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Identifying Aggregate Demand & Aggregate Supply Components of the Inflation Rate: An Application to Jamaica

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The paper identifies the underlying macroeconomic factors which drive inflation dynamics as they are critical to the design of anti-inflation monetary policy. This is achieved by estimating a trivariate output-price-exchange rate structural vector autoregression (VAR) model for Jamaica to decompose the inflation rate time-series into two components explained by aggregate demand (AD) and aggregate supply (AS) shocks. For the model's main identifying restriction, we assume that an AD shock has no long-run impact on the level of output. Dynamic properties of the estimated model are shown to be generally consistent with the predictions of the conventional AS-AD framework. The coincidence of large and negative AS and AD shocks explains the combination of price stability and weak growth that characterized the late 1990s. However, care should be taken when attributing inflation solely to exogenous aggregate supply shocks as underlying demand conditions are a large part of what promotes the propagation of these shocks.

JEL Classification: E31, E32
Keywords: Inflation, business fluctuations, cycles, structural dynamics

[1] The views expressed are those of the author and not necessarily those of the Bank of Jamaica.

I. Introduction

Since 1995 the objective of monetary policy has been the reduction of inflation towards that of our major trading partners. The effectiveness of monetary policy in lowering inflation, however, depends on the sources of price fluctuations. Further, the response of the economy to a monetary policy action also depends on the source of the shock to prices. If a rise in inflation is due to an aggregate demand shock, then a contractionary monetary policy response will stabilize output. More critically, if the rise in inflation is due to an adverse supply shock, then contractionary monetary policy will magnify the drop in output. If inflation is due primarily to aggregate supply factors then contractionary monetary policy will exacerbate the reduction in output and ultimately inflation. Identifying the underlying macroeconomic factors, which drive inflation dynamics is therefore critical to the design of an anti-inflation monetary policy. Against this background this paper attempts to delineate the main sources of price fluctuations using a structural vector autoregression (SVAR) model of the economy.

SVARs have generally been used to examine the relative import of different shocks to output. Dolado and Jimeno (1997) review the main causes of Spanish unemployment and weigh them by estimating a simple macroeconomic model using the structural VAR methodology. They utilise a similar framework to that set out by Blanchard & Quah (1989) but augmented by specific behavioural relationships that aid in identifying a wide variety of shocks, in a context of hysteresis[2]. Dolado and Jimeno (1997) employed five equations to identify five shocks but used a minimum amount of dynamics to simplify the analysis. Their results confirm the consensus view about the existence of significant shocks and an extreme form of persistence behind the Spanish unemployment dynamics. They show that the documented dismal performance of Spanish unemployment can be explained as the result of a series of adverse shocks, which were difficult to absorb in a context of a rigid system of labour market institutions and disinflationary policies.

[2] This refers to a system that may be in any number of states independent of the inputs to the system. Hysteresis is a hypothesized property of unemployment rates: that there is a ratchet effect, so a short-term rise in unemployment rates tends to persist. An example is the notion that inflationary policy leads to a permanently higher 'natural' rate of unemployment (NAIRU), due to the proposition that inflationary expectations are 'sticky' downward because of wage rigidities and imperfections in the labour market.

Bernanke and Mihov (1998) develop a model-based VAR methodology for measuring innovations in monetary policy and its macroeconomic effect. With this framework they are able to compare existing approaches to measuring monetary policy shocks and derive a new measure of policy innovations based directly on estimates of the central bank's operating procedure. They also propose a new measure of the overall stance of policy that is consistent with their approach.

More recently, Jacobson et al (2002) estimated the effects of monetary policy shocks on the Swedish economy using a theoretical model of an open economy to identify a structural VAR model. The VAR model is structural in the sense that it is subject to a relatively small set of restrictions that enable the identification of various shocks and their individual effects on the Swedish economy. A primary purpose of the theoretical model is to entail a better understanding of alternative identifying restrictions on the VAR model. The solution is presented in a so called common trends form, a particular representation of structural VAR models pioneered by Shapiro and Watson (1988) and King, et all (1991)(1991). The solution has the property that all domestic shocks influence some of the variables in the long run, thus making the usual dichotomy between permanent and transitory shocks invalid.

Where the behaviour of inflation is concerned Quah and Vahey (1995) used this approach to identify 'core inflation' for the United Kingdom, which is defined as that component of headline inflation that has no medium to long-run impact on the level of output. Quah and Vahey (1995) through their uneasiness with the conceptual mismatch between measured inflation and core inflation, proposed a technique for measuring core or underlying inflation based on an explicit long-run economic hypothesis. This definition captures the commonly held view that (moderate) movements in inflation can be mild for the real economy once it has been factored into financial and wage contracts have been written taking it into account. This notion is consistent with the vertical long-run Philips curve interpretation of the comovements in inflation and output. The authors construct a measure of core inflation by placing dynamic restrictions on a vector autoregression (VAR) system. They assumed that observed changes in the measure of inflation (derived from the United Kingdom's Retail Price Index) are affected by two types of disturbance each uncorrelated with the other. The first of these shocks has no impact on the level of real output in the medium to long-run. The second has unrestricted effects on measured inflation and real output, but does not affect core inflation. They estimated a bivariate output-price model to identify “core inflation”, which is explained by the shocks that have no long run impact on the level of output. This is also the method used by the Monetary Authority of Singapore to compute their ‘output-neutral’ measure of underlying or core inflation.

More recently Mio (2002) extended Quah and Vahey (1995) to inflation in Japan. The main idea behind this literature is that output fluctuations contain important information about the sources of price variability. This follows from the fact that a positive demand shock, which raises prices also increases output and a negative supply shock which increases prices also lowers output.

The analysis in this paper follows closely Mio (2002). Given the openness of the Jamaican economy and the reliance on imported commodities for consumption and production, we estimate a trivariate SVAR with output, price and exchange rate, which is used to identify the relative importance of aggregate supply and demand disturbances to inflation. Consistent with the literature, identification is achieved through the imposition of the restriction that aggregate demand shocks, which affect prices, do not have any long run impact on output.

The rest of the paper is organized as follows: Section II delineates the structure of the econometric model while section III describes the estimation procedure, which follows closely the work of Hitoshi Mio (2002). Section IV determines the impulse responses and historical decomposition, as well as testing the robustness of the estimation results against alternative specifications. Section V concludes.

