Nowcasting South African real GDP: MIDAS models

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ABSTRACT

Economic indicators are released at unsynchronised dates and frequencies and some with considerable delay, challenging analyses of the current state of the economy. In traditional model frameworks, often frequency conversions are applied to standardise data for econometric analyses. A caveat to a general aggregation approach is that valuable information contained in the higher frequency domain is lost which could have aided in providing a more accurate view of the current economic environment.

Nowcasting techniques can provide useful forecasts of lower frequency variables such as real gross domestic product (GDP) which is published quarterly and with considerable delay. These techniques exploit the correlation between higher-frequency published indicators and the lower frequency variable to be forecasted. Conventional nowcast techniques include factor models, bridge equations and more recently Mixed data sampling (MIDAS) models.

MIDAS models are gaining more popularity as a flexible parsimonious tool to forecast low-frequency variables with unaltered high-frequency indicators via some distributed lag scheme. In this paper a MIDAS model is introduced as a tool to provide a nowcast for real GDP and is compared with FAVAR and other naïve nowcast procedures. Both monthly and quarterly information are used without the need to aggregate these to a common frequency. The choice of indicators is guided by the composition of GDP to capture a reasonable representation and the correlation, periodicity, timeous release and robustness of the indicators are also considered. The accuracy of the MIDAS model as a nowcasting tool is also compared to other nowcasting approaches in terms of forecast error analyses.

Keywords: GDP Nowcasting, Mixed-Frequency models, MIDAS models.

JEL Codes: C22, C53, E17

1. Introduction

Knowledge of the current state of the economic business cycle enriches monetary policy formulation. Accordingly, many central banks have developed analytical frameworks that econometrically incorporate the latest available observations to inform about current economic conditions (see Anesti et al (2017)).

Economic indicators that are released at differing dates and frequencies and some with considerable delay, pose challenges to the analyses of the current state of the economy. One solution is to apply missing data techniques and to interpolate the lower frequency series with for example the Kalman filter missing data approach or cubic spline techniques (see Fulton et al (2001)) to standardise the dataset at the higher frequency. Alternatively temporal aggregation can be applied where the observed high frequency data are aggregated to a lower frequency using some weight conversion technique, to standardise the dataset. A caveat of this approach is that valuable information contained in the higher frequency domain is lost which could have aided in forming a more accurate view of the current economic environment.

Formally known as nowcasting methods, these methods provide an advantage in minimising the current forecast error horizon and hence enhance longer term forecast trajectories. Nowcasting methods can provide useful signals about lower frequency variables such as real gross domestic product (GDP) which is sampled quarterly and published with considerable delay. These methods rely on the correlation between higher-frequency indicators and the lower-frequency variable under consideration. Popular methods employed by a number of central banks include dynamic factor models, bridge equations and more recently Mixed data sampling (MIDAS) models (see Foroni and Marcellino (2013) for an overview).

This paper adds to this discussion by considering an alternative approach where the observed data remains unaltered and a multiple frequency data set approach is applied. In this paper a MIDAS model is introduced as a tool to provide a nowcast for real GDP and is compared with FAVAR and other naïve nowcast procedures.

2. Nowcasting approaches

Various approaches exist to produce nowcasts ranging from pure statistical techniques such as arima and vector autoregression (VAR's) models to structural approaches that incorporate some economic theory. The choice of approach depends on the availability and periodicity of the observed data and also whether or not appropriate structural relationships exist, that can be utilised in the model specification.

One of the older and more prevalent approaches is bridge equation models which originate from Klein and Sojo (1989). This methodology addresses the multiple data frequency problem by aggregating the higher frequency data to a common lower domain (see Mitchel (2009) and Castle et al (2013)). Specifically, the higher frequency data are forecast to fill the remainder of the lower domain if incomplete. Various methods such as autoregressive (AR) specifications can be used to fill the ragged edges[1]. Then a frequency conversion is done to standardise to the lower domain and used as regressors in the bridge equation to forecast the lower frequency series.

[1] Ragged edges refers to the case where some indicators have missing data at the end of the observed sample due to unsynchronised publication dates compared to other indicators.

The quarterly dependant variable can then be regressed on lagged values of itself, the aggregated quarterly indicators as well as other actual quarterly predictors. Whilst bridge equations deliver a framework that is easily interpretable, they also suffer from a dimensionality curse where large numbers of parameters need to be estimated relative to the number of available observations. Another caveat is that valuable information contained in the higher frequency data are lost when these series are aggregated prior to the estimation and forecasting processes.

