Measuring the Costs of Investment: Lessons from Firm-Level Investment Behavior

by

Adam Reiff
Central European University

Submitted to the Economics Department
on 17 July, 2006, in partial fulfillment of the
requirements of the degree of
Doctor of Philosophy

Abstract

This dissertation consists of *three essays* investigating the different cost components of firm-level investment decisions.

The *first essay* uses a complete asset auction data of a discontinuing Hungarian manufacturing plant to directly estimate the degree of irreversibility of capital purchases. It finds that firms have to pay large discounts – relative to the replacement price – when selling used capital, and that this discount, in percentage terms, is increasing with the size of capital sold. This latter finding has no qualitative, but only quantitative implications on the behavior of firms in general investment models.

The *second essay* simultaneously estimates the different cost components of firm-level investment activity from a dynamic investment model. In doing so, both the model and the estimation technique is a somewhat modified version of what is used traditionally in the literature. The results indicate that both convex and non-convex components are significant at the firm level, and aggregate investment dynamics is different from what is observed at the firm level.

The focus of the *third essay* is on the aggregate implications of the earlier results. Controlled experiments on Hungarian data once again indicate that under the investigated cost structure, aggregate investment dynamics is different from the firm-level dynamics. Further, aggregate investment dynamics under both convex and non-convex adjustment costs is also different from aggregate dynamics under only convex costs, which is another implication of the importance of non-convex investment costs.

Thesis Supervisor: Attila Rátfai
Title: Professor

Measuring the Costs of Investment: Lessons from Firm-Level Investment Behavior

by

Adam Reiff

Submitted to the Economics Department
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

CENTRAL EUROPEAN UNIVERSITY

July 2006

Signature of the Author..
Economics Department
June 13, 2006

Certified by ....
Attila Rátfai
Professor
Thesis Supervisor

Accepted by..
Chair's Name
Chairperson

Content

1. INTRODUCTION

The importance of understanding investment cannot be overstated. For example, Hungarian data about investment (Gross Asset Formation) and GDP shows that investment is responsible for about 20-25% of total (nominal) GDP (*Table 1.1*). The GDP-share of investment is of similar magnitude in more developed countries; in the United States, for example, it was between 16.91% (1992) and 21.98% (1979) during the 1975-2004 period.[1]

Year	Gross Asset Formation (bn HUF)	Gross Domestic Product (bn HUF)	**Gross Asset Formation as % of GDP**
1995	1125.389	5700.278	**19.74%**
1996	1475.538	6900.262	**21.38%**
1997	1898.917	8550.109	**22.21%**
1998	2384.615	10031.925	**23.77%**
1999	2724.532	11198.808	**24.33%**
2000	3099.131	12834.343	**24.15%**
2001	3492.990	14694.638	**23.77%**
2002	3916.892	16657.534	**23.51%**

Table 1.1. Investment (gross asset formation) and GDP in Hungary, 1995-2002. Source: Central Statistical Office of Hungary (KSH)

Investment, however, not only constitutes a large proportion of the GDP, but it is also the most volatile part of it, and it is also one of the main determinants of medium- and long-term growth. These are just a few reasons why it has been one of the more pervasive questions in economics to understand the nature of investment.

Early investment models (known as accelerator models, see for example *Koyck (1954)*) relate investment to sales and output. Though these models performed relatively well to explain aggregate investment activity, they did not provide an underlying theory of why exactly these variables should be included into investment regressions. In search for an underlying theory, *Jorgenson (1963)* set up a neoclassical investment model in which he assumed that firms could instantaneously and costlessly adjust their stock of capital. Under these assumptions he showed that firms always equate the marginal productivity of capital to the user cost of capital. Since there are no frictions in Jorgenson's model, the firms' investment decision is a simple static problem.

[1] This proportion was calculated as the ratio of gross fixed capital formation and nominal GDP. Source: *International Financial Statistics online, http://ifs.apdi.net/imf/ifsBrowser.aspx*.

