

Cross-Country Interactions, the Great Moderation and the Role of Volatility in Economic Activity

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Abstract

This paper investigates the importance of cross-country interactions in identifying the effect of the great moderation and measuring the relationship between volatility and economic activity for the G7. A model of output growth for each G7 country is obtained taking cross-section interactions into account by augmenting univariate GARCH-M models with cross-country weighted averages of growth. The analysis shows that the effect of the great moderation and volatility on economic activity is statistically significant, and positive, only if cross-country interactions are factored in.

Keywords: Volatility, GARCH-M, Growth, the Great Moderation,
Cross-Section Dependence.

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1 Introduction

This paper investigates the relationship between volatility and economic activity for the G7 countries in a time series framework. The time series framework used to measure volatility and to estimate its effect on economic activity is the GARCH-in-mean (GARCH-M) model developed by Engle, Lilien, and Robins (1987). In this framework, it is also possible to account for structural breaks in the mean and variance of growth. Breaks in the variance that lead to a drop in volatility are of particular interest as this gives evidence for a great moderation.

The innovation of the paper is that it adjusts the GARCH-M model so that it takes country interactions into account to investigate the nature of the great moderation and the effect of volatility in economic activity. A model that takes country interactions into account is obtained by augmenting the univariate GARCH-M model with cross-country weighted averages of growth. Using cross-country weighted averages in this way is a technique developed in Pesaran, Schuermann, and Weiner (2004) and Dees, Di Mauro, Pesaran, and Smith (2007).

There is a long history of studies that investigate the relationship between volatility and economic activity with GARCH-M models and generally find a positive, but insignificant, effect of volatility (see for example Caporale & McKiernan, 1996; Fang, Miller, & Lee, 2008; Speight, 1999). These studies, however, ignore cross-country interactions. If country interactions are taken into account, however, this study finds that the impact effect of volatility is positive and significant in 4 of the G7 countries and the long-run effect of volatility on economic activity is positive and statistically significant in all G7 countries. Theoretically, there are a number of reasons for why volatility could affect growth positively. The idea of creative destruction (Schumpeter, 1942), precautionary savings (Mirman, 1971) and opportunity cost considerations (see for example Hall, 1991) all predict a positive relationship¹.

The modelling framework also allows to check for the effects of a great moderation in the G7. The analysis shows that there is evidence for a great moderation for five of the G7 countries, namely Canada, France, Italy, the United Kingdom and the United

¹There are, however, also a number of reasons for why volatility could affect growth negatively. This could be due to irreversibilities in investment (Bernanke, 1983), learning-by-doing (Martin & Rogers, 1997) or a change in the composition of investment (Stiglitz, 1993).

States. All countries experience a fall in volatility around 1985, except for France where the fall happens around 1980.

As the effect of volatility on economic activity is positive and the great moderation signifies a drop in volatility, it follows that the great moderations has a negative effect on economic activity. The long-run effect of the great moderation is found to be statistically significant for Canada, the United Kingdom and the United States.

The paper also assesses the importance of cross-country interactions by performing a simulation exercise. The results are forthcoming.

The paper is organised as follows. Section 2 describes the modelling framework. It presents the GARCH-M model with shift dummies and cross-country weighted averages and derives the long-run effects of volatility and the great moderation on economic activity. Section 3 discusses the estimation results. Before presenting these results, however, it discusses the data, an exogeneity test, the break detection procedure, the model selection procedure and the estimation method. Section 4 assesses the importance of cross-country interactions using a simulation exercise. Section 5 concludes.

2 Modelling the role of the great moderation and the effect of volatility on economic activity using GARCH-in-mean models with country interactions

The general econometric framework in this paper is the univariate generalised autoregressive conditional heteroscedasticity-in-mean model (GARCH-M) developed by Engle, Lilien, and Robins (1987). This framework models the variance of the dependent variable in a separate equation and is able to estimate its feedback on the dependent variable.

The standard GARCH-M model, however, is adjusted in two ways. First, shift dummies in the mean and variance equation are included in order to account for structural breaks. The effect of ignoring structural breaks in the mean is well known. As Perron (1989) shows, structural breaks biases the autoregressive parameters in the mean equation towards 1. Ignoring structural breaks in the variance has a similar effect. Early studies find that the persistence of volatility shocks of stock returns, interest rates and exchange rates are very high, i.e. the estimated autoregressive parameters in the variance equation are close to one (see Bollerslev, Chou, & Kroner, 1992 for a review). In

response to this empirical finding, Engle and Bollerslev (1986) propose the Integrated GARCH (IGARCH) model. Diebold (1986), in a comment to the original IGARCH paper, however, argues that this persistence could be due to structural change in the variance. Lamoureux and Lastrapes (1990) show that this is indeed the case using daily stock-return data and Monte Carlo simulations. Furthermore, Hillebrand (2005) proves it and coins this effect 'Spurious almost-integration'.

Taking structural breaks into account, however, is not only motivated by statistical considerations. The dummies also have an economic interpretation. The dummy variables in the mean equation can be interpreted as productivity changes (see for example Nordhaus, 2004), whereas the dummy variables in the variance equation can be justified by the various mechanism that could lead to shifts in the variance (see Stock & Watson, 2002). Negative breaks in the variance are of particular interest as they provide evidence for a great moderation.

The second adjustment, which is the innovation of the paper, is the inclusion of cross-country weighted averages of growth to account for cross-country interactions. The use of cross-country weighted averages in this way is a technique used in the Global VAR literature (see for example Dees, Di Mauro, Pesaran, & Smith, 2007; Pesaran, Schuermann, & Weiner, 2004).

In what follows, I first describe the univariate GARCH-M models. Then, I derive the long-run effects of volatility and the great moderation on economic activity.

2.1 The GARCH-M model with country interactions

The standard GARCH(1,1) model augmented with shift dummies and cross-country weighted averages is given by

$$\Delta y_{it} = c_{i0} + \sum_{k=1}^l c_{ik} DM_{ikt} + \lambda_i \sigma_{it} + \sum_{k=0}^s \beta_{ik} \Delta y_{it-k}^* + \sum_{k=1}^p \phi_{ik} \Delta y_{it-k} + \varepsilon_{it} \quad (2.1)$$

$$\sigma_{it}^2 = \alpha_{i0} + \sum_{k=1}^f \alpha_{ik} DV_{ikt} + \eta_i \varepsilon_{it-1}^2 + \gamma_i \sigma_{it-1}^2 \quad (2.2)$$

where Δy_{it} is the growth rate for country i at time t , DM_{ikt} are possible shift dummies in the conditional mean which are equal to 0 before the break date and equal to 1 on

and after the break date, σ_{it} is the conditional standard deviation of growth, which is the measure of volatility, and Δy_{it-k}^* are the cross-country weighted averages of growth which are defined as

$$\Delta y_{it}^* = \sum_{j=1}^7 w_{ij} \Delta y_{jt}, \quad \sum_{j=1}^7 w_{ij} = 1 \quad \text{and} \quad w_{ii} = 0, \quad (2.3)$$

where w_{ij} is the average share of total trade of country i with country j and total trade is defined as the sum of exports and imports between country i and the other countries.

The conditional variance of country i at time t , σ_{it}^2 , depends on a constant α_{i0} , possible shift dummies DV_{ikt} which are equal to 0 before the break date and equal to 1 on and after the break date, the squared lagged error term and a lag of the variance. The shift dummies with a negative coefficient are then interpreted as evidence for a great moderation. Note that equation 2.2 reduces to an ARCH(1) model if γ_i equals zero.

The standard properties for the error term in the model hold. The conditional mean and variance of the error term are equal to 0 and σ_{it}^2 , respectively, i.e. $\varepsilon_{it} \sim (0, \sigma_{it}^2)$, and the error term is serially uncorrelated, i.e. $COV[\varepsilon_{it}, \varepsilon_{it-k}] = E[\varepsilon_{it}\varepsilon_{it-k}] = 0$ for $k \neq 0$. Note that the error term of each country only consist of an idiosyncratic component as the model takes cross-country interactions into account. It follows that the error term across countries is uncorrelated, i.e. $COV[\varepsilon_{it}, \varepsilon_{jt}] = E[\varepsilon_{it}\varepsilon_{jt}] = 0$ for $i \neq j$.

2.2 Measuring the long-run effect the great moderation and volatility on economic activity

In order to find the long-run effect of the great moderation and volatility, we first calculate the short-run effect of the great moderation and volatility on the growth rate and then premultiply these short-run effects with the multiplier.

To find the short-run effect of the great moderation on economic activity, equation 2.2 is first substituted into equation 2.1 and then the derivative is taken with respect to the particular variance dummy or dummies, DV_{ikt} , that relates or relate to the great

moderation. These dummies are denoted as DV_{iGM} and their effects as α_{iGM} , i.e.

$$\frac{\partial \Delta y_{it}}{\partial DV_{iGM}} = \lambda_i \frac{1}{2} \left(\alpha_{i0} + \sum_{k=1}^f \alpha_{ik} DV_{ikt} + \eta_i \varepsilon_{it-1}^2 + \gamma_i \sigma_{it-1}^2 \right)^{-\frac{1}{2}} \alpha_{iGM} \quad (2.4)$$

$$= \frac{\lambda_i \alpha_{iGM}}{2 \sqrt{\sigma_{it}^2}} \quad (2.5)$$

$$\equiv \alpha_{iGM}^{SR} \quad (2.6)$$

The short-run effect of volatility on growth is equal to

$$\frac{\partial \Delta y_{it}}{\partial \sigma_{it}} = \lambda_i \equiv \lambda_i^{SR}. \quad (2.7)$$

In order to find the multiplier we stack the model, i.e.

$$\Delta \mathbf{y}_t = \mathbf{c}_0 + \sum_{k=1}^l \mathbf{c}_k D M_{kt} + \lambda \sigma_t + \sum_{k=0}^s \beta_k \Delta \mathbf{y}_{t-k}^* + \sum_{k=1}^p \phi_k \Delta \mathbf{y}_{t-k} + \varepsilon_t \quad (2.8)$$

$$\sigma_t^2 = \alpha_0 + \sum_{k=1}^f \alpha_k DV_{kt} + \eta \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \quad (2.9)$$

$$\Delta \mathbf{y}_t^* = W \Delta \mathbf{y}_t \quad (2.10)$$

where all the coefficient matrices are 7×7 matrices, except the constants \mathbf{c}_0 and α_0 which are 7×1 vectors. The diagonal elements of these matrices are equal to the country-specific estimates and the off-diagonal elements are equal to 0. The weights matrix is equal to

$$\mathbf{W} = \begin{bmatrix} 0 & w_{12} & \cdots & w_{17} \\ w_{21} & 0 & \vdots & w_{27} \\ \vdots & \vdots & \ddots & \vdots \\ w_{71} & w_{72} & \cdots & 0 \end{bmatrix} \quad (2.11)$$

where w_{ij} is the share of total trade of country i with country j .

