + \sum_{i=1}^{p} c_i \Delta \pi_{t-i} + e_t \tag{2}$$

By this equation, we can focus on the parameter ρ. The main advantage of this specification is that it is easier to study the evolution of inflation persistence as it is measured by just one coefficient instead of "*p*" parameters as in the *AR(p)* model.

We also estimated an *AR(1)* model with seasonal dummies. The advantage of this model is that we preserve the sample size in the estimation. With the use of an *AR(p),* the first *"p"* observations is lost in the estimation process as *"p"* lagged values for the exogenous variable are necessary to initiate the estimation. This will be important for the estimation of disaggregated data in the next section. We estimated this model also with aggregated data for the sake of comparability in the later section of this study. The model with seasonal dummy variables can be written as:

$$\pi_t = a + \lambda\pi_{t-1} + \sum_{q=2}^{4} d_q T_q + e_t \qquad (3)$$

Where q refers to the quarters and T is the dummy variable: $q=2$ indicates the second quarter of the year and so on up to the fourth quarter ($q=4$). Our measure of persistence in this case is the coefficient "*b*".

An issue usually addressed by other authors is the possibility of structural breaks in the series or model coefficients. Since we are using a small sample, the chances that a structural break occurred at some point of the sample is small. Even so, we estimate some of the structural parameters as random walks (time varying coefficient) to increase the confidence in the results.

We also include a dummy variable at the beginning of the sample in some estimations due to the initial effects of the stabilization program in 1994. The Real Plan was introduced in the beginning of 3Q94 and inflation was reduced from more than 10% per month to less than 2% in the following months (this can be clearly seen in figure 1). Our dummy variable goes up to the end of 1998. It is not clear however if the low inflation in 1997 and mainly in 1998 was due to continued effect of the stabilization plan or a consequence of low GDP growth in Brazil and also in the world as a result of several financial crises that occurred in 1997 and 1998. Global GDP growth was below the average in 1998 and commodity prices fell that year, contributing to the low inflation in Brazil (exchange rate was fixed at that moment).

Finally, we estimated this simple model including a measure of output gap and also a measure of "external" inflation and a measure of inflation expectation. Historically, many empirical works in Brazil used the exchange rate depreciation as one of the inflation determinants. Despite this being a good proxy for the 1999 and 2002 episodes of exchange rate depreciation, this is a poor proxy in other periods as this measure of foreign inflation does not capture the "global inflation" factor. We experiment with two different measures of global inflation: The CRB commodity price index and the average CPI inflation in the OECD countries. Ciccarelli and Mojon (2010) show that the "global inflation" is an "attractor" of local inflation for several countries. Ciccarelli and Mojon (2010) use a factor model to derive their global inflation factor but call attention to the fact that the average inflation is a good approximation to the global factor[1]. The results for the estimations using the "global inflation" variable are not reported: When this measure of global inflation is used, it leads to a highly significant coefficient and also makes almost all other coefficients in the model not significant at usual levels. We interpret this as one more indication that inflation is a "global" phenomenon in some aspects. But this also indicates that this measure of global inflation is not exogenous or an independent variable. Both the Brazilian inflation and the global inflation (OECD median inflation, as we defined earlier) are determined by the same factors, which characterize an endogenous regressor.

The use of commodity price index is a better proxy for the effects of changes in "external inflation" during the 1995-2011 period as Brazil had a fixed exchange rate regime in the first part of the sample and changes in foreign prices in domestic currency where dominated by changes in foreign prices in the external currency. In 1999 and also 2002 due to the large depreciation of the Real, tradable prices (and also regulated prices) presented high rates of inflation. In other periods, like in 2004-2005 and later in 2007-2008, the exchange rate appreciation was not sufficient to avoid an escalation of tradable prices as commodity prices surged around

[1] This seems clear in figure 1 in Ciccarelli and Mojon (2010).

the world. Some more theoretical papers also refer to the import price as a measure of external inflation. We consider the commodity price index as a wider definition of external inflation and preferred in our estimations. In our estimations we use the average of commodity prices and exchange rate in the last month of the quarter: $P_t^{\$*} = E_t P_t^*$ and $\pi_t^* = \ln(E_t P_t^*) - \ln(E_{t-1} P_{t-1}^*)$ where $P_t^{\$*}$ is the commodity price index in dollar and E_t is the exchange rate in R$/US$.

Our measure of output gap is derived using the deviation of GDP from a trend (HP filter). Several authors have used the variation in labor share as a measure of marginal cost. Data on labor costs in Brazil are available only after 2001 due to a change in the employment and unemployment survey. Allowing for the output gap as an addition explanatory variable is important due to the fact that some models attribute the persistence of inflation to the persistence of the driving variable, namely the output gap (or marginal cost). This is called "inherited" persistence. Some authors such as Fuhrer (2006) discuss this hypothesis.

Finally, we included the "twelve months ahead" inflation expectations (denoted by PHI_E) provided by the Brazilian Central Bank - BCB as a measure of inflation expectation. The inflation expectation is the main determinant of inflation in most economic models since the appearance of the "rational expectations" models in the 60's. This variable is provided by the BCB on a daily basis and we used the average of the last month of the quarter as our measure of inflation expectation.

We also experimented using this variable with two lags instead of just one as is the common practice. Indeed, we consider this our preferred specification. The reason is clear: The output gap used in the Phillips curve equation is y_{t-1}, which is known by market participants at time *t-1*. Therefore, exchange rate and commodity prices movements are known at time *t-1* (we use π_{t-1} and π_{t-1}^* in the Phillips curve estimation). In this case, the result of using π_{t-1}^E instead of π_{t-2}^E is clearly to overestimate the impact of π^E in the determination of π and underestimate the impact of other variables. Indeed, in this case, the impact of other variables is just the impact not pondered into π_{t-1}^E. This could include, for instance, some kind of market participants' uncertainty about the true Phillips curve or sluggish adjustment of market participants forecast projections.

There is another obvious explanation for not using π_{t-1}^E: It may also capture influences already known to affect inflation in period t. For instance, some already announced price adjustment (this is particularly true for monitored prices) and also any other kind of price shocks known at time t-1. Therefore, if market participants know inflation is persistent in a way consistent with an autoregressive model like the ones we are considering in this paper, the inclusion of π_{t-1}^E in the estimation together with π_{t-1} will also tend to underestimate the impact of π_{t-1} in the Phillips curve equation.

Considering this complete specification for the Phillips curve, the equation we estimate can be written as:

$$\pi_t = a + \rho\pi_{t-1} + \phi\pi_{t-1,t+4}^E + \beta\pi_{t-1}^* + \gamma y_{t-1} + e_t \qquad (4)$$

Dummy variables for each quarter are also incorporated into this equation to control for seasonal effects.

3.2 Inflation persistence using aggregated data

In table 2 we provided a summary of the main statistics of dependent and independent variables used in our estimations. The main highlight of this table is the high autocorrelation of all inflation data[2]. The autocorrelation of external price index is relatively small. This is an expected result as the variable is composed of exchange rate and commodity prices and both variables can be considered a financial asset and so their movements are close to random walks.

The estimation results for inflation persistence using aggregated data are presented in table 2. Overall, the inflation persistence estimates are quite similar if we use the *AR(1)* or the *AR(4)* model. The inclusion of the dummy variable leads to an increase in the inflation persistence estimate. This is not different from results reported by other authors using different techniques. Many authors report results indicating larger inflation persistence when the sample period is shorter: In most of these studies, the shorter period accounts for possible breaks in the inflation process. In this paper, we used a dummy variable instead to control for possible breaks or changes in the inflation process.

