Appendix 1. Empirical studies on the relationship between public budget and economic growth

Authors	Sample, period	Major findings
Helms (1985).	U.S. states (1965-1979)	Revenue used to fund transfer payments retards growth.
Saunders (1985)	OECD countries (1960-1981)	Little evidence that government size has been detrimental to growth.
Landau (1986)	Less developed countries (1960-1980)	Government consumption expenditures do not appear to have had much impact on economic growth. In itself, government investment has a weak positive influence, but, when we allow for the taxation and borrowing needed to finance such investment plus the crowding out of private investment, the net impact is zero.
Grier and Tullock (1989)	115 countries (1951-1980)	Growth in government share of GDP negatively affects growth of real GDP.
Koester and Kormendi (1989).	63 countries (1970-1979)	Increases in marginal tax rates have negative effects on economic activity. Reductions in the “progressivity” of tax rates induce a parallel shift upward in the growth path.
Easterly and Rebelo (1993).	100 countries (1970-1988) and 28 countries (1870-1988)	Effects of taxation difficult to isolate empirically.
Mullen and Williams (1994).	U.S. states (1969-1986)	Higher marginal tax rates reduce GDP growth.
Lemieux et al. (1994).	Micro data from a randomized survey carried out in the Metropolitan area of Quebec City, Canada.	Taxes distort labor-market activities away from the regular sector to the underground sector, but the distortion is small for the average worker. The distortion is large, however, for particular groups of the population such as welfare claimants.
Cashin (1994)	23 countries (1971-1988)	Public investment generates externalities that raise economic growth.
Devarajan et al (1996)	43 developing countries (1970-1990)	Current expenditure stimulates growth while government capital expenditure decreases growth.
Chernick (1997).	U.S. states (1977-1993)	Progressivity of income taxes negatively affects GDP growth.
Mendoza et al. (1997).	18 OECD countries, panel data, five-year average (1966-1990)	Evidence to support the Harberger’s superneutrality conjecture (although in theory the mix of direct and indirect taxes affects investment and growth, in practice tax policy is ineffective as an instrument to promote growth).
Miller and Russek (1997).	39 developed and developing countries	Tax-financed spending reduces growth in developed countries, increases growth in developing countries.
Kneller et al. (1999).	OECD countries (1970-1995)	Distortionary taxes reduce GDP growth.
Goolsbee and Maydew (2000)	Panel data for the U.S. states (1978-1994)	The apportionment formula has a significant real effect on a state’s economy.
Padovano and Galli (2001).	23 OECD countries (1951-1990)	Effective marginal income tax rates negatively correlated with GDP growth.

Appendix 1 - continued

Authors	Sample, period	Major findings
Padovano and Galli (2001).	23 OECD countries (1951-1990)	Effective marginal income tax rates negatively correlated with GDP growth.
Fölster and Henrekson (2001).	Rich countries (1970-1995)	Tax revenue as a share of GDP negatively correlated with GDP growth.
Bleaney et al. (2001).	OECD countries (1970-1995)	Distortionary taxes reduce GDP growth. Consumption taxes are not distortionary.
Blanchard and Perotti (2002).	U.S. Post-WWII (1947-1997)	The results consistently show positive government spending shocks as having a positive effect on output, and positive tax shocks as having a negative effect. The multipliers for both spending and tax shocks are typically small.
Holcombe and Lacombe (2004), cited in Gwartney and Lawson (2006), p. 40.	Counties separated by state borders (1960-1990)	States that raised their income tax rates more than their neighbors had slower income growth and, on average, a 3.4% reduction in per capita income.
Tomljanovich (2004).	Panel data for the U.S. states (1972-1998)	Higher tax rates negatively affect short run growth, but not long run growth.
Lee and Gordon (2005)	70 countries (1970-1997, cross-sectional and 5 year panels)	Statutory corporate tax rates are significantly negatively correlated with cross-sectional differences in average economic growth rates. In fixed-effect regressions, increases in corporate tax rates lead to lower future growth rates within countries.
Bania et al. (2007)	U.S. states (1962-1997)	Based on estimates for U.S. states, the incremental effect of taxes directed toward publicly provided productive inputs is initially positive, but eventually turns negative, consistent with a growth hill.
Reed (2008)	48 continental U.S. states (1970-1999)	Taxes used to fund general expenditures are associated with significant, negative effects on income growth. This finding is robust across alternative variable specifications, estimation procedures, and across different time periods.
Poulson and Kaplan (2008)	50 US states (1964-2004)	Significant negative impact of higher marginal tax rates on economic growth.
Arnold (2008)	21 OECD countries (1971-2004)	Property taxes, and particularly recurrent taxes on immovable property, seem to be the most growth-friendly, followed by consumption taxes and then by personal income taxes. Corporate income taxes appear to have the most negative effect on GDP per capita. These empirical results have been used in Arnold et al. (2011) for sustaining that economic growth can be increased by gradually moving the tax base towards consumption and immovable property (especially residential property). It was also argued that growth can also be enhanced by improving the design of individual taxes (see Arnold et al. 2011).

