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A Disaggregate Model and Second Round Effects for the CPI Inflation in Costa Rica

Jorge León

Fotografía de portada: "Presentes", conjunto escultórico en bronce, año 1983, del artista costarricense Fernando Calvo Sánchez. Colección del Banco Central de Costa Rica.

A Disaggregate Model and Second Round Effects for the CPI Inflation in Costa Rica^{*}

Jorge León[†]

The ideas expressed in this paper are those of the author and not necessarily represent the view of the Central Bank of Costa Rica.

Abstract

This paper estimates a medium-term forecasting model for the headline inflation of Costa Rica, utilizing disaggregate data from the components of the Consumer Price Index (CPI). The period used for the estimation is characterized by a process of reduction of inflation and stabilized around the Central

Bank's inflation target. The results show that the use of disaggregate data is at least as good as the aggregate data in forecast accuracy. The disaggregate model allows to differentiate the inertia and the Second-Round effects present on the inflation.

Key words: Inflation, Forecast, CPI, PPI, Second Round Effect.

JEL codes: C51, C53, E31, E58.

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[†] Department of Economic Research. Email address leonmj@bccr.fi.cr

Un modelo desagregado y los efectos de la segunda ronda para la inflación del IPC en Costa Rica

Jorge León[‡]

Las ideas expresadas en este documento son de los autores y no necesariamente representan las del Banco Central de Costa Rica.

Resumen

En este documento se estima un modelo de proyección de inflación de mediano plazo para Costa Rica. Este modelo utiliza datos desagregados de los componentes del Índice de Precios al Consumidor (IPC). Las estimaciones se realizan para un periodo en el cual la inflación se ha desacelerado y estabilizado alrededor de la meta de inflación planteada por el Banco Central de Costa Rica. Los resultados muestran que el uso de datos a nivel desagregado son al menos tan bueno como los datos agregados para la proyección de la inflación en el mediano plazo. El modelo estimado utilizando datos desagregados también permite diferenciar entre la inercia inflacionaria y los efectos de segunda ronda presentes en la inflación.

Palabras clave: Inflación, Proyección, IPC, IPPI, Efecto Segunda Ronda.

Clasificación JEL: C51, C53, E31, E58.

[‡] Departamento de Investigación Económica. División Económica, BCCR. leonmj@bccr.fi.cr

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1 Introduction

There is great diversity of methodologies used by the central banks, that have an Inflation Target (IT) regime, to predict the behaviour of inflation in the short to medium term. There exist different approaches to when it comes to forecasting inflation. Forecasting models of inflation can range from Dynamic Stochastic General Equilibrium (DSGE) Models, Macroeconomic Models, New Keynesian Phillips Curve Models, Cost Push Models, to simple Autorregresive Models (AR). Their relative success or failure depends on the each particular case.

As the Central Bank of Costa Rica has move forward to implement the Inflation Target (IT) regime, it has become apparent that it needs a diverse and flexible array of forecasting models of inflation. To help meet those needs this document provides a model using a disaggregate approach that did not exist previously.

This paper estimates a model for the medium-term forecast of inflation measured by the Consumer Price Index (CPI) in Costa Rica., from disaggregate components. In order to do this a disaggregate model of inflation using the groups that form the CPI is estimated. The estimated model not only can improve the forecast of inflation, but also explain its dynamic behaviour, allowing to decompose it into the inertial component and the Second-Round Effects.

When forecasting the aggregate inflation rate, the question that arises is if the forecasting accuracy of aggregate models can be improved by taking into account information of the disaggregate components. In this respect there still a lot discussion in the economic literature. From the theoretical stand point the use of disaggregate information should be neutral in the worst case or should improve the forecast accuracy of the models. On the other hand, from a empirical point of view, the use of disaggregate data generate problems such as model misspecification given that the Data Generating Process (DGP) is unknown.

In general the literature has concentrate on the pros and cons of using aggregate or disaggregate data to improve the forecasting accuracy of the models. The results show that the convenience of the disaggregate models is very particular, in the sense that the improvement obtained by using disaggregate

¹leonmj@bccr.fi.cr

data varies according to the country, specification of the model and period.

The theory of predictability suggests that the use of a larger information set contained in the disaggregate data should improve the forecasting accuracy. But the question of the level of disaggregation is still open.

It is possible to separate the literature into two different currents. The first one focuses on the use of disaggregate models of the components of the CPI and then aggregating the results to obtain the aggregate forecast of CPI (see Cobb(2009)). The second approach uses disaggregate data and use it as explanatory variables to increase the information available to the model of the aggregate CPI (see for example Hendry and Hubrich 2006).

In the present document I take a hybrid of these two approaches. Where not only do I model the disaggregate components of the CPI, but I also use these components as explanatory variables for the disaggregate data.

An advantage of using disaggregate models is that they provide an insight of the dynamic process and internal behavior of the aggregate variable that is not possible to obtain using standard aggregate models. This details can be very useful tools for policy analysis and forecasting, therefore complementing the existent aggregate models.

The ability to produce an accurate forecast of inflation under low and stable inflation becomes more difficult due to the lack of variance in the variable. In this sense aggregate forecasting models tend to perform better under high levels of inflation and volatility. But when they are use to forecast under low level of inflation and low volatility their accuracy is diminished. Is under this situation that disaggregate models can improve the forecasting ability by using the volatility and information at disaggregate level. This situation is particular important to the authorities of the Central Bank of Costa Rica, given the fact that the level of inflation and its volatility has decrease significantly in the last three years.

An accurate forecast of inflation gives an advantage, and therefore policy-makers can improve on their decision making process, specially under the inflation target (IT) regime. Given that an accurate forecast will signal effectively which monetary policy should be implemented before inflation affects the inflation expectations of the agents.

The paper is organized as follows. First, Section 2 briefly reviews the literature related to disaggregate forecast of inflation and models used by the Central Bank of Costa Rica. In Section 3 a I review the notion of predictability of the aggregate and disaggregation of models, and also a review of the Phillips Curve. Section 4 describes the data and the sample used for the estimation. In Section 5 the empirical framework is presented, with the main results and a forecast accuracy analysis. Section 6 concludes.

2 Literature Review

The literature has different perspectives and analysis regarding the aggregate and disaggregate modelling for forecasting. The approach followed by this document has not been done before. But is in the spirit of Cobb (2009). Where he uses a number of methods based on univariate and multivariate autoregressive models, with different levels of disaggregation. He finds that certain level of disaggregation could be beneficial under certain circumstances the disaggregate approach captures the underlying dynamics of inflation.

In a working paper by the European Central Bank, Hendry and Hubrich (2006) develop a theoretical model that suggest that using disaggregate information to forecast the aggregate variable as opposed to forecast the disaggregate variables separately and the aggregation those forecasts.

The paper by Hlédik (2003) models the second round effects for the Czech economy using a small-scale dynamic rational expectations model. Using staggered wage settings to quantify the second-round effects. The author highlight the importance of the second-round effects of import prices and the nominal exchange rate for policy-making.

For the Australian economy Ravazzolo and Vahey (2010) find that out-of-sample forecast performance of an ensemble predictives for inflation outperform a benchmark autoregressive model.

Rodríguez and Mora (2009) discuss the aggregation of a variety of forecasting models for inflation used by the Central Bank of Costa Rica. In 2001 the Central Bank of Costa Rica developed a combination of inflation forecasts which constitutes the basis for the forecasts discussed in the Inflation Report, and which is the main tool for monthly passive forecasting. The individual forecast models were revised in 2008. Using these revisions as a starting point, this document focuses in assessing the performance of alternative methodologies for combination, including those which allow for the possibility of structural change. For the period June 1996 – October 2008, dynamic forecasts were calculated using the six forecast models developed by the Central Bank of Costa Rica. These forecasts were combined through weighted least squares, state-space and smooth transition methods. In general, these techniques resulted in a reduction of the forecast error in comparison with the original models and the current optimal combination.

