Which Aspects of Central Bank Transparency Matter? A Comprehensive Analysis of the Effect of Transparency on Survey Forecasts*

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We investigate whether a higher level of central bank transparency can reduce the degree of disagreement across individual forecasters, and whether it can improve the forecasting performance of survey respondents. The analysis is carried out on a panel data set that is richer than those used by previous studies. This unique data set allows us to test both for causality and for misspecification. Moreover, it allows us to identify the effects of various aspects of transparency separately and to assign weights to them reflecting their relative importance in reducing uncertainty. Finally, we construct a new composite measure of transparency using the estimated weights.

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1. Introduction

There is no consensus in the literature with regard to how the degree of central bank transparency influences the level of uncertainty in the economy and thereby the economic performance of a country. In

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this paper we contribute to the literature by investigating empirically whether higher transparency can reduce the uncertainty regarding both future monetary policy and future macroeconomic outcomes. In addition, we analyze what aspects of transparency are important (if any).

A number of empirical and theoretical studies claim that central bank transparency has a *favorable* effect on the economy. These studies are Chortareas, Stasavage, and Sterne (2002), Crowe and Meade (2008), Demertzis and Hughes Hallett (2007), Dincer and Eichengreen (2010, 2014), Ehrmann, Eijffinger, and Fratzscher (2012), Middeldorp (2011), and Swanson (2004), inter alia. Some other papers, however, come to a different conclusion. The papers of van der Cruijsen, Eijffinger, and Hoogduin (2010), Dale, Orphanides, and Österholm (2011), Demertzis and Hoeberichts (2007), Kool, Middeldorp, and Rosenkranz (2011), Morris and Shin (2002), Neuenkirch (2013), and Walsh (2007) find either that higher transparency is *unfavorable* or that it has an *ambiguous* effect on mitigating the uncertainty.

This paper finds central bank transparency to have a mostly *favorable* effect on the economy, as it mitigates uncertainty. Our strategy to identify the relationship between transparency and uncertainty is the following. We run panel regressions where the dependent variable is a proxy for uncertainty (it measures the quality of survey forecasts on a number of economic indicators), while the independent variable is the most commonly used measure on central bank transparency developed by Eijffinger and Geraats (2006).[1] More precisely, our independent variable is the composite Eijffinger-Geraats index, one of its five sub-indices, or one of its fifteen components.

We use a *unique panel data set* that is richer in both of its dimensions than any of those used by previous panel analyses in the literature.[2] The number of countries in our data set is twenty-six, and

[1]The Eijffinger-Geraats index is used, for example, by the empirical works of Csavas et al. (2011), Demertzis and Huges Hallett (2007), Dincer and Eichengreen (2007), Ehrmann, Eijffinger, and Fratzscher (2012), Middeldorp (2011), Siklos (2011), and van der Cruijsen, Eijffinger, and Hoogduin (2010).

[2]The panel analyses of Middeldorp (2011) and Neuenkirch (2013) cover almost as many countries as ours. Their panel data set includes twenty-four and twenty-five economies, respectively.

the sample covers the period between October 1989 and December 2009. The most remarkable feature of our data is that there is *high enough variation* in almost all measurable aspects of transparency to identify their effects on the quality of forecasts. Previous papers were unable to study the effects of each of the fifteen components of the Eijffinger-Geraats index due to insufficient variation in their data.

It is also a unique feature of our data that allows us to test for causality by the Granger causality test. When testing for causality, it is crucial to know the exact timing of changes in transparency; otherwise, we do not know whether a reform in transparency is preceded or followed by a change in the quality of forecasts. Unfortunately, the original Eijffinger-Geraats index has a lower frequency than the monthly survey forecasts. Most likely, it is the difference between the frequencies that prevented previous studies from testing for causality. We circumvent the problem by harmonizing the data frequencies, i.e., we construct the monthly time series of the Eijffinger-Geraats index and sub-indices by collecting information on the timing of reforms in transparency for a subset of countries in our sample. The results of the causality tests obtained on this sub-sample of countries with monthly frequency are mixed: one-way causality is supported only by one-quarter of all the investigated specifications. However, more than two-thirds of these specifications suggest that higher transparency causes better forecasts.

Our strategy to identify the effect of central bank transparency is similar to that of the most comprehensive empirical analysis on the subject in Ehrmann, Eijffinger, and Fratzscher (2012). They also identify the relationship between transparency and uncertainty by running panel regressions. Their dependent variable also measures the quality of survey forecasts on a number of economic indicators, and their independent variable is either (i) the composite Eijffinger-Geraats index or (ii) the economic sub-index of the Eijffinger-Geraats index, or it captures (iii) whether a central bank announces a quantified inflation objective or (iv) whether a central bank publishes its internal forecasts for inflation and output. However, we deviate from their approach in some important respects.

First, the aim of this paper is not only to shed light on the effects of some selected measures of transparency, but also to analyze the *effects of each measurable dimension of transparency separately.*

Therefore, we also run regressions on those specifications where transparency is measured by the components of the Eijffinger-Geraats index.

Second, our purpose with this detailed analysis is to help central bankers decide what specific aspects of transparency should be improved. To do that, we have to test whether a higher degree of transparency can cause lower uncertainty. We think that *testing causality* is crucial from a normative perspective.[3]

Third, we proxy uncertainty not only by a measure on the dispersion of views of the individual forecasters but also by the absolute forecast error. The motivation for that is provided also by the working paper by Ehrmann, Eijffinger, and Fratzscher (2010), in which they write: “It is also important to test how forecast accuracy is affected, as we need to ensure that transparent and communicative central banks do not align forecasts at *lower* levels of accuracy.” This paper points out that their parameter estimates regarding the effect of transparency on forecast accuracy are biased, unfortunately.

Our fourth contribution relates to learning the magnitude of the *bias* and also to *eliminating* it. Here, the idea is to estimate the model not only on those variables whose forecasts are hypothesized to be influenced by central bank transparency, but also on oil price, which is exogenous to monetary policy.[4] When working with the model and data frequency used by Ehrmann, Eijffinger, and Fratzscher (2010), we detect *misspecification* by finding a significant relationship between some measures of transparency and oil price forecast errors. However, when working with a modified version of the Ehrmann, Eijffinger, and Fratzscher (2010) model and data with different frequency, the oil price predictions seem to be independent of transparency, as is in line with our intuition. In addition to the oil price regressions, econometric theory also underpins that both the parameter estimates and the estimated standard errors are biased when following the methodology of Ehrmann, Eijffinger, and Fratzscher (2010) or Ehrmann, Eijffinger,

[3]Ehrmann, Eijffinger, and Fratzscher (2012) do not test whether the relationship between transparency and uncertainty is causal.

[4]Whether oil price is unaffected by monetary policy in general, and especially by monetary policies of large economies such as the United States or China, is not obvious. The test of Kilian and Vega (2011), however, underpins oil price exogeneity.

and Fratzscher (2012), while neither of these problems arises with our methodology.

The composite Eijffinger-Geraats index is criticized for being an *equally weighted* sum of its components.[5] Even Eijffinger and Geraats (2006) share the view that the weights of the components of the composite index should be established empirically. To the best of our knowledge, this paper is the first that fills the gap by *constructing a weighted index of central bank transparency*. The index we propose aggregates the same fifteen components as the composite Eijffinger-Geraats index. The weights we assign to the components are estimated and reflect the relative importance of the components in reducing uncertainty. Our purpose with publishing the weights and the weighted composite transparency index is to give central bankers guidance about which types of transparency have worked best so far. We find that the best practice of central banking involves (i) preparing and publishing own forecasts, (ii) providing an explicit policy rule or strategy that describes the monetary policy framework, and (iii) promptly announcing policy decisions.

The rest of the paper is structured as follows. Section 2 presents our benchmark econometric model. Section 3 describes our data set. Section 4 presents the results obtained with the benchmark model. It also presents a number of robustness checks and the Granger causality tests. Finally, it introduces the weighted transparency index. The conclusions are presented in section 5.

2. Benchmark Regression Model

This section describes our benchmark model, which is a modified version of the Ehrmann, Eijffinger, and Fratzscher (2012) model.[6] The model is given by

[5]For instance, Claussen (2008) argues that the Eijffinger-Geraats index can be misleading, because its crude scores blow up the difference between countries, and the equal weighting does not take into account that some aspects are more important for transparency than others.

[6]The main difference between our model and that of Ehrmann, Eijffinger, and Fratzscher (2012) is that the former is static, while the latter is a dynamic one. Our motivation to deviate from the approach of Ehrmann, Eijffinger, and Fratzscher (2012) is discussed in section 4.1.

$$y_{i,t} = \beta x_{i,t} + \alpha_i + \gamma_1 \sigma_{i,t} + \gamma_2 \left|\Delta \text{oil}_{t-1}\right| + \epsilon_{i,t}, \qquad (1)$$

where $y_{i,t}$ denotes the dependent variable characterizing the forecasts in country i at time t. More precisely, it measures the quality of forecasts either by the degree of disagreement across individual forecasters or by the forecast accuracy. The measure on central bank transparency in country i at time t is denoted by $x_{i,t}$. To be more specific, $x_{i,t}$ can be the composite transparency index, one of its five sub-indices, or one of its fifteen components.

The main parameter of our interest is β. Our hypothesis is $\beta < 0$, i.e., forecasters disagree less and make smaller forecast errors if the central bank is more transparent. The only forecasted variable where the hypothesis is different from the above is the oil price. As the oil price is considered to be exogenous to monetary policy, the corresponding hypothesis is $\beta = 0$.

We control for country fixed effects by α_i. *The country fixed effect* captures some unobserved country-specific characteristics, such as how difficult it is in general to predict some country-specific economic indicators, and also what is the overall level of skills of the forecasters in the country.

In addition to the country fixed effects, we include the conditional volatility of the variable to be forecasted $\sigma_{i,t}$,[7] and the absolute change in oil price in the previous period $|\Delta\text{oil}_{t-1}|$. We expect that the higher the volatility of the economic indicator to be forecasted, the higher the degree of disagreement and the less precise the forecasts ($\gamma_1 > 0$). Finally, larger absolute changes in oil price are likely to be associated with higher general uncertainty in the oil-dependent globalized world economy that may increase both the degree of disagreement and the forecast errors ($\gamma_2 > 0$).

We estimate model (1) in *levels,* as we find evidence for a unit root neither in the processes of the sub-indices and the composite Eijffinger-Geraats transparency index, nor in the processes of almost all the dependent variables.[8] All the regressions are estimated by the *least square dummy variable* (LSDV) estimator. Standard errors are calculated by the White cross-section method that is designed to accommodate arbitrary heteroskedasticity.

[7]Section 3.3 discusses in detail how the conditional volatility is measured.

[8]See Csavas et al. (2012) for the details of the unit-root tests.

3. Data

In our empirical exercise, we use data on the transparency index, survey forecasts on various macro variables, and historical data of the same set of variables. This section provides a detailed description of these data.

Our data cover twenty-six countries. Twelve of them are advanced economies. These countries are Canada, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States. In addition to the developed countries, our sample covers also fourteen European emerging countries: Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Slovakia, Slovenia, Turkey, and Ukraine.

