Modelling investment when relative prices are trending: Theory and evidence for the United Kingdom

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Abstract

In recent work, Tevlin and Whelan (2002) argue that aggregate econometric models fail to capture the US investment boom in plant and machinery in the second half of the 1990s, whereas a disaggregate approach does much better. In particular, they show that aggregate models do not capture the increase in replacement investment associated with compositional shifts in the capital stock towards high depreciation rate assets, such as computers. And aggregate models invariably find little or no role for the real user cost, so do not pick up the strong effects of relative price falls on investment in computers. In this paper, a dataset for the United Kingdom is constructed in order to investigate the ability of different equations to account for the UK boom in plant and machinery investment in the second half of the 1990s. We report similar findings to Tevlin and Whelan (2002). We extend Tevlin and Whelan's analysis in two main ways. First, the failure of the aggregate equations is explained more formally in terms of misspecification when relative prices are trending. Second, the econometric analysis is conducted in a formal cointegration framework. As in the United States, it is shown that asset-level equations can explain the investment boom in plant and machinery in the second half of the 1990s in the United Kingdom, whereas the aggregate equation completely fails.

Keywords: investment, computers, relative prices
JEL classification: C51, E22

Summary

Recent research by Stacey Tevlin and Karl Whelan in the United States has shown that aggregate economic models fail to explain the investment boom in real plant and machinery in the second half of the 1990s. In contrast, a disaggregate modelling approach does much better. This appears to reflect two factors. First, aggregate models do not capture the increase in replacement investment associated with compositional shifts in the capital stock towards shorter-lived assets, such as computers. Second, aggregate models invariably find little or no role for the real user cost of capital, so they understate the positive effects of falls in the relative price of computers on investment in computers.

The United Kingdom also experienced a boom in real plant and machinery investment in the second half of the 1990s. But undertaking similar research is beset with difficulties in the United Kingdom, not least the relative paucity of disaggregate investment data in the published National Accounts. In this paper, we carefully construct a dataset for the United Kingdom that is consistent with the National Accounts. We then use this to investigate the ability of different investment equations to account for the UK investment boom in plant and machinery. We report similar results to Stacey Tevlin and Karl Whelan for the United States. In particular, the traditional aggregate modelling approach completely fails to explain the investment boom in plant and machinery in the second half of the 1990s.

Our analysis consists of two main elements: a theoretical section setting out the relationship between aggregate and disaggregate approaches to modelling investment; and an empirical analysis setting out our econometric results.

In our theoretical analysis, we first derive the relationship between firms' desired capital stocks and the real user cost of capital that is predicted by standard economic theory. We show how that relationship breaks down in the presence of trend falls in the relative price of investment goods. Such trends have been a particularly important feature of investment in recent years. In contrast, we show that well-specified relationships exist at the disaggregate level.

Our empirical exercise involves using time-series cointegration methods to model investment at disaggregate and aggregate levels. We compare the ability of the two approaches to explain the boom in plant and machinery investment. Recognising that cointegration techniques can have low power, particularly in small samples, we further evaluate the comparative performance of the two approaches by conducting out of sample forecasting exercises.

In all cases, our empirical results support the theoretically superior disaggregate modelling approach. First, compositional shifts in the capital stock towards shorter-lived computer assets appear to have been important in the United Kingdom too in the second half of the 1990s. That explains some, though not all, of the inability of the aggregate model to explain the investment boom. The second factor behind the strong investment growth has been falls in the relative price of computers. Echoing the finding of Stacey Tevlin and Karl Whelan for the United States, we find that firms' investment in computers appears to be highly sensitive to falls in the real user cost for computers. And interestingly, our models suggest that the increase in the size of firms'

computer capital stocks in the second half of the 1990s are fully accounted for by the sharp falls in the real user cost for computers.

Given the great uncertainties surrounding measures of the real user cost of capital and the price of investment goods in particular, we investigate the sensitivity of our results to alternative measures of the real user cost of capital. We find that our results are reassuringly robust. In all they provide strong support to attempts to model and forecast investment at the disaggregate level.

1.Introduction

Traditional attempts to model investment using time-series methods have for the most part been unsuccessful[(1)]. At best, only a limited role is found for the real user cost of capital. And the overall fit of investment equations is invariably poor. That is particularly true of the 1990s, when these models failed to predict the rapid real investment growth in the United Kingdom and in the United States.

A host of explanations have been put forward in the literature for the failure of time-series investment equations. These include (a) mismeasurement of structural variables such as the real user cost or marginal q [(2)]; (b) aggregation biases[(3)]; and (c) estimation biases[(4)]. In this paper we suggest that at least part of the difficulty arises because aggregate investment equations do not hold when differences across assets are important.

In particular, the long run of investment equations is typically designed to satisfy the properties of a one-sector model. But that model cannot account for the persistent shifts in the relative prices of different investment goods that we observe in the data[(5)]. We argue in **section 2** that the aggregate relationship between capital, output and the real user cost of capital breaks down in the presence of such trends in relative prices.

Having established misspecification of the aggregate equation, we then illustrate its empirical importance for the United Kingdom. In **section 3** we summarise the main properties of our dataset for plant and machinery investment, including and excluding computers. In **section 4** we follow the work of Tevlin and Whelan (2002) in the United States by estimating separate time-series econometric equations for the computer and non-computer components of UK plant and machinery investment. We extend Tevlin and Whelan's work by conducting our econometric

(1) See, for example, Oliner, Rudebusch and Sichel (1995).

(2) See, for example, Chirinko (1993).

(3) See, for example, Caballero (1999), in which the author illustrates that, in general, information about the cross-sectional distribution of capital imbalances is needed to explain aggregate investment. This has motivated attempts to model investment at the micro level. See, for example, Bond et al (2002).

(4) Caballero (1994) suggested that traditional estimation approaches downwardly bias estimates of the elasticity of the cost of capital with respect to the capital-output ratio. The poor performance of traditional time-series investment equations has also been attributed by some to factors such as financing constraints and the irreversibility of investment under conditions of uncertainty.

(5) As discussed in OECD (2001a), the relative price of capital goods in most countries has trended down, at least since the early 1980s. See also Bakhshi and Larsen (2001), for a discussion of UK developments, and Whelan (2001), for a US perspective.

analysis within an explicit cointegrating framework. Given the inherent measurement difficulties, we take particular care to investigate the sensitivity of our results to alternative measures of the real user cost. Finally, in **section 5**, we compare out-of-sample forecasts from the disaggregate equations with forecasts generated from the traditional, aggregate model of plant and machinery investment. Like Tevlin and Whelan for the US, we find that our asset-level investment equations can together generate much more accurate forecasts of plant and machinery investment compared with the (misspecified) aggregate approach.

2. The theory

Investment in the United Kingdom in recent decades has been characterised by persistent shifts in the relative price of investment goods. That has manifested itself in two main ways. First, there has been a decline in the price of investment goods, such as plant and machinery, relative to prices in the economy as a whole (see chart 1)[6]. Second, there have been shifts in the price of high-tech investment goods relative to other investment goods. Chart 2 demonstrates that computer prices have fallen dramatically relative to the price of non-computer plant and machinery.

Chart 1

Ratio of plant and machinery investment good deflator to GDP deflator (in logs)

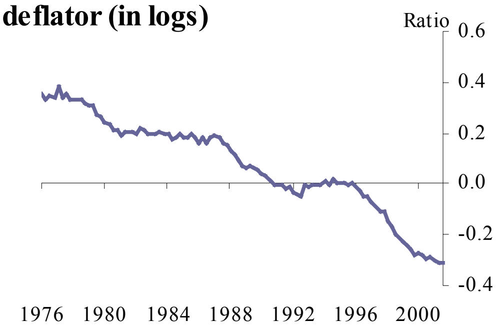
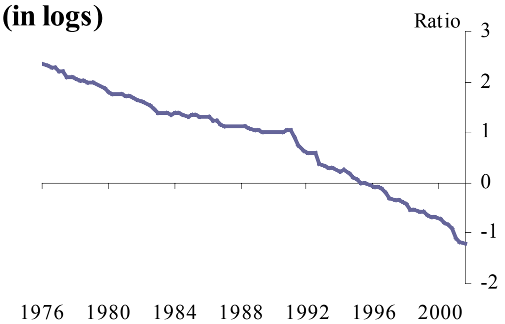


Chart 2

Ratio of computer prices to non-computer plant and machinery prices (in logs)



In this section we show how easy it is for an aggregate investment equation to go wrong when the relative prices of capital goods are changing.

