



**LOUVAIN**  
School of Management

**UNIVERSITE CATHOLIQUE DE LOUVAIN**  
**LOUVAIN SCHOOL OF MANAGEMENT**

## Can The IMF Commodity Price Index Forecast U.S. Inflation?

Promoteur: Mr. Leonardo Iania

Mémoire-recherche présenté par Boris Ishimwe

en vue de l'obtention du titre de

Master en sciences de gestion

ANNEE ACADEMIQUE 2014-2015

## ACKNOWLEDGEMENTS :

As a preamble to this thesis, I would like to thank those who have contributed directly or indirectly to its elaboration.

I thank my thesis promoter, Mr. Leonardo Iania, for his help and supervision.

I especially want to express my gratitude to my dear family, for the unconditional support and providing valuable advice throughout my studies.

I would also like to pay particular tribute to my faithful friends who have infused me courage and motivation throughout my research.

## Table of Contents

<b>Introduction .....</b>	<b>5</b>
<b>Chapter 1 .....</b>	<b>8</b>
<b>Literature Review.....</b>	<b>8</b>
1.1 Forecasting inflation .....	8
1.2 Alternatives models used to forecast inflation.....	13
1.3 Link between commodity prices and consumer price inflation.....	20
1.4 Research conducted in the field.....	24
<b>Chapter 2 .....</b>	<b>29</b>
<b>Methodology of Macro-economic Forecasts .....</b>	<b>29</b>
2.1 The standard notation for forecasting inflation .....	29
2.2 Autoregressive system.....	30
2.3 Stationary time series.....	32
2.4 Integration of information .....	34
2.5 Forecast evaluation criterion.....	35
<b>Chapter 3 .....</b>	<b>36</b>
<b>Data .....</b>	<b>36</b>
3.1 Data selection.....	36
3.2 Validation of the unit root test .....	37
3.3 Correlation between Commodity Index and Inflation .....	40
<b>Chapter 4 .....</b>	<b>41</b>
<b>Results of the forecasting model .....</b>	<b>41</b>
4.1 Out of sample forecasting of the time series.....	41
<b>Conclusion.....</b>	<b>49</b>
<b>Tables .....</b>	<b>56</b>
<b>Charts.....</b>	<b>62</b>



## Introduction

Economists agree on the relevant role of monetary policy in the process of maintaining sustained economic growth. That same growth is constrained and weakened by high inflation due to changes in the investment decision of the related economic agents. Price stability and support for economic growth are therefore inevitably erected as the priorities of monetary authorities. In terms of inflation, central banks use a common measure known as “inflation-targeting policy” in order to maintain the inflation rate a 2%. (Bernanke and Woodford, 2005).

In this framework, an intermediate objective of central banks is the use of forecasting future pressures on the price level in a short-term horizon in order to adjust the instruments of monetary policy. This way, future inflationary trends effects can be mitigated or taken better into account. For this purpose, economists are interested in commodity prices since they are known to be leading indicators for inflation, also because they have real effects on the economy. Indeed, rising prices of energy commodities such as crude oil petroleum, gasoline and natural gas are considered to be disturbing due to their large share in household’s budgets. (Edelstein, 2007)

However, although some economists confer on the commodities predictive capacity of inflation, the empirical reality remains divided on the subject. Indeed, according to the literature a debate started in the 1980s (Blomberg and Harris, 1995) when researches revealed that commodity prices were leading predictors of inflation during the 1970s and mid 1980s. But since the mid 1980s, commodity prices predictive ability decreased and after that period, they were no longer considered as a leading indicator for inflation. (Furlong and Ingenito, 1996)

Nonetheless, even though this relation seemed to be somewhat out-dated, the debate recently revived again when commodity prices such as energy, oil and food increased and reached all time highs mid-2008, which raised up inflation rates above central banks targets around the world (Bermingham, 2008). Reversely, due to the recession, commodity prices also decreased rapidly during the 2008 subprime crisis.

The link between commodity prices and inflation seems highly established, many authors in the literature have tried through research to estimate this link in order to predict inflation using various kinds of forecasting models. According to the empirical literature, forecasting inflation has been for a long time held in a linear framework. The specifications commonly adopted are the univariate autoregressive (AR) and the multivariate autoregressive (VAR) models.

Therefore, the research hypothesis raised in this thesis is that a linear model such as a vector autoregressive (VAR) can assess the forecasting ability of commodity prices to forecast inflation.

In the past, several empirical results have demonstrated this hypothesis. Indeed, Blomberg and Harris, (1995), Acharya (2010) and other authors have assessed the predictive ability of commodity prices to forecast inflation through a linear methodology and they found interesting and encouraging results for their commodity price based model performance.

The inflation forecasting model that we propose in order to estimate this relationship is the vector autoregressive (VAR) model. We made the choice for this model thanks to its known ability to make good inflation forecasts and because it integrates macroeconomic variables and variables based on financial assets prices.

However, despite their theoretical appeal, vector autoregression models are, like all models, the subjects of criticism. Several authors believe that this type of model makes bad forecasts of inflation and it suffers from a lack of stability.

The aim of this thesis is to investigate whether it is possible to improve forecasts results of the autoregression model (VAR) when integrating commodity prices indicators.

The reason behind this approach provides from the empirical literature that demonstrate that the link between these variables can be captured by linear models. Similarly, the theoretical literature provides a set of corroborating reasons that explain the close relationship between commodities and inflation.

The remainder of this thesis is structured in four chapters. The first chapter, we will conduct a brief review of the literature, in which we discuss the economic and empirical theories that justify the linear relation between commodity prices and inflation. This chapter also focuses on the various models for forecasting inflation. Then, the second chapter will present the methodology for forecasting inflation, where we will detail the creation of our economic model, which will incorporate relevant macroeconomic information such as commodity price index and consumer price inflation. Then chapter three will present the transformation process of the data. Finally, the fourth chapter will present the forecast results of our VAR model.

## **Chapter 1**

### **Literature Review**

The current literature on inflation forecasting has influenced the stages of our forecasting model. In this chapter we will review forecasting inflation as we have reached a good time for such a review, as there have been an explosion in numbers and variety of methods for forecasting inflation through years. Indeed, we will first present different approaches proposed by the documentation that guided our reflections on the development of our own model. We shall also present alternatives models, then analyse the link between the commodities and the consumer price index, and finally, present the various research that has been conducted in the field of forecasting inflation with commodities.

#### 1.1 Forecasting inflation

Several studies describe ways to predict inflation, but the first challenge for a forecast model is to achieve to a better prediction than can do the random approach. Different macroeconomists have published several works of inflation forecasts. In this section we will present some empirical results related to inflation and its forecasting.

##### 1.1.1 Empirical results from the Philips Curve

With the aim of improving forecasting inflation, it is essential to go back to the contribution of Stock and Watson (1999). These authors researched the predictive ability of the Phillips curve over a 12-month horizon. They exposed the possibility to

improve the Phillips curve, by using the unemployment rate, capacity utilization rate, output gap and the leading indicator of economic conditions.

Several conclusions were drawn from the authors. The first is that models incorporating money supply indicators in the Phillips curve have marginal improvement during several periods. The second is that commodity prices do not improve the prediction of inflation in the United States in a 12-month horizon. And the third is that the only variables that improve the prediction by the Phillips curve would be the activity measurements of the 168 variables of economic conditions, since they seem to describe stably real and financial activity in the economy, unlike money supply, which deteriorates the forecasting.

Moreover Stock and Watson asserts that the Root mean squared errors is lower in this type of model compared to other forecasting methods.

Finally, the study by Stock and Watson (1999) stated that the Phillips curve produced the best prediction for short-term inflation in the United States between 1970 and 1996. That inflation prediction has the ability to interpret the relationship between real economic activity and future inflation.

From a theoretical point of view, the reproduction of the inflation dynamics is mostly done using the New-Keynesian Phillips Curves (NKPC). Inflation is represented as a phenomenon totally turned towards the future (forward-looking).

The New Keynesian Phillips Curves, which represent actual inflation as linear function of expected inflation and output gap, are the most widely used approaches to price forecasts. However these models have difficulties to reproduce correctly inflation persistence, which refers to the tendency of inflation to converge slowly to its long-run value following a shock, or other monetary shocks (Mankiw, 2001).

Kozicki and Tinsley (2002) feel that since the traditional formulation of the Phillips curve excludes lagged inflation, it implies that inflation does not present inertia. Taking into account the empirical persistence of inflation observed in their research, these authors have completed the basic model by adding past inflation values.

Finally, the New-Keynesian Phillips Curves distinguishes three main determinants of inflation that is the output gap, which represent the difference between effective and potential output, expected or lagged inflation and supply shocks.

### 1.1.2 Forecasting using financial information.

In order to better predict inflation and output growth in the economy, some authors have proposed to introduce the price of financial assets. The reason is that these assets represent a class of potential indicators by their warning signs. Assets such as interest rates, exchange rates, commodity prices and asset prices quoted on the stock exchange are some examples.

The first authors to introduce financial information in the inflation forecasting were Stock and Watson (2001). They predicted inflation in the US using the prices of financial assets in an inflation-forecasting model. They also mentioned that the prices of financial assets represent potential variables of inflation because it anticipates the economic variables. The authors go back to the instability in the 1970s and early 1980s, while the forecast was only based on monetary aggregates and the Phillips curve.

They affirm that the main explanatory variables of US inflation are the interest rates, the stock performance, the dividends and exchange rates.

Stock and Watson consider data between 1959 and 1999 from 38 indicators of seven developed countries. But also they add to their model data of some economies, such as Canada, France, Germany, Britain, Italy and Japan in order to make a comparison of the impact of certain assets from a country to another. Their work has had significant results for many countries. Hence, they conclude that the prices of financial assets are useful to forecast inflation. They also maintained that a good indicator that forecasts for a period of time is not obliged to do the same over the following periods.

These authors performed tests of significance and performance of the coefficients then they conclude that the regressions make better predictions with a bivariate and multivariate model. Therefore, they used prices of financial assets as indicators in the

forecast since these assets indicate productivity growth, which is valuable information for forecasting.

The main conclusions of their research were:

- *Some financial assets can predict growth for some countries at certain periods.*
- *Forecasts based on accurate data, in a forecast horizon would be unstable because an indicator that dominates over a period will not guarantee the same for the following periods.*
- *Tests that identify the causal links between indicators do not guarantee whether they are good for prediction.*
- *The combination of several variables would dissolve instability and make better forecasts with a smaller sample.*

More over Cecchitti, Chu and Steindel (2000), define three major categories of variables used to forecast inflation, which these authors added the average hourly wage that is related to the increase in inflation.

- *Commodity prices (Petroleum price, gold price or indexes of a group of such goods.) Increases in on these measures either in their level or in their rate of growth are linked to an increase in inflation.*
- *Financial indicators (Exchange rate, monetary aggregates or difference between long-term and short-term interest rates). A decline in exchange rates or a faster growth in monetary aggregates, and a widening of the term premium are all supposed to signal an increase in inflation.*
- *Indicators of the status of the real economy (the capacity utilization and unemployment rates) Higher capacity utilization and lower unemployment*

*(both presumably exceeding some threshold) are regarded as signs that inflation is rising.*

In summary, the literature suggests that forecasts based on financial asset prices are a potential in contributing, however the combination of these has good performance in different periods in not guaranteed.

Furthermore, it is possible that a specific methodology works for one country, but not for another. Finally, the choice of financial assets in explaining inflation does matter.

