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Investment Adjustment Costs: An Empirical Assessment

We evaluate the empirical evidence for costs that penalize changes in investment using U.S. 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. So far no attempt has been made to estimate these costs directly at a disaggregated level. We consider an industry model with investment adjustment costs and estimate its parameters using generalized methods of moments. The findings indicate small costs associated with changing the flow of investment at the industry level. The weighted average of the industry elasticities with respect to the shadow price of capital, which depends inversely on the adjustment cost parameter, is eight times larger than the largest estimate reported in Levin et al. (2006). We examine a variety of factors that may account for this discrepancy, but a substantial part of it remains unexplained. Our results therefore suggest that more caution is needed when giving policy advice that hinges on a structural interpretation of large investment adjustment costs.

JEL codes: E2, E3
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FOLLOWING CHRISTIANO ET AL. (2005), costs to changing the level of investment—*investment adjustment costs*—have featured prominently in the recent literature on aggregate dynamic general equilibrium models to help account for a variety of macroeconomic phenomenon. In this paper, we attempt to estimate these

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costs directly using a disaggregated approach. This has not been done previously, as existing estimates have been based solely on aggregate data.

More specifically, we conduct an empirical assessment of investment adjustment costs in 18 U.S. manufacturing industries over the period 1949–2000 by deriving an investment Euler equation for the representative industry, and estimate it using the generalized method of moments (GMM). Based on the estimated values of the parameters in the Euler equation, we compute industry-specific adjustment cost parameters and derive the implied elasticity of investment with respect to the shadow value of capital. The main finding is that estimates of investment adjustment costs are small, implying that industry investment is relatively responsive to movements in the shadow value of capital.

Turning to the more detailed results, the estimates of the investment adjustment costs parameter in 16 of the 18 manufacturing industries are positive but small, with the implied investment elasticities ranging between 1.1 and 37.7, with a weighted average of 15.2. This suggests that investment is sensitive to the current shadow value of capital in U.S. manufacturing industries, which contrasts with the results obtained at the aggregate level. In particular, the average industry elasticity is eight times larger than the highest estimate based on U.S. aggregate data as reported in Levin et al. (2006). We discuss several possibilities for why industry estimates of investment adjustment costs might be smaller compared to those reported in aggregate studies and explore in more detail identification issues, the role of internal versus external adjustments costs, data frequency, and the possibility that manufacturing industries may not be representative of the whole economy. None of these factors appear to account for the difference. The unexplained difference therefore suggests that persistence in investment at the aggregate level may reflect an aggregation bias. We explore this by conducting a pooled estimation, which generates an investment elasticity of around half of the weighted industry average. The pooled estimate is also significantly different from the unconstrained industry estimate for all of the industries. This suggests that an aggregation bias may explain part of the discrepancy between aggregate and industry estimates. Although this possibility reduces the size of the puzzle, there is still a substantial difference between industry and aggregate estimates, with the pooled elasticity estimate about four times as large as the largest estimate reported in Levin et al. (2006). Our findings therefore suggest that more caution is needed when giving policy advice, based on aggregate models, that hinges on a structural interpretation of large investment adjustment costs.

As mentioned above, the focus on investment adjustment costs in this paper stems from their widespread use in aggregate models. By inducing inertia in investment, which slows down its response to shocks, the presence of investment adjustment costs significantly improves the quantitative performance of these models along a number of dimensions. As was shown by Christiano et al. (2005), the presence of such costs means that a sticky-price model can generate hump-shaped investment dynamics consistent with the estimated response of investment to a monetary policy shock. Moreover, when investment adjustment costs are included, 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 (2009) show that news shocks, as discussed in Beaudry and Portier (2006), can drive business cycles; and 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 costs*—do not perform well along these dimensions. But in contrast to the large empirical literature on capital adjustment costs, which often takes a disaggregated approach, no attempt has so far been made to estimate investment adjustment costs at a disaggregated level.[1]

There is, however, a growing literature that attempts to provide a theoretical basis for investment adjustment costs. Basu and Kimball (2005) present a 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 costs. Their findings suggest that investment adjustment costs 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) and explicitly modeled by Gertler and Gilchrist (2000) and Casares (2006), by considering time-to-plan and time-to-build constraints. More recently, Lucca (2007) also considers a variant of the time-to-build model that generates dynamics similar to investment adjustment costs models. While these interpretations are appealing, by pursuing an empirical strategy of estimating investment adjustment costs at the industry level we are able to provide direct evidence on the magnitude of such costs.

The paper is organized as follows. Section 1 briefly highlights the role of investment adjustment costs in aggregate models. Section 2 turns to the industry analysis. It presents a simple model of industry investment with investment adjustment costs and discusses the data and estimation methodology. Section 3 presents the empirical results. Section 4 compares the industry estimates with existing aggregate estimates. Section 5 conducts robustness analysis. Section 6 concludes.

1. INVESTMENT ADJUSTMENT COSTS IN AGGREGATE MODELS

In this section, we illustrate how the presence of investment adjustment costs affects investment dynamics in aggregate models, considering the formulation proposed by Christiano et al. (2005). The representative household makes consumption, labor supply, and capital accumulation decisions. The stock of capital is accumulated according to

1. For disaggregated capital adjustment cost estimates, see, for example, recent work by Cooper and Haltiwanger (2006) and the overviews by Hammermesh and Pfann (1996) and Chirinko (1993). More recently, Khan and Thomas (2008) study the consequences of nonconvex capital adjustment costs for aggregate investment dynamics, and Hall (2004) finds evidence for small capital adjustment costs.

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

where K_t denotes capital, I_t is investment, δ is the depreciation rate, and $S(.)$ is the adjustment cost function, which is an increasing function of I_t/I_{t-1}, satisfying the properties $S(1) = S'(1) = 0$ and $S''(1) \equiv \kappa^A > 0$. 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 of investment and capital around the steady state are therefore influenced only by the curvature of the adjustment cost function, κ^A.

The log-linearized first-order condition for investment in this model can be expressed as

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} E_t i_{t+1} + \frac{1}{\kappa^A(1+\beta)} q_t, \tag{2}$$

where small letters denote log-deviations from steady state, $E_t[\cdot]$ 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 is 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 elasticity of investment with respect to a temporary increase in the current shadow value of installed capital is inversely related to the adjustment costs parameter and given by $\zeta^A \equiv 1/\kappa^A$ (this is formally shown in Section 4).

2. INDUSTRY ANALYSIS

We next turn to the main contribution of this paper. Specifically, we conduct an industry analysis to investigate if there is empirical support for the investment adjustment costs structure often assumed in aggregate models.

2.1 The Model

We assume that the representative industry, n, is characterized by the variable cost function, C_t (where industry subscript has been suppressed for convenience) given as

$$C_t = C\left(W_t, P_t^m; Y_t, K_t, I_t, \Delta I_t\right), \tag{3}$$

where W_t and P_t^m are the prices of labor and material inputs, both taken as given by the individual industry and that evolve stochastically over time, Y_t is gross output, K_t is capital, I_t is investment at time t, and $\Delta I_t = I_t/I_{t-1}$ is a measure of the change in investment between periods t and $t-1$.[2] The assumption is that for given levels of output and capital, the representative industry needs to use resources to undertake activities that make changing the flow of investment costly. Thus, the cost of output lost when investment is varied is internal to the production process. As an extension, we also consider external investment adjustment costs in Section 5.1.