Appendix 1 - continued

Authors	Sample, period	Major findings
Hakro (2009)	Developing countries in Asia (1981-2005)	Government expenditure is pro growth.
Alesina and Ardagna (2010)	OECD countries (1970-2007)	Fiscal stimuli based upon tax cuts more likely to increase growth than those based upon spending increases. Fiscal consolidations based upon spending cuts and no tax increases are more likely to succeed at reducing deficits and debt and less likely to create recessions.
International Monetary Fund (2010).	15 advanced countries (170 fiscal consolidations over the last 30 years)	1% tax increase reduces GDP by 1.3% after two years.
Romer and Romer (2010).	U.S. Post-WWII (104 tax changes)	Tax (federal revenue) increase of 1% of GDP leads to a fall in output of 3% after about 2 years, mostly through negative effects on investment.
Johannesen (2010).	Impact of introducing the source tax on interest income on Swiss bank deposits held by EU residents.	The 15% source tax caused Swiss bank deposits of EU residents to drop by more than 40% with most of the response occurring in two quarters immediately before and after the source tax was introduced.
Strategies (2011).	31,412.3 thousand small businesses of USA.	Overall, compliance burdens increase as the size of a small business increases. These vary significantly by industry. Some industries have more. Compliance burdens are lowest for small businesses organized as sole proprietors.
Gemmell et al. (2011)	17 OECD countries (early 1970s to 2004)	Taxes on income and profit are most damaging to economic growth over the long run, followed by deficits, and then consumption taxes.
Barro and Redlick (2010)	U.S (1912-2006)	Cut in the average marginal tax rate of one percentage point raises next year's per capita GDP by around 0.5%.
Xing (2011)	17 OECD countries (1970-2004)	Shifts in total tax revenue towards property taxes may be associated with a higher steady-state level of income per capita
Ferede and Dahlby (2012).	Canadian provinces (1977-2006)	Reducing corporate income tax 1 percentage point raises annual growth by 0.1 to 0.2 points
Mertens and Ravn (2012).	U.S.: Effects of tax changes operated in 1948, 1954, 1958, 1959, 1962, 1964, 1965, 1966, 1967, 1971, 1971, 1976, 1977, 1978, 1980, 1981, 1984, 1986, 1987, 1990, 1993, 2003	A 1 percentage point cut in the average personal income tax rate raises real GDP per capita by 1.4 percent in the first quarter and by up to 1.8 percent after three quarters. A 1 percentage point cut in the average corporate income tax rate raises real GDP per capita by 0.4 percent in the first quarter and by 0.6 percent after one year.
Bonucchi et al. (2014)	Italy, (1996-2013)	The user cost of capital to labor is strongly affected by the system of corporate taxation in place. The user cost of capital relative to labor have significant positive effect on business investment, both in the short and longer-term.

Appendix 1 - continued

Authors	Sample, period	Major findings
Cevik and Teksoz (2014)	Panel data for 24 advanced and 25 developing economies during the period 1990–2012.	The discretionary fiscal policy is influenced by policy inertia, the level of public debt, and the output gap. Some macro-financial factors (real exchange rate, financial development, interest rates, asset prices), natural resource rents, demographic and institutional factors (old-age dependency ratio, quality of institutions, fiscal rules and IMF-supported stabilization programs) tend to have a significant effect on fiscal policy behavior.
Magazzino (2014)	Italy: (1861-2008)	The study shows the presence of a non-linear relationship between the size of public sector (measured by the share of government expenditure over GDP) and the economic growth rate for Italy. In general, the presence of an inverted “U-shape” curve emerges for the last two decades, suggesting that expenditure cuts might faster GDP dynamic.

Appendix 2. Countries included in the analysis

Code	Country	Code	Country	Code	Country	Code	Country
ARG	Argentina	GBR	United Kingdom	LKA	Sri Lanka	PNG	Papua New Guinea
AUS	Australia	GEO	Georgia	LSO	Lesotho	POL	Poland
AUT	Austria	GRC	Greece	LTU	Lithuania	PRT	Portugal
BEL	Belgium	GRD	Grenada	LUX	Luxembourg	ROU	Romania
BGR	Bulgaria	GTM	Guatemala	LVA	Latvia	RUS	Russian Federation
BHS	Bahamas, The	HRV	Croatia	MAC	Macao SAR, China	SGP	Singapore
BLR	Belarus	HUN	Hungary	MAR	Morocco	SLE	Sierra Leone
BLZ	Belize	IDN	Indonesia	MDA	Moldova	STP	Sao Tome and Principe
BRA	Brazil	IND	India	MDG	Madagascar	SUR	Suriname
BTN	Bhutan	IRL	Ireland	MDV	Maldives	SVK	Slovak Republic
CAN	Canada	IRN	Iran, Islamic Rep.	MEX	Mexico	SVN	Slovenia
CHN	China	ISL	Iceland	MLI	Mali	SWE	Sweden
COD	Congo, Dem. Rep.	ISR	Israel	MNG	Mongolia	SYC	Seychelles
CYP	Cyprus	ITA	Italy	MYS	Malaysia	SYR	Syrian Arab Republic
CZE	Czech Republic	JOR	Jordan	NAM	Namibia	TTO	Trinidad and Tobago
DEU	Germany	JPN	Japan	NIC	Nicaragua	TUN	Tunisia
DNK	Denmark	KAZ	Kazakhstan	NLD	Netherlands	TUR	Turkey
EGY	Egypt, Arab Rep.	KEN	Kenya	NOR	Norway	UGA	Uganda
ESP	Spain	KGZ	Kyrgyz Republic	NZL	New Zealand	UKR	Ukraine
EST	Estonia	KNA	St. Kitts and Nevis	OMN	Oman	URY	Uruguay
ETH	Ethiopia	KOR	Korea, Rep.	PAK	Pakistan	USA	United States
FIN	Finland	KWT	Kuwait	PAN	Panama	VCT	St. Vincent and the Grenadines
FRA	France	LBN	Lebanon	PER	Peru	VEN	Venezuela, RB
		LCA	St. Lucia	PHL	Philippines	ZAF	South Africa

