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On the Nature of Capital Adjustment Costs

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This paper studies the nature of capital adjustment at the plant level. We use an indirect inference procedure to estimate the structural parameters of a rich specification of capital adjustment costs. In effect, the parameters are optimally chosen to reproduce a set of moments that capture the non-linear relationship between investment and profitability found in plant-level data. Our findings indicate that a model, which mixes both convex and non-convex adjustment costs, fits the data best.

1. MOTIVATION

The goal of this paper is to understand the nature of capital adjustment costs. This topic is central to the understanding of investment, one of the most important and volatile components of aggregate activity. Moreover, understanding the nature of adjustment costs is vital for the evaluation of policies, such as tax credits, that attempt to influence investment, and thus aggregate activity. Despite the obvious importance of investment to macroeconomics, it remains an enigma.

Costs of adjusting the stock of capital reflect a variety of interrelated factors that are difficult to measure directly or precisely so that the study of capital adjustment costs has been largely indirect through studying the dynamics of investment itself. Changing the level of capital services at a business generates disruption costs during installation of any new or replacement capital and costly learning must be incurred as the structure of production may have been changed. Installing new equipment or structures often involves delivery lags and time to install and/or build. The irreversibility of many projects caused by a lack of secondary markets for capital goods acts as another form of adjustment cost.

Some industry case studies (*e.g.* Holt, Modigliani, Muth and Simon, 1960; Peck, 1974; Ito, Bresnahan and Greenstein, 1999) provide a detailed characterization of the nature of the adjustment costs for specific technologies. A reading of these industry case studies suggest that there are indeed many different facets of adjustment costs and that, in terms of modelling these adjustment costs, both convex and non-convex elements are likely to be present.[1]

1. Holt *et al.* (1960) found a quadratic specification of adjustment costs to be a good approximation of hiring and lay-off costs, overtime costs, inventory costs, and machine set-up costs in selected manufacturing industries. These components of adjustment costs for changing the level of production are relevant here but are by no means the only relevant costs. In terms of changes in the level of capital services, Peck (1974) studies investment in turbo-generator sets for a panel of 15 electric utility firms and found that "The investments in turbogenerator sets undertaken by any firm took place at discrete and often widely dispersed points of time". In their study of investment in large scale computer systems, Ito *et al.* (1999) also find evidence of lumpy investment. Their analysis of the costs of adjusting the stock of computer

Despite this perspective from the industry case studies, the workhorse model of the investment literature has been a standard neoclassical model with convex costs (often approximated to be quadratic) of adjustment. This model has not performed that well even at the aggregate level (see Caballero, 1999), but the recent development of longitudinal establishment databases has raised even more questions about the standard convex cost model.

An alternative approach, highlighted in the work of Abel and Eberly (1994, 1996), Doms and Dunne (1994), Caballero, Engel and Haltiwanger (1995), and Cooper, Haltiwanger and Power (1999), argues that non-convexities and irreversibilities play a central role in the investment process. The primary basis for this view, reviewed in detail in the following, is plant-level evidence of a non-linear relationship between investment and measures of fundamentals, including investment bursts (spikes) as well as periods of inaction.

One limitation of this recent empirical literature is that it has focused primarily on reduced-form implications of non-convex vs. convex models. The results that emerge reject the reduced-form implications of a pure convex model and are consistent with the presence of non-convexities. The reduced-form nature of the results have left us with several important, unresolved questions: what is the nature of the capital adjustment process at the micro-level? Does the micro-evidence support the presence of both convex and non-convex components of adjustment costs as might be expected based upon the limited number of industry case studies? More specifically, what are the structural estimates of the convex and non-convex components of adjustment costs that are consistent with the micro-evidence? Finally, what are the aggregate and policy implications of the estimated investment model?

To address these questions, this paper considers a rich model of capital adjustment, which nests alternative specifications. To do so, we specify a dynamic optimization problem at the plant level, which incorporates both convex and non-convex costs of adjustment as well as irreversible investment. The model's implications are matched with plant-level observations from the Longitudinal Research Database (LRD) as part of a minimum distance estimation routine. We recover structural estimates of adjustment costs.

There are a couple of key features of the data, which guide the estimation: the frequency of large bursts of investment, the positive correlation between investment, and the marginal profitability of capital and the relatively low serial correlation of investment. All of these moments are computed at the plant level. These moments are chosen partly due to their prominence in the literature and partly due to their informativeness about the underlying structural parameters, which we estimate.

Our results can be summarized by referring to extreme models.[2] In the absence of adjustment costs, investment is excessively responsive to shocks and is negatively serially correlated. From this perspective, the role of adjustment costs is to temper the response of investment to fundamentals and to create the slightly positive serial correlation of investment observed at the plant level. The convex cost of adjustment model is not sufficiently sensitive to shocks and creates excessively significant positive serial correlation of investment rates. In particular, a model with convex costs alone cannot produce the bursts of investment and inaction observed in the data. Thus, richer models of adjustment are needed. Both the non-convex and the irreversibility models are able to produce relationships between investment and fundamentals, which are much closer to the data. Both of these models imply inactivity and investment bursts. Interestingly, irreversibility creates an asymmetry as well since the loss from capital sales is more relevant

capital include items, which they term "... intangible organization capital such as production knowledge and tacit work routines". Hamermesh and Pfann (1996) also provide a detailed review of convex adjustment cost models and numerous references to the motivation and results of that lengthy literature.

2. These comments pertain to the models studied in Section 3 and summarized in Tables 2 and 3. As explained, these statements reflect not only the adjustment costs but also the driving processes.

when profitability shocks are below their mean. *From our estimation of a structural model of adjustment, a combination of non-convex adjustment costs and irreversibility enables us to fit prominent features of observed investment behaviour at the plant level. In particular, a model of adjustment in which the non-convex costs entail disruption of the production process fits the data best.*

In terms of macroeconomic implications, the natural question is whether these non-convexities "matter" for aggregate investment. Our findings indicate that at the plant level, the non-convexities identified in our estimation are important: a model with only convex adjustment does poorly at the plant level. However, a model with only convex adjustment costs fits the aggregate data created by our estimated model reasonably well though (as reported independently by Cooper *et al.*, 1999, hereafter CHP) the convex models tend not to track investment well at turning points. Thus, we find that the non-convexities are less important at the aggregate relative to the plant level. We relate this finding to results reported by Caballero and Engel (1999) and Thomas (2002) in Section 5.

2. FACTS

In this section we discuss our data-set. We then present some moments from the data, which will guide the remainder of the analysis.

2.1. *Data-set*

Our data are a balanced panel from the LRD consisting of approximately 7000 large, manufacturing plants that were continually in operation between 1972 and 1988.[3] This particular sample period and set of plants is drawn from the data-set used by Caballero *et al.* (1995), hereafter CEH. The unique feature of this data relative to other studies that have used the LRD to measure investment is that information on both gross expenditures and gross retirements (including sales of capital) are available for these plants for these years (Census stopped collecting data on retirements in the late 1980's in its Annual Survey of Manufactures, which is why our sample ends in 1988). Incorporating retirements (and in turn sales of capital) is especially important in this exploration of adjustment costs and frictions in adjusting capital at the micro-level. Investigating the role of transactions costs and irreversibilities is quite difficult with the use of expenditures data alone.

The use of the retirements data requires a somewhat modified definition of investment. The definition of investment and capital accumulation follows that of CEH and satisfies

$$I_t = \mathrm{EXP}_t - \mathrm{RET}_t \qquad (1)$$

$$K_{t+1} = (1-\delta_t)K_t + I_t, \qquad (2)$$

where I_t is our investment measure, EXP_t is real gross expenditures on capital equipment, RET_t is real gross retirements of capital equipment, K_t is our measure of the real capital stock (generated via a perpetual inventory method at the plant level), and δ_t is the in-use depreciation rate. This measurement specification differs from the usual one that uses only gross expenditures data and the depreciation rate captures both in-use and retirements. Following the methodology used in CEH, we use the data on expenditures and retirements along with investment deflators and

3. While the balanced panel enables us to avoid modelling the entry/exit process there is likely a selection bias induced. Our use of the balanced panel is based on the difficult measurement issues for measuring real capital stocks and in turn real capital expenditures and real capital retirements. The details of this measurement are described in Caballero *et al.* (1995).

Bureau of Economic Analysis (BEA) depreciation rates to construct real measures of these series and also an estimate of the in-use depreciation rate.[4] In what follows, we focus on the investment rate, I_t/K_t, which can be either positive or negative.

