# Chapter 11

# Econometric Investigation of Monthly Time Series

## 11.1 Introduction

In contrast to the real-side variables investigated in the previous chapter, for which only yearly series are available, most nominal and financial variables, such as the Consumer Price Index, exchange rate and the interest rates, are available on a monthly basis for all or most of the period in question. We are thus able to conduct much more rigorous statistical hypothesis testing, and proceed to do so in the present chapter. We restrict ourselves to analyzing the behavior of two key nominal prices, namely the Consumer Price Index (CPI) and the exchange rate (cedis to the dollar), and of the broad money supply. We use the Stata statistical package throughout. As in the previous chapter, we provide individual summaries for each section, instead of one chapter summary; the summaries in this chapter are brief and technical, with the discussion of implications for theory and policy reserved for later chapters.

Let us denote the natural log of the consumer price index by `cpi`, the natural log of the exchange rate by `er`, and the natural log of the broad money supply `m2`. (As changes in the value of either macro price are typically in proportion to its current value, it is common practice to consider them in log form). As we will see below, all these three variables are first order integrated (I(1)), as is common for nominal time series.

We begin by listing the explanatory variables suggested by economic theory for each of our three dependent variables, and running a regular least squares regression using these. Unfortunately, since all three dependent variables are I(1) nonstationary, the results of these regressions are only meaningful if the variables are cointegrated. Using the Durbin-Watson statistic, we fail to find cointegration in all three cases

In the absence of cointegration, we have to resort to ARIMA-X (Autoregressive Integrated Moving Average with eXogenous variables) regressions using first differences and lags of independent variables (Stata command `arima`).

For those independent variables that are only available yearly (namely GDP and export and import dollar price indices), we first interpolate them to monthly using an algorithm due to Prof. Clopper Almon, and then only use the 12 month-seasonal difference `S12.X(t)=X(t)-X(t-12)`[1] in

[1]For those of our readers unfamiliar with Stata, an explanation of the notation is in order at this point. The expression `D.X` or `D1.X` refers to the first difference of the variable `X`, that is, `D.X(t)=X(t)-X(t-1)`. `LN.X` refers to lag of order $N$; for example, is, `L5.X(t)=X(t-5)`. `SN.X(t)` refers to

the regressions, as results arising from using any shorter differences would likely be an artifact of the interpolation method used.

To find out the correct lag structure for the variables where original data series were monthly, we first regress the dependent variable on fifteen lags of each independent variable in turn, as well as `ar(1/6,12)` and `ma(1/6,12)`, with the 12-month autoregressive lag inserted to account for possible seasonal effects, and note down the lags of the independent variable that prove significant.

We use the information thus obtained to formulate a first, rather generously overparametrized regression, and use it as a first in a model identification process, generating a sequence of ever simpler models while at each step computing several statistics to make sure that residuals still behave as white noise and that we are not losing substantial quality of fit.

Finally, we test the predictive qualities of the model we have thus identified by using it to predict its corresponding dependent variable from January 1998 onwards, one time with coefficients estimated from the whole dataset, and one time with coefficients estimated using only pre-1998 data. The details for each dependent variable are presented below.

## 11.2 Consumer Price Index

To explain the behavior of the Consumer Price Index, we use the following variables: Money supply (broad money `m2`, computed from the side of liabilities of the banking system) and real GDP as the traditional price level determinants in the velocity of money equation; exchange rate, wholesale price of food crops and price of fuel (the latter being government-controlled) as important components of cost; and the interest rate on government bonds. All of these variables except the interest rate are taken in natural log terms.

The relationship between the price level and the money supply is of particular interest to us due to its relevance to both theory and policy, as we have discussed in Chapters 3 and 4. Figure 11.1 shows inflation and broad money growth rate for our period.

On the policy side, a vision of an active money supply that drives the aggregate price level while being itself to a large extent controlled by the government is at the core of IMF-inspired adjustment programs. On the theoretical side, the direction of causality between the price level and the money supply is one of the key differences between structuralist and Walrasian/monetarist CGE models.

As we have seen in Chapter 4, in structuralist models prices are determined from the side of costs, with no direct influence of the money supply on prices; the main indirect channel would be through interest rates, larger money supply leading to more credit supply, lower interest rates and thus lower inflation pressure from the cost of borrowing.

In Walrasian/monetarist models the picture is almost exactly reversed. To begin with, the standard money demand equation $Py = V(r)M$ means that an increase in the money supply translates ceteris paribus directly into a proportional increase in the price level; secondly, increasing interest rates will increase money demand, lowering the velocity of money and *lowering* the price level. The question of which of these two views is correct is crucial for choosing and evaluating monetary policy options.

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the "seasonal difference"; for example, `S4X(t)=X(t)-X(t-4)`. These operators can be nested – for example, `L2S3.X(t)=X(t-2)-X(t-5)=L2D.X(t)+L3D.X(t)+L4D.X(t)`.

Further, `1/5` is a short notation for 1,2,3,4,5 (as the usual notation 1-5 could be confused with subtracting 5 from 1).

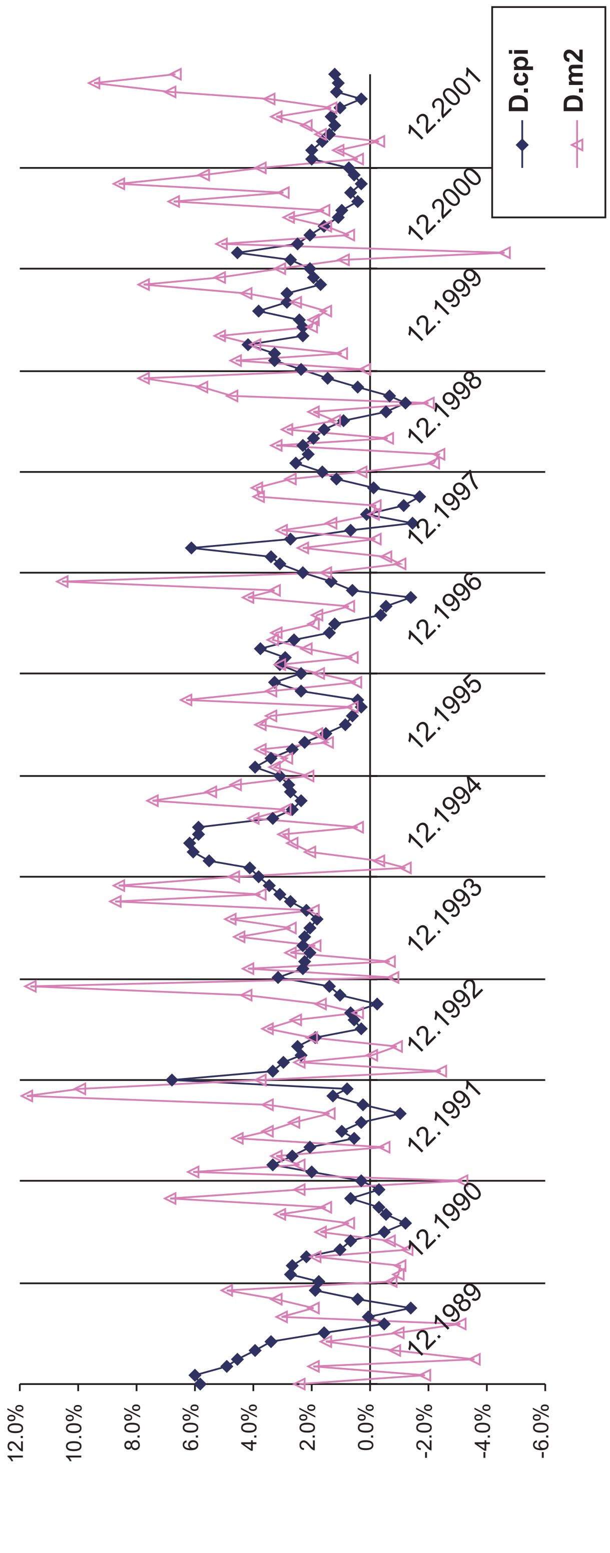


Figure 11.1: *Inflation and Money Supply Growth*

| D.cpi | D.m2 | D.er | D.fuel | D.food | D.rtb |
|---|---|---|---|---|---|
| Significant lags | 1-9 | - | 1 | 0-2 | 1-3 |

Table 11.1: *Preliminary Lag Structure Examination for CPI*

The role of the interest rate is important as the interest rate is a common policy tool for inflation control. It was for inflation control purposes that the interest rates in the 1990s were set so high in Ghana. The interest rate is an interesting variable in this context, as it is considered by monetarists to stimulate money demand and thus its increase would be expected to *decrease* inflation; while structuralists consider it primarily as a component of cost and thus would expect its increase to lead to an *increase* in inflation. Thus the sign of its coefficient will be quite interesting to see. We take the interest rate on treasury bills rather than, say, the interest rate on deposits, because it is closely related to the other key domestic interest rates, and because it is the actual instrument that the Bank of Ghana uses for the purposes of inflation control.

