Investment Adjustment Costs: An Empirical Assessment*

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Abstract

We evaluate empirical evidence for costs that penalize changes in investment using US industry data. In aggregate models, such investment adjustment costs have been introduced to help account for a variety of business cycle and asset market phenomena. 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 fifteen times larger. Our results suggest that from a disaggregated empirical perspective it remains difficult to motivate and interpret the investment friction considered in recent macroeconomic models.

JEL classification: E2, E3

Key words: Investment adjustment costs, capital adjustment cost

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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 et al. (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 et al. (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 macro

[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), and the overview by Hammermesh and Pfann (1996).

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 et al. (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 US, 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 Generalized 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 18 US manufacturing industries over the period 1949 to 2000. Hall (2004) uses this data 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 CAC structures, and obtain industry-specific estimates. The point estimate of the weight on IAC turns out to be zero, or close to zero, for all industries. In other words, industry data does not support the investment adjustment cost structure and instead favours the traditional capital adjustment costs. We find instrument weakness to be pervasive, however, identification robust inference based on F and K test statistics indicate that our estimates are plausible, given the data.

When we estimate the constrained model which imposes either the IAC or the CAC structure on the data, we find similar support for the two models. The estimate of the adjustment cost parameter under IAC is, however, 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

[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 penalized by higher costs.

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.

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 organized 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 stylized facts.

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

$$K_{t+1} = (1-\delta)K_t + (1 - S(I_t, I_{t-1}, K_t))\, I_t \tag{2.1}$$

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

$$S(.) \equiv S(I_t/I_{t-1}) \tag{2.2}$$

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-linearized 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

$$S(.) \equiv S(I_t/K_t) \tag{2.3}$$

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 (2.3) have been considered extensively in the neoclassical investment literature (see, for example, Hayashi (1982), Abel and Blanchard (1983) and Shapiro (1986)).

The log-linearized first-order condition for investment under the assumption of IAC is given as (see Appendix A.1 for details)

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} \mathrm{E}_t i_{t+1} + \frac{1}{\kappa(1+\beta)} q_t \tag{2.4}$$

where small letters denote log-deviations from steady state, $\mathrm{E}_t[\cdot]$ denotes 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-linearized first-order condition given as,

$$i_t - k_t = \frac{1}{\epsilon\delta^2} q_t, \tag{2.5}$$

where $\epsilon\delta^2$ is the elasticity of investment with respect to the shadow value of capital (or, Tobin's Q).

2.1 Monetary and fiscal shocks

A large body of literature has documented that identified monetary shocks in the US have persistent hump-shaped effects on output, consumption, and investment.[4]

[4]See, for example, Christiano et al. (1999) and references therein.

Christiano et al. (2005) find that a dynamic general equilibrium model with IAC in (2.2) matches the strong, hump-shaped response of investment to a monetary policy shock in the US data. By contrast, CAC in (2.3) 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 reduce output on impact. This countercyclical response occurs because of a sharp increase in equilibrium markup 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 co-movement 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 modeling approaches. Jaimovich and Rebelo (2006), however, propose a model in which IAC is one of the key elements. This model can generate a positive co-movement between consumption and investment in response to news shocks.[5]

2.3 Asset returns and business fluctuations

As discussed in Rouwenhorst (1995), the framework of 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 stylized facts on asset returns and business cycles. Boldrin et al. (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) considers IAC in a one sector model. They find that the model successfully matches key business cycle stylized facts in US (co-movement and volatilities of output, consumption, investment, and hours) and asset returns (generates highly volatile return on equity 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 markets 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,

$$Y_t = F\left(L_t, M_t, K_t, I_t, \Delta I_t\right) \tag{3.1}$$

where L_t denotes labour input, M_t material inputs, K_t capital, I_t investment, and ΔI_t 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.[6] IAC imply that the change in investment has a similar impact on output. The production

[5] Jaimovich and Rebelo (2006) also consider replacing IAC with adjustment costs to capital utilization. This model, however, requires a high elasticity of labour supply to generate a co-movement in consumption and investment following a news shock.

[6] Instead of producing marketable output, firms need to use resources to, for example, train labour, reorganize work, and install new equipment. This is the standard modeling approach in the investment

technology can also be represented from the dual cost side; conditional on the level of output and capital, and for a given flow of current and lagged investment, the minimum of the variable cost, C_t, is given by

$$C_t = C\left(W_t, P_t^m, Y_t, K_t, I_t, \Delta I_t\right) \tag{3.2}$$

where W_t is the price of labour and P_t^m the price of material inputs, both taken as given by the individual industry. A well-behaved variable cost function is non-decreasing in W_t, P_t^m and Y_t, and non-increasing in K_t. For the firm's investment decision to be well-defined, C_t also has to be nondecreasing in I_t and ΔI_t.

