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Investment adjustment costs: evidence from UK and US industries

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Abstract

In aggregate models, costs that penalise changes in investment – investment adjustment costs – have been introduced to help account for a variety of business cycle and asset market phenomena. In this paper, we evaluate empirical evidence for these types of costs using US and UK industry data. We consider a general adjustment cost structure which nests both investment adjustment costs and the traditional capital adjustment costs as special cases. The estimated weight on the former is close to zero for all the industries. When only the investment adjustment cost structure is considered, the estimates of the adjustment cost parameter are small relative to those based on aggregate data, and imply an elasticity of investment with respect to the shadow price of capital (the value to the firm of one additional unit of capital) fifteen times larger than that found in aggregate studies. Our results suggest that from a disaggregated empirical perspective it remains difficult to motivate and interpret the investment friction considered in recent macroeconomic models.

Key words: Investment adjustment costs, capital adjustment costs.

JEL classification: E2, E3.

Summary

If wages and prices were perfectly flexible, and if labour and capital could move costlessly between firms and sectors, the economy would always operate at potential. In this case, large fluctuations in output, consumption and investment would not be observed. But from the past we know that some of these variables exhibit large fluctuations over the business cycle. To understand these movements, it is important to acknowledge the presence of frictions in the economy, that prevent prices and the factors of productions – labour and capital – from adjusting in response to shocks.

The literature has recognised the importance of both nominal and real frictions. Nominal frictions arise when wages and prices are sticky and therefore do not respond to changes in the economic environment. These types of frictions have been stressed in the New Keynesian literature, and give rise to the well-known Phillips trade-off between inflation and some measure of real activity. Real frictions prevent labour and capital from costlessly adjusting in response to changes in the economy. As an example, consider a firm that wants to increase its stock of capital, to be able to meet an increase in demand. In addition to the cost for buying new equipment, it may also need to spend resources on physically installing the capital, training labour and reorganising the production process, to make full use of the capital. These types of costs prevent firms from costlessly adjusting the level of capital. In turn, this means that firms will only slowly respond to shocks that alter the optimal level of capital, since it may prove costly to adjust capital in response to short-lived changes in economic conditions.

Frictions to adjusting the level of capital are common in models of the business cycle, to better replicate and explain economic fluctuations. But there are some shortcomings with these models. For example, they fail in generating the hump-shaped response of output, investment and consumption that is typically observed after a monetary policy shock – an unexpected change in the stance of monetary policy. They are not able to account for the volatility of asset returns over the business cycle. And they are not able to match the response of wages and hours worked in response to fiscal shocks. For this reason, recent studies instead introduce a friction to changing investment, instead of capital, into models of the business cycle – a so-called investment adjustment cost. This friction prevents investment quickly responding to changes in economic conditions. By introducing this friction, the performance of business cycle models are improved

along a number of dimensions, such as those discussed above.

Investment adjustment costs therefore appear to have important implications for understanding the aggregate dynamics of the economy. It is, however, unclear whether there is empirical support for these types of costs at the firm or industry level, or whether they are largely an *ad hoc* friction, introduced to better match aggregate data. Some motivations have been made for these types of costs – they may proxy delays in investment planning, or inflexibility in changing the planned pattern of investment. While this interpretation is appealing, so far no attempt has been made to estimate investment adjustment costs directly at a disaggregated level. In comparison, a large body of literature has estimated capital adjustment costs using disaggregated data. The disaggregated approach is also extensively used to assess evidence on other important frictions in the economy.

In this paper we conduct an empirical assessment of investment adjustment costs and investigate whether industry-level data provide support for this cost structure. We use industry data for both the United States and the United Kingdom, and estimate a theoretical model for capital and investment under different assumptions of the adjustment cost structure. In particular, we consider a model which is a weighted average of the investment and the capital adjustment cost model, and obtain industry-specific estimates of the relevant parameters in the adjustment cost function. The main result is that the relative weight on the investment adjustment cost model turns out to be close to zero, for all industries, in both countries. In other words, industry data do not support the investment adjustment cost structure and instead favour the traditional capital adjustment costs.

We also estimate a constrained model which imposes the investment adjustment costs on the data. Based on the estimated parameters from this model, we are able to quantify the importance of the investment adjustment cost friction. We compare this estimate to those typically obtained in aggregate models of the economy. Our results suggest that at the industry level, the friction arising from investment adjustment costs is significantly smaller than that assumed at the aggregate level. From this, we conclude that from a disaggregated empirical perspective it remains difficult to motivate and interpret the investment friction considered in recent macroeconomic models.

1 Introduction

Recent literature on dynamic general equilibrium models considers the cost of changing the level of investment – *investment adjustment cost* – as a key mechanism that significantly improves the quantitative performance of the models along a number of dimensions. Investment adjustment costs induce inertia in investment, causing it to adjust slowly to shocks. When these costs are present, Christiano, Eichenbaum and Evans (2005) show that a sticky-price model can generate hump-shaped investment dynamics consistent with the estimated response of investment to a monetary policy shock. Burnside, Eichenbaum and Fisher (2004) find that a real business cycle model can account for the quantitative effects of fiscal shocks on hours worked and real wages. Basu and Kimball (2005) show that a sticky-price model can generate output expansions after a fiscal shock. Jaimovich and Rebelo (2006) show that news shocks, as discussed in Beaudry and Portier (2006), can drive business cycles. Beaubrun-Diant and Tripier (2005) show that it is possible to account for both volatility of asset returns and business cycle facts within a single model. By contrast, models with costs to adjusting the level of capital – *capital adjustment cost* – as in the neoclassical investment literature, do not match any of these aspects.

Investment adjustment costs, therefore, have important implications for understanding the aggregate dynamics of an economy. It is, however, unclear whether there is empirical support for these types of costs at a disaggregated level, or whether they are largely an *ad hoc* friction, introduced to better match aggregate data. Basu and Kimball (2005), for example, present a theoretical model with 'investment planning costs' in which the effects of monetary and fiscal shocks on output and investment resemble those in models with investment adjustment cost. Their findings suggest that investment adjustment cost may proxy delays in investment planning or inflexibility in changing the planned pattern of investment, as considered in Christiano and Todd (1996) and Edge (2000).[1] While this interpretation is appealing, so far no attempt has been made to estimate investment adjustment costs directly at a disaggregated level. In comparison, a large body of literature has estimated capital adjustment costs using disaggregated data.[2] The disaggregated approach is also extensively used to assess evidence on other important frictions such as nominal price stickiness and habit-formation in consumption that are incorporated in

(1) Gertler and Gilchrist (2000) and Casares (2002), for example, explicitly model time-to-plan and time-to-build constraints.

(2) See, for example, recent work by Hall (2004), Cooper and Haltiwanger (2006) and the overview by Hammermesh and Pfann (1996).

macro models. Existing estimates of investment adjustment costs are instead based on aggregate data as, for example, in Christiano *et al* (2005), Smets and Wouters (2003), and Altig, Christiano, Eichenbaum and Lindé (2005), among others.[(3)]

In this paper we conduct an empirical assessment of investment adjustment costs and investigate whether industry-level data provides support for this cost structure. We estimate a model with investment adjustment costs (hereafter IAC) for the United States and the United Kingdom, using two-digit industry data. We follow the Euler equation approach and estimate the first-order condition for capital to obtain estimates of the adjustment cost parameters using generalised method of moments (GMM). Specifically, we consider a functional form that allows for both investment and capital adjustment costs, and nests the standard neoclassical analysis as a special case. To estimate the model, we use annual industry data for 27 industries for the United Kingdom, spanning the whole economy, for the period 1970-2000. For the United States, we use data on 18 manufacturing industries over the period 1949 to 2000, also used by Hall (2004) to estimate capital adjustment costs.

One of the major challenges under the GMM methodology is to confront the weak instrument (or, instrument relevance) problem which makes inference on estimated parameters difficult. Diagnostic checks, using Shea (1997) partial R^2 statistic, reveal that instruments are indeed weak. To address this issue, we use the Anderson and Rubin (1949) F statistic and Kleibergen (2002) K statistic for identification robust inference.

We consider a general industry model which is a weighted average of the IAC and the capital adjustment cost (CAC) structures, and obtain industry/sector-specific estimates. The point estimate of the weight on IAC turns out to be zero, or close to zero, for all industries/sectors. In other words, industry data does not support the investment adjustment cost structure and instead favours the traditional capital adjustment costs. However, we find instrument weakness to be pervasive. But inference based on F and K test statistics, which are robust to weak instruments, do not reject the parameter estimates. Based on that, we conclude that our estimates are valid, given the data.

When we estimate the constrained model which imposes either the IAC or the CAC structure on the data, we find slightly different results for the two countries: for the United States, there is

(3) An early paper by Topel and Rosen (1988) presents and estimates a model of new housing supply in which rapid changes in the level of construction are penalised by higher costs.

similar support for the CAC and the IAC model while, for the United Kingdom, the data strongly favours the CAC model while rejecting the IAC model. For both countries, however, the estimate of the adjustment cost parameter under IAC is substantially smaller relative to that obtained under CAC, across all industries. Moreover, the estimates of the adjustment cost parameter under the IAC structure are substantially smaller compared to the estimates from aggregate data as in Christiano *et al* (2005) and Smets and Wouters (2003). We compute the elasticity of investment with respect to the shadow price of capital. Our estimates imply elasticities that are around 6, while the estimate of Christiano *et al* (2005) based on aggregate data, for example, is 0.4. That is, in aggregate models, frictions to investment are much larger implying that investment responds less to a change in the shadow price of capital, than our industry estimates suggest.

While evidence supports the presence of CAC, as stressed by the standard neoclassical investment literature, these costs do not help improve the empirical performance of aggregate models, along the dimensions mentioned above. The lack of evidence in favour of investment adjustment costs at the industry level suggests that from a disaggregated empirical perspective it remains difficult to motivate and interpret the investment friction considered in recent macroeconomic models.