Let the production function for the whole economy (or for a sector) take the constant elasticity of substitution (CES) form:

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(6) This has also been a feature of investment for many other industrialised countries. See OECD (2001a). For a full discussion of the UK trends see Bakhshi and Thompson (2002).

$$Y^t = \left[a_d (K_d^t)^\phi + a_e (K_e^t)^\phi + a_l (e^{\mu t} h^t)^\phi\right]^{1/\phi}, \quad a_d, a_e, a_l > 0,\ \phi \le 1 \qquad \textbf{(1)}$$

Here we assume that output is produced by two types of capital, computer capital ("exciting", labelled subscript e) and non-computer capital ("dull", labelled subscript d), and by labour hours (*h*).[(7)] The K_i^t are the service flows from the two types of capital. The rate of labour-augmenting technical progress is denoted by μ. Denote the elasticity of substitution by $\sigma = 1/(1-\phi) > 0$, noting that in the Cobb-Douglas case $\sigma = 1$.

Equating the marginal products of capital to the real user costs (denoted by r_d^t, r_e^t), we obtain after rearrangement

$$K_i^t / Y^t = (a_i / r_i^t)^\sigma, \qquad i = d, e \qquad \textbf{(2)}$$

Taking logs and then differentiating with respect to time,

$$\dot{k}_i^t - \dot{y}^t = -\sigma(d \ln r_i^t / dt), \qquad i = d, e \qquad \textbf{(3)}$$

where lower case letters denote logs and a dot denotes a time derivative.

The real user cost is given by the Hall-Jorgenson formula[8]:

$$r_i^t = [\rho^t + \delta_i - \pi_i^t] P_i^t, \qquad i = d, e \qquad \textbf{(4)}$$

where P_i^t is the asset price, measured relative to the price of output, ρ^t is the real rate of return (ie the nominal rate minus the growth rate of the price of output), δ_i is the depreciation rate, and $\pi_i^t = d \ln P_i^t / dt$ is the growth rate of the relative price of asset *i*.

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(7) The interpretation of the production function as being for the whole economy can be rigorously justified in two ways. Either we can assume that the two types of capital good are imported, in which case domestic output is of some third good. Or we can assume that the home economy produces one of the capital goods while the other is imported. If the home economy produces more than one good, then an aggregate production function can only be justified if some restrictions are put on technology. This is what the model of Greenwood et al (1997) does.

8 See Jorgenson (1963) and Hall and Jorgenson (1967). The user cost expression is derived under profit maximisation using the capital accumulation identity (equation A1 in appendix 1) and the assumption of no adjustment costs. It is also assumed that the rate of return is equated across assets, as is required for equilibrium.

Now consider the problem of aggregating equation **(3)** across asset types. Theory suggests that it is the flow of capital services, not the stock of capital, which belongs in the production function, in just the same way as hours worked are preferable to numbers employed as a measure of each type of labour input. The correct way to aggregate the capital services of different asset types is to use weights based on the Hall-Jorgenson rental price formula. This amounts to calculating the proportion of aggregate profit that is generated by flows from each asset type.[9] Suppose we have an index (fixed-weight or chain-linked) of the growth rate of aggregate capital services

$$\dot{k}^t = w\dot{k}_d^t + (1-w)\dot{k}_e^t, \quad 0 < w < 1 \qquad \textbf{(5)}$$

Plugging the capital services index into equations **(3)** we obtain

$$\dot{k}^t - \dot{y}^t = -\sigma\left[w(d\ln r_d^t / dt) + (1-w)(d\ln r_e^t / dt)\right] \qquad \textbf{(6)}$$

This shows that, if we want to derive a relationship for aggregate capital from the asset level relationships (equations (3)), we must use the same pattern of weights to aggregate the growth of real user costs as we use to aggregate capital services. In practice, this is not easy to do. The UK National Accounts do not immediately provide us with either aggregate capital services or an aggregate real user cost. Researchers have often employed aggregate measures of capital that use weights appropriate for a wealth rather than a services concept of capital. And they have used measures of the aggregate real user cost that differ from the theoretically correct measure in the last equation.

If asset prices are changing at very different rates, it is unlikely that the typical aggregate measure of the real user cost of capital will be a good approximation for the theoretically correct measure. We can see this even in the simplified case of a steady state. In a steady state, the growth of relative prices, the depreciation rates and the real rate of return are all constant. Hence $d\ln r_i^t / dt = d\ln P_i^t / dt$ and plugging this into the last equation we get

$$\dot{k}^t - \dot{y}^t = -\sigma\left[w(d\ln P_d^t / dt) + (1-w)(d\ln P_e^t / dt)\right] \qquad \textbf{(7)}$$

[9] See OECD (2001b) and Oulton (2001b) for the theory of capital services measurement. The alternative aggregate measure is the aggregate capital stock, the "wealth stock" measure of aggregate capital.

The expression in square brackets looks like a price index for aggregate investment, but it is not identical to this latter concept since the weights are not the same. The weight *w* is the share of non-computer capital in aggregate capital services. In a price index for investment, the corresponding share is the share of non-computer investment in aggregate investment; these shares are not the same. So if we use an aggregate index of capital services on the left hand side and an aggregate price index for investment on the right hand side, there will be an inconsistency and any econometric estimates based on these measures will be biased. The only case when the bias disappears is when the two asset prices are growing at the same rate relative to the price of output, ie relative to each other asset prices are constant, in which case the weights do not matter. Otherwise, the typical aggregate measure of the real user cost will be misleading.

The derivation of equation **(7)** also assumes that the elasticity of substitution is the same for all inputs. If this assumption is relaxed then no measure of the aggregate real user cost derived from observable data exists. This provides a further motivation for considering disaggregated investment equations. In most of our results, we maintain the CES assumption. But we do also consider more general formulations below.

In practice, researchers usually fit equations for gross investment, not net investment as in equation (6), and this leads to further difficulties. Expressing equation **(3)** in terms of the net investment rate, $\dot{k}_i^t$ and adding the depreciation rate gives the gross investment rate:

$$I_i^t / K_i^t = \delta_i + \dot{y}^t - \sigma(d \ln r_i^t / dt), \qquad i = d, e \qquad \textbf{(8)}$$

where I_i^t is gross investment and δ_i is the depreciation rate for the *i*th type of capital. Again, this can be turned into an aggregate equation by applying the same weights to both sides. But this is *not* the same as aggregating gross investment and capital services separately and then dividing the one by the other to obtain *I*/*K*, since different weights would be normally used for numerator and denominator. So if a researcher takes aggregate investment and some measure of aggregate capital from the national accounts, the ratio of the two aggregates will not be appropriate for estimating equation **(8)**.

Notice too that the aggregate *I*/*K* ratio is likely to drift up over time if the pattern of investment is shifting towards assets with short lives, since depreciation will become increasingly important.

Hence it is a mistake to treat the aggregate depreciation rate as a constant when an aggregate version of equation **(8)** is estimated, a point to which we return below.(10)

These issues suggest there are important misspecification problems that arise when estimating aggregate investment equations when relative prices are trending. That points to a disaggregate approach to modelling investment.

3 Stylised facts

This section considers the key features of our dataset (details of the construction of this dataset are given in Appendices 1 and 2; summary statistics of the series are provided in table A3.8 of Appendix 3).

Capital stock

The capital stock as a share of GDP appears highly trended for aggregate plant and machinery and its computer component, but less obviously so for non-computer plant and machinery (chart 3).

Cost of capital

Chart 4 shows our estimates of the real user cost of capital (as defined in equation 4) for aggregate plant and machinery and, at the asset level, for computers and non-computers(11). In each case, there is evidence of a downward trend, although this is rather less pronounced in the non-computer case.

(10) See Whelan (2001). An example is the steady-state growth path of the two-sector growth model where the relative price of investment goods is trending down. In this case, under fixed weights, the aggregate deprecation rate is trending along the steady-state path and the aggregate investment equation is misspecified.

(11) Note that we proxy the real rate of return term in equation (4) with a measure of the real cost of finance. The volatility of our cost of capital measures in the earlier part of the sample reflects the volatility of this cost of finance measure, the ratio of Private Non-Financial Corporations' profits to the current financial valuation of the corporate sector. We use an alternative, weighted average cost of capital measure in our sensitivity analysis. The corresponding cost of capital measure is also smoother, but alternative cost of finance components have no material impact on our econometric results. (See appendices 1 and 4 for further details.)