II. Econometric Model

To motivate the statistical analysis, the theoretical or structural model in logs, outlined below, is comprised of a simplified open economy Phillips curve (1), aggregate demand (2) and uncovered interest parity relation (4), respectively.

$$p_t = a_1 s_t + a_2 (y_t - \bar{y}) \qquad [1]$$

$$y_t = a_3(m_t^s - m_t^d) + a_4\theta_t \qquad [2]$$

$$m_t^s - p_t = a_5 y_t - a_6 r_t \qquad [3]$$

$$Es_t - s_{t-1} = r_t - r_t^* + \varepsilon_t^u \qquad [4]$$

where p, s, y, r, m^s and m^d are the price level, exchange rate, output, interest rate, money supply and money demand, respectively. Y bar is potential output, r* is the foreign interest rate which is exogenous, θ is a productivity shock and ε_t^u is a shock to the foreign exchange market which would cause a deviation from UIP. In this model aggregate demand is a function of excess balances and productivity. To close the model, the money supply and productivity evolve according to

$$m_t^s = m_{t-1}^s + \varepsilon_t^m \qquad [5]$$

$$\theta_t = \theta_{t-1} + \varepsilon_t^s \qquad [6]$$

where ε_t^m is a shock to the money supply which produces an aggregate demand shock and ε_t^s is the supply shock which affects productivity.

Invertibility

All the shocks in this model are serially uncorrelated with each other. It can be shown that the reduced form of the model has the following *general* vector moving average (VMA) form

$$X_t = \Theta(L)\varepsilon_t \qquad [7]$$

where $X_t = (\Delta y, \Delta\Delta p, \Delta s)'$ and $\varepsilon_t = (\varepsilon^s, \varepsilon^m, \varepsilon^u)'$. *L* is the lag operator, Θ*(L)* is a matrix of lag polynomials - $\Theta(L) = \sum_{i=0}^{\infty} \Theta(i)L^i$, where Θ*(i)* is a *3x3* matrix for all *i*. Assuming that Θ*(L)* is invertible equation [7] can be inverted to yield the structural VAR equation [8]:

$$\alpha(L)X_t = \varepsilon_t \qquad [8]$$

where α(L) = $\sum_{i=0}^{p} \alpha_i L^i = \Theta(L)^{-1}$. Thus under the assumptions stated above, one can decompose the observed inflation rate into its AS and AD components when the parameters in the structural VAR are identified.

Identification

Since equation [8] is a set of dynamic simultaneous equations, standard simultaneous methods can be used to estimate the parameters if the model is identified. Rewriting equation [8] in reduced form yields equation [9]:

$$\beta(L)X_t = e_t \qquad [9]$$

where $\beta(L) = \sum_{i=0}^{p} \beta_i L^i$ and

$$\beta_i = \begin{cases} I & for \;\; i = o \\ \alpha_0^{-1}\alpha_i & for \;\; i > 1 \end{cases}, \qquad [10]$$

$$e_t = \alpha_0^{-1}\varepsilon_t \qquad [11]$$

$$\alpha_0^{-1}\Omega(\alpha_0^{-1})' = \Sigma_e = E(e_t e_t'). \qquad [12]$$

Each element of B_i *(i = 1…p)* in equation [9] has 9 independent elements and the covariance matrix Σ_e has 6 independent elements. Since AS and AD shocks are assumed to be mean-zero serially uncorrelated and uncorrelated with each other, these 9p+6 parameters completely characterize the probability distribution of the data. On the other side, α_i (*i*=0,…, p) in equation [8] has a total of 9p+9 independent elements and Ω has three independent elements since it is assumed to be diagonal. Thus, six restrictions are required for identification of equation [8]. Assuming that α_0 has ones on the diagonal elements gives another three restrictions, leaving only three additional necessary restrictions. As in Blanchard and Quah (1989) we impose the restriction that aggregate demand shocks have no long run effect on the level of output. This requires that we make Θ_i lower triangular, which ensures that the cumulated effects of demand shocks on output are zero and provides the three additional restrictions.

Various simultaneous methods are available for the consistent estimation of the structural VAR parameters. Blanchard and Quah (1989) used Indirect Least Squares (ILS) which entailed estimating equation [9] through equation-by-equation ordinary least squares and then solving equation [12] for each element in α_0 using estimated $\sum_e$ and identifying restrictions. This is somewhat complex. Mio (2002) used instrumental variables, which involved some messy re-parameterization prior to estimation. We are grateful to colleagues from the CCMF who provided the source code for a program in RATS to undertake the estimation.

The Data

Inflation in Jamaica is measured by the All Jamaica Consumer Price Index (CPI) produced by the Statistical Institute of Jamaica (STATIN). The analyses use quarterly data from 1988:2 to 2008:4 which includes real gross domestic product, exchange rate, money supply and interest rate. The CPI is used in this study as it is the measure on which attention is most closely focused, it is the most comprehensive measure of consumer prices and the timeliest one available for the economy. Two inflation measures are used; there is the standard measure of quarterly inflation calculated from the end point of the quarter and average quarterly inflation. Alternatively, a number of underlying inflation measures are used, such as the trimmed mean measure, which utilizes a symmetric 20% truncation of the distribution of price changes, and four exclusion measures. These are inflation without agriculture, inflation without fuel, inflation without agriculture and fuel and finally, inflation without food and fuel.

Unit Root Tests

Phillips (1998) has shown that impulse responses and variance decomposition in VAR models with integrated variables give inconsistent estimates and tend to random variables. Consequently, the time series properties of the data are examined using the Augmented Dickey-Fuller and the Phillips-Perron tests to ensure that all variable are included as stationary processes. The tests suggest that price and average inflation are stationary or I(0) processes in their first differences. The finding that these inflation measures contain unit roots suggests the presence of a permanent component in the inflation process. Thus the eventual application of long-run restrictions to decompose the inflation rate into differing components is logical.

Table 1: Unit Root Tests

	Constant		No Constant	
	ADF	**PP**	**ADF**	**PP**
ΔLRGDP	-2.694*	-11.539***	-2.615***	-10.599***
ΔLXR	-5.697***	-3.771***	-4.838***	-3.443***
ΔINF	-13.310***	-14.361***	-13.393***	-14.463***
ΔAVINF	-7.520***	-7.369***	-7.569***	-7.439***
ΔCPIAF	-3.585***	-3.713***	-1.421	-2.099**
ΔCPIFF	-3.951***	-4.968***	-1.417	-2.393**

ΔTRIM	-3.554***	-3.590***	-1.424	-2.250**
ΔCPIA	-3.696***	-3.765***	-2.584**	-2.502**
ΔCPIF	-2.879*	-4.197***	-1.756*	-2.363**

Note: Lag length for ADF test is automatically determined. Bandwidth selection for the PP test is also set automatically. Rejection of the null hypothesis of a unit root in the first difference of each variable at the 1%, 5% and 10% level is indicated by ***, **, and *, respectively. All variables are log transformed.

