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

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We bring to light a significant aspect of firm level heterogeneity over the business cycle. Analysing the responsiveness of firm growth (quoted UK companies) to aggregate shocks, we find that the effects of aggregate shocks are more pronounced for firms in the middle range of growth. Rapidly growing and rapidly declining firms are less sensitive to aggregate shocks than firms in the interior of the growth range. This is consistent with the fact that the higher moments of the distribution of firm growth rates have significant cyclical patterns. These findings throw new light on growth of firms as well as on business cycle dynamics.

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 microeconomic adjustment behaviour (of firms as well as individual households) in the dynamics of the aggregate economy. A key stylized fact established by empirical studies of longitudinal establishment data (e.g. Davis *et al.* 1996) has been that heterogeneity is an essential characteristic of firm growth. Representative agent models used by macroeconomists, where all firms move in tandem over the business cycle, are not consistent with observed data. In any time period a few firms make a large part of the adjustments, but it is difficult to predict what any individual firm is likely to do based only on observables at the firm level.

Our objective is to add to the understanding of the cross-sectional dynamics of business cycles. The impact of aggregate shocks on firms is of direct interest once it is recognized that not all firms respond to aggregate shocks equally.[2] What types of firm are most susceptible to recessions (and recoveries)? Are they, for example, the small or the young? We report distinctive patterns in the heterogeneous growth responses of (quoted) firms to the business cycle. This is of central interest to industrial economists and policy-makers concerned with growth and performance of firms. Our analysis is also addressed to macroeconomists. A proper understanding of business cycles requires knowledge of the evolution of cross-sectional distributions of individual behaviour.[3] This should help in the design of policies to reduce the amplitude of the business cycle.

The next section provides a framework for our analysis. It considers 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

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been the focus of much empirical research. Can changes in the growth impacts and changes in the distributions of these firm-level features explain the dynamics of the growth rates in the cross-section? The second hypothesis relates to the possibility that the growth responses of firms to changes in the overall business environment is determined not so much by firm characteristics, but according to the relative rate of firm growth itself. The effect of the business cycle on firms in a rapid growth phase may differ from its effect on firms in a decline phase, or on firms growing at intermediate rates.

To the best of our knowledge, no other studies have compared the explanatory power of these two hypothesis, but in the extant literature on macroeconomic influences on firm-level performance two contributions are directly relevant to our work.[4] The analysis of Geroski and Gregg (1997) of the effect of the 1991 recession using data from a survey of UK firms found that only some firms were severely affected by a collapse in demand. They found it difficult to predict the vulnerability of firms (firms either declaring themselves more vulnerable, or actually going out of business) using balance sheet variables. One of their findings was that firms that grew rapidly during the early stages of the recession proved less vulnerable to the recession than others (p. 59). These results are consistent with our findings.

Boeri and Bellmann (1995) examined the relationship between the growth and exit of cohorts of establishments and macroeconomic fluctuations in Western Germany. Using a large data-set of establishments, small as well as large, over a period spanning two cyclical peaks and a recession, they found that in general the growth of survivors was not cyclical, but tended to become more responsive to aggregate business fluctuations as cohorts aged.[5] The main difference between our study and that of Boeri and Bellmann is that our population consists of quoted companies; we work with data on UK listed company accounts from 1968 to 1997 comprising over 43,000 company years. Thus, our results are derived from relatively large and more mature firms than the set of all establishments.

Following the discussion of hypotheses in the next section, we proceed in Section II to characterize the cross-sections of growth rates of UK quoted firms. We find that there is a significant 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). These patterns are analysed in Section III by operationalizing the hypotheses set out in Section I and bringing them to data. We conclude that there is little evidence in favour of the first hypothesis. Section IV explores the second hypothesis in more detail by investigating the impact of aggregate shocks, differentiating firms according to the percentiles of growth rates. We show that the (cyclical) aggregate shocks have a stronger impact on the central mass of the distribution and a weaker effect on the tails. Section V concludes.

I. SHOCKS, GROWTH RESPONSES AND MOMENTS OF THE CROSS-SECTION: A FRAMEWORK

Consider a set of firms producing output governed by some standard production function. Production takes place in a stochastic environment,

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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

$$\varepsilon_{it} = \xi_{it} + \zeta_{jt} + \eta_t, \tag{1}$$

with ξ_{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:[6]

$$g_{it} = \iota_{it}\xi_{it} + \kappa_{it}\zeta_{jt} + \lambda_{it}\eta_t \tag{2}$$

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 ι_{it} its response to shocks unique to the firm.

