The Business Cycle, Macroeconomic Shocks and the Cross Section: The Growth of UK Quoted Companies*

C. Higson[a], S. Holly[b], P. Kattuman[b] and S. Platis[c]
[a]London Business School, [b]Cambridge University, [c]KPMG

October 2001

Abstract

In this paper we bring to light a significant aspect of firm level heterogeneity over the business cycle. We analyse the responsiveness of firm growth (quoted UK companies, over the thirty year period to 1997) to aggregate shocks, conditioning on firm size, age and industry. We find that the effects of aggregate shocks, positive and negative, are more pronounced for firms in the middle range of growth. We show that, the higher moments of the distribution of firm growth rates are significantly counter cyclical, and that this follows from the fact that rapidly growing and rapidly declining firms are less senstive to aggregate shocks than firms in the interior of the growth range. These findings are of importance in understanding firm level as well as business cycle dynamics.

JEL Classification: E32, D21, D92

Keywords: business cycles, cross sectional moments, firm growth.

*This work was supported by the Leverhulme Trust. Comments from Peter Hart, from Melvyn Weeks and other colleagues at Cambridge, and from participants at CAED'01 conference and seminars at the Universities of York and Swansea are gratefully acknowledged. Correspondence: P.Kattuman, Tel: 44-1223-335259, Fax: 44-1223-335299, EMail: Paul.Kattuman@econ.cam.ac.uk

1 Introduction

The focus in business cycle research over most of the last century has been on movements and co-movements in aggregates at the national and international level[1]. More recently, aided by the availability of disaggregated, longitudinal micro data, increasing attention has been paid to the role of micro economic adjustment behaviour (of individual households and firms) in the dynamics of the aggregate economy. It has been powerfully argued that a proper understanding of business cycles requires knowledge of the evolution of cross sectional distributions of individual behaviour.[2] Besides, the impact of aggregate shocks on firms is of direct interest once it is recognised that not all firms respond to aggregate shocks equally.[3]

Our objective is to add to the body of stylised empirical facts on the cross sectional dynamics of business cycles. What type of firms are most susceptible to recessions (and recoveries)? Are they, for example, the small or the young? This is of central interest to industrial economists concerned with growth and performance of firms.[4] A clear answer should help in formulating policy to assist firm growth. At the same time, it should help in the design of policies to reduce the amplitude of the business cycle. Thus our analysis is also addressed to macro-economists.

[1]For a recent analysis of 130 years of UK aggregate business cycles see Chadha et al (2000).

[2]A modelling approach pioneered by Caballero and Engel (1992, 1993) and Caballero, Engel and Haltiwanger (1997) allows for heterogeneous agents that adjust 'lumpily' to shocks. Aggregated, this micro behaviour generates rich, aggregate dynamics that depend upon the cross sectional distribution. For a recent application of this approach to understanding the aggregate dynamics of inventories from a study of firm level behaviour see McCarthy and Zakrajsek (1998). For a review of the discussion on the impact of the cross sectional distribution of microeconomic actions on macroeconomic fluctuations, see Haltiwanger (1997).

[3]See for example, Caballero, Engel and Haltiwanger (1997) and Geroski and Gregg (1997).

[4]There is a literature in Industrial Economics on the cyclical nature of firm performance. Close in focus to our concerns is the work of Goudie and Meeks (1991) and of Geroski and Gregg (1997) who concentrated substantially on determining what types of firms were susceptible to recessionary pressures. Boeri (1995) examined the cyclical sensitivity of growth of firms in Germany. Related work by Audretsch (1994) and Mata (1997) examined the importance of macro economic fluctuations on start ups. There is also a rich vein of work on the cyclical nature of profitability, see Geroski and Machin (1993), Bhaskar, Machin and Reid (1993), Machin and Van-Reenen (1993) and Geroski, Machin and Walters (1997).

This paper brings to light distinctive and significant patterns in the heterogeneous growth responses of firms to external shocks. In the next section we introduce a framework to highlight the issue and organise our findings. We consider two hypotheses. The first focuses on the role played by features of firms in their growth. In industrial economics the relationship between, on the one hand the size of the firm (and its age and sector), and on the other its growth rate, has been the focus of a much empirical research. Can changes in the growth impacts (and distributions) of these firm level features explain the time series patterns of the growth rates cross section? The second hypothesis relates to the possibility that the growth responses of firms may be differentiated, not so much according to firm characteristics, but according to firm growth itself.

In section 3 we provide an initial characterisation of the cross sections of growth rates of UK quoted firms. Our empirical analysis is based on a data set of UK listed company accounts from 1968 to 1997 comprising more than 31,000 company years. We find that there is a characteristic business cycle pattern to the dynamics of the cross section. In particular, some higher moments of the cross section (variance and skewness) are counter-cyclical (while kurtosis is pro-cyclical). We analyse these patterns in Section 4 by setting out operational versions of the hypotheses set out in section 2 and bringing them to data. We conclude that there is little evidence in favour of the first hypothesis. In section 5 we explore the second hypothesis in more detail by investigating the impact of aggregate shocks, differentiating firms according to the percentiles of growth rates. We find that the (cyclical) aggregate shocks have a stronger impact on the central mass of the distribution and a weaker effect on the tails. Section 6 concludes.

2 Shocks, Growth Responses and Moments of the Cross Section: A Framework

In this section we develop a framework to discuss the issues we are concerned with. Consider a set of firms producing output according to some production function. Consider a population of firms with the ith firm producing output according to some standard production function:

$$y_{it} = f_t(A_{it}, K_{it}, L_{it}) \tag{1}$$

with y the output/sales, A the level of technical efficiency, and K and L inputs of capital and labour. We assume that production takes place in a stochastic environment, and each firm is subjected to a variety of shocks, real and nominal: idiosyncratic, industry specific and economy wide. The total shock experienced in period t by the ith firm is:

$$\epsilon_{it} = \varepsilon_{it} + \zeta_{jt} + \eta_t \tag{2}$$

with ε_{it} the firm specific shock, ζ_{jt} the jth industry shock and η_t the economy wide disturbance. The observed growth rate of any individual firm can be conceived in terms of firm specific responses to shocks:[5]

$$g_{it} = \iota_{it}\varepsilon_{it} + \kappa_{it}\zeta_{jt} + \lambda_{it}\eta_t \tag{3}$$

For the ith firm, in period t, λ_{it} is its response to the growth of the aggregate economy, κ_{it}, its response to the growth of the industry, and finally, ι_{it} its response to shocks unique to the firm.

Our primary interest is in characterising and explaining the cycle related patterns in the time series of the cross sectional distribution of growth rates (denote this by $h_t(g)$). While idiosyncratic and industry specific shocks are not likely to have cyclical patterns, aggregate shocks constitute the business cycle. Therefore the obvious area to seek explanation for cycle related patterns in $h_t(g)$ is the heterogeneity of responses of firms to aggregate shocks. To this end, the key point from (3) above is that aggregate shocks may have different impacts on different firms, as captured by the λ_{it}.[6]

There are two obvious ways in which firm specific responses to shocks could be characterised. Aggregate shocks may modify the relationship between the growth of the firm and its characteristics systematically, in ways that depend on whether the shock is positive or negative. For example, it may be that large firms grow faster than small firms in recoveries. Systematic cycle phase related changes such as these may drive the cross sectional distribution of growth rates over time.