2.1 Factor models

Factor models circumnavigate the dimensionality problem by extracting common statistical trends or factors from a large data set. In the subsequent regression step, these factors are then used as explanatory variables. The Kalman filter can then be used to estimate these unobserved common factors as well as the missing data that arises through the use of mixed frequency data.[2]

Following Leboeuf et al (2014) and Kabundi et al (2015), data can be separated into two distinct components; a common and an idiosyncratic portion. Whereas the linear combination of common factors that make up the common component is responsible for the co-movements between the variables in the data set, the idiosyncratic component can be interpreted as measurement errors. The quarterly dependent variable, Y_t can then be estimated by

$$Y_t^{(Q)} = \Lambda F_t^{(Q)} + \epsilon_t \qquad (1)$$

where Λ is the factor loading matrix and F_t is the unobservable factor at a quarterly frequency. Common factors are then modelled through a vector autoregressive (VAR) model

$$F_t^{(Q)} = \sum_{t=1}^{p} A_p\, F_{t-p}^{(Q)} + \mu_t \qquad (2)$$

with p lags.

2.2 MIDAS models

The MIDAS framework provides a flexible, parsimonious framework based on distributed lag polynomials that deal with asynchronous variables (see Ghysels et al., (2007), Andreou et al. (2010)). A lower frequency dependent variable is regressed, simultaneously, on relevant low and high frequency indicators; hence the original published data is unaltered in this modelling approach.

MIDAS models are gaining popularity as a flexible parsimonious tool to forecast low frequency variables with low- and unaltered high frequency indicators via a polynomial distributed lag scheme. These methods have been shown to be more efficient than traditional aggregation approaches and in some instances as efficient as high frequency distributed lag regressions according to Ghysels et al (2004). MIDAS models are more robust to model misspecification compared to bridge equations and state space models and are computationally simpler according to Foroni and Marcellino (2013).

[2] See Ekland and Kapetanios (2008) and Stock and Watson (2011) for a discussion of different factor models.

Foroni et al. (2011) show that unrestricted MIDAS models perform well when the differences in sampling frequencies are small, i.e. monthly to quarterly, and when a relatively small number of lags are required to capture the dynamics.

In line with, Lindgren and Nilsson (2015), the following illustrates the general specification where a low frequency variable is regressed on relevant quarterly and monthly indicator variables.

$$y_{t+h} = \alpha + \beta_1 B\left(L^{\frac{1}{m}};\theta\right) x_{t+w}^{m} + \varepsilon_{t+h} \quad (3)$$

From the above equation y is the regressand, h is the forecast horizon, w is the lead of the high frequency indicator variables and m is the frequency of the regressors (x_t) (for monthly indicators m=3).

The polynomial lag operator $B(L^{1/m};\theta)$ weights each lagged high frequency observation either unrestricted or according to some specified functional form.

$$B\left(L^{\frac{1}{m}};\theta\right) = \sum_{k=1}^{K} B(k;\theta) L^{\frac{k}{m}} \quad (4)$$

Where k = number of lags and $L^{1/m} x_t^m = x^m_{t-1/m}$ which can be different for each indicator and θ is the vector of parameters to be estimated via non-linear least squares.

Both the Almon and the exponential Almon polynomial lag structures are the most commonly used weighting functions to restrict the lag coefficients to lie on the polynomial function in order to achieve a smooth shape within the distribution. For the Almon lag, the weight on each lag (k) is

$$B(k;\boldsymbol{\theta}) = \sum_{q=0}^{Q} \theta_q k^q \quad (5)$$

where the general form of the exponential Almon lag polynomial is

$$B(k,\boldsymbol{\theta}) = \frac{e^{(\theta_1 k^1 + \cdots + \theta_Q k^Q)}}{\sum_{k=1}^{m} e^{(\theta_1 k^1 + \cdots + \theta_Q k^Q)}} \quad (6)$$

In both equation (5) and (6), Q denotes the order of the polynomial. For the two parameter exponential Almon lag case, where $\boldsymbol{\theta}=[\theta_1, \theta_2]$, equation (1) is then written as

$$y_{t+h} = \alpha + \beta_1 \sum_{k=0}^{K} \frac{e^{(\theta_1 k^1 + \theta_2 k^2)}}{\sum_{k=1}^{m} e^{(\theta_1 k^1 + \theta_2 k^2)}} L^{k/m} x_{t+w}^{m} + \varepsilon_{t+h} \quad (7)$$

