E C O N O M I C S   B U L L E T I N

Sectoral fluctuations in U.K. firms' investment expenditures

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Abstract

In this paper, employing VAR and factor analytic models with quarterly U.K. sectoral business investment data, we show that both common and sector−specific shocks play important roles in explaining business investment fluctuations.

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1 Introduction

Although business fixed investment is a relatively small component of aggregate output, its fluctuations have long been identified as a major component of aggregate fluctuations and the business cycle. In evaluating the nature of these fluctuations in investment (in particular, the comovement in investment across different sectors of the economy), one can assume that a common disturbance (for instance, monetary policy innovations) may affect investment in all sectors simultaneously.[1] Alternatively, a shock emanating from a particular sector may generate comovements in investment across sectors (possibly due to technological complementarities) which are linked to the perturbed sector.[2]

Given these two strands of literature, our objective is to empirically examine the nature of investment fluctuations in the UK. Particularly, we investigate the extent to which comovements in sectoral investment in the UK are due to aggregate (common) innovations, rather than reflecting the existence of sectoral complementarities. Employing vector autoregressive and factor analytic models, we find that both common and sectoral shocks have important effects in explaining comovements in investment across ten industrial sectors in the UK.[3]

The next section presents the data, the methodology and our basic findings. Section 3 concludes the paper.

2 Empirical analysis

2.1 The data

We use quarterly figures on business fixed investment in 16 industrial sectors obtained from the U.K. Office for National Statistics, in current prices, for 1980Q1–2000Q3. To reduce the number of sectors for systems estimation, we combine a number of industries into ten basic sectors as shown below.

[1]See Summers (1986), Lucas (1987), Cochrane (1994).

[2]See Long and Plosser (1983), Horvath (2000).

[3]Blackley (2000) found similar results using U.S. business fixed investment data.

Concordance of Basic Industrial Sectors

	Basic Sector	*Original Sectors*
1	food	food
2	mining	mining
3	textiles	textiles
4	chemrubber	chemicals, rubber
5	electronics	office machinery, radio and TV
6	transport	motor vehicles, other vehicles
7	metals	metal manufacturing, other manufacturing
8	paperpub	paper and publishing
9	utilities	electric utilities, gas and water utilities
10	constr	construction

The business fixed investment series for each sector is deflated, seasonally adjusted, and expressed in first differences of logarithms. Descriptive statistics for these stationary growth rate series,[4] presented in Table I, show that sectoral capital investment spending rates varied widely over the period.

2.2 Empirical findings

Following the previous empirical studies, we use a three–step procedure to investigate the nature of comovements in investment across different sectors in the UK economy. We first examine, in Table II, the contemporaneous correlation of growth in investment expenditures for ten basic sectors. For any sector, lack of significant correlation of its investment spending with that of other sectors may be considered as evidence against comovement of investment rates across sectors. We observe that most sectors only display one or two significant inter–sectoral correlations. However, since the absence of such correlations is not sufficient to rule out common shocks, we next examine the correlations among investment innovations, measured as the residuals from a vector autoregressive (VAR) model,

$$I_{it} = \alpha_i + \sum_{i=1}^{10} \sum_{j=1}^{4} \beta_{ij} I_{i,t-j} + e_{it}, \tag{1}$$

where I_{it} denotes investment for sector i at time t and j denotes the number of lags in our system of equations. We retrieve the residuals from the VAR model (the innovations in sectoral investment growth) and compute

[4]There were no rejections of the KPSS test's null hypothesis of stationarity (Kwiatkowski et al., 1992) at any reasonable level of significance.

their correlations. These correlations, presented in Table III, include non-contemporaneous linkages between sectors' investment growth rates arising from input–output relationships (for instance, the need for additional investment in "upstream" sectors to match an expanded level of production in "downstream" sectors).

Comparing the correlations in Table III with those in Table II, the observed differences provide evidence against the role of common shocks in explaining comovements in investment across sectors. Note that seven of the ten significant correlations in Table II are repeated in Table III, and three additional linkages emerge in the latter table.