Our primary interest is in characterizing and explaining the cycle-related dynamic patterns in the cross-sectional distribution of growth rates (denote this by $h_t(g)$). It is reasonable to assume that, among the types of shock considered, aggregate shocks constitute the business cycle: the obvious area in which to seek an explanation for cycle-related patterns in $h_t(g)$ is in the heterogeneity of responses of firms to aggregate shocks. The key point from (2) is that aggregate shocks may have different impacts on different firms, as captured by the coefficient λ_{it}.[7]

There are two obvious ways in which firm-specific responses to shocks could be characterized. Aggregate shocks may modify the relationship between the growth of the firm and the firm's exogenous characteristics systematically, possibly 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.

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 high positive growth rates as severely as it does firms that have grown at moderate rates. Firms at the extreme negative end of the growth range may face limits to their decline, *if they survive*; it is possible that the struggle of these survivors to stay alive in the face of a negative aggregate shock leads them to perform 'relatively' better than the average firm.

Faced with a 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. In summary, firms at the extreme ends of performance may respond less to aggregate shocks, both positive and negative, than firms in the middle range of growth. These mid-growth firms may prove to be the most susceptible to the changes in macroeconomic conditions. It is helpful to set out the implications of these response patterns for the growth rate cross-section in formal terms.

Denote variables relevant to the growth rate of the firm by $\mathbf{Z}_t$ (a key element of which would be 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 in which firm growth

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rates, g, depend on firm-specific features is represented by $f_t(\mathbf{Z}_t)$, observed growth rates of firms are given by $E[f_t(\mathbf{Z}_t)] + \upsilon_t$, where υ_t is that portion of the growth rate than cannot be ascribed to any systematic firm-level characteristic. By examining changes over time in $\hat{f}_t(Z_t)$ we can draw inferences on whether, for example, small firms grow faster relative to large firms in recoveries, and whether large firms contract less, relative to small firms, 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, $\hat{f}_t(Z_t)$, 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 υ_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} in (2) above, depends on the relative position of the firm in the growth range) can be framed as follows. With the firms ordered in ascending order of growth rates, let $\lambda_{(i)}$ denote the magnitude of response to aggregate shock, where the parentheses around the subscript i signify the new ordering.[9] The second hypothesis can be stated in terms of how $\lambda_{(i)}$ varies with the ordered i. If most of the 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 growth rate that is 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. 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.

A first look at evidence

Our sample consists of UK quoted companies from 1967 to 1997. The quoted sector is a clearly identified class of firms, dominating any other set of firms in terms of size. In consequence, the sample over-represents large firms relative to the population of all UK firms. This is consistent with the focus of the analysis, which is on the effects of the business cycle on large firms. Since no single database spans the long period needed to characterize cycle-related dynamics, we

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used four primary sources to construct the necessary data: the Cambridge/DTI databank, the London Share Price Database (LSPD), EXSTAT and DATASTREAM.

The Cambridge/DTI databank is an accounting data-set that dates from 1948. Companies were included only if: they were admitted to the official list of the stock exchange; they were independent companies or company groups; they operated mainly in the UK; and their principal activity was manufacturing, distribution, construction, or transport and certain services.[10] EXSTAT and DATASTREAM, dating from 1970, are company accounts based data-sets that collect published accounts data for UK quoted companies, as well as members of the *Times* 1000 list of large UK companies. These databases were expanded to include smaller quoted firms in 1975–76. The combination of databases was used to construct the underlying UK quoted population.[11] This yielded 43,612 company years of data over the period 1967–97. The number of reporting companies averaged 1400 a year, ranging from a maximum of 1844 in 1969 to a minimum of 1284 in 1992. In current prices, the median firm by size had sales of £5 million in 1967 and £57.6 million in 1997. Only 3% of the firms had sales less than £1 million in 1997, while 37% had sales greater than £100 million.

In the rest of 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. Table 1 reports the moments of annual cross-sections using continuous growth rates, and the total number of firms in each year.[12] Figure 1 plots the Bowman–Shenton test for significant skewness against the $\chi^2(1)$ 95% critical value of 3.84. What is noticeable is that periods of significant skewness are associated with periods of particularly strong macroeconomic variation or turbulence, such as the boom of 1973, the sharp downturn after the oil price shock in 1975, the recessions of 1980–81 and 1991, and so on. To explore this further, Figure 2 plots each of the moments reported in Table 1 against the rate of growth of aggregate UK GDP. To exclude outliers, the sample is truncated and the results reported are based on growth rates lying between $\pm$ 25%.[13] 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 confirm 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.

