Central banks and information provided to the private sector

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1. Introduction

The issue of central bank transparency has recently acquired a growing importance in the macroeconomic literature on monetary policy. Reasons are of varied nature.

On the one hand, it is generally acknowledged that significant suboptimal outcomes in the action of public authorities and institutions can be blamed to information asymmetries between authorities or institutions and the general public. Thus, an enquiry on the behavior regarding global information disclosure (transparency) could be important both on the positive side (helping to detect or explain major sources of non-market failures) and on the normative side (pointing out the direction of some possible solution to those market failures).[1]

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[1] The importance of the openness of central bank decision making has been highlighted by, among the others, Blinder *et al.* (2001). However, following the seminal Canzoneri's (1985) contribution, more recent theoretical studies emphasize the strategic use of information, (see, e.g., Faust and Svensson 2001 and 2002, Cukierman 2002, Grüner 2002 and Walsh 2003). Empirical evidence on the effects of transparency is provided by Demertzis and Hughes-Hallet (2003). They find that the transparency does not affect the average level of inflation and output gap, but it seems to have an effect on their volatilities.

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On the other hand, the problem of central bank transparency is relevant for the analysis and evaluation of monetary policy. There exist well known arguments generally favoring an explicit commitment by monetary authorities to a predefined course of action and/or a preference for a relevant degree of independence for the same institutions.[2] The commitment to particular policies should be supported and, thus, verifiable by the public. A particular attitude of the central bank towards information disclosure is hence required. Central bank independence poses analogous problems. A central bank endowed with strong independence from the control of other institutions could be tented to pursue goals different from social welfare improvement. Such a temptation could be higher the lower is the central bank's transparency (and accountability).

In order to develop the analysis of monetary authorities' behavior towards information disclosure, apart from theoretical studies, an empirical appraisal of central banks' transparency is certainly needed. This theme has been effectively tackled by several authors (e.g. Bernanke *et al.* 1999; Fry *et al.* 2000 and Blinder *et al.* 2001). In a recent contribution Eijffinger and Geraats (2002), EG henceforth, propose an index explicitly built to summarize the information disclosure practices adopted by central banks. This general index is a highly composite one, made up of 15 different sub-indexes in order to include different facets of information disclosure;[3] it can be justified by reckoning that transparency or information disclosure are markedly multidimensional phenomena. EG then apply their index to nine major central banks for which it has been possible to collect the relevant information.[4] They find that the most transparent central banks are the Re-

[2] The arguments for commitment stem from Barro and Gordon (1983), while those for central bank independence (as long as it ensures a high degree of inflation aversion) are traditionally due to Rogoff (1985). Those issues have been extensively debated and the standard arguments supporting commitment/independence have also undergone significant criticism and qualifications (cf. among the others, Gylfason and Lindbeck 1994; Guzzo and Velasco 1999; Cukierman and Lippi 1999; Berger, de Haan and Eijffinger 2001 and Lawler 2001).

[3] See Appendix A.

[4] They first collected all the relevant information freely available in English as of June 2001. Afterwards, for each central bank, they sent the scores obtained for that central bank (together with a description of the index) to an officer of the same institution, and asked for a review of the score itself. Finally, they used the responses to reassess and slightly modify the scores. Although the time span of the data collected is not clearly assessed, it can be thought that they cover a short-medium run period of some year.

serve Bank of New Zealand, the Bank of England and the Swedish Riksbank. An intermediate level of transparency is associated with the Bank of Canada, the European Central Bank and the US Federal Reserve. The least transparent central banks are the Reserve Bank of Australia, the Bank of Japan and the Swiss National Bank.

Our aim is to elaborate the EG's analysis by investigating more deeply the multidimensional aspect of the problem. By applying principal component analysis (PCA) to the original EG's dataset, we tackle a twofold target. First, by using a 'non-centered' PCA, section 3 refines the EG's general index to eliminate some non-informative correlation between sub-indexes. Such a 'cleaning' procedure generates a neater general index for transparency, which provides information on the absolute quantity of information disclosed by the central banks. Second, by using a 'centered' PCA, we break down and recompose the original general EG's index in order to single out different qualitative aspects of information disclosure behavior. This procedure gives rise to three specific indexes.[5] An analysis of the central banks' scores under those indexes allows us to cluster the sample of monetary authorities in three groups, each characterized by composite and different characteristics under the multiple dimensions of transparency. Assuming that central bank can use information disclosure as a strategic variable, our findings are in line with some recent theoretical results relating transparency to other aspects of the institutional framework.[6] According to this strand of literature, an optimal level of transparency is not independent of the institutional features of the economic environment. Central banks might find optimal different degrees of transparency depending on the design of other institutions, such as the government budget stance, the industrial relation system, the financial market development, etc. Furthermore, our paper opens a new angle into the literature by suggesting that central banks confront a multidimensional problem when choosing their optimal transparency behaviour. Besides choosing an overall quantitative level of transparency, monetary authorities must also decide the qualitative features and dimensions of their information disclosure.

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[5] Which are determined by factorial axis, see Okamoto (1997) and Lebart, Morineau and Piron (1995).

[6] Cf. Hughes-Hallet and Viegi (2001); Faust and Svensson (2002) and Ciccarone, Di Bartolomeo and Marchetti (2004).

The rest of the paper is organized as follows. Next section describes EG's dataset, also used in our study. Section 3, after explaining the difference between non-centered and centered PCA, illustrates our results in both cases and gives our interpretation of the principal components. Section 4 concludes.

2. Transparency and the EG's dataset

In the construction of their index of transparency, EG follow this strategy: they assume that transparency is mainly given by the total amount of information that a central bank discloses to the public. Since such information can be of varied nature, they define five major categories under which classifying the different types of transparency. Subsequently, each category is further partitioned into three specific values to obtain a finer classification of information flows. The five main categories are: 1) Political transparency; it refers to openness about policy objectives, i.e. the attitude of the central bank in communicating the form of its objective function, the values of its parameters and of its eventual target values for the main objective variable. 2) Economic transparency; it is related to information of economic nature, such as the adoption of a particular theoretical model of the economy, economic data and the knowledge of the shocks hitting the economy. 3) Procedural transparency; this is about the way monetary policy decisions are taken. It signals how the central bank discloses its strategy rule (e.g. a Taylor-kind rule) to the public. 4) Policy transparency; it involves the quickness in the communication of policy decision. Policy transparency is also about explanation of decision and clear indication for future policy actions. 5) Operational transparency; it refers to the implementation of monetary policy: the way in which policy actions are evaluated, eventual errors and disturbances, possible justifications (*ex post*) of policy actions. Table 1 describes the complete structure of the sub-indexes.

The procedure of aggregation of the 15 sub-indexes followed by EG is straightforward: they simply sum up the indexes for each country.[7] Although the partition elaborated by EG is rather fine and comprehensive, the possibility of correlations between the recorded scores for each variable (sub-index) and the strong multidimensionality of the phenomenon calls for a further analysis. To this aim, the standard methods of multivariate eigenanalysis (the most classical of which is the PCA) appear particularly suited.

