CAHIER D'ÉTUDES
WORKING PAPER

N° 97

IS THE FINANCIAL SECTOR LUXEMBOURG'S ENGINE OF GROWTH?

PAOLO GUARDA   ABDELAZIZ ROUABAH

JULY 2015

BANQUE CENTRALE DU LUXEMBOURG
EUROSYSTÈME

Is the financial sector Luxembourg's engine of growth?*

Paolo Guarda and Abdelaziz Rouabah
Banque centrale du Luxembourg

This version 11 May 2015

Abstract

This paper measures the links between financial services and other production sectors in the Luxembourg economy. The focus is on propagation within the country, without considering growth abroad. Among the 29 sectors in the annual input-output tables, financial intermediation is one of only four "key sectors" that the Leontief inverse identifies as featuring above-average forward and backward linkages to other production sectors. The links from financial services to other sectors became even stronger from 1995 to 2009. At quarterly frequency, Granger causality tests find that no sector leads financial services, although they also fail to find evidence that financial services lead other sectors. Lack of evidence may be attributed to quarter-on-quarter growth rates deviating from the normal distribution, with "fat tails" possibly reflecting volatility clustering. We therefore estimate univariate ARIMA-GARCH models to identify normally distributed innovations in each sector. Comparing these growth innovations at different leads or lags, Cheung-Ng tests find little evidence of cross-sector causality-in-mean or causality-in-variance. This time, lack of evidence could reflect time variation in cross-sector correlations, which is confirmed by the Engle-Sheppard test. Estimated dynamic conditional correlations vary significantly through time, with cross-sector correlations surging during the financial crisis. Dynamic correlations are used to decompose the overall volatility of Luxembourg's macroeconomic "portfolio" of different production sectors, which responds mostly to changes in cross-sector correlations. In conclusion, the financial sector appears to be strongly linked with the rest of the economy, benefiting from growth in other sectors, which it amplifies and propagates to the whole economy.

JEL classifications: C22; C51; C52; E0

Keywords: Output growth, GARCH models, Dynamic conditional correlations

*This paper should not be reported as representing the views of the BCL or the Eurosystem. The views expressed are those of the authors and may not be shared by other research staff or policymakers in the BCL or the Eurosystem. A previous version of this note was presented with the title "Sectoral output growth and dynamic conditional correlations" at the 2011 Banking, Productivity and Growth conference in Luxembourg. The authors wish to thank participants for comments and especially their discussant Michel Beine. Financial support from the Fonds National de la Recherche through the PERFILUX project is gratefully acknowledged. Correspondence to paolo.guarda@bcl.lu or abdelaziz.rouabah@bcl.lu

Resumé non-technique

Cette étude a pour objet la mesure des liens entre les services financiers au Luxembourg et les autres secteurs de production de l'économie nationale. L'accent est mis sur la propagation entre secteurs à l'intérieur du pays, sans considérer les externalités émanant de la croissance des économies à l'étranger. Sur les 29 secteurs repris dans le tableau entrées-sorties de l'économie luxembourgeoise, l'intermédiation financière est identifiée parmi les quatre « secteurs clés » que le processus de production lie plus étroitement aux autres secteurs, tant en amont qu'en aval. Entre 1995 et 2009, ces liens se sont même renforcés pour l'intermédiation financière. En se focalisant sur la croissance trimestrielle, les tests de causalité révèlent qu'aucune activité sectorielle ne devance celle des services financiers, signe que les services financiers sont susceptibles de jouer un rôle précurseur ou d'entrainement de la production des autres secteurs. Cependant, nos résultats ne nous permettent pas d'établir un rôle avancé du secteur financier par rapport aux autres activités. Toutefois, la fiabilité de ces résultats est limitée dans la mesure où la distribution des taux de croissance trimestriels s'écarte sensiblement d'une normale. Elle affiche des signes souvent associés avec des changements de volatilité. Pour neutraliser ces effets, nous modélisons la croissance réelle de chaque secteur séparément afin d'obtenir des « innovations » distribuées conformément à une loi normale. En comparant les valeurs futures (leads) et passées (lags) des innovations des différents secteurs, nous sommes en mesure de déterminer les éventuels décalages temporels et, par ricochet, le rôle précurseur de certaines activités sectorielles. Cependant, les tests statistiques n'indiquent que rarement l'existence d'une relation de causalité (en moyenne ou variance) entre les secteurs. Ce résultat peut être attribué à une instabilité temporelle des corrélations entre secteurs, hypothèse qui est confirmée à l'aide d'autres tests. Par conséquent, nous estimons des corrélations dynamiques, ce qui permet d'identifier une poussée de la corrélation entre secteurs lors de la crise financière. Ces corrélations dynamiques sont ensuite utilisées pour décomposer la volatilité du « portefeuille d'activités sectorielles » au Luxembourg. Au niveau agrégé, la volatilité du portefeuille est relativement peu affectée par les variations des parts des secteurs. Par contre, cette volatilité de portefeuille est plus fortement affectée par les variations de la volatilité spécifique à chaque secteur et, en particulier, par les variations des corrélations entre secteurs de production. Enfin, le secteur financier est étroitement lié au reste de l'économie, bénéficiant de la croissance des autres secteurs, qu'il amplifie et propage à l'ensemble de l'économie.

I Introduction

Since the Great Recession originated in the financial sector, it was not surprising that its effects were particularly harsh in countries such as Ireland or the UK, where financial services represent a large part of GDP. Therefore, it may seem dramatic that the impact was not as dramatic in Luxembourg, where the financial sector represents an even larger share of output, but in Luxembourg the mix of activities within the sector is different. The crisis triggered an ongoing process of reform in international financial regulation that aims to avoid repetition of the same failures. This reform process has raised costs in financial services and lowered the prospects for growth in the sector, with uncertain effects on overall potential growth in many countries.

This study applies several different approaches to measure the linkages between growth in financial services and the other sectors of production within the Luxembourg economy. The following section focuses on annual data, where the dominant role of financial services is obvious. Since 1996, this sector provided the most important contribution to aggregate output growth. Linkages to other sectors are analysed by calculating the Leontief inverse of the input-output tables to obtain Rasmussen-Hirschman indices of backward and forward linkages. These confirm that financial intermediation is one of only four "key sectors" out of the 29 in Luxembourg's input-output tables. Section 3 turns to quarter-on-quarter growth in real value added per sector, where the dominance of financial services is not as clear. According to Granger-causality tests there is no sector leading Financial services, but neither is there convincing evidence that Financial services are leading other sectors. These uncertain results may reflect quarter-on-quarter growth deviating from the normal distribution, with evidence of leptokurtosis ("fat tails") that is one sign of volatility clustering. Therefore, we estimate univariate time-series models (finding significant GARCH effects) to isolate normally-distributed innovations in sector-specific quarterly growth rates. Cheung-Ng (1996) tests applied to these growth innovations find no clear evidence of cross-sector causality-in-mean or causality-in-variance at different leads or lags. This result may reflect time-variation in the cross-sector correlations as confirmed by the Engle-Sheppard (2001) test. We therefore estimate Engle (2002) dynamic conditional correlations and find significant changes over time. Finally, we use time-varying correlations to decompose the volatility of Luxembourg's macroeconomic "portfolio" into the contributions of changing sector shares, changing sector-specific volatilities and changing cross-sector correlations. Changes in correlations play the most important role. In conclusion, the financial services industry appears to be strongly linked with the rest of the economy, benefiting from growth in other sectors, which it amplifies and propagates to the whole economy.

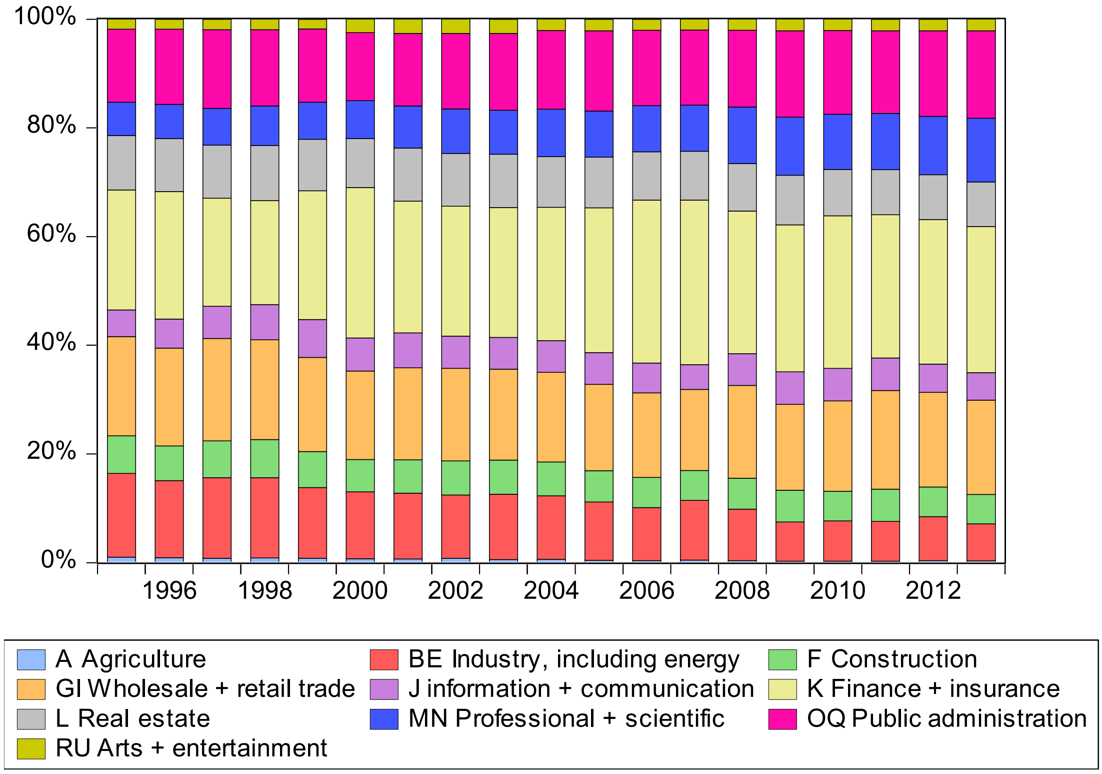
2 Annual data: Input-output linkages and key sectors

The underlying national accounts data is chain-linked. Statec (the Luxembourg statistical office) published national accounts data according to ESA2010 methodology only back to 2000, so this was linked to previously published ESA95 data for 1995-1999. Following the recent revision to the NACE nomenclature, 10 sectors of production can be defined as follows:

1. A Agriculture, forestry & fishing
2. BE Industry (total including energy)
3. F Construction
4. GI Wholesale & retail trade
5. J Information & communication
6. K Financial & insurance activities
7. L Real estate activities
8. MN Professional, scientific & technical activities
9. OQ Public administration, education, health & social work
10. RU Arts, entertainment, recreation & repair of household goods

Figure 1 plots the shares of these 10 broad sectors in gross value added (in nominal terms). Agriculture (A) is barely visible at the bottom of the graph, followed by Industry (BE), whose share has declined steadily from 15% in 1995 to less than 7% in 2013. The share of Construction (F) has declined less, from 7% in 1995 to 5% in 2013. The share of Wholesale & retail trade (GI) has no clear trend and has fluctuated between 15% and 19%. Information & communication (J) is also relatively stable around an average near 6%. The Finance and insurance (K) sector saw its share grow strongly from 22% in 1995 to peak over 30% in 2007 before settling around 27% in 2013. Real estate activities (L) saw a fairly steady decline in its share from 10% in 1995 to 8% in 2013. Professional, scientific & technical services (MN) instead rose steadily from 6% in 1995 to 12% in 2013. The share of Public administration (OQ) was more volatile, but also grew from 13% in 1995 to 16% in 2013. Arts, entertainment & recreation (RU) averaged 2%.