II. NON-PARAMETRIC ANALYSIS

Figure 3 is a three-dimensional plot of kernel densities fitted to each cross-section of continuous growth rates. The density estimates were generated with a Gaussian kernel and an automatic data-based bandwidth[14] with the density evaluated at 100 equidistant 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

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TABLE 1
SUMMARY STATISTICS: GROWTH RATES OF REAL SALES, 1968–1997

	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 is the Bowman–Shenton $\chi^2(2)$ omnibus test for normality; and BS^2 is a $\chi^2(l)$ test for skewness = 0.

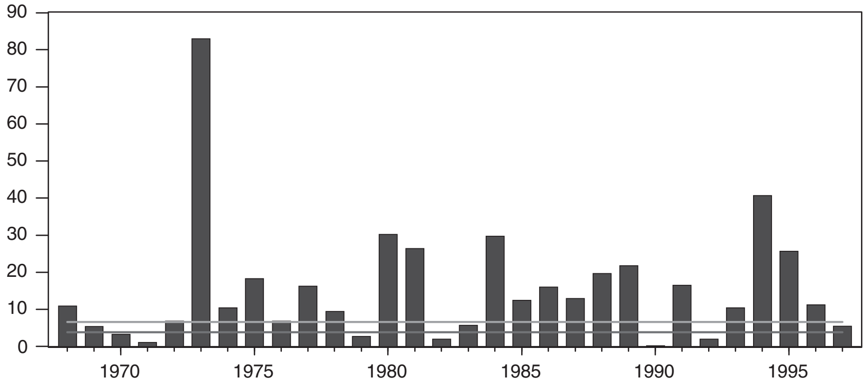

FIGURE 1. Bowman–Shenton test for significant skewness (against 95% and 99% critical values).

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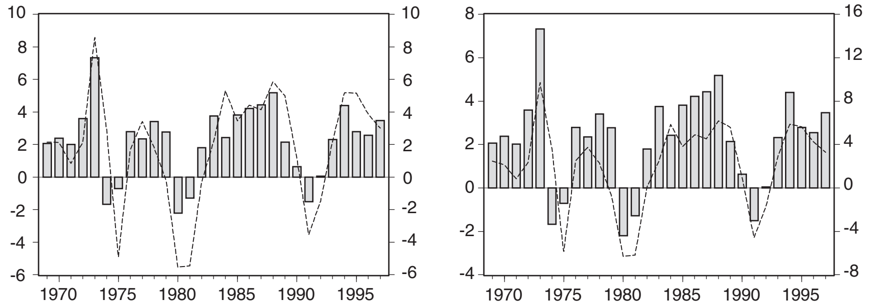
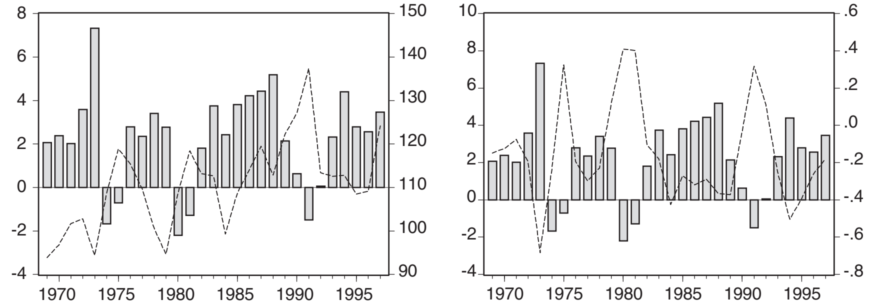


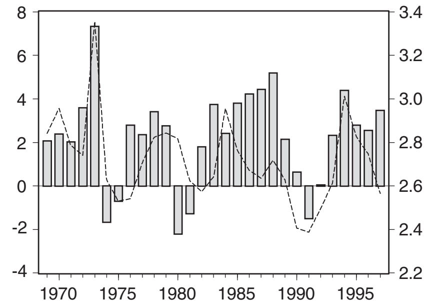
(a) Mean

(b) Median



(c) Standard Deviation

(d) Skewness



(e) Kurtosis

FIGURE 2. Moments of truncated (-25%, $+25\%$) growth cross-section distribution against GDP, 1969–1997.