TABLE 1

EG'S INDEXES

Categories	Sub-indexes	Description	Values
Political	*Formal objectives*	Explicit communication and/or prioritization of final targets.	1; 0.5; 0
	Quantitative targets	Presence of targets quantification.	1; 0
	Institutional arrangements	Presence of explicit contracts between CB and government (e.g. instrument independence).	1; 0.5; 0
Economic	*Economic data*	Provision of data on GDP, money supply, inflation, unemployment and capacity utilization.	1; 0.5; 0
	Policy models	Disclosure of the CB's formal macro-model(s) used for policy analysis.	1; 0
	Internal forecasts	Regular communication or publication of CB's forecasts.	1; 0.5; 0
Procedural	*Explicit strategy*	Provision of a description of a CB's policy rule (strategy).	1; 0
	Minutes	Release of the decision boards minutes (in 8 weeks).	1; 0
	Voting records	Publication of voting records (in 8 weeks).	1; 0
Policy	*Prompt announcement*	Decision on the main instruments or target announced at the latest day of implementation.	1; 0
	Policy explanation	Provision of explanations of CB's announced decisions on targets/instruments.	1; 0.5; 0
	Policy inclination	Disclosure of CB's likely future actions.	1; 0
Operational	*Control errors*	Provision of explanation for eventual deviation from the targets.	1; 0.5; 0
	Transmission disturbances	Regular provision of information on disturbances affecting the transmission process.	1; 0.5; 0
	Evaluation of policy outcomes	Regular provision of CB's evaluation in light of its macroeconomic objectives.	1; 0.5; 0

[7] See Appendix A, Table A1. The small number of monetary authorities considered in EG analysis (9 central banks) could appear limiting. It can however be noticed that EG proceeded by collecting all the information easily and publicly available on central banks' policies; so it can be argued that central banks not included in the dataset are (almost) completely opaque. Furthermore, the nine institutions covered by EG, put together, represent the most important and influential monetary policy makers at a global level.

3. The statistical model and results

3.1. *The methodology*

The main idea of PCA is to reduce the dimensionality of a dataset that may contain correlated variables, while retaining as much as possible of its variability. More in detail, PCA searches for a few uncorrelated linear combinations (principal components) of the original variables that capture most of the information in the original variables.

Suppose we want to measure people's satisfaction with their lives. We design a satisfaction questionnaire with various items; among other things we ask our subjects how satisfied they are with their hobbies (item 1) and how intensely they are pursuing a hobby (item 2). Most likely, the responses to the two items are highly correlated with each other. Given a high correlation between the two items, we can conclude that the information provided by the two answers of the questionnaire is quite redundant.[8]

One can summarize the correlation between two variables in a scatter plot. A regression line can then be fitted that represents the best summary of the linear relationship between the variables. If we could define a variable that would approximate the regression line in such a plot, then that variable would capture most of the essence of the two items. Subjects' single scores on that new factor, represented by the regression line, could then be used in future data analyses to represent that essence of the two items. In a sense we have rebuilt the two variables to one factor or component – the factor is in fact a vector made up of two numbers that can be conceived as weights on the former variables; see below. Note that the new factor is actually a linear combination of the two variables and its significance increases in the two-variable correlation.

The example described above, combining two correlated variables into one factor, illustrates the basic idea of principal components

[8] In a more extreme fashion, suppose to study the height of 100 people in inches and centimeters, so to have two variables that measure height. If in future studies we want to research, for example, the effect of different nutritional food supplements on height, the use of both measures should be useless since height is one characteristic of a person, regardless of how it is measured. Hence variables can be redundant with respect to the information and, in some circumstances, a large number of indicator useless.

analysis. If we extend the two-variable example to multiple variables, then the computations become more involved, but the basic principle of expressing two or more variables by a single factor remains the same. By considering more than two variables, we can think of them as defining a space, just as two variables defined a plane. Thus, when we have three variables, we could plot a three-dimensional scatter plot, and again we could fit a plane through the data (a plane will individuate by two orthogonal lines). In principal components analysis, after the first factor has been extracted, that is, after the first line has been drawn through the data, we continue and define another line that best fits remaining variability, and so on. In this manner, consecutive factors are extracted.

In order to fit the analysis in our context in a more precise way, consider the dataset organized in a matrix $\mathbf{X} \in \Re^{mxm}$, formed by n rows and m columns; in our case **X** would be the (transposed) data matrix in Table A1 (Appendix A) of the EG dataset: the rows of **X** represent the statistical units (central banks), while columns represent the variables (EG's sub-indexes). As an example, assume to have (for simplicity) a smaller number of variables, say three variables named x, y and z, coupled with many (say 30) central banks, i.e. m = 3; n = 30. The scatter plot in Figure 1a represents the data (the Cartesian axis X, Y and Z represents the three variables; each point is a statistical unit, i.e. a central bank). As said before, the aim of PCA is to reorganize information contained in the data cloud in an optimal way, i.e. by finding lines or factorial axis (the above-mentioned components) like b' in Figure 1a.[9] In order to fit data, such lines should minimize the square of distance of points like M from b' (i.e. MH^2), and this must hold for every point; in other words, they should minimize the sum of the squares of these distances.

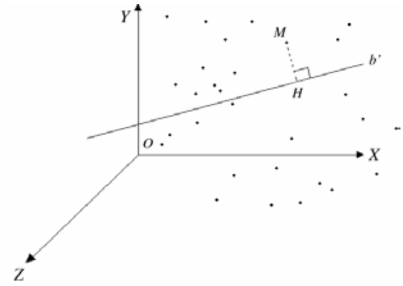
Points are all clustered in the nonnegative quadrant as the three variables can have only positive values. There can be more than one of vectors like **b'**, but we are interested in vectors that are independent one from the other[10] (i.e. orthogonal) – for instance, Figure 1b depicts

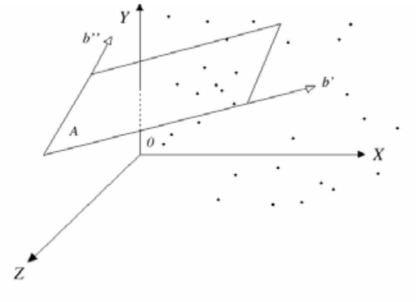
[9] The line will be individuated by some (3×1) vector, as we are in a three dimensional variables space.

[10] More formally, it can be shown (see, e.g., Okamoto 1997; Lebart, Morineau and Piron 1995) that the problem of finding vectors **b** that minimize the squared distance of each points from the same vectors is equivalent to solve the following

FIGURE 1

SCATTER-PLOTS WITH ONE AND TWO FACTORIAL AXIS-COMPONENTS





the case of a subspace individuated by two vectors **b'** and **b''**, which is a plane (*A*) for the two vectors are orthogonal.

Once calculated, each component **b** helps to explain a share of the total variability in the data, as each of the components is constructed so to best approximate the data cloud. It is possible to rank the components **b** by the (decreasing) magnitude of the share of variance explained (this is the meaning of the term *principal* components).[11] By construction, the elements of each vector **b** are non-negative and sum up to one, so that they can be used as weighting coefficients in constructing new aggregate indexes for the original variables.[12] A factorial axis can then be viewed as a vector of weights that can be applied to each row (central bank) of matrix **X**: summing up the variables scores in the row, weighted with the new coefficients, allows us to obtain a new synthetic indicator for the phenomenon under inquiry (transparency, in the present case). Each of these aggregate indexes provides a way to evaluate the global phenomenon under a particular perspective, which can be inferred from a qualitative interpretation (see below sections 3.2 and 3.3).

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maximization problem: max $\mathbf{b}^T \mathbf{X}^T \mathbf{X}\mathbf{b}$ with resptect to **b**, subject to the constraint $\mathbf{b}^T \mathbf{b} = 1$ (*T* indicates transposition).

[11] The first order conditions of the maximization problem give rises to the linear system: $\mathbf{X}^T \mathbf{X}\mathbf{b} = \lambda\mathbf{b}$, where λ is the Lagrange multiplier (and the eigenvalue of the system). Each eigenvalue is associated with a particular **b** (eigenvector) of the solution, and it can be shown that the sum of the eigenvalues is equal to the total variance of the data: thus each component **b** contribute to explain a share of the total variance.

[12] See, e.g., Dunteman (1989).