The optimal path for capital is chosen by minimizing 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

$$\frac{\partial C_t}{\partial I_t} + P_t^I - Q_t + \frac{1}{1+r_t}\mathrm{E}_t\left[\frac{\partial C_{t+1}}{\partial I_t}\right] = 0 \tag{3.3}$$

$$(1+r_t)Q_t + \mathrm{E}_t\left[\frac{\partial C_{t+1}}{\partial K_{t+1}} - (1-\delta)Q_{t+1}\right] = 0 \tag{3.4}$$

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,

$$\mathrm{E}_t\left[P_t^K + (1+r_t)\frac{\partial C_t}{\partial I_t} + \frac{\partial C_{t+1}}{\partial K_{t+1}} + \frac{\partial C_{t+1}}{\partial I_t} - (1-\delta)\left(\frac{\partial C_{t+1}}{\partial I_{t+1}} + \frac{1}{1+r_{t+1}}\frac{\partial C_{t+2}}{\partial I_{t+1}}\right)\right] = 0 \tag{3.5}$$

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

To estimate the model, we need to specify a functional form for variable costs. Let C_t^v denote the variable cost function net of adjustment costs, and let C_t^a denote the adjustment cost function. We specify the variable cost function as

$$\log C_t = \log C_t^v + \frac{\psi}{2}C_t^a, \tag{3.6}$$

literature. An alternative way to model adjustment costs would be to incorporate them into the capital accumulation identity (as in the aggregate model discussed in section 2).

where ψ is the adjustment cost parameter.[7] 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 consider an adjustment cost function of the form:

$$C_t^a = \lambda \left(\frac{I_t}{K_t} - \delta \right)^2 + (1 - \lambda) \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \tag{3.7}$$

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 (3.5)-(3.7), we get the Euler condition

$$\mathrm{E}_t \left[P_t^K + \alpha \frac{C_{t+1}}{K_{t+1}} + \psi \Gamma_t \right] = 0, \tag{3.8}$$

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 by

$$\Gamma_t = (1 + r_t) C_t f_t - C_{t+1} [g_{t+1} + (1 - \delta) f_{t+1}] + \frac{(1 - \lambda)(1 - \delta) C_{t+2}}{1 + r_{t+1}} \frac{\Delta I_{t+2}}{I_{t+1}} \frac{I_{t+2}}{I_{t+1}^2} \tag{3.9}$$

where f_t and g_t are given by

$$f_t = \lambda \frac{\Delta K_{t+1}}{K_t^2} + (1 - \lambda) \frac{\Delta I_t}{I_{t-1}^2}, \tag{3.10}$$

$$g_t = \lambda \frac{\Delta K_{t+1} I_t}{K_t^3} + (1 - \lambda) \frac{\Delta I_t I_t}{I_{t-1}^3}, \tag{3.11}$$

with $\Delta K_{t+1} = K_{t+1} - K_t$, $\Delta I_t = I_t - I_{t-1}$. Given the first-order approximation of the cost function, the marginal product of capital equals $-\alpha C_t / K_t$, where $\alpha < 0$. Equation (3.8) thus states that,

[7] This specification is common in the adjustment cost literature (see, for example, Shapiro (1986)). Alternatively, one could approximate (3.2) to the second order to provide a fully microfounded approximation of the cost function, as in Morrison (1988). For identification, we have chosen to follow the simpler approach.

[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).

[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 the Appendix A.2). The results from this specification were qualitatively similar to those presented in section 4.

in a long-run equilibrium, the user cost of capital equals the marginal product of capital. 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-linearized specification

We log-linearize the first-order condition for investment (3.3) around steady state and rearrange to get

$$q_t = p_t^I - \frac{\psi\,(r+\delta)}{\alpha}\left[\lambda\delta\,(i_t - k_t) + \frac{1-\lambda}{\delta}\Delta i_t - \frac{\beta\,(1-\lambda)}{\delta}\mathrm{E}_t\Delta i_{t+1}\right] \tag{3.12}$$

where $\beta = (1+r)^{-1}$, $\Delta i_t = i_t - i_{t-1}$. At the optimal level of investment spending, the shadow value of capital, q_t, must equal the full cost of acquiring (p_t^I) and installing one unit of capital good. The installation cost consists of the CAC as well as the IAC (the first and the second terms in the bracket), plus the marginal contribution to future IAC.