[5] Caballero, Engel, Haltiwanger (1997) and Foster and Haltiwanger (2000) suggest that adjustment in employment may be driven by non-convexities and irreversibilities and be either large or nil. This feature of lumpy adjustment is not as much of a feature in growth of sales.

[6] See also Abadir and Talmain (2000). λ_{it} can be thought akin to the β of the corporate finance literature.

Another possibility is that the growth response of any firm to an aggregate shock depends on its relative position in the entire range of firm growth rates. For example, negative aggregate shocks may not affect firms that have registered positive growth as severely as it does firms that grew moderately. Likewise, firms at the extreme negative end of the growth range may face limits to their decline, and if they survive, and may sustain better, if not actually improve, their growth performance despite a negative aggregate shock.[7] In summary, firms at the extreme ends of performance may respond less to aggregate shocks, both positive and negative, relative to firms in the middle range of growth. These mid growth firms may prove to be the most susceptible to the changes in macro economic conditions. The implications of these response patterns for the growth rate cross section can be set out in formal terms.

In formal terms: denote variables relevant to the growth rate of the firm by $\mathbf{Z_t}$ (a key element of which is firm size, s_t), and the probability distribution of growth rates conditional on $\mathbf{Z_t}$ by $h_t(g|\mathbf{Z_t})$.[8] If the way firm growth rates, g_{it}, depend on firm specific features is represented by $f_t(\mathbf{Z_t})$, observed growth rates of firms are given by $E[f_t(\mathbf{Z_t})]+\boldsymbol{\nu}_\mathbf{t}$ where $\boldsymbol{\nu}_\mathbf{t}$ is that portion of the growth rate than cannot be ascribed to any systematic firm specific influence. By examining changes over time in $\hat{f}_t(\mathbf{Z_t})$ we can draw inferences on whether, for example, small firms grow faster relative to large, in recoveries and large firms contract less relative to small, in recessions. But is the growth rate distribution driven by aggregate shocks changing the growth relationship? If so, distributional features of the systematic growth component, $\hat{f}_t(\mathbf{Z_t})$, will dominate $h_t(g)$. If on the other hand, the influence of aggregate shocks on the growth of firms is independent of these firm level determinants we would expect the distribution of $\boldsymbol{\nu}_\mathbf{t}$ to dominate $h_t(g)$.

In this latter case, our second hypothesis (that the magnitude of firm growth response to an aggregate shock (λ_{it}) depends on the relative position of the firm in the growth range, and independent of its other characteristics)

[7]Likewise, with an positive aggregate shock, firms that have registered extreme negative growth may barely turn around to positive growth, while firms that have grown very strongly may find themselves overstretched and limited in further growth.

[8]This may pertain to surviving firms or may include entering and exiting firms. In the latter case, it would be convenient to define the growth rate as $(s_{it}-s_{it-1})/[(s_{it}+s_{it-1})/2]$. This definition of growth rate has the advantage of symmetry in expansion and contraction as well as in entry (growth rate of 200% and exit, growth rate of -200%). Continuous growth rates lie in the interval $[-100\%, \infty]$.

can be framed as follows. With the firms ordered in ascending order of growth rates, denote the magnitude of response to aggregate shock by $\lambda_{(i)}$, the parantheses around the subscript i signifying the new ordering.[9] The hypothesis can be stated in terms of how $\lambda_{(i)}$ varies with the ordered i. If the mass of firms in the interior of the range of growth rates sway more according to the general economic climate than firms at either extreme end, $\lambda_{(i)}$ will have an inverted u shape with respect to i, increasing monotonically up to some i in the interior of the growth range, and declining monotonically thereafter. Such a "well behaved" and inverted u-shaped $\lambda_{(i)}$ function is consistent with countercyclical skew in the growth rate distribution.

The hypothesis about the shape of the $\lambda_{(i)}$ function can be refined. If the $\lambda_{(i)}$ function is well behaved in the above sense, and if the peak is reached for a firm at a lower position in the growth rate range than the mean growth rate, the dispersion of the cross section of growth rates will be countercyclical. In this case a positive aggregate shock will drive firms with lower than mean growth rate towards the mean, while firms with relatively higher growth rates will not respond as much to the shock. The dispersion of the growth rate cross section will decline (and the kurtosis increase) as the economy expands. Likewise in a contraction, firms with lower than mean growth will decline further away from the mean, while firms with relatively higher growth will not regress towards the mean as much. Dispersion will increase (and kurtosis decline) with negative aggregate shocks. In summary, if the $\lambda_{(i)}$ is well behaved and peaks before the mean growth rate, the dispersion of growth rates will be countercyclical, and the kurtosis cyclical; if it peaks after the mean growth rate, dispersion will be cyclical and kurtosis countercyclical.

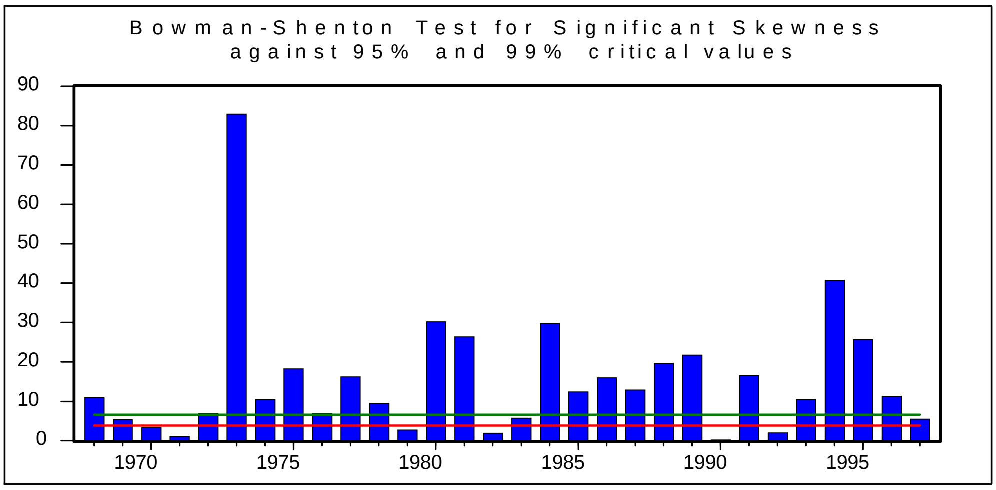
3 A First Look at Evidence

In this section we describe the central features of the cross sections of real annual growth rates of sales of UK firms between 1968 and 1997. In Table 1 we report the moments of each years cross section using continuous growth rates and the total number of firms in each year.[10] In Figure 1 we plot the Bowman-Shenton test for significant skewness against the $\chi^2(1)$ 95% critical

[9] We add structure in empirical work by restricting this response to be time invariant.

[10] m_r is the rth central moment, m is the median, $BS^1$is the Bowman-Shenton omnibus test for normality, distributed as $\chi^2(2)$, and BS^2 is a $\chi^2(1)$ test for skewness. p is the probability for the omnibus test statistic.