Table 2 – Summary Statistics of Variables: 1Q1995 to 1Q2011

	IPCA	Core	Monitored Prices	Free Prices	Tradables	Non Tradables	Output gap	Expected Inflation*	External Inflation
	π	π	π	π	π	π	y	π^E	π^*
Mean	1.9%	1.7%	2.7%	1.6%	1.4%	1.9%	0.0%	1.3%	2.5%
Median	1.4%	1.4%	1.7%	1.4%	1.0%	1.2%	0.3%	1.2%	1.7%
Std Dev	1.5%	1.4%	2.5%	1.4%	1.6%	2.1%	1.5%	0.4%	9.8%
Corr(t,t-1)	0.62	0.75	0.49	0.53	0.20	0.71	0.62	0.76	-0.01

**From 1Q00 to 1Q11; inflation expectation was divided by 4 to convert into quarterly data*

Inflation persistence is larger for core inflation than headline inflation. Core inflation excludes food prices and also monitored prices, two groups with low inflation persistence. The inflation persistence of food prices will be discussed in the next section. The low persistence of monitored prices seems to arise from the fact that this group of prices are indexed to two different price indexes, the consumer price index (IPCA) and also the "general price index" (IGP), which is a mixture of producer price index, consumer price index and also construction cost index. The indexation mechanism also changed during the last years due to the inclusion of productivity gains clauses aimed at reducing the indexation and due to the change in the composition of the baskets of price index used by regulators for determining the monitored prices adjustments. In other words, the low persistence of monitored prices inflation does not mean that this group of price does not have strong mechanisms to propagated inflation shocks.

[2] These inflation groups are not completely different from one another. For instance, core inflation excludes monitored prices and part of the food product in the CPI (IPCA) basket. So, core inflation includes most of the free prices or non-tradable prices. Non-tradable prices are also free prices and so on. Despite this overlap, the segmentation is important since these groups are usually referred to in macroeconomic analysis both by the Central Bank and by market participants.

Table 3 – Inflation persistence estimates

	IPCA	Core	Monitored Prices	Free Prices	Tradables	Non Tradables
AR (4)	0,430	0,502	0,529	0,367	0,309	0,312
ρ	0,408	0,538	0,492	0,361	0,317	0,507
With dummy for 1996:1 to 1998:4						
AR (4)	0,514	0,692	0,418	0,477	0,290	0,692
ρ	0,488	0,681	0,352	0,499	0,277	0,695
With output gap, dummy for 1996:1 to 1998:4						
ρ	0,513	0,699	0,332	0,546	0,303	0,705
γ	0,039	0,026	-0,076	0,085	0,063	0,131
With output gap, external prices, dummy for 1996:1 to 1998:4						
ρ	0,474	0,704	0,301	0,520	0,285	0,714
γ	0,008	0,015	-0,135	0,058	0,047	0,124
$\gamma/(1-\rho)$	0,015	0,051	-0,193	0,121	0,066	0,434
β	0,028	0,024	0,040	0,030	0,066	0,012
$\beta/(1-\rho)$	0,053	0,081	0,057	0,063	0,092	0,041

The inclusion of the output gap does not lead to a sensible change in the persistence estimates. The coefficient of output gap has the "wrong" sign in the monitored prices equation. This result is not completely unexpected since monitored prices inflation depends largely on past inflation: If output gap leads to an overall inflation rise in year one and then due to a more rigid monetary policy the output gap turns negative in next year, the monitored prices inflation will rise when the output gap had already fallen. Despite this "wrong" sign, the coefficient is not significant. The impact of output gap is larger on free prices and particularly in non-tradable prices as expected. The estimated impact on core prices is also small. This result seems at odds with the large impact of output gaps on free prices, which comprehends the majority of the core inflation components.

In the last group of coefficients estimates in table 3 we present the result from the estimation of a Phillips curve with external price inflation. Again, the difference in the persistence coefficient from previous estimations is minimal. The largest difference between persistence estimates arise when we allow for a time trend in the first part of our sample. This result is in line with several other papers on the subject that consider breaks in the inflation process. In our model, the time trend for the post-stabilization period is used to represent this break.

In this last group of coefficient estimates we include the estimated long-run impact ($\gamma/(1-\rho)$ and also $\beta/(1-\rho)$). The output gap coefficient, γ, is smaller when we include the external inflation variable but in some cases this difference is very small (we did not make statistical tests for this difference). The impact of output gap is larger for non-tradable inflation (services represent a good portion of this group) and negative for monitored prices as was the case in the previous set of coefficients estimates. The impact of the external price inflation is larger on tradable prices and lower for non-tradable prices, two results that are in line with conventional theory.

3.3 Time-varying inflation persistence

In this subsection we assess the evolution of inflation persistence during the last years. We do so by using a random coefficient approach for the inflation persistence coefficient. The random coefficient is estimated by using the Kalman filter. In order to reduce the number of parameters to be estimated, we adjusted the inflation series to eliminate the seasonal factors. The seasonal adjustment was made by using the X-12 procedure but the results are pretty much the same if we had used the unobserved components models previously discussed. Using the seasonally adjusted series, the model we estimate is:

$$\hat{\pi}_t = \lambda_t \hat{\pi}_{t-1} + \gamma y_{t-1} + e_t \qquad (5)$$
$$\lambda_t = \lambda_{t-1} + \varepsilon_t$$

Where $\hat{\pi}_t = \pi_t - \bar{\pi}$ is the deviation of current inflation from the average inflation. We included the dummy variable in all estimations. The reason to use deviation from mean is to eliminate the constant coefficient in the equation to be estimated. The constant coefficient in the above equation usually leads to more volatile time-varying coefficients and can also lead to non-convergence in some specifications.

The results from the time-varying coefficient display no clear trend in our sample (figures 2a and 2b). For headline inflation, the coefficient is indeed larger in the second half of our sample. The results do not change significantly if we include more variables in the Phillips curve equation. The results for core inflation show less variability and also no clear trend in the upward or downward in our sample period. It is interesting to notice that in both cases the inflation persistence parameter increases after 2006. A possible explanation for this result is the change in the CPI basket in 3Q06.

Figure 2a: time-varying *AR(1)* model (random walk coef.)

Headline inflation | Core inflation

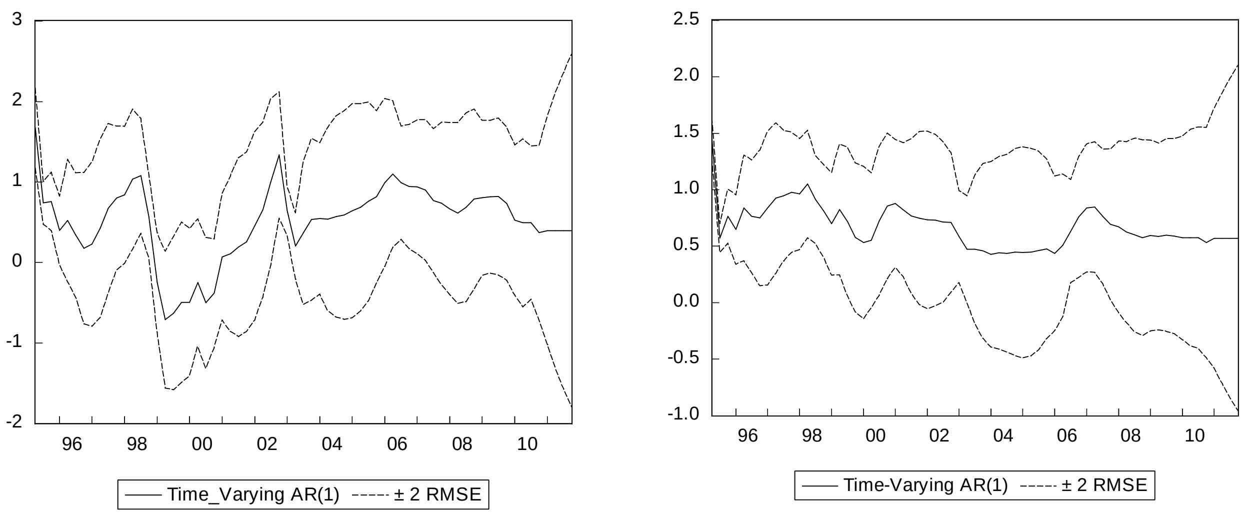
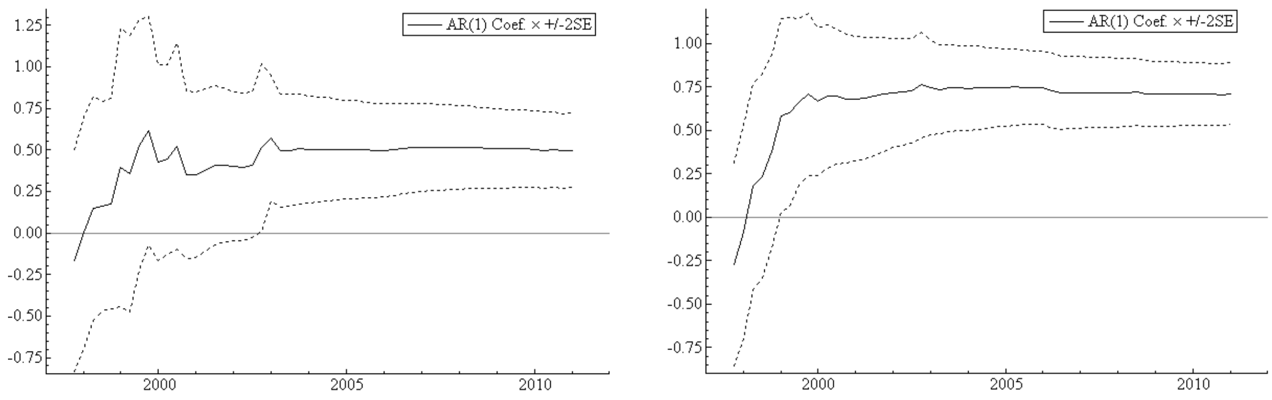


