RELATIONSHIP BETWEEN OUTPUT VOLATILITY AND OUTPUT IN OECD COUNTRIES REVISITED

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Abstract

This study revisits the empirical relationship between output volatility and output for twelve OECD countries. An extended AR-EGARCH-M model was used to identify the structural break, asymmetric effect, jump effect and spillover effect. In addition to the classical logarithmic definition of growth, the study uses the Hodrick-Prescott filter to compute the deviations from the long-term trend as the output gap. The empirical results show that (i) the effect of output volatility on output differs across countries under the same model specifications; and (ii) while the in-mean effect and spillover effect are stronger for the output gap-based models, the jump effect has a major effect on output volatility under the classical logarithmic definition.

Keywords: Output gap, volatility, business cycle, EGARCH, wavelet, asymmetric effect
JEL Classification: C22, E32, O40

1. Introduction

Is there a relationship between output volatility and output? Empirical evidence is lacking, although theory abounds. The conventional theoretical view is that short-run fluctuations and long-run trends should be studied as separate research areas, namely as business cycle models and growth models (see Friedman, 1968; Solow, 1956; Taylor, 1999). In cases where economists do integrate the two and theorize that there is a negative relationship, Keynes (1936) explained it with animal spirits, Woodford (1990) with sunspot equilibria, Bernanke (1983) and Pindyck (1991) with investment irreversibility, and Ramey and Ramey (1991) with technology commitments under endogenous growth. Others found a positive relationship: Schumpeter (1939) explained it with creative destruction, Sandmo (1970) and Mirman (1971) with a positive relationship between income uncertainty and a higher savings rate, and Black (1987) with a positive risk-return trade-off.

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On the empirical front, the results regarding the direction of the effect of volatility on growth are inconclusive. Ramey and Ramey (1995), Kneller and Young (2001), Döpke (2004), and Norrbin and Yigit (2005) found a negative relationship for OECD countries, as did Martin and Roger (2000) for industrialized countries and European regions, and Siegler (2005) for twelve countries from 1870 to 1929. On the other hand, Mills (2000) found a positive relationship for OECD countries, Dejuan and Gurr (2004) found a weak positive linkage for the ten Canadian provinces, and Lee (2010) found a positive relationship for G7 countries. Finally, Blackburn and Pelloni (2004) showed that long-run growth is negatively related to the volatility of nominal shocks but positively related to real shocks; hence, the link may be either negative or positive. In a recent study, Deniz *et al*. (2021) investigated the link between output growth and volatility for the period 1971–2014. An augmented panel GARCH-M model was employed to allow the presence of independent variables in the conditional equation. The empirical results indicate the positive and significant impact of volatility on growth for seven out of nine country groups, except emerging markets and least developed countries.

In addition to studies that use cross-country or panel data, many studies have examined the relationship between volatility and output from a time-series perspective. Speight (1999), Grier and Perry (2000), Fountas *et al.* (2004), and Beaumont *et al*. (2008) employed GARCH-type models and found no evidence of a statistically significant relationship for the UK, the United States, Japan, and twenty OECD countries respectively. Meanwhile, Henry and Olekalns (2002) found a negative relationship for the United States, Berument *et al.* (2011) found a similar finding for Turkey, Caporale and McKiernan (1996) came up with a positive relationship for the UK, and a similar finding was obtained by Caporale and McKiernan (1998) for the United States and by Bhar and Mallik (2013) for the UK.

As can be seen from the above, most of the studies based on panel data find a negative linkage between growth and growth volatility for OECD countries. On the other hand, most of the studies based on time-series data focus on the United States, the UK and Japan and produce mixed results. Beaumont *et al.* (2008) highlighted this and extended the data set to twenty OECD countries for the period 1961–2000 using GARCH-M, TGARCH-M, and EGARCH-M models. They did not find any ARCH effects for Ireland and Turkey. The asymmetric effect is significant in only two cases, Poland and the USA, in the variance model. The in-mean coefficients were positive and significant at the 5% level for Portugal and at 10% for Italy. No evidence on a linkage between the volatility and growth of output for the other 16 countries including the UK, the USA and Japan was reported.

Antonakakis and Badinger (2016) employed the VAR-based spillover index and examined the output volatility and output growth of the G7 countries over a 55-year period. They found that these two variables are closely related, and the USA was found to be the biggest transmitter of growth and volatility shocks. An examination of cross-variable effects reveals the significance of the nature of shocks: volatility shocks triggered lower growth while growth shocks meant decreased output volatility.

Trypsteen (2017) examined the relationship between growth and volatility by using data from 13 OECD countries. A GARCH-M model was used for the period February 1962 – March 2015. The study demonstrated that domestic volatility is positively correlated with growth while external volatility is negatively correlated. Another study on the volatility and growth nexus was conducted by Charles and Darne (2021). To examine the relationship between the variables, the researchers used the US monthly industrial production index values for the period January 1919 – December 2017, and the standard GARCH-M framework was used to identify the variance changes as well as presence of shocks. Based on their results, some industries, World War II, recessions and natural disasters are linked with output growth. They also identify several subperiods with different levels of volatility where the volatility declines along the subperiods, with the pre-WWII period (1919–1946) being the highest volatile period and the aftermath period of the global financial crisis (2010–2017) being the lowest volatile period. The empirical results indicate no evidence of a relationship between output volatility and its growth during the full sample 1919–2017 and for all the subperiods. From a macroeconomic point of view, this implies that economic performance, as measured by industrial production growth, does not depend on the uncertainty as measured by output volatility.

This study re-examines the relationship between business cycle volatility and long-run growth using the total industry production for twelve OECD countries over the period 1961:01–2021:10. Such an undertaking is important for at least three reasons. Firstly, previous studies based on time series models have resulted in mixed evidence even though the sign of the relationship and analysis of the effect of various channels such as asymmetric effect, jump effect or spillover effect on growth volatility have significant theoretical and political inferences. Secondly, following Beaumont *et al.* (2008), Trypsteen (2017) and Charles and Darne (2021), this study extends the classical GARCH-M model by (i) employing an AR-EGARCH-in mean model with an asymmetric effect, (ii) adding a structural break to the mean model to capture the long-term change in the growth process, (iii) capturing outliers in the growth process using the wavelet analysis and including them in the conditional variance model as a jump effect[1], and (iv) adding the first lag of the most correlated country's growth rate to the variance model as a spillover effect. Thirdly, most

1 To the best of the author's knowledge, this is the first study in the related literature to apply the wavelet analysis.

studies in the related literature use the classical log definition of the growth rate. On the other hand, Mills (2000) argues that using Hodrick and Prescott (1997) or Baxter and King (1999) filters is more appropriate for measuring business cycles. These filters decompose the output series as trend and cycle components when analysing the relationship between output volatility and growth. The cycle component measures the difference between the trend and actual output and is called the output gap in business cycle literature, and this approach goes back to Burns and Mitchell (1946). Blanchard and Simon (2001) argue that measuring output volatility as the standard deviation of the growth rate or volatility of business cycle does not show significant effects on the sources of the decline of output volatility in the US. However, Mills (2000) and Döpke (2004) pointed out that the results obtained through empirical models are closely linked with the measuring methods, and this is true both for the US and 24 OECD countries. Furthermore, Chatterjee and Shukayev (2006) indicate that using the log difference as growth rates may create a bias towards finding a negative relationship between average growth rates and the volatility of growth rates. Hence, the Hodrick-Prescott (HP) filter is used to extract the cyclical and long-run output components in addition to the classical first-difference logarithmic growth rate. Finally, we cover a long time period including the Great Moderation years, the 2008 global financial crisis, and the COVID-19 pandemic for the twelve OECD countries.

This study is organized as follows: the second section describes the data; the third section presents the methodology; the model results are presented in the fourth section; and finally, conclusions are drawn in the fifth section.

2. Data

The monthly seasonally adjusted total industry production for 12 OECD countries[2] is obtained from the OECD's Main Economic Indicators and cover the period January 1961 – October 2021[3]. The growth rate can be formalized as follows:

$$g_t^l = \left(\log y_t - \log y_{t-1}\right) \times 100 \,, \tag{1}$$

where y is the seasonally adjusted monthly total industry production, and g_t^l shows the real growth rate of total industry production. In the time series literature, the log definition of growth is well-established. Chatterjee and Shukayev (2006) argued that the use of the log definition for growth rates may create a bias towards finding a negative relationship between average growth rates and the volatility of growth rates. Mills (2000) suggested implementing

2 Canada, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Sweden, the UK and the USA.

3 Except the UK, which covers the period 1968:02–2021:10 due to data availability.

a mechanical filter, like those advocated by Hodrick and Prescott (1997), or Baxter and King (1999). The main advantage of such filters is that they refer to fluctuations of a length often seen as typical of business cycles. Therefore, this study uses a Hodrick-Prescott filter with the penalty parameter set equal to 14.400. The deviations from the long-term trend used can be formalized as follows:

$$c_t^{HP} = \left(\log y_t - \log y_{t,trend}\right) \times 100 = cycle \times 100, \tag{2}$$

where y is the seasonally adjusted monthly total industry production, $y_{t,trend}$ indicates the H-P trend of total industry production; *cycle* shows the deviation from the trend, and c_t^{HP} shows the cyclical component as percent deviation from the long-run trend.