Figure 1: Sector shares in nominal value added

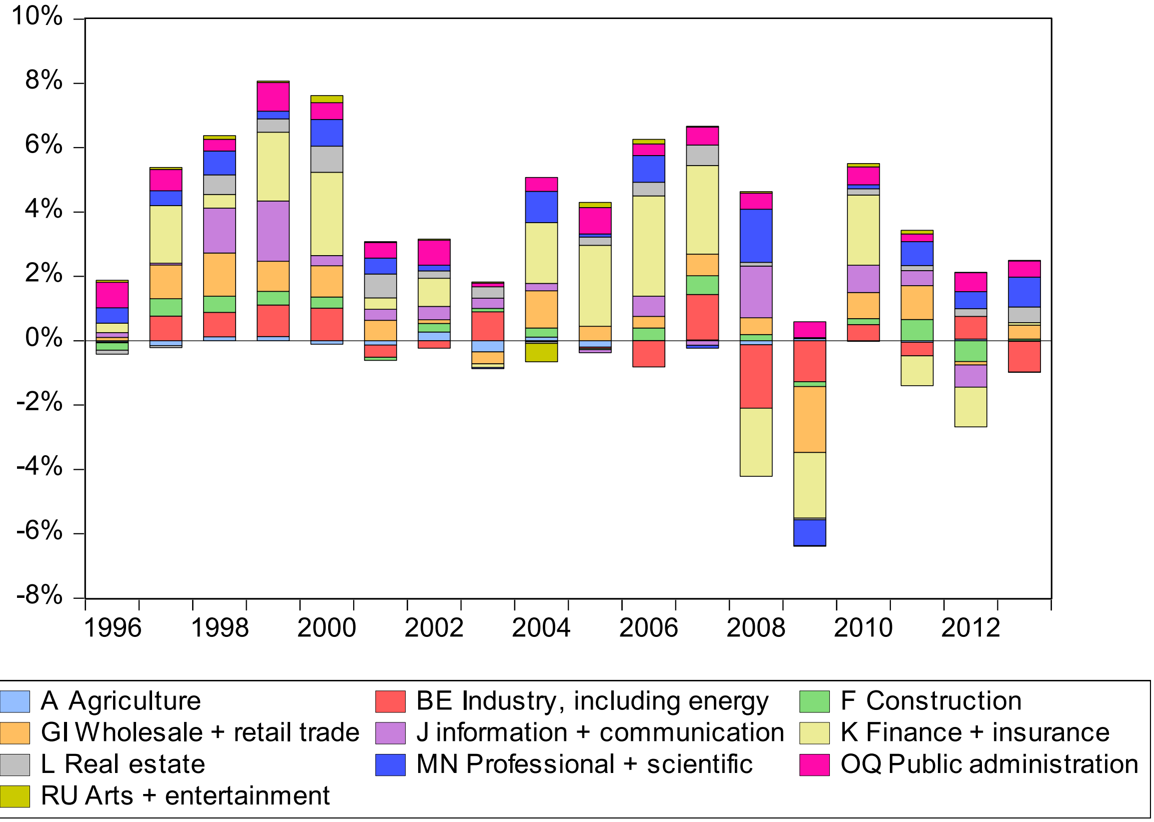


Source: Statec data

Sectoral diversification of output can be measured using the Herfindahl index, with a score of 1 indicating dominance by a single sector and a score of zero indicating all sectors are of equal size. Taking into consideration twenty-one individual sectors (from A to U), output diversification in Luxembourg barely changed on this measure, as the Herfindahl index declined from 0.89 in 1995 to 0.88 in 2013. An alternative measure of diversification can be calculated using the Shannon index of entropy, common in the ecological literature on biodiversity. This would approach 0 if all output was concentrated in one sector and would approach a maximum value of –log(n) if output was equally distributed across n sectors. The Shannon index is also broadly unchanged, declining from 84% of its maximum value in 1995 to 82% of its maximum value in 2014. Thus on both these measures of output diversification, the change since 1995 has been marginal. Of course, these measures take no account of diversification of activities within sectors such as finance or industry. For example, government initiatives aimed at encouraging innovation within industry may have helped to prevent the share of this sector from shrinking further. These Herfindahl and Shannon indices also take no account of the potential for growth in different sectors (which plays an important role in guiding government efforts at sectoral diversification) nor do they consider potential links between sectors that will be explored below. Finally, the results above focus on diversification of output as measured by value added, this does not mean that sectoral diversification of employment has not increased since 1995.

Perhaps the simplest method to evaluate the role of financial services in the Luxembourg economy is to compare the contribution of individual sectors of production to aggregate output growth. Sectoral contributions to aggregate growth depend both on growth within the sector and the sector's share of aggregate output. Figure 2 illustrates sectoral contributions to real growth in aggregate value added since 1995.

Figure 2: Sector contributions to real growth in value added



Source: Statec data, own calculations

Table A1 in the appendix reports standard descriptive statistics for each sector's contribution to aggregate output growth. Sector K (Finance and insurance) stands out with the largest average contribution (0.81pp or percentage points) to output growth of the overall economy. Figure 1 reveals that most sectors have made a negative contribution to overall growth at least once (the only exception is sector OQ, Public administration). These occasional negative contributions also appear in years when aggregate growth exceeded 4%, such as 2004 and 2006. The GDP contraction in 2009 saw negative contributions from most sectors, with sizable ones from Finance, Trade and Industry. Sector K (Finance and insurance) also made non-negligible negative contributions in 2008 and in 2011 and 2012. In fact, while sector K has the highest average contribution, it also has the highest standard deviation, meaning that this sector makes the most volatile contribution to aggregate growth. Comparing the median contribution (a measure that is more robust to outliers than the mean), sector K is still the main contributor to aggregate growth.

The apparent dominance of Finance & insurance (sector K) may reflect both forward and backward linkages, meaning that it may benefit from growth in other sectors as well as contribute to raising their growth. Inter-sector linkages can be studied through the input-output tables published along with national accounts. These tables indicate how much of the output of each sector of production is used as input in the other sectors. The static Leontief input-output model decomposes gross output in each sector of production into intermediate consumption and final consumption as follows:

$$x = Ax + f$$

Where *x* is the vector of gross output in the *n* production sectors making up the economy, *f* is the vector of final demand in these sectors and A is the matrix of direct inputs with typical element a_{ij} representing the share of total expenditure by the sector in row *i* that is devoted to buying inputs from the sector in column *j*. The fundamental equation of this model links the exogenous final demands with total output via the Leontief inverse:

$$x = (I - A)^{-1} f = Bf$$

Where I is an *n*x*n* identity matrix and B is called the Leontief inverse, with typical element b_{ij} measuring the output of sector *i* required to satisfy a unit of final demand from sector *j*.

The Leontief inverse can be used to analyse the nature and strength of connections between production sectors. In particular, the classic Rasmussen-Hirschman approach (Sonis et al., 1995, Lenzen, 2003, Sonis and Hewings, 2009) distinguishes between forward linkages and backward linkages. Forward linkages capture the “sensitivity of dispersion” or the impact on sector i of a unit increase in final demand in all other sectors. Backward linkages capture the “power of dispersion” or the impact on all other sectors of a unit increase in final demand in sector j. These are calculated as follows:

$$BL_j = \frac{1}{n}\sum_{i=1}^{n} b_{ij} \bigg/ \frac{1}{n^2}\sum_{i,j=1}^{n} b_{ij} = B_{\cdot j}/\bar{b}$$

$$FL_i = \frac{1}{n}\sum_{j=1}^{n} b_{ij} \bigg/ \frac{1}{n^2}\sum_{i,j=1}^{n} b_{ij} = B_{i\cdot}/\bar{b}$$

where BL_j is the index of backward linkages in sector *j,* FL_j is the index of forward linkages in sector *i*, $B_{\cdot j}$ is the average element of column *j*, $B_{i\cdot}$ is the average element of row *i*, and $\bar{b}$ is the average element of the whole matrix B. To allow inter-sector comparisons, Hazari (1970) proposed normalizing by this last element. This means that BL or FL will exceed unity for production sectors with above-average linkages to other sectors in the economy. However, Hazari noted that averages are sensitive to extreme values, and a relatively high BL or FL index may be attributable to a given sector being very strongly linked to only one or a few other sectors. To overcome this difficulty, he proposed corresponding measures of variability based on the coefficient of variation of the matrix elements in the rows or columns of the Leontief inverse *B*.

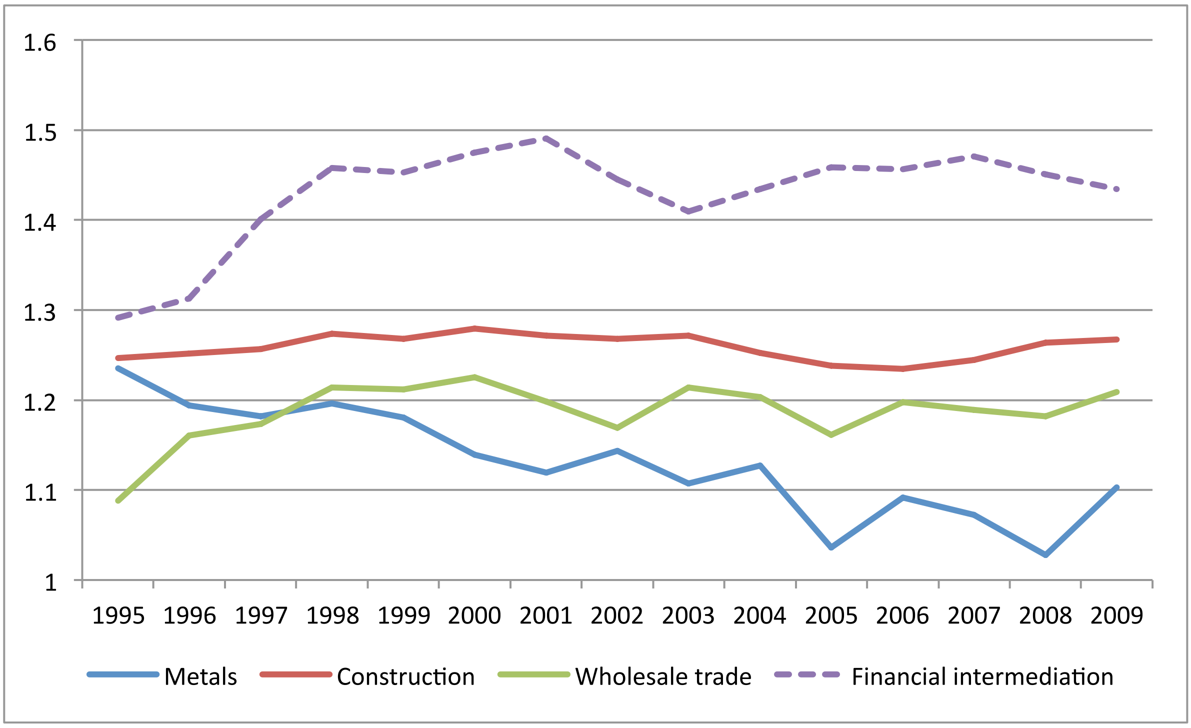
$$V_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(b_{ij} - B_{\cdot j})^2} \Big/ B_{\cdot j}$$

$$V_i = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(b_{ij} - B_{i\cdot})^2} \Big/ B_{i\cdot}$$

Hazari (1970) suggested that the **key sectors** of an economy could be empirically identified as those where (a) both BL and FL were above unity (b) both V_j and V_i are relatively low. Lenzen (2003), European Commission (2006) and Humavindu and Stage (2013) all applied this approach to identify “key sectors” in different economies. In the rest of this section this approach is applied to Luxembourg.

Input-output tables for Luxembourg are only available for the years 1995 to 2009 under ESA95 definitions. Presumably, Statec will publish tables for more recent years under ESA2010 definitions. These classify production in 29 different “products,” with the financial sector decomposed into 3 different subsectors: Financial intermediation, Insurance, and Auxiliary financial services. Only four of the 29 product categories had both BL and FL indices exceeding unity over the whole of the sample period. The backward linkages indices of these four potential “key sectors” appear in Figure 3.

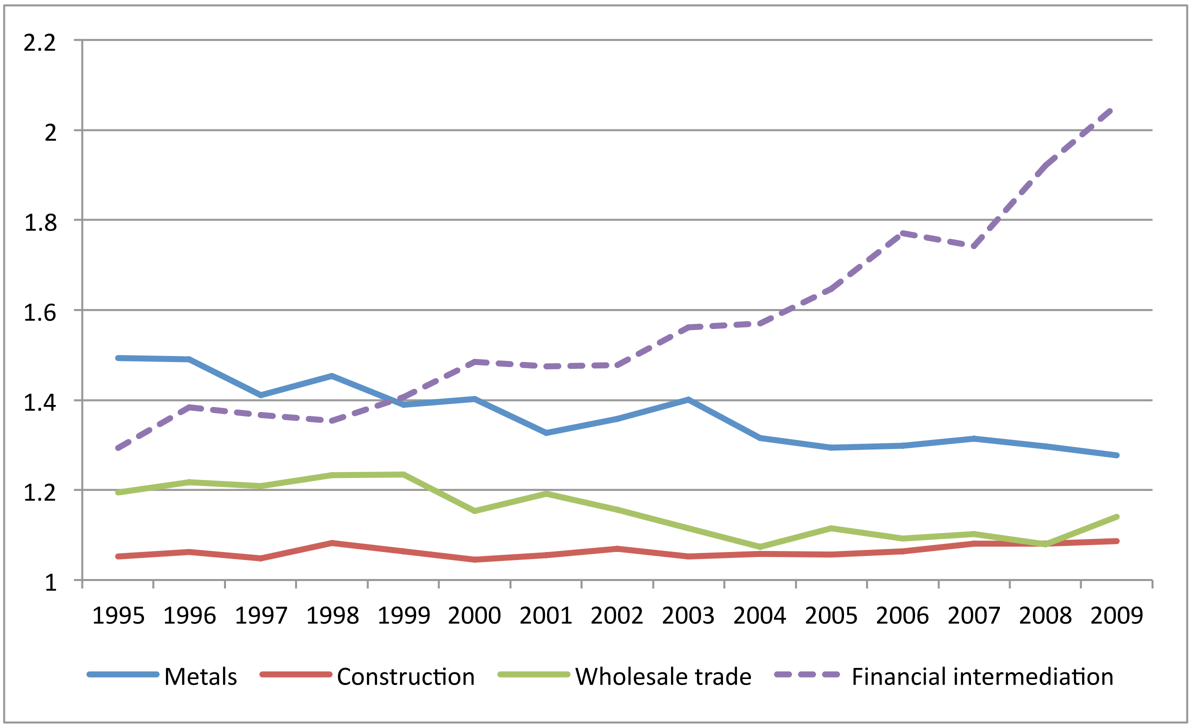
Figure 3: Key sectors - Backward Linkages



Source: Statec input-output tables, BCL calculation

Financial intermediation appears at the top, with an average value exceeding 1.4, which suggests that an increase in output in this sector draws inputs from all other sectors. The evolution through time suggests an increase in the strength of these linkages from 1996 to 2001, a mild decline in 2002 (following the bursting of the dot-com bubble) and slow recovery until 2009. It should be emphasized that these changes through time refer to the position of Financial Intermediation relative to the mean across all sectors, which changes through time. For the other potential key sectors, Metals has above average linkages, but these appear to have weakened from 1995 to 2009. Construction and Wholesale Trade also have above-average backward linkages to the rest of the economy and these have been relatively stable through time.