The PCA can also be performed on the centered original data matrix (i.e. entries of matrix **X** are transformed in deviations from the mean of the variables). Centered analysis is obtained in a similar way as the non-centered one, above described, by using the transformed data set **Y**, where each entry is the deviation of the original datum from the mean of the variable:[13]

$$y_{ik} = x_{ik} - \frac{1}{m} \sum_{k=1}^{m} x_{ik}.$$

The difference between the two procedures is however not trivial and, being relevant for our investigation, we need to discuss it.[14]

Non-centered principal components analysis implies an all-zero point (vector) of reference: a non-transparent central bank. For example, the reference point is represented in figures 1 by the origin 0, where the three original variables are equal to 0. By contrast, centering, or normalizing, by variables shifts the reference point (origin) to a hypothetical average stand. In other words, when centering is adopted, the analysis focuses on the eventual deviation from an 'average' kind of central bank.[15] For example, the centering of data in Figure 1 would produce a shift in the origin before performing the PCA.

The two procedures describe different situations. The decision about which is the more appropriate depends on the kind of variability that one wants to explain. An advantage of non-centered analysis is that it distinguishes disjunction from mere difference in between-variables from within-variables heterogeneity of clusters. Within-variables heterogeneity means that the same set of variables is relevant to the explanation of the variability of all the clusters of central banks. When within variables heterogeneity is detected – e.g. when in the non centered PCA the weighting coefficients of the first component *b* are all positive – it means that the sample of central banks is rather homogeneous: it is influenced by the same set of variables in a uniform direction, and the sample does not immediately splits into two

[13] Principal components can be also derived by centering the original data with respect to the variable (column) mean.

[14] Notice also that principal components are often calculated after data standardization. This procedure is needed when the variables are expressed in different units of measure. In our case, we do not standardize the data implicitly assuming the same metric used by EG.

[15] Of course, information regarding the absolute values is not lost, but is synthesized in the means that in such a case have to be taken into account in the data analysis (see Noy-Meir 1973).

(or more) clusters of central banks. Between-variables heterogeneity means that each cluster of central banks (or group of clusters) has significant non-zero values only on a subset of variables, i.e. the variability associated to each cluster is mainly explained by some variables only. On the other side, centered analysis generally allows for a more efficient concentration of information about between-variables information, so to extract more qualitative information in the resulting components.

Our investigation strategy is as follows. First, we use a non-centered PCA to derive a quantitative index of transparency, which is comparable to that of EG. The advantage of obtaining an index in this way is clear with respect to a simple additive index. In fact, it eliminates redundant information in the dataset and gives additional information (e.g. the second component) about the phenomenon investigated, which could be useful to explain the nature of information derived from the data. Second, we perform the PCA by centering the data with respect to variable means; this amounts to implicitly accept EG index and study the variability of the data on their mean. This allows us to study the information provided by the central banks under a more qualitative perspective.

3.2. *Non-centered analysis*

The non-centered PCA individuates two principal components that explain about the 95% of the dataset variability. As usual in non-centered analysis, the first component explains a large part of the variability (85%). The second component, however, still explains about the 9% of data variability. The weights[16] (or loadings) associated with these two components (the first two vectors **b** of section 3.1) are reported in Table 2.

The first component individuates a quantitative index, *information sharing index* (IS index, or *transparency index*), which is comparable to that of EG.[17] The index differs from that of EG with respect to

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[16] The software we used, MVSP, performs an R-mode PCA. The component loadings are scaled to unity, so that the sum of squares of an eigenvector equals one, and the component scores are scaled so that the sum of squares equals the eigenvalue.

[17] Recall that non-centered PCA explain the variability of the central banks with respect to the case of central bank associated with all zero score (i.e. a completely non transparent central bank).

the weights (which in EG's index are all the same). In our index *prompt announcement*, *institutional arrangements*, *control errors* and *formal objectives* are more relevant than in the EG's index. By contrast, *policy inclination*, *voting records*, *evaluation policy outcome*, *transmission disturbances* result less relevant.

Regarding the second component, a possible interpretation is to relate it to the relative quantity of information about the *political transparency* vs. the *procedural transparency*.[18] In fact, central banks that give relatively more quantitative information about their objective or reaction function (in terms of targets, form, or marginal rate of substitution) have high index values. By contrast, central banks disclosing more information about the way monetary policy decisions are taken (i.e. providing minutes and voting records) score low.[19] EG refer to explicit strategies as an indicator *procedural transparency*. By contrast, in our view it is an indicator of *political transparency* since it is related to the form of the policy function of the central bank (e.g. the adoption of a Taylor-kind rule to set monetary policy). We then refer to this index as *procedural/political index* (PP).

TABLE 2

MULTIVARIATE TRANSPARENCY INDEXES WEIGHTS
(first two components)

	First component	Second component
Formal objectives	0.304	0.119
Quantitative targets	0.288	0.372
Institutional arrangements	0.335	0.111
Economic data	0.288	–0.001
Policy models	0.210	–0.184
Central bank forecasts	0.246	–0.058
Explicit strategy	0.288	0.372
Minutes	0.204	–0.487
Voting records	0.158	–0.536
Prompt announcement	0.352	–0.007
Policy explanation	0.277	–0.036
Policy inclination	0.082	–0.345
Control errors	0.321	0.000
Transmission disturbances	0.189	0.051
Evaluation policy outcome	0.166	–0.114

[18] As defined by EG, see section 2.

[19] More in detail, the second component is mainly determined (with a positive weight) by *explicit strategy*, *quantitative targets*, *formal objectives* and *institutional arrangements*, and (with a negative weight) by the following variable *voting records*, *minutes*, *policy inclination*, *policy models* and *evaluation policy outcome*.

By applying the weighting coefficients found above to the variables scores of each central bank, the latter can be ranked with respect to the two new aggregate indexes.

TABLE 3

TRANSPARENCY INDEXES AMONG INDUSTRIALIZED COUNTRIES

Information sharing (IS) index			Political/Procedural (PP) index	
New Zealand	1.198	(1.35)	Australia	0.334
UK	1.154	(1.25)	Switzerland	0.297
Sweden	1.153	(1.20)	Euro zone	0.248
Canada	1.049	(1.05)	Canada	0.242
Euro zone	1.000	(1.00)	Sweden	0.113
US	0.856	(1.00)	UK	–0.114
Australia	0.845	(0.80)	New Zealand	–0.252
Switzerland	0.801	(0.75)	Japan	–0.332
Japan	0.739	(0.80)	US	–0.554

The first index of Table 3 (IS) reflects the index of EG, which is indicated in the table between brackets (original EG index divided by 10 to facilitate the comparison).

The second index (PP) indicates the kind of knowledge that central banks supply about how monetary policy is set, as the ratio between information associated with the debate inside the central bank in the policymaking process (*procedural transparency*) and quantitative information associated with the central bank targets (*political transparency*). Countries such as the United States, Japan, New Zealand and the United Kingdom give a relative more relevance on the information related to the formation of the monetary policy-making process. By contrast, Australia, Switzerland, Canada, the European Central Bank and Sweden place a more relative emphasis on the quantitative information regarding their targets.

This subsection has investigated the variability of the data set with respect to the non-transparent central bank, and therefore, it has focused on the quantity of information. According to our results, data are mainly associated with within-axes heterogeneity since the weights of first component are all positive, while those of the second component are also negative. This means that the same set of variables is relevant to all the clusters of central banks and (non-centered) principal components do not show the evidence of some interesting compositional disjunction in the sample. Hence, in order to understand and describe the data variance under a more qualitative point of view, centered PCA may result more useful than the non-centered one.[20] In the next subsection, centered PCA by focusing on the quality of information tries to introduce an additional value to our investigation.

