1 Sensitivity to Samples

In this note we discuss whether our results are sensitive to alternative sampling. In particular, we examine whether substituting our data with the data on Charles Engel's web-page, or extending the nominal exchange rate data changes our results. We find that this is not the case. In particular, the Mean Group model consistently produces half-lives under 2 years, while the pooled estimators are biased upwards.

Table 1 shows the results from *three* datasets. Data 1 is the original Eurostat price data combined with longer samples of nominal exchange rates obtained from the IFS. Data 2 combines the original price data with data from Charles Engel's web page.[1] Data 3 is data from Charles Engel's Web page only. As data for the US is not available on his page, Data 3 refers to real exchange rates relative to the UK.

In each case, coefficient homogeneity is strongly rejected. And as expected, the pooled estimators overestimate the half-lives. The Mean Group estimator consistently produces short half-lives as it allows for heterogeneity. Although these results are very much in line with the estimates reported in the paper, a number of new points do emerge:

1. The half-lives produced by heterogeneous estimators (MG estimator) are slightly higher than before but in line with the results in the main paper and the confidence intervals do not include the "consensus view".

2. *The mean group and RCM estimators are known to be asymptotically equivalent.* This should emerge much stronger in the new data as T has increased. However, using the specification above, we do not observe this if the lag structures are kept short (the RCM estimator produces half-lives substantially higher than the Mean Group model - 25, 29 and 29 respectively, using 12 lags in the autoregression). However, as figures 4 and 5 show, if the lag length is increased, the Mean Group and the RCM results converge and the estimated half-lives fall to around 16 months. There is no substantial impact of this on the Fixed Effects model.

A simple explanation for these observations goes as follows. We can show that this is a result of *underestimating* the lag length. In particular, we demonstrate that underestimating the lag length results in: i) an upward bias in MG and RCM, where the impact on RCM is much larger. ii) Pooled estimators are not really affected by this as the heterogeneity bias dominates.

1.1 Underestimating the lag length

How does underestimating the lag length affect Mean Group and RCM?

[1] The original data is corrected along the lines suggested by Charles Engel and combined with the data available at http://www.ssc.wisc.edu/~cengel/data.htm. Exchange rate data is from IFS.

1. In a cross section with a significant second lag, if an OLS regression of the form $y_t = \alpha + \rho y_{t-1} + \varepsilon_t$ is run (i.e. if we underestimate the lag length), ρ is biased upwards. As Figure 1 shows, this leads to a positive bias in RCM and MG estimates.

2. *RCM estimates are more biased than Mean group estimates.* Again if we omit a significant lag(s), the OLS estimates of the coefficients and the Variance Covariance matrix are biased. *Implication: the RCM weights are biased.* In the simple case of 2 cross sections with AR coefficients b_1 and b_2 (constants=0) and covariances V_1 and V_2 , the RCM weight for b_1 depends inversely on V_1 :

$$\Psi_1 = \frac{1}{2} \frac{b_1^2 + b_2^2 - 2b_1 b_2 + 2V_2}{b_1^2 + b_2^2 - 2b_1 b_2 + V_2 + V_1}$$

   If significant lags are ignored , V_1 *is biased downwards* and b_1 is biased upwards, thus Ψ_1 is higher. The experiment in Figure 2 confirms this. Here estimates of the RCM weights and the corresponding coefficients were obtained from a monte carlo experiment with 100 replications. The data is drawn from an AR(2) model with coefficients on the second lag equal to {-0.05,-0.1,-0.3}. Estimation is carried out assuming that the lag length equals 1. The figure plots the scatter of the weights and the coefficients (regression line). As the ignored variable becomes more important the scatter shifts and indicates that higher persistence means higher weights.

How does this affect Fixed Effects?

In the presence of heterogeneity bias, we should observe the following: If significant lags are omitted, estimated persistence is high, but as the lag length is increased (i.e. you include the optimal number of lags) this does not make much of a difference, simply because the upward heterogeneity bias (which increases with the number of heterogeneous coefficients) cancels out the impact of additional regressors. *In other words we should observe little difference between the model with the underestimated lag length and the model with the correct lag length.* This is clear from the empirical results below and from the experiment in Figure 3. Figure 3 runs the same type of Monte-Carlo simulation as Figure 1. The results show little difference between the correct and incorrect models.

1.2 Results

Table 2 lists the estimates that we obtain using longer lags. The lag lengths are chosen via a general to specific procedure. The following points are noteworthy:

1. Higher lags have little impact on fixed effect estimates. In each of the data sets, an FE regression with 36 lags produces half-lives close to 30 months.

