# Investigating the relationship between Central bank transparency and stock market volatility: A nonparametric approach

**Moïse Sidiropoulos**
Beta University of Strasbourg, France / Aristotle University of Thessaloniki, Department of Economics, Greece /
e-mail: msidiro@econ.auth.gr

**Stephanos Papadamou**[+]
University of Thessaly, Department of Economics, Korai 43, 38333 Volos, Greece,
e-mail: stpapada@uth.gr

**Nickolaos Tzeremes**
University of Thessaly, Department of Economics, Korai 43, 38333 Volos, Greece,
e-mail: bus9nt@econ.uth.gr

## Abstract

This study investigates any non-linear relationship 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 reduce significantly 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 3 to 6 level of transparency and is diminishing as long as we move on higher levels of transparency. This analysis implies that monetary authorities can contribute on equity market stability by adopting more transparent monetary policies in early stages.

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

**JEL codes:** E52; E5; C14

[+]**Correspondence address:** Stephanos Papadamou, Assistant Professor in Economics of Money and Banking, Department of Economics, University of Thessaly, Korai 43, Post Code 38333, Volos, Greece. E-mail: stpapada@uth.gr Tel. +30-2421074963.

## Introduction

Since the pioneer work of Cukierman and Meltzer (1986), there has been a continuous growing literature concerning the effect of central bank transparency on the macroeconomy[1] (inter alia Chortareas 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 limited 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 effort of central bank to guide economic agents' expectations (Blinder, 1998; Van der Cruijsen and Demertzis, 2007). Eijffinger et al. (2006) show that greater transparency should improve central bank credibility, flexibility and reputation. As far as central bank's transparency effects on macroeconomy, the results in a nutshell are that higher transparency: (a) reduces inflation and exchange rate volatilities without necessarily to increase output volatility, and (b) reduces significantly inflation and interest rates.

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

[1] For a survey, see Geraats (2002), Eijffinger and Van der Cruijsen (2007).

It is well known in the literature investigating the effect of monetary policy on stock returns that only unexpected changes in policy rates can have significant negative effects (see among others Bernanke & 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 responds 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 stage of the economy and stock market.

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

In an international content assuming a linear model Papadamou et al., (2014) developed an analytical setting indicating that higher level of central bank transparency may reduce stock market variability.

Our study contributes to the existing literature by investigating any non-linear relationship 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 reduce significantly historical as well as conditional stock market volatility. However, the relationship between stock market volatility and central bank transparency seems to be non-linear. Implying that the benefits are higher starting from a low level of transparency and adopting major processes like publication of inflation report and minutes of committee voting, instead of starting form high levels. The remainder of the paper is structured as follows. Section 2 describes the data and the methodology followed. Section 3 presents the empirical analysis, and we conclude in the last section.

## Data and Methodology

### *Data*

Our sample covers a period from1998 to 2005 where significant changes have been occurred in the level of central bank transparency for a large number of countries. Data are collected on an annual basis for a set of variables on 40 countries. More specifically, equity indices are drawn from the database Ecowin Reuters, the money market rates are taken from the IFS database of the International Monetary Fund. Two different measures of equity volatility are used, the first one referred 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.

Following previous relevant literature (Papadamou et al., 2014; Umutlu et al.,2010; Esqueda et al., 2012) a set of control variables are used in order to check the robustness of our results concerning the relationship between equity variability and central bank transparency. The stock market capitalization deflated by GDP (referred to hereafter as ‘capo100’), the ratio of the total value of shares traded over the average market capitalization (TO, 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 year2. The historical variability of interest rates (vs2rate) is measured based on the standard deviation of monthly interest rates over a year period. Finally, an 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 here after as 'residf2').

In order to take into account several aspects (political, economic, procedural, policy, and operational aspect)[3] of central bank transparency, we used the index constructed by Eijffinger and Geraats, (2006), Dincer and Eichengreen, (2007). They constructed an index of transparency by taking account of the actual information disclosed by central banks. Every aspect of the transparency is taking a value in a scale from zero to three graded by central bankers on an annual survey. Therefore the maximum level of transparency takes the value of fifteen while the lowest is the zero.

Table 1 provides information about the average level, the maximum and the minimum of the variables of interest for each country in the sample. A 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 Philippines, Turkey, Thailand, Singapore, Jamaica, Indonesia, Hungary, and Cyprus). Countries like Ukraine, Russia, Turkey, Hong-Kong and Argentina present significant variability on equity, exchange rate and interest rate markets.

*Insert Table1 about here*

*Nonparametric kernel methods*

[2] Turnover ratio and size are collected by the World Bank, while Resid2 is available on the updated and extended version of the External Wealth of Nations Mark II database developed by Lane and Milesi-Ferretti (2007). The EER data are provided by the Bank of International Settlements (BIS).