2.2.1 Factor analysis of innovations to sectoral investment growth

Next, we combine the innovation series, e_{ij}, from equation (1), in a factor–analytic model. The existence of one or more factors that explain a significant part of the variation in innovations would suggest that a common shock is likely to have an important role in the comovements of sectoral investment. Conversely, if such factors explaining variations in innovations do not exist, this would constitute *indirect* evidence for the existence of *complementarities* in explaining sectoral comovements that are separate from the role of common shocks. Estimating a factor model from the ten sectoral innovations series via maximum likelihood, we find that two factors play an important role.

The results of the analysis are displayed in Table IV. The first column contains the R^2 from each equation in the VAR used to generate the innovations. The unweighted mean R^2 is 0.55. The second column represents the R^2 from the regression of each innovation series on the two common factors. All F statistics corresponding to these auxiliary regressions are highly significant. On average, the two common factors explain 32% of the variation in the innovation series, with very weak effects in the mining and electronics sector, but very strong effects in the metals and utilities sectors. Apart from the latter sectors, these results suggest that sectoral shocks appear to have greater impact in explaining the variations in innovations to growth in investment. In contrast, for the metals and utilities sectors, common shocks appear to play the major role in explaining variations in innovations.

We also evaluate the overall effectiveness of the VAR and factor–analytic model by adding the shares of variation explained by the two models: the raw R^2 of the VAR model (as shown in column 1 of the table) plus R^2_{FA} per cent of that variation left unexplained by the VAR: $(1 - R^2)$. This measure of overall effectiveness, labelled "VAR–FA Share" in Table IV, should be contrasted with the VAR R^2 in the first column; the increase represents the value added of the factor model. Overall, the mean fraction of variation explained rises from 0.55 for the VAR alone to 0.70 for the VAR–plus–factor model. This masks a number of sectors with much greater improvement: metals and utilities, where the additional explanatory power of the factor model is sizable, with a total 99% of the variation explained for metals, and 100% for the utilities sector. In sum, the results indicate that both sectoral shocks and common shocks are important in explaining investment fluctuations.

2.2.2 The effects of aggregate demand

Several authors have used an accelerator model to explain a positive impact of growth on sectoral investment.[5] Therefore, we augment our VAR framework with lagged aggregate output growth, and test for its significance:

$$I_{it} = \alpha_i + \sum_{i=1}^{10} \sum_{j=1}^{4} \beta_{ij} I_{i,t-j} + \gamma_i AD_{t-1} + u_{it}, \tag{2}$$

where AD_{t-1} is the year–over–year growth rate of real aggregate demand and u_{it} denote the residual series for each sector. We present our observations in Table V. On average, the VAR inclusive of real GDP growth explains 57% of the variation in sectoral investment growth—a slight increase—with sizable effects in the mining, textile and metals sectors. A joint test for the significance of real GDP growth in the VAR decisively rejects the null hypothesis of zero effects.

The fraction of innovation variance explained by the factor model, in the third column of Table V, shows a mean R^2 of 0.31. Although the mean FA R^2 is similar to that of Table IV, common shocks have greater explanatory power of innovation variance for the utilities and chemical/rubber sectors. For other sectors, the fraction explained by the factor model declines, since a greater fraction of the total variation is now explained by the VAR. Altogether, the overall explanatory power of the VAR–plus–factor model modestly increases to 0.71. It is evident that the effects of real GDP growth are quantitatively unimportant compared to the effects represented by the two common factors.

3 Conclusions

In this paper, using VARs and factor analytic methods, we demonstrate that both common and sector–specific innovations play a role in the observed comovement of sectoral business investment spending in the U.K. over the

[5] Aggregate demand growth could capture investment lags experienced due to irreversibility or "time–to–build" of the investment process (e.g. Christiano and Todd (1996)).

period 1980–2000. As Long and Plosser (1987) point out, a factor model attributes all comovements to common factors, which are interpreted as the effects of aggregate shocks. It is possible that these comovements could be driven by sectoral shocks that happen to be correlated because of the existence of complementarities. Hence, our results should be interpreted as an upper bound of the explanatory power of common shocks.