Our panel data comprises 243 periods from the monthly sample between October 1989 and December 2009. However, the benchmark estimates are carried out on a sample restricted in two ways. First, it consists of forecasts with *non-overlapping forecast horizons*, i.e., if the forecast horizon is M months, then we sample every Mth observation from the monthly data. Second, the estimates are obtained on a *shorter period* that spans between January 1998 and December 2009. The cost of avoiding overlapping forecast horizons and working with a short sample period is that the time dimension of our sample reduces substantially. Later, we argue in favor of estimating the model on the restricted sample and present the relevant sensitivity analyses.

3.1 Data on Central Bank Transparency

Although the concept of central bank transparency is rather complex, there is a forming agreement on its definition. Still, it is difficult to find reasonable quantitative measures for it. In the literature, the most commonly used transparency measure is the one constructed by Eijffinger and Geraats (2006). Others, such as Minegishi and Cournède (2009), propose alternative measures. We opt to use the Eijffinger-Geraats index for most of our analyses and the Minegishi-Cournède index for a robustness check. The main advantage of the Eijffinger-Geraats index is that it has the broadest coverage of countries and periods due to the work by Dincer and Eichengreen (2007) and Siklos (2011), who have expanded and updated the original sample of Eijffinger and Geraats (2006). We use the latest update of the Eijffinger-Geraats index by Siklos (2011) with some minor modifications.[9]

The *sample* of the latest update of the transparency index spans between 1998 and 2009. Therefore, our benchmark estimates are carried out on this sample period. However, in some instances, we work with a sample *lengthened* by the period between 1989 and 1997 for which survey forecasts are available. Ehrmann, Eijffinger, and Fratzscher (2012) also lengthen their sample by a period preceding 1998 to enrich the data used in their benchmark estimation. They apply the 1998 values of the indices for a given country to all years prior to 1998. As we could not find convincing evidence for no progress in transparency in the investigated countries before 1998,[10] and our sample is rich enough even without this way of producing extra observations, we start our sample in 1998 in the benchmark estimation. But we present estimates on the longer sample, generated the same way as Ehrmann, Eijffinger, and Fratzscher (2012) do, as part of the robustness checks.

The data frequency of the Eijffinger-Geraats transparency index is annual, while the survey forecasts are on monthly frequency. We harmonize the data frequencies in two different ways. First, we transform the data on transparency into monthly by assigning the annual value to each of the twelve months in the given year. Almost all the analyses in this paper are carried out on data harmonized in this way. Second, we construct the monthly time series of the Eijffinger-Geraats index and sub-indices for a selected group of countries by

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[9] The Czech National Bank and the Central Bank of Hungary have been publishing individual voting records since 2008 and 2005, respectively. As these developments in transparency are not captured by the updated index by Siklos (2011), we make the following corrections. We change the score of the 3C component from 0.5 to 1 for both countries for the relevant periods. Furthermore, Slovakia introduced the euro in January 2009, and therefore we assign the values of the transparency indices of the European Central Bank to Slovakia since then.

[10] The reforms in the Sveriges Riksbank are counterexamples for having no progress in transparency before 1998. The Swedish central bank started announcing its inflation target in 1993 and started publishing inflation forecasts in 1995. Some further changes in transparency in nine central banks between 1989 and 2003 are collected by van der Cruijsen and Demertzis (2005) in their appendix B2.

collecting information on the timing of reforms in transparency. We use this method of frequency harmonization only for the Granger causality test, where it is crucial to learn the exact timing of changes in transparency.

The Eijffinger-Geraats index measures five distinct dimensions of transparency in the policymaking process. The first dimension, *political transparency*, concerns the central bank's openness about its policy objectives—in particular, whether it announces quantitative targets, formal goals, and the priority of these goals. The institutional arrangements, such as central bank independence and codification of roles and responsibilities of the central bank, are also vital elements of the political dimension of transparency. The second dimension, *economic transparency*, refers to the central bank's willingness to release information relevant for monetary policy, including economic data, forecasts, and policy models. Sharing this information with the public allows independent, external assessment of monetary policy decisions. The third dimension, *procedural transparency*, gauges how monetary policy decisions are made and whether an explicit policy rule or strategy is provided that the decision makers follow. This dimension indicates also whether the central bank publishes minutes and voting records that document how its policymaking committee arrives at its decisions. The fourth dimension, *policy transparency*, is about the timely communication of the policy decisions, whether decisions are announced promptly following the committee meetings, whether the public is provided with a detailed explanation underlying the decisions, and finally, whether these explanations include signals of policy inclination or explicit indication of likely future policy actions. The last distinct dimension, *operational transparency*, focuses on the implementation of monetary policy—in particular, the degree of control over the main operating instrument, whether the central bank publishes its forecast errors made in the past, and whether it assesses the attainment of its targets with the contribution of monetary policy in that achievement.

All five dimensions have three components. Out of the fifteen components, six score either 0 or 1, while nine of them score either 0, 1/2, or 1. A higher score corresponds to a higher level of transparency. The composite index, or total index, is calculated as the sum of the sub-indices. Accordingly, the total Eijffinger-Geraats index can have a minimum value of 0 and a maximum value of 15. The scoring system is summarized by the left panel of table 1.

The main advantage of our rich panel data is that the transparency indices exhibit substantial variation. When comparing the *variation in the transparency index* in all twenty-six countries in our data with that in the twelve advanced countries examined also by Ehrmann, Eijffinger, and Fratzscher (2012), we see that the emerging countries contribute to the variance of the total transparency index twice as much as the advanced countries do (680 percent/334 percent; see the right panel of table 1). And also, most of the sub-indices and components are more dispersed in the sample of twenty-six countries than in that of the twelve advanced economies. The excess variation that we gain by enlarging the sample with the emerging countries enables us to estimate the effect of each of the sub-indices on the quality of forecasts. Moreover, it also allows us to assess the optimal weighting of the fifteen components and to aggregate them to an economically meaningful composite index.

A further feature of our panel data is that the cross-sectional variance of transparency is much larger than the time-series variance. This suggests that empirical identification of any relationship between transparency and quality of forecasts comes mainly from the heterogeneity of the countries and marginally from the dynamics over time.

3.2 Data on Dependent Variables

The dependent variable in equation (1) measures either the degree of disagreement across individual forecasters or the forecast accuracy. For the former, we exclusively use the survey data of Consensus Economics. For the latter, we use historical data of the forecasted economic indicator in addition to the forecasts.

Consensus Economics surveys a large group of professional forecasters. It reports the arithmetic average and the standard deviation of the individual forecasts. The former is called the consensus forecast. We measure the *forecast accuracy by the absolute forecast error* of the consensus forecast, while the *degree of disagreement* is measured by the *standard deviation of the individual forecasts,* as these statistics are readily available to us.

Table 1. Scoring System of the Eijffinger-Geraats Transparency Measures and the Variance of the Components, Sub-Indices, and Total Eijffinger-Geraats Index by Country Groups (sample: Jan. 1998–Dec. 2009, 26 countries)

	Theoretical Scores			Sample Variance		
				Country Groups		
	Min.	Intermediate Value of Components	Max.	12 Advanced	14 Emerging	All 26
1A. Formal Objectives	0	1/2	1	6%	4%	5%
1B. Quantitative Targets	0		1	16%	21%	19%
1C. Institutional Arrangements	0	1/2	1	3%	5%	4%
1. Political Transparency	0		3	50%	46%	48%
2A. Economic Data	0	1/2	1	4%	9%	14%
2B. Policy Models	0		1	23%	16%	24%
2C. Central Bank Forecast	0	1/2	1	12%	16%	18%
2. Economic Transparency	0		3	55%	66%	108%
3A. Explicit Strategy	0		1	14%	21%	18%
3B. Minutes	0		1	22%	10%	17%
3C. Voting Records	0	1/2	1	21%	5%	14%
3. Procedural Transparency	0		3	53%	58%	64%
4A. Prompt Announcement	0		1	0%	25%	19%
4B. Policy Explanation	0	1/2	1	6%	10%	15%
4C. Policy Inclination	0		1	11%	0%	6%
4. Policy Transparency	0		3	22%	61%	75%
5A. Control Errors	0	1/2	1	3%	8%	22%
5B. Transmission Disturbances	0	1/2	1	8%	6%	8%
5C. Evaluation of Policy Outcomes	0	1/2	1	4%	6%	5%
5. Operational Transparency	0		3	21%	29%	53%
Total Index	0		15	334%	680%	966%

The list of economic indicators that are forecast consists of the three-month interest rates (in percent),[11] ten-year government bond yields (in percent), the consumer price index (CPI, percent change per annum), the growth rate of real gross domestic product (GDP, percent change per annum), the consumption growth (percent change per annum), and the oil price (WTI price in U.S. dollars).

We apply the following simple *transformation* to the oil price forecasts. We transform the forecasts and their standard deviations into percentage changes relative to the nominal oil price on the survey day. Without this transformation the uncertainty of oil price forecasts are not directly comparable across periods with substantially different nominal spot oil prices.

The *sample* of survey forecasts spans between October 1989 and December 2009, but the time series are shorter for some countries in our unbalanced panel.[12] Both the interest rates and the oil price are forecasted for fixed horizons of three months and twelve months, while all the other variables are forecasted for the end of the current year and the end of the following year.

The *frequency* of the survey data is monthly, except for the emerging countries prior to June 2007, when it is only bimonthly. For our benchmark estimates, we use only a sub-sample of the available survey data with lower than monthly frequency in order to avoid having overlapping forecast horizons. For instance, we sample every third observation from the three-month forecasts, every twelfth observation from the twelve-month forecasts and end-of-year forecasts, and every twenty-fourth observation from the end-of-next-year forecasts. These non-overlapping samples usually start with the forecast round in January 1998 in the benchmark case.[13]

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[11] The forecasted short rate is the overnight interbank interest rate for Turkey, while it is the three-month rate for all the other countries.

[12] The sample period of most of the advanced countries spans between October 1989 and April 2009 and covers 235 forecast rounds. The exceptions are the Netherlands, Spain, and Sweden, whose sample starts in January 1995, and Norway and Switzerland, whose sample starts in June 1998. The sample period for most of the emerging countries spans between January 2003 and December 2009 and covers fifty-eight forecast rounds. The exceptions are Bulgaria, Croatia, Estonia, Latvia, Lithuania, and Slovenia, whose sample starts in May 2007.

[13] The only exception is the case of the end-of-next-year forecasts, where we start the non-overlapping sample with the forecast round in January 1999 in order to maximize the sample size.

In order to assess forecast accuracy, we need *historical data* of the forecasted economic indicators. These data are mainly from the OECD's Main Economic Indicators database. For some non-OECD countries (Bulgaria, Croatia, Latvia, Lithuania, Romania) the historical data are from the European Commission's annual macroeconomic (AMECO) database. We also use the International Monetary Fund's International Financial Statistics (IFS) database to cross-check the data, and expand the time series where possible. Short-term and long-term interest rates are from Bloomberg. The data source of the oil price is Thomson Reuters Datastream.

3.3 Data on Control Variables

In order to judge how transparency affects the quality of forecasts, we control for the overall difficulty of forecasting. The control variables are the absolute change in oil price in the previous month $|\Delta \text{oil}_{t-1}|$ and the conditional volatility of the forecasted variable $\sigma_{i,t}$ in addition to the fixed effects.

