Measurement issues in political economy

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Chapter 3

Measuring central bank independence: a latent variables approach*

3.1 Introduction

Nowadays, it is widely believed that an inflation-averse ('conservative') and independent central bank may help to assure price stability. Indeed, many countries have recently adapted their central bank laws accordingly. There is quite some empirical evidence suggesting that central bank independence (CBI) helps to reduce inflation. For industrial countries, this evidence generally consists of cross-country regressions using proxies for CBI based on the statutes of the central bank. Still, this evidence has been challenged on various grounds; see Berger, de Haan and Eijffinger (2001) for an extensive review. For instance, in a widely cited paper, Campillo and Miron (1997) argue that once control variables are included, the CBI indicator they use plays no role in explaining cross-country inflation differentials in a sample of high-income countries.

One crucial question in this respect is how to measure independence, also making sure that independence is properly distinguished from what is commonly called *conservativeness* (i.e. the inflation aversion) of the central bank. Unfortunately, the concepts of independence and conservativeness are often not carefully disentangled in empirical indicators for CBI, as pointed out by Berger et al. (2001) and Romer (2001). Can central bank independence and conservativeness be measured on the basis of what the central bank law has to say on

*This chapter is an adapted version of De Haan, Leertouwer, Meijer and Wansbeek (2002).

the criteria deemed relevant? Forder (1999) argues "[W]hat are the criteria for a good measure? It cannot be 'one which gives a relation with inflation' since that makes the hypothesis unfalsifiable. [...] What we are lacking is an objective reason to prefer one [measure] over the other. Without this, there can be no test of the independence hypothesis."

Although Forder has a point, we argue that legal indicators are not useless. Independence and conservativeness are theoretical concepts defined on the basis of the unobservable loss functions of the government and the central bank. Hence they are latent variables that cannot be directly observed in practice. In order to include them in empirical models, indicators are needed to proxy independence and conservativeness. Usually this is done by setting up criteria that are thought to be related to the degree of independence, and by assigning scores to the central banks in the various countries under examination. Both steps require subjective judgement and substantive knowledge about central bank laws. It is, therefore, not surprising that different authors have come up with different indicators.

All available indicators try to measure the unobservable concepts of CBI and conservativeness and, no doubt, none of them is perfect. Following most of the literature, the focus in this chapter is on central bank independence. Conservativeness and its measurement are the topic of chapter 6. Here, we consider five CBI indicators. After disentangling the criteria related to conservativeness from those related to independence, we use a latent variables approach to develop an alternative measure of CBI. A latent variables approach to issues concerning the measurement of CBI has been used previously by Eijffinger and Schaling (1998). However, their context differs from ours: their aim is to test a model on the determinants of the optimal level of CBI, whereas in the present chapter we use a latent variable approach to develop an alternative indicator of CBI.

The remainder of this chapter is organized as follows. In section 3.2, we examine five CBI indicators that have been proposed in the literature around 1990, for 22 countries. First, we adjust some of these indicators to eliminate the aspect of conservativeness. Section 3.3 describes the factor analysis model as well as some technical issues that arise specifically in our case. In section 3.4 the results of the factor analysis are discussed. In section 3.5, we examine whether CBI is related to inflation differentials. Section 3.6 concludes.

3.2 Indicators of CBI

We consider five (legal) measures of CBI, as developed by Alesina (1988), Cukierman (1992), Cukierman, Webb and Neyapti (1992), Eijffinger and Schaling (1992) and Grilli, Masciandaro and Tabellini (1991). All indicators are based on central bank laws of the 1980s. At the end of this chapter, we consider other time periods. We have decided to use the aggregated CBI indicators in our analysis instead of the various elements on the basis of which they have been constructed, because it is the aggregate index that yields the degree of CBI according to the author(s) who constructed the index. This aggregate is basically the total score on a number of questions that, according to the author(s), are relevant in order to proxy CBI. These questions differ (sometimes) substantially across the various indicators. See Eijffinger and De Haan (1996) for a detailed comparison of the indicators used.