Continuous growth rates; bar is GDP growth, left hand axis

largely impressionistic. Nevertheless, they do suggest some interesting features of the evolution of cross-sectional growth rates in the 30-year period from 1968. Because the average or mean growth rate of the UK economy has been positive over the sample period, the mass of the distribution always 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 some churning at the sectoral and firm level. The central mass also moves with the aggregate growth rate of the macro economy. 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 at 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

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TABLE 2
REGRESSION OF FIRM GROWTH RATE CROSS-SECTION MOMENTS ON GDP GROWTH[a]

	Mean	Median	S.D.	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	0.21699	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

[a]Method: least squares; Sample (adjusted): 1970, 1997.

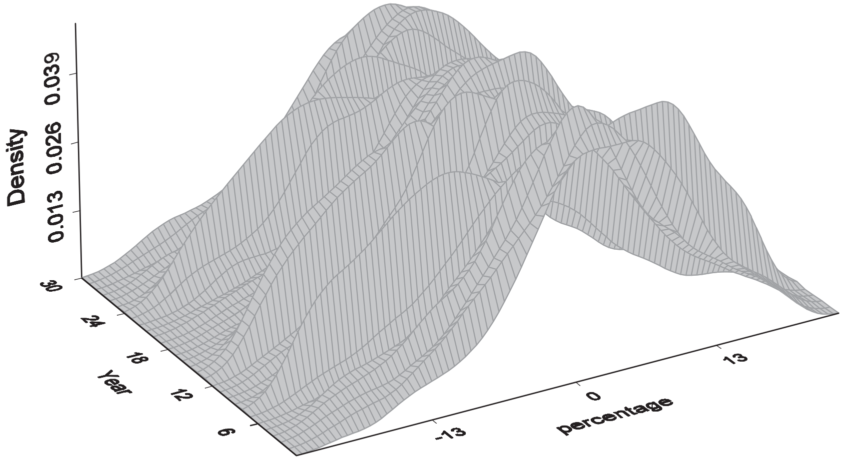

FIGURE 3. Kernel densities of growth rates of sales, 1968–1997.

suggests that there are significant deviations from normality and that these deviations are associated with the aggregate business cycle.

III. SYSTEMATIC AND STOCHASTIC GROWTH COMPONENTS OVER THE CYCLE

We now develop an operational version of the framework set out in Section I. A useful benchmark is the simplest approach to the cross-sectional firm-level growth–size relationship, a first order Galton–Markov model (which generalizes the Gibrat model) to allow past size to influence current size:

$$z_{it} = \beta_t z_{it-1} + u_{it} \tag{3}$$

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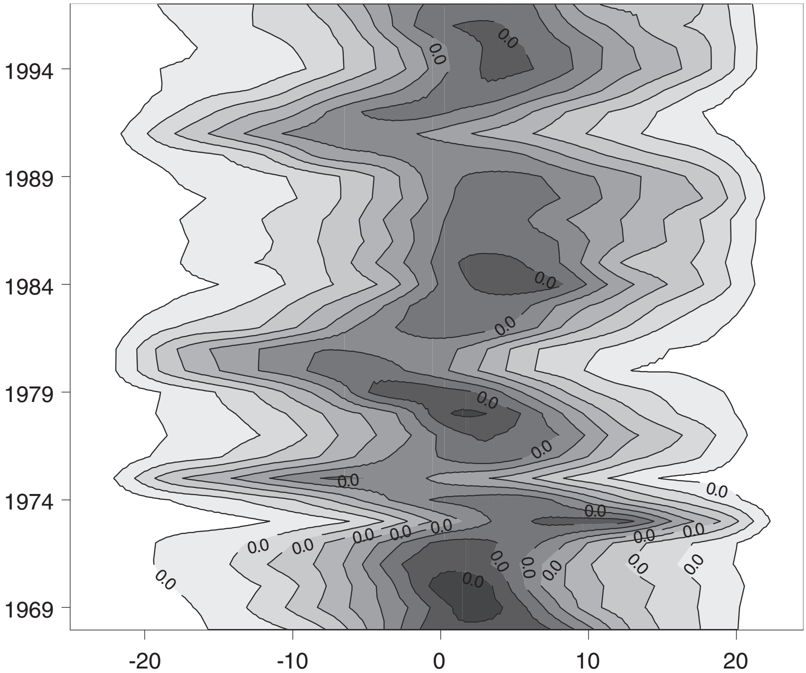

FIGURE 4. Contours of kernel densities of growth rates of sales, 1968–1997.