3.3. *Centered PCA*

The first three components of our centered PCA are reported in Table 4.[21] Since the first three eigenvalues explain about the 80% of the variance,[22] we can restrict our analysis to these components.

TABLE 4

CENTERED PRINCIPAL COMPONENT ANALYSIS
(weighting coefficients and components)

	Component 1	Component 2	Component 3
Formal objectives	0.130	0.293	0.033
Quantitative targets	0.384	0.360	−0.015
Institutional arrangements	0.119	0.053	0.131
Economic data	0.003	−0.205	−0.034
Policy models	−0.172	0.477	−0.594
Central bank forecasts	−0.047	0.291	0.206
Explicit strategy	0.384	0.360	−0.015
Minutes	−0.479	0.223	0.427
Voting records	−0.530	0.135	0.057
Prompt announcement	0.000	0.000	0.000
Policy explanation	−0.030	0.024	−0.141
Policy inclination	−0.341	0.140	−0.372
Control errors	0.011	0.240	−0.098
Transmission disturbances	0.061	0.334	0.432
Evaluation policy outcome	−0.107	0.199	0.212

The first component explains the 42% of the variance. It mainly depends on *quantitative targets*, *explicit strategies*, *formal objectives*,

[20] See Noy-Meir (1973) for a more technical discussion about principal component analysis and between and within heterogeneity.

[21] Also for centered PCA holds the normalization adopted for the non-centered analysis of the previous section (see footnote 16).

[22] The relative contribution of each variable is reported in detail in Appendix B, Table B1.

institutional arrangements (with positive contribution) and *voting records*, *minutes*, *policy inclination* (negative contribution).[23]

Notice the correlation between the first component and the PP index of Table 2. Hence, our interpretation of the first component[24] is to see it as an index of the information on the 'discussion process' that determines the monetary policy vs. the information on the final outcomes of this discussion process.[25] A central bank with a high score in the first component *ceteris paribus* attaches proportionally a high importance on providing information on its formal objectives and institutional constraints, relative to the disclosure of the internal decision process outcomes.

The second component groups with a positive *sign policy models*, *forecasts*, *transmission disturbances* and *control errors* and it is negatively affected by only the variable economic data. Notice the correlation between this component and the IS index. It opposes central banks that give quantitative information about their reaction functions to central banks that do not do it. In fact the index is negatively associated with only economic data, which has a very low variability within central banks.

The third component explains the 16% of the variance. It is mainly determined by *transmission disturbances*, *minutes*, and *evaluation of policy outcomes* (positive sign) and *policy models*, *policy inclination* and *policy explanation* (negative sign). The first group of variables (positive) seems to be associated with the *ex post* appraisal of the monetary policy (*operational transparency*) whereas the second group (negative) can be related to the *ex ante* appraisal (*policy transparency*).[26] In

[23] Relevant variables are determined by using a rule of thumb on their weight. However, principal component analysis can be also interpreted as a statistical model more than a merely descriptive one and relevance statistical determined (see Appendix C).

[24] The component interpretation has to be based on the correlations between the variables and the components themselves; these correlations can be obtained by direct calculation and are shown in Appendix B, Figure B1.

[25] According to our view in contrast with EG, the variable *explained strategies* plays a different role. It indicates the quick communication of the rules or strategies of the monetary policy. EG consider *explained strategies* as an indicator of the procedural transparency. In our case, it is more related to the *political transparency* if its relevance in the determination of the first component is considered (together with *quantitative targets*, *explained strategies*, *formal objectives* and *institutional arrangements*).

[26] Notice that also minutes has a relevant weight in explaining the index. *Minutes* is also related to the *policy transparency* since it refers to the publication of board minutes in reasonable times.

general terms, it can be said that the former represents information relevant to understand the effects of monetary policy and the latter information useful to interpret the central bank's strategies.

Summarizing, the first component highlights the way used by the central banks to communicate their strategies. It opposes quantitative indexes to more articulated information, which can be used to indirectly determine the central banks' strategies. The second component individuates central banks which provide quantitative data on their policy reaction function. It is related to the idea of transparency as the clear determination of the central bank's targets (goal transparency). The third component indicates the information associated with the *ex ante* analysis of the monetary policy vs. its *ex post* analysis. According to the above view, we refer to the three found components as the *strategy communication* (SC) index, *reaction parameter* (RP) index, and *timing-of-disclosure* (TD) index, respectively. Table 5 reports them.

TABLE 5

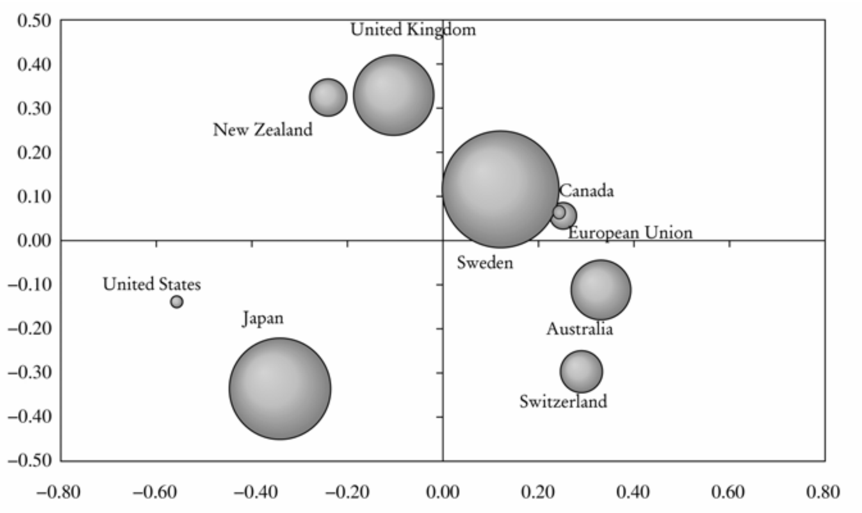
CENTERED PRINCIPAL COMPONENT ANALYSIS (INDEXES SCORES)

	SC	RP	TD
Australia	0.33	–0.11	0.02
Canada	0.25	0.06	–0.18
Euro zone	0.25	0.06	–0.16
Japan	–0.34	–0.34	0.25
New Zealand	–0.24	0.32	–0.10
Sweden	0.12	0.12	0.33
Switzerland	0.29	–0.30	–0.07
UK	–0.10	0.33	0.14
US	–0.56	–0.14	–0.24

Figure 2 describes the relationship between central banks and the first three components.

FIGURE 2

CENTRAL BANK INFORMATION
(qualitative analysis)



Legenda: the horizontal axis represent SC, the vertical axis represent RP whereas the areas of pointers are correlated with the TD.

An inspection of the above figure allows a tentative classification and interpretation of the nature of information provided by the nine central banks. By considering the first two components, there could be pointed out three groups of countries.

A) A first group is formed by all central banks scoring a positive RP index. These central banks currently (or attempt to) pursue a commitment behavior by providing information on their reaction functions. Regarding the SC index they show not extreme absolute values. New Zealand and the United Kingdom have an established tradition of inflation targeting (a strong form of commitment). By contrast, Canada and Sweden are attempting to build a reputation on a credible inflation targeting regime. This explains the relative difference in the SC index; in fact, Canada and Sweden focus their relative information on the quantitative variables. European Union can be also included in this group as it also attempts to increase its reputation in order to establish commitment regime although without a formal inflation targeting.[27]

[27] Inflation targeting regime is not the only form of commitment for a central bank.