Later models departed from the unrealistic assumption of costless capital adjustment. If there are frictions to adjust capital stock, however, then the investment decision becomes a dynamic problem in which firms have to consider future conditions when deciding about their current investment. The first models of this type (neoclassical models with adjustment costs) considered the convex costs of investment as such a friction. Among others, *Abel (1983)* showed that in a dynamic model with convex adjustment costs investment is an increasing function of the marginal value of capital (known as Tobin's marginal *Q*), connecting this way *Tobin (1969)*'s *Q*-theory to the neoclassical model with adjustment costs.

Despite their theoretical appeal, however, these traditional models did not get much empirical support. As demonstrated by several surveys (see, for example, *Caballero (1999)*), in empirical specifications investment was found to have low or no responsiveness to investment fundamentals.

Empirical work over the past decade has shown that there are at least two important factors missing from earlier models. First, by investigating the investment pattern of a panel of US manufacturing firms over 17 years, *Doms and Dunne (1998)* showed that firm-level investment is lumpy: a typical firm has huge investment bursts followed by periods of inactivity. This indicates that the continuity of capital stock adjustment – which is a consequence of convex adjustment costs – is not realistic, and implies the existence of other types of costs of capital adjustment.

A second important factor missing from traditional models was documented empirically in another influential paper by *Ramey and Shapiro (2001)*, who show that capital sales entail irreversibility costs. They find that the actual sales price of capital (when sold) can be significantly lower than its replacement value. Irreversibility is a cost of investment because it makes capital assets more expensive. If firms could sell their capital assets at the same price as they purchased them, then after a negative shock, by selling capital, they could get back the original price of investment, so the previous *decision to invest* would not entail any (sunk) cost. On the other hand, if the sales price of used capital is smaller than the purchase price (that is, if we have at least partial irreversibility), the *decision to invest* does entail sunk costs.

New investment models (*Abel and Eberly (1994)*, *Bertola and Caballero (1994)*, for example) explicitly take into account fixed and irreversibility costs of investment.[2] The main goal of this dissertation is to provide further evidence about the importance of these non-convex costs of investment. By the term "further" evidence I mean that I will not stop by asserting that observed investment behavior is lumpy, and this is consistent with the theoretical implications of investment models with fixed and/or irreversibility costs. After providing another piece of evidence that irreversibility costs (when considered on their own) are indeed significant, in the closing chapters I go one step further instead: I simultaneously estimate the key parameters of a general investment cost function in which all types of investment costs are present.[3] Obviously, the simultaneous identification of the different cost components requires that we disentangle the effects of these different types of costs on investment decisions.

The estimation of the different investment cost parameters can be important for at least two reasons. First, the estimate of the irreversibility parameter is interesting on its own right, because it is directly related to disinvestment; and the ease of disinvestment is one of the major determinants of economic flexibility and speed of adjustment to shocks. Further, as data is generally available only for gross investment, negative investment is hidden behind the generally bigger positive investment; therefore disinvestment can be directly observed only on exceptional occasions. Currently I know about one of these: based on the asset sales of a closing US aerospace plant, *Ramey and Shapiro (2001)* report that on average the ratio of the sales price and calculated replacement value of capital assets is only 28%.[4] That is, capital sales can be done at a discount as high as 72% on average, which is quite substantial. *Chapter 3* of the dissertation presents another piece of direct evidence about the significance of irreversibility.

[2] Another frequently used non-convex cost is disruption cost, which means that when undertaking investment, firms' profits decrease by a certain percentage (due to costs of installment and learning the new techniques etc). This is, however, very similar to fixed costs, which are considered to be independent from the size of investment, but are generally assumed to be proportional to the capital stock of the firm. Disruption costs are also a type of costs that are independent of the size of investment, but are proportional to the profits (which is likely to be closely connected to the firm size).