The optimal paths for investment and capital are chosen by minimizing the expected discounted value of future total costs (variable costs plus cost of new capital), subject to the capital accumulation identity, $K_{t+1} = (1-\delta)K_t + I_t$.[3] Specifically, at any date τ, the representative industry seeks to minimize

$$E_\tau \left[\sum_{t=\tau}^{\infty} \frac{1}{1+R_{\tau,t}} \left(C_t + P_t^I I_t - Q_t \left(K_{t+1} - (1-\delta)K_t - I_t \right) \right) \right], \tag{4}$$

where $(1+R_{\tau,t})^{-1}$ is the relevant discount factor between periods τ and $\tau + t$ (for simplicity, $R_{t,t+1}$ will be denoted by R_t below), P_t^I is the price of investment, and Q_t is the shadow value of capital installed in period t. The first-order conditions for investment and capital are given by

$$I_t: \qquad P_t^I + \frac{\partial C_t}{\partial I_t} + \frac{1}{1+R_t} E_t \left[\frac{\partial C_{t+1}}{\partial I_t} \right] = Q_t, \tag{5}$$

$$K_t: \qquad \frac{1}{1+R_t} E_t \left[-\frac{\partial C_{t+1}}{\partial K_{t+1}} + (1-\delta) Q_{t+1} \right] = Q_t. \tag{6}$$

Combining these two equations gives the Euler condition,

$$\begin{aligned} E_t \Bigg[& P_t^K + (1+R_t) \frac{\partial C_t}{\partial I_t} + \frac{\partial C_{t+1}}{\partial K_{t+1}} + \frac{\partial C_{t+1}}{\partial I_t} \\ & - (1-\delta) \left(\frac{\partial C_{t+1}}{\partial I_{t+1}} + \frac{1}{1+R_{t+1}} \frac{\partial C_{t+2}}{\partial I_{t+1}} \right) \Bigg] = 0, \end{aligned} \tag{7}$$

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

2. The cost function is nondecreasing and concave in the two prices and decreasing and convex in K_t. In addition, in the presence of investment adjustment costs, it is nondecreasing and convex in I_t and ΔI_t. These curvature conditions for the variable cost function are standard in the investment literature and are also satisfied when investment adjustment costs are present.

3. We consider the cost function approach since, contrary to a production function approach, it allows us to derive the optimal paths for capital and investment without having to impose restrictions on the industry demand and market structure.

2.2 *Econometric Specification*

We assume that the variable cost function (3) satisfies

$$\log C_t = \log C_t^v + C_t^a, \tag{8}$$

where C_t^v denotes the variable cost function net of adjustment costs and C_t^a is the adjustment costs function. We use a first-order approximation for C_t^v that implies that the elasticity of C_t^v with respect to capital, denoted by $\alpha < 0$, is constant. We choose the first-order approximation of the variable cost function instead of a general second-order approximation because of the lack of suitable instruments to identify all the parameters in the latter specification. We do, however, allow for potential misspecification of the variable cost function when estimating the model, as is further discussed in Section 2.4.

We consider a functional form for C_t^a similar to the one proposed by Christiano et al. (2005). This specification for investment adjustment costs is homogeneous of degree one, and given as

$$C_t^a = S\,(I_t/I_{t-1})\,I_{t-1}, \tag{9}$$

where the function S is assumed to satisfy the properties $S(1) = S'(1) = 0$ and $S'(1) \equiv \kappa > 0$ with κ denoting the adjustment cost parameter. As discussed in Christiano et al. (2005), the advantage of (9) is that we do not have to specify the precise functional form for S and that only κ matters for the log-linearized dynamics of the model that we consider below.

Log-linearized specification. Using (8) and (9), we log-linearize (7) around steady state to get a second-order investment Euler equation

$$\begin{aligned} i_t = {} & \frac{-\alpha\beta}{\kappa(1+\beta+(1-\delta)\beta)K} E_t s_{t+1} + \frac{1}{1+\beta+\beta(1-\delta)} i_{t-1} \\ & + \frac{\beta\,(1+(1+\beta)(1-\delta))}{1+\beta+(1-\delta)\beta} E_t i_{t+1} - \frac{\beta^2(1-\delta)}{1+\beta+(1-\delta)\beta} E_t i_{t+2}, \qquad \alpha < 0 \end{aligned} \tag{10}$$

where $s_{t+1} = c_{t+1} - k_{t+1} - p_t^K$ is the difference between the marginal product of capital and its user cost.[4] Current investment depends positively on s_{t+1}, given past investment and expectations about future investment. When κ is large, current investment becomes less sensitive to s_{t+1}.

We can write (10) compactly as

$$i_t = \theta_0 E_t s_{t+1} + \theta_1 i_{t-1} + \theta_2 E_t i_{t+1} - \theta_3 E_t i_{t+2}, \tag{11}$$

4. A detailed derivation is available online at: http://http-server.carleton.ca/hashkhan/Research/research.html.

TABLE 1

Industry Classification

No.	BLS classification	SIC classification & sector	
1	Food & kindred products	20	Nondurable 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 & 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 are food & kindred products and tobacco. Products are classified as industry 1, and industries textile mill products and leather products are both classified as industry 2.

where θ_0, θ_1, θ_2, and θ_3 are the reduced-form coefficients representing the coefficients of the corresponding variables in (10), which are all positive. Equation (11) is the main empirical specification of the industry model that we estimate. The key parameter of interest is θ_0 as it embeds the adjustment cost parameter κ.

2.3 Data

We employ 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). Table 1 gives the industry classifications and their corresponding SIC codes. The variable cost for industry n (denoted by $C_{n,t}$) is measured as the total wage bill plus the cost of intermediate inputs (nominal spending on energy and materials). The nominal and real values of the capital stock ($K_{n,t}$) are taken from the NIPA accounts (current-value and quantity index of capital). The real depreciation rate ($\delta_{n,t}$) is calculated as nominal spending on depreciation on fixed assets (from NIPA) divided by the nominal capital stock. Investment ($I_{n,t}$) is obtained by using the capital accumulation identity, given data on the values of capital and the depreciation rate. The price of investment ($P^{\mathrm{I}}_{n,t}$) is the price implicit in the NIPA accounts, given the current-value and the quantity index of capital. We follow Hall (2004) and calculate the rental price of capital ($P^{\mathrm{K}}_{n,t}$) as

$$P^{\mathrm{K}}_{n,t} = \frac{(1 - \tau_t \mathrm{PDA}_t - \mathrm{ITC}_t)}{1 - \tau_t}(r + \delta_{n,t})P^{\mathrm{I}}_{n,t},$$

which adjusts a standard measure of the user cost of capital ($(r + \delta_{n,t})P^{\mathrm{I}}_{n,t}$) for corporate marginal tax rate (τ_t), the present value of depreciation allowances (PDA_t), and investment tax credits (ITC_t). The after-tax financial cost of capital, r, is taken as 5%.

