Operating Leverage over the Business Cycle

Arnab Bhattacharjee, Heriot Watt University. A.Bhattacharjee@hw.ac.uk
Chris Higson, London Business School. CHigson@london.edu
Sean Holly, University of Cambridge. sh247@cam.ac.uk

Janaury 2016

Abstract

Operating leverage describes the extent to which a firm's operating costs are fixed in the short run. The effect of operating leverage is to amplify the impact on profit of a change in revenues; an effect which is further amplified by financial leverage and by asymmetry in the tax system. In this paper we provide empirical estimates of operating leverage at the firm level, using a long panel of data on UK quoted firms. We report sectoral differences in operating leverage around the business cycle, and show that these can be partly explained in terms of costly labour adjustment and asymmetric price adjustment.

Operating Leverage over the Business Cycle

January 2016

Abstract

Operating leverage describes the extent to which a firm's operating costs are fixed in the short run. The effect of operating leverage is to amplify the impact on profit of a change in revenues; an effect which is further amplified by financial leverage and by asymmetry in the tax system. In this paper we provide empirical estimates of operating leverage at the firm level, using a long panel of data on UK quoted firms. We report sectoral differences in operating leverage around the business cycle, and show that these can be partly explained in terms of costly labour adjustment and asymmetric price adjustment.

JEL Classification: E32, D4, G30.

Keywords: operating margin, panel data, fixed and flexible costs, business cycles.

I. Introduction

Operating leverage describes the extent to which a firm's operating costs are fixed in the short run. If the firm cannot, or chooses not to, fully adjust costs when revenues change, this is directly observable in operating profit margins. The operating leverage effect of a change in revenues on earnings is amplified by underlying business risk, financial leverage and by asymmetry in the tax system (Hamada (1972), Rubinstein (1973), Lev (1974), Bowman (1979), Mandelker and Rhee (1984), Mensah (1992)). Hence, operating leverage lies at the heart of the distinction between cyclical and non-cyclical firms in financial markets.

One reason for the concern with operating leverage in the finance literature is its potential to explain the value premium; the observation that 'value' stocks with high book-to-market ratios earn higher returns than growth stocks (Carlson et al. (2004), Zhang (2005) and Cooper (2006)). Value firms earn higher returns because they largely use assets in place that are riskier than growth options because of operating leverage; without operating leverage growth options are riskier than assets in place (Lev, 1974; Novy-Marx, 2011), so the value premium reflects the firm's investment behaviour (Fama and French, 1996; Chen and Zhang, 1998; Berk et al., 1999). In Fama and French (1996) the value premium compensates for financial distress risk, with potentially negative effects on intangible elements of wealth such as human capital.

Garcıa-Feijoo and Jorgensen (2010) report that the book-to-market ratio, beta, and average stock returns are all positively associated with the degree of operating leverage in the cross-section. In Gulen et al. (2008) value firms have higher operating leverage, higher fixed to total asset ratios, greater frequency of disinvestment, and higher financial leverage than growth firms, and are less flexible than growth firms in adjusting to worsening economic conditions. Other empirical studies that support a risk explanation of the value premium include Mandelker and Rhee (1984), Lord (1996), Ho et al. (2004) and Novy-Marx (2007). Novy-Marx[1] finds that the book to market ratio explains returns within an industry, though not between industries (also Zhang (2005) and Aguerrevere (2006)).

Survey-based evidence in industrial economics has suggested an asymmetric response

[1]Unconventionally, in Novy-Marx (2007) 'operating leverage' is the profit margin while the variation in that margin due to sticky costs is termed 'degree of operational inflexibility' (also, Gourio (2005)). He says: *"While higher variable costs result in effectively more levered assets, they should also be associated with more flexibility on the cost side. When capital costs are small relative to flow costs associated with production, firms should be more willing to shut down unprofitable production, even if it entails the loss of capital. ... Operating leverage is, to first-order approximation, the inverse of a firm's operating margins, and thus it is generally closer to ten than zero ... In response to negative shocks firms' revenues typically fall more quickly than they can reduce costs; prices are more responsive than firms' operations. ... While simple theory suggests that expected returns should be increasing in operating leverage, the fact that they should also be increasing in operational inflexibility, which is difficult to observe and negatively correlated with the level of operating leverage, makes direct inference on the expected return/operating leverage relationship difficult."*

to a shock to sales, with quantity adjustments more likely in recessions than in booms (Machin et al. (1993)). Liquidity constrained firms are less likely to cut prices (Gottfries (1991)), implying that additional liquidity may be more important in recessions that are driven by demand shocks. Liquidity constraints and limited access to capital markets may explain the greater procyclicity of small firms, which therefore bear the brunt of monetary policy shocks (Gertler and Gilchrist (1994)).

Though profit margins are observably procyclical (Green and Porter (1984); Machin and van Reenen (1993)), it has proven hard to extract measures of operating leverage from the observed behaviour of profit margins. For some raw materials, supply may be rapidly adjustable and reversible at little cost. Highly specific plant and equipment may be hard to sell and difficult to reacquire; it may trade in illiquid markets with a wide spread between disposal value and replacement cost. Campello and Giambona (2013) and James and Kizilaslan (2014) argue that only those tangible assets that can be easily redeployed can sustain debt capacity. In this way, operating leverage and financial leverage may be natural substitutes. In Acharya, Almeida and Campello (2013) firms with high asset betas hold more cash and have a higher cost of debt financing.

The adjustment of physical capital and human capital go hand-in-hand as they are the two key dimensions of capacity. Skilled labour has the character of specific industrial plant. Employment law and labour contracting create lags in the adjustment of labour inputs so that, on the downside, a labour-cost response may be observed significantly later than a fall in revenue. On the upside, labour may be costly to acquire or reacquire and can take both time and expenditure to equip it with organization specific knowledge. As with specific intangible assets, the replacement cost of skilled labour is likely to move procyclically.For labour cost, firms disclose both employment and wage but, otherwise, the price and quantity components of cost and revenue are not observable in panel data.

One thing that makes operating leverage empirically elusive is the role of expectations where there are asymmetric adjustment costs to increasing and reducing capacity. If a firm or an industry is undergoing secular growth or contraction that is fully anticipated then capacity can be adjusted and even 'fixed assets', physical capital, can be bought or sold in a timely way. In practice, firms may be slow to recognise secular growth or decline or slow to respond to it, especially if they are uncertain whether it will be temporary or permanent. If the firm faces what it believes to be a cyclical change in demand and if adjustment is costly then it may be rational to maintain unused capacity through the cycle. At an inflection point, firms may be unclear whether a change in revenues is secular or cyclical and how long the cycle will last.

We have the following testable predictions:

- We predict that small firms experience greater costs of adjusting capacity and, assuming size proxies financial strength, large firms are better able to bear the costs of non-adjustment. We measure size both in terms of employment and the quantity of fixed capital.

- We predict that adjustment costs may be asymmetric, so that firms exhibit higher operating leverage, that is the non-adjustment of capacity leading to relatively depressed margins, in cyclical downturns than in upturns.

- Asymmetric response of costs may also reflect price adjustments over the economic cycle, rather than quantity adjustments, where such adjustments are subject to nominal rigidities (Machin et al. (1993)).

- Since the costs of adjusting capacity are likely to reflect the nature of the inputs, we expect to see systematic differences in cyclicity between sectors.

We estimate a model of operating leverage by applying panel data methods to data on UK quoted firms from 1968 to 2011. Much of the data displays temporal non-stationarity and potentially strong dependence cross-sectionally (Petersen (2009)). This cross-sectional dependence is related to factor structure that needs to be modelled explicitly (Fama and French (1992, 1996); Griffin (2002)). We address these issues as follows.

To allow for nonstationarity of our main activity measures, sales and costs at the firm-level (in logarithms), we model the relationship between costs and sales (operating leverage) as a dynamic, non-stationary process. We allow that sales and costs may be in long-run equilibrium so that, at the firm-level, logarithms of sales and costs are potentially cointegrated. The short-run and long-run dynamics between costs and sales is modelled as an error correction process in which the underlying series are non-stationary and potentially cointegrating. Cross-section dependence is modelled using the common correlated effects approach of Pesaran (2006), which allows for potential factor-based strong dependence. This powerful framework allows us the determine how operating leverage reacts, in the short run, to variations in the use of capital and employment, and also the extent to which there is asymmetric adjustment.

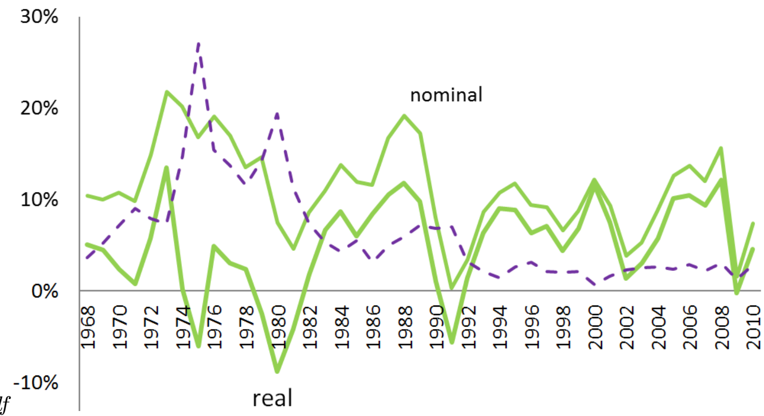
In section 2 we describe the data. In section 3 we develop and estimate a model of operating leverage and in section 4 we draw conclusions.

II. Data and descriptives

The data are drawn from the LBS/Cambridge accounting data set, which is an archive of annual company balance sheet and income statement data for all UK industrial and commercial quoted companies. In terms of coverage, the dataset attempts to be complete in companies listed on a UK exchange, principally the London Stock Exchange and also the junior markets including USM (Unlisted Securities Market) and AIM (Alternative Investments Market). We include industrial and commercial companies, but exclude financial and property companies. There is substantial attrition in the population of listed firms as firms exit through acquisition or failure, and enter through stock exchange listing. Hence, the panel is unbalanced but large. The dataset contains between 1500 and 2000 companies per annum. Since UK companies were required to disclose sales for the first time in 1967, 1968 is the first year with a measure of sales growth. The sectoral composition is described in Table 1 (top panel: 1968 to 1989; bottom panel: 1990 to 2010).

Certain features of firm panel data add measurement error and confound our ability to interpret the results. Some companies are exporters and some are multinational in operation so that their data includes the results of foreign operations, reducing the potential alignment between reported sales of these companies and domestic GDP. Equally, foreign-owned domestic firms are missing from the data, although their output forms part of domestic GDP. Data are drawn from annual financial statements with heterogeneous accounting year ends – in this data 37% of companies have a December year-end; March, 22%; September, 10%; June, 8%. Our convention is to assign observations to the previous calendar year when the financial statement date is 19 May or before.

1



1 *.pdf*

Median Sales Growth (nominal and real) and GDP deflator.

Figure 1 plots the median growth rates in annual sales in nominal and real terms, and the inflation measure (GDP deflator) used to deflate the real series. The potentially misleading nature of nominal sales growth rates in the high inflation environment of the 1970s and early 1980s is evident. In 1975, the median nominal growth rate was 17 percent but annual inflation was in excess of 20 percent, and the median firm's real growth rate was minus 6 percent. From the 1990s on, nominal and real growth rates converge.

Figure 2 plots the 10th, 25th, 50th and 75th percentiles of the distribution of annual company growth rates in real sales. A number of regularities are evident. For all of these quantiles, the growth rate is highly cyclical. The highest growth firms (the 75th percentile) display the most variance in growth rates around the cycle. Second, prior to the mid-1980s, the interquartile range of growth rates is stable but from the mid-1980s, the dispersion of growth rates significantly increases.

Table 1. Sector (1-, 2- digit) composition of the sample.

1a

	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Oil & Gas	12	15	11	12	15	16	18	16	18	16	20	21	30	35	38	34	43	44	39	45	46	44
Basic Materials	145	153	116	116	144	149	157	142	140	135	135	132	128	121	119	127	129	119	119	110	107	103
Chemicals	69	72	51	53	72	73	72	70	70	66	66	63	60	58	57	62	58	59	57	48	43	44
Basic Resources	76	81	65	63	72	76	85	72	70	69	69	69	68	63	62	65	71	60	62	62	64	59
Industrials	556	622	489	510	672	674	690	663	667	655	631	624	624	633	651	671	679	695	711	690	665	643
Construction & Materials	79	91	74	73	98	93	96	91	92	95	86	88	89	87	83	77	80	82	83	79	85	89
Aerospace & Defense	9	6	6	6	8	8	9	9	10	9	9	11	12	13	12	12	12	15	14	17	15	16
General Industrials	61	59	49	54	74	74	78	75	76	72	68	64	63	61	62	63	53	54	53	49	48	45
Electronic & Electrical Equi	73	76	62	65	85	87	90	86	87	84	86	81	88	96	106	130	135	141	153	150	128	110
Industrial Transportation	267	313	238	251	324	330	330	316	317	310	300	296	288	280	281	282	274	274	270	247	236	218
Support Services	67	77	60	61	83	82	87	86	85	85	82	84	84	96	107	107	125	129	138	148	153	165
Consumer Goods	374	389	310	325	408	405	415	400	392	395	399	387	389	370	364	370	369	369	351	360	366	345
Automobiles & Parts	6	5	6	6	6	8	8	8	8	8	8	8	9	9	10	10	11	11	11	13	12	12
Food & Beverage	119	125	97	95	126	115	118	110	107	111	119	112	118	120	117	119	126	122	110	111	109	105
Personal & Household Goo	249	259	207	224	276	282	289	282	277	276	272	267	262	241	237	241	232	236	230	236	245	228
Health Care	32	30	24	25	32	29	28	29	28	28	25	25	27	26	30	29	30	37	40	45	47	46
Consumer Services	231	255	218	235	303	330	336	334	345	345	340	341	336	339	343	358	375	391	404	408	403	396
Retail	122	151	131	142	178	182	189	185	189	188	181	180	176	178	176	180	184	172	181	178	171	159
Media	54	60	45	50	63	70	70	71	73	73	74	75	76	74	77	88	91	109	114	122	125	132
Travel & Leisure	55	44	42	43	62	78	77	78	83	84	85	86	84	87	90	90	100	110	109	108	107	105
Telecommunications	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	2	4	2	2	2	3	5
Utilities	0	0	0	0	2	0	1	0	0	1	3	2	1	2	4	7	8	10	8	12	17	20
Technology	8	5	4	4	4	5	5	7	6	6	8	9	8	9	16	20	34	41	50	61	63	66
Total	**1359**	**1469**	**1172**	**1227**	**1580**	**1608**	**1650**	**1591**	**1596**	**1581**	**1561**	**1541**	**1544**	**1536**	**1566**	**1618**	**1671**	**1708**	**1724**	**1733**	**1717**	**1668**