Data properties for growth, $g_{i,t}^{I}$

Table 1 presents the summary statistics of the monthly growth rates for the 12 OECD countries over the period. Finland has the highest mean rate of 0.26% per month, and the UK grew at the lowest rate of 0.1% per month. In terms of the unconditional standard deviation of growth, Norway is the most volatile country with 3.80%, whereas the United States is the least volatile country with 0.97%. The kurtosis of the normal distribution is 3. Thus, all countries have a high kurtosis, and the distribution is leptokurtic, that is, more peaked than a normal distribution with longer tails.

Table 1: Data properties for $g_{i,t}^{I}$

	Obs.	*Mean*	*Max.*	*Min.*	*Std. dev.*	*Skew.*	*Kurtosis*	*J-B*	*p-value*
Canada	718	0.21	4.34	–13.84	1.26	–2.13	25.06	15100	0.00
Finland	718	0.26	28.53	–21.63	2.82	0.52	24.41	13741	0.00
France	718	0.13	22.92	–37.91	2.74	–3.25	76.77	164079	0.00
Germany	718	0.15	11.61	–24.96	2.10	–2.31	35.87	32960	0.00
Italy	718	0.13	36.96	–32.86	2.98	0.03	62.44	105712	0.00
Japan	718	0.23	6.39	–17.20	1.83	–2.26	19.32	8579.9	0.00
Netherlands	718	0.19	14.13	–10.96	2.33	–0.07	7.57	625.8	0.00
Norway	718	0.21	34.23	–39.10	3.80	–0.51	29.43	20936	0.00
Portugal	718	0.19	19.12	–25.40	3.43	–0.13	9.67	1332.9	0.00
Sweden	718	0.18	25.37	–25.85	2.56	–0.55	32.92	26823	0.00
UK	645	0.10	10.60	–23.15	1.82	–3.03	47.31	53744	0.00
USA	718	0.20	6.01	–14.61	0.97	–5.01	79.62	178653	0.00

Source: Own calculation

Figure 1: Growth rate, g_t^l, for twelve OECD countries (%)

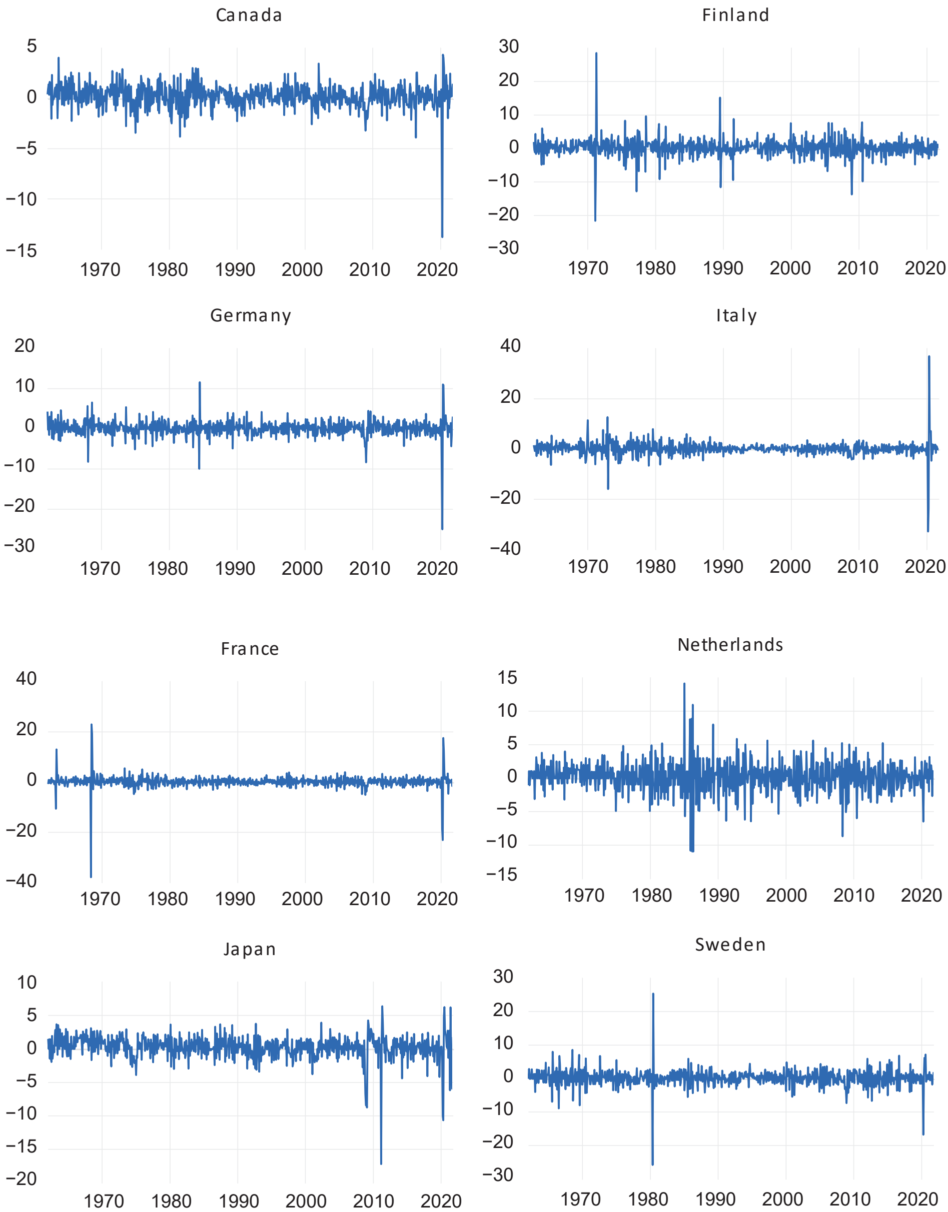
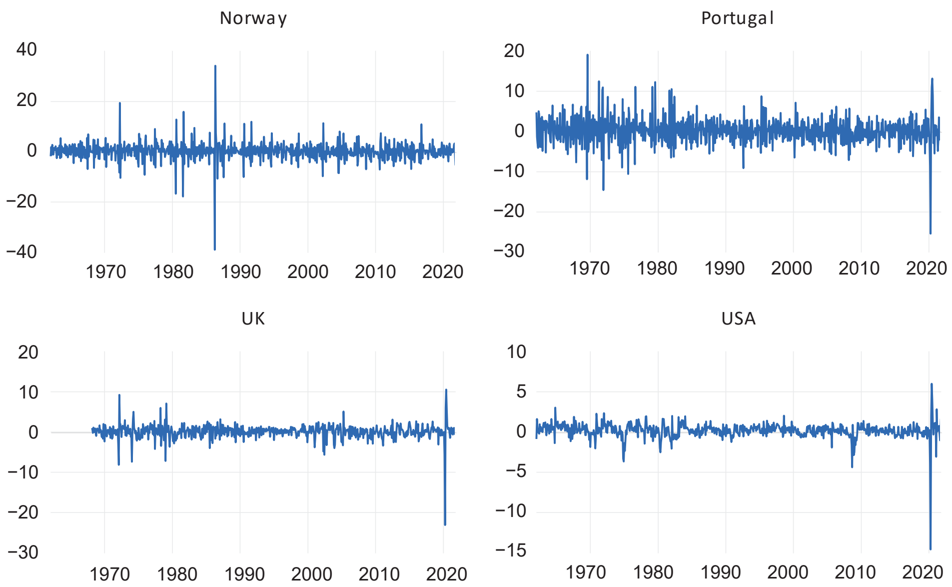


Figure 1: Continuation



Source: Own elaboration

Skewness is a measure of asymmetry, and it is expected to be zero under the normal distribution. Most of the countries, except Finland and Italy, have negative skewness, implying that the distribution has a long left tail due to the countries' high negative growth rates. Skewness is maximum in the USA at −5.01. As expected, the Jarque-Bera (J-B) test statistic rejects the null hypothesis of a normal distribution for all the countries. The high standard deviation and J-B statistics (based on skewness and kurtosis values) of the countries, which provides *a priori* knowledge about our growth models, should take non-linearities and heteroscedasticity into account.

Data properties for cycle, c_t^{HP}

The summary statistics of the cycle (in the sense of percent deviation from the long-run trend named output gap or cycle as mentioned before) calculated using the HP filter for the 12 OECD countries over the period are presented in Table 2. Using the cycle, c_t^{HP} shows an important change in summary statistics, as expected. The USA has the highest mean rate of 0.011% per month, and Japan and Portugal have the lowest with −0.029% and −0.027% per month, respectively. Italy and Japan are the most volatile countries with 3.91% and 3.71%, and the United States is the least volatile country with

2.30%. All the countries have high kurtosis, but some countries such as the Netherlands and Canada have lower kurtosis values, which are close to the normal kurtosis value, *i.e.*, 3. All the countries have negative skewness, and the skewness values are the highest for France at −5.51 and lowest for the Netherlands at −0.16. The Jarque-Bera (J-B) test statistic still rejects the null hypothesis of a normal distribution for all the countries.