According to Grunfeld and Griliches (1960) there are some advantages of using an aggregate model. They are less prone to specification errors. Disaggregate data errors cancel out when added together. On the other hand Aigner and Godfield (1974) find that using disaggregate model allow for different specification across disaggregate variables, model individual dynamics, and interaction between variables. Balancing out this pros and cons it is possible to find some middle ground using the disaggregate data of the CPI by groups and not by subgroups or categories.

The Economic Research Department of the Central Bank of Costa Rica has produce different fore-

casting models for inflation In 2001 the Central Bank of Costa Rica developed a combination of inflation forecasts which constitutes the basis for the forecasts discussed in the Inflation Report, and which is the main tool for monthly passive forecasting. The individual forecast models were revised in 2008. The document by Mora and Rodríguez (2009) focuses in assessing the performance of alternative methodologies for combination, including those which allow for the possibility of structural change. For the period June 1996 – October 2008, dynamic forecasts were calculated using the six forecast models² developed by the Central Bank of Costa Rica. These forecasts were combined through weighted least squares, state-space and smooth transition methods.

Alvarez and Torres (2011) estimate a set of short-term Phillips Curve projection models for quarterly and monthly series of headline inflation and their breakdowns in tradable and non-tradable of the consumer price index. They evaluate the hypothesis if the forecast errors from a weighted inflation projection (which results from combining inflation forecasts for the breakdowns of tradable and non-tradable) are lower than those obtained from a projection of the aggregate inflation rate. The empirical evidence provided by this paper suggests the usefulness of distinguishing between the data generating processes of inflation in tradable and nontradable sectors.

3 Theoretical Framework

Estimation uncertainty is intrinsic of any econometric model, nevertheless it is a bigger problem for disaggregate models, given that the variables used tend to be more volatile because of their microeconomic origin. Whereas aggregate data tend to behave in a more stable fashion because disturbances tend to dilute or cancel each other.

The value of disaggregate information can be off-set by an array of different reasons: estimation uncertainty, measurement errors, model selection uncertainty, structural breaks.

Another problem related to disaggregate data arise from the possibility of measurement errors. In this case the fact that disaggregate data is less used than aggregate data increases the possibility that it contains errors that has not previously been spotted. Also a disaggregate model uses more data therefore is more prone to contain some kind of measurement errors. Related to the previous fact, that disaggregate data is in general less used into models, also creates a problem that the selection of the model in general has not been previously studied making a greater uncertainty for the appropriate model. Also analysis of structural breaks is less common in the disaggregate data, raising the possibility of not taking into account a structural break in the disaggregate data.

²This six forecast models are a Univariate Inflation Model, a VAR for the Transmission Mechanism of Monetary Policy, a Model for the Effect of Oil Prices, a Model of Treasury Bonds, a model of Pass-Through Effect of Nominal Exchange Rate and a Naive Model.

Even with the previous caveat, the utilization of disaggregate data provides a larger information set, and also it is possible to produce a model that is closer to the actual data generating process present in the variable.

3.1 Predictability of the aggregate and disaggregation

In this section I follow Hendry and Hubrich (2006) in developing a theoretical framework to analyse the predictability of the aggregate and disaggregate approach. The main difference with respect to Hendry and Hubrich (2006) is that they use the implicit assumption that the information set does contain the disaggregate data, they use this disaggregate data to improve predictability of the aggregate data, while in this paper I use the disaggregate data to explain not only the aggregate variable but the disaggregate variables as well. The theory suggest that by using this interaction between disaggregate data the model will improve predictability if the model is able to approximate the data generating process.

3.1.1 Unpredictability and Predictability

A vector random variable π_t is unpredictable with respect to an information set I_{t-1} . If its conditional distribution is equal to its unconditional distribution, as shown in equation (1).

$$(1) \quad D_{\pi_t}(\pi_t|I_{t-1}) = D_{\pi_t}(\pi_t)$$

If the result of equation (1) does not hold, hence $D_{\pi_t}(\pi_t|I_{t-1}) \neq D_{\pi_t}(\pi_t)$ then the information set I_{t-1} is relevant for the predictability of π_t . This means that:

$$(2) \quad \pi_t = f_t(I_{t-1}) + \epsilon_t$$

Another important corollary of this result is that:

$$(3) \quad V[\pi_t|I_{t-1}] < V[\pi_t]$$

Which means that the conditional variance of π_t is less than the unconditional variance.

As stated by Hendry and Hubrich (2006) predictability is relative to the information set used. If an information set $J_{t-1} \subset I_{t-1}$ it is possible to show that the use of this subset of information will provide an unbiased prediction. but with a higher variance.

3.1.2 Predictability of a Disaggregation

Consider a variable π_t composed by two disaggregate variables ($p_{i_1,t}p_{i_2,t}$). As shown in equation (4).

$$(4) \quad \pi_{T+1} = \omega_{1,T+1}\pi_{1,T+1} + \omega_{2,T+1}\pi_{2,T+1}$$

$$(5) \quad E_{T+1}[\pi_{i,T+1}|I_T] = \delta_{i,T+1}I_T$$

Note that information set I_T by construction includes the η^n generated by the past of the $\pi_{i,t-j}$

Taking conditional expectation on equation (4):

$$(6) \quad E_{T+1}[\pi_{T+1}|I_T] = \sum_{i=1}^2 \omega_{i,T+1}\delta_{i,T+1}I_T = \lambda_{i,T+1}I_T$$

Restricting the information set I_T by not taking into account the interaction not only between $\pi_{CPI,t}$ and $\pi_{i,t}$ but also between the different groups will reduce the information set to J_T . According to the previous section, predictions based on i_T and J_T both will unbiased, the prediction under J_T according to equation(3) will have a larger mean square error.

The addition of interaction ³ between the $\pi_{i,t}$ not only increase the information contain in J_T but also approximates more closely the data generating process.

There are many steps between predictability and 'forecastability'. Predictability need not translate into forecastability in finite samples when the forecast model differs from the data generation process.

3.2 Phillips Curve

I use the standard Phillips Curve (PC) with some modifications to develop the mechanism between the macroeconomic variables and the groups of the CPI as well as the PPI inflation. Assuming that agents follow Adaptive Expectations ⁴ according with:

$$(7) \quad E_t(p_{i_{t+1}}) = E_t(p_{i_t}) + \theta[p_{i_t} - E_t(p_{i_t})]$$

³The data shows that there is covariance between the groups (see figure (12))

⁴adaptive expectations means that people form their expectations about what will happen in the future based on what has happened in the past, in contrast to Rational Expectations.

If θ converges to 1, meaning that the expectations will be corrected very rapidly then equation (7) will be $E_t(p_{t+1}) = p_t$. Transforming the Phillips Curve to:

$$(8) \quad \pi_t = \beta_1 + \pi_{t-1} + BZ_{t-1}$$

Where Z_{t-1} is a vector of explanatory variables which could include the product gap, the nominal exchange rate among others. This Phillips Curve is the standard Phillips Curve with backward looking expectations.

It is possible to apply equation(7) not only to the aggregate CPI, but also to the individual groups that make the CPI. For the individual group case of the Phillips Curve, the fact that agents follow Adaptive Expectations with an instantaneous corrections ($\theta = 1$), is very useful since no estimation of inflation expectation for each individual group of the CPI exists. Even more, it is very unlikely that agents do in fact have any kind of inflation expectation for each group.

$$(9) \quad \pi_t^i = \beta_1^i + \pi_{t-1}^i + B^i Z_{t-1}$$

Assuming that Z_{t-1} is common for every i ⁵ it is possible to use a common variable that takes into account the different explanatory variables. This instrumental variable could be the PPI inflation. Given that PPI could also follow a Phillips Curve.

$$(10) \quad \pi_t^{PPI} = \beta_1^{PPI} + \pi_{t-1}^{PPI} + B^i Z_{t-1}$$

Where Z_{t-1} is the product gap, the nominal exchange, oil prices and policy interest rate plus the interaction between the groups of the CPI.