Figure 4: Key sectors - Forward Linkages



Source: Statec input-output tables, BCL calculation

Figure 4 plots the forward linkage indices of the four potential "key sectors" mentioned above. In this case, Financial Intermediation was below Metals at the start of the sample, but grew steadily, overtaking it in 1999 and rising steeply until the end of the sample. The Metals industry has seen a more gradual decline in the relative strength of its forward linkages, as has Wholesale trade. For Construction, forward linkages are just above average and their position has remained relatively stable. Returning to Financial Intermediation, increasing strength of forward linkages implies that output in this sector is particularly responsive to an increase in demand in the other sectors. This is confirmed by a steep decline in the V_i index associated with Financial Intermediation (see appendix), meaning that its forward linkages have become increasingly diffuse across other sectors. Another interesting feature of the variability indices is that backward linkages in the Metal industry appear to be concentrated in few sectors (V_j exceeds unity) weakening the case to include this among the key sectors.

While the four sectors in the graphs above are the only ones to combine above-average backward and forward linkages (indices in excess of unity), they are not always the sectors with the highest backward or forward linkages. The Insurance sector has backward linkages that often exceed even those in financial intermediation, but forward linkages in Insurance are below average. The Business services sector has forward linkages far above those in financial intermediation, but its backward linkages are systematically below average.

Financial auxiliaries had higher forward linkages until 2008 when financial intermediation overtook them. For Financial auxiliaries, backward linkages have grown stronger over time, exceeding the average since 2003. In fact, if we restrict the analysis to consider only the period since 2005, then Financial auxiliaries fulfill all the requirements to qualify as a "key sector."

Input-output analysis is subject to several limitations. In particular, the Leontief model assumes a linear relationship between outputs and inputs, which requires zero fixed costs and constant returns to scale. In addition, the fixed technological coefficients do not allow any substitution between inputs. Input-output analysis also ignores the fact that the degree of economic slack in different sectors is likely to vary over the business cycle. By focusing on feedback loops within intermediate demand, the Leontief model also ignores the fact that investment in physical or human capital is likely to lead to technological changes and that fluctuations in demand can generate effects on production via employment-income-consumption channels. This is why the rest of this study focuses more on business cycle frequencies, using quarterly data to analyse the transmission of shocks across sectors of production.

3 Quartely data: Time-varying variances and correlations

This section analyses seasonally adjusted quarterly data on real growth in sectoral value added, comparing standard descriptive statistics and applying multi-variate Granger-causality tests. The results are not robust to the number of lags selected and are often counterintuitive, which we associate with the evidence of misspecification in the underlying vector autoregression. Therefore, we attempt to identify innovations in sectoral growth by estimating univariate ARIMA models with GARCH innovations. This allows us to test for correlation between the standardised residuals, first by using the Cheung-Ng (1996) test based on the bivariate cross-correlation function and then with the Engle (2002) dynamic conditional correlation approach, which we implement in a multivariate ten-variable setting. The latter allows us to decompose the time-varying covariance matrix into changes in volatility and in correlation. This decomposition establishes that shifting correlations account for much of the change in volatility of Luxembourg's macroeconomic "portfolio".

3.1 Data and descriptive statistics

Statec publishes quarterly national accounts that include chain-linked volume indices of value added by sector of production. ESA95 data was published for 1995Q1-2014Q2, but following the switch to ESA2010 the new data only goes back to 2000Q1. Haas et al (2009) indicate that Statec uses the "annual overlap" method to compile quarterly national accounts, so we have used year-on-year growth rates to link ESA95 and ESA2010 versions of each series, obtaining a sample covering 1995Q1-2014Q3.

In real terms as well as nominal terms, value added is trending upwards in most sectors, meaning that output is non-stationary in levels. Therefore in the following we focus on quarter-on-quarter growth rates obtained by first-differencing natural logarithms. Table 1

Table 1: quarter-on-quarter output growth (SA, % points) – descriptive statistics

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info. & comm.	K Fin. & insur.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
Mean	-1.1	0.0	0.8	0.6	1.6	0.8	0.9	1.3	0.9	0.5
Median	0.6	-0.1	1.1	0.7	2.0	0.9	1.0	1.7	0.9	0.7
Max	22.4	13.6	23.1	22.8	32.9	20.9	7.1	16.0	9.1	10.7
Min	-38.0	-15.5	-27.1	-21.4	-24.1	-18.0	-8.4	-22.7	-1.8	-25
St.dev.	10.0	4.9	6.3	5.0	6.9	4.3	1.8	5.5	1.4	4.5
Skew	-1.6	-0.4	-0.5	0.0	0.3	0.6	-2.0	-1.3	3.6	-2.2
Kurtosis	7.2	4.3	8.7	12.0	9.5	12.7	14.3	8.2	22.1	14.4
Normal	90.1	7.5	106.5	266	138.2	311	467	110	1354	488
p-value	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Statec data and own calculations

reports standard descriptive statistics for the quarterly growth rate of real value added by sector (after seasonal adjustment).

On average, value added in Agriculture (A) has been falling in real terms (more than -4% at an annual rate). For Industry (BE), the collapse in 2008 was so steep that real value added has only recently recovered its 1995 level (average annual growth is 0.0%). In the other sectors, real annual growth averaged 3.2% in Construction (F), 2.4% in Wholesale and retail trade (GI), 6.6% in Information & communications (J), 3.2% in Finance & insurance (K), 3.6% in Real estate activities (L), 5.3% in Professional, scientific & technical activities (MN), 3.6% in Public administration (OQ) and 2.0% in Arts, entertainment, recreation & repair of household goods (RU). Notice that the financial sector is not the fastest growing sector, although on average it makes the highest contribution to GDP growth, thanks to its larger share in aggregate nominal value added.

For each sector, the standard deviation measures the volatility of quarter-on-quarter growth (after seasonal adjustment). This is highest in Agriculture (A), Information & communication (J) and Construction (F). Skewness is very positive in Public administration (OQ) and very negative in Art, entertainment and recreation (RU) and in Real estate activities (L). Kurtosis is way above the normal value of 3.0 for all sectors, suggesting a distribution with “fat tails,” meaning some extreme observations far above or below the mean. Such leptokurtosis can also be explained by volatility clustering, a phenomenon by which a period with a large positive or negative change is likely to be followed by another large change (although in either direction). This feature is common in financial series, where it is usually modelled as AutoRegressive Conditional Heteroscedasticity (ARCH), a form of persistence in the conditional variance. In the final two rows of the table, the Jarque-Bera test combines evidence of skewness and excess kurtosis in a test of the hypothesis that growth rates are normally distributed. This test rejects the null hypothesis of normally distributed growth rates for all sectors at the 5% significance level (for most sectors also at the 1% level).

3.2 Cross-sector links: Granger-causality tests

One might expect movements in the "key sectors" to lead movements in the other sectors, so the Granger-causality test may seem a natural tool to identify which sector of production acts as "engine of growth". This requires estimating a vector autoregression (VAR) and testing the hypothesis that all lags of a given variable (the candidate causal sector) have zero coefficients in the equations determining the other variables in the system. However, it is well-known that Granger-causality results are sensitive to the variables included in the estimated VAR as well as the number of lags considered. We avoid the simple bi-variate Granger-causality test, which is known to suffer from omitted variable bias, and instead we estimate a ten-variable VAR using quarterly log-differences of real value added (seasonally adjusted) from all ten sectors of production. Table 2 reports the results in terms of p-values (probability at which the null hypothesis is rejected). Each cell corresponds to the null hypothesis that the sector in the row does not Granger cause the sector in the column. In most cases, the Granger causality test (block exogeneity Wald statistic) was not significant (the null hypothesis of **no** Granger causality could not be rejected) and only p-values below 0.05 are reported in the table (for empty cells the test was not significant at the 5% level). The top panel of the table is based on a VAR that includes only one lag of each of the ten variables, while the bottom is based on a VAR including four lags of each variable.

Even for the few cases where the Granger causality test was significant, the results are often puzzling. Starting in the first column, in the upper panel the test suggests that Real estate activities (L) and Public administration (OQ) as Granger-causal for Agriculture (A). However, this result disappears if two or more lags are included in the VAR (see lower panel for case with four lags).

Table 2: quarter-on-quarter output growth (SA) – Granger causality test p-values

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info. & comm.	K Fin. & insur.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
					1 Lag					
A									0.04	
BE										
F		0.01								
GI										
J		0.01								
K										
L	0.01		0.01							
MN		0.02								
OQ	0.02									0.05
RU								0.00		
					4 Lags					
A				0.00						
BE								0.03		
F										
GI										0.00
J		0.04								
K										
L										
MN		0.03	0.02		0.01					
OQ										
RU				0.01						

Source: Statec data and own calculations

In the second column, Industry (BE) appears to be Granger-caused by Construction (F), Information & communications (J) and Professional & scientific services (MN) in the upper panel. Only the last of these three results remains when two lags are included, no sector is Granger-causal for industry when three lags are included and two of the three sectors above reappear when four lags are included (lower panel). In the third column, Construction (F) appears to be Granger caused by Real estate activities (L) when a single lag is included. This result also holds when two or three lags are included, but disappears with four lags (lower panel), when there is a switch, with Professional & scientific services (MN) appearing as the sole candidate for Granger causality.

In columns four to seven, none of the Granger-causality tests are significant in the upper panel, but some become significant when more lags are included. With four lags, the lower panel suggests Wholesale and retail trade (GI) in column four appears to be Granger-caused by Professional & scientific services (MN), while Professional & scientific services (MN) in column eight appears to be Granger-caused by Industry (BE).

Finally, in the upper panel Public administration (OQ) in column nine appears to be Granger-caused by Agriculture (A), while Arts, entertainment and recreation (RU) in column ten appears to be Granger-caused by Public administration (OQ). Both these results disappear if two lags are included. In the lower panel (four lags) RU appears to be Granger-caused by Wholesale and retail trade (GI) instead.

The null hypothesis of no Granger causality is never rejected in the columns for Financial & insurance (K) and Real estate activities (L). This could be interpreted as evidence that these two sectors are driving the Luxembourg economy. However, in the corresponding rows for K and L there are few significant p-values. Real estate activities (L) appear to Granger-cause Agriculture (A) and Construction (F), but only when the VAR includes a single lag. Financial & insurance (K) actually does not appear to Granger cause any other sector. Given the fragility of these results, any conclusion must be taken with substantial caution. Therefore, we prefer not to take these results at face value.

Lee, Lin and Wu (2002) criticise Granger causality tests as tools to identify an engine of growth, since balanced growth conditions imply co-integrating relations that will bias the tests towards rejecting the null hypothesis of no causality. These authors provide Monte Carlo simulations demonstrating that Granger causality tests will often identify spurious causality between independently generated ARIMA(1,1,0) series and that this bias towards rejection increases with the number of variables considered.

Although the Granger causality test is a standard tool that is widely used, it relies on the assumption that the VAR model is properly specified. However, in this particular case the VAR residuals appear to be serially correlated. For the VAR(1), the multivariate LM test rejects the null of no residual correlation at lag four. For the VAR(4), the multivariate portmanteau test (based on the Box-Pierce/Ljung-Box Q-statistics) rejects the null of no residual correlation at the highest significance levels.