2.2. *Investment moments*

The histogram of investment rates that emerges from this measurement exercise is reported in Figure 1. It is transparent that the investment rate distribution is non-normal having a considerable mass around 0, fat tails, and is highly skewed to the right (standard tests for non-normality yield strong evidence of skewness and kurtosis). Some of the main features of the distribution (and its underlying components in terms of gross expenditures and retirements) are summarized in Table 1.

First, note that about 8% of the (plant, year) observations entail an investment rate near 0 (investment rate less than 1% in absolute value). Of this inaction, about 6% of the observations indicate gross expenditures less than 1% of the plant capital stock and the retirement rate is less than 1% in 42·3% of our observations. This inaction is one of the driving observations for our analysis.[5]

These observations of inaction are complemented by periods of rather intensive adjustment of the capital stock. In the analysis that follows we term episodes of investment rates in excess of 20% *spikes*. Investment rates exceed 20% in about 18% of our sample observations. On average these large bursts of investment account for about 50% of total investment activity. Decomposing the investment rate in terms of gross expenditures and retirements, there are gross expenditure spikes in approximately 23% of the observations, while negative investment spikes occur in about 1·8% of the observations.

These properties of the investment distribution illustrate a key feature of the micro-data: investment rates are highly asymmetric. It is important to emphasize that our measurement of negative investment is through a direct measurement of retirements reflecting purposeful selling or destruction of capital. We find a negative investment rate in roughly 10% of our observations, zero investment in almost 10%, and positive investment rates in the remaining 80% of our observations. This striking asymmetry between positive and negative investment is an important feature of the data that our analysis seeks to match.

Table 1 also reports the serial correlation of investment rates computed as the simple correlation of the plant-level investment rate with the lagged investment rate. Interestingly, this is surprisingly low at the plant level relative to the common perception of highly serially correlated shocks to demand and productivity. It is important to remember though that the correlation of the investment rate also reflects adjustment costs.

The second correlation is between investment rates and a measure of profitability at the plant level. This correlation is positive at the plant level, indicating that investment rates are high in periods of high profitability. In contrast to the other moments, this last correlation requires a model as a device to measure profitability shocks. Section 4.1.1 discusses this measurement.

4. A relevant measurement point is that the retirement data are based upon sales/retirements of capital, which yield a change in the book value of capital. Using a first in, first out (FIFO) structure and the history of investment and retirements, CEH develop a method to convert this to a real measure of retirements. The methodology yields a measure of the real changes in the plant-level capital stock induced by retirements. In what follows, it is important to note that this procedure does not already capture the difference between buying and selling prices of capital that may influence the adjustment process. We recover that difference in our estimation.

5. Observations of inaction and investment bursts are found in data from other countries as well. For example, Nilsen and Schiantarelli (1998) study investment in Norwegian manufacturing plants for the period 1978–1991. For production units, they report that 21% of the units have zero investment expenditures over a given year. Further, they find that investment rates exceeding 20% arise in about 10% of their observations and account for about 38% of total equipment investment. Related evidence on the lumpy nature of investment for Colombia is provided by Huggett and Ospina (2001).

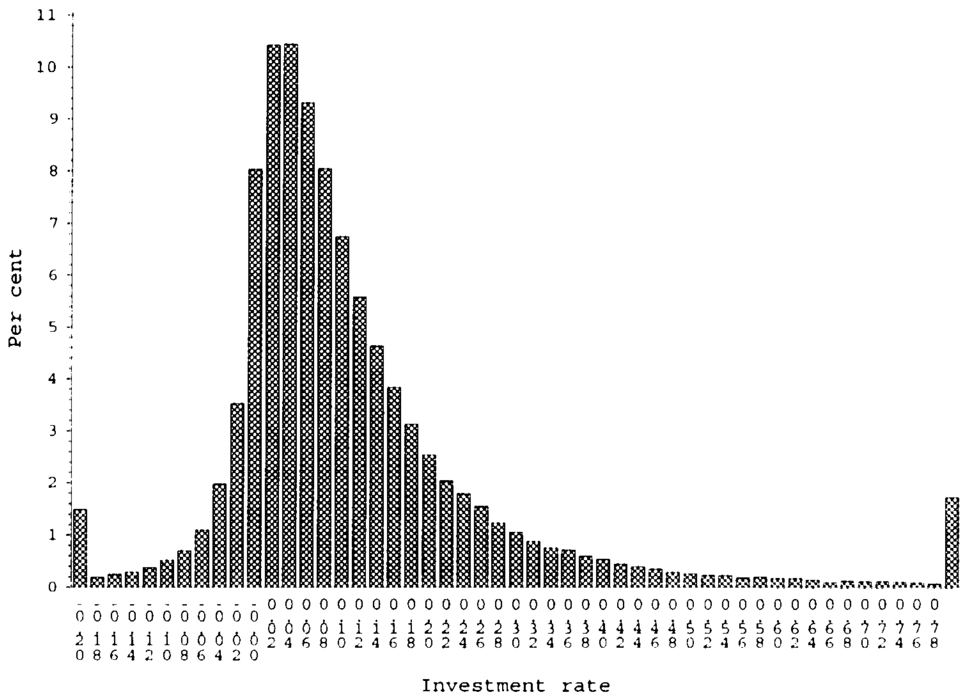

FIGURE 1

Investment rate distribution

TABLE 1

Summary statistics

Variable	LRD
Average investment rate	12·2% (0·10)
Inaction rate: investment	8·1% (0·08)
Fraction of observations with negative investment	10·4% (0·09)
Spike rate: positive investment	18·6% (0·12)
Spike rate: negative investment	1·8% (0·04)
Serial correlation of investment rates	0·058 (0·003)
Correlation of profit shocks and investment	0·143 (0·003)

LRD, Longitudinal Research Database.

The S.E. of these moments are provided in parentheses in Table 1.[6] Given the size of the data-set (these moments are all based on more than 100,000 plant–year observations), these moments are all very precisely estimated. Such precision should not be interpreted as reflecting little dispersion at the plant level. At the micro-level, there is substantial dispersion. For example, the average investment rate is 12·2, but the S.D. of micro-investment is 33·7. Nevertheless, with a very large sample we estimate the mean and other moments of micro-investment very precisely. In what follows, we exploit the micro-heterogeneity explicitly as we use the estimated dispersion of profit shocks from the micro-data.

6. The S.E. reported in Table 1 for the variables reported as percentages are in the same units. Later in the paper we use these same variables as fractions with appropriate adjustment of units of S.E.

We estimate adjustment cost parameters by using a simulated method of moments approach. This approach requires selecting moments to match. Theoretical and practical considerations suggest that the moments should be relevant in identifying the adjustment cost parameters and are also precisely estimated. We regard the four moments in Table 1 as capturing key features of the behaviour of investment at the micro-level.

The first moment is the serial correlation in investment. It is well established in the adjustment cost literature (see, for example, Caballero and Engel, 2003; and CHP) that the serial correlation of investment is sensitive to the structure of adjustment costs. The second moment is the correlation between investment and profit shocks as it reflects the covariance structure between investment and the shocks to profits. This moment and the others we match are quite sensitive to the adjustment cost parameters and in this sense satisfy the relevance criterion. The other two moments capture key features of Figure 1 that have been emphasized in the literature—namely, the investment distribution at the micro-level is very asymmetric and has a fat right tail. To capture these features, we use the positive and negative spike rates in Table 1. Each of these four moments captures key features of investment behaviour at the micro-level, but the exact choice of moments is an open question. In what follows, we use these four moments in our empirical analysis and then present some analysis of robustness of our findings to the choice of alternative moments.

Before proceeding, it is worth noting that one moment we choose not to match directly is the fraction of observations with inaction. While Table 1 shows some range of inaction, the more robust finding in Figure 1 and Table 1 is that the distribution of investment is skewed and kurtotic with a fat right tail. Identifying inaction precisely at the micro-level is difficult because in practice there is substantial heterogeneity in capital assets with associated heterogeneity in adjustment costs. For example, buying a specific tool gets lumped into capital equipment expenditures in the same way as retooling the entire production line. Explicitly analysing the role of capital heterogeneity is beyond the scope of this paper, but we discuss this as an area of future research in the concluding remarks.

3. MODELS AND QUANTITATIVE IMPLICATIONS

Our most general specification of the dynamic optimization problem at the plant level is assumed to have both components of convex and non-convex adjustment costs as well as irreversibility. Formally, we consider variations of the following stationary dynamic programming problem:

$$V(A,K)=\max_{I}\Pi(A,K)-C(I,A,K)-p(I)I+\beta E_{A'|A}V(A',K') \quad \forall(A,K), \tag{3}$$

where $\Pi(A,K)$ represents the (reduced-form) profits attained by a plant with capital K, a profitability shock given by A, I is the level of investment, and $K'=K(1-\delta)+I$. Here unprimed variables are current values and primed variables refer to future values. In this problem, the manager chooses the level of investment, denoted I, which becomes productive with a one period lag. The costs of adjustment are given by $C(I,A,K)$. This function is general enough to have components of both convex and non-convex costs of adjustment. Irreversibility is encompassed in the specification if the price of investment, $p(I)$, depends on whether there are capital purchases or sales.