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Table I.
Descriptive statistics for U.K. sectoral investment growth rates, % per annum

	mean	std.dev.	median	IQR
food	-0.198	31.655	-3.695	46.184
mining	-2.214	95.522	4.334	137.864
textile	-3.866	69.725	-2.405	71.794
chemrubber	-0.729	45.839	-5.734	49.802
electronics	1.197	72.368	-5.018	79.064
transport	-1.342	61.291	-1.348	78.930
metals	-1.445	32.317	2.300	47.322
paperpub	1.715	54.829	1.199	82.142
utilities	1.100	45.480	-3.857	57.470
construction	-4.043	67.383	-10.905	81.267
real GDP	2.228	2.826	2.502	3.554

Notes: Data series for the ten sectors are deflated, seasonally adjusted, and expressed in the first differences of logarithms. IQR is the inter–quartile range of the series.

Table II.

Correlations of sectoral investment rates

	food	min	tex	chem	elec	trpt	met	ppub	util	const
food	1.00									
min	0.26*	1.00								
tex	0.21	0.13	1.00							
chem	0.05	0.13	-0.09	1.00						
elec	0.24*	0.23*	0.01	0.10	1.00					
trpt	0.17	0.15	0.03	0.31*	0.16	1.00				
met	0.22*	0.06	0.22*	0.25*	0.19	0.11	1.00			
ppub	0.02	0.06	0.14	-0.12	0.15	-0.05	0.14	1.00		
util	0.01	-0.04	-0.19	0.15	0.02	0.24*	0.07	-0.23*	1.00	
const	0.09	-0.01	0.31*	-0.09	-0.07	-0.01	0.21	0.12	-0.21	1.00

Note: * denote significance at 5%.

Table III.

Correlations of innovations to sectoral investment rates

	food	min	tex	chem	elec	trpt	met	ppub	util	const
food	1.00									
min	0.27*	1.00								
tex	0.19	0.06	1.00							
chem	0.26	0.15	0.07	1.00						
elec	0.17*	0.11	0.03	0.14	1.00					
trpt	0.19	0.16	-0.02	0.16	0.10	1.00				
met	0.26*	0.14	0.32*	0.43*	0.17	0.25*	1.00			
ppub	0.07	0.13	-0.01	0.13	0.41*	0.04	0.20	1.00		
util	-0.04	-0.20	-0.12	0.12	0.03	0.27*	0.17	-0.21	1.00	
const	0.11	-0.02	0.26*	0.05	0.02	0.00	0.43*	0.14	-0.13	1.00

Note: * denote significance at 5%.

Table IV.
Common factor analysis of sectoral investment rates

	VAR R^2	FA R^2	VAR-FA Share
food	0.608	0.121	0.655
mining	0.609	0.091	0.645
textile	0.470	0.166	0.558
chemrubber	0.585	0.241	0.685
electronics	0.483	0.052	0.510
transport	0.662	0.134	0.707
metals	0.519	0.976	0.989
paperpub	0.477	0.126	0.542
utilities	0.515	1.000	1.000
construction	0.591	0.278	0.704
Mean	0.552	0.318	0.699

Table V.
Common factor analysis of sectoral investment rates,
augmented by aggregate demand

	VAR R^2	GDP_{t-1}	FA R^2	VAR-FA Share
food	0.608	-0.634	0.149	0.667
mining	0.648	15.326**	0.056	0.667
textile	0.508	11.082*	0.118	0.566
chemrubber	0.586	0.520	0.265	0.695
electronics	0.485	-2.594	0.070	0.521
transport	0.675	5.842	0.112	0.712
metals	0.576	6.344**	0.975	0.990
paperpub	0.502	7.184	0.094	0.549
utilities	0.515	-0.671	1.000	1.000
construction	0.592	2.105	0.294	0.712
Mean	0.570		0.313	0.708

Note: * (**) denotes significance at 10% (5%).