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Investigating the Relationship Between Central Bank Transparency and Stock Market Volatility in a Nonparametric Framework

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Abstract

This study investigates whether any non-linear relationship exists between central bank transparency and stock market variability in a non-parametric framework for a large number of countries. Our findings imply that a high level of transparency can significantly reduce historical as well as conditional stock market volatility in a non-linear manner. The negative effect of transparency on stock volatility is clearer when we move from low levels towards higher levels of transparency; this effect diminishes as long as we move to higher levels of transparency. This analysis implies that monetary authorities can contribute to equity market stability by adopting more transparent monetary policies in the early stages.

Untersuchung des Zusammenhangs zwischen der Transparenz von Zentralbanken und der Volatilität von Aktienmärkten in einem parameterfreien Rahmen

Zusammenfassung

Diese Studie untersucht, ob ein nicht-linearer Zusammenhang zwischen der Transparenz von Zentralbanken und der Varianz von Aktienmärkten in einem parameterfreien Rahmen für eine große Anzahl an Ländern existiert. Die Ergebnisse lassen darauf schließen, dass ein hoher Grad an Transparenz sowohl die historische als auch die bedingte Volatilität von Aktienmärkten auf nicht-lineare Weise signifikant reduzieren kann. Der negative Effekt von Transparenz auf die Volatilität von Aktien wird umso

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deutlicher, je mehr man sich von niedrigen Niveaus in Richtung höherer Niveaus an Transparenz bewegt. Die Untersuchung deutet darauf hin, dass die Notenbanken zur Aktienmarktstabilität beitragen können, wenn sie frühzeitig eine transparentere Geldpolitik anwenden.

Keywords: Local linear estimators, nonparametric regression, central bank, transparency

JEL Classification: E52; E5; C14

I. Introduction

Since the pioneering work of *Cukierman* and *Meltzer* (1986), there has been a steadily growing literature on the effect of central bank transparency on the macroeconomy (inter alia: *Chortarea*s et al., 2002; *Demertzis* and *Hughes-Hallet*, 2007; *Dincer* and *Eichengreen*, 2007; *Fratzscher*, 2006; *Gnabo* et al., 2009; *Evans* and *Speight*, 2010; *Rosa*, 2011) and on the stock markets (*Reeves* and *Sawicki*, 2007; *Lunde* and *Zebedee*, 2009; *Papadamou* et al., 2014). The economic desirability of central bank transparency is based on the efforts of central banks to guide economic agents' expectations (Blinder, 1998; *Van der Cruijsen* and *Demertzis*, 2007). *Eijffinger* et al. (2006) show that greater transparency should improve the credibility, flexibility and reputation of central banks. Regarding central banks' transparency effects on macroeconomy, the results in a nutshell are that higher transparency: (a) reduces inflation and exchange rate volatilities without necessarily increasing output volatility, and (b) significantly reduces inflation and interest rates.

With respect to the effect of central bank transparency on stock markets, this works indirectly through its effect on interest rates and consequently their role in equity valuation through a dividend discount model. *Neuenkirch* (2012) provides evidence that transparency reduces bias in money market expectations and dampens their variation. *De Goeij* and *Marquering* (2006) and *Ranaldo* and *Rossi* (2010) show that long-term rates are highly responsive to central bank communication. Moreover, according to *Papadamou* (2013) and *Papadamou* et al. (2015), central bank transparency plays an important role in the effective transmission of monetary policy through the interest rate channel.

It is well-known in the literature on the effects of monetary policy on stock returns that only unexpected changes in policy rates can have significant negative effects (see among others: *Bernanke* and *Kuttner*, 2005; *Ehrmann* and *Fratzscher*, 2004; *Bredin* et al.,2007; *Gregoriou* et al., 2009). Therefore, the presence of more transparent central banks implies fewer unexpected monetary policy actions. According to *Chuliá* et al. (2010), equity investors respond differently to positive and negative target rate surprises. Moreover, *Kurov* (2012) states that the information content of monetary policy statements has important implications for the economy and stock market.

However, a number of researchers (*Bomfim*, 2003; *Konrad*, 2009; *Hussain*, 2011) argue that monetary policy decisions have an immediate and significant impact not only on stock index returns, but also on their volatilities. Some studies focusing on particular aspects of central bank transparency in a specific country provide evidence of its effect on stock market volatility. For example, *Reeves* and *Sawicki* (2007), provide evidence that the publication of the inflation report by Bank of England reduces the volatility of the FTSE 100 stock market index in the UK. Regarding the US market, *Lunde* and *Zebedee* (2009) show that stock market volatility has a tendency to be relatively lower on days before and higher on days after monetary policy decisions.

In an international context assuming a linear model, *Papadamou* et al., (2014) developed an analytical setting indicating that a higher level of central bank transparency may reduce stock market variability. Our study contributes to the existing literature by investigating for the first time whether any non-linear relationship exists between central bank transparency and stock market variability by applying a non-parametric framework for a large number of countries. To this end, the applied methodological framework provides us with the advantage of relaxing any parametric assumptions which may be imposed on the data-generating process (DGP) and thus enables the data in hand to reveal the appropriate model specification (*Racine*, 2008). *Horowitz* (2011, p. 347) asserts that the strong assumptions made in parametric models in relation to the population modelled are rarely justified by economic theory and in many cases can lead to incorrect conclusions. Along the same lines, several studies (*Liu* and *Stengos*, 1999; *Maassoumi* et al. 2007; *Henderson* et al., 2012, 2013) have stressed that the misspecification of functional forms made by parametric models can lead to improper investigation of the underlying economic structure and therefore to misleading policy prescriptions. These major disadvantages of parametric specifications are avoided in our case since we analyse the examined relationships by applying a fully nonparametric setting.