Table 2: Data properties for cycle, c_t^{HP}

	Obs.	*Mean*	*Max.*	*Min.*	*Std. dev.*	*Skew.*	*Kurtosis*	*J-B*	*p-value*
Canada	718	0.003	5.65	−16.47	2.52	−1.02	6.36	462	0.00
Finland	718	−0.009	15.41	−26.97	3.17	−1.25	13.60	3550	0.00
France	718	0.000	7.58	−37.57	3.13	−5.51	60.52	102604	0.00
Germany	718	0.006	8.62	−30.52	3.16	−2.25	18.35	7655	0.00
Italy	718	0.007	9.74	−53.22	3.91	−4.43	55.08	83496	0.00
Japan	718	−0.029	9.55	−24.81	3.71	−1.56	10.75	2084	0.00
Netherlands	718	−0.015	10.96	−11.33	2.33	−0.16	4.89	110	0.00
Norway	718	−0.017	8.18	−37.18	3.13	−2.97	31.45	25279	0.00
Portugal	718	−0.027	11.13	−29.62	3.38	−1.76	16.50	5822	0.00
Sweden	718	−0.009	7.69	−21.50	2.99	−1.37	10.10	1732	0.00
UK	646	0.000	7.25	−25.47	2.64	−2.16	20.72	8957	0.00
USA	718	0.011	5.34	−16.08	2.30	−1.41	9.05	1334	0.00

Source: Own calculation

Blanchard and Simon (2001) note that the distribution of output growth exhibits excess kurtosis if large and infrequent shocks occur. This suggests that the evidence of kurtosis may reflect extreme changes in output. As expected, the Ljung-Box test leads to the presence of serial correlation in the series. According to the Lagrange multiplier test, strong conditional heteroskedasticity was noted for the cycle variable.

Figure 2: Cycle, c_t^{HP}, for twelve OECD countries (%)

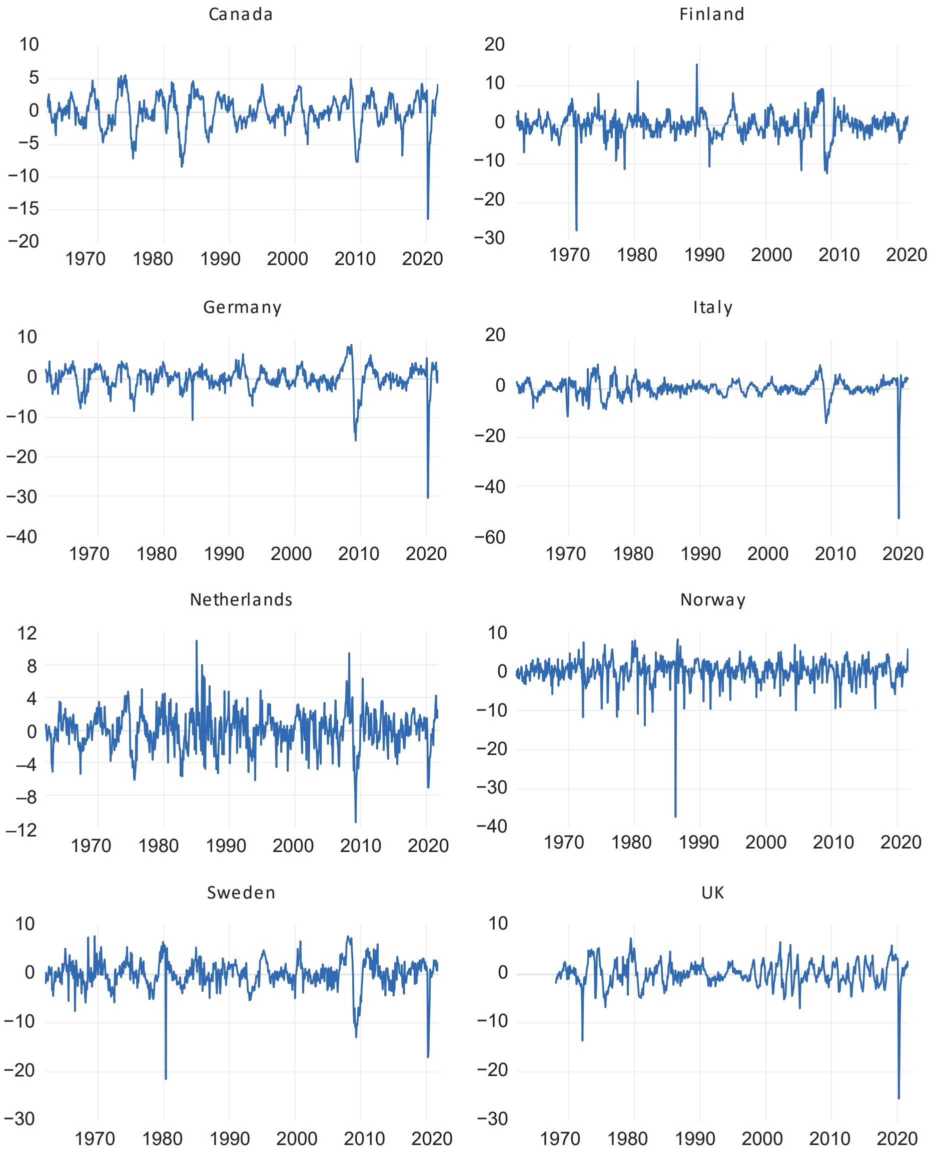
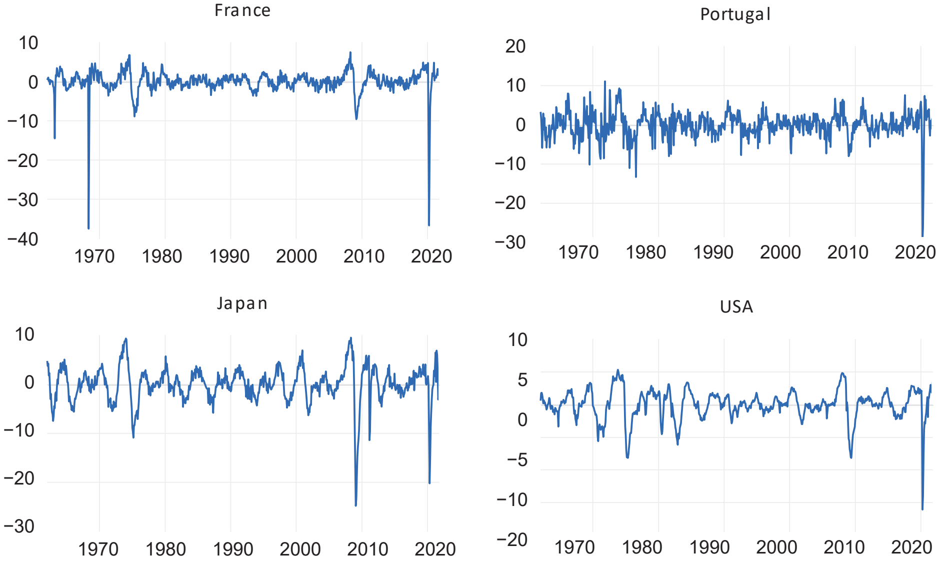


Figure 2: Continuation



Source: Own elaboration

Finding structural breaks and jumps

Conventional unit root tests, *i.e.,* Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), are carried out to identify the existence of unit roots. It can be observed that all the ADF and PP test statistics are statistically significant at the 1% level, thereby indicating that all the series are stationary[4]. The conventional unit root tests might be biased towards a false unit root null when the data include structural change. Therefore, following Perron (1997), a breakpoint ADF model is performed with a one-time break to catch the structural breaks in the growth process. A breakpoint in the model is determined by maximizing the break *t*-statistic, and lag lengths are based on SIC. The model assumes an innovational outlier break, with non-trending data. The structural break model with an innovational outlier assumes that the break occurs gradually. Tables 3 and 4 present the structural breakpoints for countries according to both growth and cycle.