The *conditional volatility* is constructed by following the approach of Capistran and Timmermann (2009) and Ehrmann, Eijffinger, and Fratzscher (2012), i.e., by estimating GARCH(1,1) models for the time series of each economic indicator separately. We include the first and the second lags of the variable in question into the mean equation. This way we handle the persistency of the time series. For estimating the conditional volatility of time t, we use not only those data that are available at time t, but also historical data from the period between 1980 and 2009. As the frequency of most of the historical data is annual, so is that of the estimated conditional volatility. The exceptions are the interest rates and oil price changes, where the frequency is monthly.

4. Empirical Analysis

In this section, we estimate the benchmark model and some alternatives of it. The alternative estimates serve to (i) check the robustness of the benchmark results, (ii) test whether the estimated relationship between transparency and quality of forecasts is causal, and (iii) construct the weighted transparency index.

4.1 Estimation Results with the Benchmark Model

This section presents and interprets the results of 144 regressions run on twenty-four distinct dependent variables by using one of the six transparency indices as an explanatory variable. As a reminder, the six transparency indices are the five sub-indices together with the total Eijffinger-Geraats index. There are twenty-four different dependent variables: six economic variables are forecasted for two different horizons each, and the forecasts are characterized either by their dispersion or by their accuracy.

Tables 11 and 12 in the appendix report the regression results for the dispersion of forecasts and the forecast accuracy as the dependent variable, respectively.[14] In order to help the reader process the tremendously large amount of information presented in these tables, we summarize the results on the main parameter of our interest, β, in table 2. This table shows the sign and significance of the estimated coefficient capturing the effect of transparency.

We start the interpretation with the results of the *oil price regressions*. It is important to see that we estimate the oil price regressions with a completely *different motivation* than the other regressions with macro variables. We do not think that central bank transparency should affect oil price forecasts by any means, as oil price is exogenous to monetary policy. However, its exogeneity helps us detect if the model is *misspecified* or the *estimation method is not adequate* for the given model. The results of the oil price regressions are presented in the last two rows of table 2. With the exception of one marginally significant coefficient estimates, our hypothesis of $\beta = 0$ cannot be rejected.[15] Therefore, model (1) with the applied estimation method (LSDV) is likely to be adequate to investigate the relationships between different aspects of central bank transparency and macro forecasts.

[14]Most of the estimates reported in tables 11 and 12 support our hypotheses with secondary importance. These hypotheses are (i) the positive relationship between the volatility of the variable to be forecasted and the dependent variable ($\gamma_1 > 0$) and (ii) the positive relationship between the absolute changes in oil price and the dependent variable ($\gamma_2 > 0$).

[15]We obtain qualitatively the same result if we start the non-overlapping subsample with the forecast round in any month other than January. That is, the coefficient of the transparency measure is significant only in a few specifications of the oil price regressions.

Table 2. Sign and Significance of the Estimated Effect of Transparency on the Quality of Forecasts: Summary of 144 Regressions with Different Specifications of the Benchmark Model (1)
(sample: Jan. 1998–Dec. 2009, 26 countries, non-overlapping forecast horizons)

Transparency Index →	Political		Economic		Procedural		Policy		Operational		Total	
	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE
Short Rate - 3M	− − −	−		− − −					− −	− −		− − −
Short Rate - 1Y	−		−								−	
Long Rate - 3M					+++							
Long Rate - 1Y			− −	−								
CPI - CY			− −	−							− −	
CPI - NY		++	− − −				− − −			++	− − −	
GDP - CY	−		− −	− − −								
GDP - NY	−		− − −							− −		
Consumption - CY				− −		− −						− − −
Consumption - NY		− −						−	+	− − −		
Oil - 3M												
Oil - 1Y					+							

Notes: This table reports the sign and significance of the estimated β parameter for different model specifications. Each row corresponds to a set of specifications where the forecasted variable and the forecast horizon are identical. The forecast horizons are abbreviated as follows: 3M = 3 month, 1Y = 1 year, CY = current year, NY = next year. Each column corresponds to a set of specifications where the transparency is captured by the same index or sub-index and the forecast is characterized either by the absolute forecast error of the consensus forecast (ABSFE) or by the standard deviation of the individual forecasts (STDEV). −, − −, and − − − indicate negative estimates at the 10 percent, 5 percent, and 1 percent significance levels, respectively. +, ++, and +++ indicate positive estimates at the 10 percent, 5 percent, and 1 percent significance levels, respectively. Empty cells correspond to insignificant estimates.

In contrast to our benchmark estimates obtained with our static model (1) on non-overlapping observations, the benchmark estimates of Ehrmann, Eijffinger, and Fratzscher (2010) and Ehrmann, Eijffinger, and Fratzscher (2012) obtained with their dynamic model on forecasts with overlapping forecast horizons are biased. We can even detect the bias empirically by the oil price regressions when the quality of forecasts is measured by the forecast accuracy. See table 3, which summarizes the results on the main parameter of our interest, β.[16]

The *theoretical reason for the presence of bias* is that their model is a dynamic model with country fixed effects and the LSDV estimator provides consistent but biased estimates in this case (see Judson and Owen 1997). In addition, if the forecast horizons of the consecutive monthly observations are overlapping, as in Ehrmann, Eijffinger, and Fratzscher (2010) and also in Ehrmann, Eijffinger, and Fratzscher (2012),[17] then the error term $\epsilon_{i,t}$ becomes autocorrelated and it results in biased standard error estimates and invalidates the standard t-test (see Hansen and Hodrick 1980; Harri and Brorsen 2009).[18]

Both of the above issues and the empirical evidence on the presence of bias support our strategy to deviate from the approach of Ehrmann, Eijffinger, and Fratzscher (2010) and Ehrmann, Eijffinger, and Fratzscher (2012) by estimating a static model on non-overlapping observations.[19]

[16]The details of the regression results can be found in the upper part of tables 26 and 27 in Csavas et al. (2012).

[17]The benchmark estimates of Ehrmann, Eijffinger, and Fratzscher (2012) are obtained in the very same way as those of Ehrmann, Eijffinger, and Fratzscher (2010), with the minor difference that fiscal transparency is also controlled for in the former. Obviously, this difference does not correct for the bias in the parameter estimates and in the standard error estimates. Another difference between Ehrmann, Eijffinger, and Fratzscher (2012) and Ehrmann, Eijffinger, and Fratzscher (2010) is that the former does not report estimates for the forecast accuracy, only for the dispersion of forecasts. Their results with the dispersion of forecasts are more reliable, as we find evidence for the presence of bias by the oil price regressions only when the dependent variable is the forecast accuracy.

[18]Csavas et al. (2012) mistakenly attributed biased parameter estimates to the overlapping nature of the data, while only bias in standard error estimates should be attributed to it.

[19]In the static model we do not control for potential persistency in the dependent variable. However, it is not necessary, because the coefficient of the lagged dependent variable in the dynamic model is no more significant when the estimation is carried out on the non-overlapping sample.

Table 3. Sign and Significance of the Estimated Effect of Transparency on the Quality of Oil Price Forecasts: Summary of 24 Regressions with Different Model Specifications (sample: Jan. 1998–Dec. 2009, 26 countries, overlapping forecast horizons, monthly data frequency)

Transparency Index →	Political		Economic		Procedural		Policy		Operational		Total	
	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE	STDEV	ABSFE
Oil - 3M												
Oil - 1Y		+		+		++		++		+		++

Notes: This table reports the sign and significance of the estimated β parameter for different model specifications. Each row corresponds to a set of specifications where the forecasted variable and the forecast horizon are identical. The forecast horizons are abbreviated as follows: 3M = 3 month, 1Y=1 year. Each column corresponds to a set of specifications where the transparency is captured by the same index or sub-index and the forecast is characterized either by the absolute forecast error of the consensus forecast (ABSFE) or by the standard deviation of the individual forecasts (STDEV). –, – –, and – – – indicate negative estimates at the 10 percent, 5 percent, and 1 percent significance levels, respectively. +, ++, and +++ indicate positive estimates at the 10 percent, 5 percent, and 1 percent significance levels, respectively. Empty cells correspond to insignificant estimates. The estimated model is the dynamic model in Ehrmann, Eijffinger, and Fratzscher (2010): $y_t = \beta x_{i,t} + \alpha_i + \gamma_1 \sigma_t + \gamma_2 |\Delta oil_{t-1}| + \gamma_3 y_{t-1} + \epsilon_{i,t}$, where y_t is either the absolute forecast error of the consensus forecast on the three-month-ahead oil price, the absolute forecast error of the consensus forecast on the one-year-ahead oil price, the standard deviation of the individual forecasts on the three-month-ahead oil price, or the standard deviation of the individual forecasts on the one-year-ahead oil price.

Next, we interpret the results for the forecasted macro variables. In the first ten rows in table 2, there is at least one minus sign in each column. It means that each of the five sub-indices has a significant negative coefficient in at least one model specification. If these estimates reflect causal relationship, then the interpretation of this finding is that each aspect of transparency can mitigate the uncertainty concerning at least one macro variable.

By comparing the number of minus signs in the first ten rows of table 2 *across columns*, we get an impression of which dimension of transparency matters the most for the quality of forecasts of the macro variables. The favorable effect of transparency is most robust in case of the *economic aspect of transparency*, as the economic sub-index is estimated to have a significant negative coefficient in eleven specifications out of twenty. The effect of economic transparency is significant not only statistically but also in economic terms. Let us suppose that the sub-index of economic transparency increases by one. It can be achieved by the central bank, for instance, by starting to publish its macroeconomic model used for policy decisions. Our estimates suggest that this measure decreases the standard deviation of the individual forecasts on the three-month-ahead short rate by 0.02 percent (2 basis points), provided everything else remains unchanged. See the first panel (upper left) in table 11. Though this effect is small, it is not negligible in relative terms, because the sample average of the standard deviation of the individual three-month-ahead short rate forecasts is 0.23 percent.

The comparison of the results across sub-indices also sheds light on the *mechanism* that transparency presumably exerts on predictions. Central banks can have both direct and indirect impact on the private sector's forecasts. An example for the *indirect channel* is the following. Suppose the central bank enhances its transparency by prioritizing its objectives, thereby making it easier for the public to predict how it will respond to shocks in order to meet its objectives. Owing to better policy rate forecasts, macroeconomic variables become easier to forecast as well, provided that market participants understand the transmission mechanism well. In contrast to the indirect channel, the *direct channel* operates by giving the opportunity to private forecasters to simply copy the forecasts of the central bank.

Our estimates cannot determine with certainty whether the direct channel or the indirect one is at work. However, the direct channel seems to be more dominant, as economic transparency has the most robust favorable effect out of the five dimensions. Just to recall, the economic sub-index indicates whether the central bank publishes its own forecasts. If transparency affected the macroeconomic variables mostly indirectly, via better understanding of monetary policy decisions, we would see more coefficients with a significantly negative sign for the sub-indices other than the economic sub-index.