Current profits, for given capital, are given by $\Pi(A,K)$, where the variable inputs (L) have been optimally chosen, a shock to profitability is indicated by A, and K is the current stock of capital. That is,

$$\Pi(A,K)=\max_{L}R(\hat{A},K,L)-Lw(L),$$

TABLE 2

Parameterization of illustrative models

Model	γ	F	λ	p_s	p_b
No AC	0	0	1	1	1
CON	2	0	1	1	1
NC-F	0	0·01	1	1	1
NC-λ	0	0	0·95	1	1
TRAN	0	0	1	0·75	1

TABLE 3

Moments from illustrative models

Moment	LRD	No AC	CON	NC-F	NC-λ	TRAN
Fraction of inaction	0·081	0·0	0·038	0·616	0·588	0·69
Fraction with positive investment bursts	0·18	0·298	0·075	0·212	0·213	0·120
Fraction with negative investment bursts	0·018	0·203	0·0	0·172	0·198	0·024
Corr (i_{it}, i_{it-1})	0·058	−0·053	0·732	−0·057	−0·06	0·110
Corr (i_{it}, a_{it})	0·143	0·202	0·692	0·184	0·196	0·346

LRD, Longitudinal Research Database.

where $R(\hat{A}, K, L)$ denotes revenues given capital (K), variable inputs (L), and a shock to revenues, denoted $\hat{A}$. Here, $Lw(L)$ is total cost of variable inputs. Clearly, this formulation assumes there are no costs of adjusting labour. Once we specify a revenue function, we can use this optimization problem to determine L and to derive the profit function $\Pi(A, K)$, where A reflects both the shocks to the revenue function and variations in costs of L. Throughout the analysis, the plant-level profit function is specified as

$$\Pi(A, K) = AK^{\theta}. \tag{4}$$

This section of the paper provides an overview of the competing models of adjustment. The parameterizations are summarized in Table 2.[7] For each, we describe the associated dynamic programming problem and display some of the quantitative predictions of the models in Table 3. At this stage these quantitative properties are meant to facilitate an understanding of the competing models. Accordingly, the parameter values are set to "reasonable" levels from the literature. The next section of the paper discusses estimation of underlying parameters.

3.1. *Common elements of the specification*

For the following simulations, the aggregate and idiosyncratic shocks are represented by first-order, Markov processes. Following Tauchen (1986), the set of aggregate and idiosyncratic profitability states as well as the transition matrices are chosen to reproduce the variance and serial correlation of the profitability shocks inferred from our analysis of plant-level profitability. For the remaining parameters, we set the annual discount factor (β) at 0·95 and the annual rate of depreciation at (δ) 6·9%. This depreciation rate is consistent with the one used to create the capital stock series at the plant level, less a retirement rate of 3·2%.

7. In the estimation, determining the value of θ and the parameterization of the stochastic process for A is, of course, critical. The simulations that follow use the estimated values, which are discussed in Section 4.1.1.

3.2. *Convex costs of adjustment*

The traditional investment model assumes that costs of adjustment are convex. Here, we adopt a quadratic cost specification and consider the following specification of the adjustment function,

$$C(I, A, K) = \frac{\gamma}{2}(I/K)^2 K,$$

where γ is a parameter. The first-order condition for the plant-level optimization problem relates the investment rate to the derivative of the value function with respect to capital and the cost of capital, p. That is, the solution to (3) implies

$$i = (1/\gamma)[\beta E V_k(A', K') - p], \tag{5}$$

where i is the investment rate, (I/K), and EV_k is the expectation of the derivative of the value function in the subsequent period. In practice, this derivative is not observable.

As suggested by (5), the investment rate reflects the difference between the expected marginal value of capital, $EV_k(A', K')$ and the cost of capital p. From this condition and the one-period time to build assumption, investment responds to predictable variations in profitability.

If profits are proportional to the capital stock, $\theta = 1$, the model reduces to the familiar "Q theory" of investment in which the value function is proportional to the stock of capital. As in Hayashi (1982), the derivative of the value function can be inferred from the average value of a firm, $V_k(A, K) = V(A, K)/K$.

In the special case of no adjustment costs, $C(I, A, K) \equiv 0$, from (3), the optimal capital stock for the plant satisfies

$$\beta E V_k(A', K') = p.$$

In the absence of adjustment costs, investment will be very responsive to shocks: there will, indeed, be bursts of positive and negative investment.

3.3. *Non-convex costs of adjustment*

Building upon the analysis of Rothschild (1971), Cooper and Haltiwanger (1993), Abel and Eberly (1999), Caballero and Engel (1999), and Cooper *et al.* (1999), during periods of investment plants incur a fixed adjustment cost. Generally, these non-convex costs of adjustment are intended to capture indivisibilities in capital, increasing returns to the installation of new capital, and increasing returns to retraining and restructuring of production activity. These fixed adjustment costs represent the need for plant restructuring, worker retraining, and organizational restructuring during periods of intensive investment.

For this formulation of adjustment costs, the dynamic programming problem is specified as:

$$V(A, K) = \max\{V^i(A, K), V^a(A, K)\} \quad \forall (A, K),$$

where the superscripts refer to active investment "a" and inactivity "i". These options, in turn, are defined by

$$V^i(A, K) = \Pi(A, K) + \beta E_{A'|A} V(A', K(1-\delta))$$

and

$$V^a(A, K) = \max_I \Pi(A, K)\lambda - FK - pI + \beta E_{A'|A} V(A', K').$$

In this second optimization problem, as in CHP, there are two types of fixed costs of adjustment. Both, importantly, are independent of the level of investment.

The first adjustment cost, $\lambda < 1$, represents an opportunity cost of investment. If there is any capital adjustment, then plant productivity falls by a factor of $(1-\lambda)$ during the adjustment period. Studies by Power (1998) and Sakellaris (2001) provide evidence that plant productivity is lower during periods of large investment.[8]

All else the same, this form of adjustment cost implies that investment bursts are less costly during periods of low profitability as adjustment costs are low. But this need not imply a negative correlation between investment and profitability, since there is a gain to investment in high productivity states if there is sufficient serial correlation in the profitability shocks.

The second fixed cost of adjustment, denoted F, is independent of the level of activity at the plant. It is proportional to the level of capital at the plant to eliminate any size effects. Similar results are obtained if the cost is proportional to the plant-specific average capital stock. Thus this cost will naturally produce a positive correlation between investment rates and profitability.

The intuition for optimal investment policy in this setting comes from CHP. In the absence of profitability shocks, the plant would follow an optimal stopping policy: replace capital if and only if it has depreciated to a critical level. Adding the shocks creates a state-dependent optimal replacement policy but the essential characteristics of the replacement cycle remain: there is frequent investment inactivity punctuated by large bursts of capital purchases/sales. Thus, the model is able to produce both the inaction and bursts highlighted in Table 1. Relative to the partial adjustment of the convex model, the model with non-convex adjustment costs provides an incentive for the firm to "overshoot its target" and then to allow physical depreciation to reduce the capital stock over time.

3.4. *Transactions costs*

Finally, as emphasized by Abel and Eberly (1994, 1996), it is reasonable to consider the possibility that there is a gap between the buying and selling price of capital, reflecting, *inter alia*, capital specificity and a lemons problem. This is incorporated in the model by assuming $p(I) = p_b$ if $I > 0$, and $p(I) = p_s$ if $I < 0$ where $p_b \geq p_s$. In this case, the gap between the price of new and old capital will create a region of inaction.

The value function for this specification is given by

$$V(A,K) = \max\{V^b(A,K), V^s(A,K), V^i(A,K)\} \quad \forall (A,K),$$

where the superscripts refer to the act of buying capital "b", selling capital "s", and inaction "i". These options, in turn, are defined by

$$V^b(A,K) = \max_I \Pi(A,K) - p_b I + \beta E_{A'|A} V(A', K(1-\delta)+I),$$

$$V^s(A,K) = \max_R \Pi(A,K) + p_s R + \beta E_{A'|A} V(A', K(1-\delta)-R),$$

and

$$V^i(A,K) = \Pi(A,K) + \beta E_{A'|A} V(A', K(1-\delta)).$$

Here, we distinguish between the purchase of new capital (I) and retirements of existing capital (R). As there are no vintage effects in the model, a plant would never simultaneously purchase and retire capital.[9]

8. Incorporating this into our model implies some potential misspecification of profitability shocks since it is necessary to distinguish λ and low realizations of profitability shocks. We return to this point in detail later.

