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The Role of Seasonality and Monetary Policy in Inflation Forecasting

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Abstract

Adequate modeling of the seasonal structure of consumer prices is essential for inflation forecasting. This paper suggests a new econometric approach for jointly determining inflation forecasts and monetary policy stances, particularly where seasonal fluctuations of economic activity and prices are pronounced. In an application of the framework, the paper characterizes and investigates the stability of the seasonal pattern of consumer prices in the Kyrgyz Republic and estimates optimal money growth and implied exchange rate paths along with a jointly determined inflation forecast. The approach uses two broad specifications of an augmented error-correction model—with and without seasonal components. Findings from the paper confirm empirical superiority (in terms of information content and contributions to policymaking) of augmented error-correction models of inflation over single-equation, Box-Jenkins-type general autoregressive seasonal models. Simulations of the estimated error-correction models yield optimal monetary policy paths for achieving inflation targets and demonstrate the empirical significance of seasonality and monetary policy in inflation forecasting.

JEL Classification Numbers: C53, E37, E52

Keywords: Inflation forecasting, seasonal unit roots, monetary policy stance, error-correction models, VAR

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I. Introduction

Following various economic adjustment programs in transition countries, inflation declined rapidly from hyperinflation levels to single-digit levels in the most successful ones, including the Kyrgyz Republic (whose data are used for illustrations throughout this paper). Despite the decline in inflation, monetary policy continues to be set on an adhoc basis, mainly due to instability of money demand and inadequate representation of the seasonal structure of the economy in inflation forecasts; unanticipated external shocks, such as world oil price increases, have also contributed. The result has been frequent revisions of inflation targets and monetary policy stance during the year. Considering that the money demand function is not well-established in these countries, the initial misspecification of seasonality in consumer prices and economic activity often yields monetary outcomes that tend to amplify variations in prices and economic activity over the seasonal cycle. This is mainly because adoption of an inappropriate monetary policy stance over the seasonal cycle distorts resource allocation and hurts macroeconomic stability.

The literature is replete with analyses of factors that determine inflation (see Blavy, 2004, and Brouwer and Ericsson, 1998) and the dynamics of inflation in transition countries - see for example, Lim and Papi, 1997; Kumah, 2003; Grigorian, Katchatryan, and Sargsyan, 2004; and Lissovolik, 2003. The problem of adequacy of the monetary policy stance over the seasonal cycle has, however, received little attention. Seeking to fill this gap, this paper suggests two approaches to integrating the seasonal structure of consumer prices into inflation forecasting and performs simulations in a search for an optimal monetary policy stance in the context of pronounced seasonality in economic data, using time series data on the Kyrgyz Republic to illustrate the relative gains from the two approaches. The first approach suggests modeling seasonality in consumer prices using general autoregressive integrated moving average (ARIMA) models with stochastic seasonality. While this approach tracks the seasonal pattern of consumer prices quite well and yields reliable forecasts, it neglects the importance of monetary policy in the inflation process. The second approach therefore introduces the role of monetary policy in modeling and forecasting inflation, particularly where seasonal variations are pronounced. Tests for integration of consumer prices at all seasonal frequencies are carried out under this approach to establish constancy, or otherwise, of the seasonal structure over time.

The results from the two approaches to modeling seasonality in consumer prices suggest seasonal integration of consumer prices in the Kyrgyz Republic, indicating that the seasonality of consumer prices could be modeled deterministically. Buoyed by this result and cointegration test results, we specify an error-correction model of inflation (with the error-correcting equation represented by a simple long-run inflation equation) augmented with autoregressive (AR(1)) data generation processes for the growth of money and exchange rate movements. This setup is further developed into a two-stage framework for forecasting inflation under two broad augmented error-correction models—including and excluding seasonal dummies. Response-surface-type simulation experiments carried out under these models yield quarterly and annual inflation forecasts—and, consistent with these forecasts, optimal monetary policy stances.

Simulations of the estimated models show empirical significance of seasonality and monetary policy stance in inflation forecasting. They also bring to the fore the empirical superiority (in terms of information content and contributions to policymaking) of the augmented error-correction model over single-equation, Box-Jenkins-type general autoregressive seasonal models of inflation. Further, the findings of the paper could help inform inflation forecasting procedures in countries interested in determining optimal monetary policy stances for short-term inflation targets. The framework could also be adapted as a toolkit for simultaneously determining medium-term money and inflation paths—especially where seasonal fluctuations of economic activity and prices are pronounced.

The rest of the paper is organized as follows. Section II describes recent developments in inflation in the Kyrgyz Republic, emphasizing the role of monetary policy and exchange rate developments. Section III presents seasonal characteristics of Kyrgyz Republic's consumer price data by identifying an ARIMA process for these and it also investigates its seasonal integration at all seasonal frequencies. Section IV assesses the impact of monetary policy on inflation. It also estimates augmented error-correction models of inflation with specifications of data generation processes for money and the nominal exchange rate and investigates the forecasting performance of the models. Based on the estimates of the models, simulations are carried out to determine the appropriate monetary policy stance consistent with any predetermined inflation forecast or target. Section V summarizes the main contributions of the paper and concludes.

II. Inflation and Monetary Policy in the Kyrgyz Republic

The dynamics of inflation in the Kyrgyz Republic since the collapse of the Soviet Union have been characterized by exogenous shocks (including effects of the Russian financial crisis of 1998) and economic policy. Seasonal factors have also been important in explaining inflation dynamics in the course of the year. Figure 1 depicts the dynamics of headline and core inflation and co-movements among inflation, money growth, and exchange rates during 1995–2004. It also shows the seasonal pattern of headline inflation during the same period. Except for a brief period before 1996 and after the Russian financial crisis of 1998, inflation rates in the third quarter of the year have generally been negative. During the period, the highest rates of inflation are recorded in the second and fourth quarters of the year, with relatively modest rates of inflation in the first quarter and price reductions in the third quarter.

Except during a brief period in the aftermath of the Russian financial crisis, inflation has been on the decline in the Kyrgyz Republic since the collapse of the Soviet Union in the early 1990s. Twelve-month consumer price inflation declined from very high levels in the early 1990s to 35 percent in 1996. It declined further to 14 percent in 1997, reaching a little below 10 percent by mid-1998 (i.e., just before the Russian financial crisis). This decline in inflation was associated with a gradual decline in the rate of growth of broad money and an associated decline in depreciation of the domestic currency vis-à-vis the dollar (Figure 1). In fact, before the Russian financial crisis, money growth was on a steady downward path, despite a few blips in 1997 and early 1998, and the rate of depreciation of the domestic currency had declined from the high levels seen in the wake of the collapse of the Soviet Union and introduction of the domestic currency—the som.

Following the Russian financial crisis of late 1998, however, inflation in the Kyrgyz Republic picked up to around 40 percent between June and December 1999, reflecting increased depreciation of the som (Figure 1) in response to the fall of the Russian ruble. During the first half of 1999, the som depreciated on average by close to 50 percent, compared to the same period in the previous year. The depreciation was accompanied by increased deposit dollarization (which reached 63 percent in June 1999) and an increase in money growth to 34 percent by end-1999, from a low of 17 percent at end 1998.[2] Inflation declined, however, quickly thereafter, as monetary policy was tightened, allowing a gradual decline in the nominal depreciation of the som.

Figure 1. Kyrgyz Republic: Broad Money Growth, Exchange Rate Depreciation, and Inflation, 1995–2004

Sources: Kyrgyz authorities; and Fund staff estimates.