Appendix 3. The algorithm applied in database extrapolations (backward and forward)

1. As in other studies, the available information was used through a moving average operator. Adopted notations are as follows:

x – time order (lag or lead) as integers from 1 (the closest term), 2, …, to m (the furthest term); x=1, 2, …m

D – type of distribution

w_{xD} – weight of the term x in distribution D with the restriction $\Sigma w_{xD}=1$

The forward extrapolation operates with the formula

$$y_{t+i}=\Sigma y_i*w_{xD} \text{ (for i=t, t-1,… t-m)} \quad \text{(A3.1),}$$

whereas backward extrapolation operates with the formula

$$y_{t-j}=\Sigma y_j*w_{xD} \text{ (for j=t, t+1,… t+m)} \quad \text{(A3.1a).}$$

In the case of interpolations, both of these relationships were used.

2. The core of the proposed methodology consists of a determination of the lags' weights w_{xD} under conditions in which we do not know what statistical distribution would be proper with this aim. Consequently, it was considered reasonable to combine several such distributions instead of using one alone (arbitrarily chosen).

2.1. The algorithm adopted in our application involves five types of distributions: normal (symbol Nor), Fisher (Fis), rectangular (Rec), normal-mirror (Nmi), and uniform (Uni). The bibliography of their individual properties is large; illustratively, we mention Fisher (1937), Fedorenko et al. (1975), Miller and Russek (1997), Verbeek (2000), Cox (2004), Bialas (2005), Joyce (2006), Haas and Pigorsch (2007), Chen et al. (2011), Jula and Jula (2012) and McLaughlin (2014).

The formal definitions of the selected distributions are presented hereinafter.

2.1.1. Normal distribution

$$F_{NOR}(x) = (1/(\sigma*(2*\pi)^{0.5})\exp[(-1/2)*((x-\mu)/\sigma)^2)] \quad \text{(A3.2)}$$

where σ is the standard deviation of x, π=3.14159, and μ is the mean of x. Using $F_{NOR}(x)$, the following are computed:

$SF_{NOR} = \Sigma F_{NOR}(x)$ (A3.2a) and the weights of interest:

$$w_{xNOR}(x) = F_{NOR}(x)/SF_{NOR} \quad \text{(A3.3)}$$

2.1.2. Fisher distribution

$$w_{xFIS}(x) = (m-x+1)*2/(m*(m+1)) \quad \text{(A3.4)}$$

2.1.3. Rectangular distribution

$$F_{REC}(x) = (x - a)/(b - a) \text{ with range } a \leq x \leq b \qquad (A3.5)$$

$$SF_{REC} = \Sigma F_{REC}(x) \qquad (A3.5a)$$

$$w_{xREC}(x) = F_{REC}(x)/SF_{REC} \qquad (A3.6)$$

In our application, a=1 and b=m+1 are assumed.

2.1.4. Normal-mirror distribution

$$F_{NMI}(x) = (1/(\sigma*(2*\pi)^{0.5})\exp[(1/2)*((x-\mu)/\sigma)^2)] \qquad (A3.7)$$

$$SF_{NMI} = \Sigma F_{NMI}(x) \qquad (A3.7a)$$

$$w_{xNMI}(x) = F_{NMI}(x)/SF_{NMI} \qquad (A3.8)$$

2.1.5. Uniform distribution

$$w_{xUNI}(x) = 1/m, \text{ constant} \qquad (A3.9)$$

2.2. Two practical considerations have guided our selection.

- It appears adequate to envelop an extended space of possible scores assigned to different lags. The pairs Fis-Rec and Nor-Nmi display symmetrical shapes of the lags' weights, whereas Uni is neutral from this perspective.
- To avoid useless computational complications, a small number of involved distributions (five) were selected. For the same reason and considering the shortness of available statistical series, the factor m (number of lags) has also been limited to five.

3. Calculated as above, the weights specific to different types of distributions are synthetized below:

	Normal	Fisher	Rectangular Continuous	Normal-mirror	Uniform
Lag (lead)	Nor	Fis	Rec	Nmi	Uni
1	0.111703	0.333333	0	0.4	0.2
2	0.236476	0.266667	0.1	0.1	0.2
3	0.303641	0.2	0.2	0	0.2
4	0.236476	0.133333	0.3	0.1	0.2
5	0.111703	0.066667	0.4	0.4	0.2
Sum	1	1	1	1	1

Thus, the five selected distributions can cover a sufficiently broad range of possible lag (lead) weights.

4. How to aggregate the resulting estimations? Similar to previous authors, such as Chbab et al. (2002), Moscarini and Squintani (2004), Forbes et al. (2011), and McLaughlin (2014), we have preferred to involve all five types of distribution. If available data y_s (s=1, 2,…n, in which n>m) are applied to weights w_{xD}, we obtain five sets of estimated $y\hat{}_{qD}$ (q=m+1. m+2,..n-m), respectively: $y\hat{}_{qNor}$, $y\hat{}_{qFis}$, $y\hat{}_{qRecr}$, $y\hat{}_{qNmi}$, and $y\hat{}_{qUni}$. Our proposal is to compute the Minkovski distances between them and the corresponding statistical data; see van de Geer (1995), Akleman and Chen (1999), Crasta and Malusa (2005), Schulz (2008) and Cordeiro de Amorim (2012). The second order of the Minkowski metric (Min2) appears to be the most convenient in our application:

$$Min2_D=\Sigma((y\hat{}_{qD}-y_q)\hat{}2)\hat{}0.5 \qquad (A3.10)$$

The sum of their inverse values (SM) is used to help determine the aggregated weights of the different types of distribution (W_D):

$$SM=(1/Min2_{Nor})+(1/Min2_{Fis})+(1/Min2_{Rec})+(1/Min2_{Nmi})+(1/Min2_{Uni}) \qquad (A3.11)$$