9. Though, as suggested by a referee, time aggregation may in fact generate observations of both sales and purchases over a period of time.

The presence of irreversibility will have a couple of implications for investment behaviour. First, there is a sense of caution: in periods of high profitability, the firm will not build its capital stock as quickly since there is a cost of selling capital. Second, the firm will respond to an adverse shock by holding on to capital instead of selling it in order to avoid the loss associated with $p_s < p_b$.

3.5. *Evaluation of illustrative models*

As indicated by Table 2, we explore the quantitative implications of five models. While these parameterizations are not directly estimated from the data, they provide some interesting benchmark cases that highlight the key issues arising between models with convex and non-convex costs of adjustment.

The first, denoted "No AC" is the extreme model in which there are no adjustment costs. The second row, denoted "CON", corresponds to a specification in which there are only convex costs of adjustment. The case labelled "NC-F" assumes that there are only non-convex costs of adjustment with $F > 0, \lambda = 0$. The case labelled "NC-λ" is a second non-convex cost of adjustment case with $F = 0, \lambda = 0{\cdot}95$. Finally, the case labelled "TRAN" imposes a gap of 25% between the buying and selling price of capital.

Our quantitative findings for the specifications in Table 2 along with data from the LRD are summarized in Table 3. As noted earlier, there is evidence of lumpiness and inaction in the LRD. In addition, there is low autocorrelation in plant-level investment, which is noteworthy, given that both aggregate and idiosyncratic shocks to profitability exhibit substantial serial correlation.

Comparing the columns of Table 3 pertaining to the illustrative models with the column labelled LRD, none of the models alone fits these key moments from the LRD. The extreme case of no adjustment costs (labelled No AC) is given in the second column. This model produces no inaction but is capable of producing bursts in response to variations in the idiosyncratic profitability shocks. It also generates a large fraction of observations with negative investment bursts. Overall, the model without adjustment costs is very responsive to shocks. Evidently, the empirical role of adjustment costs is to temper the response of investment to fundamentals.

The quadratic adjustment cost model (denoted CON) adds convex adjustment costs to the No AC model. This specification mutes the response of investment to profitability shocks as the fraction of positive and negative spikes is significantly reduced.[10] Further, the convex cost of adjustment model, through the smoothing of investment, creates serial correlation in investment relative to the shock process. Consequently, the correlation of investment and profitability is higher than in the No AC case.

Both treatment of non-convex costs of adjustment (NC-F and NC-λ) and/or the model with irreversibility (TRAN) are able to create investment inactivity at the plant level. However, the non-convex models create negative serial correlation in investment data and a lower correlation between investment rates and profitability. The negative serial correlation of the non-convex adjustment cost models is analogous to the upward sloping hazards characterized by CHP. All of the models are able to produce both positive and negative spikes but, naturally, the asymmetry in spike rates is most prominent in the irreversibility specification.

4. ESTIMATION

None of these extreme models is rich enough to match key properties of the data. The model we estimate includes convex and non-convex adjustment processes as well as irreversible investment.

10. There is a small amount of inaction, which reflects the discrete state space approximation of our quantitative approach.

This combining of adjustment cost specifications may be appropriate for a particular type of capital (with say installation costs and some degree of irreversibility) and/or may also reflect differences in adjustment cost processes for different types of capital. As the data is not rich enough to study a model with heterogeneous capital, our approach is to consider a hybrid model with all forms of adjustment costs and, in turn, to estimate the key parameters of this specification by matching the implications of the structural model with relevant features of the data.

The adjustment cost parameters are estimated using the following routine. For arbitrary values of the vector of parameters, $\Theta = (F, \gamma, \lambda, p_s)$, the dynamic programming problem is solved and policy functions are generated. Using these policy functions, the decision rule is simulated, given arbitrary initial conditions, to create a simulated version of the LRD.[11] We then calculate a set of moments from the simulated data, which we denote as $\Psi^s(\Theta)$. This vector of moments depends on the vector of structural parameters, Θ, in a non-linear way.

The estimate $\hat{\Theta}$ minimizes the weighted distance between the actual and simulated moments. Formally, we solve

$$\pounds(\Theta) = \min_{\Theta}[\Psi^d - \Psi^s(\Theta)]' W [\Psi^d - \Psi^s(\Theta)], \tag{6}$$

where W is a weighting matrix. This simulated method of moments procedure will generate a consistent estimate of θ. We use the optimal weighting matrix given by an estimate of the inverse of the variance–covariance matrix of the moments.[12]

Of course, the $\Psi^s(\Theta)$ function is not analytically tractable. Thus, the minimization is performed using numerical techniques. Given the potential for discontinuities in the model and the discretization of the state space, we used a simulated annealing algorithm to perform the optimization.

For the estimation, we consider two specifications of non-convex adjustment costs. In one, which we term the *fixed cost* case, the costs are represented by a lump-sum cost of adjustment $F > 0$ without any opportunity costs of adjustment $\lambda = 1$. In the second, which we term the *opportunity cost* case, $F = 0$ and $\lambda < 1$. These are taken as leading specifications in the literature, and thus our estimation provides insights into which is more capable of capturing relevant features of the data.[13]

In addition to the adjustment cost parameters, the dynamic optimization problem is also parameterized by the curvature of the profitability function and the process governing the shocks to profitability. The two specifications of adjustment costs, particularly the presence of disruption effects, require different approaches to uncovering the underlying shocks to profitability and characterizing the profitability function.

4.1. *Estimation with fixed costs: $F > 0$ and $\lambda = 1$*

Assume that the dynamic programming problem for a plant is given by

$$V(A, K) = \max\{V^b(A, K), V^s(A, K), V^i(A, K)\} \qquad \forall (A, K), \tag{7}$$

where, as above, the superscripts refer to the act of buying capital "b", selling capital "s", and inaction "i". These options, in turn, are defined by

11. The simulation is for 500 periods. The initial 15 periods are not used in calculating moments so that the results are independent of the assumed initial conditions. The moments are not sensitive to adding more periods to the simulation or to dropping more of the initial periods.

12. See Smith (1993) for details of methodology and measurement of the weighting matrix. In our case, given the large micro data-set we use we estimate the moments that we are attempting to match very precisely. As such, most of the moments we are attempting to match receive a very large weight in (6).

13. Caballero and Engel (1999) consider $\lambda < 1$ and $F = 0$, while Thomas (2002) assumes $\lambda = 1$, and F is random.

$$V^b(A,K) = \max_I \Pi(A,K) - FK - I - \frac{\gamma}{2}(I/K)^2 K + \beta E_{A'|A} V(A', K(1-\delta)+I),$$

$$V^s(A,K) = \max_R \Pi(A,K) - FK + p_s R - \frac{\gamma}{2}(R/K)^2 K + \beta E_{A'|A} V(A', K(1-\delta)-R),$$

and

$$V^i(A,K) = \Pi(A,K) + \beta E_{A'|A} V(A', K(1-\delta)).$$

We have specified some parameters of the model ($\beta = 0{\cdot}95$, $\delta = 0{\cdot}069$, $p_b = 1$) for the functional forms discussed above. Further, we retain our specification of the profit function, $\Pi(A,K) = AK^{\theta}$. For the structural estimation, we focus on three parameters, $\Theta \equiv (F, \gamma, p_s)$, which characterize the magnitude of the non-convex and the convex components of the adjustment process and the size of the irreversibility of investment. As explained next, we estimate the curvature of the profit function and the A process independently of the dynamic programming problem.

4.1.1. Estimates of θ and measuring profitability shocks. Using the assumption of $\lambda = 1$, profits at plant i in period t are given by

$$\Pi(A_{it}, K_{it}) = A_{it} K_{it}^{\theta}, \tag{8}$$

regardless of the level of investment activity. Suppose that $a_{it} \equiv \ln(A_{it})$ has the following structure

$$a_{it} = b_t + \varepsilon_{it}, \tag{9}$$

where b_t is a common shock and ε_{it} is a plant-specific shock. Assume $\varepsilon_{it} = \rho_\varepsilon \varepsilon_{i,t-1} + \eta_{it}$. Taking logs of (8) and quasi-differencing yields

$$\pi_{it} = \rho_\varepsilon \pi_{it-1} + \theta k_{it} - \rho_\varepsilon \theta k_{it-1} + b_t - \rho_\varepsilon b_{t-1} + \eta_{it}. \tag{10}$$

We estimate this equation via generalized method of moments (GMM) using a complete set of time dummies to capture the aggregate shocks and using lagged and twice-lagged capital and twice-lagged profits as instruments. To implement this estimation, real profits and capital stocks are calculated at the plant level. A more detailed discussion of the measurement of real profits and capital as well as the estimation of the profit function and associated robustness issues are provided in the Appendix. Our specification of the relatively simple AR(1) process for the idiosyncratic shocks is motivated by the need to keep the state space relatively parsimonious for the downstream numerical analysis and estimation.