4 Results available from the author upon request.

Table 3: Breakpoint unit root test results for $g_{i,t}^{I}$

Country	*Break date*	*ADF test statistics*	Country	*Break date*	*ADF test statistics*
Canada	2009:08	–26.14***	**Netherlands**	2015:09	–26.65***
Finland	2015:02	–27.30***	**Norway**	2013:11	–20.40***
France	1968:06	–22.03***	**Portugal**	1968:05	–18.42***
Germany	2009:04	–23.46***	**Sweden**	2015:03	–26.47***
Italy	2014:11	–23.29***	**UK**	2013:02	–25.10***
Japan	2009:03	–15.63***	**USA**	2009:06	–20.43***

Note: *** significant at 1% level.
Source: Own calculation

Table 4: Breakpoint unit root test results for c_{t}^{HP}

Country	*Break date*	*ADF test statistics*	Country	*Break date*	*ADF test statistics*
Canada	2009:08	–6.59***	**Netherlands**	1968:06	–10.82***
Finland	1971:04	–7.26***	**Norway**	1986:05	–17.22***
France	1968:06	–8.00***	**Portugal**	1971:10	–15.41***
Germany	2010:02	–9.34***	**Sweden**	2010:02	–7.72***
Italy	1973:03	–10.87***	**UK**	2013:02	–9.79***
Japan	2009:03	–6.55***	**USA**	1971:09	–6.72***

Note: *** significant at 1% level.
Source: Own calculation

As Charles and Darne (2021) indicated, infrequent large shocks in industrial production can be associated with strikes in some sub-industries, recessions, wars, political decisions and natural disasters. While the additive outlier showed the structural breaks that occurred immediately in the growth process, wavelet analysis was used for capturing large shocks in the growth process (for a discussion of outlier detection in time series, see Bilen and Huzurbazar, 2002). Wavelet analysis is analogous, in many ways, to Fourier spectral analysis as both methods can represent a time series signal in a different space. Fourier spectral analysis uses sine and cosine-basis functions and works well for approximate global variation. On the other hand, it is poorly adapted to modelling local variation by using cyclical functions such as the sine and cosine. Therefore, wavelet transformation is used for detecting jumps or outliers in the growth process following Greenblatt (1996) and Bilen and Huzurbazar (2002). Wavelets are the building blocks of wavelet transformation, and the wavelet coefficients resulting from the discrete wavelet transform (DWT) of the observed time series are used. As suggested by Bilen and Huzurbazar (2002), Haar filtering and the universal threshold have been chosen as decomposition and threshold limits, respectively. The scale parameter is an important part of wavelet transformation and determines the width of the wavelet and its central frequency. Thus, the scale was selected to be 2 for $g_{i,t}^{l}$ and 5 for c_t^{HP} since a shrunken wavelet is better for capturing jumps in high-frequency data. Detecting outliers for $g_{i,t}^{l}$ [5] and c_t^{HP} [6] are presented in Appendix A1.

3. Methodology

In the study, the growth is modelled as AR(p)-EGARCH(1,1)-M[7] as follows:

$$y_{i,t} = \varphi_i + \sum_{k=1}^{p} \beta_i y_{i,t-k} + \delta_i DSB_{i,t} + \lambda_i \log(\sigma_{i,t}^2) + \varepsilon_{i,t} \tag{3}$$

$$\log(\sigma_{i,t}^2) = \omega_i + \alpha_i \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma_i \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_i \log(\sigma_{t-1}^2) + \phi_i JMP_{i,t} + \vartheta_i SP_{c,t-1}\ , \tag{4}$$

where $y_{i,t}$ is the growth rate for the country i at the time t, φ_i is the constant term, $DSB_{i,t}$ is a structural break dummy based on Perron's (1997) breakpoint unit root test results; $\log(\sigma_t^2)$ is the conditional volatility obtained from Equation (4) and included as an independent variable in the mean equation to test the effect of growth volatility on growth, and ε_t is the error term where $\varepsilon \sim (0, \sigma_t^2)$. Since Jansen and Cosimona (1988) argue that the autocorrelated residuals may show the ARCH effect incorrectly, the order of the AR process is determined by the Final Prediction Error (FPE) criteria. The FPE criteria select the optimal lag length by ensuring the residuals which are no longer autocorrelated. While the Ljung-Box Q-test statistics do not reject the null hypothesis of residual serial independence, the ARCH Lagrange Multiplier statistics confirm the presence of heteroskedasticity for each country.

The EGARCH model, first proposed by Nelson (1991), has several advantages over a GARCH specification for modelling growth volatility. One advantage is that it represents volatility as the logarithm of the conditional variance, $\log(\sigma_t^2)$, rather than the conditional variance, σ_t^2, which avoids the non-negativity constraints on the model parameters. Thus,

5 See Appendix A1: Wavelet outlier detection for $g_{i,t}^{l}$.

6 See Appendix A2: Wavelet outlier detection for c_t^{HP}.

7 The autoregressive-exponential general autoregressive conditional heteroskedastic-in mean model.

numerical optimization becomes simpler, and a more flexible class of possible dynamic models of the variance can be estimated (Hamilton, 1994). Moreover, asymmetries are allowed under the EGARCH specification; γ measures the presence of the asymmetric effect in the variance equation, and when $\gamma < 0$, it implies that negative shocks generate higher volatility than positive shocks of the same magnitude, and vice versa. The asymmetric effect has been well-established and employed in the literature focusing on the understanding of the asymmetric characteristics of asset price volatility using the asymmetric GARCH-type models (see Alberg *et al.*, 2008; Charles and Darné, 2019; Bhowmik and Wang, 2020). On the other hand, asymmetric GARCH-type models have been used for modelling volatility with asymmetric effect, not only for output (see Henry and Olekalns, 2002; Ho and Tsui, 2003; Beaumont *et al*., 2008) but also for other macroeconomic variables (see Fallahi *et al.*, 2012; Neanidis and Savva, 2013; Calmes and Théoret, 2014).

$JMP_{i,t}$ stands for jump effect and shows the outliers detected by wavelet analysis and equals 1 for the outlier dates and 0 otherwise. Balke and Fomby (1991), Darné and Diebolt (2004), Darné (2009) and Charles and Darné (2021) show that infrequent large shocks such as oil shocks, wars, geopolitical tensions, financial slumps, changes of policy regimes, recessions or natural disasters have an important impact on industrial production volatility in the USA. An outlier is a known or unknown event in the time series. Hence, detecting outliers is an important task due to their unpredictable nature, especially when studying long-time and high-frequency data. Charles and Darné (2021) apply the semi-parametric procedure to detect jumps proposed by Laurent *et al*. (2016). In this study, wavelet analysis is used to detect known or unknown outliers following Greenblatt (1996) and Bilen and Huzurbazar (2002) (see “Finding structural breaks and jumps”).

$SP_{c,t-1}$ is called the spillover effect and is the first lag of the most correlated country’s growth rate[8]. It indicates the effect of external factors on conditional volatility. While Kose *et al*. (2008) show that output growth is strongly correlated across countries, Diebold and Yilmaz (2009, 2012) indicate that both growth and volatility spillovers are important for G7 countries. Antonakakis and Badinger (2016) use a VAR-based spillover index approach, and Trypsteen (2017) includes the cross-country weighted averages of growth in the GARCH-M model to account for cross-country interactions. In this study, the spillover effect is used for capturing the cross-country interactions. The jump and asymmetric effects have a direct impact on conditional volatility, but an indirect effect on average growth through the in-mean coefficient, λ. The model is estimated using the Marquardt algorithm to obtain the maximum-likelihood estimates of the parameters under a Generalized Exponential Distribution (GED) as suggested by Speight (1999).

8 See Appendix B: Correlation table.

4. Model Results

The AR(P)-EGARCH(1,1)-M model results for $g_{i,t}^{I}$ and c_t^{HP} are presented in Tables 5 and 6 respectively. The first column represents the country, the second and third columns show the optimal lag of the AR process and the in-mean coefficient λ, which are presented in Equation (3). The later columns demonstrate the conditional variance equation coefficients presented in Equation (4). The constant term, ω, show the time-invariant volatility; α is an ARCH term, and it represents the short-term effect on conditional volatility, while β is a well-known GARCH term that indicates the persistence effect. The asymmetric effect, jump effect and spillover effect are represented with the γ, Φ and ϑ coefficients, respectively.

Estimation results for $g_{i,t}^{I}$

The relationship between growth and growth volatility is at best still mixed. The in-mean coefficient λ is insignificant for most of the countries, including Finland, France, Germany, Italy, Portugal, Sweden and the UK. However, it is positive for Canada at the 10% significance level and for Japan, Norway and the USA at the 1% significance level, and negative for the Netherlands at the 5% significance level. These results indicate the effect of growth volatility on growth changes across countries under the same model specification.

The asymmetry coefficient γ is significant and negative for Canada, France and the USA, indicating that negative shocks to growth generate higher growth volatility than positive shocks of the same magnitude. Japan is the only country which has a positive and significant asymmetric effect. Therefore, in contrast to the negative asymmetric effect, growth volatility has been affected by positive shocks more than negative shocks in Japan. However, the asymmetric effect cannot have any impact on average growth for the countries which do not have a significant in-mean coefficient: Finland, Germany, Italy, the Netherlands, Norway, Portugal, Sweden and the UK.

The jump effect measures the effect of outliers on growth volatility. These exogenous shocks, which could be referred to as outliers in this context, directly affect the growth volatility and were detected based on the wavelet analysis. The jump effect is positive and significant for ten out of the twelve countries, except Sweden and the UK, indicating that exogenous shocks have a sizeable effect on growth volatility.

The spillover effect shows the effect of the most related country's growth rate on growth volatility. The spillover effect is negative and significant for France, Portugal and Sweden. The growth volatility in France and Portugal has been negatively affected by growth in Germany. In other words, when German growth increases at the time t, growth volatility in France and Portugal decrease at the time $t + 1$. Similarly, the growth volatility in Sweden has been negatively affected by the USA growth rate.