[3] The idea of structural estimation of a general investment model is not new: *Cooper and Haltiwanger (2005)*, and *Bayrakhtar, Sakellaris and Vermeulen (2005)* are just two examples with similar focus. There are some novelties in my approach however: on the one hand, I use an investment model that distinguishes between new and replacement investment. Second, the estimation technique is somewhat different from the "traditional" methods. For a detailed description of these innovations, see *Chapter 4*.

[4] Of course, while this estimate cannot be directly compared to other estimates of the extent of irreversibility that are based on panels of continuously operating firms, it clearly indicates that the extent of irreversibility is significant.

The estimation of the different investment cost parameters is also important because with the cost parameter estimates (besides having better insights into micro-level investment behavior) one can also investigate the *aggregate implications* of micro-based investment models. Using controlled experiments, one can examine the responsiveness of *aggregate* investment to *aggregate* shocks, which can be different from the micro-level responsiveness (see *Caballero (1992)* about the "fallacy of composition"). I devote *Chapter 5* to the analysis of these types of questions.

The outline of the dissertation is the following. *Chapters 3-5* are three separate studies about firm-level investment behavior, while *Chapter 2* contains a literature survey about earlier developments in related areas. It is well known that non-convex costs of adjustment lead to periods of inaction at the micro level. This creates a link between the non-convex investment adjustment models and similar lumpy adjustment models for other factors (labor, inventories, durable goods, prices, consumption etc). This modeling framework is the well-known *S-s* type model family, originally applied to micro-level inventory adjustment. *Chapter 2* therefore describes the evolution of the *S-s* modeling family in the different contexts, with special focus on the evolution of this type of models in the investment literature.

In *Chapter 3* I provide another piece of evidence of the significance of irreversibility. The analysis is on a similar data set that *Ramey and Shapiro (2001)* used: data from an asset auction of a discontinuing firm (in which all capital assets were sold). I use these data to directly estimate the extent of irreversibility at a single firm. While the estimation framework is similar to that of set up by *Ramey and Shapiro (2001)*, the novelty of my approach is that I find an alternative (non-linear) specification that is more appropriate to estimate the extent of irreversibility. I also analyze the theoretical implications of this alternative specification.

Chapter 4 presents a structural and simultaneous estimation of fixed, convex and irreversibility investment costs in a model that is similar (though not identical) to the model of *Abel and Eberly (1994)*. The estimation technique is a somewhat modified version of indirect inference (developed by *Gourieroux and Monfort (1996)*), which was previously used in a similar framework by several studies (see for example *Bayraktar, Sakellaris and Vermuelen (2005)*, though I use an unbalanced panel for the estimation). Here I modify the indirect inference method in such a way that it leads to better identification for all of the parameters.

While I comment on the aggregate implications of my results already at the end of *Chapter 4*, I devote *Chapter 5* to analyze these with some controlled experiments. In particular, I simulate a panel of hypothetical firms that behave according to the model that I estimated previously, and investigate how these hypothetical firms react to aggregate shocks. In this context it is possible to address the question how certain policies (like a monetary policy tightening) influence aggregate investment.

Chapter 6 summarizes the results.

2. THEORETICAL BACKGROUNDS

In models positing constant and instantaneous microeconomic adjustment, the implicit assumption is that this adjustment is cost- and effortless. Relaxing this unrealistic assumption leads to models in which deviations from optimal behavior under costless adjustment is rational; in fact, the optimal timing of adjustments can be determined by equating the marginal costs and benefits of them. Therefore the seemingly irrational behavior at the micro-level (like the frequently observed lumpy adjustment patterns) is the result of a rational decision.

A second common aspect of the models under my focus is that they allow for the possibility that micro-level decisions are sometimes (at least partially) irreversible. This can have important implications for the optimizing behavior of agents, as the cost structure of the decision problem is altered. Therefore it is essential to observe empirically the extent of irreversibility, and consider the theoretical consequences of this.