Substituting equation 2.10 in equation 2.8 gives

$$\Delta \mathbf{y}_t = \mathbf{c}_0 + \sum_{k=1}^l \mathbf{c}_k \mathbf{D} \mathbf{M}_{kt} + \lambda \sigma_t + \sum_{k=0}^s \beta_k \mathbf{W} \Delta \mathbf{y}_{t-k} + \sum_{k=1}^p \phi_k \Delta \mathbf{y}_{t-k} + \varepsilon_t \quad (2.12)$$

and using the lag operator and rearranging gives

$$\Delta \mathbf{y}_t = \left(\mathbf{I}_7 - \mathbf{B}(\mathbf{1}) - \Phi(\mathbf{1}) \right)^{-1} \left(\mathbf{c}_0 + \sum_{k=1}^l \mathbf{c}_k \mathbf{D} \mathbf{M}_{kt} + \lambda \sigma_t + \varepsilon_t \right) \quad (2.13)$$

where $\mathbf{B}(\mathbf{1}) = \sum_{k=0}^s \beta_k \mathbf{W}$ and $\Phi(\mathbf{1}) = \sum_{k=1}^p \phi_k$. It follows that the multiplier is equal to $\left(\mathbf{I}_7 - \mathbf{B}(\mathbf{1}) - \Phi(\mathbf{1}) \right)^{-1}$ and so the long-run effect of the great moderation and volatility are

$$\alpha_{GM}^{LR} \equiv \left(\mathbf{I}_7 - \mathbf{B}(\mathbf{1}) - \Phi(\mathbf{1}) \right)^{-1} \alpha_{GM}^{SR} = \begin{bmatrix} \alpha_{(1,1)GM}^{LR} & \alpha_{(1,2)GM}^{LR} & \cdots & \alpha_{(1,7)GM}^{LR} \\ \alpha_{(2,1)GM}^{LR} & \alpha_{(2,2)GM}^{LR} & \cdots & \alpha_{(2,7)GM}^{LR} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{(7,1)GM}^{LR} & \alpha_{(7,2)GM}^{LR} & \cdots & \alpha_{(7,7)GM}^{LR} \end{bmatrix} \quad (2.14)$$

and

$$\lambda^{LR} \equiv \left(\mathbf{I}_7 - \mathbf{B}(\mathbf{1}) - \Phi(\mathbf{1}) \right)^{-1} \lambda^{SR} = \begin{bmatrix} \lambda_{(1,1)}^{LR} & \lambda_{(1,2)}^{LR} & \cdots & \lambda_{(1,7)}^{LR} \\ \lambda_{(2,1)}^{LR} & \lambda_{(2,2)}^{LR} & \cdots & \lambda_{(2,7)}^{LR} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{(7,1)}^{LR} & \lambda_{(7,2)}^{LR} & \cdots & \lambda_{(7,7)}^{LR} \end{bmatrix}, \quad (2.15)$$

respectively. Note that the short-run effect of the great moderation, α_{iGM}^{SR} , includes the contemporaneous variance, σ_{it}^2 . In order to find the long-run effect of the great moderation the contemporaneous variance is replaced by the long-run variance.

Because the model takes country interactions into account through the weight matrix \mathbf{W} , the off-diagonal elements of the matrices with the long-run effects are nonzero. The diagonal elements are the long-run effects of country i on the growth rate of country i . The off-diagonal elements are the long-run effects of country j on the growth rate of country i . To arrive at the effect of total long-run effects, the row elements of the matrices with the long-run effects are summed. This total effect incorporates the internal and external effects. Thus the total long-run effects of the great moderation and volatility

are equal to

$$\alpha_{GM}^{TLR} \equiv \alpha_{GM}^{LR} \mathbf{S} = \begin{bmatrix} \sum_j \alpha_{(1,j)GM}^{LR} \\ \sum_j \alpha_{(2,j)GM}^{LR} \\ \vdots \\ \sum_j \alpha_{(7,j)GM}^{LR} \end{bmatrix} \quad \text{and} \quad \lambda^{TLR} \equiv \lambda^{LR} \mathbf{S} = \begin{bmatrix} \sum_j \lambda_{(1,j)}^{LR} \\ \sum_j \lambda_{(2,j)}^{LR} \\ \vdots \\ \sum_j \lambda_{(7,j)}^{LR} \end{bmatrix}, \quad (2.16)$$

respectively, where \mathbf{S} is a 7×1 vector of ones.

3 Assessing the role of the great moderation and the effect of volatility on economic activity

3.1 Properties of economic activity in the G7

The measure of economic activity in this study is the seasonal adjusted monthly growth rate of industrial production from the OECD's Main Economic Indicators (MEI) database². The analysis is done for the G7 over the period February 1961 – May 2013. The G7 consist of Canada (CAN), France (FR), Germany (GER), Italy (ITA), Japan (JAP), the United Kingdom (UK) and the United States (US). Figure 1 presents the monthly growth rates and table 1 presents the summary statistics³. The monthly growth rates of industrial production are found to be stationary, serially correlated, conditional heteroscedastic and not normally distributed⁴. The data used to calculate the average trade weights in the definition of the cross-country weighted averages, w_{ij} in equation 2.3, is

²This measure is compared with GDP in the appendix. Figure 2 in appendix A plots the two series together. The two series follow the same path, except for France and the United Kingdom where the growth rate of industrial production is slower than GDP from 1975 and 1970 onwards, respectively. Table 6 shows some numbers expressing the relatedness of the two series. Panel A shows that the correlation between the two series is quite high, irrespective if the series are in levels, in logs or in growth rates. Panel B shows that, as expected, the IPI series is much more volatile than GDP for all G7 countries.

³France and Japan have extreme observations and these are replaced by the median growth rate of the original data over the full sample. In particular, the extreme observations are March–April 1963 for France due to a miner strike, May–July 1968 for France due to the May '68 uprising and March–June 2011 for Japan due to an earthquake.

⁴The unit root test is the Elliott, Rothenberg, and Stock (1996) test. This test has more power than the original augmented Dickey-Fuller unit root test. This test has also another advantage. When a break is present in the data, the Dickey-Fuller test is biased towards non-rejection of a unit root (Perron, 1989). The ERS DF-GLS unit root test, in contrast, is asymptotically robust to level breaks (Elliott et al., 1996, p. 816). To test for serial correlation and conditional heteroscedasticity in the data I calculate the Ljung-Box Q-statistics for the data and the Ljung-Box Q-statistics for the squared data, respectively. To test if the data is normally distributed I use the Jarque-Bera test statistic. See table 5 in appendix A for the results of these tests.

Table 1: Summary statistics of the monthly growth rates of industrial production for the G7 (in %), 1961:02-2013:05

	N	Median	Mean	Sta. Dev.	Min	Max
CAN	628	0.19	0.24	1.10	-3.76	4.13
FR	628	0.04	0.14	1.35	-4.70	5.66
GER	628	0.23	0.20	1.75	-9.46	12.31
ITA	628	0.18	0.18	2.16	-14.78	13.51
JAP	628	0.38	0.34	1.54	-8.38	6.60
UK	628	0.10	0.09	1.36	-7.88	9.73
US	628	0.29	0.24	0.76	-4.21	3.09

import and export data from the IMF's Direction of Trade Statistics⁵.

3.2 Exogeneity test of Δy_{it}^*

An important assumption in the model in equation 2.1-2.2 is that the contemporaneous cross-country weighted average is exogenous, i.e. the country specific growth rate at time t , Δy_{it} , does not affect the cross-country weighted average at time t , Δy_{it}^* . In statistical terms this assumptions implies that Δy_{it}^* and the error term are uncorrelated, i.e. $COV(\Delta y_{it}^*, \varepsilon_{it}) = 0$.