We can log-linearize (3.4) to get an expression that relates the shadow price of capital, q_t, to the marginal product of capital, and future adjustment costs. By combining the expression for q_t with (3.12), we get

$$p_t^K = \mathrm{E}_t\left[c_{t+1} - k_{t+1} + \frac{\psi}{\alpha}\gamma_t\right] \tag{3.13}$$

where

$$\gamma_t = \frac{1}{\beta}\left[\lambda\delta\,(i_t - k_t) + \frac{1-\lambda}{\delta}\Delta i_t\right] - \lambda\delta\,(i_{t+1} - k_{t+1}) - \frac{1-\lambda}{\delta}\left(\gamma_1\Delta i_{t+1} - \gamma_2\Delta i_{t+2}\right) \tag{3.14}$$

Equation (3.13) states that, at the optimal level of capital, the user cost of capital (p_t^k) equals the marginal product of capital ($c_{t+1} - k_{t+1}$), plus the marginal adjustment cost. It is convenient to rewrite (3.13)-(3.14) as

$$E_t\left[\lambda\delta\,(i_t - k_t) + \frac{1-\lambda}{\delta}\Delta i_t - \frac{\beta\alpha}{\psi}s_{t+1} - \beta\lambda\delta\,(i_{t+1} - k_{t+1}) - \frac{\beta(1-\lambda)}{\delta}\left(\gamma_1\Delta i_{t+1} - \gamma_2\Delta i_{t+2}\right)\right] = 0 \tag{3.15}$$

where $s_{t+1} = c_{t+1} - k_{t+1} - p_t^K$, $\gamma_1 = 1 + (1-\delta)$, $\gamma_2 = \beta\,(1-\delta)$. 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. The adjustment cost parameter ψ will govern the speed at which capital adjusts to its long-run equilibrium. When ψ is 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 (3.15) forward to get

$$i_t - k_t = -\frac{\beta\alpha}{\psi\delta}\mathrm{E}_t\left[\sum_{\tau=0}^{\infty}\beta^{\tau}s_{t+1+\tau}\right]. \tag{3.16}$$

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, 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

$$\Delta i_t = \beta\mathrm{E}_t\left[\frac{-\delta\alpha}{\psi}s_{t+1} + \gamma_1\Delta i_{t+1} - \gamma_2\Delta i_{t+2}\right], \tag{3.17}$$

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

$$\Delta i_t = -\frac{\beta\delta\alpha}{\psi}\mathrm{E}_t\left[\sum_{\gamma=0}^{\infty}(1-\delta)^{\gamma}\beta^{\gamma}\sum_{\tau=0}^{\infty}\beta^{\tau}s_{t+1+\tau+\gamma}\right]. \tag{3.18}$$

Equation (3.16) and (3.18) show that the two cost structures give different predictions about movements in the model variables over the business cycle. The CAC imply that the investment-to-capital ratio should lead variable s_t, in the sense that a rise (decline) in the current investment 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 turned out to be inconclusive. We, therefore, take the direct approach of estimating the parameters using the nested specification of the cost structure in (3.7).

3.3 GMM estimation

We estimate the non-linear, (3.8), and the log-linearized, (3.15), specifications, using Generalized 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. 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.

To avoid weak identification, the instruments also need to be adequately correlated with the model variables, as discussed by Stock et al. (2002). Ideally, the instrument set should be strong for all the expected variables in (3.8) and (3.15) (that is, variable s_{t+1}, $ik_{t+1} = i_{t+1} - k_{t+1}$, Δi_{t+1}, and Δi_{t+2} in (3.15)). 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 partial (adjusted) R^2 statistics for each of variables needing instruments. The partial R^2 statistics indicates the explanatory power of the instrument set for each variable once the instruments are orthogonalized to account for their contribution in explaining the remaining variables (to be instrumented).[11]

[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 (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 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 et al. (1995), Burnside (1996), and Fuhrer and Rudebusch (2003).

One advantage with the log-linearized specification is that this model permits a relatively straightforward computation of instrument relevance and identification robust statistics (discussed 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. The key parameters of interest are the adjustment cost parameter ψ and the weight parameter, λ, which we estimate. 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 to the interest rate r to calibrate β.

3.4 The data

We use the dataset 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 and their corresponding SIC codes.