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 idiosyncratic component in growth. Gibrat's law holds if β_t is unity. A value for β_t of less than 1 would suggest regression towards the mean with small firms, on average, growing faster than large; a value for β_t of greater than 1 would suggest that large firms, on average, grow faster than small.[15] We augment (3) with the other observable growth determinants: firm age y_{it} and an industry dummy $I_{i.}$,[16] and write the growth equation, for each period, t, as

$$g_{it} = z_{it} - z_{it-1} = \alpha_t + (\beta_t - 1)z_{it-1} + \gamma_t y_{it} + \delta_t I_{i.} + u_{it}. \tag{4}$$

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,[17] 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

$$\begin{aligned} V(g_{it}) =& (\beta_t - 1)^2 V(z_{it-1}) + \gamma_t^2 V(y_{it}) \\ & + 2(\beta_t - 1)\gamma_t \mathrm{Cov}(z_{it-1}, y_{it}) + \varsigma_t + V(u_{it}) \end{aligned} \tag{5}$$

where ς_t incorporates the variance and covariance terms involving the industry indicator variables.[18] Under the assumption of independence of z_{it-1}, y_{it}, $I_{i.}$

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and u_{it}, the third central moment, which measures skewness, evolves as

$$E(g_{it}-\bar{g}_{it})^3 = (\beta_t-1)^3E(z_{it-1}-\bar{z}_{it-1})^3+\gamma_t^3E(y_{it}-\bar{y}_{it-1})^3 + \delta_t^3E(I_{i.}-\bar{I}_{i.})^3+E(u_{it}-\bar{u}_{it})^3 \tag{6}$$

The coefficient of skewness, obtained from (6) by normalizing it with the standard deviation term to be dimensionless, evolves as

$$Sk(g_{it}) = [(\beta_t-1)^3+Sk(z_{it-1})\sigma(z_{it-1})^3+\gamma_t^3Sk(y_{it})\sigma(y_{it})^3 +Sk(I_i)\sigma(I_i)^3+Sk(\varepsilon_{it})\sigma(\varepsilon_{it})^3]\frac{1}{\sigma(g_{it})^3} \tag{7}$$

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 (5) and (6), the terms on the right-hand side (RHS), excluding the last one, capture aspects of the systematic mechanism that work upon the dispersion of growth rates: the growth coefficients of size, age and industry, and the moments of firm sizes, firm ages and industry indicator variables. 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 nonlinearity and time variation in the cross-correlation of residual components of growth, i.e. the component that is unrelated to *ex ante* observed firm characteristics.

We estimate the Galton process in (4) by OLS for successive pairs of years using data on firms that survive from one year to the next.[19] The decompositions of the higher moments of the growth rate distributions given by (5) and (6) are reported in Tables 3 and 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 increase 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, by other explanatory factors. This suggests 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 the 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 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, then, as the economy grows (declines), firms in the middle of the growth

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Table 3
Decomposition of Variance of Firm Growth Rates (m_2^2 in Table I)

	Size	Age	Variance due to Covariance (size, age)	Industry[a]	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

[a] Values in the ‘Industry’ column are the sum of the variance–covariance components involving industry, size and age.

range move closer to firms at the top (bottom) of the growth range. The probability mass will shift upwards in a recovery and downwards in a recession, leaving a long tail at the bottom end or the top, and generating the countercyclical 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 more on the lower of the medium-growth firms than on the higher of such firms. The relative gain of firms growing at less than the 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.

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TABLE 4
DECOMPOSITION OF SKEWNESS (m_3 IN TABLE 1)

	Skew 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

IV. RELATIVE GROWTH RATES AND THE CYCLE

Our choice of method is guided by two considerations. The panel of firms is unbalanced, and it is not possible to obtain continuous records for more than a small number of firms. Even if a large balanced panel were available, it is not possible to model individual firms to answer the question of interest. Individual firms cannot be characterized, in terms of invariant relative positions in the range of growth rates, for the thirty-year duration—the growth rate of any individual firm is likely to vary from year to year and to cover a wide range over the years. We proceed to extract from the (unbalanced) panel of observations a set of time series that can be used to capture the evolution of a cross-sectional distribution over time. We then use regression models of the time series of percentiles to identify the responsiveness of different relative

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growth rates of firms to the aggregate economic growth rate. We describe the method employed below.