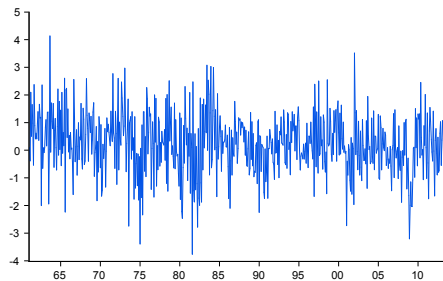
A standard procedure to test if a variable is exogenous is to compare OLS and 2SLS estimates as proposed by Hausman (1978). If the estimates of the two estimation methods differ significantly, then the suspected endogenous variable is endogenous. Unfortunately, GARCH models cannot be estimated with OLS and 2SLS. Therefore, I adjust the models discussed in section 2 so that OLS and 2SLS estimation are possible and we can still test if Δy_{it}^* is exogenous. In particular, I exclude the variance equation and the conditional standard deviation in the mean equation. This gives a standard AR(p) model augmented with the cross-country weighted averages. As the error term in this framework is not conditionally homoscedastic, I use adjusted standard errors throughout the procedure. I find the optimal number of lags by allowing for up to six lags of the lagged variables and use the model where the AIC is maximized. Thus the adjusted model is

$$\Delta y_{it} = c_{i0} + \sum_{k=1}^l c_{ik} DM_{ikt} + \sum_{k=0}^s \beta_{ik} \Delta y_{it-k}^* + \sum_{k=1}^p \phi_{ik} \Delta y_{it-k} + \varepsilon_{it} \quad (3.1)$$

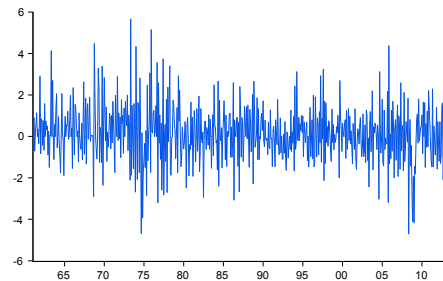
⁵The average trade weights can be found in table 7 in appendix A. The cross-country weighted averages are plotted in figure 3 in appendix A

Figure 1: Monthly growth rates of industrial production for the G7, 1961:02–2013:05

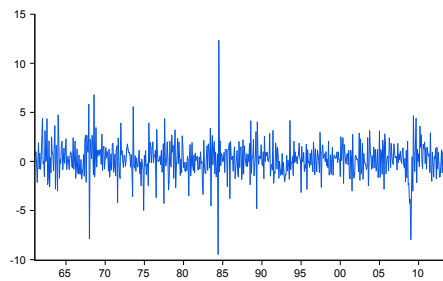
(a) Canada



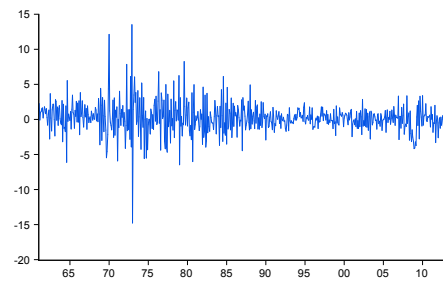
(b) France



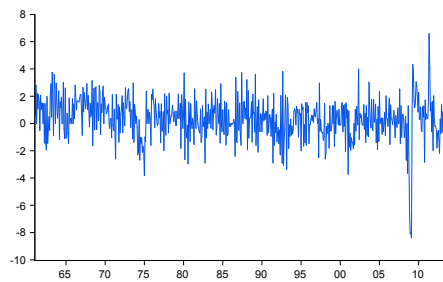
(c) Germany



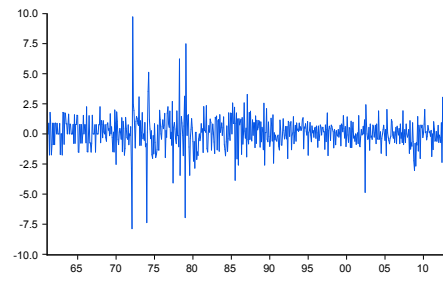
(d) Italy



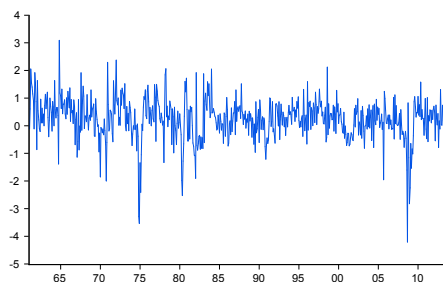
(e) Japan



(f) United Kingdom



(g) United States



where s and p are the optimal lags.

To check if Δy_{it}^* is exogenous, we need to test if $COV(\Delta y_{it}^*, \varepsilon_{it}) = 0$ in the above model. This can be done through a regression test based on the reduced form of Δy_{it}^* . In order to do the regression based test, we set the reduced form of Δy_{it}^* equal to

$$\Delta y_{it}^* = c_{i0} + \sum_{k=1}^l c_{ik} DM_{ikt} + \sum_{k=1}^{s+1} \beta_{ik} \Delta y_{it-k}^* + \sum_{k=1}^{p+1} \phi_{ik} \Delta y_{it-k} + \xi_{it} \quad (3.2)$$

Note that the number of lags of Δy_{it} and Δy_{it}^* is now one more than in equation 3.1. This implies that the instruments are an extra lag of Δy_{it} and Δy_{it}^* .

As all the exogenous variables are uncorrelated with ε_{it} , it follows that $COV(\Delta y_{it}, \Delta y_{it}^*) = 0$ if and only if $COV(\varepsilon_{it}, \xi_{it}) = 0$. Writing $\varepsilon_{it} = \theta_i \xi_{it} + e_{it}$, where e_{it} is uncorrelated with ξ_{it} and has a mean of zero, implies that $COV(\varepsilon_{it}, \xi_{it}) = 0$ if and only if $\theta_i = 0$. An easy way to test this is to include ξ_{it} in the original model and check if it is significant. As ξ_{it} is unobserved the estimated residuals of equation 3.2 are used, $\hat{\xi}_{it}$, i.e.

$$\Delta y_{it} = c_{i0} + \sum_{k=1}^l c_{ik} DM_{ikt} + \sum_{k=0}^s \beta_{ik} \Delta y_{it-k}^* + \sum_{k=1}^p \phi_{ik} \Delta y_{it-k} + \theta_i \hat{\xi}_{it} + v_{it} \quad (3.3)$$

Table 2 shows the results of the above procedure. The reported t -statistics are based on the White heteroskedasticity-consistent standard errors. For all countries, θ_i is insignificant at the 5 % level and so we can conclude that Δy_{it}^* is exogenous.

Table 2: Exogeneity test of Δy_{it}^*

	CAN	FR	GER	ITA	JAP	UK	US
θ_i	-1.330	0.684	-0.700	-0.767	-2.405	-0.132	0.452
	(-1.72)	(0.49)	(-0.98)	(-0.52)	(-0.67)	(-0.34)	(0.64)

Notes: - t -statistics based on White heteroskedasticity-consistent standard errors are in brackets.

3.3 Determining potential structural breaks in the mean and variance of growth

The procedure to determine structural breaks is based on Bai and Perron (1998) and Bai and Perron (2003). Bai and Perron (1998) develop various procedures to identify multiple structural breaks in the linear model and Bai and Perron (2003) discuss practical

issues for empirical applications of these procedures. In particular, Bai and Perron (2003, p.15-16) recommend to first calculate the $UDmax$ and $WDmax$ test statistics to check if there is at least one level break in of data. If this is the case, then the $SupF(\ell+1|\ell)$ statistic should be used sequentially to determine higher order breaks. The procedure allows for a maximum number of 5 possible breaks, this implies that the maximum ℓ equals 4. In order to account for cross-country interactions, the cross-country weighted averages are included in the procedure.

In particular, to find the break dates in the mean growth rates, the $UDmax$, $WDmax$ and $SupF(\ell+1|\ell)$ statistics are calculated for the error term of the following equation

$$\Delta y_{it} = c_{i0} + \sum_{k=0}^6 \beta_k \Delta y_{it-k}^* + \varepsilon_{it}. \quad (3.4)$$

To find the breaks in the variance, the statistics are calculated for the absolute values of the error term (as in Herrera & Pesavento, 2005 and Fang & Miller, 2009) of the following equation

$$\Delta y_{it} = c_{i0} + \sum_{k=1}^l c_{ik} DM_{ikt} + \sum_{k=0}^6 \beta_k \Delta y_{it-k}^* + \varepsilon_{it} \quad (3.5)$$

where DM_{ikt} are the mean shift dummy variables.

Table 3 shows the results of the above procedure. Panel A shows that Canada, France, Germany, Italy and the United States experienced one break in their mean growth rate, whereas Japan and the United Kingdom experienced two. The particular dates of the mean breaks of the G7 countries do not really coincide with each other. The results for the breaks in the variance are shown in panel B. Two countries, namely Germany and Japan, did not experience a break in the variance. Canada, France and the United States, in contrast experienced one break and Italy and the United Kingdom two. Most of the break dates, however, happened around the mid-80s.

3.4 Model selection procedure and estimation method

In order to find the most parsimonious model, an important issue with GARCH models needs to be taken into account and that is the possibility of the Zero-Information-Limit Condition (ZILC) introduced by Nelson and Startz (2007). In many econometric

Table 3: Results of the break detection procedure

Panel A: Breaks in the mean								
	CAN	FR	GER	ITA	JAP	UK	US	C.V.
<i>UDmax</i>	29.56	29.97	18.70	33.52	44.45	18.40	27.09	21.70
<i>WDmax</i>	29.56	33.14	24.13	33.52	49.67	26.35	33.26	23.31
SupF(2 1)	22.03	13.19	22.77	22.40	74.67	25.14	22.15	23.62
SupF(3 2)	15.81	7.17	15.43	13.74	17.27	23.85	22.15	24.74
SupF(4 3)	10.52	11.09	11.21	8.79	25.05	7.31	9.98	25.63
SupF(5 4)	0.00	0.00	11.21	5.69	0.00	11.92	0.00	26.39
Break 1	1970:03	1978:04	1969:05	1985:10	1970:07	1974:03	1991:03	
Break 2					2005:01	1981:12		
Panel B: Breaks in the variance								
	CAN	FR	GER	ITA	JAP	UK	US	C.V.
<i>UDmax</i>	18.85	8.83	4.91	46.19	2.45	22.14	15.97	7.46
<i>WDmax</i>	18.85	11.94	5.49	46.19	3.91	23.49	15.97	8.20
SupF(2 1)	8.27	7.86	4.13	13.06	1.73	11.42	3.41	8.51
SupF(3 2)	6.68	7.12	0.55	2.34	2.53	2.05	1.85	9.41
SupF(4 3)	4.95	1.76	0.65	9.53	4.94	5.62	1.02	10.04
SupF(5 4)	0.00	0.14	0.00	0.00	0.00	0.00	0.00	10.58
Break 1	1984:11	1979:08		1969:08		1972:01	1984:02	
Break 2				1985:12		1987:08		

models the asymptotic variance of a parameter estimate depends on the value of another structural parameter. If the parameter estimate is close to a critical value, then the asymptotic variance is very large and the model is weakly identified. More formally, Nelson and Startz (2007, p.49) argue that ZILC holds for an estimator $\hat{\theta}$ if there is a value of γ , say γ_0 , such that $\lim_{\gamma \rightarrow \gamma_0} I_{\hat{\theta}} = 0$, where $I_{\hat{\theta}}$ is the inverse of the variance of $\hat{\theta}$. Nelson and Startz (2007) introduce ZILC as a way to identify such model where the above leads to spurious inference.