2.4 *Estimation Methodology*

We estimate (11) using the GMM. We replace the conditional expectations in (11) with the realized values of the model variables and introduce an expectation error, defined as $\varepsilon_{t+2} = i_t - \theta_0 s_{t+1} - \theta_1 i_{t-1} - \theta_2 i_{t+1} + \theta_3 i_{t+2}$. The error term ε_{t+2} is uncorrelated with any information known at the decision date under the assumption of rational expectations. Given this identifying assumption, any period t variable could be used as an instrument to form the moment conditions used to estimate the model parameters.

Under a more general representation that 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 an evidence, however, that this may not be an appropriate identifying assumption.[5] 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 that 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 (lags $t-2$ to $t-6$) and we exclude the first lag of variables from the instrument set.

Denoting the instrument set containing variables dated $t-2$ and earlier as Z_t and the parameter vector as $\theta = [\theta_0, \quad \theta_1, \quad \theta_2, \quad \theta_3]$, we can define the unconditional moment condition as

$$E\left[\varepsilon_{t+2}(\theta) Z_t\right] = 0. \tag{12}$$

We use the iterative GMM estimator and compute the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) estimator of the optimal weight matrix using four lags.[6] We conduct the estimation using detrended data

5. 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).

6. The overidentifying restrictions test statistic, J, is distributed χ^2 with six degrees of freedom.

TABLE 2

INSTRUMENT DIAGNOSTICS

Industry (n)	Partial R^2		
	$E_t s_{t+1}$	$E_t i_{t+1}$	$E_t i_{t+2}$
1	0.36	0.51	0.53
2	0.24	0.18	0.26
3	0.41	0.48	0.61
4	0.25	0.53	0.26
5	0.37	0.43	0.47
6	0.50	0.37	0.48
7	0.55	0.40	0.42
8	0.26	0.39	0.44
9	0.25	0.43	0.38
10	0.39	0.32	0.41
11	0.23	0.47	0.27
12	0.42	0.46	0.37
13	0.18	0.28	0.38
14	0.25	0.38	0.22
15	0.28	0.44	0.43
16	0.27	0.55	0.52
17	0.32	0.41	0.39
18	0.34	0.58	0.49

NOTES: The table shows explanatory power of the instrument set for a given variable. Instruments: lags 2–6 of oil-shock dummies and the innovation in federal defense spending.

using the Hodrick–Prescott (HP) filter with a smoothing parameter of 6.25 for annual data, as recommended by Ravn and Uhlig (2002).

2.5 Instrument Relevance and Identification Robust Inference

To avoid weak identification, the instruments also need to be adequately correlated with the model variables. Ideally, the instrument set should be strong for all expected model variables (s_{t+1}, i_{t+1}, and i_{t+2} in (11)). Since we have multiple endogenous regressors, the conventional first-stage F-statistic used for testing for weak instruments may not provide adequate information. To assess instrument weakness, we instead compute Shea's 1997 partial (adjusted) R^2 statistics for each of the variables that needs to be instrumented. This statistic indicates the explanatory power of the instrument set for each variable once the instruments have been orthogonalized to account for their contribution in explaining the remaining variables to be instrumented.[7] Table 2 presents the partial correlations between the instrument set and the instrumented variables, ranging from 0.18 to 0.58. This range is consistent with the findings of Burnside (1996), who estimates production function regressions using two-digit U.S. industry data, and with Shea (1997), and suggests that instruments are weak for at least a subset of the industries. As Fuhrer and Rudebusch (2004) note, however, in the absence of a distribution theory for this statistic, it is unclear what the critical

7. The partial R^2 has been considered in several studies with GMM estimation (see, e.g., Fuhrer, Moore, and Schuh 1995, Burnside 1996, Fuhrer and Rudebusch 2004).

correlation level is to avoid the problem of instrument relevance. Moreover, instead of pretesting for instrument relevance, simulation evidence favors a strategy in which the choice of instruments is taken as given and a particular statistical theory is used perform inference on the parameters of interest (see Hall 2005, Section 8.2.3 for details). In light of these points, we take the instrument set as given, while recognizing that potentially weak instruments may lead to not only imprecise estimates of the structural parameters, but also the standard J-statistics to draw inference may be unreliable.[8]

To address the potential issue of weak instruments, we compute two identification robust tests statistics considered in the recent literature and use them as specification tests, in addition to the conventional J-statistic. The first is the Anderson and Rubin (1949) (AR) statistic. 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 $\bar{K}$ statistic proposed by Kleibergen (2002), which remedies this problem.[9]

3. ESTIMATION RESULTS

Table 3 presents the estimates of the Euler equation (11). The parameter of interest, θ_0, is positive in 16 of the 18 industries. It is statistically significant for five industries (the three nondurable industries apparel and related products ($n = 3$), printing and publishing ($n = 5$), and rubber and plastic ($n = 8$), and the two durable goods industries primary metal industries ($n = 12$) and instruments ($n = 17$)). In two industries (paper and allied products ($n = 4$) and industrial machinery ($n = 14$)), the estimated coefficient is negative, which is inconsistent with theory.[10] The p-values associated with the J-statistic (sixth column of Table 3) indicate that the overidentifying restrictions are not rejected for any of the industries. We also implement the identification robust AR and $\bar{K}$ tests as additional specification tests. The null hypothesis for these tests is H_0: $\theta_n = \hat{\theta}_n$ for each industry n, where $\hat{\theta}_n$ is the vector of point estimates.[11] A rejection of the null hypothesis may indicate model misspecification. If the null is not

8. The reason, as discussed in Stock, Wright, and Yogo (2002) and Dufour (2003), is that if instruments are weak then the limiting distribution of GMM statistics is in general non-normal and depend on nuisance parameters. The standard statistics that are based on the normality of sampling distribution may, therefore, be incorrect.

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

10. The negative sign on the estimated coefficient may possibly be due to pure sampling errors, measurement errors, or misspecification. One source of measurement error, as highlighted in the recent literature, is mismeasurement of user cost. See, for example, Gilchrist and Zakrajsek (2007).

11. Under the null, the AR statistic follows an asymptotic χ_z^2/z distribution where z is the number of instruments and is equal to 10. Under the null, the $\bar{K}$-statistic follows a $\chi^2(4)$ where 4 is the number of elements of the estimated parameter vector θ.