Figure 1:



value of 3.84. What is noticeable is that periods of significant skewness are associated with periods of particular macroeconomic variation or turbulence, such as the boom of 1973, the sharp downturn after the oil price shock in 1975, the recession of 1980-81, and 1991 and so on. To explore this further in Figure 2 we plot each of the moments reported in Table 1 against the rate of growth of aggregate UK GDP. To exclude outliers we truncate the sample and the results reported are based on growth rates lying between ±25 percent[11]. The Mean (m_1) and median (m) of the cross sections track the aggregate quite closely while skewness appears to be counter-cyclical and kurtosis pro-cyclical. For much of the sample there appears to be an upward trend in dispersion. Regressions of the moments on GDP in Table 2 confirms the visual impression. The central moments are well accounted for by current and lagged rates of change of GDP, while dispersion and skewness are negatively related to the business cycle. Increasing dispersion of firm performance during recessions suggests that firms may be differentially affected by aggregate shocks.

[11] We have replicated the analysis with cutoff points at ±50%, ±75%, ±100% and ±150%, as well as cutoff points based on mean±k*Std Dev, with k taking values between 1 and 2. The patterns in the results we report are robust across all these experiments.

Table 1: Summary statistics - Growth rates of real sales: 1968-97

Year	m_1	m	m_2	m_3	m_4	BS^1	BS^2	n
1968	3.67	3.80	9.18	-0.239	2.95	11.02	10.91	1145
1969	2.16	2.48	9.69	-0.148	2.84	6.89	5.36	1474
1970	2.12	2.12	9.84	-0.125	2.96	3.35	3.25	1244
1971	0.84	0.83	10.09	-0.076	2.78	3.30	1.10	1137
1972	2.11	2.34	10.14	-0.194	2.74	9.90	6.85	1087
1973	8.56	9.69	9.72	-0.683	3.35	88.54	82.95	1067
1974	2.95	3.62	10.42	-0.235	2.63	16.93	10.44	1131
1975	-4.91	-5.86	10.91	0.323	2.53	27.97	18.29	1051
1976	1.68	2.50	10.75	-0.195	2.54	16.31	6.84	1082
1977	3.40	3.73	10.47	-0.298	2.71	20.15	16.23	1094
1978	1.83	2.29	10.04	-0.229	2.82	10.84	9.44	1077
1979	-0.19	-0.68	9.73	0.120	2.84	3.85	2.69	1118
1980	-5.54	-6.30	10.43	0.409	2.82	31.73	30.21	1085
1981	-5.45	-6.19	10.89	0.401	2.62	32.21	26.39	984
1982	-0.31	0.08	10.64	-0.104	2.57	10.17	1.94	1083
1983	2.16	2.45	10.62	-0.180	2.64	11.46	5.74	1066
1984	5.30	5.83	9.97	-0.425	2.96	29.85	29.77	991
1985	3.45	3.82	10.43	-0.270	2.76	14.78	12.41	1019
1986	4.41	4.90	10.68	-0.320	2.67	20.21	15.99	939
1987	4.14	4.51	10.94	-0.290	2.64	18.00	12.89	921
1988	5.85	6.16	10.63	-0.366	2.72	22.54	19.64	879
1989	5.00	5.58	11.06	-0.373	2.63	27.16	21.77	940
1990	1.19	1.02	11.27	-0.036	2.41	15.26	0.22	1024
1991	-3.53	-4.58	11.73	0.316	2.39	32.03	16.52	990
1992	-1.49	-1.77	10.65	0.110	2.50	12.26	1.97	970
1993	2.16	2.83	10.62	-0.255	2.61	16.53	10.46	967
1994	5.17	5.87	10.62	-0.504	3.01	40.72	40.71	960
1995	5.16	5.63	10.42	-0.394	2.83	26.89	25.64	992
1996	3.89	4.25	10.45	-0.261	2.75	13.82	11.21	986
1997	3.00	3.29	11.15	-0.183	2.57	13.13	5.46	979

Note: m_r is the rth central moment, m, the median, BS^1,the Bowman-Shenton $\chi^2(2)$ omnibus test for normality and BS^2 a $\chi^2(1)$ test for skewness = 0.

3.1 Non-Parametric Analysis

Figure 3 is a three-dimensional plot of the kernel densities fitted to each cross section of continuous growth rates. The density estimates were generated with a gaussian kernel and an automatic bandwidth[12], with the density evaluated at 100 equi-distant points in the common range of the cross sections. The same kernels are plotted as a contour map in figure 4. These non-parametric estimates of the cross sectional distributions should be regarded as largely impressionistic. Nevertheless, they do suggest some interesting features of the evolution of cross sectional growth rates in the 30 year period from 1968 to 1997. Because the average or mean growth rate of the U.K. economy has been positive over the sample period, the mass of the distribution alwyas lies to the right of zero. There is considerable dispersion in performance with many firms experiencing negative growth even when the economy is booming, suggesting churning at the sectoral and firm level. The central mass also moves with the aggregate growth rate of the macroeconomy. What is striking is that these fluctuations in the mean are associated with changes in the asymmetry in the distribution. Note the accumulation of firms in the poor growth end during the recessions of 1975, 1981 and 1991. These cycle related contortions of the distribution show up clearly in the contour map of figure 4. This picture suggests that there are significant deviations from normality and that these deviations are associated with the aggregate business cycle.

4 Systematic and Stochastic Growth Components over the Cycle

We now turn to an operational version of the framework set out in section 2. A useful benchmark is the simplest approach to the cross sectional growth-size relationship, a first order Galton-Markov model (which generalises the Gibrat model) to allow past size to influence current size:

$$z_{it} = \beta_t z_{it-1} + u_{it} \tag{4}$$

[12]The bandwidth is data based, following Silverman (1986). See Cosh, Hughes, Lee and Pudney (1998) for an application of non-parametric and semi-parametric methods to analyse corporate growth in the UK.

Table 2: Regression of firm growth rate cross section moments on GDP growth

	Mean	Median	SD	Skewness	Kurtosis
constant	-1.5753	-1.8674	49.8787	0.083	1.6995
	-3.04	-3.04	2.67	1.86	2.89
moment_{t-1}	0.2039	0.1421	0.6644	0.2169	0.3894
	1.18	0.83	2.93	1.22	1.7
moment_{t-2}	-0.1668	-0.1734	-0.0838	-0.2585	-0.0576
	-1.62	-1.67	-0.45	-2.36	-0.33
$\Delta\ln(gdp_t)$	1.054	1.1927	-1.7389	-0.0798	0.0532
	7.8	7.32	-2.42	-6.54	3.3
$\Delta\ln(gdp_{t-1})$	0.4929	0.6299	0.5628	-0.0309	-0.0029
	1.97	2.19	0.68	-1.53	-0.14
Adjusted R^2	0.832	0.812	0.387	0.774	0.425
LM(2)	3.85	3.409	3.031	2.591	3.693

Method: Least Squares

Sample(adjusted): 1970 1997

where z_{it} is the deviation of the log of size of firm i at time t from the mean of the logs of sizes of firms at time t, β_t is the size growth coefficient and u_{it} is the disturbance. Gibrat's law holds if β_t is unity. A value of β_t less than 1 would suggest regression towards the mean with small firms, on average, growing faster than large. A value of β_t greater than 1 would suggest that large firms, on average, grow faster than small.[13] We augment (4) with the other crucial growth determinants, such as firm age (y_{it}), as well as an industry dummy ($I_{i.}$),[14] and write the growth equation, for each period, t, as :

$$g_{it} = z_{it} - z_{it-1} = \alpha_t + (\beta_t - 1)z_{it-1} + \gamma_t y_{it} + \delta_t I_{i.} + u_{it} \tag{5}$$

[13]See Hart and Oulton (2001) who estimate a time series of size coefficients in a comprehensive empirical exercise testing Gibrat's law. This branch of literature started in the 1950s and has generally found violations of the law, though it is often used as a first approximation. See Dunne and Hughes (1994) and Sutton (1997) for reviews.