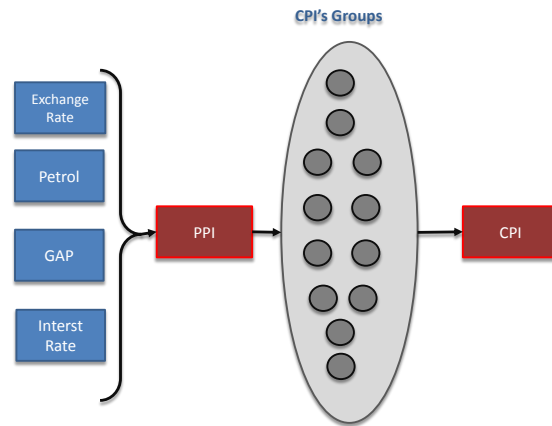
Transforming equation(9) into:

$$(11) \quad \pi_t^i = \beta_1^i + \pi_{t-1}^i + B_2^i \sum_{i \neq j}^G \pi_t^j + B_2^{IPPI} \pi_t^{PPI}$$

The figure (1) shows the transmission mechanism of the model in a diagram. Where it is possible to observe the only four exogenous variables: exchange rate, oil prices, policy interest rate and product gap. This four variables enter directly in the model via the PPI and then they affect the groups that form the CPI indirectly via the effect of the PPI on each group. Then the different groups interact with each other and at the end the CPI is constructed using the weights for each particular group.

⁵The use of PPI inflation as an explanatory variable for each group, that takes into account the information in Z_{t-1} , and can also capture the common factor present in the variables or other type of unobservable variable.

Figure 1: Transmission Mechanism in the Model



4 Data

The main objective of the Central Bank of Costa Rica is to obtain a low and stable level of inflation. But it was not until 2009 that the level of inflation was below one digit. Previously Costa Rica suffered a period of almost 26 years of inflation above ten percent. This period of high inflation had two characteristics, an important inertia of inflation, and a high degree of pass-through. After the implementation of the crawling band regime for the exchange rate the level of pass-through decreased significantly. Also the inertia in the inflation has decrease with the recent reduction of the level of inflation. In this respect Chaverri and Torres (2010) and Torres (2012) found some supporting evidence of an structural break in inflation after 2006.

The sample used in this paper starts on July 2007 and finishes on April 2012 for a total of 58 observations. The reason to cut the sample is twofold, first is to use a consistent measurement of CPI, this is specially important given the use of disaggregate data for the estimation of the CPI inflation. On the other hand this reduced sample allows to concentrate the estimation on a period of low and stable inflation, that relates to the implementation of a more flexible exchange rate regime and the possible presence of a structural break. ⁶

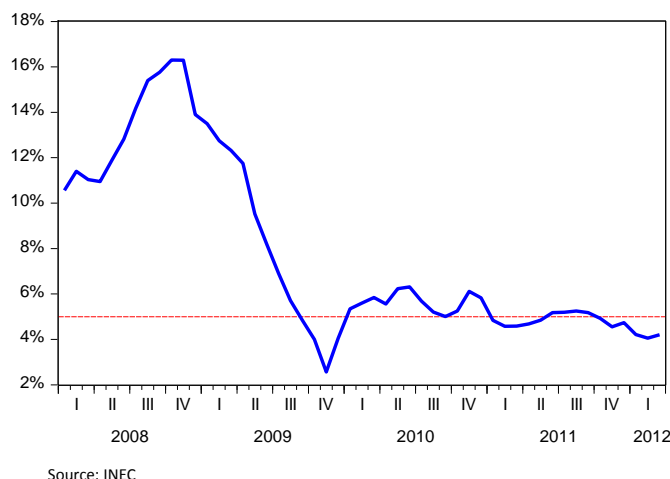
Another advantage of using a shorter sample is that it allows the use of the policy interest rate, instead of the *Tasa Básica Pasiva*, which has been the interest rate of reference for a long period of time. While the policy interest rate has just been officially only until 2010. Nevertheless the policy interest rate is set to become the interest rate of reference in the economy as the Central Bank moves

⁶In 2006 the Central Bank of Costa Rica established an exchange rate crawling band to substitute a crawling peg regime that was in place from 1982

closer to an Inflation Target Regime in the near future.

Though the sample selection does impose some limitations to the empirical analysis. This is one of the explanations of why a SVAR was not estimated. Also poses a problem establishing whether the series have a unit root or not. But because this model capture the recent dynamic of inflation and it will be updated the problem of a short sample will be overcome.

Figure 2: Consumer Price Index yearly change



As the graph in figure(2) it is possible to divide the recent history of inflation in two periods. One before 2009 and one afterwards. The first part has shows an important period of deflation explained by the commodity prices reduction after the international crisis. While the second part shows a stable level of inflation around 5 percent, which is also the inflation target set by the Central Bank for those years.

The CPI of Costa Rica is done by the INEC (National Institute of Statistics and Census). And is composed by 292 goods and services, which are band together into 54 categories. This categories are bound into 31 subgroups and these are finally grouped into 12 main groups. This groups are: 1) Food and Non Alcoholic Beverages. 2) Alcoholic Beverages and Cigarettes. 3) Food and Drinks out of home. 4) Clothing and Footwear. 5) Rent and Housing Services. 6) Articles for Housing and Domestic Services. 7)Health. 8)Transport. 9) Communications. 10) Entertainment and Culture. 11) Education and 12) Various Goods and Services ⁷.

The calculus of the CPI was updated in July 2006 by the INEC. This new CPI substituted the old CPI with base 1995. The new CPI with base 2006 ⁸ include some important changes that have an effect on the estimation of the disaggregate model. This changes are:

⁷The observed inflation for each group is presented on figure(13)

⁸For a detail comparison between the CPI base 1995 and 2006 see *Metodología del Índice de Precios al Consumidor Base Julio 2006, INEC*

- Update the basket of goods and services.
- Update the weights.
- Update on the number of Groups.
- Application of a new formula for changing prices.
- Application of a new classification of the goods and services.
- Updating of the sample of establishments used to collect the data.

Regarding this changes the fact that some goods where dropped from the new CPI and that the classification of the goods and services in different groups changed, makes almost impossible to estimate a disaggregate model without incurring in serious consistency problems. Therefore a shorter sample was preferred.

Figure 3: Groups and Weights of the CPI

Group	Name of Group	Weights
G01	Food and Non Alcoholic Beverages	18,61%
G02	Alcoholic Beverages and Cigarettes	0,69%
G03	Food and Drinks out of home	8,61%
G04	Clothing and Footwear	5,86%
G05	Rent and Housing Services	10,64%
G06	Articles for Housing and Domestic Services	8,65%
G07	Health	4,81%
G08	Transport	18,19%
G09	Communication	4,45%
G10	Entertainment and Culture	7,25%
G11	Education	5,89%
G12	Various Goods and Services	6,35%
CPI	Total	100,00

On the other hand, even if the sample is reduced because of the use of disaggregate data. One advantage of using a disaggregate model during a period of lower and less volatile level of inflation is the fact that it is possible to obtain information from the volatility within the components of the head line CPI inflation.

In this sense figures (4) and (5) show how a twelve months moving variance of the groups that form part of the CPI and the CPI itself have had a negative trend during the sample. But if you take the relative twelve month moving variance of the groups, it is possible to see that not only it does not have a negative trend, but that after the inflation stabilizes around 5 percent the dispersion of the relative variance has increase. These results show that it is possible to extract more information of the behaviour of the CPI inflation using the disaggregate data than using aggregate data.