The indicators of Alesina (ALES) and Eijffinger and Schaling (ES) are constructed by quantifying the final responsibility for monetary policy, the number of government officials on the governing board and the appointment of board members by the government. Grilli, Masciandaro and Tabellini (GMT) present indices of political and economic independence, which are combined to serve as an indicator of legal independence. The indicators of Cukierman (CUK) and Cukierman, Webb and Neyapti (CWN) are aggregated from sixteen legal characteristics of central-bank charters, grouped into eight variables. The only difference between the two is that the CUK indicator is an unweighted average of the eight variables concerned while the CWN indicator consists of a weighted average. Because of this small difference, the CUK and CWN indicators are highly correlated. How we deal with this will be discussed later. Table 3.1 presents the values of the various indicators.

It appears that the indicators are scaled differently. More importantly, countries are ranked differently according to the various indicators. For instance, the central bank of Canada is seen as quite independent by GMT and the Cukierman indicators, but as quite dependent by ES. For an extensive review of the differences, see Eijffinger and De Haan (1996).

Before we describe how to handle the indicators we need to examine them a little closer. De Haan and Kooi (1997) show that CUK, CWN and GMT include issues related to the objective(s) of monetary policy. Although the concept of (goal) independence would suggest otherwise, the measures have a higher score if the law stipulates that stable prices are the primary objective of the central bank. The reason for this is that economic theory implies that a conservative and independent central bank are necessary to reduce inflation. In other words, CUK, CWN and GMT measure the conservativeness of central banks "as embodied in the law" (Cukierman 1992, p.377), in addition to the various aspects of legal independence proper. As we are only interested in independence proper, we adjust the indicators such that the element of conservativeness is removed.

Table 3.1: Indicators of CBI

Country	ALES	CUK	CWN	ES	GMT
Australia	1	.31	.36	1	9
Austria	–	.58	.63	3	9
Belgium	2	.19	.16	3	7
Canada	2	.46	.45	1	11
Denmark	2	.47	.50	4	8
Finland	2	.27	.28	3	–
France	2	.28	.29	2	7
Germany	4	.66	.69	5	13
Greece	–	.51	.55	–	4
Iceland	–	.36	.34	–	–
Ireland	–	.39	.44	–	7
Italy	1.5	.22	.25	2	5
Japan	3	.16	.18	3	6
Netherlands	2	.42	.42	4	10
New Zealand	1	.27	.24	3	3
Norway	2	.14	.16	2	–
Portugal	–	.41	.41	2	3
Spain	1	.21	.17	3	5
Sweden	2	.27	.29	2	–
Switzerland	4	.68	.64	5	12
UK	2	.31	.34	2	6
USA	3	.51	.49	3	12

This is done by subtracting the score on the question of whether the bank by law has to pursue monetary stability from the value of the indicator, after which the adjusted versions of CUK and CWN are rescaled. The adapted indicators are denoted by CUK-a, CWN-a and GMT-a and are shown, along with ALES and ES, in table 3.2. These are the idicators that are used in our latent variables approach.

3.3 The factor analysis model

In this section, we describe the latent variables approach we use in order to evaluate to which extent the CBI indicators describe the same unobservable phenomenon. The different indicators of CBI are correlated, as they should, because they are intended to measure the same concept. The correlation matrix of the indicators is given in table 3.3. Because of missing data (not all authors have considered the same set of countries, as is apparent from table 3.2), the correlations are computed by the expectation-maximization (EM) algorithm based on

Table 3.2: Indicators of CBI excluding conservativeness

Country	ALES	CUK-a	CWN-a	ES	GMT-a
Australia	1	.29	.35	1	8
Austria	–	.58	.62	3	8
Belgium	2	.22	.19	3	7
Canada	2	.49	.50	1	10
Denmark	2	.45	.48	4	7
Finland	2	.19	.18	3	–
France	2	.32	.28	2	7
Germany	4	.61	.64	5	12
Greece	–	.47	.51	–	4
Iceland	–	.35	.33	–	–
Ireland	–	.33	.37	–	6
Italy	1.5	.22	.26	2	5
Japan	3	.18	.21	3	5
Netherlands	2	.37	.35	4	9
New Zealand	1	.25	.22	3	3
Norway	2	.16	.20	2	–
Portugal	–	.47	.48	2	3
Spain	1	.15	.17	3	4
Sweden	2	.28	.31	2	–
Switzerland	4	.78	.75	5	11
UK	2	.32	.28	2	6
USA	3	.52	.49	3	11

the assumption of multivariate normality. The EM algorithm was suggested by Dempster, Laird and Rubin (1977) to solve maximum likelihood problems with missing data. It is an iterative method, in which the expectation step involves forming a log-likelihood function for the latent data as if they were observed and taking its expectation. In the maximization step, the resulting expected log-likelihood is maximized. More on the use of the EM algorithm in missing-data problems can be found in Ruud (1991).