[14]Firms change their sectors very rarely, and in our data, not at all. Thus the Industry variable is devoid of time dimension.

The constant captures the linear shared effect of aggregate shocks, while the industry dummies capture the linear effects of industry wide shocks shared by firms within the industry. β_t and γ_t capture the systematic component of growth responses to shocks that depend on size and age. As usual, the residual u_{it} stands for that component of growth that cannot be accounted for by observable firm or industry level characteristics. If there is no significant serial correlation[15], and if u_{it} is independent of z_{it-1}, y_{it} and $I_{i.}$, then the variance of growth rates evolves, in each period, according to:

$$\begin{aligned} V(g_{it}) &= (\beta_t - 1)^2 V(z_{it-1}) + \gamma_t^2 V(y_{it}) \\ &\quad +2(\beta_t - 1)(\gamma_t) Cov(z_{it-1}, y_{it}) + \kappa + V(\epsilon_{it}) \end{aligned} \tag{6}$$

where κ is the variance and covariance terms involving the industry indicator variables.[16]

The third central moment, which measures skewness evolves as:

$$\begin{aligned} E(g_{it} - \bar{g_{it}})^3 &= (\beta_t - 1)^3 E(z_{it-1} - \bar{z}_{it-1})^3 + \gamma_t^3 E(y_{it} - \bar{y}_{it})^3 \\ &\quad +\delta_t{}^3 E(I_{i.} - \bar{I}_{i.}) + E(\epsilon_{it} - \bar{\epsilon}_{it})^3 \end{aligned} \tag{7}$$

It is easy to see that the coefficient of skewness, (7) normalised by the standard deviation to be dimensionless, evolves as:

$$\begin{aligned} Sk(g_{it}) &= [(\beta_t - 1)^3 Sk(z_{it-1})\sigma(z_{it-1})^3 + \gamma_t^3 Sk(y_{it})\sigma(y_{it})^3 \\ &\quad +Sk(I_i)\sigma(I_i)^3 + Sk(\epsilon_{it})\sigma(\epsilon_{it})^3] \frac{1}{\sigma(g_{it})^3} \end{aligned} \tag{8}$$

These decompositions, when applied to the series of estimated cross section models, tell us what proportions of growth rate moments are explained by firm characteristics (their distributions and growth impacts). In (6) and (7), the terms on the rhs excluding the last one capture aspects of the systematic mechanism that work upon the dispersion of growth rates: the growth

[15] Demeaning will have taken out any serial correlation at business cycle frequencies.

[16]

$$\kappa = (\delta_t)^2 V(I_{i.}) + (\delta_t)(\beta_t - 1) Cov(I_{i.}, z_{it-1}) + (\delta_t)(\gamma_t) Cov(I_{i.}, y_{it})$$

coefficients of size, age, and industry, and the variances of firm sizes, firm ages, and industry indicator variables and the covariances among them. If these terms together account for only a small part of the lhs, the time series patterns in growth moments must be accounted for by non-linearity and time variation in the cross-correlation of residual component of growth, i.e., the component that is unrelated to ex-ante observed firm characteristics.

We estimate the Galton process in (5) by OLS for successive pairs of years using data on firms that survive from one year to the next.[17] The decompositions of the higher moments of the growth rate distributions given by (6) and (8) are reported in Table 3 and Table 4. The main feature that stands out is that the contribution of the moments of the residual component in growth, given in the final columns in the two tables, dominate the growth rate moments in all years.

We can draw out some implications. To start with, take the upward drift of the cross sectional dispersion of growth rates. It is clear that the variance of the purely idiosyncratic residual term accounts for nearly all the variance of growth rates. It is this that has driven the increasing in variance of growth rates. Empirical studies of firm growth have established that growth rates of firms cannot be predicted well by size or age, or indeed, other explanatory factors. What this suggests is that the degree of unpredictability, of volatility in the growth rates of firms, has increased over time.

Moving to the countercyclicality of the higher moments, Tables 3 and 4 show that the cycle related patterns in the moments of the growth rate cross sections are driven almost entirely by similar patterns in the moments of

[17] It is worth reporting that there is evidence that Gibrat's law is violated in different ways in the up and down phases of the cycle. These results are reported in detail in forthcoming work. One important point about short run growth is that transitory components may dominate permanent components in the short run. Transitory components bias the OLS estimate of coefficients downwards: firms that are of transitorily low size will show higher growth rates than firms that are of transitorily high size. It is possible to treat this as an errors in variables problem, as Hart and Oulton (1995, 2001) have, and control for the transitory influences by estimating a reverse regression to get compromise estimates of coefficients (the geometric mean of the standard coefficient and the inverse of the reverse regression coefficient). See Prais(1958) and Maddala(1992). This also assumes there is zero correlation between errors in dependent and independent variables. It may be that transitory components are larger among the small firms than the large. We find that this coefficient is quite close to the standard Galtonian coefficient. It is clear that the transitory components are not responsible for the increasing dispersion or the counter cyclical skew of the growth rate distribution.

Table 3: Decomposition of Variance of firm growth rates (m_2^2 in Table 1)

	Due to				
	Size	Age	Covariance (Size, Age)	Industry	Residual
1968	1.142	0.191	-0.092	1.352	81.56
1969	0.818	0.058	-0.042	1.685	91.19
1970	0.312	0.250	-0.065	1.370	94.82
1971	0.133	0.106	0.032	2.729	98.46
1972	0.003	2.332	-0.021	7.186	92.03
1973	2.030	1.010	-0.319	3.415	86.60
1974	1.459	0.342	-0.132	5.851	100.89
1975	0.855	0.003	0.010	2.902	115.20
1976	0.851	0.400	-0.128	2.822	110.85
1977	0.514	0.324	0.095	2.074	105.84
1978	0.955	1.560	0.290	2.039	93.04
1979	0.008	1.324	0.020	0.410	92.59
1980	0.287	0.164	0.042	5.901	100.94
1981	1.630	1.820	-0.383	7.012	107.72
1982	0.664	2.241	-0.295	3.248	107.37
1983	0.195	1.339	-0.124	2.858	106.82
1984	0.261	0.123	-0.046	-0.500	98.63
1985	0.006	0.751	0.016	0.304	106.80
1986	0.678	0.564	0.190	-0.185	112.47
1987	0.045	4.149	0.124	-0.301	114.97
1988	0.163	1.153	-0.127	4.636	103.68
1989	0.609	2.827	-0.452	4.341	115.55
1990	0.055	1.926	0.108	0.231	122.72
1991	0.248	1.946	0.204	4.655	129.03
1992	0.222	1.470	-0.174	2.982	106.81
1993	1.693	0.378	-0.243	-0.997	114.04
1994	0.213	2.247	-0.199	1.821	107.51
1995	0.492	1.451	-0.246	4.654	102.41
1996	0.150	0.950	-0.103	1.355	103.49
1997	0.005	4.220	-0.046	1.114	118.78