### 1.1.3 The short term forecast

The short-term forecasting exercise aims mostly to clear the evolution of a variable for the next 12 months or 6 quarters. After 6 quarters, the forecast activity requires the use of various assumptions on exogenous variables and a more developed conceptual system than the forecast model that we will use for our study.

The short-term forecast can be done in different ways. According to Clements and Hendry (2002), there are different approaches to forecasting in general, which can also be adopted for short-term forecast:

- 1) Models and informal rules
- 2) Judgments and expert assessments
- 3) Surveys of specialists or public
- 4) Extrapolations
- 5) Use of leading indicators
- 6) Univariate or multivariate time series model
- 7) Econometrics models

These seven approaches are classified from the most informal to the most formal modelling. In other words, by increasing degree of econometric modelling. Approach 2), 3), 4) and 5) are developed in section 1.2.2.

The approach 6) and 7) are the most used by economists in forecasting.

Regarding approach 6), it attempts to explain best the existence of contemporary and dynamic links between several economic variables. The VAR model is a perfect illustration of this approach. Unlike the econometrics models that base its modelling structure on theoretical preconception, VAR models give a more central importance to the data used.

#### 1.1.4 Importance of out-of-sample forecasting

To evaluate an out-of- sample model one must begin with the division of observations into two parts. The first part is the main sample, used to make statistical inference on the variable of interest, while the second part is the comparison sample is used to compare the out-of-sample forecasts with a benchmark.

The estimated forecasts on the sample allow the testing of the variables linearity and assess in a dynamic way, the predictive power of the model. The addition of components allows the incorporation of the new information available for forecasting. (Clements, 2002)

### 1.2 Alternatives models used to forecast inflation

In this section, we will group into three the different approaches used to forecast inflation that is: econometrics models, judgemental forecasts such as surveys and opinion polls (often complementary to econometrics models) and the dynamic stochastic general equilibrium (DSGE).

#### 1.2.1 Econometrics models

Faust and Wright (2011) describe the set of methods (mostly either univariate or multivariate times series model) to describe inflation,  $\pi_t$ , by considering a few models with stationary specifications for inflation. Thus, the forecast of these models

converges to an unconditional mean, as the horizon gets larger. For example, long horizon forecasts of inflation using stationary models made during the period of Great Inflation have been over 4 percent.

The results seem to be excessive as they ignore the slowly varying trend in inflation.

Thereby, in order to take this varying mean into account, these authors advice to measure the trend level of inflation using the most recent five to ten years ahead inflation forecast from Blue Chip<sup>1</sup> (for further explanations, refer to section 1.2.2)

Then, we think inflation as:

$$\pi_t = \tau_t + g_t$$

$$\tau_t = \tau_{t-1} + \epsilon_t, \text{ is assumed to follow a random walk.}$$

$$g_t = \pi_t - \tau_t$$

Where,  $g_t$  is inflation “gap” is treated as stationary and  $\tau_t$  is the trend level of inflation.

This method of forecasting inflation in “gap” form around slowly varying local mean has been successful according to Kozicki and Tinsley (2001) and Stock and Watson (2010). This tool is quite important because it controls a low frequency variable that has a big impact in the behaviour of inflation. This “gap” form is integrated in most of the stationary forecasting methods.

Faust and Wright (2011) described a set of competing forecasting models that are used following the type or quantity of factor used. Here below are presented some alternatives model for forecasting inflation:

- Direct autoregression (DAR), for each horizon,  $h$ , this regression is used in order to obtain the inflation forecast of the following  $h$  period, by using past inflation.

$$\pi_{t+h} = \rho_j + \rho_j \pi_{t-j} + \epsilon_t$$

---

<sup>1</sup> Blue Chip has asked respondents to predict the average inflation levels from five to ten years, hence twice a year (March and Octobre), since 1979

- Recursive autoregression (RAR) is the model that we will use in our forecasting process (chapter 2). “The h-period forecast is constructed by recursively iterating the one-step forecast forward. If the AR model is correctly specified, then the AR forecast will asymptotically outperform the direct benchmark, but the direct forecast may be more robust to misspecification. Like the direct autoregression, this treats inflation as a stationary process.” (Faust and Wright, 2011)

$$\pi_t = \rho_0 + \rho_j \pi_{t-j} + \varepsilon_t$$

- A Phillips-curve-motivated forecast (PC)

$$\pi_{t+h} = \rho_0 + \rho_j \pi_{t-j} + \lambda \mu_{t-1} + \varepsilon_t$$

Where,  $\mu_{t-1}$  is the unemployment rate in t-1 is used to forecast  $\pi_{t+1}$ . Philips Curve is sometimes interpreted broadly because the unemployment variable is often replaced by other economic activity like industrial production growth or the output gap.

- A Random Walk model. Two variants of random walks are considered: The RW that takes  $\pi_{t-1}$  as the forecast for  $\pi_{t+1}$ , for horizons 0,...5. This RW is often used comparative model in order to assess the forecast accuracy of an autoregression model.
- The autoregression in gap form (AR-GAP),

$$g_{t+h} = \rho_0 + \rho_j g_{t-j} + \varepsilon_t$$

After estimating this regression for h horizons in order to have  $g_{t+h}$ , we add the trend back to the forecast to get the prediction of inflation.

“All the time series predictions that are considered in “gap” form they yield a forecast of  $g_{t+h}$ , to which we add back the final observation on the trend to get the implied prediction of inflation.”

- A Phillips curve forecast in gap form (PC-GAP). We do apply the regression to the inflation gap and not the Philips Curve. For each horizon estimated we estimate

$$g_{t+h} = \rho_0 + \rho_j g_{t-j} + \lambda \mu_{t-1} + \epsilon_t$$

Where,  $\mu_{t-1}$  is the unemployment rate in t-1 is used to forecast  $g_{t+1}$ .

- The factor augmented vector autoregression (FAVAR). The model is actually a multivariate VAR autoregression.

$$\xi_t = \mu_0 + \mu_j \xi_{t-j} + \epsilon_t$$

Where,  $\xi_t = (g_t, z_{1t} \dots z_{mt})$  are the m variables of  $x_{it}$ .

The representation of several variables by extracting the principal component and the forming factors would summarize the behaviour of several variables. Thereby there is an improved forecast, given the reduced number of coefficients in the regression. The only constraint is that it takes more observations than variables.

This small sample of models is a fairly comprehensive list of the sort of models that have appeared in the literature.

### 1.2.2 Judgemental forecasts

Even though, model-based forecasts are widely used when it is time to predict inflation, at short-term horizon they seem to be outperformed by institutional forecasts and professional forecasters, such as the Federal Reserve’s Greenbook, the Survey of Professional Forecasters or Blue Chip Survey. (Monti, F., 2008)

The judgment that is common sense of forecasters (flair or expertise) uses information that is not taken into account by the models, especially the effects of recent or anticipated shock and the forecast errors. It takes better account of the recent past, the present period and the very near future.

Moreover, the judgement has the advantage of being efficient for the short-term forecasts and it can also combine an unlimited amount of information. Actually, according to Francesca Monti, (2008) Judgmental forecasters monitor and analyse literally hundreds of data series, using informal methods to work on information from the available data. Not only they access various data series released by the statistical agencies (as for example, GDP or industrial production), they also gather other information, such as the quantity of goods transported by railway in each month, the electricity consumed each month and survey evidence.

Moreover, judgmental forecasters can incorporate new data and new information as it becomes available throughout the different periods, thus can make use of opportuneness of this information. Indeed, timely information seems to play a key role in improving the quality of the forecasts, and particularly in the nowcasts.

Nevertheless, judgmental forecasters also lack sometimes in providing precise quantified assessment and account for inaccurate judgmental information. For instance, the adjustments of the forecasts made in 1999 in order to account for the fear of the year 2000 bug. In that period it seemed to be a very important event, but since it had never happened no econometric model could be expected to include it, while the judgmental forecasters could. (Monti F., 2008)

Faust and Wright (2011) consider three fully real time judgmental forecasts, each of which contains an immense range of information processed through an economics-influenced subjective filter:

i. Blue Chip survey (BC for the US):

Blue Chip is a survey that provides forecasts in many economic indicators such as GDP deflator and CPI for this year and next from each panel member, plus an average or consensus, of their forecasts for each variable.

As we mentioned earlier regarding inflation forecasting in “Gap” form is affected by long-term Blue Chip survey predictions.

Blue Chip forecasts are released at the start of each month. For each quarter, we take the second Blue Chip forecast, which is always released before the time at which our forecasts are made being white (the middle of the middle month of the quarter).

ii. Survey of Professional Forecasters (SPF):

The SPF also provides quarterly survey of expectations for the rates of inflation, real GDP growth and unemployment in the US and euro area for several horizons, together with a quantitative assessment of the uncertainty surrounding them<sup>2</sup>.

These forecasts are released at the start of the middle month of each quarter, again just before the time at which our forecasts are being made.

iii. The Fed’s Greenbook forecast

The Greenbook provides projections of various economic indicators such as GDP deflator, CPI and CPI- Core forecasts. It is known as a judgmental forecast even though myriad small-scale and large-scale models inform the Greenbook forecasts.

The forecast is made only once before each meeting of the Federal Open Market Committee (FOMC). The projections are referred to as Greenbook projections or Greenbook forecasts. Many of the variables projected coincide with variables covered in the Survey of Professional Forecasters. (Faust and Wright, 2011)

---

<sup>2</sup> <http://www.ecb.europa.eu/stats/prices/indic/forecast/html/index.en.html>

According to Faust and Wright (2011), all these judgemental forecasts do outstandingly well, since they dominate model-based forecasts even when models are chosen in function of known behaviour of inflation in the forecast period.

### 1.2.3 Dynamic Stochastic General Equilibrium

Dynamic Stochastic General Equilibrium models are an extension of the general equilibrium theory. These models are important in assessing the macroeconomic impact of fiscal and monetary policies by central banks and international institutions like the IMF.

The methodology of these models is based on two principles: a description of the economic agents behaviour on a microeconomic level, which stipulates their economic rationality and the incorporation of past data to calibrate a model.

The goal is to model macroeconomic variables such as growth, inflation, and unemployment.

According to Smets-Wouters model (2003), The DSGE models have three main advantage compared traditional macroeconometric models:

- I. *They provide a theoretical discipline on the structure of the model that is being estimated, which may be particularly helpful in those cases where the data themselves are not very informative, for example regarding the long-run behaviour of the economy or because there has been a regime change.*
  
- II. *Being able to relate the reduced-form parameters to deeper structural parameters makes the use of the model for policy analysis more appropriate, i.e. less subject to the Lucas critique, as those structural parameters are less likely to change in response to changes in policy regime.*

*III. Micro-founded models may provide a more suitable framework for analysing the optimality of various policy strategies as the utility of the agents in the economy can be taken as a measure of welfare.*

Thus, DSGE model of the European Central Bank (Smets-Wouters model) is the heart of the institution forecasting process. Moreover, the model is a stationary specification that is very effective to reproduce the long-term equilibrium inflation.

However, central banks use more than one model in order to forecast inflation. They use several models to retain the expected values of inflation. For the European Central Bank (ECB) inflation projections focus on the horizons of one to two years, based on monthly series, quarterly and annually.