3.3 Literature survey: GARCH models in macroeconomics

One important reason why the Granger-causality results are not reliable may be that they are based on Wald tests that are known to be vulnerable to deviations from normality. The excess kurtosis indicated in Table 1 revealed that (even after seasonal adjustment) quarterly growth in sectoral output may contain outliers and/or be characterized by a “fat tailed” distribution. In the following, we estimate Generalised AutoRegressive Heteroscedatic (GARCH) models that may account for these deviations from the normality assumption. In fact, the standardized residuals from these GARCH models are better behaved and can be used to estimate the cross-sector correlation between growth innovations, including at different leads and lags.

GARCH models are more widely applied in the finance literature than in macroeconomics. However, the seminal Engle (1982) paper on autoregressive conditional heteroskedasticity (ARCH) actually adopted a macroeconomic perspective, focussing on aggregate UK inflation. Since then, the enormous literature applying ARCH methods in finance has been accompanied by the development of a smaller ARCH literature in macroeconomics.

For example, Lee (1999) explored the conjecture that monetary authorities targeting a certain level of inflation or output would face a “Taylor curve” tradeoff between variability in output and variability in inflation. Lee estimated a bivariate GARCH(1,1) model on quarterly US data on inflation and the output gap. Results indicated significant ARCH effects, transmission of variability from output to inflation, and higher persistence in inflation variability than output variability. This analysis was extended in Lee (2002) to evaluate the impact of anticipated and unanticipated changes in monetary policy on the conditional volatility of output and inflation.

Caporale and McKiernan (1998) explored the Fischer Black hypothesis that output volatility should have a positive effect on the *level* of output growth. The ARCH-M model provides a natural framework to simultaneously estimate the conditional volatility of growth and test for its effect on the level of growth. These authors acknowledged that ARCH effects may be stronger at higher frequencies, but argued that low-frequency data was more appropriate to test the Fischer Black hypothesis because time is required to invest new capital. Using a long annual series on US GNP (1870-1993), they found significant ARCH effects in the ARMA(1,2) residuals and provided evidence of a positive impact of volatility on mean growth. Using even longer annual series on industrial production, Fountas and Karanasos (2006) estimated AR-GARCH-M models and confirmed significant GARCH effects and the positive impact on output growth for Germany and Japan. Using quarterly US GDP on a shorter period, Henry and Olekalns (2002) found a negative effect, which they attributed to the impact of irreversibility on firm-level investment decisions. This result was based on a modified threshold GARCH model, focusing on asymmetric effects during recessions. Using data for Australia, Macri and Sinha (2000) found no ARCH effects in quarterly GDP but significant GARCH in quarterly industrial production, with a negative impact of growth volatility on the level of growth. Using quarterly GDP data, Ho and Tsui (2003) estimated an ARMA-EGARCH model and found significant GARCH in Canada, the UK and the US, with high persistence and significant asymmetries in volatility for Canada and the US. Using quarterly GDP for Japan, Fountas, Karanasos and Mendoza (2004) found highly significant

GARCH effects with three different specifications, but no evidence that growth volatility affects the level of growth and no evidence of asymmetry.

Fang and Miller (2008) interpret the “Great Moderation” as a structural change in growth volatility, identifying a single break in the unconditional variance of quarterly US GDP growth. Following this adjustment, evidence of integrated GARCH appears to be spurious and there is no significant relationship between output growth and its volatility. Fang, Miller and Lee (2008) show that after allowing for breaks in variance[1], GARCH persistence also drops in quarterly growth series for Canada, Germany, Italy, Japan and the UK. Fang and Miller (2009) focus on Japan’s quarterly GDP and find that excess kurtosis is eliminated by careful treatment of additive outliers, GARCH persistence remains when correcting for two level shifts in the mean, but disappears once a break is incorporated in the variance. They find no evidence of a link between growth and its volatility. Fang, Miller and Lee (2010) use the Bai-Perron multiple structural change test to confirm the finding in Fang and Miller (2008) that leptokurtosis (and integrated GARCH) in US quarterly GDP growth disappear once a dummy in the variance equation accounts for the Great Moderation.

Grier and Perry (2000) extended this framework to also include inflation. This allowed them to test the Friedman hypothesis that higher inflation increases inflation uncertainty and therefore lowers the level of growth. It also allowed them to consider the Cukierman-Meltzer hypothesis that higher inflation uncertainty raises the average level of inflation (reversing the direction of causation). Using monthly US data on producer prices and industrial production, Grier and Perry estimated a system of simultaneous equations with bivariate GARCH-M imposing constant conditional correlation. Results confirmed that growth uncertainty increases the level of growth but also suggested that inflation uncertainty significantly lowers growth. Fountas, Karanasos and Kim (2006) found similar results for all G7 countries using a bivariate VAR-GARCH-M model with constant conditional correlation. Fountas and Karanasos (2007) analyzed the same G7 data by a two-step procedure: first they estimated conditional variances for inflation and growth from a VAR model with two-component asymmetric GARCH, and then they performed Granger causality tests in separate regressions (allowing them to consider longer lags). Their results suggested that growth uncertainty raises growth and that higher inflation raises inflation uncertainty. However, evidence was mixed on the impact of inflation uncertainty on the level of inflation or growth. They also found little support for the Devereux hypothesis that growth uncertainty raises the level of inflation.

[1] Fang, et al. (2008) identify breaks in variance by applying an iterated cumulated sum of squares (ICSS) algorithm to the squares of the residuals.

Elder (2004a and 2004b) added monetary policy as a third variable, estimating a VAR for consumer prices, industrial production and the federal funds rate with multivariate GARCH-M effects. Results indicated that inflation volatility significantly lowered output growth, but volatility in the federal funds rate did not (suggesting that monetary authorities successfully smoothed short-term interest rates). His results were robust to alternative measures of output and inflation based on interpolated GDP and GDP deflator series.

Lee and Crowley (2005) applied a bivariate version of the Engle (2002) Dynamic Conditional Correlation (DCC) model to study the links between quarterly GDP fluctuations in different countries with those in the EU aggregate. Lee (2006) also used a bivariate DCC model to study co-movement between output and prices in quarterly US data. He found evidence that the US GDP deflator switched from a procyclical pattern of behaviour before World War I to a countercyclical pattern since. Lee also reported evidence of high persistence in the conditional variance of output and prices and could reject the hypothesis of constant conditional correlations.

Higher-dimensional DCC models have also been estimated using weekly financial data (see Wong and Vlaar, 2003, and Cappiello, Engle and Sheppard, 2006). Below we estimate the DCC model in a ten-variable context to capture the joint dynamics of output across the major sectors of production in the Luxembourg economy. This sectoral perspective of the business cycle is a relatively under-researched area, as indicated in Afonso and Furceri (2009).

3.4 Univariate ARIMA models with GARCH

The results in the preceding section suggest that the dynamics of the individual series need to be modeled more carefully. We therefore analysed the seasonally unadjusted data, applying the pretesting procedure in the Tramo-Seats software to identify the appropriate degree of differencing (including seasonal differencing) and the treatment of possible outliers (including additive outliers, level shifts and transitory changes). A separate seasonal ARIMA model was estimated for each of the seasonally unadjusted series, accounting for outlier effects and allowing for generalized autoregressive conditional heteroskedastic (GARCH) in the innovations process. The estimated equation appears below, with the first equation specifying the transformation of real value added in sector *k* (denoted va_{kt}) using the lag operator L such that $L^s x_t = x_{t-s}$. Ordinary differencing is determined by the exponent D=1,0 and seasonal differencing by the exponent S=1,0. The symbol μ stands for deterministic effects possibly including a constant mean term, Easter effect, Trading day effect and outliers (additive outliers, transitive changes, or level shifts).

$$
\begin{aligned}
&(1-L)^{D}\left(1-L^{4}\right)^{S}\ln\left(va_{kt}\right)=\mu+u_{t}\\
&(1-\rho L)\left(1-\kappa L^{4}\right)u_{t}=(1-\theta L)\left(1-\phi L^{4}\right)\varepsilon_{t}\\
&\varepsilon_{t}=z_{t}\sqrt{h_{t}}\quad z_{t}\sim N(0,1)\\
&h_{t}=\omega+\alpha\varepsilon_{t-1}^{2}+\beta h_{t-1}
\end{aligned}
$$

The second equation specifies the ARIMA process: ρ denotes the AR(1) parameter, κ the seasonal AR(1) parameter, θ the MA(1) parameter and ϕ the seasonal MA(1) parameter. The remaining equations describe the GARCH process, with z_t denoting the standardized residuals *and* h_t the time-varying conditional variance which follows the process determined by the parameters ω, α and β. For simplicity, the deterministic part related to the mean and outlier treatment is omitted in the equation above.

As a starting point for our analysis, we used the seasonal ARIMA model selected by the specification search in the seasonal adjustment package Tramo-Seats (using option rsa=5). We retained the deterministic effects that Tramo-Seats found significant for the different series (Easter Effect, Trading Day effects, and outliers whether additive, transitory changes, or level shifts). In several cases, we modified the preferred specification to improve residual properties. In particular, we found significant asymmetric GARCH effects (see TARCH(1) tem) in Agriculture (A), Construction (F), Information & communication (J), Professional & scientific services (MN) and Public administration (OQ). We also included an ARCH-in mean term (ARCH-M) in Construction (F) as this raised the log-likelihood significantly. ARCH-in-mean terms were significant in Industry (BE), Finance & insurance (K), and Information & communications (J) but had to be dropped as they lead to negative estimates of the conditional variance.

Estimation results from the univariate models are reported in Table 2. Figures marked in bold are statistically significant at the 5% level. Note that the GARCH coefficient α is significant in three of the ten columns and that the ARCH coefficient β is significant in seven. In only two sectors neither ARCH nor GARCH effects are statistically significant: J (Information & communciations) and RU (Arts, entertainment & recreation), although this may be due to the limited size of the sample. Overall, there is convincing evidence of persistence in conditional heteroscedasticity. In fact, the ARCH coefficient β exceeds unity in absolute value in four sectors, suggesting integrated GARCH. However, the GARCH coefficient α is of opposite sign and the restriction for integrated GARCH (α+β=1) is not satisfied for any of these cases.

Table 3: Univariate ARIMA-GARCH models – parameter estimates and diagnostics

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info & comm.	K Fin. & insur.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
1st diff.	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes
seas.diff.	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No
ARCH-M			0.01							
AR(1)	0.47					**0.79**		**-0.31**		**-0.61**
AR(2)	0.01									0.44
AR(3)	-0.01									0.02
SAR(1)						**-0.64**	**0.31**			
MA(1)	0.53	-0.02	**-0.60**		**-0.27**				**0.24**	0.26
MA(2)										**-0.74**
SMA(1)	0.11	**-0.96**	**-0.78**	**-0.62**	**-0.95**			**-0.66**		
GARCH(1)	0.01	**-0.10**	**0.35**	-0.11	0.38	-0.14	**0.29**	**0.17**	0.10	0.35
TARCH(1)	**-2.80**		**0.50**		**-0.52**			**0.22**	**-0.21**	
ARCH(1)	0.45	-0.16	**-0.32**	**1.09**	0.36	**1.07**	**-0.76**	**-0.63**	**0.99**	-0.12
LB Q(8)	**16.3**	5.95	7.55	5.05	6.21	2.42	10.6	10.0	12.1	**17.3**
p-value	0.00	0.31	0.18	0.65	0.29	0.88	0.16	0.07	0.10	0.00
LB Q^2(8)	7.13	9.41	10.6	4.88	14.1	6.93	4.58	7.00	11.0	10.8
p-value	0.62	0.04	0.30	0.85	0.12	0.64	0.87	0.64	0.28	0.29
skew	0.33	-0.36	0.22	-0.52	0.23	0.22	-0.40	0.20	0.06	0.76
kurtosis	2.89	4.00	2.30	3.46	2.72	2.42	2.73	3.05	3.11	4.39
normal χ^2	1.34	4.76	2.11	3.92	0.88	1.59	2.23	0.48	0.07	**13.1**
p-value	0.51	0.09	0.35	0.14	0.64	0.45	0.33	0.79	0.96	0.00

Note: Among the diagnostic tests, LB Q(8) indicates the Ljung-Box test for autocorrelation up to 8th order, normal χ^2 indicates the Jarque-Bera test for normality. In the bottom panel, ρ^bar indicates the linear correlation coefficient and ES χ^2 indicates the Engle-Sheppard test of the null hypothesis of constant conditional correlation. Source: Statec data, own calculations

In almost all cases, the estimated equations pass the diagnostic tests in the bottom panel. Ljung-Box Q-statistics for serial correlation up to order 8 are only significant for Agriculture (A), and Arts, entertainment & recreation (RU). However, the Q-statistics are not significant at lower lags, suggesting that the rejection at lag 8 may be attributed to outliers in the series. The Ljung-Box Q2-statistics for autocorrelation in the squared residuals (up to lag 8) are never significant, suggesting the models have captured any nonlinear dependence.

