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The link between output growth and volatility: Evidence from a GARCH model with panel data

Jim Lee *

Texas A&M University, Corpus Christi, TX 78412, USA

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ABSTRACT

Estimation results from a dynamic panel GARCH model for G7 countries over the 1965–2007 period support that higher output growth is associated with higher volatility of the innovations to growth, but higher growth does not lead to more economic uncertainty.

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1. Introduction

Long-term economic growth and business cycle fluctuations have long been treated as separate issues in macroeconomics. Despite the increasing attention to integrate growth and business cycle theories in recent decades (e.g., Kyland and Prescott, 1982), empirical evidence on the interrelationship between output growth and economic fluctuations remains equivocal.

Zarnowitz and Moore (1986) find that U.S. output growth tends to be lower during periods of higher volatility. However, using a GARCH-in-mean model, Caporale and McKiernan (1996) find a *positive* relationship between output growth and volatility for both the U.K. and the U.S. Still, Fountas and Karanasos (2006) apply a similar model to the G3 but find a positive relationship for Germany and Japan but not for the U.S. Based on cross-country evidence data, Kormendi and Meguire (1985) find that countries with a higher standard deviation of output growth also tend to experience higher mean growth rates. This finding is further supported by Grier and Tullock (1989) with a broader country sample. On the other hand, Ramey and Ramey (1995), and Martin and Rogers (2000) find a *negative* relationship from different samples.

Most of the above studies draw conclusions from time-series data of individual countries or cross-country data over a given time horizon. However, the time-series method neglects possible interdependence across countries, while cross-country studies do not consider their heterogeneity. Moreover, as Ramey and Ramey (1995) point out, it is important to distinguish between volatility of growth and volatility of the *innovations* to growth, the latter of which corresponds more closely to the notion of uncertainty that plays a key role in the development of macroeconomic theories. Volatility of innovations is commonly modeled as a conditional variance process within an ARCH or GARCH framework. However, most GARCH-based studies report results on a country-by-country basis, ignoring possible cross-sectional dependence.

This paper draws on Cermeño and Grier's (2006) approach that extends traditional GARCH models, as in Lee (2006), to a panel context. As with panel data models for estimating conditional means, panel GARCH models entail potential efficiency gains in estimating the conditional variance and covariance processes by incorporating relevant information about heterogeneity across economies as well as their interdependence.

* Tel.: +1 361 8255831; fax: +1 361 8255609.
E-mail address: jim.lee@tamucc.edu.

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2. The model and data

2.1. The model

For a cross-section of N countries and T time periods, the conditional mean equation for output (y_{it}) can be expressed as a dynamic panel with fixed effects:

$$y_{it} = \mu_i + \sum_{k=1}^{K} \alpha_k y_{i,t-k} + x_{it}\beta + \varepsilon_{it}, \quad i = 1, \ldots, N; t = 1, \ldots, T, \quad (1)$$

where μ_i captures possible country-specific effects, x_{it} is a vector of exogenous variables, β is a vector of coefficients, and ε_{it} is a disturbance term with a zero mean and normal distribution along with the following conditional moments:

$$E[\varepsilon_{it}\varepsilon_{js}] = 0 \qquad \text{for } i \neq j \text{ and } t \neq s, \quad (2)$$

$$E[\varepsilon_{it}\varepsilon_{js}] = 0 \qquad \text{for } i = j \text{ and } t \neq s, \quad (3)$$

$$E[\varepsilon_{it}\varepsilon_{js}] = \sigma^2_{ij,t} \qquad \text{for } i \neq j \text{ and } t = s, \quad (4)$$

$$E[\varepsilon_{it}\varepsilon_{js}] = \sigma^2_{it} \qquad \text{for } i = j \text{ and } t = s. \quad (5)$$

The first condition assumes no non-contemporaneous cross-sectional correlation, and the second condition assumes no autocorrelation. The third and fourth assumptions define the general conditions of the conditional variance–covariance process. The conditional variance and covariance processes of output are assumed to follow a GARCH(1,1) process largely due to its popularity:

$$\sigma^2_{it} = \phi_i + \gamma\sigma^2_{i,t-1} + \delta\varepsilon^2_{i,t-1}, \quad i = 1, \ldots, N, \quad (6)$$

$$\sigma_{ij,t} = \varphi_{ij} + \eta\sigma_{ij,t-1} + \rho\varepsilon_{i,t-1}\varepsilon_{j,t-1}, \quad i \neq j. \quad (7)$$