Table 5: EGARCH model results for $g_{i,t}^{I}$

	Mean equation		Variance equation					
Country	**AR (p)**	**λ "in-mean effect"**	**ω "time-invariant volatility"**	**α "short-term effect"**	**γ "asymmetric effect"**	**β "persistence effect"**	**Φ "jump effect"**	**θ "spillover effect"**
Canada	AR (6)	0.2951* (0.1628)	−0.0860** (0.0427)	0.1137** (0.0527)	−0.1151** (0.0482)	0.8520*** (0.0434)	1.7239*** (0.4160)	−0.0113 (0.0350)
Finland	AR (3)	−0.1511 (0.1457)	0.1293 (0.0889)	0.3057* (0.0899)	−0.0720 (0.0613)	0.7305* (0.0590)	2.9056* (0.5142)	−0.0236 (0.0230)
France	AR (5)	0.1118 (0.1965)	0.0085 (0.0646)	0.2262* (0.0789)	−0.1419** (0.0571)	0.6932*** (0.0520)	7.2431*** (1.3391)	−0.0182*** (0.0316)
Germany	AR (2)	−0.0356 (0.1359)	−0.0325 (0.0901)	0.4622*** (0.0714)	−0.0894 (0.0630)	0.6157*** (0.0655)	2.2060*** (0.4728)	−0.0870 (0.0564)
Italy	AR (8)	0.1525 (0.0994)	−0.1520** (0.0767)	0.4416*** (0.0882)	−0.0893 (0.0617)	0.7819*** (0.0486)	2.7126*** (0.5434)	0.0626** (0.0345)
Japan	AR (6)	0.4206*** (0.1077)	0.2331** (0.1046)	0.7030*** (0.0953)	0.2113** (0.0842)	0.0243 (0.0473)	1.7738*** (0.3594)	−0.0732 (0.0531)
Netherlands	AR (5)	−0.3795** (0.1679)	0.1744* (0.0977)	0.1645*** (0.0613)	−0.0422 (0.0462)	0.7459*** (0.0695)	1.7879*** (0.3450)	−0.0544 (0.0341)
Norway	AR (4)	0.6115*** (0.2367)	0.5299** (0.2102)	0.0869 (0.0765)	−0.0956 (0.0630)	0.6802*** (0.1041)	2.0860*** (0.7164)	
Portugal	AR (4)	0.3151 (0.1964)	0.1019 (0.0751)	0.2012*** (0.0531)	−0.0324 (0.0429)	0.8670*** (0.0390)	1.5801*** (0.4212)	−0.0334* (0.0191)
Sweden	AR (3)	−0.1065 (0.1639)	0.9637*** (0.2372)	0.4531*** (0.1032)	0.0644 (0.0764)	0.1034 (0.1479)	1.6457 (1.4650)	−0.2625*** (0.0566)
UK	AR (6)	−0.1021 (0.1072)	−0.2017*** (0.0783)	0.6631*** (0.0769)	−0.0097 (0.0659)	0.5610*** (0.0822)	0.1548 (0.3049)	−0.0921 (0.0654)
USA	AR (4)	0.1555*** (0.0543)	−0.4839*** (0.0787)	0.2758*** (0.0658)	−0.3059*** (0.0514)	0.7726*** (0.0429)	1.9867*** (0.4085)	0.0495 (0.0337)

Notes: The numbers in parentheses are standard errors; * significant at 1% level; ** significant at 5% level; *** significant at 10% level.

Source: Own calculation

The countries having insignificant "in-mean effect" cannot carry the effect of growth volatility on growth. Thus, the asymmetric effect, jump effect and spillover effect are meaningful when assessing these effects on growth volatility, not growth. In that case, the countries having significant in-mean coefficients deserve further attention. The growth rate of Canada's total industry production has been affected positively when jump effects and negative shocks occur. Japan also has positive in-mean and jump effects but with a positive asymmetric coefficient. Thus, positive growth shocks increase growth volatility more than negative ones in Japan and increase the average growth in Japan.

There is no asymmetric effect for the Netherlands, but with a negative in-mean coefficient, the jump effect contributes to a decrease in conditional average growth in the Netherlands. In contrast to the Netherlands, Norway has a positive in-mean coefficient, and the jump effect increases the conditional average growth in Norway. Lastly, growth in the USA with a positive in-mean effect has a negative asymmetry and positive jump effects. Negative shocks in growth generate higher growth volatility in the USA than positive shocks of the same magnitude, and they increase the average growth. The external shocks on growth volatility increase the growth in the USA by increasing the growth volatility.

Estimation results for c_t^{HP}

The in-mean coefficient λ is significant for nine[9] out of twelve countries when using the cycle. While the jump effect is positive and significant for ten countries for g_t^l, it is significant and negative for Sweden and positive for the USA for c_t^{HP}. Whereas the spillover effect was statistically significant for seven countries according to output gap-based models, with the classical growth model it was four.

While the in-mean coefficient for Canada is still positive and significant at the 5% level, and the asymmetric effect is negative, the jump effect is insignificant. However, the spillover effect is positive at the 5% level, indicating that an increase in the output gap in the USA increases the business cycle volatility for the next month and increases the long-run growth as well by the effect of the positive in-mean coefficient. Finland has a positive in-mean coefficient with a positive spillover effect. Therefore, an increase in the output gap of Sweden positively affects the business cycle volatility and long-run growth in Finland. France has a positive in-mean coefficient at the 1% significance level with a negative asymmetric effect. Germany has no significant in-mean effect the same as the former, but the negative spillover effect in Italy indicates that an increase in the output gap decreases the business cycle volatility. Italy has a positive in-mean coefficient at the 5% significance level with a positive spillover effect. It means that an increase in the output gap in Germany increases the volatility and long-run growth in Italy.

9 Finland, France, Italy, Portugal and Sweden are added among the countries having a significant volatility effect on growth, but the USA is insignificant now. Five countries had significant in-mean coefficients according to the logarithmic growth definition.

Table 6: EGARCH model results for c_t^{HP}

	Mean equation		Variance equation					
Country	AR (p)	λ "in-mean effect"	ω "time-invariant volatility"	α "short term effect"	γ "asymmetric effect"	β "persistence effect"	Φ "jump effect"	θ "spillover effect"
Canada	AR (6)	0.1325** (0.0572)	−0.3087*** (0.0560)	0.3931*** (0.0647)	−0.1528*** (0.0389)	0.7729*** (0.0656)	0.4603 (0.4233)	0.0289** (0.0126)
Finland	AR (4)	0.5080*** (0.1516)	0.1275 (0.1236)	0.3912*** (0.0886)	−0.0438 (0.0616)	0.7222*** (0.0763)	0.5381 (0.3751)	0.0381*** (0.0144)
France	AR (3)	0.0143*** (0.1063)	−0.2771*** (0.0903)	0.6774 (0.0849)	−0.0292*** (0.0519)	0.6782 (0.0716)	−0.0803 (0.5005)	0.0090 (0.0147)
Germany	AR (7)	−0.0822 (0.1055)	0.0015 (0.1138)	0.5986*** (0.0888)	−0.0096 (0.0668)	0.4226*** (0.0939)	0.1098 (0.3898)	−0.0354** (0.0153)
Italy	AR (7)	0.1739** (0.0872)	−0.1772*** (0.0651)	0.4730*** (0.0875)	0.0093 (0.0649)	0.8688*** (0.0423)	−0.1181 (0.5352)	0.0276*** (0.0107)
Japan	AR (10)	−0.1636** 0.0713	−0.1671*** (0.0654)	0.4444*** (0.0892)	0.0283 (0.0649)	0.7592*** (0.0745)	−0.3749 (0.3932)	−0.0133 (0.0150)
Netherlands	AR (6)	−1.9040*** (0.3581)	0.2639*** (0.0773)	0.2513*** (0.0480)	0.0088 (0.0477)	0.6400*** (0.0630)	−0.0277 (0.1388)	−0.0454*** (0.0103)
Norway	AR (2)	−0.8901*** (0.3095)	1.7801*** (0.2635)	0.5165*** (0.1206)	−0.0068 (0.0760)	−0.0910 (0.1113)	−0.3649 (0.3028)	
Portugal	AR (2)	−0.9154*** (0.3359)	2.9501*** (0.3004)	0.1438*** (0.0544)	−0.1406*** (0.0514)	−0.5499*** (0.1367)	−0.4142 (0.3630)	−0.0917*** (0.0246)
Sweden	AR (10)	−0.5565*** 0.1149	1.4347*** (0.2656)	0.3887*** (0.1098)	0.0538 (0.0745)	−0.2598 (0.1611)	−0.6584** (0.3083)	−0.0878*** (0.0223)
UK	AR (2)	−0.1390 (0.1059)	−0.1873** (0.0890)	0.6428*** (0.0846)	−0.0330 (0.0707)	0.4738*** (0.1082)	−0.0671 (0.5263)	-0.0240 (0.0193)
USA	AR (7)	−0.0313 (0.0268)	−0.4779*** (0.0818)	0.3442*** (0.0785)	−0.3143*** (0.0546)	0.7980*** (0.0438)	0.6577** (0.3367)	0.0090 (0.0141)

Notes: The dummies were added in mean equations for Italy (2020:04) and Portugal (2020:04–05) to ensure an insignificant ARCH effect in standardized residuals. The numbers in parentheses are standard errors; * significant at 1% level; ** significant at 5% level; *** significant at 10% level.