There is no statistically significant evidence of skewness or excess kurtosis. Only for Arts, entertainment & recreation (RU) can the Jarque-Bera statistic reject the null hypothesis of normally distributed residuals at conventional levels. Overall, these univariate models appear to have successfully accounted for the non-normality that dominated the results in Table 1.

3.5 Cross-sector links: cross-correlation function and Cheung-Ng test

In this subsection we calculate the cross-correlation function (CCF) of the standardised residuals from the univariate models. This is a first measure of correlations across innovations from different sectors of production. The CCF considers both simultaneous correlation and correlation at different lags and leads. Cheung-Ng (1996) proposed a portmanteau test for causality in mean and variance based on the CCF. Kanas and Kouretas (2002) applied this test to detect volatility spillovers between official and parallel currency markets in Latin America. Constantinou et al. (2005) used it to check for mean and variance causality across different equity markets using daily data. Hanabusa (2009) implemented this approach to study causality between oil prices and economic growth in Japan. It is worth noting the study by Hafner and Herwartz (2004) comparing the asymptotic and finite sample properties of the CCF test to those of the Wald test based on the BEKK multivariate GARCH model. Their Montecarlo results suggest that the CCF test has good size properties but lower power than the Wald test, meaning it is likely to find less evidence of correlation. However, the Wald test may also be subject to power losses if the multivariate (quasi) log-likelihood required for its calculation suffers from misspecification.

Table 4 reports the cross-correlation of the standardised residuals from the univariate ARMA-GARCH model for real value added in sector K (Finance & insurance) with the standardised residuals from each of the other univariate models in Table 3. The top panel refers to causality in mean (CCF of growth innovations in levels) and the bottom panel to casuality in variance (CCF of squared growth innovations). Row zero refers to contemporaneous correlations between growth innovations in sector K and growth innovations in the other sector (indicated at the top of the column). Rows above zero refer to cross-correlations between period *t* innovations from sector K and lagged innovations from the other sectors. Rows below zero refer to cross-correlations between period *t* innovations in sector K and period *t-i* innovations (leads) from other sectors.

The top (and bottom) row of each panel reports the Cheung-Ng (1996, p.38) modified S_M small-sample statistic, which is approximately distributed as a $\chi^2(5)$ under the null hypothesis that the correlations at all lags (or leads) from 1 to 5 are zero. Under the null hypothesis of no correlation, the cross-correlations at individual leads and lags should asymptotically converge to a normal distribution with mean zero and variance equal to the number of observations. Values in boldface are statistically significant at the 5% level.

Table 4: Finance & insurance (K) cross-correlations and Cheung-Ng statistics S_M

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info. & comm.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
					Panel 1: Causality in Mean				
S_M(lags)	7.20	5.23	10.79	6.18	5.86	4.43	9.39	3.27	5.67
-5	-0.00	-0.11	-0.03	-0.11	-0.22	0.16	-0.05	-0.17	0.11
-4	0.04	0.15	0.19	0.09	0.13	0.10	-0.03	-0.03	0.14
-3	0.04	-0.12	0.11	0.16	0.05	0.13	**0.24**	-0.03	0.19
-2	-0.05	0.05	**0.30**	0.11	0.03	-0.06	**0.25**	-0.01	0.07
-1	**0.30**	0.12	-0.04	0.15	-0.08	0.05	-0.03	0.10	-0.06
0	0.09	-0.11	0.18	0.01	0.02	-0.17	-0.02	0.07	-0.03
1	0.21	**0.23**	-0.06	-0.09	0.05	0.07	0.02	-0.14	-0.07
2	-0.06	-0.03	0.03	**0.28**	0.01	-0.02	-0.18	0.03	-0.17
3	0.05	-0.11	-0.16	-0.10	0.07	0.03	0.10	0.11	**0.23**
4	**0.23**	0.01	0.06	-0.16	-0.12	-0.01	0.04	-0.06	-0.11
5	-0.09	-0.05	-0.21	-0.04	-0.02	0.08	-0.03	-0.02	**0.23**
S_M(leads)	8.84	5.22	6.07	9.41	1.69	1.00	3.51	2.89	**11.86**
					Panel 2: Causality in Variance				
S_M(lags)	7.53	2.21	8.35	4.41	9.12	0.94	**13.32**	5.47	5.96
-5	-0.10	-0.04	-0.14	-0.16	0.20	-0.07	-0.12	0.04	0.14
-4	0.06	0.15	**0.27**	-0.07	0.12	0.04	**0.31**	0.10	-0.06
-3	-0.13	-0.07	-0.09	-0.02	-0.10	-0.02	**0.23**	-0.08	0.19
-2	-0.17	0.01	0.03	-0.05	-0.22	-0.04	-0.04	-0.16	-0.02
-1	0.20	-0.00	-0.08	0.15	-0.06	-0.06	-0.09	-0.17	-0.13
0	-0.07	0.06	0.04	-0.20	0.13	-0.02	0.02	0.07	0.03
1	-0.07	-0.07	0.22	0.18	-0.04	-0.06	-0.01	-0.02	0.04
2	-0.11	-0.08	-0.16	0.07	-0.11	-0.05	-0.05	0.04	-0.10
3	**0.24**	-0.13	-0.02	-0.07	0.12	0.11	-0.19	0.12	0.20
4	0.06	0.06	0.19	0.15	0.23	0.08	-0.08	0.22	-0.10
5	-0.05	0.17	-0.22	-0.05	0.00	0.06	0.08	-0.00	0.14
S_M(leads)	6.15	4.87	**12.54**	4.94	6.40	2.19	3.83	4.86	6.47

Source: Statec data, own calculations

Starting with causality in the mean (in the top panel), the *contemporaneous* correlations in the zero row are weak and none of them appears to be statistically significant. Moving up the panel, we see that sector K innovations in period *t* appear to be significantly correlated with innovations at lag *t-1* in Agriculture (A), at lag *t-2* in Construction (F) and at lag *t-2* and *t-3* in Professional, scientific & technical services (MN). However, the Cheung-Ng portmanteau test in the top row is not significant for any of these sectors, failing to reject the null of no causality-in-mean.

Below the zero line in the top panel, period *t* innovations in sector K seem to be correlated with innovations at lag *t+1* in Industry (BE) at lag *t+2* in Wholesale and retail trade (GI), at lag *t+3* in Arts, entertainment & recreation (RU) and at lag t+4 in Agriculture (A). In this case, the Cheung-Ng portmanteau statistic in the bottom row final column of the top panel is significant at the 5% level, suggesting that sector K leads sector RU at lags 1-5.

Turning to causality in variance (lower panel of Table 4), at lag zero there is no significant contemporaneous correlation between squared innovations in sector K and squared innovations in other sectors. Squared period *t* innovations in sector K appear to be correlated with squared innovations in sector MN (Professional, scientific & technical services) at *t-3* and *t-4*. The Cheung-Ng portmanteau statistic is also significant in the top row, suggesting sector MN leads sector K in terms of causality-in-variance. For sector F (Construction), squared innovations in period t-2 also seem to be correlated with squared innovations for period *t* in sector K, although the portmanteau test is not significant.

Finally, below the zero line in the bottom panel squared period t+3 innovations in Agriculture (A) appear to be correlated with squared period t innovations in sector K. However, the portmanteau test in the bottom row is not statistically significant. On the other hand, the portmanteau test in the bottom row is significant for Construction (F), suggesting causality-in-variance from squared innovations in sector K.

3.6 Cross-sector links: Dynamic Conditional Correlations

The mixed evidence of causality-in-mean or causality-in-variance could reflect violations of the implicit assumption that correlations are constant over the whole sample. If correlations are strongly negative over some parts of the business cycle and strongly positive at others, then analysis based on this assumption may misleadingly conclude that correlations are near zero over the whole sample. Table 5 reports the simultaneous correlations between growth innovations in different sectors (in the upper triangle) as well as the p-value of the Engle-Sheppard (2001) test of the hypothesis that this correlation is constant through time (in the lower triangle). At the 5% significance level, the constant correlation null hypothesis is rejected in 19 of the 45 possible pair-wise comparisons (at the 10% level another six pairs are at least borderline significant).

Table 5: Simultaneous correlation (upper triangle) & Engle-Sheppard p-value (lower)

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info. & comm.	K Fin. & Insur.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
A		0.26	0.02	-0.12	0.06	0.09	0.04	0.13	0.19	0.01
BE	**0.00**		0.18	0.03	0.09	-0.11	0.16	-0.03	0.04	0.04
F	0.92	**0.02**		0.15	0.16	0.18	-0.00	0.34	-0.09	0.14
GI	0.16	0.40	**0.04**		-0.08	0.01	0.18	0.22	-0.04	-0.04
J	0.14	0.08	0.09	0.33		0.02	-0.04	0.10	0.11	0.28
K	0.14	0.42	**0.04**	0.10	0.85		-0.17	-0.02	0.07	-0.03
L	0.51	**0.05**	**0.04**	**0.01**	0.77	**0.04**		0.17	-0.02	0.41
MN	0.20	**0.01**	**0.00**	**0.01**	0.44	0.09	**0.01**		-0.16	0.21
OQ	**0.04**	**0.05**	0.10	0.06	0.30	0.13	0.42	**0.00**		0.03
RU	0.47	0.38	**0.03**	0.35	**0.00**	0.76	**0.00**	**0.01**	0.62	

Source: Statec data, own calculations

Based on this evidence of time-variation in cross-sector correlation, we proceed to apply the dynamic conditional correlation approach proposed by Engle (2002). This two-stage approach involves first estimating conditional variances and standardised residuals using univariate GARCH models reported in Table 3. In the second stage, the standardised residuals are used to derive time-varying correlations by postulating the following model:

$$H_t = D_t R_t D_t$$

Where the time-varying variance-covariance matrix H_t is decomposed using the diagonal matrix $D_t = diag\{\sigma_{it}\}$ whose elements are time-varying standard deviations obtained as the square root of the conditional variances in the first stage by estimating univariate GARCH models. The matrix of time-varying correlations R_t is estimated by restricting correlation dynamics to follow a structure analogous to that of GARCH:

$$Q_t = \left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B\right) + A'z_{t-1}z'_{t-1}A + B'Q_{t-1}B$$
$$R_t = diag\left[Q_t\right]^{-1} Q_t \, diag\left[Q_t\right]^{-1}$$

Where $\overline{Q} = E\left[z_t z'_t\right]$ is the unconditional correlation matrix and the diagonal matrices A and B contained the parameters to be estimated. In the simplest form of DCC, A and B are scalars (as in the two-variable case). Below we use the generalised DCC model, simultaneously estimating different parameter values for each variable in the system. Engle and Sheppard (2001) establish the consistency and asymptotic normality of the two-stage maximum-likelihood estimator that estimates the conditional correlations in the second stage conditioning on the parameters estimated in the first stage using individual univariate GARCH models.

We estimated the model with 100 different sets of initial values of the parameters A and B. These were set along a grid, with B ranging from 0.00 to 0.9 (step size 0.10) and A ranging in ten steps from 0.00 to just below the limit of integrated correlation condition ($A^2+B^2=1$). Table 4 reports the parameter estimates from the run which converged to the highest point of the likelihood function. Estimates in boldface are statistically significant at the 5% level. For ease of comparison with the univariate GARCH parameters in table 3, we also report the squared values of A and B.