In general, we find no strong evidence against the null that higher transparency is associated with better forecasts. Our one-sided test rejects the null $\beta < 0$ at the 10 percent significance level only four times out of 120 specifications presented in the first ten rows of table 2. Given that the corresponding probability of the type I error is 10 percent, the expected number of rejections is twelve out of every 120 independent estimations. However, our 120 estimates are not independent for a number of reasons. By counting only those estimates among which there is no trivial linear dependence, we get twenty as a product of five (number of roughly independent sub-indices), four (number of roughly independent macro variables, the two real variables count as one), one (the two forecast horizons count as one), and one (number of independent measures on the quality of forecasts). As we obtain only four rejections out of twenty independent estimates, we do not have strong evidence against the hypothesis $\beta < 0$, even if we take into account the dependence between regressions. The picture is even better if we consider that the four rejections are not independent either: out of the four rejections, two fall to those twenty independent estimates where the quality of forecasts is measured by the forecast accuracy, while the other two rejections fall to those other twenty independent estimates where the quality of forecasts is measured by the dispersion of forecasts. Hence, the ratio of the number of independent rejections to the number of independent estimates is 10 percent.

Table 2 also reveals which macro forecast correlates with most of the dimensions of transparency. It is the *short-term interest rate* that can be forecasted with either significantly higher precision or significantly less disagreement or both, if the central bank improves on the political, economic, or operational aspect of transparency.

This finding is not surprising, because the short rate is the variable most closely related to monetary policymaking and communication, as the policy instrument itself is a specific short-term rate at many central banks. Regarding the forecasts on the other two nominal variables, the *ten-year interest rate* and the *inflation rate*, much fewer estimates are significant. This finding reflects that central banks are able to affect these variables only indirectly. The effect of monetary policy on *real variables* is even less direct than that on the long rate and inflation rate, as they are less tightly connected to the policy instrument through the monetary transmission mechanism.[20] Finding a significant relationship between central bank transparency and *GDP* or *consumption* forecasts could be interpreted as *indirect evidence for the effectiveness of monetary policy* that is often debated in the literature. An alternative interpretation attributes the significant relationship to the *direct channel* functioning through publishing central bank forecast on real variables. This alternative interpretation seems to be more plausible, as a significant favorable impact of transparency on real variables is found mostly in those specifications where transparency is measured by the economic sub-index. It is worth mentioning that the economic sub-index of transparency, more precisely its 2C component, indicates whether the central bank publishes forecasts, but the published forecasts should not necessarily be on real variables. In order to obtain a clearer view on the relevance of the second interpretation, one needs to use detailed data on what variables are forecasted by central banks.

4.2 Robustness Analysis

This section provides some robustness checks on the benchmark results. We investigate whether our estimates are sensitive to changes in model specification and sample.[21]

[20] This finding is in line with Dovern, Fritsche, and Slacalek (2012), who investigate the determinants of dispersion across forecasters using the Consensus Economics data set. They show that the degree of disagreement about nominal variables (inflation and interest rate) is affected more significantly by central bank independence than the degree of disagreement about real variables (GDP, consumption, investment, and unemployment).

[21] A number of further robustness checks can be found in Csavas et al. (2012).

Whether *lengthening the sample* by the period preceding 1998 has any effect on the results is investigated by comparing our benchmark estimates summarized by table 2 with the alternative estimates summarized by table 4.[22] It is apparent that the estimates for β are significantly negative in many more specifications when estimation is carried out on the longer sample, and the hypothesis of $\beta < 0$ cannot be rejected in any of the specifications.

When reestimating equation (1) on a restricted sample covering only the twelve *advanced countries*, we obtain similar qualitative results to those obtained on the broader sample (see table 5). The number of significantly positive and negative estimates is more or less the same as in the benchmark case.[23]

The above two sensitivity analyses are relevant for comparing our benchmark estimates with those of Ehrmann, Eijffinger, and Fratzscher (2012). Ehrmann, Eijffinger, and Fratzscher (2012) estimate their benchmark model on the sample of the twelve advanced economies, and their sample period spans between January 1990 and December 2008. As we see, choosing the sample as Ehrmann, Eijffinger, and Fratzscher (2012) do makes the hypothesis $\beta < 0$ harder to reject, and the estimates for β are significantly negative in many more specifications.

We also test whether our findings are robust to an *alternative measure of transparency*. For this exercise, we use the Minegishi and Cournède (2009) index, which quantifies the degree of transparency differently from the popular Eijffinger-Geraats index.[24] Our standard regressions confirm that a higher Minegishi-Cournède

[22]The details of the regression results in the sensitivity analyses can be found in Csavas et al. (2012). For instance, tables 30, 31, 32, 33, 46, and 47 in Csavas et al. (2012) present those results that are summarized by tables 4, 5, and 6 in this paper.

[23]One of the most puzzling results in table 5 is that political transparency increases the dispersion of inflation forecasts significantly. However, this result is not robust: when Norway is excluded from the sample, the coefficient in question is no longer significant. This sensitivity of the estimates is in line with the finding of Cecchetti and Hakkio (2009), who document that the adoption of inflation targeting by the central bank of Norway was associated with a rise in the standard deviation of inflation forecasts.

[24]The sample of Minegishi and Cournède (2009) covers the period between 1999 and 2009. It consists of eleven OECD countries, out of which eight overlap with our sample of twenty-six countries. The eight countries that are common in the samples are Canada, Germany (representing the euro zone), Japan, Norway, Sweden, Switzerland, the United Kingdom, and the United States.

Table 4. Sign and Significance of the Estimated Effect of Transparency on the Quality of Forecasts: Summary of 120 Regressions with Different Specifications of the Benchmark Model (1), Longer Sample Period (sample: Oct. 1989–Dec. 2009, 26 countries, non-overlapping forecast horizons)

Transparency Index →	**Political**		**Economic**		**Procedural**		**Policy**		**Operational**		**Total**	
	STDEV	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**
Short Rate - 3M	– – –	– –	– – –	– – –			–	–	– – –	– – –	– – –	– – –
Short Rate - 1Y	–		– – –						–		– – –	
Long Rate - 3M				– –					–			–
Long Rate - 1Y			– – –	– – –			– –		– – –		– – –	– –
CPI - CY			– – –	– –			– –	–			– – –	–
CPI - NY			– – –				– –				– – –	
GDP - CY	– – –		– – –	– – –					– – –		– – –	–
GDP - NY	– – –		– – –				–				– – –	
Consumption - CY				– – –	– –	– –						– – –
Consumption - NY		– –	– –							– – –		

Note: See notes for table 2.

Table 5. Sign and Significance of the Estimated Effect of Transparency on the Quality of Forecasts: Summary of 120 Regressions with Different Specifications of the Benchmark Model (1) (sample: Jan. 1998–Dec. 2009, 12 advanced countries, non-overlapping forecast horizons)

Transparency Index →	Political		Economic		Procedural		Policy		Operational		Total	
	STDEV	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**
Short Rate - 3M	– – –	– –		– –					– –	– – –		– –
Short Rate - 1Y	– –											
Long Rate - 3M												
Long Rate - 1Y			– –	–					– –			
CPI - CY	++			–								
CPI - NY		++	– – –			+++	– –	+			– –	+
GDP - CY	– –	–		– – –				–	– –	– – –	– –	– – –
GDP - NY	– – –		– – –			++	– – –				– – –	
Consumption - CY		– – –						–		–		–
Consumption - NY			– – –								– –	

Note: See notes for table 2.

transparency index is associated with significantly lower dispersion of forecasts and higher forecast accuracy in general (see table 6). Interestingly, the most robust results are obtained when transparency is measured either by the policy objective sub-index or by the economic analysis sub-index. These sub-indices essentially correspond to the political and economic sub-indices of the Eijffinger-Geraats index, respectively.[25] In the benchmark estimations obtained with the sub-indices of the Eijffinger-Geraats index, the political aspect of transparency has not been found to be as important as the economic aspect. Another interesting difference between the estimates obtained with the Minegishi-Cournède index and those obtained with the Eijffinger-Geraats index is that in the latter case, the most robust impact of enhanced transparency is found on the short rate forecasts out of the investigated forecasted variables. If we measure the degree of transparency by the Minegishi-Cournède index, then it is the GDP forecast upon which most of the dimensions of transparency have significant favorable effect. The two findings above contribute to our previous view on two related issues already touched upon in this paper: first, whether the forecasts are effected through the direct channel or the indirect one, and second, whether monetary policy is effective. The results obtained with the Minegishi-Cournède indices point toward the functioning of the indirect channel and provide indirect evidence for the effectiveness of monetary policy.

4.3 Testing for Causality

In this section, we apply Granger causality tests in order to see whether a higher degree of transparency contributes to better forecasts.

For the test we estimate the following two equations for each of the twelve advanced economies on data of monthly frequency:[26]

[25] The sub-indices of policy objective, economic analysis, decision-making process, and policy decision in the Minegishi-Cournède index correspond the most to the political, economic, procedural, and policy sub-indices in the Eijffinger-Geraats index, respectively.

[26] In constructing the monthly time series of the transparency indices for the advanced economies, the supplementary data appendix of Eijffinger and Geraats (2004) and the notes written to the data set of Siklos (2011) (available at http://www.central-bank-communication.net/links/) were a great help. Unfortunately, there is no similar detailed and comprehensive description of data on emerging countries.

Table 6. Sign and Significance of the Estimated Effect of the Minegishi-Cournède Transparency Index and Sub-Indices on the Quality of Forecasts: Summary of 100 Regressions with Different Specifications of the Benchmark Model (1) (sample: Jan. 1999–Dec. 2009, 8 OECD countries, non-overlapping forecast horizons)

Transparency Index →	Political Objective		Policy Decision		Economic Analysis		Decision-Making Process		Total	
	STDEV	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**	**STDEV**	**ABSFE**
Short Rate - 3M	– – –	–				– –				– –
Short Rate - 1Y					– –				–	
Long Rate - 3M										
Long Rate - 1Y										
CPI - CY							++			
CPI - NY		+	– –		– –			++		
GDP - CY	– –	– –	– –	– –	– – –		– –		– – –	–
GDP - NY	– – –									
Consumption - CY		– – –		– –				– –		– – –
Consumption - NY	– – –			– –						

Note: See notes for table 2.

$$y_{i,t} = \beta_{y,i} x_{i,t-1} + \gamma_{1,y,i}\sigma_{i,t} + \gamma_{2,y,i} |\Delta \text{oil}_{t-1}| + \gamma_{3,y,i} y_{i,t-1} + \sum_{m=1}^{11} \Theta_{i,m} I_{m,t} + \epsilon_{y,i,t}, \tag{2}$$

$$x_{i,t} = \beta_{x,i} y_{i,t-1} + \gamma_{1,x,i}\sigma_{i,t} + \gamma_{2,x,i} |\Delta \text{oil}_{t-1}| + \gamma_{3,x,i} x_{i,t-1} + \epsilon_{x,i,t}. \tag{3}$$

The notation of the variables is the same as before, with the following exceptions: $y_{i,t}$ denotes only the dispersion of forecasts (but not the forecast accuracy) at time t for country i. $I_{m,t}$ is an indicator function taking value 1 if time t is in month m and 0 otherwise. Accordingly, the term $\sum_{m=1}^{11} \Theta_{i,m} I_{m,t}$ stands for the month fixed effects. We control for the month fixed effects only for those variables that are forecast with changing forecast horizons.