Table 3.3: Correlations between the five CBI indicators

Indicator	ALES	CUK-a	CWN-a	ES	GMT-a
ALES	1.000				
CUK-a	.628	1.000			
CWN-a	.609	.980	1.000		
ES	.625	.439	.406	1.000	
GMT-a	.632	.624	.589	.349	1.000

As can be seen from table 3.3, the correlations between the different indicators are not perfect. Therefore, we consider the different indicators of CBI as imperfect measures of this concept, generated by the factor analysis model

$$x_{ni} = \tau_i + \lambda_i \xi_n + \delta_{ni}, \tag{3.1}$$

where x_{ni} is indicator i for country n, ξ_n is the CBI of country n, τ_i is the parameter that captures the mean of indicator i, λ_i is the factor loading that captures both the scale of indicator i and the strength of its relation to the factor ξ, and δ_{ni} is a random measurement error, with mean zero and variance ψ_{ii}. Further, δ_{ni} and δ_{nj} are assumed uncorrelated for $i \neq j$, and both are assumed uncorrelated with the factor ξ_n.

The covariance of indicator i and indicator j is

$$\sigma_{ij} \equiv \mathrm{E}(x_i - \tau_i)(x_j - \tau_j) = \lambda_i \lambda_j,$$

where $i \neq j$. The variance of indicator i is

$$\sigma_{ii} \equiv \mathrm{E}(x_i - \tau_i)^2 = \lambda_i^2 + \psi_{ii}.$$

We have to address a few further technical issues when applying the factor analysis model to the CBI data. The first one is that the indicators CUK-a and CWN-a are differently weighted combinations of the same components. Consequently, they are always expected to be highly correlated a priori, whether or not they measure CBI satisfactorily. This conflicts with the model assumptions, which state that two indicators should be approximately uncorrelated when one or both do not measure the concept well. There are two ways in which this problem can be solved. The first is to choose one of these indicators as the 'preferred' one and omit the other from the analysis. Then, we have a factor analysis model with four indicators that better satisfies the assumptions. The second solution is to augment the model with a parameter ψ_{23}, say, that reflects the covariance between the measurement errors of these two indicators. In this way, no information is lost and no arbitrary choice has to be made, whereas the new model is still reasonably consistent with our prior ideas. Therefore, we have chosen this solution. The proposed model is depicted in figure 3.1, where the assumed correlation is depicted using an arrow with arrowheads on both sides.

A second technical issue concerns the nonnormality of the data and the small sample size. The indicators are (weighted) combinations of yes/no dummies and are thus clearly nonnormally distributed. Explicit methods for nonnormal data, such as the asymptotically distribution-free method of Browne (1984), exist, but require large sample sizes (1000 or larger) to estimate the model well.

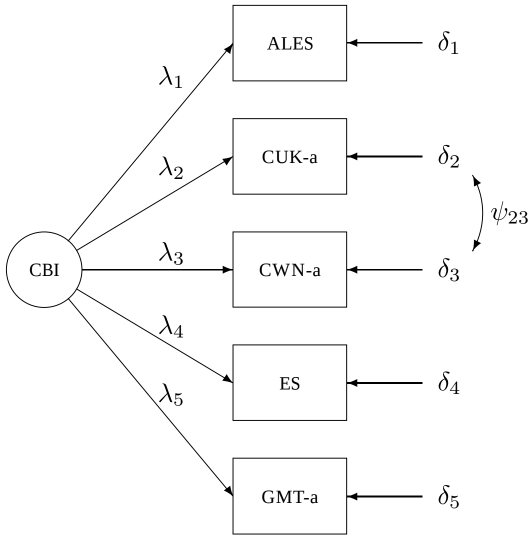

Figure 3.1: Path diagram of the proposed model

We have, however, a small sample of only 22 countries. The literature suggests that for small samples the maximum likelihood method based on the assumption of multivariate normality generally gives the most reliable estimates, even if the data are clearly nonnormally distributed (e.g. Chou and Bentler, 1995; West, Finch and Curran, 1995). Standard errors based on likelihood theory are, however, incorrect in this situation. Therefore, we use the method of White (1982) in order to get standard errors and t-statistics that are robust to this kind of misspecification.