TABLE 3

Industry Estimation Results

	Parameters				Specification tests		
						p-value	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry (n)	θ_0	θ_1	θ_2	θ_3	J	AR	$\bar{K}$
			Nondurable industries				
1	0.265	0.442	0.954	0.661	0.65	0.95	0.96
	(0.373)	(0.310)	(0.208)	(0.172)			
2	0.779	−0.039	1.300	−0.454	0.97	0.12	0.00
	(1.982)	(0.737)	(0.946)	(0.750)			
3	1.595*	0.540	0.471	0.139	0.80	0.35	0.32
	(0.726)	(0.495)	(0.214)	(0.389)			
4	−1.654	0.984	0.252	0.935	0.96	0.00	0.00
	(2.163)	(0.282)	(0.607)	(0.807)			
5	1.308*	0.689	0.175	0.429	0.68	0.90	0.49
	(0.591)	(0.514)	(0.466)	(0.514)			
6	0.087	0.397	0.959	0.485	0.57	0.12	0.31
	(0.179)	(0.123)	(0.372)	(0.192)			
7	0.369	0.272	0.382	1.089	0.76	0.41	0.44
	(0.632)	(0.337)	(0.176)	(0.308)			
8	1.697*	0.251	1.070	0.254	0.91	0.37	0.16
	(0.766)	(0.983)	(1.005)	(0.822)			
9	1.064	−0.673	−0.7416	1.905	0.78	0.00	0.04
	(0.796)	(0.274)	(0.256)	(0.255)			
			Durable industries				
10	0.178	0.260	0.267	0.451	0.63	0.13	0.11
	(0.597)	(0.306)	(0.350)	(0.279)			
11	0.775	0.6266	0.581	0.170	0.66	0.25	0.63
	(0.852)	(0.478)	(0.362)	(0.316)			
12	1.348*	−0.410	−0.656	−0.389	0.77	0.00	0.00
	(0.906)	(0.228)	(0.265)	(0.251)			
13	0.050	0.689	0.664	0.003	0.97	0.84	0.42
	(0.722)	(0.324)	(0.297)	(0.413)			
14	−2.241	1.234	1.450	1.969	0.99	0.00	0.00
	(1.533)	(0.851)	(0.992)	(0.696)			
15	0.838	0.039	0.492	0.538	0.51	0.80	0.80
	(0.866)	(0.285)	(0.245)	(0.232)			
16	0.104	0.637	0.652	0.618	0.67	0.59	0.97
	(0.958)	(0.376)	(0.280)	(0.234)			
17	1.867*	0.866	−0.543	0.368	0.80	0.75	0.53
	(1.052)	(0.526)	(0.367)	(0.261)			
18	0.085	−0.381	−0.590	−0.207	0.53	0.00	0.00
	(0.264)	(0.187)	(0.093)	(0.239)			

Notes: Estimates of Euler equation (11). Instruments: lags 2–6 of oil-shock dummies and the innovation in federal defense spending. Standard errors in parentheses. * θ_0 is significant at 5% level.

rejected, then the estimated parameters are feasible, given the data. In other words, the estimates lie in the weak instrument robust confidence set.

We report the p-values associated with these tests in Table 3 (the last two columns). In 12 (n = 1, 3, 5, 6, 7, 8, 10, 11, 13, 15, 16, and 17) of the 16 industries with a positive estimate of θ_0, the p-values associated with both the AR and the $\bar{K}$-statistics do not reject the null. For the two industries with a negative estimate of θ_0 ($n = 4$ and

14), the AR and $\bar{K}$-statistics reject the specification.[12] In five industries ($n = 2$, 9, 12, 17, and 18), estimated parameters other than θ_0 have a negative sign. Although the J test does not reject the specification for these industries, either the AR or the $\bar{K}$ test, or both, do (except for industry 17).

Using the estimates of $\hat{\theta}_0 = \{\hat{\theta}_{1,0}, \ldots, \hat{\theta}_{n,0}, \ldots, \hat{\theta}_{18,0}\}$ reported in Table 3, and the expression for θ_0 in (10), we derive the implied estimates of the adjustment costs parameter for each industry n as follows:

$$\hat{\kappa}_n = \frac{-\alpha_n \beta}{\hat{\theta}_{n,0}\,(1 + \beta + (1 - \delta_n)\beta)\,K_n}, \quad \alpha_n < 0, \tag{13}$$

where we calibrate the right-hand-side parameters α_n, δ_n, K_n, and β. Specifically, δ_n is calibrated as the mean of industry n's depreciation rate, K_n is set equal to the mean of industry n's capital stock, α_n is calibrated using the steady-state relation $\alpha_n = -P_n^{\mathrm{K}} K_n / C_n$, and we use the sample mean of the interest rate R to calibrate $\beta = 0.946$, which is common across industries. Table 4 reports the industry-specific calibrated parameters (columns 2–4) and the implied estimates of the adjustment cost parameter (column 8). For the industries with positive estimates of θ_0, the adjustment cost parameter is small and ranges from 0.0004 ($n = 15$) to 0.001 ($n = 2$, 7, 9, 11, and 16). The estimates are statistically significant at the 5% level for four industries ($n = 1$, 3, 5, and 12).[13]

To give the adjustment costs parameter an economic interpretation, we compute the elasticity of industry investment with respect to the current shadow price of capital. To obtain an expression for this elasticity, we log-linearize (5) for each industry n to get

$$i_{n,t} = \frac{1}{1+\beta} i_{n,t-1} + \frac{\beta}{1+\beta} E_t i_{n,t+1} + \frac{P_n^{\mathrm{I}}}{\kappa_n C_n}\left(q_{n,t} - p_{n,t}^{I}\right). \tag{14}$$

We use standard methods to solve (14) as

$$i_{n,t} = i_{n,t-1} + \frac{P_n^{\mathrm{I}}}{\kappa_n C_n} E_t \left[\sum_{s=0}^{\infty} \beta^s \tilde{q}_{n,t+s}\right], \tag{15}$$

where $\tilde{q}_{n,t+s} = q_{n,t+s} - p_{n,t+s}^{\mathrm{I}}$ is the real shadow price of capital. As in Christiano et al. (2005), we can express the elasticity of industry n's investment with respect to a 1% temporary change in the real shadow price of capital as

12. There are several potential reasons for this. In the context of capital adjustment costs, for example, Oliner, Rudebusch, and Sichel (1995) draw attention to a variety of reasons that include convexity of the adjustment cost function, the assumption of full reversibility of investment, and the "putty-putty" nature of the neoclassical technology. Similar reasons may apply to the Euler equation under IAC considered here.

13. The standard errors were computed using the delta method.

TABLE 4

Industry Estimates of the Investment Adjustment Costs Parameter (κ) and the Investment Elasticity (ζ)