Lag Length Tests

For quarterly data, it is suggested that lag length tests begin at 12 periods as it is argued that 3 years would be sufficient time for the dynamics of the system to develop fully (Enders, 1995). However, at this lag length there was significant indeterminacy amongst the selection criteria. In particular, two of the criteria suggested 11 lags while another two selected 2 lags and one selected 7 lags. This motivated a reduction in the number of lags but the indeterminacy remained up until the eighth lag, where four out of the five selection criteria chose the number of lags to be seven. At lower lags, indeterminacy again was present.

Initial VAR Estimation

As a first step in the analysis, an unrestricted 3-variable (GDP, exchange rate and inflation), seven-lag VAR with a constant term, trend and a dummy for liberalization was estimated. Two measures of inflation – average quarterly inflation and point-to-point quarterly inflation - were used alternatively to determine which performs better in the VAR. On the basis of the AIC and SC measures and residual plots, average quarterly inflation was marginally better. The trend variable was never significant in any of the estimations and hence was omitted from further analysis. The liberalization dummy was significant in both the exchange rate and GDP equations. Visual examinations of the residuals and corresponding correlograms revealed mean zero error terms and lags within the standard error bands of the correlograms. Further, serial correlation tests showed strong rejection of the null hypotheses of unit roots in the residuals from the initial estimation.

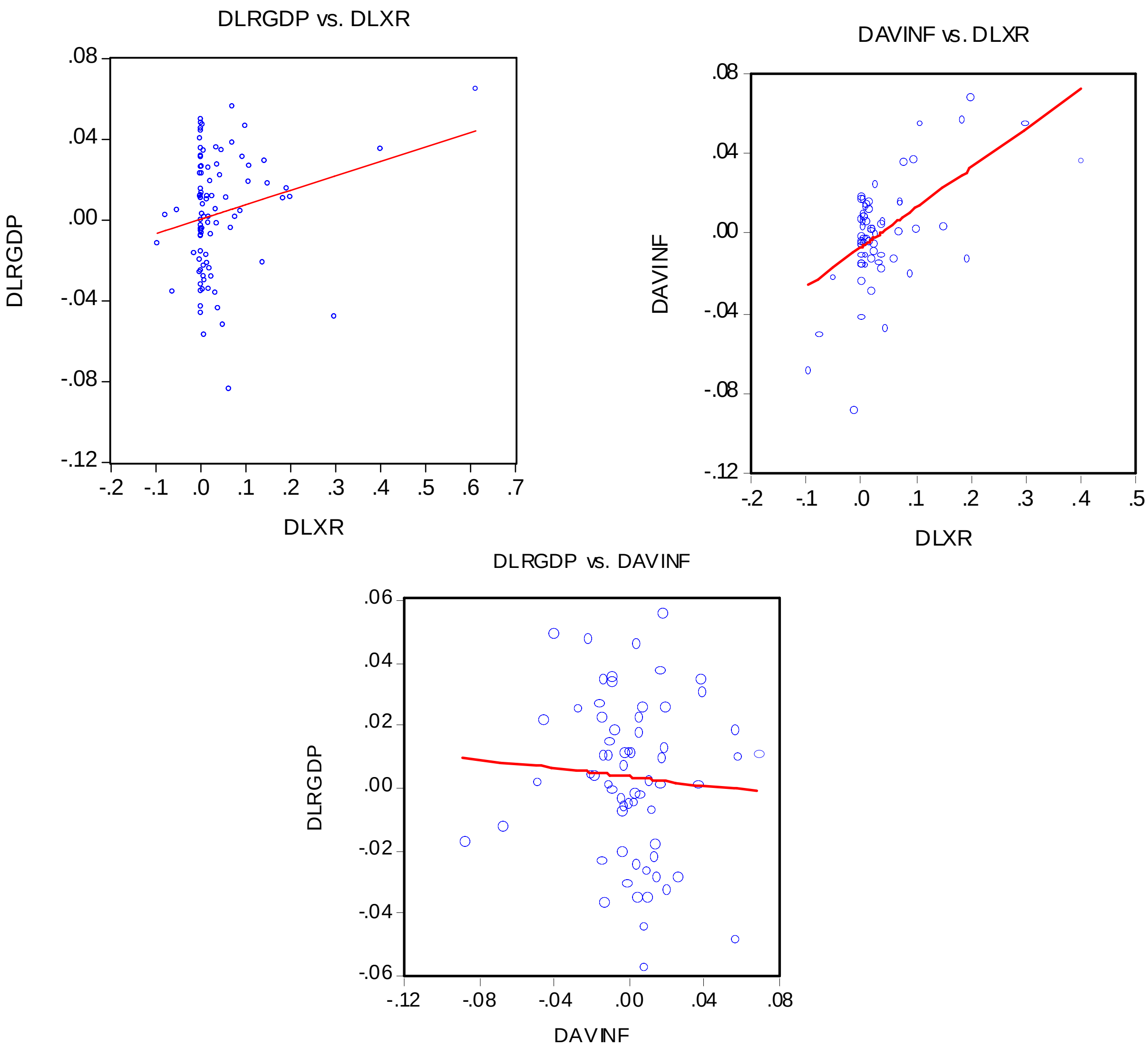
Table 2: The Variance-Covariance Matrix

Avg Inf	Ex Rate	GDP
0.00037	0.00036	-4.088e-05
0.00036	0.00171	7.751e-05
-4.088e-05	7.751e-05	0.00035

Engle-Granger/Johansen Tests for Cointegration

Though the three variables included in the VAR are stationary, the findings of their similar levels of integration necessitated testing for cointegration. A preliminary examination of the three pair wise combinations via scatter plots revealed no indications of common trends. In particular, none of the scatter plots showed definitive, systematic deviations around their respective regression lines.

Figure 0



Using the Engle-Granger methodology, the three pairs of variables were tested, with each pair checked for the long run equilibrium relationship in the form:

$$y_t = \beta_0 + \beta_1 z_t + e_t. \qquad [13]$$

If the residual sequence, e_t, from this regression is found to be stationary then the pair of variables is cointegrated of order one. A Dickey-Fuller test on these residuals could determine their order of integration. This could be done through an autoregression of the residuals:

$$\Delta \hat{e}_t = a_1 \hat{e}_{t-1} + \in_t (11) \qquad [14]$$

Notice, however, that because the sequence is a residual from a regression equation, there is no need for an intercept term and the parameter of interest is a_1. If the null hypothesis that $a_1 = 0$ cannot be rejected then the residual series contains a unit root. This would imply that the $\{y_t\}$ and $\{z_t\}$ sequences are *not* cointegrated. Put another way, if it is *not* possible to reject the null hypothesis $/a_1=0/$, we *cannot* reject the hypothesis that the variables are *not* cointegrated. Conversely, the rejection of the null hypothesis implies that the residual sequence is stationary. In the absence of the Engle and Granger statistics to test the hypothesis of $a_1=0$ a further test was conducted. The following autoregression was estimated:

$$\Delta \hat{e}_t = a_1 \hat{e}_{t-1} + \sum_{i=1}^{n} a_{i+1} \Delta \hat{e}_{t-i} + \in_t \qquad [15]$$

If $-2 < a_1 < 0$, we can conclude that there is cointegration. This was the case in only one of the equations: the GDP/Exchange rate equation.