Our findings imply that a high level of transparency can significantly reduce historical as well as conditional stock market volatility. However, the relationship between stock market volatility and central bank transparency seems to be non-linear. This implies that the benefits are greater starting from a low level of transparency and adopting major processes like publication of inflation reports and minutes of committee voting, instead of starting from high levels. The remainder of this paper is structured as follows: section 2 describes the data and the methodology followed, section 3 presents the empirical analysis, and the last section presents our conclusions.

II. Data and Methodology

1. Data

Our sample covers the period from 1998 to 2005 when significant changes occurred in the level of central bank transparency in a large number of countries. Annual data for 40 countries for a particular set of variables was collected for our study. More specifically, equity indices were drawn from the Ecowin Reuters database, while the money market rates were taken from the IFS database of the International Monetary Fund. Two different measures of equity volatility are used, the first one referring to conditional volatility based on the estimation of a GARCH(1,1) model on daily data, while the second one refers to historical volatility measured as the standard deviation of monthly equity returns over a year. GARCH models have been extensively used in order to estimate conditional volatility of stock returns during crisis and non-crisis periods (*Karanasos* et al., 2014). Based on the coefficients estimated in GARCH(1,1) models, we construct the daily conditional standard deviation (conditional volatility). To aggregate volatilities from daily to annual frequencies, we take the average over that year and scale by $\sqrt{365}$, allowing for the possibility of missing days due to, for instance, holidays.

Following previous relevant literature (*Papadamou* et al., 2014; *Umutlu* et al., 2010; *Esqueda* et al., 2012; *Liu* et al., 2012), a set of control variables is used in order to check the robustness of our results concerning the relationship between equity variability and central bank transparency. These variables are as follows: the stock market capitalisation deflated by GDP (referred to hereafter as 'capo100'); the ratio of the total value of shares traded over the average market capitalisation ('tro', turnover ratio); the real GDP growth (wbgdp100); and the effective exchange rate volatility measured by the standard deviation of the effective exchange rate (vseer100) monthly series over a year. The historical variability of interest rates (vs2rate) is measured based on the standard deviation of monthly interest rates over a period of one year. Finally, the index of financial integration is calculated as the ratio of a country's foreign equity inflows and outflows plus foreign direct investment inflows and outflows over the GDP (referred to hereafter as 'residf2').

In order to take into account several aspects (political, economic, procedural, policy and operational) of central bank transparency, we used the index constructed by *Eijffinger* and *Geraats* (2006) and *Dincer* and *Eichengreen*, (2007). They constructed a transparency index by taking account of the actual information disclosed by central banks. Every aspect of transparency has a value on a scale from zero to three graded by central bankers in an annual survey. Therefore, the maximum level of transparency has the value of fifteen, while the lowest is zero.

Table 1 (see next pages) provides information about the average level, as well as the maximum and the minimum levels, of the variables of interest for each country in the sample. As can be easily recognised, there have been countries starting from very low levels of central bank transparency moving towards higher levels over the period investigated (inter alia the Philippines, Turkey, Thailand, Singapore, Jamaica, Indonesia, Hungary and Cyprus). Countries like Ukraine, Russia, Turkey, Hong Kong and Argentina present significant variability on the equity, exchange rate and interest rate markets.

2. *Nonparametric Kernel Methods*

In this paper, without assuming any specific functional form concerning the way that central bank transparency affects stock market volatility, we leave data in a non-parametric framework to reveal any relationship that may exist. Following the representation by *Li* and *Racine* (2007, p.136), let X_i^d denote an $r \times 1$ vector of regressors of the discrete values and $X_i^c \in \Re^q$ denote the remaining continuous regressors. Let X_{is}^d denote the s^th^ component of X_i^d. Moreover, X_{is}^d assumes $c_s \geq 2$ different values. Therefore, $X_{is}^d \in \{0,1,...,c_s - 1\}$ for $s = 1,...,r$ and $X_i = \left(X_i^d, X_i^c\right)$. Then the nonparametric regression model is given by:

$$Y_i = g(X_i) + u_i, \tag{1}$$

where $E(u_i | X_i) = 0$. Let the joint probability density function (PDF) of $\left(X_i^d, X_i^c\right)$ be denoted as $f(x) = f\left(x^c, x^d\right)$. For the continuous variables $x^c = \left(x_1^c, ..., x_q^c\right)$ we define the following function:

$$W_h\left(x^c, X_i^c\right) \equiv \prod_{s=1}^{q} \frac{1}{h_s} w\left(\frac{x_s^c - X_{is}^c}{h_s}\right), \tag{2}$$

where w is the second-order Gaussian kernel. Moreover, for the discrete variables $x^d = \left(x_1^d, ..., x_r^d\right)$, we define the following function:

$$L\left(x^d, X_i^d, \lambda\right) = \prod_{s=1}^{r} l\left(x_s^d, X_{is}^d, \lambda_s\right). \tag{3}$$

In our study, for the unordered discrete variable in our sample (id), we have applied the *Aitchison* and *Aitken* (1976) kernel:

$$l\left(x_s^d, X_{is}^d, \lambda_s\right) = \begin{cases} 1 - \lambda_s, & \text{if } X_{is}^d = x_s^d \\ \lambda_s / \left(c_s - 1\right), & \text{if } X_{is}^d \neq x_s^d \end{cases}. \tag{4}$$

