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Testing for central bank independence and inflation using the wild bootstrap

Andrea Monticini
Catholic University Milan

David Peel
Lancaster University

Abstract

This paper reviews the relationship between Central Bank Independence (CBI) and Inflation both in high income economies (as proposed in Campillo and Miron 1997 and Temple 1998) and in developing countries (as proposed in Brumm 2006)1 when a variety of Heteroskedasticity Consistent Covariance Matrix Estimators as well as the wild bootstrap are employed.

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1 Introduction

Davidson and Flachaire (2008) show that the usual robust, asymptotic theory can be very misleading in sample, cross-section, heteroskedastic, high leveraged data. In these circumstances the wild bootstrap should be adopted to obtain correct inference.

The aim of this paper is to review the significance of the relationship between measures of Central Bank Independence and Inflation both in high income economies (as proposed in Campillo and Miron 1997 and Temple 1998) and in developing countries (as proposed in Brumm 2006) when a variety of Heteroskedasticity Consistent Covariance Matrix Estimators as well as the wild bootstrap are employed.

2 The wild bootstrap

Consider the following linear heteroskedastic model:

$$\boldsymbol{y}_t = \boldsymbol{X}_t \beta + u_t \tag{1}$$

where $\boldsymbol{y}_t$ is the dependent variable, $\boldsymbol{X}_t$ an exogenous k-vector β is an unknown parameter and u_t ~iid$(0, \sigma_t^2)$, with $\sigma_t^2 \neq \sigma_s^2$ for $t \neq s$. In this case, the inference on the parameters requires attention because the OLS estimator of the co-variances in the estimates of $\widehat{\boldsymbol{\beta}}$ is, generally, biased and inconsistent, and the usual t does not follow the t distribution, even asymptotically.

This problem is usually solved by using an *Heteroskedasticity Consistent Covariance Matrix Estimator* (HCCME)

$$(X'X)^{-1}X'\widehat{\Omega}X(X'X)^{-1}$$

where $\widehat{\Omega}$ is a square (n) diagonal matrix with elements $a_t^2 \widehat{u}_t^2$, $\widehat{u}_t$ is the OLS restricted residual and a_t can assume different forms.

In the basic version (HC_0) of the HCCME - proposed by Eicker (1963) and White (1980) - $a_t = 1$ while MacKinnon and White (1985) propose

$$HC_1 : a_t = \sqrt{\frac{n}{n-k}} \qquad HC_2 : a_t = \frac{1}{\sqrt{1-h_t}} \qquad HC_3 : a_t = \frac{1}{1-h_t}$$

where $h_t = X_t(X'X)^{-1}X_t'$ is the tth element of the orthogonal projection matrix on to the span of the columns of X.

In term of the errors in the rejection probability (ERP), MacKinnon and White (1985) show that HC_2 and HC_3 outperform HC_0 and HC_1.

HC_2 and HC_3 cannot, in general, be ranked because while the simulations by Long and Ervin (2000) support the use of HC3, the theoretical works by Chesher (1989) and Chesher and Austin (1991) suggest that HC2 might sometimes outperform HC3 (See Davidson and MacKinnon, 2004, p. 200). However, in small samples, the ERP of both HC_2 and HC_3 remain significant and the bootstrap may be applied to obtain less size distortion.

The bootstrap methods are based on simulations to obtain a distribution of statistics under the null. The bootstrap data-generating process (DGP) has to be as close as possible to the true (unknown) DGP. The standard bootstrap cannot replicate any DGP which admits heteroskedasticity of an unknown form. In this case, the so-called wild bootstrap is the appropriate bootstrap method (see Wu 1986, Beran 1986, Liu 1988, Mammen 1993, Davidson and Flachaire 2008 and Davidson Monticini and Peel 2007).

The wild bootstrap DGP is given by

$$\boldsymbol{y}_t = \beta_0 \mathbf{X}_t + \widehat{u}_t^{**}$$

where β_0 is the value of β under the null,

$$\widehat{u}_t^{**} = a_t \widehat{u}_t \eta_p$$

and η_p is a random variable with the properties $E\eta_p = 0$[1] and $E\eta_p^2 = 1$ and is independent of $(\widehat{u}_1, ..., \widehat{u}_n)$

There are, in principle, many ways of specifying the random variable η_a. Liu (1988) and Mammen (1993) suggest alternative means of meeting the above requirements, the most widely used of which appeared to be the two point distribution

$$\eta_1 = \begin{cases} \frac{1+\sqrt{5}}{2} & \text{with probability } p = \frac{\sqrt{5}-1}{2\sqrt{5}} \\ \frac{1-\sqrt{5}}{2} & \text{with probability } 1-p \end{cases}$$

which has the property $E\eta_1 = 0$, $E\eta_1^2 = 1$, $E\eta_1^3 = 1$ and $E\eta_1^4 = 2$.

The so-called Radamacher distribution is an alternative two point distribution:

$$\eta_2 = \begin{cases} 1 & \text{with probability } p = \frac{1}{2} \\ -1 & \text{with probability } 1-p \end{cases}$$

which has the property $E\eta_2 = 0$, $E\eta_2^2 = 1$, $E\eta_2^3 = 0$ and $E\eta_2^4 = 1$.

Chesher and Jewitt (1987) show that the ERP of the asymptotic tests based on various versions of the HCCME depend greatly on whether or not high leverage observations are present in the sample. This fact emerges from the Edgeworth expansion for the asymptotic test, but, as showed in Davidson and Flachaire (2008), it is almost absent from that for the bootstrap test based on η_2.