Figure 4: Twelve Months Moving Variance of Groups

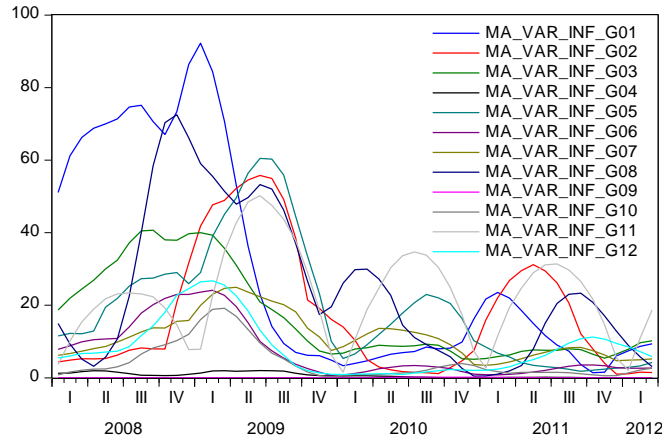
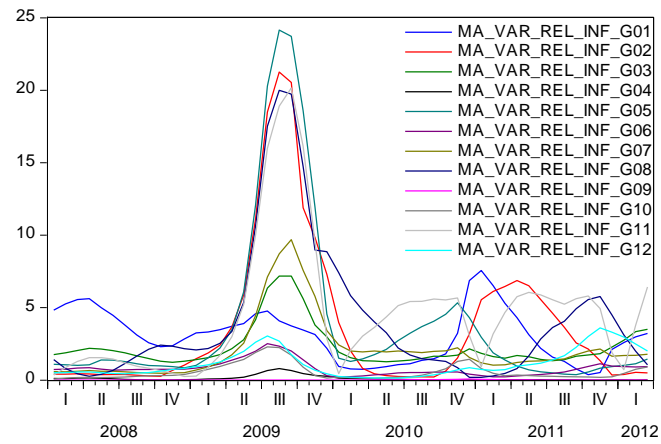


Figure 5: Twelve Months Moving Variance of Groups Relative to CPI



Figure(4) shows a generalized reduction of volatility starting in 2010. Not only does the volatility was reduced but also the volatility across groups seem to fall as well. Though if we take figure(5) a different picture emerge. In that graph the relative volatility across groups actually increases after 2010. And in 2009 which is the year were the inflation fall from almost 15 percent to 5 percent, the relative volatility increased for almost all groups with respect to the volatility of the aggregate CPI. This could be explained by the fact that the volatility of the groups cancelled up during this period once you aggregate the groups. Or that in this period there was an increase in the volatility but some groups had a big disinflation while other kept with the inertia they had from previous years.

4.1 Variables

Both the PPI and the CPI data is collected and calculated by the National Institute of Statistics and Census (INEC) on a monthly bases. The exchange rate data is the average buy-sell exchange rate of the month. The oil prices used in the estimation is the West Texas Intermediate and the data is obtain from the IFS As a proxy for the monthly GDP the Monthly Index of Economic Activity (IMAE) is used. To obtain the product gap the trend is obtained using the Hodrick Prescott Filter. The policy interest rate is calculated for the first part of the sample, and after 2010 is the observed one.

Unit Root tests were applied to the level of inflation for the CPI, PPI and each Group of the CPI, in each particular case except for two groups it is impossible to discard the null hypothesis of unit root. But given the short sample available and the low power of the tests there is no conclusive evidences. Furthermore the aggregate model does not behave explosively, instead it converge rapidly when an exogenous shock is applied to the system.

5 Empirical Framework

There are two main objectives in this document. The first objective is to provide a disaggregate model for forecasting headline inflation of CPI using disaggregate data. The second objective is to estimate the second round effects that generate from a shock to the exogenous variables in the model. Both of which are tackle by the estimation of the disaggregate model.

The coefficients for the aggregate and disaggregate model are estimated equation by equation using OLS. Estimation of the respective lag are obtain running all different combinations of lags from zero to twelve for every explanatory variable. The equation is then choose following the AIC, BIC, the adjusted R^2 and the F-Statistic.

In this section an aggregate inflation model is presented along with a second aggregate model that mimic the disaggregate model. And then the disaggregate inflation model is also shown.

5.1 Aggregate Inflation Model

This section presents a modified version of the standard New Keynesian Philip Curve. Is a single equation model. Where the CPI inflation depends on its lagged value to capture the inertia in the system or a backward looking expectations. It also depends on the level yearly percentage change of the exchange rate, the oil prices, the product gap, the policy interest rate and a exogenous shock.

$$(12) \quad \pi_{cpi,t} = \beta_0 + \beta_1\pi_{cpi,t-1} + \beta_2e_{t-8} + \beta_3oil_{t-3} + \beta_4gap_t + \beta_5i_{t-8} + \epsilon_{cpi,t}$$

An alternative specification (equation (13)) reduces the number of coefficients and takes into account the relation of causality found between CPI inflation and PPI inflation. And mimic in an aggregate level the estimation of the disaggregate model.

$$(13) \quad \pi_{cpi,t} = \beta_0 + \beta_1\pi_{cpi,t-1} + \beta_2\pi_{ppi,t-2} + \epsilon_{cpi,t}$$

The results for these two equations are presented in the second and third column of figure(7). Note that using both specifications the equation doesn't take into account the information related to the interaction between groups.

The estimated coefficients of equation(12 show the expected sign. All but the GAP_t are statically significant at 5 percent. The coefficient of the lag inflation is close to 1, meaning a great level of inertia in the inflation. The effect of the nominal exchange rate (pass-through) is almost 5 percent. The estimation has a high level of fit with an R^2 equal to 0.97 There seem to be some problems of autocorrelation in the residuals with a Durbin-Watson statistic of 1.47.

5.2 Disaggregate Inflation Model

Using the data available from the dynamics of the components of the CPI it is possible to obtain a disaggregate model for inflation. This model not only could improve the forecast of inflation, but given its flexibility is able to explain the interaction across the different groups that form the CPI.

$$(14) \quad \pi_{PPI,t} = \delta_0 + \delta_1\pi_{ppi,t-1} + \delta_2et + \delta_3oilt + \delta_4gap_t + \delta_5it + \epsilon_{PPI,t}$$

$$(15) \quad \pi_t^i = \beta_0 + \beta_1^i\pi_t^i + \sum_{i \neq j} \sum_{k=0}^L B_k^{ij} \pi_{t-k}^j + \gamma^i \pi_{t-m}^{PPI} + \epsilon_t^i$$

It is possible to observe that the number of coefficients present in equation (15) is very large, specially given the expression $\sum_{i \neq j}^G \sum_{k=0}^L B_k^{ij}$ ⁹ which by itself add 143 coefficients to the estimation. This makes that equation (15) alone has a total of 146 coefficients. Given that this equation has to be estimate for every group in the CPI the and given the equation (14) the total number of coefficients for the whole systems is a total of 1,758. In order to reduce the number of coefficients to estimate given the short sample ¹⁰ the strategy use was to limit the number of interaction between groups to those only significant according to the Granger Causality Test, and using only the most significant lag.

$$(16) \quad \pi_t^{CPI} = \sum_i^G \alpha^i \pi_t^i$$

Where the α^i are the weights of the groups in the CPI, as shown in figure (3).

The disaggregate model used in this document is composed by the equations (14), (16) and twelve individual equation for each group following the equation (15), ordered from the more exogenous to the more endogenous. To solve the model the Broyden's Method is used. The Broyden's Method is a modification of Newton's method ¹¹.