To begin our analysis, let us first test the CPI for stationarity. Augmented Dickey-Fuller test (`dfuller cpi,trend regress`) returns ADF=-0.51, corresponding to $p = .98$. Augmented Dickey-Fuller test on *D.cpi* and *D.er* returns ADF=-4.6, corresponding to $p = 0.001$. Thus we conclude that `cpi` is I(1).

We proceed to run a regular least-squares regression

```
reg cpi mb gdp er fuel food rtb; dwstat
```

which returns a $d$-value of .285, well below the cointegration significance threshold. Thus the variables are not cointegrated and we have to run an ARIMA-X regression.

To find out the correct lag structure, we first run

```
arima D.cpi X L.X ... L15.X, ar(1/6,12) ma(1/6,12)
```

where the variables `X` are listed in Table 11.1. GDP does not appear in the table because it has been interpolated from a yearly series and thus we will only use `S12.gdp`.

From Table 11.1 we see that the impacts of money supply are significant over a long period, while impacts of rises in wholesale food crop prices (denoted `food`) and fuel prices are almost instantaneous and the results are less clear for the other variables. Based on that information, we formulate the first regression which is reported in Table 11.2.

The meaning of the different columns of Table 11.2 bears some explanation. Akaike's Information Criterion and Schwarz's Criterion are used to compare quality of fit for different models while adjusting for the different number of coefficients in different models, with more negative values meaning better fit (as both are derived from log-likelihood). We computed them using the Stata command `arimafit`. Portemanteau (Q) statistic (Stata command `wntestq`)and Bartlett's (B) statistic (`wntestb`) are measures of whether the residuals behave like white noise. For compactness reasons, we only report the corresponding $p$-values, that is, the probabilities that a given residuals sequence has been produced by a white noise process. Therefore, higher $p$-values are evidence for white noise and therefore for a good model.

We start from a generously overparametrized regression, including autoregressive and moving average terms `1/6` and `12`, the latter being there to account for possible seasonal effects. In successful steps we can whittle that down to `ar(1)` which is then highly significant and remains so throughout the latter regressions.

In the next step, we proceed to trim down the independent variables. To see whether a variable (meaning all of its lags) belongs into the regression, we use two measures: firstly, we use the Stata command `test` to test the hypothesis that the coefficients of all of the lags of that variable are

| ARMA terms | Exo terms | AIC | SIC | wntestq | wntestb |
|---|---|---|---|---|---|
| ar(1,2,12) ma(1,2,12) | D.m2. . . L12D.m2,<br>S12.gdp,<br>D.er. . . L6D.er,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L3D.food,<br>D.rtb. . . L4D.rtb | -781 | -668 | 77% | 92% |
| ar(1,2) ma(1,2) | D.m2. . . L12D.m2,<br>S12.gdp,<br>D.er. . . L6D.er,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L3D.food,<br>D.rtb. . . L4D.rtb | -778 | -671 | 84% | 99.90% |
| ar(1) ma(1) | D.m2. . . L12D.m2,<br>S12.gdp,<br>D.er. . . L6D.er,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L3D.food,<br>D.rtb. . . L4D.rtb | -779 | -677 | 76% | 78% |
| ar(1) | D.m2. . . L12D.m2,<br>S12.gdp,<br>D.er. . . L6D.er,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L3D.food,<br>D.rtb. . . L4D.rtb | -779 | -681 | 47% | 36% |
| ar(1) | D.m2. . . L12D.m2,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L3D.food,<br>D.rtb. . . L4D.rtb | -782 | -700 | 74% | 70% |
| ar(1) | D.m2. . . L12D.m2,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L3D.food | -781 | -719 | 13% | 78% |
| ar(1) | D.m2. . . L12D.m2,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L2D.food | -783 | -724 | 13% | 79% |
| ar(1) | D.m2. . . L12D.m2,<br>D.fuel. . . L2D.fuel,<br>D.food. . . L2D.food | -783 | -724 | 13% | 79% |

Table 11.2: *ARIMA-X model identification for* `D.cpi`

| | | |
|---|---|---|
| Sample: 13 to 136 | Number of obs = 124 | Semi-robust |
| Wald chi2(20) = 244.07 | Log likelihood = 412.7643 | Prob > chi2 = 0 |

| D.cpi | | Coeff. | Stdev. | $z$ | $P > z$ | 95% Conf. Interval | |
|---|---|---|---|---|---|---|---|
| m2 | D1 | 0.025 | 0.028 | 0.90 | 36.9% | -0.030 | 0.080 |
| | LD | 0.074 | 0.036 | 2.10 | 3.6% | 0.005 | 0.144 |
| | L2D | 0.079 | 0.041 | 1.91 | 5.6% | -0.002 | 0.160 |
| | L3D | 0.080 | 0.042 | 1.89 | 5.9% | -0.003 | 0.163 |
| | L4D | 0.163 | 0.039 | 4.21 | 0.0% | 0.087 | 0.239 |
| | L5D | 0.133 | 0.042 | 3.16 | 0.2% | 0.051 | 0.215 |
| | L6D | 0.096 | 0.042 | 2.27 | 2.3% | 0.013 | 0.179 |
| | L7D | 0.009 | 0.041 | 0.21 | 83.0% | -0.072 | 0.089 |
| | L8D | 0.005 | 0.030 | 0.18 | 86.0% | -0.053 | 0.064 |
| | L9D | 0.008 | 0.034 | 0.23 | 81.5% | -0.058 | 0.074 |
| | L10D | -0.013 | 0.032 | -0.43 | 67.1% | -0.076 | 0.049 |
| | L11D | 0.004 | 0.033 | 0.14 | 89.3% | -0.061 | 0.070 |
| | L12D | -0.025 | 0.028 | -0.91 | 36.5% | -0.079 | 0.029 |
| fuel | D1 | -0.001 | 0.010 | -0.10 | 92.4% | -0.021 | 0.019 |
| | LD | 0.042 | 0.015 | 2.73 | 0.6% | 0.012 | 0.072 |
| | L2D | 0.016 | 0.013 | 1.24 | 21.7% | -0.009 | 0.040 |
| food | D1 | 0.015 | 0.010 | 1.47 | 14.2% | -0.005 | 0.035 |
| | LD | 0.022 | 0.011 | 1.97 | 4.9% | 0.000 | 0.045 |
| | L2D | 0.029 | 0.009 | 3.31 | 0.1% | 0.012 | 0.046 |
| _cons | | 0.0004 | 0.0063 | 0.06 | 95.5% | -0.0120 | 0.0127 |
| ar | L1 | 0.706 | 0.072 | 9.85 | 0.0% | 0.566 | 0.847 |
| /sigma[2] | | 0.0086 | 0.0006 | 15.28 | 0.0% | 0.0075 | 0.0098 |

Table 11.3: *ARIMA-X regression for* `D.cpi`

zero; secondly, we use `lincom` to test whether the sum of all the lags' coefficients is zero. If both of these give $p$-values above 30%, the variable is a candidate for elimination.

In the first step, we eliminate GDP and the exchange rate, without any losses in quality of fit or in the likeness of residuals to white noise. Then we do the same to the interest rate, ending up with a regression presented in Table 11.3.

The regression of Table 11.3 is further summarized in Table 11.4, where we report the values and standard deviations of the sum of each variable's coefficients (describing the total impact of a change in that variable on the price level), as well as the probability that all of that variable's coefficients are zero. The column "Total Impact" shows the overall impact of each variable after accounting for the positive feedback loop between prices and money supply (see Section 11.4) that increases all impacts by 27%.