Finally, when investigating aggregate variables it is often assumed that aggregate behavior can be captured through the behavior of a representative (or average, median) agent. This assumption is practically equivalent to the idea that individual heterogeneity can be disregarded, as micro-level differences are averaged out when aggregation is undertaken. This is, however, not necessarily true when the behavior of the individuals is lumpy (or more generally: not continuous). In these cases, individual heterogeneity can have important implications for aggregate dynamics.

The models discussed below incorporate various elements of these ideas.

2.1. The Evolution of *S-s* Models: Early Models for Inventories

Apparently, while *S-s* type models were widely used in the operational research literature, the first economic application is due to *Arrow et al. (1951)*, who investigate the optimal (non-speculative) inventory policy.[5] The main result of the paper is that if demand is either deterministic or stochastic, and if order delivery is

[5] This context is not surprising: inventories are possibly the easiest to observe among the variables that are controlled by the firms and are costly to adjust.

immediate, it is optimal for the firms to adjust their inventory holdings only when their level reaches 0, with all the optimal orders being of the same magnitude, *S*.

Arrow et al. (1951) also investigate a possible extension of this model, when orders can not be placed continuously. In this case (in their terminology, in the "dynamic model") the reordering point is no longer 0, but becomes $s > 0$, chosen by the firms, with the maximum stock (or order size) still being a constant, $S > s$.

Following this line of research, optimal *S-s* bands for inventory holdings were calculated under many alternative scenarios (see, for example, *Ehrhardt (1979)*); the optimality of these under general circumstances was established by *Scarf (1959)*. Still, two possible generalizations were not considered until the end of the 1970s: possible extensions of the models to other costly adjustable factors, and the implications of the *S-s* type models to the aggregate variables.[6]

2.2. The Aggregate Effects of *S-s* Decision Rules

Although *Arrow et al. (1951)* noted that they have investigated the issue of aggregation, this section is omitted from their paper "for reasons of space". This issue remained unmentioned until 1979, when *Akerlof (1979)* showed that under *S-s* type money holding policies, the income elasticity of aggregate money demand is zero (as any increase in the income does not change the location of the individual *S-s* bands). In fact this is a direct consequence of a similar invariability result at the micro level.

The next step in aggregation the micro-level *S-s* policies is due to *Blinder (1981)*, who investigated more complicated issues in the context of aggregate inventory holdings. Having noted that "aggregation across firms is inherently difficult… [and] it is precisely this difficulty that has prevented *S, s* model from being used in empirical work to date",[7] he presents the results of some interesting controlled experiments (in his words: "simulations") about the behavior of aggregate variables after different micro-level shocks. The results show that even in case of fairly simple microeconomic shocks (like temporary demand shocks, anticipated/unanticipated rises in sales) aggregate inventories behave quite abruptly,

[6] Interestingly, the first paper containing *either* of these ideas actually contains both: *Akerlof (1979)* introduces "threshold-target" rules for optimal money holdings, and also investigates the effects of these on *aggregate* money demand.
[7] *Blinder (1981), pp. 459.*

and the adjustment pattern can be very irregular. Blinder also discusses the importance of the distribution of the individuals inside the *S-s* bands: he asserts that different initial distributions can lead to very different behavior of the aggregate variables, so aggregate level investigations should necessarily depart from this distribution.

The distribution of the individuals inside the *S-s* band is the main focus of the influential paper by *Caplin (1985)*. He shows that under very general conditions[8] the stationary distribution of the individuals' inventory holdings within the *S-s* band is the uniform distribution: for arbitrary initial within-band distribution, in the long run individual inventory holdings (relative to their *S-s* bands) will be uniformly distributed. This finding has two major implications. First, in the long run each individual is equally likely to hold any of her possible inventory levels (within the *S-s* band). Second, the inventory holdings of any two individuals will be independent from each other in the long run, even if their demand shocks are (not perfectly) correlated.[9]

A further investigation of the importance of the within-band distribution of individuals for the aggregate variables is provided by *Caballero (1992)*. In the context of labor force holding, the *S-s* model generalizes to a two-sided adjustment model: adjustments are possible on both sides of the band. By focusing on the evolution of the within-band distribution of individuals, the paper shows that certain micro-level asymmetries (arising from the asymmetric adjustment on the two edges of the band) in the labor force adjustment do not necessarily result in asymmetries on the aggregate level. This result is still valid even if the individual shocks are (not perfectly) correlated, and in order to generate macro-level asymmetries one has to assume some alternative source of asymmetry (like asymmetric shocks at the aggregate level).