Unlike the benchmark regression, we estimate equations (2) and (3) for each country separately. This deviation has the following consequences for the model, the estimation method, and the data. First, there is no need for country dummies in the regressions. Second, the estimates obtained with LSDV will be unbiased (in contrast with the LSDV estimates for the dynamic panel model with individual effects). Third, we have to work with the sample of forecasts with overlapping forecast horizons; otherwise, we would have too short time series. The overlapping nature of the data necessitates the inclusion of month fixed effects.[27]

Table 7 summarizes the results of Granger causality tests. Unfortunately, the vast majority of these tests are not conclusive on the direction of causality, either because of finding causality in both directions or because of finding it in neither of the directions. However, in those specifications and for those countries where the causality points to one definite direction, it is dominantly the one that can be exploited by central banks: it is transparency that seems to cause the quality of forecasts, and not vice versa.

[27]Fortunately, the overlapping nature of the data is less of an issue when the quality of forecasts is measured by the standard deviation of the individual forecasts as opposed to being measured by the absolute forecast errors. Csavas et al. (2012) present the results of the Granger causality tests also for the latter.

Table 7. Summary of the Granger Causality Tests between Transparency and Dispersion of Forecasts (sample: Jan. 1998–Dec. 2009, 12 advanced countries)

	Transparency Is Measured by Index or Sub-index											
	Political	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**	**Political**	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**
Quality of Forecast	*Standard Deviation of the Individual Three-Month-Ahead Short Rate Forecasts*						*Standard Deviation of the Individual Twelve-Month-Ahead Short Rate Forecasts*					
TR → QF	1	2	0	2	3	2	0	3	0	2	1	3
TR ← QF	1	2	0	1	0	1	0	0	0	1	0	1
TR ↔ QF	0	0	0	0	0	1	0	0	0	1	0	0
TR QF	1	7	1	6	2	8	3	8	1	5	4	8
Num. of Countries	3	11	1	9	5	12	3	11	1	9	5	12
Quality of Forecast	*Standard Deviation of the Individual Three-Month-Ahead Long Rate Forecasts*						*Standard Deviation of the Individual Twelve-Month-Ahead Long Rate Forecasts*					
TR → QF	0	1	0	1	0	2	0	3	0	1	0	3
TR ← QF	0	2	0	0	0	1	0	1	0	0	1	2
TR ↔ QF	1	1	0	0	0	2	0	0	0	0	1	0
TR QF	2	6	1	7	5	6	3	6	1	7	3	6
Num. of Countries	3	10	1	8	5	11	3	10	1	8	5	11
Quality of Forecast	*Standard Deviation of the Individual Current-Year CPI Forecasts*						*Standard Deviation of the Individual Next-Year CPI Forecasts*					
TR → QF	1	2	0	2	1	2	0	1	0	2	1	3
TR ← QF	0	1	0	0	2	1	0	0	0	0	0	0
TR ↔ QF	0	0	0	0	1	1	1	0	0	0	0	0
TR QF	2	8	1	7	1	8	2	10	1	7	4	9
Num. of Countries	3	11	1	9	5	12	3	11	1	9	5	12

(*continued*)

Table 7. (Continued)

	Transparency Is Measured by Index or Sub-index											
	Political	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**	**Political**	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**
Quality of Forecast	*Standard Deviation of the Individual Current-Year GDP Forecasts*						*Standard Deviation of the Individual Next-Year GDP Forecasts*					
TR → QF	0	2	0	1	0	2	0	3	0	0	0	3
TR ← QF	1	1	0	0	1	1	1	2	0	2	2	0
TR ↔ QF	0	0	0	0	0	0	0	1	0	2	0	1
TR QF	2	8	1	8	4	9	2	5	1	5	3	8
Num. of Countries	3	11	1	9	5	12	3	11	1	9	5	12
Quality of Forecast	*Standard Deviation of the Individual Current-Year Consumption Forecasts*						*Standard Deviation of the Individual Next-Year Consumption Forecasts*					
TR → QF	0	2	0	2	0	3	0	3	0	2	0	4
TR ← QF	0	0	0	0	1	0	0	0	0	2	0	0
TR ↔ QF	0	0	0	0	0	0	1	0	0	1	0	0
TR QF	3	9	1	7	4	9	2	8	1	4	5	8
Num. of Countries	3	11	1	9	5	12	3	11	1	9	5	12

Notes: This table reports the number of countries with different results of the Granger causality test. The significance level for the Granger causality tests is set to 10 percent. "TR → QF" means one-way causality, i.e., we can reject the hypothesis that transparency does not Granger-cause the quality of forecast, but we cannot reject the hypothesis that quality of forecast does not Granger-cause transparency. "TR ← QF" means one-way causality to the opposite direction. "TR ↔ QF" means two-way causality. "TR QF" means no causal relationship. "Num. of Countries" indicates the total number of countries for which we could run the causality test. Central bank transparency is measured by the Eijffinger-Geraats index on monthly frequency.

4.4 Weighted Transparency Index

Composite indices are often used in social sciences. Some of these indices are calculated as the averages or sums of *equally weighted sub-indices*, while others use various *weighting schemes.* Choosing the weights is based either on the value judgments of experts or on well-documented and replicable methods such as factor analysis or regressions.

In this section we use the *regression method* to construct a weighted transparency index. In section 4.1, we already identified the important sub-indices of transparency through their effects on uncertainty. Here, we apply a similar approach in order to assign weights to each of the fifteen components of the Eijffinger-Geraats index. The weights are chosen so that the resulting composite index explains the maximum variation in the dependent variable. The method is demonstrated on the standard deviation of the individual current-year consumer price index forecasts as the dependent variable, because this forecast is available for all countries in our sample.[28]

First, we run our workhorse regression (1) with the explanatory variable $x_{i,t}$ being one of the components and the dependent variable $y_{i,t}$ being the standard deviation of the individual CPI forecasts. The coefficient of each of the fifteen components is estimated to be negative whenever it is significant (see table 8).

Second, we assign weights to the components by estimating model (4).

$$y_{i,t} = \beta \sum_{j=1}^{15} \lambda_j x_{i,t,j} + \alpha_i + \gamma_1 \sigma_{i,t} + \gamma_2 \left|\Delta \mathrm{oil}_{t-1}\right| + \eta_{i,t},$$

$$\text{where} \sum_{j=1}^{15} \lambda_j = 1 \tag{4}$$

[28]However, the method can be applied to alternative dependent variables as well, resulting in different weighting schemes. Csavas et al. (2012) demonstrates the method of estimating weights on the standard deviation of the individual short rate forecasts as the dependent variable. Unfortunately, these forecasts are available for far fewer countries than the CPI forecasts.

Table 8. Components of the Central Bank Transparency Index and the Dispersion of Individual Current-Year CPI Forecasts: Benchmark Model (sample: Jan. 1998–Jan. 2009, 26 countries, non-overlapping forecast horizons)

	Transparency Is Measured by One of the Components														
	Political			Economic			Procedural			Policy			Operational		
	Formal Objectives	Quantitative Targets	Institutional Arrangements	Economic Data	Policy Models	Central Bank Forecast	Explicit Strategy	Minutes	Voting Records	Prompt Announcement	Policy Explanation	Policy Inclination	Control Errors	Transmission Disturbances	Evaluation of Policy Outcomes
	1A	1B	1C	2A	2B	2C	3A	3B	3C	4A	4B	4C	5A	5B	5C
Dependent Variable	*Standard Deviation of the Individual Current-Year CPI Forecasts*														
Transparency	−0.08	−0.13	−0.21	−0.34	−0.08	-0.26^{***}	-0.6^{***}	−0.01	0.05	-0.65^{**}	−0.14	0	−0.02	−0.08	0.13
(t-stat)	(−1.02)	(−0.62)	(−1.23)	(−1.2)	(−1.62)	(−2.83)	(−7.71)	(−0.14)	(0.96)	(−2.05)	(−1.04)	(−0.07)	(−0.2)	(−1.27)	(0.72)
Cond. Volatility	0.11	0.11	0.11	0.11	0.12	0.12	0.11	0.11	0.11	0.1	0.12	0.11	0.11	0.11	0.11
(t-stat)	(1.46)	(1.48)	(1.47)	(1.46)	(1.51)	(1.63)	(1.47)	(1.45)	(1.44)	(1.27)	(1.51)	(1.45)	(1.46)	(1.45)	(1.45)
$\vert\Delta \mathrm{oil}_{t-1}\vert$	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.03^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}
(t-stat)	(4.8)	(4.25)	(4.99)	(4.48)	(4.8)	(5.86)	(4.66)	(4.72)	(4.79)	(4.89)	(4.26)	(4.86)	(4.37)	(4.99)	(4.9)
Number of Obs.	210	210	210	210	210	210	210	210	210	210	210	210	210	210	210
R^2	75.94%	76.02%	76.02%	76.13%	76.20%	78.04%	76.59%	75.92%	75.95%	76.64%	76.16%	75.92%	75.92%	75.95%	75.94%

Note: To save space, the regression coefficients for the country fixed effects are not reported.

The explanatory variable $x_{i,t,j}$ denotes the jth component of the transparency index in country i at time t and λ_j is its weight. The weighted transparency index is then $\sum_{j=1}^{15} \lambda_j x_{i,t,j}$. In this model, β captures the effect of the weighted transparency index on the quality of forecasts. $\eta_{i,t}$ is a Gaussian error term. The notation of all the other variables is the same as before.

It is worth noting that we do not rule out a priori to obtain negative weights. This is a principal difference relative to the equally weighted Eijffinger-Geraats index. Negative weights correspond to the case when higher transparency is associated with higher forecast dispersion, provided $\beta < 0$. Tables 2–6 suggest that estimating negative weights does not only have a theoretical possibility.

Once model (4) is estimated, we test the hypothesis $\lambda_j = \lambda$ for all $j \in \{1..15\}$. The standard F-test rejects the equality of the weights at any meaningful significance level; therefore, a weighted index may better reflect the actual degree of central bank transparency than the equally weighted one.

Table 9 reports the estimated weights λ_j and the estimates on the coefficient of the weighted transparency index ($\widehat{\beta} = -1.78$). The latter is significantly negative as is in line with our intuition, suggesting that the higher the weighted transparency index, the lower the degree of disagreement. There are three components to which high and significantly positive weights are assigned. These are "central bank forecasts" (2C), "explicit strategy" (3A), and "prompt announcement" (4A). The rest of the components have either negative weights or positive but insignificant weights. The lack of significance and the negative sign of these weights might reflect either that the components in question do not influence uncertainty in the economy substantially, or that they take non-zero values for too few countries and too short of a period to identify their effects by the regressions,[29] or that these components are highly correlated with some others. High correlation can not only make the standard errors high, but can also result in negative weights of some components

[29] For instance, the component for policy inclination (4C) takes a non-zero value only for the Riksbank from 2002 on and for the Federal Reserve from 1999 on in our sample. Although our intuition suggests that official policy inclination is a great help for the private forecasters, its estimated coefficient is insignificant.