In accordance with Clements and Galvão (2008) the functional form of equation 7 is extended to include autoregressive term into the specification to obtain

$$y_{t+h} = \alpha + \beta_1 \sum_{k=0}^{K} \frac{e^{(\theta_1 k^1 + \theta_2 k^2)}}{\sum_{k=1}^{m} e^{(\theta_1 k^1 + \theta_2 k^2)}} L^{k/m} x_{t+w}^{m} + \lambda\, y_t + \varepsilon_{t+h} \quad (8)$$

They found that that this specification outperforms on short horizon forecasts when compared to benchmark AR or AR distributed-lag models. Kuzin et al (2009) also find that their AR-MIDAS model outperforms a vector autoregressive (VAR) model over a one-quarter horizon.

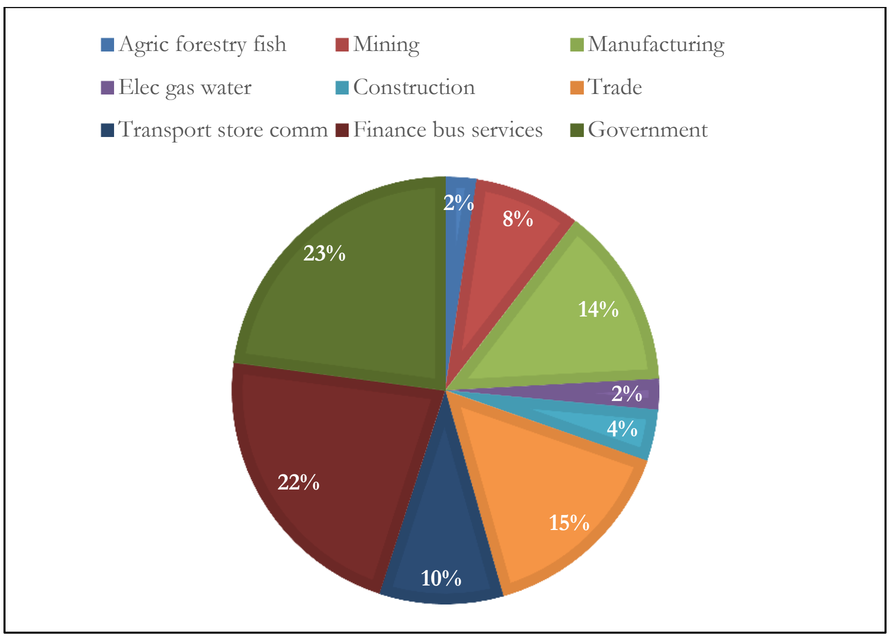
3. Indicators for nowcasting real GDP

MIDAS models use richer information sets to estimate parameters due to the non-altered original observations. The corresponding cost to this is parameter proliferation especially if many lags of the indicators are included in the estimation. The trade-off is to preserve as much of the observed information, yet parsimoniously limiting the number of parameters to be estimated (see Ghysels et al (2004)). The lead time, periodicity, timeous release and robustness of the indicators were also considered. Inclusion into the model specification was based on the existence of a relatively stable and positive correlation of a particular indicator with its representative sub-sector of real GDP.

South Africa is characterized as a commodity export economy, based on the importance of commodities to the external trade position and hence the country's competitiveness in terms of exchange rates. Specifically, commodity exports contribute 63 per cent of total exports[3]. In real terms this distinction is not as prevalent since the primary sector contributes only around 10 per cent to real GDP. The main contributors to real GDP are government (23%), finance, business services and real estate (22%), trade (15%) and manufacturing (14%) sectors.

The indicators included in the MIDAS model, range from macroeconomic data to survey data (see Table 1), all with differing release dates and reporting frequencies, representing about 70 per cent of the total real GDP basket. The government, construction, electricity and agriculture sectors are not represented at this stage due to a lack of suitable leading indicators.

Figure 1: Sectorial contribution relative to real GDP[4]



[3] Source: South African Revenue Services, average for 2016.
[4] Based on 2016 real annual figures.

4. Nowcasting real GDP

All indicators were included as the first differences of their log forms, except for the two survey indicators which were included in as published. The model was estimated from 2003 to capture relationships across a few business cycles phases. The diagnostic tests indicate normally distributed residuals and an in-sample forecast was conducted from 2010 to analyse the robustness of the model specification, delivering forecasts that seem to track the actual outcomes notably well.