In matrix notation, Eq. (1) can simply be expressed as:

$$y_t = \mu + Z_t\theta + \varepsilon_t, \quad t = 1, \ldots, T, \quad (8)$$

where $Z_t = [y_{t-1} \ldots \vdots X_t]$ is a matrix with their corresponding coefficients in $\theta = [\alpha_k \ldots \vdots \beta']'$. The disturbance term has a multivariate normal distribution $N(0, \Omega_t)$. The log-likelihood function of the complete fixed-effects panel model with the time-varying conditional covariance can be written as:

$$L = -\frac{1}{2} NT \ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \ln|\Omega_t| - \frac{1}{2}\sum_{t=1}^{T} [(y_t - \mu - Z_t\theta)' \times \Omega_t (y_t - \mu - Z_t\theta)]. \quad (9)$$

Because the disturbance term ε_t is conditional heteroskedastic and cross-sectionally correlated, the least-squares estimator is no longer efficient even though it is still consistent. We resolve this problem by adopting Cermeño and Grier's (2006) maximum-likelihood (ML) method, which maximizes the log-likelihood function given by Eq. (9).

2.2. Data and model specification

For estimation, we consider the data of G7 members ($N = 7$). Output is measured by the industrial production index in logarithm. The sample includes monthly observations covering the period 1965:1–2007:9 ($T = 513$). Because unit-root test results (not reported here to conserve space) for the individual time-series and panel data support that the data are stationary only after first differencing, we use first-differenced data (output growth) in model estimation.

Our empirical work begins with estimating an AR(12) specification for the conditional mean equation (Eq. (1)). In panel data regression, it is important to first evaluate the poolability of the data. If the data are poolable, then country-specific effects do not exist and a single intercept instead of different intercepts for different countries is warranted. We test for individual effects in the conditional mean equation using the least-squares dummy variable estimator along with a heteroskedasticity and autocorrelation-consistent (HAC) covariance matrix. The Wald test statistic for testing the null hypothesis H_0: $\mu_1 = \mu_2 \ldots = \mu_7$ is 1.88, which is not statistically significant. We therefore apply a common intercept to all countries.

Table 1 contains diagnostics for testing serial correlation. The Ljung–Box Q-statistics and partial correlations are computed for both the residuals and squared residuals. There is no evidence of serial correlation in the residuals, meaning that the condition in Eq. (3) is satisfied. However, the partial correlations for squared residuals suggest a rather high-order ARCH process, which supports the application of the GARCH (1,1) model.

Next, we evaluate country-specific effects in the variance and covariance equations by applying likelihood-ratio (LR) tests based on the log-likelihood values of the panel GARCH model estimated with and without individual effects. The LR statistics for testing individual effects in the variance and covariance equations are respectively 218.75 and 27.54. Both statistics are statistically significant, supporting the presence of country-specific effects.

3. Model estimation results

Table 2 shows the estimation results of various panel model specifications. For comparison purposes, column A shows the AR(12) using the OLS with HAC standard errors. Column B shows the ML estimates of the baseline panel GARCH model with individual effects in the variance and covariance equations. The implied log-likelihood value of the ML estimation is appreciably higher than its OLS counterpart, even though the coefficient estimates in the conditional mean equation are quite similar. The estimated coefficients on the autoregressive term in both conditional variance and covariance equations are around 0.6, meaning that the G7 output volatility and their comovements are captured by moderately persistent GARCH processes.

Table 1
Autocorrelation diagnostics.

Lag	Partial correlation	
	Residuals	Squared residuals
1	−0.001	0.155*
2	0.000	0.261*
3	0.001	0.051*
4	0.002	0.009**
5	0.004	0.007**
6	0.005	0.009**
7	0.004	0.003
8	0.010	0.005
9	0.009	0.008***
10	0.007	0.006***
11	0.005	0.007***
12	−0.013	0.003
13	−0.044	0.006***
14	−0.035	0.002
15	−0.006	0.002
16	−0.024	0.003
17	−0.032	0.004
18	0.019	0.004
19	−0.005	0.003
20	−0.019	0.003
Q(20)	21.765	342.830*

* Statistical significance at the 1% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 10% level.

Table 2
Estimation results.