(1) n	(2) α_n	(3) K_n	(4) δ_n	(5) P_n^I	(6) C_n	(7) ω_n	(8) κ_n	(9) ζ_n
				Nondurable industries				
1	−0.06	128.84	0.06	0.45	138.53	0.071	0.0006* (0.0002)	5.20* (0.001)
2	−0.45	199.16	0.07	0.43	23.00	0.078	0.001 (0.002)	18.46* (0.013)
3	−0.14	65.03	0.08	0.47	29.85	0.053	0.0005* (0.0002)	34.61* (0.007)
4	−0.13	60.37	0.07	0.47	36.72	0.051	—	—
5	−0.09	55.64	0.09	0.49	47.95	0.051	0.0004* (0.0002)	24.19* (0.004)
6	−0.06	57.39	0.07	0.48	66.14	0.049	0.004 (0.009)	1.60* (0.014)
7	−0.09	70.85	0.05	0.45	66.33	0.047	0.001 (0.002)	5.72* (0.011)
8	−0.09	52.10	0.09	0.46	18.76	0.050	0.0004 (0.0003)	29.20* (0.008)
9	−0.25	74.32	0.09	0.45	22.90	0.062	0.001 (0.001)	18.42* (0.014)
				Durable industries				
10	−0.25	61.72	0.07	0.45	18.76	0.050	0.007 (0.025)	3.18* (0.081)
11	−0.23	82.84	0.07	0.46	25.91	0.061	0.001 (0.001)	14.46* (0.02)
12	−0.11	90.61	0.05	0.46	52.50	0.056	0.0003* (0.0001)	27.73* (0.003)
13	−0.06	64.04	0.06	0.47	69.79	0.051	0.006 (0.004)	1.11* (0.004)
14	−0.04	57.21	0.08	0.52	99.31	0.048	—	—
15	−0.04	43.70	0.08	0.51	65.40	0.038	0.0004 (0.0004)	18.86* (0.008)
16	−0.07	124.34	0.09	0.47	130.69	0.079	0.001 (0.017)	1.90* (0.033)
17	−0.07	46.48	0.09	0.50	47.22	0.040	0.0003 (0.0002)	37.66* (0.006)
18	−0.33	67.13	0.07	0.46	14.28	0.055	0.019 (0.059)	1.701* (0.101)
								$\zeta^{\text{AVG}} = 15.24$
								$\zeta^{\text{AVG,ALT}} = 14.56$

Notes: ζ^{AVG} is a weighted average across industries with positive κ and computed as (17). $\zeta^{\text{AVG,ALT}}$ is a weighted average across industries 1, 3, 5, 6, 7, 8, 10, 11, 13, 15, 16, and 17. * Significant at 5% level.

$$\zeta_n = \frac{P_n^{\mathrm{I}}}{\kappa_n C_n}, \quad n = 1, \ldots, 18. \tag{16}$$

The elasticity in the case of a permanent change in the price of capital is $(1-\beta)^{-1}\zeta_n > \zeta_n$.[14]

14. The elasticity in the case of persistent changes in the shadow price of capital, for example, would lie between ζ_n and $(1-\beta)^{-1}\zeta_n$.

To compute the implied estimate of the elasticity in (16), we calibrate P_n^{I}/C_n using the average values from the data, as shown in columns 5 and 6 in Table 4. The last column in Table 4 provides the estimates of the elasticity ζ_n for industries with a positive adjustment costs parameter. The estimated elasticities are all greater than one, range from 1.1 ($n = 3$) to 37.7 ($n = 17$), and are significant for 16 of the 18 industries. These large elasticities suggest that investment in most of U.S. manufacturing industries is sensitive to the current shadow value of capital.

4. COMPARING INDUSTRY VERSUS AGGREGATE ESTIMATES

How do the industry estimates compare with the aggregate estimates reported in previous studies? To answer this question, we compute the *average* elasticity of 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. The average elasticity is computed as a weighted average across industries (excluding industries $n = 4$ and 14 for which we get negative adjustment cost estimates), where the weights are based on the average share of an industry's nominal investment in total manufacturing investment (reported in column 7 in Table 4):

$$\omega_n = \frac{\sum_{t=1948}^{2000} \left(P_{n,t}^{\mathrm{I}} I_{n,t} \Big/ \sum_{n=1}^{18} P_{n,t}^{\mathrm{I}} I_{n,t} \right)}{53}.$$

We then calculate the average industry elasticity of investment with respect to the current shadow price of capital as

$$\zeta^{\mathrm{AVG}} \equiv \sum_n \omega_n \zeta_n, \tag{17}$$

where the summation is over all the industries except $n = 4$ and 14. The average industry estimate of the elasticity is 15.24, which we refer to as our benchmark industry estimate. We also compute an alternative estimate, denoted by $\zeta^{\mathrm{AVG,ALT}}$, calculated as the average elasticity in industries where all estimated coefficients in (11) are positive and neither the AR or $\bar{K}$ tests rejects the specification. There are 12 industries that meet this criteria ($n = 1, 3, 5, 6, 7, 8, 10, 11, 13, 15, 16,$ and 17). The average industry estimate based on these industries is 14.56.

To compare the average industry elasticity with an estimate of the aggregate elasticity, we solve the aggregate specification (2) as

$$i_t = i_{t-1} + \frac{1}{\kappa^{\mathrm{A}}} E_t \left[\sum_{s=0}^{\infty} \beta^s q_{t+s} \right], \tag{18}$$

TABLE 5

A COMPARISON OF ESTIMATED ELASTICITIES FOR THE U.S. ECONOMY

		Estimation methodology	Elasticity ζ
	Aggregate (quarterly) data		
1	Levin et al. (2006)	Bayesian DSGE	1.82
2	Altig et al. (Forthcoming)	Impulse response matching	0.45
3	Christiano et al. (2005)[a]	Impulse response matching	0.40
4	Justiniano and Primiceri (2008)	Bayesian DSGE	0.30
5	Smets and Wouters (2007)	Bayesian DSGE	0.17
6	This paper	Euler equation	[0.004, 0.005]
	Industry (annual) data		
7	This paper	Euler equation (internal IAC[b])	[14.56, 15.24]
8	This paper	Euler equation (external IAC)	16.21

[a]Christiano et al. (2005) benchmark estimate.
[b]IAC is investment adjustment costs.

where the elasticity of aggregate investment with respect to the current shadow price of capital is given as

$$\zeta^{\mathrm{A}} = \frac{1}{\kappa^{\mathrm{A}}}. \tag{19}$$

We compare the average elasticity estimate based on industry data, ζ^{AVG}, with that based on aggregate data, ζ^{A}. For comparison purposes, we take the aggregate estimates of the elasticity for the U.S. economy reported in five recent contributions to the DSGE literature. These are Christiano et al. (2005), Altig et al. (Forthcoming), Levin et al. (2006), Smets and Wouters (2007), and Justiniano and Primiceri (2008).[15] Table 5 provides a comparison of the elasticity estimates across the aggregate and the industry estimates. The aggregate elasticity estimates in the literature range from 0.17 (corresponding to the largest investment adjustment costs estimate) in Smets and Wouters (2007) to 1.82 (smallest investment adjustment costs estimate) in Levin et al. (2006), as shown in rows 1–5 in the table. Row 7 reports the average industry elasticity obtained in this study ranging from 14.56 to 15.24 (from Table 4). The benchmark average industry estimate of the elasticity is therefore around eight times as large as the highest estimate reported in Levin et al. (2006).[16] In contrast to the aggregate estimates, the industry estimates therefore point to a much smaller role for costs associated with changing the flow of investment.

15. The latter three use the Bayesian estimation methodology whereas Christiano et al. (2005) and Altig et al. (Forthcoming) consider impulse response matching.

16. For three industries, namely, chemical and allied products ($n = 6$), transportation and equipment ($n = 16$), and miscellaneous manufacturing ($n = 18$), the estimates of the elasticity are, however, similar to those in Levin et al. (2006).