4 Estimation results

We first conduct industry-specific estimation using the non-linear (3.8) and the linearized (3.15) model, respectively. The section also discusses the issue of instrument relevance and provide tests that are robust to weak instruments and excluded instruments.

4.1 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. Table 2 presents the estimates of the non-linear specification (3.8).[12] 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 percent 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 esti-

[12] 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. We use the Newey-West optimal weighting matrix with 8 lags.

mated weight parameter λ. It ranges between 0.92 and 1.0, and is statistically significant at the one percent 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. 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 not reject the joint null hypotheses of correct model specification and that instrument satisfy the orthogonality condition.

Next, we estimate the log-linearized specification (3.15) for each industry (Table 3).[13] The second and third column of Table 3 present the estimates of the adjustment cost parameter ψ and the weight parameter λ. The adjustment cost parameter is positive and statistically significant in twelve 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 over-identifying restrictions, for any of the industries.[14]

4.2 Instrument relevance and identification robust inference

We conduct a diagnostic check to examine the potential issue of instrument weakness, using the Shea (1997) partial R^2 statistic, which we carry out for the linearised model.[15]

Column 5 to 8 in Table 3 show the partial R^2 statistics for each of the instrumented variables (ik_{t+1}, s_{t+1}, Δi_{t+1}, Δi_{t+2}). No distribution theory is available for this 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 are consistent with those of Burnside (1996) who estimated production function regressions using two-digit US industry data, and with

[13]Figures 1 to 6 presents data on the variables s_t, $i_t - k_t$, and Δi_t and their various transformations. The variable s_t, in particular, 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.

[14]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.

[15]The set of endogenous variables in (3.15) to be instrumented is $X = \{ik_{t+1} \;\; s_{t+1} \;\; \Delta i_{t+1} \;\; \Delta i_{t+2}\}$. Let Z be the matrix of instruments. $R_p^2(X_i)$ in Table 3 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 orthogonalized relative to their contributions to explaining X_i.

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 (eg the J statistics, reported in Table 2 and 3) 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 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 instrument 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.[16]

Given the estimated values of the adjustment cost parameter $\hat{\psi}$ and weight parameter $\hat{\lambda}$ in Table 3, 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. Under the null, the K statistic follows a $\chi^2(m)$ where m is the number of elements of θ_0.[17] We report the p-values associated with these statistics in Table 3 (columns 9 and 10). In thirteen 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 percent level. That is, the estimates are plausible, given the data. For one industry (number 4), the result is inconclusive. The AR statistic does not reject the model but the K-statistic does. For the remainig four industries (11, 12, 14, and 18), however, the model is rejected by the AR and/or the K statistics.

[16] For recent applications of these statistics in empirical work see, for example, Dufour et al. (2006) and Yazgan and Yilmazkuday (2005).

[17] To compute the AR and K statistics we follow Kleibergen (2002). Formal expressions for the statistics are given in the Appendix A.3. A RATS program to compute them is available upon request.

4.3 IAC and CAC structures

We estimate the constrained models with either IAC ($\lambda = 0$) or CAC ($\lambda = 1$), using the non-linear model (3.8). This exercise provides an estimate of the adjustment cost parameter based on a particular assumption regarding the underlying cost structure. As shown in Table 4, under both the IAC (column 2-4) and the CAC (column 5-7) constraint, the adjustment cost parameter, ψ, is positive and significant in one-third of the industries. The estimates under IAC, however, are substantially smaller relative to those under CAC.[18]

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. The constrained model, which imposes either the IAC or the CAC structure on the data, gives similar support for the two cases; the estimated adjustment cost parameter is positive and significant in one third of the industries, but it is substantially smaller under IAC relative to the CAC case. Given the importance of IAC for aggregate models, how do the industry estimates of the adjustment cost parameter compare with the aggregate estimates in the recent literature? To answer this question we compute the elasticity of investment with respect to the shadow price of capital implied by the industry estimates. We consider the *largest* estimate of ψ obtained under the constraint $\lambda = 0$ using the non-linearised model (column 3, Table 4). To get an implied estimate of the corresponding adjustment cost parameter in the aggregate model, we rewrite (3.12) under the assumption of IAC as

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} E_t i_{t+1} - \frac{\delta\alpha}{\psi\,(r+\delta)\,(1+\beta)} \left(q_t - p_t^I\right). \tag{5.1}$$

We can solve this equation forward to get

$$i_t = i_{t-1} - \frac{\delta\alpha}{\psi\,(r+\delta)} \sum_{\tau=0}^{\infty} \beta^{\tau} \left(q_{t+\tau} - p_{t+\tau}^I\right) \tag{5.2}$$

This gives an expression for the elasticity of investment with respect to the current shadow price of capital,

$$\frac{\partial i_t}{\partial q_t} = -\frac{\delta\alpha}{\psi\,(r+\delta)} \tag{5.3}$$

[18]The estimation results from the linearized specification with λ constrained reveal similar results on the magnitude of the estimates.