Ma, Nelson, and Startz (2007) show that ZILC can also hold for GARCH models. They show that if the true ARCH effect, η_i in equation 2.2, is small, then the GARCH(1,1) model is weakly identified. The effect of this is that the GARCH coefficient, γ_i in equation 2.2, is biased upward and the corresponding standard error is too small. Thus the results point to persistence where in fact this is not the case. Ma, Nelson, and Startz (2007, p16-17) also propose a procedure to detect this spurious result. To check for ZILC in the GARCH(1,1) model, the implied autocorrelation function of the conditional variance from the GARCH(1,1) should be compared with the one im-

plied by an ARCH(q) model. If they differ a lot, then this is evidence that ZILC holds. Also, if the estimated conditional variance of the GARCH(1,1) and an ARCH(q) models are very different, then this also gives evidence for ZILC. Ma, Nelson, and Startz (2007) propose to model the variance as an ARCH(q) model if ZILC is detected. Thus if ZILC is detected, the variance equation, equation 2.2, is replaced with

$$\sigma_{it}^2 = \alpha_{i0} + \sum_{k=1}^f \alpha_{ik} DV_{ikt} + \sum_{k=1}^q \eta_{ik} \varepsilon_{it-k}^2. \quad (3.6)$$

There are, however, a few other issues that also need to be taken into account in order to find the most parsimonious model for each country. A first one is the possibility of a nonnormal error process as ignoring this leads to inconsistent standard errors⁶. Estimating the models with the normal and the t -distribution as error distribution allows us to test which distribution fits the data better. The model with the t -distribution, however, has one more parameter than the model with the normal distribution, namely the degrees of freedom. A second issue is that the Hessian of the log-likelihood function of the GARCH-M model is not block diagonal and so the mean and variance parameters are correlated. Therefore, all the parameters need to be estimated simultaneously. Finally, the models should be well-specified. The models are well-specified if the mean and variance of the standardized residuals are equal to 0 and 1, respectively, the distribution of the residuals corresponds to the one assumed in the estimation procedure and there is no evidence of serial correlation and conditional heteroscedasticity in the standardized residuals.

Taking the above issues into account, the most parsimonious model for each country is determined by estimating up to a GARCH(1,1) model with the t -distribution as error distribution and up to six lags of all the possible lagged variables in the mean model. The well-specified model that maximises the Akaike Information Criteria (AIC) where ZILC does not hold is then picked as the best representation of the data.

The Marquardt optimization algorithm is used to estimate the models. As with any iterative process, however, the algorithm could stop at a local maximum instead of the global maximum. To counter this problem, all the models are estimated with various

⁶Previous studies remedied this by estimating GARCH models with the normal distribution but applying the consistent variance-covariance estimator developed by Bollerslev and Wooldridge (1992).

initial values to check if the likelihoods are the same⁷.

3.5 Estimation results

Table 4 shows the estimation results of the well-specified models⁸. Panel A and B show the estimates for the mean and variance equation, respectively.

A first thing to note is that the cross-country weighted averages are numerous in the models. Looking at the estimates on volatility, λ , we see that the impact effect of volatility is positive for all countries and statistical significant at conventional levels in four of the G7 countries, namely Canada, Japan, the United Kingdom and the United States. The long-run effect of total volatility, λ^{TLR} , is statistical significant at the 1% level for all G7 countries. The standard errors for the long-run effect of volatility are obtained with the delta method.

The mean dummy variables are only statistically significant for Germany, Japan and the United States. The signs of these significant estimates, however, are different. Japan experienced a productivity slowdown around 1970, whereas Germany and the United States experienced an increase in productivity around 1970 and 1990, respectively.

Panel B shows that all models are estimated with the t -distribution as error distribution, except for Canada. The variance model picked by the model selection procedure is the ARCH(1) model for all countries, except for Italy and Japan where the best model is a GARCH(1,1) model⁹.

All the variance dummies included in the models are significant at the 5% level. The results show that volatility drops in the 1980s or around 1980 for all the countries that experienced at least one break in the variance of growth. These countries are Canada, France, Italy, the United Kingdom and the United States. Thus for these countries there is evidence for a great moderation. The effect of the great moderation, α_{iGM} ,

⁷I estimate the models with the estimates of the OLS regression for the mean equation as starting values and various fractions of these OLS estimates. The fractions of the OLS estimates are 0.8, 0.5 and 0.3.

⁸A series of residual diagnostic tests are shown in table 8 in appendix A. Figure 4 in appendix A for plots of the distribution of the residuals together with the theoretical distribution assumed in the estimation process.

⁹For France, there was evidence for ZILC and therefore the variance model is a ARCH(q) process. The number of lags q is determined by estimating up to lag 6 and picking the highest lag order while ignoring models where one or more lags have a negative estimate. Figure 6 in appendix A shows that the implied autocorrelation function of the conditional variance and the estimated conditional standard deviation for the GARCH(1,1) and ARCH(q) model is very different. For Japan, I report the GARCH(1,1) model as the standardized residuals of the ARCH(1) model are not conditional homoscedastic.

Table 4: Estimation results

Panel A: Mean Equation							
	CAN	FR	GER	ITA	JAP	UK	US
c_0	-0.641* (0.344)	-0.480 (0.724)	-0.561 (0.378)	-0.345 (0.448)	-0.117 (0.326)	-0.364* (0.211)	-0.260** (0.118)
c_1	0.020 (0.138)	-0.053 (0.238)	0.247* (0.147)	-0.002 (0.254)	-0.400*** (0.132)	-0.206 (0.205)	0.128*** (0.046)
c_2					-0.050 (0.133)	0.234 (0.213)	
λ	0.710** (0.303)	0.477 (0.538)	0.310 (0.249)	0.223 (0.203)	0.449* (0.245)	0.365* (0.190)	0.493** (0.192)
β_0	0.578*** (0.058)	0.513*** (0.043)	0.502*** (0.065)	0.529*** (0.064)	0.346*** (0.073)	0.400*** (0.047)	0.271*** (0.026)
β_1	0.193** (0.076)	0.364*** (0.051)	0.350*** (0.070)	0.468*** (0.070)	0.200** (0.080)	0.244*** (0.047)	0.144*** (0.027)
β_2	0.056 (0.070)	0.357*** (0.052)	0.077 (0.069)	0.267*** (0.068)			0.019 (0.029)
β_3	0.078 (0.067)	0.234*** (0.050)	0.199*** (0.062)	0.128* (0.071)			-0.051 (0.032)
β_4	0.113* (0.066)		0.110* (0.063)	0.028 (0.071)			0.085*** (0.029)
β_5				0.114* (0.069)			
β_6				-0.158** (0.065)			
ϕ_1	-0.240*** (0.045)	-0.494*** (0.041)	-0.352*** (0.045)	-0.370*** (0.045)	-0.254*** (0.045)	-0.271*** (0.041)	0.042 (0.044)
ϕ_2	-0.054 (0.045)	-0.249*** (0.043)	-0.146*** (0.033)	-0.123*** (0.048)	0.165*** (0.039)	-0.127*** (0.033)	0.104*** (0.036)
ϕ_3	0.136*** (0.040)	-0.148*** (0.043)		-0.022 (0.043)	0.309*** (0.037)		0.117*** (0.032)
ϕ_4		-0.125*** (0.039)		-0.007 (0.044)	0.133*** (0.035)		0.052 (0.035)
ϕ_5		-0.093** (0.037)		0.035 (0.043)			-0.052* (0.031)
ϕ_6		0.102*** (0.033)		0.116*** (0.038)			
λ^{TLR}	2.278*** (0.621)	1.384*** (0.474)	1.501*** (0.454)	1.679*** (0.503)	2.218*** (0.747)	1.045*** (0.280)	1.928*** (0.555)

Table 4: Continued

Panel B: Variance Equation							
	CAN	FR	GER	ITA	JAP	UK	US
α_0	1.093*** (0.096)	1.655*** (0.210)	1.541*** (0.160)	1.137** (0.458)	0.954*** (0.176)	0.835*** (0.186)	0.375*** (0.055)
α_1	-0.508** (0.106)	-0.854*** (0.209)		1.174** (0.576)		1.285*** (0.357)	-0.196*** (0.054)
α_2				-1.880*** (0.679)		-1.551*** (0.323)	
η	0.095** (0.047)	0.092* (0.054)	0.334*** (0.095)	0.217*** (0.072)	0.284*** (0.085)	0.199*** (0.068)	0.346*** (0.091)
γ				0.452*** (0.144)	0.158 (0.102)		
ν		12.926* (7.829)	6.171*** (1.144)	10.042** (4.565)	6.616*** (1.787)	6.845*** (1.565)	5.625*** (1.248)
α_{GM}^{TLR}	-0.307*** (0.109)	-0.131 (0.125)		-0.165 (0.108)		-0.187* (0.097)	-0.205** (0.082)

Notes: - The model is:

$$\Delta y_{it} = c_{i0} + \sum_{k=1}^l c_{ik} DM_{ikt} + \lambda_i \sigma_{it} + \sum_{k=0}^s \beta_{ik} \Delta y_{it-k}^* + \sum_{k=1}^p \phi_{ik} \Delta y_{it-k} + \varepsilon_{it}$$

$$\sigma_{it}^2 = \alpha_{i0} + \sum_{k=1}^f \alpha_{ik} DV_{ikt} + \eta_i \varepsilon_{it-1}^2 + \gamma_i \sigma_{it-1}^2$$

where Δy_{it-k}^* are cross-country weighted averages defined as

$$\Delta y_{it}^* = \sum_{j=1}^7 w_{ij} \Delta y_{jt}, \quad \sum_{j=1}^7 w_{ij} = 1 \quad \text{and} \quad w_{ii} = 0,$$

where w_{ij} is the average share of total trade of country i with country j and total trade is defined as the sum of exports and imports between country i and the G7 other countries.