The third technical issue is induced by the missing data. Not all indicators are available for all 22 countries. The two standard approaches to dealing with missing data are *listwise deletion*, which removes all countries that have at least one missing indicator, and *pairwise deletion*, which computes the covariance of two indicators on the basis of the countries that have no missing values on those two indicators, but may have other missing indicators. The drawback of listwise deletion is that many cases may be removed. In our case, 8 countries would have to be removed, leaving only 14 to analyze. This is, of course, a relatively large reduction and throws away a lot of information. Pairwise deletion uses almost all information in the data, but is not guaranteed to give a positive semidefinite covariance matrix. This is exactly what happens in our case. Fortunately, with maximum likelihood estimation, there is a solution that uses all information and that does not suffer from this problem. This full information maximum likelihood method is described in Arbuckle (1996) and implemented in the program AMOS (Arbuckle, 1997). Therefore, we use AMOS to estimate our FA model.

3.4 Empirical findings

In this section, we present the results of the analysis described above. The estimates of the parameters and corresponding White-corrected t-statistics are given in table 3.4. In the table, superindices * and ** denote significance at 5% and 1% levels, respectively. With a few exceptions, the parameters are statistically significantly different from zero at the conventional level of $\alpha = .05$. For the parameters that are not significantly different from zero, this is probably due to small sample size, and not because the parameter is actually zero.

Table 3.4: Factor analysis estimation results

	Estimate	t-stat	Reliability
Intercept (τ_i)			
ALES	2.1361^{**}	11.40	
CUK-a	0.3638^{**}	10.62	
CWN-a	0.3717^{**}	10.81	
ES	2.7710^{**}	11.29	
GMT-a	6.8743^{**}	11.58	
Loading (λ_i)			
ALES	0.7328^{*}	2.08	.7922
CUK-a	0.1192	1.78	.5503
CWN-a	0.1147	1.78	.5064
ES	0.6907	1.28	.4063
GMT-a	1.8622	1.86	.5059
Error variance (ψ_{ii})			
ALES	0.1409	1.20	
CUK-a	0.0116^{**}	3.41	
CWN-a	0.0128^{**}	3.69	
ES	0.6970^{**}	2.94	
GMT-a	3.3876^{**}	2.81	
Error covariance (ψ_{23})			
CUK-a, CWN-a	0.0117^{**}	3.44	

The χ^2-statistic has a value of 2.75 with 4 degrees of freedom, which lies well below the 5% critical value of 9.49. The comparative fit index CFI has a value of 1. According to these measures, the model fits very well.

In addition to the estimates and their t-values, the last column of table 3.4 gives the estimates of the reliability of each indicator, which is its squared correlation with the factor CBI. In terms of the model parameters as introduced above, the reliability of indicator i is given by λ_i^2/σ_{ii}.

According to this measure, ALES performs the best and ES the worst, with reliabilities of .7922 and .4063, respectively. The indicator of Alesina has the highest correlation with the latent variable CBI, but is still an imperfect reflection of it.[1] In other words, using the ALES indicator of CBI is not the best approach conceivable. The other four indicators, even though they correlate less with CBI than ALES, still convey some information on CBI that is not captured by ALES. Hence, a next logical step is to compute the factor scores for the latent variable CBI. As described in chapter 2, the linear combination of the indicators that has minimum mean squared error is given by $\lambda'\Sigma^{-1}(x-\tau)$, where λ, x and τ are vectors with typical elements λ_i, x_i and τ_i, respectively, and the matrix Σ has typical element σ_{ij}. Of course, in practical applications the parameters are replaced by the corresponding consistent estimators.

The computed factor scores are given in table 3.5. We order the countries by the values of their CBI (for the period to which the data apply), from high (Switzerland) to low (Spain). In fact, when the assumptions underlying the factor analysis model are maintained, these country scores are the best indicator of CBI in the 1980s given the input. In the remainder of this thesis, this indicator is dubbed the Factor Score (FS) indicator. Just as with the individual indicators, we can assess the quality of the result by its reliability. Its estimate is .8714, at least for those countries for which all five indicators are available. For countries for which not all indicators are available, reliabilities are lower, which reflects the according loss of information.