Table 1

Descriptive Statistics over the Period 1998–2005

	Argentina			**Australia**			**Canada**			**China**		
Variable	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
tr	3,94	3,00	5,50	8,50	8,00	9,00	10,50	10,50	10,50	2,38	1,00	4,50
vs2rate	0,43	0,09	0,81	0,04	0,00	0,12	0,11	0,04	0,32	0,06	0,00	0,17
gar1	0,35	0,26	0,47	0,15	0,09	0,20	0,19	0,13	0,30	0,26	0,23	0,30
vss	0,14	0,09	0,24	0,05	0,02	0,07	0,09	0,04	0,14	0,09	0,04	0,17
wbgdp100	0,01	–0,11	0,09	0,04	0,02	0,05	0,03	0,02	0,06	0,09	0,08	0,11
tro	0,13	0,01	0,30	0,67	0,51	0,78	0,63	0,52	0,77	1,06	0,68	1,58
residf2	0,44	0,30	0,25	1,00	0,80	1,20	1,55	1,30	1,70	0,24	0,20	0,30
capo100	0,46	0,15	0,60	1,06	0,82	1,27	1,07	0,78	1,31	0,35	0,23	0,48
vseer100	0,13	0,03	0,50	0,02	0,01	0,04	0,02	0,01	0,04	0,02	0,01	0,03
	EMU			**Estonia**			**Hong Kong**			**Hungary**		
Variable	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
tr	9,56	8,50	10,50	5,38	5,00	6,00	6,38	5,00	7,00	6,19	3,00	9,50
vs2rate	0,09	0,02	0,15	0,16	0,02	0,48	0,44	0,13	1,34	0,09	0,04	0,25
gar1	0,25	0,13	0,36	0,28	0,17	0,66	0,29	0,15	0,53	0,31	0,23	0,53
vss	0,11	0,04	0,23	0,15	0,06	0,47	0,11	0,06	0,18	0,13	0,06	0,28
wbgdp100	0,02	0,01	0,05	0,07	0,00	0,10	0,03	–0,06	0,09	0,04	0,03	0,05
tro	1,20	0,80	1,61	0,33	0,12	1,14	0,48	0,35	0,61	0,72	0,43	1,11
residf2	0,89	0,60	1,10	0,78	0,40	1,20	6,34	3,30	8,30	0,65	0,50	0,80
capo100	0,77	0,61	0,96	0,31	0,09	0,52	3,28	2,03	3,93	0,26	0,20	0,34
vseer100	0,02	0,01	0,03	0,01	0,01	0,05	0,02	0,01	0,03	0,02	0,02	0,03
	Jamaica			**Jordan**			**Japan**			**Korea**		
Variable	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
tr	4,94	3,00	6,50	1,19	1,00	2,00	8,44	8,00	9,50	7,94	6,50	8,50
vs2rate	0,07	0,03	0,12	0,12	0,04	0,29	0,71	0,00	1,92	0,12	0,03	0,55
gar1	0,17	0,12	0,23	0,18	0,13	0,30	0,25	0,18	0,29	0,40	0,21	0,61
vss	0,08	0,04	0,16	0,11	0,02	0,20	0,12	0,03	0,17	0,19	0,06	0,32
wbgdp100	0,01	–0,01	0,02	0,05	0,03	0,09	0,01	–0,02	0,02	0,04	–0,07	0,09
tro	0,03	0,02	0,04	0,27	0,08	0,85	0,76	0,40	1,19	2,73	1,69	3,77
residf2	0,53	0,40	0,70	0,71	0,20	1,70	0,26	0,20	0,40	0,31	0,20	0,50
capo100	0,69	0,24	1,42	1,14	0,58	2,99	0,74	0,53	1,04	0,55	0,32	0,89
vseer100	–	–	–	–	–	–	0,03	0,01	0,05	0,03	0,01	0,09

Croatia			Cyprus			Denmark			Egypt		
Mean	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
2,13	1,50	2,50	4,50	2,50	6,50	5,38	5,00	6,00	1,13	1,00	2,00
0,33	0,02	0,64	0,11	0,04	0,23	0,09	0,01	0,18	0,10	0,00	0,31
0,32	0,21	0,52	0,32	0,16	0,60	0,22	0,17	0,28	0,12	0,06	0,22
0,11	0,05	0,25	0,23	0,04	0,83	0,10	0,05	0,18	0,08	0,01	0,15
0,03	–0,01	0,05	0,04	0,02	0,05	0,02	0,00	0,04	0,04	0,02	0,06
0,05	0,03	0,07	0,53	0,04	1,64	0,73	0,61	0,92	0,23	0,10	0,43
0,28	0,20	0,40	0,71	0,30	1,00	1,15	0,70	1,30	0,26	0,20	0,40
0,17	0,11	0,29	0,45	0,27	0,71	0,59	0,44	0,69	0,40	0,25	0,89
0,01	0,01	0,02	0,01	0,00	0,03	0,01	0,01	0,02	–	–	–
Iceland			**Indonesia**			**India**			**Israel**		
Mean	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
6,88	5,50	7,50	5,50	3,00	8,00	2,00	2,00	2,00	7,81	5,50	8,50
0,15	0,05	0,48	0,23	0,06	0,58	0,03	0,00	0,08	0,11	0,04	0,29
0,13	0,09	0,17	0,32	0,24	0,55	0,32	0,23	0,44	0,24	0,20	0,29
0,10	0,03	0,16	0,16	0,04	0,28	0,16	0,07	0,31	0,10	0,05	0,18
0,05	0,00	0,08	0,02	–0,13	0,06	0,07	0,04	0,09	0,03	–0,01	0,09
0,52	0,07	0,94	0,42	0,31	0,54	1,66	0,92	3,06	0,51	0,27	0,96
0,64	0,20	1,70	0,20	0,10	0,40	0,14	0,10	0,20	0,54	0,30	0,80
0,82	0,37	1,71	0,24	0,14	0,46	0,39	0,22	0,66	0,59	0,36	0,90
0,05	0,01	0,11	0,08	0,02	0,19	0,02	0,01	0,05	0,03	0,01	0,08
Malaysia			**Malta**			**Mexico**			**Norway**		
Mean	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
4,75	4,00	5,00	5,94	5,00	7,00	4,44	4,00	5,50	7,06	6,00	8,00
0,08	0,00	0,34	0,03	0,00	0,09	0,19	0,05	0,37	0,14	0,02	0,36
0,26	0,11	0,73	0,17	0,12	0,27	0,29	0,18	0,43	0,25	0,19	0,34
0,12	0,03	0,29	0,12	0,05	0,36	0,13	0,10	0,17	0,14	0,07	0,23
0,04	–0,07	0,09	0,03	–0,02	0,07	0,03	0,00	0,07	0,02	0,01	0,04
0,31	0,18	0,45	0,08	0,03	0,25	0,28	0,21	0,32	0,92	0,72	1,17
0,76	0,70	0,90	0,74	0,30	1,00	0,35	0,30	0,50	0,94	0,60	1,20
1,41	1,23	1,84	0,43	0,21	0,69	0,22	0,16	0,32	0,43	0,31	0,63
0,02	0,01	0,04	0,01	0,00	0,01	0,05	0,02	0,11	0,02	0,01	0,04