Due to the publication of the high frequency data intra-quarterly, three dataset vintages are created where vintage one represents a dataset where all the high frequency data for the first month is observed, vintage two where the second month data is observed and vintage three where all three months are observed. In each forecast round all missing disaggregated data is computed via a random walk process in order to smooth the ragged edge.

Table 1: Indicators included in the MIDAS model

Monthly	**Quarterly**
Real manufacturing production	Financial services index[5]
Real mining production	Real GDP lagged
Real retail trade sales	
Real wholesale trade sales	
Real new vehicle sales	
ABSA/BER Purchasing Managers Index (PMI)	

In Table 2 it can be seen that the first nowcast for the first quarter GDP can only be made during the third week of March, as soon as the January monthly indicator series are released. During April the second nowcast vintage is made one week earlier, when all February monthly are released. By the third week of March the third nowcast of the first quarter is made when all the monthly indicator series for March have been released, roughly 10 days before the actual Statistics South Africa release. This process provides a learning platform where the forecaster has the opportunity to twice revisit and revise the initial nowcast for a specific quarter, by incorporating the latest available observations and any potential revisions made to earlier observations.

[5] The BER Financial Services Index (FSI) reflects the unweighted average confidence of four sectors of financial services, namely: retail banking, investment banking, asset management and life insurance. The percentage of respondents answering "satisfied" to the question, "Are prevailing business conditions satisfactory or unsatisfactory?" is taken as the indicator of financial sector confidence.

Table 2: Timeline: MIDAS nowcast process

Vintage	1				2				3				
	Mar				Apr				May				Jun
Week	1	2	3	4	1	2	3	4	1	2	3	4	1
Official indicator release	PMI (Feb)				PMI (Mar)								
			NVS (Jan)			NVS (Feb)					NVS (Mar)		
			WHL (Jan)			WHL (Feb)					WHL (Mar)		
			RET (Jan)			RET (Feb)					RET (Mar)		
		MAN (Jan)				MAN (Feb)				MAN (Mar)			
		MIN (Jan)				MIN (Feb)				MIN (Mar)			
					FSI (Q1)								GDP (Q1)
			Nowcast Q1			Nowcast Q1					Nowcast Q1		

PMI :	Purchasing Managers Index	MAN :	Real manufacturing production
NVS :	Real new vehicle sales	MIN :	Real mining production
WHL :	Real wholesale trade sales	GDP :	Gross Domestic Product
RET :	Real retail trade sales	FSI :	Financial services index

5. Forecast evaluation

To assess the accuracy of the MIDAS nowcasts over time, current quarter forecasts are compared to a FAVAR[6] model, a random walk as well as Reuter's consensus forecasts, for the period 2006Q1 to 2017Q1.

The FAVAR model draws on the research done by Kabundi et al. (2015). Though the model in Kabundi et al. (2015) utilised 21 explanatory series, the dataset for this FAVAR model comprise of only 7 series of real variables, nominal variables as well as financial variables. These variables were specifically chosen to compare closely with those used in the MIDAS model. Similar to the Reuters consensus forecasts, the MIDAS model and the FAVAR model are used to make three consecutive forecasts for GDP for each individual quarter, i.e. one for every new monthly indicator data release[7].

The a priori expectation is that as more information become available during the quarter that the forecasting accuracy of a particular approach should improve. Based on the root mean squared errors[8] (RMSE's) shown in Table 3 it appears that using only the first month's intra-quarter observed data (i.e. vintage 1), the MIDAS model appears to be outperformed by both the FAVAR model and Reuters, but the result is not statistically significant (see Table 4). However, the MIDAS forecast performance improves significantly as new information is included in the process, contrary to all the other noted models. This result compares favourably with Anesti et al (2017) who find that the forecast performance of a MIDAS model for United Kingdom real GDP also improves progressively over the quarter with new available observations and it outperforms their dynamic factor model as well. When using two and three months' observed intra-quarter data in the forecast process the FAVAR model, the random walk and the Reuters consensus forecasts do not seem to notable improve their forecasting accuracy.

[6] Factor-Augmented VAR model.

[7] When for example forecasting GDP for the first quarter of 2016, an initial estimate is made when the January monthly data is released. Thereafter two additional forecasts for 2016Q1 GDP is made after the February and March data releases.