2. Mean Group and RCM produce almost identical results.

3. The half-lives from these heterogeneous models are very similar to those reported in the paper.

2 Conclusions

This note set out the results of robustness checks on our original estimates. We find that extending the sample or using Charles Engel's data has little impact on our estimates. We consistently obtain results very similar to our original ones using the Mean Group model. Figures 4 and 5 show that this is true for every possible lag length. A number of new points (regarding the RCM estimator) do emerge, but we show that they are a result of model mis-specification.

3 Tables and Figures

Table 1										
$P_{i,j,t} = \alpha_{i,j} + \sum_{k=1}^{K} \rho_k P_{i,j,t-k} + \varepsilon_{i,j,t}$										
		Data 1			Data2			Data 3		
Method	K	$\sum \rho$	Half-Life	CI	$\sum \rho$	Half-Life	CI	$\sum \rho$	Half-Life	CI
OLS	12	0.9997	2303	1283,∞	0.999741	2836	1864,∞	0.999903	6921	2283,∞
FE	12	0.9735	30	22,35	0.978634	37	31,40	0.978779	31	24,36
MG	12	0.9524	19	13,22	0.961864	23	17,24	0.96689	21	10,23
H0: $\beta_i = \beta^a$		3065[0.00]			3063[0.00]			1831[0.00]		
H0: $\beta_i = \beta^b$		25.0[0.00]			72.3[0.00]			93.9[0.00]		

Notes: "a" is the Swami test for homogeneity and "b" is the Hausman test for homogeneity. The CI's are calculated via non-parametric bootstrap based on 500 replications.

Table 2										
$P_{i,j,t} = \alpha_{i,j} + \sum_{k=1}^{K} \rho_k P_{i,j,t-k} + \varepsilon_{i,j,t}$										
		Data 1			Data2			Data 3		
Method	K	$\sum \rho$	Half-Life	CI	$\sum \rho$	Half-Life	CI	$\sum \rho$	Half-Life	CI
FE	36	0.9652	28	16,30	0.97159	33	20,38	0.976057	26	16,39
RCM	36	0.9260	16	14,18	0.947941	18	15,25	0.9714	16	15,25
MG	24	0.9439	17	14,18	0.9540	20	16,25	0.965960	16	15,27