(Continue next page)

Table 1 continued

	New Zealand			**Philippines**			**Romania**			**Russia**		
Variable	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
tr	12,94	10,50	13,50	7,44	3,50	10,00	3,50	1,50	6,50	1,75	1,50	2,50
vs2rate	0,13	0,03	0,41	0,08	0,01	0,22	0,21	0,05	0,37	0,49	0,31	0,87
gar1	0,14	0,09	0,21	0,23	0,18	0,37	0,33	0,22	0,45	0,55	0,29	1,09
vss	0,06	0,02	0,12	0,11	0,04	0,22	0,19	0,03	0,46	0,23	0,06	0,49
wbgdp100	0,03	0,01	0,05	0,04	−0,01	0,07	0,03	−0,05	0,08	0,05	−0,05	0,10
tro	0,41	0,37	0,46	0,21	0,08	0,51	0,25	0,09	0,73	0,34	0,06	0,52
residf2	0,94	0,80	1,10	0,25	0,20	0,30	0,21	0,10	0,30	0,40	0,10	0,60
capo100	0,40	0,33	0,49	0,42	0,28	0,54	0,09	0,02	0,21	0,36	0,08	0,72
vseer100	0,03	0,01	0,04	0,04	0,01	0,07	0,12	0,02	0,34	0,25	0,01	1,74
	Sweden			**Switzerland**			**Thailand**			**Turkey**		
Variable	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
tr	11,25	9,00	13,00	8,06	6,00	9,50	6,06	2,00	8,00	6,06	2,00	8,50
vs2rate	0,08	0,02	0,14	0,33	0,06	0,80	0,26	0,05	0,77	0,20	0,06	0,51
gar1	0,27	0,14	0,36	0,23	0,13	0,33	0,32	0,19	0,53	0,57	0,34	0,76
vss	0,13	0,04	0,24	0,09	0,02	0,18	0,14	0,02	0,32	0,26	0,13	0,55
wbgdp100	0,03	0,01	0,05	0,02	0,00	0,04	0,03	−0,11	0,07	0,04	−0,06	0,09
tro	1,03	0,73	1,24	0,87	0,42	1,11	0,90	0,53	1,15	1,61	1,11	1,97
residf2	1,73	1,20	2,00	3,51	2,90	3,90	0,45	0,30	0,60	0,15	0,10	0,20
capo100	1,08	0,71	1,44	2,40	1,93	3,09	0,50	0,24	0,85	0,25	0,12	0,45
vseer100	0,02	0,01	0,03	0,01	0,01	0,02	0,03	0,01	0,08	0,27	0,03	0,74

Note: gar1: conditional stock market volatility from GARCH model; vss: historical stock market volatility; tr: transparency index; capo100: stock market capitalisation; tro: turnover ratio; wbgdp100: real GDP growth; vseer100: effective exchange rate volatility; vs2rate: historical variability of interest rates; residf2: index of financial integration.

South Africa			Saudi Arabia			Singapore			Slovenia		
Mean	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
7,25	4,00	9,00	1,00	1,00	1,00	4,75	2,50	6,50	6,25	5,00	7,50
0,10	0,01	0,21	0,14	0,03	0,31	0,22	0,07	0,44	0,11	0,01	0,23
0,29	0,24	0,40	0,21	0,16	0,28	0,28	0,14	0,59	0,14	0,11	0,21
0,16	0,03	0,24	0,13	0,04	0,21	0,12	0,04	0,23	0,07	0,03	0,14
0,03	0,01	0,05	0,04	–0,01	0,09	0,05	–0,02	0,09	0,04	0,03	0,05
0,39	0,29	0,49	0,92	0,27	2,32	0,49	0,32	0,67	0,22	0,09	0,34
0,91	0,60	1,10	0,88	0,70	1,20	4,33	3,10	5,10	0,28	0,20	0,40
1,70	1,18	2,29	0,71	0,29	1,97	1,86	0,99	2,56	0,18	0,10	0,29
0,07	0,02	0,15	0,02	0,01	0,03	0,01	0,00	0,02	0,01	0,00	0,03