### 1.3 Link between commodity prices and consumer price inflation

As it is well known commodity prices have played an important role in analyses of the global economic conditions mainly because of their importance for developing countries. Indeed, for more than 70 countries derive at least 70 percent of their export earning are from commodities. Seen this importance if a change occurred in terms of trade, one might say that it would impact on the countries consumer price inflation, thus commodity prices could act as a leading indicator. However, some authors question the fact that commodity impact has still its ability to perform as a leading indicator. (Moosa, 1998)

In this section, we will present the reasons why the link is strong and the reasons why it has weakened.

#### 1.3.1 Reason why there is a strong relationship

Firstly, overall commodity prices may give early signals of an inflationary rise in global demand for final goods. Indeed, a high demand in final goods increases the

demand for commodity prices inputs. Although inflation is eventually experienced in final goods market, the first real increase in prices occurs from the commodity markets. Since commodities are traded in continuous auction markets, they react instantaneously to expected fluctuation in supply and demand, meanwhile final consumer goods are sticky and thus will adjust more slowly because producers are restricted by lengthy contractual agreements and other rigidities (Kudyba and Diwan, 1998), (Cheung, 2009).

Thus, a strong aggregate demand in commodity prices may lead to early signals of inflationary pressure, although demands provide from the final good market. (Blomberg and Harris, 1995)

Secondly, commodity prices and inflation can be directly linked seen the importance that commodities input have in goods production, which represents about 13% of United State's output (Haksever and Render, 2013). Therefore, all else being equal, an increase in commodity prices automatically ends up affecting consumer prices. In fact, commodities such as food and energy imply direct input price effects in final goods prices.

Thirdly, another indicator of the link between commodity prices and inflation is the fact that investors consider commodity prices as valuable inflation hedge since they respond quickly to general inflation pressures. In fact, the more that investors consider commodities as inflation hedge, the most likely they will use them in anticipation of inflation (Blomberg and Harris, 1995). For instance, precious metals, mostly gold have been the most popular commodities used for hedge inflation.

In addition, it is also important to discern the difference between the influences that commodity prices may have on global inflation. There is, on one hand, the direct effect that occurs because the commodity price (such as food and energy) are included in the consumer price index (CPI), and hence when they increase they impact directly into aggregate inflation. However, with the intervention of monetary policy, these relative price changes do not necessarily lead to higher generalized inflation. On the other hand, there is also the indirect effect, which comes from movements of commodity prices from their impact on inflation expectations. (Cheung, 2009)

Most of the studies that have examined the usefulness of commodity prices as leading indicators of inflation were made around late 1980s to the 1990s. (Cheung, 2009)

Commodity literature has provided mixed results and varies depending on the nature of a given shock studied and the reaction of the monetary policy. Therefore, a positive linkage could be expected between commodity prices and inflation. (Cheung, 2009)

### 1.3.2 Reason why it could be a weakened relationship

Turning now to the other side, there are also signs that indicate the ineffectiveness of the commodity prices as a leading indicator of consumer goods prices. Indeed, even though several studies over time had concluded that commodity prices had significant explanatory power for short-run inflation before the mid-1980s, according to these authors, the relationship may have weakened over time. (Furlong, 1989; Blomberg and Harris, 1995; Furlong and Ingenito, 1996). Here we will explain the different reasons to this.

First, one reason to the decreasing linkage between commodity prices movements and inflation is that commodity prices are playing a smaller role in the industrialized countries. Indeed, in the case of absence of major oil and food shocks, final demand has changed towards goods with less commodity intensity such as electronics, engineering products, plastics, and services. Therefore, fluctuations in commodity prices may have not been relevant enough to be passed through to consumer prices. This reduced role for commodities means that they are a less dependable inflation indication.

Due to weakened pass through price effects of commodities, consequently a rising part of the economy has become more independent of commodity markets. An increase in commodity prices is more likely to impact an increase in final goods in a smaller part of the economy (Blomberg and Harris, 1995).

A second reason is the effect of rising commodity prices on input costs could have been reduced thanks to productivity gains, while reducing final good prices and hence mitigating the effect on global inflation (Cheung, 2009).

Another potential reason for a weakened relationship between commodity prices and CPI is explained through the low interest rates today in comparison to high interest rates during the 1970s and 1980s. Currently, producers face low interest rates costs, which allow them to afford higher commodity prices more easily (Krichene, 2008).

Furthermore, according to Cheung (2009), there are some reasons to expect that commodity price fluctuations and inflation may differ between commodity exporters and commodity importers. Indeed, an increase in commodity prices would have an opposite effect on the terms of trade of the commodity importers against exporters. This would have as consequence a dampening income effects on the domestic economy of commodity importers, and on the other side stimulating effects for commodity exporters.

Moreover, in order to respond to commodity price changes, the exchange rate of major commodity exporter is adjusted in an offsetting way so that the effect on domestic currency prices is neutralized. Thus, an increase in commodity prices would not affect domestic consumer prices. (Carney, 2008)

Finally, an additional reason to think that commodity prices' strong influence on inflation has mild is the low general inflation environment in industrialized countries. Indeed, monetary policy's aim is to monitor price stability at the mark of 2% (in the U.S and the Euro Zone) despite fluctuations in commodity prices. (De Gregorio, Landerretche and Neilson, 2007)

These reasons may pour some cold water on the use of commodity prices as a leading indicator of inflation, however even if they do poorly in predicting inflation in individual countries, they should still preserve some role as global inflation predictors (Bloomberg and Harris, 1995).

Moreover, Blomberg and Harris suggest that in the absence of a major supply shock, the commodity prices should still be a secondary indicator of future inflation.

## 1.4 Research conducted in the field

Forecasting inflation with commodity prices is a central topic in econometrics in such a way that there is an abundance of literature on almost any kind of imaginable model. Indeed, a numerous of research exists on the link between commodity prices and inflation, more specifically consumer prices. Most of the majority of researches are on US inflation however countries like Canada and Australia have also been covered. (Bloch & Al., 2006)

The general finding concerning the usefulness of the commodity prices on inflation is that they used to be the leading indicators for inflation during the high inflation era of the 1970s and early 1980s (Bloomberg & Harris, 1995). However, since the mid 80s, forecasting inflation using commodities with linear models became more difficult.

The following table classifies previous researches into the three groups. There is the group of Successes, where the commodities seem to be useful in inflation forecasts, then there is group of mixed results, where results obtained from the forecasting process are found to make marginal but insignificant improvement and finally, the group of Failures, where the commodities have no additional key information in forecasting inflation.

<b>Past Research Classified by Forecasting Performance</b>				
	<b>Area</b>	<b>Period</b>	<b>Frequency</b>	<b>Model</b>
<b>Successes</b>				
Edelstein (2007)	US	1993-2004	Monthly	Bagging, Bayesian, Shrinkage & Factor
Browne and Cronin (2009)	US	1959-2008	Quarterly	Vector ECM
Gospodinov and Ng (2010)	G7	1983-2008	Monthly	PC's of convenience yields
<b>Mixed Results</b>				
Webb (1988)	US	1954-1988	Monthly	VAR
Moosa (1998)	OECD aggregate	1972-1993	Monthly	Causality tests
Blomberg and Harris (1995)	US	1970-1994	Monthly	VAR
Cecchetti, Chu and Steindel (2000)	US	1975-1998	Quarterly	ADL
Stock and Watson (2003)	G7	1959-1999	Quarterly	ADL
Cecchetti and Moessner (2008)	19 countries	1992-2008	Monthly	ADL
Acharya (2010)	US	1957-2005	Annual	VAR
<b>Failures</b>				
Boughton and Branson (1988)	G7 aggregate	1962-1987	Monthly	Polynomial distributed lag
Eugeni and Kruger (1994)	US	1970-1994	Monthly	ADL
Garner (1995)	US	1983-1994	Monthly	ADL
Furlong and Ingenito (1996)	US	1960-1995	Monthly	VAR
Mahdavi and Zhou (1997)	US	1958-1994	Quarterly	ECM

(Juhani Koskinen, 2014)

The most popular commodity prices used in these commodity prices are Commodity Research Bureau (CRB), Journal of Commerce (JOC) and the International Monetary Fund (IMF). Blomberg and Harris (1995) and Eugeni and Kruger (1994) used both the CRB and JOC commodity indexes. Moreover Acharya & al. (2010), Cecchetti and Moessner (2008), Furlong and Ingenito (1996), Gospodinov and Ng (2010) used the CRB index, while the commodity prices collected by the IMF were used by Boughton and Branson (1988), and Edelstein (2007). Nevertheless, the results are somehow similar when using a commodity index to another. On the other hand it is possible to improve forecasts by forming an index with customized weights as was done by Edelstein (2007).

Concerning the table, we notice that authors who were able to demonstrate that commodities played a predictive role for inflation are the recent studies (Edelstein, 2007; Gospodinov and Ng, 2010). Indeed, this difference in the results from previous studies is the fact of performing with state-of-the-art prediction models. This is because the new models are no longer simple linear models (for instance a VAR model), which were heavily used in the past but are still used in the present. However these results may suggest that future models, more sophisticated and complicated on forecasting inflation will be done outside linear specifications.

Even though the framework of this study is mainly based on a more traditional linear VAR model, it is important to briefly outline the achievements of these recent successes despite that there are not directly comparable to this study.

In his research, Edelstein (2007) used various techniques such as bootstrap aggregating (or bagging)<sup>3</sup>, Bayesian model averaging, shrinkage estimation and factor models. Concerning the commodities analysis, unlike other authors, Edelstein formed customised sub-indexes depending on the models used. This led his studies to explore efficiently the predictive ability of the commodities in the forecasting process.

Regarding the other researches that ended up with mixed results and failures the types of models used were linear models. In these two groups, results are relatively uniform. The group qualified as a failure of the commodity model had to obtain forecasts results worse than the comparable alternative model (benchmark). On the other hand, the group that was qualified as a mixed result of the commodity model had outperformed with an insignificant and minor amount, the comparative alternative model.

In those mixed results, Bloomberg and Harris (1995) reached to a conclusion where certain commodity and producer price indexes are good indicators of future inflation but they lose their predictive power of inflation during the mid 1980s. These authors demonstrate that the absence of significant food and oil price shocks didn't impact on consumer prices thus on inflation.

According to the mixed results obtained by Cecchetti, Chu and Steindel (2000), they added a series of individual indicators of future inflation such as commodity prices, growth of the monetary aggregates, exchange rates, interest rates and unemployment rates, to an autoregressive model to estimate CPI inflation. The results were that the model containing certain commodity price indexes (JOC price index, gold price index or oil price index) outperformed the autoregressive more often than the models based on other indicators during the period 1975-1998. Nevertheless, a simple autoregressive inflation model was more accurate than indicator based forecasts. Hence, this led them to classify their study as mixed.

---

<sup>3</sup> It is a class of learning models, which predicts by averaging the results of k models. Its goal is to improve the accuracy of one model by using its multiple copies.

According to Stock and Watson (2003), they obtained two different results. First their forecasting model using commodity price index increased the forecast accuracy by 21% for the monthly CPI inflation compared to an autoregressive benchmark for a period from 1971-1984. However when forecasting the period 1985 to 1999, the forecast accuracy of the model decreases by 26%, which also lead to mixed results. In conclusion, Stock and Watson show that these forecasting improvements are sporadic and unstable.