B) Other central banks are more extreme regarding the SC index. The United States and Japan form another group. Their information disclosure appears coherent with a general propensity for discretion in the monetary policy. In fact, they show low levels of the indexes. As for the SC index, their information policy appears relatively more oriented to explaining the monetary strategies without providing the quantitative variables. However, the RP index signals that their information policy is procedural-oriented not only in relative terms but also in absolute ones, since the US Federal Reserve and the Bank of Japan provide low quantitative data on their policy reaction function.

C) The last group is formed by Australia and Switzerland. The information disclosure associated with these central banks appears somehow unbalanced. They provide relatively more information on *political transparency* than on *procedural transparency*, but are associated with poor scores in the provision of information regarding quantitative data of their policy. Hence they can be associated with a low standard of general transparency.

The above grouping of countries well-describe the relation between central banks and information disclosure focusing on the different monetary policy regime (i.e. discretionary or commitment). However, the third component (TD index) helps to point out a further dimension of the information disclosure, transversal with respect to our grouping. Countries as the United Kingdom, Sweden and Japan, which for mandatory or cultural reasons are more inclined to be involved in a more general (coordinate) setting of the economic policy, show higher values of the TD index, as result of the *ex post* evaluation of the monetary policy. It could be thought that in a centralized economic policy framework[28] an *ex post* revision of the policy measures on the basis of their effects is needed. The lack of a fiscal coordination among the European Union members seems to confirm our intuition. The European Central Bank scores low TD index, hence it provides more *ex ante* information than *ex post* as expected if coordination is not present (an analogous claim can be made for the United States).

[28] That could also involve social partners as, e.g., centralized trade unions and business organizations.

Finally, the proposed centered PCA should be evaluated with respect to the quality of the representation on the chosen factorial axis. The inspection of the total absolute contribution and of the representation quality sufficiently confirms the validity of the centered PCA (see Appendix C). With respect to the first component, it should be noticed the particular weight of the United States that contributes to explain the variance of the first component for about 37%. This is confirmed also by a visual inspection of Figure 2, in which the position of the United States appears to be rather an outlier. Anyway, the impact of the United States is not outside the usual range accepted for this kind of analysis. For the second and third component, the impact of the various countries is more evenly distributed.[29]

Although the aim of the present paper is a rather descriptive (or positive) one, given our description of *transparency universe*, we can also attempt to give some normative interpretations of our results. The second index clearly reflects the institutional framework of central banks following two different strategies: commitment and discretionary, since commitment requires information about the policy function (and credibility). The y-axis of Figure 2 clearly distinguishes the two kind of central bank.

It is useful to compare the ranking of the two largest central banks: the European Central Bank and the US Federal Reserve. These central banks are very active in promoting their transparency degree. Greesnpan (2001), for example, recalls that in the 1980s central bankers reckon that financial markets work more efficiently when effort need not be wasted to infer the stance of monetary policy. Similar statements are provided by European Central Bank staff. However, notwithstanding the efforts of their personnel, in our analysis their records are rather poor.[30] Both central banks do not provide a great

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[29] As for the representation quality, the first three components absorb a significant percentage of the variance among the countries, ranging from a minimum of 69% for Australia to a maximum of 96% for the United States. This confirms the quality of the representation assured by the first three components. The results of the PCA highly depends upon the structure of the data matrix (see Table A1 in Appendix A); a direct inspection of this dataset shows the relative low impact of certain variables, due to their uniformity of distribution among countries. For instance, *prompt announcement* plays no role, for its score is one for all the countries. Similarly, *institutional arrangements*, *quantitative targets* and *control errors* have only a minor impact for they are quite evenly distributed among countries.

[30] Because its supranational nature, the European Central Bank – as recently stressed by a CEPR report (Favero *et al.* 2000) – faces also the additional problem of a

amount of information, in particular, on their policy rule (this hardly contrasts with the Greesnpan's claim above). Both are more active to provide *ex ante* information instead of *ex post* information raising a problem of accountability. In fact, *ex ante* information might be used strategically whereas *ex post* information is more useful to evaluate the central bank policy.[31] This point seems to be particularly relevant for the European Central Bank. The two central banks only differ for the kind of information that they produce: that of the European Central Bank is more elaborated than the information coming from the Federal Reserve.

Finally, we should consider the recent experience of Japanese monetary policy. Japan is probably the worst mix of our index. No information based on rules or targeting is provided associated with a low general level of information that might be manipulated (*ex ante* information). Among other things, according to Posen (1997), Japan can be seen as an example of the dangers of a lack of monetary transparency. Monetary policy in Japan – since the structural change following the burst asset price bubble – has given the public no explicit announcement of its goals. Hence, every time the Bank of Japan has moved interest rates or left them steady, no one could tell whether the monetary-policy orientation was due to political pressure from the Ministry of Finance or financial interests, a reassessment of the growth and inflation forecasts, or an extended displacement of macroeconomic goals in pursuit of renewed financial stability. The inability of markets and businesses to guess the future stance of Japanese monetary policy not only had direct negative effects on investment and spending, this uncertain response interfered with the transmission of monetary policy in an environment where expansionary monetary policy

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tension within Europe between the desire for more integration and a reluctance to cede national political control. For example, attributing votes and opinions to members from different countries would increase the focus on national differences, and so undermine the Bank's credibility. The CEPR report considers ways to reduce this tension. First, the European Central Bank should be set an explicit inflation target by the European Parliament, so there can be no disagreement about the goal of monetary policy. Second, it recommends that the power of the executive board be increased relative to that of national central bank governors, who are more likely to be influenced by national interests. At the moment, all 11 governors can vote, outweighing the six-member executive board. Better, perhaps, if only five, say, were allowed to vote at any time, with revolving terms – like the arrangements for district-bank presidents in America's Federal Reserve System.

[31] The problem is even more serious since both central banks, as said, do not clearly explain their strategies.

could have benefited from a larger impact. This uncertainty can be a more likely explanation for the relative ineffectiveness of the Bank of Japan's interest rate cuts to stimulate the economy than appeals to a nominal interest rate floor at zero percent. Moreover, without a target there was no clear floor for inflation below which the Japanese operators could know the central bank would not allow the price-level to drop. Deflation occurred.

4. Conclusions

Although the presumption today is that – absent compelling reasons to the contrary – central banks should strive for transparency, some basic questions about *what*, *how* and *to what end* central banks should communicate with the public remain decidedly open. In the economic and political debates, the word 'transparency' is commonly used in a vague and often contradictory terms. The academic literature on transparency in monetary policy making tried to give some precision to the term 'transparency'. However, it has largely done so in the context of models, which do not allow the critical issue of how best to communicate monetary policy to be addressed in a satisfactory way or how central bank effectively communicate.

Aimed to qualify the transparency definition, in this paper we have investigated the information provided by the central bank to the public on both a quantitative and a qualitative side. We found that a simple index as that developed by EG (refined in our non centered PCA by the IS general index) performs well in synthesizing information about the general quantity of transparency. However, being the information strategic, single indexes are not sufficient to fully understand the central bank's information disclosure. Once we recognize that we are in a world where computational constraints and cognitive limits matter, more information and greater detail may in fact no longer necessarily translate into greater transparency. Hence, together with the quantity, the quality issue matters: multiple indexes are needed.