UK			Ukraine			USA			Chile		
Mean	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*
11,88	11,00	12,00	2,50	2,00	3,00	8,38	7,50	8,50	7,38	7,00	7,50
0,08	0,03	0,16	0,47	0,35	0,63	0,17	0,06	0,41	0,34	0,06	1,36
0,20	0,11	0,29	0,41	0,28	0,67	0,22	0,13	0,30	0,12	0,09	0,18
0,07	0,02	0,16	0,21	0,04	0,48	0,07	0,03	0,15	0,09	0,03	0,17
0,03	0,02	0,04	0,05	–0,02	0,12	0,03	0,01	0,05	0,04	–0,01	0,06
0,91	0,52	1,42	0,08	0,02	0,19	1,52	1,06	2,03	0,10	0,06	0,15
1,83	1,40	2,10	0,16	0,10	0,20	0,69	0,60	0,90	0,99	0,70	1,20
1,49	1,16	1,95	0,10	0,01	0,29	1,41	1,05	1,79	0,90	0,65	1,16
0,02	0,01	0,02	–	–	–	0,02	0,01	0,03	0,04	0,02	0,06

Moreover, for the ordered discrete variable (year) in our sample, the *Wang* and *Ryzin* (1981) kernel has been applied:

(5)
$$l\left(x_s^d, X_{is}^d, \lambda_s\right) = \begin{cases} 1-\lambda_s, & \text{if } \left|X_{is}^d - x_s^d\right| = 0 \\ \dfrac{(1-\lambda_s)}{2}\lambda_s^{\left|X_{is}^d - x_s^d\right|}, & \text{if } \left|X_{is}^d - x_s^d\right| > 1 \end{cases}.$$

In all cases the bandwidths (smoothing parameters) λ_s and h_s are calculated using the Least Squares Cross-Validation (LSCV) criterion (*Hall* et al., 2004; *Li* and Racine, 2004, 2007) with $0 < h_s < \infty$ and $0 \leq \lambda_s \leq 1$. The LSCV method selects $h_1, ..., h_q, \lambda_1, ..., \lambda_r$ to minimise the following cross-validation function:

(6)
$$CV_r(h, \lambda) = \sum_{i=1}^{n} \left(Y_i - \hat{g}_{-i}(X_i)\right)^2 M(X_i),$$

where $\hat{g}_{-i}(X_i)$ is the leave-one-out kernel estimator of $g(X_i)$ and $M(\cdot)$ is a weight function. The kernel function for the vector of mixed variables $x = \left(x^c, x^d\right)$ is the product of $W_h(\cdot)$ and $L(\cdot)$. Usually the irrelevant variables are assigned a large bandwidth.

However, as suggested by *Li* and *Racine* (2009, p. 72), the LSCV criterion sometimes can assign a larger bandwidth to a relevant variable or place a small bandwidth on an irrelevant variable. Therefore, an analyst should follow standard nonparametric significance tests in order to explore the significance of the regressors in a more coherent way.

3. *The Local Linear Estimator*

By assuming that the second derivative of $g(x)$ then exists as described by *Racine* and *Li* (2004) and *Racine* (2008, p.38):

(7)
$$\begin{aligned} g(x_0) &\approx g(x) + \left(\frac{\partial g(x)}{\partial x}\right)(x_0 - x) \\ &= \alpha + b(x_0 - x). \end{aligned}$$

Then we choose an α and b in order to minimise:

(8)
$$\begin{aligned} \Omega &= \sum_{i=1}^{n} \left(Y_i - \alpha - b(X_i - x)\right)^2 K\left(\frac{X_i - x}{h}\right) \\ &= \sum_{i=1}^{n} \left(Y_i - \alpha - b(X_i - x)\right)^2 K(Z_i). \end{aligned}$$

The solutions of $\hat{\alpha}$ and $\hat{b}$ are the local linear estimators of the estimated nonparametric regression (*Fan* and *Gijbels*, 1996).

4. Nonparametric Significant Tests

In order to test the significance of our explanatory variables in a nonparametric regression framework, we apply the bootstrap-based consistent significance tests for continuous (*Racine*, 1997) and for categorical (*Racine et al.*, 2006) regressors. These tests are analogous to a simple t-test (F-test) in a parametric regression setting. Let z denote the categorical (discrete)/continuous variable that might be redundant and let x be the remaining explanatory variables in our regression framework. Furthermore, x contains both categorical (discrete) and continuous variables. Then the null and the alternative hypothesis can be expressed as:

(9)
$$\begin{aligned} H_0: &\quad E(y|x,z) = E(y|x) \\ H_1: &\quad E(y|x,z) \neq E(y|x). \end{aligned}$$