5. ROBUSTNESS

In this section, we present a variety of robustness checks and discuss potential reasons for the large difference between industry and aggregate estimates reported in Section 4.

5.1 Internal versus External Investment Adjustment Costs

The industry model in Section 2 assumes that investment adjustment costs are internal to the production process. In other words, they are defined as the cost of output lost when the level of investment is varied. By contrast, the aggregate model discussed in Section 1 assumes external investment adjustment costs. These are accounted for in the capital accumulation identity—the implicit assumption in that model is that part of investment captures services provided to change the flow of investment rather than providing new capital goods. If investment adjustment costs are viewed as primarily external to the industry, then industry estimates of investment adjustment costs may underestimate the true costs of adjustment, and therefore be smaller compared to the aggregate estimates. To investigate this possibility, we consider an environment where investment adjustment costs are external to the industry. The variable cost function in this case is

$$C_t = C\left(W_t, P_t^m; Y_t, K_t\right). \tag{20}$$

The representative industry minimizes current and expected future costs with respect to i_t and k_{t+1}:

$$\begin{aligned} E_\tau\Bigg[\sum_{t=\tau}^{\infty}\frac{1}{1+R_{\tau,t}}\Bigg[C_t + P_t^I I_t - Q_t\Bigg(K_{t+1}-(1-\delta)K_t \\ -\left(1-S\left(\frac{I_t}{I_{t-1}}\right)\right)I_t\Bigg)\Bigg]\Bigg], \end{aligned} \tag{21}$$

where we have used (1) to get an expression for the capital accumulation identity. In any period t, the first-order condition for investment is

$$\begin{aligned} Q_t\left[\left(1-S\left(\frac{I_t}{I_{t-1}}\right)\right)-S'\left(\frac{I_t}{I_{t-1}}\right)\left(\frac{I_t}{I_{t-1}}\right)\right] \\ +\frac{1}{1+R_t}E_t\left[Q_{t+1}S'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right] = P_t^I, \end{aligned} \tag{22}$$

while the first-order condition for capital remains the same as in (6). Log-linearizing (22) and introducing industry subscript n gives

$$i_{n,t} = \frac{1}{1+\beta}i_{n,t-1} + \frac{\beta}{1+\beta}E_t i_{n,t+1} + \frac{1}{\kappa_n^{\mathrm{EXT}}(1+\beta)}\left(q_{n,t} - p_{n,t}^{\mathrm{I}}\right), \tag{23}$$

where superscript EXT denotes external. Comparing (23) with (14) indicates that investment dynamics under internal and external IAC are observationally equivalent. The only difference is that the coefficient on the shadow cost of capital does not depend on the ratio P^{I}/C under the assumption of external investment adjustment costs. Consequently, the specification (11) remains the same except that the coefficient on variable s_{t+1} is modified. The mapping to derive the implied estimate of the external investment adjustment cost parameter changes from (13) for internal adjustment costs to

$$\hat{\kappa}_n^{\mathrm{EXT}} = \frac{1 - \beta(1 - \delta_n)}{\hat{\theta}_{0,n}^{\mathrm{EXT}}(1 + \beta + (1 - \delta_n)\beta)}. \tag{24}$$

In addition, the estimate of the elasticity parameter changes to $\zeta^{\mathrm{EXT}} = 1/\kappa^{\mathrm{EXT}}$, as in the aggregate model of Section 1.[17] Table 6 presents the estimates of external investment adjustment costs and the implied estimated elasticity. The point estimates of external investment adjustment costs are indeed larger relative to those of internal investment adjustment costs. The important thing to note, however, is that the elasticity estimates are similar to those obtained under the internal investment adjustment costs specification. The benchmark ($\zeta^{\mathrm{EXT,AVG}}$) and alternative criteria ($\zeta^{\mathrm{EXT,AVG,ALT}}$) estimates of the elasticity are 16.21 and 15.66, respectively, compared to 15.24 and 14.56 for the baseline model. Thus, the fact that we model adjustment costs as internal in the industry analysis, whereas aggregate studies have assumed that they are external, appear not to explain the large discrepancy between the industry and the aggregate estimates of the investment elasticity.

5.2 Aggregate Euler Equation Estimation

In Section 4, we compared the aggregate investment estimates (based on Bayesian estimation and impulse response matching approaches) with the industry estimates (based on the Euler equation approach and estimated using GMM). Here we ask if the difference in estimation methodology could explain the large difference in the estimates of the implied investment elasticity.

To analyze this, we obtain an aggregate analog of the industry Euler equation (11) by taking the aggregate model described in Section 1, for which we can express the log-linearized first-order condition for the optimal level of capital as

$$q_t = -(r_t - E_t\pi_{t+1}) + \gamma_1 E_t q_{t+1} + \gamma_2 E_t r_{t+1}^k, \tag{25}$$

where $E_t r_{t+1}^k$ is the expected real return on capital (or, equivalently, the expected real rental rate on capital), and $\gamma_1 = (1 - \delta)/(1 - \delta + \bar{r}^k)$, $\gamma_2 = \bar{r}^k/(1 - \delta + \bar{r}^k)$, where $\bar{r}^k = 1/\beta - 1 + \delta$.

17. One caveat to note in estimating (11) under the assumption of external adjustment costs is that conventional capital stock measures are constructed under the assumption that all investment spending generates new capital. Therefore, the available data do not exactly map into the capital accumulation equation with the investment adjustment costs term as in (21).

TABLE 6

Industry Estimates of the Investment Adjustment Costs Parameter (κ^{EXT}) and the Investment Elasticity (ζ^{ext}) under External Adjustment Costs

Industry (n)	IAC κ_n^{EXT}	Elasticity ζ_n^{EXT}
	Nondurable industries	
1	0.16	6.23
	(0.021)	(8.79)
2	0.07	13.10*
	(0.083)	(4.32)
3	0.03*	32.88*
	(0.022)	(0.455)
4	—	—
5	0.038*	25.79*
	(0.01)	(0.47)
6	0.523	1.90
	(1.07)	(2.05)
7	0.09	10.08*
	(0.105)	(1.71)
8	0.03	32.42*
	(0.023)	(0.76)
9	0.047	21.03*
	(0.03)	(0.73)
	Durable industries	
10	0.251	3.95
	(0.845	(3.34)
11	0.057	17.27
	(0.063)	(1.10)
12	0.028*	35.42*
	(0.009)	(0.35)
13	0.841	1.18
	(12.07)	(14.35)
14	—	—
15	0.058	17.24*
	(0.06)	(1.03)
16	0.476	2.10
	(4.37)	(9.19)
17	0.027*	36.98*
	(0.01)	(0.56)
18	0.531	1.87
	(1.64)	(3.08)
		$\zeta^{\mathrm{EXT,AVG}} = 16.21$
		$\zeta^{\mathrm{EXT,AVG,ALT}} = 15.66$

Notes: Standard errors in parentheses. * Significant at 5% level.