3 Central Bank Independence and Inflation

Temple (1998) reports a significant negative relationship between average inflation and an index of Central Bank Independence (CBI)[2]based on HC1 standard errors for 18 high income countries over the period 1974-1994 after removing some outliers from the sample used by Campillo and Miron 1997. The regression for the complete Campillo and Miron sample is reported as regression 1 in Table 1. and the Temple results[3] are regressions 2 , 3 and 4 where Iceland is removed from the Campillo and Miron regression in regression 2; Iceland and Switzerland in regression 3; Iceland and Norway in regression 4.

We estimate the standard errors for these regressions based both on HC1, HC2 and HC3 and the two wild bootstraps.

In order to compute the wild bootstrap p values we perform the following steps.

[1] E denotes the expected value.

[2] The CBI index is taken from Cukierman et al. (1992), Table 2.

[3] See Central bank Independence and inflation: good news and bad news by J. Temple p.216

- We estimate the Temple's regression by ordinary least square and we compute a t-test $\widehat{\tau}$ ($H_0 : CBI = 0$). The residuals from this regression we denote by $a_t^2\widehat{u}_t^2$ (where $\widehat{u}_t$ and a_t are defined above).

- We create 10,000 set of new series of residuals based on $\widehat{u}_t^{**}$(where $\widehat{u}_t^{**}$ is defined above).

- For each bootstrap iteration a series of *fake* or artificial average inflation is constructed, imposing the null hypothesis CBI = 0. We regress this *fake* dependent variable on the same regressors as in step 1 and we store the bootstrap t-test (τ_j^*)on the null hypothesis CBI = 0.

- The wild bootstrap p value ($\widehat{p}^*(\widehat{\tau})$) is computed as $\widehat{p}^*(\widehat{\tau}) = 1-\widehat{F}(\widehat{\tau}) = 1/B\sum_{j=1}^{B} I(\tau_j^* > \widehat{\tau})$, where $\widehat{F}(\widehat{\tau})$ is the empirical distribution function, B is the number of bootstrap replications, and $I(.)$ denotes the indicator function, which is equal to 1 when its argument is true and 0 otherwise.

We observe from the results that CBI no longer is significant at the 10% level of significance in regressions 2 and 3 based on the Wild Bootstrap but does remain significant in regression 4.

Table 1: Inference on CBI based on different HC, and on the wild bootstrap

	Coeff.	Rob. std. errors			Wild boot. on η_1			Wild boot. on η_2		
Regression 1		HC1	HC2	HC3	HC1	HC2	HC3	HC1	HC2	HC3
CBI	-3.45									
p-values		0.649	0.653	0.77	0.612	0.619	0.588	0.65	0.613	0.617
Regression 2										
CBI	-4.27									
p-values		0.06	0.083	0.34	0.16	0.2	0.289	0.15	0.216	0.3
Regression 3										
CBI	-4.27									
p-values		0.054	0.083	0.34	0.17	0.207	0.27	0.14	0.216	0.3
Regression 4										
CBI	-7.33									
p-values		0	0	0	0.035	0.015	0.01	0.008	0.005	0.006

In another study, Brumm (2006) reports a significant positive relationship between average inflation and two out of three different indicators of CBI[4]: Cukierman's unweighted legal independence index (LVAW), turnover rate of governors (TURNOVER), and an index of the central bank's political vulnerability (VULNERBL)[5] for twenty four developing countries over the period 1973-1994 (see Brumm 2006 Table 1 p. 191). He reports "not robust to heteroskedasticity" standard errors i.e. Ordinary Least Square standard errors with no adjustment for heteroskedasticity (OLS in Table 2). Employing Brumm's samples of data

[4] Average inflation is explained by some regressors and one indicator of CBI. The three different regressions differ from each other only for the indicator of CBI

[5] Brumm 2006 finds a significant positive relationship between average inflation and TURNOVER and between average inflation and VULNERBL.

we compute the robust standard errors for LVAW, TURNOVER and VULNERBL based on both HC1, HC2 and HC3 and the wild bootstraps. The results are reported in table 2. We observe that LWAV is insignificant at normal levels of significance regardless of the method of computation of the standard errors. However both TURNOVER and VULNERBL which appear highly significant based on both HC1 and HC2 are not significant at the 10% level of significance based on both the wild bootstrap and HC3.

The two examples considered confirm that, in a small sample featuring heteroskedasticity, use of asymptotic robust standard errors can produce results which differ from those obtained from the theoretically preferred wild bootstrap. Our results suggest that the empirical case for the significant impact of some measures of Independent Central Banks on inflation, particularly in developing countries, is less compelling than previously thought

Table 2: Inference on different indicators of CBI proposed by Brumm 2006 based on different HC, and on the wild bootstrap

	Coeff.	Rob. Std. errors			Wild boot. on η_1			Wild boot. on η_2			OLS.
		HC1	HC2	HC3	HC1	HC2	HC3	HC1	HC2	HC3	
LVAW	10.9196										
p-values		0.5	0.54	0.699	0.46	0.48	0.55	0.48	0.51	0.52	0.628
TURNOVER	4.28										
p-values		0.004	0.012	0.123	0.125	0.13	0.185	0.13	0.15	0.19	0.001
VULNERBL	21.97										
p-values		0.019	0.054	0.24	0.11	0.119	0.196	0.132	0.142	0.206	0.076

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