[3] For more details about these five aspects of transparency see Geraats (2002),

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

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

where $E\left(u_i \middle| X_i\right) = 0$ and let the joint probability density function (PDF) of $\left(X_i^d, X_i^c\right)$ to be donated as $f\left(x\right) = f\left(x^c, x^d\right)$. For the continues 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:

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

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

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

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

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

where $\hat{g}_{-i}\left(X_i\right)$ is the leave-one-out kernel estimator of $g\left(X_i\right)$ and $M\left(\cdot\right)$ is a weight function. The kernel function for the vector of mixed variables $x=\left(x^c, x^d\right)$ is the product of $W_h\left(\cdot\right)$ and $L\left(\cdot\right)$. Usually the irrelevant variables are assigned by 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, the analyst should follow standard nonparametric significance tests in order to explore in more coherent way the significance of the regressors.

*The local linear estimator*

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

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

Then we choose an $\alpha$ and $b$ in order to minimize:

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

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

*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 $z$ to 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:

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

Then by calculating the bootstrapped-based *P*-values we can reject the null hypothesis at the conventional 1%, 5%, and 10% levels[4]. Finally, by following Racine (2008, p.45) we use a unit-free measure of goodness of fit for our nonparametric regression. This measure range between 0 (no predictive power) and 1 (perfect fit to the sample data), it is a 'within-sample' measure goodness of fit and is analogous to the R-squared $\left(R^2\right)$:

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

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

## Empirical findings

Initially we investigate empirically 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 GARCH model (gar1) and transparency index (tr), whereas, subfigure 1b presents the conditional density plots of historical stock market volatility (vss) and transparency index.[5] The results reveal in both cases that the probability mass of stock market volatility is located on higher transparency levels. From both graphs we can realize that the highest peaks are located on lower stock market volatility and higher transparency levels. Finally, the distinctive peaks (especially for gar1) suggest a nonlinear relationship. In fact when looking the results from the local linear nonparametric regression analysis we found a highly nonlinear negative relationship both for gar1 (subfigure 1b) and for vss (subfigure 1d). This is indicated by the two decreasing nonparametric regression lines alongside with bootstrapped error bounds (Hayfield and Racine, 2008) suggesting that higher transparency levels result on minimizing stock market volatility. Moreover, Table 2 presents the estimated bandwidths using the LSCV criterion alongside 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.

*Insert Figure 1 about here*

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

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[6] the results verify our previous empirical findings suggesting a highly nonlinear negative relationship of transparency both for the cases of 'gar1' (subfigure 2a) and for '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 variable 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[7] we account for the individual country effects-factor (id) when we examine the transparency-stock market volatility relationship. Subfigure 2b investigates the effect on 'gar1' variable, whereas, subfigure 2d on 'vss' variable. The empirical findings suggest again a negative nonlinear nonparametric relationship which is more pronounced for the 'vss' variable. The results presented on Table 2 (models 3) indicate that in both cases the individual country effects and transparency levels are statistically significant on explaining stock market volatility.

*Insert Figure 2 about here*

In contrast to Figure 2, subfigures 3a and 3b investigate simultaneously the time and individual effects on the transparency- stock market volatility relationship. The results indicate that when we account both for time and individual effect, the effect of transparency on stock market volatility is again negative. However the estimated

[6]We have applied also 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.

[7]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.

negative relationship is nonlinear for the ‘gar1’ case, whereas, for the ‘vss’ case is almost linear. When looking the results from the bootstrapped significant tests (Table 2-Models 4) the individual country, time effects and transparency levels are again statistically significant on explaining stock market volatility levels.

*Insert Figure 3 about here*

**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 if the effect and the significance of transparency on stock market volatility levels will change. Specifically as stated previously we examine alongside with individual and time effects 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 capitalization on an annual basis (tro); (4) the index of financial integration (residf2); the stock market capitalization deflated by GDP (caqpo100) and the effective exchange rate volatility (vser100). The results both for the ‘gar1’ and the ‘vss’ variables are presented on subfigures 3c and 3d. When accounting for those variables the results indicate in both cases a negative relationship between the transparency levels and stock market volatility. However, since the effect of transparency on stock market volatility now accounts also for the effect of all those pre-mentioned variables (alongside with individual and time effects), nonlinearities can not be traced since they are masked over. The sign of the other variables on stock market volatility verifies the empirical findings suggested on the relative literature (Mun, 2007; Umutlu et al.,2010; Esqueda et al., 2012). Specifically, we found a positive effect on stock market volatility (both on ‘gar1’ and ‘vss’) from: ‘vs2rate’, ‘tro’ and ‘vser100’, whereas, we find a negative effect from: ‘wbgdp100’ (verified only for the ‘vss’ case), ‘residf2’ and ‘capo100’ (verified only for the ‘gar1’ case). When looking the results on Table 2 we can realise that even though we account simultaneously for the effect of all the pre-mentioned variables, the transparency levels is statistically significant on explaining stock market volatility for both models (Models 5). However, as can been realised when we are using ‘gar1’ as dependent variable we obtain a better fit of our data compared to the ‘vss’ case. As 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.

*Insert Figure 4 and Table 2 about here*

**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 variable may not affect our main findings.

This result has also significant economic implications for economic authorities. It seems that starting from low levels of central bank transparency, the adoption of higher transparency strategies may reduce significantly the level of uncertainty in the equity markets. The negative effect of transparency on stock volatility is clearer when we move from 3 to 6 levels and is diminishing as long as we move on higher levels of transparency. Therefore, steps towards higher level of transparency can be especially beneficial for countries with high levels of markets variability and low levels of central bank transparency (inter alia Russia, Ukraine, Hungary and others). Given that market stability has beneficial effects on investment assumed that investors prefers more stable markets, central banks by adopting more transparent policies may help economy on this direction.