[2] In the wake of the Russian financial crisis, credit to the economy slowed down, nonresidents repatriated their deposits, while residents rushed to dollar cash, contributing to a large deceleration of money growth in 1998.

Since 2001, the domestic currency tended to appreciate in the context of increasing foreign inflows to finance investments, especially in the mining sector. This contributed to a further decline in headline inflation despite the rather high rates of money growth. This juxtaposition of low inflation and high money growth was consistent with the fact that the increase in the money supply was demand-determined and hence had little inflationary impact. As the foreign inflows intensified, and the central bank was prohibited by law from extending credit directly to the government, reserve money increased in line with the increase in net foreign assets of the central bank—in a pseudo currency board manner. The nominal exchange rate appreciated gradually, driving headline inflation down, despite the increase in money supply. Thus, the pass-through of exchange rate appreciations to inflation overshadowed the monetary expansion effect.

III. Seasonal Characteristics of Consumer Prices

Section II emphasized the role of seasonal factors, monetary policy and exchange rate developments in explaining the dynamics of inflation in the Kyrgyz Republic. As a precursor to a deeper analysis of the effect of last two set of factors on inflation in the Kyrgyz Republic—and the implications of these for inflation forecasting—this section investigates the nature (including constancy and empirical pattern) of the seasonal structure of consumer prices in the Kyrgyz Republic. To check for stochastic seasonality in consumer prices in the Kyrgyz Republic, we estimate general autoregressive integrated moving average (ARIMA) models with seasonal autoregressive (SAR) and moving average (MA) terms for monthly and quarterly consumer price indices (CPI_t). The general specification of the models is as follows

$$\rho(L)(\omega_s L^s)(cpi_t - \mu) = \theta(L)\varphi_s(L^s)\varepsilon_t \qquad (1)$$

where μ is a constant, L is the lag operator, s denote the seasonal components of the data generation process,
$\rho(L) = (1 - \rho_1 L - \rho_2 L^2 - ... - \rho_p L^p)$, $\theta(L) = (1 + \theta_1 L^1 + \theta_2 L^2 + ... + \theta_q L^q)$, $\omega_s(L) = (1 - \omega_s L^s)$,

$\varphi_s(L^s) = (1 - \varphi_s L^s)$, and ε_t is and an identically and independently distributed series of disturbances with a zero mean and constant variance, σ_ε^2. To check for the specific ARMA process for consumer prices (the consumer price index and inflation), we use the general Box-Jenkins approach to search for parsimonious specifications. The results summarized in Table 1 indicate the significance of seasonality in the consumer price indices. In particular, almost all the autoregressive seasonal coefficients for the four consumer price series considered are significant at the 1 percent significance level, and only the indices at the monthly frequency displays a two-month lag autoregressive process with a one-month lag moving average process. In summary, while the CPI indices at the monthly frequency display an ARIMA(2,0,1) process with a two-period lag seasonal autoregressive process, the consumer price series at the quarterly frequency display a simple ARIMA(1,0,1) process with a seasonal AR(1) process.

This exercise does not only pin down the significance of seasonality in the consumer price index, but more essentially, it reveals the structure of the observed seasonality. A further analysis is required on the degree of integration of the seasonality to make it useful for forecasting purposes—in other words, we need to investigate whether or not the series follows a constant stochastic process. The latter process is necessary for modeling the seasonality in the data, as it yields information on the evolution of the observed seasonality over time. For this investigation, we adopt the methodology suggested by Canova and Hansen, 1995, for testing for stationarity in time series data at all seasonal frequencies.

Table 1. Stochastic Seasonality in the Consumer Price Index 1/

	Monthly CPI Indices		Quarterly CPI Indices	
	ln CPI	$\Delta \ln CPI$	ln CPI	$\Delta \ln CPI$
Constant				
μ	0.0037	2.7514	0.0249**	3.0872
Autocorrelation coefficients				
ρ_1	0.8983*	1.3196*	-0.8738*	0.9326*
ρ_2	-0.3394*	-0.3327*		
Moving Average Coefficients				
θ_1	-0.2515	0.2753**	1.3221*	
Seasonal autocorrelation				
ω_1	0.6882*	-0.5591*	0.3570**	-0.5377*
ω_2	-0.4240*			
R-squared	0.9982	0.9835	0.9882	0.8302
Root Mean Square Error (RMSE)	0.0020	0.7632	0.0414	0.8534

Source: Author's estimations.

1/ An asterisk (*) or a double asterisk (**) indicates statistical significance at the 1 percent level or 5 percent level respectively.

Suppose the seasonality in consumer prices can be modeled as follows:

$$\ln CPI_t = \alpha + x_t'\beta + \sum_{j=1}^{q-1}(\gamma_j S_{j,t} + \chi_j C_{j,t}) + \delta_q C_{qt} + \varepsilon_t \qquad (2)$$

where $q = \frac{s}{2}$, $S_{j,t} = \sin\frac{2\pi jt}{s}, C = cos\frac{2\pi jt}{s}, and\ \varepsilon_t$ is a disturbance term assumed to be identical and independently distributed with a zero mean and a constant variance, σ_ε^2. Additionally, s denotes the number of seasons in the year (4 for quarterly data, and 12 for monthly data), x_t is a vector of lagged observations of the dependent variable (which, in our specification is either the one period lag of the logarithm of the consumer price index or its first difference, the inflation rate), and β is an appropriately dimensioned coefficient vector.

Following Canova and Hansen,1995, equation (2) is used to test seasonal integration of the data, or equivalently, to test for constancy of the seasonal patterns in the data at all seasonal frequencies. The test adopts a null hypothesis of stationary seasonality against an alternative of nonstationary seasonality. Thus, by investigating seasonality of time series data at all seasonal frequencies, the Canova-Hansen test generalizes the KPSS (Kwiatkowski, Phillips, Schmidt, and Shin, 1992) framework from the zero frequency to the seasonal frequencies, just as the HEGY test (of Hylleberg, Engel, Granger, and Yoo, 1990) —which investigates the existence of seasonal unit roots at the zero frequency—extends Dickey and Fuller, 1979, tests. A nontrivial difference between the HEGY test and the Casanova-Hansen (CH) test is the specification of the null hypothesis. While the former test adopts a null hypothesis of nonstationarity—which implies, given the documented low power of the tests, that nonrejection of the null "cannot be interpreted as evidence for the presence of a seasonal unit root" (Canova and Hansen, 1995) —the later uses a null of stationary seasonality.[3]

In implementing the CH test, we use the logarithm of the consumer price index and its first difference (the inflation rate). The results presented in Table 2 show the absence of seasonal unit roots at the biannual and annual frequencies—indicated by the nonsignificance of the l_π *and* $l_{\pi/2}$ statistics respectively, compared to the critical value of 1.01 (derived from the *generalized Von Mises distribution with 3 degrees of freedom*)[4] at the 5 percent significance level. The results of the joint tests (for instability at the zero frequency as well as at the seasonal frequencies) indicate the absence of seasonal instability. Individual dummy stability tests yield similar conclusions carried out by regressing inflation on the quarterly seasonal dummies. The results show that no seasonal inversion has occurred, that seasonal components continue to be significant in the inflation process, and that seasonal patterns have generally remained flat over the sample period, which is an indication of seasonal integration. An additional observation is that the third-quarter seasonal dummy remained negative for the most part of the sample, with its significance becoming stronger in the later parts of the sample period. Again, the first and second quarters of the year display the highest inflation rates, with relatively moderate rates in the fourth quarters.