In his study Edelstein (2007) found necessary in the commodity price-inflation literature to point out several drawbacks that these research had:

- Forecasting inflation with broad commodity price indexes irrelevant commodities for forecasting, thus may the raise the variance of the forecast and lower the forecast accuracy.
- Then, the failure to use state-of-the-art forecasting techniques for most of the mixed results research.
- The assessment of commodity prices is not done on an out-of-sample forecast. For example: “*Blomberg and Harris (1995) estimate model parameters for the first half of their sample and use them to forecast inflation for the quarters in the second half of their sample. While their forecasts are out-of-sample, they are based on information sets that do not include the most up-to-date set of data. Cecchetti, Chu, and Steindel (2000) use a bivariate iterated multi-step ahead forecasting model, yet they only forecast future values of inflation and use ex-post realizations of commodity prices instead of their forecasted values. Their forecasts are based on data that would not have been included in a forecaster’s information set.*” (Edelstein, 2007)
- Finally, these mixed results literature are more focused on the usefulness of the commodity prices to reduce the RMSE<sup>4</sup> of an inflation forecast rather than

---

<sup>4</sup> Root Mean Squared Errors. (For further explanations, refer to chapter 2)

the necessity of these forecast help to understand monetary policy. Indeed, users of inflation forecasts are interested in inflation as it indicates the perceived policy reaction function of the central bank.

## Chapter 2

### Methodology of Macro-economic Forecasts

In this section, we introduce the different aspects of developing a forecasting model. The reason why we start with a section on methodology is to help understand explicit documentation of the next chapters. First, we introduce the standard notation for forecasting inflation. Second, we describe the characteristics of autoregressive systems. Third, we will explain the steps characteristic of stationary time series. Fourth, we will see how to introduce a maximum of information through factor analysis and fifth, we will review a forecast endpoint.

#### 2.1 The standard notation for forecasting inflation

First, as we already stated above, the forecasts are made several ways. Let us first define a model of one general forecast that is similar to Stock and Watson (1999) model:

$$Y_{t+h} = \alpha + \beta X_t + \gamma Y_t + \varepsilon_{t+h},$$

Where,  $Y_{t+h}$ , describes the value that may take inflation to a predetermined period  $h$ . The coefficient,  $\alpha$ , describes the reference level of the growth of inflation at  $t$ ,  $\beta$  and  $\gamma$  are the coefficients of the polynomial that affect lagged values  $X_t$  and  $Y_t$  generated by the autoregressive model. This type of autoregressive model combines the available information in order to make the forecasts.

Furthermore, several models compare themselves to the random walk, which is a non-stationary and univariate processes. The forecasting following the random walk is known to be more precise than the autoregressive models but less profitable. However

it is limited to provide for future periods, as the best estimate of the present value, without integrating the new information available. In other words, the random walk is that best forecast of contemporary variable it derives from the sum of past shocks that have a permanent effect, since they preserve in memory one or more periods to predict the future. The error term follows a weak white noise, which means it is zero mean, constant variance and no linear relation over time.

For comparison purposes, random walks and simple autoregressive models are often used as comparative models in order to assess and validate the forecast ability of model. (Ca' Zorzi, Muck and Rubaszek, 2013)

In this study, inflation measure is defined by indices in time (consumer price index) and is represented by the abbreviation  $\Delta \text{LogCPI}_t$  where  $t$  represents a period time  $t$  for the changes in the consumer price index. These notations will help us construct our autoregressive equation system necessary for the forecasting.

## 2.2 Autoregressive system

The autoregressive models are models that have as main characteristics, a dependent variable explained by explanatory variables and lags. In this category of model, there are models such as AR (autoregressive), VAR (vector autoregressive models) and FAVAR models (autoregressive vector models increased by factors).

In this study, we make use of the so-called vector autoregressive model (VAR). The idea of using the VAR model for analysis and economic forecasting was issued by Sims (1980) in order to evaluate the predictive ability of commodity prices for future inflation, because of its simplicity and intuitive appeal.

The general idea that is exploited in the short-term forecasting models of vectors autoregressive models (VAR) can be expressed as follows. The short-term dynamics of relationships that drive an interrelated time series system can be exploited to

forecast. Since in the VAR models, every variable is modelled as an endogenous variable whose function is its own lagged values and all other endogenous variables retained in the system, the dynamic link at short term represent the main determinant of each variable future changes. If this hypothesis is acceptable for a short-term development, it is obvious that for mid- to long-term forecasts, VAR modelling proves to be of limited use. (Parnisari, 2002)

The advantage of using a VAR model is that it is known to often provide superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models.

Even though the VAR model is small and highly aggregated, it has an advantage of being simple to understand and to be available.

Moreover, thanks to its simplicity it is intended to provide potential users a road map of how to implement another VAR based forecasting model. (Robertson and Tallman, 1999)

Furthermore, most studies such as Blomberg and Harris (1995) and Furlong (1996), use VAR models to assess predictive ability of commodity prices to forecast consumer price inflation. Indeed, the vector autoregressive (VAR) model seems to be the most efficient model to analyse multivariate in times series due to its flexibility. It has proved to be useful in describing dynamic behaviour of economic and in forecasting.

Therefore, the relationship between commodity prices and inflation is generally examined using a vector autoregressive (VAR) models. The VAR methodology assumes that each variable can be best explained by using past values of both itself and all other relevant variables. (Blomberg and Harris, 1995)

In general a VAR model is a system of equations. i.e.,

$$Y_t = \theta D_t + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + \varepsilon$$

Where  $Y_t$  is a  $(k*1)$  vector of endogenous variables and the  $\theta D_t$  is a  $(k*1)$  vector Intercepts that account for the possibility of observing nonzero means.  $A_p$  is a  $(k*k)$  Matrix of polynomials in the lag operator (L) and  $\varepsilon$  is a  $(k*1)$  vector of error terms that is referred as white noise vector process. (Achayra R. N, Gentle P., Mishra A.K. and Paudel K., 2008)

The system has k equations, each containing p lags on all k variables. If these lag operators are identical, the system is estimated using an ordinary least square (OLS) method without any loss of efficiency.

Using a VAR (p) system the relationship between commodity prices and inflation can be expressed as:

$$(1) \quad PCom_t = a_{01} + \sum_{i=1}^p b_{1i} PCom_{t-i} + \sum_{i=1}^p c_{1i} Inf_{t-i} + \varepsilon_{1,t}$$

$$(2) \quad Inf_t = a_{02} + \sum_{i=1}^p b_{2i} PCom_{t-i} + \sum_{i=1}^p c_{2i} Inf_{t-i} + \varepsilon_{2,t}$$

Where  $PCom_t$  is the commodity price Index and  $Inf_t$  is U.S. inflation rate. Each equation is estimated by ordinary least squares (OLS) regression.

### 2.3 Stationary time series

For the modelling of economic and financial time series, it is important to perform previously stationarity tests on variables. We must identify the trend of the series and validate what type it is, either deterministic (stationary) or stochastic (non stationary). The unit root tests on time series can target if there is a unit root.

Therefore, when working with time series variables, there are some empirical and statistical procedures that are involved before estimating a VAR system equation.

First a unit root tests will be applied in order to determine the stability of the equation system. Indeed, before any estimation or testing procedures can be done in a dynamic time series model, it is required to test the stationarity of the different variables in the time series, since the majority of the econometric is built on the assumption of stationarity.

Chart 1 exhibits the evolution of CPI and IMF commodity index in logarithm over time. The reason why variables are set in logarithm is because it helps mitigate the effect of some aberrant values in the data.

We can observe on the chart that both variables have an upward trend throughout the time. Therefore, according to the chart, there appears to be nonstationarity for both variables.

According to Verbeek's (2004) definition of stationarity:

“Stationarity requires that all the moments of the series, and not only the first and second (mean and variance), are unaffected by time”

In other words a time series is stationary if its mean, variance and covariance remain constant over time. Thereby, a time series that is non-stationary is whether trending upwards or downwards. It will then be nonstationary if their mean values seem to evolve over time. (Thomas R.L., 1996)

### **Why do time series shouldn't be nonstationary?**

One main reason is to avoid spurious regressions such as false relation between two variables. Indeed, if one of the explanatory variables in a regression equation is non-stationary because it displays a distinct trend, it is very likely that the dependant variable in the equation will present a similar trend.

One other reason why we need to have stationary variables in our model is that according to economic theory, stationary variables will tend to return to its mean after a shock independently of the magnitude of the shock.

According to chart1, our variables seem to be non-stationaries. There are formal test to test the stationarity. The most frequently used test for stationarity is the Dickey-

Fuller test and its augmented forms. There are also other common tests such as Phillips-Perron (PP), which is a derivative of the ADF and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS). The Dickey-Fuller and PP test the null hypothesis is nonstationary.

Also an informal way of testing the stationarity of a time series is to analyse the correlogram. Indeed, the slow decline in simple autocorrelation coefficients consolidates the presumption of non-stationary series. On the contrary, when simple autocorrelation coefficients decline rapidly to around zero, some being positive and others negative reinforce the idea of stationary series.

We will focus on an augmented Dickey-Fuller test to test the stationarity of the variables in our model. If this test confirms the non-stationarity of some variables, we will differentiate these variables in order to have stationary variables.

## 2.4 Integration of information

After solving, the eventual problem of nonstationarity, we will next estimate the link between the IMF commodity price index and the U.S. inflation through a VAR (p) system. Indeed, this model can integrate several information. In our case, we will only integrate the IMF commodity price index in order to explain the model.

Therefore, we will analyse the predictive content of each variable using both lagged variables.

Nevertheless, before going further, it will be necessary to use an Akaike Information Criteria (AIC) statistical test in order to determine the suitable order of the VAR system.

Then, we will estimate each equation by an ordinary least squares regression after examining the number of lags.

Next a significance test on the variables will be conducted in order to assess whether variables included in the model are enough significant to the dependant variable.

## 2.5 Forecast evaluation criterion

Lastly, we will investigate whether the commodity price index  $PCom_t$  has added predictive power in an out-of-sample forecast for inflation  $Inf_t$ .

To do so, there are several assessment criteria for the prediction of a model. The one used for evaluating the forecast performance is the root mean squared errors (RMSE). The RMSE is derived from the mean squared error (MSE) associated with the forecast, which is defined as the linear projection of  $Y_{t+k}$  on  $Y_t$ , for any k horizon. Regarding the autoregressive processes, the MSE is described with respect to the variance of the error terms. In order to predict horizon k, the variable  $Y_t$  will depend on observed variables at time t and will incorporate the new information as time progresses  $Y_{t+k}$ .

Thus, the criterion of the squared error is used to evaluate the predictive capacity of the autoregressive model within the estimation periods. A small deviation squared error will naturally record better forecasts. By its explanatory capacity, this test is used to check the evolution of forecasts of a time series. (Doornik and Hendry, 2013)

## Chapter 3

### Data

In this chapter we will mainly present the data used in our model. Then we will elaborate the transformation process on the variables and the validation performed to obtain stationary times series.

#### 3.1 Data selection

The data for the U.S. CPI<sup>5</sup> was acquired from the bureau of labor statistics of the U.S. The sample chosen was the monthly data on changes in prices paid by urban consumers for a representative basket of goods and services provided by private and public sectors<sup>6</sup>.

The data for the commodity prices index was collected from the IMF total primary commodity prices<sup>7</sup>. The commodity prices are monthly averages of world spot market prices measured in U.S. dollars. The data is only available since January 1992.

In order to have consistency the sample period for the model starts from April 1992 to December 2013, which corresponds to 237 months. This assessment window is chosen due to its enough large size to obtain accurate estimates of the model parameter value.