## References


Aitchison, J. and C. G. G. Aitken (1976). Multivariate binary discrimination by the kernel method. *Biometrika* 63(3), 413–420.

Bernanke, B.S. and Kuttner, K.N. (2005). What explains the stock market's reaction to Federal Reserve policy? *The Journal of Finance*, 60(3), 1221-1257.

Blinder, A.S., (1998). Central Banking in Theory and Practice. MIT Press, Cambridge, MA.

Bomfim, A.N., (2003). Pre-announcement effects, news effects, and volatility: monetary policy and the stock market. *Journal of Banking and Finance* 27, 133–151.

Bredin, D., Hyde, S., Nitzsche, D., O'Reilly, G., (2007). UK stock returns and the impact of domestic monetary policy shocks. *Journal of Business Finance and Accounting* 34 (5–6), 872–888.

Chortareas, G., Stasavage, D., Sterne, G., (2002). Does it pay to be transparent? International evidence from central bank forecasts. *Federal Reserve Bank of St. Louis Review* 84 (4), 99–117.

Chuliá, H., Martens, M., van Dijk, D., (2010). Asymmetric effects of Federal funds target rate changes on S&P100 stock returns, volatilities and correlations. *Journal of Banking & Finance* 34, 834–839.

Cukierman, A., Meltzer, A., (1986). The theory of ambiguity, credibility, and inflation under discretion and asymmetric information. *Econometrica* 54, 1099–1128.

de Goeij, P., Marquering, W., (2006). Macroeconomic announcements and asymmetric volatility in bond returns. *Journal of Banking & Finance* 30, 2659–2680.

Demertzis, M., Hughes-Hallet, A., (2007). Central bank transparency in theory and practice. *Journal of Macroeconomics* 29 (4),760–789.

Dincer, N., Eichengreen, B., (2007). Central bank transparency: where, why, and with what effects? NBER Working Paper Nr.13003.

Ehrmann, M., Fratzscher, M., (2004). Taking stock: monetary policy transmission to equity markets. *Journal of Money, Credit, and Banking* 36 (4), 719–736.

Eijffinger, S., Geraats, P.M., (2006). How transparent are central banks? *European Journal of Political Economy* 22, 1–21.

Eijffinger, S., Geraats, P.M., Van der Cruijsen, C., (2006). Does Central Bank Transparency Reduce Interest Rates? CEPR Discussion Papers Nr. 5526.

Eijffinger, S., Van der Cruijsen, C., (2007). The Economic Impact of Central Bank Transparency: A Survey. CEPR Discussion Paper Nr. 6070.

Esqueda, O.A., Assefa, T.A., Mollick, A.V., (2012). Financial globalization and stock market risk. *Journal of International Financial Markets, Institutions and Money* 22, 87–102

Evans, K., Speight, A., (2010). International macroeconomic announcements and intraday euro exchange rate volatility. *Journal of the Japanese and International Economies* 24, 552–568.

Fan, J. and I. Gijbels (1996), Local Polynomial Modelling and Its Applications. London: Chapman and Hall.

Fratzscher, M., (2006). On the long-term effectiveness of exchange rate communication and interventions. *Journal of International Money and Finance* 25 (1), 146–167.

Geraats, P.M., (2002). Central bank transparency. *Economic Journal* 112 (483), 532–565.

Gnabo, J.-Y., Laurent, S., Lecourt, C., (2009). Does transparency in central bank intervention policy bring noise to the FX market? The case of the Bank of Japan. *Journal of International Financial Markets, Institutions and Money* 19, 94–111.

Gregoriou, A., Kontonikas, A., MacDonald, R., Montagnoli, A., (2009). Monetary policy shocks and stock returns: evidence from the British market. *Financial Markets and Portfolio Management* 23 (4), 401–410.

Hall, P., Racine, J.S., Li, Q., (2004). Cross-Validation and the Estimation of Conditional Probability Densities. *Journal of the American Statistical Association* 99, 1015–1026.

Hayfield T, Racine J.S. (2008). “Nonparametric Econometrics: The np Package.” Journal of Statistical Software, 27 (5). URL: http://www.jstatsoft.org/v27/i05/

Hussain, S.M., (2011). Simultaneous monetary policy announcements and international stock markets response: an intraday analysis. *Journal of Banking & Finance* 35, 752–764.

Konrad, E., (2009). The impact of monetary policy surprises on asset return volatility: the case of Germany. *Financial Markets and Portfolio Management* 23 (2), 111–135.

Kurov, A., (2012). What determines the stock market’s reaction to monetary policy statements? *Review of Financial Economics* 21, 175–187.

Lane, P.R., Milesi-Ferretti, G.M., (2007). The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004. *Journal of International Economics* 73 (2), 223–250

Li Q., J.S. Racine (2004) Cross-validated local linear nonparametric regression *Statistica Sinica* 14, 485-512.

Li Q., J.S. Racine (2007) Nonparametric econometrics: Theory and practice, Princeton University Press: Oxford.