Figure 2b: recursive estimate of *AR(1)* model

Headline inflation Core inflation



3.4 *Sources of inflation persistence in aggregated data*

The previous section presented evidence that inflation persistence in Brazil is high if we use simple autoregressive models but low if we include some explanatory variables in the inflation dynamics. This result can be explained by using the "inherited" versus "intrinsic" hypothesis for inflation persistence.

Let us consider a simple rational expectations model for inflation (usually called New Keynesian Phillips Curve, NKPC) in which the output gap follows an AR(1) process[3]:

$$\begin{aligned}\pi_t &= \beta E_t \pi_{t+1} + \gamma y_t + e_t \\ y_t &= \rho y_{t-1} + u_t\end{aligned} \quad (6)$$

In this case, it is possible to show that:

$$\pi_t = \frac{\gamma\rho}{1-\rho\beta} y_{t-1} + \kappa_1 e_t + \kappa_2 u_t \quad (7)$$

Where parameters κ_1 and κ_2 are functions of the other parameters in the first equation. It is clear from the equation above that the "persistence" of the inflation variable depends on the degree of persistence of the output gap. This is called the "inherited" inflation persistence. If we assume $e_t \equiv 0$, it is also possible to express the inflation equation as:

$$\pi_t = \gamma\pi_{t-1} + \kappa u_t \quad (8)$$

Again, the inflation persistence will depend on the persistence of the driving forces of the inflation process. If we use more complex specification like equation (4), it gets very difficult to get an analytical solution for the inflation equation. Despite that, it is possible to get some indication about the forces behind the inflation

[3] This example is based on Fuhrer (2006).

persistence by looking at the impact of each variable that entered into the Phillips curve equation, its coefficient and is autocorrelation.

With the use of the results from table 3 and summary statistics of the variables in table 2, it is difficult to infer the causes of inflation persistence in Brazil. Except for external price inflation, the explanatory variables are all highly persistent and have almost the same standard deviation. The expected inflation variable is the most persistent variable but this is clearly a result of using expected inflation for the next twelve months on a quarterly basis. The results indicate that more information is still needed for us to have a better understanding of the high inflation persistence in Brazil.

4 Inflation Persistence in Brazil: Disaggregated Data

4.1 Introduction

Aggregate inflation dynamics depends on the dynamics of disaggregated inflation dynamics. But this natural result alone does not help in our task of understanding the forces behind inflation dynamics and particularly inflation persistence. Another result of the aggregation process is that the persistence of aggregated data will have a "tilt" towards the most persistent individual series. Cecchetti and Debelle (2006) offer a good explanation for this result and also a graphical illustration of it. Granger (1980) and Zaffaroni (2004) give a more theoretical explanation about the consequences of aggregation of individual series. In these papers, the importance of the distribution of individual persistence parameters is commonly expressed as the individual series being stationary or not having a mass in distribution at the unit root point.

4.2 Inflation Persistence in Disaggregated Data without Common Factors

In this sub-section we estimate inflation persistence for disaggregated data. Several papers have demonstrated that aggregate inflation persistence is larger than disaggregated inflation persistence. We calculate disaggregated inflation persistence for 342 products using IPCA data during 3Q1999 to 1Q2010. Since 1995 there has been three changes in IPCA components: In 1996, in 1999 and 2006. The items in the 1999 and 2006 poll are pretty much similar but the items in the 1996 poll are very different and were not included in this analysis. The 1999 poll had 511 items and the 2006 poll had 384 items. There are 341 common items among these two samples. Among these 341 items, 9 were excluded due to lack of dynamics and unreliable results from the autoregressive models used in estimation. Most of these items are monitored prices where price changes occur seldom and several entries are zeroed. Due to this, the *AR(1)* or *AR(4)* models used were not reliable. In order to check for common items we used the items coding provided by IBGE. The final sample consists of 332 inflation series from 3Q1999 to 1Q2011.

The table bellow presents the descriptive statistics of the disaggregated data. As one can see in such table, the median inflation is close to the aggregate inflation (both weighted, "original data" or unweighted) and is much more volatile and presents less autocorrelation than the aggregate inflation. Klenow and Kristosov (2008) present similar results for US inflation data: In their sample, the persistence of inflation is much larger in the aggregate than in the disaggregated data. The same results were found by Clark (2006) also using data for US inflation.

Table 3: Summary Statistics of Disaggregated Inflation Data

	Mean	Std Dev	Corr(t,t-1)
Agreggate	1,65%	1,12%	0,447
Unweighted Aggregate	1,97%	1,50%	0,252
Minimum	-1,92%	0,67%	-0,545
Median	1,77%	2,80%	0,072
Maximum	12,06%	50,33%	0,843

In this section we estimate several simple models of inflation dynamics (or Phillips curves) by using disaggregated data. The objective of these estimations is to understand the differences in inflation persistence in different inflation groups. This is important due to the impact that highly persistent series can have on the aggregated data. Granger (1980), Zaffaroni (2004) and Pesaran (2003) have shown that under certain assumptions, the dynamics of the aggregated data can be analyzed from the disaggregated data. In particular, by considering a simple *AR(1)* model for inflation dynamics in disaggregated data, Granger (1980) shows that the aggregated data can present long memory. This result was later refined by Zaffaroni (2004) and Pesaran (2003). We will use some results presented in Pesaran (2003) to discuss our disaggregated results and its implication for aggregated inflation persistence. Debelle and Ceccheti (2008) discuss in a much less rigorous way the impact of aggregation of inflation series with different persistence on aggregated inflation dynamics. The general results of these papers can be summarized as follows: a) assuming independence of all disaggregated inflation series, the aggregated inflation persistence will be determined by the distribution of the inflation persistence of the individual series and b) also depending on the distribution of the individual series, the aggregated series can display long memory. The result expressed in (a) is very intuitive while (b) is not. In both cases, a beta distribution is used to characterize the distribution of the *AR(1)* parameters for individual series and it is possible to show that the presence or not of long memory can be inferred from specific parameters of the beta distribution.