The proportions (W_D) in which different distributions are involved in the final aggregation are approximated as follows:

$W_{Nor}=Min2_{Nor}/SM$ (A3.12a)
$W_{Fis}=Min2_{Fis}/SM$ (A3.12b)
$W_{Rec}=Min2_{Rec}/SM$ (A3.12c)
$W_{Nmi}=Min2_{Nmi}/SM$ (A3.12d)
$W_{Uni}=MinUni_r/SM$ (A3.12e)

Consequently, the initial lag (lead) weights w_{xD} become W_D*w_{xD}, resulting in a new type of distribution that is itself compatible with the properties of the available statistical data.

5. Using the above-described forward and backward extrapolations, slightly over 6% of the entire database was generated:

Indicator, WB code	Number of forward and backward extrapolations	Proportion, %
GC.XPN.TOTL.GD.ZS	405	18.342
NY.GDP.MKTP.KD.ZG	59	2.6721
NE.GDI.TOTL.ZS.	69	3.125
NY.GDP.PCAP.CD	36	1.6304
Total	569	6.4425

Appendix 4. The Hurst exponent methodology

1. With the goal of attenuating the penuriousness of available information, these data were combined into sub-samples (symbol S) of different lengths (from 8 to 23), consisting of successive observations (taken in direct or inverted order). In addition to the initial symbol S, the codes of the R/S sub-samples that are thus made contain

- The subscript dir for direct ordered data, or inv for inverted ordered ones
- The number of terms included (the length of S)
- The small letter a or b when the series is divided into two sub-samples

The observations are noted with 1 for 1990, 2 for 1991,…, 23 for 2012; the R/S sub-samples were composed as shown below:

Code of R/S sub-sample	Included observations	Code of R/S sub-sample	Included observations	Code of R/S sub-sample	Included observations	Code of R/S sub-sample	Included observations
$S_{dir}23$	1, 2,…, 23			$S_{inv}23$	23, 22,…, 1		
$S_{dir}22$	1, 2,…, 22			$S_{inv}22$	22, 21,…, 1		
$S_{dir}21$	1, 2,…, 21			$S_{inv}21$	21, 20,…, 1		
$S_{dir}20$	1, 2,…, 20			$S_{inv}20$	20, 19,…, 1		
$S_{dir}19$	1, 2,…, 19			$S_{inv}19$	19, 18,…, 1		
$S_{dir}18$	1, 2,…, 18			$S_{inv}18$	18, 17,…, 1		
$S_{dir}17$	1, 2,…, 17			$S_{inv}17$	17, 16,…, 1		
$S_{dir}16$	1, 2,…, 16			$S_{inv}16$	16, 15,…, 1		
$S_{dir}15a$	1, 2,…, 15	$S_{dir}8b$	16, 17,…, 23	$S_{inv}15a$	15, 14,…, 1	$S_{inv}8b$	23, 22,…, 16
$S_{dir}14a$	1, 2,…, 14	$S_{dir}9b$	15, 16,…, 23	$S_{inv}14a$	14, 13,…, 1	$S_{inv}9b$	23, 22,…, 15
$S_{dir}13a$	1, 2,…, 13	$S_{dir}10b$	14, 15,…, 23	$S_{inv}13a$	13, 12,…, 1	$S_{inv}10b$	23, 22,…, 14
$S_{dir}12a$	1, 2,…, 12	$S_{dir}11b$	13, 14,…, 23	$S_{inv}12a$	12, 11,…, 1	$S_{inv}11b$	23, 22,…, 13
$S_{dir}11a$	1, 2,…, 11	$S_{dir}12b$	12, 13,…, 23	$S_{inv}11a$	11, 10,…, 1	$S_{inv}12b$	23, 22,…, 12
$S_{dir}10a$	1, 2,…, 10	$S_{dir}13b$	11, 12,…, 23	$S_{inv}10a$	10, 9,…, 1	$S_{inv}13b$	23, 22,…, 11
$S_{dir}9a$	1, 2,…, 9	$S_{dir}14b$	10, 11,…, 23	$S_{inv}9a$	9, 8,…, 1	$S_{inv}14b$	23, 22,…, 10
$S_{dir}8a$	1, 2,…, 8	$S_{dir}15b$	9, 10,…, 23	$S_{inv}8a$	8, 7,…, 1	$S_{inv}15b$	23, 22,…, 9

Forty-eight sub-samples were compiled by such a procedure that obviously facilitated the regression analysis but not without cost because of a possible disturbing effect induced by the repetition of some data.

2. The regression analysis itself is not devoid of computational problems. Based on the R/S values for all 48 mentioned sub-samples, the simplest specification of the Hurst exponent (H) has been estimated:

$$\log(R/S)=c(1)+H*\log(n) \qquad (A4.1)$$

in which c(1) represents the intercept and n represents the number of observations included in the corresponding sub-samples.