The paper is organised as follows. Section 2 discusses the role of investment adjustment costs in recent macroeconomic models. Section 3 turns to the industry analysis. It presents a simple model of investment that allows for both investment and capital adjustment costs, and discusses the data and estimation method. Section 4 presents the empirical results. Section 5 comments on the discrepancy between the aggregate and the industry results. Section 6 concludes.

2 Investment adjustment costs in aggregate models

In this section we illustrate how the presence of investment adjustment cost modifies investment dynamics relative to capital adjustment costs. We also provide a brief discussion of recent literature which demonstrates the importance of investment adjustment costs in accounting for a broad range of business cycle and asset markets stylised facts.

We consider the formulation proposed by Christiano *et al* (2005). The representative household makes consumption, labour supply, and capital accumulation decisions. Capital is accumulated according to

$$K_{t+1} = (1-\delta)K_t + (1 - S(I_t, I_{t-1}, K_t))\, I_t \quad \textbf{(1)}$$

where K_t denotes capital, I_t investment, δ the depreciation rate, and $S(.)$ the adjustment cost function. When households face IAC, the adjustment cost function depends on current and lagged investment and given as

$$S(.) \equiv S(I_t/I_{t-1}) \quad \textbf{(2)}$$

where $S(1) = S'(1) = 0$ and $S''(1) \equiv \kappa > 0$. This functional form implies that it is costly to change the level of investment, the cost is increasing in the change in investment, and there are no adjustment costs in steady state. The log-linearised dynamics around the steady state are influenced only by the curvature of the adjustment cost function, κ. When households face CAC, the adjustment cost function is given by

$$S(.) \equiv S(I_t/K_t) \quad \textbf{(3)}$$

where $S(\delta) = S'(\delta) = 0$ and $S''(\delta) \equiv \epsilon > 0$. The functional form implies that it is costly to change the level of capital, and there are no adjustment costs in steady state. The dynamics around the steady state are influenced by the curvature parameter ϵ. The CAC in **(3)** have been considered extensively in the neoclassical investment literature (see, for example, Hayashi (1982), Abel and Blanchard (1983) and Shapiro (1986)).

The log-linearised first-order condition for investment under the assumption of IAC is given as (see Appendix A for details)

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} \mathrm{E}_t i_{t+1} + \frac{1}{\kappa(1+\beta)} q_t \quad \textbf{(4)}$$

where small letters denote log-deviations from steady state and $\mathrm{E}_t\,[\cdot]$ expectations, conditional on information available in period t, q_t is the shadow price of installed capital (the shadow value of one unit of k_{t+1} at the time of the period t investment decision), and β the subjective discount factor. The presence of investment adjustment costs introduces inertia in investment, as reflected by the lagged investment term. The investment decision also becomes forward looking, as it is costly to change the level of investment. The larger the IAC parameter κ, the less sensitive is current investment to the shadow value of installed capital.

By contrast, investment under the assumption of CAC responds immediately to movements in the current shadow value of capital, with the log-linearised first-order condition given as,

$$i_t - k_t = \frac{1}{\epsilon \delta^2} q_t \quad \textbf{(5)}$$

where $\epsilon\delta^2$ is the elasticity of investment with respect to the shadow value of capital (or, Tobin's Q). Hence, CAC are not, by themselves, able to generate inertia in investment, as observed in the aggregate data.

2.1 Monetary and fiscal shocks

A large body of literature has documented that identified monetary shocks in the United States have persistent hump-shaped effects on output, consumption, and investment.[(4)] For the United Kingdom, we find that identified monetary policy shocks have a very similar impact on these variables.[(5)]

Christiano *et al* (2005) find that a dynamic general equilibrium model with IAC in **(2)** matches the strong, hump-shaped response of investment to a monetary policy shock in the US data. By contrast, CAC in **(3)** are unable to generate the shape of the estimated response. The inertia in investment induced by IAC is important for accounting the effects of monetary policy on investment.

Burnside *et al* (2004) identify fiscal policy shocks in the post-war US data. They find that these shocks are followed by persistent declines in real wages and rises in government purchases, tax rates, and hours worked. Accompanying these effects is a transitory increase in investment and some movement in consumption.

The standard real business cycle model substantially overstates the response of investment. Burnside *et al* (2004) find that IAC are necessary to improve the quantitative performance of the model along this dimension.

Basu and Kimball (2005) point out that in dynamic general equilibrium models with price stickiness or 'New Keynesian' models, fiscal expansions (financed by lump-sum taxes) tend to

(4) See, for example, Christiano, Eichenbaum and Evans (1999) and references therein.

(5) There is little evidence on the response of UK output and investment to a monetary policy shock. We therefore estimate a VAR, following the approach of Christiano *et al* (1999), to identify the monetary policy shock. The VAR includes seven variables (real GDP, consumption, investment, GDP deflator, real exchange rate, nominal interest rate, and commodity prices). The variables are ordered such that the interest rate is the second last variable followed by commodity prices. The implications of this ordering are that *(i)* real GDP, consumption, investment, GDP deflator and real exchange rate do not respond contemporaneously to a monetary policy shock, and *(ii)* the interest rate at time t is set prior to observing commodity price data for that period. We use seasonally adjusted data for the period 1970 Q1 to 2004 Q2 to estimate the model.

reduce output on impact. This countercyclical response occurs because of a sharp increase in equilibrium mark-up which reduces labour demand. This effect tends to dominate the increase in labour supply due to the negative wealth effect which would increase labour supply and output. Basu and Kimball (2005) explore how an environment of IAC deliver positive effects of fiscal shocks on output by preventing investment to not respond instantaneously to the shock.

2.2 News shocks

Recently Beaudry and Portier (2006) have stressed the quantitative importance of 'news shocks' in driving business fluctuations. A 'news shock' reflects changes in agents expectations about future economic conditions. Beaudry and Portier (2006) show that an identified news shock predicts future measured total factor productivity by several years and over this period, consumption, investment, and hours worked increase. The standard one-sector neoclassical model generates negative comovement between consumption and investment in response to changes in expectations about future productivity. Beaudry and Portier (2005) show that introducing CAC does not improve the performance of the model, and discuss alternative modelling approaches. Jaimovich and Rebelo (2006), however, propose a model in which IAC is one of the key elements. This model can generate a positive comovement between consumption and investment in response to news shocks.[(6)]

2.3 Asset returns and business fluctuations

As discussed in Rouwenhorst (1995), the framework of a dynamic general equilibrium model is a useful starting point to investigate the relationship between asset prices and business fluctuations. Previously, Jermann (1998) showed that a one-sector model with habit formation and CAC can match the stylised facts on asset returns and business cycles. Boldrin, Christiano and Fisher (2001), however, show that it is necessary to consider a multi-sector model to avoid the implication that hours are countercyclical in the model. Recently, Beaubrun-Diant and Tripier (2005) consider IAC in a one-sector model. They find that the model successfully matches key business cycle stylised facts in the United States (comovement and volatilities of output, consumption, investment, and hours) and asset returns (generates highly volatile return on equity

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(6) Jaimovich and Rebelo (2006) also consider replacing IAC with adjustment costs to capital utilisation. This model, however, requires a high elasticity of labour supply to generate a comovement in consumption and investment following a news shock.

along with a smooth risk-free rate).

3 Industry analysis

As evident from the discussion above, IAC have begun to play a prominent role in accounting for business fluctuations and asset market movements. We now turn to the main contribution of this paper. Specifically, we conduct an industry analysis to investigate if there is empirical support for the IAC structure assumed in aggregate models.

3.1 The model

We assume that the representative industry has a production function for gross output, Y_t, on the following form,

$$Y_t = F\left(L_t, M_t, K_t, I_t, \Delta I_t\right) \qquad \textbf{(6)}$$

where L_t denotes labour input, M_t material inputs, K_t capital, I_t investment, and ΔI_t a measure of the change in investment. CAC implies that, conditional on the level of variable inputs, capital and output, a rise in investment results in foregone output, due to costs associated with changing the level of capital. IAC imply that the change in investment has a similar impact on output. The implicit assumption is that, instead of producing marketable output, firms need to use resources to, for example, train labour, reorganise work, and install new equipment. These adjustment costs are internal to the production process; that is, the cost of output lost when capital and investment are varied. By contrast, the aggregate model discussed in Section 2 made the assumption of external adjustment costs. These were accounted for in the capital accumulation identity – the implicit assumption in that model is that part of investment will capture services provided to install new capital, rather than providing new capital goods. Although the first-order conditions for capital and investment will differ across the two ways of measuring the costs, the implied investment dynamics around steady state are identical. For conducting the industry analysis, there is a practical advantage in choosing the production function approach. First, this approach is consistent with the available capital data used to estimate the model, since conventional capital measures are constructed under the assumption that all investment spending generates new capital. Second, the production function approach is also the standard way of modelling adjustment costs in the investment literature (see, for example, Morrison (1988)).