3.5 Is CBI related to inflation?

In order to see how the approach described in the previous section can be applied in practice, we present a simple model for (average) inflation during 1980–1989, where CBI is included as an explanatory variable, and compare the results for the different measures that have been discussed. We use the influential paper of Campillo and Miron (1997) as a benchmark. Campillo and Miron claim that CBI is a relatively unimportant determinant of inflation performance, using the CUK indicator as measure of CBI. Campillo and Miron do not examine how sensitive their results for high-income countries are with respect to the choice of the CBI indicator. As we will show below, this omission crucially affects their

[1] This finding is quite remarkable, as the Alesina index has been severely criticised in the literature; see Eijffinger and De Haan (1996).

Table 3.5: CBI scores of the FS indicator

Country	Score	Reliability
Switzerland	2.3923	.8714
Germany	2.1986	.8714
USA	1.1384	.8714
Austria	0.7298	.7477
Netherlands	0.2404	.8714
Japan	0.2141	.8714
Denmark	0.1775	.8714
Canada	0.0805	.8714
Iceland	0.0273	.5566
France	−0.2070	.8714
Greece	−0.2125	.6950
Belgium	−0.2262	.8714
UK	−0.2633	.8714
Finland	−0.3168	.8519
Ireland	−0.3222	.6950
Sweden	−0.3591	.8519
Portugal	−0.4774	.7477
Norway	−0.5660	.8519
Italy	−0.8686	.8714
Australia	−1.0340	.8714
New Zealand	−1.1252	.8714
Spain	−1.2206	.8714

conclusion.

We start with a very simple bivariate cross-sectional model that describes the relation between inflation and CBI for the 22 OECD countries mentioned earlier. Since the data for the various indicators of CBI refer to the 1980s, our sample period runs from 1980 until 1989. Inflation data, measured as the change in consumer prices, have been obtained from the IMF's International Financial Statistics, and have been averaged for the sample period of interest. A constant term is included in the specification, and the model coefficients are estimated using OLS. Because Greece and Iceland seemed to behave somewhat erratically during the sample period, we have added dummies to the model specifications that include the CBI indicators for these countries. Without these dummies, the explanatory power of the model is much lower, see also Eijffinger and De Haan (1996). The results, including the corresponding t-statistics and adjusted R^2 measures, are shown in table 3.6.

The results in the table indicate a negative relation between CBI and inflation, i.e. a greater independence of the central bank is related to a lower inflation

Table 3.6: Estimation results for a simple bivariate regression model of inflation

Measure	CBI-coeff	t-stat	$\bar{R}^2$
ALES	-0.0256^{**}	-5.356	0.610
CUK-a	-0.0681	-1.557	0.795
CWN-a	-0.0640	-1.446	0.792
ES	-0.0168^{*}	-2.527	0.211
GMT-a	-0.0105^{**}	-4.332	0.648
FS	-0.0251^{**}	-4.151	0.872

rate, which is consistent with theory. With the exception of the Cukierman indicators, the estimated coefficients are statistically significant. The model specification that uses the FS indicator has the highest $\bar{R}^2$-value.

Of course, the model described above is extremely simple. In order to examine whether the results are robust, we look at the extended model in section 3.2 of Campillo and Miron (table 5), where the following additional variables are included:

- Average inflation in the previous period
- Political instability
- The degree of openness
- Log of GDP per capita
- Participation in a fixed exchange rate regime
- The need for tax revenue

As our sample periods runs from 1980 until 1989, we use averaged inflation over the period 1970–1979 as the first control variable (INFL7079). Political instability (POLINST) is measured as the total number of government changes during the sample period.[2]

Traditionally, the degree of openness is measured as the level of imports relative to GDP. Lane (1997) shows that the link between openness and inflation only holds for the most highly developed countries when country size is held constant. To correct for this effect, the log of real GDP in 1985 (LGDP85) is also included as a regressor. Romer (1993) argues that openness puts a check on the government's incentive to engage in unanticipated inflation, because of induced exchange rate depreciation. He has found that over a large sample of

[2]Alternatively, we have used the number of changes in the colour of the government (from left-wing to right-wing and vice versa) as measure of political instability. This produces similar results.

countries and over a broad time frame average inflation is significantly lower in smaller, more open countries. However, Terra (1998) argues that the negative link between inflation and openness is largely driven by the response of severely indebted countries to the debt crisis of the 1980s. The smaller a country's trade share, the more depreciated the real value of the currency must be in order to generate a given trade surplus. And the more depreciated the currency, the greater the pressure on the government's budget, and, hence, the pressure to inflate. See also Romer (1998) for a critique on this view.