The main problem arises when OLS estimations of H exceed the standard limits ($0<H<1$). EViews, for instance, has generated 50 such cases (from 95); re-computed in STATA, this number decreased to ten. We could abandon such estimations as being nonsensical; see Quantitative Finance Stack Exchange (2012). However, because we considered this problem instead as a sign of serial correlation in the data, the adopted solution was to determine these “outliers” by regressions with restrictions for coefficients:

$$\log(R/S)=c(1)+((1-0)*@atan(c(2))*2/@acos(-1)+0)*\log(n) \qquad (A4.2)$$

from which H is deduced (suggested by D. Jula) by H=(1-0)*@atan(c(2))*2/@acos(-1)+0.

The estimations obtained by EViews and STATA without restrictions, and estimations obtained from EViews with restrictions are provided in the Supplementary material S5.

3. The above-described methodology has been contrasted with the corrected-size procedure, provided by numXL and based on the Anis-Lloyd-Peters algorithm (Wang et al., 2011). The results of the size-corrected procedure follow (with certain expectable variations) the overall configuration of our estimations.

Appendix 5. LSVAR for the cbe series

Series	Lags	Series	Lags	Series	Lags	Series	Lags	Series	Lags
ARGcbe	5	ESTcbe	7	JPNcbe	7	MEXcbe	8	SGPcbe	10
AUScbe	8	ETHcbe	6	KAZcbe	8	MLIcbe	10	SLEcbe	6
AUTcbe	7	FINcbe	9	KENcbe	10	MNGcbe	8	STPcbe	5
BELcbe	7	FRAcbe	7	KGZcbe	9	MYScbe	2	SURcbe	8
BGRcbe	10	GBRcbe	7	KNAcbe	6	NAMcbe	2	SVKcbe	9
BHScbe	10	GEOcbe	4	KORcbe	9	NICcbe	10	SVNcbe	7
BLRcbe	7	GRCcbe	Reject*	KWTcbe	8	NLDcbe	9	SWEcbe	10
BLZcbe	10	GRDcbe	9	LBNcbe	3	NORcbe	8	SYCcbe	2
BRAcbe	10	GTMcbe	10	LCAcbe	4	NZLcbe	2	SYRcbe	8
BTNcbe	7	HRVcbe	10	LKAcbe	3	OMNcbe	3	TTOcbe	5
CANcbe	9	HUNcbe	9	LSOcbe	6	PAKcbe	7	TUNcbe	4
CHNcbe	5	IDNcbe	9	LTUcbe	7	PANcbe	10	TURcbe	10
CODcbe	10	INDcbe	3	LUXcbe	10	PERcbe	9	UGAcbe	9
CYPcbe	10	IRLcbe	7	LVAcbe	6	PHLcbe	9	UKRcbe	Reject*
CZEcbe	8	IRNcbe	7	MACcbe	8	PNGcbe	10	URYcbe	8
DEUcbe	10	ISLcbe	8	MARcbe	5	POLcbe	10	USAcbe	8
DNKcbe	5	ISRcbe	7	MDAcbe	10	PRTcbe	6	VCTcbe	3
EGYcbe	10	ITAcbe	9	MDGcbe	5	ROUcbe	5	VENcbe	10
ESPcbe	5	JORcbe	7	MDVcbe	7	RUScbe	8	ZAFcbe	Reject*

*For all possible lags at least one root outside the unit circle.

Appendix 6. PSE dependence on m, MS, and PDP

Dependent Variable: PSE

Included observations: 91

Variable	Coefficient	t-Statistic	Prob.	Standardized coefficient	Uncentered VIF
m	10.44361	1.593631	0.115	0.072073	11.60664
MS	251.5905	2.011703	0.0476	0.069391	5.648074
PDP	2150178	2.877523	0.0051	0.10652	5.529847
R-squared	0.847606				
Adjusted R-squared	0.828557				

Appendix 7. Estimated attractor as an AR process (ATT1)

Series code	ATT1	Series code	ATT1	Series code	ATT1	Series code	ATT1	Series code	ATT1
ARGcbe	0.18699	ESTcbe	0.29978	JPNcbe	0.16871	MDVcbe	0.78687	ROUcbe	0.34923
AUScbe	0.25471	ETHcbe	0.13655	KAZcbe	0.10833	MEXcbe	0.17845	RUScbe	0.23445
AUTcbe	0.35943	FINcbe	0.3708	KENcbe	0.17621	MLIcbe	0.14313	SGPcbe	0.13872
BELcbe	0.42998	FRAcbe	0.44927	KGZcbe	0.1914	MNGcbe	0.48594	SLEcbe	0.20821
BGRcbe	0.30246	GBRcbe	0.42091	KNAcbe	0.30922	MYScbe	0.19461	STPcbe	0.22908
BHScbe	0.16157	GEOcbe	0.17682	KORcbe	0.16284	NAMcbe	0.28528	SURcbe	0.23862
BLRcbe	0.29	GRDcbe	0.19214	KWTcbe	0.34445	NICcbe	0.16221	SVKcbe	0.37314
BLZcbe	0.23553	GTMcbe	0.13266	LBNcbe	0.29195	NLDcbe	0.40273	SVNcbe	0.39704
BRAcbe	0.25478	HRVcbe	0.35189	LCAcbe	0.19649	NORcbe	0.33577	SWEcbe	0.29265
BTNcbe	0.19426	HUNcbe	0.43551	LKAcbe	0.06068	NZLcbe	0.67238	SYCcbe	0.19792
CANcbe	0.18252	IDNcbe	0.17691	LSOcbe	1.83051	OMNcbe	0.29951	SYRcbe	0.18153
CHNcbe	0.2165	INDcbe	0.1505	LTUcbe	0.50836	PAKcbe	0.17838	TTOcbe	0.25352
CODcbe	0.09942	IRLcbe	0.34195	LUXcbe	0.37025	PANcbe	0.22161	TUNcbe	0.39663
CZEcbe	0.33748	IRNcbe	0.61402	LVAcbe	0.29229	PERcbe	0.17862	TURcbe	0.33743
DEUcbe	0.27428	ISLcbe	0.53704	MACcbe	0.14087	PHLcbe	0.17031	UGAcbe	0.17619
DNKcbe	0.36884	ISRcbe	0.35288	MARcbe	0.30167	PNGcbe	0.25815	URYcbe	0.27935
EGYcbe	0.29412	ITAcbe	0.39703	MDAcbe	0.30138	POLcbe	0.33926	USAcbe	0.2132
ESPcbe	0.30973	JORcbe	0.93909	MDGcbe	0.1066	PRTcbe	0.44229	VCTcbe	0.23961
								VENcbe	0.24341