Table 9. Estimated Weights of the Weighted Transparency Index (sample: Jan. 1998–Jan. 2009, 26 countries, non-overlapping forecast horizons)

	Relative Weights	t-stat
1A. Formal Objectives	−0.036	(−0.47)
1B. Quantitative Targets	0.151	(1.11)
1C. Institutional Arrangements	0.092	(0.94)
1. Political Transparency	0.207	
2A. Economic Data	0.104	(1.33)
2B. Policy Models	−0.037	(−0.89)
2C. Central Bank Forecast	0.23***	(3.06)
2. Economic Transparency	0.297	
3A. Explicit Strategy	0.31***	(4.47)
3B. Minutes	−0.003	(−0.05)
3C. Voting Records	−0.025	(−0.51)
3. Procedural Transparency	0.282	
4A. Prompt Announcement	0.41***	(3.77)
4B. Policy Explanation	−0.16*	(−1.84)
4C. Policy Inclination	0.093	(1.45)
4. Policy Transparency	0.343	
5A. Control Errors	−0.075	(−0.53)
5B. Transmission Disturbances	0.015	(0.19)
5C. Evaluation of Policy Outcomes	−0.07	(−0.34)
5. Operational Transparency	−0.13	
Weighted Transparency	−1.78***	(−5.21)
Number of Obs.	210	
R^2	80.34%	

Notes: This table reports the λ_j weights and the β coefficient of the weighted index in equation (4). The dependent variable is the standard deviation of the individual current-year CPI forecasts. The weight assigned to each of the sub-indices is calculated as the sum of weights of its components.

whose role is partly taken over by a correlating component. This phenomenon is called *multicollinearity*. Although multicollinearity can lead to coefficient estimates with counterintuitive signs in some instances, it is likely to affect neither the ranking of the countries nor the aggregate transparency index we propose, as the sum of scores assigned to a group of highly correlating sub-indices reflects the degree of the given aspects of transparency correctly.

Whether some components are assigned to significantly positive weights only because of being correlated with some other important aspects of transparency can be checked by looking at their unconditional effects on uncertainty. Among the three components with significantly positive weights, each is found to have a favorable impact, even in those specifications where no other aspects of transparency are controlled for, as is reported by table 8. Based on this finding, central banks are advised to (i) prepare and publish their own forecasts, (ii) provide an explicit policy rule or strategy that describes the monetary policy framework, and (iii) promptly announce policy decisions.

The estimated weighting scheme allows us to calculate the weighted composite transparency index characterizing each central bank for which the Eijffinger-Geraats index is available. In addition, we can rank these central banks based upon the weighted index. Table 10 reports two rankings: one is based on the Eijffinger-Geraats index, and the other is based on the weighted index. When comparing these rankings, we find some similarities and differences as well. The Spearman rank-order correlation is 0.85 between the two rankings. Out of ninety-seven central banks, there are thirty-seven whose relative position in the Eijffinger-Geraats ranking is out of the 90 percent confidence interval of our ranking.

5. Conclusions

Whether enhanced central bank transparency is favorable is not evident from the literature. For instance, Morris and Shin (2002) argue as follows. If central banks have only noisy information on the future evolution of some variables, and their noisy information is less precise than that of the market, then achieving a higher

Table 10. Country Rankings Based on the Degree of Transparency of Their Central Banks in 2009

	Eijffinger-Geraats Index		Weighted Index			
					Percentile of the Ranking	
Country Name	**Score**	**Ranking**	**Score**	**Ranking**	**5th**	**95th**
Albania	9.0	17	0.94	23	11	34
Argentina	7.5	26	0.61	46	22	76
Armenia	8.0	21	0.77	36	19	54
Aruba	0.5	97	0.05	88	82	95
Australia	10.5	8	0.87	31	19	38
Bahamas	4.5	58	0.51	57	44	71
Bahrain	5.0	51	0.56	52	41	63
Bangladesh	3.5	66	0.25	79	69	84
Barbados	4.0	61	0.58	50	39	69
Belarus	5.0	51	0.58	49	40	63
Belize	3.0	69	0.42	66	46	83
Bermuda	1.0	92	0.03	89	85	91
Bhutan	3.0	69	0.41	68	54	78
Brazil	9.0	17	1.23	1	1	6
Bulgaria	5.5	44	0.54	54	38	71
Canada	11.0	6	0.96	18	10	30
Chile	7.5	26	0.96	20	7	35
China	4.5	58	0.43	63	49	77
Colombia	7.5	26	1.12	3	3	12
Croatia	6.0	39	0.43	64	38	81
Cuba	2.5	76	0.38	73	59	76
Czech Rep.	11.5	4	1.00	14	3	32
Denmark	7.5	26	0.81	34	23	45
East Caribbean	7.0	30	0.67	43	22	66
Egypt	3.0	69	0.26	77	53	95
El Salvador	3.0	69	0.28	76	51	91
EMU	11.0	6	0.96	18	10	30
Estonia	6.0	39	0.76	38	17	52
Ethiopia	1.0	92	0.03	89	85	91
Fiji	4.0	61	0.74	39	26	56
Georgia	5.5	44	1.04	8	1	36
Ghana	5.5	44	0.67	42	38	57
Guatemala	5.5	44	0.63	45	30	66
Guyana	1.5	89	0.01	95	84	96
Hong Kong	7.0	30	0.39	71	54	79
Hungary	11.5	4	1.00	16	5	30
Iceland	8.5	20	1.10	5	1	23

(*continued*)

Table 10. (Continued)

	Eijffinger-Geraats Index		**Weighted Index**			
					Percentile of the Ranking	
Country Name	**Score**	**Ranking**	**Score**	**Ranking**	**5th**	**95th**
India	2.0	84	0.11	86	75	94
Indonesia	8.0	21	1.03	9	5	22
Iraq	2.5	76	0.38	73	59	76
Israel	9.5	12	0.88	30	19	37
Jamaica	6.5	37	1.06	7	1	29
Japan	10.0	9	0.38	75	46	84
Jordan	2.0	84	0.44	62	48	76
Kazakhstan	5.5	44	0.90	27	8	41
Kenya	5.0	51	0.54	55	43	68
Korea	9.0	17	0.91	26	16	35
Kyrgyzstan	5.0	51	0.53	56	41	71
Kuwait	2.0	84	0.18	82	65	93
Latvia	7.0	30	0.73	40	21	55
Lesotho	3.5	66	0.39	70	51	80
Libya	2.0	84	0.18	82	65	93
Lithuania	4.5	58	0.57	51	30	76
Malawi	2.5	76	0.39	72	49	82
Malaysia	6.0	39	0.77	37	12	61
Mauritius	5.5	44	0.90	29	14	36
Mexico	7.0	30	0.60	47	38	61
Moldova	6.0	39	0.91	25	11	36
Mongolia	6.0	39	0.55	53	41	68
Namibia	7.0	30	1.01	13	7	26
New Zealand	14.0	2	1.03	11	4	30
Nigeria	4.0	61	0.46	59	52	74
Norway	8.0	21	0.84	33	21	42
Oman	1.5	89	0.20	81	69	87
Pakistan	3.5	66	0.45	60	53	73
Papua New Guinea	5.0	51	0.42	65	45	83
Peru	8.0	21	0.90	28	14	37
Philippines	9.5	12	1.15	2	1	20
Poland	10.0	9	1.01	12	6	22
Qatar	3.0	69	0.49	58	45	74
Romania	6.5	37	0.92	24	10	36
Russia	3.0	69	0.02	94	80	97
Rwanda	2.5	76	0.16	84	63	97
Saudi Arabia	1.0	92	0.03	89	85	91

(*continued*)

Table 10. (Continued)

	Eijffinger-Geraats Index		Weighted Index			
					Percentile of the Ranking	
Country Name	**Score**	**Ranking**	**Score**	**Ranking**	**5th**	**95th**
Sierra Leone	1.0	92	0.03	89	85	91
Singapore	7.0	30	0.87	32	9	46
Solomon Islands	2.0	84	0.11	86	75	94
South Africa	9.5	12	0.94	22	3	41
Sri Lanka	7.0	30	0.96	21	12	28
Sudan	2.5	76	0.15	85	76	95
Sweden	15.0	1	1.00	15	4	31
Switzerland	9.5	12	1.03	10	2	36
Tajikistan	2.5	76	0.01	97	79	97
Tanzania	5.0	51	0.44	61	55	73
Thailand	8.0	21	1.10	4	2	14
Trinidad and Tobago	5.5	44	0.78	35	24	52
Tunisia	4.0	61	0.65	44	39	61
Turkey	9.5	12	1.08	6	3	23
Uganda	2.5	76	0.25	78	53	93
Ukraine	4.0	61	0.39	69	48	83
United Arab Emirates	3.0	69	0.59	48	34	71
United Kingdom	12.5	3	0.97	17	8	31
United States	10.0	9	0.42	66	40	85
Uruguay	5.0	51	0.68	41	19	67
Vanuatu	2.5	76	0.23	80	57	94
Yemen	1.0	92	0.03	89	85	91
Zambia	1.5	89	0.01	95	84	96

Notes: This table reports two rankings of ninety-seven central banks. The weights of the weighted index are estimated on data of twenty-six countries with twenty independent central banks and are reported by table 9 (the names of the additional seventy-seven countries are typeset in italic). The 10 percent confidence band of the ranking is calculated by simulation. First, we generate 1,000 independent random vectors of weights from multivariate Gaussian distribution with expected value being the vector of point estimates of the weights and covariance being the estimated covariance matrix of the weights. Second, for each of the 1,000 vectors of weights we determine the corresponding ranking of countries and the 5th and 95th percentile of the distribution of the relative position of each country.

degree of transparency can crowd out valuable private information and increase forecast error of private agents.[30]

This paper contributes to the literature by investigating empirically whether a higher degree of central bank transparency can mitigate the uncertainty in the economy. This question is examined also by Ehrmann, Eijffinger, and Fratzscher (2010, 2012) with a similar model to ours and on data from the same source. We come to the same conclusion as they do, i.e., our regression results mostly support the view that enhancing central bank transparency is favorable. In contrast to Ehrmann, Eijffinger, and Fratzscher (2012), we show in this paper not only that a higher degree of transparency is associated with less disperse views of the private forecasters, but also that it is associated with more accurate forecasts. What makes this finding important is that becoming more transparent is definitely undesirable if it synchronizes the private forecasts, but at a lower level of accuracy.

The effect of transparency on forecast accuracy is estimated also by Ehrmann, Eijffinger, and Fratzscher (2010); however, their parameter estimates are biased due to being obtained from a dynamic panel model with individual fixed effects by the least-squares method. This paper and Csavas et al. (2012) demonstrate the presence of bias by regressions on oil price forecasts. Here, the idea is that one should not find a significant relationship between the accuracy of oil price forecasts and any measure of central bank transparency, as oil price is exogenous to monetary policy. When using the same model and estimation method as Ehrmann, Eijffinger, and Fratzscher (2010), we can falsely reject exogeneity; however, we find no significant relationship between accuracy of oil price forecasts and transparency with a more rigorous approach.