There are several other studies investigating the behavior of aggregate variables when individual behavior is of *S-s* type. But the main lesson seems to be identical: the cross-sectional distribution of individuals within the band is important,

---

[8] Effectively these conditions require that individual shocks should not be perfectly correlated.

[9] These results are considered by Caplin only as by-products of his analysis. In fact, the main goal of the paper is to show that *S-s* inventory policies are consistent with the empirical observation that orders are more volatile than sales, a phenomenon that is impossible to be explained with previous inventory models.

and therefore any aggregate investigation *must* consider the effects of the evolution of this distribution.

2.3. Application of *S-s* Models to the Adjustments of Factors Other Than Inventories

Bertola and Caballero (1990) provide a list about those territories where the main idea behind the *S-s* models had been applied with success until the early 1990s. These include early models of money demand (like *Baumol (1952), Tobin (1956)*), models of pricing decisions (*Barro (1972)*), and asset pricing models in the presence of fixed transaction costs (*Constantinides (1986)*). These early papers generally do not state explicitly that they belong to the *S-s* family.

I concentrate here only to the post-1990 literature, where the common root of these applications has already become apparent. The lines of research applying the *S-s* approach primarily include optimal labor force determination, pricing, durable goods consumption and investment models.[10]

Job creation – Job destruction

In the context of the *job creation-job destruction models*, the main challenge was to solve the puzzle of why the variance of job destruction was higher than that of job creation in the vast majority of empirical studies. As mentioned earlier, *Caballero (1992)* pointed out that micro-level asymmetries are not necessarily responsible for the asymmetry in the aggregate figures. He claimed that in order to generate asymmetries in the macro-level, one has to assume that the aggregate (as opposed to individual) shocks are asymmetric: for example, negative aggregate shocks are higher and occur with smaller probabilities.

An important contribution to this debate is due to *Foote (1998)*, who pointed out that the result of higher variance for job destruction than for job creation is mainly observed in the US manufacturing industry, which shows strong declining trend over time.[11] Foote shows that if the desired level of employment has a negative

[10] This list is far from being complete.
[11] That is, firms are hit by asymmetric aggregate shocks, which are more likely to be negative than positive.

trend, then the within-band distribution of the actual employment (relative to the desired level) will be skewed to the right. Therefore, it will be optimal for the firms to have underemployment (relative to their desired level) after any job destruction, so firing is likely to be of higher magnitude than hiring.[12] On the other hand, *Campbell and Fisher (2000)* provide an explanation for the apparently higher variance of job destruction that stems from the micro-level asymmetry of adjustment. As they claim, the cost of the next job created is higher than the wage because of the additional costs emerging, while the cost of the last job retained is smaller than the wage as the costs of firing are avoided then. This type of micro-level asymmetry in the cost structure generates an asymmetric micro-level adjustment pattern (as usually), but in this case it can be shown that this micro-level asymmetry does create an asymmetric aggregate dynamics.

Finally, another important contribution in this area is due to *Caballero et al. (1997)*, who estimate the cross-sectional within-band distribution of individual firms in a panel of US manufacturing plants, and then analyze the relative importance of the aggregate and idiosyncratic shocks to micro- and macro-level adjustment patterns.[13] The paper concludes that idiosyncratic shocks are the dominant factors explaining the micro-level adjustment patterns. The results are also based on the analysis of the within-band distribution of firms, and highlight the importance of this distribution when investigating aggregate responses to different shocks.