We will follow Blomberg and Harris (1995) data collection methodology by selecting the total primary commodity price index for our empirical analyses, instead of estimating each commodity price index individually. This commodity price index contains 53 primary commodities of which non-fuel, crude oil petroleum, food, energy, beverages, agricultural, industrial inputs and metals categories are included.

---

<sup>5</sup> <http://www.seattle.gov/financedepartment/cpi/historical.htm>

<sup>6</sup> <http://www.bls.gov/cpi/>

<sup>7</sup> <http://www.imf.org/external/np/res/commod/index.aspx>

For our econometric analysis we split the sample in April 2013. This sample ranging from April 2013 to December 2013 (8 months) will be used for the forecasting process. In fact, a one-step forecasts method will assess the predictive ability of the commodity-based model to forecast inflation.

Concerning the exchange rates, the IMF total primary commodity prices is denominated in U.S. dollars, which is the same currency as U.S. consumer prices index. In this situation we don't have to deal with difference of currencies and exchange rates issues.

Boughton and Branson (1988) explain that it is better to isolate commodity price movements on inflation from those of exchange rates. It is preferred that commodity and consumer prices be expressed in the same currency.

### 3.2 Validation of the unit root test

Macroeconomic and financial time series are the realization of stochastic process in time through the observed series. Thus, in this section we describe the validation performed to obtain stationary time series and the necessary changes made on the variables.

Many economic and financial times series such as prices, exchange rates or real GDP contain trending behaviour or nonstationarity in the mean.

As we exhibited on chart 1, the variables seem to be nonstationary, Moreover when observing Chart 3(a), we notice that “r” declines gradually when “k” increases, which is typical for a strongly trending variables. While on the contrary a typical correlogram for a stationary variable falls rapidly to zero when k increases. (Thomas, 1996)

Consequently, we will assume first difference stationarity where the time series can be modelled as first differences in logarithm. This is a process frequently used in times series studies.

If we work in terms of first differences of the logarithms of variables, then our variables become a proportional rate of growth,

$$\ln(CPI_t) - \ln(CPI_{t-1}) = \ln\left(\frac{CPI_t}{CPI_{t-1}}\right) \approx \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} = \text{Inflation}$$

$$\begin{aligned} \ln(PCom_t) - \ln(PCom_{t-1}) &= \ln\left(\frac{PCom_t}{PCom_{t-1}}\right) \approx \frac{PCom_t - PCom_{t-1}}{PCom_{t-1}} \\ &= \text{Commodity price index growth rate} \end{aligned}$$

If it is expressed in logarithms difference terms, it is more likely to involve stationary variables only. Therefore using simple first differencing logarithms does provide a satisfactory solution to the problem of non-stationary variables.

As we can see on Chart 1, the commodity price index rate of change and the inflation rate appear to be stationary. Indeed, the trends are now much less marked and seem to have disappeared, which means that this time series appears to be stationary.

However, it is still important to examine and make things clear by using a unit-root test for stationarity.

To determine the stationarity of inflation and growth rate of the commodity price index, we perform an augmented Dickey-Fulher (ADF) test.

The ADF test originates from the Dickey Fulher test by adding lagged differences.

For instance we write an ADF(1),

$$\Delta Y_t = \alpha + \phi Y_{t-1} + \phi \Delta Y_{t-1} + \epsilon_t$$

Hypothesis test:

The null hypothesis of the ADF test is the hypothesis of unit root (or nonstationarity) of the variable  $Y_t$  is  $H_0:\phi=0$ ,

Therefore, the ADF test consists in comparing the t-value of the parameter  $\phi$  and the critical values from the statistical tables for unit root tests.

The null hypothesis of nonstationary of the time series is rejected when the t-value associated to the parameter  $\phi$  is less than the critical values from the statistical tables for unit root tests. If we reject  $H_0$ , it will imply a stationary process.

The unit root test results are listed in Table 1. They indicate that all the variables lie in the unit circle. Indeed, the ADF(3) test demonstrates that they are stationary with relative confidence. Hence our variables are stationary in first difference logarithm by rejecting the null hypothesis at the 1% level of significance.

We can now observe on chart 3(b) the correlogram of inflation and log differenced commodity price index, contrary to chart 3(a), we remark that all “r” for  $k>0$  seem to be close to zero, some are positive and other are negative. A typical correlogram for stationary variables is that as “k” increases, “r” falls rapidly to around zero. (Thomas, 1996)

In Table 1, the column with “t-DY\_lag” and “t-prob”, give the t-value of the longest lag (0, 1,2,3) and the p-value of the concerning lag. In order to select the order of the ADF(p) test, we select the lag with highest t-value for both variables.

Hence, when using the lag criterion, both inflation and commodity price index, we use an ADF(1) test.

This finding implies that the selected VAR system satisfies the stability condition.

### 3.3 Correlation between Commodity Index and Inflation

Chart 2 displays the evolution of the monthly change in U.S. Inflation and IMF Commodity Price index. The first impression implies a really close link between commodity price index and inflation rate from the beginning of the sample 1992(4) up to the end of the sample in 2013(12). We can justify that impression when computing the correlation of both coefficients. Indeed, we find a positive correlation of 0.62 when regarding through the whole sample.

These empirical findings seem to confirm the assumptions that there is a strong relation between commodity prices and inflation.

## Chapter 4

### Results of the forecasting model

In this section, we will describe the development stages of our model for forecasting inflation in the US. After validating in section 3.1 the stationarity in the time series, this section will proceed to the inflation forecast using a vector autoregressive system (VAR). This will include the validation of the contribution of the factors in the model and finally the results of the forecasting performance.

#### 4.1 Out of sample forecasting of the time series

This section describes the steps in the construction of our prediction model according to the use of the VAR model. As described in the equation (2) in section 2.2, our model is made of an autoregressive system composed of 1 lagged inflation and commodity prices. To build this model we will determine the order of the model, we will validate its contribution of the variables within the model and we will discuss the results obtained of the forecast.

The goal of this process is to present forecasts of inflation and compare it to a simple Autoregressive model AR(1).

Our approach is structured in two steps:

1. Estimate the autoregressive model of order  $k$  (composed by an autoregressive part with a number of determined lags) in order to describe the significance of the factors of the model.
2. Assess the forecast performance according to the criterion of the recursive mean square error (RMSE) in order to determine if the model gives good forecasting performance compared to the benchmark AR (1).

#### 4.1.1 Validation of the variables contribution: 1992(4)-2013(12)

In this section, we will assess the factors by conducting two regressions via the ordinary least squares for the period April 1992 to December 2013. In the next section, this choice will allow us to make out-of-sample predictions between May 2013 and December 2013, for 8 months.

In order to determine the order of the VAR system for our estimations, we use statistical tests to determine the order. There are four tests such as final prediction error (FPE) criteria, Hannan-Quinn criterion (HQ), Akaike information criteria (AIC), and Schwarz criteria (SC).

However for this test we will focus on the AIC. Indeed, the estimation model that has the lowest AIC is the best fit for the estimation process. Thereby, AIC indicate that our regression is a second order VAR system. (Table 3)

As a mean to examine whether there is a two-way relationship between the IMF Commodity price index and the U.S. inflation, equation (1) and (2) are first estimated via ordinary least squares over the entire sample 1992 (4)- 2013 (12).

The hypothesis test:

$$H_0: t > 1.96 \text{ or } t < -1.96; H_A: t < 1.96 \text{ or } t > -1.96$$

We accept  $H_0$ : if the coefficient is significant, thus the variable has an explanatory role in the model.

Table 4 presents the output of the estimation process. It reports lagged months in IMF Commodity price index and U.S. inflation associated with the IMF Commodity price index in equation (1)

Returns for equation 1 reveal that  $\Delta \text{Log CPI}_{t-2}$  is not significant to explain commodity price index. Thus, we can reject  $H_0$ .

Through the estimation process we observe that  $\Delta \text{Log CPI}_{t-2}$  does not possess significant information content in order to explain change in commodity price index. In fact, it is associated with poor t-values.

However,  $\Delta \text{Log CPI}_{t-1}$  is significant, thus we can accept  $H_0$ . An increase of 1% in inflation would lower commodity price index by 2.42%.

Regarding lagged commodity price index, they are significant to explain their next month change in price. In fact, they are significant in both months.

On the other side, Table 4 reports results in equation (2) for lagged months in the IMF Commodity price index and the U.S. inflation. As expected, the coefficient associated with the lagged commodity index variables in inflation equation is highly significant suggesting that commodity price index affect inflation.

Results report that lagged inflation has influence in today's inflation. Moreover, the IMF commodity price index is also highly significant (6.04) based on its t-value, which suppose that there is a high influence on inflation in the first lag. An increase of one percent in commodity price index would increase inflation by 0.03%.

Nevertheless, the IMF  $\Delta \text{Log Commodity}_{t-2}$  is insignificant. Indeed, this lack of significance in the second lag could be a consequence of persistent changes in commodity prices realized over one month to another. Since commodity prices prone to short-term idiosyncratic movements (Furlong, 1989), their prices fluctuate often, which makes inflation adjust slowly in high frequencies. Thus, this insignificant result could be a consequence of using high frequency data such as monthly.

To dig a little bit further, we broke down the IMF commodity index into main categories that were cited in the data section. Those categories were also estimated individually with U.S. inflation (results are reported in Table 6).

Results suggest that Industrial Inputs, Metals and Crude Oil Petroleum commodity category are significant for monthly inflation and they maintain their impact on inflation at both lags. Indeed, these categories are the only to be significant with two

months lags, while Fuel Energy, Food, Beverage and Non Fuel are only significant in the first month lag and their impact is more likely to disappear in the second month.

However, gains are not the same across categories in the IMF Commodity index and horizons. For instance, Agricultural Raw Material seems to be the only category to have no influence in inflation.

#### 4.1.2 Forecasts results

Results from the estimation process demonstrate that commodity prices are significant enough to estimate inflation through a linear regression.

In this section, we will only forecast inflation using lagged values of the commodity price index and inflation (equation 2).

Reasons for this choice are diverse. Indeed, even though inflation is still significant for the commodity price index in the first lag, results for the different categories that compose the whole commodity price index estimation reveal that inflation is not significant at all, (for 8/9 categories).

Therefore the forecast of commodity price index using inflation may lead to misleading conclusion.

Moreover, since commodity price index prone to short-term idiosyncratic movements due to supply and demand mechanism in the market, commodity price index can't be forecasted, otherwise the situation would violate efficient market hypothesis.

We make use of equation (2) in order to investigate the forecast ability of commodity price index by estimating the one step forecasts inflation.

Forecast results of our VAR model allow us to discuss the performance of the models of equation (2) and a simple autoregressive AR (1) that will be developed in section 4.1.3.

Thus, we estimated the regression in order to obtain forecasts. The forecasts are made at each horizon, between May 2013 and December 2013 (8 months). The outputs are exhibited in Table 5.

The output of inflation of a one-step forecast for 8 months compares the forecast values and the actual/realised values. Specifically, the errors standard deviations are the difference between actual/realised and forecast inflation values.

Therefore low standard deviations in errors imply that the commodity index-based model might have signalling power for predicting future inflation. However in order to confirm this assumption the commodity index-based must be compared to the alternative model, AR (1).

According to the forecasting output in Table 5, results of the commodity-based model may lead to predict inflation with consistency over the 8 months forecast horizons. Indeed, we observe that standard deviations errors for each of the 8 months seem to be very low. The standard deviation error for all 8 horizons between the commodity index-based model and realised inflation is 0.0016, while it is 0.0016 between the AR(1) alternative model and the realised inflation. The difference is zero. This means that in average for the 8 months the commodity index-based model perform the same way as the AR (1) model, which is our benchmark.