Chart 3

Capital-output ratios (constant prices)

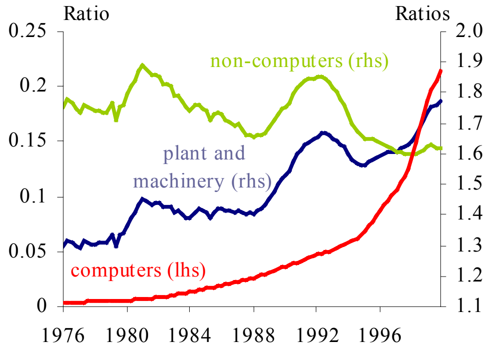
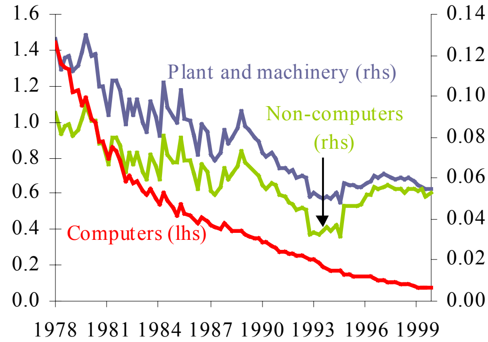


Chart 4

Cost of capital



Expressed in logs, these estimates are the sum of two components: the relative price of capital; and a non-relative price component. The first component is simply the price of capital relative to the price of output. The second component conflates the cost of finance, depreciation, capital gain, and tax factor terms described above.

Charts 5 and 6 show that for our assets, at both the aggregate and disaggregate level, the 'price' and 'non-price' elements exhibit very different persistence trends. The price series are trended, as the price of capital goods has fallen relative to general output prices. This is particularly true for computers where quality-adjusted prices have fallen dramatically, less so for non-computer plant and machinery. But there is little obvious trend to the non-price components.[12]

(12) Although (our alternative measures of) the cost of finance declined in the latter half of the 1990s, the non-price cost of capital actually rose. This reflects declines in our capital gain term over this period, which tended to raise the cost of capital. Note that the sharp movements between 1992 and 1994 in the non-price cost of capital series for non-computer plant and machinery reflect sharp movements in this asset's deflator, most notably in 1992 Q4 when it fell by some 9%. This causes a sharp fall in our capital gain term and a sharp rise in the non-price cost of capital at this time. Since we measure our capital gain term as a trailing eight-quarter moving average, there is also a corresponding fall in the non-price cost of capital eight quarters later, as can be seen in chart 6. As discussed in appendix 4, alternative capital gain terms have no material impact on the results we report in section 4.

Chart 5

Relative price of capital

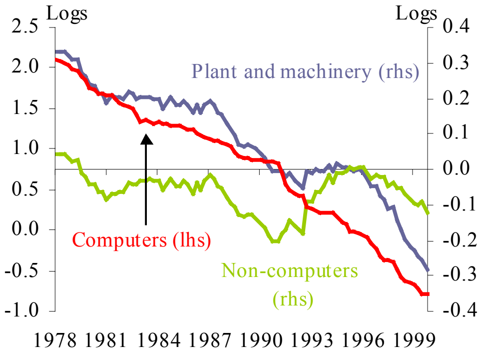
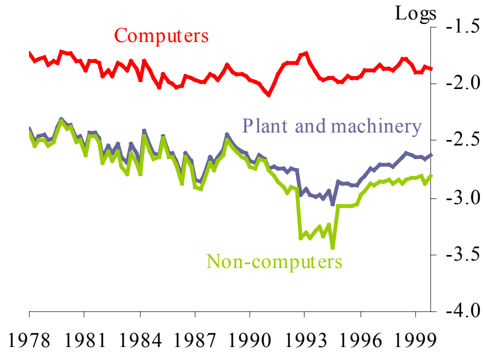


Chart 6

Non-price cost of capital

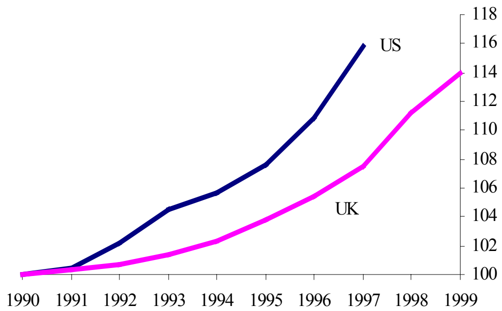


Depreciation

Chart 7 shows that the estimated aggregate depreciation rate for plant and machinery has risen quite sharply in recent years[13]. And that is consistent with the US experience too[14].

Chart 7

Implied real depreciation rates for plant and machinery in UK and US (1990=100)



4 Econometric analysis

In section 2, we argued that the aggregate relationship between standard measures of the capital-output ratio and the real user cost tend to break down when relative investment prices are trending. And we illustrated that such trends have been an important feature of UK investment in recent decades. But equation 2, reproduced below as equation 9 for ease of reference, provides an estimable long-run relationship at the disaggregate level.

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[13] This assumes a geometric depreciation rate – see Appendix 1 for details.

[14] US data to 1997 kindly provided by Stacey Tevlin. These series are backed out using fixed-weight National Accounts data and so are not subject to the bias identified by Tevlin and Whelan for chain-weighted data in an earlier version of their paper. For chart 7, we rebased both UK and US real depreciation rates to 1990=100.

$$K_i^t / Y = (a_i / r_i^t)^{\sigma}, \qquad i = d, e \qquad \textbf{(9)}$$

We first consider the stationarity properties of our variables. Table 1 shows the results from formal unit root tests.

Table 1: Augmented Dickey-Fuller and Phillips-Perron unit root tests

		Constant, no time trend				*Constant and time trend*			
		ADF(1)	**ADF(4)**	**PP(1)**	**PP(4)**	**ADF(1)**	**ADF(4)**	**PP(1)**	**PP(4)**
Aggregate plant and machinery	***k/y***	-0.1	-0.7	-0.3	-0.6	-1.5	-3.0	-1.3	-1.8
	Δ k/y	-3.6**	-2.6	-6.9**	-7.3**	-3.6*	-2.6	-6.9**	-7.3**
	r	-1.3	-1.2	-1.7	-1.6	-2.6	-2.0	-3.6*	-3.8*
	Δ r	-9.4**	-4.2**	-13.7**	-14.7**	-9.3**	-4.2**	-13.6**	-14.6**
Computers	***k/y***	0.2	1.1	0.3	0.5	-1.5	-2.1	-0.3	-0.9
	Δ k/y	-3.4*	-2.5	-3.7**	-4.0**	-3.3	-2.5	-3.7*	-4.0*
	r	0.6	1.1	0.3	0.5	1.2	-0.5	-1.8	-1.7
	Δ r	-8.3**	-4.2**	-12.6**	-13.2**	-8.3**	-4.3**	-12.6**	-13.4**
Non-computers	***k/y***	-0.9	-2.0	-0.6	-1.1	-1.6	-2.9	-1.6	-2.0
	Δ k/y	-3.4*	-2.6	-6.8**	-7.2**	-3.5*	-2.5	-6.7**	-7.2**
	r	-1.8	-1.7	-1.9	-1.8	-1.9	-1.7	-2.4	-2.5
	Δ r	-8.4**	-3.6**	-12.7**	-13.0**	-8.4**	-3.7**	-12.7**	-13.1**

Notes:
1. Asterisks signify null hypothesis of unit root rejected at 5% (*)or 1% (**) level.
2. ADF() and PP() indicate Augmented Dickey-Fuller and Phillips-Perron tests, where number in brackets is number of lagged first difference terms in test regression.

Although the results are somewhat mixed, depending on the model-DGP combination, taken together the tests broadly suggest that the capital-output ratio and the real user cost are non-stationary at both the aggregate and disaggregate level. We proceed on the assumption that the variables are all I (1).

Our estimation strategy is two-fold. First, we examine the relationship between the capital-output ratio and the real user cost in a cointegration framework, given the non-stationarity of these variables. Evidence of cointegration means that either investment or capital dynamics can be described by an error correction mechanism (ECM), with accelerator and dynamic user cost terms describing dynamics around a long-run equilibrium relationship between the capital-output ratio and the real user cost. Given our interest in gross investment, we focus on investment rather than capital dynamics.[15]

[15] Note that on the assumption of non-zero depreciation, it follows from the capital accumulation identity that investment and the capital stock are integrated of the same order and cointegrate.

Second, we exploit any covariance between the shocks driving computer and non-computer investment by estimating the asset-level equations using Seemingly Unrelated Regression (SUR) techniques. That also allows us to test explicitly the CES cross-equation restriction that the elasticity of substitution between capital inputs is equal in the two equations. We take the significance of the ECM coefficient in our SUR equations at the asset level to be evidence for a cointegrating relationship, even though the critical values on the *t*-statistic will not in general have precisely the same distribution as in Banerjee et al (1986)'s analysis of single equation cointegration tests based on OLS [(16)] [(17)]. Given the well-known low power of cointegration tests in small samples, we also implement the system-based Johansen cointegration test[(18)] and the dynamic OLS method, as robustness checks on our results[(19)].