We assume that the production function has standard properties, defined implicitly by the regularity conditions for the dual variable cost function, C_t, specified below

$$C_t = C\left(W_t, P_t^m, Y_t, K_t, I_t, \Delta I_t\right) \tag{7}$$

where W_t and P_t^m are the prices of labour and material inputs, both taken as given by the individual industry. The cost function is non-decreasing and concave in the two prices, decreasing and convex in K_t, and non-decreasing and convex in I_t and ΔI_t.[7]

The optimal path for capital is chosen by minimising the expected discounted value of future costs, subject to the capital accumulation identity, $K_{t+1} = (1-\delta)K_t + I_t$. The first-order conditions for investment and capital are given by

$$\frac{\partial C_t}{\partial I_t} + P_t^I - Q_t + \frac{1}{1+r_t}\mathrm{E}_t\left[\frac{\partial C_{t+1}}{\partial I_t}\right] = 0 \tag{8}$$

$$(1+r_t)Q_t + \mathrm{E}_t\left[\frac{\partial C_{t+1}}{\partial K_{t+1}} - (1-\delta)Q_{t+1}\right] = 0 \tag{9}$$

where $1 + r_t$ is the relevant discount factor for costs accrued in period $t+1$, P_t^I the price of investment, and Q_t the shadow value of capital installed in period t. Combining the first-order conditions for capital and investment gives the Euler condition,

$$\mathrm{E}_t\left[P_t^K + (1+r_t)\frac{\partial C_t}{\partial I_t} + \frac{\partial C_{t+1}}{\partial K_{t+1}} + \frac{\partial C_{t+1}}{\partial I_t} - (1-\delta)\left(\frac{\partial C_{t+1}}{\partial I_{t+1}} + \frac{1}{1+r_{t+1}}\frac{\partial C_{t+2}}{\partial I_{t+1}}\right)\right] = 0 \tag{10}$$

where P_t^K is the user cost of capital, $P_t^K \equiv P_t^I\left[r_t + \delta - (1-\delta)\,\pi_t^I\right]$, where $\pi_t^I \equiv \left(P_{t+1}^I - P_t^I\right)/P_t^I$.

3.2 Econometric specification

Let C_t^v denote the variable cost function net of adjustment costs, and let C_t^a denote the adjustment cost function. For estimation, we specify the variable cost function as

$$\log C_t = \log C_t^v + \frac{\psi}{2}C_t^a \tag{11}$$

where ψ is the adjustment cost parameter. We use a first-order approximation for C_t^v, which means that the elasticity of C_t^v with respect to capital is constant, here denoted by $\alpha < 0$.[8] We

[7] The curvature conditions for the variable cost function under the assumption of capital adjustment costs are standard in the investment literature. Here we also assume similar curvature conditions for the change in investment. When these conditions are fulfilled, a well-defined dual production function exists.

[8] The choice of a first-order approximation is mainly driven by the lack of suitable instruments for parameter identification. We do, however, allow for potential misspecification of the variable cost function when estimating the model, as is further discussed in Section 3.3.

consider an adjustment cost function of the form:

$$C_t^a = \lambda\left(\frac{I_t}{K_t} - \delta\right)^2 + (1-\lambda)\left(\frac{I_t}{I_{t-1}} - 1\right)^2 \tag{12}$$

with $0 \leq \lambda \leq 1$.[(9)] The functional form nests both IAC and CAC, and assumes that adjustment costs are zero in steady state. The parameter λ determines the weight on CAC, relative to that on IAC. When $\lambda = 1$, it is only costly to adjust capital. When $\lambda = 0$, it is only costly to change the level of investment.

3.2.1 Non-linear specification

By combining **(10)-(12)**, we get the Euler condition

$$\mathrm{E}_t\left[P_t^K + \alpha\frac{C_{t+1}}{K_{t+1}} + \psi\Gamma_t\right] = 0 \tag{13}$$

where $\psi\Gamma_t$ is the marginal cost of adjusting the level of capital and/or investment. An expression for Γ_t, which is a function of current and expected future changes in investment and capital, and of the weight parameter λ, is given in Appendix C. Equation **(13)** states that, in a long-run equilibrium, the user cost of capital equals the marginal product of capital, $-\alpha C_t/K_t$. Due to costly adjustment of capital and/or investment, capital may deviate from its long-run equilibrium by the term $\psi\Gamma_t$.

3.2.2 Log-linearised specification

We log-linearise the first-order condition for investment and capital **(8)-(9)** around steady state and combine to get

$$\mathrm{E}_t\left[\lambda\delta\left(i_t - k_t\right) + \frac{1-\lambda}{\delta}\Delta i_t - \frac{\beta\alpha}{\psi}s_{t+1} - \beta\lambda\delta\left(i_{t+1} - k_{t+1}\right) - \frac{\beta(1-\lambda)}{\delta}\left(\gamma_1\Delta i_{t+1} - \gamma_2\Delta i_{t+2}\right)\right] = 0 \tag{14}$$

where $s_{t+1} = c_{t+1} - k_{t+1} - p_t^K$, $\gamma_1 = 1 + (1-\delta)$, $\gamma_2 = \beta\left(1-\delta\right)$. The term s_{t+1} is the difference between the marginal product of capital and its user cost. As such, it is a measure of the deviation of capital from its long-run equilibrium. When s_{t+1} is positive, it is optimal for firms to invest in new capital, so that $i_t - k_t$ and/or Δi_t is positive (recall that $\alpha < 0$). The adjustment cost parameter ψ will govern the speed at which capital adjusts to its long-run equilibrium. When ψ is

(9) We consider an adjustment cost function that is homogenous of degree zero in its arguments. By contrast, the q literature typically assumes a capital adjustment cost function that is homogenous of degree one in investment and capital, to ensure that marginal Q equals average Q. It is not clear, *a priori*, which is the more appropriate specification. We, therefore, considered an alternative specification that is homogenous of degree one in its arguments (given in Appendix B). The results from this specification were qualitatively similar to those presented in Section 4.

large, so that it is costly to adjust capital and/or investment, firms put little weight on s_{t+1} relative to the dynamic adjustment cost terms.

Under the CAC assumption ($\lambda = 1$), we can solve **(14)** forward to get

$$i_t - k_t = -\frac{\beta\alpha}{\psi\delta}\mathrm{E}_t\left[\sum_{\tau=0}^{\infty}\beta^{\tau}s_{t+1+\tau}\right] \tag{15}$$

Since it is costly to adjust capital, the investment decision is forward looking. When the return to capital is expected to be greater than its user cost (that is, s_t greater than zero), today and in the future, it is optimal for firms to increase the investment to capital ratio relative to its steady-state value. With IAC, we instead have

$$\Delta i_t = \beta\mathrm{E}_t\left[\frac{-\delta\alpha}{\psi}s_{t+1} + \gamma_1\Delta i_{t+1} - \gamma_2\Delta i_{t+2}\right] \tag{16}$$

Investment growth now depends on the excess return to capital, and future investment growth. We can solve this difference equation forward to get

$$\Delta i_t = -\frac{\beta\delta\alpha}{\psi}\mathrm{E}_t\left[\sum_{\gamma=0}^{\infty}(1-\delta)^{\gamma}\beta^{\gamma}\sum_{\tau=0}^{\infty}\beta^{\tau}s_{t+1+\tau+\gamma}\right] \tag{17}$$

The two cost structures therefore give different predictions about movements in the model variables over the business cycle – CAC imply that the investment to capital ratio should lead variable s_t, in the sense that a rise (decline) in the current ratio should signal a subsequent rise (decline) in s_t. The IAC structure instead predicts that the change in investment should lead s_t. These predictions, however, are unable to distinguish between the two cost structures. The reason being that these predictions are not 'nested' as they are about different variables. Hence, evidence in favour of one would not necessarily imply the absence of the other. Moreover, Granger causality tests, not reported here, turned out to be inconclusive. We, therefore, take the direct approach of estimating the parameters using the nested specification of the cost structure in **(12)**.

3.3 GMM estimation

We estimate the non-linear, **(13)**, and the log-linearised, **(14)**, specifications, using generalised method of moments (GMM). Both specifications have their relative advantages, which we discuss further below.

To estimate the model using GMM, we replace the conditional expectations in the Euler condition with actual values and introduce an expectation error, ε_t. Under rational expectations, ε_t is uncorrelated with any information known at the decision date. Given this identifying assumption, any period t variable could be used as an instrument to form the moment conditions to estimate the model parameters.

Under a more general representation, which allows for potential misspecification, identification requires some additional assumptions about the error terms. It is common in the investment literature to assume that they follow a first-order moving average process, in which case any variable known in period $t-1$ could be used as instrument. There is evidence, however, that this may not be an appropriate identifying assumption.[(10)] Following Hall (2004), we therefore use a more general specification, that allows for serially correlated error terms. In this case, we cannot rely purely on timing considerations in the choice of instrument. Instead, we need to use strongly exogenous variables, that are uncorrelated with the Euler condition residual in any period t. For the United States, we use the instruments from Hall (2004); a dummy variable which takes the value of one in the years when there was a shock to the oil price (1956, 1974, 1979, and 1990) and a measure of the shock to federal defence spending. We include four lags of these variables as instruments (lag $t-2$ to $t-6$) and, following the previous literature, we exclude the first lag of variables from the instrument set. For the United Kingdom, we use an instrument set consisting of lagged values of the growth rates of two variables; the price of oil and exogenous demand.[(11)] Due to the shorter sample for the United Kingdom, we only include lag $t-2$ of the instruments in the UK regressions.

To avoid weak identification, the instruments also need to be adequately correlated with the model variables, as discussed by Stock, Wright and Yogo (2002). Ideally, the instrument set should be strong for all the expected variables in **(13)** and **(14)** (that is, variable s_{t+1}, $ik_{t+1} = i_{t+1} - k_{t+1}$, Δi_{t+1}, and Δi_{t+2} in **(14)**). Since we have multiple endogenous regressors, the conventional first-stage F-statistic for checking evidence for weak instruments may not provide adequate information (as discussed, for example, in Shea (1997) and Stock *et al* (2002)). To assess instrument weakness, we instead follow the recommendation of Shea (1997) and compute the

(10) Previous investment regressions that use lagged endogenous variables for identification typically find strong evidence against the overidentifying restrictions, reflecting either model misspecification or invalid instruments (see discussions in Chirinko (1993), Whited (1998)). Hall (2004) argues that movements in factor shares are too slow to be only the result of adjustment costs, pointing to potential misspecification problems. In a similar model, Garber and King (1983) show that serially correlated technology shocks will invalidate most candidate instrumental variables (including lagged endogenous variables).