What do we learn from these tables? First of all we see that interest rates, exchange rate and GDP do not have a significant direct impact on the price level. On the other hand, the impact of changes in broad money supply is substantial, with a 1% increase in broad money supply leading to over a .85% increase in the CPI after inflation inertia is taken into account; the total impacts of fuel prices and wholesale food crop prices are smaller but also not negligible, with a 1% increase in either leading to a total .08% resp. .07% increase in CPI. These two price indices are much more volatile, and their impacts are almost instantaneous, whereas the impact of increases in money

[2] /sigma refers to the standard error of the disturbance

| Variable | Terms included | Value | Stdev | Coeff. $p$ | Variable $p$ | Total Impact |
|---|---|---|---|---|---|---|
| m2 | D...L12D | 0.673 | 0.213 | 0.20% | 0.51% | 0.85 |
| fuel | LD...L2D | 0.057 | 0.024 | 1.90% | 2.70% | 0.07 |
| food | D...L2D | 0.066 | 0.025 | 0.90% | 1% | 0.08 |
| cons | | 0.0004 | 0.0062 | 96.00% | 95% | |
| ar(1) | | 0.706 | 0.071 | 0.00% | | |

Table 11.4: *Summary of ARIMA-X regression for* `D.cpi`

supply takes about a year to fully work itself out. Thus, the contributions of the price of fuel and the wholesale price of food crops to inflation at any given time could in principle be larger than those of money supply. However, we can see that this is rarely the case from Figure 11.2, which shows the respective contributions to inflation over time of each of the three independent variables (reconstructed from the regression in Table 11.3).

A hopeful sign is that the constant turns out to be entirely non-significant ($p = 96\%$), so that inflation is completely predicted by changes in our chosen independent variables, without a constant term that would have stood for an exogenous trend in the price level and thus would have suggested we have omitted some of the inflation determinants, namely those causing that trend.

Another way of assessing how well the regression of Table 11.3 is by using it for forecasting part of the data, in the manner of Chapter 9. For this, we use the `predict` command of Stata to predict `cpi` from January 1998 onwards. We have several options to construct such a forecast: firstly, we can use the *actual* values of the variable in a previous month to predict the value of the variable at the next time step. This will result in a very good fit as that was the expression whose error was maximized in the regression in the first place. However, this is not a good indicator of prediction quality as we would not know the previous' month inflation when predicting a moment several months into the future. Thus, to get a better estimate of predictive power of our regression, we should determine each month's inflation recursively, using last month's predicted value in the autoregressive term (option `dynamic()` in Stata). If such an approach gives good results, that would be encouraging, but not quite enough - after all, the regression coefficients were determined using the data for the whole period, not just the pre-1998 period. Thus, the next step is to re-run the regression of Table 11.3 using only data up to January 1998, and use the resulting coefficients to do post-January 1998 predictions. If that approach is good at prediction, we have some reason for confidence.

We should note that even the latter approach is not fully equivalent to the approach of Chapter 9, as model identification, that is the choice of variables and lags in Table 11.3 was also made using the whole dataset. To make the testing quite clean, we should repeat the model identification process using only pre-1998 data; however, as this step would require much more effort than the previous ones, we regretfully omit it. The results are shown in Figure 11.3 and are quite encouraging - all three versions do quite well at predicting the CPI several years into the future. The predictions are both accurate and robust with respect to the choice of estimation time period.

A plausible way of interpreting the deviations would be to say that the CPI occasionally outgrows our prediction due to some short-term cost shock, but always tends back to the medium-term value that is predicted by our regression.

On this hopeful note, we conclude the investigation of the price level and turn to understanding

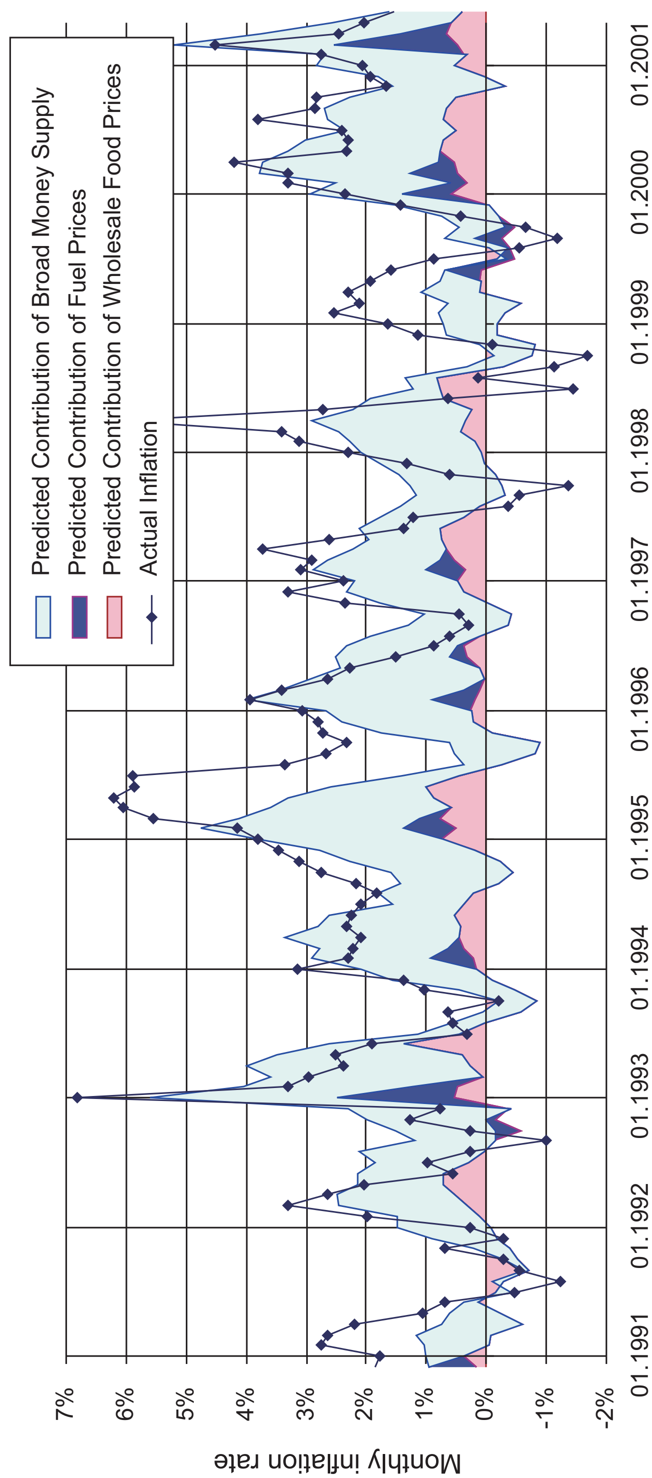


Figure 11.2: *Contributions to Inflation Derived from Table 11.3*

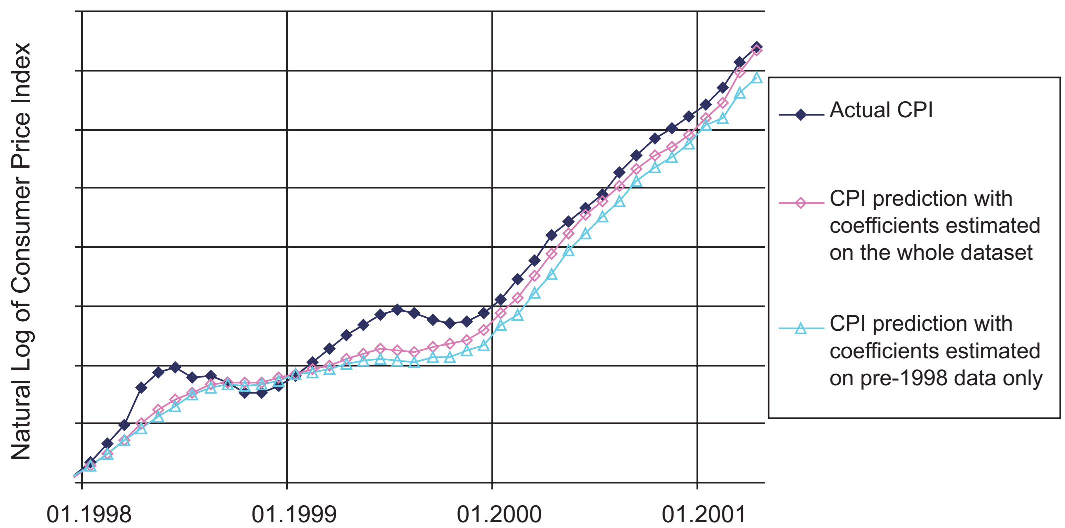


Figure 11.3: *Actual CPI vs. predictions from ARIMA-X regressions*

one of its major determinants, namely the broad money supply.

### 11.2.1 Summary

Investigation of the price behavior gives us both expected and unexpected results. On the expected side, money supply is highly significant for price formation, and takes its effect gradually over with a lag of two to nine months. Increases in fuel and wholesale food crop prices are also highly significant, but their impacts happen over a much shorter period (lags 0-2). Using just these three variables, we can predict `cpi` surprisingly well four years into the future (1998-2001), with coefficients estimated using pre-1998 data only.

On the surprising side, exchange rate depreciation, interest rate changes, and GDP growth appear to not have significant direct influence on inflation.