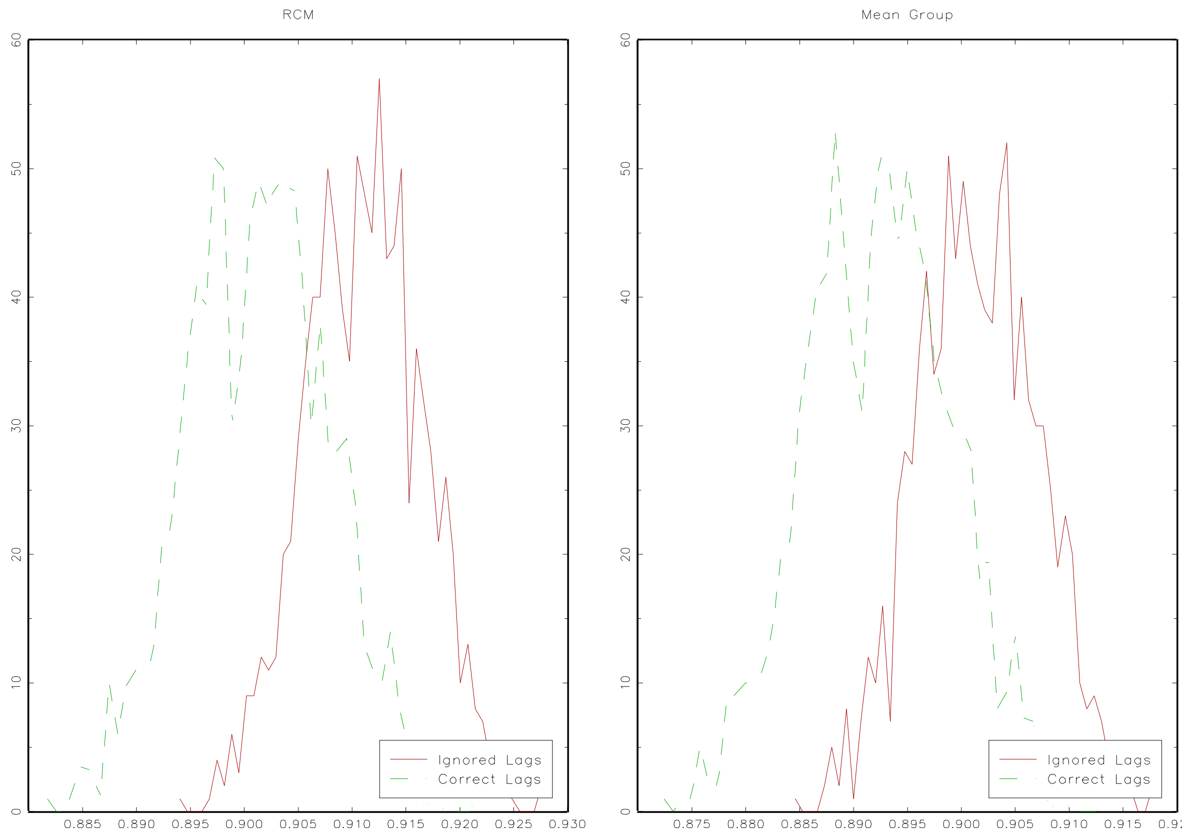


Figure1

Data is generated from the following dgp:

$y_{i,t} = \alpha_i + \left(1+\eta_{i,1}\right) y_{i,t-1} - \left(0.1+\eta_{i,2}\right) y_{i,t-2} + \varepsilon_{i,t}$ where $\eta_i \tilde{} N(0, 0.002)$. The solid Line shows the distribution of estimates obtained when an AR(1) model is estimated using the generated data. The dotted line is the distribution of the sum of AR coefficients when the correct lag length is used. Results are based on 1000 replications with N=220, T=250.

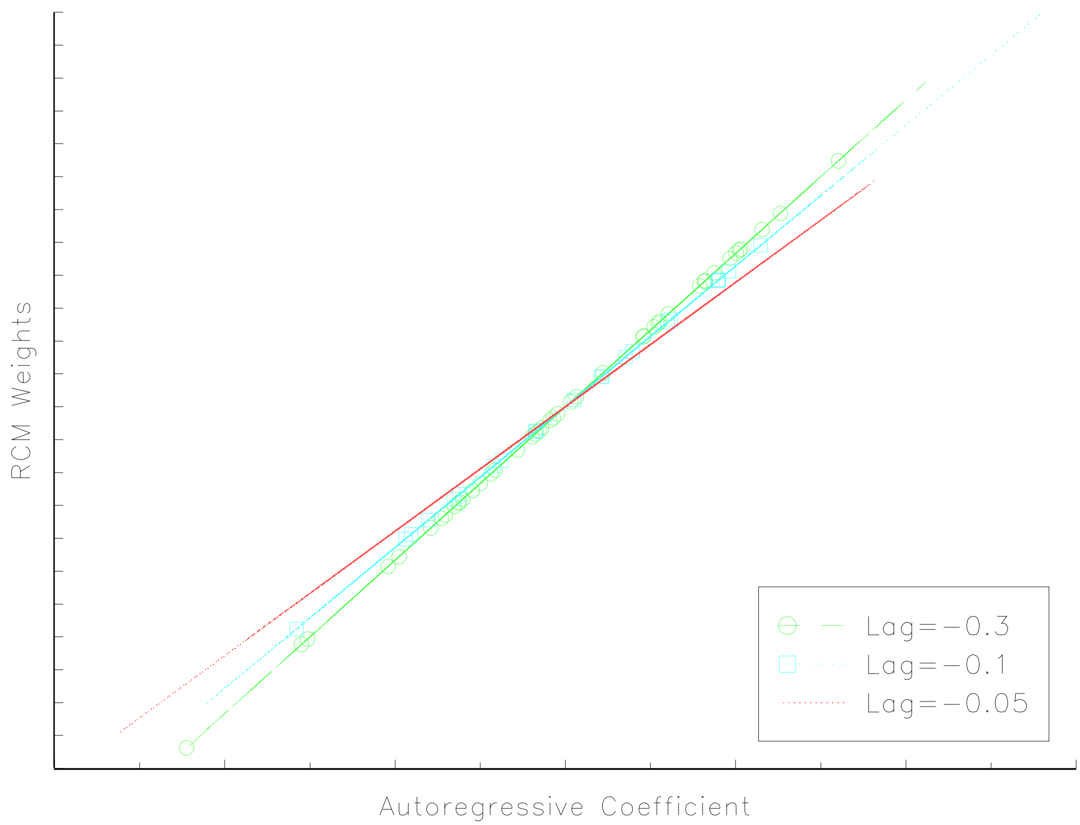


Figure2

The figure plots the relationship between RCM weights and cross section specific coefficients. Data is generated from the following dgp:
$y_{i,t} = \alpha_i + \left(\rho_1 + \eta_{i,1}\right) y_{i,t-1} + \left(\rho_2 + \eta_{i,2}\right) y_{i,t-2} + \varepsilon_{i,t}$ such that $\sum \rho = 0.9$, $\rho_2 = \{-0.05, -0.1, -0.3\}$ and $\eta_i \tilde{} N(0, 0.002)$. Estimation is carried out assuming that the true model is AR(1). Results are based on 100 replications with N=220, T=250.