2.pdf

1b

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	
Oil & Gas	49	47	43	45	44	39	44	42	41	38	40	50	67	79	96	101	107	110	120	120	122	
Basic Materials	96	88	88	90	87	90	91	90	81	75	72	73	92	105	108	124	134	144	170	167	157	
Chemicals	40	38	41	42	42	43	47	45	40	34	28	29	31	32	31	36	36	38	44	40	34	
Basic Resources	56	50	47	48	45	47	44	45	41	41	44	44	61	73	77	88	98	106	126	127	123	
Industrials	580	554	550	544	549	557	613	605	548	495	472	479	500	544	556	566	566	536	528	481	443	
Construction & Materials	81	83	83	83	86	93	96	89	83	71	63	58	59	67	65	66	67	62	62	57	53	
Aerospace & Defense	17	16	15	15	15	16	18	17	17	16	15	12	14	15	19	19	16	15	16	14	13	
General Industrials	39	37	35	41	42	43	39	38	34	27	19	19	20	21	20	18	18	20	19	18	17	
Electronic & Electrical Equi	91	78	80	81	77	73	82	74	64	55	59	59	63	73	73	75	75	65	65	58	54	
Industrial Transportation	209	198	198	186	187	190	196	183	159	134	121	121	110	115	118	120	118	119	116	111	103	
Support Services	143	142	139	138	142	142	182	204	191	191	195	210	233	252	260	267	271	254	249	222	202	
Consumer Goods	330	315	302	305	294	292	301	295	268	245	230	210	209	203	182	187	175	162	150	145	130	
Automobiles & Parts	12	12	12	13	13	13	14	16	12	13	11	12	14	13	12	11	10	7	7	8	7	
Food & Beverage	106	103	103	102	104	99	105	99	90	82	75	68	67	73	69	71	67	66	63	64	59	
Personal & Household Goo	212	200	187	190	177	180	182	180	166	150	144	130	128	117	101	105	98	89	80	73	64	
Health Care	50	54	53	69	68	77	88	92	87	84	97	115	126	140	154	178	167	166	152	135	122	
Consumer Services	388	361	362	379	371	373	437	448	432	421	438	452	460	441	469	483	465	428	406	355	322	
Retail	156	147	144	153	140	147	170	161	155	154	146	141	140	132	137	142	127	117	108	94	91	
Media	125	115	113	115	119	115	134	134	125	123	133	154	157	162	187	180	181	172	166	144	135	
Travel & Leisure	107	99	105	111	112	111	133	153	152	145	159	157	164	148	146	162	158	140	133	118	97	
Telecommunications	5	5	5	6	8	7	21	20	25	28	29	32	36	39	45	45	45	44	42	30	24	
Utilities	34	43	48	49	50	53	45	45	35	32	28	27	28	24	25	32	34	34	36	32	33	
Technology	72	73	80	96	97	96	141	158	159	172	220	253	240	259	302	289	297	262	244	212	190	
Total	**1604**	**1540**	**1531**	**1583**	**1568**	**1584**	**1781**	**1795**	**1676**	**1590**	**1626**	**1691**	**1758**	**1834**	**1937**	**2005**	**1990**	**1886**	**1848**	**1677**	**1543**	**70467**

3.pdf

Third, in any year a significant proportion of the corporate population do not grow and have real sales that are either flat or declining. Fourth, the median growth rate in real sales is stationary throughout this 40 year period at only slightly above zero. Fifth, negative real growth is the norm at the first quartile. Real growth at this quantile is never positive; even in boom periods it may reach but does not exceed the zero axis. Finally, during the deepest downturn during this 40 year period, which was the 1980s recession, even at the third quartile (75th percentile) growth of zero. At that time, 75 percent of firms experienced negative real growth.

Table 2 reports median annual real sales growth rates by one-digit and two-digit industry sectors. For reference the table also reports the percentage annual change in real GDP (Office of National Statistics (ONS) data series IHYP). We want to observe how individual company fundamentals (sales, costs, profits) move around the business cycle. Using sales as the measure of a firm's activity and aggregate GDP to proxy the

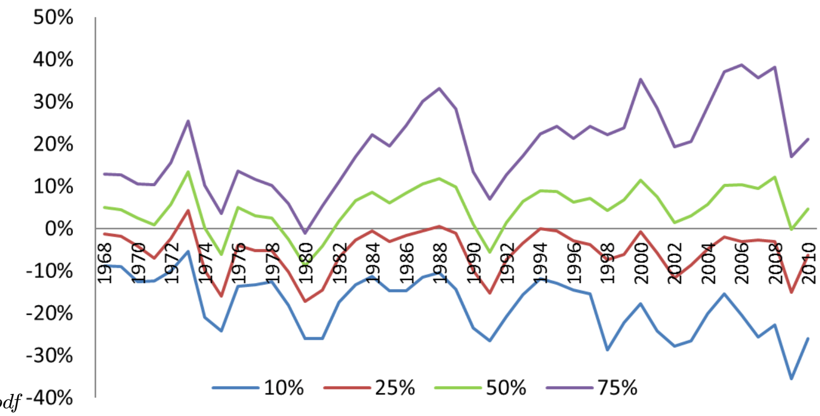


Figure 1: Distribution of company growth rates (selected percentiles)

average response, we examine the dynamics of activity, taking into account heterogeneity across sectors in their relation to the aggregate cycle. We expect to find that sectors may lag or lead the aggregate economy in the response to a downturn, and may display a greater or smaller response, or in some cases no response at all.

Table 2 flags recessionary years, that is, calendar years experiencing negative growth rate in aggregate GDP. Although there is substantial alignment between sector sales growth and change in aggregate GDP, the disaggregate analysis points to variations in the experience of firms during different episodes of downturn. For example, the deep 1980-1981 recession in the observed in aggregate data was also associated with declining real sales in almost all sectors. However, most sectors also reported negative sales growth in 1979 and in 5 of 18 sectors there was a fourth year of negative sales growth in 1982. There was a similar, though less intense, pattern around the 1991 downturn, with 6 sectors reporting sales downturn in 1990. The recession that followed the recent financial crisis is often described as the deepest in living memory. The 2009 recession was uniquely sharp in terms of the decline in GDP. But for the 'industrial' economy that we are examining in this paper, with the notable exception of construction the impact of recession was both smaller, and less consistent across sectors, than in the 1980-1981 downturn. Table 1b also flags the 'quasi recessionary' year, 2002. In terms of the impact on median sales growth this was a worse year than 2009 in many sectors. However this is not equally reflected in aggregate GDP.

Figure 3 plots the median return on capital employed (profit/capital employed), where capital employed is the sum of equity shareholders' funds and long- plus short-term borrowing less cash. Profit is earnings before interest and tax, depreciation, amortisation and impairment, and exceptional items. For comparison, the dotted line in Figure 3 is the median real sales growth series from Figure 1. It is clear that most, though not all, of the time series variation (cyclicity) in real sales growth is reflected in return on capital employed.

Table 2. Cyclicity of company growth at the sector level.

2a

	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Oil & Gas	6%	1%	3%	6%	-1%	23%	37%	-15%	13%	3%	1%	2%	4%	20%	3%	12%	26%	-6%	-25%	-5%	-5%	8%
Basic Materials	7%	7%	2%	-2%	2%	17%	10%	-14%	9%	3%	0%	-2%	-9%	-7%	0%	5%	10%	4%	2%	5%	11%	9%
Chemicals	6%	8%	0%	1%	2%	16%	8%	-11%	9%	4%	1%	-2%	-10%	-6%	1%	7%	10%	4%	7%	4%	5%	7%
Basic Resources	9%	6%	3%	-4%	1%	19%	12%	-16%	9%	2%	-1%	-2%	-9%	-8%	-2%	4%	8%	6%	-1%	6%	14%	9%
Industrials	5%	6%	3%	1%	4%	14%	1%	-6%	4%	3%	2%	-2%	-10%	-6%	1%	7%	8%	5%	9%	12%	12%	11%
Construction & Materials	6%	3%	4%	3%	8%	13%	-7%	-3%	4%	-1%	3%	2%	-8%	-3%	4%	10%	7%	4%	10%	12%	14%	8%
Aerospace & Defense	13%	9%	16%	4%	7%	25%	4%	-14%	8%	12%	13%	-3%	-6%	-13%	9%	7%	10%	9%	14%	9%	8%	18%
General Industrials	3%	8%	3%	0%	7%	15%	0%	-10%	6%	4%	0%	2%	-12%	-8%	-1%	6%	8%	4%	8%	16%	11%	6%
Electronic & Electrical Eq	8%	7%	3%	3%	3%	11%	1%	-9%	4%	5%	3%	-5%	-10%	-1%	6%	9%	19%	9%	11%	17%	10%	9%
Industrial Transportation	5%	8%	2%	-1%	0%	14%	3%	-5%	4%	4%	2%	-4%	-11%	-9%	-1%	0%	5%	2%	6%	6%	11%	10%
Support Services	7%	5%	6%	8%	7%	7%	8%	2%	3%	-2%	-1%	-2%	0%	-1%	11%	14%	15%	3%	3%	-3%	-3%	5%
Consumer Goods	3%	2%	1%	0%	7%	12%	-2%	-6%	4%	2%	1%	-5%	-10%	-4%	0%	5%	6%	6%	7%	6%	9%	5%
Automobiles & Parts	16%	12%	5%	3%	-3%	20%	-3%	-7%	12%	-1%	-2%	0%	-9%	-11%	-4%	-3%	2%	4%	13%	0%	11%	12%
Food & Beverage	3%	4%	1%	-1%	5%	11%	1%	-3%	8%	4%	0%	-5%	-7%	3%	3%	6%	4%	4%	6%	3%	6%	6%
Personal & Household Gc	3%	1%	2%	0%	9%	14%	-3%	-7%	1%	2%	1%	-5%	-11%	-8%	-2%	4%	7%	7%	10%	9%	12%	3%
Health Care	7%	6%	5%	2%	3%	12%	2%	-8%	6%	2%	0%	-7%	-7%	-5%	8%	10%	13%	12%	7%	10%	21%	12%
Consumer Services	4%	3%	3%	4%	9%	11%	-4%	-4%	5%	5%	6%	-2%	-7%	-1%	4%	7%	10%	8%	10%	14%	13%	12%
Retail	3%	3%	3%	5%	9%	10%	-5%	-3%	6%	5%	6%	-2%	-7%	-2%	5%	8%	9%	7%	9%	11%	12%	11%
Media	6%	4%	1%	1%	10%	12%	-1%	-7%	4%	3%	6%	1%	-7%	2%	5%	10%	12%	9%	11%	20%	12%	12%
Travel & Leisure	4%	5%	4%	3%	10%	12%	-5%	-4%	4%	5%	6%	-3%	-7%	-1%	0%	4%	10%	9%	9%	18%	17%	14%
Telecommunications												3%	0%	11%	7%	23%	23%	2%	2%	16%	15%	42%
Utilities											7%	14%	34%	4%	1%	9%	11%	15%	11%	3%	0%	7%
Technology	12%	10%	-1%	-1%	-2%	14%	-1%	-6%	9%	-2%	5%	0%	-7%	8%	7%	23%	24%	14%	13%	21%	20%	23%
GDP% (IHYP)	4.2	2.1	2.2	2.1	3.7	7.2	-1.3	-0.6	2.6	2.4	3.2	2.7	-2	-1.2	2.2	3.7	2.7	3.6	4	4.6	5	2.3

5.pdf

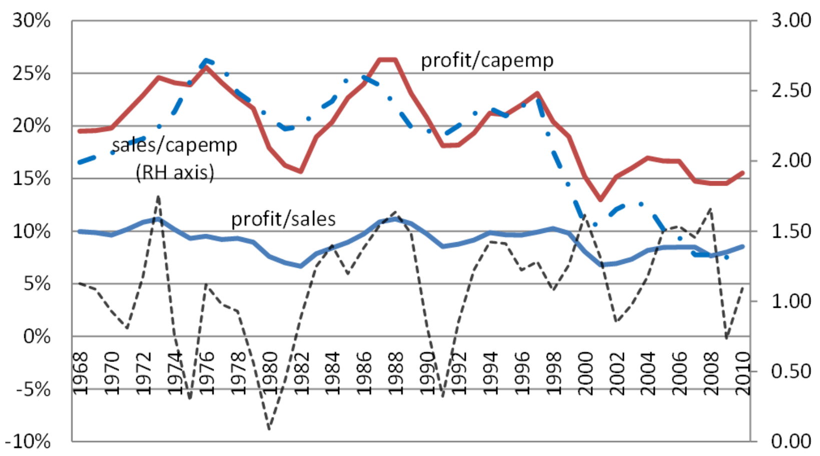
2b

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Oil & Gas	17%	1%	3%	12%	4%	16%	23%	10%	-26%	20%	37%	-1%	-4%	18%	12%	45%	23%	37%	46%	-7%	22%
Basic Materials	-4%	-5%	1%	5%	9%	14%	2%	-2%	-4%	-2%	7%	0%	-7%	-1%	2%	12%	11%	7%	19%	-1%	24%
Chemicals	-3%	-4%	5%	5%	5%	11%	2%	-1%	-5%	-3%	3%	-2%	-8%	-5%	-1%	2%	4%	8%	6%	-4%	12%
Basic Resources	-6%	-7%	-2%	6%	11%	20%	1%	-2%	-4%	-1%	17%	2%	-4%	8%	15%	20%	27%	7%	29%	0%	33%
Industrials	1%	-8%	-1%	5%	10%	10%	5%	7%	4%	5%	11%	5%	-1%	2%	5%	10%	11%	11%	12%	-5%	2%
Construction & Materials	-1%	-11%	-3%	5%	10%	3%	0%	5%	2%	6%	8%	11%	4%	3%	1%	5%	11%	8%	11%	-16%	0%
Aerospace & Defense	4%	-7%	4%	5%	2%	6%	6%	9%	-2%	8%	21%	8%	-9%	1%	10%	18%	8%	15%	22%	-2%	2%
General Industrials	-3%	-6%	2%	6%	11%	16%	4%	5%	1%	4%	7%	3%	2%	-2%	0%	1%	4%	0%	5%	-6%	5%
Electronic & Electrical Eq	1%	-10%	5%	8%	10%	12%	7%	5%	3%	3%	14%	0%	-13%	0%	5%	7%	13%	3%	12%	-2%	9%
Industrial Transportation	-1%	-6%	-1%	4%	10%	12%	5%	2%	1%	0%	6%	1%	-1%	-1%	2%	8%	10%	11%	12%	-8%	4%
Support Services	3%	6%	3%	2%	-2%	-6%	-11%	-12%	-9%	-3%	-1%	5%	2%	4%	8%	10%	0%	-5%	7%	11%	3%
Consumer Goods	-2%	-6%	0%	5%	7%	6%	4%	2%	-3%	0%	4%	2%	1%	3%	0%	1%	3%	5%	2%	0%	2%
Automobiles & Parts	0%	-11%	3%	7%	19%	16%	1%	0%	2%	5%	-9%	2%	-11%	28%	32%	0%	5%	18%	9%	-5%	17%
Food & Beverage	1%	1%	4%	4%	6%	8%	3%	1%	-5%	-1%	3%	5%	3%	4%	2%	1%	5%	6%	10%	3%	3%
Personal & Household Gc	-4%	-9%	-3%	7%	9%	4%	4%	3%	-1%	0%	5%	0%	-1%	2%	-3%	1%	1%	3%	-3%	-1%	2%
Health Care	9%	3%	7%	12%	6%	12%	9%	11%	10%	22%	19%	19%	10%	5%	11%	20%	13%	17%	19%	12%	11%
Consumer Services	3%	-4%	4%	7%	9%	7%	10%	10%	10%	11%	14%	11%	6%	5%	6%	9%	6%	8%	7%	1%	3%
Retail	3%	-4%	4%	8%	8%	7%	9%	9%	7%	6%	8%	8%	5%	4%	5%	5%	5%	5%	2%	2%	3%
Media	0%	-7%	3%	8%	11%	9%	7%	7%	9%	12%	25%	12%	3%	9%	11%	19%	13%	9%	9%	-5%	-1%
Travel & Leisure	9%	2%	5%	2%	10%	6%	12%	17%	15%	15%	13%	22%	12%	4%	6%	9%	4%	13%	12%	3%	4%
Telecommunications	2%	10%	-2%	2%	7%	43%	79%	32%	31%	29%	41%	27%	28%	15%	21%	14%	7%	5%	14%	6%	4%
Utilities	3%	5%	6%	4%	2%	2%	4%	1%	3%	4%	7%	8%	0%	7%	2%	1%	14%	11%	25%	6%	3%
Technology	2%	-10%	2%	15%	16%	22%	9%	17%	17%	20%	28%	10%	-4%	-2%	6%	17%	17%	9%	11%	3%	4%
GDP% (IHYP)	0.8	-1.4	0.1	2.2	4.3	3.1	2.9	3.3	3.6	3.5	3.9	2.5	2.1	2.8	3	2.2	2.8	2.7	-0.1	-4.9	1.4

6.pdf

Figure 3 then decomposes the return on capital employed into its profit margin (profit/sales) and asset utilisation (sales/capital employed, right hand axis) components. Apparently, most of the variation in return on capital employed is coming from sales. Profit margins are procyclical, but profit margins display a dampened response to shocks to sales, suggesting that there is some pass through to costs. At the same time, the pass-through is not perfect, otherwise profit margins would not exhibit the cyclical pattern

3



7.pdf

Figure 2: Components of returns, 1968 – 2010.

observed in the data.