When studying the mechanism of how forecasts are affected by transparency, we obtain somewhat controversial results. When

[30] Although the result of Morris and Shin (2002) is challenged by Svensson (2006), it is underpinned by alternative theories. For instance, Kool, Middeldorp, and Rosenkranz (2011) show how greater transparency can reduce forecasting accuracy if market participants choose to refrain from investing in private information when they can get costless guidance on future rates from the central bank's public signals. Unlike Morris and Shin, this result does not rely on coordination effects and higher-order expectations or what Svensson (2006) identifies as implausible calibration of the relative precisions of the public and private signals.

transparency is measured by the Eijffinger-Geraats index, we find that the economic sub-index has the most robust favorable effect out of the five sub-indices. As the economic sub-index captures whether central banks publish their own forecasts, this finding supports the view that transparency exerts its effect dominantly through the direct channel. However, when transparency is measured by the Minegishi-Cournède index, the policy aspect of transparency turns out to be equally important as the economic aspect. This latter finding underpins the operation of the indirect channel, i.e., the uncertainty of private forecasters can be mitigated not only by directly providing the market with the predictions of the central bank but also by informing the public about the goals of the central bank and clarifying the priority of these goals.

Another contribution of this paper is that it makes an attempt to test the direction of causality between transparency and uncertainty. Unfortunately, the vast majority of our tests find causality either in both directions or neither of the directions. However, in those specifications where the Granger causality points to one definite direction, then it is dominantly the one that supports our normative perspective.

In addition, we construct a weighted index of central bank transparency. The index we propose aggregates the same fifteen components as the composite Eijffinger-Geraats index. The weights we assign to the components are established empirically and reflect the relative importance of the components in reducing uncertainty. There are three components that are assigned to high and significantly positive weights. Along these lines, the best practice of central banking involves (i) preparing and publishing own forecasts, (ii) providing an explicit policy rule or strategy that describes the monetary policy framework, and (iii) promptly announcing policy decisions.

The composite index we propose in this paper, although being a weighted index, is still subject to some criticisms. First, it is a linear function of fifteen components that do not necessarily complement each other in a linear manner. Second, there are certain aspects of central bank transparency that are captured neither by the components of the Eijffinger-Geraats index nor by our weighted composite index. Just to mention one of these aspects, it is not accounted for whether detailed information is provided on the views of the individual council members.[31] Third, while our regression method allows us to identify which aspects of transparency are effective, it does not allow us to conclude that some other newer or less employed aspects of transparency are ineffective. Our regression method might fail to recognize the importance of any type of transparency that has only been employed recently or by only a few countries. These points call for future research on measuring central bank transparency.

[31]This information can be shared by the central bank watchers by publishing attributed minutes. Attributed minutes are unique in the sense that one can learn from them not only the points raised in the council or board meetings but also who made the given point during the discussion. The advantages of providing detailed information about individual committee members' views are discussed by Svensson (2009).

Appendix

Table 11. Central Bank Transparency and Dispersion of Forecasts: Benchmark Model (sample: Jan. 1998–Dec. 2009, 26 countries, non-overlapping forecast horizons)

	Transparency Is Measured by Index or Sub-index											
	Political	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**	**Political**	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**
Dependent Variable	*Standard Deviation of the Individual Three-Month-Ahead Short Rate Forecasts*						*Standard Deviation of the Individual Twelve-Month-Ahead Short Rate Forecasts*					
Transparency	−0.07***	−0.02	0	−0.01	−0.05**	−0.01	−0.11*	−0.06*	−0.02	0.01	−0.05	−0.03*
(t-stat)	(−3.1)	(−1.42)	(−0.11)	(−0.44)	(−2.12)	(−1.63)	(−1.74)	(−1.69)	(−0.41)	(0.24)	(−0.78)	(−1.94)
Cond. Volatility	0.16*	0.16*	0.16*	0.16*	0.16*	0.16*	0.13	0.1	0.12	0.13	0.13	0.11
(t-stat)	(1.68)	(1.69)	(1.67)	(1.7)	(1.69)	(1.66)	(0.75)	(0.59)	(0.69)	(0.73)	(0.71)	(0.61)
$\lvert \Delta oil_{t-1} \rvert$	0	0	0	0	0	0.01	0	0.01	0	0	0	0
(t-stat)	(1.17)	(1.18)	(0.99)	(1.01)	(1.08)	(1.21)	(0.27)	(0.63)	(0.19)	(0.13)	(0.2)	(0.5)
Number of Obs.	624	624	624	624	624	624	170	170	170	170	170	170
R^2	47.8%	47.24%	46.99%	47.01%	47.21%	47.39%	54.31%	54.61%	54.05%	54.04%	54.08%	54.41%
Dependent Variable	*Standard Deviation of the Individual Three-Month-Ahead Long Rate Forecasts*						*Standard Deviation of the Individual Twelve-Month-Ahead Long Rate Forecasts*					
Transparency	0.01	0	0.06***	0.02	0.02	0	0.02	−0.02**	0	0	−0.04	−0.01
(t-stat)	(0.66)	(−0.14)	(3.07)	(1.11)	(0.94)	(0.77)	(0.72)	(−2.08)	(0.02)	(−0.03)	(−1.55)	(−0.96)
Cond. Volatility	0.6***	0.59***	0.6***	0.61***	0.6***	0.61***	1.25***	1.19***	1.24***	1.24***	1.24***	1.22***
(t-stat)	(5.61)	(5.83)	(5.44)	(5.65)	(5.58)	(5.74)	(8.07)	(8.26)	(8.01)	(8.19)	(7.84)	(8.34)
$\lvert \Delta oil_{t-1} \rvert$	0	0	0	0	0	0	0.01*	0.01**	0.01*	0.01*	0.01*	0.01**
(t-stat)	(1.08)	(1.14)	(1.01)	(0.98)	(1.07)	(0.98)	(1.69)	(2.08)	(1.72)	(1.75)	(1.92)	(1.99)
Number of Obs.	554	554	554	554	554	554	146	146	146	146	146	146
R^2	27.71%	27.63%	28.68%	27.84%	27.75%	27.78%	53.42%	53.9%	53.35%	53.35%	53.65%	53.56%
Dependent Variable	*Standard Deviation of the Individual Current-Year CPI Forecasts*						*Standard Deviation of the Individual Next-Year CPI Forecasts*					
Transparency	−0.1	−0.1**	−0.03	−0.1	−0.02	−0.05**	−0.13	−0.19***	−0.05	−0.21***	−0.06	−0.08***
(t-stat)	(−0.87)	(−2.55)	(−0.44)	(−1.4)	(−0.54)	(−2.18)	(−1.58)	(−2.77)	(−0.7)	(−2.64)	(−0.77)	(−3.98)
Cond. Volatility	0.11	0.12	0.11	0.11	0.11	0.12	0.18	0.19	0.18	0.17	0.18	0.18
(t-stat)	(1.48)	(1.59)	(1.45)	(1.5)	(1.46)	(1.57)	(1.23)	(1.34)	(1.22)	(1.23)	(1.22)	(1.29)
$\lvert \Delta oil_{t-1} \rvert$	0.02***	0.03***	0.02***	0.02***	0.02***	0.03***	0.01	0.01***	0.01	0.01	0.01	0.01**
(t-stat)	(4.37)	(5.38)	(4.38)	(4.51)	(4.64)	(4.56)	(1.07)	(3.31)	(0.97)	(1.29)	(1.02)	(2.54)
Number of Obs.	210	210	210	210	210	210	110	110	110	110	110	110
R^2	76.06%	77.14%	75.94%	76.2%	75.93%	76.71%	75.11%	76.86%	75.01%	73.54%	75.01%	76.13%

(continued)

Table 11. (Continued)

	Transparency Is Measured by Index or Sub-index											
	Political	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**	**Political**	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**
Dependent Variable	*Standard Deviation of the Individual Current-Year GDP Forecasts*						*Standard Deviation of the Individual Next-Year GDP Forecasts*					
Transparency	−0.1*	−0.05**	0.05	−0.02	−0.08	−0.02	−0.1*	−0.08***	0.04	−0.03	0	−0.03
(t-stat)	(−1.8)	(−2.25)	(0.79)	(−0.25)	($-n1.34$)	($-n1.27$)	($-nn1.72$)	(−1.06)	(0.85)	(−0.39)	(−0.04)	(−1.31)
Cond. Volatility	0.01	0.02	0	0	0.01	0.01	0.02	0.04	0.01	0.02	0.02	0.03
(t-stat)	(0.18)	(0.45)	(0.06)	(0.15)	(0.18)	(0.33)	(0.82)	(1.28)	(0.53)	(0.64)	(0.65)	(0.89)
$\lvert\Delta oil_{t-1}\rvert$	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.02***	0.02***	0.02**	0.02***	0.02**	0.02***
(t-stat)	(3.34)	(3.46)	(3.25)	(3.12)	(3.3)	(3.42)	(2.75)	(3.26)	(2.54)	(2.61)	(2.44)	(3.11)
Number of Obs.	202	202	202	202	202	202	105	105	105	105	105	105
R^2	58.22%	58.61%	57.97%	57.81%	58.03%	58.24%	80.53%	81.61%	80.28%	80.25%	80.2%	80.73%
Dependent Variable	*Standard Deviation of the Individual Current-Year Consumption Forecasts*						*Standard Deviation of the Individual Next-Year Consumption Forecasts*					
Transparency	0.04	−0.02	−0.11	0.13	0.05	0	0.18	−0.01	0.12	0.24	0.1*	0.03
(t-stat)	(0.29)	(−0.7)	(−1.51)	(1.28)	(0.69)	(0.04)	(0.98)	(−0.2)	(1.08)	(1.41)	(1.71)	(1.03)
Cond. Volatility	−0.03	−0.03	−0.02	−0.03	−0.03	−0.03	−0.1	−0.11	−0.12	−0.09*	−0.11	−0.11*
(t-stat)	(−0.06)	(−0.58)	(−0.43)	(−0.59)	(−0.6)	(−0.59)	(−1.61)	(−1.5)	(−1.47)	(−1.79)	(−1.61)	(−1.68)
$\lvert\Delta oil_{t-1}\rvert$	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.01***	0.02***	0.01***	0.01***	0.01***	0.01***
(t-stat)	(3.12)	(2.72)	(2.99)	(2.76)	(2.98)	(2.84)	(6)	(3.59)	(3.85)	(5.28)	(3.45)	(4.82)
Number of Obs.	202	202	202	202	202	202	105	105	105	105	105	105
R^2	78.7%	78.72%	78.91%	79.09%	78.72%	78.68%	83.77%	83.32%	83.57%	84.57%	83.47%	83.68%
Dependent Variable	*Standard Deviation of the Individual Three-Month-Ahead Oil Price Forecasts*						*Standard Deviation of the Individual Twelve-Month-Ahead Oil Price Forecasts*					
Transparency	0	0	0	0	0	0	0.01	0.02	0.03*	0.04	0.02	0.01
(t-stat)	(−0.41)	(−0.06)	(1.27)	(0.17)	(0.08)	(0.07)	(0.08)	(1.29)	(1.93)	(1.28)	(1.5)	(1.43)
Cond. Volatility	0.1***	0.1***	0.1***	0.1***	0.1***	0.1***	0.34***	0.38***	0.34***	0.38***	0.34***	0.4***
(t-stat)	(2.97)	(2.85)	(3.03)	(2.95)	(2.97)	(2.87)	(4.52)	(4.78)	(4.65)	(5.22)	(4.69)	(5.28)
$\lvert\Delta oil_{t-1}\rvert$	0***	0***	0***	0***	0***	0***	0	0	0	0	0	0
(t-stat)	(3.96)	(3.89)	(3.9)	(3.85)	(3.96)	(3.81)	(0.97)	(0.11)	(1)	(0.26)	(0.87)	(−0.17)
Number of Obs.	790	790	790	790	790	790	242	242	242	242	242	242
R^2	66.56%	66.55%	66.62%	66.56%	66.55%	66.55%	79.85%	80.68%	80.26%	81.08%	79.99%	81.36%

Notes: To save space, the country fixed effects are not reported. Regressions are estimated by LSDV estimator; the standard errors are calculated by the White cross-section method that is designed to accommodate arbitrary heteroskedasticity and robust to contemporaneous correlation across countries. The data frequency of the non-overlapping sample is three months for the three-month-ahead forecasts, annual for the twelve-month-ahead forecasts and the end-of-year forecasts, and biannual for the end-of-next-year forecasts. *, **, and *** indicate significant estimates at the 10 percent, 5 percent, and 1 percent significance levels, respectively.