The results give us an estimate of θ and an estimate of the process for the idiosyncratic components of the profitability shocks. From the plant-level data, θ is estimated at 0·592 (0·006) and ρ_ε is estimated at 0·885 (0·004).[14] The estimate of θ is significantly below 1, and this is interesting in its own right. Using the LRD plant-level data on cost shares we estimate $\alpha_L = 0{\cdot}72$, which implies a demand elasticity of −6·2 and a mark-up of about 16%.[15]

Having estimated θ we recover a_{it} from (8) and decompose it into aggregate and idiosyncratic components using (9). This latter step amounts to measuring the aggregate shock as the mean of a_{it} in each year and the idiosyncratic shock as the deviation of a_{it} from the year-specific

14. The S.E. are in the parentheses. The R^2 of the regression was 0·58.

15. While we do not estimate a production function in this paper, the existing plant-level literature suggests that constant returns to scale (CRS) is a reasonable assumption (see, for example, Baily, Hulten and Campbell, 1992; Olley and Pakes, 1996). If α_L denotes labour's coefficient in the Cobb–Douglas technology and ξ is the elasticity of the demand curve, then $\theta = ((1-\alpha_L)(1+\xi))/(1-\alpha_L(1+\xi))$.

TABLE 4

Parameter estimates: $\lambda = 1$

	Structural parameter estimates (S.E.)			Moments				
Spec.	γ	F	p_s	Corr (i, i_{-1})	Corr (i, a)	Spike$^+$	Spike$^-$	$\pounds(\hat{\Theta})$
LRD				0·058	0·143	0·186	0·018	
all	0·049 (0·002)	0·039 (0·001)	0·975 (0·004)	0·086	0·31	0·127	0·030	6399·9
γ only	0·455 (0·002)	0	1	0·605	0·540	0·23	0·028	53,182·6
p_s only	0	0	0·795 (0·002)	0·113	0·338	0·132	0·033	7673·68
F only	0	0·0695 (0·00046)	1	−0·004	0·213	0·105	0·0325	7390·84

LRD, Longitudinal Research Database.

mean. Using this decomposition, we find that b_t has an S.D. of 0·08, and with an AR(1) specification, the relevant AR(1) coefficient (denoted as ρ_b in what follows) is given by 0·76 with an S.E. of 0·19. We also find that the S.D. of ε_{it} is 0·64.

To sum up, in what follows, we use the following key estimates from the data in our estimation of adjustment costs: $\theta = 0{\cdot}592$, $\sigma_\varepsilon = 0{\cdot}64$, $\rho_\varepsilon = 0{\cdot}885$, $\sigma_b = 0{\cdot}08$, $\rho_b = 0{\cdot}76$. These were the parameter values used in Section 3.5. These statistics imply that the innovations to the aggregate shock process have an S.D. of 0·05 and the innovations to the idiosyncratic shock process have an S.D. of 0·30. Neither process is estimated to have a unit root.

These moments of the shock processes are critical for understanding the nature of adjustment costs since key moments, such as investment bursts, reflect the variability of profitability shocks, the persistence of these shocks, and the adjustment costs associated with varying the capital stock. Moreover, the characterization of these processes provide the necessary information for the solution of the plant-level optimization problem, which requires the calculation of a conditional expectation of future profitability.

4.1.2. Estimates of (F, γ, p_s). Table 4 reports our results for different specifications along with S.E.[16] The last column presents $\pounds(\hat{\Theta})$ from (6), a measure of fit for the model. The first row estimates the complete model with three structural parameters used to match four moments. We are able to come fairly close to matching the moments with a vector of structural parameters given by $\gamma = 0{\cdot}049$, $F = 0{\cdot}039$, $p_s = 0{\cdot}9752$, where $\lambda \equiv 1$ throughout.

These parameter estimates imply relatively modest, but statistically and economically significant, convex, and non-convex adjustment costs. The estimates indicate that a model, which mixes the various forms of adjustment costs, is able to best match the moments. This model can produce the low serial correlation in investment as well as the muted response of investment to shocks. Further, with the non-convex adjustment and the irreversibility, the model produces both positive and negative investment bursts of the frequency found in the data.

Restricted versions of the estimated model are also reported for purposes of comparison. Note how poorly the estimated quadratic adjustment cost does as it creates excessive serial correlation as well as a large contemporaneous correlation between investment and the shocks. Interestingly, the quadratic adjustment cost model can produce both positive and negative investment

16. In this table, corr(i, i_{-1}) is the serial correlation of the plant-level investment rate and corr(i, a) is the correlation of the investment rate and plant-level profitability.

spikes, reflecting the underlying shocks to profitability. In fact, the model with quadratic adjustment costs has the largest fraction of positive investment spikes.

The various non-convex adjustment costs mute the response of investment to shocks. Further, these other adjustment costs tend to produce negative serial correlation in investment rates (such as the estimated model with F only). Both specifications with non-convex adjustment costs are closer to the LRD moments than the quadratic model alone.

4.1.3. Evaluation. Are these results reasonable? Of interest relative to other studies are our estimates of γ and p_s. The quadratic adjustment cost parameter has received enormous attention in the literature since a regression of investment rates on the average value of the firm (termed average Q) will identify this parameter when the profit function is proportional to K, and the cost of adjustment function is convex and homogeneous of degree 1. Using the Q-theoretic approach, estimates of γ range from over 20 (Hayashi, 1982) to as low as 3 (Gilchrist and Himmelberg, 1995, unconstrained subsamples, bond rating).

Our estimates of $\gamma = 0{\cdot}049$ appear extremely low relative to other estimates.[17] Direct comparison with other estimates should be viewed with caution given differences in methods and data-sets. Moreover, our best-fitting model is the mixed model so it would be surprising if our estimate of the convex costs are the same as that found by others as we are capturing in other parameters what some studies are attempting to capture with only convex costs. Note, however, that even if we use the estimate of γ from the γ-only model, our estimate of γ is low relative to those in the literature.

In addition, much of the literature uses a Q-theory approach, and given the curvature in the profit function in our analysis (recall we estimate $\theta = 0{\cdot}59$), the assumptions underlying Q-theory do not hold. Put differently, the substitution of average for marginal Q produces a measurement error. Following the arguments in Cooper and Ejarque (2001), this misspecification of Q-theory-based models implies that any inferences about the size of the quadratic adjustment cost as well as the significance about financial variables may be invalid.

To study this latter point, we simulated a panel data-set using our estimated model with all forms of adjustment costs. From this data-set and the associated values from the dynamic programming problem, we constructed measures of expected discounted average Q. We then regressed investment rates on these measures of average Q and then inferred the value of γ from the regression coefficient on average Q. When $\gamma = 0{\cdot}049$, along with the other estimated parameters, is used in the simulation, the coefficient on average Q in a regression of investment rates on a constant and average Q is very precisely estimated at 0·2, implying an estimate of $\gamma = 5$! Thus, the measurement error induced by replacing marginal with average Q creates an inferred value of the quadratic adjustment cost parameter that is well within the range of conventional estimates.[18]

Further, while others have considered models with non-convex costs of adjustment, there are no estimates comparable to our estimate of the fixed cost.[19] This estimate implies that the

17. One exception is the recent study by Hall (2002) in which he estimates quadratic adjustment costs for both labour and capital. Hall finds an average (across industries) value of 0·91 for γ and essentially no adjustment costs for labour.

18. Essentially, the substitution of average for marginal Q creates a negative correlation close to unity between the "error" and average Q. Of course, this correlation goes to 0 if the profit function is proportional to K. Cooper and Ejarque (2001) develop this point to argue that the same measurement error can explain the significance of profit rates in Q regressions in the absence of capital market imperfections. That same result obtains here with non-convex adjustment costs: profit rates are also significant when added as a regressor along with average Q.