Table 3. Effect of the cycle on the median margin at the sector level.

3a

	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Oil & Gas	11.6%	11.5%	11.0%	11.3%	9.5%	11.3%	10.0%	10.7%	8.7%	9.6%	9.4%	8.6%	12.4%	12.4%	10.9%	10.4%	14.3%	14.8%	11.3%	12.0%	18.4%	13.1%
Basic Materials	9.5%	10.8%	9.7%	9.3%	9.8%	11.7%	11.6%	10.4%	10.0%	9.1%	9.1%	9.4%	7.6%	6.9%	7.1%	7.4%	8.1%	8.8%	9.7%	10.2%	10.7%	11.0%
Chemicals	10.3%	11.4%	10.7%	11.1%	11.3%	12.2%	12.5%	10.6%	10.1%	9.4%	10.5%	9.6%	7.6%	7.6%	7.7%	8.9%	8.6%	9.3%	10.8%	11.2%	11.2%	11.7%
Basic Resources	9.0%	10.6%	9.3%	8.5%	8.9%	10.6%	11.0%	10.3%	9.8%	8.7%	8.6%	8.8%	7.7%	6.7%	6.1%	6.5%	7.6%	8.3%	8.4%	9.8%	10.5%	9.7%
Industrials	10.7%	10.0%	10.3%	10.4%	10.6%	11.4%	10.8%	10.2%	10.1%	9.9%	9.9%	9.2%	8.3%	7.2%	6.8%	7.6%	8.2%	8.8%	9.4%	10.4%	11.0%	10.9%
Construction & Materials	10.8%	9.3%	9.2%	10.7%	11.6%	12.6%	10.7%	9.7%	9.3%	9.7%	9.3%	10.0%	9.1%	8.6%	7.6%	8.4%	9.1%	9.7%	9.8%	10.3%	10.9%	11.7%
Aerospace & Defense	11.6%	9.9%	12.3%	10.2%	11.2%	12.6%	12.1%	10.8%	10.2%	11.7%	10.0%	8.4%	8.0%	7.4%	6.3%	6.0%	9.0%	9.7%	9.7%	11.6%	12.7%	10.9%
General Industrials	10.3%	9.1%	9.9%	8.9%	8.9%	10.6%	10.2%	8.7%	8.6%	8.8%	9.6%	8.8%	7.8%	7.0%	7.1%	7.5%	7.7%	8.8%	8.7%	9.9%	11.1%	11.1%
Electronic & Electrical Equi	10.5%	12.8%	13.5%	12.9%	13.1%	14.1%	12.1%	12.3%	12.0%	12.9%	11.6%	10.7%	9.7%	8.7%	8.9%	11.4%	10.6%	11.4%	11.0%	12.4%	12.7%	10.7%
Industrial Transportation	10.7%	10.1%	10.0%	10.2%	10.3%	10.8%	11.0%	10.4%	10.2%	10.2%	9.8%	9.1%	8.0%	6.2%	5.7%	5.6%	6.7%	7.6%	8.5%	9.2%	10.5%	10.6%
Support Services	10.6%	9.5%	10.5%	10.4%	10.8%	11.0%	9.4%	8.0%	7.3%	7.6%	8.4%	8.4%	7.7%	6.7%	8.0%	7.9%	7.9%	8.3%	10.0%	10.4%	11.2%	11.0%
Consumer Goods	8.4%	8.6%	9.0%	9.7%	10.6%	11.2%	9.8%	8.6%	8.5%	8.5%	8.5%	8.9%	7.7%	6.9%	6.5%	7.3%	7.7%	8.1%	8.8%	10.0%	10.7%	10.1%
Automobiles & Parts	9.7%	10.7%	13.3%	12.8%	13.4%	11.3%	10.7%	9.5%	11.2%	11.6%	10.9%	11.2%	9.6%	6.9%	7.6%	6.4%	5.6%	4.8%	9.2%	9.9%	10.9%	12.4%
Food & Beverage	9.1%	9.6%	9.7%	10.1%	10.4%	9.9%	8.3%	8.2%	7.8%	8.2%	8.3%	8.4%	8.0%	7.9%	8.0%	8.5%	8.4%	8.7%	8.7%	8.4%	9.5%	10.1%
Personal & Household Goo	9.2%	8.2%	8.8%	9.5%	10.7%	11.4%	10.2%	8.8%	8.6%	8.8%	8.5%	9.1%	7.4%	6.4%	5.7%	6.8%	7.5%	7.9%	8.8%	10.4%	11.0%	10.1%
Health Care	10.6%	10.7%	8.6%	11.1%	11.0%	12.5%	11.3%	11.5%	12.5%	10.8%	8.3%	9.9%	9.9%	7.8%	8.3%	9.8%	10.7%	10.6%	8.7%	13.3%	15.2%	15.8%
Consumer Services	10.4%	9.8%	8.8%	9.2%	10.3%	11.2%	9.1%	8.2%	7.8%	8.2%	8.2%	8.6%	7.2%	6.2%	5.8%	6.3%	7.1%	8.0%	8.7%	9.4%	10.4%	10.3%
Retail	9.1%	7.1%	6.9%	7.4%	8.5%	8.1%	7.3%	6.5%	6.0%	6.5%	6.8%	7.4%	6.1%	5.4%	4.6%	4.6%	5.6%	5.8%	6.8%	7.5%	7.6%	7.7%
Media	12.0%	12.7%	11.1%	11.6%	12.3%	13.9%	12.2%	10.3%	10.4%	10.3%	10.0%	10.3%	7.9%	8.3%	8.0%	8.2%	8.8%	10.1%	10.3%	12.1%	13.3%	13.1%
Travel & Leisure	10.4%	14.1%	12.9%	13.2%	12.5%	13.0%	10.8%	10.5%	10.2%	10.1%	9.3%	10.5%	10.0%	8.9%	6.9%	8.0%	8.7%	11.7%	11.6%	11.0%	12.2%	13.2%
Telecommunications													30.5%	30.1%	26.2%	36.0%	29.4%	35.7%	37.1%	38.5%	31.2%	34.0%
Utilities													22.1%	16.6%	10.6%	11.6%	11.9%	9.9%	14.4%	17.2%	19.9%	14.9%
Technology	8.4%	19.4%	14.2%	13.8%	16.7%	14.1%	13.4%	12.8%	14.0%	16.7%	12.5%	15.3%	14.6%	10.0%	12.7%	14.7%	17.0%	14.0%	11.1%	13.5%	11.5%	11.7%
GDP% (IHYP)	**4.2**	**2.1**	**2.2**	**2.1**	**3.7**	**7.2**	**-1.3**	**-0.6**	**2.6**	**2.4**	**3.2**	**2.7**	**-2**	**-1.2**	**2.2**	**3.7**	**2.7**	**3.6**	**4**	**4.6**	**5**	**2.3**

8.pdf

3b

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Oil & Gas	18.2%	18.0%	18.3%	17.4%	21.2%	17.7%	11.2%	15.8%	13.8%	14.3%	14.3%	13.0%	6.7%	1.3%	5.2%	2.5%	0.0%	2.0%	0.0%	0.0%	0.0%
Basic Materials	10.6%	9.5%	9.8%	10.2%	11.2%	11.0%	9.4%	10.5%	9.3%	10.1%	9.7%	4.8%	5.9%	3.3%	5.4%	6.6%	0.0%	0.0%	0.0%	0.0%	3.5%
Chemicals	11.0%	10.5%	10.1%	10.0%	11.1%	11.2%	9.6%	10.7%	10.0%	11.5%	11.7%	8.8%	7.6%	7.0%	7.0%	8.4%	6.4%	2.7%	1.4%	0.0%	-12.8%
Basic Resources	10.4%	8.1%	7.0%	10.3%	11.3%	9.6%	7.6%	9.4%	8.5%	5.7%	7.5%	2.8%	4.2%	0.6%	3.1%	6.2%	0.0%	0.0%	0.0%	0.0%	7.1%
Industrials	10.0%	8.5%	8.0%	7.8%	8.4%	9.1%	9.3%	9.3%	9.7%	10.1%	8.7%	7.4%	6.6%	6.7%	7.2%	7.3%	7.7%	7.9%	7.9%	7.8%	7.5%
Construction & Materials	10.8%	7.3%	6.0%	6.1%	9.0%	7.7%	6.4%	6.8%	8.2%	8.3%	7.1%	6.5%	8.5%	7.7%	6.8%	7.7%	10.3%	7.6%	5.7%	4.9%	5.9%
Aerospace & Defense	7.6%	8.5%	8.3%	7.2%	6.3%	8.1%	8.5%	9.0%	11.2%	12.7%	9.7%	10.8%	8.8%	7.7%	9.9%	14.3%	11.9%	11.4%	12.7%	12.3%	11.9%
General Industrials	10.5%	10.6%	11.3%	11.4%	10.1%	10.7%	11.2%	12.3%	11.7%	12.4%	12.4%	11.2%	10.9%	9.6%	9.4%	9.6%	7.9%	6.2%	9.4%	8.6%	10.1%
Electronic & Electrical Equi	11.1%	9.8%	9.9%	9.2%	10.1%	11.1%	10.9%	10.5%	9.4%	10.9%	10.2%	8.3%	4.8%	4.5%	6.2%	4.8%	4.7%	4.7%	7.9%	4.9%	4.6%
Industrial Transportation	9.9%	8.1%	7.8%	7.4%	8.3%	8.9%	9.3%	9.5%	10.5%	10.2%	9.6%	8.6%	8.2%	7.7%	7.9%	8.3%	9.7%	10.8%	9.3%	9.8%	10.0%
Support Services	9.6%	9.3%	7.0%	7.3%	7.8%	7.7%	8.9%	8.3%	8.8%	8.9%	7.7%	5.8%	5.0%	5.4%	6.5%	6.9%	7.0%	7.4%	6.5%	6.9%	6.3%
Consumer Goods	8.4%	7.7%	8.3%	8.2%	9.4%	9.3%	9.0%	9.7%	10.0%	9.6%	8.9%	8.3%	8.0%	9.0%	9.0%	9.2%	8.1%	8.6%	6.4%	3.9%	6.5%
Automobiles & Parts	11.1%	8.0%	6.6%	8.7%	9.1%	8.8%	9.2%	11.7%	9.6%	9.7%	10.2%	3.3%	0.7%	0.0%	-5.1%	-18.1%	-2.0%	0.0%	-49.1%	-75.3%	-75.2%
Food & Beverage	9.5%	10.7%	11.3%	10.3%	10.9%	10.5%	10.3%	10.4%	10.9%	10.5%	9.9%	9.0%	9.9%	11.1%	11.1%	11.1%	9.4%	9.7%	8.7%	7.4%	8.4%
Personal & Household Goo	8.0%	6.8%	6.6%	7.1%	8.5%	8.8%	8.3%	9.2%	9.6%	8.3%	8.7%	8.1%	7.0%	7.8%	7.8%	8.1%	7.8%	7.5%	4.3%	3.0%	5.4%
Health Care	14.2%	12.1%	13.1%	12.7%	14.1%	10.4%	11.3%	5.6%	3.6%	-2.8%	-1.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	-1.3%	0.0%	0.0%	0.0%
Consumer Services	8.6%	7.3%	6.7%	7.6%	8.5%	9.6%	9.3%	10.0%	10.9%	10.2%	7.8%	7.2%	7.0%	7.7%	8.2%	7.7%	6.4%	6.9%	7.1%	7.3%	7.7%
Retail	7.0%	6.3%	5.5%	5.5%	6.5%	7.0%	6.2%	7.1%	8.0%	6.7%	6.6%	6.1%	6.2%	6.9%	6.6%	7.5%	5.9%	6.4%	5.3%	5.5%	6.6%
Media	10.1%	8.0%	9.7%	11.5%	12.2%	11.4%	11.5%	11.1%	11.8%	13.1%	8.9%	3.9%	4.1%	5.0%	7.8%	5.6%	6.6%	7.0%	7.2%	7.1%	7.6%
Travel & Leisure	9.3%	9.7%	9.1%	12.1%	11.0%	14.8%	15.0%	14.1%	16.2%	14.6%	10.3%	11.2%	10.1%	10.6%	10.2%	8.1%	7.1%	7.5%	8.1%	9.9%	12.3%
Telecommunications	32.8%	31.3%	29.7%	28.9%	14.6%	16.5%	7.6%	4.0%	4.4%	9.2%	5.2%	2.1%	0.0%	6.1%	6.1%	7.2%	5.7%	5.4%	1.5%	7.0%	7.3%
Utilities	16.5%	18.9%	24.7%	25.8%	28.5%	26.6%	31.9%	33.2%	34.3%	34.1%	38.8%	26.1%	20.3%	26.9%	27.9%	26.3%	20.2%	13.4%	10.4%	10.4%	9.6%
Technology	9.4%	10.0%	8.2%	9.1%	9.3%	8.1%	8.9%	8.4%	9.1%	8.8%	2.7%	0.0%	0.0%	0.5%	3.7%	4.6%	4.5%	5.8%	6.5%	5.7%	8.3%
GDP% (IHYP)	**0.8**	**-1.4**	**0.1**	**2.2**	**4.3**	**3.1**	**2.9**	**3.3**	**3.6**	**3.5**	**3.9**	**2.5**	**2.1**	**2.8**	**3**	**2.2**	**2.8**	**2.7**	**-0.1**	**-4.9**	**1.4**

9.pdf

Table 3 reports the median annual profit margin by (1 digit and 2 digit) sector. Broadly, the data display some compression in profit margins in economic downturns, however the story is a complex one. Some industries, for example oil and gas, displayed temporal patterns in margins that are apparently unconnected to the aggregate business cycle, while margins in other industries appear to have responded more strongly to some downturns than to others.

Geroski and Gregg (1998) focused on two major UK recessions, which they dated 1980-1981 and 1990-1991. They concluded that the recession caused a sea change in profit margins that, having fallen in recession, never fully recovered. Inspection of Table 3 offers some limited evidence of this. At least in some sectors, the fall in margin persisted for a number of years beyond the 'recessionary' period.

The sector medians reported in Table 3 need to be interpreted with caution. As seen in Table 1, some of these sectors are thinly populated in some years, so that the medians are maybe unrepresentative. For instance, although the automobile industry accounts for a significant proportion of UK GDP, since 1990 the major UK automobile companies (assemblers) are foreign-owned and are thus missing from our data.

III. A basic model of operating leverage

In the corporate finance literature, papers (for example, Ang and Peterson (1984); DeYoung and Roland (2001); Griffin and Dugan (2003); Ho et al. (2004)) commonly employ some variant of the approach in Mandelker and Rhee (1984), who estimate the 'degree of operating leverage', DOL, as the slope coefficient in a time-series regression of profit, or costs, on sales. Other researchers proxy operating leverage as a financial ratio such as the ratio of fixed assets to total assets (Ferri and Jones, (1979); Lord (1998)). In Novy-Marx (2007) 'operating leverage' is the profit margin while the variation in that margin due to sticky costs is termed 'degree of operational inflexibility' (also Gourio (2005))[2]. This approach, that uses average profit margin as a proxy for operating leverage can at best only indirectly capture the notion of operating leverage, as it is popularily used, and in its role as a risk factor in theories of the risk premium. That is a story about changes in margin in response to a shock to sales and about the determinants of the stickiness in costs. Studies that regress the logarithm of operating costs on the logarithm of sales and use the coefficient on sales to measure operating leverage come closer to examining the

[2] He says: *"While higher variable costs result in effectively more levered assets, they should also be associated with more flexibility on the cost side. When capital costs are small relative to flow costs associated with production, firms should be more willing to shut down unprofitable production, even if it entails the loss of capital. ... Operating leverage is, to first-order approximation, the inverse of a firm's operating margins, and thus it is generally closer to ten than zero ... In response to negative shocks firms' revenues typically fall more quickly than they can reduce costs; prices are more responsive than firms' operations. ... While simple theory suggests that expected returns should be increasing in operating leverage, the fact that they should also be increasing in operational inflexibility, which is difficult to observe and negatively correlated with the level of operating leverage, makes direct inference on the expected return/operating leverage relationship difficult."*

issues (Lev (1974) is an early example and Kahl et al. (2013) a recent one.