- All models are estimated with the t -distribution as error distribution where ν are the estimated degrees of freedom, except for Canada.
- DM_{ikt} and DV_{ikt} are country-specific shift dummies in the mean and variance equation, respectively. The specific dates of the breaks can be found in table 3.
- Standard errors are in brackets. The standard errors for the total long-run effects are found using the delta method.
- *, **, ***: Significant at the 10%, 5% and 1% level, respectively.

corresponds to the first variance dummy for Canada, France and the United States. For Italy and the United Kingdom the great moderation corresponds to the second variance dummy. Also note that Italy and the United Kingdom experienced an increase in volatility around 1970¹⁰.

As the effect of volatility on economic activity is positive and the great moderation signifies a drop in volatility, it follows that the great moderations has a negative effect on economic activity. The long-run effect of the great moderation is statistically significant in three countries, namely Canada, the United Kingdom and the United States.

4 Testing the importance of country interactions

This section assesses the importance of cross-country interactions in the relationship between volatility and economic activity with a simulation exercise. The simulation exercise is done as follows. The null hypothesis is that cross-country interactions are unimportant for measuring volatility effects. First, we estimate a model under the null hypothesis, i.e. a model that does not allow for cross-country interactions. Thus,

$$\Delta y_{it} = \tilde{c}_{i0} + \tilde{c}_{i1} \tilde{D}M_{it} + \tilde{\lambda}_i \tilde{\sigma}_{it} + \sum_{k=1}^p \tilde{\phi}_{ik} \Delta y_{it-k} + \tilde{\varepsilon}_{it} \quad (4.1)$$

$$\tilde{\sigma}_{it}^2 = \tilde{\alpha}_{i0} + \sum_{k=1}^f \tilde{\alpha}_{ik} \tilde{D}V_{ikt} + \tilde{\eta}_i \tilde{\varepsilon}_{it-1}^2 + \tilde{\gamma}_i \tilde{\sigma}_{it-1}^2 \quad (4.2)$$

$$COV[\varepsilon_{it}, \varepsilon_{jt}] = 0. \quad (4.3)$$

The break detection procedure is the same as for the model with country interaction, except that there are no cross-country weighted averages in the relevant equation. The estimation procedure is the same as for the model with cross-country interactions discussed in section 3.4. Then, we use this model and the estimated parameters to construct S simulated series.

For each simulated series, we estimated the model without and with the cross-country weighted averages and use the estimates to calculate the respective total long-run effect of volatility, i.e. $\tilde{\lambda}^{TLR}$ for the model in 4.1-4.3 and λ^{TLR} for the model in 2.1-2.3. This procedure gives a distribution of $\tilde{\lambda}^{TLR} - \lambda^{TLR}$ and so we can test if the observed

¹⁰The estimated conditional standard deviation for all G7 countries are shown in figure 5 in appendix A.

difference is statistically different from 0. The results are forthcoming.

5 Conclusion

This paper investigated the importance of cross-country interactions in identifying the role of the great moderation and the effect of volatility on economic activity in the G7. The general framework used to measure volatility and to estimate its effect on economic activity was the GARCH-M framework with shift dummies in the mean and variance equation to account for structural change. This framework was then augmented with cross-country weighted averages to account for cross-section dependence.

The analysis showed that volatility has a positive and statistically significant effect on economic activity in 4 of the G7 countries, namely Canada, Japan, the United Kingdom and the United States. The total long-run effect of volatility is found to be positive and significant for all G7 countries.

The analysis found evidence for a great moderation for five of the G7 countries, namely Canada, France, Italy, the United Kingdom and the United States. All countries experience a fall in volatility around 1985, except for France where the fall happens around 1980. Moreover, the long-run effect of the great moderation on economic activity is found to be negative and significant in three of the 5 countries that experienced a great moderation, namely Canada, the United Kingdom and the United States.

The paper also developed a simulation exercise to assess the importance of cross-country interactions. The results are forthcoming.

A Appendix A

Table 5: Properties of the monthly growth rates of industrial production for the G7, 1961:02–2013:05

Panel A: *Unit root test*

	CAN	FR	GER	ITA	JAP	UK	US
ERS DF-GLS	-8.25	-7.69	-2.45	-8.03	-4.02	-3.08	-6.59
C.V. at 5%	-1.94	-1.94	-1.94	-1.94	-1.94	-1.94	-1.94

Panel B: *Distribution*

	CAN	FR	GER	ITA	JAP	UK	US
Skewness	-0.133	0.129	0.058	0.197	-0.856	0.026	-0.899
Kurtosis	3.496	4.391	9.431	10.704	7.538	12.882	7.357
Jarque-Bera	8.28 [0.0159]	52.34 [0.0000]	1082.62 [0.0000]	1556.96 [0.0000]	615.55 [0.0000]	2555.16 [0.0000]	581.39 [0.0000]

Panel C: *Tests for serial correlation and conditional heteroscedasticity*

	CAN	FR	GER	ITA	JAP	UK	US
Q(3)	48.23 [0.0000]	59.65 [0.0000]	67.52 [0.0000]	49.14 [0.0000]	92.04 [0.0000]	22.04 [0.0000]	170.51 [0.0000]
Q(9)	81.39 [0.0000]	100.63 [0.0000]	76.37 [0.0000]	89.99 [0.0000]	117.89 [0.0000]	35.94 [0.0000]	250.32 [0.0000]
Q ² (3)	14.49 [0.0020]	25.11 [0.0000]	87.63 [0.0000]	109.95 [0.0000]	377.60 [0.0000]	109.25 [0.0000]	128.05 [0.0000]
Q ² (9)	27.68 [0.0010]	66.56 [0.0000]	89.46 [0.0000]	138.60 [0.0000]	399.19 [0.0000]	113.75 [0.0000]	140.66 [0.0000]
ARCH(3)	12.36 [0.0063]	23.11 [0.0000]	104.95 [0.0000]	104.45 [0.0000]	235.24 [0.0000]	114.04 [0.0000]	96.84 [0.0000]
ARCH(9)	21.33 [0.0113]	48.49 [0.0000]	105.51 [0.0000]	114.38 [0.0000]	241.40 [0.0000]	118.48 [0.0000]	100.05 [0.0000]

Notes: - The unit root test is the Elliott et al. (1996) test.

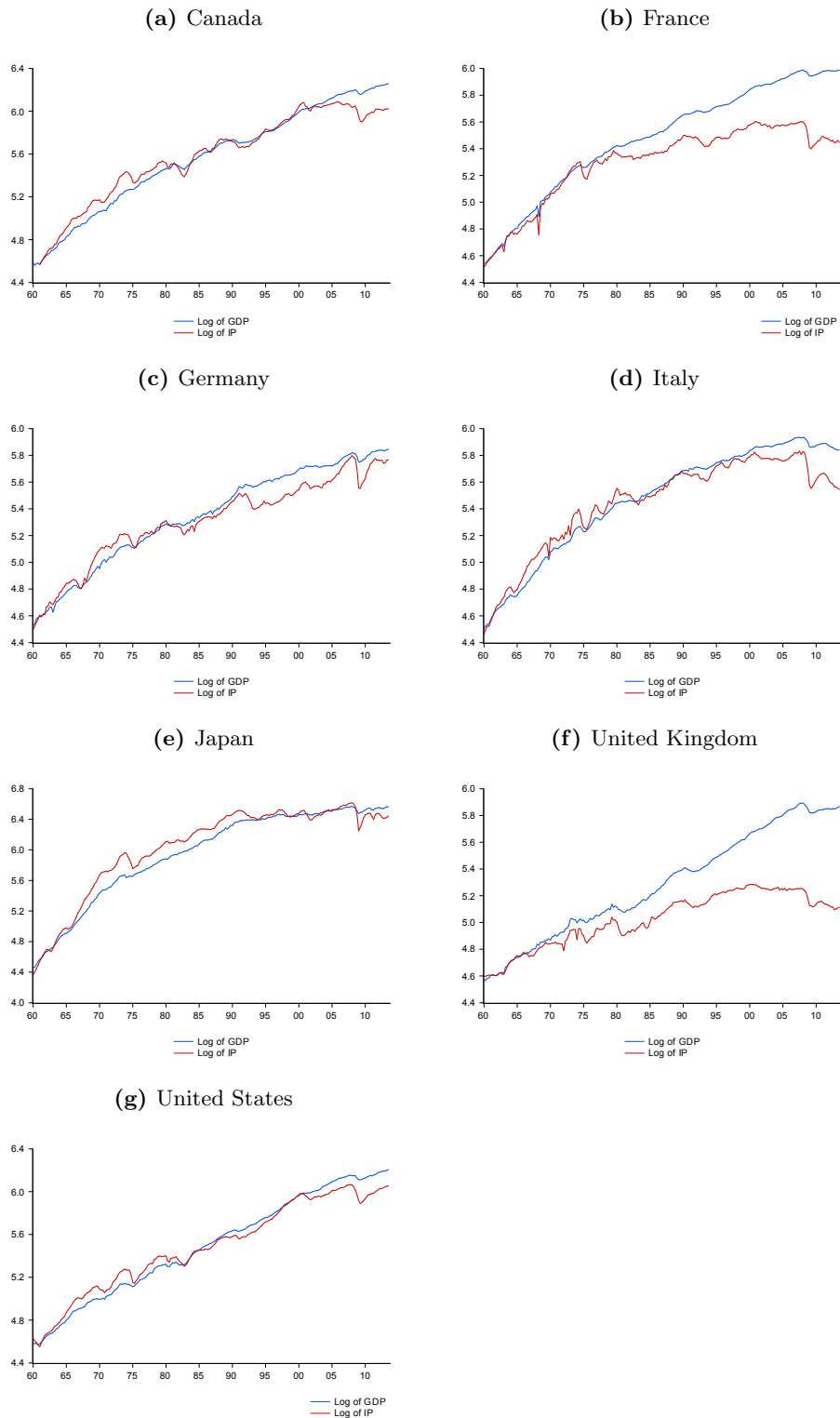
- p-values are in square brackets.