5.2.1 Granger Causality Between Groups

In order to reduce the number of possible interaction between the groups of the CPI, I use the standard Granger Causality Test ¹² to include in equation (15) only the groups for which the test show a 1 percent significance. The use of the Granger Causality to exclude interactions between groups of the CPI helps to maintain a parsimonious model, and reduce the noise in the forecast created by non-significant interactions. Also by applying this rule the $\sum_i^G \sum_{i \neq j}^G B_k^{ij}$ can be reduced from 132 to a total of 30 interactions, without taking into account the lags.

Using the same results one can order the groups from the most exogenous to the most endogenous. This order could be implemented counting the number of groups that are used to explain the each group behaviour and also counting the number of times each group appears as an explanatory group for other group. By following this approach I find that the two most exogenous groups are *Food and Non*

⁹The expression $\sum_{i \neq j}^G \sum_{k=0}^L B_k^{ij}$ could also be represented as a B_M matrix of (11x13) given the eleven explanatory groups and lags between zero to twelve.

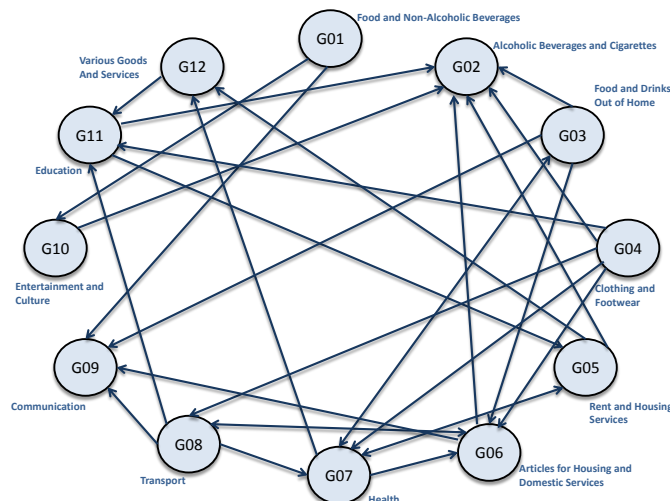
¹⁰The sample include 70 observations of CPI level and 58 of CPI inflation

¹¹Newton's method for solving a system of non-linear equations consists of repeatedly solving a local linear approximation to the system.

¹²The Granger (1969) approach to the question of whether x causes y is to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. y is said to be Granger-caused by x if x helps in the prediction of y , or equivalently if the coefficients on the lagged x 's are statistically significant. Note that two-way causation is frequently the case; x Granger causes y and y Granger causes x .

Alcoholic Beverages and Clothing and Footwear. While the two most endogenous groups are *Alcoholic Beverages and Cigarettes* and *Health*.

Figure 6: Granger Causality



The groups *Alcoholic Beverages and Cigarettes* and *Communications* do not affect any of the other groups While *Clothing and Footwear* affect a total of 5 other groups.

5.2.2 Equation for Producer Price Index

The model uses the inflation of the PPI as an instrumental variable for the four exogenous variables. The result of the estimation using OLS for this equation are presented on the first column of figure(7). The adjusted R^2 is 0.99 which is quite high. All the coefficients have the expected sign and all are statistically significant at 1 percent.

Some interesting results of this estimation is that on the contrary of the equation estimated for the CPI, the level of pass-through of the nominal exchange rate is quite large almost 0.5. While on the contrary the inertia present in the PPI inflation is 0.45, smaller than the one of the CPI. Also no problem of autocorrelation with a Durbin Watson statistic of 1.98. It is possible to say that the model of PPI is better than the model for CPI inflation.

5.2.3 Equations for each Group

Each equation was chosen using the Akaike Information (AIC) and Schwarz (SIC) criterion the F-statistic and the Adjusted R^2 . Allowing for lags from zero to twelve for each variable. No a priori restriction regarding the sign of the coefficient was applied. The result of the estimation of each group equation is shown in figure(8).

Figure 7: Equation for PPI and CPI Inflation

	π^{PPI}	π^{CPI}	π^{CPI}
C	0.066 1.08	0.017 2.96	0.005 2.15
π^{CPI}		0.935 36.21 -1	0.832 18.09 -1
π^{PPI}	0.450 4.62 -1		0.070 3.95 -1
e	0.486 5.41 0	0.046 2.51 -8	
Oil	0.057 4.97 -2	0.006 2.27 -3	
GAP	0.567 2.67 -8	0.060 1.41 -8	
i	-0.700 -3.14 -5	0.185 2.77 -5	
Adj. R²	0.99	0.97	0.96
F – Statistic	669.36	376.23	772.27
AIC	-6.02	-7.16	-6.98
BIC	-5.76	-6.94	-6.88

Figure 8: Estimated Equation for the Groups of CPI

Group	G01	G02	G03	G04	G05	G06	G07	G08	G09	G10	G11	G12
G01	0.870 18.28 -1								-0.031 -2.94 -1	0.100 2.44 -10		
G02		0.162 1.62 -1										
G03		-0.393 -3.41 0	0.817 11.61 -1			0.379 10.32 0			0.032 1.60 -1			
G04		-1.40 -6.07 -10		0.821 15.72 -1		-0.322 -4.83 -7	0.478 7.07 0	1.694 6.84 -11			0.135 2.85 0	
G05		0.450 3.57 -2			0.442 3.90 -1		0.338 3.87 -6					0.057 -1.94 -12
G06		0.394 2.09 -11				0.127 1.52 -1		0.256 3.06 -12	0.013 1.38 -12			0.140 2.11 -3
G07			0.133 1.37 -1		0.147 1.47 -12	0.199 3.80 -3	0.093 0.81 -1					
G08						0.045 4.70 -2	0.136 5.48 -1	0.367 3.50 -1	-0.035 -6.14 -4		0.039 3.23 -6	
G09									0.338 2.89 -1			
G10		-0.563 -3.16 -12								0.566 5.27 -1		
G11		1.581 3.583 -3			1.352 4.68 0						0.865 14.10 -1	
G12							-0.085 -2.07 -7				0.015 0.46 -8	0.570 6.78 -1
PPI	0.115 2.74 12	-0.282 -5.26 -8	0.088 3.96 0	0.025 2.97 -12	0.040 1.86 -1	0.066 5.16 -6	-0.102 -4.20 -1	0.480 5.55 -1	0.051 5.94 -4	0.129 5.61 -5	0.030 3.54 0	0.108 5.57 -3
Adj. R2	0.97	0.96	0.98	0.91	0.95	0.99	0.98	0.91	0.97	0.96	0.97	0.97

In general all estimated equation have a fit the data well, with adjusted R^2 ranging from 0.98 to 0.91. The group of Education (G11) has the highest level of inertia, while Health (G07) exhibit almost no inertia at all. Also groups of Health and Alcoholic Beverages and Cigarettes (G07 and G02) show a negative but significant relationship with PPI inflation. The optimal lag for the PPI inflation varies greatly across estimation from a twelve month lag to no lag at all.

5.3 Forecast Performance

To analyse the performance of the aggregate model of CPI and the disaggregate model, I use the standard procedure that consist in estimate the Mean Square Error (MSE) and the Mean Absolute Error (MAE) for a dynamic forecast of 6 months rolling window starting on January 2009. The

The results show that according to the MSE the aggregate model outperform the disaggregate model by a small margin. But the disaggregate model performed better during the period of disinflation. But the results using the MAE favour the disaggregate model. These contradictory results arise from the fact that both models perform remarkably similar within de samples. And the fact that the MSE penalize larger error. The second aggregate model and AR(2)¹³ benchmark model perform poorly relative to the disaggregate and first aggregate model, this suggest that the information set used on the last two does increase the *forecastability*.

Figure 9: Forecasting Accuracy

	Disaggregate Model	Aggregate Model 1	Aggregate Model 2	AR(1) Model
MSE	0.9648	0.9292	1.4577	3.9555
MEA	0.7420	0.7986	1.0484	1.4690

Nevertheless the results show that using the disaggregate model for forecasting will not reduce the forecasting accuracy, and on the other hand will provide the policy maker with a more detail forecast, because it not only will produce a forecast for the CPI but also for its components and the PPI.