We combine the first-order condition for investment (2) with (25) to get

$$i_t = \frac{\zeta^{\mathrm{A}}}{1+\beta+\gamma_1}\left(\gamma_2 E_t r_{t+1}^k - (r_t - E_t\pi_{t+1})\right) + \frac{1}{1+\beta+\gamma_1} i_{t-1} + \frac{\beta+\gamma_1(1+\beta)}{1+\beta+\gamma_1} E_t i_{t+1} - \frac{\beta\gamma_1}{1+\beta+\gamma_1} E_t i_{t+2}, \tag{26}$$

where $\zeta^{\mathrm{A}} \equiv 1/\kappa^{\mathrm{A}}$. Equation (26) is the aggregate analog of the Euler equation (10). We can write (26) compactly as

$$i_t = \alpha_0 E_t w_{t+1} + \alpha_1 i_{t-1} + \alpha_2 E_t i_{t+1} - \alpha_3 E_t i_{t+2}, \tag{27}$$

where $w_{t+1} = (\gamma_2 E_t r^k_{t+1} - (r_t - E_t \pi_{t+1}))$ and where the reduced-form coefficients α_1, α_2, and α_3 are given by the coefficients on the corresponding variables in (26), which are all positive.

We estimate (27) using quarterly U.S. data from the Bureau of Economic Analysis (BEA) over the period 1954 Q1 to 2000 Q4. The data, further described below (with mnemonics in square brackets), are obtained from the FRED database at the Federal Reserve Bank of St Louis. Investment (I_t) is real private nonresidential fixed investment (billions of chained 2000 dollars, seasonally adjusted) [PNFIC1]. The model is estimated in per capita terms, where population is civilian noninstitutional population (in thousands) [CNP16OV]. The nominal interest rate (r_t) is the 3-month Treasury bill rate [TB3MS]. Inflation (π_t) is computed using the GDP chain type price index (2000 = 100) [GDPCTPI], with $\pi_t = 400 * (\mathrm{GDPCTPI}_t/\mathrm{GDPCTPI}_{t-1} - 1)$.[18] We detrend the data using the HP filter with a smoothing factor of 1600. The annualized real return on capital (r^k_{t+1}) is based on stock market data and computed as

$$400 * \left(\frac{\text{real S\& P composite price}_{t+1} + \text{real dividends}_t}{\text{real S\& P composite price}_t} - 1 \right),$$

where the real S&P composite price index is obtained from Robert Shiller's http://www.econ.yale.edu/ shiller/data.htm website.[19] This is consistent with the measure used in Christiano and Davis (2006).

We conduct GMM estimation of (27) using the three exogenous instruments considered in Basu, Fernald, and Kimball (2006) (denoted by BFK): the oil price and government defense spending, and an updated quarterly Federal Reserve monetary shocks from an identified VAR (as considered in Burnside 1996). We consider two sets of these instruments, BFK(1) consists of four lags and BFK(2) consists of five lags of each of the three variables, respectively. The results are reported in Table 7, where the upper half of the table shows the estimates of the model parameters, for the two instruments sets BFK(1) and BFK(2).[20]

Based on these estimates, we can compute the implied estimates of the investment elasticity ζ^{A}, which, from (26) and (27), is given by $\hat{\zeta}^{\mathrm{A}} = \hat{\alpha}_0(1 + \beta + \gamma_1)$ where $\gamma_1 = (1 - \delta)/(1 - \delta + \bar{r}^k)$ with $\bar{r}^k$ defined above. The implied point estimates of the investment elasticity are 0.005 and 0.004 for the two instrument sets, respectively, but they are not statistically significant. Nevertheless, as shown in Table 5 (row 6),

18. The monthly data for the last two series are converted to quarterly using a 3-month average.

19. http://www.econ.yale.edu/ shiller/data.htm.

20. The Newey and West (1987) optimal weight matrix is computed using four lags. The J-statistic is distributed with 9 and 11 degrees of freedom, respectively.

TABLE 7

Aggregate Euler Equation Estimation

	α_0	α_1	α_2	α_3	J	AR p-value	$\bar{K}$
			Quarterly data				
BFK(1)	0.001	0.569	0.313	−0.118	0.85	0.94	0.25
	(0.001)	(0.144)	(0.278)	(0.226)			
BFK(2)	0.001	0.613	0.303	0.198	0.93	0.19	0.03
	(0.002)	(0.102)	(0.231)	(0.181)			
			Annual data				
BFK(1)	0.002	0.790	1.364	0.194	0.76	0.02	0.90
	(0.002)	(0.294)	(0.314)	(0.294)			
BFK(2)	0.003	0.786	1.388	0.456	0.82	0.01	0.75
	(0.010)	(0.093)	(0.084)	(0.118)			

Notes: Estimates based on specification (27). Standard errors in parentheses.

the Euler equation based aggregate estimates of the investment elasticity are smaller than that reported in previous studies (corresponding to even larger adjustment cost estimates). This suggests that large estimates of the elasticity at the industry level are not driven by the GMM estimation methodology itself.

5.3 Data Frequency

We have used annual data in our empirical assessment of investment adjustment costs, mainly due to the lack of reliable industry-level data at the quarterly frequency. One might argue that delays in investment planning or inflexibility in changing the planned pattern of investment are the likely sources of investment adjustment costs. If that were the case, and if project planning and completion times were less than 1 year, then one may not expect investment adjustment costs to have much effect on capital outlays at annual frequency.

There are several pieces of evidence, however, that suggest that the use of annual data may not be restrictive in estimating investment adjustment costs. First, evidence for firms in the manufacturing industries indicates an average time-to-build of 23 months (Koeva 2001) while, for private structures, the average planning and completion time is approximately 20 months (Edge 2000). These estimates are both well above 1 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 preshock level after 3 years (Christiano et al. 2005), suggesting that not all adjustment at the aggregate level takes place within the first year of the shock. These observations suggest that if investment adjustment costs are the main mechanism behind this slow adjustment, we should be able to identify them at the annual as well as the quarterly frequency.

To assess the impact of data frequency on our estimates, we reestimate the aggregate specifications (27) using annual data.[21] As shown in Table 7 (bottom half), the aggregate estimates of the investment elasticity obtained at the quarterly frequency are similar to those at the annual frequency, which suggests that differences in elasticity estimates are not likely to reflect differences in data frequency. In particular, the aggregate estimates of the investment elasticity at the annual frequency for the two instrument sets BFK(1) and BFK(2) are 0.007 and 0.009, respectively, compared to 0.005 and 0.004 for quarterly data.

5.4 Manufacturing versus Whole Economy

We have only considered data from the manufacturing sector whereas estimates in aggregate studies are based on whole-economy investment data. The main reason for focusing on the manufacturing sector is data availability. Moreover, there are measurement issues that are particularly severe for the services sector (Griliches 1994). One caveat to our results is therefore that if investment adjustment costs are more prominent in nonmanufacturing investment relative to manufacturing investment, then estimates based only on manufacturing data may be biased downward. One reason for why this could be the case is that investment adjustment costs may be more likely to arise in structures relative to equipment investment, and the former has a larger share in share in whole economy compared to manufacturing investment (15% and 30%, respectively).[22]

Although we cannot address this issue directly using industry data, we can confirm if estimates of the elasticity are higher for equipment investment relative to structures in the aggregate data. If this was indeed the case, then it is likely to matter for disaggregated data as well. We reestimated (27) using data on real nonresidential investment in equipment and software [NRIPDC1]. The estimated elasticities from this specification are around 0.01 for both instrument sets. These estimates are only slightly higher relative to those reported in Table 5 (row 6) where the investment measure includes structures. This finding therefore suggests that, at the aggregate level, the elasticity estimates are not very sensitive to whether the investment measure includes structures or not.