(11) The demand instrument is industry specific and created as an attempt to increase the correlation between the exogenous variables and the model variables, to avoid weak identification. To create the demand instrument we build on work by Shea (1993), discussed in more detail in Groth (2007).

partial (adjusted) R^2 statistics for each of the variables needing instruments. The partial R^2 statistics indicates the explanatory power of the instrument set for each variable once the instruments are orthogonalised to account for their contribution in explaining the remaining variables (to be instrumented).[12]

One advantage with the log-linearised specification is that this model permits a relatively straightforward computation of instrument relevance and identification robust statistics (discussed further in Section 4). For the non-linear model, these types of tests are not available. On the other hand, it is not possible to identify separately all parameters of the linearised model. Instead, a subset of parameters needs to be calibrated. For this reason, we estimate both the non-linearised and the linearised model. For the linearised model, we calibrate an industry-specific value for α, using the steady-state relation $\alpha = -P^K K/C$. The depreciation rate is calibrated as the mean of the industry-specific depreciation rate, and we use the mean of the interest rate r to calibrate β.

3.4 The data

For the United States, we use the data set that Hall (2004) constructs for the estimation of capital adjustment costs. It consists of annual data for 18 manufacturing industries for the period 1949-2000, compiled using data from the Bureau of Labour Statistics (BLS) and the National Income and Product Accounts (NIPA). To get investment, depreciation rates, and a measure of the user cost of capital, we follow Hall (2004). Table 1 gives the industry classifications.

For the United Kingdom, we use data for 27 manufacturing and services industries for the period 1970 to 2000, taken from the Bank of England Industry Data set.[13] It contains industry data on gross output, value added and inputs of capital services, labour and intermediates.[14] To construct the user cost of capital, we assume that economic profits are zero. Table 2 classifies the industries for the United Kingdom. The model is estimated using data for the private non-farm economy (excluding agriculture and the government sectors) and also excluding oil and gas, and coal and mining.

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(12) The partial R^2 statistics proposed by Shea (1997) is a useful diagnostics to check for instrument relevance and has been considered in several studies with GMM-IV estimation. See, for example, Fuhrer, Moore and Schuh (1995), Burnside (1996), and Fuhrer and Rudebusch (2003).

(13) The data set is described in detail in Oulton and Srinivasan (2005).

(14) The capital services data is a quality-adjusted measure of capital that takes into account the composition of capital by weighting different assets together by their rental prices. To aggregate investment data, we use a method which is consistent with the rental-price weighted index of capital, discussed in Groth (2007).

4 Estimation results

We conduct industry-specific estimation using the non-linear **(13)** and the linearised **(14)** model, respectively. We start with the US estimation, and then provide the UK results. The section also discusses the issue of instrument relevance and provides tests that are robust to weak instruments and excluded instruments.

4.1 US results

4.1.1 Industry-specific estimates

We estimate the weight parameter λ in the adjustment cost function freely and let the data choose between the CAC and the IAC structures. That is, we only constrain λ to lie between zero and one for a meaningful interpretation. Table 3 presents the estimates of the non-linear specification **(13)**.[(15)] Column 2 shows the estimated elasticity of the variable cost function with respect to capital, α. It is negative, as predicted by theory, and statistically significant at the 1% level for all the industries. Column 3 shows the estimates of the adjustment cost parameter, ψ. It is positive and statistically significant in two thirds of the industries. Column 4 shows the estimated weight parameter λ. It ranges between 0.92 and 1.0, and is statistically significant at the 1% level in all industries. For industries where the weight is less than one and $\hat{\psi} > 0$, the null hypothesis of $\lambda = 0$ (IAC) is clearly rejected. By contrast, we cannot reject the null hypothesis that $\lambda = 1$. The data, therefore, seem to favour the CAC structure over the IAC structure. The *J*-statistic for the test of overidentifying restrictions indicates that overidentifying restrictions are not rejected. That is, we cannot reject the joint null hypotheses of correct model specification and that the instruments satisfy the orthogonality condition.

Next, we estimate the log-linearised specification **(14)** for each industry.[(16)] The second and third columns of Table 4 present the estimates of the adjustment cost parameter ψ and the weight

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(15) We used $\lambda_0 = 0.5$ and $\psi_0 = 0.5$ as starting values in the estimation. For α_0, we used the implied industry-specific mean (mentioned in Section 3.3) as the starting value. The model is estimated using the Newey-West optimal weighting matrix with 8 lags.

(16) Some of the variables, in particular s_t, exhibits a trend for most industries, except industries 6, 11 and 12. The unit root tests (Dickey-Fuller and Phillips-Perron) did not reject the null of a unit root for industries 1, 5, 10, 13 and 14. We used the Hodrick-Prescott (HP) filter with a weight parameter of 100 to remove the stochastic trend for these industries. For industries 2, 3, 4, 7, 8, 9, 15, 16 and 17 we removed a quadratic trend. Our results are robust to different different methods of detrending the data.

parameter λ. The adjustment cost parameter is positive and statistically significant in two thirds of the industries. It takes a negative sign in two industries. The point estimate of λ is one in all the industries, and statistically significant at the 1% level. The estimates reveal that the industry data strongly favour the CAC structure ($\lambda = 1$) and does not support the IAC structure ($\lambda = 0$). The J test (column 4) does not reject the overidentifying restrictions, for any of the industries. (17)

4.1.2 Instrument relevance and identification robust inference

We conduct a diagnostic check to examine the potential issue of instrument weakness, that would invalidate the standard statistics to draw inference (eg the J statistics), using the Shea (1997) partial R^2 statistic, which we carry out for the linearised model. (18)

Columns 5 to 8 in Table 4 show the partial R^2 statistics for each of the instrumented variables (s_{t+1}, ik_{t+1}, Δi_{t+1}, Δi_{t+2}). No distribution theory is available for these statistics, but the low statistics (ranging between 0.03 and 0.38) suggest that the exogenous instruments are, in general, weak for all industries. Our findings of instrument weakness for the United States are consistent with those of Burnside (1996) who estimated production function regressions using two-digit US industry data, and with Shea (1997). Both of these found low partial R^2 for the instrument set which included the growth rate of military expenditure and the growth rate of the world oil price.

The weak instrument problem appears pervasive. This problem means that we may not only have imprecise estimates of the structural parameters but also the standard statistics to draw inference may be unreliable. The reason, as discussed in Stock *et al* (2002) and Dufour (2003), is that if instruments are weak then the limiting distribution of GMM-IV statistics are in general non-normal and depend on nuisance parameters. The standard statistics which are based on the normality of sampling distribution may, therefore, be incorrect.

To address this issue, we compute two identification robust tests statistics considered in recent literature. The first is the Anderson and Rubin (1949) (AR) statistic, discussed in Dufour and

(17) Our estimates of ψ, conditional on the support for the CAC structure, are broadly consistent with the estimates of Hall (2004). However, our results are not directly comparable due to the differences in model specifications.

(18) The set of endogenous variables in **(14)** to be instrumented is $X = \{ik_{t+1} \quad s_{t+1} \quad \Delta i_{t+1} \quad \Delta i_{t+2}\}$. Let Z be the matrix of instruments. $R_p^2(X_i)$ in Table 4 is computed as the sample squared correlation between $\tilde{X}_i$ and $\bar{X}_i$. $\tilde{X}_i$ is the component of X_i that is orthogonal to other variables in X. $\bar{X}_i$ is the component of the projection of X_i on Z that is orthogonal to the projections of other endogenous variables on Z. $R_p^2(X_i)$ indicates the explanatory power of Z for variable X_i once the instruments are orthogonalised relative to their contributions to explaining X_i.

Jasiak (2001) and Dufour (2003). The main advantage of this statistic is that its limiting distribution is robust to weak and excluded instruments. One deficiency, however, is that when the number of instruments exceeds the number of estimated structural parameters, as in our context, the AR statistic has a low power. We therefore also compute the K statistic proposed by Kleibergen (2002), which remedies this problem.[19]

Given the estimated values of the adjustment cost parameter $\hat{\psi}$ and weight parameter $\hat{\lambda}$ in Table 4, we test the null hypothesis $H_0 : \Theta = \Theta_0$ for each industry, where Θ_0 contains the model parameters (both estimated and calibrated). Under the null, the AR statistic follows an $F(k, T-k)$-distribution where k is the number of instruments and T is the number of observations, whereas the K-statistic follows a $\chi^2(m)$ where m is the number of elements of θ_0.[20] We report the p-values associated with these statistics in Table 4 (columns 9 and 10). In fourteen industries, the p-values associated with both the AR and the K-statistics indicate that we do not reject the null hypothesis at the 5% level. Thus, for these industries, we cannot reject the null hypotheses of correct model specification and that the instruments satisfy the orthogonality condition. For two industries (number 4, 11), the results are inconclusive, with one of the statistics rejecting the model and the other one accepting it, at the 5% level. For the remaining two industries (12 and 14), the model is rejected by both tests.

4.1.3 Imposing the IAC and CAC structures on the data

So far, we have estimated an unconstrained version of the model, where we let the data choose between the IAC and the CAC structures. In that case, the data put a high weight on the CAC model, for all industries. By contrast, aggregate studies that consider IAC have imposed this adjustment cost structure on the data. To be able to compare our estimates of the adjustment cost parameter with those obtained in aggregate studies, this section estimates constrained versions of the non-linearised model, where either the IAC ($\lambda = 0$) or the CAC ($\lambda = 1$) structure are imposed. Thus, this exercise provides an estimate of the adjustment cost parameter based on a particular assumption regarding the underlying cost structure.

As shown in Table 5, under both the IAC (columns 2-4) and the CAC (columns 5-7) constraint, the

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(19) For recent applications of these statistics in empirical work see, for example, Dufour, Khalaf and Kichian (2006) and Yazgan and Yilmazkuday (2005).

(20) To compute the AR and K statistics we follow Kleibergen (2002). Formal expressions for the statistics are given in Appendix D. A RATS program to compute them is available upon request.

adjustment cost parameter, ψ, is positive and significant in around one third of the industries. The estimates under IAC, however, are substantially smaller relative to those under CAC.[21] We will return to these estimates in Section 5.