Machin and van Reenen (1993) regress the change in profit margin on the business cycle, proxied by the unemployment rate, allowing for firm-level controls and dynamics. Their sample is larger UK firms over the 1970s and 1980s, covering one major recession - the early 1980s. They find that the profit margin is stationary and cyclical. Margins decline sharply in recessions, though the timing of the impact of aggregate shocks appears to differ across sectors.

We draw upon a number of recent developments in panel data and spatial econometrics to estimate a panel error correction model. We first estimate the model using conventional panel methods where slopes are homogeneous and possible cross sectional correlation is ignored. Next, we model potential heterogeneity caused by slope coefficients varying across firms using the mean group estimator of Pesaran and Smith (1995). This method involves first separately estimating a time series error correction model for each cross section unit. Next, under the assumption of random slope coefficients (Swamy (1970)), the mean slope is estimated as the average of these cross-section specific slope estimates; the standard error is also estimated in a similar way. If a test that the slope estimates for the long run effect are actually the same across firms is not rejected, we use the pooled mean group estimator (Pesaran *et al.*, 1999).

To allow for nonstationarity of our main activity measures, sales and costs at the firm-level (in logarithms), we model the relationship between costs and sales (operating leverage) as a dynamic, non-stationary process. In doing so, we admit the possibility that sales and costs may be in long-run equilibrium. In other words, at the firm-level, logarithms of sales and costs are potentially cointegrated. Importantly, this framework allows us the determine how operating leverage reacts, in the short run, to variations in the use of capital and employment, and also the extent to which there is asymmetric adjustment. The short-run and long-run dynamics between costs and sales is modelled as an error correction process in which the underlying series are non-stationary and potentially cointegrating. Cross-section dependence is modelled using the common correlated effects approach of Pesaran (2006), which allows for potential factor-based strong dependence.

The first model we work with is a fixed effects panel error correction model with homogeneous slopes,

$$\Delta \ln c_{it} = \alpha_i + \beta \Delta \ln s_{it} - \gamma \left(\ln c_{i,t-1} - \delta \ln s_{i,t-1} \right) + \varepsilon_{it}, \qquad i = 1, N, \; t = 1, T. \tag{1}$$

Here c_{it} and s_{it} denote the costs and sales of firm i in year t. The form of the model allows us to treat the determination of the change in margin, $\Delta \ln(c_{it}/s_{it})$, simultaneously with the margin itself, $\ln(c_{it}/s_{it})$. The model includes firm-specific fixed effects α_i capturing unobserved firm-level heterogeneity, including the hazard rates (Mill's ratio) of attrition from the sample. Hence, potential sample selection bias is accounted for. The relationship between costs and sales includes partial adjustment (γ) to a hypothesized long run equilibrium relationship between log-costs and log-sales, the effect of sales on costs in long-run equilibrium (δ), and the short-run dynamic effect of sales on costs (β).

Specified this way, if $\delta \approx 1$, $(\ln c_{it} - \delta_i \ln s_{it}) \approx \ln(1 - \pi_{it})$, where π_{it} denotes the profit margin of firm i in year t. We test the stationarity of $\ln(1 - \pi_{it})$, and test for a homogeneous long run equilibrium, implying that $\delta_i = \delta$, with, in the limit, $\delta = 1$. In such an equilibrium, the value of $\ln(1 - \pi_{it})$ is $-\alpha_i/\gamma_i$ and the firm would anticipate partial adjustment of $\gamma(\ln c_{i,t-1} - \delta \ln s_{i,t-1})$ to this equilibrium.

The short-run firm-specific slope coefficient β captures the effect of a shock to sales – our estimate of operating leverage. If a firm can pass a shock to sales completely through to costs, margin stays unchanged, so $\beta = 1$. If pass-through is incomplete, $E(\beta) < 1$. We test $\mathbb{H}_0 : E(\beta) = 1$ against the left-tailed alternative $\mathbb{H}_1 : E(\beta) < 1$. We start with an analysis of the basic statistical properties of our firm-level data.

A. Stationarity and cointegration

We have a large, very unbalanced data set so the power of the tests for panel unit roots can have low power when the number of observations are small. Table 4 reports panel unit root tests for a more limited set using the Im-Pesaran-Shin test (Im et al., 2003), when there are at least 20 and 30 complete observations for each firm. Heterogeneity across firms in the slope (autoregressive parameter) is allowed. The null hypothesis is that all firms have unit roots against the alternative that a finite proportion of firms have stationary sales (or costs).

Table 4: Panel Unit Root Tests

Observations	>20	>30
Firms	849	373
Average years	30.5	37.4
lnCosts	$0.380^{\dagger}$	$0.941^{\dagger}$
lnSales	$0.025^{\dagger}$	$0.436^{\dagger}$
ΔlnCosts	$0.000^{\dagger}$	$0.000^{\dagger}$
ΔlnSales	$0.000^{\dagger}$	$0.000^{\dagger}$

† p-values

The null that all firms in the panel have unit roots for both real sales and real costs (in logarithms) is not rejected at the 1% level. However, the unit root hypothesis is rejected for growth in real sales and real costs. Thus,

$$\ln s_{it}, \ln c_{it} \sim I(1),$$

where s_{it} and c_{it} denote real sales and real costs respectively, for firm i in year t.

Given that sales and costs have unit roots the next question is whether sales and costs are cointegrated and that there is a proportionate relationship between costs and sales, so that the profit margin in the long run is stationary. An indirect test of cointegration (Stock, 1987 and Stock and Watson, 1993) is whether the non-stationary terms in the log of sales and costs are statistically significant in a regression of the (stationary) change in the log of costs. This test is reported in Table 5. In all cases both terms are significantly different from zero. A joint test for whether the two coefficients are zero ($\gamma = \delta = 0$) is also rejected.

The coefficient on $\Delta \ln s_{it}$ in Table 5 provides a measure of whether a shock to sales produces a proportionate change in costs. Depending upon the sample size this varies from 68 percent to 85 percent. A test for the null restriction that $\text{lncosts}_{t-1} - \text{lnsales}_{t-1} = 0$ ($\gamma = -\delta$) is also rejected. This suggests that when we assume both homogeneous slopes and cross sectional independence, profit margins are non-stationary. At the same time, unit root tests indicate that profit margins are stationary. Together, this points to substantial heterogeneity across firms, so that the slope homogeneity assumption may be somewhat misplaced.

Table 5: Tests for Cointegration

Response: $\Delta\,\mathrm{lncosts}_t$	Pooled	Panel, FE	Panel, FE	Panel, FE	Panel, FE
Included firms	all	all	>10 years	>20 years	>30 years
$\Delta\,\mathrm{lnsales}_t$	0.676***	0.698***	0.777***	0.857***	0.851***
	(0.00206)	(0.00211)	(0.00225)	(0.00231)	(0.00231)
$\mathrm{lncosts}_{t-1}$	-0.212***	-0.500***	-0.452***	-0.417***	-0.4635***
	(0.00223)	(0.00359)	(0.00388)	(0.00492)	(0.00718)
$\mathrm{lnsales}_{t-1}$	0.191***	0.438***	0.415***	0.405***	0.4546***
	(0.00207)	(0.00337)	(0.00370)	(0.00484)	(0.00707)
Constant	0.157***	0.425***	0.244***	0.0644***	0.0364***
	(0.00345)	(0.00858)	(0.00804)	(0.00702)	(0.00755)
Observations	55,330	55,330	42,931	24998	13571
R-squared	0.674	0.719	0.767	0.860	0.890
Number of firms	4,901	4,901	2,147	849	373
Joint Test: p-values					
$\mathrm{lncosts}_{t-1} = \mathrm{lnsales}_{t-1} = 0$	0.000	0.000	0.000	0.000	0.000
$\mathrm{lncosts}_{t-1} - \mathrm{lnsales}_{t-1} = 0$	0.000	0.000	0.000	0.000	0.000
Standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					
Panel, FE: fixed effects regression; Pooled: pooled OLS					

IV. Slope Heterogeneity and Mean Group Estimators

An assumption in the previous section is that the estimates of the slopes in the model are constant across firms. We now relax the assumption of constant slopes and report mean group estimates of the slopes in equation (1). Our basic model is now a panel error correction model with heterogeneous slopes,

$$\Delta \ln c_{it} = \alpha_i + \beta_i \Delta \ln s_{it} - \gamma_i \left(\ln c_{i,t-1} - \delta_i \ln s_{i,t-1}\right) + \varepsilon_{it}, \quad i = 1, N,\ t = 1, T. \tag{2}$$

In other words we estimate the model for each firm and then take the average of the slopes (Pesaran and Smith, 1995). In the panel error correction model (1), an assumption is sometimes made that the long run effect is homogeneous across firms ($\delta_i = \delta$), while the short run effect and partial adjustment is potentially heterogeneous. The pooled mean group estimator (Pesaran et al., 1999) can then be used. The mean group and pooled mean group estimates are shown in Tables 6a and 6b for different numbers of observations for each firm.

The short run effects - estimates of the coefficients on sales growth ($\Delta\,\mathrm{lnsales}$), as a measure of operating leverage - are now around 94 to 95 percent. This is much larger and closer to unity than the homogeneous slope estimates in Table 5. However, the difference from unity, $E(\beta_i) = 1$, is statistically significant in a one tailed test, suggesting that there is substantial operating leverage. In response to a shock to sales, on average, costs are adjusted by 94 percent within the same year.

Together, there is evidence of a cointegrating long term equilibrium relationship between logarithm of costs and sales. The partial adjustment in one year to this long-run equilibrium is estimated by the mean group estimator at around 42-47 percent. The pooled mean group estimates are statistically significantly different. This is not unexpected, since the assumption of a common long run sales-cost equilibrium across all firms in all the sectors may be too strong. A Hausman test (Hausman (1978)) rejects, at the 1% level, the null hypothesis of a homogenous long-run coefficient across all firms. This may be different when we conduct sectoral analyses later in the paper. Firms within a specific sector may well have in equilibrium a common sector-specific profit margin.

Table 6: Mean Group and Pooled Mean Group Estimators

6a) Firm observations>20	Mean Group		Pooled Mean Group	
Response: $\Delta\,\text{lncosts}_t$	error correction	short run	error correction	short run
Regressors				
Partial adj., γ: Ecm_{t-1}		-0.466***		-0.392***
		(0.00928)		(0.00916)
Δ lnsales		0.938***		0.936***
		(0.00435)		(0.00418)
lnsales_{t-1}	1.064***		1.005***	
	(0.0404)		(0.000536)	
Constant		-0.0507***		-0.0386***
		(0.0121)		(0.00151)
Observations	24,998	24,998	24,998	24,998
p-value				
$\text{lnsales}_{t-1} = 1$	0.111		0.000	

6b) Firm Observations>30	Mean Group		Pooled Mean Group	
Response: $\Delta\,\text{lnCosts}_t$	error correction	short run	error correction	short run
Regressors				
Partial adj., γ: Ecm_{t-1}		-0.418***		-0.353***
		(0.0119)		(0.0115)
Δ lnsales		0.952***		0.952***
		(0.00543)		(0.00536)
lnsales_{t-1}	1.014***		1.001***	
	(0.00686)		(0.000756)	
Constant		-0.0372***		-0.0280***
		(0.0112)		(0.00131)
Observations	13,571	13,571	13,571	13,571
p-values				
$\text{lnsales}_{t-1} = 1$	0.0431		0.0539	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

V. Cross Section Dependence

Thus far we have reported results for both homogeneous and heterogeneous slopes. However, the recent literature on large panels has highlighted the need to test for cross-sectional strong dependence generated by latent (or unobservable) factors with loadings that are heterogeneous across firms. These latent factors may generate strong cross section dependence among firms and, if omitted from the model, may invalidate inferences from panel data models. To proxy the effect of potentially multiple latent factors, the common correlated effects (CCE) method (Pesaran, 2006; Holly *et al.*, 2011; Bailey *et al.*, 2013) includes cross section averages of the dependent and independent variables as additional regressors.[3]

Strong cross-sectional dependence comes from factors that affect all cross section units, though by differing amounts. An example is macroeconomic developments - if we expand the number of cross section units, even as $N \rightarrow \infty$, then all firms are still affected by macroeconomic developments. Weak cross-sectional dependence is more localised. Firms may be correlated because they belong to the same industry which is subject to some common technological developments, because they belong to the same regional (spatial) area which is subject to local shocks, or through supply or demand side linkages.

Table 7: CD Test for Cross Section Dependence

Observations	>30
Firms	373
Average years	37.4
Fixed Effects	46.58 (0.000)†
Mean Group	175.1 (0.000)†
CCE	171.4 (0.000)†

† *p*-values

Table 7 reports tests for strong cross-sectional dependence, for which we use the CD test (Pesaran, 2013). There is significant evidence of cross-sectional strong dependence. We account for this by following the common correlated effects methodology, where cross-section averages of the explanatory variables are included in the estimated model. Cross sectional averages are included in the short run dynamics and cross section averages of $\ln c_{i,t-1}$ and $\ln s_{i,t-1}$ in the long run part of the model. We approximate these cross sectional averages by logarithms of average costs and sales, $\ln \bar{c}_{t-1}$ and $\ln \bar{s}_{t-1}$, calculated across all firms[4] .

[3]It should be noted that we do not use the common correlated effects approach with homogeneous panels because in this case this would be equivalent to including time effects.

[4]In other words, we take $\ln \bar{c}_{t-1} = \ln \left(n^{-1} \sum_{i=1}^{n} c_{i,t-1} \right)$ as an approximation for $n^{-1} \sum_{i=1}^{n} \ln c_{i,t-1}$. The justification goes as follows. Let $s_{it} = c_{it} / (n\bar{c}_t)$ denote the (total costs) market share of firm i in year t, and let s_i^* denote a hypothesized equilibrium (or average) market share for firm i, defined by $s_i^* = E(s_{it})$. Then, $\ln c_{it} = \ln(n s_{it} \bar{c}_t) = \ln n + \ln \bar{c}_t + \ln [s_i^* + (s_{it} - s_i^*)] \approx \ln n + \ln \bar{c}_t + \ln s_i^* + (s_{it} - s_i^*) / s_i^*$, by first order Taylor approximation, which holds when s_{it} is close to its equilibrium value, that is $(s_{it} - s_i^*)$ is small. Further, $E(s_{it}/s_i^*) = 1 \Rightarrow E\left[\frac{s_{it} - s_i^*}{s_i^*}\right] = 0$, and hence as $n \rightarrow \infty, n^{-1} \sum_{i=1}^{n} (s_{it} - s_i^*) / s_i^* \rightarrow 0$ almost surely. Hence, $n^{-1} \sum_{i=1}^{n} \ln c_{it} \approx \ln n + \ln \bar{c}_t + n^{-1} \sum_{i=1}^{n} (s_{it} - s_i^*) / s_i^*$, which converges to $\ln \bar{c}_t$ as $n \rightarrow \infty$. Likewise, $\ln \bar{s}_{t-1} = \ln \left(n^{-1} \sum_{i=1}^{n} s_{i,t-1} \right)$ is an approximation to $n^{-1} \sum_{i=1}^{n} \ln s_{i,t-1}$.