[3] According to CH, stationary seasonality (or the absence of seasonal unit roots) indicates existence of stable seasonal patterns, such as the association between high retail activity and Christmas.

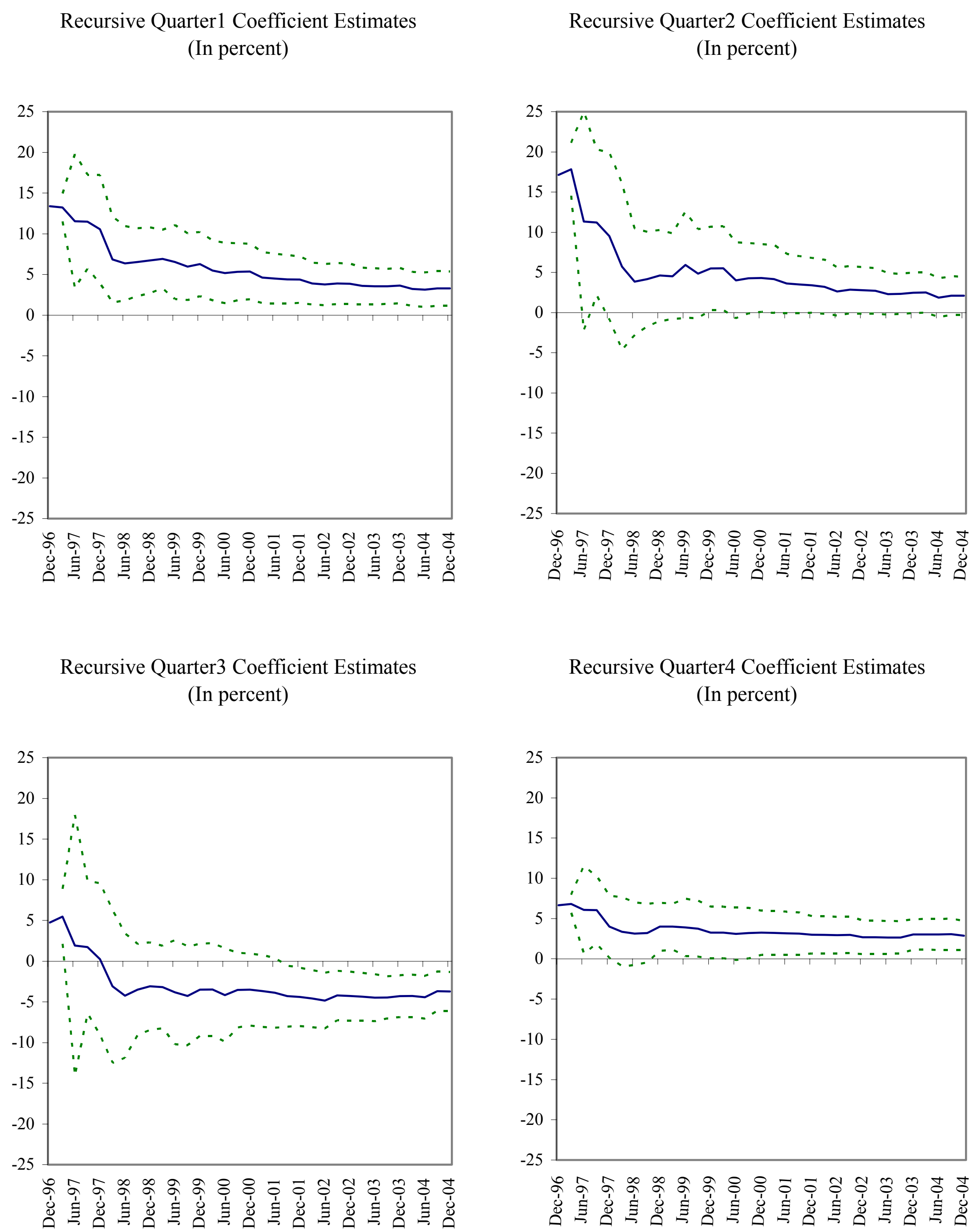
[4] See Canova and Hansen, 1995, for the *generalized Von Mises* distribution.

Table 2. Tests for Stability of the Seasonal Pattern in Consumer Prices, 1995:01–2004:04

Coefficients	Dependent Variables	
	ln CPI	Δ ln CPI
α	0.2997*	1.5709**
β	0.9507*	0.5062*
γ_1	0.0279*	3.0745*
χ_1	-0.0017	0.3759
δ_2	0.0159*	0.9677
Casanova-Hansen statistics		
ℓ_{π}	0.4800	0.1300
$\ell_{\pi/2}$	0.1300	0.4200
ℓ_{joint}	0.6600	0.6500
R squared	0.9924	0.4887
F-ratio	1103.08*	8.1249*
Durbin's h -statistics	0.4849	0.4982

Note: An asterisk (*) indicates statistical significance at the 1 percent level. The first two l -statistics correspond to the tests for stationarity at the biannual and annual seaonal frequencies respectively, while the last l- statistics tests for joint stationarity at the zero and seasonal frequencies.

Figure 2. Recursive Estimates of Seasonal Coefficients, 1996–2004



Source: Author's simulations.

IV. Modeling and Forecasting Inflation

A. A Simple Monetary Model of Inflation

Inflation in most developing countries is characterized as driven by structural rigidities (or cost-push pressures) and excess liquidity (or demand-pull factors). Proponents of the structural approach to inflation attribute increases in price levels to the existence of supply rigidities that hinder optimal use of resources to expand output and reduce price variability. Factors typically cited by the proponents of the structural theory include the existence of administratively determined prices, labor market rigidities, changes in costs of production (wages in particular), and exogenous shocks such as world oil price shocks and shifts in terms of trade. The monetary approach, on the other hand, attributes inflation to excess liquidity—essentially the failure of monetary policy to synchronize money supply with its demand. While structural factors and excess liquidity may be jointly responsible for the dynamics of inflation, in the long run, inflation is essentially a monetary phenomenon. This paper adopts the monetary approach to modeling inflation in the Kyrgyz Republic. Assume, in line with the literature, the general domestic price level can be modeled as a linear combination of the prices of tradable goods (p_t^T) and nontradable goods (p_t^{NT}), where θ denotes the weight of the tradable goods such that 0<θ< 1. Then, the general domestic price level can be expressed as

$$p_t = \theta p_t^T + (1-\theta) p_t^{NT} \qquad (3)$$

Suppose we equate the price of tradable goods to the cost, in domestic currency, of imported goods. Then, the price of the tradable good can be expressed as the product of the price of the imported good denominated in foreign currency (q_t) and the nominal exchange rate (s_t) as in equation (4).

$$p_t^T = q_t s_t \qquad (4)$$

The price of the nontradable goods is a function of excess money supply ($m_t^s - m_t^d$) where m_t^s denotes money supply and m_t^d is money demand. In our specification, we utilize the standard money demand function where output and prices determine money holdings, to derive the price of nontradable goods as

$$p_t^{NT} = \varphi(m_t^s - m_t^d(y_t, p_t)) \qquad (5)$$

Substituting equations (4) and (5) into (3), yields the domestic price level as implicitly dependent on output, the price of tradables (or foreign prices, $Pfor_t$, calculated as the trade-weighted average of the CPIs of trade partners (Kazakhstan, Russia, Uzbekistan, China, the United Kingdom, Turkey, Turkmenistan, Germany, Ukraine, and Belarus with trade weights of 0.28, 0.23, 0.19, 0.12, 0.05, 0.03, 0.03, 0.02, 0.02, and 0.01, respectively), the nominal exchange rate, and money supply. Given the importance of gold in the economy, we also include the price of gold ($Pgold_t$) and express the relation in a log-linear form as

$$\ln p_t = \text{constant} + \ln \text{Pgold}_t + \ln Pfor_t + \beta_1 \ln y_t + \beta_2 \ln s_t + \beta_3 \ln m_t + \mu_t \qquad (6)$$

where μ_t is an error term assumed to be independent and identically distributed with mean zero and a constant variance, σ_μ^2.