Appendix 8. Relative attractor-mean deviation (in module)

No.	rAM1	rAM2	No.	rAM1	rAM2	No.	rAM1	rAM2
1	0,05176	0,104655	31	0,068339	0,022939	61	0,045474	0,120517
2	0,029829	0,04298	32	2,225356	0,018076	62	0,000557	0,02963
3	0,097237	0,152766	33	0,824267	0,027984	63	0,085543	0,09398
4	0,00234	0,074582	34	0,188027	0,034164	64	0,954531	0,164374
5	0,115419	0,013466	35	0,024762	0,04166	65	0,00928	0,034978
6	0,013086	0,041929	36	3,448416	0,105499	66	0,002528	0,020027
7	0,020729	0,177795	37	0,027301	0,068351	67	0,00357	0,221891
8	0,093999	0,049771	38	0,25186	0,155955	68	0,015425	0,069968
9	0,028792	0,105737	39	0,062557	0,042705	69	0,003902	0,505474
10	0,013763	0,061974	40	0,026206	0,134293	70	0,040995	0,242512
11	0,097394	0,050289	41	0,188551	0,062347	71	0,012811	0,056006
12	0,303037	0,075701	42	0,003114	0,025687	72	0,210795	0,060859
13	0,102998	0,106755	43	0,267733	1,3606	73	0,012678	0,154979
14	0,066198	0,144303	44	0,002165	1,606541	74	0,016903	0,042895
15	0,119698	0,116873	45	0,004353	0,003577	75	0,048466	0,019122
16	0,004854	0,009399	46	0,723491	0,040448	76	0,003834	0,131653
17	0,024058	0,027985	47	3,512598	0,031703	77	0,012104	0,049233
18	0,022196	0,003957	48	0,738273	0,05705	78	0,103808	0,07719
19	0,021689	0,006331	49	0,021122	0,000518	79	0,01658	0,223374
20	0,039979	0,051217	50	0,007761	0,19752	80	0,045615	0,059061
21	0,037666	0,080508	51	0,04201	0,052327	81	0,167639	0,010613
22	0,007082	0,088049	52	0,032621	0,316039	82	0,515718	0,038121
23	0,116296	0,026568	53	0,044392	0,225427	83	0,041498	0,143472
24	0,023967	0,204754	54	0,007019	0,028003	84	0,016754	0,045349
25	0,028908	0,009062	55	2,290595	0,058522	85	0,441144	0,077617
26	0,212192	0,036682	56	0,119495	0,042579	86	0,034772	0,026337
27	0,017917	0,30735	57	0,029286	0,076177	87	0,000446	0,099909

28	0,005348	0,299857	58	1,351	0,012586	88	0,025558	0,423522
29	0,237373	0,087868	59	0,060737	0,133765	89	0,002629	0,023527
30	0,000116	0,206469	60	0,002363	0,030475	90	0,061834	0,024904
						91	0,101738	0,037111

Appendix 9. Dependent Variable: rAM1

Variable	Coefficient	t-Statistic	Prob.	Standardized Coefficient	Uncentered VIF
CVS	0.23117	3.063029	0.003	0.041996	2.672828
ESP	0.04173	2.491672	0.0148	0.011722	2.604578
R-squared	0.986296				
Adjusted R-squared	0.984388				