Note: Values in the 'Industry' column are the sum of the variance -covariance components involving industry, size and age.

residual growth component. The distributions and growth impacts of factors such as firm size, age and industry do not have explanatory power here. These findings drive home the importance of understanding the countercyclical pattern in residual growth moments. They also suggest that the explanation might lie in the how growth responses of firms to (cyclical) aggregate shocks are differentiated on the basis of growth itself. If aggregate shocks impact relatively more on mid growth firms than on firms at either tail of the growth range, as the economy grows (declines), firms in the middle of the growth range move closer to firms at the top (bottom) of the growth range. The probability mass will shift up in a recovery and down in a recession, leaving behind a long tail at the bottom end or the top, and generating the counter cyclical skew. Concurrently, and not contradicting this, growth rates will be less dispersed in a recovery and more dispersed in a recession, if positive and negative aggregate shocks impact on the lower of the medium growth firms more than on the higher of the medium growth firms. The relative gain of firms growing at the less than mean in recovery, and their relative loss in a recession could explain countercyclical dispersion. We turn to an analysis of this conjecture on differential impacts of aggregate shocks: the shape of the $\lambda_{(i)}$ function.

5 Relative Growth Rates and the Cycle

We now examine differentials in impact of aggregate shocks on firms at different locations in the growth rate cross section. The panel of firms is unbalanced so that it is not possible to obtain a continuous record for more than a small number of firms. We work with the time series of the cross section obtained from the percentiles of the cross section of growth rates. This amounts to selecting 100 firms selected systematically from the order statistics of each year's growth rate distribution. The selection function for the kth percentile is unlikely to settle on the same firm in successive years. Nevertheless, the time series of percentiles (p_{kt}, for the kth percentile) captures the dynamics of relative locations within the cross section[18].

To examine whether firms out on the tails of the growth rate distribution are less sensitive to business cycle fluctuations than firms closer to the centre,

[18]For an example of the use of the deciles to capture the time series dimension of cross sections see Harvey and Bernstein (2000).

we estimate a simple dynamic model for each of the percentiles on GDP growth:

$$(1 - \alpha_{1k}L - \alpha_{2k}L^2)p_{kt} = \alpha_{0k} + (\lambda_{1k} + \lambda_{2k}L)\rho_t \tag{9}$$

where L is the lag operator, p_k the kth growth rate percentile and ρ the continuous growth rate of aggregate GDP. Figure 5 plots the estimates[19] of λ_{1k} and $\lambda_{1k}+\lambda_{2k}$. The full regression results for selected percentiles are shown in Table 5. The last column reports the p-value for a likelihood ratio test that $\lambda_{1k} + \lambda_{2k} = 0$. It is striking that the impact of the aggregate economy is much stronger upon firms in the interior of the growth rate range compared to the tails. $\lambda_{(k)}$ increases monotonically up to nearly the 25th percentile and declines monotonically thereafter. This means that an aggregate shock has differential effects on firms that grow at different rates; the central mass of firms moves closer to the fast growing firms in a boom and away from declining firms generating negative skewness. On the other hand in a downturn the mass of firms shifts to the left, closer to declining firms and leaves the group of rapidly expanding firms behind so the cross sectional distribution exhibits positive skewness. This is sufficient to generate the counter-cyclical skewness we observe in the data.

It is also clear that the peak of $\lambda_{(i)}$ is reached at a lower growth rate in the range than the mean growth rate. The implication is that a positive aggregate shock will drive firms with lower than mean growth rate towards the mean, while firms with relatively higher growth rates will not respond as much to the shock. The dispersion of the growth rate cross section will decline (and the kurtosis increase). Likewise in a contraction, firms with lower than mean growth will decline relative to the mean, while firms with relatively higher growth will not regress towards the mean as much. Dispersion will increase (and kurtosis decline) with negative aggregate shocks. The pattern in 5 is sufficient to account for countercyclical dispersion of growth rates, and cyclical kurtosis.

In Table 6 we report, for completeness, a breakdown of firm growth according to the size of the firm. For each year we have taken the percentiles from the cross sectional distribution of the *logarithm of firm size*, measured by sales and then calculated the real percentage change of each of these log

[19] These are OLS estimates. A Durban-Hausman-Wu test for the exogeneity of ρ clearly indicated that instrumental variables were unnecessary.

Table 4: Decomposition of Skewness (m_3 in Table 1)

	Due to			
	Size	Age	Industry	Residual
1968	0.001	0.000	-0.079	-0.158
1969	0.001	0.000	-0.038	-0.108
1970	0.000	0.000	-0.017	-0.113
1971	0.000	0.000	-0.008	-0.068
1972	0.000	0.003	-0.035	-0.166
1973	0.002	0.001	-0.153	-0.516
1974	0.001	0.000	-0.032	-0.206
1975	0.000	0.000	0.083	0.238
1976	0.000	0.000	-0.096	-0.094
1977	0.000	0.000	-0.002	-0.299
1978	0.000	0.001	0.062	-0.277
1979	0.000	0.001	0.068	0.044
1980	0.000	0.000	0.115	0.296
1981	0.001	0.001	0.040	0.370
1982	0.000	0.001	-0.064	-0.035
1983	0.000	0.000	-0.041	-0.137
1984	0.000	0.000	-0.013	-0.430
1985	0.000	0.000	0.024	-0.296
1986	0.000	0.000	0.018	-0.340
1987	0.000	0.000	0.022	-0.317
1988	0.000	0.000	-0.015	-0.331
1989	0.000	-0.001	-0.006	-0.356
1990	0.000	-0.001	0.015	-0.038
1991	0.000	-0.001	0.071	0.278
1992	0.000	-0.001	-0.029	0.166
1993	0.001	0.000	-0.060	-0.178
1994	0.000	-0.001	-0.029	-0.500
1995	0.000	-0.001	-0.074	-0.353
1996	0.000	0.000	-0.031	-0.267
1997	0.000	-0.003	0.075	-0.261

Table 5: Regression of growth rate percentiles on gdp growth

Percentile	$\alpha_{0.}$	$\alpha_{1.}$	$\alpha_{2.}$	$\lambda_{1.}$	$\lambda_{2.}$	R^2	DW	LM(2)
5	-16.5188	0.2316	-0.0737	0.8676	0.3097	0.74	2.03	1.76
	-6.86	1.37	-0.64	6.83	1.57			
30	-7.5908	0.1563	-0.1786	1.3139	0.6038	0.85	1.90	0.93
	-7.84	1.02	-1.97	9.33	2.36			
50	-1.8257	0.1630	-0.1714	1.2214	0.5608	0.81	1.72	2.06
	-3.10	0.99	-1.70	7.94	2.11			
70	3.1817	0.3511	-0.1766	1.1045	0.2703	0.79	1.63	5.49
	3.64	1.95	-1.58	7.48	1.04			
95	10.0225	0.4505	-0.0717	0.7554	0.1091	0.75	1.82	3.19
	4.21	2.36	-0.55	6.65	0.57			

size percentiles for 1968 to 1997. Thus we are now selecting our growth rates according to the percentiles of the log size distribution rather than the percentiles of the cross section of growth rates. For brevity we only tabulate the deciles in Table 6, though similar results emerge for all the percentiles. There does appear to be a correlation between the growth rate of each decile and the aggregate growth rate of the economy but the relationship does not vary in a systematic way with the size of the firm.