B. Monetary Policy and Seasonal Factors in the Inflation Process

This section estimates error-correction models (with and without seasonality terms) augmented with assumptions on data generation processes for money growth and exchange rate developments. It assesses the forecast performance of the various models and estimates the relative roles of money and seasonality in forecasting inflation in the Kyrgyz Republic. It also derives the optimal monetary policy stance for given levels of inflation forecasts under various assumptions on the data generation process for exchange rates. As a background to modeling augmented error-correction models (ECMs) for forecasting and simulating the monetary policy stance (and the implied exchange rate path in the absence of unanticipated shocks), this section investigates the relative contributions of monetary and real factors to the inflation process in the Kyrgyz Republic with a simple six-variable VAR with two lags that uses the Choleski decomposition to identify the various shocks.

The results from this simple VAR based on the variables in $x_t = [\ln Pgold_t, \ln Pfor_t, \ln y_t, \ln m_t \; \ln s_t, \ln cpi_t]'$—the elements of which are the logarithms of gold prices, foreign prices, real output, nominal money, the nominal exchange rate (soms/dollar), and the consumer price index, respectively—and exogenous seasonal dummies, are summarized as follows (Figure 1 and Table 1 in the Appendix):

- A temporary 1 percent increase in the price of gold yields insignificant reductions in consumer prices throughout the forecast horizon (as gold price increases tend to be associated with appreciation of the domestic currency), while a similar increase in foreign prices increases consumer prices significantly in the first five quarters following the shock.

- A 1 percent positive temporary output shock reduces consumer prices for significantly in the first two quarters immediately following the shock, but the effect tends to zero and remains statistically insignificant in subsequent horizons.

- A temporary 1 percent increase in money growth induces an increase in consumer prices two quarters after the shock. Exchange rate depreciation, on the other hand, passes through quickly to prices, with the effect reaching a pick about four quarters after the shock.

- Monetary factors (changes in money and exchange rates) contribute two-thirds of the forecast variation in consumer prices over the forecast horizon after a two-period lag. The remainder of the variation in prices is explained by changes in gold prices, foreign prices, and output (Appendix Table 1).

Thus, consistent with the inflation dynamics in the Kyrgyz Republic during the sample period (as described in Section II), inflation is driven by real and monetary factors (exchange rate depreciation and monetary expansion). While monetary factors explain 36 percent of the variation in consumer prices in the immediate horizon, real factors explain only 14 percent. The effect of real factors increases, however, to 43 percent of the second-quarter forecast error in consumer prices (Appendix Table 1), but the effect of monetary factors increased as well, albeit slightly. In the long run, however, monetary factors dominate in explaining the variation in inflation, accounting for 77 percent of the 12-quarter forecast mean square error of consumer prices.[5] Results from cointegration tests could not reject the null hypothesis of three cointegrating vectors, implying the existence of an error-correction specification, which we now proceed to specify and analyze.

1. Augmented Error-Correction Mechanism

This section presents augmented error-correction specifications of the inflation process that incorporate the role of both monetary policy and exchange rate movements. The estimation procedure allows assessment of model performance under alternative monetary policy stances and exchange rate rules and investigation of the roles of monetary policy, exchange rate movements, and seasonality in the inflation dynamics. In particular, the set-up yields estimates consistent with a simple AR(1) process and random walk specifications for exchange rate movements. In the baseline, however, we consider only simple AR(1) data generation processes for money and exchange rates in the preferred error-correction models—the modeling process starts from a broader model including all variables in the long-run inflation equation, which is then parsimoniously reduced until a preferred model is identified for further analysis.

Consistent with the theory and empirical findings in the previous section, we consider the preferred augmented ECM of the form

$$
\begin{aligned}
\Delta \ln cpi_t &= \alpha_{10} + \alpha_{11}\Delta \ln cpi_{t-1} + \sum_{j=0}^{p_1} \alpha_{2j}\Delta \ln m_{t-j} + \sum_{j=0}^{p_2} \alpha_{3j}\Delta \ln s_{t-j} + \beta_0 EC_{t-1} + \sum_{j=1}^{p_3} \omega_j dum\_{}_j + \xi_{pt} \\
\Delta \ln m_t &= \gamma_{10} + \gamma_{11}\Delta \ln m_{t-1} + \xi_{mt} \qquad (7) \\
\Delta \ln s_t &= \delta_{10} + \delta_{11}\Delta \ln s_{t-1} + \xi_{st}
\end{aligned}
$$

where $dum\_{}_j$ denotes the j-*th* seasonal dummy, $\alpha_{10}, \alpha_{11}, \alpha_{21}, ..., \alpha_{2p_1}, \alpha_{31}, ..., \alpha_{3p_2}, \beta_0, \omega_1, \omega_2, \omega_3, \gamma_{10}, \gamma_{11}, \delta_{10}, and\ \delta_{11}$ are coefficients to be

[5] This finding is consistent with results from other developing countries—see Chapter VI of the IMF's *World Economic Outlook*, "The Rise and Fall of Inflation—Lessons from the Post-War Experience," October 1996.

estimated. In addition, the coefficients, γ_{11} *and* δ_{11} are assumed to have absolute values less than 1, and the innovations ξ_{pt}, ξ_{mt} *and* ξ_{st} are assumed to be serially uncorrelated, zero-mean disturbances with constant variances σ_p^2, σ_m^2 *and* σ_s^2 respectively, and are mutually uncorrelated at all leads and lags. The most general form of the models assumes $p_1 = p_2 = p_3 = 6$, which is then subsequently reduced until the preferred model, as presented in Table 4, is derived. Further, EC_{t-1} is the series of one-period lags of the estimated disturbances (ξ_{ect}) from the long-run equation

$$\ln cpi_t = \beta_{10} + \beta_{21}\ln cpi_{t-1} + \beta_{31}\ln Pgold_t + \beta_{41}\ln Pfor_t + \beta_{51}\ln y_t + \beta_{61}\ln m_{t-2} + \beta_{71}\ln s_t + \xi_{ect} \tag{8}$$

where ξ_{ect} is an *i.i.d.* disturbance term with a zero mean and constant variance. Estimation of the system of equations proceeds as follows: (i) we estimate the long-run equation (8) and derive the estimated series of residuals, ξ_{ect}; then (ii) we estimate equation (7) using the lagged estimated residuals from (i). The estimates of the parameters of equation (8), as presented in Table 3 below, are consistent with our a priori theoretical expectations—foreign trade partner price increases, monetary expansion, and exchange rate depreciation increase inflation.