4.2 UK results

For the United Kingdom, we only have 30 years of data. To avoid small sample bias, we estimate the model using pooled data, both at the aggregate and the sectoral level, where the sectors include non-manufacturing – or services – industries, and manufacturing industries.[22] For the manufacturing group, we also estimate the model for durable and non-durable industries separately.[23]

4.2.1 Sector-specific estimates

We estimate the unconstrained version of the non-linearised Euler equation **(13)** for the aggregate private non-farm economy, where we let the data choose the relative weight parameter λ, as shown in the first row of Table 6.[24] The estimate of α is negative and significant, in line with theory. The adjustment cost parameter, ψ, is positive but not significant, and similar in size to what has been found in previous studies.[25] The weight parameter λ is close to one, and significant at the 1% level, supporting the CAC model. The table also gives the J-statistic for the test of overidentifying restrictions and the corresponding significance level. These restrictions are not rejected.

To see whether these results appear to be robust across industry subgroups, the model is re-estimated for the manufacturing and services sectors, and for the durables and non-durables manufacturing industries, also shown in Table 6. The results are similar to those obtained under pooled estimation; the adjustment cost parameter is positive and significant and the estimate of λ is equal to one, in all sectors. Overall, these results suggest that, at the sectoral level, the null

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(21) The estimation results from the linearised specification with λ constrained reveal similar results on the magnitude of the estimates.

(22) Note that the services sector includes the construction industry, which is not classified as a services industry. For simplicity, however, we denote non-manufacturing industries services.

(23) To remove any industry-specific fixed effects that could otherwise bias the pooled estimates, we work with first-differenced data when we estimate the linearised model. The model could be estimated at a more disaggregated level for the services industries. As this quickly reduces the number of observations, we have chosen a slightly more aggregated approach, however.

(24) For starting values, we use λ and ψ equal to 0.5, and $\alpha = -0.1$.

(25) See Groth (2007) for UK capital adjustment cost estimates.

hypothesis of $\lambda = 0$ (IAC) is clearly rejected, while we cannot reject the hypothesis of $\lambda = 1$ (CAC).

Next, we estimate the log-linearised specification **(14)** for the aggregate economy and at the sectoral level, as shown in Table 7.[26] For the linearised verson of the model, we also include lag $t - 3$ and $t - 4$ of the instrument variables into the instrument set. The point estimate of λ is one and the adjustment cost parameter is positive and significant, both at the aggregate and the sectoral level. Once again, the estimates reveal that the industry data strongly favour the CAC structure ($\lambda = 1$) and does not support the IAC structure ($\lambda = 0$). The J test, however, indicate that the overidentifying restrictions are rejected for the manufacturing sector. For the remaining sectors, the restrictions cannot be rejected.

4.2.2 Instrument relevance and identification robust inference

Table 8 reports partial R^2 statistics for the United Kingdom, at the industry level. As in the case of the United States, the low values of this statistics suggest that instruments are weak. We therefore proceed by computing the (AR) and the K statistic, as shown in columns 5-6 in Table 7. The p-values indicate no evidence against the null hypothesis, indicating that our estimates are plausible given the data.

4.2.3 Imposing the IAC and CAC structures on the data

We also estimate the two constrained cases where we impose the CAC ($\lambda = 1$) and the IAC model ($\lambda = 0$), respectively, using the non-linear model. Table 9 reports the results. Under the CAC model (columns 5-7), the estimated adjustment cost parameter ψ is positive and statistically significant, both at the aggregate and the sectoral level. When we impose the IAC model (columns 2-4), the estimate of ψ is negative, which is inconsistent with theory, or close to zero. In addition, the estimated parameter is insignificant at both the aggregate and the sectoral level.

[26] As for the United States, we find that some of the variables exhibit a trend over the sample, in some of the industries. Due to the shorter sample period, it is difficult to evaluate the trend statistically, which we did for the United States (see footnote 17). We therefore choose to work with first differenced data. One advantage of using this approach is that industry-specific effects, that could otherwise bias the pooled estimates, are removed.

5 Discussion

The results from Section 4 show that when both the IAC and the CAC structures are considered the industry data put almost full weight on the latter. In particular, we reject the hypothesis that $\lambda = 0$, but cannot reject the hypothesis that $\lambda = 1$. This result is obtained both for US manufacturing industries, and for UK services and manufacturing industries.

By contrast, the constrained model, which imposes either the IAC or the CAC structure on the data, gives slightly different results for the two countries. For the United States, it gives similar support for the two cost structures; the estimated adjustment cost parameter is positive and significant in around one third of the industries, but it is substantially smaller under IAC relative to the CAC case. For the United Kingdom, there is strong support for the CAC case, but no support for the IAC case; the estimated adjustment cost parameter is positive and significant under the assumption of CAC, but negative or close to zero and insignificant under the assumption of IAC.

Given the importance of IAC in aggregate models, we next ask how the US industry estimates of the adjustment cost parameter compare with the aggregate estimates in the recent literature. To do so, we compute the elasticity of aggregate investment with respect to the shadow price of capital implied by the industry estimates, and compare this to estimates of the elasticity obtained using aggregate data. We linearise **(8)** around steady state under the assumption of IAC, which gives

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} E_t i_{t+1} - \frac{\delta\alpha}{\psi\,(r+\delta)\,(1+\beta)} \left(q_t - p_t^I\right) \qquad \textbf{(18)}$$

In each industry, the elasticity of investment with respect to the current shadow price of capital is given by

$$\frac{\partial i_t}{\partial q_t} = -\frac{\delta\alpha}{\psi\,(r+\delta)} \qquad \textbf{(19)}$$

In the aggregate model **(4)**, the elasticity of aggregate investment with respect to aggregate Tobin's q is given by κ^{-1}. Under certain conditions further discussed in Appendix E, the aggregate elasticity will be a weighted average of the industry-specific elasticities,

$$\frac{1}{\kappa} = -\sum_{j=1}^{J} \omega_j \left[\frac{\delta_j \alpha_j}{\psi_j\,(r+\delta_j)}\right] \qquad \textbf{(20)}$$

where j denotes industry and where ω_j is the weight of investment in industry j in aggregate investment. To get an implied estimate of the aggregate elasticity, we consider the *largest* estimate of ψ (thus giving the strongest possible support to the IAC model) obtained under the constraint $\lambda = 0$ using the non-linearised model (column 3, Table 5). Based on the sample averages of the model parameters, we have $\delta = 0.08$, $\alpha = -0.10$, $r = 0.05$, $\psi = 0.01$. This gives an estimate of κ^{-1} of 6, which is substantially higher (approximately fifteen times) than, for example, the estimate of 0.4 based on aggregate data reported in Christiano *et al* (2005).[27] Our industry results thus imply a much smaller cost for adjusting investment than the aggregate estimates.

One important criticism to our study is that, if delays in investment planning or inflexibility in changing the planned pattern of investment are indeed the source of IAC, and if project planning and completion times typically last less than a year, then one may not expect IAC to have much effect on capital outlays at the annual frequency. There are several reasons, however, which suggest that the use of annual data may not be restrictive in estimating IAC. First, evidence on project planning and completion times for firms in the manufacturing industries, indicates an average time-to-build of 23 months (Koeva (2001)). For private structures the average planning and completion time is approximately 20 months (Edge (2000)), both well above one year. Second, empirical evidence of the response of investment to a monetary policy shock shows a humped-shaped response that typically peaks after around six quarters, and returns to its pre-shock level after three years (Christiano *et al* (2005)), suggesting that not all adjustment at the aggregate level takes place within the first year of the shock. If IAC are the main mechanism behind this slow adjustment, then we should be able to identify them at the annual as well as the quarterly frequency.

Another issue, related to the frequency of the data is the mapping between the elasticity of investment with respect to Tobin's q obtained at the annual frequency and that obtained at the quarterly frequency. Recent studies have made an adjustment to the elasticity, to account for the difference in data frequency. However, it can be shown that the elasticity of investment with respect to Tobin's q at the *annual* frequency equals the elasticity of investment with respect to Tobin's q at the *quarterly* frequency. Hence, we argue that no such adjustment needs to be made for interpreting the results.[28]

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(27) We also identify the industries with the highest adjustment cost estimates (industry 2 and 3) and use their industry-specific values of δ and α to calibrate a value for the industry-specific elasticity of investment with respect to Tobin's q. By doing so, we get an even higher estimate of the elasticity than what is obtained using the sample means.
(28) See Appendix F.

6 Conclusion

Recent literature on dynamic general equilibrium suggests that investment adjustment costs are necessary to account for a variety of business cycle and asset market phenomena. We conducted a disaggregated analysis using US and UK industry data to estimate the capital Euler condition via GMM.

When both investment and capital adjustment costs structures are considered, the industry-specific data appear to strongly support the latter. We find that instrument weakness is pervasive, however, identification robust tests indicate that our estimates are plausible, given the data. When investment adjustment costs alone are considered, the adjustment cost estimates are small relative to the estimates based on aggregate data, and imply an elasticity of investment with respect to the shadow price of capital that are fifteen times larger.

Overall, the industry data seem to support capital adjustment costs. But, as shown in the recent literature, these types of frictions do not improve the ability of aggregate models to account for a variety of macroeconomic phenomena. Our results suggest that from a disaggregated empirical perspective it remains difficult to motivate and interpret the investment friction considered in recent macroeconomic models.