19. In particular, neither CHP nor CEH estimate adjustment costs directly. Further, while fixed costs of adjustment are present in the Abel and Eberly (1999) model they do not appear to be estimated either.

fixed cost of adjustment is almost 4% of average plant-level capital. This is a substantial fixed cost.[20]

On p_s, Ramey and Shapiro (2001) suggest that for some plants in the aerospace industry that the value of p_s is about 0·75 (this is based upon the resale prices of capital in this industry). Our estimate is higher, but one problem with making such a direct comparison is that Ramey and Shapiro focused on plants that were being shut down. Our empirical and theoretical analysis, in contrast, focuses exclusively on continuing plants. The nature of irreversibility may be different for a continuing business compared to a business that is shutting down. Understanding the nature of how adjustment costs vary between continuing and entering and exiting plants is obviously an important topic for research in this area but is beyond the scope of this paper. Another related problem for comparison is that Ramey and Shapiro consider plants that shut down due to the shock associated with the end of the cold war and the fall of the Berlin Wall. For present purposes, we do not believe the Ramey–Shapiro estimates are directly comparable to our estimate of p_s.

4.2. *Estimation with opportunity costs: $F = 0$ and $\lambda < 1$*

As other studies, such as Caballero and Engel (1999) and CHP, have introduced λ into the analysis, we broadened our empirical model to incorporate this type of non-convex adjustment cost.[21] With $\lambda < 1$, we capture any adjustment cost that disrupts the production process from, for example, the shutting down of a production line or the reallocation of labour from production to the installation of machines or training.

4.2.1. Estimates of θ and measuring profitability shocks. Introducing $\lambda < 1$ implies that inferring profitability shocks and estimating θ separately from the estimation of the adjustment costs is no longer possible. In particular, the presence of λ in the production function implies that we must identify periods of low productivity from periods of capital adjustment.

One way to proceed would be to expand the set of moments to include the estimated serial correlation and S.D. of the aggregate and idiosyncratic shocks in the set of moments. Then, for each vector of parameters we could re-estimate the moments for the shocks following the methodology outlined in Section 4.1.1. However, this would leave results that were not directly comparable to those reported in Table 4.[22]

Instead, we adopted a two-step iterative procedure. We start with the curvature of the profit function and the serial correlation and S.D. of the aggregate and idiosyncratic shock processes as directly estimated in Section 4.1.1. We then proceed with the best fit of the estimation of the adjustment cost parameters, including λ. We then use the simulated data on profits and capital to estimate (10) and in so doing recover a new estimate of the curvature and the shock processes based upon the simulated data. We compare the latter estimates from the simulated data with the estimates of the curvature and shock processes from the actual data using (10). If they match, we stop. If they don't, we adjust the curvature and shock processes and repeat the process. While in

20. As noted by a referee, one possible concern with our specification is that the fixed cost is proportional to K, and this will influence the investment decision. With this in mind, we estimated a version of the model in which the fixed cost was proportional to the average capital stock of the plant. The resulting estimates were $F = 0{\cdot}05$, $\lambda = 1$, $\gamma = 0{\cdot}069$, $p_s = 0{\cdot}90$, and $\pounds(\Theta) = 6801{\cdot}8$. As the value of $\pounds(\Theta)$ is higher for this specification, we focus on the model given in (7).

21. In Caballero and Engel (1999), λ is treated as a random variable. This introduces an additional element of plant-level heterogeneity that we do not consider. Instead, the plant-specific profitability shock interacts with a deterministic λ to create plant-specific adjustment costs.

22. Further, it is computationally quite expensive to estimate all of these parameters.

TABLE 5

Parameter estimates: $F = 0$

	Structural parameter estimates (S.E.)			Moments				
Specification	γ	λ	p_s	Corr (i, i_{-1})	Corr (i, a)	Spike^{+}	Spike^{-}	$\pounds(\hat{\Theta})$
LRD				0·058	0·143	0·186	0·018	
λ only	0	0·796 (0·0040)	1·0	−0·009	0·06	0·107	0·042	9384·06
All	0·153 (0·0056)	0·796 (0·0090)	0·981 (0·0090)	0·148	0·156	0·132	0·023	2730·97

LRD, Longitudinal Research Database.

principle this might take many iterations, in practice only very modest changes in the curvature and shock processes are required to converge in one iteration.

4.2.2. Estimates of (λ, γ, p_s). Table 5 summarizes our results. We find support for all forms of adjustment costs. The row labelled "all" reports the results with all three types of adjustment costs.[23] The estimated value of λ is significantly less than 1, indicating substantial disruption costs of the capital adjustment process. We again find a modest degree of quadratic adjustment costs and some evidence of irreversibility as well. This model fits the data much better than the specification with $F > 0, \lambda = 1$. This is seen by comparing the values of $\pounds(\hat{\Theta})$.

The row in the table labelled "λ only" focuses solely on disruption costs. There is evidence here of disruption costs but the model does not fit the moments as well as the "all" specification. This result indicates that it is important to have all forms of adjustment costs in the specification.

Relative to previous results, Caballero and Engel (1999) estimate a model in which the disruption costs are random. Further, they do not allow any other forms of adjustment costs. Caballero and Engel (1999) report a mean adjustment cost of 16·5%, which, in our notation, is a value of $\lambda = 0{\cdot}835$. This latter value is quite close to ours, which is striking given that they estimate their model with industry-level data, while we estimate ours using micro-data. There are a number of subtle additional differences in methodology that may be at work as well. Caballero and Engel assume that capital becomes immediately productive and also has stochastic adjustment costs. Both of the latter imply lower average adjustment costs, which is consistent with the pattern of the estimated λ values across the studies.

To obtain a better sense of the magnitude of adjustment costs in this model, we simulated the estimated policy functions and calculated the resulting costs of adjusting the capital stock. The average adjustment cost paid relative to the capital stock was 0·0091 and was 0·031 as a fraction of profits.[24]

Though not reported in the table, we also estimated all four adjustment cost parameters, $\Theta = (F, \gamma, \lambda, p_s)$. We were unable to improve upon the fit summarized in Table 5: allowing $F > 0$ did not enable us to better match the moments.

23. For these results we set the serial correlation of the idiosyncratic (aggregate) shock at 0·92 (0·82) and the S.D. of the innovation to the shock was at 0·22 (0·05). At these parameter values, we are able to reproduce the serial correlation and S.D. for the shocks reported using the methodology described above. In effect, this constitutes another indirect inference procedure. Further, when we re-estimated the profitability function using the simulated data using the same techniques as in Section 4.1.1 (but ignoring the effect of λ), we obtained a value of θ quite close to the value assumed in the analysis.

24. We appreciate conversations with Anil Kashyap on these calculations. In the calculations reported here, when we refer to the average adjustment costs as a fraction of profits, we are referring to the ratio of the expected value of adjustment costs to the expected value of profits. An alternative would be to take the average of the ratio of adjustment costs to profits. The latter is equal approximately to $(1 - \lambda)$ times the fraction of periods with adjustment. Back-of-the-envelope calculations suggest that these two alternatives yield roughly similar results.

TABLE 6

Sectoral parameter estimates

	Parameter estimates (S.E.)				Moments				
Sector	γ	F	λ	p_s	corr(i, i_{-1})	corr(i, a)	spike$^+$	spike$^-$	$£(\hat{\Theta})$
331-LRD					0·086	0·133	0·064	0·02	n/a
331-est.	0·0	0·07	1	0·946	−0·03	0·249	0·076	0·022	62·19
	(0·0003)	(0·0017)		(0·0046)					
	0·015	0	0·70	0·76	0·041	0·146	0·073	0·018	8·13
	(0·0037)		(0·0344)	(0·0167)					
371-LRD					0·082	0·132	0·204	0·013	n/a
371-est.	0·012	0·069	1	0·962	0·069	0·338	0·112	0·037	452·96
	(0·0026)	(0·0057)		(0·0106)					
371-est.	0·051	0	0·679	0·8082	0·251	0·132	0·096	0·027	318·04
	(0·0068)		(0·0398)	(0·0218)					

LRD, Longitudinal Research Database; est., estimates.

4.3. *Sectoral results*

Our analysis of plant-level investment imposes the equality of various parameters (*e.g.* depreciation rates, mark-ups, transition matrices for shocks, etc.) across sectors. Further, the overall fit of the model, as measured by the $£(\hat{\Theta})$ statistic leaves some room for improvement. Thus, it is interesting to study some specific sectors in detail. In this subsection, we re-estimate the model for some leading sectors: steel (331) and transportation (371). For this exercise, we re-estimated the curvature of the profit function and recalculated depreciation rates and transition matrices for profitability shocks by sector.[25]

The estimation results for the structural parameters of the adjustment processes for the two sectors are also reported in Table 6. Once again we find support for the presence of both convex and non-convex adjustment costs along with irreversibility. Further, the specification in which the non-convexity takes the form of disrupting the production process again fits the data best. We again find small quadratic adjustment costs and evidence of irreversibility.