The table bellow presents the results for several specification of the Phillips. In all cases, except for model 5, we present the coefficients for the aggregated specification and also the mean and median coefficients of the disaggregated specification. We will focus our discussion on models 1, 2 and 5. Each model presents estimations results for individual inflation items specifications as follows: Let $\pi_{i,t}$ be the inflation rate of product *i* at the quarter *t* (one of the 332 products we are using in this section as we defined in the beginning of this sub-section). We estimate product specific Phillips curves similar to equations (1) to (4) for each product *i*. This can be written as:

$$\pi_{i,t} = \lambda_i \pi_{i,t-1} + \phi \pi^{E}_{t-1,t+4} + \beta \pi^{*}_{t-1} + \gamma y_{t-1} + u_{i,t}, \quad \text{i=1,...,332} \qquad (9)$$

For each specification, we present the mean and the median of the *AR(1)* coefficient and also the mean and the median of the individual coefficients of the other explanatory variables. The “aggregated” row represents the coefficient estimated by using the aggregated inflation data, both weighted and unweighted. The results are not exactly the same as in table 2 for headline inflation due to the different sample periods: In table 2, we estimated the models using the whole sample (1Q95 to 1Q11) and for disaggregated data we are using just data from 3Q99 to 1Q11 (this is the data available for disaggregated data). We estimated the equations one at once by using a simple routine written to estimate each of the 332 equations and then store the coefficients in a specific matrix.

The estimation results in model 1 shows that inflation persistence in disaggregated data is much smaller than in aggregated data. This result is similar to the one reported by Clark (2006) and also Klenow and Krystosov (2005) for US data.

The inclusion of the output gap in the inflation equation lowers the persistence of inflation both in aggregated data equation and in disaggregated data. In opposition to what happens to inflation persistence, the impact of the output gap is larger in disaggregated data than aggregate data.

In model 4 we also add inflation expectation and commodity prices in the inflation equation. The results indicate a larger role for expected inflation than lagged inflation. The impact of output gap is lower than in model 2 and the impact of commodity prices is small. This low impact of commodity prices can be considered a puzzle since both exchange rate movements and also commodity prices inflation are considered relevant variables in inflation dynamics almost everywhere.

In model 5 we included the lagged aggregated inflation as an explanatory variable. The reason behind this is quite simple: Indexation mechanisms are almost always related to lagged "aggregated" inflation and it is considered a "conventional wisdom" that several indexation mechanisms are still in practice in Brazil not only among "monitored" or "regulated" prices but also among "free" prices. The results of model 5 contradict this conventional wisdom: Expected inflation is more important than lagged inflation as an explanatory variable for disaggregated inflation dynamics.

The estimated impact of expected inflation is lower when we consider $\pi^E_{t-2,t+4}$ instead of $\pi^E_{t-1,t+4}$. Our interpretation to this results is that expected inflation incorporates several price adjustments announced in advance and also some "macro trends" or "common factors" in the sense of Granger (1987) already known to affect inflation in the next quarter. In other words, our measure of expected inflation[4] may be at the same time a driving force of inflation and a variable that is being impacted by current inflation. If this is true, this could be an important cause of inflation persistence in Brazil. Nevertheless we recognize that this explanation is just "tentative" and we consider this hypothesis as a direction for further research on inflation persistence in Brazil. If we run a regression of the variation in inflation expectation ($\pi^E_{t,t+4} - \pi^E_{t-1,t+4}$) on the variation of the underlying level of inflation ($\pi^L_t - \pi^L_t$), we find regression coefficients as large as 0.5 by using core inflation. When using headline inflation, the impact is lower - close to 0.15.

$$\pi^E_{t,t+4} - \pi^E_{t-1,t+4} = \underset{(0,072)}{0,504}(\pi^L_t - \pi^L_{t-1}) + e_t \qquad (10)$$

[4] This is also the measure commonly used by the Central Bank.

Table 4

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8*
AR(1)								
Aggregate	0,477	0,505	0,344	0,098	0,438			
Unweighted Agg.	0,351	0,370	0,182	0,032	0,232			
Disaggr. Mean	0,129	0,118	0,050	0,091	0,030			
Disaggr. Median	0,154	0,143	0,041	0,055	0,016			
Output gap								
Aggregate		0,099	0,038	0,036	0,059	0,048	0,071	0,058
Unweighted Aggregate		0,209	0,125	0,127	0,155	0,118	0,158	0,144
Disaggregated Mean		0,161	0,149	0,115	0,139	0,118	0,158	0,144
Disaggregated Median		0,086	0,042	0,055	0,072	0,067	0,081	0,061
Commodity Prices								
Aggregate				0,074	0,066	0,078	0,080	0,046
Unweighted Aggregate				0,096	0,099	0,094	0,098	0,060
Disaggregated Mean				0,010	0,097	0,094	0,098	0,060
Disaggregated Median				-0,008	0,062	0,058	0,057	0,030
Expected inflation (t-1) & (t-2)			**t-1**	**t-1**	**t-2**	**t-1**	**t-2**	**t-2**
Aggregate			0,285	0,318	-0,002	0,354	-0,071	0,149
Unweighted Aggregate			0,354	0,342	0,076	0,461	-0,097	0,151
Disaggregated Mean			0,314	0,312	0,115	0,461	-0,096	0,151
Disaggregated Median			0,308	0,311	0,179	0,331	-0,042	0,113
Lagged Aggreg. Inflation								
Aggregate						-0,026	0,147	-0,020
Unweighted Aggregate						-0,080	0,144	-0,044
Disaggregated Mean						-0,080	0,144	-0,044
Disaggregated Median						-0,010	0,167	0,022

**Identical to model 7 excepts for the Inclusion of a dummy variable for 4Q02 and 1Q03*

The impact of different weights is attributed to different items in the aggregation process as fig. 3 shows. There is no correlation between the weight of each item and its estimated persistence. The distribution of inflation persistence in model 1 is depicted in fig. 4. The distribution is skewed to the left with mean of 0.131 and median of 0.157. These values are much lower than the *AR(1)* coefficient from the aggregated equation (close to 0.5). The persistence of unweighted aggregated inflation is lower than the persistence of weighted inflation (the weighted inflation is current data informed by IBGE). In the next section we compare this distribution with the Beta distribution and the values upon which a long memory in aggregated series could arise.

The figures 5, 6, 7 and 8 present the estimated coefficients for expected inflation, lagged inflation, output gap and the R^2 of each equation in model 5. The figures just make it easier to see the impact of each variable in disagreed inflation dynamics as summarized in table 4. In the appendix we provide more inflation regarding the mean and median for other groups of inflation components, like the “exclusion” core inflation (which excludes foods and monitored prices) and also services inflation. This is important since these two groups have been subject to scrutiny by policy makers, market participants and also the press.

Figure 3: AR(1) Persistence (model 1) x Weight

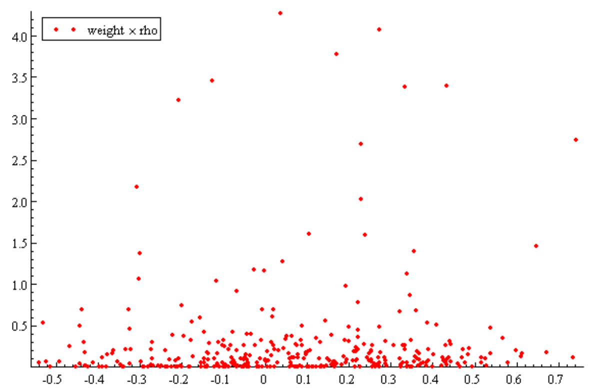
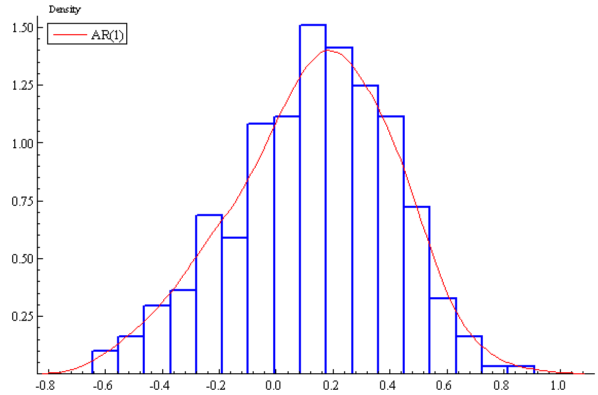


Figure 4: AR(1) Persistence (Model 1)



For each graph we present the estimated coefficient in the *y axis* followed by the group from which the specific product belongs to. We did not write the exact name of the product because it would be almost impossible for anyone to read it. Therefore, the several bars labeled "food" are indeed the several products belonging to the food group in the same order as presented by IBGE in its inflation (IPCA) releases. For example, the very first bar represents the coefficients for "rice" (FOOD group) and the last bar represents "telecommunication handset" (COMMUNICATION group). Since the communication group has only 5 products, in most graphs the last label that appears is EDUCATION.