Appendix A: The aggregate model

Consider a representative household with a period utility function given as

$$U_t(C_t, H_t) = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{H_t^{1+\phi}}{1+\phi} \tag{A.1}$$

where $0 < \beta < 1$ is the discount factor, $C_t = \left(\int_0^1 C_t(z)^{(\theta-1)/\theta} dz\right)^{\theta/(\theta-1)}$ is the composite consumption aggregate and $C_t(z)$ is the demand for differentiated good of type $z \in [0,1]$, $\theta > 1$ is the elasticity of substitution between the differentiated goods, $\sigma > 0$ is the inverse of the intertemporal elasticity of substitution for consumption expenditure by the household, H_t denotes hours worked in period t, and $\phi > 0$ captures the disutility of work effort. The household minimises the total cost of purchasing differentiated goods, taking as given their nominal prices $P_t(z)$. This gives consumption demand for each good $C_t(z) = (P_t(z)/P_t)^{-\theta} C_t$ where P_t is the aggregate price level defined as $P_t = \left(\int_0^1 P_t(z)^{1-\theta} dz\right)^{1/(1-\theta)}$. Households own capital K_t, which they rent to firms at rental rate R_t^k. Capital is accumulated according to

$$K_{t+1} = (1-\delta)K_t + (1 - S(I_t, I_{t-1}, K_t))\, I_t \tag{A.2}$$

where $S(.)$ is the adjustment cost function. When households face investment adjustment costs (IAC), the adjustment cost function depends on current and lagged investment and given as

$$S(.) \equiv S(I_t/I_{t-1}) \tag{A.3}$$

where $S(1) = S'(1) = 0$ and $S''(1) \equiv \kappa > 0$. When households face capital adjustment costs (CAC), the adjustment cost function is given by

$$S(.) \equiv S(I_t/K_t) \tag{A.4}$$

where $S(\delta) = S'(\delta) = 0$ and $S''(\delta) \equiv \epsilon > 0$. In each period $t = 0, 1, ...$, the household chooses consumption C_t, labour H_t, nominal bonds B_t, capital K_{t+1}, and investment I_t to maximise **(A.1)** subject to **(A.2)-(A.4)** and a sequence of period budget constraints

$$C_t + I_t + \frac{B_{t+1}}{P_t} = \frac{R_t B_t}{P_t} + \frac{W_t H_t}{P_t} + D_t + \Pi_t + R_t^k K_t \tag{A.5}$$

where B_t denotes the amount of nominal riskless one-period bonds purchased by the household at the end of period t that pay a gross return of R_t in period $t+1$, D_t denotes the real dividend income, Π_t are the lump-sum profits received from the ownership of firms. The resulting first-order conditions are as follows:

$$C_t^{\sigma} = \lambda_{1t} \tag{A.6}$$

$$\beta E_t \left[\left(\frac{\lambda_{1t+1}}{\lambda_{1t}} \right) \frac{P_t}{P_{t+1}} R_t \right] = 1 \tag{A.7}$$

$$H_t^{\phi} C_t^{\sigma} = \frac{W_t}{P_t} \quad \textbf{(A.8)}$$

$$Q_t = \frac{\lambda_{2t}}{\lambda_{1t}} \quad \textbf{(A.9)}$$

where λ_{1t} is the Lagrange multiplier associated with the budget constraint and λ_{2t} is the Lagrange multiplier associated with **(A.2)**. Q_t is the shadow value, in consumption units, of a unit of K_{t+1} at time t. The capital and investment first-order conditions are, under the assumption of IAC, given by

$$Q_t = \beta E_t \left[\left(\frac{\lambda_{1t+1}}{\lambda_{1t}} \right) ((1-\delta) Q_{t+1} + R_{t+1}^k) \right] \quad \textbf{(A.10)}$$

$$Q_t S'(I_t/I_{t-1}) \frac{I_t}{I_{t-1}} + 1 - \beta E_t \left[\left(\frac{\lambda_{1t+1}}{\lambda_{1t}} \right) Q_{t+1} S'(I_{t+1}/I_t) \left(\frac{I_{t+1}}{I_t} \right)^2 \right] = Q_t \left[1 - S(I_t/I_{t-1}) \right] \quad \textbf{(A.11)}$$

After log-linearising **(A.11)** around a non-stochastic steady state, we get **(4)**. Under CAC, we instead obtain

$$Q_t \left(1 - S'(I_t/K_t) \left(\frac{I_t}{K_t} \right)^2 \right) = \beta E_t \left[\left(\frac{\lambda_{1t+1}}{\lambda_{1t}} \right) ((1-\delta) Q_{t+1} + R_{t+1}^k) \right] \quad \textbf{(A.12)}$$

$$Q_t \left(1 - S(I_t/K_t) - S'(I_t/K_t) \left(\frac{I_t}{K_t} \right) \right) = 1 \quad \textbf{(A.13)}$$

After log-linearising **(A.13)** around a non-stochastic steady state, we get **(5)**.

Appendix B: An alternative adjustment cost specification

The adjustment cost function which is homogeneous of degree zero in its arguments is given by

$$C_t^a = \left(\frac{I_t}{K_t} - \delta\right)^2 K_t + \left(\frac{I_t}{I_{t-1}} - 1\right)^2 I_{t-1} \qquad \textbf{(B.1)}$$

Under this cost structure, the log-linearised equation **(14)** is replaced by

$$E_t\left[\lambda\delta\left(i_t - k_t\right) + \left(1-\lambda\right)\Delta i_t - \beta\frac{\alpha}{K\tilde{\psi}}s_{t+1} - \beta\lambda\delta\left(i_{t+1} - k_{t+1}\right) - \beta\left(1-\lambda\right)\left(\gamma_1\Delta i_{t+1} - \gamma_2\Delta i_{t+2}\right)\right] = 0 \qquad \textbf{(B.2)}$$

where $\tilde{\psi}$ is the adjustment cost parameter under the alternative adjustment cost structure **(B.1)**, and where $\gamma_1 = 1 + (1-\delta)\,, \gamma_2 = \beta\left(1-\delta\right)$. The mapping between the industry and the aggregate elasticity is modified as

$$\frac{1}{\kappa} = -\frac{\delta\alpha}{\psi\left(r+\delta\right)} = \frac{\alpha}{\tilde{\psi}K\left(r+\delta\right)} \Leftrightarrow \tilde{\psi} = \frac{\psi}{\delta K}$$

The difference, compared to **(14)**, is the presence of the steady-state value of capital, K.

Appendix C: An expression for Γ

The term Γ in **(13)** is given by

$$\Gamma_t = (1 + r_t)\, C_t f_t - C_{t+1} \left[g_{t+1} + (1 - \delta)\, f_{t+1} \right] + \frac{(1 - \lambda)(1 - \delta) C_{t+2}}{1 + r_{t+1}} \frac{\Delta I_{t+2}}{I_{t+1}} \frac{I_{t+2}}{I_{t+1}^2} \qquad \textbf{(C.1)}$$

where f_t and g_t are given by

$$f_t = \lambda \frac{\Delta K_{t+1}}{K_t^2} + (1 - \lambda)\, \frac{\Delta I_t}{I_{t-1}^2} \qquad \textbf{(C.2)}$$

$$g_t = \lambda \frac{\Delta K_{t+1} I_t}{K_t^3} + (1 - \lambda)\, \frac{\Delta I_t I_t}{I_{t-1}^3} \qquad \textbf{(C.3)}$$

with $\Delta K_{t+1} = K_{t+1} - K_t$, $\Delta I_t = I_t - I_{t-1}$.

Appendix D: AR **and** K **statistics**

Following Kleibergen (2002), we can represent **(14)** as a limited information simultaneous equation model

$$y = Y\Theta + \epsilon \quad \textbf{(D.1)}$$

$$Y = X\Pi + V \quad \textbf{(D.2)}$$

where $y = ik_t (\equiv i_t - k_t)$, $Y = [\Delta i_t \;\; ik_{t+1} \;\; sk_{t+1} \;\; \Delta i_{t+1} \;\; \Delta i_{t+2}]$ is of dimension Tx5, $\Theta \equiv [\;\; (1-\lambda)/\lambda\delta^2 \quad \beta\alpha/(\psi\lambda\delta) \quad -\beta \quad \beta(\lambda-1)(1+(1-\delta))/\lambda\delta^2 \quad \beta^2(1-\lambda)(1-\delta)/\lambda\delta^2]'$ is a 5x1 vector, ϵ is a Tx1 vector of structural errors, X is Txk matrix of instruments, Π is the parameter matrix for the second equation, and V is Txm matrix of reduced-form errors. Under the null hypothesis $H_0 : \Theta = \Theta_0$, where $\lambda = \hat{\lambda}$ and $\psi = \hat{\psi}$ and the remaining parameters are calibrated, the AR statistic is

$$AR(\Theta_0) = \frac{\frac{1}{k}(y - Y\Theta_0)' P_X (y - Y\Theta_0)}{\frac{1}{T-k}(y - Y\Theta_0)' M_X (y - Y\Theta_0)} \sim F(k, T-k) \quad \textbf{(D.3)}$$

where $P_X = X(X'X)^{-1}X'$ and $M_X = I - P_X$.