The results in this section confirm that firms that grow at different rates are affected in different ways by aggregate shocks. Firms that are declining as well as those that are growing rapidly are less affected by aggregate shocks than firms with medium low growth rates. The observed cycle related dynamics of the growth rate cross sectional moments is consistent with this micro growth behaviour.

6 Conclusions

In the empirical exercise reported in this paper we examined the relationship between the business cycle and the cross sectional distribution of firm growth rates for the UK over the period 1968 to 1997. We found that the distribution of annual growth rates varies in a systematic way with the business cycle. Both dispersion and skewness of the growth rates cross section are countercyclical. In trying to explain this we found that the most important firm level determinants of firm growth held virtually no explanatory power. On the other hand, the differentiation of growth responses to aggregate shocks of firms that grow at different rates appear to be largely responsible for the cyclical pattern in the cross section. While aggregate shocks do affect all firms and appear to be pervasive, both rapidly growing and rapidly declining firms are clearly less sensitive to aggregate shocks than the mass of firms in the interior of the growth range. When there is an economic upturn, firms growing at lower medium rates speed up and move closer to rapidly growing firms and away from the stragglers. In a downturn these firms slow down relative to rapidly growing firms and move closer to those in the left tail of the cross sectional distribution.

To analysts of growth of firms in industrial economics these findings suggest the importance of designing policies with due consideration given to nonlinear responses of firms to aggregate shocks. To macroeconomists concerned with the amplitude of business cycles, the finding of differential responsiveness to aggregate shocks suggest a clear policy focus on low medium growth firms, more than merely the small or the young.

References

[1] Acs, Zoltan and Audretsch, David (1990) *Innovation and Small Firms*, Cambridge, MA: MIT Press.

[2] Audretsch, David and Acs, Zoltan (1994) New-Firm Startups, Technology, and Macroeconomic Fluctuations, *Small Business Economics*, 6(6), 439-49.

[3] Bak, P., K. Chen, J. Scheinkman, and M. Woodford, (1993), Aggregate Fluctuations from Independent Sectoral Shocks: Self-organized Criticality in a Model of Production and Inventory Dynamics, *Ricerche Economiche*, 47, 3-30.

[4] Boeri, Tito and Bellmann, Lutz (1995) Post-entry Behaviour and the Cycle: Evidence from Germany, *International Journal of Industrial Organization*, 13(4), 483-500.

[5] Bowman, K.O. and Shenton, L.R. (1975), Omnibus Test Contours for Departures from Normality based on $\sqrt{b_1}$and b_2, *Biometrika, 62, 243-50.*

[6] Caballero, Ricardo (1992), A Fallacy of Composition, *American Economic Review,* 82, 1279-92.

[7] Caballero, Ricardo and E.M.R.A. Engel, (1992), Beyond the Partial-adjustment Model, *American Economic Review, Papers and Proceedings,* 82, 360-64.

[8] Caballero, Ricardo and E.M.R.A. Engel, (1993), Microeconomic Adjustment Hazards and Aggregate Dynamics, *Quarterly Journal of Economics,* 108, 359-383.

[9] Caballero, Ricardo, E.M.R.A. Engel, and J. Haltiwanger, (1997), Aggregate Employment Dynamics: Building up from Microeconomic Evidence, *American Economic Review,* 87, 115-137.

[10] Caplin, Andrew and Spulber, Daniel (1987) Menu Costs and the Neutrality of Money, *Quarterly Journal of Economics*, 102(4), 703-25.

[11] Chadha, J.S., Nolan, C. , and Janssen, N. (2000), An Examination of UK Business Cycle Fluctuations: 1871-1997, Department of Applied Economics Working Paper 0024, University of Cambridge.

[12] Cooper, R., and Haltiwanger, John (1990), Inventories and the Propagation of Sectoral Shocks, *American Economic Review,* 80, 170-90.

[13] Cosh, A., Hughes A., Lee, H. and Pudney, S. (1998), Semi-parametric Estimation of the Company Size Growth Relationship, in Iain, Begg and Henry, Brian (eds.) *Applied Economics and Public Policy*, Cambridge University Press.

[14] Dunne, Paul and Hughes, Alan (1994) Age, Size, Growth and Survival: UK firms in the 1980s, *Journal of Industrial Economics,* 42(2), 115-40.

[15] Foster, Lucia (1999) Employment Adjustment Costs and Establishment Characteristics, Center for Economic Studies, US Bureau of Census, CES-WP-99-15

[16] Geroski, Paul and Gregg, Paul (1997) *Coping with Recession: UK Company Performance in Adversity*, Cambridge, New York and Melbourne: Cambridge University Press.

[17] Geroski, Paul and Machin, Stephen (1993) Innovation, Profitability and Growth over the Business Cycle, *Empirica*, 20(1), 35-50.

[18] Geroski, Paul, Machin, Stephen and Walters, Christopher (1997) Corporate Growth and Profitability, *Journal of Industrial Economics,* 45(2), 171-89.

[19] Gibrat R (1931) *Les Inégalités Economiques*, Paris: Sirey.

[20] Goudie, A.W. and Meeks, G. (1991), The Exchange Rate and Company Failure in a Macro-micro Model of the UK Company Sector, *Economic Journal*, 101, 444-57.

[21] Haltiwanger, John (1997), Measuring and Analysing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence, *Federal Reserve Bank of St Louis Review*, May/June, 55-77

[22] Hart, Peter and Oulton, Nicholas (1995) Growth and Size of Firms, National Institute of Economic and Social Research Discussion Paper No. 77.

[23] Hart, Peter and Oulton, Nicholas (1996) Growth and Size of Firms, *Economic Journal*, 106(438), 1242-52.

[24] Hart, Peter and Oulton, Nicholas (2001), Galtonian Regression, Company Age and Job Generation 1986-95, *Scottish Journal of Political Economy*, 48, 1, February.

[25] Harvey, Andrew and Bernstein, Jared (2000), Measurement and Testing of Inequality from Time Series of Deciles with an Application to US Wages, Mimeo, University of Cambridge.

[26] Higson, C., Holly, S. and Kattuman, P. (2001), The Cross Sectional Dynamics of the US Business Cycle: 1950-1999, Mimeo, Department of Applied Economics, University of Cambridge. forthcoming in *Journal of Economic Dyanmics and Control.*

[27] Machin, Stephen and Van Reenen, John (1993) Profit Margins and the Business Cycle: Evidence from UK Manufacturing Firms, *Journal of Industrial Economics*, 41(1), 29-50.