In Table 8 we report results for the heterogeneous case using the common correlated effects estimator with group mean estimates. Two cases are distinguished. The mean group estimator in the left hand side of the table reports cross sectional averages of all of the parameters in equation (1). The pooled mean group estimates in the right hand side of the table still take the cross sectional averages of the estimates of $\Delta\,\text{lnsales}_t$ (and in general any estimates of the short run part of the equation) but the coefficients on the long run part, impose (and test for) a common set of coefficients.

As with the results in Table 5 the estimates of operating leverage with constant slopes suggests that firms adjust costs much more slowly in response to a shock to sales. By contrast when the mean group estimator is used with common correlated effects, as in Table 8, the partial adjustment to the cost-sales equilibrium is again much quicker.

Table 8: Common Correlated Effects with Heterogeneity

8a) Firm observations>20	Mean Group		Pooled Mean Group	
Response: $\Delta\,\text{lncosts}_t$	error correction	short run	error correction	short run
Regressors				
Partial adj., γ: Ecm_{t-1}		-0.424***		-0.350***
		(0.00998)		(0.00937)
$\Delta\,\text{lnsales}_t$		0.949***		0.947***
		(0.00426)		(0.00407)
lnsales_{t-1}	1.017***		1.009***	
	(0.0146)		(0.000738)	
Constant		-0.0499***		-0.0388***
		(0.00824)		(0.00156)
Observations	24,998	24,998	24,998	24,998
p-values				
$\text{lnsales}_{t-1} = 1$	0.235		0.000	

8b) Firm observations>30	Mean Group		Pooled Mean Group	
Response: $\Delta\,\text{lncosts}_t$	error correction	short run	error correction	short run
Regressors				
Partial adj., γ: Ecm_{t-1}		-0.409***		-0.341***
		(0.0122)		(0.0118)
Δ lnsales		0.958***		0.959***
		(0.00512)		(0.00504)
lnsales_{t-1}	1.013***		0.996***	
	(0.0261)		(0.00106)	
Constant		-0.0140**		0.00593***
		(0.00696)		(0.00111)
Observations	13,571	13,571	13,571	13,571
p-values				
$\text{lnsales}_{t-1} = 1$	0.622		0.000	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Nevertheless, it is also clear that the use of the CCE approach does not actually eliminate cross sectional dependence when we use the cross section across all firms. It appears that the common factors lie less with averages across firms and more with sector-specific factors.[5]

VI. Sectoral Effects on Operating Margin

The results in the previous section suggest that to eliminate the possible presence of strong cross section dependence we need to look more closely at the sectoral level. In Table 9 we report mean group estimates for sectors, again allowing for heterogeneous slopes. We find now that our estimates of operating margin vary across sectors with most sectors above 90% but with mining at 83% and Automobiles at 84%. One outlier is Beveridges, with an operating margin at 104%.

[5] In an analysis of house price dynamics across urban areas in the US, Bailey et al. (2013) find that once regional cross-section averages are included, in addition to national averages, cross-section dependence can be made weak enough to proceed with spatial modeling.

Table 9: Sector Mean Group Estimates with Heterogeneity
Dependent Variable:$\Delta costs_t$

Sector	$constant$	$\Delta lnsales_t$	$lncosts_{t-1}$	$lnsales_{t-1}$
Oil & Gas Producers	0.022076	0.90857	-0.48965	0.476073
(MG, years >10)	-(0.209)	-(0.055)	-(0.053)	-(0.055)
Chemicals	-0.09991	0.93324	-0.52582	0.531384
(MG, years >32)	-(0.069)	-(0.019)	-(0.047)	-(0.047)
Forestry & Paper	-0.10366	0.9146	-0.53993	0.55258
(MG, years >17)	-(0.073)	-(0.016)	-(0.064)	-(0.062)
Industrial Metals	0.031626	0.91747	-0.57009	0.559036
(MG, years >10)	-(0.063)	-(0.016)	-(0.056)	-(0.053)
Mining	0.027867	0.83094	-0.43195	0.424336
(MG, years >10)	-(0.207)	-(0.050)	-(0.094)	-(0.095)
Construction & Materials	-0.04174	0.95941	-0.4232	0.423853
(MG, years >31)	-(0.029)	-(0.010)	-(0.041)	-(0.039)
Aerospace & Defense	-0.00858	0.96147	-0.52653	0.521714
(MG, years >8)	-(0.032)	-(0.019)	-(0.067)	-(0.067)
General Industrials	-0.07523	0.97265	-0.6418	0.644411
(MG, years >23)	-(0.062)	-(0.019)	-(0.050)	-(0.049)
Electronic & Electrical Equipment	-0.08005	0.91339	-0.47163	0.477743
(MG, years >21)	-(0.029)	-(0.014)	-(0.027)	-(0.026)
Industrial Engineering	-0.03209	0.95513	-0.48275	0.482819
(MG, years >37)	-(0.031)	-(0.011)	-(0.033)	-(0.032)
Industrial Transportation	-0.23447	0.94004	-0.53256	0.559906
(MG, years >25)	-(0.097)	-(0.021)	-(0.049)	-(0.056)
Support Services	-0.08068	0.97234	-0.41437	0.422153
(MG, years >30)	-(0.018)	-(0.009)	-(0.037)	-(0.037)
Automobiles & Parts	-0.15654	0.84275	-0.52893	0.549875
(MG, years >11)	-(0.128)	-(0.086)	-(0.067)	-(0.077)
Beverages	-0.02535	1.04193	-0.35401	0.346237
(MG, years >16)	-(0.053)	-(0.015)	-(0.047)	-(0.047)
Food Producers	-0.1095	0.98123	-0.56362	0.577696
(MG, years >19)	(0.127)	(0.028)	(0.054)	(0.054)

Table 9 continued: Sector Mean Group Estimates with Heterogeneity
Dependent Variable:$\Delta costs_t$

Sector	$constant$	$\Delta lnsales_t$	$lncosts_{t-1}$	$lnsales_{t-1}$
Household Goods	0.050976	0.92049	-0.44078	0.428728
(MG, years >36)	-(0.043)	-(0.015)	-(0.042)	-(0.041)
leisure Goods	-0.19495	0.90235	-0.49304	0.517244
(MG, years >14)	-(0.120)	-(0.025)	-(0.060)	-(0.061)
Personal Goods	-0.00646	0.93423	-0.51442	0.510294
(MG, years >31)	-(0.032)	-(0.011)	-(0.037)	-(0.035)
Health Care Equip. & Services	-0.14492	0.95097	-0.61781	0.632681
(MG, years >10)	-(0.046)	-(0.021)	-(0.060)	-(0.060)
Pharmaceuticals & Biotechnology	-0.04	0.8977	-0.65084	0.664873
(MG, years >16)	-(0.155)	-(0.044)	-(0.072)	-(0.079)
Food & Drug retailers	-0.0537	0.9863	-0.61156	0.617842
(MG, years >24)	-(0.032)	-(0.012)	-(0.063)	-(0.064)
General retailers	0.02606	0.93527	-0.48686	0.470425
(MG, years >30)	-(0.059)	-(0.015)	-(0.043)	-(0.045)
Media	-0.03999	0.93773	-0.48339	0.483064
(MG, years >21)	-(0.053)	-(0.021)	-(0.039)	-(0.041)
Travel & leisure	-0.02935	0.92203	-0.46887	0.467155
(MG, years >32)	-(0.039)	-(0.019)	-(0.044)	-(0.043)
Gas, Water & Multiutilities	-0.23943	1.10378	-0.50946	0.519696
(MG, years >16)	-(0.342)	-(0.060)	-(0.049)	-(0.071)
Software & Computer Services	-0.0179	0.88451	-0.60622	0.592866
(MG, years >14)	-(0.102)	-(0.036)	-(0.054)	-(0.055)
Technology Hardware & Equipment	0.137669	0.8516	-0.63956	0.612473
(MG, years >15)	-(0.151)	-(0.045)	-(0.087)	-(0.084)

In Table 10 we repeat the exercise but we now also allow for cross sectional dependence. We find that there is a general increase in our estimates of operating margin, as we found at the aggregate level, but in some instances there is a fall.

Table 10: Sector Common Correlated Effects with Heterogeneity

Dependent Variable: $\Delta costs_t$

Sector	$constant$	$\Delta lnsales_t$	$lncosts_{t-1}$	$lnsales_{t-1}$
Oil & Gas Producers	-0.1505	0.9619	-0.4588	0.4486
(CCE, years >10)	(0.168)	(0.035)	(0.079)	(0.088)
Chemicals	-0.1088	0.9521	-0.7046	0.7180
(CCE, years >32)	(0.146)	(0.019)	(0.040)	(0.042)
Forestry & Paper	0.0631	0.9593	-0.8001	0.8600
(CCE, years >17)	(0.148)	(0.027)	(0.098)	(0.097)
Industrial Metals	0.0449	0.9500	-0.8945	0.8777
(CCE, years >10)	(0.141)	(0.019)	(0.058)	(0.061)
Mining	-0.4414	0.9313	-0.5664	0.4161
(CCE, years >10)	(1.414)	(0.033)	(0.194)	(0.151)
Construction & Materials	-0.1140	0.9759	-0.5843	0.5840
(CCE, years >31)	(0.066)	(0.011)	(0.051)	(0.049)
Aerospace & Defense	0.0836	0.9938	-0.7460	0.7323
(CCE, years >8)	(0.213)	(0.025)	(0.108)	(0.116)
General Industrials	-0.0915	0.9861	-0.7296	0.7348
(CCE, years >23)	(0.077)	(0.012)	(0.060)	(0.059)
Electronic & Electrical Equipment	0.0373	0.9277	-0.6540	0.6611
(CCE, years >21)	(0.078)	(0.013)	(0.035)	(0.034)
Industrial Engineering	-0.0506	0.9659	-0.5990	0.6041
(CCE, years >37)	(0.057)	(0.011)	(0.041)	(0.040)
Industrial Transportation	-0.4916	0.9517	-0.6730	0.7207
(CCE, years >25)	(0.233)	(0.019)	(0.053)	(0.064)
Support Services	-0.1819	0.9950	-0.5414	0.5550
(CCE, years >30)	(0.065)	(0.008)	(0.042)	(0.044)
Automobiles & Parts	-0.0425	0.8553	-0.6313	0.6419
(CCE, years >11)	(0.172)	(0.085)	(0.043)	(0.049)
Beverages	0.0635	1.0344	-0.5152	0.5028
(CCE, years >16)	(0.094)	(0.017)	(0.063)	(0.066)
Food Producers	-0.0308	0.9712	-0.6221	0.6156
(CCE, years >19)	(0.127)	(0.028)	(0.054)	(0.054)

Table 10 continued: Sector Common Correlated Effects with Heterogeneity
Dependent Variable: $\Delta costs_t$

Sector	$constant$	$\Delta lnsales_t$	$lncosts_{t-1}$	$lnsales_{t-1}$
Household Goods	0.1164	0.9478	-0.5818	0.5677
(CCE, years >36)	(0.099)	(0.014)	(0.046)	(0.046)
Leisure Goods	0.1842	0.9468	-0.8883	0.8948
(CCE, years >14)	(0.165)	(0.030)	(0.095)	(0.090)
Personal Goods	-0.0610	0.9592	-0.7218	0.7272
(CCE, years >31)	(0.054)	(0.010)	(0.038)	(0.038)
Health Care Equip. & Services	0.2477	0.9588	-0.7654	0.7998
(CCE, years >10)	(0.303)	(0.033)	(0.069)	(0.067)
Pharmaceuticals & Biotechnology	-0.3381	0.8617	-0.6227	0.6090
(CCE, years >16)	(0.208)	(0.065)	(0.092)	(0.092)
Food & Drug retailers	-0.1005	0.9917	-0.6716	0.6873
(CCE, years >24)	(0.088)	(0.010)	(0.062)	(0.065)
General retailers	0.0271	0.9389	-0.5971	0.5781
(CCE, years >30)	(0.078)	(0.017)	(0.052)	(0.055)
Media	0.0324	0.9593	-0.6106	0.6266
(CCE, years >21)	(0.212)	(0.021)	(0.047)	(0.050)
Travel & leisure	-0.1096	0.9342	-0.6237	0.6179
(CCE, years >32)	(0.092)	(0.020)	(0.053)	(0.049)
Gas, Water & Multiutilities	-0.4865	1.1796	-0.4771	0.5823
(CCE, years >16)	(0.453)	(0.061)	(0.182)	(0.211)
Software & Computer Services	-0.4625	0.9045	-0.7090	0.7031
(CCE, years >14)	(0.314)	(0.043)	(0.063)	(0.066)
Technology Hardware & Equipment	-0.0600	0.8267	-0.7344	0.6972
(CCE, years >15)	(0.379)	(0.047)	(0.107)	(0.103)

VII. Firm, sector, and common shocks

The use of cross-sectional averages to address cross-sectional dependence also provides a potential source of extra information because we can interpret these cross-sectional averages at the sectoral level as measures of sectoral disturbances. Suppose that firms respond to a number of shocks. First, there is the response of the i-th firm to idiosyncratic shocks both to demand and supply. Secondly there are responses to shocks at the level of the industry/sector. Finally there are responses to aggregate economy wide shocks.

In the basic model (1) the long run dynamics were modelled solely in terms of a profit margin equilibrium term:

$$LR_{\text{margin}} = -\gamma_i \left(\ln c_{i,t-1} - \delta_i \ln s_{i,t-1} \right). \tag{3}$$

Now, consider the more general long run model for a firm i in industry j ($i \in I_j$):

$$LR_j = \theta_{0i} y_{t-1} + \theta_{1i} \ln c_{i,t-1} + \theta_{2i} \ln s_{i,t-1} + \theta_{3i} \ln \overline{c}_{t-1}^{(j)} + \theta_{4i} \ln \overline{s}_{t-1}^{(j)}, \;\; i = 1, N_j, \;\; i \in I_j, \;\; t = 1, T, \tag{4}$$

where the superscript (j) in $\bar{c}_{t-1}^{(j)}$ and $\bar{s}_{t-1}^{(j)}$ indicate that these are averages of the industry j in which the i-th firm resides, and y_{t-1} is a (stationary) measure of the aggregate economy wide shock in the previous year.

Including the cross-section averages, there are now 4 $I(1)$ variables with temporal variation, $\ln c_{i,t-1}$, $\ln s_{i,t-1}$, $\ln \bar{c}_{t-1}^{(j)}$ and $\ln \bar{s}_{t-1}^{(j)}$. All four have time series variation, while only two, $\ln c_{i,t-1}$ and $\ln s_{i,t-1}$, have cross-sectional variation as well. There are up to 3 cointegrating relations between these variables, described below. This enriches our specification of the long run equilibria and of the partial adjustment to these different equilibria. We use the latent factor structure to include these potential long run equilibrium relationships in the model.

Profit margin equilibrium. The leading equilibrium relation, as before, is the profit margin cointegration between log costs and log sales:

$$LR_{\text{margin}} = -\gamma_i \left(\ln c_{i,t-1} - \delta_i \ln s_{i,t-1}\right). \tag{5}$$

At the firm level, costs adjust to their long run equilibrium with sales, with γ_i as the rate of partial adjustment to the departure from equilibrium in the previous year, $\ln c_{i,t-1} - \delta_i \ln s_{i,t-1}$. Potentially the long run coefficient δ_i is heterogenous across firms, but as discussed earlier is expected to have approximately unit value, $\delta_i \approx 1$. For firms within the same sector, the long run coefficient may be homogeneous. Further, if $\delta_i = 1$ for all firms within the sector, the average profit margin is approximately $-E\left(\alpha_i\right)/E\left(\gamma_i\right)$, where these two parameters (fixed effect and partial adjustment) are allowed to vary across firms within a sector.

Market share equilibrium. The second equilibrium is a market share relation for sales, where sales of each firm potentially maintain an equilibrium market share to total sales of all firms in a sector.There are only 2 long run coefficients connecting the sales and average sales terms in (4), and each equilibrium relation requires identification of 2 parameters (the partial adjustment and long run coefficient). Now, since the coefficient on sales is fixed by the profit margin equilibrium (5), these 2 long run coefficients cannot be separately identified.