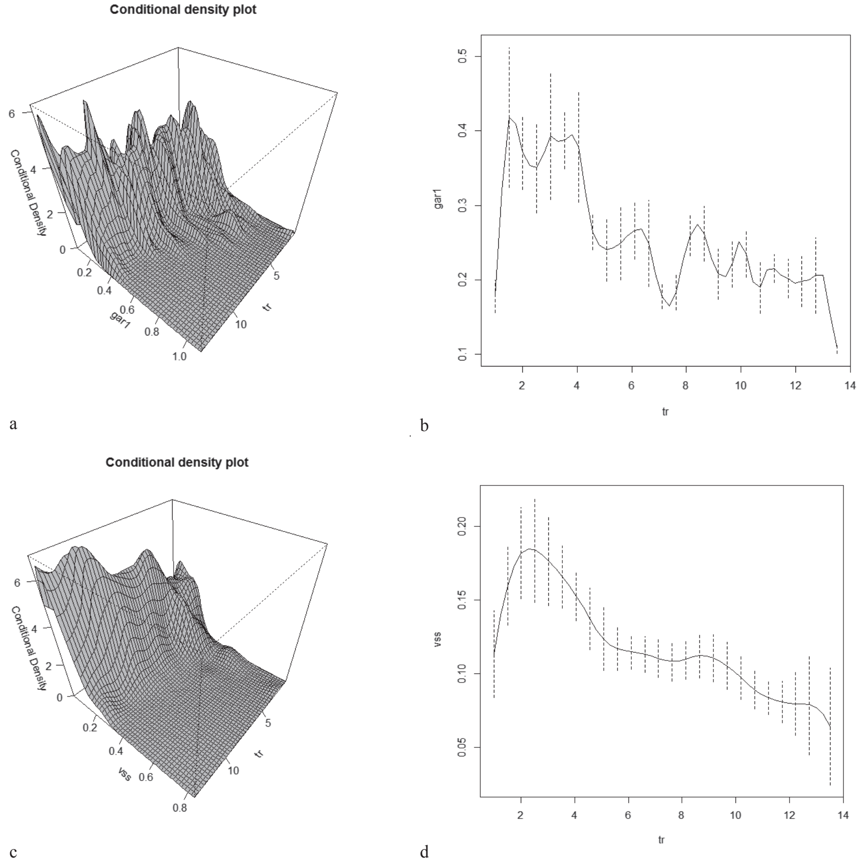
Then, by calculating the bootstrapped-based P-values, we can reject the null hypothesis at the conventional 1%, 5% and 10% levels[1]. Finally, by following Racine (2008, p. 45), we use a unit-free measure of goodness of fit for our nonparametric regression. This measure ranges between 0 (no predictive power) and 1 (perfect fit to the sample data); it is a 'within-sample' measure of goodness of fit and is analogous to the R-squared (R^2):

(10)
$$R^2 = \frac{\left[\sum_{i=1}^{n}(Y_i - \bar{y})(\hat{Y}_i - \bar{y})\right]^2}{\sum_{i=1}^{n}(Y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{Y}_i - \bar{y})^2}.$$

III. Empirical Findings

Initially, we empirically investigate the stock market volatility-transparency relationship by using "pooled" empirical models. Specifically, subfigure 1a provides the conditional density plots for conditional stock market volatility from the GARCH model (gar1) and transparency index (tr), whereas subfigure 1b presents the conditional density plots of historical stock market volatility (vss)

[1] As suggested by *Li* and *Racine* (2007, p. 378), we use the 'wild bootstrap' instead of the 'naïve i.i.d. bootstrap' since it is resistant to the presence of conditional heteroskedasticity.

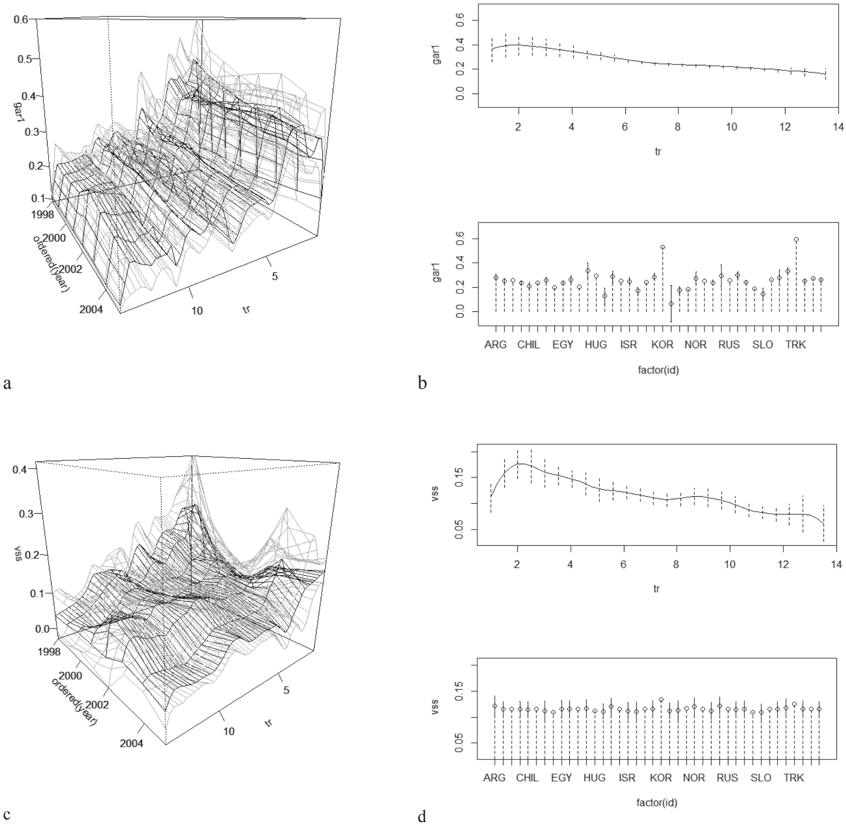


Note: gar1: conditional stock market volatility from GARCH model; vss: historical stock market volatility; tr: transparency index.

Figure 1: Conditional Density and Local Linear Regression Plots

and the transparency index.[2] In both cases, the results reveal that the probability mass of stock market volatility is located at the higher transparency levels. From both graphs it is evident that the highest peaks are located at the lower stock market volatility levels and higher transparency levels. Finally, the distinctive peaks (especially for gar1) suggest a nonlinear relationship. In fact, when looking at the results from the local linear nonparametric regression analysis,

[2] The reason for examining two different proxies of stock market volatility in relation to a countries' transparency index (throughout our analysis) is to enable us to empirically perform a robustness check of the examined relationship.