In the section at the end of the document on the figure(14) the forecast with the 6 month windows for each group of the CPI using the disaggregate model.

¹³The use of an AR(2) model as the benchmark model is suggested by Vindas (2011), as the best performing AR(p,q) model for the case of the inflation in Costa Rica.

5.4 Dynamic Decomposition

The specification of the disaggregate model let differentiate the dynamic behaviour of the aggregate CPI into inertia and second round effect dynamics. This is important because for policy making the reaction should be to minimize the second round effects, but a policy response to reduce inertia could overreach.

Having the possibility to differentiate between this two dynamics will create a more effective policy response to supply shocks such as an increase in the price of oil, or an un expected movement on the exchange rate, or even a change in the sales tax.

Using the model it is possible to obtain an algebraic expression for the dynamics of an exogenous shock on the PPI inflation.

$$(17) \quad \pi_t^{PPI_1} - \pi_t^{PPI_0} = \sum_{t_0}^t \delta_1^{t-t_0} \varepsilon_t^{PPI}$$

$$(18) \quad \pi_t^{i_1} - \pi_t^{i_0} = \sum_{t_0}^t \beta_1^{it} \left\{ \varepsilon_t^i + \sum_{j \neq i}^G B_k^{i,j} \varepsilon_t^j + \gamma^i \sum_{t_0}^t \delta_1^{t-t_0} \varepsilon_t^{PPI} \right\}$$

$$(19) \quad \pi_t^{CPI_1} - \pi_t^{CPI_0} = \sum_{i=j}^G \alpha^i \left(\sum_{t_0}^t \beta_1^{it} \left\{ \varepsilon_t^i + \sum_{j \neq i}^G B_k^{i,j} \varepsilon_t^j + \gamma^i \sum_{t_0}^t \delta_1^{t-t_0} \varepsilon_t^{PPI} \right\} \right)$$

Where ε_t^{PPI} , ε_t^{CPI} and ε_t^i are the exogenous shocks for the PPI, the CPI and the i group respectively. And where $\pi_t^{PPI_0}$, $\pi_t^{i_0}$ and $\pi_t^{CPI_0}$ are the base line scenarios for the PPI inflation, group i inflation and CPI inflation respectively.

Using equations (17), (18) and (19) is possible to study and extract the inertial component and the second round effect component at any time t for the model. Defining $B_k^{i,j} = 0, \forall i$ the model only takes into account the inertia in the system. This feature is important because it allows to extract the Second-Round Effect

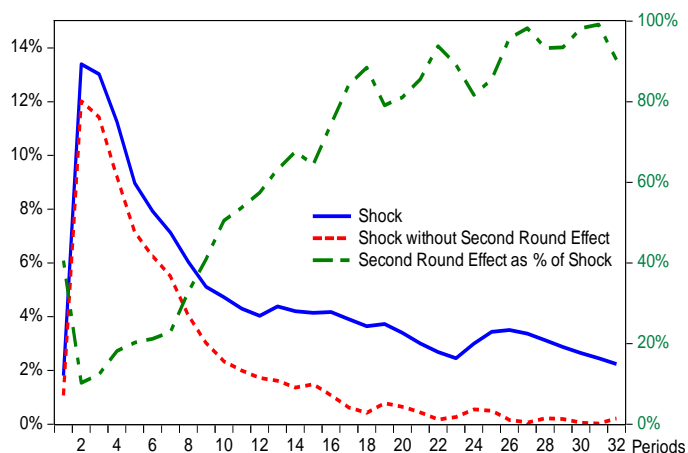
5.4.1 Decomposition of Shocks

To clarify the results of the dynamic decomposition and to show the flexibility of the model, I do two possible scenarios from a vast array of possibilities ¹⁴. The first scenario is a an exogenous transitory

¹⁴Other possibilities include, shocks to the nominal exchange rate, to the product gap, oil prices, policy interest rate, or an individual shock for a group of the CPI (See figures (15) (16) and (17)) or even a shock to a particular good or services on the CPI. Also each of this shocks could be permanent or temporary.

shock to the PPI inflation, and the second one is a scenario simulating a permanent increase in sale tax of 1 percent for each good and service in the CPI.

Figure 10: Effect of an Exogenous Shock on PPI



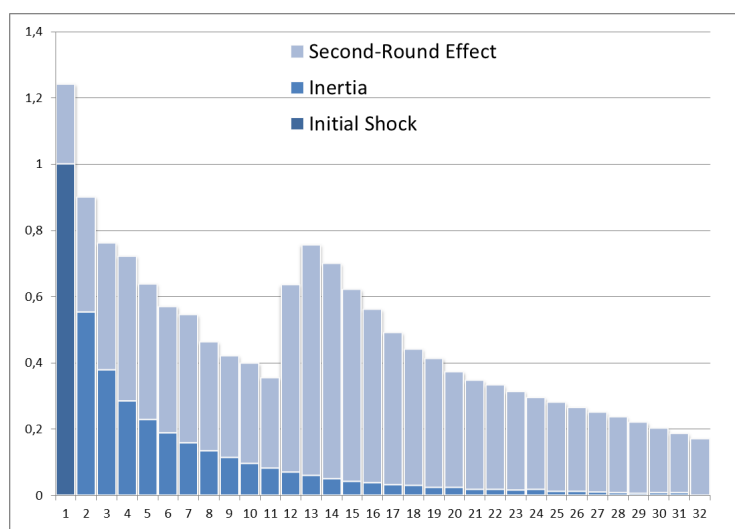
Figure(10) shows the response of the disaggregate model to a 1 percent exogenous shock on the PPI inflation. This shock has a total effect 0.13 on the head line CPI inflation with a two months lag. The dotted line show the dynamic of the same shock if we do not take into account the interaction between groups (Second-Round Effect). As suggested by the literature the inertia is an important component during the first periods before the shock but for latter periods the second round effects kicks in and becomes the main driving force behind the dynamics of the aggregate CPI inflation. An interesting result is that after the 10th month the Second-Round Effect represent more than 50 percent of the inflation generated by the exogenous shock. And while the inertia dissipate after 18 month, the Second-Round Effect keeps going on after 32 months.

The persistence present in the Second-Round Effect should be noted, because even if it dissipates in the long-run. A combination of exogenous shocks could add-up and have an effect on the expected inflation by the agents in the economy.

A possible situation that a policy maker could face is an increase of the sale tax imposed by the central government. This increase in the sale tax will have an effect on the inflation that could be subject to a policy response by the Central Bank. To make the scenario simple, I assume that there are no exemptions to the sale tax, and that the increase is symmetric for all good and services that compose the CPI ¹⁵. Figure(11) the response of headline inflation to this particular shock is shown. In the first period there an increase of inflation equal to 1.24 percent which is greater than the actual 1 percent

¹⁵This assumption of symmetry could be relaxed to create a more realistic scenario

Figure 11: Dynamic Decomposition of a Exogenous Tax Shock



shock. This difference rises from the effect of the shock of the each group on other groups inflation.

The inertia in the system dissipates rapidly, being almost negligible after twelve months. On the other hand the Second-Round Effect shows a more persistent behaviour, there is even an increase in the head line inflation one year after the initial shock, passing from 0.35 percent in the eleventh month to 0.76 percent by the thirteenth month. This unexpected acceleration in the inflation is explained completely by the interactions between the groups present in the model. The results provided by the model show that even if the policy-makers decide not to act directly on the effect of the increase in tax on inflation, it could be optimal to react before the Second-Round Effect takes place and deviate the inflation from its target.

5.5 Results

In this section I summarize some of the most important results obtained by the model. The results derive from the interaction of the different variables in the model and allow to put some non parametric estimates on different economic values.