Table 6: Dynamic Conditional Correlation Stage 2 Parameter Estimates

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info. & comm.	K Fin. & insur.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
A	0.10	0.45	0.39	**0.51**	0.55	**0.52**	0.41	0.26	0.22	0.21
A^2	0.01	0.20	0.15	**0.26**	0.31	**0.27**	0.17	0.07	0.05	0.04
B	0.67	0.66	0.00	-0.86	-0.00	0.89	0.17	0.59	0.60	0.07
B^2	0.45	0.44	0.00	0.74	0.00	0.79	0.03	0.35	0.36	0.00

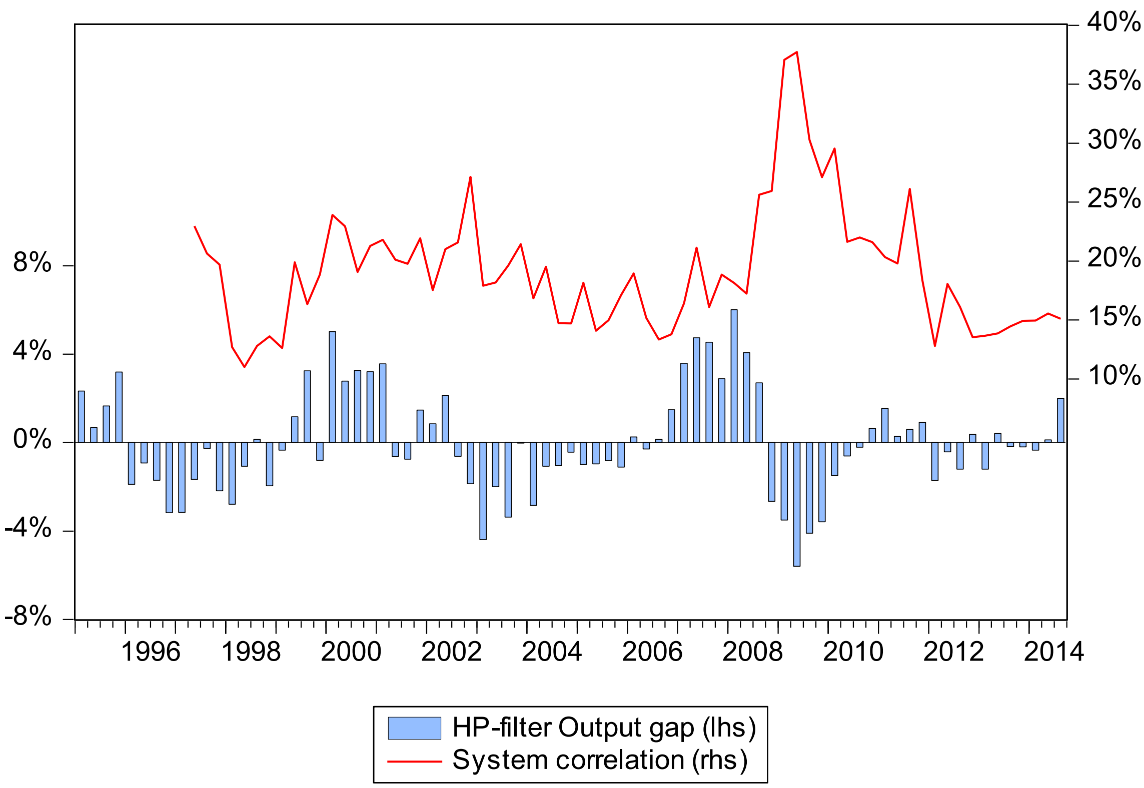
Source: Statec data, own calculations

There is significant uncertainty surrounding these parameter estimates, as estimates are not statistically different from zero except in sectors GI (Wholesale & retail trade) and K (Finance & insurance). The two sectors (previously identified as key sectors) are the only ones where the A parameters are above 0.5 and the B parameter is above 0.8, indicating substantial smoothing of fluctuations in correlation. The integrated correlation condition $A^2+B^2=1$ is only fulfilled in these two sectors, which could lead to violations of the condition that the conditional variance-covariance matrix is positive-definite. This was avoided in estimation by modifying the likelihood function to include a penalty associated with correlation estimates above unity in absolute value.

As there are n=10 variables in our system, there are n(n-1)/2=45 different series of estimated time-varying correlations linking growth innovations in different sectors. The annex reports four of these correlations, each pairing Finance & insurance (K) with one of the other major sectors of production. Instead, Figure 5 reports a system-wide measure of these pair-wise correlations, obtained as a weighted average using the quadratic form $w_t' R_t w_t$ where w_t is the vector of (time-varying) shares of each sector in nominal value added and the (time-varying) correlation matrix R_t has ones along its main diagonal.

Figure 5 compares the output gap estimated from quarterly real GDP using the Hodrick-Prescott filter to the system-wide correlation in innovations across sectors (right-hand axis). The system-wide correlation is relatively high, averaging over 19% since 1997Q2. The linear correlation coefficient between the two series is -21%, suggesting that system-wide correlation increases when the output gap falls (and vice-versa). However, this simultaneous correlation is only statistically significant at the 10% level. This negative contemporaneous correlation disguises a positive cross-correlation when the output gap lags system correlation, with a peak above 48% when the lag on the output gap is lagged 7 quarters. This may reflect the fact that during the first part of a recession (when correlation is likely to increase) slower growth means the output gap will continue increasing but at a slower rate. The output gap will only fall into negative territory several quarters into the recession, after several quarters with growth below potential.

Figure 5: System-wide correlation (weighted by sector shares in value added)



Source: Statec data, own calculations

Looking at the recent crisis, the output gap peaked in 2008Q1, as growth began to slow. System correlation first rose in 2008Q3, the output gap turned negative in 2008Q4 and the peak in correlation (at 38%) came in 2009Q2, just as the output gap reached its minimum value. System-wide correlation was also relatively high in 2000Q1, when the internet bubble and the output gap were still growing. This finding may be related to the literature on asymmetries in the business cycle. The consensus view is that recessions involve sharper and more co-ordinated movements than expansions and should therefore imply higher cross-sector correlations.

3.7 Variance of Luxembourg's macroeconomic portfolio

Historically, Luxembourg has moved from being dominated by its steel sector to being dominated by its financial sector. This is why policy discussions often raise the issue of increasing diversification in the production structure. As is well-known from portfolio theory, the overall risk of the portfolio can be reduced by increasing the share allocated to assets that are less correlated with the others in the portfolio. By analogy, in this subsection we construct a measure of the variance of Luxembourg's macroeconomic portfolio, treating the ten sectors of production as if they were different assets in which to invest. Our DCC estimates allow us to generalise the analysis in Bourgain et al. (2000), which assumed a constant variance-covariance matrix (and was also limited to the branches of sector BE, industry). We also update the similar exercise in Rouabah (2007) which used a sample from 1995 to 2005 with data prior to the revision to NACE that provided a finer disaggregation of value added (at the time only six sectors of production were considered).

Allowing for time-variation in the variance-covariance matrix, we can write the portfolio variance as follows:

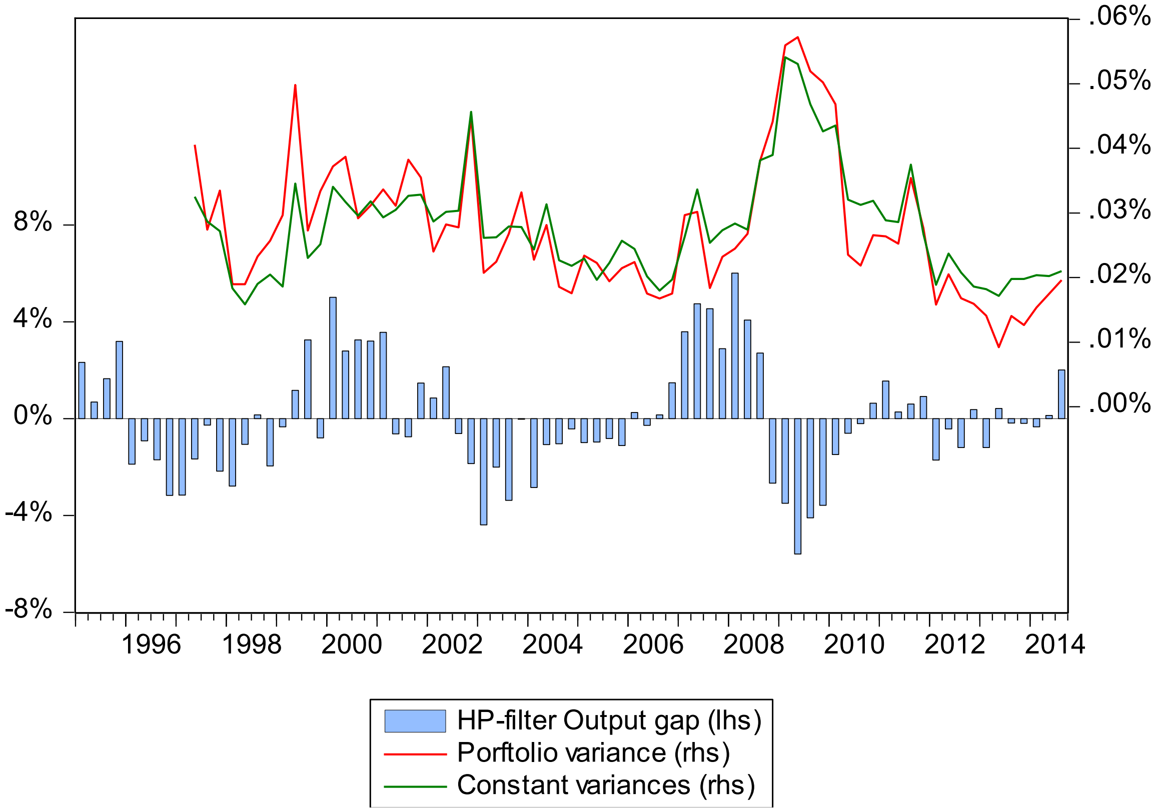
$$\sigma_t^2 = w_t' H_t w_t = w_t' D_t^{1/2} R_t D_t^{1/2} w_t$$

where the variance-covariance matrix H_t is decomposed into the diagonal matrix D_t containing the conditional variances and the matrix R_t of time-varying conditional correlations. Below we calculate this series two different ways: with conditional variances set at their sample mean so that $D_t = \overline{D}$, with conditional correlations set at their sample mean so that $R_t = \overline{R}$, and with both conditional variances and conditional correlations set at their sample mean (only sector shares change). This allows us to see how much of the fluctuations in portfolio variance are due to changes in these different components. The impact of changes in sector shares is minimal and is not reported.

Figure 6 plots the portfolio variance across time (red line), as well as the portfolio variance calculated with sector-specific variances held constant at their sample mean (green line). There is a peak in portfolio variance in 1999Q2, which is lower for the green line that holds variances constant. This difference implies that a rise in sector-specific conditional variances contributed to this spike. As the recession followed the dot-com bust in 2000, the two lines grew closer, suggesting that changes in conditional variances did not explain much of the movement. The lines separate briefly in 2004Q2, 2005Q4 and 2007Q2. However, in these three cases the green line was above, meaning that changes in conditional variances appear to have been dampening these spikes in portfolio variance. The green line dips below the red line during the international financial crisis from 2008Q4 to 2010Q1, suggesting that increases in conditional variances were driving the increase in portfolio volatility. However, the configuration is reversed for the rest of the sample, suggesting that conditional variances have been lower since then, dampening portfolio volatility.

Relative to the output gap series, the 2002Q4 and 2009Q2 peaks in portfolio variance occurred just as the output gap turned negative (therefore some quarters after GDP growth began to slow).

Figure 6: Portfolio Variance – contribution of time-varying variances

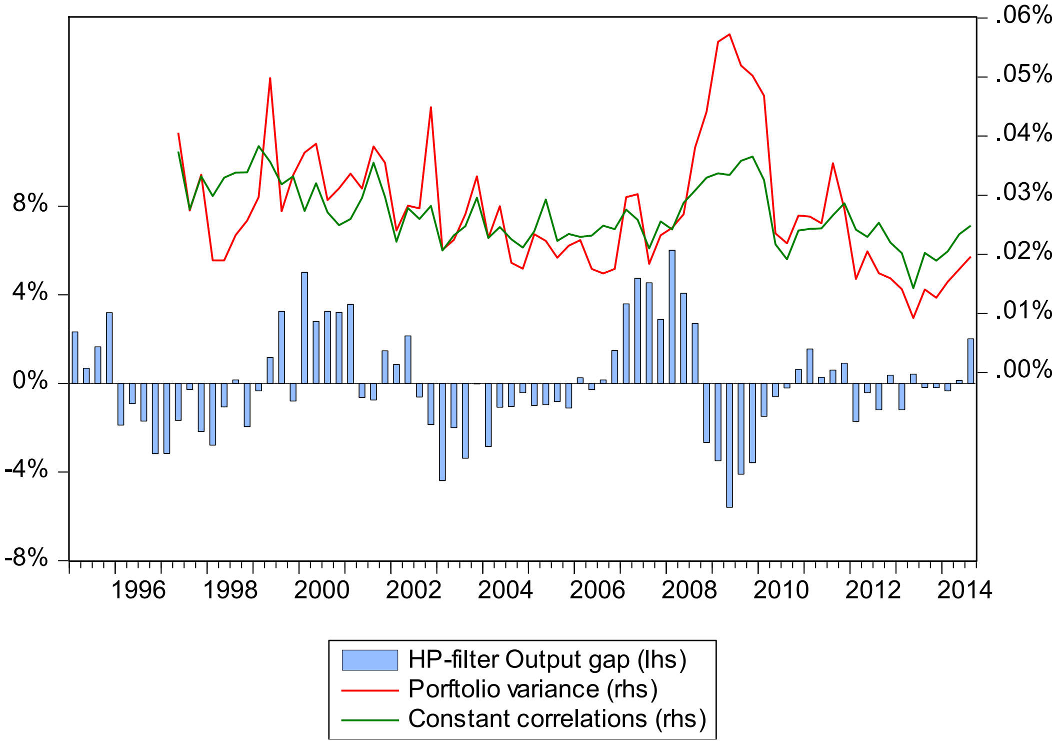


Source: Statec data, own calculations

Since the constant-variance series tracks portfolio variance fairly closely, changes in conditional variances do not appear to be the key force driving portfolio variance. However, portfolio variance peaks are generally higher than those in the constant variances series, suggesting that at these times conditional variances did rise significantly above their sample average

Figure 7 performs a similar exercise holding the time-varying correlations constant at their sample mean values. Here the differences are much more striking. Unlike the constant-variances series, the constant-correlations series is relatively flat. At each of the peaks in portfolio variance, the constant-correlation series lies clearly below. This means the time-

Figure 7: Portfolio Variance – contribution of time-varying correlations



Source: Statec data, own calculations

varying correlations contributed to boosting portfolio variance at these periods.