## 11.3 Money Supply

The first issue we have to address in this section is the justification of the definition of money supply that we will use. The main options are definition from the liability vs. asset side of the banking system and monetary base vs. broad money (for an introduction to these terms, see Chapter 5).

Regarding the first of the two choices, we choose to define money supply from the side of the banking system's liabilities. This is preferable from both monetarist and structuralist theoretical perspectives as the money supply is meant to represent the liquidity held by the private sector.

#### Broad Money vs. Monetary Base

As for the choice between monetary base and broad money, the first question one might ask is whether it makes any difference. In fact, if the reserve requirement is exactly observed, simple algebra shows the two are proportional. Thus, while from the theoretical side it would seem preferable to take broad money as a measure of private sector's liquid assets, it is common in CGE models [Kraev 2003, Table 2.2] to take the monetary base as the money supply whose market is cleared by the price level.

However in the case of Ghana, where interest rates above 30% were not at all unusual in the 1990s, the reserve requirement was *not* exactly observed. In fact, it was common for the banks to have liquidity (in the form of government bonds) well in excess of the reserve requirement, making base money and broad money two independent variables.

We test the constancy of the ratio between monetary base and broad money by first computing the log of that ratio for each month (by subtracting the log of monetary base `mb` from the log of broad money `m2`) and then testing it for stationarity using the Augmented Dickey-Fuller test, which returns $Z(t) = -2.202,\ p = 0.4900$. Thus, we conclude that the two definitions of money supply are not in fact proportional, and it does make a difference as to which one we use. We use broad money `m2` as it would seem a better measure of the private sector's liquid assets, and use the monetary base `mb` as one of its explanatory variables.

### Choice of Explanatory Variables

We choose the following explanatory variables: Consumer Price Index `cpi`, the interest rate on government bonds `rtb`, the exchange rate `er`, and the monetary base `mb`. Of these, all are in log terms except `rtb`, which is measured in percentage points.

We choose these independent variables for the following reasons: We have seen in Section 11.2 that the direct effect of interest rate increases on inflation is not significant. In itself, this did not settle the question of the total effect of the interest rates on inflation, as a theoretically important channel is the influence of interest rates on money supply - something we would not observe in the regression of Table 11.3 as money supply is also an independent variable there.

As we have discussed in the previous section, an important way in which raising interest rates could combat inflation is by reducing the money supply (as the private sector chooses to hold government bonds rather than liquidity when interest rates rise). Whether they do so or not is an important question for monetary policy.

The role of the CPI is important to complement our understanding of the CPI-money supply causality. In monetarist theory, money supply drives prices through clearing of the money market. In structuralist theory, prices can drive money supply through demand for working capital - firms are assumed to create/repay loans so as to hold an amount of liquidity proportional to the nominal value of their stock of goods being processed, and thus proportional to the price level.

We have seen in the `cpi` section that the money supply has a strong influence on the price level, but the question still remains whether there is also causality pointing in the other direction, creating a feedback loop, or whether the money supply is largely unaffected by the price level.

Exchange rate is included because the money supply has a substantial foreign currency-denominated component, making revaluation a potentially important contribution to money supply growth. Finally, monetary base is important as it is more or less directly controlled by the central bank and is an important policy instrument.

### Model Identification and Estimation

First of all, let us note that `m2` is nonstationary, I(1): ADF for `m2` gives Z(t)=-2.26, $p = 0.26$, ADF for `D.m2` gives Z(t)=-9.7999, $p = 0.0000$. Regressing `m2` on `rtb`,`cpi`, `er` and `mb` gives us a $d = .1844$, way below the 10% significance level (.322) for cointegration. Thus the variables in question are not cointegrated, and we will resort to ARIMA-X regression as before. We have seen

| ARMA terms | Exogenous terms | AIC | SIC | wntestq | wntestb |
|---|---|---|---|---|---|
| ar(1/6,12) ma(1/6,12) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -698 | -558 | 97% | 100% |
| ar(1/2) ma(1/2) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -668 | -557 | 98% | 92% |
| ar(1/2) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -670 | -565 | 97% | 92% |
| - | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -672 | -574 | 97% | 61% |
| - | D.rtb...L3D.rtb, D.cpi...L3D.cpi, D.er...L4D.er, D.mb...L2D.mb | -705 | -653 | 95% | 54% |
| - | D.rtb...L3D.rtb, D.cpi...L3D.cpi, D.er...LD.er, D.mb...L2D.mb | -713 | -671 | 95% | 81% |
| - | D.rtb...L2D.rtb, D.cpi...L3D.cpi, D.er...LD.er, D.mb...L2D.mb | -714 | -674 | 96% | 87% |

Table 11.5: *ARIMA-X model identification for* `D.m2`

before that `cpi` is I(1). So are the other independent variables: ADF for `rtb` gives $p = .91$, and ADF for `D.rtb` gives $p = 0.0000$; ADF for `er` gives $p = .83$, and ADF for `D.er` gives $p = 0.0000$; ADF for `mb` gives $p = .23$, and ADF for `D.rtb` gives $p = 0.0000$.

Now we proceed to identify and estimate the model using the same strategy as in the previous section, with the regressions described in Table 11.5. The regression we ultimately arrive at is shown in Table 11.6 and summarized in Table 11.7.

Looking at these tables, we see that `cpi` has no significant influence on the money supply. Further, in contrast to the `cpi` regression, all variables' impacts are quite quick, taking no more than two months to develop. Monetary base increase by one percent increases money supply by about .3%, and exchange rate depreciation of 1% increases money supply by a little under .2%. An increase in the interest rate by ten percentage points results in an extra 3.5% decrease in the money supply[3], in accordance with the portfolio balance theory.

[3] It is perhaps worth reminding the reader that unlike the other variables, `rtb` is measured in percentage points (`rtb`=17 corresponding to 17%) and not considered in log terms. Thus, while a one percent change in the growth rate of the money supply means `D.m2`=0.01, an increase of the interest rate by one percentage point means `D.rtb`=1. This is the reason that the coefficients of the interest rate typically have two leading zeros after the comma.

| | | |
|---|---|---|
| Sample: 4 to 156 | Number of obs = 153 | Semi-robust |
| Wald chi2(12) =111.1 | Log likelihood = 370.0599 | Prob > chi2 = 0 |

| D.m2 | | Coeff. | Stdev. | $z$ | $P > z$ | 95% Conf. Interval | |
|---|---|---|---|---|---|---|---|
| rtb | D1 | 0.0002 | 0.0011 | 0.18 | 86.0% | -0.0020 | 0.0024 |
| | LD | -0.0010 | 0.0010 | -0.98 | 32.9% | -0.0031 | 0.0010 |
| | L2D | -0.0027 | 0.0012 | -2.21 | 2.7% | -0.0051 | -0.0003 |
| cpi | D1 | -0.104 | 0.183 | -0.57 | 56.9% | -0.462 | 0.254 |
| | LD | 0.129 | 0.267 | 0.48 | 62.9% | -0.394 | 0.651 |
| | L2D | -0.062 | 0.312 | -0.20 | 84.1% | -0.674 | 0.549 |
| | L3D | -0.089 | 0.198 | -0.45 | 65.2% | -0.477 | 0.299 |
| er | D1 | 0.028 | 0.082 | 0.34 | 73.5% | -0.134 | 0.189 |
| | LD | 0.157 | 0.070 | 2.24 | 2.5% | 0.020 | 0.295 |
| mb | D1 | 0.195 | 0.047 | 4.18 | 0.0% | 0.104 | 0.287 |
| | LD | 0.114 | 0.020 | 5.79 | 0.0% | 0.076 | 0.153 |
| | L2D | 0.016 | 0.023 | 0.68 | 49.5% | -0.030 | 0.062 |
| _cons | | 0.017 | 0.004 | 4.35 | 0.0% | 0.009 | 0.025 |
| /sigma | | 0.022 | 0.001 | 14.63 | 0.0% | 0.019 | 0.024 |

Table 11.6: *ARIMA-X regression for* `D.m2`

| Variable | Terms included | Value | Stdev | Coefficient $p$ | Variable $p$ |
|---|---|---|---|---|---|
| rtb | D ...L2D | -0.0035 | 0.0015 | 2.0% | 1.0% |
| cpi | D ...L3D | -0.127 | 0.203 | 29.0% | 86.0% |
| er | D ...LD | 0.185 | 0.870 | 3.3% | 3.8% |
| mb | D ...L2D | 0.326 | 0.052 | 0.0% | 0.0% |
| cons | | 0.017 | 0.004 | 0.0% | |