In figure 8 we presente the R^2 for model 6. The explanatory power is lower for disaggregated data than for aggregated inflation data. By using model 6, the mean R^2 is just 0.41. The result is very different from the ones observed by other authors using a similar dataset for other countries. For instance, the mean R^2 in Gianoni *et al* (2010) is just 0.15 when using a factor model[5] for disaggregated data. The R^2 rises close to 0.70 when using aggregated data. In Chudik and Pesaran (2011) the estimated R^2 varies from 0.36 to 0.39 by using an autoregressive model for disaggregated data and the estimated R^2 rises to values between 0.48 and 0.56 when the author includes "common factors" in the estimated model. Gianonni *et al* (2010) use US data and Chudik and Pesaran (2011) use data from Germany, France and Italy.

Figure 5: Expected inflation coef. (model 6)

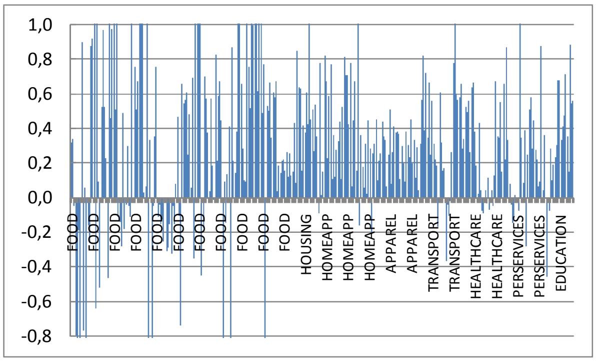
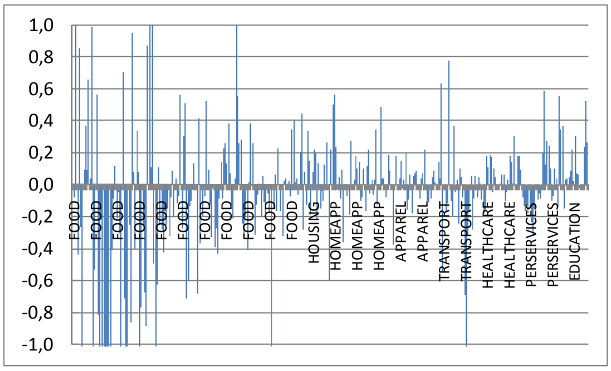


Figure 6: Lagged inflation coef. (model 6)



[5] The factors are extracted from a large dataset of macroeconomic variables. Most of the variables are economic activity indicators. The nominal interest rate is also used as a factor.

Figure 7: Output gap coef. (Model 6)

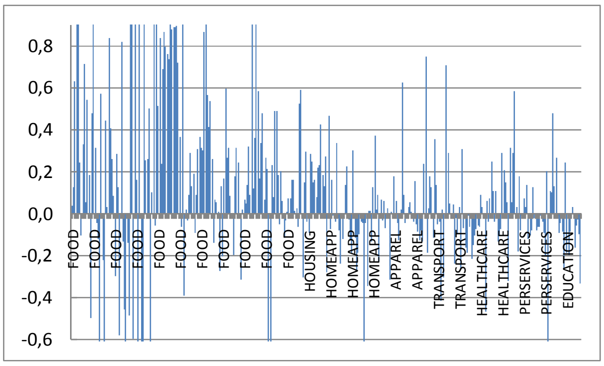


Figure 8: R^2 (Model 6)

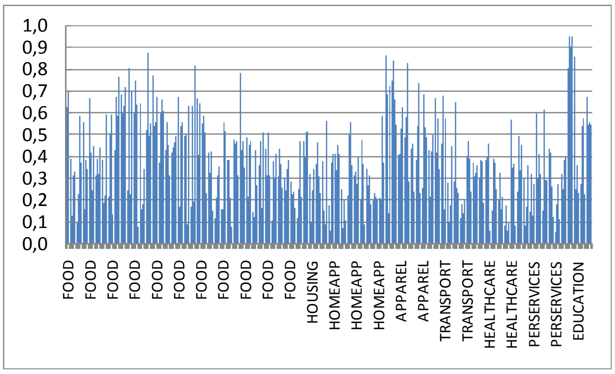
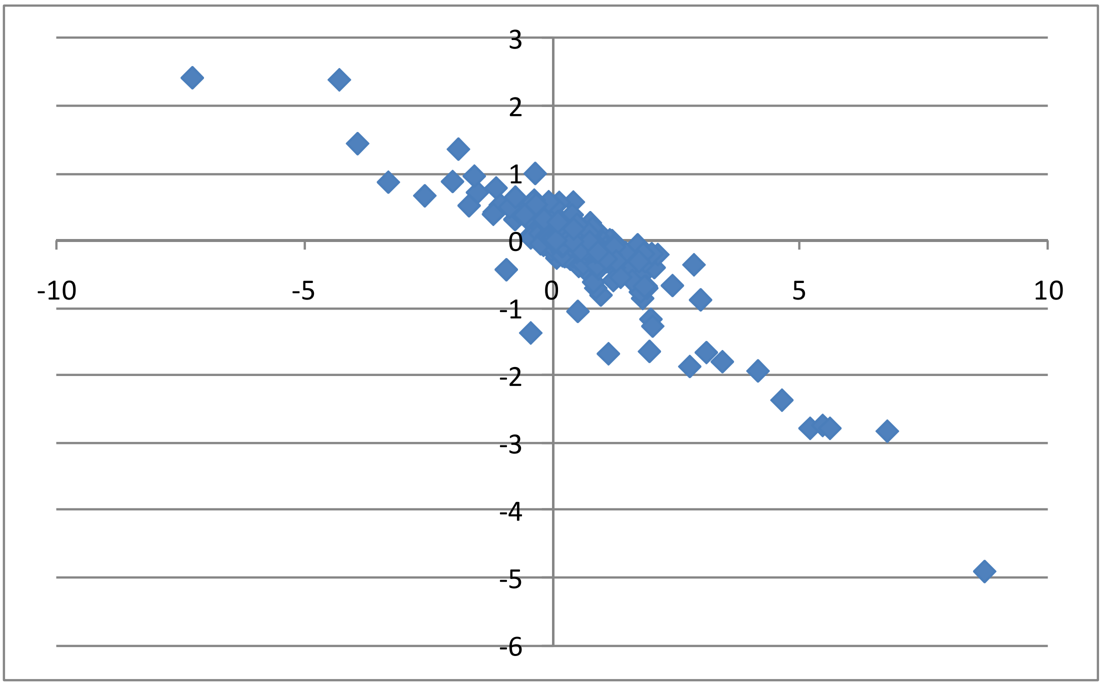


Figure 9 shows the dispersion of the estimated coefficient of lagged inflation and expected inflation on disaggregated inflation dynamics. There is a clear negative relation between the coefficients: Items with strong response to lagged inflation present a low response to expected inflation. This result was somehow expected: When inflation is stable, the sum of coefficients of lagged inflation and expected inflation must not exceed one in modulus[6]. The estimated impact of inflation expectation is usually larger than the impact of lagged inflation (both last 12 months cumulated inflation and the AR(1) coefficient). Among the several different estimated equations, the lagged inflation coefficient is larger than the estimated coefficient on expected inflation in almost 80 equations out of 332. The products that show greater impact of lagged inflation are evenly distributed across the several inflation groups.