Appendix 10. Regular oscillatory convergence towards steady state

No.	Country code	EC	CVEC	CEC	CVCEC	No.	Country code	EC	CVEC	CEC	CVCEC
1	AUScbe	61	0.162009	20 (3)	0.05385	27	LCAcbe	18	0.029669		
2	BLRcbe	42	0.079208			28	LUXcbe	377	0.072857		
3	BLZcbe	6	0.219089	3 (2)	0	29	LVAcbe	37	0.131687	18 (2)	0.067673
4	BTNcbe	9	0.036585			30	MARcbe	8	0.061797		
5	CANcbe	117	0.058882			31	MDAcbe	94	0.025298		
6	CHNcbe	57	0.131946	19 (3)	0.020956	32	MDGcbe	17	0.049137		
7	CZEcbe	49	0.136283	16 (3)	0.031408	33	OMNcbe	23	0.034684		
8	DNKcbe	10	0.031942			34	PANcbe	50	0.221974	16 (3)	0.081236
9	EGYcbe	89	0.1446	29 (3)	0.048131	35	PERcbe	102	0.192539	34 (3)	0.063648
10	ETHcbe	34	0.13572	17 (2)	0.072708	36	PHLcbe	27	0.095835		
11	FINcbe	44	0.152879	14 (3)	0.043755	37	PNGcbe	27	0.109026	13 (2)	0.047507
12	FRAcbe	113	0.13784	37 (3)	0.035133	38	POLcbe	23	0.090943		
13	GEOcbe	6	0			39	ROUcbe	14	0.049417		
14	GRDcbe	55	0.201079	27 (2)	0.038207	40	SGPcbe	138	0.088676		
15	GTMcbe	48	0.106299	24 (2)	0.059049	41	SLEcbe	9	0.025604		
16	HRVcbe	58	0.043912			42	STPcbe	51	0.0409		
17	IDNcbe	157	0.161956	52 (3)	0.051657	43	SVKcbe	16	0.033752		
18	INDcbe	54	0			44	SVNcbe	12	0.042464		
19	IRLcbe	65	0.129428	21 (3)	0.0625	45	SYRcbe	40	0.124131	13 (3)	0.037832
20	ITAcbe	115	0.092447			46	TTOcbe	15	0.03136		
21	JPNcbe	177	0.184591	59 (3)	0.041382	47	TUNcbe	5	0.010032		
22	KENcbe	50	0.059513			48	UGAcbe	81	0.117563	27 (3)	0.030022
23	KGZcbe	52	0.12243	26 (2)	0.07303	49	URYcbe	50	0.143269	16 (3)	0.024845
24	KNAcbe	34	0.065002			50	USAv	7	0.057695		
25	KWTcbe	215	0.202885	71 (3)	0.01692	51	VENcbe	66	0		

26	LBNcbe	16	0.06515

Appendix 11. Irregular oscillatory convergence towards steady state

No.	Contry code	EC	CVEC	CEC	CVCEC
1	ARGcbe	51	0.35259	10 (5)	0.287086
2	BELcbe	31	0.14956	15 (2)	0.122833
3	BGRcbe	25	0.23514	8 (3)	0.130286
4	BHScbe	59	0.16411	29 (2)	0.153852
5	BRAcbe	37	0.18838	12 (3)	0.149508
6	CODcbe	20	0.32348	10 (2)	0.305548
7	DEUcbe	53	0.24421	17 (3)	0.224999
8	ESPcbe	14	0.78541	3 (2)	0.330719
9	ESTcbe	20	0.56458	10 (2)	0.576283
10	GBRcbe	3	0.74048		
11	HUNcbe	24	0.53476	12 (2)	0.332486
12	KAZcbe	14	0.58851	7 (2)	0.48111
13	KORcbe	30	0.72303	10 (3)	0.73474
14	MACcbe	51	0.53856	17 (3)	0.4972
15	MEXcbe	13	0.73736	6 (2)	0.7484
16	MLIcbe	45	0.36322	15 (3)	0.19556
17	NICcbe	19	0.19048	9 (2)	0.16366
18	NLDcbe	12	0.55831	6 (2)	0.5665
19	NORcbe	32	0.22989	16 (2)	0.20448
20	PAKcbe	32	0.23206	10 (3)	0.20595
21	RUScbe	24	0.32746	12 (2)	0.30592
22	SURcbe	41	0.13693	13 (3)	0.10758
23	SWEcbe	30	0.31839	10 (3)	0.2601
24	TURcbe	78	0.44333	26 (3)	0.2494

Note: It is evident that a too small number of EC did not allow to compute multiples for GBRcbe.

Appendix 12. Estimated attractor by the BARS curve (ATT2)

Series code	ATT2	Series code	ATT2	Series code	ATT2	Series code	ATT2	Series code	ATT2
ARGcbe	0.19639	ESTcbe	0.30448	JPNcbe	0.17546	MEXcbe	0.16619	SGPcbe	0.14858
AUScbe	0.27383	ETHcbe	0.12457	KAZcbe	0.12222	MLIcbe	0.14965	SLEcbe	0.18149
AUTcbe	0.45896	FINcbe	0.41633	KENcbe	0.196	MNGcbe	0.20409	STPcbe	0.2152
BELcbe	0.46314	FRAcbe	0.49231	KGZcbe	0.17016	MYScbe	0.20801	SURcbe	0.24571
BGRcbe	0.34652	GBRcbe	0.36704	KNAcbe	0.24394	NAMcbe	0.27724	SVKcbe	0.44904
BHScbe	0.1528	GEOcbe	0.20804	KORcbe	0.15816	NICcbe	0.19042	SVNcbe	0.35729
BLRcbe	0.24348	GRCcbe	0.39723	KWTcbe	1.1104	NLDcbe	0.41443	SWEcbe	0.35533
BLZcbe	0.20458	GRDcbe	0.19966	LBNcbe	0.75933	NORcbe	0.40168	SYCcbe	0.39311
BRAcbe	0.29007	GTMcbe	0.10543	LCAcbe	0.19665	NZLcbe	0.40056	SYRcbe	0.19931
BTNcbe	0.20917	HRVcbe	0.24818	LKAcbe	0.21056	OMNcbe	0.28638	TTOcbe	0.24614
CANcbe	0.21239	HUNcbe	0.30656	LSOcbe	0.39278	PAKcbe	0.17525	TUNcbe	0.29658
CHNcbe	0.15357	IDNcbe	0.13041	LTUcbe	0.30914	PANcbe	0.27176	TURcbe	0.33468
CODcbe	0.12267	INDcbe	0.18156	LUXcbe	0.37843	PERcbe	0.18821	UGAcbe	0.19371
CYPcbe	0.78886	IRLcbe	0.37545	LVAcbe	0.34733	PHLcbe	0.25539	UKRcbe	0.36603
CZEcbe	0.36221	IRNcbe	0.19381	MACcbe	0.13935	PNGcbe	0.33446	URYcbe	0.38775
DEUcbe	0.34799	ISLcbe	0.28615	MARcbe	0.38447	POLcbe	0.32442	USAcbe	0.21765
DNKcbe	0.37413	ISRcbe	0.44944	MDAcbe	0.24428	PRTcbe	0.34306	VCTcbe	0.22004
EGYcbe	0.29525	ITAcbe	0.42407	MDGcbe	0.10883	ROUcbe	0.2989	VENcbe	0.22914
ESPcbe	0.30421	JORcbe	0.23338	MDVcbe	0.25312	RUScbe	0.22825	ZAFcbe	0.313