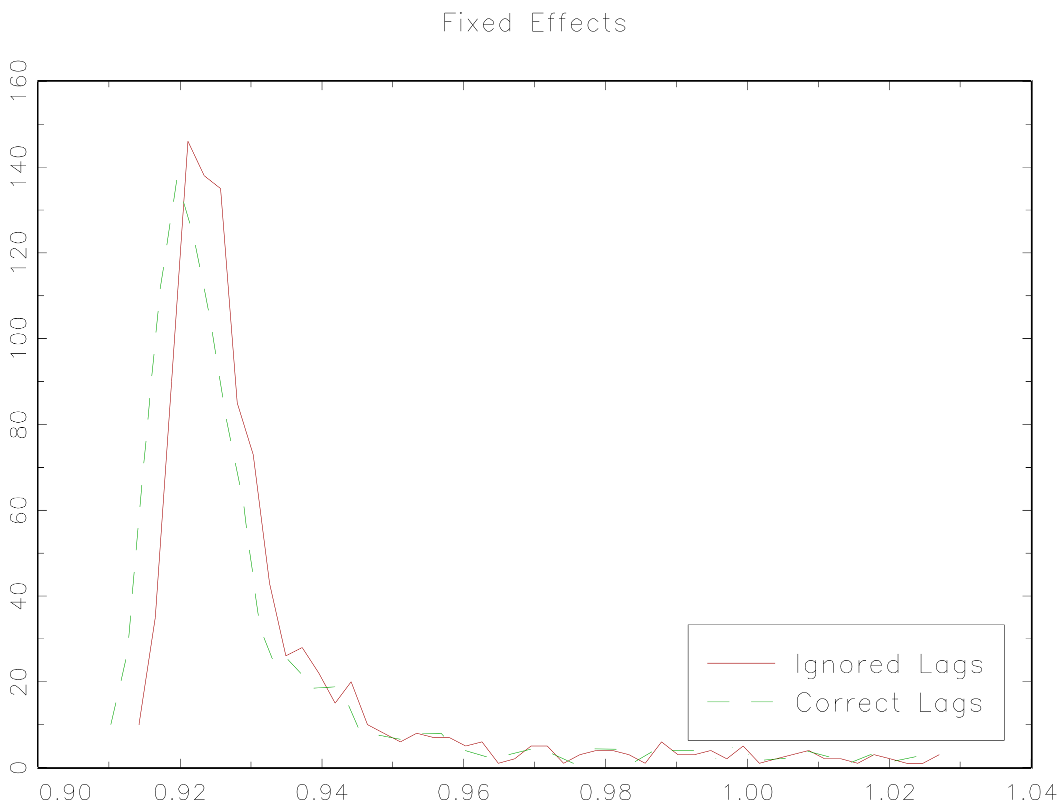


Figure3

Data is generated from the following dgp:
$y_{i,t} = \alpha_i + (1+\eta_{i,1})\, y_{i,t-1} - (0.1+\eta_{i,2})\, y_{i,t-2} + \varepsilon_{i,t}$ where $\eta_i \tilde{} N(0, 0.0002)$. The solid Line shows the distribution of estimates obtained when an AR(1) model is estimated using the generated data. The dotted line is the distribution of the sum of AR coefficients when the correct lag length is used. Results are based on 1000 replications with N=220, T=250.