Note: gar1: conditional stock market volatility from GARCH model; vss: historical stock market volatility; tr: transparency index; factor(id): countries; ordered(years): time period.

Figure 2: Local Linear Regression Plots Accounting Separately for Individual and Time Effects

we find a highly nonlinear negative relationship for both gar1 (subfigure 1b) and vss (subfigure 1d). This is indicated by the two decreasing nonparametric regression lines along with the bootstrapped error bounds (*Hayfield* and *Racine*, 2008), suggesting that higher transparency levels result in the minimising of stock market volatility. Moreover, Table 2 presents the estimated bandwidths using the LSCV criterion along with the estimated bootstrap significance test and the additional R-square (Model 1). The results reveal that the transparency variable has a statistically significant effect on stock market volatility. What is really worth mentioning is the significant drop observed in subfigures 1b and 1d when the transparency index increases from level three to level six. This finding implies significant benefits for stock market stability mainly when central banks with low levels of transparency adopt policies aimed at increasing transparency.

Figure 2 examines in a similar manner the effect of transparency on stock market volatility when we account separately for time (subfigures 2a & 2c) and individual (subfigures 2b & 2d) effects. By using the *Wang* and *Ryzin* (1981) kernel in order to account for time effects[3], the results verify our previous empirical findings suggesting a highly nonlinear negative relationship of transparency for both 'gar1' (subfigure 2a) and 'vss' (subfigure 2c). When we apply the bootstrap significance test proposed by *Racine* (1997) and *Racine* et al. (2006), our findings provided on Table 2 (models 2) suggest that both the year-ordered (year) and the transparency variables have a statistically significant effect on stock market volatility. In a similar manner, by applying the *Aitchison* and *Aitken* (1976) kernel for unordered discrete variables[4], we account for the individual country effects factor (id) when we examine the transparency-stock market volatility relationship. Subfigure 2b investigates the effect on the 'gar1' variable and subfigure 2d on the 'vss' variable. The empirical findings again suggest a negative nonlinear nonparametric relationship, which is more pronounced for the 'vss' variable. The results presented in Table 2 (models 3) indicate that in both cases the individual country effects and transparency levels are statistically significant for explaining stock market volatility.

In contrast to Figure 2, subfigures 3a and 3b simultaneously investigate the time and individual effects on the transparency-stock market volatility relationship. The results indicate that when we account both for time and individual effects, the effect of transparency on stock market volatility is again negative. However, the estimated negative relationship is nonlinear for the 'gar1' case, whereas for the 'vss' case, it is almost linear. When looking at the results from the bootstrapped significant tests (Table 2-Models 4), the individual country effects, time effects and transparency levels are again statistically significant for explaining stock market volatility levels.

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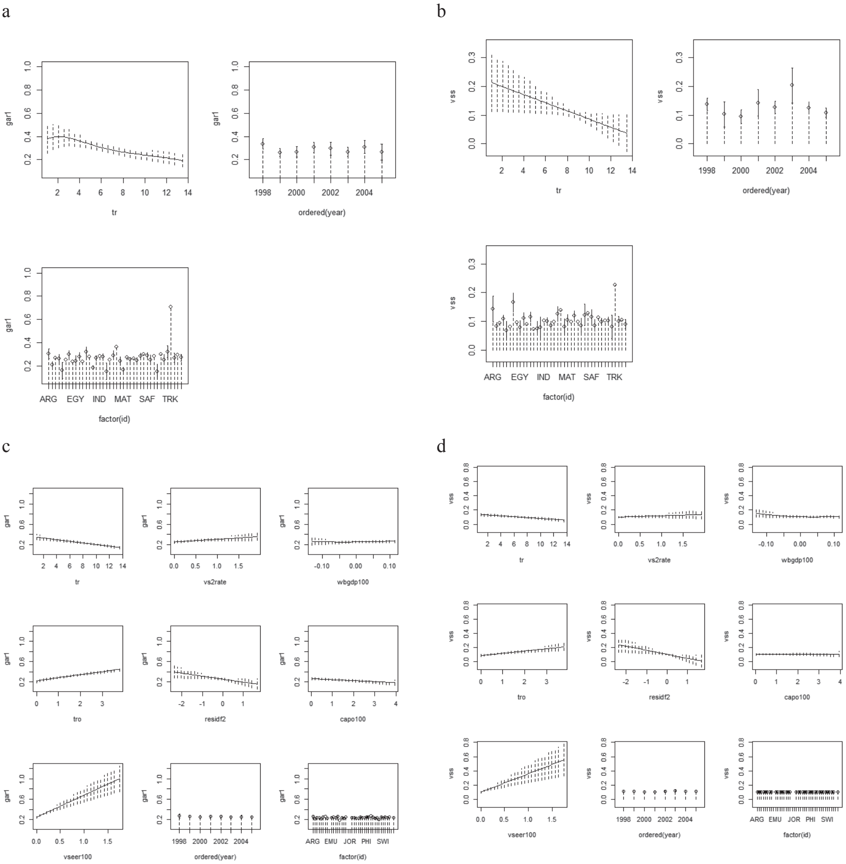
[3] We have also applied the *Li* and *Racine* (2004) kernel for ordered categorical variables. However, the *Wang* and *Ryzin* (1981) kernel performed better in our case. The results of the *Li* and *Racine* (2004) kernel for ordered categorical variables are available upon request.

[4] As previously stated, we have also applied the *Li* and *Racine* (2004) kernel for unordered discrete variables. However, the *Aitchison* and *Aitken* (1976) kernel provide us with a better fit. The results of the *Li* and *Racine* (2004) kernel for unordered discrete variables are available upon request.