Li Q., Racine J.S. (2009) *Nonparametric Econometric Methods (Advances in Econometrics, Volume 25)*, Emerald Group Publishing Limited, UK.

Lunde, A., Zebedee, A., (2009). Intraday volatility responses to monetary policy events. *Financial Markets and Portfolio Management* 23 (4), 383–399.

Mun, K.-C., (2007). Volatility and correlation in international stock markets and the role of exchange rate fluctuations. *Journal of International Financial Markets, Institutions and Money* 17, 25–41.

Neuenkirch, M., (2012). Managing financial market expectations: the role of central bank transparency and central bank communication. *European Journal of Political Economy* 28, 1–13.

Papadamou, S., (2013). Market anticipation of monetary policy actions and interest rate transmission to US Treasury market rates. *Economic Modelling,* 33, 545-551.

Papadamou, S., Sidiropoulos, M., Spyromitros, E., (2014). Does central bank transparency affect stock market volatility? *Journal of International Financial Markets, Institutions and Money* 31, 362-377.

Papadamou, S., Sidiropoulos, M., Spyromitros, E., (2015). Central Bank Transparency and the Interest Rate Channel: Evidence from Emerging Economies. *Economic Modelling* 48, 167-174.

Racine, J. S. (1997). Consistent significance testing for nonparametric regression. *Journal of Business and Economic Statistics* 15(3), 369–379.

Racine, J. S., (2008) Nonparametric Econometrics: A primer. *Foundations and Trends in Econometrics* 3(1) 1-88.

Racine, J. S., J. D. Hart, and Q. Li (2006), 'Testing the significance of categorical predictor variables in nonparametric regression models'. *Econometric Reviews* 25, 523–544.

Racine, JS and, Q. Li (2004). Nonparametric estimation of regression functions with both categorical and continuous data. *Journal of Econometrics* 119, 99-130.

Ranaldo, A., Rossi, E., (2010). The reaction of asset markets to Swiss National Bank communication. *Journal of International Money and Finance* 29, 486–503.

Reeves, R., Sawicki, M., (2007). Do financial markets react to bank of England communication? *European Journal of Political Economy* 23 (1), 207–227.

Umutlu, M., Akdeniz, L., Altay-Salih, A., (2010). The degree of financial liberalization and aggregated stock-return volatility in emerging markets. *Journal of Banking & Finance* 34, 509–521.

Van der Cruijsen, C., Demertzis, M., (2007). The impact of central bank transparency on inflation expectations. *European Journal of Political Economy* 23 (1), 51–66.

Vithessonthi, C., Techarongrojwong, Y., (2012). The impact of monetary policy decisions on stock returns: evidence from Thailand. *Journal of International Financial Markets, Institutions and Money* 22 (3), 487–507.

Wang, M. C. and J., van Ryzin (1981). A class of smooth estimators for discrete distributions. *Biometrika* 68, 301–309.