Equation **(9)** summarises the system we estimate using SUR techniques. Note there is a cross-equation restriction on the elasticity of substitution, σ being the same in the two equations, which we test in our empirical work. To facilitate comparison with Tevlin and Whelan (2002) for the United States, we also report results for their specification (we call these **investment *rate* equations** (equation 11) as distinct from our dynamic **investment *growth* equations** (equation (10)). These should in principle be inferior to our dynamic equations as they make no use of the information contained in the long-run relationship between the variables.

$$\Delta i_{it} = \alpha_i + \sum_{j=1}^{8} \beta_{ij} \Delta gdp_{t-j} + \sum_{k=1}^{8} \gamma_{ik} \Delta rcc_{it-k} + \tau_i[(k_i / y)_{t-1} - \sigma rcc_{it-1}] \ , i = d \ , e \qquad \textbf{(10)}$$

$$i_{it} / k_{it-1} = \alpha_i + \sum_{j=1}^{8} \beta_{ij} \Delta gdp_{t-j} + \sum_{k=1}^{8} \gamma_{ik} \Delta rcc_{it-k} \quad , i = d \ , e \qquad \textbf{(11)}$$

(16) Single equation tests are valid in this context, as the investment equations we estimate are bivariate and so there can at most be one cointegrating vector. And the regressors are always found to be weakly exogenous with respect to the parameters of interest.

(17) For all our single equations, we adopted a general-to-specific estimation approach in order to obtain a parsimonious dynamic specification. Specifically, we tested down from a general model containing eight lags of the dynamic terms, to a parsimonious dynamic specification containing only terms significant at the 10% level.

(18) In order to determine the appropriate lag structure for our VECMs in the Johansen test, we first estimated unrestricted VARs over our full sample period (1978Q1-1999Q4). Lag length was then determined by lag length selection criteria, subject to the VAR passing serial correlation tests.

(19) Specifically, we implemented the dynamic OLS method suggested by Saikkonen (1991) and Stock and Watson (1993) of adding dynamic leads and lags of regressors to a levels regression, in order to check the robustness of estimated elasticities. We also applied the Banerjee et al (1998) ECM version of this test, in which leads of the regressors are added to an ECM specification, as a further test of cointegration. We report results from regressions including two leads, but results were not sensitive to number of leads chosen.

Of course, the estimation results reported below are only as good as the dataset underlying it. Given the absence of official estimates in the UK for many of the series in our econometric analysis, we need to make a number of assumptions (discussed in Appendix 1). That leaves our results potentially open to the criticism that they reflect mismeasurement of the variables of interest. We go some way to address this in a thorough sensitivity analysis. In particular, we investigate the robustness of our results to a range of alternative measures of the real user cost, to computer price mismeasurement and to different interpolation techniques used to derive a quarterly investment dataset. Appendix 4 shows how these changes reassuringly have no material impact on our results.

Aggregate plant and machinery

In our equation for plant and machinery, we find only weak evidence of cointegration using both single-equation and system techniques (for full results see tables A1 and A2 in Appendix 3). In the single equation case, the ECM coefficient has a *t*-statistic of –2.2 (similar results were obtained using the Banerjee et al (1998) dynamic OLS procedure). This *t*-statistic is respectable compared to the usual student-*t* critical values, but is low compared with the critical values tabulated by Banerjee *et al* (1986). Using the Johansen approach, neither the maximum-eigenvalue test nor the trace test indicate cointegration at the 20% significance level (see table A7 in appendix 3)[20].

Table 2

Estimated ECM coefficient and elasticity of substitution[1]

	Single-ECM equation, Least Squares[2]	*Single-ECM equation, dynamic OLS[2]*	*Long-run equation, dynamic OLS*	*Long-run equation, Johansen*
Plant & machinery				
ECM	-0.22 (-2.16)	-0.24 (-2.18)	-	-
elasticity	0.32 (5.13)	0.32 (5.46)	0.28 (21.54)	0.78 (8.4)
Computers				
ECM	-0.11 (-3.78)	-0.11 (-3.69)	-	-
elasticity	1.33 (24.26)	1.33 (23.59)	1.35 (71.53)	1.33 (28.43)
Non-computer plant & machinery				
ECM	-0.15 (-2.04)	-0.16 (-2.15)	-	-
elasticity	-0.02 (-0.23)	-0.01 (-0.14)	-0.04 (-1.77)	-0.09 (-1.18)

Note: 1. T-statistics in parentheses; 2. For computers and non-computer plant & machinery, the first two columns refer to estimates in individual asset-level equations in SUR system.

(20) We estimated our system over five lags, given that there was evidence of serial correlation at four lags, the number suggested by lag order selection criteria. The equation diagnostics were satisfactory.

Chart 8 reports fitted values against actual outturns of investment growth from the model. The estimated response of investment to the real user cost of capital is small: its elasticity with respect to the capital-output ratio is only -0.3 [21]. (This is in line with the estimates from the dynamic OLS method, reported in table 2 above). The equation performs reasonably for much of the sample, but fails completely to capture the strength of investment in the second half of the 1990s, mirroring Tevlin and Whelan's (2002) finding for the United States. We find no role for the real user cost in the investment rate equation, so in this case it collapses to a simple accelerator model: see chart 9.

Chart 8

Investment growth equation

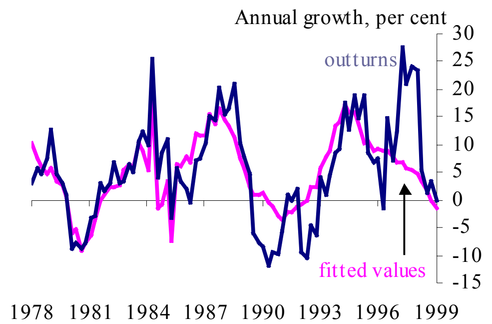
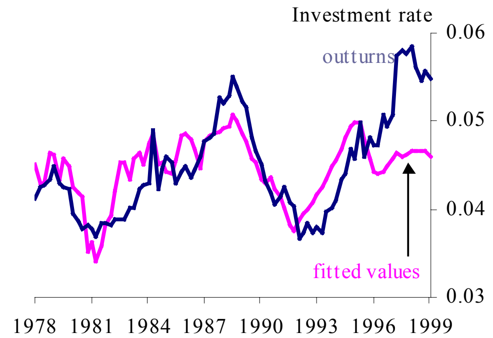


Chart 9

Investment rate equation



Tevlin and Whelan (2002) suggest two main reasons why their aggregate equation fails to capture the strength of plant and machinery investment in the United States in the second half of the 1990s. First, the aggregate equation ignores increases in replacement investment associated with compositional shifts in the capital stock towards computers, which have a higher deprecation rate than other plant and machinery. Second, in finding no significant role for the real user cost of capital, the aggregate equation misses the strong effect that relative price declines appear to have had on investment in computers. We find that these two factors are behind our results too.

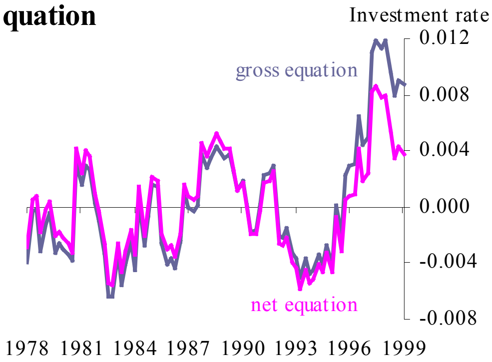
First, following Tevlin and Whelan (2002) we estimate an alternative version of the investment equation where the dependent variable is *net* investment (that is gross investment net of replacement investment). Chart 10 compares the residuals from the gross investment equation with the residuals from the net investment equation. Clearly the underprediction in the net equation is much less marked, though (unlike in Tevlin and Whelan (2002)) it is still apparent.

(21) If we drop the levels terms because of insufficient evidence of cointegration, the real user cost of capital plays even less of a role: only one term is significant at the 10% level in the equation's dynamics, and that term is incorrectly signed.

That suggests that compositional shifts in the capital stock towards higher depreciation rate computers can explain some, though not all, of the puzzle.