Note: gar1: conditional stock market volatility from GARCH model; vss: historical stock market volatility; tr: transparency index; factor(id): countries; ordered(years): time period; capo100: stock market capitalisation; tro: turnover ratio; wbgdp100: real GDP growth; vseer100: effective exchange rate volatility; vs2rate: historical variability of interest rates; residf2: index of financial integration.

Figure 3: Nonparametric Regression Plots

1. *Robustness Tests*

Finally, in order to check the robustness of our empirical findings, we include in our analysis some other control variables in order to visualise whether the effect of transparency on and its significance for stock market volatility levels will change.

More specifically, as stated previously, alongside individual and time effects, we examine the effect of several other control variables, namely: (1) interest rate volatility (vs2rate); (2) real GDP growth (wbgdp100); (3) the ratio of the total value of shares traded over the average market capitalisation on an annual basis (tro); (4) the index of financial integration (residf2); (5) the stock market capitalisation deflated by GDP (capo100) and (6) the effective exchange rate volatility (vser100).

The results for both the conditional and historical volatilities are presented in subfigures 3c and 3d. When accounting for those variables, the results in both cases indicate a negative relationship between transparency levels and stock market volatility. However, since the effect of transparency on stock market volatility now also accounts for the effect of all those pre-mentioned variables (alongside individual and time effects), nonlinearities cannot be traced since they are masked over. The sign of the other coefficients of explanatory variables on stock market volatility verifies the empirical findings suggested in the relevant literature (*Mun*, 2007; *Umutlu* et al., 2010; *Esqueda* et al., 2012). Specifically, we find a positive effect on stock market volatility (both on conditional and historical volatility measures) from interest rate and exchange rate volatilities and the turnover ratio. In contrast, we find a negative effect on stock market volatility from real GDP growth (verified only for the historical volatility case), the financial integration index and stock market capitalisation (verified only for the conditional volatility case).

When looking at the results in Table 2, we can conclude that even though we can account simultaneously for the effect of all the pre-mentioned variables, the transparency levels are statistically significant for explaining stock market volatility for both models (Models 5). However, as can be seen when we use conditional volatility as a dependent variable, we obtain a better fit of our data compared to the historical volatility measure.

As a result, in many cases we can observe large bandwidth values under the LSCV criterion of bandwidth selection. As indicated by *Li* and *Racine* (2009, p.72), the LSCV criterion can assign large values for both relevant and irrelevant variables and therefore the bootstrapped based p-values for variable significance (*Racine* 1997; *Racine* et al., 2006) need to be adopted.

IV. Conclusion

In this paper, by adopting the local linear estimators of the estimated nonparametric regression between stock market volatility and central bank transparency, we provide evidence of a non-linear negative relationship. This result is robust across historical and conditional measures of equity volatility for a large number of countries. The inclusion of other control variables does not affect our main findings.

This result also has significant economic implications for economic authorities. It seems that starting from low levels of central bank transparency, the

Table 2

Bandwidth Estimates, Bootstrapped P-values, and R-squared Values of the Estimated Nonparametric Regression Models

Variables		**Model 1 (gar1)**	**Model 1 (vss)**	**Model 2 (gar1)**	**Model 2 (vss)**	**Model 3 (gar1)**	**Model 3 (vss)**	**Model 4 (gar1)**	**Model 4 (vss)**	**Model 5 (gar1)**	**Model 5 (vss)**
tr	bandwidth	0.2450	0.7756	0.2819	0.5123	2.0544	0.6825	2.8058	5357952	6.6901	7643931
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
vs2rate	bandwidth									2414952	15032
	p-value									*0.0050*	*0.1554*
wbgdp100	bandwidth									0.1401	0.0946
	p-value									*0.0952*	*0.2531*
tro	bandwidth									1.6848	1490706
	p-value									*0.0000*	*0.0000*
residf2	bandwidth									1036873	2.3497
	p-value									*0.0000*	*0.0100*
capo100	bandwidth									3593193	2893063
	p-value									*0.1454*	*0.6817*
vser100	bandwidth									1629944	791387
	p-value									*0.0175*	*0.0150*
ordered(year)	bandwidth			0.8149	0.2853			0.0353	0.7871	0.9367	0.6421
	p-value			*0.0877*	*0.0752*			*0.0000*	*0.0301*	*0.0000*	*0.0226*
factor (id)	bandwidth					0.0759	0.8732	0.0209	0.6669	0.6594	0.9722
	p-value					*0.0000*	*0.0250*	*0.0000*	*0.0000*	*0.0000*	*0.2406*
R-squared		0.3679	0.1446	0.5022	0.4060	0.7417	0.3084	0.8967	0.6144	0.9033	0.8213

Note: gar1: conditional stock market volatility from GARCH model; vss: historical stock market volatility; tr: transparency index; factor(id): countries; ordered(years): time period; capo100: stock market capitalisation; tro: turnover ratio; wbgdp100: real GDP growth; vseer100: effective exchange rate volatility; vs2rate: historical variability of interest rates; residf2: index of financial integration.

adoption of strategies to increase transparency may significantly reduce the level of uncertainty in the equity markets. The negative effect of transparency on stock volatility is clearer when we move from level of transparency three to level six. Therefore, steps towards higher levels of transparency can be especially beneficial for countries with high levels of markets variability and low levels of central bank transparency (such as Russia, Ukraine and Hungary). Given that market stability has beneficial effects on investment, and assuming that investors prefer more stable markets, central banks can help the economy move in this direction by adopting more transparent policies.

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