**Figure 1:** Conditional density and local linear regression plots.

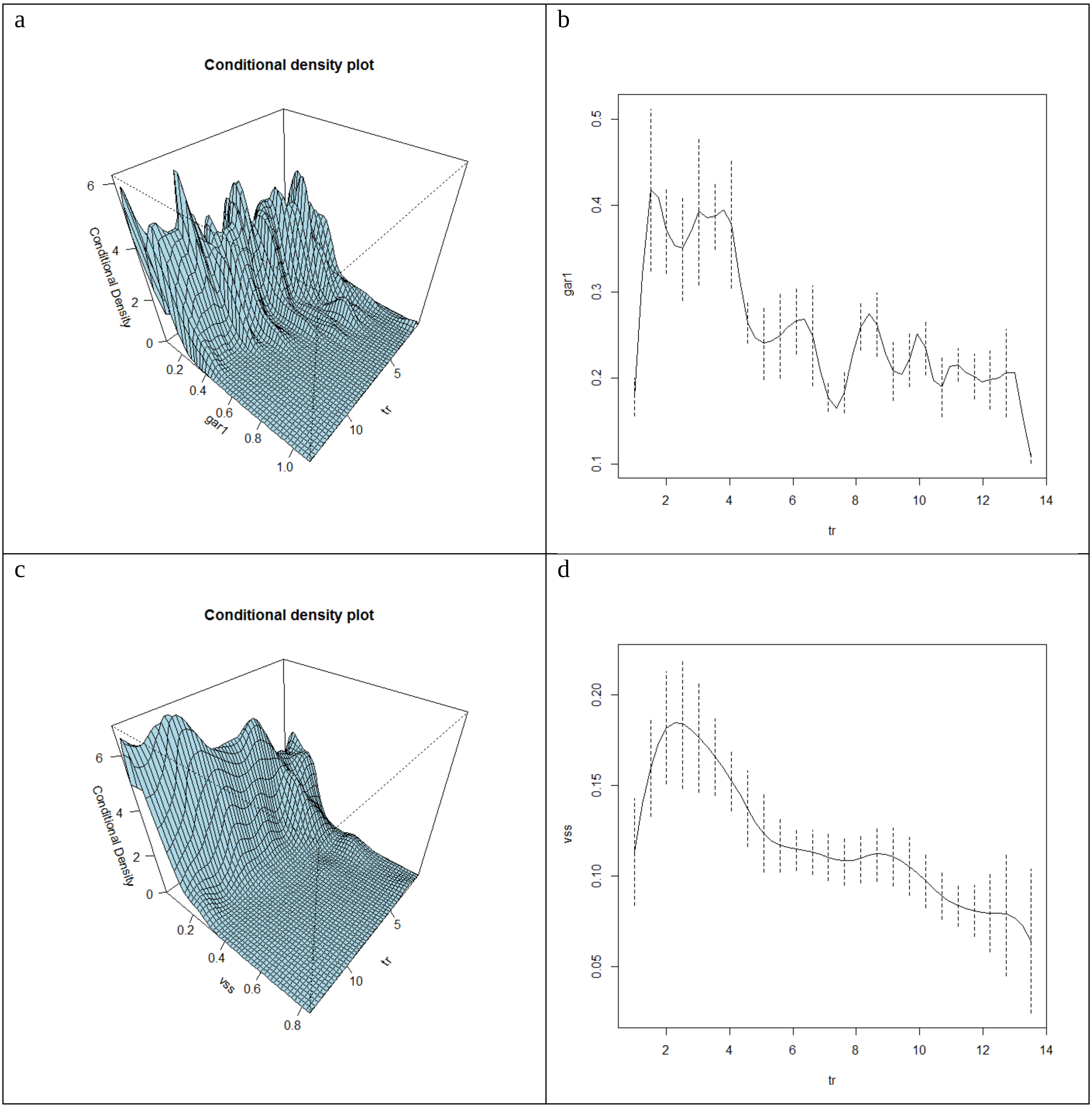

**Figure 2:** Local linear regression plots accounting separately for individual and time effects.

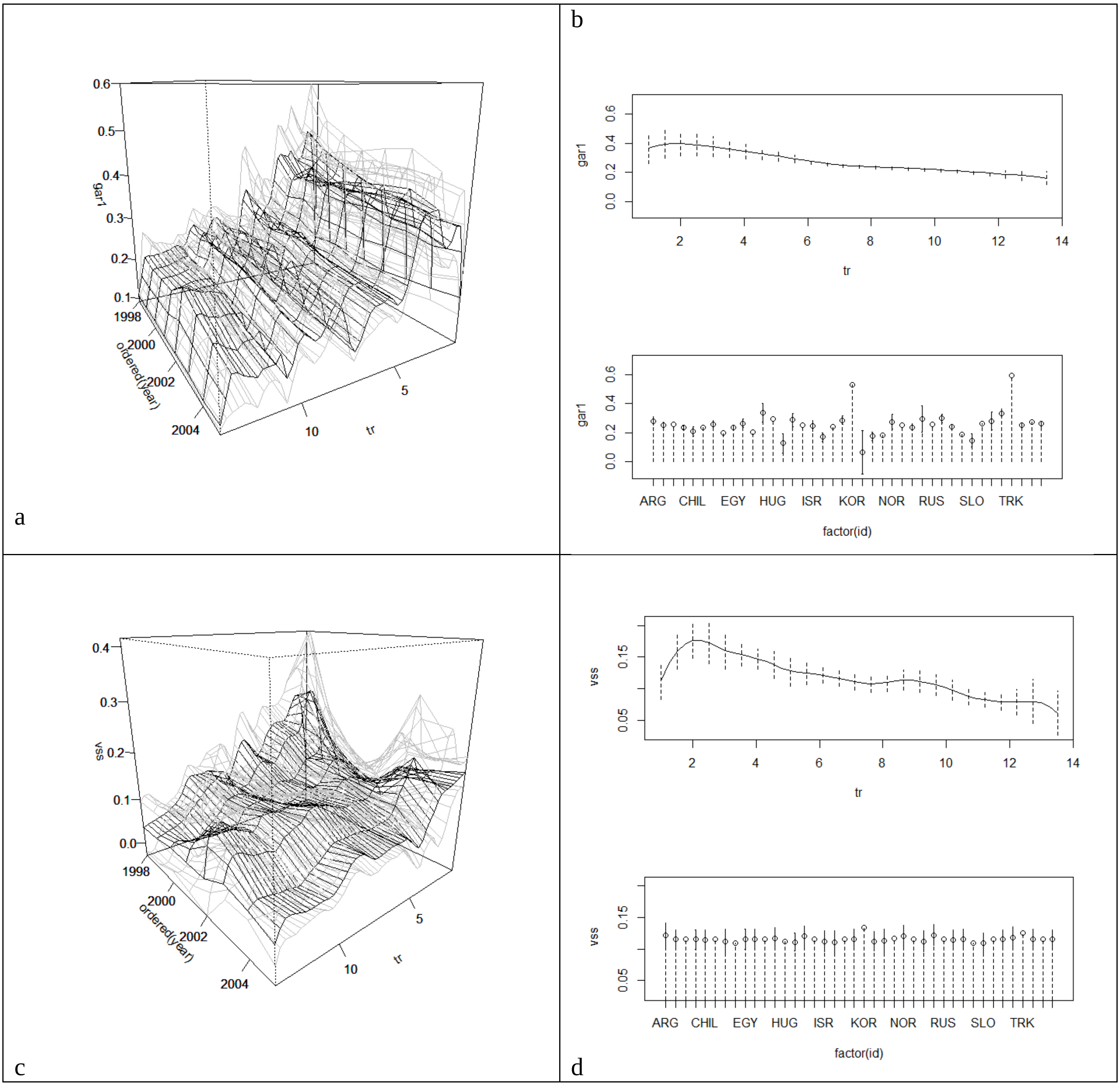

**Figure 3:** Nonparametric regression plots

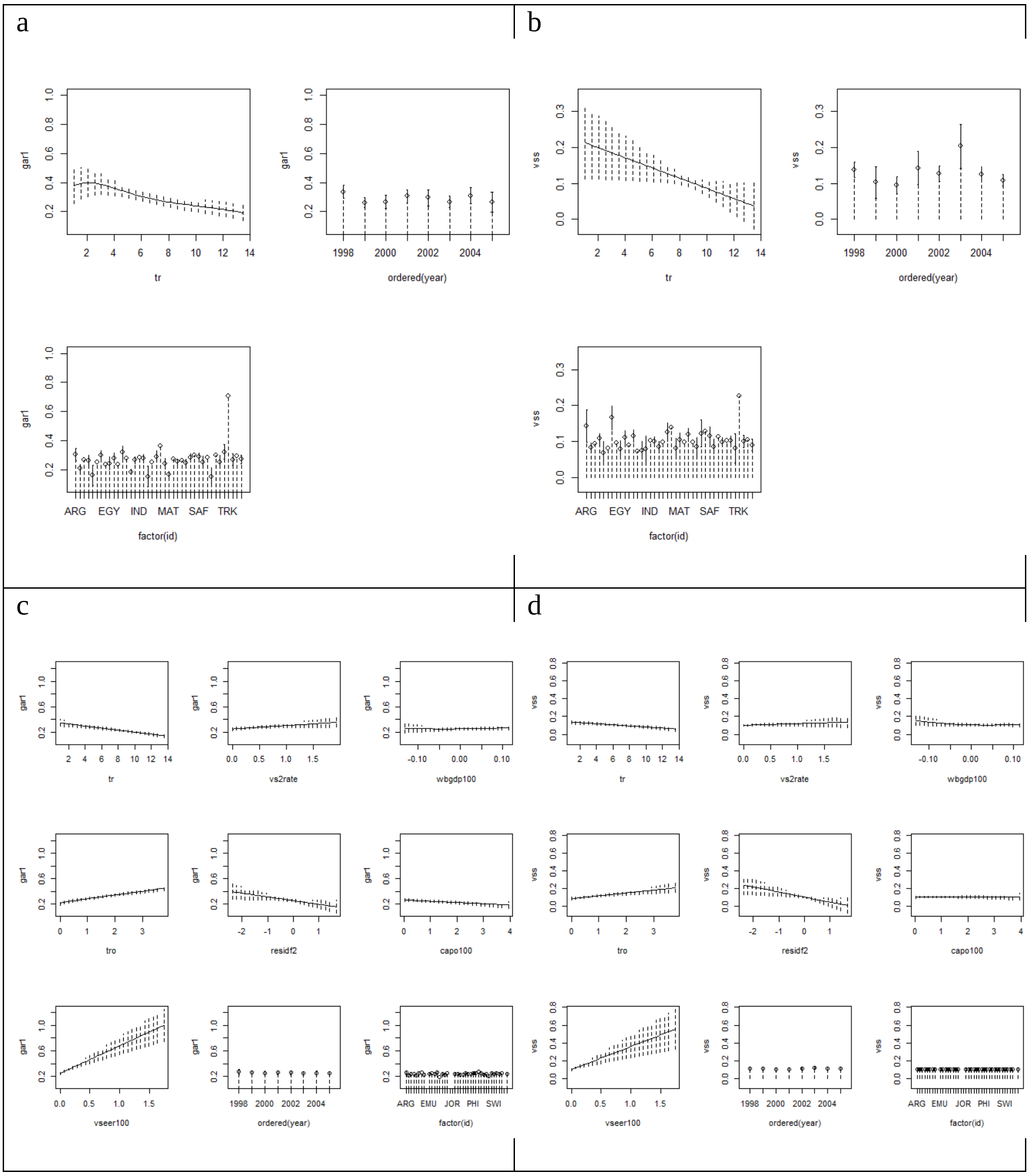

**Table 1** Descriptive Statistics over the period 1998-2005

| | **Argentina** | | | **Australia** | | | **Canada** | | | **China** | | | **Croatia** | | | **Cyprus** | | | **Denmark** | | | **Egypt** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *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 | 2.13 | 1.50 | 2.50 | 4.50 | 2.50 | 6.50 | 5.38 | 5.00 | 6.00 | 1.13 | 1.00 | 2.00 |
| 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 | 0.33 | 0.02 | 0.64 | 0.11 | 0.04 | 0.23 | 0.09 | 0.01 | 0.18 | 0.10 | 0.00 | 0.31 |
| 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 | 0.32 | 0.21 | 0.52 | 0.32 | 0.16 | 0.60 | 0.22 | 0.17 | 0.28 | 0.12 | 0.06 | 0.22 |
| 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 | 0.11 | 0.05 | 0.25 | 0.23 | 0.04 | 0.83 | 0.10 | 0.05 | 0.18 | 0.08 | 0.01 | 0.15 |
| 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 | 0.03 | -0.01 | 0.05 | 0.04 | 0.02 | 0.05 | 0.02 | 0.00 | 0.04 | 0.04 | 0.02 | 0.06 |
| 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 | 0.05 | 0.03 | 0.07 | 0.53 | 0.04 | 1.64 | 0.73 | 0.61 | 0.92 | 0.23 | 0.10 | 0.43 |
| 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 | 0.28 | 0.20 | 0.40 | 0.71 | 0.30 | 1.00 | 1.15 | 0.70 | 1.30 | 0.26 | 0.20 | 0.40 |