Table 11.7: *Summary of ARIMA-X regression for* `D.m2`

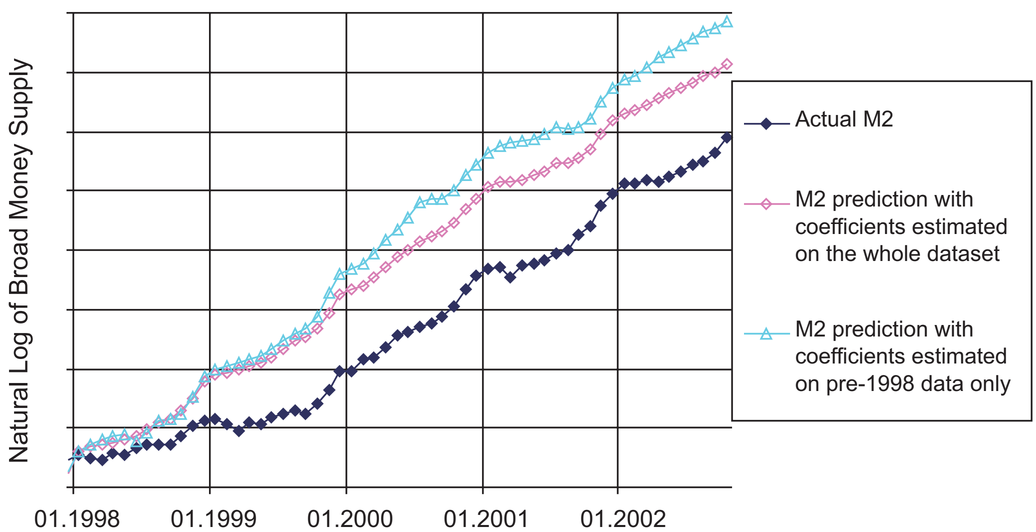


Figure 11.4: *Actual M2 vs. predictions from ARIMA-X regressions*

A more worrying development is a constant of .017, corresponding to an exogenous yearly growth rate of money supply of $.017 \times 12 \approx 20\%$. This becomes even more worrying once we use the model of Table 11.6 to predict `m2` from January 1998 onwards, once using the coefficients of Table 11.6 and once using the model of Table 11.6 re-estimated using only pre-1998 data. As Figure 11.4 shows, the constant trend dominates the predictions in both cases, and the predictions fail to capture the slowdown of money supply growth in 1998. We would like the behavior of money supply to be explained by the explanatory variables and its own past values – there is little theoretical justification for an exogenous constant growth rate. Therefore, we repeat the model identification process, this time forcing the constant in the regressions to be zero throughout. The model identification process is portrayed in Table 11.8, with the model we arrive at shown in Table 11.9 and summarized in Table 11.10. The predictions derived from that model are shown in Figure 11.5. As before, Total Impact refers to the total medium-term impact after accounting for the effect of the feedback loop between money supply and prices, discussed below in Section 11.4.

As the constant was significant in the regressions of Table 11.5, removing it naturally results in lower Akaike and Schwarz scores; however, we are compensated by much better behavior of the predictors, as well as higher significance values. We see that both predictors still over-estimate the values of `m2`, but by a lower margin, and their behavior is much more similar to actual `m2` behavior. Furthermore, the predictor from the model estimated with pre-1998 data has very similar behavior to that estimated using the full data. Thus we conclude that the model seems to be robust with respect to choice of estimation data period and reasonably-well behaved, even if unfortunately not as precise as the model for `cpi`.

Our explanation for the comparatively poor precision of the model is that our definition of `m2` perforce had to omit foreign exchange cash (mostly dollar bills) held by the populace. Anecdotal evidence suggests that this is a not insubstantial component, as dollars are widely used as a store of value; however it is not easy to measure and thus no data on it was readily available. While it is thus not included in our definitions of either `m2` or `mb`, it still affects them through portfolio re-balancing, introducing the imprecision we observe. It would be interesting to attempt to deduce the actual amount of foreign currency held by the populace by optimizing this predictor, but we will not attempt that here.

| ARMA terms | Exo terms | AIC | SIC | wntestq | wntestb |
|---|---|---|---|---|---|
| ar(1/6, 12) ma(1/6, 12) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -658 | -518 | 99% | 100.00% |
| ar(1/3) ma(1/3) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -663 | -546 | 95% | 50.00% |
| ar(1/3) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -655 | -547 | 95% | 86.00% |
| ar(1) | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -656 | -555 | 96% | 78.00% |
| - | D.rtb...L5D.rtb, D.cpi...L9D.cpi, D.er...L9D.er, D.mb...L9D.mb | -658 | -560 | 96% | 77% |
| - | D.rtb...L3D.rtb, D.cpi...L2D.cpi, D.er...L2D.er, D.mb...L3D.mb | -691 | -646 | 89% | 40% |

Table 11.8: *ARIMA-X model identification for `D.m2`, no constant*

| | | |
|---|---|---|
| Sample: 4 to 156 | Number of obs = 153 | Semi-robust |
| Wald chi2(14) =333.62 | Log likelihood = 360.889 | Prob > chi2 = 0 |

| D.m2 | | Coeff. | Stdev. | $z$ | $P > z$ | 95% Conf. Interval | |
|---|---|---|---|---|---|---|---|
| rtb | D1 | -0.0007 | 0.0013 | -0.52 | 60.1% | -0.0033 | 0.0019 |
| | LD | -0.0021 | 0.0010 | -1.97 | 4.9% | -0.0041 | 0.0000 |
| | L2D | -0.0038 | 0.0014 | -2.68 | 0.7% | -0.0066 | -0.0010 |
| | L3D | 0.0006 | 0.0008 | 0.65 | 51.6% | -0.0011 | 0.0022 |
| cpi | D1 | 0.071 | 0.178 | 0.40 | 68.9% | -0.278 | 0.421 |
| | LD | 0.150 | 0.290 | 0.52 | 60.5% | -0.418 | 0.718 |
| | L2D | 0.108 | 0.227 | 0.47 | 63.5% | -0.338 | 0.553 |
| er | D1 | 0.144 | 0.096 | 1.50 | 13.5% | -0.045 | 0.332 |
| | LD | 0.223 | 0.089 | 2.50 | 1.2% | 0.048 | 0.398 |
| | L2D | -0.001 | 0.084 | -0.01 | 99.3% | -0.166 | 0.165 |
| mb | D1 | 0.222 | 0.051 | 4.31 | 0.0% | 0.121 | 0.323 |
| | LD | 0.138 | 0.021 | 6.54 | 0.0% | 0.097 | 0.180 |
| | L2D | 0.034 | 0.028 | 1.20 | 22.9% | -0.021 | 0.090 |
| | L3D | -0.032 | 0.022 | -1.45 | 14.6% | -0.075 | 0.011 |
| /sigma | | 0.023 | 0.002 | 12.84 | 0.0% | 0.019 | 0.026 |

Table 11.9: *ARIMA-X regression for `D.m2`, no constant*

| Variable | Terms included | Value | Stdev | Coefficient $p$ | Variable $p$ | Total Impact |
|---|---|---|---|---|---|---|
| rtb | D...L3D | -0.006 | 0.0018 | 0.1% | 0.0% | -0.008 |
| cpi | D...L2D | 0.329 | 0.085 | 0.0% | 0.1% | 0.418 |
| er | D...L2D | 0.366 | 0.103 | 0.0% | 0.2% | 0.465 |
| mb | D...L3D | 0.363 | 0.053 | 0.0% | 0.0% | 0.461 |

Table 11.10: *Summary of ARIMA-X regression for `D.m2`, no constant*

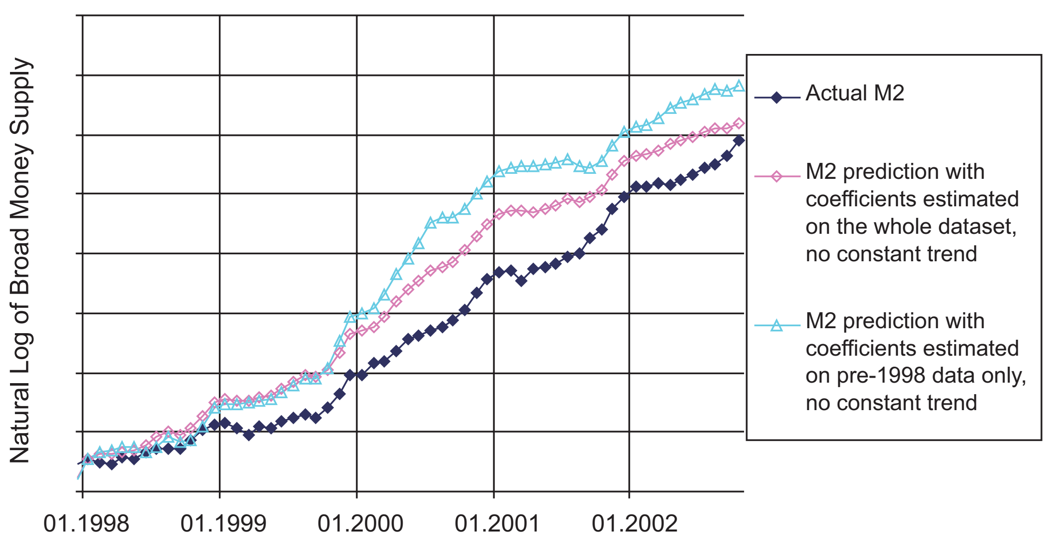


Figure 11.5: *Actual M2 vs. predictions from ARIMA-X regressions without a constant term*