Chart 10

Residuals from investment rate equation



Second, an analysis of the fitted values from the aggregate investment growth equation in chart 8 suggests that the contribution to investment growth in the second half of the 1990s from relative price falls, through the dynamic user cost terms, is minimal. In particular, according to that equation, the fall in the price of investment relative to final output explains around only one-fifth of the 71% rise in investment over that period. That is at least suggestive that an important source of investment growth, the rapid decline in computer prices in chart 2, is missing in the aggregate equation.

Computers

Tables A3 and A5 in Appendix 3 summarise the results from SUR estimation of investment equations for computers and non-computer plant and machinery separately. For computers, the ECM coefficient has a *t*-statistic of –3.5 (and –3.7 in the Banerjee et al (1998) dynamic OLS case). That *t*-statistic is high relative to the usual student *t*-critical values, but is modest compared with the critical values tabulated by Banerjee et al (1986) in their analysis of single equations estimated using OLS. In any case, the appropriate critical values would be sensitive to the particular DGP-model combination in hand. And, as discussed in Maddala and Kim (1998), the Banerjee *et al* critical values do not take into account the fact that a restriction that the ECM coefficient equals zero also implies that the coefficient on the real user cost of capital equals zero. For computers, the Johansen cointegration tests also provide some evidence for cointegration between the capital-output ratio and the real user cost[22]. Trace and maximum eigenvalue tests point towards cointegration at the 20% level (see table A7 in appendix 3). Considered together, we conclude from these results that there is some evidence of cointegration in the case of computers[23].

As in Tevlin and Whelan (2002), the estimated response of investment to the real user cost of capital for computers is very high, with an elasticity of -1.3[24]. (This is robust to the alternative dynamic OLS and Johansen estimation approaches – see table 2.) The equation now broadly captures the pattern of investment over the sample, though still struggles to match the precise dynamics and the 1998 boom in particular.

Consistent with these results, there is also a significant role for the real user cost of capital in the investment rate equation (10) for computers. The coefficients on the dynamic real user cost of capital terms this time sum to a much higher –3.3. But given the evidence above for a long-run equilibrium relationship between the real user cost and the stock of computers, we would certainly put less weight on an equation that makes no use of this information.

Non-computer plant and machinery

In contrast with the results for computers, there is little evidence of cointegration in the non-computer case. In the SUR model, the ECM and cost of capital terms are insignificant in the cointegrating vector; the cost of capital term is also incorrectly signed. These results are echoed in the Johansen and dynamic OLS tests (see tables 5 and 6 in Appendix 3). While in the three-lag system, the trace test supports cointegration at the 20% level, the real user cost of capital is again incorrectly signed. Given the lack of evidence for cointegration, we estimate a variant of the investment growth equation (9) that excludes the error correction term. In this case too, there is little role for real user cost terms[25].

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(22) We estimate our system over three lags, given that there was evidence of serial correlation at two lags, the number suggested by lag order selection criteria. Allowing for an outlier, the equation diagnostics are satisfactory.

(23) Note that the single equation ECM approach is a robust method of estimating a cointegrating relationship only if the variables other than the dependent variable are weakly exogenous with respect to the parameters of interest. To test that, we estimate a VAR in k/y and r with the estimated long-run relationship included as an exogenous variable. The estimated long-run relationship is only significant in the k/y equation, indicating that r is indeed weakly exogenous.

(24) Interestingly, the estimated long run suggests that the actual capital-output ratio was close to its equilibrium level in the late-1990s. In other words, our equation suggests that the rise in the computer capital-output ratio is fully accounted for by the sharp falls in the computer cost of capital.

(25) As in the aggregate case, we still struggle to find a role for the cost of capital when we exclude the ECM term: only one term is significant at the 10% level in the equation's dynamics, and that term is positively signed.

The negative evidence of cointegration for non-computers appears robust to model specification: there is no role for the real user cost of capital in Tevlin and Whelan's investment rate specification. Though interestingly, even for non-computer plant and machinery, the under-estimation of the investment rate in the late-1990s is much less pronounced than in the aggregate case.

The CES assumption: a diagnostic test

Our earlier assumption that firms' production technologies can be described by a CES production function has the effect of imposing a cross-equation restriction on our equations for computers and plant and machinery excluding computers. In particular, the elasticity of substitution for both types of capital should be equal. A LR test of this restriction on our equations estimated using SUR is not rejected at conventional significance levels. But it is apparent that that result reflects the poorly determined elasticity of non-computers with respect to the real user cost. In absolute terms the estimated elasticity of substitution for computers, at –1.3, is much greater than that estimated for non-computers (which is not significantly different to zero). That result again echoes Tevlin and Whelan's finding for the United States.

Given the poorly determined elasticity outside computers, we offer two potential explanations for both the UK and US results. The first, discussed by Tevlin and Whelan (2002), is consistent with the CES production function. They argue that the *estimated* elasticity of substitution will be greater for capital inputs where shocks to the real user cost are more persistent, compared with shocks that are temporary. Intuitively, profit-maximising firms will respond by a greater amount in their investment decisions to shocks that are perceived to be more persistent. Tevlin and Whelan (2002) further argue that shocks to the real user cost of capital for computers are likely to reflect the long-run tendency for technological progress in the computer sector to exceed that in other plant and machinery. In that case reductions in the real user cost are likely to be driven by trend declines in the relative price of computers. We have seen that the evidence for the UK is clearly also consistent with that explanation: see Charts 5-6.

An alternative explanation is that the CES production function itself is an inadequate description of the substitutability between computers and other forms of plant and machinery. As a diagnostic on this hypothesis we experimented including the real user cost measure for computers in a single-equation for non-computer plant and machinery. Interestingly, that variable is statistically significant and positive - an increase in the real user cost for computers leads to an increase in demand for non-computer capital. Including this variable also has dramatic implications for the equilibrium properties of the equation, in that there is now evidence for cointegration: the *t*-statistic on the ECM term jumps to –4.2, and the non-computer cost of capital term is correctly signed and significant. Experimenting with production technologies that are more flexible than the CES case is clearly an area worthy of further research.

5 Forecasting

Given the rather mixed evidence for cointegration, even at the disaggregate level, a critical test of our analysis is whether the disaggregate equations can better capture the strength of investment in the second half of the 1990s when compared with the aggregate equation. We investigate this by re-estimating the equations over the period 1978Q1 to 1994Q4, and generating out-of-sample forecasts for the second half of the 1990s, conditional on actual outturns for each of the explanatory variables.

Charts 11 and 12 shows how the disaggregate model can now explain the investment boom of the latter half of the 1990s. Both aggregate and disaggregate models struggle to capture the precise dynamics of plant and machinery investment. But unlike the forecasts from the aggregate equations, the aggregate investment profiles implied by the disaggregate equations are broadly in line with the strong investment outturns during this period.

Chart 11

Out-of-sample forecasts from investment growth equations

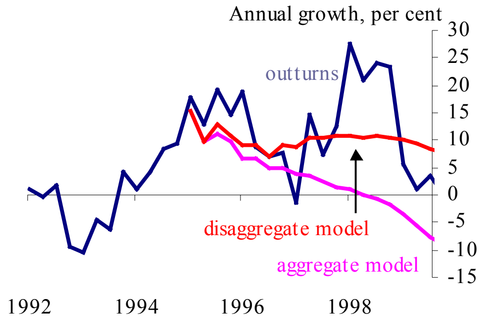
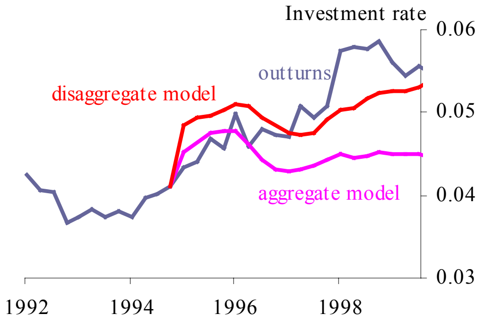


Chart 12

Out-of-sample forecasts from investment rate equations



6 Conclusions

In this paper we have argued that traditional methods of modelling aggregate investment are incapable of explaining the investment boom in the United Kingdom in the second half of the 1990s. The aggregate long-run relationship between the capital-output ratio and the real user cost of capital breaks down in the presence of trending relative investment good prices - and such trends have been an important feature of investment in recent decades. In contrast, well specified, estimable, long run relationships exist at the disaggregate level.

Empirical evidence appears to support this theoretically superior, disaggregate modelling approach, as Tevlin and Whelan (2002) find for the United States. First, compositional shifts in the plant and machinery capital stock towards computers have led to increases in replacement investment that are not captured in aggregate investment equations. Second, we find evidence of cointegration between the capital-output ratio and the real user cost of capital in the computers case, and the real user cost enters significantly and quantitatively more importantly for computers than for other assets. The sharp falls in relative computer prices that lie behind the persistent falls in the computer real user cost of capital appear to have played an important role in the real investment boom of the latter half of the 1990s. But this role is hidden in the aggregate modelling approach, in which the real user cost of capital plays only a small role.