Table 3

Probit Regression for Wavelet-Filtered Credit Spread of AA- Class

Lag	d1-d2 (1-8 months)			d3-d5 (8-64 months)		
k	β	*z-statistic*	*Pseudo-*R^2	β	*z-statistic*	*Pseudo-*R^2
1	0.09	0.43	0.00	-0.31	-2.01**	0.02
2	0.09	0.44	0.00	-0.30	-2.00**	0.02
3	0.10	0.49	0.00	-0.27	-1.85*	0.01
4	-0.17	-0.93	0.00	-0.20	-1.35	0.01
5	-0.06	-0.30	0.00	-0.07	-0.45	0.00
6	-0.03	-0.15	0.00	0.11	0.77	0.00
7	-0.04	-0.20	0.00	0.32	2.14**	0.02
8	0.00	-0.01	0.00	0.50	3.22***	0.05
9	0.05	0.24	0.00	0.62	3.78***	0.07
10	0.05	0.26	0.00	0.68	4.01***	0.09
11	0.05	0.25	0.00	0.71	3.93***	0.09
12	0.03	0.14	0.00	0.74	3.90***	0.10

Lag	d6-d7 (64-256 months)			s7 (over 256 months)		
k	β	*z-statistic*	*Pseudo-*R^2	β	*z-statistic*	*Pseudo-*R^2
1	0.09	0.33	0.00	7.56	2.92***	0.04
2	0.01	0.05	0.00	7.13	2.74***	0.03
3	-0.06	-0.21	0.00	6.66	2.55**	0.03
4	-0.12	-0.46	0.00	6.16	2.35**	0.02
5	-0.18	-0.67	0.00	5.62	2.14**	0.02
6	-0.24	-0.86	0.00	5.04	1.91*	0.02
7	-0.28	-1.02	0.00	4.44	1.67*	0.01
8	-0.32	-1.14	0.01	3.80	1.43	0.01
9	-0.33	-1.21	0.01	3.77	1.41	0.01
10	-0.35	-1.26	0.01	3.73	1.39	0.01
11	-0.36	-1.31	0.01	3.69	1.36	0.01
12	-0.37	-1.36	0.01	3.63	1.33	0.01

Note: The asterisks *, **, *** denote the significance of the estimate at the 10, 5, and 1% level.

Table 4

Probit Regression for Wavelet-Filtered Credit Spread of BBB- Class

Lag *k*	d1-d2 (1-8 months)			d3-d5 (8-64 months)		
	β	*z-statistic*	*Pseudo-*R^2	*β*	*z-statistic*	*Pseudo-*R^2
1	-0.23	-0.25	0.00	0.06	0.51	0.00
2	0.12	0.14	0.00	0.19	1.53	0.01
3	-0.05	-0.05	0.00	0.33	2.61**	0.04
4	-0.36	-0.39	0.00	0.47	3.66***	0.07
5	-0.66	-0.73	0.00	0.60	4.54***	0.10
6	-0.71	-0.78	0.00	0.71	5.12***	0.14
7	-0.37	-0.40	0.00	0.79	5.40***	0.16
8	-0.14	-0.15	0.00	0.84	5.46***	0.18
9	0.89	0.99	0.01	0.85	5.36***	0.18
10	1.27	1.41	0.01	0.84	5.13***	0.18
11	0.96	1.08	0.01	0.80	4.79***	0.16
12	0.12	0.13	0.00	0.74	4.38***	0.15
Lag *k*	d6 (64-128 months)			S6 (over 128 months)		
	β	*z-statistic*	*Pseudo-*R^2	*β*	*z-statistic*	*Pseudo-*R^2
1	-0.65	-5.01***	0.16	-0.06	-0.41	0.00
2	-0.63	-4.90***	0.16	-0.09	-0.64	0.00
3	-0.61	-4.78***	0.15	-0.12	-0.87	0.00
4	-0.59	-4.64***	0.14	-0.16	-1.11	0.01
5	-0.56	-4.49***	0.13	-0.19	-1.36	0.01
6	-0.54	-4.33***	0.12	-0.23	-1.62	0.02
7	-0.51	-4.15***	0.12	-0.27	-1.88*	0.02
8	-0.48	-3.97***	0.11	-0.31	-2.16**	0.03
9	-0.46	-3.77***	0.10	-0.36	-2.44**	0.04
10	-0.43	-3.57***	0.09	-0.41	-2.73***	0.05
11	-0.40	-3.37***	0.08	-0.46	-3.03***	0.06
12	-0.37	-3.16***	0.07	-0.51	-3.34***	0.08

Note: See note to Table 3.