Quantile time series

Consider a real random variable, denoted G (to recall that the variable of interest is the growth rate of firms), which follows some continuous distribution F. The pth quantile (denoted G_p) of the distribution is the value below which $100p\%$ of the distribution lies; $F(G_p) = p$. Quantiles are easily estimated. Consider a sample of size n. In the increasing rearrangement of the sample, let $G_{(i)}$ denote the ith smallest variate, and denote the value taken by it by $g_{(i)}$, the ith-order statistic ($g_{(1)} \leqslant g_{(2)} \ldots \leqslant g_{(n)}$). Quantiles are readily estimated as the specific order statistics that divide (assuming the necessary divisibility) the total frequency of the sample, n, into equal parts; for example, for $p = 4$ we have the quartiles and $p = 10$ gives the deciles. These estimators are non-parametric and do not depend on the form of F.

For each period t, $t = 1,2,\ldots, T$, consider the set of order statistics; $g_{t(k)}$ denotes the kth-order statistic in year t. The number of observation in the cross-section, n_t, varies from year to year. But we can select a balanced panel of quantiles for analysis once we fix the number of p-quantiles. In this study we work with percentiles. This amounts to selecting 100 firm growth rates systematically from the order statistics of each year's growth rates. The selection function for $p_{t(k)}$ (the kth percentile in year t) will almost never settle on the same firm in successive years, but we can characterize the dynamics of relative cross-section locations by modelling the series, $p_{t(k)}$, for each k.[20]

Given our sample sizes, we can be confident that the estimated quantiles are good estimates of population quantiles. For any two sample order statistics, $g_{t(k)}$, $g_{t(k+r)}$, the amount of probability in the population distribution contained in the interval ($g_{t(k)}$, $g_{t(k+r)}$) is a random variable, which does not depend on F. Thus, confidence intervals for any given quantile as well as distribution-free tolerance intervals can be easily obtained from the sample order statistics (Wilks 1962, chapter 11). Our sample sizes comfortably exceed the smallest n for which 99% of the probability in the population distribution is covered by the extreme-order statistics. For example, if $n \geqslant 645$, we get a 99% tolerance interval for 99% of the population.

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, we first estimated a simple dynamic model for each of the percentiles on GDP growth.[21] Since we have a time series corresponding to each percentile, we also examine the possibility of persistence in the growth rate percentiles by including up to two lags:

$$(8) \qquad \left(1 - \alpha_{ik}L - \alpha_{2k}L^2\right) g_{t(k)} = \alpha_{0k} + (\lambda_{1k} + \lambda_{2k}L)\rho_t,$$

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 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 $\lambda_{1k} + \lambda_{2k} = 0$.

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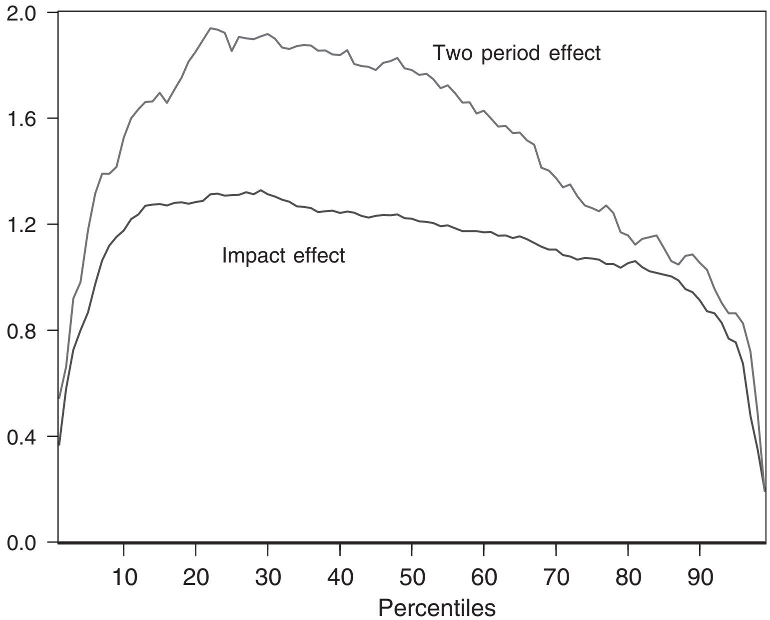

FIGURE 5. Estimates of λ_1 and $\lambda_1 + \lambda_2$ for growth rate percentiles.