Source: Own calculation

Japan has a negative in-mean effect, in contrast to the positive effect in the classical growth definition model, g_t^l. There are no asymmetric, jump or spillover effects in the variance equation, and a pure GARCH process determines the cycle volatility. The Netherlands has a negative in-mean effect with a spillover effect in the variance equation. An increase in the cycle volatility decreases the average growth in the Netherlands. The positive and significant spillover effect also provides another explanation for the effect of the German output gap on the average growth and cycle volatility of the Netherlands. An increase in the German output gap at the time t decreases the cycle volatility and long-run growth in the Netherlands at the time $t + 1$. Norway is the second country with a negative in-mean coefficient when it has a positive effect for g_t^l. Similar to Japan, Norway has a pure GARCH process, *i.e.*, conditional volatility based on the constant, ARCH and GARCH terms.

Portugal has a negative in-mean coefficient at the 1% significance level with negative asymmetric and spillover effects. An increase in cycle volatility decreases growth in Portugal, and negative shocks in growth (negative residuals from the mean equation) generate higher cycle volatility, resulting in a decrease in the average growth. For Sweden, the in-mean effect is negative and significant at the 1% level. The jump effect and spillover effects are negative at the 5% and 1% levels, respectively. The jumps in the output gap decrease the cycle volatility and then decrease the average growth in Sweden. An increase in the German output gap decreases the cycle volatility in Sweden through spillover channels and increases the average growth in Sweden. Again, cycle volatility has no effect on long-run growth in the UK. The USA has an insignificant in-mean coefficient with significant asymmetric and jump effects. Negative shocks and jumps increase the cycle volatility but have no effect on the long-run growth itself.

5. Conclusion

As the relationship between business cycle volatility and long-run growth is theoretically and empirically ambiguous, this study revisits the relationship for 12 OECD countries over the period 1961:01–2021:10 by employing the AR(P)-EGARCH(1,1)-M framework, but expands the model with structural breaks, asymmetric effects, jump effects and spillover effects. Furthermore, in addition to the logarithmic definition of growth, g_t^l, the study also uses the HP filter to get the cyclical component/output gap, c_t^{HP}, which depends on business cycle theory.

Several conclusions can be drawn from the analysis. The effect of output volatility on output differs across countries under the same model specification. The in-mean coefficients are positive and significant for four countries[10], negative and significant for one country[11], and insignificant for seven countries for g_t^l. The in-mean effect is stronger for c_t^{HP} in terms of the number of significant coefficients. Cycle volatility has a significant negative effect on long-run growth for five countries, namely Japan, the Netherlands, Norway, Portugal and Sweden, and a positive effect for four countries, namely Canada, Finland, France, and Italy. It is insignificant for three countries, namely Germany, the UK

10 Canada, Japan, Norway and the USA.

11 The Netherlands.

and the USA. It is important to note that the in-mean coefficient turns negative for Japan and Norway and is insignificant for the USA.

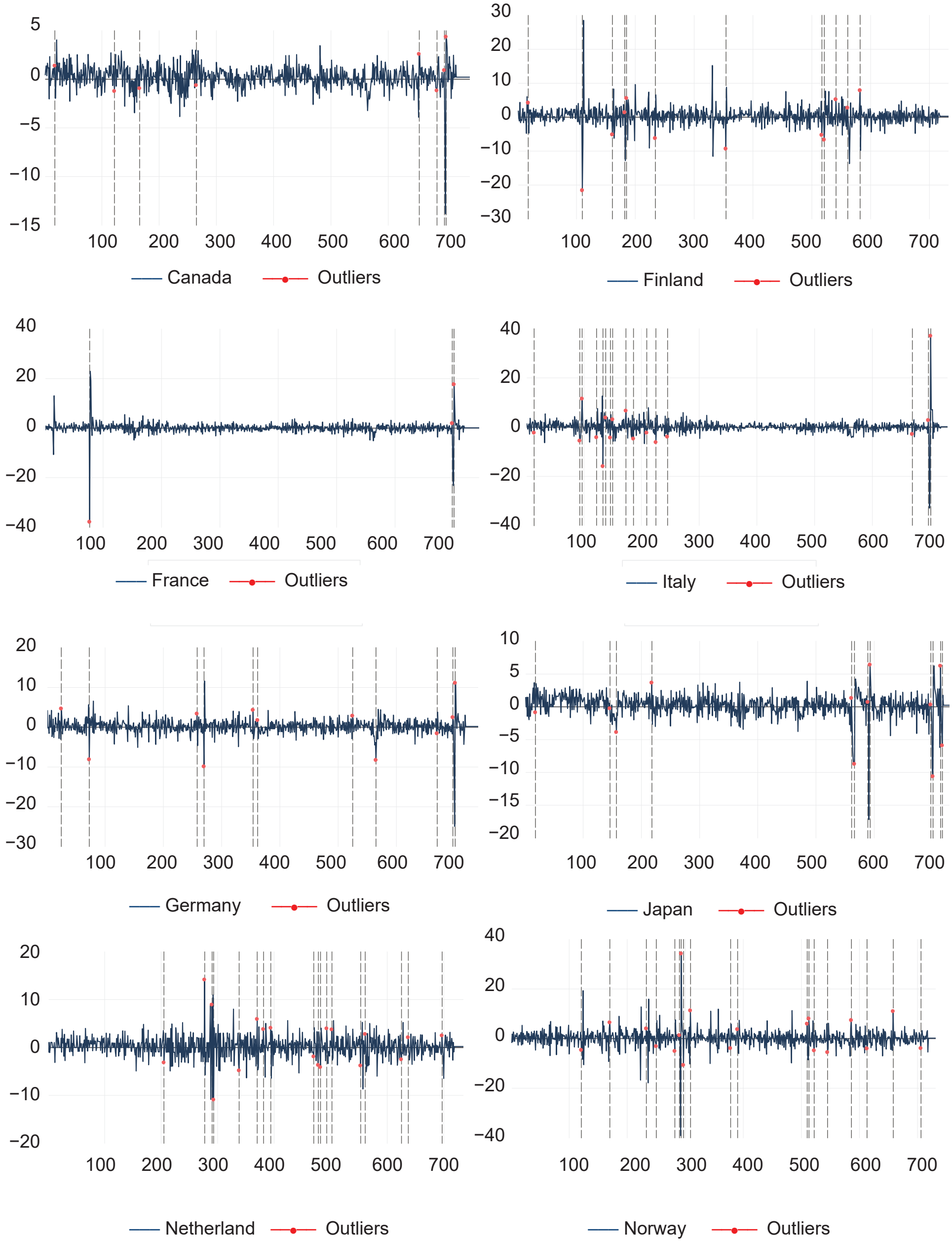
Under the classical log definition of growth, the asymmetric effect is significant and negative for Canada, France and the USA. Japan is the only country which has a positive and significant asymmetric effect. Canada, Japan and the USA can carry the asymmetric effect of growth volatility on conditional growth. Thus, the negative shocks to growth in Canada and the USA generate higher growth volatility than positive shocks of the same magnitude and increase the growth. This is valid for positive shocks in Japan's economy. Model results based on c_t^{HP} show that the asymmetric effect is significant and negative for Canada, France, Portugal and the USA; however, this effect is only transferable to long-run growth in France and Portugal, with significant in-mean coefficients.

The jump effect has been detected based on wavelet analysis, and it measures the effect of exogenous shocks on industry production growth. The jump effect has a major effect on growth volatility for g_t^l, which is positive and significant for ten out of the twelve countries, except Sweden and the UK. However, the jump effect has disappeared for output gap-based models. That is to say, it is significant only for Sweden and the USA.

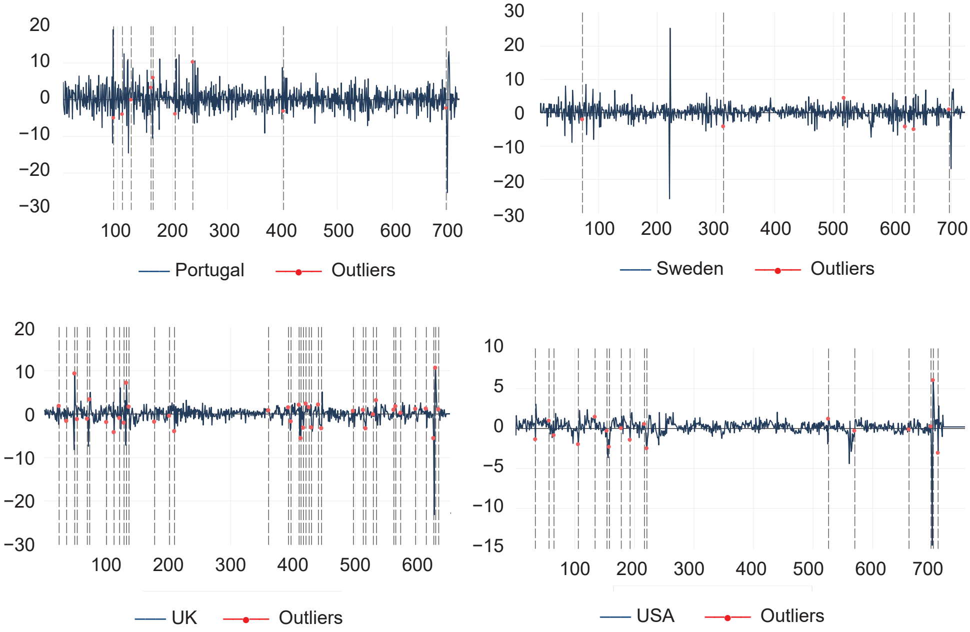
The spillover effect shows the effect of the country's growth rate on growth volatility. The spillover effect is significant and negative for France, Portugal and Sweden and positive for Italy. However, none of these countries has a significant in-mean coefficient. Then, the spillover effect can increase/decrease the growth volatility but does not have any significant effect on growth. On the contrary, the spillover effect is important when using the output gap. It is significant and positive for Canada, Finland and Italy, and negative for Germany, the Netherlands, Portugal and Sweden. All of these countries, except Germany, have a significant in-mean coefficient.