| 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 | 0.17 | 0.11 | 0.29 | 0.45 | 0.27 | 0.71 | 0.59 | 0.44 | 0.69 | 0.40 | 0.25 | 0.89 |
| 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 | 0.01 | 0.01 | 0.02 | 0.01 | 0.00 | 0.03 | 0.01 | 0.01 | 0.02 | - | - | - |

| | **EMU** | | | **Estonia** | | | **Hong - Kong** | | | **Hungary** | | | **Iceland** | | | **Indonesia** | | | **India** | | | **Israel** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *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 | 6.88 | 5.50 | 7.50 | 5.50 | 3.00 | 8.00 | 2.00 | 2.00 | 2.00 | 7.81 | 5.50 | 8.50 |
| 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 | 0.15 | 0.05 | 0.48 | 0.23 | 0.06 | 0.58 | 0.03 | 0.00 | 0.08 | 0.11 | 0.04 | 0.29 |
| 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 | 0.13 | 0.09 | 0.17 | 0.32 | 0.24 | 0.55 | 0.32 | 0.23 | 0.44 | 0.24 | 0.20 | 0.29 |
| 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 | 0.10 | 0.03 | 0.16 | 0.16 | 0.04 | 0.28 | 0.16 | 0.07 | 0.31 | 0.10 | 0.05 | 0.18 |
| 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 | 0.05 | 0.00 | 0.08 | 0.02 | -0.13 | 0.06 | 0.07 | 0.04 | 0.09 | 0.03 | -0.01 | 0.09 |
| 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 | 0.52 | 0.07 | 0.94 | 0.42 | 0.31 | 0.54 | 1.66 | 0.92 | 3.06 | 0.51 | 0.27 | 0.96 |
| 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 | 0.64 | 0.20 | 1.70 | 0.20 | 0.10 | 0.40 | 0.14 | 0.10 | 0.20 | 0.54 | 0.30 | 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 | 0.82 | 0.37 | 1.71 | 0.24 | 0.14 | 0.46 | 0.39 | 0.22 | 0.66 | 0.59 | 0.36 | 0.90 |