4.4. *Robustness to alternative moments*

In this subsection, we consider the robustness of our results to the choice of alternative moments. As stated in Section 2.2, the moments we have chosen to match capture key features of investment behaviour at the micro-level. We consider two alternative moments that capture the shape and dispersion of investment illustrated in Figure 1.[26] Specifically, rather than using the positive and negative spike rates to capture the asymmetry and fat right tail of the investment distribution, we use the 90th percentile and the 10th percentile of the investment rate distribution for each year averaged over time.

The average 90th percentile from the LRD is 0·299 and the 10th percentile is given by −0·014. These moments capture the asymmetry and fat right tail of the investment distribution. When we use these two moments along with the two correlation moments in our analysis, the estimated adjustment cost parameters are qualitatively and quantitatively similar to the parameter

25. The rates of physical depreciation were 0·076 for sector 331 and 0·063 for sector 371. The curvature of the profit functions differs across these sectors and was 0·66 for 331 and 0·78 for 371, respectively. The AR(1) coefficients for idiosyncratic and aggregate (sectoral) shocks, respectively, were 0·69 and 0·85 for 331 and 0·85 and 0·62 for 371. The S.D. of the innovations for idiosyncratic and aggregate (sectoral) shocks, respectively, were 0·28 and 0·23 for 331 and 0·32 and 0·16 for 371.

26. These were suggested to us by the reviewers and the editor.

estimates reported in Table 5. That is, matching these alternative moments requires a relatively modest convex cost component and substantial disruption adjustment costs and transaction adjustment costs. To be specific, the best fit for matching this alternative set of moments implies an estimate of $\gamma = 0{\cdot}042$, $\lambda = 0{\cdot}86$, and $p_s = 0{\cdot}80$. These parameter estimates yield simulated moments of $\text{corr}(i, i_{-1}) = 0{\cdot}033$, $\text{corr}(i, a) = 0{\cdot}133$, the average 90th percentile investment rate of 0·308, and the average 10th percentile investment rate equal to 0·00. As these alternative moments are estimated precisely in the actual data, the adjustment cost parameters are as tightly estimated as those in Table 5.

5. AGGREGATE IMPLICATIONS

The estimation results reported in Table 5 indicate that a model, which mixes both convex and non-convex adjustment processes can match moments calculated from plant-level data quite well. An issue for macroeconomists, however, is whether the presence of non-convexity at the microeconomic level "matters" for aggregate investment. In particular, there are economic forces, such as smoothing by aggregation and relative price movements, which imply that non-convexities at the micro-level may be less important for aggregate investment.

This issue of aggregate implications has already drawn considerable attention in the literature. CEH find that introducing the non-linearities created by non-convex adjustment processes can improve the fit of aggregate investment models for sample periods with large shocks. CHP similarly find that there are years where the interaction of an upward sloping hazard (investment probability as a function of age) and the cross-sectional distribution of capital vintages matters in accounting for aggregate investment.

We study the contribution of non-convex adjustment costs to aggregate investment (defined by aggregating across the plants in our sample) in two ways. First, we compare aggregated and plant-level moments. We use the term aggregated to indicate that the results pertain to aggregation over our sample and thus may not accord with aggregate investment from, say, the National Income and Product Accounts (NIPA). Second, we compare the aggregate time series implications of our estimated model, termed the *best fit*, against a model with quadratic adjustment costs.

For moments, we calculate the serial correlation of investment rates and the correlation of investment rates and profitability from aggregated investment using the panel of manufacturing plants. To be precise, we compute aggregate statistics from the LRD by creating a measure of the aggregate investment rate and, using the series of profitability shocks described in Section 4.1.1, a measure of aggregate profitability.

The results stand in stark contrast with the moments reported in Table 1. The serial correlation of aggregate investment is 0·46, and the correlation between investment and the profitability shock is 0·51 for the aggregated data. In contrast, the plant-level data exhibits much less serial correlation, 0·058, and much less contemporaneous correlation between investment and shocks, 0·143.

How well does the best-fit model match these aggregate facts? If we compute aggregate investment and the aggregate shock from a simulation using the best-fit model, the serial correlation of aggregate investment is 0·63 and the correlation between investment and the profitability shock is 0·54. Thus, aggregation of the heterogeneous plants alone substantially increases both the serial correlation of investment and its correlation with profitability.

In fact, the aggregate moments reported above seem to be much closer to the prediction of a quadratic cost of adjustment model: from Table 3, a model with quadratic adjustment costs implies high serial correlation and high contemporaneous correlation of investment and shocks. This suggests a second exercise in which we ask how well a quadratic adjustment cost model can match the aggregate data created by the estimated model. To study this, we created a time series simulation (periods) for the estimated model. We then searched over quadratic adjustment costs models to find the value of γ to maximize the R^2 between the series created by the best-fit model and that created by the quadratic model. A value of $\gamma = 0{\cdot}195$ solved this maximization problem, and the R^2 measure was 0·859. Thus, the quadratic model explains most but not all of the time series variation from the best-fit model.

This analysis of the aggregate implications is potentially incomplete in that we ignore two important factors. First, we do not explicitly consider general equilibrium effects.[27] As emphasized by Caballero (1999), Thomas (2002), Veracierto (2002), and Kahn and Thomas (2003), it is likely that there is further smoothing by aggregation due to the congestion effects that are potentially present in the capital goods supply industry and/or due to endogenous interest rate fluctuations.

Second, we work with a subset of manufacturing plants. In particular, we have selected a balanced panel and have thus ignored entry and exit, including the investment associated with that decision. Thus, our "aggregate results" refer to the aggregation over a fixed set of plants.

Nonetheless, the analysis uncovers strong effects of smoothing over heterogeneous plants without variations in relative prices. While identifying the mechanisms that smooth out plant-specific non-convexities is of interest, it should be clear that both smoothing by aggregation and variations in factor prices are important to the smoothing process. That said, it is also clear that the non-convexities at the plant level are not totally smoothed by aggregation: our goodness-of-fit measure is 0·859 not 1!

6. CONCLUSIONS

The goal of this paper is to analyse capital dynamics through competing models of the investment process: what is the nature of the capital adjustment process? The methodology is to take a model of the capital adjustment process with a rich specification of adjustment costs and solve the dynamic optimization problem at the plant level. Using the resulting policy functions to create a simulated data-set, the procedure of indirect inference is used to estimate the structural parameters.

Our empirical results point to the mixing of models of the adjustment process. The LRD indicates that plants exhibit periods of inactivity as well as large positive investment bursts but little evidence of negative investment. The resulting distribution of investment rates at the micro-level is highly skewed even though the distribution of shocks is not. A model, which incorporates both convex and non-convex aspects of adjustment, including irreversibility, fits these observations best. In particular, a model of adjustment in which the non-convex cost entails the disruption of production fits the data best.

In terms of further consideration of these issues, we plan to continue this line of research by introducing costs of employment adjustment. This is partially motivated by the ongoing literature on adjustment costs for labour as well as the fact that the model without labour adjustment costs implies labour movements that are not consistent with observation (see, *e.g.* Caballero, Engel and Haltiwanger, 1997).

Further, it would be insightful to utilize this model to study the effects of investment tax subsidies. Here, those subsidies enter quite easily through policy induced variations in the cost of capital. Clearly, one of the gains to structural estimation is to use the estimated parameters for policy analysis. An interesting aspect of that exercise will be a comparison of the estimated

27. Recall that we have been able to identify the adjustment costs using cross-sectional differences in investment dynamics across plants having controlled for aggregate shocks. However, even though we have been able to identify the adjustment costs, aggregate variation in investment will reflect the complex interaction of shocks, endogenous factor prices, and adjustment dynamics.

model and a quadratic adjustment cost model in terms of their predictions of the aggregate effects of an investment tax credit.

Finally, there are some methodological issues worth exploring further. For this exercise, we have chosen to estimate the model using a simulated method of moments approach. There are, of course, competing approaches, including maximum likelihood estimation (MLE) as well as estimation from the Euler equations, including periods of inaction. In future research, we plan on exploring these competing approaches. These alternative approaches have the potential advantage in that they do not rely on matching specific moments but rather can confront the micro-data directly.