Concerning the forecast accuracy in Table 5, we will consider one measure that is based on errors in order to assess the accuracy of the inflation forecast of our models: the recursive mean squares errors (RMSE). This criterion will enable us to compare both models.

The RMSE is the square root of the variance of residuals. It indicates how close the actual data points are to the model's predicted values. As the R-squared is a measure of fit, the RMSE is an absolute measure of fit. It is a good measure of the predictive accuracy of the model. Lower values of RMSE indicate better fit. (Martin, K.G., 2012)

The RMSE reports low errors (0.0020), for the commodity-based model, while the alternative model AR (1) reports low errors as well (0.0018).

On the graphics level, as Chart 4(a) and (b), displays the evolution of the one step forecasts of the commodity based model and the actual/realised U.S. inflation across time (a), then the one step forecasts alternative model AR (1) and the actual/realised U.S. inflation (b). The vertical deviation at each horizon between forecast and actual inflation represents the errors. Hence, the closer they get at horizon, the less errors appear.

#### 4.1.3 Test of the forecasting accuracy

The accuracy of the forecasting method performed in this study is assessed relative to an inflation-only model, AR(1), which uses lags of inflation to forecast future inflation.

“A commodity or commodity group’s predictive ability is measured as the recursive RMSE of a forecasting method that includes these commodity prices, relative to a model without them.” (Edelstein, 2007)

This basis for comparison is common to a number of research papers about inflation forecasting. Indeed, according to Litterman (1986), there are two commonly used method: random walks forecasts, which are usually used as benchmark for comparison in the VAR literature, reporting Theil’s U statistic, without a formal measure of the statistical significance of differences in forecast accuracy. On the other hand there is also the comparison of the forecasting method to the autoregressive models AR (1), since, for many (not all) variables of interest, an autoregressive model forecast is more accurate than a random walk. Thereby, this last autoregressive model will be our benchmark in this study in order to assess the accuracy of our commodity-based model.

Therefore, we test the accuracy of its forecasts by considering a simulated out-of-sample forecasting exercise. Indeed, in this sort of exercise, a simulated series is constructed AR (1).

Therefore, we compare the forecast performances of the commodity index-based model with the alternative model AR (1), following the model specified by Atkeson and Ohanian (2001) that is widely adopted in the literature.

The simple autoregressive AR (1) model is specified as follow:

$$\Delta \text{LogCPI}_t = c + \Delta \text{LogCPI}_{t-1}$$

In order to obtain forecasts, we proceed as for equation (2), by estimating the regression from April 1992 through December 2013. Then, we construct the out-of-sample simulated forecasts of inflation from May 2013 to December 2013 over the next 8 months by estimating the AR (1).

The simulated forecasts obtained in the forecasting process of the commodity index-based model regression are directly compared to this AR (1) model.

Finally, we compare the ratio of the RMSE of the forecast from the commodity-based model to the RMSE of the alternative model's forecast.

A ratio greater than 1 will indicate that the commodity index-based model forecast is less accurate than the AR (1) model's. Subtracting 1 from the ratio and multiplying the result by 100 gives the percentage difference in RMSE between the two models.

We find that the forecasts from the commodity index-based model are considerably less accurate than those from the AR (1) model. The ratio of the commodity index-based model RMSE to the alternative model RMSE is  $\frac{0.0020}{0.0018} = 1.11$ . This indicates that the forecast error is only 11.11% higher for the commodity index-based model than for the AR (1) model. We conclude from this evidence that the commodity index-based model has not been a useful inflation-forecasting tool over 8 months, since the alternative model outperformed our commodity based model.

The results of our investigation are in line with the researches from previous authors such as Chu and Steindel (2000) and Stock and Watson (2001), who obtained mixed results. Indeed, we can qualify these as mixed since, as these authors, the alternative

model outperformed slightly the commodity-based model for the forecasting period of 8 months. Moreover, we can observe that for two months, July and October 2013, the commodity-based model did perform better than the alternative model.

Despite the results, there is a lot of motivation to make this commodity based-model more efficient. Indeed, a possible improvement would be to make a more ingenious selection of time series and compare the sensitivity to inflation using significance tests.

Another possibility would be to select some types of commodities and assign to each a certain weight in the forecasting model so they can give a significant contribution, so as to remove useless information.

The results of our US inflation forecast using the VAR model have a potential given the positive results of two months. Nevertheless, the results of the other six months leave the door open to the improvement of the forecasting model concerning the selection of variables to be considered.

## Conclusion

Today's world of increasing globalization is characterized by the rise of commodities prices such as oil petroleum and food, and inflation rates moving above the mark of two percent per year, which is used by the Federal Reserve as the reference for price stability. In this context, this has led to a rising interest in whether global variables such as commodities can forecast inflation. Therefore, this thesis investigates the predictive content of the IMF commodity price index for inflation in the U.S. through a linear vector autoregressive model.

In order to do this, we first researched the empirical literature concerning this topic. Indeed, we analyzed liner relationship between commodity prices and inflation, which reveals that although previous studies had asserted that there was a strong link in the 1970s to mid 1980s, the relationship between both seems to have weakened over time due to the increasing share of the services sector compared to the shares of the goods sector in U.S. economy. Further we presented various alternatives models used to forecast inflation. Then, based on empirical statistical tests, a second order VAR system was estimated in order to analyze whether the IMF commodity price index can forecast U.S inflation. Finally, we performed an out of sample forecast of the commodity-based model and an alternative benchmark model in order to assess the accuracy of the predictive content of the commodity-based model.

Thereby, our study's main objective was to provide comprehensive analysis of the predictive content of commodity price index through a VAR model in order to improve US inflation forecasts from those of an Autoregressive model during a horizon of 8 months (April to December 2013).

The analysis revealed that the outputs obtained are inline with previous authors who used the same linear model in the literature (Achayra, 2010; Blomberg and Harris, 1995). Indeed, our commodity-based model was slightly outperformed by the autoregressive model forecasts. However, it did outperform the benchmark on two forecast periods. Thus we can qualify these results as mixed.

Nevertheless, it is important to point out that our work did involve limitations that may have affected our results, and thus also the sharpness of our interpretations. One of these limitations would be the selection of commodity index. In fact, considering the whole commodity index for predicting US inflation can lead to inaccurate information since US consumer price index is balanced differently. Moreover, the selection of the forecast period could also be a limitation because of its short forecasts horizon as consumer price index always reacts with a lag to variation in commodity prices. Thus, choosing a longer forecasts horizon could capture better the impact of commodity prices on inflation.

Having detected these limitations, it would be interesting to use them in a future investigation. We could therefore bounce back these limitations as an extension of this thesis, especially by using other alternatives models presented in chapter one. Going beyond these limitations would enable us to expand the reflection on the relation between commodity prices and inflation.

## Reference

Achayra R. N, Gentle P., Mishra A.K. and Paudel K.. (2008). « Examining CRB Index as an indicator for U.S. Inflation ». Southern Agricultural Economics Association Annual Meeting, Dallas, TX, February 2-6, 2008

Atkeson, Andrew, and Lee E. Ohanian (2001), “Are Phillips Curves Useful for Forecasting Inflation?”,

Federal Reserve Bank of Minneapolis Quarterly Review Volume 25, No. 1.

Blomberg, S. Brock and Harris. (1995). “The Commodity. Consumer Price Connection: Fact or Fable?” Federal Reserve Bank of New York Economic Policy Review, October 1995, pages 21. 38.

Bermingham, C. (2008). Quantifying the Impact of Oil Prices on Inflation, Research Technical Paper 8/08, November, Economic Analysis and Research Department, Central Bank and Financial Services Authority of Ireland.

Bernanke, S.B. and Woodford, M., (2005). “The Inflation-Targeting Debate” National Bureau of Economic Research Studies in Business Cycles.

Bloch, H., Dockery, A., and Sapsford, D. (2006). “Commodity Prices and the Dynamics of Inflation in Commodity-Exporting Nations: Evidence from Australia and Canada” Economic Record.

Borio, C. and Filardo, A. (2007): Globalisation and Inflation: New Cross-country Evidence on the Global Determinants of Domestic Inflation, BIS Working Paper No. 227, May.

Boughton, J.M., and Branson, W.H. (1988), “Commodity Prices as a Leading Indicator of Inflation”, NBER Working Paper Series 2750.

Bureau of Labor Statistics. (2014). Consumer Price Index: <http://www.bls.gov/cpi/> (Consulted October 28<sup>th</sup>).

Ca' Zorzi, M. Muck, J. and Rubaszek, M. (2013). "Real exchange rate forecasting a calibrated half-life PPP model can beat the random walk" Working paper series, August 2013.

Carney, M. (2008). "Capitalizing on the Commodity Boom: the Role of Monetary Policy." Speech made to the Haskayne School of Business, Calgary, Alberta, June 19.

C. Cheung. (2009) «Are commodity prices useful leading indicators of inflation?» Bank of Canada.

Cecchiti, R.S., Chu and Steindel C. (2000). "The unreliability of Inflation Indicators" Current Issues in Economics and Finance. Federal Reserve Bank of New York. April 2000.

Clements, M. 2002. «Why forecast performance does not help us choose a model». Mimeo University of Warwick, Journal of Labor Economics, Vol. 1, No. 4, p.331-344.

Clements, M and Hendry, D. (2002). "A Companion to Economic Forecasting" Blackwell Companions to Contemporary Economics.

De Gregorio, J., Landerretche, O. and Neilson, C. (2007): Another Pass-Through Bites the Dust? Oil Prices and Inflation, Central Bank of Chile Working Papers, No. 417, May.

Doornik, J.A. and Hendry, D.F. (2013). "Empirical Econometric Modelling". PC Give: 14 volume I.

Edelstein, P. (2007), “Commodity Prices, Inflation Forecasts, and Monetary Policy”, Working Paper, University of Michigan.

Eugeni, Francesca and Joel Kruger (1994), “The Ups and Downs of Commodity Price Indexes”, Federal Reserve Bank of Chicago, Chicago Fed Letter Number 88.

Faust, J. and Wright J.H. (2011). “Forecasting Inflation” forthcoming in Handbook of Forecasting. Department of Economics  
September 2011.

Fuhrer, J. and G. Moore. (1992). “Monetary Policy Rules and the Indicator Properties of Asset Prices.” Journal of Monetary Economics 29 (2): 303–36.

Furlong, Fred and Robert Ingenito (1996), “Commodity Prices and Inflation”, Federal Reserve Bank of San Francisco Economic Review 1996, Number 2.

Green, K. and Tashman, L. (2009). “Forecast Accuracy Measurement” Foresight, Issue 12, Winter 2009.

Hafer, R.W. and Sheehan. (1989). .The Sensitivity of VAR Forecasts to Alternative Lag Structures. International Journal of Forecasting 5:399-408.

Haksever, C. and Render, B. (2013). “The Important Role Services Play in an Economy”. Financial Times: Press.

International Money Funds (2014). IMF Primary Commodity Prices: <http://www.imf.org/external/np/res/commod/index.aspx> (Consulted October 28).

Koskinen, J. (2014). “Forecasting Finnish Inflation with Commodity Indexes” Department of Economics, Aalto University School Business.

Kozicki, S. and Tinsley, P.A., (2002). "Alternatives Sources of the Lag Dynamics of Inflation" Research Working Paper. Federal Reserve Bank of Kansas City.