A further control variable is the log of real GDP per capita in the year 1985 (LGDPPC85). A dummy variable is included to control for participation in an exchange rate system, the European Monetary System in this case. This variable has value 1 if the corresponding country is a member of the Exchange Rate Mechanism of the EMS and 0 otherwise. Finally, the need for tax revenue is measured by the level of debt relative to output at the start of the sample period (DEBT80). Due to data availability and the fact that we are only interested in OECD countries, we have excluded the Summers-Heston measure for quality of the data as a control variable.

Instead of including all control variables simultaneously, as Campillo and Miron suggest, we use a step-wise procedure. Each time, only one control variable is added to the bivariate model, in order to assess its specific effect on the relation between CBI and inflation. This avoids the possibility of overfitting due to a large number of regressors with a small sample size. In these regressions, the FS indicator of CBI is used. The results are given in table 3.7.

Table 3.7: Estimation results for regressions for inflation including control variables

Control	coeff	t-stat	CBI-coeff	t-stat	$\bar{R}^2$
INFL7079	0.9290^{**}	5.321	-0.0035	-0.614	0.941
POLINST	0.0004	0.116	-0.0249^{**}	-4.027	0.865
OPENNESS	-0.0552	-1.059	-0.0205^{**}	-3.172	0.870
LGDP85	-0.0095	-1.542			
LGDPPC85	-0.0724^{**}	-2.781	-0.0156^{*}	-2.511	0.900
EMS	-0.0113	-0.906	-0.0243^{**}	-4.053	0.870
DEBT80	-0.0258	-0.703	-0.0294^{**}	-4.005	0.868

From the table it is clear that the coefficient for CBI remains significant in all cases, except when inflation in the previous period is included in the regression. The conclusion by Campillo and Miron that CBI is a relatively unimportant determinant of inflation performance is largely based on this phenomenon. The model with inflation in the previous period included is, however, not very satisfactory. It merely states that countries with an above average inflation rate in the 1970s also had an above average inflation rate in the 1980s. It does not give an explanation of inflation differences among countries or why these differences are maintained, nor does it give directions based on which policy makers could attempt to reduce inflation rates if that is considered desirable.

The second reason why Campillo and Miron reach a different conclusion is because they only use the Cukierman indicator to measure CBI, which is insignificant in the bivariate model as well as when the control variables are included. In order to see to which extent the choice of indicator influences the results, we give adjusted R^2 values for the different model specifications using the various indicators of CBI in table 3.8.

Table 3.8: $\bar{R}^2$ values of the regressions for inflation including control variables, using different CBI indicators

	Indicator					
Control	ALES	CUK-a	CWN-a	ES	GMT-a	FS
INFL7079	0.657	0.943	0.943	0.742	0.831	0.941
POLINST	0.589	0.786	0.783	0.172	0.624	0.865
OPENNESS[a]	0.678	0.822	0.823	0.305	0.636	0.870
LGDPPC85	0.583	0.873	0.873	0.596	0.675	0.900
EMS	0.604	0.796	0.793	0.165	0.631	0.870
DEBT80	0.555	0.778	0.776	0.113	0.628	0.868

[a] Model specification includes LGDP85.

The results show that in all cases except (barely) the one including inflation in the previous period, the specification that uses the FS indicator has the highest explanatory power. We conclude that the negative, significant relation we have found between inflation and CBI is robust.

CALS estimators As discussed in section 2.2, the use of a latent variable as a regressor in a regression model leads to inconsistent estimation results due to measurement error, and underestimation of the coefficient of the latent variable. Since we have an estimate of the reliability of the construct of CBI here, we can get rid of the underestimation and get consistent estimates by calculating CALS estimators. The results for the specifications with and without control variables are presented in table 3.9. In the second and third column, estimated coefficients and t-values ignoring measurement error are given. In the last two columns, CALS estimates are shown.