The effect of an temporary ¹⁶ increase of 1 percent in the inflation of PPI produces an increase of 0.1343 percent in the aggregate CPI inflation.

Another interesting result regards the pass-through of exchange rate on headline inflation. Recent studies show that for the case of Costa Rica this coefficient has decrease significantly, and given the its lower level it has been difficult to obtain a statically significant measurement of it. Rodríguez (2009)

¹⁶A transitory shock is define as an increase of 1 percent for one month only.

found that the pass-through coefficient was estimated to be 0.05 in the short run and 0.36 in the long run. And also found evidence that '*stability analysis suggests that there has been a decrease in the pass-through coefficient which coincides with the crawling band period.*'

Using the model it is possible to obtain a measurement and the dynamics of the effect of the pass-through given a transitory and permanent shock on the exchange rate. In the case of a transitory shock the maximum effect is 6.44 percent and occurs with lag of one month. While the permanent effect reaches a total of 74.39 percent after 30 months. The results show that even if the effect of a transitory shock is relatively small, a permanent shock on the exchange rate will have an almost 3/4 of pass-through

If we control for the second round effect the pass-through decreases to 5.91 percent with one lag for the transitory shock and to 36.65 percent for the permanent shock.

Other results for the exogenous variables show that an increase of 1 percent in the price of oil has different effects if it is permanent or transitory. If it is permanent the effect is 8.54 percent and if it is transitory is only 0.81 percent. The effect of an increase of 100 base points in the policy interest rate will decrease inflation if it is transitory or permanent by -9.42 and 107.23 respectively.

6 Conclusion

The disaggregate model used to forecast inflation not only improves the tools at hand of the policy-maker. But also provides estimations on the effect and its dynamics of variations in the nominal exchange rate, oil prices, output gap and effect of the interest rate. This estimated effects can shed light into what policy should be implemented.

Also provides an insight on which movements on a group of the CPI could have an effect on the aggregate CPI. By doing so it allows to weight the effect of a shock in one group of the CPI not by its weight in the Index per se but by its contribution on the dynamic of the system.

Utilizing the disaggregate model, one can decompose the dynamics of the model on initial shocks, inertial inflation, and second round effect of the shocks. As well a non parametric estimation of some important characteristics of inflation such as pass-through of nominal exchange rate, oil prices can be done.

The model could be used to provide information regarding different types of scenarios regarding external and internal shocks. Policy implications:(i) Models not taking into account the second round effect may underestimate the policy response needed to reduce its effects. (ii) The authorities need to analyse closely movements in the disaggregate groups of CPI to take the effective measurements.(iii) The effectiveness of the policy interest rates varies across groups.

It is possible to conclude that disaggregate information might help for forecasting the aggregate in

the particular case of Inflation in Costa Rica. This is in line with the theoretical results on predictability. Nevertheless the theoretical prediction that disaggregate information should increase forecast accuracy, is not strongly supported by the MSE.

The aggregate and disaggregate model estimated in this paper can be add to the other forecasting models for inflation that the Central Bank has. This addition will improve the forecast accuracy in general given the use of a larger information set, that has not been use before.

The empirical framework presented in this document allow to use the information available for the CPI with base year 2006. Even if the sample available is short the model uses the information set efficiently.

This is a first attempt of using a disaggregate approach to forecast and analyse the dynamics of the CPI inflation in Costa Rica. More studies must be done as the sample of CPI with base 2006 increases.

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Figure 12: Covariance Matrix of Groups of CPI

Covariance Probability	INF_G01	INF_G02	INF_G03	INF_G04	INF_G05	INF_G06	INF_G07	INF_G08	INF_G09	INF_G10	INF_G11	INF_G12
INF_G01	0.00776 -----											
INF_G02	0.00071 0.25770	0.00251 -----										
INF_G03	0.00386 0.00000	0.00107 0.00150	0.00242 -----									
INF_G04	-0.00105 0.00010	0.00064 0.00000	-0.00025 0.10610	0.00050 -----								
INF_G05	0.00273 0.00000	0.00188 0.00000	0.00214 0.00000	0.00031 0.07750	0.00308 -----							
INF_G06	0.00305 0.00000	0.00093 0.00050	0.00191 0.00000	-0.00014 0.27310	0.00173 0.00000	0.00158 -----						
INF_G07	0.00111 0.00060	0.00101 0.00000	0.00102 0.00000	0.00023 0.00580	0.00137 0.00000	0.00082 0.00000	0.00074 -----					
INF_G08	0.00270 0.00080	-0.00157 0.00050	0.00090 0.05250	-0.00089 0.00000	-0.00060 0.26260	0.00060 0.11160	-0.00022 0.40200	0.00450 -----				
INF_G09	0.00022 0.00070	0.00018 0.00000	0.00020 0.00000	0.00002 0.21600	0.00020 0.00000	0.00017 0.00000	0.00011 0.00000	-0.00002 0.74250	0.00003 -----			
INF_G10	0.00223 0.00000	0.00158 0.00000	0.00181 0.00000	0.00022 0.11230	0.00188 0.00000	0.00153 0.00000	0.00100 0.00000	-0.00010 0.81030	0.00022 0.00000	0.00193 -----		
INF_G11	0.00090 0.00020	0.00080 0.00000	0.00076 0.00000	0.00015 0.01960	0.00109 0.00000	0.00063 0.00000	0.00052 0.00000	-0.00041 0.03770	0.00008 0.00000	0.00075 0.00000	0.00043 -----	
INF_G12	0.00231 0.00000	0.00105 0.00000	0.00148 0.00000	-0.00003 0.80900	0.00127 0.00000	0.00129 0.00000	0.00063 0.00000	0.00017 0.63630	0.00016 0.00000	0.00143 0.00000	0.00050 0.00000	0.00131 -----