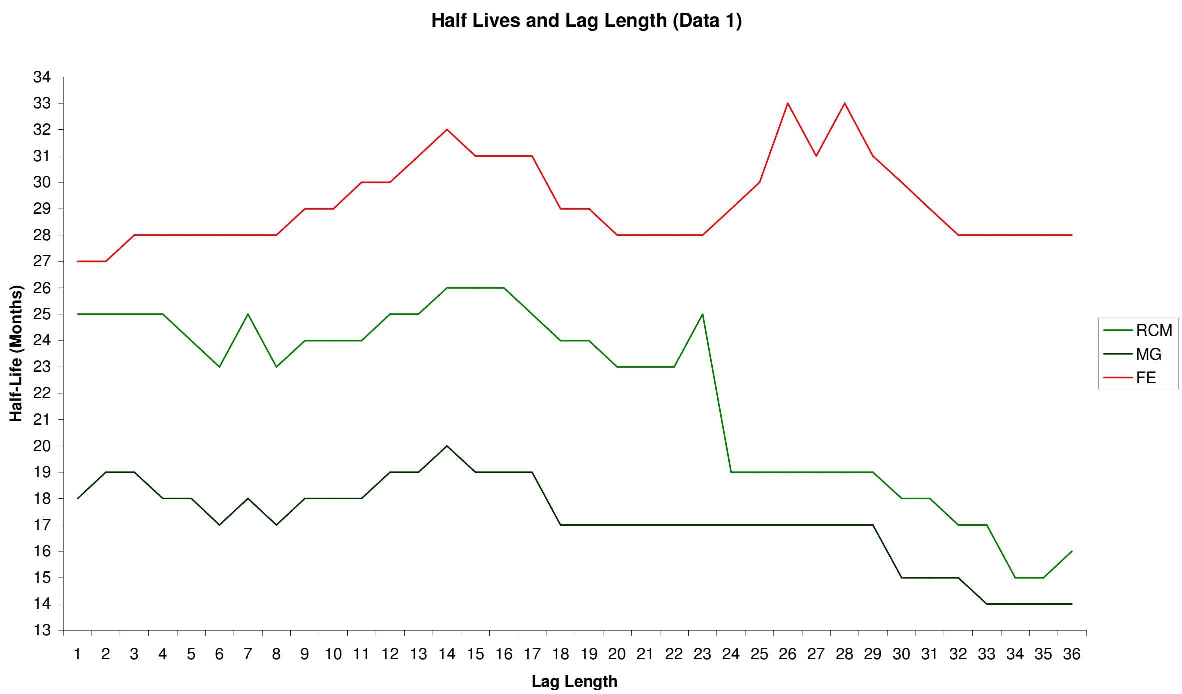
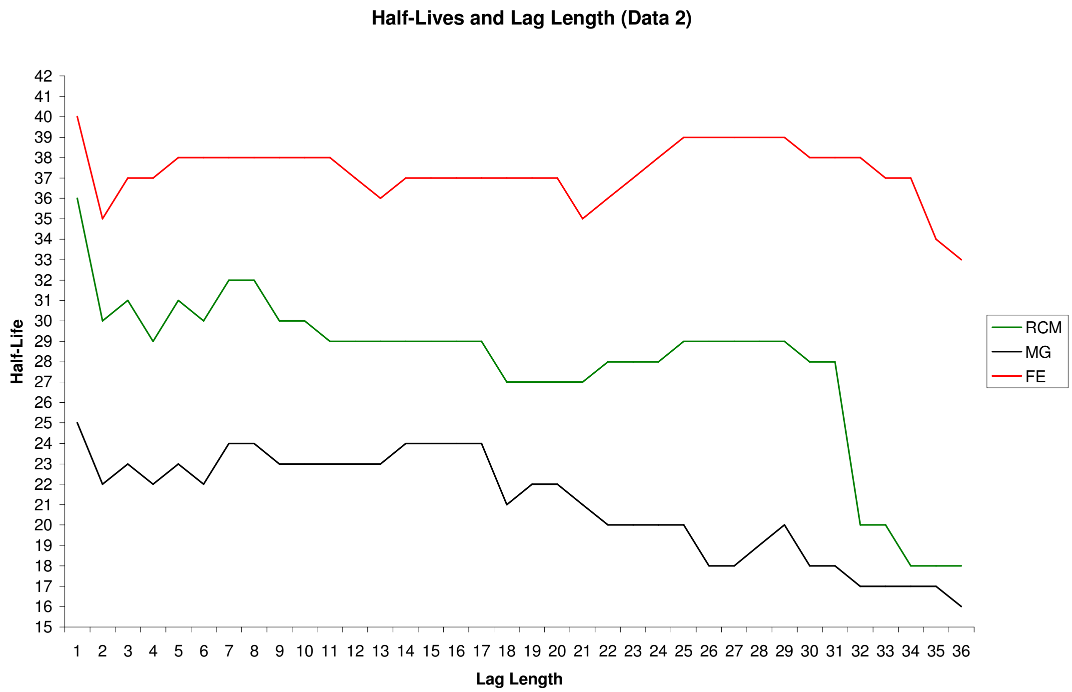

Half Lives and Lag Length (Data 1)
Half-Life (Months)
Lag Length
RCM
MG
FE

Figure 4


Half-Lives and Lag Length (Data 2)
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Half-Life
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Lag Length
RCM
MG
FE

Figure 5