This prompted testing via the Johansen methodology. Under this assessment, both the trace and max-eigenvalue tests indicated three cointegrating equations at the 5% level of confidence (see **Appendix**). Given that the critical values may not be valid with exogenous variables in the regression, the test was rerun without the liberalization dummy. However, the result was the same. This was a cause for concern as the finding of the same number of cointegrating relationships as there are variables corresponds to the case where none of the series has a unit root, for which we have clear evidence to the contrary. Alternatively, a stationary VAR may be specified in terms of the levels of all the included series. Given the indeterminacy and the known behavior of the constituent series we opted to treat with the analysis as suggested by Enders (1995). That is, firstly, if the variables are stationary then standard time series methods apply and secondly, if the variables are integrated of different orders, it is possible to conclude that they are not cointegrated.

Estimation Results

The impulse responses are shown below. Each dynamic response indicates the cumulative percentage deviation of price (DAVINFN/CPIAF) and output (DLRGDP) in response to an AS shock (shock 1) and an AD shock (shock 2) normalized at one standard deviation. Figure 1 shows that in response to a supply shock, prices rise strongly but a demand shock produces a much more muted response. On the other hand, output responds more strongly to an aggregate demand shock relative to its response to a supply shock.

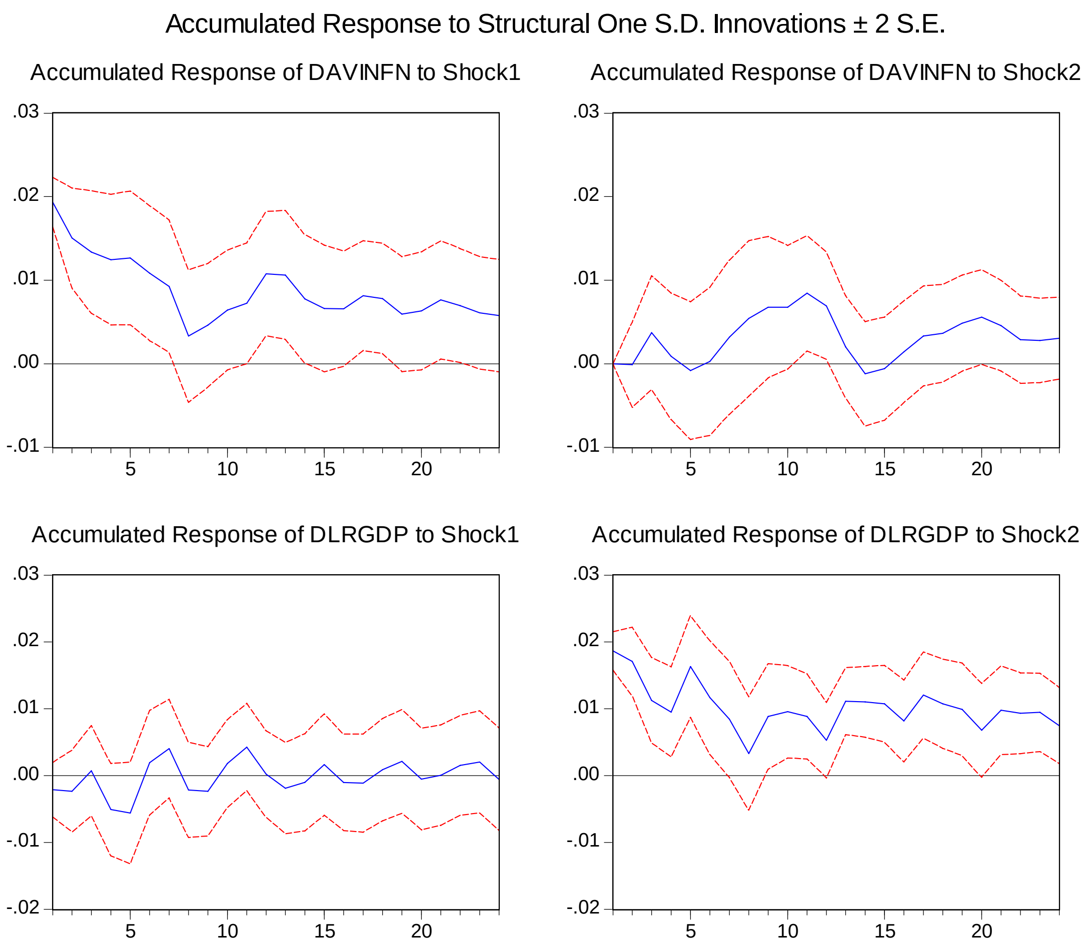


Figure 1