In the aggregate model (2.4), the corresponding elasticity is given by κ^{-1}. We therefore have

$$\frac{1}{\kappa} = -\frac{\delta\alpha}{\psi\,(r+\delta)}. \tag{5.4}$$

Based on the sample averages of the parameters and the estimates of ψ reported in Table 4, 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). Our industry-results thus imply a much smaller cost for adjusting investment than the aggregate estimates which help account for the different stylized facts discussed in section 2.

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 industry data to estimate the capital Euler condition via GMM.

When both investment and capital adjustment costs structures are considered, the industry-specific data appears 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.

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A Appendix

A.1 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 minimizes 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 the capital stock K_t, which they rent to firms at rental rate R_t^k. The stock of 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 stock K_{t+1}, and investment I_t to maximize (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:

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

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

$$H_t^{\phi} C_t^{\sigma} = \frac{W_t}{P_t}, \tag{A.8}$$

$$Q_t = \frac{\lambda_{2t}}{\lambda_{1t}}, \tag{A.9}$$

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} as of time t. The capital and investment first-order conditions are, under the assumption of IAC, given by

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

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

After log-linearizing (A.11) around a non-stochastic steady state, we get (2.4). Under CAC, we instead obtain

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

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

After log-linearizing (A.13) around a non-stochastic steady state, we get (2.5).

A.2 An alternative adjustment cost specification

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

$$C_t^a = \left(\frac{I_t}{K_t} - \delta \right)^2 K_t + \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 I_{t-1}. \tag{A.14}$$

Under this cost structure, the log-linearized equation (3.15) is replaced by

$$E_t \left[\lambda\delta \left(i_t - k_t \right) + (1-\lambda) \Delta i_t - \beta \frac{\alpha}{K\tilde{\psi}} s_{t+1} - \beta\lambda\delta \left(i_{t+1} - k_{t+1} \right) - \beta \left(1-\lambda \right) \left(\gamma_1 \Delta i_{t+1} - \gamma_2 \Delta i_{t+2} \right) \right] = 0 \tag{A.15}$$

where $\gamma_1 = 1 + (1-\delta)$, $\gamma_2 = \beta(1-\delta)$. The difference, compared to (3.15), is the presence of the steady state value of the capital stock, K. The mapping between the industry and the aggregate elasticity is modified as

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

A.3 AR and K statistics

Following Kleibergen (2002), we can represent (3.15) as a limited information simultaneous equation model

$$y = Y\Theta + \epsilon \tag{A.16}$$

$$Y = X\Pi + V \tag{A.17}$$

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 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 5x1, 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

$$AR(\Theta_0) = \frac{\frac{1}{k}(y - Y\Theta_0)'P_X(y - Y\Theta_0)}{\frac{1}{T-k}(y - Y\Theta_0)'M_X(y - Y\Theta_0)} \sim F(k, T-k) \tag{A.18}$$

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

The K-statistic is

$$K(\Theta_0) = \frac{(y - Y\Theta_0)'P_{\tilde{Y}(\Theta_0)}(y - Y\Theta_0)}{\frac{1}{T-k}(y - Y\Theta_0)'M_X(y - Y\Theta_0)} \sim \chi^2(m) \tag{A.19}$$

where

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

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

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

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

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

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	Miscelenous 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: Estimation Results (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 (3.8). Instruments: lags 2 to 6 of oil-shock dummies and the innovation in federal defense spending. Standard errors in parenthesis * significant at 10-percent; ** significant at 5-percent; *** significant at 1-percent.

Table 3: Estimation Results (Linearized 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 (3.13). Instruments: lags 2 to 6 of oil-shock dummies and the innovation in federal defense spending. Standard errors in parenthesis: * significant at 10-percent; ** significant at 5-percent; *** significant at 1-percent.

Table 4: Estimation Results (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 (3.8). Instruments: lags 2 to 6 of oil-shock dummies and the innovation in federal defense spending. Standard errors in parenthesis: * significant at 10-percent; ** significant at 5-percent; *** significant at 1-percent.