Table 3. Estimates of the Long-Run Inflation Equation, 1995–2004

	β_{10}	β_{21}	β_{31}	β_{41}	β_{51}	β_{61}	β_{71}
OLS estimates	1.321	0.402	0.062	0.141	-0.043	0.058	0.062
(p-values)	(0.022)	(0.000)	(0.335)	(0.038)	(0.001)	(0.014)	(0.000)
R-squared	0.995						
Regression F (6,31)	1,529.717						
Significance of F	0.000						
Durbin's *h*-statistics	-0.206						

Source: Author's simple OLS estimates.

The estimated recursive coefficients are broadly stable over the sample period (Appendix Figure 2). Two broad specifications of equation (7)—with and without seasonal dummies—are estimated, assuming autoregressive data generation processes (i.e., an AR(1) processes[6] for broad money growth and exchange rate changes. In a preliminary estimate of the short-

[6] For the forecast exercise, we derive the *h*-period ahead forecast growth rate of money using the well-known formula, $\ln\Delta m_{t+h} = \gamma_{10}\dfrac{1-\gamma_{11}^{h+1}}{(1-\gamma_{11})} + \gamma_{11}^{h+1}\ln\Delta m_{t-1}$ under the assumption of stationary AR(1) data generation process for money growth. For the random walk process, γ_{10} is set to zero and γ_{11} is set to 1 for all forecast horizons, *h*. The same approach is adopted for forecasting the exchange rate depreciation rates.

run dynamics as specified in equation (7), the real output variable turns out to be statistically insignificant, especially in the presence of seasonal dummies, and was therefore not included as one of the short-run regressors in subsequent estimations of the two broad specifications. The statistical insignificance of output partly reflects the unsurprisingly high seasonality in output data, which is possibly captured by the seasonal dummies when included in the set of regressors.

A modified version of the system of equations shown in (7)—which excludes output and its data generation process—is jointly estimated using a nonlinear systems estimator based on the BFGS algorithm with an exact line search. We infer from the results that, it takes between five and six months for any deviations of inflation from the long-run path to be corrected under both model variants. This finding implies the existence of symmetry in the adjustment mechanism, as the speed of adjusting upward to the long-run path (as is more likely in the case of the model with seasonal components) is the same as the speed of adjusting downward (as in the case of the model that excludes seasonal components) (Table 4). Also, the pass-through from instantaneous exchange rate changes to inflation is faster, and the impact higher, than from instantaneous monetary expansion. More specifically, while a 1 percent money growth increase raises inflation by 0.1 percent under both models (with an insignificant effect in the model that excludes seasonal components), the instantaneous effect of exchange rate depreciation is to increase inflation significantly by about 0.3 percent under both models.

Given the importance of money and exchange rate processes—or, simply, of monetary policy—in the dynamics of inflation, we tested three hypotheses to determine subsequent modeling of these in our inflation forecasting exercise. The null hypotheses are (i) that the change in money follows a random walk process with no drift—i.e., $H_0 : \gamma_{10} = 0 \textit{ and } \gamma_{11} = 1$, (ii) that the change in the exchange rate follows a random walk process with no drift—i.e., $H_0 : \delta_{10} = 0 \textit{ and } \delta_{11} = 1$, and finally, that (iii) the levels of the money and exchange rate series follow AR(1) processes with no constants— i.e., $H_0 : \gamma_{10} = \delta_{10} = 0$. We found sufficient evidence at the 5 percent significance level for rejection of the null hypotheses in the first two cases, (i) and (ii), but not enough evidence for rejection of the null hypotheses of AR(1) processes for money growth and exchange rate changes. In the forecasting exercise that follows, however, we adopt an agnostic approach to modeling the data generation processes for money and the nominal exchange rate, and consider in addition to AR(1) specifications, random walk specifications for changes in the nominal exchange rate (DS)—yielding four models in all.

Table 4. Estimates of Augmented Error-Correction Models of Inflation

Parameter Estimates	Augmented Error-Correction Models	
	Without Seasonal Dummies	With Seasonal Dummies
CPI Equation		
α_{10}	-0.009	0.024
α_{11}	0.028	0.471*
α_{21}	-0.003	-0.039
α_{22}	0.142*	0.111
α_{23}	0.239*	0.006
α_{31}	0.264*	0.285*
α_{32}	0.071	-0.079
α_{33}	0.137*	0.059
β_0	-0.678*	-0.679*
ω_1		-0.013
ω_2		-0.009
ω_3		-0.064*
Money Equation		
γ_{10}	0.0615*	0.0615*
γ_{11}	-0.0334	-0.0334
Exchange Rate Equation		
δ_{10}	0.0239**	0.0239**
δ_{11}	0.3366*	0.3366*
Log Likelihood	82.862	92.883
Durbin's h -statistics	0.7043*	0.3186*
Hypothesis Tests		
$H_0 : \gamma_{10} = 0 \; and \; \gamma_{11} = 1$	39.4729*	39.4729*
$H_0 : \delta_{10} = 0 \; and \; \delta_{11} = 1$	18.1046*	18.1046*
$H_0 : \gamma_{10} = \delta_{10} = 0$	4.7006	4.7006

Source: Author's estimates.

Note: The estimates are derived from equation (7) with stationary AR (1) specifications for the rate of growth of money and exchange rate depreciation. An asterisk (*) and double asterisk (**) indicate statistical significance at the 5 and 10 percent levels, respectively. The figures reported under the last three rows are chi-square statistics with 2, 2, and 1 degrees of freedom, respectively.

2. Forecast Performance

To investigate the relative forecasting performance of the various models, we use the mean absolute forecast error, the root mean square forecast error, and Theil's U inequality coefficient. Table 5 shows the out-of-sample forecasts derived under the two broad models (with an added random walk specification for exchange rate movements), and compares these with the inflation outcome in 2005.

Table 5. Out-of-Sample Inflation Forecasts

Forecast Horizon	Benchmark	Single-Equation ARIMA Models		Error-Correction Models				Actual
				With Seasonal Dummies		Without Seasonal Dummies		
		ln CPI	$\Delta \ln CPI$	DGP=AR(1)	DGP (for S) =RW	DGP=AR(1)	DGP (for S) =RW	
Quarterly inflation								
1	3.04	1.20	3.63	3.16	1.68	3.57	2.61	2.50
2	0.87	0.69	3.08	4.96	3.21	2.63	1.40	1.80
3	-0.90	-0.91	2.84	-0.01	-2.33	3.27	1.50	-0.90
4	1.44	1.60	4.14	4.56	2.15	3.96	2.21	1.70
RMSE	0.27	0.43	1.22	2.27	1.13	2.51	1.27	
Mean Absolute Error	1.53	2.51	8.78	7.77	4.31	8.53	3.62	
Theil's U-statistics	0.15	0.24	0.69	1.28	0.64	1.42	0.72	

Source: Author's estimates.

Using all three measures, the models that include seasonal components outperformed those without these components, and a random walk process for exchange rates outperforms an AR(1) process in forecasting inflation. In particular, the forecast performance statistics are lower for the models with seasonal dummies as they track seasonality in the inflation process and duplicate turning points in the data better than those without seasonal components. For example, while the former group of models projects negative inflation in the third quarter (which is consistent with the historical data) the latter group predicts relatively high positive inflation of between 1.5 percent and 3.3 percent in the third quarter. These results support our arguments for including seasonal dummies in simulations and when forecasting inflation. In the context of a flexible exchange rate regime, the choice of a data generation process for the exchange rate is better determined along with the monetary policy stance—this is the issue we turn to in the next section.