[28] Mata, Jose (1996) Small Firm Births and Macroeconomic Fluctuations, *Review of Industrial Organization*, 11(2), 173-82.

[29] McCarthy, J. and Zakrajsek, E. (1998), Microeconomic Inventory Adjustment and Aggregate Dynamics, Federal Reserve Bank of New York, Staff Reports, December, No. 54.

[30] Prais, S. J. (1958) Statistical Conditions for a Change in Business Concentration, *Review of Economics and Statistics*, 40, 268-72.

[31] Sutton, J., (1997) Gibrat's Legacy, *Journal of Economic Literature*, 35(1), 40-59.

Table 6: Regression of growth rate of firms at deciles of log size, on gdp

SIZE PERCENTILES	$\alpha_{0.}$	$\alpha_{1.}$	$\alpha_{2.}$	$\lambda_{1.}$	$\lambda_{2.}$	R^2	LM(2)	p-LR
10	-7.4684	0.3480	-0.0883	0.3414	1.7189	0.13	4.46	0.106
	-2.07	1.90	-0.45	0.28	1.52			
20	-6.3768	0.3470	0.0115	0.0095	2.2732	0.28	4.21	0.027
	-2.20	1.95	0.06	0.01	2.45			
30	-5.6995	0.2698	0.0987	0.3594	1.7889	0.24	6.76	0.018
	-2.22	1.48	0.55	0.42	2.05			
40	-5.1737	0.1915	0.0670	0.0455	2.1943	0.18	3.43	0.024
	-1.83	1.02	0.36	0.05	2.42			
50	-4.6205	0.1271	0.0526	0.8126	1.4385	0.16	10.88	0.007
	-1.95	0.68	0.30	1.04	1.74			
60	-3.4978	0.0280	0.0652	0.4062	1.5800	0.08	10.08	0.024
	-1.41	0.15	0.36	0.52	1.99			
70	-4.2822	0.0683	0.0104	0.3949	2.0424	0.18	4.84	0.007
	-1.66	0.41	0.06	0.50	2.51			
80	-3.0670	0.2326	0.0292	0.2692	1.6399	0.16	4.93	0.035
	-1.17	1.42	0.18	0.34	2.05			
90	1.0754	0.0057	-0.0188	0.4269	0.4851	-0.15	5.33	0.424
	0.33	0.03	-0.09	0.44	0.50			

Figure 2:

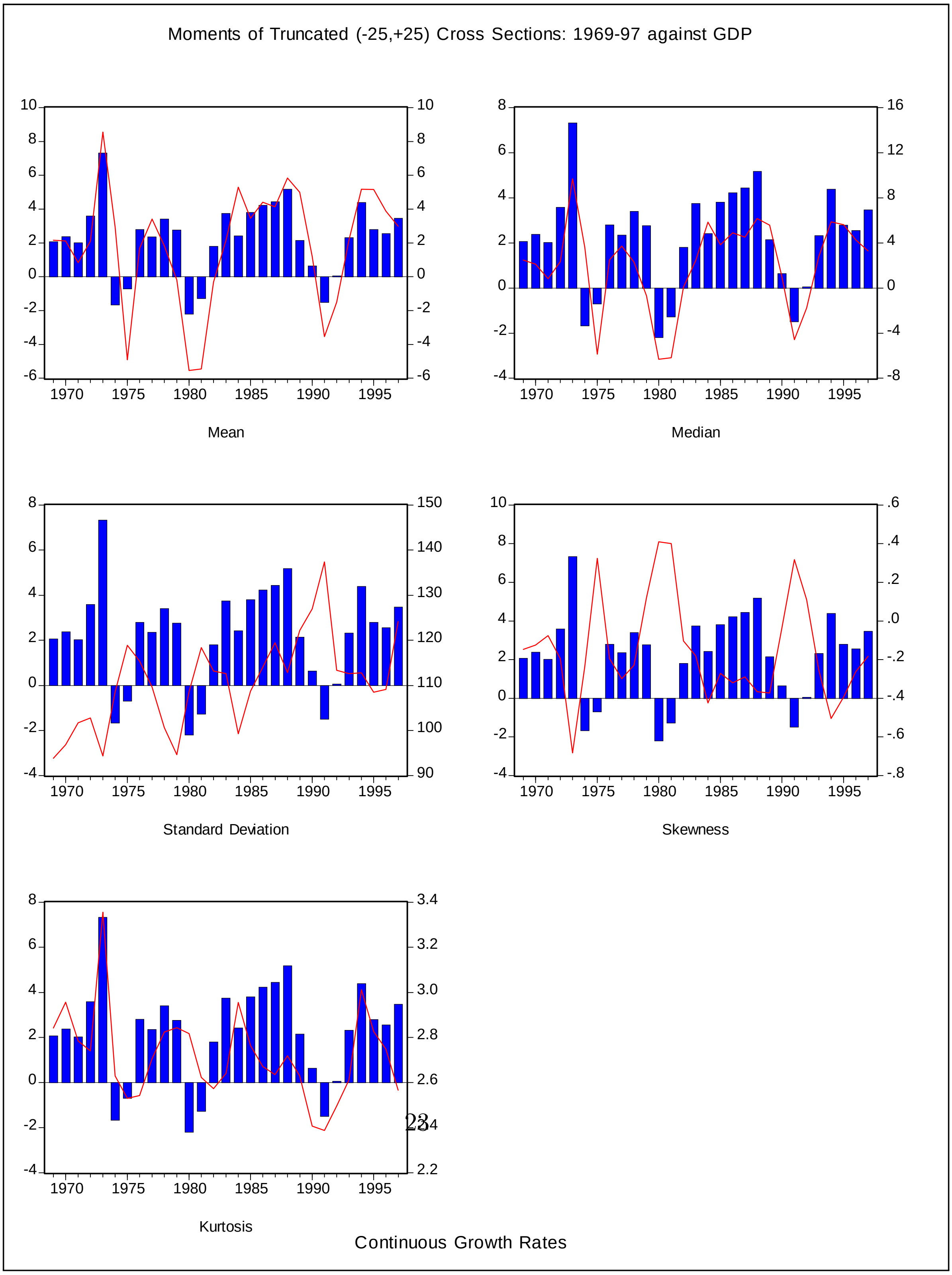

Moments of Truncated (-25,+25) Cross Sections: 1969-97 against GDP
Mean
Median
Standard Deviation
Skewness
Kurtosis
Continuous Growth Rates

Figure 3:

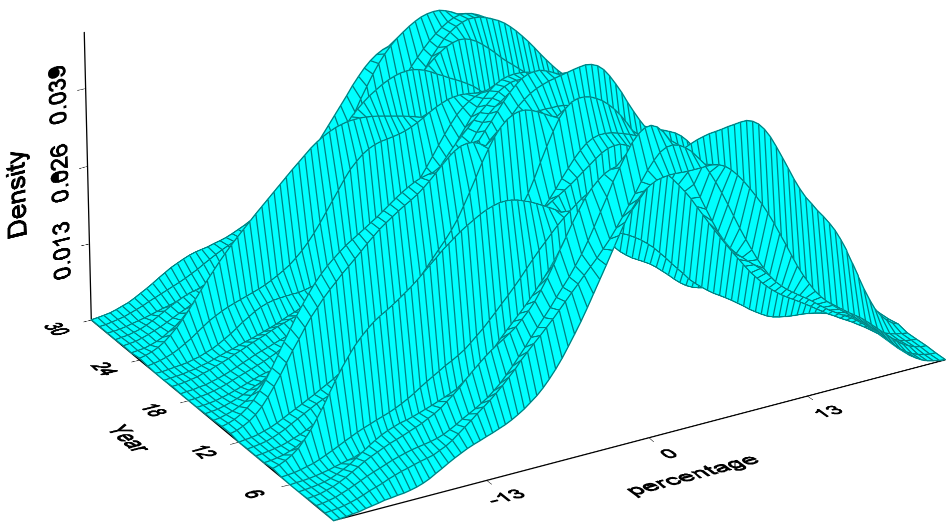
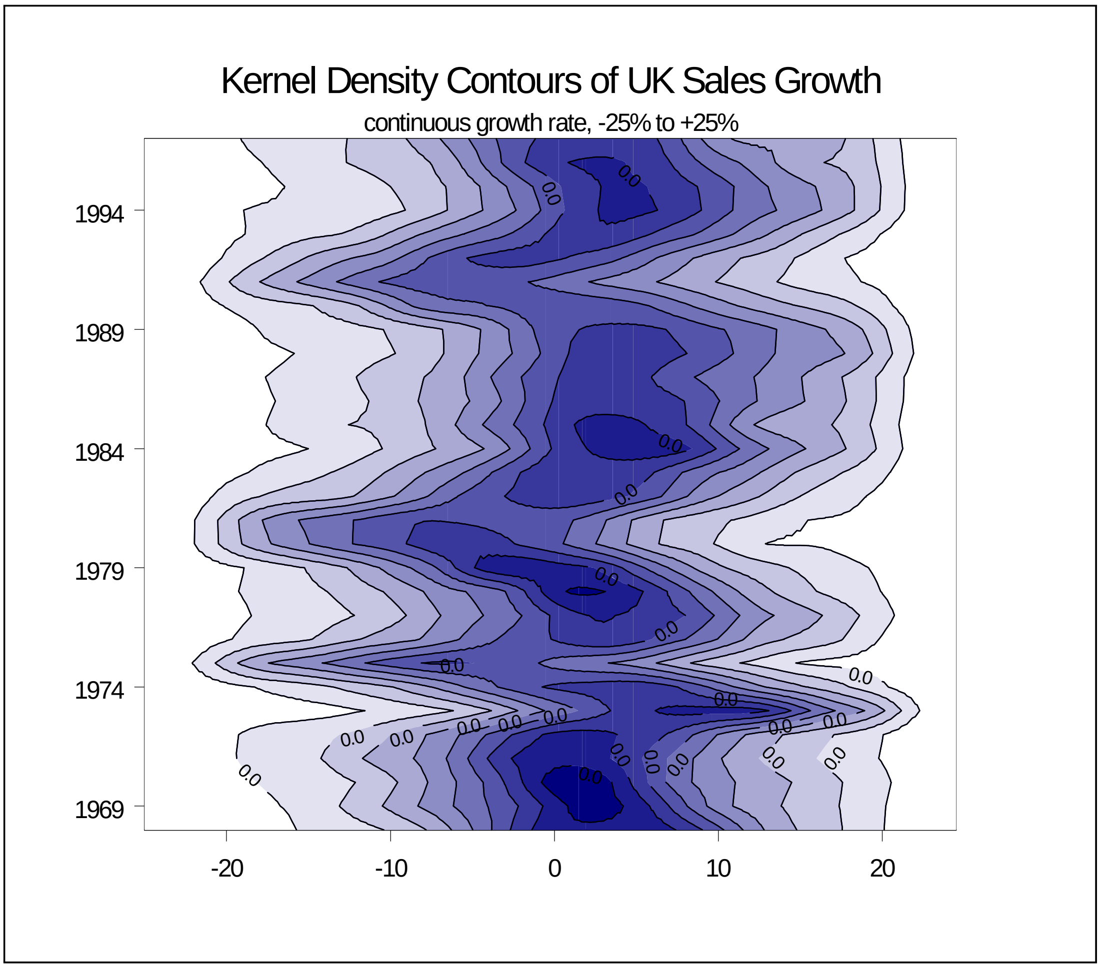
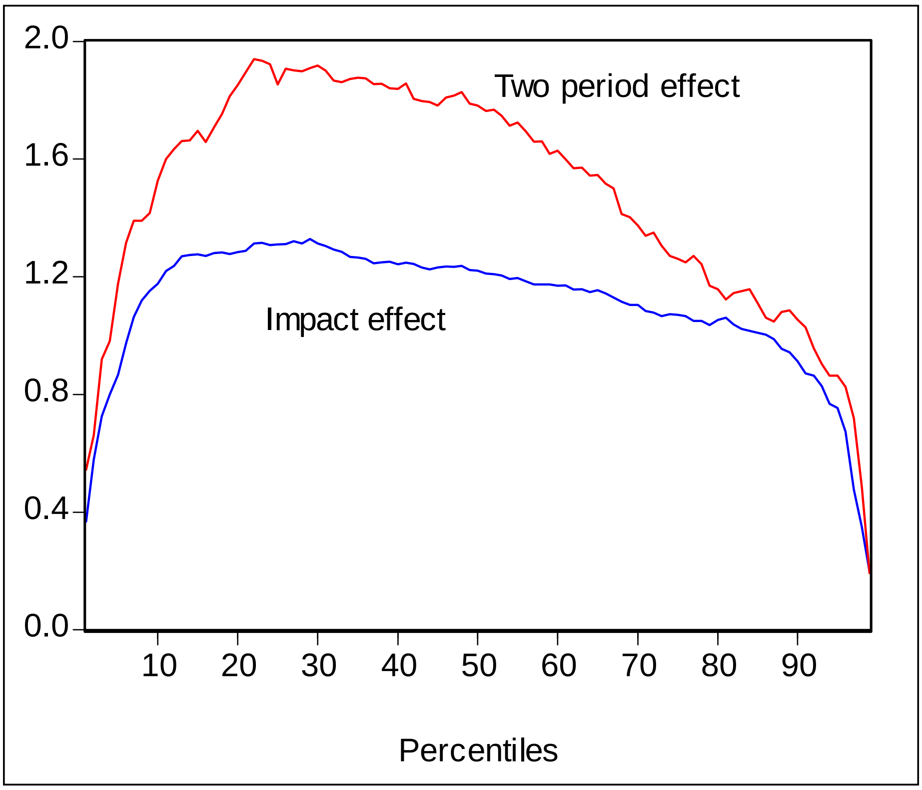


Figure 4:



Kernel Density Contours of UK Sales Growth
continuous growth rate, -25% to +25%
1994
1989
1984
1979
1974
1969
-20
-10
0
10
20

Figure 5:


2.0
1.6
1.2
0.8
0.4
0.0
10
20
30
40
50
60
70
80
90
Two period effect
Impact effect
Percentiles