In particular, by running a qualitative analysis (namely centered PCA), we individuate three indexes that better characterize central banks' behaviour and explain some difference in the information that they produce. The use of these refined indexes allows us to disentangle aspects of central banks' behavior that can be related to the institutional framework in which they operate and to other structural characteristics of monetary policy making. By taking account of these indexes, the nine central banks considered in our study can be clustered into three groups with respect to the monetary policy regime adopted and further differentiated according to the general propensity of policy coordination due to cultural or political reasons. We show that central banks provide very different information in terms of both quantity and quality. This observation raises important theoretical and practical questions. By considering the information provided by the central bank as an endogenous choice of the same central bank, analysts should be able to develop theories that can explain the different behaviour and wandering against policy implication coming from simple representation of the real world. According to us, the empirical analysis of previous sections supports the view that information disclosure in monetary policy setting is significantly related to the overall economic and institutional environment; different attitudes towards transparency probably reflect different constraints and features of national (or economic areas) economic and policy frameworks. By considering information as the results of an institutional design, it raises the question of the optimality of the central bank design and the costs associated with different designs. The grouping of central banks highlighted in our multivariate analysis suggests that the optimal choice of transparency should be influenced by other structural political-economic characteristics in a definite way. Such remark, together with the fact that our indexes are by construction uncorrelated, suggests to use the latter in further empirical studies as panel or cross-country econometric investigations aimed to test the contrasting theoretical implications of different models.[32]

Our analysis is a step further in the recent transparency debate by highlighting the quantitative perspective from an empirical point of view. Regarding our further steps toward, we aim to investigate more in general the variability of central bank procedures regarding not only transparency but also accountability and independence in order to better understand the central bank institutional design.

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[32] See for instance Ciccarone, Di Bartolomeo and Marchetti (2004), where optimal choice of transparency degree is studied in a game-theoretic model encompassing the behaviour of wage setters and fiscal policy authorities.

APPENDIX A

DATASET AND DATA MATRICES

TABLE A1

DATASET (Eijffinger and Geraats 2002)

	Aus	Can	Eur	Jap	NZ	Swe	Swi	UK	US
Formal objectives	1	1	1	0.5	1	1	0.5	1	0.5
Quantitative targets	1	1	1	0	1	1	1	1	0
Institutional arrangements	1	1	1	1	1	1	1	1	0.5
Economic data	0.5	1	1	1	0.5	1	1	0.5	1
Policy models	0	1	1	0	1	0	0	1	1
Central bank forecasts	0.5	0.5	0.5	0.5	1	1	0.5	1	0.5
Explicit strategy	1	1	1	0	1	1	1	1	0
Minutes	0	0	0	1	1	1	0	1	1
Voting records	0	0	0	1	1	0	0	1	1
Prompt announcement	1	1	1	1	1	1	1	1	1
Policy explanation	0.5	1	0.5	0.5	1	1	1	0.5	1
Policy inclination	0	0	0	0	1	0	0	0	1
Control errors	1	1	1	0.5	1	1	0.5	1	1
Transmission disturbances	0.5	0.5	0.5	0.5	0.5	1	0	1	0
Evaluation policy outcome	0	0.5	0.5	0.5	0.5	1	0	0.5	0.5

Legenda: Aus: Australia; Can: Canada; Eur: Euro Zone; Jap: Japan; NZ: New Zealand; Swe: Sweden; Swi: Switzerland; UK: United Kingdom; US: United States.

TABLE A2

CENTERED DATA FROM TABLE A1

	Aus	Can	Eur	Jap	NZ	Swe	Swi	UK	US
Formal objectives	0.166	0.166	0.166	–0.333	0.166	0.166	–0.333	0.166	–0.333
Quantitative targets	0.222	0.222	0.222	–0.777	0.222	0.222	0.222	0.222	–0.777
Institutional arrangements	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	–0.444
Economic data	–0.333	0.166	0.166	0.166	–0.333	0.166	0.166	–0.333	0.166
Policy models	–0.555	0.444	0.444	–0.555	0.444	–0.555	–0.555	0.444	0.444
Central bank forecasts	–0.166	–0.166	–0.166	–0.166	0.333	0.333	–0.166	0.333	–0.166
Explicit strategy	0.222	0.222	0.222	–0.777	0.222	0.222	0.222	0.222	–0.777
Minutes	–0.555	–0.555	–0.555	0.444	0.444	0.444	0.555	0.444	0.444
Voting records	–0.444	–0.444	–0.444	0.555	0.555	–0.444	–0.444	0.555	0.555
Prompt announcement	0	0	0	0	0	0	0	0	0
Policy explanation	–0.277	0.222	–0.277	–0.277	0.222	0.222	0.222	–0.277	0.222
Policy inclination	–0.222	–0.222	–0.222	–0.222	0.777	–0.222	–0.222	–0.222	0.777
Control errors	0.111	0.111	0.111	–0.388	0.111	0.111	–0.388	0.111	0.111
Transmission disturbances	0	0	0	0	0	0.5	–0.5	0.5	–0.5
Evaluation policy outcome	–0.444	0.0556	0.055	0.055	0.055	0.555	–0.444	0.055	0.055

TABLE A3

SIMILARITY MATRIX (NON-CENTERED PCA)

	FO	QT	IA	ED	PM	CBF	ES	M	VR	PA	PE	PI	CE	TD	EPO
FO	0.844														
QT	0.813	0.875													
IA	0.906	0.875	1.031												
ED	0.750	0.688	0.875	0.844											
PM	0.563	0.500	0.563	0.500	0.625										
CBF	0.656	0.625	0.719	0.594	0.438	0.563									
ES	0.813	0.875	0.875	0.688	0.500	0.625	0.875								
M	0.500	0.375	0.563	0.500	0.375	0.500	0.375	0.625							
VR	0.375	0.250	0.438	0.375	0.375	0.375	0.250	0.500	0.500						
PA	0.938	0.875	1.063	0.938	0.625	0.750	0.875	0.625	0.500	1.125					
PE	0.719	0.688	0.813	0.750	0.500	0.594	0.688	0.500	0.375	0.875	0.750				
PI	0.188	0.125	0.188	0.188	0.250	0.188	0.125	0.250	0.250	0.250	0.250	0.250			
CE	0.875	0.813	0.938	0.813	0.625	0.688	0.813	0.563	0.438	1.000	0.781	0.250	0.938		
TD	0.531	0.500	0.563	0.438	0.313	0.438	0.500	0.375	0.250	0.563	0.406	0.063	0.531	0.406	
EPO	0.438	0.375	0.469	0.438	0.313	0.375	0.375	0.375	0.250	0.500	0.406	0.125	0.469	0.313	0.313

Legenda: FO: formal objectives; QT: quantitative targets; IA: institutional arrangements; ED: economic data; PM: policy models; CBF: central bank forecasts; ES: explicit strategy; M: minutes; VR: voting records; PA: prompt announcement; PE: policy explanation; PI: policy inclination; CE: control errors; TD: transmission disturbances; EPO: evaluation policy outcomes.

TABLE A4

COVARIANCE MATRIX (CENTERED PCA)

	FO	QT	IA	ED	PM	CBF	ES	M	VR	PA	PE	PI	CE	TD	EPO
FO	0.06														
QT	0.08	0.19													
IA	0.02	0.05	0.03												
ED	−0.03	−0.04	−0.01	0.06											
PM	0.04	0.01	−0.03	−0.02	0.28										
CBF	0.03	0.04	0.01	−0.03	0.02	0.06									
ES	0.08	0.19	0.05	−0.04	0.01	0.04	0.19								
M	−0.02	−0.11	−0.03	−0.02	0.03	0.08	−0.11	0.28							
VR	−0.04	−0.14	−0.04	−0.04	0.10	0.04	−0.14	0.22	0.28						
PA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00					
PE	−0.01	0.01	−0.01	0.02	0.01	0.01	0.01	0.01	−0.01	0.00	0.07				
PI	−0.02	−0.07	−0.05	−0.02	0.11	0.02	−0.07	0.11	0.14	0.00	0.06	0.19			
CE	0.04	0.04	−0.01	−0.02	0.07	0.02	0.04	0.01	−0.01	0.00	0.00	0.03	0.05		
TD	0.06	0.06	0.03	−0.03	0.00	0.06	0.06	0.06	0.00	0.00	−0.03	−0.06	0.03	0.13	
EPO	0.02	−0.01	0.00	0.02	0.04	0.04	−0.01	0.10	0.03	0.00	0.02	0.01	0.02	0.06	0.09

APPENDIX B

CENTERED PCA

The principal components in the centered PCA (the first three of which are shown in Table 4) are obtained as eigenvectors **b** of the equation: $\mathbf{X}^T \mathbf{X}\mathbf{b} = \lambda\mathbf{b}$, where $\mathbf{X}^T$ is the centered data matrix of Table A2; the resulting eigenvalues λ are shown in Table B1 (the last seven eigenevalues are all zero).