The gap between the two lines is greatest after the output gap turned negative in 2002Q4 and in 2008Q4, suggesting that time-varying correlations increased at these points. It is intriguing to note that since 2011Q4 the constant-correlations series is always above the portfolio variance series, suggesting that time-varying correlations have been dampening portfolio variance over the recent period.

4 Conclusions and Directions for Further Research

In conclusion, this study provided empirical evidence supporting the consensus view that Financial Services functions as the "engine of growth" in Luxembourg. Historically, the financial sector has provided the largest contribution to aggregate real growth. In addition, the Rasmussen-Hirschman indices, based on the Leontief inverse of the annual input-output tables, identify Financial Services as one of only four "key sectors" of the Luxembourg economy. Quarterly data on growth in value added by sector of production also supports this conclusion. Multivariate Granger-causality tests find no sector leading Financial services, although they also do not find clear evidence of Financial services leading other sectors.

These results may be unreliable given the evidence that quarter-on-quarter growth rates deviate from a normal distribution, featuring leptokurtosis ("fat tails") that may reflect volatility clustering. Therefore we estimate seasonal ARIMA models with time-varying variance to isolate sector-specific growth innovations. Using these normally distributed innovations, the Cheung-Ng test does not find clear evidence of causality-in-mean or causality-in-variance across sectors, which may reflect time-variation in correlations, as is confirmed by the Engle-Sheppard test. Therefore, we estimate Engle (2002) dynamic conditional correlations, finding significant time-variation in cross-sector correlation, which tends to increase during recessions. We use the estimated dynamic conditional correlations to decompose the variance of the Luxembourg macroeconomic "portfolio" into the contributions of changing sectoral shares, time-varying sectoral variances and time-varying conditional correlations. Changes in cross-sector correlation appear to be the main driver of overall volatility. In conclusion, the financial services industry appears to be strongly linked with the rest of the economy, benefiting from growth in other sectors, which it amplifies and propagates to the whole economy.

In terms of future research, an interesting point of departure is the observation that correlations appear to rise during recessions and fall during expansions. This suggests possible asymmetries in the process determining conditional variances and conditional correlations. Such asymmetries are well researched in the finance literature on asset returns, where they have been ascribed to the leverage effect and the volatility feedback effect (e.g. Wong and Vlaar, 2003 or Cappiello, Engle and Sheppard, 2006). However, these explanations are not necessarily applicable to macroeconomic data, where other mechanisms may be at work. Our results suggest that it may be worth repeating the analysis with the asymmetric version of the generalised DCC model used by the authors mentioned.

Given the very small, very open nature of Luxembourg's economy, a more important direction for future research could be to analyse linkages with foreign output and other variables abroad. In separate work, we analyse links to sectoral value-added in other EU countries, as well as cross-country links between movements in credit and GDP. This may require other tools than those used here, including dynamic factor models or analysis in the frequency domain.

5 References

Afonso, A. and D. Furceri (2009) "Sectoral business cycle synchronization in the European Union," *Economics Bulletin*, 29(4):2996-3014.

Bauwens, L., S. Laurent and J.V.K. Rombouts (2006) "Multivariate GARCH Models: A Survey," *Journal of Applied Econometrics*, 21:79-109.

Bourgain, A., P. Guarda and P. Pieretti (2000) “Dynamique de croissance et specialisation: analyse en panel des branches industrielles,” *Cahiers Economiques de Bruxelles*, 167(3):275-298.

Caporale, T. and B. McKiernan (1998) “The Fischer Black Hypothesis: some time-series evidence,” *Southern Economic Journal*, 64(3):765-771.

Cappiello, L., R.F. Engle and K. Sheppard (2006) “Asymmetric dynamics in the correlations of global equity and bond returns,” *Journal of Financial Econometrics*, 4(4):537-572 (also available as ECB WP 204)

Cheung, Y.-W. and L.K. Ng (1996) “A causality-in-variance test and its application to financial market prices,” *Journal of Econometrics*, 72:33-48.

Constantinou, E., R. Georgiades, A. Kazandjian and G.P. Kouretas (2005) “Mean and variance causality between Cyprus Stock Exchange and major equity markets,” University of Crete Economics Working Paper 501.

Elder, J. (2004a) “Some empirical evidence on the real effects of nominal volatility,” *Journal of Economics and Finance*, 28(1):1-13.

Elder, J. (2004b) “Another perspective on the effects of inflation uncertainty,” *Journal of Money, Credit and Banking*, 28(1):1-13.

Engle, R.F. (1982) “Autoregressive Conditional Heteroskedasticity with estimates of the Variance of UK Inflation,” *Econometrica*, 50:987-1008.

Engle, R.F. (2002) “Dynamic Conditional Correlation: a simple class of multivariate generalised autoregressive conditional heteroskedasticity models,” *Journal of Business & Economic Statistics*, 20(3):339-350.

Engle, R.F. and K. Sheppard (2001) “Theoretical and Empirical Properties of Dynamic Conditional Multivariate GARCH,” NBER WP 8554 (also available as USCD Economics WP).

European Commission (2007) “Joint Research Centre’s Institute for Prospective Technological Studies contribution to the report on guiding principles for product market and sector monitoring,”

Fang, W. and S.M. Miller (2008) “The Great Moderation and the relationship between output growth and its volatility,” *Southern Economic Journal*, 74(3):819-838.

Fang, W. and S.M. Miller (2009) “Modeling the volatility of real GDP growth: the case of Japan revisited,” *Japan and the World Economy*, 21(3):312-324.

Fang, W., S.M. Miller and C. Lee (2009) “Cross-country evidence on output growth volatility: nonstationary variance and GARCH models,” *Japan and the World Economy*, 55(4):509-541.

Fang, W., S.M. Miller and C. Lee (2010) “The Great Moderation and Leptokurtosis after GARCH Adjustment,” *Empirical Economics Letters*, 9(6):627-633.

Fernández-Villaverde, J. and J.F. Rubio-Ramirez (2010) “Macroeconomics and volatility: data, models and estimation,” Centre for Economic Policy Research DP 8169

Fountas, S. and M. Karanasos (2006) “The relationship between economic growth and real uncertainty in the G3,” *Economic Modelling*, 23:638-647.

Fountas, S. and M. Karanasos (2007) “Inflation, output growth, and nominal and real uncertainty: empirical evidence for the G7,” *Journal of International Money and Finance*, 26:229-250.

Fountas, S., M. Karanasos and J. Kim (2006) “Inflation uncertainty, output growth uncertainty and macroeconomic performance,” *Oxford Bulletin of Economics and Statistics*, 68(3):319-343.

Fountas, S., M. Karanasos and A. Mendoza (2004) “Output variability and economic growth: the Japanese case,” *Bulletin of Economic Research*, 56(4):353-363.

Grier, K.B. and M.J. Perry (2000) “The effects of real and nominal uncertainty on inflation and output growth: some GARCH-M evidence,” *Journal of Applied Econometrics*, 15:45-58.

Haas, J., J.-P. Hermes, R. Wiltgen, M. Kafai and V. Elter (2009) “Inventaire des sources et methodes de calcul des comptes nationaux trimestriels du Luxembourg,” Economie et Statistiques, Working Paper 27 du Statec.

Hafner, C.M. and H. Herwartz (2004) “Testing for causality in variance using multivariate GARCH models,” Christian-Albrechts-Univeristät Kiel Economics Working Paper 2004-03.

Hanabusa, K. (2009) “Causality relationship between the price of oil and economic growth in Japan,” *Energy Policy*, 37(5):1953-1957.

Hazari, B.R. (1970) “Empirical identification of key sectors in the Indian economy,” Review of Economics and Statistics, 52(3):301-305.

Henry, O.T. and N. Olekalns (2002) “The effect of recessions on the relationship between output variability and growth,” *Southern Economic Journal*, 68(3):683-692.

Ho, K.Y. and A.K.C. Tsui (2003) “Asymmetric volatility of real GDP: some evidence from Canada, Japan, the United Kingdom and the United States,” *Japan and the World Economy*, 15(4):437-444.

Humavindu, M.N. and J. Stage (2013) “Key sectors of the Namibian economy,” *Journal of Economic Structures*, 2(1):1-15.

Kanas, A. and G.P. Kouretas (2002) "Mean and variance causality between official and parallel currency markets: evidence from four Latin American countries," *The Financial Review*, 37:137-164.

Lee, J. (1999) "The inflation and output variability tradeoff: Evidence from a GARCH model," *Economics Letters*, 62:63-67.

Lee, J. (2002) "The inflation-output variability tradeoff and monetary policy: Evidence from a GARCH model," *Southern Economic Journal*, 69(1):175-188.

Lee, J. (2006) "The comovement between output and prices: Evidence from a dynamic conditional correlation GARCH model," *Economics Letters*, 91:110-116.

Lee, J. and P. Crowley (2005) "Decomposing the co-movement of the business cycle: a time-frequency analysis of growth cycles in the euro area," Bank of Finland DP 12/2005.

Lee, H.-Y., K.S. Lin and J.-L. Wu (2002) "Pitfalls in using Granger causality tests to find an engine of growth," *Applied Economics Letters*, 9:411-414.

Lenzen, M. (2003) "Environmentally important paths, linkages and key sectors in the Australian economy," *Structural Change and Economic Dynamics*, 14:1-34.

Rouabah, A. (2007) "Co-variation des taux de croissance sectoriels au Luxembourg: l'apport des correlations conditionnelles dynamiques," Banque Centrale du Luxembourg WP 25.

Sonis, M. and G.J.D. Hewings (2009) "New developments in input-output analysis," in M. Sonis and G.J.D. Hewings (eds.) **Tool Kits in Regional Science**, Berlin: Springer.

Sonis, M., J.J.M. Guilhoto, G.J.D. Hewings and E.B. Martins (1995) "Linkages, key sectors, and structural change: some new perspectives," *The Developing Economies*, 33(3):233-270.

Wong, A.S.K. and P.J.G. Vlaar (2003) "Modelling time-varying correlations of financial markets," De Nederlandsche Bank Research Memorandum WO&E no. 739.

6 Annex 1: Annual data

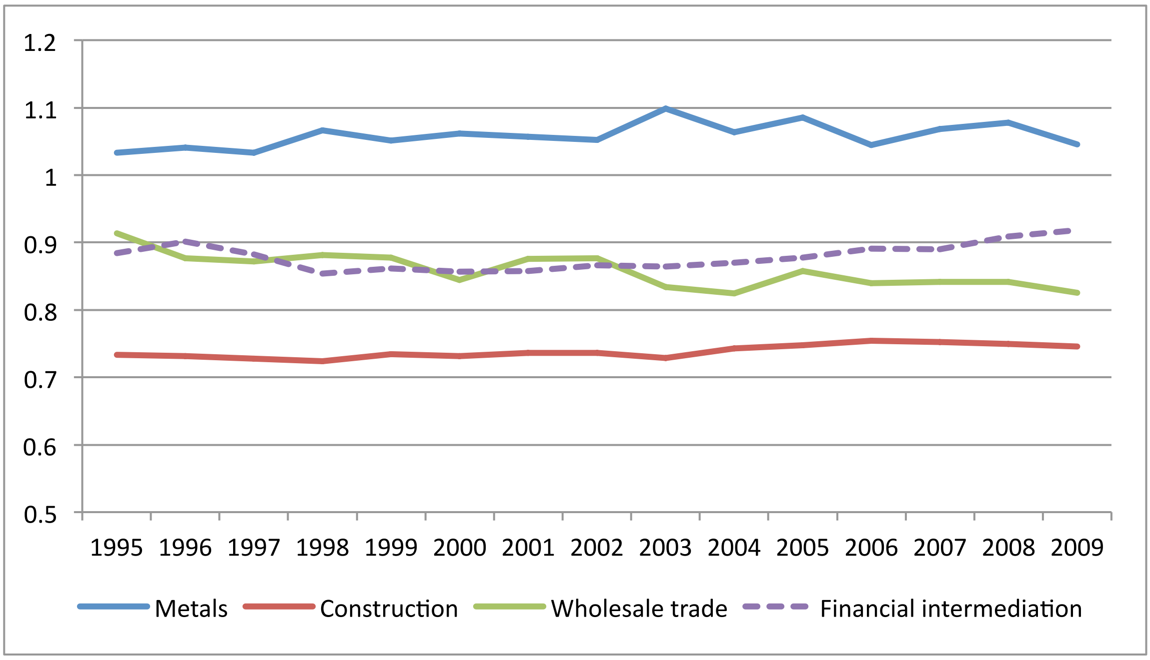
Table A1 below reports standard descriptive statistics of each sector's contribution to real growth in aggregate output from 1996 to 2013. Sector K (Finance and insurance) stands out with the largest average contribution (0.81pp or percentage points) to output growth of the overall economy. This is followed by sector OQ (Public administration) with 0.54pp and sector MN (Professional and scientific services) with 0.47pp. Two other important sectors are GI (Wholesale & retail trade) which contributed 0.45pp and sector J (Information and communications) which contributed 0.43pp. Sector L (Real estate services) contributed 0.30pp and sector F (Construction) only 0.19pp. The average contribution of sector BE (Industry) was only 0.05% and that of sector A (Agriculture) was marginally negative -0.02pp.