- Q(*p*): Ljung-Box Q-statistics at lag *p* for the data.

- Q²(*p*): Ljung-Box Q-statistics at lag *p* for the squared data.

- ARCH(*p*): ARCH LM test at lag *p* (Engle, 1982).

Figure 2: Industrial production versus GDP, 1961:02–2013:05



Notes: Data on industrial production is the monthly industrial production index (IPI) from the OECD over the period 1960m01–2013m09. The data on GDP is quarterly GDP over the period 1960Q1–2013Q3. To get the two series in the same time frame, I transform the monthly IPI into quarterly frequencies by taking the average of the respective months. Once the two series have the same frequencies, I transform the GDP series into an index with base year 1961. I also change the base year of the IPI series to 1961. The base number is for both series 100.

Table 6: Properties of GDP and IPI series

Panel A: *Correlation between GDP and IPI series*

	CAN	FR	GER	ITA	JAP	UK	US
Correlation of series in levels	0.97	0.92	0.98	0.96	0.98	0.88	0.99
Correlation of series in logs	0.99	0.96	0.98	0.98	0.99	0.93	0.99
Correlation of series in log differences	0.73	0.89	0.66	0.75	0.64	0.68	0.76

Panel B: *Volatility of GDP growth and IPI growth*

	CAN	FR	GER	ITA	JAP	UK	US
Growth GDP	0.88	1.16	1.11	1.04	1.33	0.99	0.84
Growth IPI	1.73	2.42	2.07	2.62	2.86	1.68	1.59

Figure 3: Cross-country trade weighted averages of the monthly growth rates of industrial production, 1961:02–2013:05

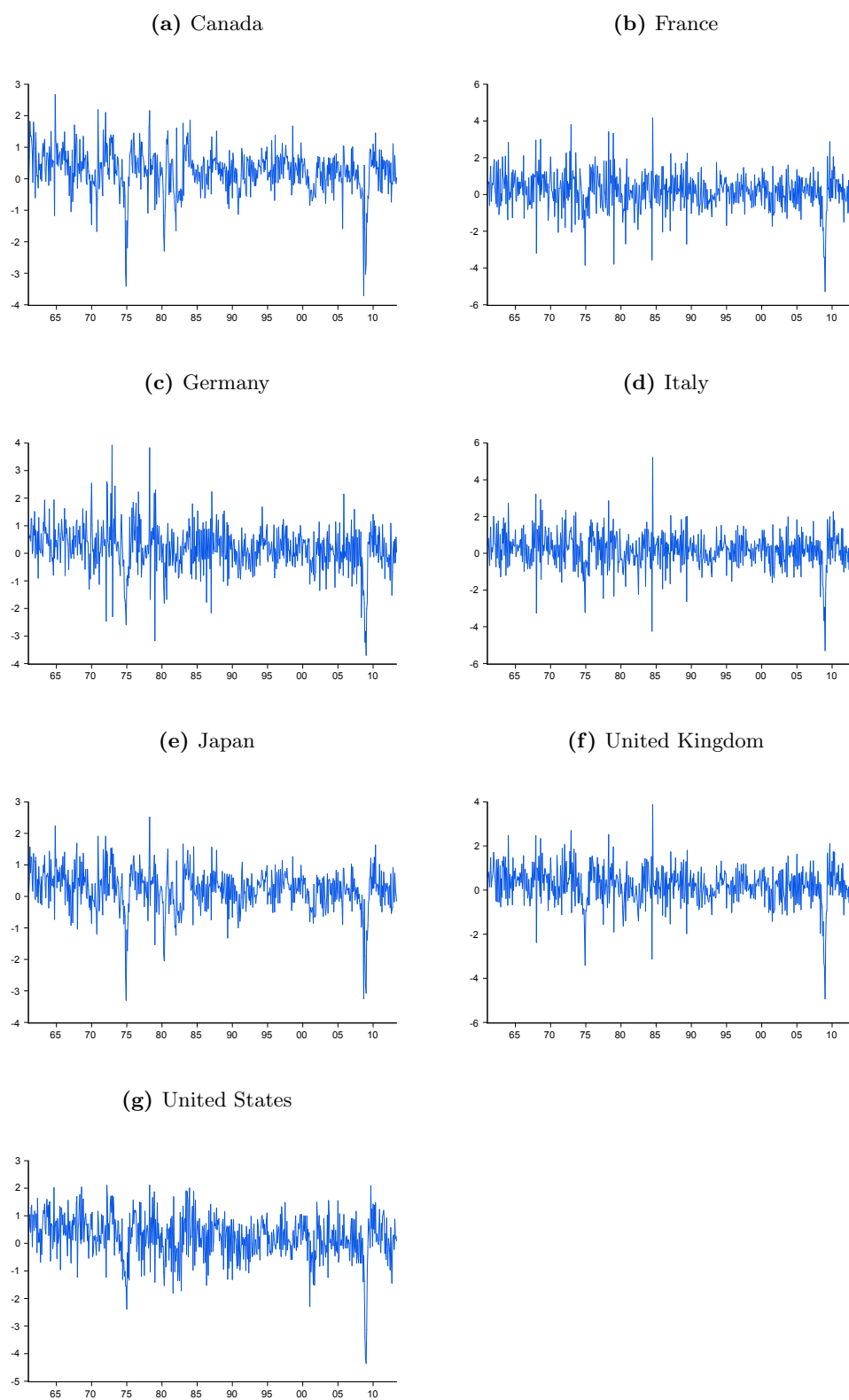


Table 7: Average trade share of country i with country j as a percentage of total trade

$i \setminus j$	CAN	FR	GER	ITA	JAP	UK	US
CAN	0.00	1.31	2.27	1.10	4.71	3.41	87.21
FR	1.56	0.00	40.83	21.43	4.25	17.29	14.64
GER	1.84	30.02	0.00	20.52	7.41	19.74	20.47
ITA	1.71	28.50	39.29	0.00	3.85	12.48	14.18
JAP	6.41	4.79	11.51	3.51	0.00	6.96	66.82
UK	4.68	19.82	30.15	10.49	7.06	0.00	27.80
US	45.66	5.84	11.32	4.42	23.29	9.47	0.00

Notes: - The table corresponds to the trade weights matrix \mathbf{W} in equation 2.11.

Table 8: Residual diagnostics for the models with cross-country weighted averages

	Mean	Variance	Q(3)	Q(9)	Q ² (3)	Q ² (9)	ARCH(3)	ARCH(9)
CAN	-0.006 [0.873]	1.002 [0.482]	0.031 [0.999]	5.903 [0.750]	1.628 [0.653]	5.115 [0.824]	1.658 [0.646]	5.476 [0.791]
FR	-0.003 [0.930]	0.999 [0.500]	0.474 [0.925]	5.074 [0.828]	2.159 [0.540]	8.753 [0.460]	2.148 [0.542]	9.599 [0.384]
GER	-0.008 [0.843]	1.041 [0.232]	3.993 [0.262]	9.551 [0.388]	4.486 [0.214]	6.070 [0.733]	4.430 [0.219]	5.937 [0.746]
ITA	-0.018 [0.653]	0.997 [0.487]	0.459 [0.928]	5.596 [0.780]	1.372 [0.712]	11.204 [0.262]	1.370 [0.713]	10.235 [0.332]
JAP	-0.016 [0.697]	0.999 [0.499]	0.678 [0.878]	3.415 [0.946]	3.697 [0.296]	15.861 [0.070]	3.931 [0.269]	16.147 [0.064]
UK	-0.036 [0.365]	1.015 [0.387]	0.736 [0.865]	6.047 [0.735]	3.604 [0.307]	6.262 [0.713]	3.713 [0.294]	6.475 [0.692]
US	-0.041 [0.308]	0.996 [0.482]	0.909 [0.823]	9.101 [0.428]	0.591 [0.898]	5.182 [0.818]	0.575 [0.902]	5.283 [0.809]

Notes: - p-values are in square brackets.

- The mean and variance is of the standardized residuals, i.e. $(\hat{\varepsilon}_{it} - \bar{\varepsilon}_{it})/\hat{\sigma}_{it}$.
- $Q(p)$: Ljung-Box Q-statistics at lag p for the residuals.
- $Q^2(p)$: Ljung-Box Q-statistics at lag p for the squared residuals.
- ARCH(p): ARCH LM test at lag p (Engle, 1982).