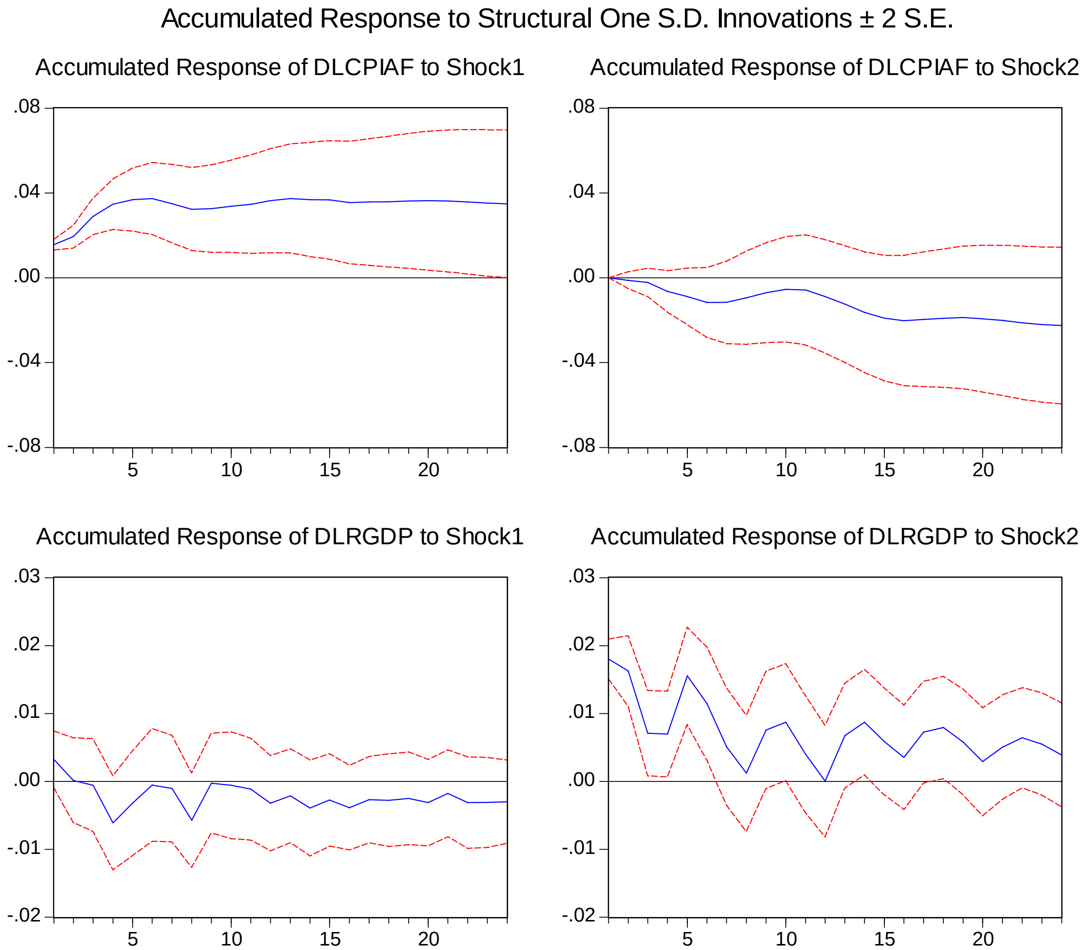

Accumulated Response to Structural One S.D. Innovations ± 2 S.E.
Accumulated Response of DLCPIAF to Shock1
Accumulated Response of DLCPIAF to Shock2
Accumulated Response of DLRGDP to Shock1
Accumulated Response of DLRGDP to Shock2
.08
.04
.00
-.04
-.08
.03
.02
.01
-.01
-.02
5
10
15
20

Figure 2

Historical Decomposition and Events

Figure 3 below depicts the rate of inflation explained by aggregate supply (AS) shocks and the rate of inflation explained by the aggregate demand (AD) shocks. The most striking feature of the decomposition is the amplitude of the swings in the early half of

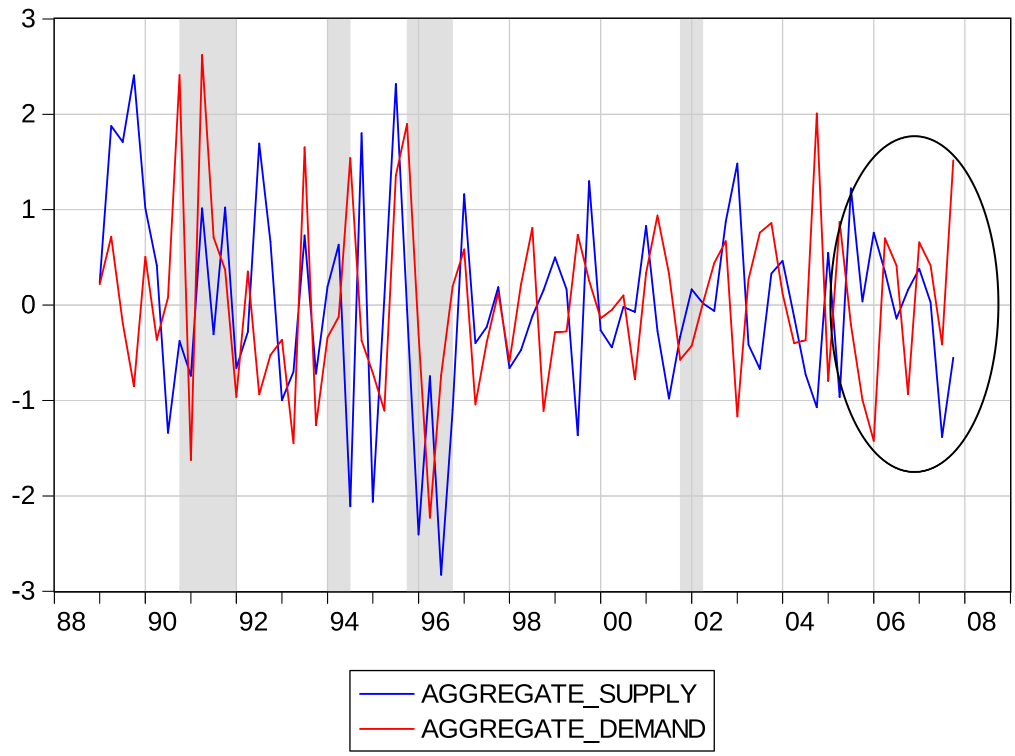


Figure 3

the period of review. These were challenging times which included a significant hurricane, the advent of significant foreign exchange market liberalization, commodity price shocks, financial sector instability and the highest rate of annual inflation ever recorded. Where this record was attained (first shaded region), aggregate demand shocks were at their highest for the entire sample. The second shaded region coincides with a recession and a sharp downturn in aggregate supply. However, this turbulent period was concluded by concerted measures by the monetary authorities, which lay the groundwork for the more stable period that followed but also saw the steepest declines in aggregate supply and demand (third shaded region). The second half of the historical decomposition was much more sedate in terms of the swings in AS and AD shocks. The late nineties into the early 2000s also occasioned an extended period of low inflation but anaemic growth.