TABLE 5
REGRESSION OF GROWTH RATE PERCENTILES ON GDP GROWTH

Percentile	α_0	α_1	α_3	λ_1	λ_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			

Our finding is that the lagged GDP growth and GDP growth in the current period are good explanators for the growth rate at any particular percentile. It is worth reiterating that in the above model the lagged terms apply not to the past growth rate of the same firm, but to the past growth rate at the same percentile. The λ_{1k} and λ_{2k} coefficients reflect the degree of persistence of the kth growth rate percentile. What is striking is that the impact of the aggregate economy is much stronger upon firms in the interior of the growth rate range than on those in 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

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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 countercyclical 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 Figure 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 size percentiles for the period 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 tabulate only 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

TABLE 6
REGRESSION OF GROWTH RATE OF FIRMS AT DECILES OF LOG SIZE, ON GDP

Size percentiles	α_0	α_1	α_2	λ_1	λ_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			

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and the aggregate growth rate of the economy, but the relationship does not vary in a systematic way with the size of the firm.

Interpretation

It is now widely accepted that heterogeneity in performance is endemic among firms across all phases of the business cycle—some firms will grow rapidly even in recessions, while other firms will decline severely even in recoveries. In this paper we report a pattern in this heterogeneity. The simplest explanation for our finding that fastest growers in a recovery are less responsive to macroeconomic conditions than firms growing at lower rates is that rapid growers are overstretched and have little slack to meet the higher demand that recovery brings. At the other end, the slowest growers in any year—firms that are sharply declining in size—may be doing so badly that nothing at the macroeconomic level in a recovery can salvage their growth performance.

In a recession, on the other hand, firms at the bottom of the growth league must be the ones for whom any further decline in size is likely to trigger exit. Their relative insulation from adverse macroeconomic conditions could be due to their efforts to resist exit. Geroski and Gregg (1997) found these firms strenuously engaged in business strategies aimed at cutting costs. They also found, as we did, that the fastest growers stay relatively immune in a recession; this could be attributed to the momentum of the rapid growth which softens the blow of recession.

Not all firms growing at rates in the intermediate range ride the business cycle in the same way, but on average we find that growth rates in the mid–low range are twice as sensitive to moves in GDP growth as the fastest or slowest growth rates. This is consistent with the observed cycle-related dynamics of the cross-sectional moments of firm growth rates. One reason why the dispersion of companies' growth performance tends to fall in recoveries is that firms growing at rates below average do not lag as much below the average rate of growth. The dispersion of growth rates tends to increase in recessions, when firms growing at less than average rates of growth lag behind by more.

V. CONCLUSIONS

An important feature of firm-level data is the substantial variability in the fortunes of firms over time. This has been noted particularly in the turnover (entry and exit) of firms and establishments, but also in growth and profitability of firms. In this paper have we attempted to characterize the heterogeneity in response of firms to the aggregate business cycle and, specifically, the way this response is related to the position of the firm within the growth rate distribution.

In the empirical exercise we report, we examined the relationship between the business cycle and the cross-sectional distribution of firm growth rates for the UK over a thirty-year period to 1997. As in the US case (Higson *et al.* 2002) we found that the distribution of annual growth rates, the mean and higher-order moments, varies in systematic ways with the business cycle as captured by GDP growth. To explore the drivers of this pattern, we decomposed the

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variance and skew of the firm-level growth rate distribution, based on the results of a regression model of the growth rate on firm-level characteristics. From these results we showed that almost all of the growth rate variance and skew is accounted for by the idiosyncratic component of firm growth. We concluded that observable firm level characteristics—size, age and industry—hold almost no explanatory power in determining cyclical variations in the distribution of growth rates.

We then turned to an examination of the impact of aggregate shocks on firm growth at different points in the growth distribution. We established that the magnitude of the firm growth response to an aggregate shock depended on the relative position of the firm's growth rate: rapidly growing and rapidly declining firms are less sensitive to aggregate shocks than firms in the interior of the growth range. 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. This differentiation in growth responses to aggregate shocks of firms that grow at different rates appears to be largely responsible for the cyclical pattern in the cross-section.