Figure 9: Dispersion of expected inf. coefficient (X-axis) and lagged inf. coefficient (Y-axis)



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[6] In almost 40 equations out of 332 the sum of coefficients on lagged inflation and expected inflation exceeds one in modulus. We did not perform any test to check if the sums are statistically different from one.

4.3 *Inflation Persistence in Disaggregated Data: The Relevance of Common Factors*

A possible explanation for the low R^2 of the estimated equation in the previous sub-section is the presence of common factors at the cross-section of the estimated model. This problem was first studied by Granger (1987). The presence of common factors at the cross section can explain the existence of a good fit of statistical models at the aggregate level but almost no fit at the disaggregated level.

Let us consider a simple dynamic linear model for disaggregated data:

$$\pi_{i,t} = \lambda_i \pi_{i,t-1} + \alpha_i \eta_t + u_{i,t} \tag{11}$$

Where $\pi_{i,t}$ is the inflation rate in the item *i* at the time interval *t* and η_t is the common factor for all items at t. This model is similar to the ones presented previously except for the inclusion of a common factor η_t at every cross-section. There is a large literature on estimation and inference in such kind of specification and we will not review the different approaches and results from this literature[7].

Coakley *et al* (2002) propose using principal components techniques to construct instruments for η_t. Pesaran (2006) proposes the average of the disaggregate variable, $\overline{\pi}_t = N^{-1}\sum_i \pi_{i,t}$, as an instrument for η_t. This approach is similar to model 6, model 7 and model 8 in our previous estimations. The difference is that we used the lagged (and aggregated) dependent variable instead of contemporaneous aggregated variable. We will use the principal components approach to derive the common factor at the cross-section of our data. In order to do so, we will used model 1 and model 5 residuals to estimate the principal components. In model 1 we incorporated no "macro" structure to each individual inflation series whereas in model 5 we incorporated several variables that could be a proxy for the common factor. This could indicate higher and lower bonds common factors. However, the two factors are pretty much similar to a correlation close to 0.9. Due to this result, we will only present results with the use of the common factor extracted from residuals of model 5. After extracting the common factor, we estimate the model again by using the augmented equation:

$$\pi_{i,t} = \lambda_i \pi_{i,t-1} + \alpha_i f_t + u_{i,t} \tag{11'}$$

Where f_t is the common factor extracted from the residuals of model 5.

Overall, the inclusion of the common factor does not cause great changes in the estimated coefficients of the model. When we use the common factor into model 6, the common factor is almost always non-significant and the model results do not change much: The estimated coefficients on lagged and expected inflation are very similar and the R^2 is also similar. When we include the common factor into model 1, the results change but not much. There is a sensible increase in the R^2 but this can be explained by the simple structure of the model and its lack of macroeconomic variables as explanatory variables. The t-statistic is larger than two for several products indicating this common factor is significant in most regressions.

[7] Coakley *et al* (2002) and Chudik and Pesaran (2011) are the most similar research we found. Pesaran (2006) presents a more theoretical discussion of the subject.

4.4 Relation to long memory models

In the last years several papers estimated long memory models for aggregated inflation data on the grounds of the results presented by Granger (1980)[8]: Assuming a simple autoregressive model for disaggregated data, the aggregated data may present long memory depending on the distribution of the autoregressive coefficients of disaggregated data. This results is not only applicable to inflation but for any aggregated data. See Pesaran (2003) and Zaffaroni (2004) for more examples.

Let y_{it} represent the value of the y variable observed at time t for i-th individual[9]. Thus let us consider that the dynamics of this variable follows an AR(1) model for all individuals:

$$y_{it} = \lambda_i y_{i,t-1} + u_{it}, \quad \text{i=1,2, ..., N,} \quad \text{t=1,2, ..., T} \tag{12}$$

Therefore, let us assume λ_i follows a Beta distribution of the second type on the range (0,1):

$$f(\lambda) = \frac{2}{B(p,q)} \lambda^{2p-1}(1-\lambda^2)^{q-1}, \quad 0 \le \lambda \le 1 \tag{13}$$

In this case:

$$\lambda^j = \frac{B(p + j/2, q)}{B(p,q)} \tag{14}$$

And for a large *j*:

$$\lambda^j = (p + j/2)^{-q} \tag{15}$$

In this case, the aggregated data, $Y_t = \sum_{i=1}^{N} y_{it} / N$ will present long memory when *0<q<1*.

By using the results from the previous section for disaggregated data, we could approximate a Beta distribution for the AR(1) coefficients as a form to estimate the parameters *p* and *q* of the Beta distribution and check if it is consistent with long memory models for aggregated inflation data in Brazil. Usually, the long memory hypothesis is tested directly from the aggregated data. In some circumstances, for instance in our small sample of quarterly inflation data, this approach can be considered an alternative to the more traditional tests of long memory in time series data.

It is clear from figure 4 that the case proposed initially by Granger (1980) does not apply to our estimation results. The distribution of the $\lambda's$ are not restricted to the interval [0,1] and the Beta distribution cannot be applied. It does not mean that aggregated inflation does not have long memory. The generalization of long memory proposition is not an easy task and we do not intend to do it in this paper.

[8] Pesaran (2003) and Zaffaroni (2004) present some refinements of the Granger (1980) results.

[9] This explanation for the long memory result arising from aggregation is based in Pesaran (2003).

5 Inflation Persistence in Emerging Markets

In this section we study inflation persistence in other developing countries. The sample of countries we use is based in two aspects related to the history of these countries. Firstly, we include in our sample countries with a history of high inflation in the recent past, particularly in the 90's. Secondly, we include in our sample countries that introduced a clear strategy to pursue monetary stability, in particular by using the inflation target regime. These countries resemble Brazil and are more prone to show the same problems in dealing with inflation cycles and also inflation expectations. Therefore, high inflation can lead to several mechanisms of indexation similar to the ones observed in Brazil and thus lead to high inflation persistence.

Table 5: Summary Statistics of Emerging Markets Inflation

	Headline Inflation			Core Inflation		
	Mean	Std Dev	Corr(t,t-1)	Mean	Std Dev	Corr(t,t-1)
Chile	3,8%	1,8%	0,443	2,3%	1,2%	0,337
Czech Republic	4,0%	2,4%	0,174	3,9%	2,6%	-0,019
Hungary	8,9%	3,9%	0,643	8,5%	4,0%	0,734
Israel	3,6%	2,5%	0,362	3,3%	2,6%	0,379
Mexico	10,1%	5,5%	0,760	9,6%	5,3%	0,775
Poland	6,4%	3,6%	0,650	6,0%	3,3%	0,869
Turkey	29,3%	12,2%	0,849	29,1%	12,1%	0,913
South Africa	5,6%	2,1%	0,592	n.a.	n.a.	n.a.
Colombia	8,7%	4,0%	0,411	5,2%	1,9%	0,045
Peru	4,0%	2,0%	0,565	n.a.	n.a.	n.a.
Brazil	7,3%	2,7%	0,714	7,3%	2,7%	0,714
Mean	8,3%	3,9%	0,560	8,4%	4,0%	0,527
Median	6,4%	2,7%	0,592	6,0%	2,7%	0,714

Source: OECD and authors' calculation

Table 6 presents the results for inflation persistence estimates for our sample of developing countries. The estimated inflation persistence is larger in Brazil than for most of other developing countries considered in our sample. Only Poland shows inflation persistence larger than the one estimated for Brazil. It is important to notice the low inflation persistence for most of the countries. This result seems to indicate that inflation persistence is similar for most of the countries. The difference in inflation dynamics among emerging countries and developed countries may lie on other aspects of the inflation dynamics and not on persistence.