The K-statistic is

$$K(\Theta_0) = \frac{(y - Y\Theta_0)' P_{\tilde{Y}(\Theta_0)} (y - Y\Theta_0)}{\frac{1}{T-k}(y - Y\Theta_0)' M_X (y - Y\Theta_0)} \sim \chi^2(m) \quad \textbf{(D.4)}$$

where

$$P_{\tilde{Y}(\Theta_0)} = \tilde{Y}(\Theta_0)(\tilde{Y}(\Theta_0)'\tilde{Y}(\Theta_0))^{-1}\tilde{Y}(\Theta_0)'$$

$$\tilde{Y}(\Theta_0) = X\tilde{\Pi}(\Theta_0)$$

$$\tilde{\Pi}(\Theta_0) = (X'X)^{-1}X'\left[Y - (y - Y\Theta_0)\frac{s_{\epsilon V}(\Theta_0)}{s_{\epsilon\epsilon}(\Theta_0)}\right]$$

$$s_{\epsilon V}(\Theta_0) = \frac{1}{T-k}(y - Y\Theta_0)' M_X Y$$

$$s_{\epsilon\epsilon}(\Theta_0) = \frac{1}{T-k}(y - Y\Theta_0)' M_X (y - Y\Theta_0)$$

Appendix E: Aggregate and industry estimates of the investment elasticity

The linearised first-order condition for investment in the aggregate model is given by **(4)**, which can be rewritten as

$$i_t^A = \frac{1}{1+\beta}\sum_j \omega_{jt-1} i_{jt-1} + \frac{\beta}{1+\beta}\sum_j \omega_{jt+1} i_{jt+1} + \frac{1}{\kappa(1+\beta)} q_t^A \qquad \textbf{(D.1)}$$

where i_t^A denotes aggregate investment, which satisfy

$$i_t^A = \sum_j \omega_{jt} i_{jt} \qquad \textbf{(D.2)}$$

where i_{jt} is investment in industry j, and ω_{jt} is the share of investment in industry j in aggregate investment. At the industry level, investment is given by **(18)**. Aggregation of both sides of **(18)** together with **(D.2)** gives

$$i_t^A = \sum_j \omega_{jt}\left(\frac{1}{1+\beta} i_{jt-1} + \frac{\beta}{1+\beta} i_{jt+1} + \frac{\Phi_j}{1+\beta} q_{jt}\right) \qquad \textbf{(D.3)}$$

where

$$\Phi_j = \frac{\delta_j \alpha_j}{\psi_j (r+\delta_j)} \qquad \textbf{(D.4)}$$

and where, for simplicity, we have treated p_t^I as a constant. Combining this with **(D.1)** gives

$$\sum_j \omega_{jt-1} i_{jt-1} + \beta \sum_j \omega_{jt+1} i_{jt+1} + \frac{1}{\kappa} q_t^A = \sum_j \omega_{jt}\left(i_{jt-1} + \beta i_{jt+1} + \Phi_j q_{jt}\right) \qquad \textbf{(D.5)}$$

In the aggregate model the elasticity of aggregate investment with respect to aggregate Tobin's q is given by $1/\kappa$. Solving for the aggregate elasticity from the expression above gives

$$\frac{1}{\kappa} = \frac{1}{q_t^A}\left(\sum_j (\omega_{jt} - \omega_{jt-1}) i_{jt-1} + \beta \sum_j (\omega_{jt} - \omega_{jt+1}) i_{jt+1} + \sum_j \omega_{jt} \Phi_j q_{jt}\right) \qquad \textbf{(D.6)}$$

Under the assumption that the share of each industry in aggregate investment is constant over time, we get an approximate solution given by

$$\frac{1}{\kappa} = \left(\sum_j \omega_{jt} \Phi_j \frac{q_{jt}}{q_t^A}\right) \qquad \textbf{(D.7)}$$

The elasticity of aggregate investment with respect to q $(1/\kappa)$ equals a weighted average of the elasticity of industry investment with respect to industry q, times a term that captures how industry q deviates from aggregate q. In the short run, q_{jt}/q_t may not equal one in all industries, due to costs of adjustment. But in the longer run, reallocation of capital across industries means that the shadow value of capital should be equalised across industries.

Appendix F: Annual and quarterly estimates of the investment elasticity

From **(18)-(20)**, we have that the elasticity of investment with respect to the shadow value of capital equals $-\delta\alpha/\left(\psi\left(r+\delta\right)\right)$ at the annual frequency. For simplicity, assume that all other variables than i_t and q_t equal zero, and let $\xi = -\delta\alpha/\left(\psi\left(r+\delta\right)\right)$. We then have $i_t = \xi q_t$, or $dI_t/I = \xi dQ_t/Q$ where I and Q are the steady-state values of I_t and Q_t. Annual investment I_t is the sum of quarterly investment, $I_t = \sum_{k=1}^{4} I_{kt}$, where I_{kt} denotes investment in quarter k in year t. The shadow value of capital at the annual frequency is the average of the shadow values in the different quarters, $Q_t = \sum_{k=1}^{4} Q_{kt}/4$. We then have

$$\frac{d\left(\sum_{k=1}^{4} I_{kt}\right)}{I} = \xi\frac{d\left(\sum_{k=1}^{4} Q_{kt}\right)}{4Q} \qquad \textbf{(D.8)}$$

Rewriting gives

$$\sum_{k=1}^{4}\frac{dI_{kt}}{I_k}\frac{I_k}{I} = \frac{\xi}{4}\sum_{k=1}^{4}\frac{dQ_{kt}}{Q_k}\frac{Q_k}{Q} \qquad \textbf{(D.9)}$$

In steady state, we have $I_k = I/4$, $Q_k = Q$. This gives

$$\sum_{k=1}^{4}\frac{dI_{kt}}{I_k}\frac{1}{4} = \frac{\xi}{4}\sum_{k=1}^{4}\frac{dQ_{kt}}{Q_k} \qquad \textbf{(D.10)}$$

which can be rewritten as

$$\sum_{k=1}^{4} i_{kt} = \xi\sum_{k=1}^{4} q_{kt} \qquad \textbf{(D.11)}$$

That is, the elasticity of quarterly investment with respect to the quarterly shadow price of capital equals the elasticity of annual investment with respect to the shadow value of capital at the annual frequency.

Tables

Table 1: US industry classification

No.	BLS classification	SIC classification	Sector
1	Food and kindred products	20	Non-durable goods
2	Textile mills products	22	
3	Apparel & related products	23	
4	Paper & allied products	26	
5	Printing & publishing	27	
6	Chemical & allied products	28	
7	Petroleum & refining	29	
8	Rubber & plastic products	30	
9	Lumber & wood products	24	Durable goods
10	Furniture and fixture	25	
11	Stone, clay & glass	32	
12	Primary metal industries	34	
13	Fabricated metal	34	
14	Ind machinery, comp equipment	35	
15	Electric & electrical equipment	36	
16	Transportation equipment	37	
17	Instruments	38	
18	Miscellaneous manufacturing	39	

Notes: The NIPA industries Food and kindred products and tobacco products are classified as industry 1, and industries textile mill products and leather products are both classified as industry 2.

Table 2: UK industry classification

No.	Industry	Sector
1	Agriculture	NA
2	Oil and gas	
3	Coal and mining	
4	Manufactured fuels (ND)	Manufacturing
5	Chemicals and pharmaceuticals (ND)	
6	Non-metallic mineral products (D)	
7	Basic metals and metal goods (D)	
8	Mechanical engineering (D)	
9	Electrical engineering and electronics (D)	
10	Vehicles (D)	
11	Food, drink and tobacco (ND)	
12	Textiles, clothing and leather (ND)	
13	Paper, printing and publishing (ND)	
14	Other manufacturing (D)	
15	Electrical supply	Services
16	Gas supply	
17	Water supply	
18	Construction	
19	Wholesale and vehicle sales	
20	Retailing	
21	Hotels and catering	
22	Rail transport	
23	Road transport	
24	Water tranport	
25	Air tranport	
26	Other transportation	
27	Communications	
28	Finance	
29	Business services	
30	Public administration and defence	NA
31	Education	
32	Health and social work	
33	Waste treatment	
34	Miscellaneous services	Services

Notes: (D) denotes durables manufacturing. (ND) denotes non-durables manufacturing.

Table 3: Estimation results for the United States (non-linear specification)

	Parameters			J
Industry	α	ψ	λ	p-value
1.	-0.08***	0.23***	1.00***	0.86
	(0.00)	(0.01)	(0.00)	
2.	-0.45***	-0.32	0.93***	0.94
	(0.01)	(0.71)	(0.13)	
3.	-0.22***	0.98***	1.00***	0.94
	(0.00)	(0.19)	(0.00)	
4.	-0.13***	0.04	0.96***	0.85
	(0.00)	(0.04)	(0.00)	
5.	-0.09***	0.14*	1.00***	0.87
	(0.00)	(0.08)	(0.02)	
6.	-0.07***	0.06***	0.97***	0.74
	(0.00)	(0.02)	(0.00)	
7.	-0.09***	-0.08	1.00***	0.98
	(0.00)	(0.10)	(0.01)	
8.	-0.12***	0.19***	0.97***	0.95
	(0.00)	(0.03)	(0.00)	
9.	-0.22***	0.10	1.00***	0.92
	(0.01)	(0.24)	(0.07)	
10.	-0.26***	-0.12	0.92***	0.84
	(0.01)	(0.32)	(0.17)	
11.	-0.23***	0.05	1.00***	0.92
	(0.00)	(0.04)	(0.05)	
12.	-0.13***	0.27***	1.00***	0.95
	(0.00)	(0.03)	(0.00)	
13.	-0.08***	0.25***	1.00***	0.93
	(0.00)	(0.02)	(0.00)	
14.	-0.06***	0.17***	0.96***	0.83
	(0.00)	(0.01)	(0.00)	
15.	-0.09***	0.29***	0.97***	0.85
	(0.01)	(0.07)	(0.00)	
16.	-0.09***	0.26***	0.95***	0.72
	(0.00)	(0.05)	(0.00)	
17.	-0.10***	0.16***	1.00***	0.98
	(0.00)	(0.03)	(0.01)	
18.	-0.34***	0.06***	0.98***	0.84
	(0.01)	(0.29)	(0.10)	

Notes: Estimates of Euler equation **(13)**. Instruments: lags 2 to 6 of oil-shock dummies and the innovation in federal defense spending.
Standard errors in parentheses: * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 4: Estimation results for the United States (linearised specification) with weak instrument diagnostics and identification robust tests