Out-of-sample forecasts suggest that our asset-level investment equations can together generate far more accurate forecasts of plant and machinery investment compared with the (misspecified) aggregate model. These findings support attempts to model, and forecast, investment at the asset level.

Appendix 1: Constructing the UK dataset

Our dataset consists of quarterly series over 1978 Q1-1999 Q4 for real investment, real capital stock and the real user cost of capital – all calculated separately for aggregate plant and machinery, and at the asset level, for computers and non-computer plant and machinery. Our preferred output measure would be the value added of just those sectors using plant and machinery. But that is not available. We use instead GDP at constant (1995) prices (ONS alias code: ABMM). A brief discussion of how we constructed this dataset is provided below; ONS alias codes are provided in brackets where relevant.

Investment

Our real plant and machinery investment series is published by the ONS in the Quarterly National Accounts as 'other machinery and equipment' investment (DLWO). Deriving quarterly disaggregated series is problematic, as the ONS does not publish computer investment data on a quarterly basis. We follow the approach of Oulton (2001a), who constructed an annual, nominal computer investment series from Input-Output Supply and Use tables for 1989 onwards; prior to 1989, the series is constructed from the various IO tables, with missing years interpolated. We update the estimates in Oulton (2001a) using the supply and use tables 1992-99 consistent with the 2001 Blue Book.

We then interpolate these annual data to get a quarterly series, using the statistical procedure described in Chow and Lin (1971). That involves using an indicator variable to inform the quarterly profile of our known annual series. Given the high correlation between nominal computer investment and plant and machinery investment at the annual frequency - growth rates have a correlation coefficient of over 0.6 for our sample period - we use published, quarterly, nominal plant and machinery investment series as our indicator (TLPW). Further details are provided in appendix 2. We then deflate the (interpolated) quarterly, nominal computer investment series by the corresponding quarterly, ONS producer price index (PQEK) to obtain our real computer investment series.

The ONS does not publish constant price investment data for the level of plant and machinery investment excluding computers. And deriving this component is non-trivial, given the non-additivity of published ONS fixed-weight series prior to 1994. The approach we take is to estimate the series that the ONS would have arrived at, had they decided to exclude computers from plant and machinery investment. See appendix 2 for further details.

Capital stock

We start by deriving annual, rather than quarterly, constant-price capital stock data. Specifically, we use the standard, constant-price capital accumulation identity:

$$K_t = (1-\delta)K_{t-1} + i_t \qquad \textbf{(A1)}$$

where the variables are:

K Constant-price capital stock
δ Real depreciation rate (assumed geometric)
I Constant-price investment

The real investment data are the annual equivalent of the data described above, dating back to 1948 for aggregate plant and machinery and to 1976 for computers. For depreciation rates, we follow Oulton (2001a) and use US depreciation rates from Fraumeni (1997). For non-computer plant and machinery, we assume a (constant) annual depreciation rate of 13%. For computers, we assume a (constant) depreciation rate of 31.5%. The (time-varying) real aggregate implied depreciation rate for plant and machinery is a weighted average of these rates, the weights being their constant-price shares in the aggregate capital stock in the previous period.

For aggregate plant and machinery, the initial stock in 1947 is provided by the ONS. This value is also used for non-computer plant and machinery. For computers, the initial value in 1975 is from Oulton (2001a). The initial stocks for our quarterly series are then taken from these end-year annual observations, and quarterly capital stocks calculated using the above capital accumulation approach[26].

Real user cost of capital

We construct Hall-Jorgensen real user cost of capital measures for aggregate plant and machinery and, at the asset level, for computers and non-computers. These measures take the form:

[26] For aggregate plant and machinery, the quarterly real investment series begins in 1965Q1, so the annual capital stock series provides the 1964 Q4 observation. For computers, the annual series provides the 1975 Q4 observation.

$$RCC = \frac{P_K}{P_Y}(r + \delta - E(\dot{P_K / P_Y}))T \qquad \textbf{(A2)}$$

where the variables are:

r	Real cost of finance
δ	Depreciation rate
P_k	The price of capital goods
P_y	The price of output
T	Tax factor
$E(\dot{P_K / P_Y})$	Expected change in the relative price of capital goods.

For aggregate plant and machinery, the price of capital goods is the ONS deflator implicit in the published constant and current price investment series (TLPW/DLWO). For computers, we again use the relevant ONS PPI series. The price of output is measured by the GDP deflator (ABML/ABMM). Given that the expected change in the relative price of investment goods is unobservable, we use a proxy: an eight-quarter average of the actual relative price. The real cost of finance measure is the ratio of Private Non-Financial Corporations' profits (specifically, gross operating surplus less tax and depreciation) to the current financial valuation of the corporate sector[27]. At the asset level, depreciation rates are as discussed above. For aggregate plant and machinery, we follow the standard approach and assume a constant depreciation rate. A 'tax factor' series, capturing the impact of taxes and allowances on the cost of capital, is supplied by HMT.

[27] This approach is taken in Flemming et al (1976). As discussed by Whitaker (1998), the real cost of finance is the rate at which a company's future real earnings are discounted by the capital market in valuing the securities upon which those earnings will accrue. Assuming that (unobservable) real earnings in future years are equal to current earnings, a measure of the real cost of finance is therefore the ratio of current real earnings to the market value of a firm's liabilities.

Appendix 2: Backing out non-computer investment from total investment

This annex considers how to construct the series that the ONS would have arrived at, had they decided to exclude computer investment from total investment in "Other machinery and equipment" (*OME*). Hence we aim to produce a series which is fully consistent with the national accounts. We have ONS data on total investment in "Other machinery and equipment" (*OME*) and also on a component of *OME*, computer investment, in both constant and current prices, for the period 1976-2000. We want to derive investment in *OME* excluding computers (*OMEXC*). There is no problem in doing this in current prices by simple subtraction, but how to do it in constant prices is not so straightforward.

The chain-linked solution

For the period 1994 to the present, the ONS uses 1995 prices. So for this period we can indeed calculate *OMEXC* by subtracting computer investment in 1995 prices from total *OME* in 1995 prices. But prior to 1994 the ONS used different weights: successively 1990, 1985, 1980 and 1975 prices as we go back in time. In other words the ONS does not use fixed base indices but instead a type of chain index in which the weights are periodically updated (about every 5 years in practice)[28].

For each of the periods over which the weights are constant, the index of *OME* investment is in effect constructed by the ONS as follows:

$$QOME = w \cdot QCOMP + (1 - w) \cdot QOMEXC \qquad \textbf{(A3)}$$

where *QOME* is the index of total investment, set equal to 1 in the base year, *QCOMP* is a similar index for computer investment, *QOMEXC* is the index for other plant and machinery, and w is the weight for computers. This weight is the nominal share of computer investment in the total in the base year (successively 1975, 1980, 1985, 1990 and 1995). We can find the *OME* index for (say) 1984 relative to 1985 by dividing *OME* investment in 1995 prices for 1984 by *OME* investment in 1995 prices for 1985. This works because rebasing to 1995 prices does not change growth rates for earlier periods. We can calculate the *COMP* index similarly. Therefore for each period covered by a singe base, we can solve this equation for *QOMEXC*:

(28) For this reason saying that such indices are "in 1995 prices" or "in constant prices" is potentially misleading. It might be better to say that these series are in "chained 1995 pounds" (copying the BEA usage of "chained 1996 dollars").

$$QOMEXC = [QOME - w \cdot QCOMP]/(1-w) \qquad \textbf{(A4)}$$

We can then link all these fixed base index numbers together, so that we have a type of chain index which covers the whole period. This chain index can be referenced to any year we choose, without changing its growth rate. Suppose we choose 1995 as the reference year when the index takes the value 1. Then we can multiply the chain index in each year by the nominal value of *OMEXC* in 1995, thus obtaining *OMEXC* in constant 1995 prices.

To illustrate the process, consider the following imaginary data for an *OMEXC* index calculated using equation **(A4)**. Here the base periods are assumed to be periods 1 and 4 and the link period is 3.

Illustrative calculation of chain index from sequence of fixed base indices

	Fixed base index		*Chain index*	
Period	*Base: Period 1*	*Base: Period 4*	*Reference: period 1*	*Reference: period 4*
1	1.00	—	1.00	0.888
2	1.05	—	1.05	0.932
3	1.07	0.95	1.07	0.950
4	—	1.00	1.126	1.00
5	—	1.10	1.239	1.10

When the reference period for the chain index is period 4, the value of the index in eg period 2 is calculated as (1.05 ÷ 1.07) x 0.95.