TABLE B1

EIGENVALUES OF MATRIX $\mathbf{X}^T \mathbf{X}$ AND EXPLAINED VARIANCE
(percentage and cumulative percentage)

	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8
Eigenvalues	0.827	0.466	0.317	0.145	0.14	0.05	0.012	0.009
Percentage	42.072	23.711	16.108	7.391	7.117	2.551	0.615	0.436
Cum. percent.	42.072	65.783	81.891	89.282	96.399	98.949	99.564	100

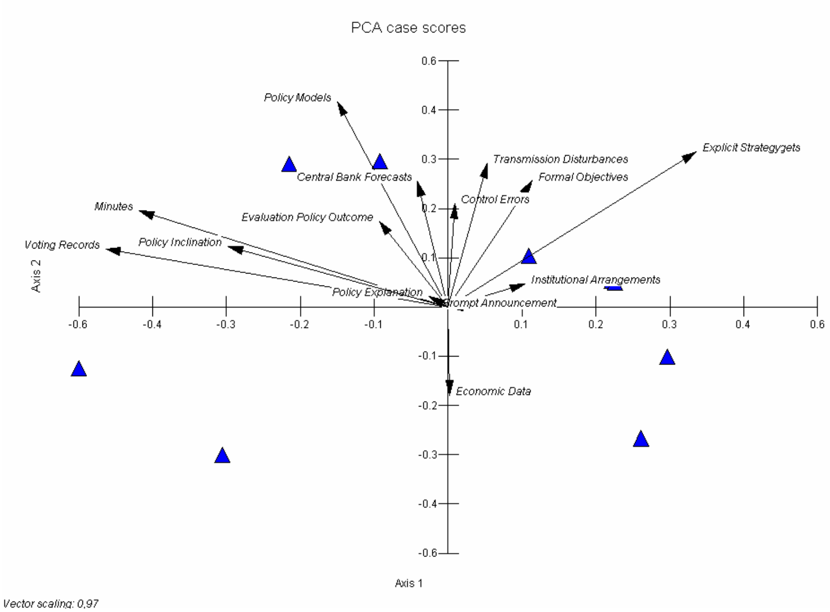
The above mentioned problem has a dual in the space of the units, i.e. $\mathbf{X}\mathbf{X}^T\mathbf{c} = \mathbf{c}\mu$, so that λ and μ are identical. An indication of the correlation between variables (columns of **X**) can be obtained by the definition of the components c in the space of the units (cfr. Lebart, Morineau and Piron 1995); the j-th element of c relative to α -th eigenvalue μ_α, i.e. c_α (j) is given by:

$$c_\alpha(j) = \frac{1}{\sqrt{\lambda_\alpha}} x'_j b_\alpha = \sum_{i=1}^{n} \frac{x_{ij} b_\alpha(i)}{\sqrt{\lambda_\alpha}} = s_j \ corr(j, b_\alpha)$$

where s_j is the standard deviation of variable j computed from Table A1. Figure B1 plots the values of c_α (j) for the two first eigenvalues (1st and 2nd components in Table B1).

FIGURE B1

NON-CENTERED PRINCIPAL COMPONENT ANALYSIS
(Euclidean biplot)



Variables which span a small angle with the first component (axis) b_1 are those more correlated with the same factorial axis, and determine the interpretation of the latter.

APPENDIX C

TOTAL CONTRIBUTIONS AND REPRESENTATION QUALITY FOR CENTERED PCA

The main instrument to control the quality of a PCA are the Total absolute contribution index (TAC) and the Representation quality (RQ). The first index is given by the formula:

$$TAC_\alpha(i) = \frac{c_\alpha(i)^2}{\sum_{i=1}^{n} c_\alpha(i)^2} = \frac{c_\alpha(i)^2}{\lambda_\alpha}$$

where $c_\alpha(i)$ is the score of country i under the α-th component. It explains how much of the variance explained by the i-th component is due to the i-th unit, so signaling potentials outliers. Table C1 shows the TAC values for the first eight non zero components.

TABLE C1

TAC VALUES FOR THE CENTERED PCA

	Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6	Axis 7	Axis 8
Australia	0.132480	0.026918	0.001817	0.081938	0.132114	0.48672	0.010083	0.016000
Canada	0.073175	0.007725	0.102208	0.006628	0.158579	0.02738	0.002083	0.484000
EU	0.076788	0.006730	0.075789	0.038793	0.201600	0.00288	0.147000	0.324000
Japan	0.140606	0.242266	0.194019	0.089628	0.021607	0.01800	0.147000	0.036000
New Zealand	0.069649	0.225270	0.030297	0.024007	0.266064	0.00242	0.261333	0.009000
Sweden	0.017704	0.028876	0.347710	0.420752	0.035000	0.02178	0.005333	0.011111
Switzerland	0.101693	0.189290	0.016353	0.032834	0.171607	0.30258	0.033333	0.040111
UK	0.012828	0.232277	0.057492	0.256890	0.000028	0.07200	0.252083	0.009000
US	0.375150	0.041461	0.174211	0.049828	0.014464	0.06962	0.147000	0.018778

The representation quality index is given by:

$$RQ_\alpha(i) = \frac{c_\alpha(i)^2}{\sum_{\alpha=1}^{p} c_\alpha(i)^2}$$

where p is the number of the significant eigenvalues λ considered in the analysis. It gives a measure for contribution of the α-th factor in the representation (or explanation) of the i-th element. The RQ values for the centered PCA are given in Table C2.

TABLE C2

RQ VALUES FOR THE CENTERED PCA

	Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6	Axis 7	Axis 8
Australia	0.616693	0.070607	0.003242	0.066875	0.10411	0.136982	0.000681	0.000811
Canada	0.482476	0.028702	0.258316	0.007662	0.177002	0.010915	0.000199	0.034729
EU	0.490993	0.024247	0.185754	0.043491	0.218219	0.001113	0.013639	0.022546
Japan	0.375475	0.364545	0.198599	0.041965	0.009768	0.002906	0.005696	0.001046
New Zealand	0.266361	0.485443	0.044412	0.016097	0.172251	0.000560	0.014502	0.000375
Sweden	0.071252	0.065485	0.536414	0.296905	0.023846	0.005300	0.000311	0.000487
Switzerland	0.378541	0.397036	0.023334	0.021430	0.108138	0.068097	0.001800	0.001625
UK	0.058602	0.597904	0.100672	0.205757	0.000022	0.019886	0.016710	0.000447
US	0.776673	0.048368	0.138249	0.018087	0.005069	0.008714	0.004416	0.000423

APPENDIX D

CENTERED PRINCIPAL COMPONENT ANALYSIS: THE STATISTICAL MODEL[1]

Principal component analysis is a descriptive tool. However, it can also be interpreted as a statistical model and, therefore, its asymptotic standard errors for covariance matrix and the percentage of explained variance can be computed.[2]

The principal component model can be written in matrix terms as:

$$\mathbf{X} = \mathbf{AB}^{\mathrm{T}} + \varepsilon$$

where $\mathbf{X} \in \Re^{nxm}$ is the matrix of observations, $\mathbf{A} \in \Re^{nxf}$ is a matrix of factor scores, $\mathbf{B} \in \Re^{nxf}$ is a matrix of factor loadings, and $\varepsilon \in \Re^{nxm}$ is a matrix of (normal distributed) residuals. In the principal component analysis model, **A** are unknown parameters (*fixed effects*) to be estimated, and so **X** is restricted to be of rank k.