	Parameters		J	partial-R^2				AR	K
Industry	ψ	λ	p-value	$R_p^2(s_{t+1})$	$R_p^2(ik_{t+1})$	$R_p^2(\Delta i_{t+1})$	$R_p^2(\Delta i_{t+2})$	p-value	p-value
1.	0.59***	1.00***	0.90	0.14	0.08	0.09	0.24	0.78	0.72
	(0.18)	(0.00)							
2.	2.68***	1.00***	0.96	0.07	0.26	0.21	0.15	0.30	0.25
	(0.82)	(0.00)							
3.	0.08	1.00***	0.88	0.06	0.30	0.21	0.24	0.45	0.19
	(0.22)	(0.02)							
4.	0.93***	1.00***	0.83	0.26	0.18	0.36	0.14	0.11	0.01
	(0.20)	(0.00)							
5.	0.18	1.00***	0.82	0.08	0.12	0.13	0.14	0.20	0.21
	(0.22)	(0.00)							
6.	0.40***	1.00***	0.79	0.31	0.23	0.10	0.15	0.43	0.44
	(0.15)	(0.00)							
7.	1.64***	1.00***	0.86	0.35	0.23	0.23	0.18	0.27	0.13
	(0.55)	(0.00)							
8.	-0.27	1.00***	0.84	0.05	0.09	0.15	0.13	0.58	0.75
	(0.36)	(0.02)							
9.	-0.46	1.00***	0.89	0.10	0.29	0.38	0.10	0.12	0.18
	(0.42)	(0.00)							
10.	1.92***	1.00***	0.88	0.09	0.22	0.07	0.08	0.17	0.12
	(0.39)	(0.00)							
11.	1.00***	1.00***	0.94	0.10	0.17	0.24	0.09	0.07	0.04
	(0.35)	(0.00)							
12.	2.52***	1.00***	0.96	0.15	0.13	0.11	0.10	0.04	0.00
	(0.85)	(0.00)							
13.	0.59***	1.00***	0.98	0.03	0.06	0.07	0.08	0.21	0.71
	(0.18)	(0.00)							
14.	0.50***	1.00***	0.91	0.16	0.13	0.14	0.09	0.03	0.03
	(0.15)	(0.00)							
15.	0.14**	1.00***	0.89	0.12	0.05	0.11	0.13	0.25	0.37
	(0.06)	(0.00)							
16.	0.10	1.00***	0.80	0.05	0.04	0.09	0.15	0.22	0.47
	(0.12)	(0.01)							
17.	0.50***	1.00***	0.98	0.12	0.23	0.24	0.23	0.85	0.60
	(0.12)	(0.00)							
18.	0.77	1.00***	0.94	0.06	0.24	0.19	0.19	0.05	0.06
	(0.57)	(0.00)							

Notes: Estimates of Euler equation **(17)**. Instruments: lags 2 to 6 of oil-shock dummies and the innovation in federal defense spending. Standard errors in parentheses: * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 5: Estimation results for the Untied States (non-linear specification) with λ constrained

	Investment Adjustment Costs (λ=0)			Capital Adjustment Costs (λ=1)		
	Parameters		J	Parameters		J
Industry	α	ψ	p-value	α	ψ	p-value
1.	-0.06***	0.00	0.90	-0.06***	0.01	0.90
	(0.00)	(0.00)		(0.00)	(0.10)	
2.	-0.46***	0.01***	0.93	-0.46***	3.26***	0.94
	(0.00)	(0.00)		(0.00)	(0.92)	
3.	-0.19***	0.01***	0.91	-0.20***	1.38***	0.93
	(0.00)	(0.00)		(0.00)	(0.00)	
4.	-0.12***	-0.00	0.91	-0.12***	-0.01	0.90
	(0.00)	(0.00)		(0.00)	(0.07)	
5.	-0.09***	0.001***	0.90	-0.09***	0.19**	0.90
	(0.00)	(0.00)		(0.00)	(0.09)	
6.	-0.07***	-0.001*	0.82	-0.07***	-0.08**	0.83
	(0.00)	(0.00)		(0.00)	(0.04)	
7.	-0.09***	-0.00	0.97	-0.09***	-0.04	0.97
	(0.00)	(0.00)		(0.00)	(0.10)	
8.	-0.102***	-0.00	0.88	-0.10***	-0.20***	0.89
	(0.00)	(0.00)		-(0.00)	(0.08)	
9.	-0.21***	0.00	0.97	-0.21***	0.26*	0.97
	(0.00)	(0.00)		(0.00)	(0.15)	
10.	-0.24***	-0.01***	0.82	-0.28***	-0.30	0.87
	(0.00)	(0.00)		()0.00	(0.58)	
11.	-0.22***	-0.00	0.94	-0.22***	0.10	0.94
	(0.00)	(0.00)		(0.00)	(0.19)	
12.	-0.10***	0.001***	0.92	-0.12***	0.15	0.87
	(0.00)	(0.00)		(0.00)	(0.10)	
13.	-0.06***	0.001***	0.90	-0.06***	0.37*	0.87
	(0.00)	(0.00)		(0.00)	(0.21)	
14.	-0.04***	0.001***	0.93	-0.04***	0.22***	0.93
	(0.00)	(0.00)		(0.00)	(0.09)	
15.	-0.04***	0.00	0.93	-0.04***	-0.01	0.94
	(0.00)	(0.00)		(0.00)	(0.06)	
16.	-0.07***	0.00	0.81	-0.07***	0.25***	0.91
	(0.00)	(0.00)		(0.00)	(0.03)	
17.	-0.09***	-0.00	0.90	-0.09***	-0.03	0.90
	(0.00)	(0.00)		(0.00)	(0.12)	
18.	-0.34***	-0.00	0.90	-0.34***	-0.06	0.90
	(0.00)	(0.00)		(0.00)	(0.31)	

Notes: Estimates of Euler equation **(13)**. Instruments: lags 2 to 6 of oil-shock dummies and the innovation in federal defense spending. Standard errors in parentheses: * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6: Estimation results for the United Kingdom (non-linear specification)

	Parameters			J
Sector	α	ψ	λ	p-value
Non-farm private	-0.16**	2.27	0.99**	0.82
	(0.08)	(0.70)	(0.00)	
Services	-0.21**	3.74**	1.00**	0.92
	(0.01)	(1.73)	(0.00)	
Manufacturing	-0.11**	0.98**	1.00**	0.72
	(0.00)	(0.49)	(0.00)	
Durables	-0.10**	0.84*	1.00**	0.97
	(0.01)	(0.45)	(0.01)	
Non-durables	-0.12**	1.60*	1.00**	0.93
	(0.00)	(0.99)	(0.00)	

Notes: GMM estimation of **(13)** using pooled data. Instruments: lag 2 of oil and demand variable, constant. Starting value for $\lambda = \psi = 0.5$
Standard errors in parentheses: **(*) denotes significance at the 5% (10%) level.

Table 7: Estimation results (linearised specification) with weak instrument diagnostics and identification robust tests

	Parameters		J	AR	K
Sector	ψ	λ	p-value	p-value	p-value
Non-farm private	1.81**	1.00**	0.19	0.27	0.32
	(0.79)	(0.00)			
Services	2.64*	1.00**	0.87	0.31	0.42
	(1.42)	(0.00)			
Manufacturing	0.43**	1.00**	0.01	0.07	0.12
	(0.18)	(0.00)			
Durables	0.69*	1.00**	0.02	0.10	0.14
	(0.41)	(0.00)			
Non-durables	0.30*	1.00**	0.04	0.08	0.11
	(0.16)	(0.01)			

Notes: Estimates of Euler equation **(17)**. Instruments: lags 2 to 4 of oil and demand variables. Standard errors in parentheses: **(*) denotes significant at the 5% (10%) level.

Table 8: Shea (1997) partial R^2 for UK industries

Industry	s_{t+1}	ik_{t+1}	Δi_{t+1}	Δi_{t+2}
4	0.04	0.16	0.26	0.18
5	0.06	0.04	0.02	0.07
6	0.01	0.01	0.01	0.02
7	0.01	0.00	0.13	0.00
8	0.00	0.15	0.03	0.03
9	0.00	0.01	0.03	0.05
10	0.02	0.13	0.01	0.02
11	0.04	0.04	0.27	0.17
12	0.03	0.04	0.01	0.00
13	0.00	0.19	0.00	0.07
14	0.00	0.02	0.01	0.00
15	0.00	0.02	0.02	0.06
16	0.01	0.01	0.00	0.00
17	0.13	0.08	0.07	0.00
18	0.04	0.00	0.02	0.00
19	0.04	0.02	0.03	0.04
21	0.07	0.01	0.01	0.00
22	0.02	0.13	0.04	0.00
23	0.00	0.00	0.00	0.03
24	0.06	0.10	0.10	0.08
25	0.15	0.04	0.02	0.07
26	0.04	0.00	0.00	0.00
27	0.00	0.00	0.02	0.10
28	0.03	0.02	0.08	0.00
29	0.04	0.02	0.03	0.00
34	0.04	0.16	0.15	0.13

Table 9: UK estimation results (non-linear specification) with λ constrained

	Investment Adjustment Costs (λ=0)			Capital Adjustment Costs (λ=1)		
	Parameters		J	Parameters		J
Sector	α	ψ	p-value	α	ψ	p-value
Non-farm private	-0.19**	-0.00	0.19	-0.16**	2.31*	0.66
	(0.02)	(0.01)		(0.01)	(1.31)	
Services	-0.25**	0.00	0.57	-0.21**	3.71*	0.52
	(0.02)	(0.00)		(0.01)	(1.72)	
Manufacturing	-0.11**	0.00	0.01	-0.11**	0.92*	0.31
	(0.00)	(0.00)		(0.00)	(0.00)	
Durables	-0.01**	0.01	0.08	-0.10**	0.81	0.67
	(0.00)	(0.00)		(0.01)	(0.45)	
Non-durables	-0.13**	-0.00	0.01	-0.13**	1.55*	0.53
	(0.00)	(0.00)		(0.00)	(0.88)	

Notes: GMM estimation of **(13)** using pooled data. Instruments: lag 2 of oil and demand variable, constant.
Standard errors in parentheses: **(*) denotes significance at the 5% (10%) level.

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