5.5 Alternative Empirical Specification

In our baseline specification, we estimated four coefficients (θ_0 to θ_3). These reduced-form coefficients depend on structural parameters that are not directly of interest. As evident from (10), the coefficients on the lag and leads of investment (θ_1, θ_2, and θ_3) depend entirely on the discount factor β (common to all industries)

21. To obtain annual data, investment and population are summed, and the rate of return measure and the GDP deflator are averaged, over the four quarters.

22. Note, however, that although planning delays are shorter for equipment than for structures investment, they are still higher than in other types of investment, such as residential investment (Christiano et al. 2005).

and the industry-specific depreciation parameter δ. The coefficient θ_0 also depends on the industry-specific parameters α and K. To increase the precision of the estimates of the adjustment costs parameter, κ, we use calibrated values of α, β, δ, and K (based on values reported in Table 4) to reduce the number of estimated parameters from four to one.[23] This allows us to estimate κ directly, given that the relevant reduced-form parameter θ_0 in (10) is given by

$$\theta_0 = \left[\frac{-\alpha\beta}{\kappa(1+\beta+(1-\delta)\beta)K} \right], \tag{28}$$

with the corresponding expression for the elasticity given by (16). Table 8 reports the findings. Overall, the significance of the estimates of the adjustment cost parameter improves slightly, while the pattern of the estimates remains similar to that obtained in the benchmark estimation (Table 4) for most industries (16 of the 18 industries). There are two main exceptions: adjustment cost estimates for industry $n = 16$ (transportation equipment) and $n = 18$ (miscellaneous manufacturing) are substantially lower than in the benchmark estimation. The average estimate of the elasticity ζ^{AVG} is now 19.4, which is slightly higher than the benchmark estimate of 15.24.[24]

5.6 Aggregation Bias

The evidence of small investment adjustment costs in the industry data relative to large investment adjustment costs in the aggregate data suggests that aggregation over heterogenous industries may impart the appearance of investment adjustment costs on aggregate investment. In the context of capital adjustment costs, Gordon (1992) points out that aggregation can lead to a substantial overestimation of adjustment costs when the model is estimated using aggregate data. One way to investigate this is to pursue an empirical strategy along the lines of Burnside (1996), which in our model would correspond to imposing cross-equation restrictions on the adjustment cost parameters across the 18 industries. If the estimated adjustment cost parameter in this constrained regression were large (corresponding to a small elasticity), at the same time as the cross-equation restrictions were rejected, this could be interpreted as an "aggregation bias" that caused aggregation across heterogenous industries to give rise to differences in estimates obtained at the industry and the aggregate level.[25] Due to difficulties with the convergence of the objective function in the system GMM estimation, we pursue an alternative strategy. We instead estimate equation (11) using pooled data. This could be interpreted as imposing the restriction that all model parameters are equal across all industries. We can then compare the pooled estimate with the industry-specific estimates reported above, and with aggregate estimates, along the lines discussed above.

23. We thank an anonymous referee for this suggestion.

24. The standard errors of the industry elasticity estimates are similar to those obtained for the external adjustment costs specification.

25. We thank an anonymous referee for this suggestion.

TABLE 8

ALTERNATIVE EMPIRICAL SPECIFICATION

Industry (n)	IAC κ_n	Elasticity ζ_n
	Nondurable industries	
1.	0.0008	4.25
	(0.001)	(5.20)
2.	0.012*	15.51*
	(0.0005)	(6.00)
3.	0.0003	59.42*
	(0.0001)	(14.39)
4.	—	—
5.	0.0004*	25.05*
	(0.0001)	(8.25)
6.	0.019	0.376
	(0.156)	(3.04)
7.	0.002	2.82
	(0.002)	(1.71)
8.	0.0003*	33.27*
	(0.0001)	(11.31)
9.	0.011	1.78*
	(0.05)	(9.56)
	Durable industries	
10.	0.001	24.11*
	(0.0005)	(11.65)
11.	0.005	3.42
	(0.010)	(6.55)
12.	0.0006*	14.35*
	(0.0003)	(7.02)
13.	0.0006	10.72
	(0.0005)	(8.86)
14.	—	—
15.	0.0002*	36.62*
	(0.0001)	(17.85)
16.	0.0001*	41.08*
	(0.00001)	(10.46)
17.	0.0005*	22.67*
	(0.0002)	(8.27)
18.	0.002	15.52
	(0.002)	(17.89)
		$\zeta^{AVG} = 19.40$

NOTES: Standard errors in parentheses. * Significant at 5% level.

The pooled estimate of the adjustment costs parameter is 0.001 with a standard error of 0.001, implying a value for the investment elasticity equal to 7.65, with a standard error of 0.66, therefore significant at the 5% level. The pooled estimate of the elasticity is roughly half the size of the weighted average of the industry-specific estimates (reported in Table 4). We construct the 95% confidence interval around the pooled estimate, and similarly for the industry-specific estimates of the elasticities (as reported in column 9 in Table 4). We find that the confidence interval of the pooled estimate and those of the industry estimates do not overlap for any of the industries. This indicates that the restriction that all parameters are equal across all industries is strongly rejected by the data and that an aggregation bias causes aggregate estimates to significantly deviate from industry-specific estimates. In other words, aggregation bias is likely to contribute to the discrepancy between aggregate and industry estimates of the investment elasticity. However, it does not fully account for the discrepancy, as there remains a substantial difference between the pooled industry estimate and aggregate estimates. In particular, the pooled elasticity is about four times as large as the largest aggregate estimate reported in Levin et al. (2006).

6. CONCLUSION

In this paper, we estimate investment adjustment costs in U.S. manufacturing industries. Our findings indicate small costs associated with changing the flow of industry investment. They imply that industry investment is very responsive to changes in the shadow value of capital. The benchmark average industry elasticity of investment with respect to the current shadow value of capital is eight times larger than the largest estimate based on aggregate U.S. data (as reported in Levin et al. 2006). We discuss several possibilities for why industry estimates of investment adjustment costs might be smaller compared to those reported in aggregate studies and explore in more detail identification issues, the role of internal versus external adjustments costs, data frequency, and the possibility that manufacturing industries may not be representative of the whole economy. None of these factors appear to account for the difference. We also explore if an aggregation bias could explain the difference and find that it may account for around half of the discrepancy between industry and aggregate estimates of the investment elasticity, leaving a substantial difference unexplained. Our findings therefore suggest that more caution is needed when giving policy advice, based on aggregate models, that hinges on a structural interpretation of large investment adjustment costs.

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