As the model without a constant trend exhibits more reasonable prediction behavior and is the more reasonable from a theoretical perspective, we will use it as the base for further analysis. Thus, from Table 11.10 we observe that a ten percentage point increase in the interest rate actually decreases the money supply growth rate by 6%, monetary base growth and exchange rate depreciation both have coefficients of about 0.36, and the CPI is now highly significant with a coefficient of 0.33. All of these effects happen within three months, and are then all increased by a factor of about 1.27 over the next year, as discussed in the next section.

### 11.3.1 Summary

This section investigated the dependence of the broad money supply growth on the changes in interest rates, inflation, exchange rate depreciation, and base money growth, as well as its own past values. The results show no autoregressive or moving-average components, but a strong dependence on the exchange rate, monetary base, and Consumer Price Index, as well as a significant but not huge response to interest rates; all coefficients have signs and magnitudes that are reasonable from a theoretical standpoint.

From a .37 coefficient of the depreciation rate in the `m2` regression, combined with the fact that exchange rate depreciation was not significant in the `cpi` regression, we draw the somewhat surprising conclusion that the main channel for the impact of currency depreciation on inflation is not through cost-push, but through revaluation of the money supply.

In contrast to the CPI regression, all effects are quite fast, taking at most 3 months for the full impact to be felt; the predictions of post-January 1998 values based on the regressions exhibited realistic behavior and were quite robust with respect to the estimation time period, but were not as precise as the CPI predictors, tending to over-estimate money supply.

## 11.4 Price Level - Money Supply Feedback Loop

As we have seen in the previous sections, if we consider broad money supply `m2` to be given in advance (as a function of time), a change of one percent in `m2` will over time lead to a change of about .33 percent in `cpi`; conversely, if we consider the price level to be exogenous, a one percent increase in it will lead over time to about a .67 percent increase in `m2`.

In reality, neither of them is given, but rather both evolve (approximately) according to their behavioral equations that we have estimated in the previous section. Therefore, the two variables form a feedback loop - a change in the money supply, happening for whatever reason, will lead to an increase in the price level, which will in turn lead to an increase in money supply, etc., amplifying the initial impact. In fact, the total impact can be computed as a geometric progression and found to be $1/(1 - 0.33 * 0.67) \approx 1.28$, so that the extra impact of the feedback loop equals 28% - not huge, but not negligible either.

Out of curiosity, we also plot the incremental and cumulative impacts of a unit increase in `m2` on `cpi` and vice versa, as a function of time, with and without taking into account the feedback loop. The time profiles are shown in Figures 11.6 and 11.7, respectively. We see that the feedback loop in each case plays out during about a year after the no-feedback impact is over, and increase the total impact by the expected 28%.

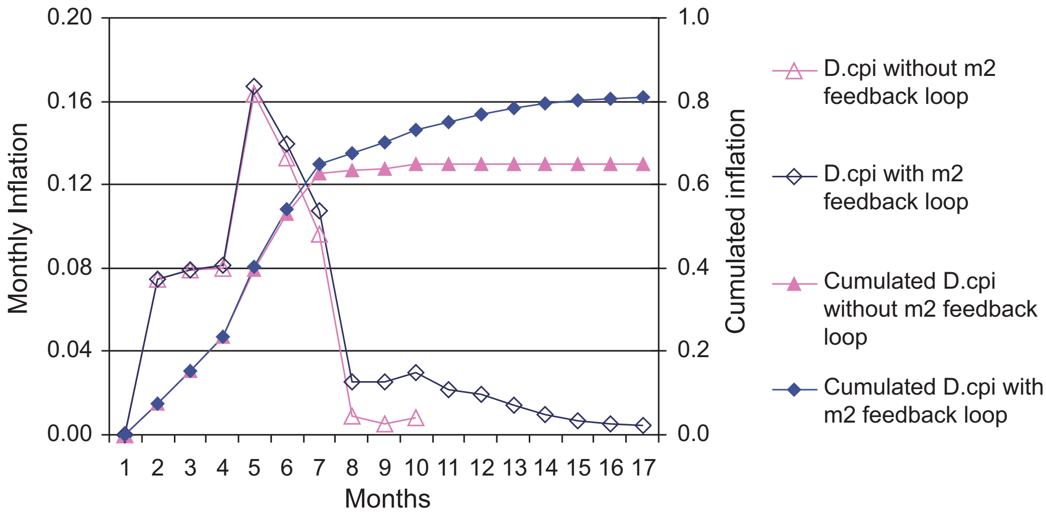


Figure 11.6: *Impact of a unit increase in* `m2` *on* `cpi`

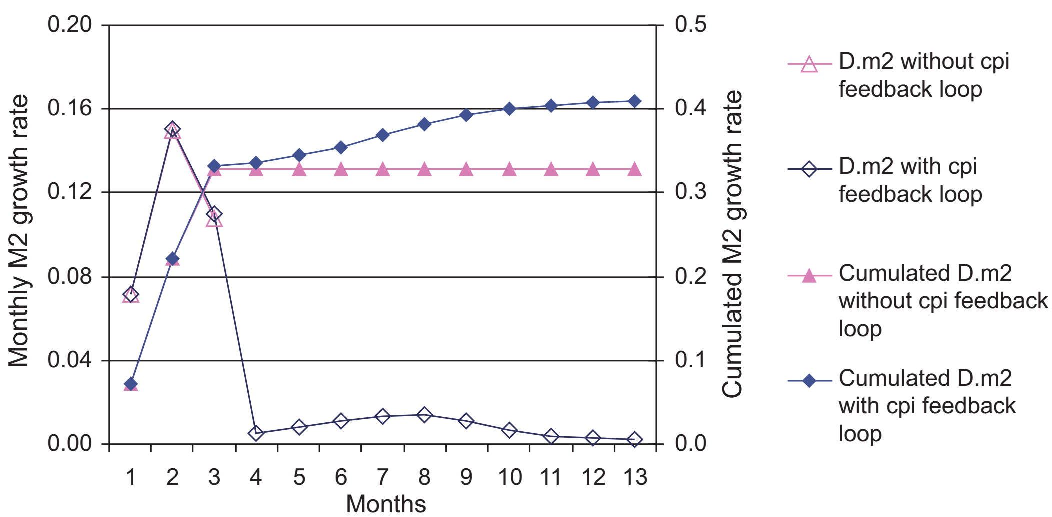


Figure 11.7: *Impact of a unit increase in* `cpi` *on* `m2`

| D.er | D.rtb | D.cpi | D.total_res |
|---|---|---|---|
| Significant lags | 0,4 | 6,7,12 | - |

Table 11.11: *Preliminary Lag Structure Examination for the Exchange Rate*

## 11.5 Exchange Rate

Let us now turn to the investigation of the exchange rate. We will use the following explanatory variables: The interest rate on government bonds `rtb`, as it is claimed to influence the exchange rate via the Uncovered Interest Parity (UIP) condition; the Consumer Price Index `cpi`, dollar index of import prices `impp`, and dollar index of export prices `expp` (these three in log terms) as determinants of the real exchange rate (that the nominal exchange rate is supposed to regulate in Walrasian CGE models); real GDP `gdp` as proxy for import demand, also in log terms; and total foreign exchange reserves `total_res`, defined for our purposes as foreign-denominated assets of the central bank and the Deposit Money Banks, measured in months of imports. All of these are available monthly, with the exception of `expp`, `impp` and `gdp`. The latter are only available yearly and have been interpolated to monthly with an algorithm due to Prof. Clopper Almon (a form of piecewise cubic interpolation). To lower the chances for the choice of interpolation method to influence our regression results, we only use yearly differences (`S12`) of these three variables where differences are required.