3. The Role of Seasonality and Money

The estimated models are simulated in deriving inflation forecasts under various assumptions on the data generation processes for changes in the money supply (DM) and the exchange rate (DS). The objective here is to discern optimal money and exchange rate paths in support of ex ante inflation forecasts (in this case, a 4 percent annual inflation). The process is carried out in two stages, as follows. In the first stage, the estimated augmented error-correction model is simulated under varying assumptions on the autoregressive coefficient for money growth while keeping unchanged the estimated data generation process for nominal exchange rate changes—AR(1) and random walk processes. [7]

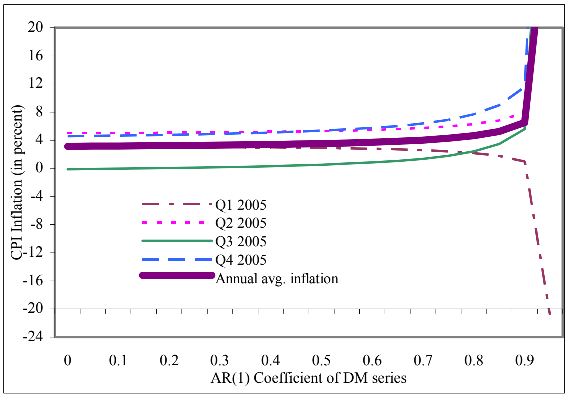
[7] These simulation exercises are very similar to response surface experiments where each individual experiment yields results for a single data generation process only. In these (continued)

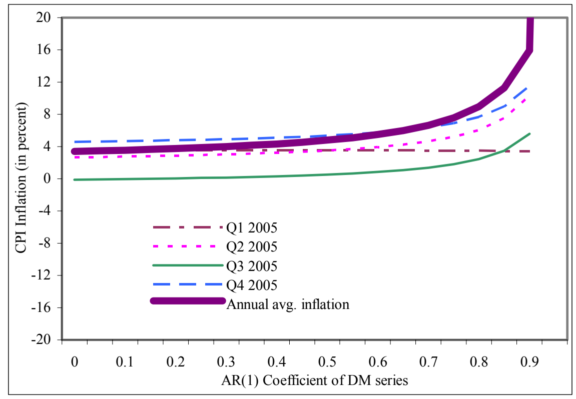
Figure 3. Seasonality and Optimal Monetary Policy

a) Augmented EC model, including seasonal dummies

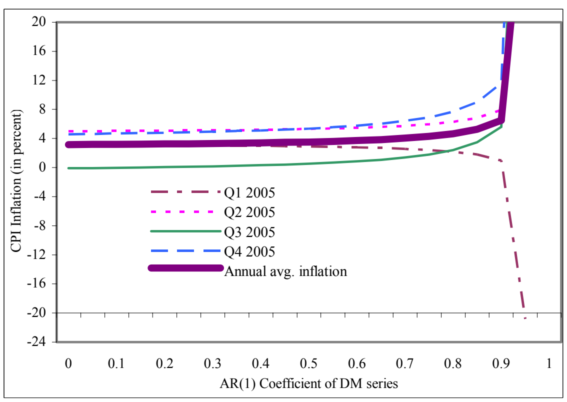
b) Augmented EC model, excluding seasonal dummies

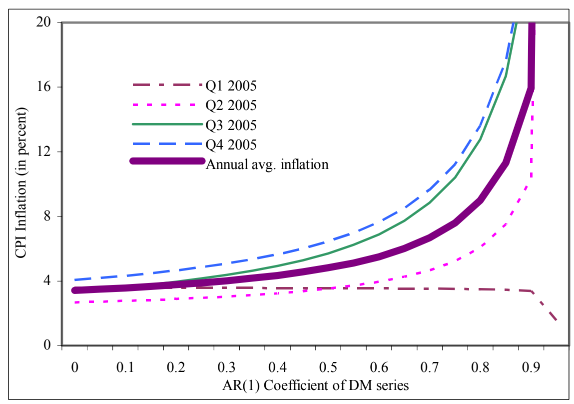
i) Assumes an AR(1) process for DS series





ii) Assumes a Random Walk process for DS series





Source: Author's simulations based on estimated augmented EC models.

These first-stage simulations yield corresponding "optimal" growth paths for money growth (or, simply AR(1) coefficients for the money growth process) under varying assumptions on the data generation process for exchange rate changes (Figure 3). It turns out that, for an ex ante inflation forecast of 4 percent, the optimal autoregressive coefficient for the money

experiments, the dependent variable is some quantity estimated in the experiments, and the independent variables are functions of the various parameter values chosen by the experimenter—and which characterize each experiment. For examples and discussions of the advantages of response surfaces over other simulation experiments (such as Monte Carlo and bootstrapping), see Davidson and MacKinnon, 1993.

growth process under the model with seasonal dummies is 0.7 for both the AR(1) and random walk specifications for exchange rate movements. Excluding seasonal dummies from the model, the corresponding AR(1) coefficient for the money growth process is about 0.3 for both data generation processes for exchange rates. We therefore use the optimal money growth autoregressive coefficients of 0.7 and 0.3 for the second-stage simulations. Note from Table 5 above that the inflation-expanding effects in the second and fourth quarters are higher under the model without seasonal components than under the model with seasonal components, while inflation-dampening effects in the first and third quarters are far higher under the latter model—implying a higher annual inflation in the model without seasonal components and the need for a relatively tighter monetary stance (consistent with a lower AR(1) coefficient for money growth) in this case.

Given these optimal AR(1) coefficients for money growth, the system is simulated in the second stage for the data generation process of nominal exchange rate changes that would be consistent with attaining the predetermined inflation forecast. The results from the second stage simulations indicate the significance of seasonality in the choice of an appropriate monetary policy stance and exchange rate path (Figure 4).[8,9] Simulations under the augmented error-correction model without seasonal components seem inconsistent with the historical seasonal pattern of inflation in the Kyrgyz Republic—they suggest a bunching of positive quarterly forecasts of inflation, and this bunching does not disappear at any level of the AR(1) coefficient for nominal exchange rate changes. When seasonal components are included under the augmented EC model, the simulation results are consistent with the historical pattern of inflation and its relationship with money and the exchange rate. Further, the simulation results for the latter model variant suggest that, conditional on an optimal money supply process with an AR(1) coefficient of 0.7, an AR(1) coefficient of below 0.4 for the nominal exchange rate depreciation would be consistent with the observed inflation dynamics in the Kyrgyz Republic (Figure 4).