Table 6: Inflation persistence estimates for emerging markets

	Headline Inflation		Core Inflation	
	ξ	AR(4)	ξ	AR(4)
Chile	0,151	0,375	0,223	0,295
Czech Republic	-0,076	0,174	0,328	0,505
Hungary	0,482	0,508	-0,041	0,236
Israel	-0,226	0,022	0,226	0,404
Mexico	0,438	0,423	0,488	0,487
Poland	**0,543**	**0,670**	**0,708**	**0,650**
Turkey	0,393	0,411	0,209	0,198
South Africa	0,368	0,448	n.a.	n.a.
Colombia	0,310	0,412	0,461	0,682
Peru	-0,052	0,033	n.a.	n.a.
Brazil	**0,594**	**0,598**	**0,681**	**0,692**
Mean	0,266	0,370	0,365	0,461
Median	0,368	0,412	0,328	0,487

Several authors have used Hansen (1999) bootstrap method to estimate the mean of the autoregressive coefficients in dynamic models like the ones we have estimated so far. The first reason to use Hansen (1999) is the bias in OLS estimation. The second reason is to construct confidence intervals to the estimated coefficients. Considering these reasons we have also used Hansen (1999) method for emerging markets inflation (using this method also make it easier to compare our results with those reported by other authors). All models were estimated including both a constant and a time trend. The time trend is not a dummy variable as in the previous estimation (results from table 6). This makes the results not directly comparable. A possible future refinement of this estimation would be to reduce the estimation interval to exclude the stabilization period in most countries (usually from 1995 to 2000). The constant term and trend coefficients were not reported. The complete estimation results are presented in the appendix.

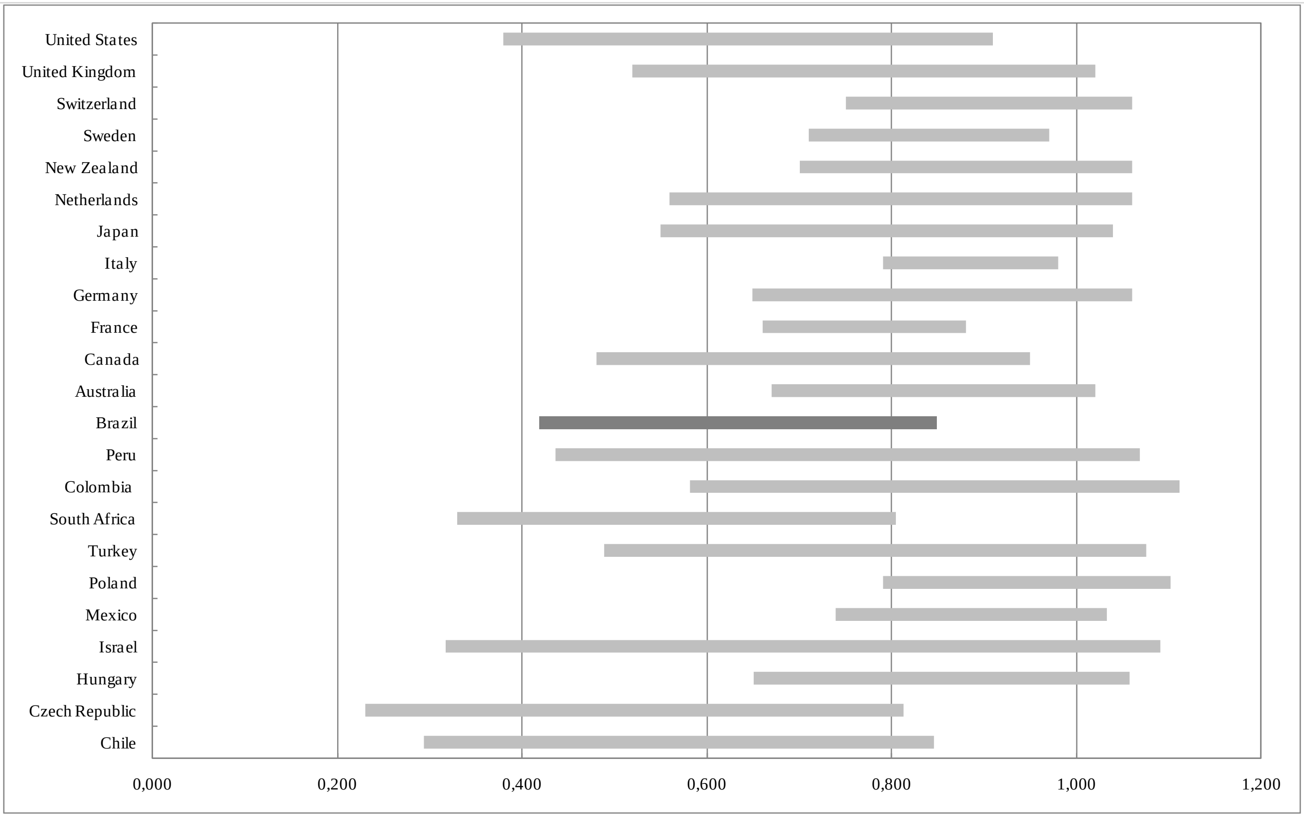
In table 7 we report the results of emerging markets estimates. In figure 10 we show both coefficients estimates for both emerging and developed countries. Using this alternative estimation procedure, inflation persistence is lower than average in Brazil and not higher as in other cases. This can be a result of the estimated model, which did not allow for structural break or a dummy trend variable. In many emerging markets, the estimated 90% confidence interval for ρ is very large. Again, this can be a result of the post stabilization period, which could have made the coefficients unstable in the first part of our sample. The estimated confidence interval for emerging markets is usually larger to the estimated for developed countries by Levin and Piger (2004): in our 11 countries sample, the average interval is 0.51while in the Levin and Piger (2004) sample of 12 countries, the average interval is 0.38.

Using Hansen (1999) method, the inflation persistence is higher for all countries but Brazil. This result was expected since OLS estimation of autoregressive models are biased downward as expressed by Hansen (1999) among others.

Table 7: Inflation persistence in emerging markets – Hansen (1999) median unbiased approach

	Coef. Estimate		Grid Confidence Interval (90%)	
	ρ	S.E.	lower	higher
Chile	0,453	0,141	0,294	0,846
Czech Republic	0,408	0,147	0,230	0,812
Hungary	0,732	0,086	0,651	1,058
Israel	0,487	0,172	0,317	1,091
Mexico	0,797	0,061	0,740	1,032
Poland	0,837	0,084	0,791	1,102
Turkey	0,608	0,135	0,489	1,076
South Africa	0,480	0,124	0,330	0,804
Colombia	0,686	0,132	0,581	1,112
Peru	0,574	0,136	0,436	1,069
Brazil	0,547	0,110	0,418	0,848
Mean	0,601	0,121	0,480	0,986
Median	0,574	0,132	0,436	1,058

Figure 10: Inflation persistence in emerging markets and developed countries*



**The results for emerging markets are those from table 7. The results from developed countries were extracted from Levin and Piger (2004), figure 2.*

6 Conclusion

This paper estimates inflation persistence for Brazil using both aggregated and disaggregated data and also estimates inflation persistence for other emerging countries. The results can be summarized as follows: inflation persistence in Brazil is larger than in other emerging markets when traditional OLS estimation is used. Using the median unbiased estimation, inflation persistence in Brazil is not different from other countries.

Disaggregated inflation persistence is much lower than aggregated inflation persistence. Such results hold for both the mean and median of disaggregated inflation persistence. Despite the large role for lagged inflation in aggregated inflation dynamics, our estimates indicate that expected inflation plays a major role in disaggregated inflation dynamics in Brazil.

Our results did not identify the sources of inflation persistence. One of main difficulties in identifying the sources of inflation persistence is the similar levels of autocorrelation in the variables we used as inflation determinants. The most persistent variable in our study is inflation expectation but this variable is very persistent by construction (we used inflation expectation for the next twelve months on at quarterly frequency). In this paper we did not analyze carefully the existence of common factor among disaggregated inflation data. One possible explanation for the large persistence in aggregated inflation in Brazil is the presence a common persistent factor in disaggregated inflation. We consider this possibility as a refinement of this paper.