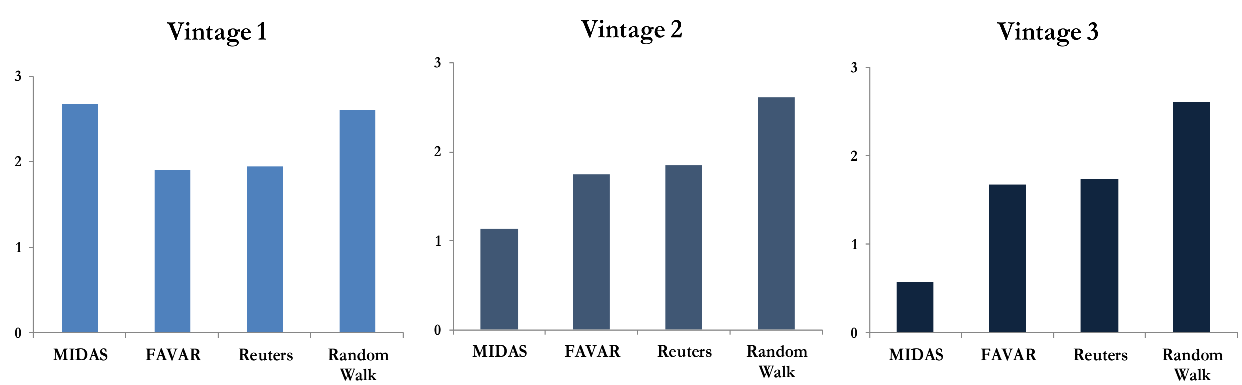
[8] Root mean squared errors are informative since these statistics penalise larger errors more than e.g. mean absolute error statistics.

Performance metrics such as RMSE's informs practitioners to the weight that should be put on a particular methodology at what stage of the nowcast process. It appears that early in the quarter when only the first intra-quarter monthly observations are available, the FAVAR and off-model information can be consulted to enhance the MIDAS nowcast. However, when two or three intra-quarter monthly observations are available, the MIDAS model nowcast should receive the most attention.

Table 3: Forecast errors per data vintage (1,2,3)

	MIDAS			FAVAR			Reuters			RW
	1	2	3	1	2	3	1	2	3	
RMSE	2.678	1.137	0.573	1.907	1.746	1.678	1.944	1.843	1.740	2.608
Relative to RW	1.027	0.436	0.220	0.731	0.669	0.644	0.745	0.707	0.667	1.000

Figure 2: Root mean square errors



To establish if there are statistically significant differences in the forecasting performance of the MIDAS model and the other sources, the Diebold-Mariano (DM) test is used. The accuracy of each forecast is measured through either a squared-error or an absolute-error loss function, with the null hypothesis being that these are equal for the two competing models. Each MIDAS forecast is individually compared to the corresponding FAVAR, Reuters consensus and a random walk forecast.

According to the Diebold-Mariano test results (see Table 4) the differences in the vintage 1 MIDAS forecasts compared to the other three sources are not statistically significant. The null hypothesis, that the forecasts are equal, cannot be rejected at the 5% level of significance for data vintage 1 as all the DM-AE and DM-SE values are smaller than 1.96. However, for both vintage 2 and 3 there are a significant differences at the 5% level according to both the absolute-error-loss tests as well as the squared-error-loss tests. The lower RMSE values of the MIDAS model forecasts (vintage 2 and 3) relative to the FAVAR model, the random walk and the Reuters consensus is statistically significant according to the Diebold Mariano test and confirms its advantage as a suitable nowcasting approach.

Table 4: Forecast evaluation: Diebold-Mariano test

	MIDAS vs FAVAR			MIDAS vs Reuters			MIDAS vs RW		
Vintage	1	2	3	1	2	3	1	2	3
DM-AE	-1.475	-2.578*	-6.921*	1.741	-2.652*	-5.888*	-0.241	-5.036*	-7.679*
p-Value	0.148	0.013	0.000	0.089	0.011	0.000	0.811	0.000	0.000
DM-SE	-1.767	-2.581*	-4.671*	1.697	-2.256*	-3.227*	0.164	-4.318*	-5.071*
p-Value	0.084	0.013	0.000	0.097	0.029	0.002	0.870	0.000	0.000

Note: DM-AE denotes the Diebold-Mariano test statistic based on absolute-error loss; DM-SE denotes the Diebold-Mariano test statistic based on squared-error loss. * Indicates a significance forecast difference at the 5% level

6. Conclusion

Real GDP observations are published with a lag and on a quarterly frequency which complicates assessments of the current state of the economy and resulting economic policy formulation. High frequency data can be used to obtain a signal of where the economy is and these methods are called nowcasting. A large and increasing number of literature contributions are exploring these that range from pure statistical to more structural approaches. Recent contributions are providing solutions that can incorporate mixed frequency data simultaneously e.g. MIDAS models, where low-frequency variables are forecast with high frequency indicators which are published unsynchronised.