Appendix A: Outliers

A1: Wavelet outlier detection for $g^{l}_{i,t}$



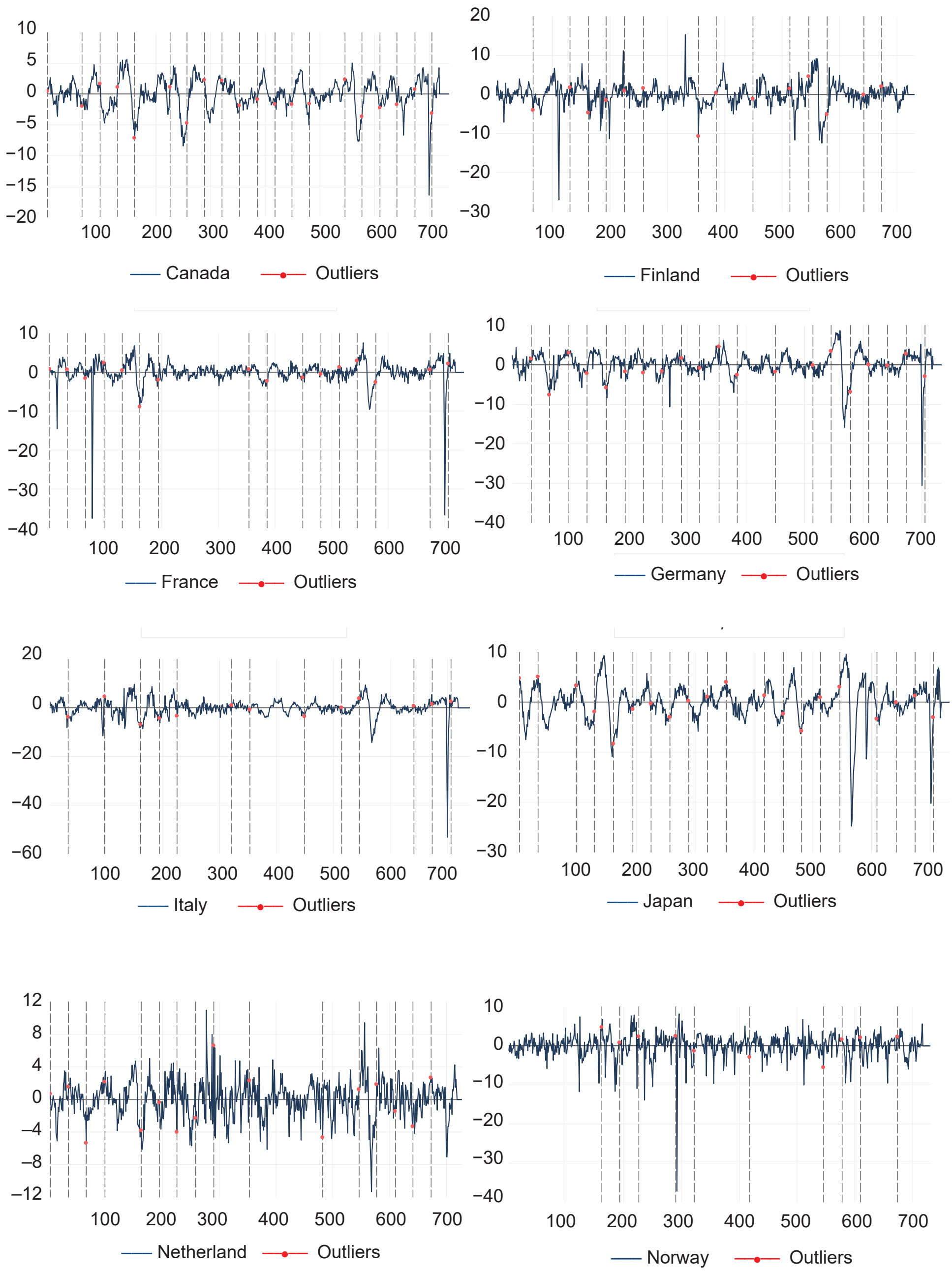
A1: Continuation



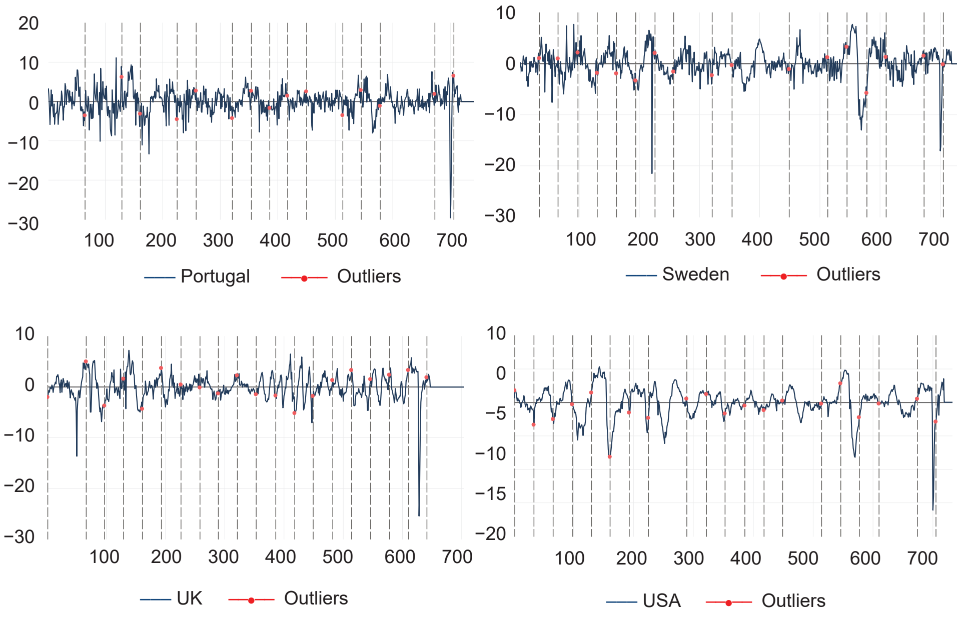
Source: Own elaboration

Outlier dates: 1963M06, 1972M02, 1975M10, 1984M01, 2016M06, 2019M01, 2020M02, 2020M05 for **Canada**; 1963M06, 1971M02, 1975M05, 1977M02, 1977M05, 1981M06, 1991M06, 2005M01, 2005M05, 2007M01, 2008M09, 2010M06 for **Finland**; 1968M05, 2020M02, 2020M05 for **France**; 1964M01, 1968M01, 1983M06, 1984M06, 1991M06, 1992M02, 2005M09, 2009M01, 2017M10, 2020M01, 2020M05 for **Germany**; 1963M02, 1969M09, 1970M01, 1972M02, 1973M01, 1973M06, 1974M02, 1974M06, 1976M05, 1977M06, 1979M05, 1980M09, 1982M05, 2017M09, 2020M01, 2020M05 for **Italy**; 1963M06, 1974M02, 1975M01, 1980M02, 2008M09, 2009M02, 2011M01, 2011M05, 2020M01, 2020M05, 2021M06, 2021M09 for **Japan**; 1979M01, 1985M01, 1986M02, 1986M05, 1990M02, 1992M10, 1993M09, 1994M10, 2001M02, 2001M10, 2002M02, 2003M01, 2003M10, 2008M01, 2008M09, 2014M01, 2015M01, 2020M01 for **the Netherlands**; 1972M01, 1976M02, 1981M05, 1982M10, 1985M06, 1986M02, 1986M05, 1986M09, 1987M09, 1993M06, 1994M06, 2004M06, 2004M09, 2005M06, 2007M05, 2010M10, 2013M01, 2016M10, 2020M10 for **Norway**; 1969M09, 1971M01, 1972M05, 1975M05, 1975M09, 1979M01, 1981M09, 1995M06, 2020M02 for **Portugal**; 1968M01, 1988M01, 2005M02, 2013M10, 2015M01, 2020M01 for **Sweden**; 1964M01, 1965M01, 1966M02, 1966M06, 1967M10, 1968M02, 1970M05, 1971M05, 1972M02, 1972M09, 1973M01, 1973M05, 1976M10, 1978M10, 1979M06, 1992M01, 1994M09, 1995M01, 1996M02, 1996M05, 1996M09, 1997M01, 1997M06, 1997M10, 1998M09, 1999M02, 2003M05, 2004M09, 2005M01, 2006M01, 2006M06, 2008M10, 2009M01, 2009M09, 2011M09, 2013M02, 2014M02, 2014M05, 2014M10 for **the UK**; 1964M10, 1966M09, 1967M05, 1970M10, 1973M02, 1974M10, 1975M02, 1976M10, 1978M01, 1980M01, 1980M05, 2005M10, 2009M06, 2017M01, 2020M02, 2020M06, 2021M02 for **the USA**.