As before, we find out that `er`, that is, the natural log of the nominal exchange rate, is I(1): Augmented Dickey-Fuller test (`dfuller er,trend regress`) returns -1.475, corresponding to $p =$ .83; while Augmented Dickey-Fuller test on `D.er` returns -6.636, corresponding to $p = 0.0000$. Upon running a least squares regression on all of our independent variables (`reg er rtb cpi impp expp gdp total_res; dwstat`) we get a $d$-value of .096, far below the .322 10% significance threshold for cointegration. Thus again we resort to the ARIMA-X procedure as we had done for `cpi` and `m2`.

First, we regress `D.er` on fifteen lags of the first difference of each of the independent variables that are available monthly, with the significant lags listed in Table 11.11. We now use that information to choose a starting point for the model identification process. The model identification process is summarized in Table 11.12. The model we arrive at is presented in Table 11.13 and summarized in Table 11.14. The meaning of the columns is the same as in the CPI discussion above. The only additional aspect worth discussing is the different way of computing "Total Impact" when it is based on a coefficient of a seasonal difference.

The "Total Impact" column is meant to describe the long-term (aggregated) impact on the dependent variable of a unit change in the corresponding independent variable. Thus, when several lags of the independent variable are used, we have to add up the coefficients of all these lags. Now using a 12-month seasonal difference of a variable `X` means that a sudden jump in `X` from one month to the next will show up in all 12-year periods that include these two months, that is, twelve times. Therefore to compute the total impact of a variable that enters the regression as a seasonal difference we need to multiply the coefficient of the seasonal difference by the length of the "season", in our case 12. A different way of looking at that is that `S12.X` refers to a *yearly* change in `X`, while `D.er` is a *monthly* depreciation rate. Therefore the factor 12 is needed to make the units match. Thus, the total impact of a change in the import dollar price index `impp` is composed of the coefficient of `impp` in the regression (0.196) and the factor 12 coming from the seasonal difference.

| ARMA terms | Exo terms | AIC | SIC | wntestq | wntestb |
|---|---|---|---|---|---|
| ar(1/6) ma(1/6) | D.rtb. . . L4D.rtb,<br>D.cpi. . . L12D.cpi,<br>S12.impp,<br>S12.expp,<br>S12.gdp,<br>D.total_res. . . L8D.total_res | -634 | -527 | 85% | 99.55% |
| ar(1/3) ma(1/3) | D.rtb. . . L4D.rtb,<br>D.cpi. . . L12D.cpi,<br>S12.impp,<br>S12.expp,<br>S12.gdp,<br>D.total_res. . . L8D.total_res | -626 | -531 | 85.24% | 90% |
| ar(1/3) | D.rtb. . . L4D.rtb,<br>D.cpi. . . L12D.cpi,<br>S12.impp,<br>S12.expp,<br>S12.gdp,<br>D.total_res. . . L8D.total_res | -606 | -517 | 98% | 98% |
| ar(1) | D.rtb. . . L4D.rtb,<br>D.cpi. . . L12D.cpi,<br>S12.impp,<br>S12.expp,<br>S12.gdp,<br>D.total_res. . . L8D.total_res | -610 | -526 | 98% | 72% |
| ar(1) | D.rtb. . . L4D.rtb,<br>D.cpi. . . L4D.cpi,<br>S12.impp,<br>S12.expp,<br>S12.gdp | -611 | -567 | 87% | 85% |
| ar(1) | D.rtb. . . L2D.rtb,<br>D.cpi. . . LD,cpi,<br>S12.impp,<br>S12.expp | -614 | -588 | 87% | 95% |

Table 11.12: *ARIMA-X model identification for* `D.er`

Sample: 13 to 144 Number of obs = 132

Wald chi2(6) =89.76 Log likelihood = 314.5662 Prob > chi2 = 0

| D.er | | Coeff. | Stdev. | $z$ | $P > z$ | 95% Conf. Interval | |
|---|---|---|---|---|---|---|---|
| rtb | D1 | 0.0021 | 0.0007 | 3.21 | 0.1% | 0.0008 | 0.0034 |
| | LD | 0.0006 | 0.0011 | 0.50 | 61.4% | -0.0016 | 0.0027 |
| | L2D | 0.0010 | 0.0014 | 0.76 | 44.9% | -0.0017 | 0.0038 |
| impp | S12 | 0.197 | 0.068 | 2.88 | 0.4% | 0.063 | 0.331 |
| expp | S12 | -0.033 | 0.028 | -1.19 | 23.6% | -0.088 | 0.022 |
| _cons | | 0.023 | 0.005 | 4.39 | 0.0% | 0.013 | 0.033 |
| ar | L1 | 0.425 | 0.058 | 7.26 | 0.0% | 0.310 | 0.539 |
| /sigma | | 0.022 | 0.001 | 20.02 | 0.0% | 0.020 | 0.024 |

Table 11.13: *ARIMA-X regression for* `D.er`

| Variable | Terms included | Value | Stdev | Coefficient $p$ | Variable $p$ | Total Impact |
|---|---|---|---|---|---|---|
| rtb | D...L2D | 0.0037 | 0.0019 | 5.4% | 1.3% | 0.0037 |
| impp | S12 | 0.196 | 0.068 | 0.4% | 0.4% | 2.35 |
| expp | S12 | -0.033 | 0.028 | 23.0% | 23.0% | -0.40 |
| cons | | 0.022 | 0.005 | 0.0% | | |
| ar(1) | | 0.424 | 0.058 | 0.0% | | |

Table 11.14: *Summary of ARIMA-X regression for* `D.er`

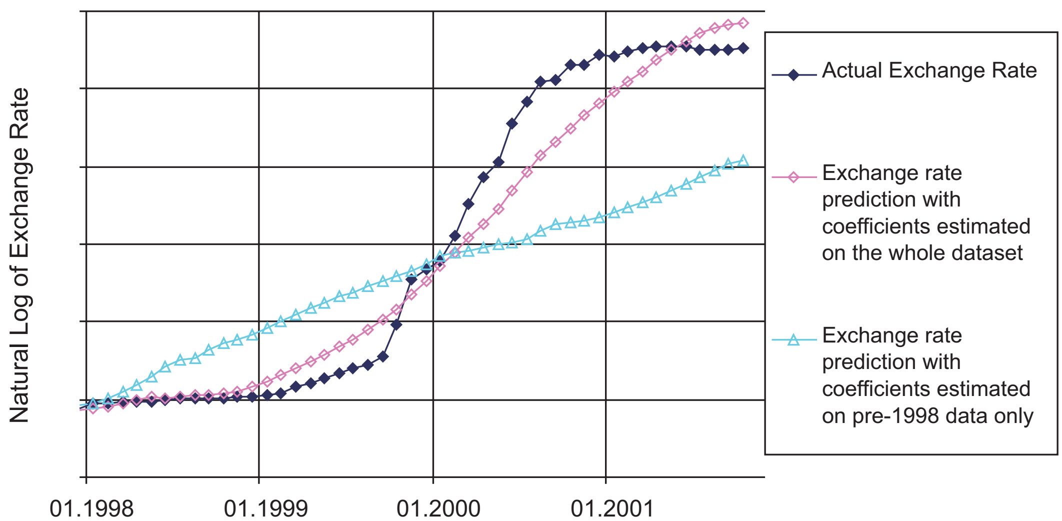


Figure 11.8: *Actual exchange rate vs. predictions from ARIMA-X regressions*

Before discussing the implications of the model we have just estimated, we proceed to test the predictive abilities of the chosen model, similarly to the previous two sections.

We compare the actual course of `er` after January 1998 (an arbitrary cut-off point chosen for compatibility with Chapter 9) with two different forecasts: the coefficients of the first were estimated using all data and the coefficients of the second were estimated using only pre-Jan. 1998 data. The results are shown in Figure 11.8.

Unfortunately, we see that this model performs much worse than the models for `cpi` and `m2` did. The predictor whose coefficients use all data performs decently if not brilliantly, but the predictor using the same model but with coefficients estimated from pre-1998 data comes out as essentially only a trend line, unable to reproduce, even partially, the sharp depreciation of 2000. Thus we get neither good prediction, nor even a moderate degree of robustness with respect to choice of the estimation data period.

This failure leads us to attempt, in analogy to our procedure in the case of `m2`, a fresh model identification while forcing the constant to be zero in all the regressions. Unlike the case of `m2`, however, this attempt does even worse at prediction, as shown in Figure 11.9. Therefore we take the with-constant regressions as the more reliable and base our subsequent discussion on them, while keeping in mind that their results should be taken with a larger dose of scepticism than those of the previous sections.