Figure 4: Kernel estimate of the residuals and the relevant theoretical distribution for the model with cross-country weighted averages

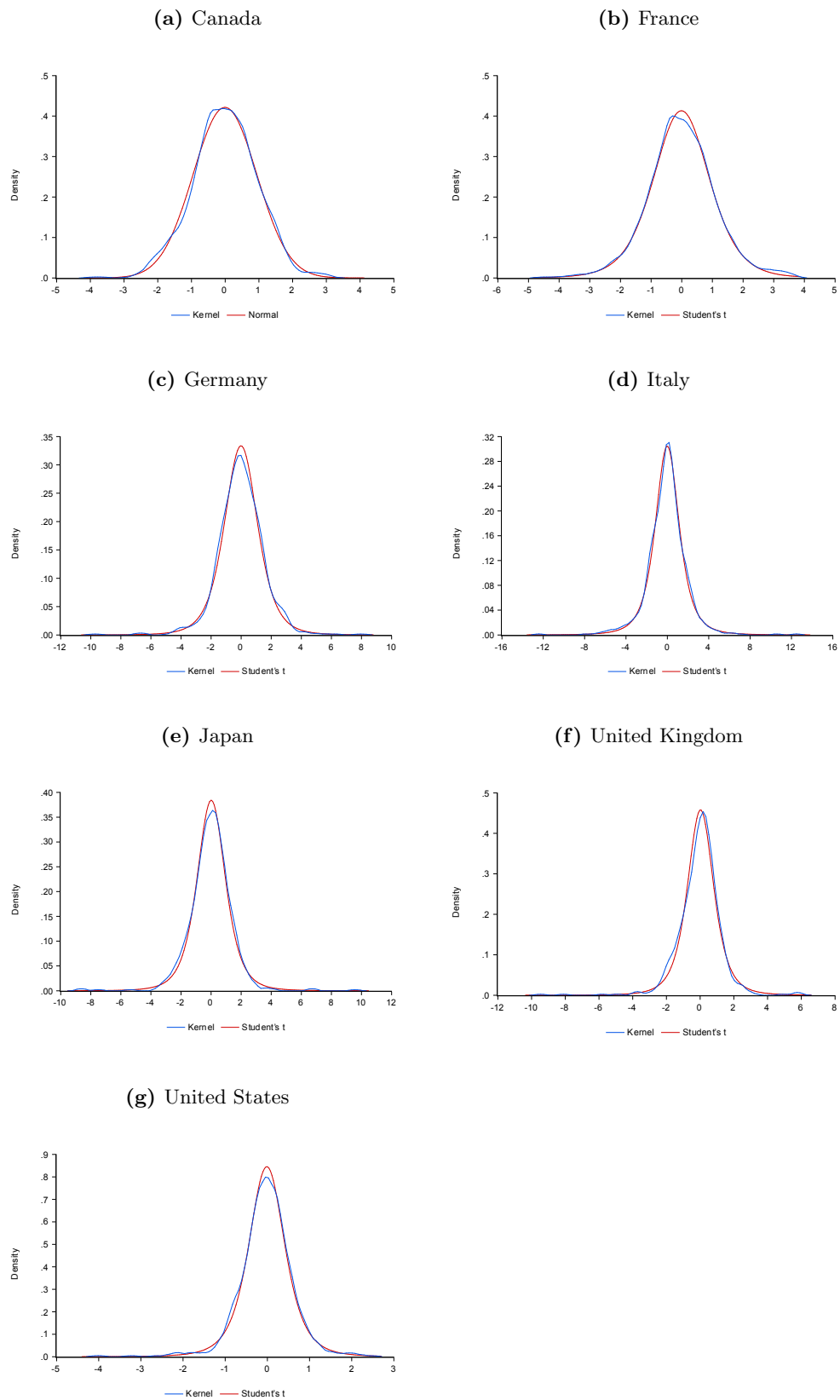
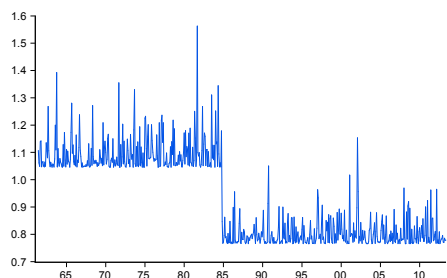
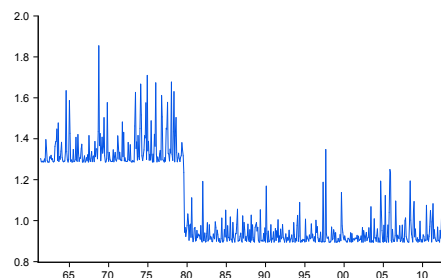


Figure 5: Estimated conditional standard deviation for the model with cross-country weighted averages

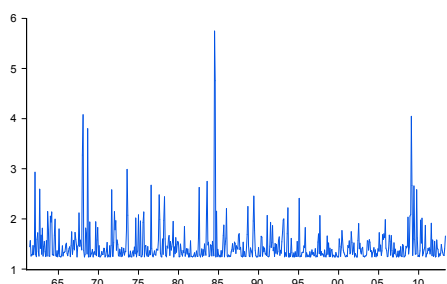
(a) Canada



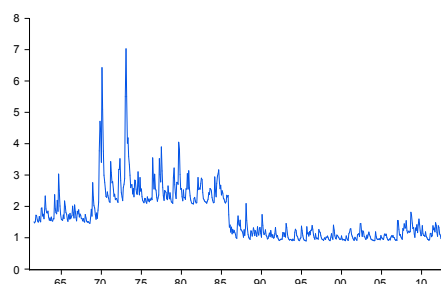
(b) France



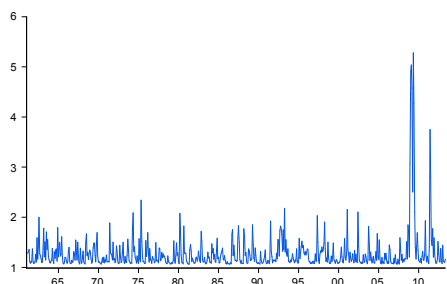
(c) Germany



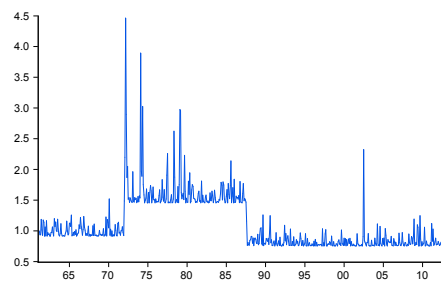
(d) Italy



(e) Japan



(f) United Kingdom



(g) United States

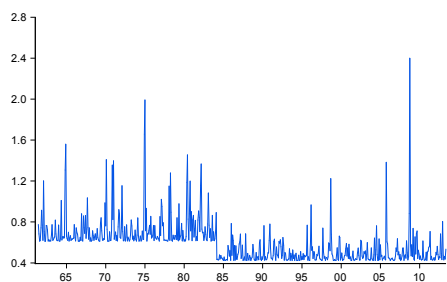
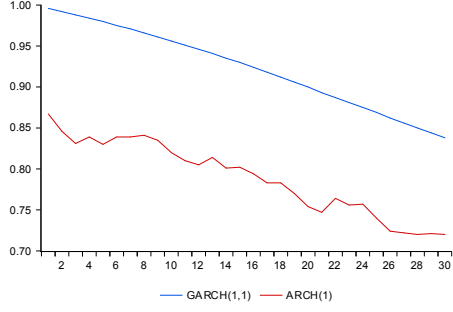


Figure 6: ZILC: The model with cross-country weighted averages

France

(a) Autocorrelation of conditional variance



(b) Conditional Standard deviation

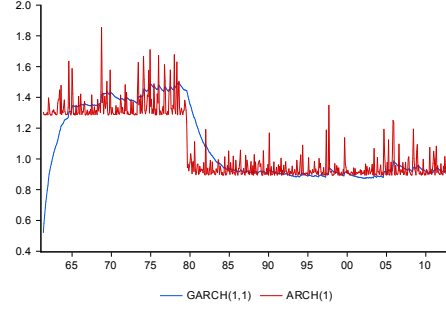


Table 9: Estimation results for the model without cross-country weighted averages

Panel A: Mean Equation							
	CAN	FR	GER	ITA	JAP	UK	US
\tilde{c}_0	0.176 (0.308)	0.277 (0.290)	0.083 (0.298)	0.595** (0.257)	-0.010 (0.334)	0.122 (0.144)	0.079 (0.154)
\tilde{c}_1	-0.251** (0.112)	-0.375*** (0.119)		-0.556*** (0.171)	-0.434*** (0.121)	-0.248*** (0.085)	-0.129 (0.081)
$\tilde{\lambda}$	0.172 (0.272)	0.180 (0.220)	0.098 (0.202)	0.025 (0.116)	0.438* (0.253)	0.078 (0.133)	0.239 (0.179)
$\tilde{\phi}_1$	-0.105** (0.045)	-0.359*** (0.044)	-0.300*** (0.045)	-0.308*** (0.044)	-0.220*** (0.045)	-0.219*** (0.046)	0.138*** (0.044)
$\tilde{\phi}_2$	0.063 (0.042)	-0.105** (0.043)	-0.053 (0.038)	-0.053 (0.046)	0.192*** (0.040)	-0.079** (0.037)	0.175*** (0.039)
$\tilde{\phi}_3$	0.241*** (0.042)	0.021 (0.042)	0.136*** (0.032)	0.053 (0.041)	0.327*** (0.038)	0.062* (0.037)	0.153*** (0.035)
$\tilde{\phi}_4$	0.097** (0.042)	-0.021 (0.038)	0.086*** (0.031)	0.077* (0.043)	0.138*** (0.037)	0.033 (0.037)	0.086** (0.036)
$\tilde{\phi}_5$	0.052 (0.040)	-0.011 (0.038)	0.056 (0.034)	0.110*** (0.042)		0.079** (0.034)	
$\tilde{\phi}_6$		0.152*** (0.035)	0.079** (0.034)	0.144*** (0.038)			
$\tilde{\lambda}^{TLR}$	0.2642 (0.420)	0.136 (0.169)	0.098 (0.204)	0.026 (0.119)	0.778 (0.471)	0.069 (0.119)	0.533 (0.413)