| 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 | 0.05 | 0.01 | 0.11 | 0.08 | 0.02 | 0.19 | 0.02 | 0.01 | 0.05 | 0.03 | 0.01 | 0.08 |

| | **Jamaica** | | | **Jordan** | | | **Japan** | | | **Korea** | | | **Malaysia** | | | **Malta** | | | **Mexico** | | | **Norway** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *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 | 4.75 | 4.00 | 5.00 | 5.94 | 5.00 | 7.00 | 4.44 | 4.00 | 5.50 | 7.06 | 6.00 | 8.00 |
| 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 | 0.08 | 0.00 | 0.34 | 0.03 | 0.00 | 0.09 | 0.19 | 0.05 | 0.37 | 0.14 | 0.02 | 0.36 |
| 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 | 0.26 | 0.11 | 0.73 | 0.17 | 0.12 | 0.27 | 0.29 | 0.18 | 0.43 | 0.25 | 0.19 | 0.34 |
| 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 | 0.12 | 0.03 | 0.29 | 0.12 | 0.05 | 0.36 | 0.13 | 0.10 | 0.17 | 0.14 | 0.07 | 0.23 |
| 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 | 0.04 | -0.07 | 0.09 | 0.03 | -0.02 | 0.07 | 0.03 | 0.00 | 0.07 | 0.02 | 0.01 | 0.04 |
| 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 | 0.31 | 0.18 | 0.45 | 0.08 | 0.03 | 0.25 | 0.28 | 0.21 | 0.32 | 0.92 | 0.72 | 1.17 |
| 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 | 0.76 | 0.70 | 0.90 | 0.74 | 0.30 | 1.00 | 0.35 | 0.30 | 0.50 | 0.94 | 0.60 | 1.20 |
| 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 | 1.41 | 1.23 | 1.84 | 0.43 | 0.21 | 0.69 | 0.22 | 0.16 | 0.32 | 0.43 | 0.31 | 0.63 |
| vseer100 | - | - | - | - | - | - | 0.03 | 0.01 | 0.05 | 0.03 | 0.01 | 0.09 | 0.02 | 0.01 | 0.04 | 0.01 | 0.00 | 0.01 | 0.05 | 0.02 | 0.11 | 0.02 | 0.01 | 0.04 |