Kozicki, S. and Tinsley, P.A., (2001). "Shifting Endpoints in the Term Structure of Interest Rates" *Journal of Monetary Economics*, 47.

Krichene, N. (2008): *Recent Inflationary Trends in Commodities Markets*, IMF Working Paper No. 08/130, May.

Kudyba, S. and Romesh D. (1998) "Rising Commodities and Higher Inflation (It.s not that simple)". *Futures*, February, 1998, pages 48 . 50.

Litterman, Robert B. (1986), "Forecasting with Bayesian Vector Autoregressions-Five Years of Experience," *Journal of Business and Economic Statistics* 4, 25-38.

Mankiw, G. and Reis, R. (2001) "Sticky Information versus Sticky Prices: a Proposal to replace the New Keynesian Phillips Curve" National Bureau of Economic Research. Cambridge, May 2001.

Martin, K.G. (2012). "Assessing the Fit of Regression Models". *StatNews* No. 68. Seattle Government. (2014). *Inflation-Consumer Price Index*: <http://www.seattle.gov/financedepartment/cpi/historical.htm> (Consulted, October 1<sup>st</sup> 2014).

Moosa, A., (1998). "Are Commodity Prices a Leading Indicator of Inflation?" *Journal of Policy Modeling*.

Monti,F. (2009). "Forecasting with Judgment and Models" ECARES, Université Libre de Bruxelles. January 2008.

Robertson, J.C. and Tallman, E.W. (1999). "Vector Autoregressions: Forecasting and Reality" Federal Reserve Bank of Atlanta, *Economic Review*, First quarter, 1999.

Sims, C.A. (1992). "Interpreting the Macroeconomic Time Series".

Thomas, R.L. (1996). "Modern Econometrics: an Introduction" Department of Economics, Manchester Metropolitan University. Pearson Education Limited.

Smets, F. and Wouters, R., (2003). "An Estimated Stochastic Dynamic General Equilibrium Model of the Euro Area, Journal of the European Economic Association, 1.

Verbeek, M. (2004), "A Guide to Modern Econometrics, Second Edition", John Wiley & Sons Ltd.

Verheyen, F. (2010) "Monetary Policy, Commodity Prices and Inflation: Empirical Evidence from the US" Ruhr Economic Papers #216, Ruhr-Universität Bochum.

Wright, J. and Faust, J. (2012). "Inflation Forecasting" forthcoming in Handbook of Forecasting.

## Tables

**Table 1: Unit root tests-ADF tests**

**Unit-root tests**

The sample is: 1992(6) - 2013(12) (263 observations and 11 variables)

**U.S Inflation: ADF tests (T=259, Constant; 5%=-2.87 1%=-3.46)**

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	-8,322**	0,26	0,00	0,25	0,81	-11,63	
2	-9,598**	0,27	0,00	1,25	0,21	-11,64	0,81
1	-10,74**	0,32	0,00	4,10	0,00	-11,64	0,45
0	-9,787**	0,46	0,00			-11,59	0,00

**IMF Commodity Price Index: ADF tests (T=259, Constant; 5%=-2.87 1%=-3.46)**

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	-6,818**	0,40	0,04	0,18	0,86	-6,38	
2	-7,456**	0,40	0,04	0,23	0,82	-6,39	0,86
1	-8,293**	0,41	0,04	-1,52	0,13	-6,40	0,96
0	-11,11**	0,35	0,04			-6,39	0,50

**Table 2: Correlation Matrix**

The sample is: 1992(2) - 2013(12) (263 observations and 2 variables)

Correlation matrix:

	U.S Inflation	IMF Commodity Price Index
U.S Inflation	1	0,61
IMF Commodity Price Index	0.61	1

**Table 3: VAR lag order selection test results****Modelling IMF Commodity Price Index by OLS**

The estimation sample is: 1992(4) - 2013(12)

D-lag	AIC	HQ	SC	FPE
3	-3,54	-3,50	-3,44	0,03
2	-3,58*	-3,55	-3,51	0,03
1	-3,54	-3,52	-3,49	0,03

**Modelling U.S. Inflation by OLS**

The estimation sample is: 1992(4) - 2013(12)

D-lag	AIC	HQ	SC	FPE
3	-8,94	-8,90	-8,85	0,00
2	-8,94*	-8,91	-8,87	0,00
1	-8,91	-8,90	-8,87	0,00

\* Indicates lag order selected by the Akaike information criterion

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Table 4: Estimated Parameters for the Second Order VAR System

## Equation (1) Modelling IMF Commodity Price Index by OLS

The estimation sample is: 1992(5) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
IMF Commodity Price Index_1	0,40	0,07	5,38	0,00	0,10
IMF Commodity Price Index_2	0,23	0,08	2,85	0,00	0,03
U.S. Inflation_1	-2,44	1,08	-2,27	0,02	0,02
U.S. Inflation_2	-1,14	0,96	-1,19	0,24	0,01
Constant	0,01	0,00	2,74	0,01	0,03

## Equation (2) Modelling U.S. Inflation by OLS

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_2	-0,22	0,07	-3,30	0,00	0,04
U.S. Inflation_1	0,27	0,07	3,69	0,00	0,05
IMF Commodity Price Index_1	0,03	0,01	6,04	0,00	0,12
Constant	0,00	0,00	7,54	0,00	0,18
IMF Commodity Price Index_2	0,01	0,01	1,21	0,23	0,01

Table 5: One-step Forecast Output

## Commodity based model

Modelling U.S. Inflation by OLS

The estimation sample is: 1992(4) - 2013(4)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
DLCPI USA_1	0,29	0,07	3,96	0,00	0,06
DLCPI USA_2	-0,18	0,06	-3,11	0,00	0,04
Constant	0,00	0,00	7,61	0,00	0,19
DLAll_Commodity_Price_Index_1	0,03	0,01	6,24	0,00	0,14

1-step forecasts for U.S. Inflation (SE with parameter uncertainty)

Horizon	Forecast	SE	Actual	Error	t-value
2013-5	5,15E+00	0,0028	0,0018	0,0017	0,6220
2013-6	0,0024	0,0028	0,0024	-2,3827	-0,0090
2013-7	0,0020	0,0028	0,0004	-0,0016	-0,5710
2013-8	0,0021	0,0028	0,0012	-0,0009	-0,3230
2013-9	0,0023	0,0028	0,0012	-0,0011	-0,4060
2013-10	0,0017	0,0028	-0,0026	-0,0042	-1,5320
2013-11	0,0002	0,0028	-0,0020	-0,0023	-0,8190
2013-12	0,0011	0,00278	-8,58E+00	-0,0011	-0,41

mean(Error) =	-0,0012	RMSE =	0,0020
SD(Error) =	0,0016	MAPE =	91,47

## Autoregressive AR(1) model è Benchmark

Modelling DLCPI USA by OLS

The estimation sample is: 1992(4) - 2013(4)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
DLCPI USA_1	0,45	0,06	8,01	0,00	0,20
Constant	0,00	0,00	4,91	0,00	0,09

1-step forecasts for U.S. Inflation (SE with parameter uncertainty)

Horizon	Forecast	SE	Actual	Error	t-value
2013-5	0,0006	0,0031	0,0018	0,0011	0,3740
2013-6	0,0019	0,0031	0,0024	0,0005	0,1610
2013-7	0,0022	0,0031	0,0004	-0,0018	-0,5830
2013-8	0,0013	0,0031	0,0012	-7,6227	-0,0250
2013-9	0,0016	0,0031	0,0012	-0,0005	-0,1570
2013-10	0,0016	0,0031	-0,0026	-0,0042	-1,3710
2013-11	-6,2644	0,0031	-0,0020	-0,0020	-0,6440
2013-12	0,0002	0,0031	-8,5815	-0,0003	-0,0860

mean(Error) =	-0,0009	RMSE =	0,0018
SD(Error) =	0,0016	MAPE =	73,33

Table 6: Results for IMF commodity Categories

## (1) Modelling U.S. Inflation by OLS

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,40	0,06	6,46	0,00	0,14
U.S. Inflation_2	-0,25	0,06	-4,23	0,00	0,07
DLNon Fuel_1	0,04	0,01	4,98	0,00	0,09
DLNon Fuel_2	0,01	0,01	1,89	0,06	0,01
Constant U	0,00	0,00	7,19	0,00	0,17

## (2) Modelling U.S. Inflation by OLS

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,44	0,06	7,18	0,00	0,17
U.S. Inflation_2	-0,23	0,06	-4,01	0,00	0,06
DLFood&Beverage_1	0,04	0,01	6,12	0,00	0,13
DLFood&Beverage_2	0,01	0,01	0,97	0,33	0,00
Constant U	0,00	0,00	6,95	0,00	0,16

## (3) Modelling U.S. Inflation by OLS

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,46	0,06	7,95	0,00	0,20
U.S. Inflation_2	-0,22	0,06	-3,98	0,00	0,06
LFood_1	0,04	0,01	6,44	0,00	0,14
LFood_2	-0,04	0,01	-6,53	0,00	0,14
Constant U	0,00	0,00	1,60	0,11	0,01

## (4) Modelling U.S. Inflation by OLS

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,55	0,06	9,00	0,00	0,24
U.S. Inflation_2	-0,23	0,06	-3,87	0,00	0,06
DLBeverage_1	0,01	0,00	3,24	0,00	0,04
DLBeverage_2	0,00	0,00	-0,29	0,77	0,00
Constant U	0,00	0,00	6,04	0,00	0,12

**(5) Modelling U.S. Inflation by OLS**

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,48	0,06	7,67	0,00	0,19
U.S. Inflation_2	-0,27	0,06	-4,45	0,00	0,07
DLIndustrialInputs_1	0,01	0,01	2,42	0,02	0,02
DLIndustrial_Inputs_2	0,01	0,01	2,09	0,04	0,02
Constant U	0,00	0,00	6,71	0,00	0,15

**(6) Modelling U.S. Inflation by OLS**

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,55	0,06	8,71	0,00	0,23
U.S. Inflation_2	-0,28	0,06	-4,48	0,00	0,07
DLAgriculturalR.M_1	0,01	0,01	0,89	0,37	0,00
DLAgriculturalR.M_2	0,01	0,01	1,49	0,14	0,01
Constant U 0	0,00	0,00	6,33	0,00	0,14

**(7) Modelling U.S. Inflation by OLS**

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,49	0,06	7,89	0,00	0,20
U.S. Inflation_2	-0,25	0,06	-4,08	0,00	0,06
DLMetals_1	0,01	0,00	2,57	0,01	0,03
DLMetals_2	0,01	0,00	2,01	0,05	0,02
Constant U	0,00	0,00	6,47	0,00	0,14

**(8) Modelling U.S. Inflation by OLS**

The estimation sample is: 1992(4) - 2013(12)