Figure 4 illustrates the relationship between monetary policy stance and seasonality in inflation forecasting. It shows that attaining an ex ante inflation forecast would require tighter monetary policy stance under the model without seasonal components than under that which includes these components. For example, an annual inflation forecast of 3 percent requires a monetary policy stance that is consistent with an exchange rate change path with an AR(1) coefficient at 0.3 under the seasonal components model (as indicated by the vertical line AA

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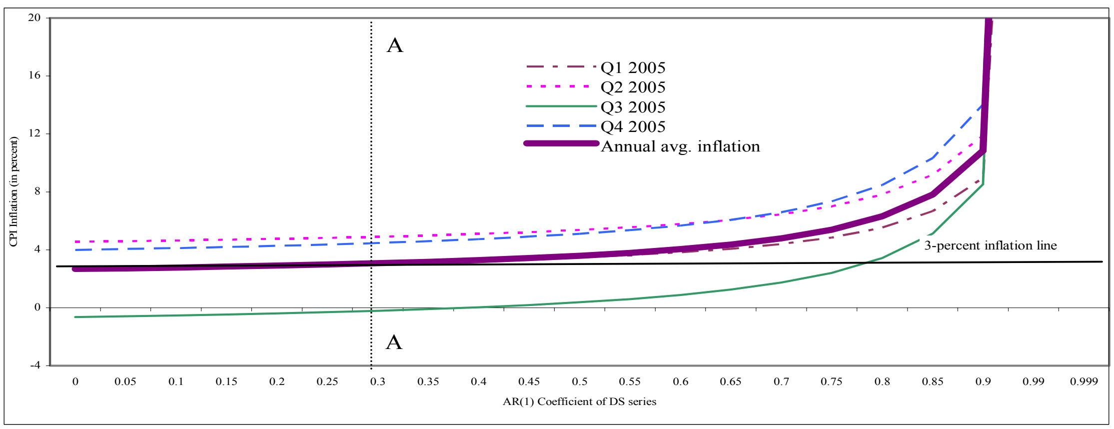
[8] Indeed, in practice, the two stages of this procedure could be implemented simultaneously. In particular, the monetary authorities could determine the level of foreign exchange market intervention or domestic open market operations (and other monetary operations that influence liquidity)—or some combination of these policy instruments in a sterilized or nonsterilized fashion—that yield the required monetary policy stance and corresponding exchange rate change consistent with the ex ante inflation forecast or target.

[9] These results are for the model variants that assume AR(1) data generation process for the exchange rate. A random walk exchange rate specification in the second-stage simulations yields lower quarterly and annual inflation forecasts under both model variants, consistent with the results summarized in Table 5.

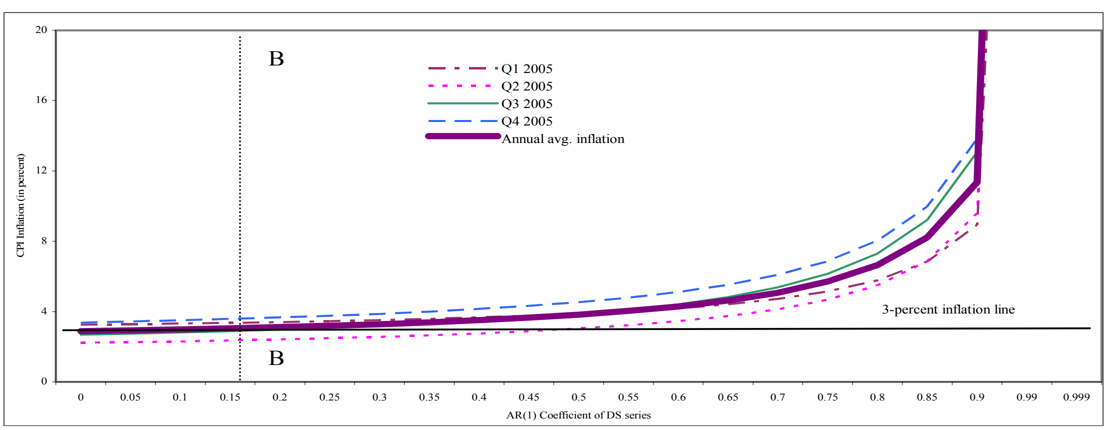
in Figure 4). Achieving the same inflation forecast under the model without seasonal components would require a tighter monetary policy stance with a lower exchange rate depreciation than under the former model (as indicated by a lower AR(1) coefficient for exchange rate changes along the vertical line BB in Figure 4)—the explanation for this is exactly as outlined earlier in this section. Thus, accounting for seasonality in modeling and forecasting inflation yields quarterly inflation forecast paths that are consistent with observed seasonal variation in consumer prices. For example, along line AA, inflation in quarters 1 through 4 are 3.1 percent, 4.9 percent, -0.2 percent, and 4.5 percent, respectively—corresponding figures along line BB are 3.4 percent, 2.4 percent, 2.9 percent, and 3.6 percent, respectively.

Figure 4. Exchange Rate Movements under Optimal Monetary Policy

a) Augmented EC model, including seasonal dummies



b) Augmented EC model, excluding seasonal dummies



Source: Author's simulations based on estimated augmented EC models.

V. Concluding Remarks

Forecasting inflation by using only the historical dynamics of the consumer price (or inflation) series may be useful, but it is more expedient and policy-relevant to adopt an approach that takes into account the impact of seasonality, the monetary policy stance, and the implied exchange rate movements in a more encompassing set-up. This paper suggests a new econometric approach (call it a toolkit) for inflation forecasting that informs the choice of an appropriately consistent monetary policy stance. It establishes the nature and stability of seasonality in consumer prices in the Kyrgyz Republic as a necessary precursor to implementing the framework. The simulations yield annual and quarterly inflation forecasts and a corresponding monetary policy stance. In addition, they yield movements in exchange rates that are consistent with the monetary policy stance that delivers the inflation target. The framework is generally applicable to countries that are interested in determining a monetary policy stance for given short-term inflation forecasts or targets (or, equivalently, jointly determining money growth and inflation paths)—especially where seasonal fluctuations of economic activity and prices are pronounced.

Notwithstanding the practicability of the framework, the efficacy of the approach depends critically on stability of the seasonal structure of consumer prices, and the approach may, to some extent, be subject to the “velocity instability problem,” as the relationship between inflation and money might change over time. Luckily, however, the latter problem is mainly detrimental to inflation forecasts over long periods of time—and thus, may only be of limited implication in short-term inflation forecast exercises of the type carried out in this paper—and the stability of the seasonal structure can easily be tested before implementing the procedure. Nevertheless, the likelihood of the “velocity instability problem” certainly underscores the need for continual empirical updates and tests for stability of the money-inflation relationship in countries for which the framework may be implemented.

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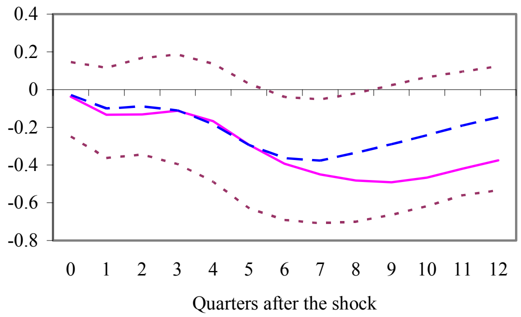
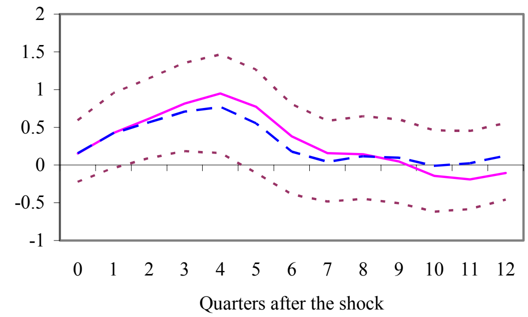
Appendix. Further Empirical Results

Appendix Figure 1. Estimated Consumer Price Response Functions, 1995–2004
(In percent)