It is clear from table 3.9 that, as predicted, the estimated coefficients increase while the t-values decrease when CALS estimators are used. The first effect is

Table 3.9: CALS estimates of the FS indicator

Control	coeff	t-stat	CALS coeff	CALS t
–	-0.0251^{**}	-4.151	-0.0305^{**}	-4.005
INFL7079	-0.0035	-0.614	-0.0055	-0.611
POLINST	-0.0249^{**}	-4.028	-0.0307^{**}	-3.878
OPENNESS[a]	-0.0205^{**}	-3.172	-0.0266^{**}	-3.053
LGDPPC85	-0.0156^{*}	-2.511	-0.0210^{*}	-2.430
EMS	-0.0243^{**}	-4.053	-0.0297^{**}	-3.910
DEBT80	-0.0294^{**}	-4.005	-0.0396^{**}	-3.684

[a] Model specification includes LGDP85.

much larger than the second, however, and in none of the cases the significance of the results is affected.

CBI in other decades The analysis in this chapter has been performed for the period 1980–1989. It can, however, be performed for other time periods as well. Data on the Cukierman indicators are also available for the periods 1950–1959, 1960–1971 and 1972–1979. An update for the period 1990–1997 has been constructed by van Lelyveld (2000).[3] The other indicators are only available for the 1980s. Since the level of CBI has not changed dramatically between 1960 and 1989, a factor analysis for 1960–1971 and 1972–1979 can be performed using the relevant values of the Cukierman indicators while assuming the values of the remaining indicators still valid for these periods. Due to the fact that there have been a number of changes in central bank laws since 1990, as van Lelyveld describes, this assumption is less straightforward for the 1990s. In spite of this, we have also constructed the FS indicator for the period 1990–1997, using the updated Cukierman indicators and the unchanged others. In empirical applications, however, we use both the FS indicator and the Cukierman indicator of CBI if the sample period includes the 1990s. The values of the FS indicator for the different decades are shown in table 3.10.

[3] Van Lelyveld's updated value for Spain contains an error. We have corrected this.

Table 3.10: Scores of the FS indicator for different decades

Country	1960–1971	1972–1979	1980–1989	1990–1997
Australia	−1.0664	−1.1892	−1.0340	−1.1623
Austria	0.8057	0.8263	0.7298	0.5872
Belgium	−0.1365	−0.2181	−0.2262	−0.0616
Canada	−0.0279	−0.0983	0.0805	−0.0901
Denmark	0.0590	0.0180	0.1775	0.0989
Finland	−0.1789	−0.2356	−0.3168	−0.2217
France	−0.1018	−0.2477	−0.2070	−0.1410
Germany	2.2598	2.2717	2.1986	2.3210
Greece	−0.6219	−0.0323	−0.2125	−0.3995
Iceland	−0.3610	−0.1974	0.0273	−0.3163
Ireland	−0.0232	−0.0645	−0.3222	−0.3280
Italy	−0.6896	−0.7800	−0.8686	−0.7318
Japan	0.7573	0.7144	0.2141	0.6032
Netherlands	0.0351	−0.0002	0.2404	0.1384
New Zealand	−1.2554	−1.3094	−1.1252	−1.2219
Norway	−0.2136	−0.2799	−0.5660	−0.3340
Portugal	−1.0824	−0.6282	−0.4774	−0.4407
Spain	−1.2265	−1.3146	−1.2206	−1.1518
Sweden	−0.1476	−0.2256	−0.3591	−0.2117
Switzerland	2.2638	2.2495	2.3923	2.3005
UK	−0.0881	−0.2873	−0.2633	−0.2927
USA	1.0401	1.0284	1.1384	1.0559

3.6 Conclusions

In this chapter, we have shown how the partial conflict between competing indicators of CBI can to a certain extent be resolved by using latent variables modeling. The resulting ordering of countries by the degree of CBI is of interest by itself, but the results also allow for more satisfactory statistical inference in regression models where CBI is an explanatory variable.

In contrast to the results of the influential study by Campillo and Miron (1997), we find that the CBI indicator we have constructed is significantly related to inflation, also when various control variables as suggested by Campillo and Miron are included.

Finally, the CALS estimator can be used to deal with problems concerning measurement error and underestimation of regression coefficients. This leads to a reasonable increase of the estimated coefficients of the CBI indicator, while the significance of the results remains intact.