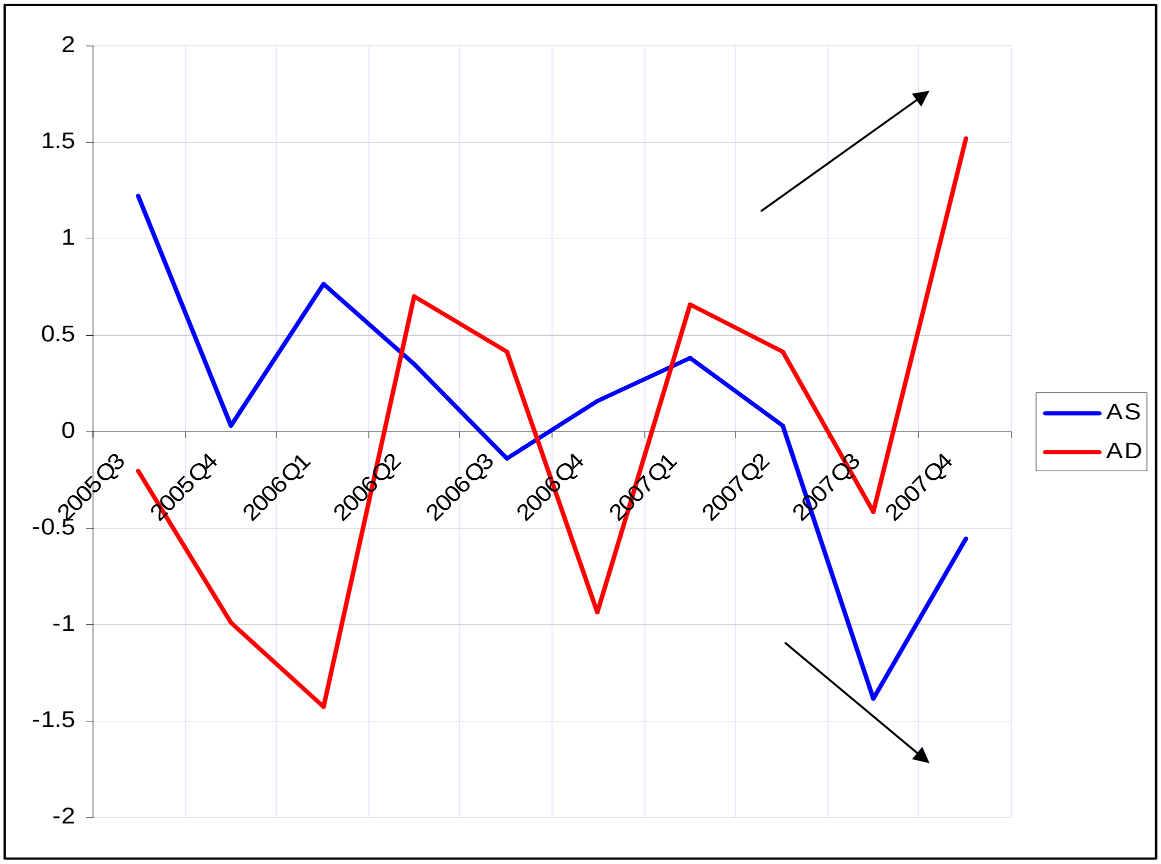


Figure 4

Towards the end of the review period (highlighted in figure 4) a distinct pattern emerges. From 2006 onwards, there was a trend increase in aggregate demand while a trend decrease in aggregate supply ensued. This was coincident with higher income and spending as wages were rising, remittances were strong, alternative investment schemes flourished and the policy framework was not as restrictive as in earlier years. The downturn in AS could have been seen as underlying signs of weakness in the real economy.

Alternative Choices for the Price Variable

Historical decompositions for the AD component of inflation for different price variables are expected to be at least qualitatively similar if the identified shocks and dynamic responses are similar among different output-price combinations. The figure below presents three identified components of inflation using three price variables. While there are some sharper swings in differing components, the timing and magnitude of peaks and troughs generally coincide with the each other. This implies that similar AD shocks and dynamic responses are being identified regardless of the price variable used. Thus, it can be said that the benchmark historical decomposition is robust to the alternative choices for the price variable.

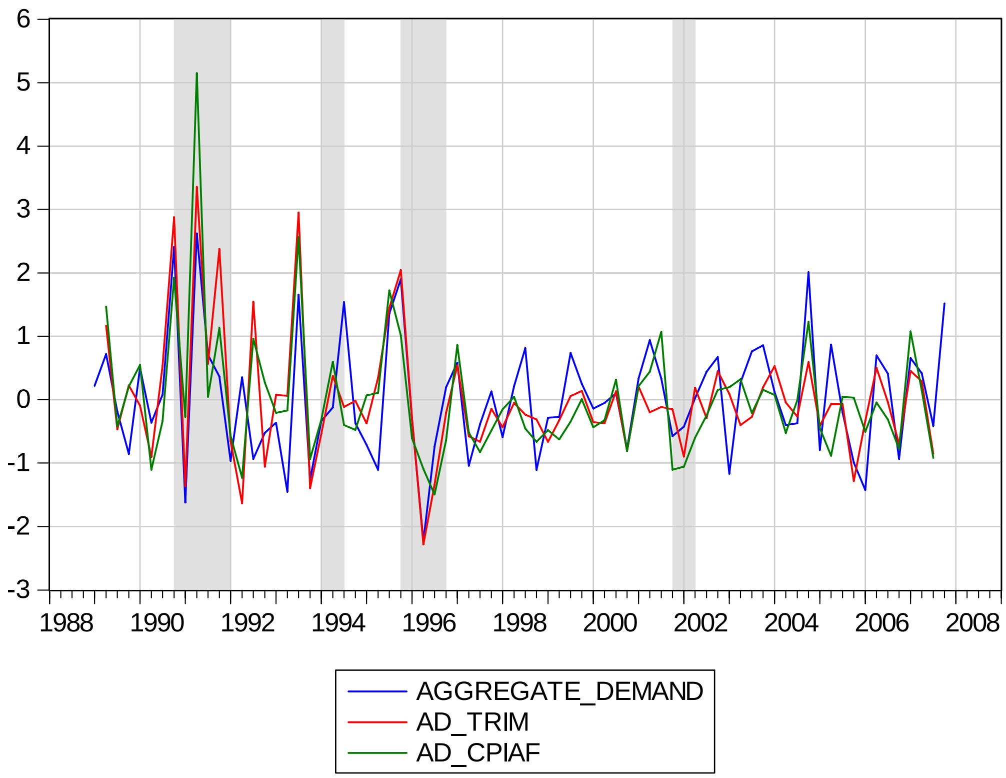


Figure 5

Robustness to Assumptions of Lag Length

When long-run restrictions are used for identification of the model, the lag length of the VAR also plays the role of an identifying restriction (Faust and Leeper (1997)). Given this important role, the robustness of the historical decomposition to alternative assumptions for the lag length of the VAR is worth investigating. The figure below indicates five AD series identified for VARs of two, four, six, and eight lags as well as the benchmark. As shown in the figure, there are no significant differences among the historical decompositions. The most discordant is that of Lag 2, which is also the most implausible.