Table A1: Sector contributions to aggregate output growth (1996-2013) in pp

	A Agri.	BE Indus.	F Constr.	GI Trade	J Info. & comm.	K Fin. & insur.	L Real estate	MN Prof., scien.	OQ Publ. adm.	RU Arts, other
Mean	-0.02	0.05	0.19	0.45	0.43	0.81	0.30	0.47	0.54	0.04
Median	-0.02	-0.03	0.23	0.58	0.32	0.65	0.25	0.49	0.51	0.04
Max	0.27	1.41	0.66	1.34	1.88	3.12	0.82	1.65	0.89	0.22
Min	-0.35	-1.97	-0.64	-2.05	-0.69	-2.12	-0.12	-0.80	0.11	-0.57
St.dev.	0.14	0.91	0.33	0.78	0.65	1.66	0.29	0.53	0.20	0.16
Skew	-0.19	-0.52	-0.75	-1.89	0.82	-0.34	0.21	-0.17	-0.10	-2.96
Kurtosis	3.20	2.50	3.26	7.04	3.21	1.94	2.05	3.76	2.68	12.04

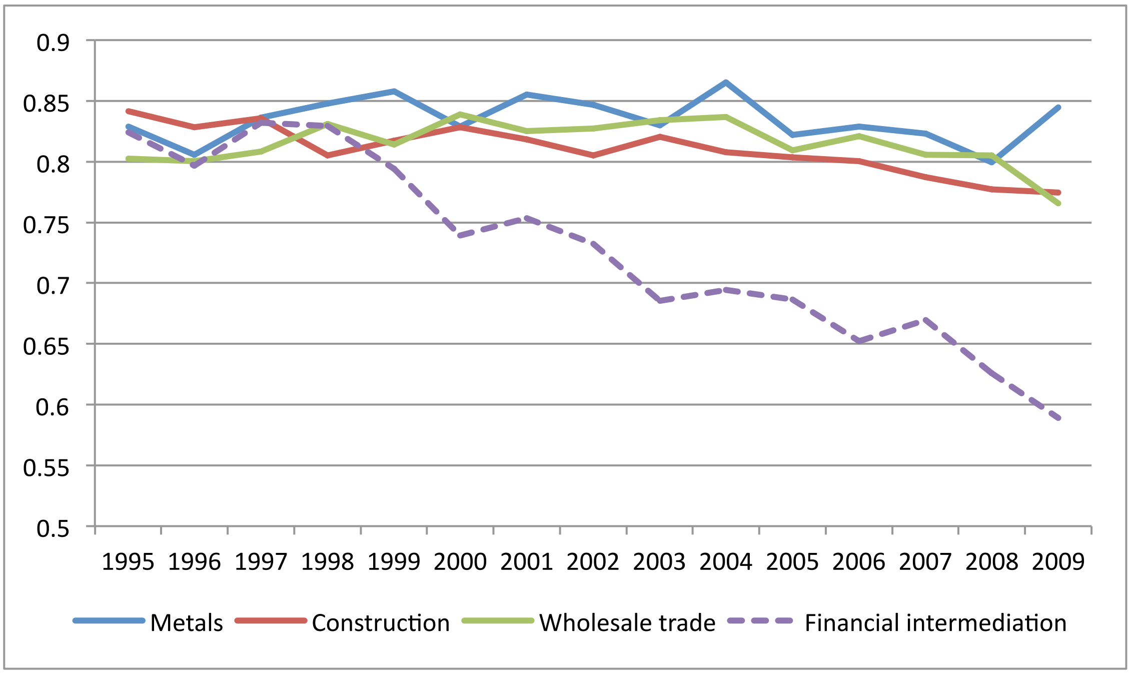
Source: Statec data, own calculations

Figure 8: Key sectors - Backward Linkages variability indices



Source: Statec input-output tables, BCL calculation

Figure 9: Key sectors - Forward Linkages variability indices



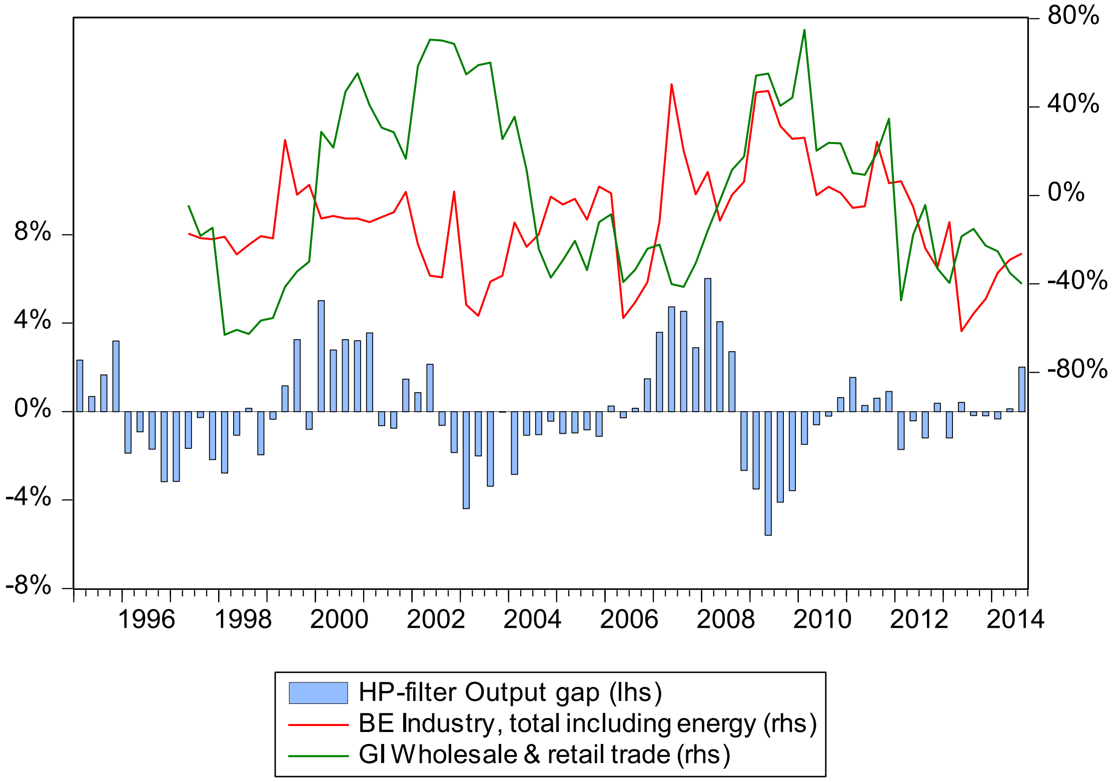
Source: Statec input-output tables, BCL calculation

7 Annex 2: Quarterly data

Figure 10 plots the time-varying conditional correlations between growth innovations in Finance & insurance (K) and growth innovations in two other sectors: Industry (BE) and Wholesale & retail trade (GI). The HP filter estimate of the output gap is plotted as a bar chart (against the left-hand axis) to allow a comparison with a measure of the business cycle. The correlation with Industry (BE) averages only -0.11 over the sample. It is below zero over most of the first half of the sample and swings to positive territory in 2007, peaking at 0.50 in the second quarter. After dipping briefly below zero in 2008, it exceeds 0.50 again during the recession of 2009, returning to zero only in 2010Q2. In 2012 and 2013 it plunged to negative values below -0.4 as the economy began to recover. This is again consistent with the hypothesis that correlation is higher during recessions.

The correlation between sector K and Wholesale & retail trade (GI) averages 0.01 but is much more volatile (standard deviation nearly twice the one of the correlation with Industry).

Figure 10: Bilateral correlations of sector K Finance & insurance



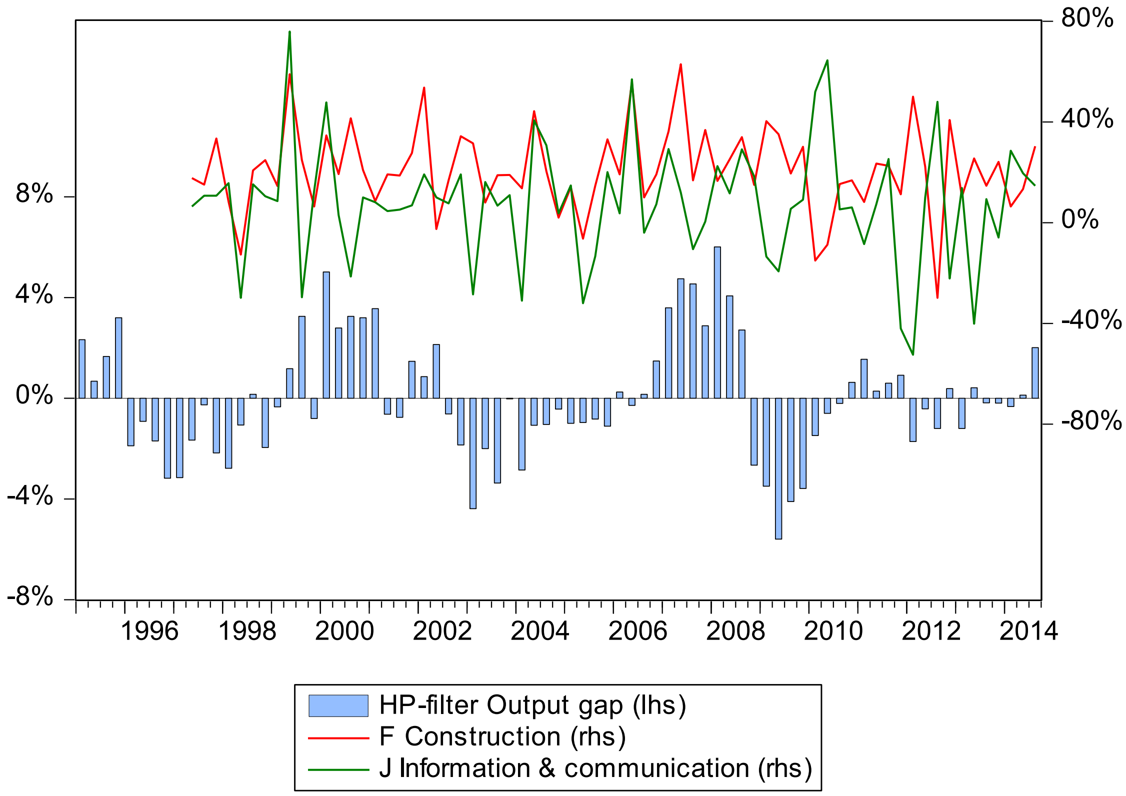
Source: Statec data, own calculations

It turns positive in 2000Q1 and climbs steadily until 2000Q4, peaking above 0.5. After falling in 2001 it spikes upwards in 2002Q1 as the recession takes hold and remains positive until end 2004. When the output gap turns positive in 2007 the correlation remains negative, but then climbs with the euro area crisis to reach a peak above 0.7 in 2010Q1.

Figure 11 plots the time-varying conditional correlations between growth innovations in Finance & insurance (K) and growth innovations in Construction (F) and in Information & communication (J). The correlation with Construction (F) averages 0.21 over the sample and is mostly positive except for isolated quarters early in the sample and for 2010Q1-2010Q2. The correlation exceeds 0.5 in 1999Q2, 2002Q1, 2006Q2 and 2007Q2. Since 2012Q4 it has remained in positive territory.

The correlation between growth innovations in Finance & insurance (K) and in Information & communication (J) averages 0.08 and is more volatile. It is more often negative, but again only for isolated quarters. It also exceeds 0.5 in 1999Q2 and 2006Q2. It turns positive

Figure 11: Bilateral correlations of sector K Finance & insurance



Source: Statec data, own calculations

during 2009Q3-2010Q4 (euro area crisis), with a large positive spike (0.64) in 2010Q2. It was positive in the first three quarters of 2014.

BANQUE CENTRALE DU LUXEMBOURG
EUROSYSTÈME

2, boulevard Royal
L-2983 Luxembourg

Tél.: +352 4774-1
Fax: +352 4774 4910

www.bcl.lu • info@bcl.lu