In this paper current-quarter nowcasts were generated for South African GDP using an AR-MIDAS model and its forecast performance was compared to a FAVAR model, a random walk model and Reuters' consensus forecasts. The MIDAS model produced more accurate forecasts, especially when using vintage 2 and 3 datasets, than the benchmark random walk, the basic FAVAR model and Reuters' consensus view. As more intra-quarter observation of the high frequency data become available, the MIDAS model forecast performance improves dramatically compared to the FAVAR and the random walk where no significant improvements were found. This highlights the predictive performance of MIDAS models especially when two or more intra-quarter observations are available and hence MIDAS model approach give useful indications of near-term GDP.

Performance metrics such as RMSE's can inform practitioners to the weight that should be placed on a particular methodology and at what stage of the nowcast process. It appears that early in the quarter when only the first intra-quarter monthly observations are available, the FAVAR and off-model information can be consulted to enhance the MIDAS nowcast. However, from the middle of the quarter when two or three intra-quarter monthly observations are available, the MIDAS model nowcast for real GDP should receive the most attention based on the forecast error analyses.

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8. Appendix A: The estimated MIDAS model

Dependent Variable: GDPR
Method: MIDAS
Sample: 2003Q1 2016Q4
Included observations: 56
Method: PDL/Almon (polynomial degree: 3)
Automatic lag selection, max lags: 5
Chosen selection: 3 4 3 3 5 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPR(-1)	0.516345	0.053205	9.704898	0.0000
FSI	0.006119	0.002428	2.519876	0.0169
Page: MON Series: MANR Lags: 3				
PDL01	0.110418	0.074371	1.484700	0.1474
PDL02	-0.108946	0.079759	-1.365933	0.1815
PDL03	0.040079	0.018954	2.114530	0.0424
Page: MON Series: MINR Lags: 4				
PDL01	-0.003025	0.020015	-0.151157	0.8808
PDL02	0.072701	0.018660	3.896048	0.0005
PDL03	-0.016207	0.003659	-4.429244	0.0001
Page: MON Series: RETR Lags: 3				
PDL01	-0.099463	0.063912	-1.556250	0.1295
PDL02	0.032586	0.070461	0.462473	0.6469
PDL03	0.006647	0.017432	0.381313	0.7055
Page: MON Series: WHOLR(-1) Lags: 3				
PDL01	0.199181	0.056971	3.496185	0.0014
PDL02	-0.168510	0.067554	-2.494452	0.0180
PDL03	0.039076	0.016472	2.372296	0.0239
Page: MON Series: PMI_BACT Lags: 5				
PDL01	-0.012981	0.016447	-0.789282	0.4358
PDL02	0.012050	0.013109	0.919176	0.3649
PDL03	-0.002164	0.002159	-1.002355	0.3237
Page: MON Series: NCSR Lags: 4				
PDL01	0.043299	0.016725	2.588933	0.0144
PDL02	-0.048145	0.014433	-3.335833	0.0022
PDL03	0.010535	0.002912	3.617799	0.0010

R-squared	0.964409	Mean dependent var	0.676498
Adjusted R-squared	0.960850	S.D. dependent var	0.661004
S.E. of regression	0.130789	Akaike info criterion	-0.486647
Sum squared resid	0.855290	Schwarz criterion	0.381361
Log likelihood	37.62611	Hannan-Quinn criter.	-0.150122
Durbin-Watson stat	1.981433		

MON	Lag	Coefficient	Distribution
	0	0.041551	*
	1	0.052842	*
	2	0.144291	*

MON	Lag	Coefficient	Distribution
	0	0.053468	*
	1	0.077547	*
	2	0.069211	*
	3	0.028460	*

MON	Lag	Coefficient	Distribution
	0	-0.060229	*
	1	-0.007701	*
	2	0.058121	*

MON(-1)	Lag	Coefficient	Distribution
	0	0.069748	*
	1	0.018466	*
	2	0.045336	*

MON_BACT	Lag	Coefficient	Distribution
	0	-0.003095	*
	1	0.002462	*
	2	0.003691	*
	3	0.000593	*
	4	-0.006834	*

MON	Lag	Coefficient	Distribution
	0	0.005688	*
	1	-0.010852	*
	2	-0.006323	*
	3	0.019275	*