However, two observations can be made. First, there is potentially a restriction that would ensure identification. As discussed above, the long run effect of sales on costs is likely to be close to unity ($\delta_i \approx 1$), even if the short run dynamic effect suggests operating leverage ($\beta_i < 1$). In fact, our empirical results show that this relation holds approximately across all the sectors. Hence imposing this constraint would allow us to identify the two long run coefficients in the market share equilibrium. Nevertheless, this is not satisfactory because it restricts the partial adjustment to both the above two equilibria to be identical.

Second, there is also a third relation implied by our model. Since costs and sales are linked together in equilibrium through (5), sales being related to total sales through a hypothesized market share equilibrium suggests that costs of a firm are also similarly related to total costs of all firms in the sector. Further, the partial adjustment and long run effect for both these equilibria should be exactly the same. Thus we have 4 long run coefficients (firm sales, firm costs, total sales and total costs) and 2 long run coefficients to be identified. The above two constraints ensure that the two parameters of the market share equilibrium are exactly identified:

$$
\begin{aligned}
LR_{\text{share}} &= -\gamma_i^* \left(\ln c_{i,t-1} - \delta_i^* \ln \bar{c}_{t-1}^{(j)}\right) - \gamma_i^* \left(\ln s_{i,t-1} - \delta_i^* \ln \bar{s}_{t-1}^{(j)}\right) \\
&= -\gamma_i^* \left[(\ln c_{i,t-1} + \ln s_{i,t-1}) - \delta_i^* \left(\ln \bar{c}_{t-1}^{(j)} + \ln \bar{s}_{t-1}^{(j)}\right)\right]. \qquad (6)
\end{aligned}
$$

We call this cointegrating relationship the market share equilibrium.

The profit market equilibrium and the market share equilibrium involve only two variables, hence the partial adjustment term and long run slope have to be identified, and two other lagged $I(1)$ variables included with heterogenous slopes in the short run dynamic part of the model. The long run relations for these two equilibria are as follows:

$$
\begin{aligned}
LR_j &= -(-\theta_{0i})\, y_{t-1} - (-\theta_{1i}) \left[\ln c_{i,t-1} - \left(-\frac{\theta_{2i}}{\theta_{1i}}\right) \ln s_{i,t-1}\right] \qquad (7) \\
&\quad +\theta_{3i} \ln \bar{c}_{t-1}^{(j)} + \theta_{4i} \ln \bar{s}_{t-1}^{(j)} \\
&= -(-\theta_{0i})\, y_{t-1} - (-\theta_{2i}) \left[(\ln c_{i,t-1} + \ln s_{i,t-1}) - \left(-\frac{\theta_{4i}}{\theta_{2i}}\right) \left(\ln \bar{c}_{t-1}^{(j)} + \ln \bar{s}_{t-1}^{(j)}\right)\right] \\
&\quad + (\theta_{1i} - \theta_{2i}) \ln c_{i,t-1} + (\theta_{3i} - \theta_{4i}) \ln \bar{c}_{t-1}^{(j)} \qquad (8)
\end{aligned}
$$

Under the margin equilibrium, the model is estimated using the mean group estimator, setting the long run as (7) and including (9) in the short run dynamics. Assuming homogeneity in the long run coefficient $\delta_i = -\theta_{2i}/\theta_{1i} = \delta$, the model is also estimated as a pooled mean group model. We apply a Hausman test for the homogeneity assumption. Estimation under the market share equilibrium is similar, in this case using (8) as the long run specification; however, in this case, pooled mean group estimation is not used because equilibrium market shares for different firms are expected to vary across firms.

Cycle equilibrium The third equilibrium is the potential partial adjustment of log costs and log sales (and therefore profit margin) to the economic cycle represented by $LR_{\text{cycle}} = -\gamma_i^{**} y_{t-1}$. This equilibrium captures the effect of an aggregate economy wide shock. Even though this equilibrium relation does not exploit cross section variation, it is important to allow for its potential influence in some sectors. Identification of the cycle equilibrium is straightforward, as it involves a distinct variable y_{t-1} and only one parameter has to be identified from its coefficient: the partial adjustment $-\gamma_i^{**}$.

In addition, the model includes short run dynamics. The short-run firm-specific slope coefficient β_i captures the effect of an unanticipated shock to sales, which as discussed earlier, is our estimate of operating leverage. If a firm can pass any shock to sales proportionately through to costs, $\beta_i = 1$, otherwise if pass-through is incomplete, $\beta_i < 1$. Allowing for slope heterogeneity across firms, for each specific sector I_j, we test $\mathbb{H}_0 : b_j = 1$ against the left-tailed alternative $\mathbb{H}_1 : b_j < 1$, where $b_j = E(\beta_i | i \in I_j)$. If there is operating leverage, that is, if the null hypothesis is rejected, we investigate potential reasons for incomplete pass-through.

VIII. Determinants of operating leverage

There are several reasons why pass-through may be incomplete. The costs of employment or fixed capital may be sticky. Alternatively, the firm may intend to make price adjustments, rather than quantity adjustments, but finds that prices are sticky on the downside, leading to an asymmetric adjustment of costs to sales. To test these conjectures, we model the short run effect, β_i, as a function of employment (n_{it}), the log of real fixed capital (k_{it}), and an indicator that sales have positive growth over the previous year ($I(\Delta \ln s_{it} > 0)$). Thus, for sector I_j:

$$\beta_i = \beta_{0i} + \beta_{1i} I(\Delta \ln s_{it} > 0) + \beta_{2i} k_{it} + \beta_{3i} n_{it} + \beta_{4i} n_{i,t+1}, \quad i \in I_j. \tag{9}$$

β_{1i} now measures the short run effect of asymmetry and β_{2i} measures the effect of sticky capital costs. Descriptive analysis of the data suggests that many firms adjust labour with a lag, so β_{3i} and β_{4i} now capture the sticky costs associated with labour adjustment in terms of contemporaneous and one-year ahead labour costs.

Combining (4) with (9) provides our estimation model. β_{0i} captures residual operating leverage effects after controlling for these sources of operating leverage. We test residual operating leverage as $\mathbb{H}_0 : E(\beta_{0i}) = 1$ versus $\mathbb{H}_1 : E(\beta_{0i}) < 1$. The asymmetry and sticky capital channels are tested as $\mathbb{H}_0 : E(\beta_{1i}) = 0$ versus $\mathbb{H}_1 : E(\beta_{1i}) < 0$, and $\mathbb{H}_0 : E(\beta_{2i}) = 0$ versus $\mathbb{H}_1 : E(\beta_{2i}) < 0$ respectively, while the sticky labour explanation is tested as $\mathbb{H}_0 : E(\beta_{3i}) = E(\beta_{4i}) = 0$ against the alternative $\mathbb{H}_1 : \min\{E(\beta_{3i}), E(\beta_{4i})\} < 0$.

Employment (n_{it}) is measured by number of employees. We use a Hodrik Prescott filter of quarterly output per capita averaged over the four quarters of every calendar year as a measure of the business cycle (y_t).[6] Capital (k_{it}) is measured as logarithm of gross fixed assets (in real terms), while s_{it} and c_{it} represent sales revenue and cost of sales respectively, in real terms. The model is estimated separately for firms in each of 25 sectors.[7] We draw inferences on average slopes across the cross-section using the mean group estimator of the individual firm estimates and corresponding standard errors. If the long run effect is homogeneous across the firms ($\delta_i = \delta$) more efficient inferences are delivered by pooled mean group estimation. This means that while the individual short run responses of shocks to sales are allowed to vary across firms, the long run relationship between costs and sales are tested, and accordingly constrained, to be equal.

We estimate the full model using the pooled mean group (PMG) method and including firm fixed effects, short run dynamics (9) and the long run margin specification (7) as an unrestricted model. We also estimated restricted models omitting short run dynamics and long run equilibria, retaining in each case the components of the base model (1). This provides us with (pseudo) likelihood ratio tests for the joint significance of our short run and long run specifications. Detailed results are not reported, but all sectors reject the null hypothesis that our specification of short run dynamics and long run equilibria are not significant.[8] We also estimate the full model as a mean group (MG), that is, without the assumption that there is a homogeneous long run profit margin coefficient for each firm within the sector.

[6] Machin and van Reenen (1993) used unemployment rate as a measure of the business cycle. This measure is based on the assumption of the unemployment rate is stationary, which is not true for the long time period that our study covers.

[7] Using the Stata program *xtpmg* (Blackburne III and Frank, 2007).

[8] For the "Healthcare Equipment & Services" sector, pooled mean group estimation omitting short run dynamics does not converge. This is likely due to an extremely flat nature of the pseudo log-likelihood surface. This we take as evidence of a rejection of the null hypothesis of no short run dynamics, beyond $\beta_i \Delta \ln s_{it}$ included our base model.

A Hausman test (Wu, 1973; Hausman, 1978) is conducted to verify the validity of the common long run effect assumption underlying the PMG estimates. In 23 of the 25 sectors (except Industrial Metals and General Retailers), the null hypothesis of validity of the PMG assumption cannot be rejected at the 5% significance level. These results are reported in Table 9 below.[9] This provides confirmation that a homogeneous costs-sales equilibrium relationship exists within most sectors.

Nonetheless the efficiency gain from making the PMG assumption is not always substantial. Because of considerable attrition in the data, the estimation can only be conducted over a limited sample of firms that have a substantial number of years of data, which in turn leads to larger standard errors for the PMG estimates. This data issue is considerably reduced for mean group estimation. Hence, our choice between PMG and MG estimates is based on validity of the PMG assumption but also on sample size considerations. Table 9 reports the chosen model for each of the 25 sectors, the minimum number of years of data for sampled firms within the sector, together with the number of firms and the number of firm-year observations in each case.

We also estimate a model using the market share specification of the long run equilibrium (8) using the mean group method only; this provides us with estimates of a partial adjustment to the market share equilibrium. The pooled mean group assumption of a common long run coefficient is expected to be invalid in this case, since all firms within a sector are not expected to have the same market share in equilibrium, and hence PMG estimation is not conducted. Estimates of partial adjustment to the third (business) cycle equilibrium are also obtained. Both the PMG and MG models provide evidence of this equilibrium relationship only for a few sectors, indicating thereby that sectoral cycles are often asynchronous with the aggregate business cycle. In effect, the profit margin equilibrium captures sector-specific cyclical activity in our context.

[9] In 3 other sectors – Beverages, Leisure Goods and Technology Hardware & Equipment – the null hypothesis of homogenous long run profit margin coefficient is rejected at the 10 percent level.

Table 9: Estimates of long run coefficient on log-sales and partial adjustment terms

(coefficients on common correlated effects terms are not reported)

Sector	No. of firms	Firm-years	Constant	Long-run - Margin, Mkt. share & Cycle eqbm.			
				Log-sales	Margin adj.	Mkt.share adj.	Cycle adj.
Oil & Gas Producers	36	467	-1.2705	**1.0179**	**-0.5949**	**-0.4242**	-0.8378
(pooled mean group, years >8)			(0.961)	(0.007)	(0.229)	(0.112)	(1.028)
Chemicals	24	744	-0.0388	**1.0049**	**-0.6401**	**-0.6524**	0.1197
(pooled mean group, years >27)			(0.112)	(0.003)	(0.128)	(0.078)	(0.126)
Forestry & Paper	16	307	-0.1689	**1.0880**	**-0.4704**	**-0.5906**	0.0338
(mean group, years >17)			(0.136)	(0.086)	(0.136)	(0.114)	(0.132)
Industrial Metals	30	448	-0.2626	**0.7598**	***-0.3485***	**-0.3137**	**-0.4187**
(mean group, years >8)			(0.443)	(0.075)	(0.195)	(0.113)	(0.208)
Construction & Materials	33	1103	-0.1465	**0.9966**	**-0.5386**	0.0199	-0.3703
(pooled mean group, years >31)			(0.101)	(0.004)	(0.058)	(0.423)	(0.291)
Aerospace & Defense	16	401	-0.4300	**1.0995**	**-0.8604**	**-0.6939**	-0.0418
(mean group, years >13)			(0.319)	(0.092)	(0.222)	(0.169)	(0.296)
General Industrials	19	565	**-0.1266**	**1.0116**	**-0.5568**	**-0.6452**	-0.1314
(pooled mean group, years >23)			(0.056)	(0.004)	(0.083)	(0.092)	(0.127)
Electronic & Electrical Equipment	40	1043	-0.1369	**0.9875**	**-0.3974**	**-0.6797**	0.0132
(pooled mean group, years >21)			(0.100)	(0.005)	(0.124)	(0.077)	(0.098)
Industrial Engineering	43	1319	0.1197	**0.9869**	**-0.6021**	**-0.5964**	0.0681
(mean group, years >31)			(0.109)	(0.027)	(0.045)	(0.046)	(0.155)
Industrial Transportation	38	776	-0.0256	**1.0152**	**-0.7396**	**-0.7129**	***-0.6395***
(mean group, years >18)			(0.098)	(0.017)	(0.137)	(0.082)	(0.399)
Support Services	32	1123	-0.1040	**0.9912**	**-0.3897**	0.0262	0.0540
(pooled mean group, years >32)			(0.076)	(0.001)	(0.067)	(0.576)	(0.041)
Automobiles & Parts	9	267	0.1454	**1.0205**	**-0.5840**	**-0.7257**	0.1285
(pooled mean group, years >12)			(0.154)	(0.009)	(0.142)	(0.135)	(0.097)
Beverages	28	761	-0.3719	**0.5852**	**-0.4736**	**-0.4748**	**-0.2509**
(mean group, years >19)			(0.325)	(0.292)	(0.087)	(0.086)	(0.056)
Food Producers	40	941	-0.0604	**1.0050**	**-0.6635**	**-0.7408**	0.0123
(pooled mean group, years >19)			(0.082)	(0.001)	(0.075)	(0.075)	(0.090)
Household Goods	7	263	-0.1178	**1.0230**	**-0.3928**	**-0.4071**	0.1820
(pooled mean group, years >36)			(0.121)	(0.014)	(0.058)	(0.069)	(0.224)
Leisure Goods	10	198	0.1078	**0.9930**	**-0.6047**	3.1371	0.2044
(pooled mean group, years >14)			(0.119)	(0.013)	(0.101)	(3.506)	(0.195)
Personal Goods	18	559	0.1988	**1.0136**	**-0.6402**	**-0.6484**	-0.2680
(pooled mean group, years >31)			(0.148)	(0.004)	(0.105)	(0.064)	(0.271)
Health Care Equip. & Services	19	431	***-0.2617***	**1.0408**	**-0.5839**	**-0.7988**	-0.1305
(pooled mean group, years >17)			(0.150)	(0.006)	(0.136)	(0.131)	(0.295)
Pharmaceuticals & Biotechnology	21	361	0.3116	**1.0122**	**-0.4821**	**-0.3160**	1.1543
(mean group, years >11)			(0.654)	(0.323)	(0.151)	(0.111)	(1.189)
Food & Drug Retailers	10	288	**0.1426**	**0.8878**	**-0.6334**	**-0.6301**	***-0.1115***
(mean group, years >24)			(0.062)	(0.099)	(0.140)	(0.141)	(0.069)
General Retailers	29	898	-0.2299	**0.9055**	**-0.6224**	**-0.5529**	-0.0613
(mean group, years >30)			(0.173)	(0.056)	(0.098)	(0.061)	(0.085)
Media	41	1013	-0.0708	**1.0024**	**-0.5686**	**-0.6578**	0.4366
(pooled mean group, years >21)			(0.145)	(0.002)	(0.061)	(0.066)	(0.439)
Gas, Water & Multiutilities	11	179	0.1253	**0.7735**	**-0.2564**	***-1.6307***	1.1015
(pooled mean group, years >15)			(0.294)	(0.000)	(0.111)	(0.886)	(6.842)
Software & Computer Services	30	583	-0.1941	**1.0249**	**-0.7663**	**-0.8704**	***1.4897***
(pooled mean group, years >16)			(0.186)	(0.001)	(0.127)	(0.129)	(0.794)
Technology Hardware & Equipment	27	402	0.3267	0.1684	**-0.8777**	**-0.6939**	11.4419
(mean group, years >8)			(0.629)	(0.535)	(0.227)	(0.204)	(11.162)

estimates (p-values in parentheses)

Bold (***Italics***): Significant at 5% (10%)

Finally, we estimate two restricted models. First, we exclude the latent factor structure (common correlated effects and lagged business cycle). Second, we use only the base model (1). A comparison of estimates of the coefficient on sales growth from the short run dynamics for the full model, with those from the restricted models, allows some inferences about the operating leverage hypothesis.