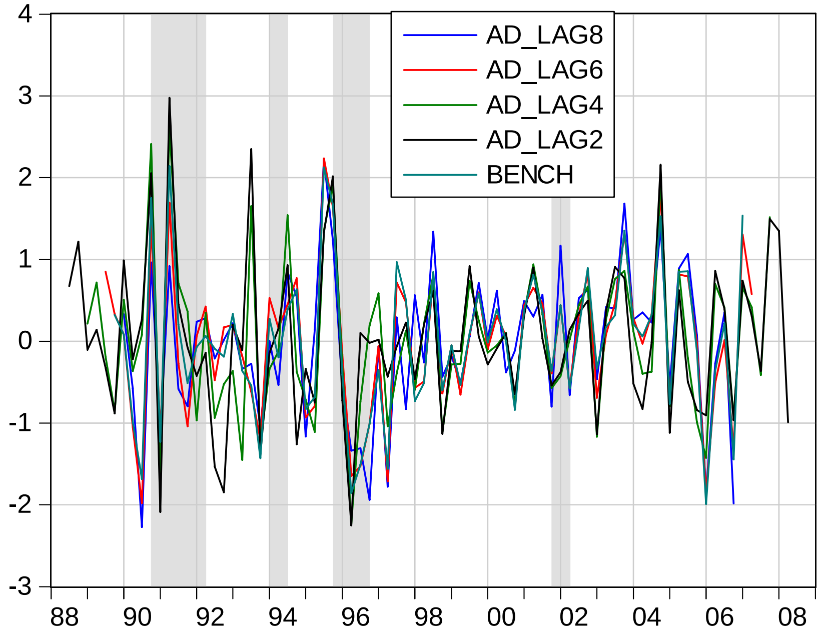


Figure 6

Robustness to Effects from Sectoral Shocks

Besides AS and AD shocks, it is well known that short-run fluctuations in the observed inflation rate is also affected by sectoral shocks. For example, the sudden reduction in the supply of agricultural produce caused by adverse weather raises its relative price and the aggregate CPI sharply. Therefore it is necessary to examine whether the contamination causes serious difficulty for the interpretation of the historical decomposition.

For the measures of inflation caused by sectoral shocks, we use the difference between the changes in headline inflation and the trimmed mean inflation, CPIAF and CPIFF. When some sectors face large shocks, prices of products for those sectors are likely to experience large relative price changes. Consequently, the price change distribution tends to skew and a divergence is likely to emerge between the changes in the headline CPI and the core measures: the larger the skewness, the greater the divergence between the two. Focusing on this, this analysis adopts this disjuncture as a proxy for the inflation rate explained by the sectoral shocks or put another way, the transient noise that should not be related to long-run movements in AD. The figure below depicts the inflation rate explained by the sectoral shocks and the AS and AD components of inflation.

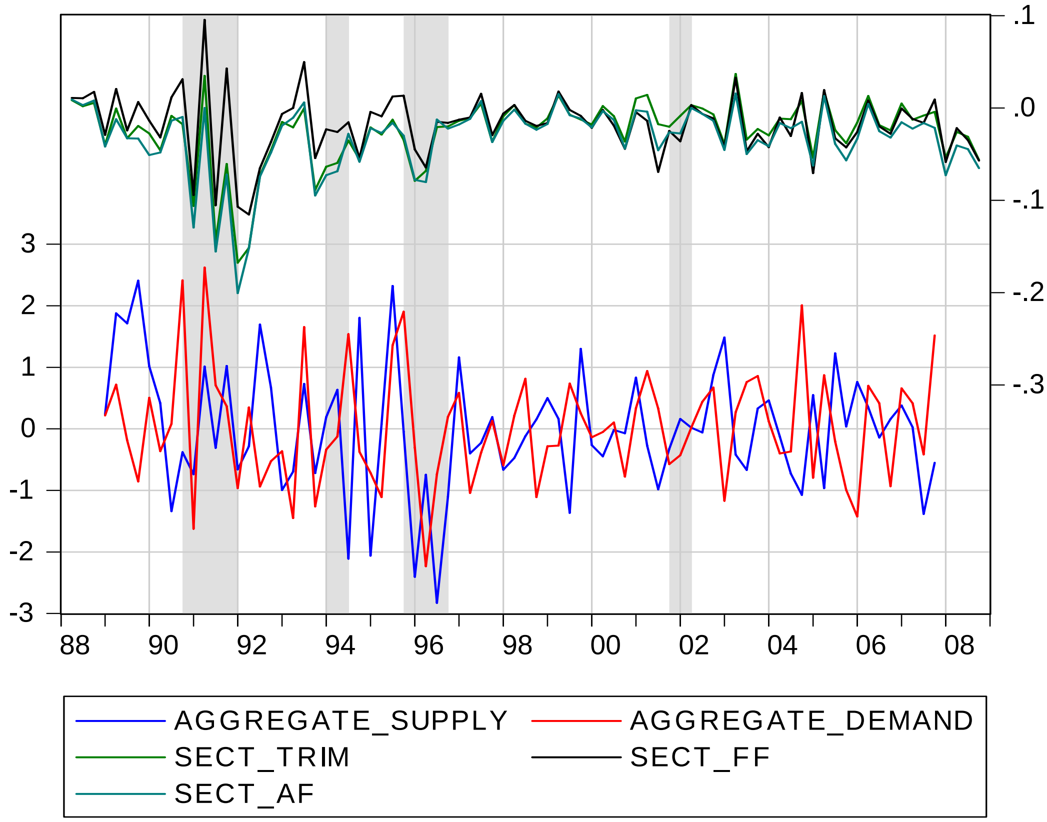


Figure 7

The coefficients of correlation of the sectoral inflation and the AS and AD components of inflation are shown in Table 10. As expected AD correlations are much stronger than the correlations with AS. However, more importantly, the sectoral inflation measure for CPIAF had the lowest correlation with the AD component of inflation. This is evidence that the measure of underlying inflation which includes the least amount of transient information and is best suited for targeting by the monetary authorities is CPIAF.

Table 3

Measure of Sectoral Inflation	AD Component	AS Component
Trimmed	**0.343**	**0.056**
CPIFF	**0.516**	**0.104**
CPIAF	**0.317**	**0.021**

Conclusion and Policy Implications

The historical decomposition is generally compatible with the conventional view of the major Jamaican historical episodes since 1985. A feature is particularly striking: the coincidence of large and negative AS and AD shocks appears to explain the price stability and weak growth in the late 1990s to the early 2000s. The historical decomposition is qualitatively robust to alternative choices for the price variable and assumptions for the lag length of the VAR. There is evidence that since 2006, there has been a trend divergence between AS and AD shocks with AD shocks accounting for a much larger portion of inflation than anticipated. Also, the measure of core inflation found to be most consistent with demand conditions was the CPIAF. Hence, care should taken when attributing inflation solely to exogenous supply shocks as underlying demand conditions are a large part of what promotes the propagation of the shocks. It seems that in a number of episodes, supply shocks have been accompanied by a number of accommodating demand shocks. Additionally, monetary policy should continue to focus on the CPIAF measure of core inflation as highlighted by the analysis.