Identification and parameterization of rank models is non-trivial. Let $\mathbf{L} \in \Re^{fxf}$ be a regular (invertible) matrix, then

$$\mathbf{AB}^{\mathrm{T}} = (\mathbf{AL})\,(\mathbf{L}^{-1}\,\mathbf{B}^{\mathrm{T}})$$

Thus, there is considerable freedom to transform ('rotate') **A** and **B** into a standardized format. We use an identifying restriction that **B** is row-wise orthogonal, i.e., the columns of **B** have norm 1, and are uncorrelated with each other.

Principal component analysis are computed as maximum-likelihood estimators based on the assumption that the ε_{ij} are independently and identically normal distributed with a common variance σ (see Anderson 1963). Estimates may be sensitive to violations of the normality assumption and, therefore, asymptotic results should be interpreted cautiously. Results of principal component analysis are reported in the following tables. Prompt announcement has been removed since its variability in the sample is zero.

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[1] Principal components are computed by using STATA with a freeware ado-file written by Jeroen Weesie (Department of Sociology, Utrecht University) and MVSP of Kovach Computers.

[2] See Anderson (1963) and Tyler (1981).

TABLE D1

PRINCIPAL COMPONENTS OF COVARIANCE MATRIX

Components	1	2	3	4	5	6	7	8
Eigenvalues	0.827	0.466	0.317	0.145	0.140	0.050	0.012	0.009
% of var. explained	0.421	0.237	0.161	0.074	0.071	0.026	0.006	0.004
Cum. % of var. explained	0.421	0.658	0.819	0.893	0.964	0.990	0.996	1.000
Standard errors	0.130	0.098	0.060	0.041	0.015	0.004	0.002	0.000
Number of observations 14, number of factors 4 (ρ= 0.893%, standard error 0.041)								

Notice that components from 9 to 14 are ruled out since the first 8 components explain about the 100% of the variance. Standard errors are based on multivariate normality.

TABLE D2.A

FIRST COMPONENT (detail)

	coefficient	std. err.	Z	P>|z|	95% confidence interval	
Formal objectives	0.130	0.172	–0.755	0.451	–0.467	0.207
Quantitative targets	0.384	0.212	–1.810	0.070	–0.799	0.032
Institutional arrangements	0.119	0.065	–1.821	0.069	–0.247	0.009
Economic data	0.003	0.148	–0.017	0.986	–0.294	0.288
Policy models	0.172	0.348	0.494	0.621	–0.510	0.854
Central bank forecasts	0.047	0.185	0.256	0.798	–0.315	0.409
Explicit strategy	–0.384	0.212	–1.810	0.070	–0.799	0.032
Minutes	0.479	0.195	2.451	0.014	0.096	0.861
Voting records	0.530	0.115	4.628	0.000	0.306	0.755
Prompt announcement	0.030	0.119	0.248	0.804	–0.204	0.263
Policy explanation	0.341	0.174	1.953	0.051	–0.001	0.682
Policy inclination	0.011	0.152	–0.071	0.943	–0.308	0.286
Control errors	–0.061	0.244	–0.249	0.803	–0.540	0.418
Transmission disturbances	0.107	0.166	0.645	0.519	–0.218	0.431
Evaluation policy outcome	–0.130	0.172	–0.755	0.451	–0.467	0.207

TABLE D2.B

SECOND COMPONENT (detail)

	coefficient	std. err.	z	P>|z|	95% confidence interval	
Formal objectives	0.293	0.094	3.103	0.002	0.108	0.478
Quantitative targets	0.360	0.232	1.551	0.121	–0.095	0.816
Institutional arrangements	0.053	0.142	0.371	0.710	–0.226	0.332
Economic data	–0.205	0.144	–1.425	0.154	–0.487	0.077
Policy models	0.477	0.534	0.893	0.372	–0.570	1.525
Central bank forecasts	0.291	0.188	1.549	0.121	–0.077	0.660
Explicit strategy	0.360	0.232	1.551	0.121	–0.095	0.816
Minutes	0.223	0.461	0.483	0.629	–0.681	1.126
Voting records	0.135	0.334	0.403	0.687	–0.520	0.790
Prompt announcement	0.024	0.210	0.113	0.910	–0.388	0.436
Policy explanation	0.140	0.400	0.349	0.727	–0.645	0.925
Policy inclination	0.240	0.115	2.092	0.036	0.015	0.465
Control errors	0.334	0.378	0.884	0.377	–0.407	1.076
Transmission disturbances	0.199	0.245	0.812	0.417	–0.281	0.680
Evaluation policy outcome	0.293	0.094	3.103	0.002	0.108	0.478

TABLE D2.C

THIRD COMPONENT (detail)

	coefficient	std. err.	z	P>|z|	95% confidence interval	
Formal objectives	0.033	0.263	0.124	0.901	–0.484	0.549
Quantitative targets	–0.015	0.352	–0.042	0.967	–0.704	0.675
Institutional arrangements	0.131	0.095	1.381	0.167	–0.055	0.318
Economic data	–0.034	0.276	–0.124	0.901	–0.575	0.507
Policy models	–0.594	0.457	–1.300	0.194	–1.490	0.302
Central bank forecasts	0.206	0.265	0.777	0.437	–0.314	0.726
Explicit strategy	–0.015	0.352	–0.042	0.967	–0.704	0.675
Minutes	0.427	0.265	1.611	0.107	–0.093	0.946
Voting records	0.057	0.289	0.196	0.845	–0.510	0.623
Prompt announcement	–0.141	0.261	–0.540	0.589	–0.653	0.371
Policy explanation	–0.372	0.273	–1.361	0.174	–0.907	0.164
Policy inclination	–0.098	0.230	–0.427	0.669	0.550	0.353
Control errors	0.432	0.306	1.411	0.158	–0.168	1.032
Transmission disturbances	0.212	0.291	0.727	0.467	–0.359	0.783
Evaluation policy outcome	0.033	0.263	0.124	0.901	–0.484	0.549

TABLE D2.D

FOURTH COMPONENT (detail)

	coefficient	std. err.	z	P>|z|	95% confidence interval	
Formal objectives	–0.049	0.633	–0.077	0.938	–1.290	1.192
Quantitative targets	0.071	2.223	0.032	0.975	–4.287	4.428
Institutional arrangements	–0.104	0.512	–0.203	0.839	–1.108	0.900
Economic data	0.296	3.674	0.081	0.936	–6.905	7.498
Policy models	–0.225	3.712	–0.061	0.952	–7.499	7.050
Central bank forecasts	0.137	1.397	0.098	0.922	–2.600	2.875
Explicit strategy	0.071	2.223	0.032	0.975	–4.287	4.428
Minutes	0.204	0.600	0.340	0.734	–0.972	1.380
Voting records	–0.397	2.118	–0.188	0.851	–4.548	3.753
Prompt announcement	0.598	0.953	0.627	0.530	1.270	2.466
Policy explanation	0.351	3.296	0.106	0.915	–6.109	6.811
Policy inclination	0.055	1.134	0.049	0.961	–2.167	2.277
Control errors	–0.122	1.993	–0.061	0.951	–4.028	3.783
Transmission disturbances	0.349	4.011	0.087	0.931	–7.512	8.211
Evaluation policy outcome	–0.049	0.633	–0.077	0.938	–1.290	1.192

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