To analysts of the growth of firms in industrial economics, these findings suggest the importance of designing policies with due consideration given to nonlinear growth responses of firms to aggregate business cycle shocks. To macroeconomists concerned with the amplitude of business cycles, the finding of differential responsiveness to aggregate shocks may suggest an additional policy focus on low to medium growth firms.

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NOTES

1. For a recent analysis of 130 years of UK aggregate business cycles see Chadha *et al.* (2000).
2. This paper does not examine firm responses to uncertainty arising from volatility in the business environment. Our focus is on the differential responsiveness of firms to common underlying cyclical ups and downs of aggregate economic activity: does the business cycle translate into a representative agent type movement where all firms move up or down together? The term 'shock' does not have a connotation of uncertainty in the current analysis.
3. On the impact of the cross-sectional distribution of microeconomic actions on macroeconomic fluctuations, see Haltiwanger (1997). A modelling approach pioneered by Caballero and Engel (1992, 1993) and Caballero *et al.* (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).
4. In a different vein, Audretsch and Acs (1994) and Mata (1996) examined the importance of macroeconomic fluctuations on startups. There is also some work on the cyclical nature

of profitability; see Geroski *et al.* (1993), Bhaskar *et al.* (1993), Machin and Van-Reenen (1993) and Geroski and Walters (1997).

5. One explanation they offer is that small firms are more prone to exit when hit with negative shocks, while older and larger firms shrink till forced to close down. However, this line of argument would imply that small firms respond more to expansionary shocks. The authors suggest other possible explanations. Older and larger firms may be more specialized. Capital constraints and irreversibility of technologically indivisible investments may explain why young small firms do not respond as much to positive shocks. Larger and older plants may have more slack and be able to respond more either way.
6. Caballero *et al.* (1997) 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.
7. See also Abadir and Talmain (2002). λ_{it} can be thought akin to the β of the corporate finance literature.
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 $[-100\%, \infty]$.
9. We add structure in empirical work by restricting this response to be time-invariant.
10. This databank is documented in Meeks *et al.* (1999). Companies whose main activities were in agriculture, mining, shipping, insurance, property, banking and finance were excluded. There was no size qualification in 1948–58. In stages, the size qualification rose to net assets of £5.0 million, or gross income of £500,000 (by 1973), for the firms included in the 1975–1977 period.
11. One difficulty with the data was that the industry codes used by EXSTAT did not reliably match to SIC codes. The industry codes we use are defined broadly to enable splicing across the databases.
12. 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.
13. We have replicated the analysis with cutoff points at $\pm 50\%$, $\pm 75\%$, $\pm 100\%$ and $\pm 150\%$, as well as cut-off points based on mean $\pm k *$Std Dev., with k taking values between 1 and 2. The patterns in the results we report are robust across all these experiments. It has not been possible to distinguish between growth of the firms in this population through acquisitions and organic growth. But the above robustness checks reassure us that cross-sectional dynamics are not sensitive to the inclusion or exclusion of growth through acquisitions. It is also worth noting that only small proportions of firms went bankrupt or were acquired from this population of large firms. We identified 166 instances of bankruptcy and 1859 acquisitions over the 34 years to 1998, amounting to an average hazard rate of 3% for being acquired, and 0.3% for going bankrupt. These proportions cannot give rise to the patterns we report; see Bhattacharjee *et al.* (2002).
14. See Silverman (1986); Cosh *et al.* (1998) for an application of non-parametric and semi-parametric methods to analyses corporate growth in the UK.
15. 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 began 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.
16. Firms change their sectors very rarely, and in our data not at all. Thus, the industry variable is devoid of time dimension.
17. Demeaning will have taken out any serial correlation at business cycle frequencies.
18. 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 (1996, 2001) have, and to 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). 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 for the countercyclical skew of the growth rate distribution.

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19. For an example of the use of the deciles to capture the time series dimension of cross-sections, see Harvey and Bernstein (2003).
20. In a companion paper (Chadha *et al.* 2002) we have established that the pattern reported is robust with respect to monetary policy variables—specifically, the term structure of interest rates. We found that firms that are most responsive to variations in interest rates are firms experiencing medium rates of growth. The fastest and the slowest growers are relatively unresponsive, in terms of growth, to interest rate variations.
21. These are OLS estimates. A Hausman–Wu test for the exogeneity of ρ clearly indicated that instrumental variables were unnecessary.

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