APPENDIX

VAR Lag Order Selection Criteria
Endogenous variables: DAVINFN DLXR DLRGDP
Exogenous variables: C LIBDUM92
Date: 04/20/09 Time: 08:14
Sample: 1988Q1 2009Q1
Included observations: 84

Lag	LogL	LR	FPE	AIC	SC	HQ
0	496.4057	NA	1.70e-09	-11.67633	-11.50270	-11.60653
1	522.0913	48.31341	1.15e-09	-12.07360	-11.63953	-11.89911
2	553.5056	56.84478	6.73e-10	-12.60728	-11.91276*	-12.32808
3	569.2130	27.30101	5.75e-10	-12.76698	-11.81201	-12.38309
4	584.5210	25.51328	4.98e-10	-12.91717	-11.70176	-12.42858
5	594.7415	16.30427	4.87e-10	-12.94623	-11.47037	-12.35295
6	606.5227	17.95221	4.61e-10	-13.01244	-11.27615	-12.31447
7	626.7939	29.44153*	3.58e-10*	-13.28081*	-11.28406	-12.47813*
8	634.5476	10.70747	3.76e-10	-13.25113	-10.99395	-12.34376
9	637.8718	4.353182	4.41e-10	-13.11600	-10.59836	-12.10393
10	645.3202	9.221795	4.73e-10	-13.07905	-10.30098	-11.96229

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Date: 04/17/09 Time: 11:01
Sample (adjusted): 1988Q1 2008Q4
Included observations: 84 after adjustments
Trend assumption: Linear deterministic trend
Series: DAVINFN DLXR DLRGDP
Exogenous series: LIBDUM92
Warning: Critical values assume no exogenous series
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.649981	163.6933	29.79707	0.0001
At most 1 *	0.492039	75.51291	15.49471	0.0000
At most 2 *	0.198775	18.61549	3.841466	0.0000

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.649981	88.18040	21.13162	0.0000
At most 1 *	0.492039	56.89743	14.26460	0.0000
At most 2 *	0.198775	18.61549	3.841466	0.0000

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

DAVINFN	DLXR	DLRGDP
7.211955	-2.956340	-52.22759
48.47063	3.171924	3.696140
49.69463	-20.38155	24.82186

Unrestricted Adjustment Coefficients (alpha):

D(DAVINFN)	-0.005614	-0.019936	-0.000282
D(DLXR)	0.017550	-0.022847	0.018324
D(DLRGDP)	0.029992	0.000258	-0.003949

1 Cointegrating Equation(s):		Log likelihood	515.7491

Normalized cointegrating coefficients (standard error in parentheses)

DAVINFN	DLXR	DLRGDP
1.000000	-0.409922	-7.241808
	(0.19108)	(0.64530)

Adjustment coefficients (standard error in parentheses)

D(DAVINFN)	-0.040487
	(0.02346)
D(DLXR)	0.126571
	(0.04410)
D(DLRGDP)	0.216299
	(0.01938)

2 Cointegrating Equation(s):		Log likelihood	544.1978

Normalized cointegrating coefficients (standard error in parentheses)

DAVINFN	DLXR	DLRGDP
1.000000	0.000000	-0.931176
		(0.14306)
0.000000	1.000000	15.39471
		(1.36720)

Adjustment coefficients (standard error in parentheses)

D(DAVINFN)	-1.006776	-0.046637
	(0.11475)	(0.01015)
D(DLXR)	-0.980836	-0.124353
	(0.27148)	(0.02402)
D(DLRGDP)	0.228794	-0.087848
	(0.13165)	(0.01165)

Inflation variance decomp

Period	Shock1	Shock2	Shock3
1	0.019328	0.000000	0.000000
2	-0.004285	0.010498	-0.001918
3	-0.001679	7.14E-06	0.003905
4	-0.000908	-0.007380	-0.001624
5	0.000207	-0.003676	-0.001099
6	-0.001823	-0.006644	0.002251
7	-0.001569	0.000411	0.002871
8	-0.005970	0.005855	0.001278
9	0.001319	0.003222	0.000813
10	0.001799	0.002657	-0.000472
11	0.000813	-0.001322	0.001934
12	0.003548	-0.004051	-0.000842
13	-0.000159	-0.001840	-0.004669
14	-0.002854	-0.001359	-0.003030
15	-0.001163	-0.000242	0.000653
16	-2.87E-05	0.002075	0.001706
17	0.001570	0.000791	0.001787
18	-0.000333	0.000690	0.000205
19	-0.001882	0.001056	0.001049
20	0.000398	-0.000986	0.000909
21	0.001317	-0.002024	-0.000702
22	-0.000687	-0.001676	-0.001415
23	-0.000870	0.000201	-0.000136
24	-0.000335	0.002111	-7.76E-05

GDP Variance Decomposition

Period	Shock1	Shock2	Shock3
1	-0.002115	0.003147	0.018381
2	-0.000211	0.000432	-0.001666
3	0.003060	-0.000740	-0.005775
4	-0.005822	-0.000923	-0.001615
5	-0.000508	0.000765	0.006790
6	0.007539	-0.000421	-0.004664
7	0.002106	-0.002199	-0.002905
8	-0.006203	0.001425	-0.005447
9	-0.000198	0.003665	0.004995
10	0.004152	0.000503	0.000632
11	0.002478	-0.004276	1.58E-05
12	-0.004059	-0.001864	-0.003283
13	-0.002114	0.003603	0.005296
14	0.000902	0.002242	-0.000479
15	0.002654	-0.003029	0.000239

16	-0.002685	-0.001617	-0.002340
17	-9.79E-05	0.003059	0.003390
18	0.002013	0.002025	-0.001652
19	0.001228	-0.002472	-0.000429
20	-0.002640	-0.002114	-0.002808
21	0.000589	0.001683	0.002750
22	0.001459	0.001688	-0.000749
23	0.000522	-0.001725	0.000425
24	-0.002622	-0.001057	-0.001836

Exchange rate

Period	Shock1	Shock2	Shock3
1	0.019328	0.000000	0.000000
2	0.015043	0.010498	-0.001918
3	0.013364	0.010505	0.001987
4	0.012455	0.003125	0.000362
5	0.012662	-0.000551	-0.000737
6	0.010839	-0.007195	0.001514
7	0.009270	-0.006784	0.004385
8	0.003300	-0.000929	0.005662
9	0.004618	0.002292	0.006476
10	0.006417	0.004950	0.006004
11	0.007231	0.003627	0.007938
12	0.010778	-0.000424	0.007097
13	0.010620	-0.002264	0.002427
14	0.007766	-0.003623	-0.000602
15	0.006603	-0.003865	5.10E-05
16	0.006575	-0.001790	0.001757
17	0.008145	-0.000999	0.003544
18	0.007812	-0.000309	0.003749
19	0.005930	0.000747	0.004798
20	0.006327	-0.000239	0.005707
21	0.007644	-0.002264	0.005005
22	0.006957	-0.003940	0.003590
23	0.006087	-0.003739	0.003454
24	0.005751	-0.001628	0.003376

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