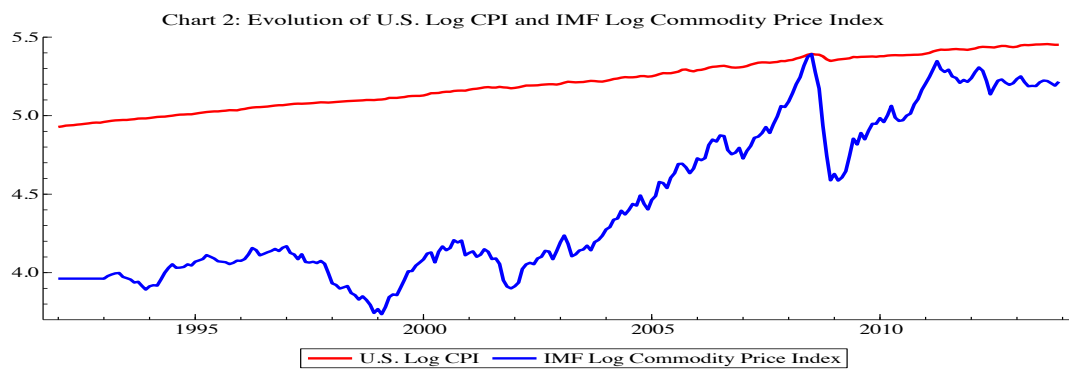
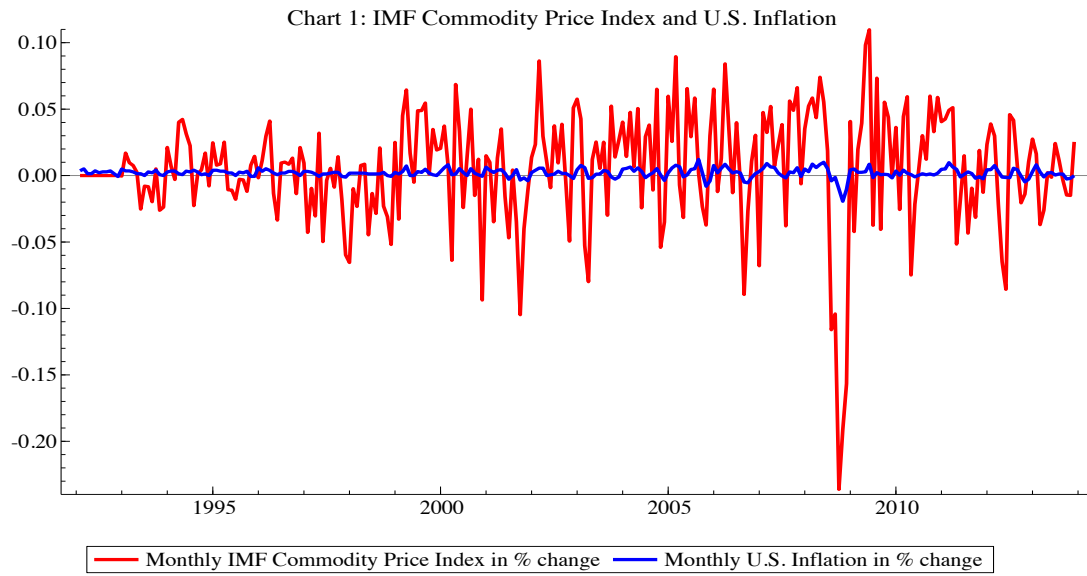
	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,37	0,07	5,16	0,00	0,09
U.S. Inflation_2	-0,20	0,07	-3,01	0,00	0,03
DLFuel_Energy_1	0,02	0,00	4,61	0,00	0,08
DLFuel_Energy_2	0,00	0,00	0,16	0,88	0,00
Constant U	0,00	0,00	6,71	0,00	0,15

**(9) Modelling U.S. Inflation by OLS**

The estimation sample is: 1992(4) - 2013(12)

	Coefficient	Std.Error	t-value	t-prob	Part.R <sup>2</sup>
U.S. Inflation_1	0,39	0,07	5,45	0,00	0,10
U.S. Inflation_2	-0,21	0,07	-3,14	0,00	0,04
DLCrudeOilpetrol_1	0,01	0,00	4,21	0,00	0,06
DLCrudeOilpetrol_2	0,00	0,00	0,30	0,76	0,00
Constant U	0,00	0,00	6,66	0,00	0,15

## Charts



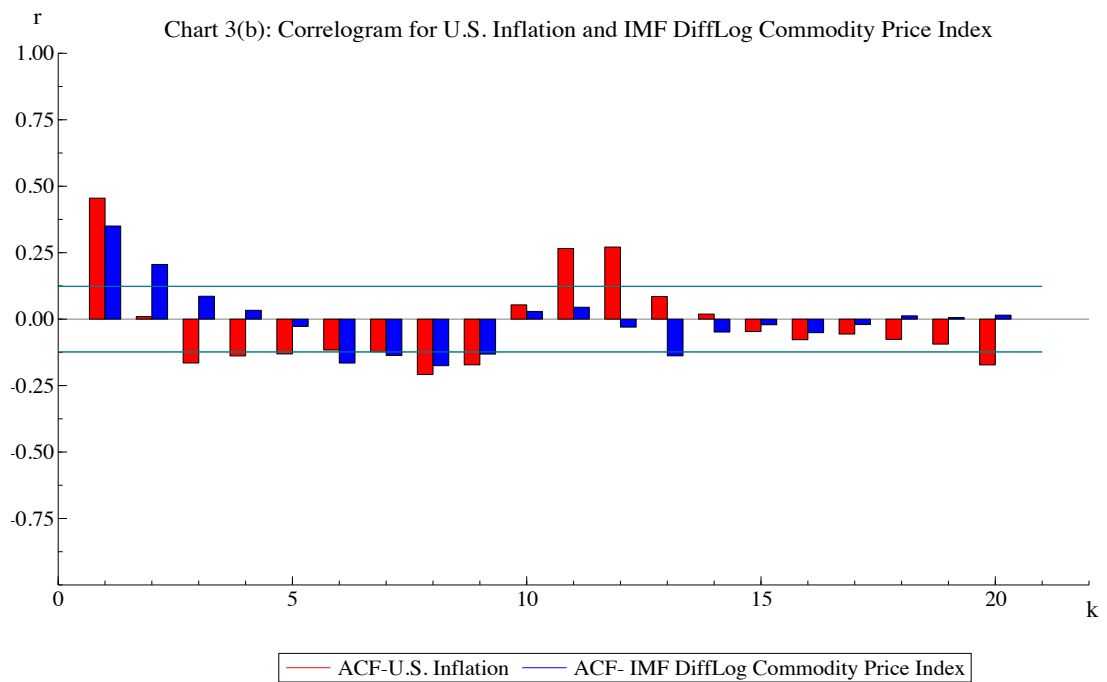
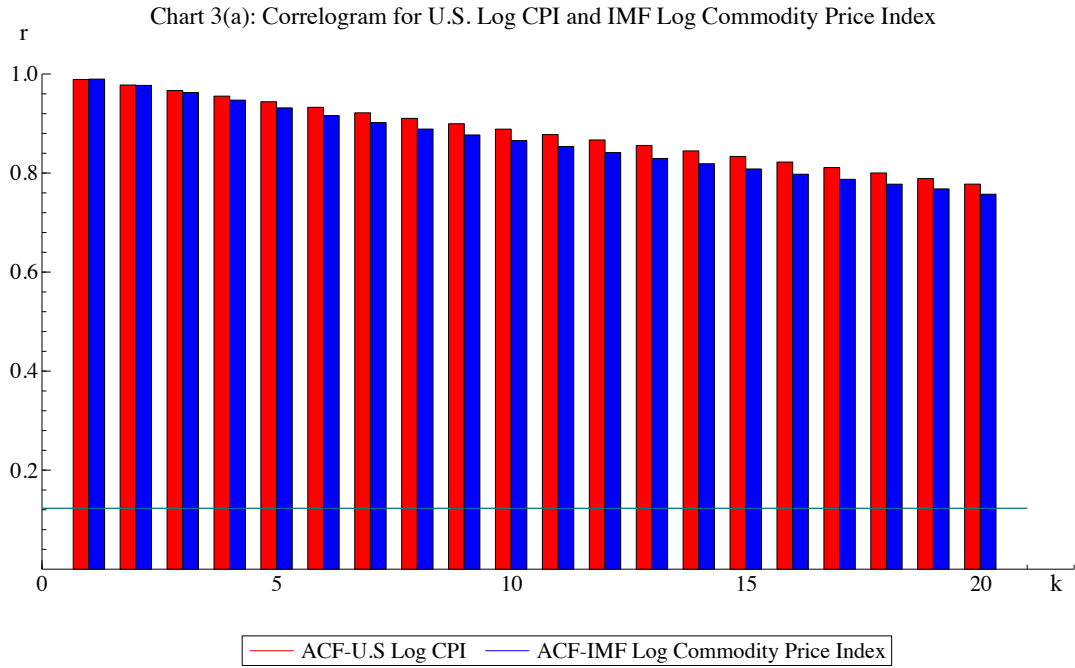


Chart 4 (a): Evolution of the 1-step forecasts commodity index-based Model and US inflation

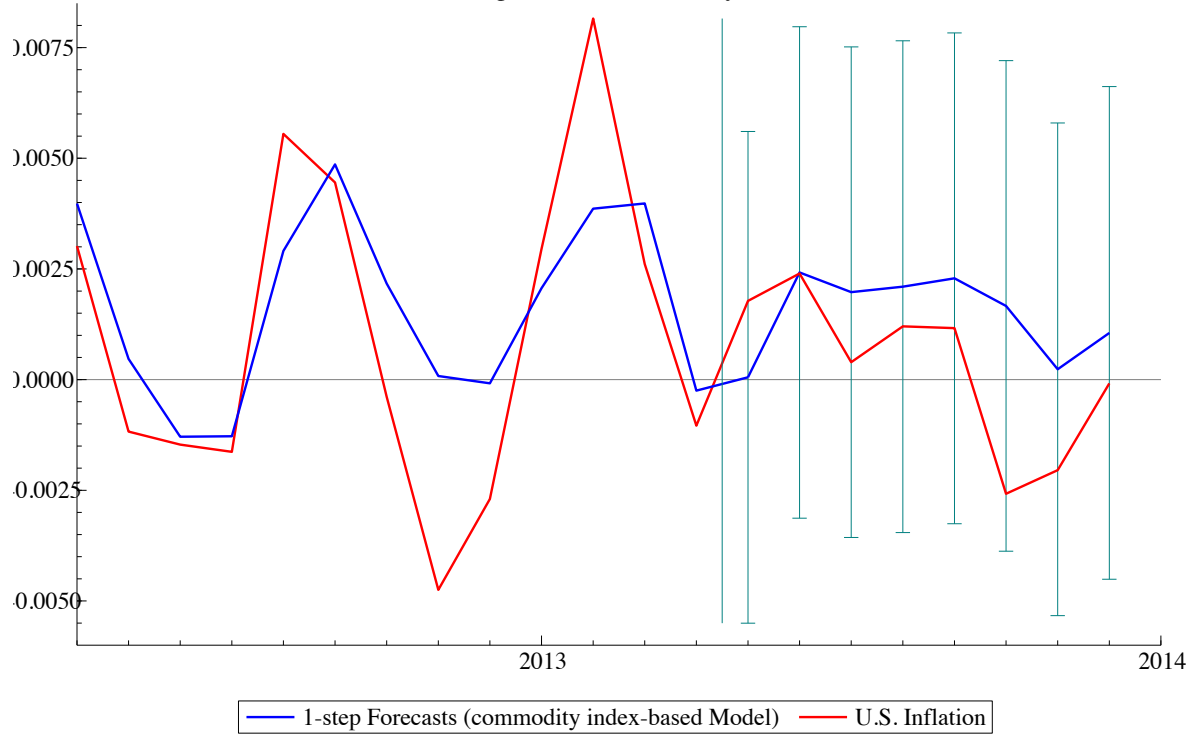


Chart 4 (b): Evolution of the 1-step forecasts AR(1) and US inflation