	A	B	C
Mean equation			
Intercept	0.190*	0.185*	0.161*
	(0.034)	(0.033)	(0.033)
$y_{i,t-1}$	−0.255*	−0.261*	−0.257*
	(0.071)	(0.017)	(0.017)
$y_{i,t-2}$	−0.099	−0.105	−0.101
	(0.086)	(0.018)	(0.017)
$y_{i,t-3}$	0.045	0.039	0.043
	(0.044)	(0.018)	(0.017)
$y_{i,t-4}$	0.069**	0.064**	0.067**
	(0.028)	(0.018)	(0.017)
$y_{i,t-5}$	0.049**	0.046**	0.047**
	(0.024)	(0.018)	(0.017)
$y_{i,t-6}$	0.102*	0.100*	0.100*
	(0.024)	(0.018)	(0.017)
$y_{i,t-7}$	0.027	0.027	0.025
	(0.022)	(0.018)	(0.017)
$y_{i,t-8}$	0.080*	0.079*	0.078*
	(0.023)	(0.018)	(0.017)
$y_{i,t-9}$	0.038***	0.036**	0.036**
	(0.023)	(0.018)	(0.017)
$y_{i,t-10}$	0.017	0.015	0.015
	(0.023)	(0.018)	(0.017)
$y_{i,t-11}$	0.009	0.008	0.008
	(0.022)	(0.018)	(0.017)
$y_{i,t-12}$	−0.011	−0.013	−0.013
	(0.018)	(0.017)	(0.017)
σ_{it}			0.048**
			(0.024)
Variance equation			
$\sigma^2_{i,t-1}$		0.570*	0.570*
		(0.002)	(0.002)
$\varepsilon^2_{i,t-1}$		0.205*	0.211*
		(0.002)	(0.002)
$y_{i,t-1}$			−0.025
			(0.034)
Covariance equation			
$\sigma_{ij,t-1}$		0.563*	0.560*
		(0.002)	(0.002)
$\varepsilon_{i,t-1}\ \varepsilon_{j,t-1}$		0.880*	0.921*
		(0.002)	(0.002)
σ^2	2.528		
Log-likelihood	−6754.107	−6162.447	−6157.247

Standard errors are in parentheses.
* Statistical significance at the 1% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 10% level.

To investigate the possible interrelationship between mean output growth and output volatility, we augment the baseline panel GARCH model with two additional variables. First, we add the conditional standard deviation of output to the conditional mean equation in the form of GARCH-in-mean. Competing economic theories bear different implications for the correlation between output growth and output volatility. Bernanke (1983) argues for a negative relationship because output volatility raises economic uncertainty and thus hampers investment due to its irreversibility nature. Lower investment leads to lower long-term economic growth. However, Mirman (1971) maintains that greater economic uncertainty raises precautionary saving, which in turn leads to higher growth rates.

Second, a lagged output growth variable is added to the conditional variance equation. The literature regarding the causal effect of output growth on output volatility is sparse. Fountas and Karanasos (2006) maintain that higher output growth leads to lower output volatility. Their justification begins with the Phillips curve, which implies that higher output growth leads to higher inflation in the short run. Friedman (1977) argues that a higher inflation rate raises inflation volatility. Brunner (1993) also asserts that higher output growth leads to more aggressive monetary policy responses and thus higher inflation volatility. Finally, output volatility and inflation volatility are negatively related, according to Taylor (1979).

Column C of Table 2 reports results for the panel model augmented with the above two variables. In the conditional mean equation, a single intercept term is used for all countries because the Wald statistic for testing individual effects is 1.61, which is statistically insignificant. In that equation, the coefficient estimate for the conditional standard deviation term enters with a positive sign and is statistically significant. This is in line with the findings by Kormendi and Meguire (1985), and Grier and Tullock (1989), but at odds with the finding of a negative relationship by Ramey and Ramey (1995). In the conditional variance equation, the coefficient estimate for lagged output growth is not statistically significant.

Our findings differ from those in previous studies for two main reasons. First, our panel involves a relatively smaller set of countries than the samples in those studies. Second, our estimation results reflect the effects of taking into account cross-country correlations and volatility clustering when assessing the relationship between output growth and output volatility.

4. Concluding remarks

This paper has revisited the empirical relationship between output growth and volatility based on panel data of G7 countries over the period 1965–2007. A fixed-effects dynamic panel data model with GARCH supports the hypothesis that higher output growth is associated with higher volatility of the innovations to growth, but there is little evidence to support that higher growth leads to more economic uncertainty. Avenues for future research might involve a larger panel, like the OCED, or a framework that accounts for time effects in addition to individual effects.

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