Figure 13: Observed Inflation for CPI Groups

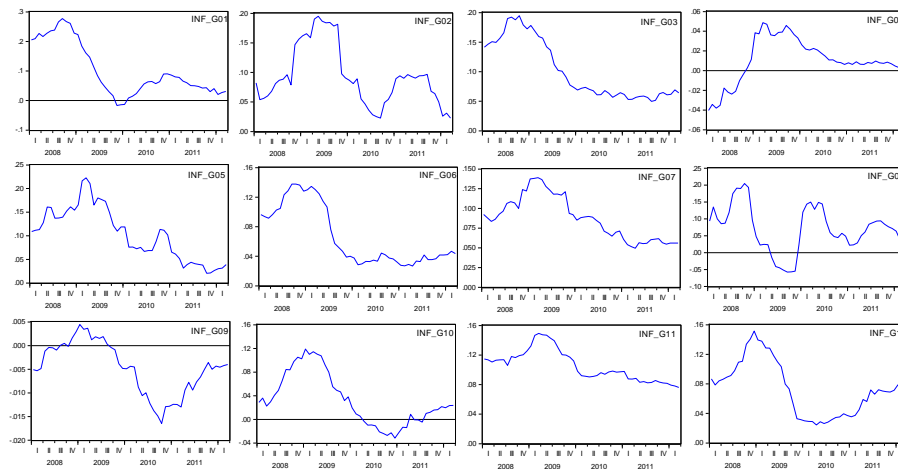


Figure 14: Six Month Window Forecast by Group

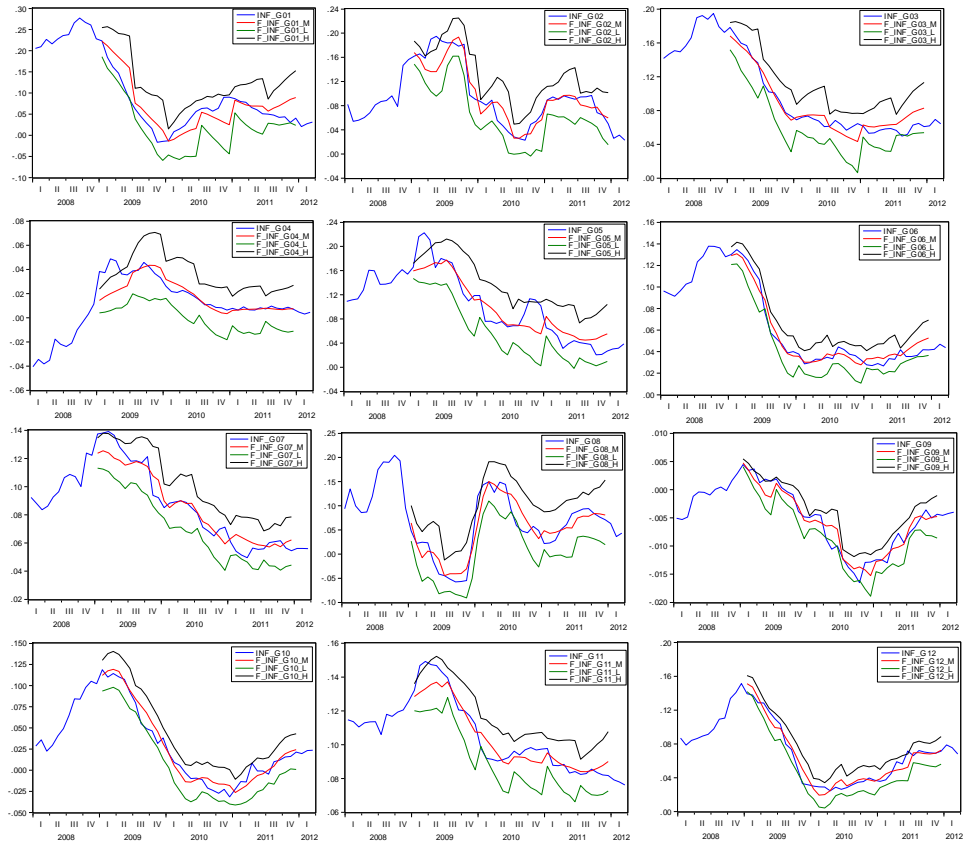


Figure 15: Effect of a 10pp Shock on the Groups and CPI

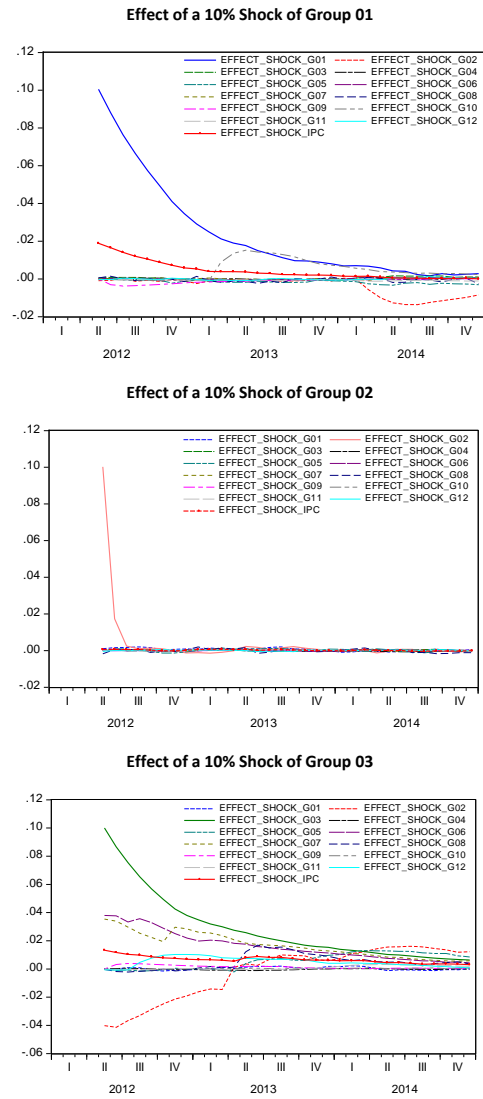


Figure 16: Effect of a 10pp Shock on the Groups and CPI

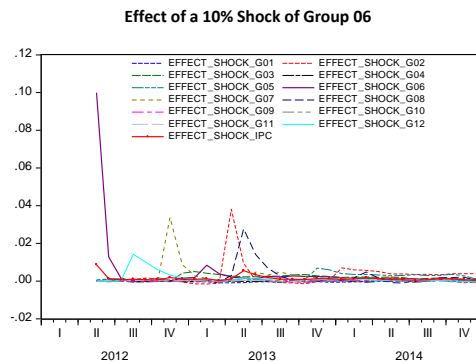
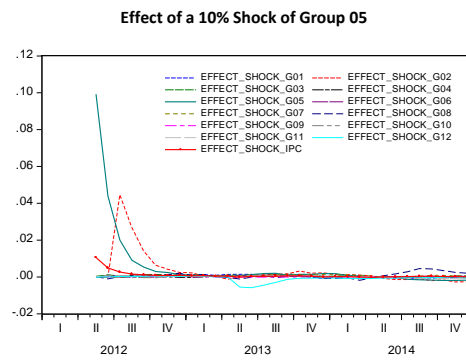
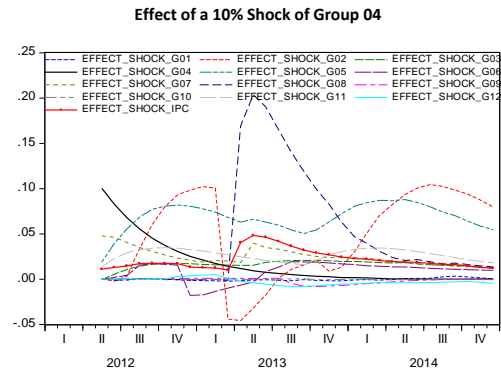


Figure 17: Effect of a 10pp Shock on the Groups and CPI

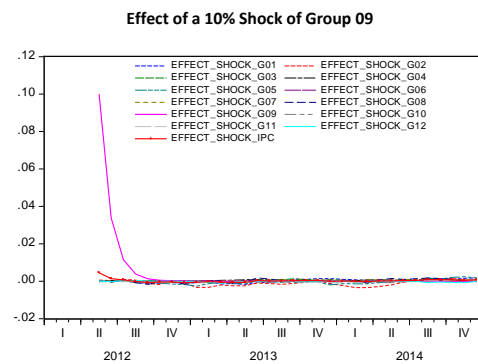
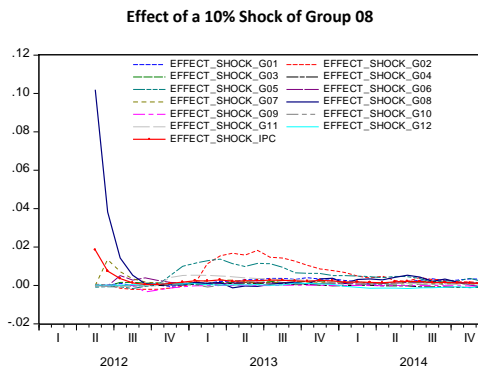
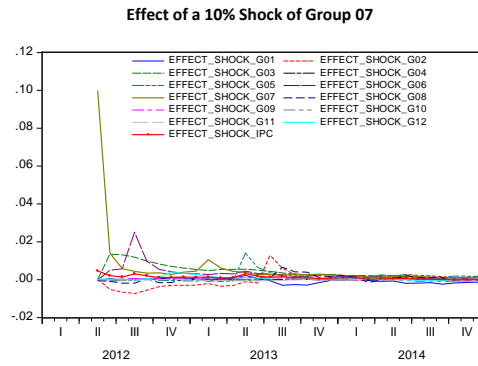


Figure 18: Effect of a 10pp Shock on the Groups and CPI