Table 12. Central Bank Transparency and Forecast Accuracy: Benchmark Model (sample: Jan. 1998–Dec. 2009, 26 countries, non-overlapping forecast horizons)

	Transparency Is Measured by Index or Sub-index											
	Political	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**	**Political**	**Economic**	**Procedural**	**Policy**	**Operational**	**Total**
Dependent Variable	*Absolute Forecast Error of the Average Three-Month-Ahead Short Rate Forecasts*						*Absolute Forecast Error of the Average Twelve-Month-Ahead Short Rate Forecasts*					
Transparency	−0.19*	−0.1***	0.04	−0.11	−0.24**	−0.06***	−0.31	−0.14	−0.62	−0.14	−0.39	−0.13
(t-stat)	(−1.94)	(−2.62)	(0.4)	(−1.35)	(−2.48)	(−2.58)	(−0.84)	(−1.07)	(−1.22)	(−0.71)	(−1.08)	(−1.53)
Cond. Volatility	0.31	0.3	0.32	0.31	0.31	0.29	−0.04	−0.12	−0.18	−0.05	−0.07	−0.16
(t-stat)	(1.26)	(1.26)	(1.28)	(1.27)	(1.26)	(1.22)	(−0.12)	(−0.33)	(−0.56)	(−0.14)	(−0.17)	(−0.46)
$\lvert \Delta oil_{t-1} \rvert$	0.03	0.04	0.03	0.03	0.03	0.04	0.05	0.05*	0.05**	0.05	0.05	0.06**
(t-stat)	(1.33)	(1.44)	(1.22)	(1.31)	(1.32)	(1.44)	(1.54)	(1.69)	(1.98)	(1.63)	(1.58)	(2.04)
Number of Obs.	624	624	624	624	624	624	170	170	170	170	170	170
R^2	24.03%	24.59%	23.38%	23.63%	24%	24.55%	23.68%	23.95%	25.74%	23.46%	23.79%	24.8%
Dependent Variable	*Absolute Forecast Error of the Average Three-Month-Ahead Long Rate Forecasts*						*Absolute Forecast Error of the Average Twelve-Month-Ahead Long Rate Forecasts*					
Transparency	0	−0.04	0.04	−0.03	−0.03	−0.01	−0.08	−0.33*	−0.13	−0.39	−0.39	−0.15
(t-stat)	(0.05)	(−1.28)	(0.6)	(−0.43)	(−0.38)	(−0.74)	(−0.28)	(−1.77)	(−0.52)	(−1.35)	(−1.15)	(−1.48)
Cond. Volatility	0.84**	0.78**	0.85**	0.82**	0.84**	0.8**	0.88	0.08	0.89	0.63	0.9	0.36
(t-stat)	(2.21)	(2.02)	(2.2)	(2.2)	(2.21)	(2.15)	(0.73)	(0.07)	(0.72)	(0.54)	(0.75)	(0.32)
$\lvert \Delta oil_{t-1} \rvert$	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**	−0.04**	−0.03	−0.04**	−0.04**	−0.04**	−0.03
(t-stat)	(2.18)	(2.56)	(2.17)	(2.24)	(2.24)	(2.39)	(−2.48)	(−1.46)	(−2.54)	(−2.05)	(−2.53)	(−1.47)
Number of Obs.	554	554	554	554	554	554	146	146	146	146	146	146
R^2	15.45%	16.11%	15.51%	15.53%	15.48%	15.7%	25.59%	34.24%	25.66%	28.68%	27.12%	31.67%
Dependent Variable	*Absolute Forecast Error of the Average Current-Year CPI Forecasts*						*Absolute Forecast Error of the Average Next-Year CPI Forecasts*					
Transparency	−0.23	−0.16*	0.2	−0.18	−0.08	−0.06	1.1**	0.1	0.03	0.56	1.85**	0.21
(t-stat)	(−0.96)	(−1.94)	(0.9)	(−0.89)	(−0.26)	(−0.94)	(2.08)	(0.64)	(0.08)	(0.83)	(2.56)	(1.51)
Cond. Volatility	0.38***	0.39***	0.38***	0.38***	0.38***	0.39***	0.86***	0.84***	0.84***	0.86***	0.85***	0.85***
(t-stat)	(4.4)	(4.52)	(4.39)	(4.37)	(4.44)	(4.47)	(4.05)	(4.13)	(4.32)	(3.83)	(4.47)	(3.84)
$\lvert \Delta oil_{t-1} \rvert$	0.01	0.01	0.01	0.01	0.01	0.01	−0.22	−0.21	−0.21	−0.21	−0.23*	−0.22*
(t-stat)	(0.8)	(1)	(0.41)	(0.84)	(0.69)	(0.87)	(−1.64)	(−1.55)	(−1.48)	(−1.51)	(−1.73)	(−1.67)
Number of Obs.	210	210	210	210	210	210	84	84	84	84	84	84
R^2	51.76%	52.12%	51.8%	51.79%	51.66%	51.88%	57.46%	56.74%	56.69%	57.08%	59.32%	57.38%

(*continued*)

Table 12. (Continued)

	Transparency Is Measured by Index or Sub-index											
	Political	Economic	Procedural	Policy	Operational	Total	Political	Economic	Procedural	Policy	Operational	Total
Dependent Variable	*Absolute Forecast Error of the Average Current-Year GDP Forecasts*						*Absolute Forecast Error of the Average Next-Year GDP Forecasts*					
Transparency	0.03	−0.27***	0.09	−0.2	−0.56	−0.11	−0.31	0.16	0.13	−0.37	−0.86**	−0.04
(t-stat)	(0.06)	(−3.52)	(0.32)	(−0.52)	(−1.15)	(−1.22)	(−1.61)	(0.95)	(0.38)	(−0.74)	(−2.44)	(−0.36)
Cond. Volatility	0.25**	0.31**	0.25**	0.26**	0.26**	0.29**	−0.05	−0.12	−0.07	−0.04	0.01	−0.03
(t-stat)	(2.17)	(2.38)	(2.16)	(2.16)	(2.09)	(2.27)	(−0.26)	(−0.53)	(−0.38)	(−0.24)	(0.05)	(−0.16)
$\lvert \Delta oil_{t-1} \rvert$	0.13***	0.14***	0.13***	0.13***	0.14***	0.14***	−0.09	−0.1*	−0.09*	−0.09**	−0.08	−0.09
(t-stat)	(4.45)	(4.85)	(4.15)	(4.34)	(4.62)	(5.2)	(−1.62)	(−1.7)	(−1.67)	(−2)	(−1.54)	(−1.63)
Number of Obs.	202	202	202	202	202	202	81	81	81	81	81	81
R^2	71.3%	71.73%	71.31%	71.36%	71.56%	71.55%	29.61%	29.81%	29.41%	30.1%	31.8%	29.42%
Dependent Variable	*Absolute Forecast Error of the Average Current-Year Consumption Forecasts*						*Absolute Forecast Error of the Average Next-Year Consumption Forecasts*					
Transparency	−0.31	−0.4**	−0.97**	−0.16	−0.61	−0.23***	−0.86**	0.14	−0.79	−1.12*	−1.61***	−0.2
(t-stat)	(−0.91)	(−2.4)	(−2.38)	(−0.35)	(−1.4)	(−3.41)	(−2.23)	(0.44)	(−1.45)	(−1.8)	(−4.57)	(−1.01)
Cond. Volatility	0.77**	0.8**	0.87***	0.77**	0.77**	0.8**	0.42	0.4	0.55	0.29	0.43	0.48
(t-stat)	(2.09)	(2.24)	(2.69)	(2.08)	(2.08)	(2.21)	(1.48)	(1.07)	(1.35)	(1.6)	(1.64)	(1.51)
$\lvert \Delta oil_{t-1} \rvert$	0.03	0.04	0.03	0.03	0.03	0.05*	−0.02	−0.04	−0.03	−0.03	−0.01	−0.02
(t-stat)	(1.08)	(1.62)	(1.15)	(1.03)	(1.25)	(1.8)	(−0.43)	(−0.56)	(−0.77)	(−1.2)	(−0.3)	(−0.42)
Number of Obs.	202	202	202	202	202	202	81	81	81	81	81	81
R^2	77.5%	78.11%	78.2%	77.47%	77.65%	78.17%	59.45%	58.82%	59.62%	61.04%	61.99%	59.74%
Dependent Variable	*Absolute Forecast Error of the Average Three-Month-Ahead Oil Price Forecasts*						*Absolute Forecast Error of the Average Twelve-Month-Ahead Oil Price Forecasts*					
Transparency	−0.02	−0.02	0.01	−0.03	−0.06	−0.01	−0.03	−0.03	0.03	−0.01	−0.06	−0.01
(t-stat)	(−0.77)	(−0.86)	(0.22)	(−0.64)	(−1.19)	(−0.78)	(−0.61)	(−0.58)	(0.66)	(−0.11)	(−1.05)	(−0.51)
Cond. Volatility	−0.47*	−0.49*	−0.46*	−0.47*	−0.47*	−0.49*	−0.2	−0.26	−0.18	−0.19	−0.22	−0.25
(t-stat)	(−1.67)	(−1.7)	(−1.65)	(−1.66)	(−1.7)	(−1.7)	(−0.2)	(−0.26)	(−0.18)	(−0.19)	(−0.22)	(−0.24)
$\lvert \Delta oil_{t-1} \rvert$	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0	0	−0.01	0	0	0
(t-stat)	(2.5)	(2.51)	(2.48)	(2.48)	(2.55)	(2.49)	(−0.1)	(−0.02)	(−0.13)	(−0.11)	(−0.08)	(−0.04)
Number of Obs.	790	790	790	790	790	790	242	242	242	242	242	242
R^2	34.8%	35.22%	34.69%	34.87%	35.06%	35.23%	6.28%	6.5%	6.27%	6.19%	6.46%	6.4%

Notes: To save space, the country fixed effects are not reported. Regressions are estimated by LSDV estimator; the standard errors are calculated by the White cross-section method that is designed to accommodate arbitrary heteroskedasticity and robust to contemporaneous correlation across countries. The data frequency of the non-overlapping sample is three months for the three-month-ahead forecasts, annual for the twelve-month-ahead forecasts and the end-of-year forecasts, and biannual for the end-of-next-year forecasts. *, **, and *** indicate significant estimates at the 10 percent, 5 percent, and 1 percent significance levels, respectively.

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