Non-additivity

In general, chain indices are non-additive: the components do not necessarily sum to the total. In other words, if we add *OMEXC* in 1995 prices to *COMP* in 1995 prices, the result will not be equal to *OME* in 1995 prices, except for the period 1994 to the present when the ONS has used 1995 as the base. If the component (computers) which is growing more rapidly has a falling relative price, as is the case here, then the ONS's chain index of *OME* grows more rapidly than the sum of the components before the base year, here 1995. This is because the sum of the components in 1995 prices is just a fixed base index of investment, the base being 1995. It then follows that the *level* of the ONS's chain index for OME is less than the sum of the components in constant prices in all years prior to 1994:

$$OME < OMEXC + COMP$$

hence

$$OMEXC > OME - COMP$$

In other words, our (and implicitly the ONS's) chain-based estimate of the non-computer component (*OMEXC*) will be greater than the estimate one would obtain by naively subtracting computer investment from total investment, in all years prior to 1994. Consequently, the growth rate of *OMEXC* will be less than the growth rate of the naïve (fixed base) estimate prior to 1995, since the levels are the same from 1994 onwards.

This is illustrated in charts A1 and A2. The level of the naïve, fixed base index is 25% below that of the chain index of *OMEXC* in 1976. Between 1976 and 1994 the fixed base index grew at 2.34% pa, while the chain index grew at only 0.76% pa. Putting it another way, the sum of computer investment (*COMP*) and the new chain series of the total excluding computers (*OMEXC*) exceeds the actual total of *OME* investment by a growing amount as we go back further in time. By 1976 the sum of the two components exceeds the total by 33%. But to reiterate, this is just a consequence of chain-linking in the form used up to now by the ONS. That the difference between the two types of estimate is so large reflects the substantial fall in the relative price of computers which occurred over this period. If we had used the more rapidly falling US price index for computers, instead of the UK one, the difference would have been even more striking. But in order to ensure consistency with the other ONS data, our aim here is to construct the series for non-computer investment which the ONS would have arrived at themselves had they chosen to do so and so we employ their methods and data.

Chart A1

Comparison of chain and fixed base indices of *OMEXC:* levels

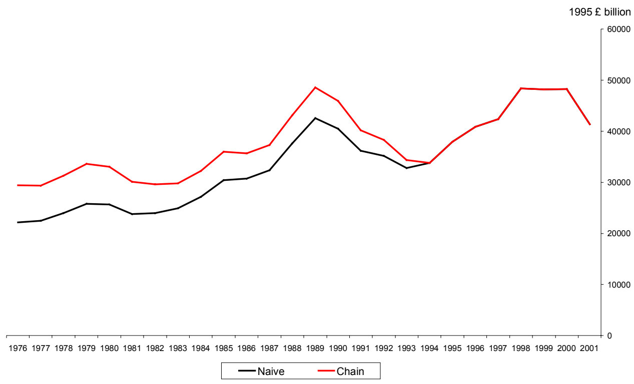
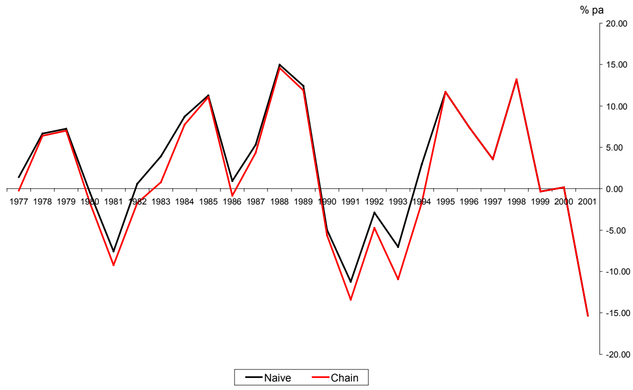


Chart A2

Comparison of chain and fixed base indices of *OMEXC:* growth rates



Appendix 3: Econometric results

Table A3.1: Aggregate plant and machinery[29]

Dependent variable: DLOG(INV)

dynamics	Single-ECM equation, Least Squares: Coefficient	t-Statistic	Single-ECM equation, dynamic OLS: Coefficient	t-Statistic
C	-0.09	-1.92	-0.09	-1.99
DLOG(GDP(-2))	1.09	2.27	1.06	2.18
DLOG(RCC_(-1))	0.09	2.11	0.09	2.09
DLOG(RCC_(-3))	0.10	2.16	0.10	2.18
DLOG(RCC_(1))			-0.05	-1.04
DLOG(RCC_(2))			0.02	0.53
ECM	-0.22	-2.16	-0.24	-2.18
dummy	-0.14	-4.28	-0.15	-4.41
dummy(1)	0.10	2.95	0.12	3.20
long run: LOG(K(-1)/GDP(-1)) + olog(rcc(-1))				
log(rcc(-1))	0.32	5.13	0.32	5.46
R-squared	0.439		0.453	
Adjusted R-squared	0.390		0.390	
S.E. of regression	0.032		0.032	
Sum squared resid	0.084		0.082	
Log likelihood	181.013		182.178	
Durbin-Watson stat	2.366		2.264	

Investment rate equation

Dependent variable: LOG(I/K(-1))

dynamics	Coefficient	t-Statistic
C	-3.23	-276.45
DLOG(gdp(-4))	1.96	2.07
DLOG(gdp(-5))	3.14	3.40
DLOG(gdp(-6))	3.21	3.46
DLOG(gdp(-7))	3.70	4.10
DLOG(gdp(-8))	3.62	4.02
R-squared	0.582	
Adjusted R-squared	0.549	
S.E. of regression	0.069	
Sum squared resid	0.295	
Log likelihood	88.522	
Durbin-Watson stat	0.511	

Table A3.2: Aggregate plant and machinery

Sakkinonen dynamic OLS

Dependent variable: LOG(K/GDP)

	Coefficient	t-Statistic
C	-0.32	-9.48
LOG(RCC)	-0.28	-21.54
DLOG(RCC(-2))	-0.04	-0.88
DLOG(RCC(-1))	-0.08	-1.75
DLOG(RCC)	-0.08	-1.58
DLOG(RCC(1))	-0.30	-6.05
DLOG(RCC(2))	-0.20	-4.30
R-squared	0.859	
Adjusted R-squared	0.848	
S.E. of regression	0.032	
Sum squared resid	0.083	
Log likelihood	181.734	
Durbin-Watson stat	0.229	

Johansen

Dependent variable: DLOG(K/GDP)

dynamics	Coefficient	t-Statistic
C	0.00	1.16
DLOG(K(-1)/GDP(-1))	0.32	2.51
DLOG(K(-2)/GDP(-2))	0.31	2.73
DLOG(K(-3)/GDP(-3))	0.08	0.81
DLOG(K(-4)/GDP(-4))	0.08	0.79
DLOG(K(-5)/GDP(-5))	0.13	1.36
DLOG(RCC(-1))	0.05	1.33
DLOG(RCC(-2))	0.07	3.12
DLOG(RCC(-3))	0.10	2.84
DLOG(RCC(-4))	0.06	1.83
DLOG(RCC(-5))	0.01	0.19
ECM	-0.03	-0.67
long run: LOG(K(-1)) - LOG(GDP(-1)) + β + olog(rcc(-1)		
c	2.93	
log(rcc(-1))	0.78	8.39

(29) Where significant, we have included a dummy variable to allow for the impact on investment of tax allowance changes in 1985.