Specifically, we examine:

(a) how large the operating leverage effect would appear to be if we considered partial adjustment only to the profit margin equilibrium and we ignored spatial strong dependence;

(b) how much is explained by the two other potential equilibria and corresponding latent factors; and

(c) how much is explained by sticky labour costs, sticky capital and asymmetric price adjustments.

Finally, we conduct cross section dependence (CD) tests (Pesaran, 2013) on the residuals of our model to ensure that our specification of latent factors and equilibria has mitigated issues relating to strong dependence; these tests are not reported, but are available on request.

A. Long run equilibria

Table 9 reports estimates of the long run coefficient on lagged (log) sales (profit margin equilibrium) together with partial adjustment to the three potential equilibrium relationships investigated here. There is substantial evidence of cointegration, supporting the existence of a long run profit margin equilibrium relationship between log costs and log sales. The partial adjustment to this equilibrium shows substantial variation across the sectors, and is statistically significant at the 5% level in 24 out of 25 sectors, and the 10% level in the remaining sector, Industrial Metals. Correspondingly, the long run effect of sales on costs is numerically close to $\delta_i = 1$ in 21 sectors out of 25. Partial adjustment to this equilibrium is slow in Industrial Metals and Gas, and Water & Multiutilities (-0.35 and -0.26 respectively). In Technology Hardware & Equipment there is strong partial adjustment (-0.88), but effectively to a fixed cost equilibrium.

There is evidence (significant at the 5% level) of a long run market share equilibrium in 21 out of 25 sectors. By contrast, the data suggest that in Construction & Materials, Support Services, and Leisure Goods, perhaps because competition is so severe that market shares of firms are continuously updated and do not fluctuate around firm specific equilibrium levels.

There is little evidence of a partial adjustment to the economic cycle equilibrium, which was the central focus of investigation in Machin and van Reenen (1993). Only Industrial Metals and Beverages show significant (at the 5% level) evidence of partial adjustment to the business cycle, and Industrial Transportation and Food & Drug Retailers show weak evidence significant at the 10% level.

There are two ways to interpret these results. From an econometric point of view, latent factors account for most of the strong dependence in the data, and are in turn modeled using common correlated effects. Hence, a measured factor such as the business cycle may consequently show considerably less importance. From an industrial economics point of view, sectoral cycles in the UK are often claimed to be largely asynchronous so that an aggregate economic cycle may not appropriately capture cyclical patterns at the industry level. The results are consistent with this inetrpretation.

Table 10: Estimates of short run effects of sales growth and operating leverage explanations

(also growth coefficients in restricted models, excl. leverage explanations, and excl. factor structure as well)

Sector	Short-run - Sales growth & operating lev. Explanations					LR + Only growth	Growth plus factors
	Growth	x Positive	x Capital	x Employment	x Empl. (t+1)		
Oil & Gas Producers	**0.6355**	*0.5603*	-0.0846	**-0.2654**	0.0170	**0.8219**	**0.9796**
(pooled mean group, years >8)	(0.184)	(0.339)	(0.282)	(0.130)	(0.146)	(0.062)	(0.038)
Chemicals	**0.9241**	0.0255	0.0250	-0.1420	**-0.2331**	**0.9849**	**0.9909**
(pooled mean group, years >27)	(0.067)	(0.071)	(0.109)	(0.145)	(0.107)	(0.014)	(0.011)
Forestry & Paper	**1.0690**	-0.1224	**0.2753**	**0.7965**	0.5244	**0.9310**	**1.0066**
(mean group, years >17)	(0.082)	(0.085)	(0.116)	(0.389)	(0.321)	(0.032)	(0.066)
Industrial Metals	**0.9045**	0.1056	0.3774	-0.6460	**0.3082**	**0.9153**	**0.9264**
(mean group, years >8)	(0.087)	(0.097)	(0.242)	(0.503)	(0.114)	(0.017)	(0.021)
Construction & Materials	**0.9806**	0.0069	0.0564	-0.1067	0.1262	**0.9679**	**0.9710**
(pooled mean group, years >31)	(0.025)	(0.028)	(0.068)	(0.078)	(0.091)	(0.011)	(0.011)
Aerospace & Defense	**1.0238**	-0.0811	0.6017	0.5638	-0.2567	**0.9799**	**0.9850**
(mean group, years >13)	(0.130)	(0.179)	(0.592)	(0.613)	(0.185)	(0.023)	(0.022)
General Industrials	**0.9776**	-0.0256	-0.1655	0.2958	0.0454	**0.9684**	**0.9619**
(pooled mean group, years >23)	(0.056)	(0.095)	(0.120)	(0.203)	(0.098)	(0.015)	(0.017)
Electronic & Electrical Equipment	**1.0312**	**-0.1179**	0.1503	0.5427		**0.9565**	**0.9525**
(pooled mean group, years >21)	(0.038)	(0.055)	(0.113)	(0.339)		(0.024)	(0.023)
Industrial Engineering	**0.8631**	0.1628	-0.0507	-0.1590	0.0763	**0.9548**	**0.9566**
(mean group, years >31)	(0.058)	(0.120)	(0.094)	(0.120)	(0.049)	(0.019)	(0.021)
Industrial Transportation	**0.8486**	0.0816	-0.2735	0.1775	0.0503	**0.9751**	**0.9119**
(mean group, years >18)	(0.123)	(0.189)	(0.179)	(0.535)	(0.151)	(0.050)	(0.100)
Support Services	**0.9833**	-0.0407	0.0645	0.0498		**0.9789**	**0.9849**
(pooled mean group, years >32)	(0.021)	(0.037)	(0.046)	(0.075)		(0.012)	(0.012)
Automobiles & Parts	**1.0420**	-0.1217	0.0983	**0.3710**	-0.0199	**0.9236**	**0.9314**
(pooled mean group, years >12)	(0.060)	(0.076)	(0.181)	(0.104)	(0.083)	(0.035)	(0.041)
Beverages	**1.0172**	-0.0479	-0.0504	0.3554	-0.0064	**1.0748**	**1.0704**
(mean group, years >19)	(0.057)	(0.067)	(0.088)	(0.351)	(0.086)	(0.080)	(0.012)
Food Producers	**1.0891**	*-0.1142*	-0.0057	0.1310	*0.1526*	**0.9967**	**0.9966**
(pooled mean group, years >19)	(0.065)	(0.069)	(0.071)	(0.094)	(0.087)	(0.008)	(0.013)
Household Goods	**0.9350**	0.0470	**0.1551**	**-0.2325**	-0.0049	**0.9182**	**0.9176**
(pooled mean group, years >36)	(0.076)	(0.080)	(0.052)	(0.068)	(0.039)	(0.039)	(0.036)
Leisure Goods	**0.8625**	*0.1001*	-0.1077	-0.0772	0.0634	**0.8867**	**0.8972**
(pooled mean group, years >14)	(0.061)	(0.060)	(0.249)	(0.131)	(0.068)	(0.029)	(0.041)
Personal Goods	**0.9057**	0.0595	0.0255	-0.1587	0.0965	**0.9709**	**0.9651**
(pooled mean group, years >31)	(0.035)	(0.058)	(0.073)	(0.169)	(0.075)	(0.014)	(0.015)
Health Care Equip. & Services	**1.1980**	-0.3581	0.0332	0.1800	-0.1185	**0.7644**	**0.7735**
(pooled mean group, years >17)	(0.246)	(0.279)	(0.231)	(0.263)	(0.261)	(0.053)	(0.072)
Pharmaceuticals & Biotechnology	0.3700	0.1916	1.3560	-3.6183	*0.3018*	**0.8450**	**0.9367**
(mean group, years >11)	(0.539)	(0.467)	(1.179)	(3.563)	(0.164)	(0.069)	(0.063)
Food & Drug Retailers	-6.4881	7.3715	0.0012	0.0194	-0.0919	**0.9844**	**0.9770**
(mean group, years >24)	(7.422)	(7.422)	(0.140)	(0.077)	(0.073)	(0.020)	(0.020)
General Retailers	**0.9233**	0.1013	0.0213	0.0713	0.0291	**1.0523**	**0.9795**
(mean group, years >30)	(0.045)	(0.112)	(0.070)	(0.050)	(0.115)	(0.110)	(0.010)
Media	**0.9466**	0.0657	0.0161	-0.0105	-0.1377	**0.9552**	**0.9467**
(pooled mean group, years >21)	(0.074)	(0.095)	(0.132)	(0.196)	(0.117)	(0.017)	(0.019)
Gas, Water & Multiutilities	**1.0622**	0.5196	-2.4321	0.1621	0.4086	**1.0172**	**1.0917**
(pooled mean group, years >15)	(0.430)	(0.730)	(2.899)	(0.918)	(0.568)	(0.069)	(0.118)
Software & Computer Services	**1.1066**	-0.3539	0.0830	0.4925	0.5283	**0.8566**	**0.8588**
(pooled mean group, years >16)	(0.213)	(0.339)	(0.184)	(0.427)	(0.331)	(0.040)	(0.051)
Technology Hardware & Equipment	**0.6380**	-0.3000	0.4666	*-0.9848*	3.3236	**0.7797**	**0.8207**
(mean group, years >8)	(0.121)	(0.400)	(0.328)	(0.532)	(3.378)	(0.062)	(0.064)

estimates (p-values in parentheses)

Bold (***Italics***): Significant at 5% (10%)

B. Short run dynamics

The principal subject of study in this paper is operating leverage, that is, the question of whether, and by how much, the coefficient on sales growth in short run dynamics falls below unity, and to what extent this can be explained by asymmetric price adjustments, and by sticky labour and capital costs. Table 10 reports the estimates of the short run dynamics. In the full model the estimated short run coefficient on sales growth is below unity in 16 of the 25 sectors, but this is statistically significantly in only 5 sectors: Personal Goods, Industrial Engineering, Leisure Goods, Oil & Gas Producers, and General Retailers.

However, estimates of the base model without latent factors and explanatory interaction variables reveal a strikingly different story. The coefficient is less that unity in all but three sectors – Beverages, General Retailers and Gas, Water & Multiutilities – and significantly so in 17 sectors.

A partial explanation comes from the use of long run latent factors and partial adjustment to different equilibria. When these common correlated effects and the economic cycle are adjusted for, the coefficient is lower than unity for 22 of the 25 sectors and this is statistically significant in 14. Mostly, this explanation comes from sticky employment, but also in some sectors from fixed capital costs and asymmetric price adjustments. The combined effect of asymmetric price adjustment and sticky labour and fixed capital explains operating leverage fully in 9 of these 14 sectors,[10] including some of the most important sectors in the UK economy. However, these inferences are more clearly apparent in statistical tests.

Table 11 presents left-tailed tests of statistical hypotheses for operating leverage. Based on estimates of the base model (1), there is a statistically significantly (at 5% significance level) evidence of margin contraction due to an unexpected shock to sales, in 17 out of 25 sectors. However, in the base model there is partial adjustment only to one cointegrating relationship, the log cost and log sales profit margin equilibrium. This model is probably too simplistic. We find evidence that in certain sectors costs and sales may also adjust to market share and economic cycle equilibria. Presumably, firms would anticipate partial adjustment to multiple equilibria in these sectors so that the unanticipated component in sales growth may be lower, and therefore also the operating leverage channel.

This turns out to be the case in most (11 out of 17) of the sectors where margin shrink is significantly lower after accounting for the other equilibrium relationships.[11] Nevertheless, the operating leverage effect is still statistically significant in 14 sectors. In all but 5 of the sectors (Oil & Gas Producers, Industrial Engineering, Leisure Goods, Personal Goods and General Retailers) explanatory interaction variables fully explain operating leverage up to the point where it is no longer statistically significant. In the main, the explanation comes from sticky labour costs. This consistent with a world where frictions in the labour market ensure that, faced with an unanticipated fall in sales, firms choose not to, or may not be able to, fully adjust their employment.

Our descriptive analysis suggests that employment is partly adjusted in the following year and we allow for delayed adjustment in the estimated model. The sticky labour costs explanation is statistically significant in 9 sectors.[12] In addition, sticky fixed capital is also significant, at the 10% level, in 2 other sectors, General Industrials and Industrial

[10] Industrial Metals, Construction & Materials, General Industrials, Electronic & Electrical Equipment, Automobiles & Parts, Household Goods, Media, Software & Computer Services and Technology Hardware & Equipment.

[11] Oil & Gas Producers, Forestry & Paper, Industrial Metals, Construction & Materials, Industrial Engineering, Support Services, Automobiles & Parts, Leisure Goods, Healthcare Equipment & Services, Software & Computer Services and Technology Hardware & Equipment.

[12] At the 5 percent level in 4 sectors - Oil & Gas Producers, Chemicals, Household Goods and Tech-

Transportation. So, in total, there are 11 sectors where sticky costs explain operating leverage effects.