In sum, our results points out that inflation persistence in Brazil is larger than in other countries but this result is not common to all methods we used. There are still several questions that should be addressed before calling inflation persistence a critical problem in Brazil.

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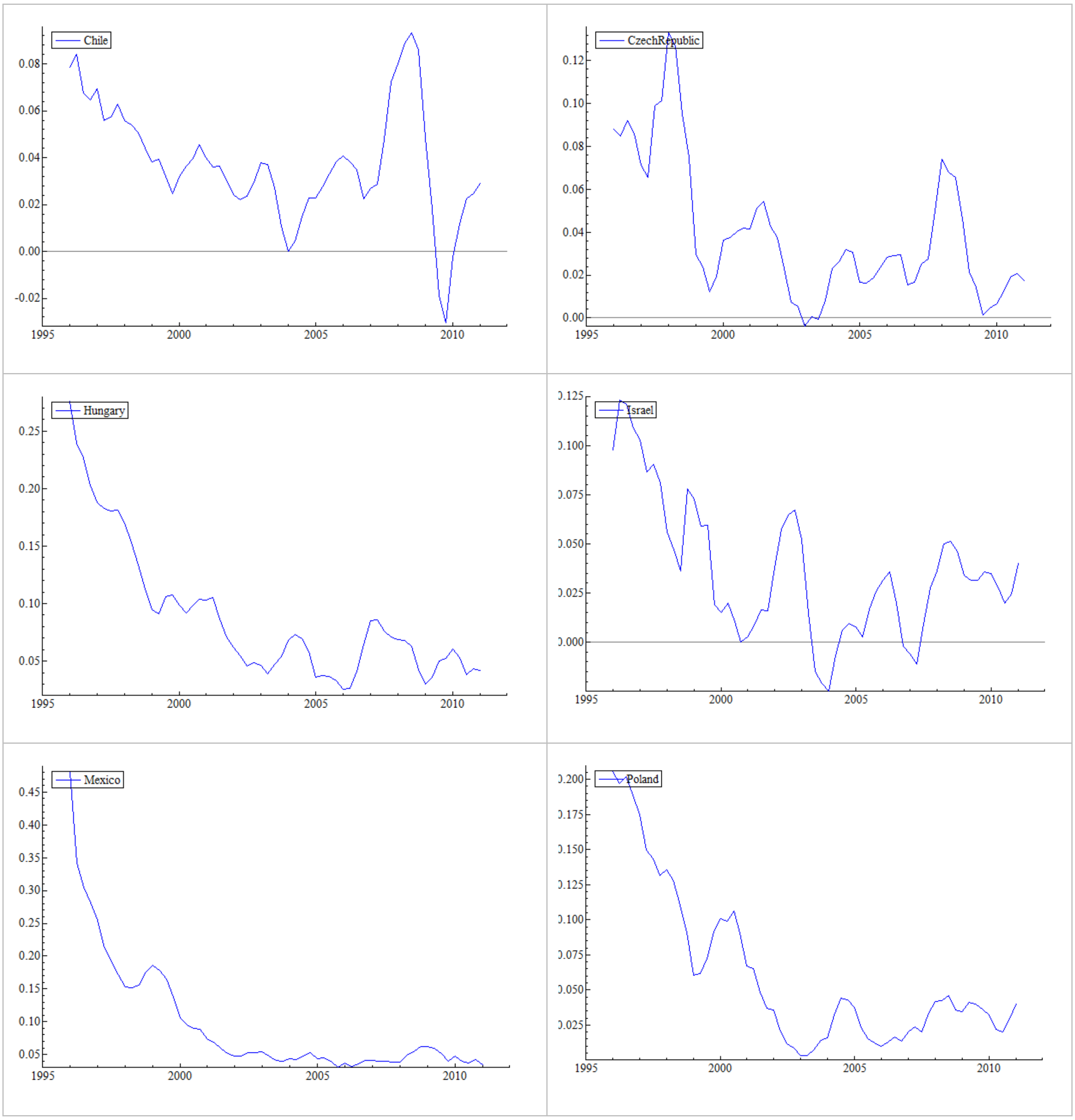
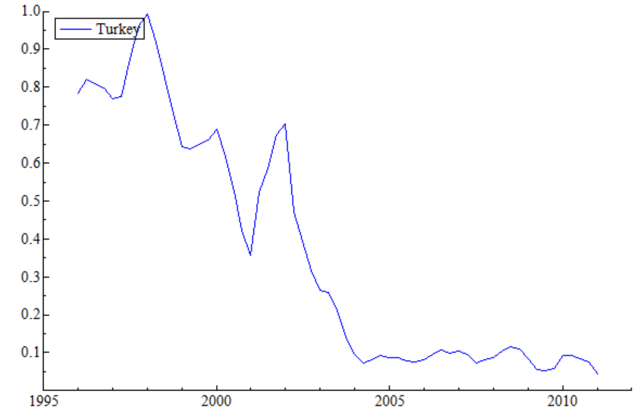
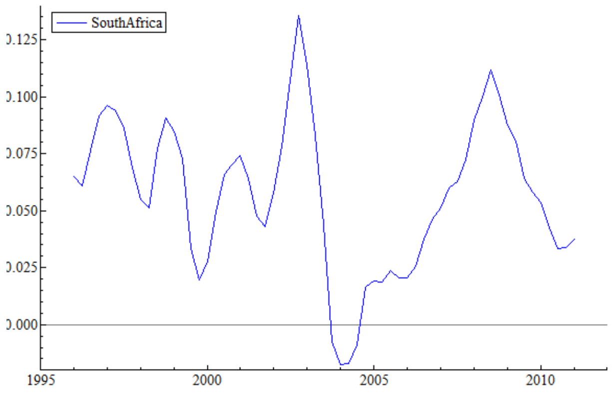
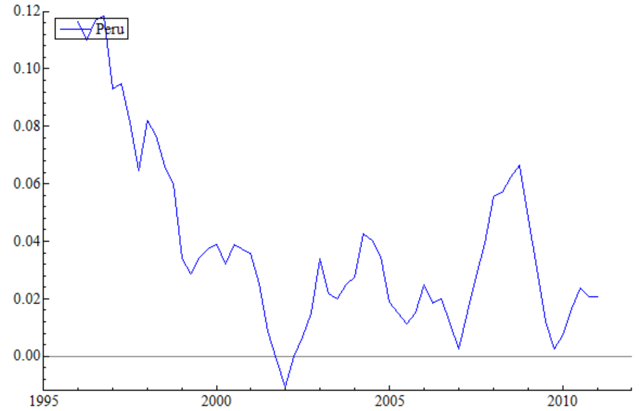
8 Appendix

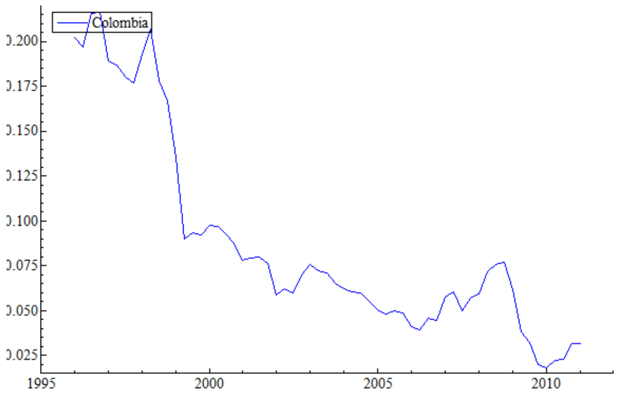
8.1 Inflation graphs




Turkey
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
1995
2000
2005
2010


SouthAfrica
0.125
0.100
0.075
0.050
0.025
0.000
1995
2000
2005
2010


Peru
0.12
0.10
0.08
0.06
0.04
0.02
0.00
1995
2000
2005
2010


Colombia
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
1995
2000
2005
2010