Table A3.3: Computers

single-ECM equation, SUR | single-ECM equation, dynamic OLS

Dependent variable: DLOG(INV)

	single-ECM equation, SUR: Coefficient	t-Statistic	single-ECM equation, dynamic OLS: Coefficient	t-Statistic
dynamics				
C	-0.50	-3.41	-0.49	-3.34
DLOG(GDP(-2))	1.01	1.76	0.97	1.67
DLOG(RCC_(-1))				
DLOG(RCC_(-3))	0.15	1.63	0.15	1.64
DLOG(RCC_(1))			-0.06	-0.59
DLOG(RCC_(2))			-0.02	-0.22
ECM	-0.11	-3.78	-0.11	-3.69
dummy	-0.19	-4.22	-0.19	-4.26
dummy(1)				
long run: LOG(K(-1)/GDP(-1)) + οlog(rcc(-1))				
log(rcc(-1))	1.33	24.26	1.33	24.26

	SUR	dynamic OLS
R-squared	0.282	0.281
Adjusted R-squared	0.236	0.215
S.E. of regression	0.045	0.046
Sum squared resid	0.158	0.158
Durbin-Watson stat	2.431	1.895

Investment rate equation

Dependent variable: LOG(I/K(-1))

	Coefficient	t-Statistic
dynamics		
C	-2.12	61.93
DLOG(gdp(-1))	3.74	2.32
DLOG(gdp(-4))	3.24	2.33
DLOG(gdp(-5))	3.93	2.87
DLOG(RCC(-4))	-0.66	-2.60
DLOG(RCC(-5))	-0.87	-3.26
DLOG(RCC(-6))	-0.58	-2.21
DLOG(RCC(-7))	-0.78	-2.93
DLOG(RCC(-8))	-0.53	-2.14

R-squared	0.330
Adjusted R-squared	0.250
S.E. of regression	0.098
Sum squared resid	0.677
Log likelihood	75.884
Durbin-Watson stat	0.414

Table A3.4: Computers

Sakkinonen dynamic OLS

Dependent variable: LOG(K/GDP)

	Coefficient	t-Statistic
C	-4.90	-125.63
LOG(RCC)	-1.35	-71.53
DLOG(RCC(-2))	0.99	3.10
DLOG(RCC(-1))	1.37	4.03
DLOG(RCC)	1.51	4.43
DLOG(RCC(1))	0.34	1.01
DLOG(RCC(2))	0.20	0.61

R-squared	0.986
Adjusted R-squared	0.985
S.E. of regression	0.131
Sum squared resid	1.342
Log likelihood	55.686
Durbin-Watson stat	0.142

Johansen

Dependent variable: DLOG(K/GDP)

	Coefficient	t-Statistic
dynamics		
C	0.02	4.36
DLOG(K(-1)/GDP(-1))	0.57	5.40
DLOG(K(-2)/GDP(-2))	0.22	2.17
DLOG(K(-3)/GDP(-3))	-0.13	-1.40
DLOG(RCC(-1))	0.06	2.52
DLOG(RCC(-2))	0.05	2.01
DLOG(RCC(-3))	0.02	0.95
ECM	-0.03	-3.35
long run: LOG(K(-1)) - LOG(GDP(-1)) + β + οlog(rcc(-1)		
c	5.09	
log(rcc(-1))	1.39	28.43

Table A3.5: Non-computer plant and machinery

Dependent variable: DLOG(INV)

	Single-ECM equation, SUR: Coefficient	t-Statistic	Single-ECM equation, dynamic OLS: Coefficient	t-Statistic
dynamics				
C	0.09	1.53	0.09	1.55
DLOG(GDP(-2))	1.38	2.98	1.39	3.09
DLOG(RCC_(-3))	0.09	2.65	0.09	2.67
DLOG(RCC_(-5))	0.05	1.73	0.05	1.72
DLOG(RCC_(1))			-0.05	-1.43
DLOG(RCC_(2))			0.02	0.63
ECM	-0.15	-2.04	-0.16	-2.15
dummy	-0.13	-4.02	-0.14	-4.30
dummy(1)	0.11	3.54	0.12	3.86
long run:	LOG(K(-1)/GDP(-1)) + olog(rcc(-1))			
log(rcc(-1))	-0.02	-0.23	-0.01	-0.14
R-squared	0.478		0.502	
Adjusted R-squared	0.428		0.439	
S.E. of regression	0.033		0.033	
Sum squared resid	0.082		0.078	
Durbin-Watson stat	2.431		2.284	

Investment rate equation

Dependent variable: LOG(I/K(-1))

	Coefficient	t-Statistic
dynamics		
C	-3.31	-235.08
DLOG(gdp(-5))	2.74	2.25
DLOG(gdp(-7))	3.94	3.35
DLOG(gdp(-8))	4.81	4.16
R-squared	0.330	
Adjusted R-squared	0.306	
S.E. of regression	0.093	
Sum squared resid	0.727	
Log likelihood	86.158	
Durbin-Watson stat	0.557	

Table A3.6: Non-computer plant and machinery

Sakkinonen dynamic OLS

Dependent variable: LOG(K/GDP)

	Coefficient	t-Statistic
C	0.64	11.34
LOG(RCC)	0.04	1.77
DLOG(RCC(-2))	-0.15	-3.02
DLOG(RCC(-1))	-0.21	-4.07
DLOG(RCC)	-0.22	-4.29
DLOG(RCC(1))	-0.16	-3.01
DLOG(RCC(2))	-0.09	-1.84
R-squared	0.317	
Adjusted R-squared	0.263	
S.E. of regression	0.042	
Sum squared resid	0.138	
Log likelihood	150.142	
Durbin-Watson stat	0.154	

Johansen

Dependent variable: DLOG(K/GDP)

	Coefficient	t-Statistic
dynamics		
C	0.00	-0.38
DLOG(K(-1)/GDP(-1))	0.37	3.65
DLOG(K(-2)/GDP(-2))	0.28	3.22
DLOG(K(-3)/GDP(-3))	0.10	1.03
DLOG(RCC(-1))	0.00	0.56
DLOG(RCC(-2))	0.01	1.23
DLOG(RCC(-3))	0.00	0.50
ECM	-0.03	-1.96
long run:	LOG(K(-1)) - LOG(GDP(-1)) + β + olog(rcc(-1)	
c	-0.80	
log(rcc(-1))	-0.09	-1.18

Table A3.7: Johansen cointegration test results

Null: r	Trace	Max-eigenvalue
Plant and machinery		
0	9.14	7.94
<=1	1.20	1.20
Trace and max-eigenvalue tests indicate no cointegration at 20% level		
Computers		
0	13.31	11.96
<=1	1.35	1.35
Trace and max-eigenvalue tests indicate cointegration at 20% level		
Non-computer plant and machinery		
0	11.50	8.56
<=1	2.94	2.94
Trace test indicates cointegration at 20% level; max-eigenvalue test indicates no cointegration at 20% level		

Table A3.8: Summary statistics

1978-1999	Mean	Median	Standard deviation
Plant and machinery			
K/Y	1.51	1.48	0.12
RCC	0.08	0.07	0.02
Computers			
K/Y	0.05	0.03	0.05
RCC	0.45	0.38	0.34
Non-computers			
K/Y	1.73	1.73	0.08
RCC	0.06	0.06	0.01

Appendix 4: Sensitivity analysis

How sensitive are these results to potential mismeasurement? In this section, we examine the implications of using alternative approaches to constructing our UK dataset. We identify two key areas of data uncertainty. First, in the absence of quarterly computer investment data, we have adopted an interpolation technique that made use of the indicator information contained in plant and machinery investment data (see appendix 1). Although the annual growth rates of current price computer investment and plant and machinery investment appear quite closely related, the relationship on a quarterly frequency may be poor. We examine the impact of using an alternative, a more simple linear interpolation technique.

Second, great uncertainty surrounds our estimates of the real user cost of capital. We consider alternative measures of each component. In particular, we examine the implications of using an alternative measure of computer investment prices, based on US computer investment price data;

a weighted average cost of capital as a measure of the real cost of finance in the user cost; two alternative proxies for expected relative price inflation (actual relative price inflation and, as in Tevlin and Whelan (2001), a three-year moving average); an alternative tax factor measure(30); and for aggregate plant and machinery equations, a time-varying real aggregate implied average depreciation rate, rather than a constant.

We re-estimated our computer equations for all of the alternative approaches(31). **These changes have no material impact on our results**. That is illustrated by Table A4, which shows the impact of these changes on the elasticity of substitution in our investment growth equation **(10)** for computers(32).

Table A4: Sensitivity of computer elasticity of substitution estimates to alternative assumptions

	elasticity of substitution
1. Alternative interpolation procedure	1.4
2. Alternative cost of capital measures, based on alternative:	
(a) computer prices	1.1
(b) cost of finance	1.3
(c) expected capital gain - actual gain	1.3
(d) expected capital gain - 12-quarter average of actual	1.3
(e) tax factor	1.4

(30) This measure was estimated as (1-PVIC)/(1-corptax), where 'PVIC' is the present value of investment allowances and 'corptax' is the effective corporate tax rate.

(31) We also adjusted other affected data. For example, the alternative interpolation procedure has implications for our capital stock estimates as well as for investment. In the case of alternative computer prices, we also adjusted computer investment and computer capital stock data. Strictly speaking, the use of US computer price data additionally requires adjustment of our GDP data. It seems unlikely that this would have any material impact on the results presented in Table A4.

(32) The alternative regression results are available on request.

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