Table 11: (Left-tailed) tests for operating leverage and its explanations

Sector	Test for operating leverage (lower margin)			Explanations for operating leverage		
	Only growth	Incl. factors	All variables	Sticky capital	Sticky employment	Asymmetry
Oil & Gas Producers	**2.8746**	0.5326	**1.9795**	0.3001	**2.0407**	-1.6551
(pooled mean group, years >8)	(0.002)	(0.297)	(0.024)	(0.382)	(0.021)	(0.951)
Chemicals	1.1206	0.7980	1.1408	-0.2286	**2.1844**	-0.3608
(pooled mean group, years >27)	(0.131)	(0.212)	(0.127)	(0.590)	(0.014)	(0.641)
Forestry & Paper	**2.1661**	-0.1007	-0.8400	-2.3820	-1.6321	***1.4367***
(mean group, years >17)	(0.015)	(0.540)	(0.800)	(0.991)	(0.949)	(0.075)
Industrial Metals	**5.0398**	**3.4266**	1.1035	-1.5620	***1.2852***	-1.0937
(mean group, years >8)	(0.000)	(0.000)	(0.135)	(0.941)	(0.099)	(0.863)
Construction & Materials	**3.0201**	**2.7282**	0.7777	-0.8329	***1.3709***	-0.2493
(pooled mean group, years >31)	(0.001)	(0.003)	(0.218)	(0.798)	(0.085)	(0.598)
Aerospace & Defense	0.8930	0.6780	-0.1836	-1.0161	***1.3860***	0.4525
(mean group, years >13)	(0.186)	(0.249)	(0.573)	(0.845)	(0.083)	(0.325)
General Industrials	**2.0559**	**2.2674**	0.3983	***1.3792***	-0.4638	0.2711
(pooled mean group, years >23)	(0.020)	(0.012)	(0.345)	(0.084)	(0.679)	(0.393)
Electronic & Electrical Equipment	**1.7953**	**2.0648**	-0.8240	-1.3290	-1.6024	**2.1355**
(pooled mean group, years >21)	(0.036)	(0.019)	(0.795)	(0.908)	(0.945)	(0.016)
Industrial Engineering	**2.4420**	**2.0823**	**2.3670**	0.5399	***1.3268***	-1.3538
(mean group, years >31)	(0.007)	(0.019)	(0.009)	(0.295)	(0.092)	(0.912)
Industrial Transportation	0.4974	0.8768	1.2272	***1.5247***	-0.3317	-0.4323
(mean group, years >18)	(0.309)	(0.190)	(0.110)	(0.064)	(0.630)	(0.667)
Support Services	**1.7187**	***1.2813***	0.8089	-1.4091	-0.6609	1.1136
(pooled mean group, years >32)	(0.043)	(0.100)	(0.209)	(0.921)	(0.746)	(0.133)
Automobiles & Parts	**2.1555**	**1.6888**	-0.7046	-0.5414	0.2396	***1.5905***
(pooled mean group, years >12)	(0.016)	(0.046)	(0.759)	(0.706)	(0.405)	(0.056)
Beverages	-0.9389	-5.6549	-0.3037	0.5754	0.0742	0.7198
(mean group, years >19)	(0.826)	(1.000)	(0.619)	(0.283)	(0.470)	(0.236)
Food Producers	0.3920	0.2671	-1.3616	0.0805	-1.3987	**1.6456**
(pooled mean group, years >19)	(0.348)	(0.395)	(0.913)	(0.468)	(0.919)	(0.050)
Household Goods	**2.1052**	**2.2594**	0.8547	-2.9752	**3.4075**	-0.5887
(pooled mean group, years >36)	(0.018)	(0.012)	(0.196)	(0.999)	(0.000)	(0.722)
Leisure Goods	**3.9306**	**2.5350**	**2.2569**	0.4333	0.5886	-1.6766
(pooled mean group, years >14)	(0.000)	(0.006)	(0.012)	(0.332)	(0.278)	(0.953)
Personal Goods	**2.1377**	**2.3450**	**2.6856**	-0.3510	0.9370	-1.0258
(pooled mean group, years >31)	(0.016)	(0.010)	(0.004)	(0.637)	(0.174)	(0.848)
Health Care Equip. & Services	**4.4063**	**3.1286**	-0.8038	-0.1436	0.4538	***1.2836***
(pooled mean group, years >17)	(0.000)	(0.001)	(0.789)	(0.557)	(0.325)	(0.100)
Pharmaceuticals & Biotechnology	**2.2522**	1.0052	1.1687	-1.1496	1.0155	-0.4104
(mean group, years >11)	(0.012)	(0.157)	(0.121)	(0.875)	(0.155)	(0.659)
Food & Drug Retailers	0.7760	1.1305	1.0089	-0.0083	***1.2653***	-0.9931
(mean group, years >24)	(0.219)	(0.129)	(0.157)	(0.503)	(0.100)	(0.840)
General Retailers	-0.4775	**2.0691**	**1.7206**	-0.3044	-0.2533	-0.9059
(mean group, years >30)	(0.683)	(0.019)	(0.043)	(0.620)	(0.600)	(0.818)
Media	**2.6113**	**2.8486**	0.7200	-0.1220	1.1753	-0.6951
(pooled mean group, years >21)	(0.005)	(0.002)	(0.236)	(0.549)	(0.120)	(0.756)
Gas, Water & Multiutilities	-0.2499	-0.7785	-0.1447	0.8390	-0.1766	-0.7119
(pooled mean group, years >15)	(0.599)	(0.782)	(0.558)	(0.201)	(0.570)	(0.762)
Software & Computer Services	**3.5994**	**2.7469**	-0.4998	-0.4510	-1.1529	1.0444
(pooled mean group, years >16)	(0.000)	(0.003)	(0.691)	(0.674)	(0.876)	(0.148)
Technology Hardware & Equipment	**3.5544**	**2.8164**	2.9876	-1.4209	**1.8518**	0.7503
(mean group, years >8)	(0.000)	(0.002)	(0.001)	(0.922)	(0.032)	(0.227)

z-stats (p-values in parentheses)
Bold (***Italics***): Significant at 5% (10%)

There are 4 other sectors where asymmetric price adjustments provide an explanation; the effect is statistically significant at the 5% level in 2 sectors (Electronic & Electrical Equipment and Food Producers) and at the 10% level in 2 others (Forestry & Paper

nology Hardware & Equipment, and at 10 percent in 5 other sectors - Industrial Metals, Construction & Materials, Aerospace & Defence, Industrial Engineering and Food & Drug Retailers.

and Automobiles & Parts). We conjecture that the forces of domestic and international competition restrict producers in these sectors from being able to adjust prices fully on the downside.

IX. Conclusions

In this paper we have sought to operationalise the analysis of operating leverage in a model in which we allow for short run variations in margin but test and control for an equilibrating relationship for margins in the long run. To do this we use some recent developments in panel econometrics which allows for heterogeneity in slopes and the possibility of common factors. We found that aggregate models using data for all sectors failed to make full allowance for cross sectional dependence, and failed to adequately capture sectoral variation in operating leverage and its explanations. We examine how operating leverage functions in 25 UK sectors. Our results suggest that the behaviour of operating leverage over the business cycle reflects sticky labour costs and some degree of asymmetric price adjustment. But we also find that there are two main equibrating long run relationships to which operating profit adjusts – the relationship between costs and sales and a market share relationship between firm sales and total sales in a sector.

References

[1] Acharya, V.; H. Almeida; and M. Campello. "Aggregate Risk and the Choice Between Cash and Lines of Credit." *Journal of Finance*, 68 (2013), 2059–2116.

[2] Bailey, N., Holly, S. and Pesaran, H.M. (2015) "A Two Stage Approach to Spatiotemporal Analysis with Strong and Weak Cross-Sectional Dependence", Forthcoming, *Journal of Applied Econometrics.*

[3] Bhattacharjee, A., Higson, C., Holly, S.and Kattuman, P. (2009) "Business Failure in UK and US Quoted Firms: Impact of Macro-Economic Instability and the Role of Legal Systems". *Review of Law and Economics.*

[4] Bhattacharjee, A., Higson, C., Holly, S. and Kattuman, P. (2009) "Macro Economic Instability and Business Exit: Determinants of Failures and Acquisitions of Large UK Firms". *Economica*, 76, 301, 108-131.

[5] Bhattacharjee, A. and Holly, S. (2013) "Understanding interactions in social networks and committees", *Spatial Economic Analysis.* 8, 1, 23-53.

[6] Blackburne, E.F. and Frank, M.W.. (2007). "Estimation of nonstationary heterogeneous panels", *Stata Journal*, StataCorp LP, 7, 2, 197-208.

[7] Bils, M., 1987. "The Cyclical Behavior of Marginal Cost and Price", *American Economic Review.* 77, 5, 838-55.

[8] Bowman, R.G. (1979). "The Theoretical Relationship between the Systematic Risk and Financial (Accounting) Variables," *Journal of Finance* 34, 617-630.

[9] Campello, M., and E. Giambona. “Real Assets and Capital Structure.” *Journal of Financial and Quantitative Analysis*, 48 (2013), 1333–1370.

[10] Carlson, M., A. Fisher, and R. Giammarino (2004). “Corporate Investment and Asset Price Dynamics: Implications for the Cross Section of Returns,” *Journal of Finance* 59, 2577-2603.

[11] Chen, N. and F. Zhang (1998). “Risk and Return of Value Stocks,” *Journal of Business* 71, 501-535.

[12] Cooper, I. (2006). “Asset pricing implications of non-convex adjustment costs and irreversibility of investment,” *Journal of Finance* , 61, pp. 139–170.

[13] Darrat, A. F. and Mukherjee, T. K. (2005) “Inter-Industry Differences and the Impact of Operating and Financial Leverages on Equity Risk”, *Review of Financial Economics.*Spring 141-155.

[14] DeYoung, R. and K.P. Roland (2001). “Product Mix and Earnings Volatility at Commercial Banks: Evidence from a Degree of Total Leverage Model,” *Journal of Financial Intermediation* 10, 54-84.

[15] Dichev, I.D. (1998). “Is the Risk of Bankruptcy a Systematic Risk?” *Journal of Finance* 53, 1131-1147.

[16] Dugan, Michael T., Donald Minyard, and Keith A. Shriver (1994) “A Reexamination of the Operating Leverage-Financial Leverage Tradeoff”, *Quarterly Review of Economics & Finance.* Fall, 327-334.

[17] Fama, E.F. and K.R. French (1992). “The Cross-Section of Expected Stock Returns,” *Journal of Finance* 47, 427-465.

[18] Fama, E.F. and K.R. French (1996). “Multifactor Explanations of Asset Pricing Anomalies,” *Journal of Finance* 51, 55-84.

[19] Farinas, J.C. and Huergo, E. (2003) "Profit Margins, Adjustment costs and the Business Cycle: An Application to Spanish Manufacturing Firms". *Oxford Bulletin of Economics and Statistics*, 65, 1, 49-72.

[20] Ferri, M.G. and W.H. Jones (1979). “Determinants of Financial Structure: A New Methodological Approach,” *Journal of Finance* 34, 631-644.

[21] Gertler, M. and Gilchrist, S. (1994). “Monetary Policy, Business Cycles and the Behavior of Small Manufacturing Firms”, *Quarterly Journal of Economics*, 109, 2, 309-340.

[22] Geroski, P.A. and P. Gregg (1997). *UK company performance in adversity*, Cambridge University Press, Cambridge.

[23] Griffin, H.F. and M.T. Dugan (2003). “Systematic Risk and Revenue Volatility,” *Journal of Financial Research*, 26, 179-189.

[24] Griffin, J.M. (2002). “Are the Fama and French factors global or country specific?” *Review of Financial Studies* **15**(3), 783-803.

[25] Gourio, F. (2005). "Operating Leverage, Stock Market Cyclicity, and the Cross-Section of Returns," working paper, Jan.

[26] Gourio, F. (2008) "Disasters and Recoveries," *American Economic Review*, 98, number 2,

[27] Gulen, H., Y. Xing, and L. Zhang. (2008). "Value versus Growth: Time-Varying Expected Stock Returns," University of Michigan Working Paper.

[28] Ghosh, Dilip K. and Robert G. Sherman (1993), "Leverage, Resource Allocation and Growth" ,*Journal of Business Finance & Accounting.* June, 575-582.

[29] Gottfries, Nils (1991). "Customer Markets, Credit Market Imperfections and Real Price Rigidity", *Economica*, 58, 231, 317-23, August.

[30] Green, E.J. and Porter, R.H. (1984) "Noncooperative collusion under imperfect price competition", *Econometrica*, 52, 87-100.

[31] Hamada, R.S. (1972). "The Effect of the Firms Capital Structure on the Systematic Risk of Common Stock," *Journal of Finance* 27, 435-452.

[32] Hausman, J.A. (1978) "Specification tests in econometrics", *Econometrica*, 46, 125l-1271.

[33] Higson, C., Holly, S., Kattuman, P. and Platis, S. (2004) "The Business Cycle, Macroeconomic Shocks and the Cross Section: The Growth of UK Quoted Companies", *Economica*, 71, 281, 299-318.

[34] Holly, S., Pesaran, H.M. and Yamagata, T. (2011) "The Spatial and Temporal Diffusion of House Prices in the UK", J*ournal of Urban Economics* , vol 69, pp. 2-23.

[35] Ho, Y.K., Z. Xu, and C.M. Yap, C.M. (2004). "R&D Investment and Systematic Risk," *Accounting and Finance* 44, 393-418.

[36] Huffman, L., 1983, "Operating Leverage, Financial Leverage, and Equity Risk," *Journal of Banking and Finance*, 7, 197-212.

[37] Im, K.S., Pesaran, M.H. and Shin, Y. (2003) "Testing for Unit Roots in heterogeneous Panels". *Journal of Econometrics.* 115:53-74

[38] James, C. and Kizilaslan, A. "Asset Specificity, Industry-Driven Recovery Risk, and Loan Pricing" *Journal of Financial and Quantitative Analysis* Vol. 49, No. 3, June 2014, pp. 599–631

[39] Kahl, M., Lunn, J. and Nilsson, M. (2013). "Operating leverage and corporate financial policies". Working Paper, University of Colorado at Boulder.

[40] Lang, Larry, Eli Ofek, and Rene M. Stulz (1996), "Leverage, Investment, and Firm Growth", *Journal of Financial Economics* January, 3-29.

[41] Li, Rong-Jen and Glenn V. Henderson, Jr. (1991) "Combined Leverage and Stock Risk", *Quarterly Journal of Business & Finance.* Winter. 18-39.

[42] Lev, B. (1974). "On the association between operating leverage and risk," *Journal of Financial and Quantitative Analysis.* 9,4, 627–641.

[43] Ljungqvist, A. andW.J.Wilhelm, Jr. (2005). "Does Prospect Theory Explain IPO Market Behavior?" *Journal of Finance* 60, 1759-1790.

[44] Lord, R., 1996, "The Impact of Operating and Financial Risk on Equity Risk," *Journal of Economics and Finance*, 20, 27-38.

[45] Lord, R., 1998, "Properties of Time-Series Estimates of Degree of Leverage Measures," *Financial Review* 33, 69-84.

[46] Machin, S and Van Reenen, J. (1993) "Profit margins and the business cycle: evidence from UK manufacturing firms". *Journal of Industrial Economics*, XLI (1). 29-50.

[47] Mandelker, G.N. and Rhee, S.G. (1984). "The Impact of the Degrees of Operating and Financial Leverage on Systematic Risk of Common Stock," *Journal of Financial and Quantitative Analysis* 19, 45-57.

[48] Mensah, Y.M., "Adjusted Accounting Beta, Operating Leverage and Financial Leverage as Determinants of Market Beta: A Synthesis and Empirical Evaluation," *Review of Quantitative Finance and Accounting*, 2, p187–203, 1992

[49] Novy-Marx, R.(2007a), "Real Options and Investment in a Dynamic Model of Oligopoly," working paper.

[50] Novy-Marx, R. (2007b), "Investment-Cash Flow Sensitivity and the Value Premium" working paper.

[51] Novy-Marx, R. (2011) "Operating Leverage", *Review of Finance.* 15, 1, 103-134.

[52] O'Brien, T.J. and Vanderheiden P.A. (1987). "Empirical Measurement of Operating Leverage for Growing Firms". *Financial Management* 16, 45-53.

[53] Petersen, M.A. (2009) "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches", *Review of Financial Studies,* 22, 1, 435-480.

[54] Pesaran, M. H. (2006). "Estimation and inference in large heterogenous panels with multifactor error structure". *Econometrica* 74, 967–1012.

[55] Pesaran, M.H. (2013). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, forthcoming.

[56] Pesaran, M. H. and R. Smith (1995). "Estimating long-run relationships from dynamic heterogeneous panels". *Journal of Econometrics* 68, 79–113.

[57] Pesaran, M. H., Shin, Y. and Smith, R. J. (2000). "Structural analysis of vector error correction models with exogenous I(1) variables", *Journal of Econometrics*, 97, 2, 293-343.

[58] Reid, G. C., Bhaskar, V. & Machin, S. (1993) "Price and Quantity Adjustment over the Business Cycle: Evidence from Survey Data", *Oxford Economic Papers.* 45, 2, p. 257-68

[59] Rosett, J.G. (2001). "Equity Risk and the Labor Stock: The Case of Union Contracts," *Journal of Accounting Research* 39, 337-364.

[60] Rotemberg, J.J. and Saloner, G. (1986) "A supergame-theoretic model of price wars during booms", *American Economic Review*, 76, 390-407.

[61] Rubinstein, M.E., 1973, "A Mean-Variance Synthesis of Corporate Financial Theory," *Journal of Finance* 28, 167-182.

[62] Shumway, T. and V. Warther, 1999, "The Delisting Bias in CRSP's NASDAQ Data and Its Implications for the Size Effect," *Journal of Finance* 54, 2361-2379.

[63] Stock, J.H. (1987). "Asymptotic Properties of Least Squares Estimation of Cointegrating Vectors," Econometrica, 55, 1035-1056.

[64] Stock, J.H. and M.W. Watson (1993). "A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems," Econometrica, 61, 783-820.

[65] Wu, D.-M. (1973) "Alternative tests of independence between stochastic regressors and disturbances", *Econometrica,* 41, 733-750.

[66] Zhang, L., 2005, "The Value Premium," *Journal of Finance* 60, 67-103.