Still, it is useful to emphasize that the simulated method of moments approach we use here has a number of distinct advantages especially in this context. First, structural models of investment with non-convex adjustment costs obviously imply a range of inaction. In the actual micro-data, while we do observe some range of inaction as we report in Table 1, the more robust finding is that the distribution of investment is skewed and kurtotic with a mass around 0 and a fat right tail. Identifying inaction precisely at the micro-level is difficult because in practice there is substantial heterogeneity in capital assets with associated heterogeneity in adjustment costs. For example, buying a specific tool gets lumped into capital equipment expenditures in the same way as retooling the entire production line. The former presumably has little or no adjustment costs while the other is subject to presumably high adjustment costs. The implication is that in pursuing MLE or Euler equation estimation using the actual micro-data a researcher must define "inaction" without observing the underlying capital heterogeneity. Specifically, should a researcher identify inaction as literally zero investment or small investment expenditures that reflect "buying a wrench?"[28] In contrast, we exploit robust moments of the investment and profit distributions.

While we believe the moments we match are robust to capital heterogeneity, this discussion reminds us of the limitations of even high-quality micro-data such as the LRD. The class of adjustment cost models we focus on in this paper are best interpreted as applying to variations in capital expenditures that are relatively homogeneous in type. It is unlikely that we will have a rich longitudinal micro data-set on establishments with annual data on capital expenditures by detailed asset class; unobserved heterogeneity in capital is a feature of reality that estimation of investment dynamics with micro-data on plants needs to confront, regardless of the methodology used.

Another strength of our approach is that analysis and estimation does not require direct and continuous access to the micro-data. Given that virtually all of the high-quality longitudinal micro data-sets are proprietary, it is very useful to have methods available that can take advantage of moments from the micro-data that can be analysed off-site. The research community at large has a much better chance of exploring alternative models of investment using the simulated method of moments approach given limited direct access to the micro-data. Our findings suggest there would be considerable value to statistical agencies producing summary measures of the distributions of micro-investment behaviour and its auto covariance and cross-covariance with other micro-measures.

In the end, there are many dimensions to improve the match between the models we specify and estimate and the full richness of the actual micro-data. Despite these limitations, we have identified features of the micro-data that can only be reconciled with models that contain both convex and non-convex adjustment costs. In particular, a modest convex component and substantial transaction and disruption costs are required to capture key features of micro-investment.

28. In related earlier work, CHP took a stand on this by defining investment spikes of investment greater than 20% as the investment that is subject to fixed adjustment costs. They investigated the robustness of this admittedly *ad hoc* threshold but noted that this was a limitation of their analysis. Note as well that Goolsbee and Gross (1997) consider a model with heterogeneous capital goods.

APPENDIX

In this section, we discuss the measurement of key variables and the details and robustness of estimation for the profit function. Real variable profits are measured as revenue less variable costs (labour and material) deflated by the gross domestic product implicit price deflator for consumption. We make the assumption that measured real variable profits provide an estimate of $\Pi(A,K) = \lambda A K^{\theta}$ in the model. The question then is how adjustment costs in the model are captured in the measured real variable profits or other cost measures in the data. We think it is reasonable to assume that some part of capital adjustment costs are reflected in real variable measured profits either due to the disruption of productivity and/or perhaps equivalently that some of the labour that might have normally been used for production is used for installing capital. It is precisely these arguments that motivate us to consider including an adjustment cost factor via λ. We also think it is reasonable to assume that some adjustment costs take the form of purchased services or contract work that are not captured in measured real variable profits. It is precisely these arguments that motivate us to include adjustment costs that are additively separable from real variable profits and may be either convex or non-convex in nature—hence we consider adjustment costs in the form of both γ or F. In terms of measurement in the LRD, there are no annual data on such purchased services or contract work and so we cannot directly measure these costs. However, we can infer the presence of these costs through the dynamics of investment.

As described in the text, we estimate the parameters of the real variable profit function using the quasi-differenced (10). In practice, we use a transformed version of (10) taking advantage of assumptions that the production function is Cobb–Douglas and that the demand function has constant elasticity. Specifically, we assume that the plant faces an inverse demand function given by $p = y^{-\eta}$ and so has a revenue function of $R(y) = y^{1-\eta}$. Assuming that the production function is given by $y = AK^{\alpha}L^{\phi}$ and that K is predetermined, L is the variable factor(s), and ω is the price of the variable factor(s). The equations that follow are based on one variable factor for expositional purposes but extend easily to multiple variable factors and in our case there are two: labour and materials. Optimization over the variable factor yields a revenue function $R(K, A, \omega)$, a profit function $\pi(K, A, \omega)$, and variable factor demand of $L = h(K, A, \omega)$. The implied revenue and profit functions are given by

$$R(K,A,\omega) = A^{1/(1-\tilde{\phi})} K^{\tilde{\alpha}/(1-\tilde{\phi})} \left(\frac{\omega}{\tilde{\phi}}\right)^{\tilde{\phi}/(\tilde{\phi}-1)} \tag{11}$$

$$\pi(K,A,\omega) = (1-\tilde{\phi}) A^{1/(1-\tilde{\phi})} K^{\tilde{\alpha}/(1-\tilde{\phi})} \left(\frac{\omega}{\tilde{\phi}}\right)^{\tilde{\phi}/(\tilde{\phi}-1)}. \tag{12}$$

where $\tilde{\alpha} = \alpha(1-\eta)$ and $\tilde{\phi} = \phi(1-\eta)$. So the coefficient on K in both the revenue and profit functions is the same, given by $\theta = \frac{\tilde{\alpha}}{1-\tilde{\phi}}$. Moreover, the properties of the shocks to revenue and profits are the same up to a factor of proportionality. So the estimation strategy is to estimate θ from either a quasi-differenced profit or revenue regression on the capital stock. The latter seems preferred since there is potentially less measurement error involved. There are a small number of observations with negative measured real variable profits but by construction there are no businesses with negative real revenue. While it may be that negative real variable profits are possible we suspect that this largely reflects measurement error. To explore this issue we estimated the log-linear quasi-differenced real revenue function on all observations and the log-linear quasi-differenced real profit function on only those observations with non-negative real variable profits. We obtained very similar estimates of θ using both approaches. In the analysis in the paper we use the estimate of θ from the real revenue quasi-differenced estimation, but this is not critical for the reported results.

To obtain the profit shocks, we use the estimate of θ and use (12) to infer the shock. We decompose the shock into aggregate and idiosyncratic components (the aggregate shock is the first moment of the profit shock in any given year, and the idiosyncratic shock is the residual after controlling for year effects). We then estimate the properties of the aggregate and idiosyncratic shocks (both the degree of first-order autocorrelation and the variance of the innovations). We note again that the properties of these shocks are quite similar across alternative ways of estimating θ.

To provide a sense of the robustness of both the estimates of θ as well as the properties of the shocks, we performed a number of cross-checks. One cross-check that we perform is that the above procedures yield two alternative estimates of ρ_ε—one estimate is as described from inferring the shock from the profit function and the second is from the estimation of the quasi-differenced revenue function. These two estimates of ρ_ε are very similar to each other providing support for this estimation strategy.

As a second cross-check, we explored the properties of the innovations to this first-order process. We found that the innovations to the AR(1) representation of ε_{it} had a serial correlation very close to 0 (−0·05).

In addition, as a check on the robustness of our estimate of θ, we also estimated AR(2) specifications with appropriate second quasi-differencing in our estimation of θ. We found θ was 0·60 when we assumed an AR(2) compared to the estimate of 0·592 reported in the text with the AR(1) specification. There was essentially no improvement in the overall fit of the model with an AR(2) specification. Interestingly, even for the ordinary least squares estimation we obtained an estimate of θ of 0·591. Thus, the estimate of θ is very robust. As noted above, once we have an estimate of θ (which is apparently very robust), the properties of the aggregate and idiosyncratic shocks are well captured by an AR(1) process (*e.g.* the implied innovations are serially uncorrelated).

We note in closing that is it not uncommon in the firm-level literature to assume a first-order process for the underlying shocks. For example, the Olley and Pakes (1996) and Levinsohn and Petrin (2000), hereafter LP, methods for estimating production functions are based on the assumption of first-order Markov processes. A key difference between the approach in their papers and that pursued here is that they use a more general first-order Markov process. For example, LP specify the first-order process as the productivity shock in period t being a polynomial function of the productivity shock in $t-1$. As a further point of comparison, unlike these papers we are not seeking to identify the factor elasticities of both variable and quasi-fixed factors of production. Rather, we seek to identify the coefficient on the quasi-fixed factor in the profit function after having already maximized out the variable factors of production. As such, we are similar to LP's "second stage" where they identify the coefficient on capital. In LP's second stage, they employ a GMM approach with lagged values of inputs as instruments in a manner similar to that employed here (although again with the polynomial specification for the first-order process their estimation is more complex).

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