A2: Wavelet outlier detection for c_t^{HP}



A2: Continuation



Source: Own elaboration

Outlier dates: 1962M02, 1967M05, 1970M02, 1972M10, 1975M05, 1980M10, 1983M05, 1986M01, 1988M09, 1991M05, 1994M02, 1996M10, 1999M05, 2002M01, 2007M06, 2010M01, 2012M10, 2015M05, 2018M02, 2020M09 for **Canada**; 1967M06, 1972M10, 1975M06, 1978M01, 1980M09, 1983M06, 1991M06, 1994M01, 1999M05, 2004M09, 2007M06, 2010M02, 2015M06, 2018M01 for **Finland**; 1962M02, 1964M09, 1967M05, 1970M02, 1972M10, 1975M05, 1978M02, 1991M06, 1994M02, 1999M05, 2002M01, 2004M10, 2007M05, 2010M02, 2018M02, 2020M10 for **France**; 1964M10, 1967M05, 1970M02, 1972M09, 1975M06, 1978M02, 1980M09, 1983M05, 1986M02, 1988M09, 1991M06, 1994M01, 1999M06, 2004M10, 2007M05, 2010M02, 2012M09, 2015M05, 2018M01, 2020M09 for **Germany**; 1964M10, 1970M02, 1975M05, 1978M02, 1980M09, 1988M09, 1991M05, 1999M05, 2004M10, 2007M05, 2015M05, 2018M01, 2020M10 for **Italy**; 1962M01, 1964M09, 1970M02, 1972M09, 1975M05, 1978M02, 1980M09, 1983M05, 1986M01, 1988M09, 1991M05, 1996M10, 1999M06, 2002M01, 2004M09, 2007M06, 2012M09, 2015M06, 2018M02, 2020M09 for **Japan**; 1962M02, 1964M10, 1967M05, 1970M02, 1975M06, 1978M02, 1980M09, 1983M06, 1986M02, 1991M05, 2002M02, 2007M06, 2010M01, 2012M10, 2015M05, 2018M01 for **the Netherlands**; 1975M06, 1978M01, 1980M10, 1986M02, 1988M10, 1996M10, 2007M06, 2010M02, 2012M10, 2018M02 for **Norway**; 1967M05, 1972M09, 1975M05, 1980M09, 1983M06, 1988M09, 1991M06, 1994M02, 1996M09, 1999M06, 2004M09, 2007M05, 2010M02, 2018M01, 2020M10 for **Portugal**; 1964M10, 1967M05, 1970M02, 1972M10, 1975M06, 1978M02, 1980M10, 1983M05, 1988M09, 1991M06, 1999M05, 2004M09, 2007M05, 2010M02, 2012M10, 2018M01, 2020M09 for **Sweden;** 1962M01, 1967M06, 1970M01, 1972M09, 1975M05, 1978M01, 1980M10, 1983M06, 1986M01, 1988M09, 1991M05, 1994M02, 1996M10, 1999M05, 2002M02, 2004M10, 2007M06, 2010M02, 2012M10, 2015M05 for **the UK**; 1962M02, 1964M10, 1967M06, 1970M02, 1972M10, 1975M05, 1978M01, 1980M09, 1986M01, 1988M10, 1991M05, 1994M02, 1996M10, 1999M05, 2004M10, 2007M06, 2010M01, 2012M10, 2018M02, 2020M09 for **the USA**.

Appendix B: Correlation table

B1: Correlation table for $g^{I}_{i,t}$

	CA	*FI*	*FR*	*DE*	*IT*	*JP*	*NL*	*NO*	*PT*	*SE*	*UK*	*USA*
CA	1.00											
FI	0.13	1.00										
	3.25											
	0.00											
FR	0.34	0.02	1.00									
	9.06	0.55										
	0.00	0.58										
DE	0.39	0.08	**0.40**	1.00								
	10.73	2.04	11.17									
	0.00	0.04	0.00									
IT	0.35	0.03	0.39	**0.41**	1.00							
	9.45	0.75	10.75	11.51								
	0.00	0.46	0.00	0.00								
JP	0.23	0.01	0.14	0.23	0.05	1.00						
	5.88	0.37	3.47	5.88	1.31							
	0.00	0.71	0.00	0.00	0.19							
NL	0.14	0.06	0.16	0.15	0.17	0.09	1.00					
	3.67	1.45	4.06	3.88	4.47	2.22						
	0.00	0.15	0.00	0.00	0.00	0.03						
NO	0.05	−0.03	−0.04	−0.02	0.04	0.00	−0.10	1.00				
	1.25	−0.84	−0.90	−0.43	0.92	0.08	−2.54					
	0.21	0.40	0.37	0.66	0.36	0.94	0.01					
PT	0.19	0.12	0.19	**0.28**	0.23	0.14	0.13	0.03	1.00			
	4.87	2.96	4.80	7.48	6.03	3.49	3.21	0.87				
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.39				
SE	0.17	**0.15**	0.21	0.22	0.22	0.09	0.05	0.04	0.11	1.00		
	4.43	3.72	5.55	5.84	5.64	2.18	1.31	1.07	2.78			
	0.00	0.00	0.00	0.00	0.00	0.03	0.19	0.28	0.01			
UK	0.37	0.04	0.31	0.41	0.40	0.16	**0.19**	−0.04	0.26	0.25	1.00	
	10.15	1.06	8.28	11.30	11.21	4.21	4.97	−0.95	6.83	6.64		
	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.34	0.00	0.00		
USA	**0.59**	0.06	0.35	**0.49**	0.37	**0.31**	0.13	0.01	0.24	**0.28**	**0.46**	1.00
	18.32	1.64	9.52	14.41	10.23	8.41	3.32	0.18	6.38	7.30	13.26	
	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.85	0.00	0.00	0.00	

Note: Each column shows correlation, *t*-statistic and probability for each country respectively. The bold figures indicate the country added to the variance equation.

Source: Own calculation

B2: Correlation table for c_t^{HP}

	CA	*FI*	*FR*	*DE*	*IT*	*JP*	*NL*	*NO*	*PT*	*SE*	*UK*	*USA*
CA	1.00											
FI	0.42	1.00										
	11.60											
	0.00											
FR	0.54	0.34	1.00									
	16.48	9.04										
	0.00	0.00										
DE	0.59	0.47	**0.71**	1.00								
	18.73	13.35	25.49									
	0.00	0.00	0.00									
IT	0.56	0.37	0.70	**0.72**	1.00							
	17.26	10.13	25.15	26.54								
	0.00	0.00	0.00	0.00								
JP	0.61	0.42	0.54	0.71	0.57	1.00						
	19.42	11.79	16.31	25.27	17.83							
	0.00	0.00	0.00	0.00	0.00							
NL	0.45	0.34	0.46	**0.54**	0.46	0.52	1.00					
	12.65	9.27	13.12	16.40	13.27	15.64						
	0.00	0.00	0.00	0.00	0.00	0.00						
NO	0.06	0.03	−0.03	0.01	0.03	0.04	0.07	1.00				
	1.40	0.88	−0.74	0.30	0.87	1.02	1.80					
	0.16	0.38	0.46	0.76	0.38	0.31	0.07					
PT	0.28	0.22	0.47	**0.494**	0.489	0.38	0.27	−0.04	1.00			
	7.45	5.71	13.50	14.45	14.23	10.28	7.08	−1.02				
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31				
SE	0.48	**0.50**	0.52	**0.68**	0.56	0.54	0.43	0.06	0.33	1.00		
	13.89	14.69	15.50	23.41	17.28	16.20	12.13	1.60	8.88			
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00			
UK	0.38	0.18	**0.48**	0.43	0.45	0.34	0.24	0.00	0.39	0.35	1.00	
	10.54	4.77	13.72	12.03	12.83	9.24	6.23	−0.05	10.68	9.50		
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00		
USA	**0.85**	0.39	0.60	0.65	0.59	**0.68**	0.46	−0.02	0.40	0.49	0.44	1.00
	41.58	10.68	18.88	21.95	18.70	23.76	13.20	−0.43	11.17	14.08	12.34	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.67	0.00	0.00	0.00	

Note: Each column shows correlation, *t*-statistic and probability for each country respectively. The bold figures indicate the country added to the variance equation.

Source: Own calculation

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