Table 9: Continued

Panel B: Variance Equation							
	CAN	FR	GER	ITA	JAP	UK	US
$\tilde{\alpha}_0$	1.052*** (0.133)	1.150*** (0.190)	1.668*** (0.168)	0.534** (0.257)	0.872*** (0.170)	0.778*** (0.179)	0.414*** (0.098)
$\tilde{\alpha}_1$	0.579** (0.259)	1.509*** (0.573)		1.207** (0.566)		1.979*** (0.587)	-0.215*** (0.071)
$\tilde{\alpha}_2$	-0.911*** (0.231)	-1.649*** (0.551)		-1.409** (0.609)		-1.468** (0.634)	
$\tilde{\alpha}_3$						-0.762*** (0.296)	
$\tilde{\eta}$	0.084* (0.046)	0.190*** (0.061)	0.367*** (0.099)	0.208*** (0.068)	0.257*** (0.076)	0.317*** (0.085)	0.272*** (0.083)
$\tilde{\gamma}$				0.594*** (0.119)	0.248** (0.107)		0.110 (0.125)
$\tilde{\nu}$		8.498** (3.497)	5.932*** (1.152)	7.355*** (2.476)	7.222*** (1.926)	7.880*** (2.593)	5.027*** (1.124)
$\tilde{\alpha}_{GM}^{TLR}$	-0.109 (0.177)	-0.083 (0.102)		-0.008 (0.039)		-0.057 (0.099)	-0.075 (0.061)

Notes: - The model is:

$$\Delta y_{it} = \tilde{c}_{i0} + \tilde{c}_{i1} \tilde{D}M_{it} + \tilde{\lambda}_i \tilde{\sigma}_{it} + \sum_{k=1}^p \tilde{\phi}_{ik} \Delta y_{it-k} + \tilde{\varepsilon}_{it}$$

$$\tilde{\sigma}_{it}^2 = \tilde{\alpha}_{i0} + \sum_{k=1}^f \tilde{\alpha}_{ik} \tilde{D}V_{ikt} + \tilde{\eta}_i \tilde{\varepsilon}_{it-1}^2 + \tilde{\gamma}_i \tilde{\sigma}_{it-1}^2$$

- All models are estimated with the t -distribution as error distribution where $\tilde{\nu}$ are the estimated degrees of freedom, except for Canada.
- $\tilde{D}M_{it}$ and $\tilde{D}V_{ikt}$ are country-specific shift dummy in the mean and variance equation, respectively. The specific dates of the breaks can be found in table 11.
- Standard errors are in brackets. The standard errors for the total long-run effects are found using the delta method.
- *, **, ***: Significant at the 10%, 5% and 1% level, respectively.

Table 10: Residual diagnostics for the models without cross-country weighted averages

	Mean	Variance	Q(3)	Q(9)	Q ² (3)	Q ² (9)	ARCH(3)	ARCH(9)
CAN	-0.011 [0.781]	1.001 [0.482]	0.062 [0.996]	4.607 [0.867]	0.687 [0.876]	5.112 [0.824]	0.682 [0.877]	4.948 [0.839]
FR	-0.022 [0.587]	0.993 [0.458]	0.998 [0.802]	8.229 [0.511]	2.222 [0.528]	8.209 [0.513]	2.202 [0.532]	8.548 [0.480]
GER	-0.020 [0.625]	1.028 [0.304]	1.669 [0.644]	4.367 [0.886]	3.987 [0.263]	5.804 [0.759]	3.991 [0.263]	5.557 [0.783]
ITA	-0.022 [0.580]	0.993 [0.455]	0.391 [0.942]	8.752 [0.460]	1.622 [0.654]	11.377 [0.251]	1.586 [0.663]	11.049 [0.272]
JAP	-0.026 [0.519]	1.002 [0.479]	1.181 [0.758]	6.250 [0.715]	5.682 [0.128]	13.563 [0.139]	6.266 [0.099]	14.055 [0.120]
UK	-0.045 [0.262]	1.000 [0.494]	0.359 [0.949]	4.492 [0.876]	2.854 [0.415]	6.444 [0.695]	2.860 [0.414]	6.725 [0.666]
US	-0.025 [0.533]	0.982 [0.379]	1.920 [0.589]	6.951 [0.642]	5.469 [0.141]	8.398 [0.495]	5.859 [0.119]	8.759 [0.460]

Notes: - p-values are in square brackets.

- The mean and variance is of the standardized residuals, i.e. $(\hat{\varepsilon}_{it} - \bar{\hat{\varepsilon}}_{it})/\hat{\sigma}_{it}$.
- $Q(p)$: Ljung-Box Q-statistics at lag p for the residuals.
- $Q^2(p)$: Ljung-Box Q-statistics at lag p for the squared residuals.
- $ARCH(p)$: ARCH LM test at lag p (Engle, 1982).

Figure 7: Kernel estimate of the residuals and the relevant theoretical distribution for the model without cross-country weighted averages

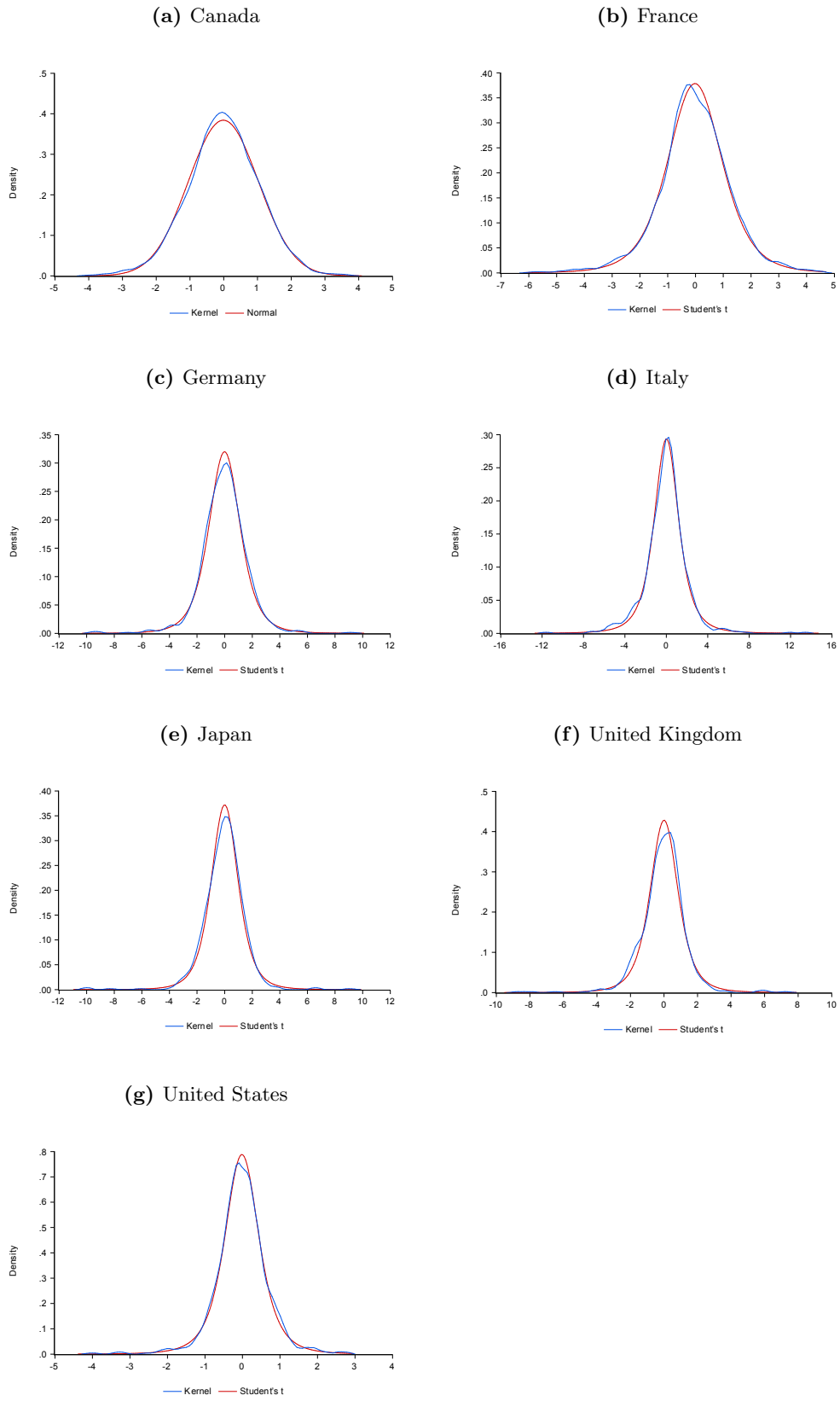


Table 11: Results of the break detection without cross-country weighted averages

Panel A: <i>Breaks in the mean</i>								
	CAN	FR	GER	ITA	JAP	UK	US	C.V.
<i>UDmax</i>	25.26	19.33	6.34	9.24	44.46	10.07	22.88	7.46
<i>WDmax</i>	25.26	19.33	6.81	12.02	44.46	10.07	22.88	8.20
SupF(2 1)	5.68	3.28	1.26	5.96	2.43	1.16	4.36	8.51
SupF(3 2)	8.74	1.42	4.49	0.62	1.97	1.25	7.86	9.41
SupF(4 3)	2.46	0.24	0.70	0.49	1.59	3.49	4.31	10.04
SupF(5 4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.58
Break1	1973:08	1974:08		1974:07	1973:09	2000:07	1969:04	
Panel B: <i>Breaks in the variance</i>								
	CAN	FR	GER	ITA	JAP	UK	US	C.V.
<i>UDmax</i>	18.29	8.71	5.41	38.61	2.03	19.89	10.85	7.46
<i>WDmax</i>	18.29	12.96	6.07	38.61	2.99	19.89	10.87	8.20
SupF(2 1)	11.24	10.96	1.07	15.65	2.79	10.06	5.06	8.51
SupF(3 2)	5.97	8.65	0.94	3.20	0.62	16.53	2.44	9.41
SupF(4 3)	0.14	2.80	0.95	5.98	2.99	3.83	2.29	10.04
SupF(5 4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.58
Break1	1973:07	1971:09		1968:12		1972:01	1984:02	
Break2	1984:11	1979:08		1985:10		1980:05		
Break 3						1990:08		

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