**Table 1 continued** Descriptive Statistics over the period 1998-2005

| | **New Zealand** | | | **Philippines** | | | **Romania** | | | **Russia** | | | **South Africa** | | | **Saudi Arabia** | | | **Singapore** | | | **Slovenia** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *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 | 7.25 | 4.00 | 9.00 | 1.00 | 1.00 | 1.00 | 4.75 | 2.50 | 6.50 | 6.25 | 5.00 | 7.50 |
| 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 | 0.10 | 0.01 | 0.21 | 0.14 | 0.03 | 0.31 | 0.22 | 0.07 | 0.44 | 0.11 | 0.01 | 0.23 |
| 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 | 0.29 | 0.24 | 0.40 | 0.21 | 0.16 | 0.28 | 0.28 | 0.14 | 0.59 | 0.14 | 0.11 | 0.21 |
| 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 | 0.16 | 0.03 | 0.24 | 0.13 | 0.04 | 0.21 | 0.12 | 0.04 | 0.23 | 0.07 | 0.03 | 0.14 |
| 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 | 0.03 | 0.01 | 0.05 | 0.04 | -0.01 | 0.09 | 0.05 | -0.02 | 0.09 | 0.04 | 0.03 | 0.05 |
| 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 | 0.39 | 0.29 | 0.49 | 0.92 | 0.27 | 2.32 | 0.49 | 0.32 | 0.67 | 0.22 | 0.09 | 0.34 |
| 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 | 0.91 | 0.60 | 1.10 | 0.88 | 0.70 | 1.20 | 4.33 | 3.10 | 5.10 | 0.28 | 0.20 | 0.40 |
| 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 | 1.70 | 1.18 | 2.29 | 0.71 | 0.29 | 1.97 | 1.86 | 0.99 | 2.56 | 0.18 | 0.10 | 0.29 |
| 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 | 0.07 | 0.02 | 0.15 | 0.02 | 0.01 | 0.03 | 0.01 | 0.00 | 0.02 | 0.01 | 0.00 | 0.03 |

| | **Sweden** | | | **Switzerland** | | | **Thailand** | | | **Turkey** | | | **UK** | | | **Ukraine** | | | **USA** | | | **Chile** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *Mean* | *Min* | *Max* | *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 | 11.88 | 11.00 | 12.00 | 2.50 | 2.00 | 3.00 | 8.38 | 7.50 | 8.50 | 7.38 | 7.00 | 7.50 |
| 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 | 0.08 | 0.03 | 0.16 | 0.47 | 0.35 | 0.63 | 0.17 | 0.06 | 0.41 | 0.34 | 0.06 | 1.36 |
| 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 | 0.20 | 0.11 | 0.29 | 0.41 | 0.28 | 0.67 | 0.22 | 0.13 | 0.30 | 0.12 | 0.09 | 0.18 |
| 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 | 0.07 | 0.02 | 0.16 | 0.21 | 0.04 | 0.48 | 0.07 | 0.03 | 0.15 | 0.09 | 0.03 | 0.17 |
| 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 | 0.03 | 0.02 | 0.04 | 0.05 | -0.02 | 0.12 | 0.03 | 0.01 | 0.05 | 0.04 | -0.01 | 0.06 |
| 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 | 0.91 | 0.52 | 1.42 | 0.08 | 0.02 | 0.19 | 1.52 | 1.06 | 2.03 | 0.10 | 0.06 | 0.15 |
| 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 | 1.83 | 1.40 | 2.10 | 0.16 | 0.10 | 0.20 | 0.69 | 0.60 | 0.90 | 0.99 | 0.70 | 1.20 |
| 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 | 1.49 | 1.16 | 1.95 | 0.10 | 0.01 | 0.29 | 1.41 | 1.05 | 1.79 | 0.90 | 0.65 | 1.16 |
| 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 | 0.02 | 0.01 | 0.02 | - | - | - | 0.02 | 0.01 | 0.03 | 0.04 | 0.02 | 0.06 |

**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* | bandiwdth | 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* | bandiwdth | | | | | | | | | 2414952 | 15032 |
| | *p-value* | | | | | | | | | *0.0050* | *0.1554* |
| *wbgdp100* | bandiwdth | | | | | | | | | 0.1401 | 0.0946 |
| | *p-value* | | | | | | | | | *0.0952* | *0.2531* |
| *tro* | bandiwdth | | | | | | | | | 1.6848 | 1490706 |
| | *p-value* | | | | | | | | | *0.0000* | *0.0000* |
| *residf2* | bandiwdth | | | | | | | | | 1036873 | 2.3497 |
| | *p-value* | | | | | | | | | *0.0000* | *0.0100* |
| *caqpo100* | bandiwdth | | | | | | | | | 3593193 | 2893063 |
| | *p-value* | | | | | | | | | *0.1454* | *0.6817* |
| *vser100* | bandiwdth | | | | | | | | | 1629944 | 791387 |
| | *p-value* | | | | | | | | | *0.0175* | *0.0150* |
| *ordered(year)* | bandiwdth | | | 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)* | bandiwdth | | | | | 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 | 0.4622 |