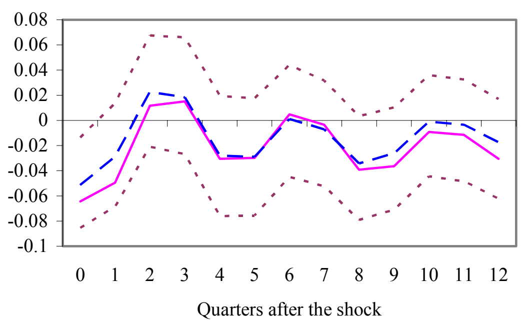
Consumer Price Responses to a One Percent Increase in Gold Prices (Pgold)



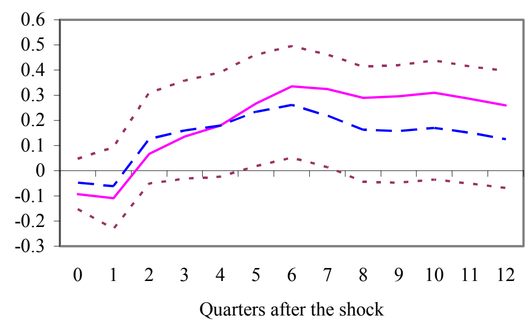
Consumer Price Responses to a One Percent Increase in Foreign Prices (Pfor)



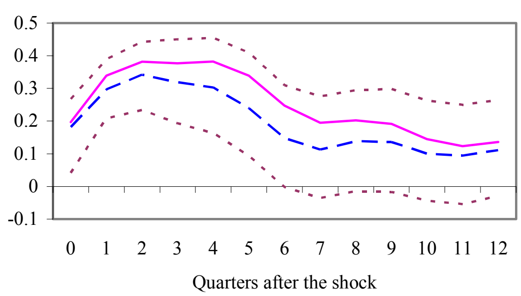
Consumer Price Responses to a One Percent Increase in Real GDP (y)



Consumer Price Responses to a One Percent Increase in Broad Money (M)



Consumer Price Responses to a one Percent
Increase in the
Exchange Rate (S)



Source: Author's estimates.

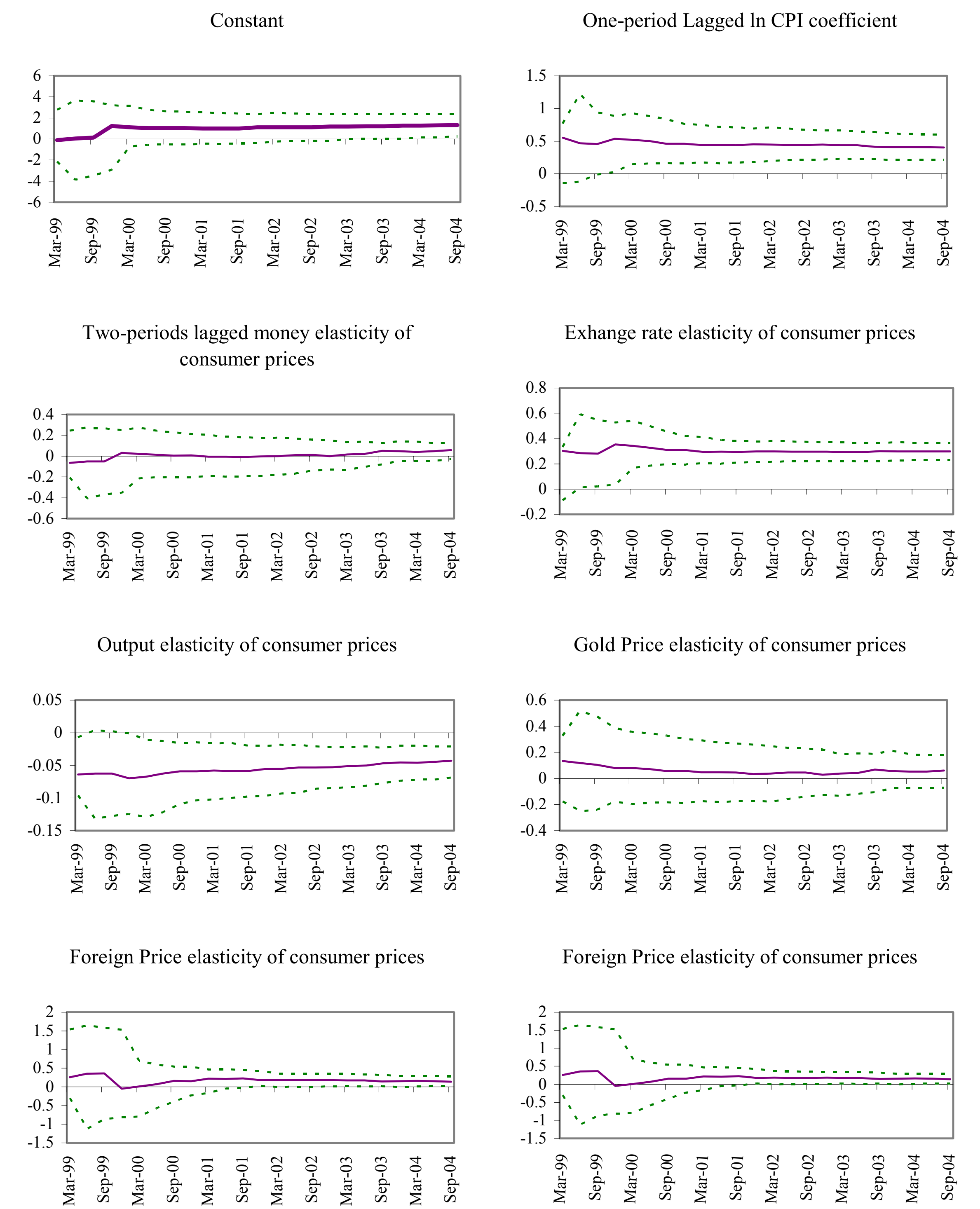
Note: The dotted lines show 95 percent confidence bands derived using a bootstrapping approach that replicates the estimated VAR 2,000 times. Estimated responses (indicated by full lines) and median responses (the 50-th percentile of the distribution of estimated responses (shown as dashed lines) of the variables are derived using this approach.

Appendix Table 1. Forecast Error Variance Decomposition for Log CPI

Forecast horizon (in quarters)	Forecast MSE (of log CPI)	Percent of Forecast MSE of log CPI explained by shocks to:					
		Gold Prices	Foreign Prices	Real GDP	Broad Money	Exchange Rates	Consumer Prices
0	0.020	0.32	0.82	24.51	4.19	24.11	46.06
1	0.030	2.13	3.26	18.25	4.63	44.70	27.03
2	0.037	2.66	6.11	12.28	3.71	57.42	17.82
3	0.043	2.58	9.37	9.16	4.60	61.05	13.24
4	0.050	3.02	11.96	7.72	5.94	60.44	10.93
5	0.057	5.01	12.06	6.78	9.09	56.99	10.09
6	0.061	8.28	10.74	5.75	13.55	52.42	9.26
7	0.065	11.93	9.53	5.07	16.76	48.44	8.27
8	0.070	15.32	8.52	5.28	18.29	45.21	7.39
9	0.073	18.20	7.67	5.36	19.66	42.42	6.69
10	0.076	20.42	7.11	4.97	21.35	39.99	6.16
11	0.079	21.94	6.75	4.72	22.63	38.16	5.80
12	0.081	22.90	6.42	4.82	23.46	36.88	5.51

Source: Author's estimates from a simple recursive VAR.

Appendix Figure 2. Estimated Recursive Parameters of the Long-Run Equation



Source: Author's recursive OLS estimates.