The only variables having a significant influence on the exchange rate are interest rates and the

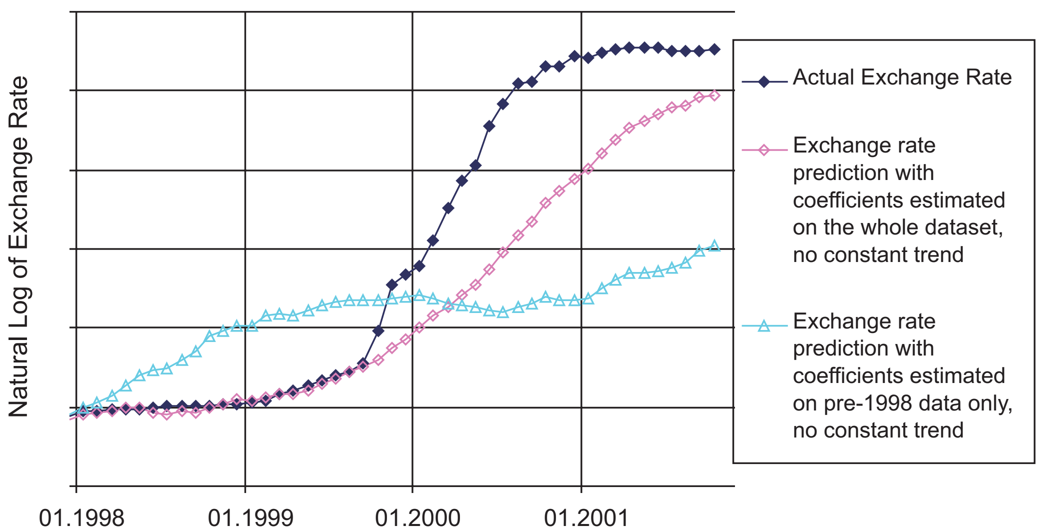


Figure 11.9: *Actual exchange rate vs. predictions from ARIMA-X regressions without a constant term*

import price index, together with a strong constant (meaning a stable exogenous depreciation). Further, inflation, GDP growth and the change in total foreign exchange reserves appear to not have a significant influence on currency depreciation, at least not the kind of linear influence that can be detected by a regression.

How can we explain such strange results? The reason for the results we get, we think, is that the exchange rate dynamics appear to have two distinct regimes, managed floating and freely falling, that correspond to quite different relationships between the exchange rate and the other variables. The difference between the two was discovered, tested and discussed in Reinhart and Rogoff [2004], who also provide a classification into freely floating and freely falling periods for most countries, including Ghana.

The classification of Reinhart and Rogoff [2004] was based on parallel exchange rates, of which they also provide monthly time series for most countries. The depreciation of their parallel exchange rate, along with the depreciation of the official exchange rate we have been using, is shown in Figure 11.11. The upper horizontal bars at the bottom of Figure 11.11 indicate the periods classified in Reinhart and Rogoff [2004] as "Freely Falling/Managed Floating" (as opposed to 'Managed Floating"). In our view, their classification is somewhat puzzling, in particular the classification of 1993 as non-falling and of the first half of 1999 as falling. Thus, we did an ad-hoc re-classification, with the lower horizontal bars at the bottom of Figure 11.11 indicating our definition of freely falling periods.

During our period of study, there were two freely falling and three managed floating episodes, as can be seen from Figure 11.11. Freely falling periods are characterized not only by higher depreciation values, but also by much higher volatility of the depreciation rate; furthermore, when plotting `D.er` against `D.cpi` in Figure 11.10 separately for all freely falling and all managed floating episodes, we see a fairly close association between the two during managed floating, but not freely falling episodes. Running a simple least squares regression gives us $R^2 = .007$ for the freely falling group and $R^2 = .1058$ for the managed float group. (When doing the same regressions using the classification of Reinhart and Rogoff [2004], the two groups appeared much more similar, with $R^2 = .0052$ and $R^2 = .0403$, respectively).


Figure 11.10: *Inflation vs. Depreciation for Falling vs. Floating Periods*

The different relationship between `er` and `cpi` during the two modes might be the reason for the low significance of the exchange rate in the `cpi` regressions, and of `cpi` in the exchange rate regressions.

We thus conclude that a better understanding of the exchange rate behavior and its relationship to other variables would require separate study of freely falling and managed floating episodes, as well as of the (perforce nonlinear) mechanics of the switch between the two regimes, which is unfortunately beyond the scope of the present study.

### 11.5.1 Summary

Following the same model identification strategy that led us to success in explaining the behavior of `cpi` and `m2`, we identify a model of exchange rate behavior. The only two significant variables turn out to be the import price index, each 1% increase in it translating into a 4% depreciation over a year's time; and the interest rate, with interest rate increase by 1% *increasing* depreciation by one third of a percent.

Unlike in the cases of `cpi` and `m2`, however, the estimated model proves to be quite bad at predicting values of `er` when used as a recursive equation. When we estimate the same model using only pre-January 1998 data, essentially only the constant term survives. The prediction behavior is even worse when we repeat the model estimation over regressions without a constant.

These problems, together with a brief qualitative discussion of exchange rate behavior, lead us to conjecture that better understanding of the exchange rate behavior would require separate study of managed floating and freely falling periods, as well as of the conditions for the change between the two modes.

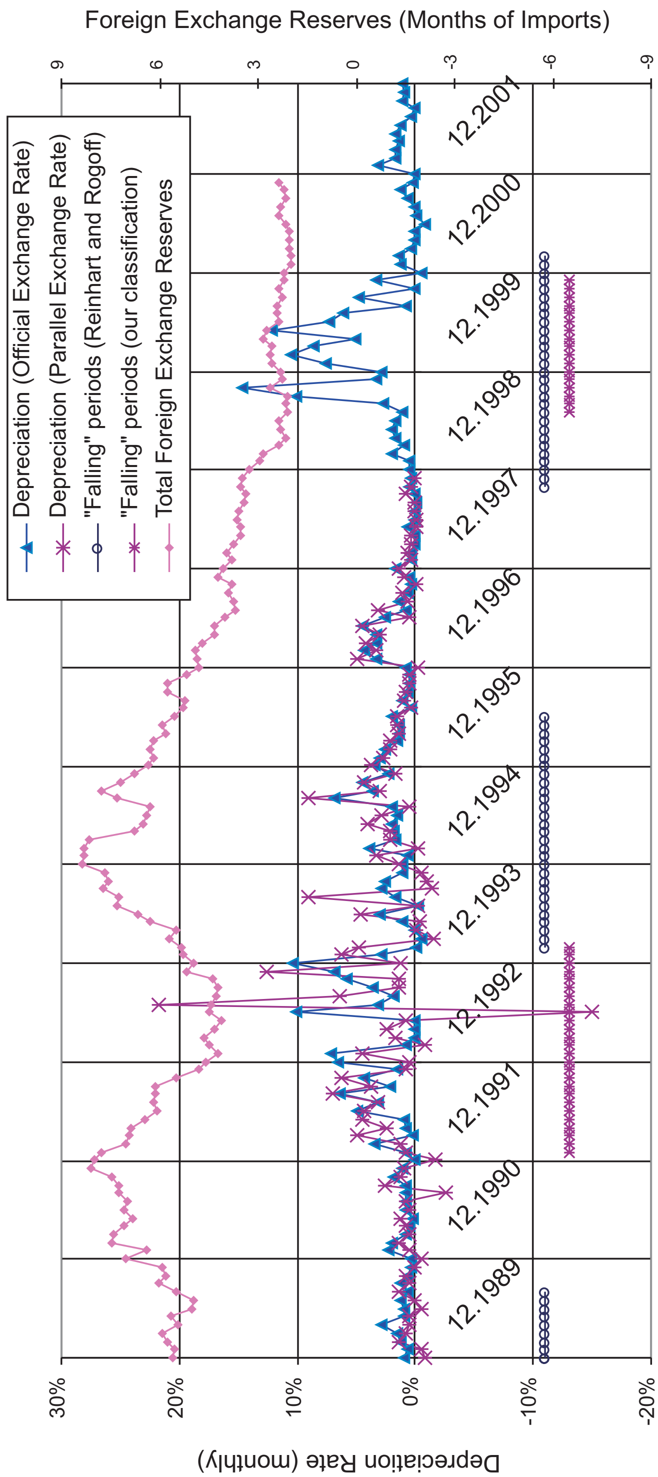


Figure 11.11: *Exchange Rate Depreciation, Falling/Floating Periods, and Foreign Exchange Reserves*