Price adjustment

The *S-s* models are also used to study *price adjustment*. It has been established long ago that there is price stickiness on the micro level (for surveys on this, see *Wynne (1995)*, *Bils-Klenow (2004)*, *Álvarez et al (2005)*). The possible and most common explanation of this phenomenon is the existence of menu-costs,[14] which are directly estimated by *Levy et al. (1998)*. Using data from five US supermarket chains, they estimate that menu costs are as high as 0.52$/price change

[12] Note that this line of argument also emphasizes the importance of the within-band distribution of individuals for the aggregate variables.
[13] This paper is different from the previous two in the sense that it does not address the question of why job destruction is more volatile than job creation.
[14] An alternative explanation is provided by *Klenow-Willis (2006)*, who consider the effect of real rigidities induced by Kimball-type consumer preferences, which lead to increasing price elasticity of demand as prices increase.

(or, more than $100,000/year in each store), comprising 0.7 % of total revenues of the stores. Therefore, similarly to the inventory and labor force adjustments, it is optimal for the stores if they adjust their prices only infrequently, and by higher magnitudes.

An *S-s*-based model of optimal pricing decisions is presented by *Ball and Mankiw (1994)*. Their main idea is very similar to the idea of *Foote (1998)*: as generally there is a positive trend in the price level, the desired price of stores is increasing over time. This means that the actual nominal price (relative to the desired price) follows a decreasing trend. Ball and Mankiw show that under these circumstances, after small positive inflation shocks it is optimal to increase the price, but price-cuts should only be undertaken after large negative inflation shocks, resulting in an asymmetric adjustment pattern in the micro-level. From these results, several macro-level consequences can be stated. First, it can be shown that in this case asymmetric micro-level adjustment patterns lead to asymmetric macro-level responses. The reasoning is very similar to that of *Foote (1998)*: it is the aggregate shocks that are asymmetric, and therefore any demand shock will have asymmetric aggregate effects. Following a negative aggregate demand shock, prices are likely *not* to decrease substantially, so it is the output that falls. On the other hand, a positive aggregate demand shock (of similar magnitude) will rather increase the prices, so the output effects will be smaller in this case. As a direct consequence of this, inflation in general (that leads to more frequent changes in relative prices) will have a negative output effect; so according to this argument the optimal rate of inflation is zero.

Ireland (1997) adds another important aggregate implication of the asymmetric micro-level price adjustment. If inflation is high, then disinflation can lead to substantial negative shocks: shocks that are big enough to induce negative price adjustment in the micro-level. That is, in case of high inflation, a quick disinflation will induce price adjustment, and output loss will be of smaller magnitude. In contrast, stopping moderate inflation will not force the agents to downward adjust their prices (as the negative shocks are not big enough for this), so immediate inflation cuts are likely to have substantial output effects in this case.

Rátfai (2002) presents a further application of the *S-s* models to pricing decisions. By studying Hungarian store-level price data, and estimating the within-band distribution of price deviations,[15] the paper finds evidence that the asymmetry of this distribution is a significant explanatory variable for the aggregate price increase, i.e. inflation.

Durable goods consumption

Patterns in *durable goods consumption* can also be investigated in the context of *S-s* models. By investigating households' automobile purchases in the US, *Eberly (1994)* finds that about half of the households behave in a manner that is consistent with the existence of transaction costs. A typical household of this type behaves in the following way: after purchasing an automobile, the household lets it depreciate, and when the value of the car has passed a certain lower threshold, adjusts.[16] The estimates of the within-band distribution of households are consistent with this finding. Eberly also notes that from this micro-level decision rule, several interesting macro-consequences emerge. First, following a shock on aggregate expenditures on durable goods, as controlled experiments show, micro-level adjustment should take a substantial amount of time, explaining the empirically observed persistence in aggregate data. Further, as growing income is shown to narrow the *S-s* band, the income elasticity of aggregate expenditures on durable goods is substantial.

In a similar framework, *Attanasio (2000)* estimates the *S-s* band for the automobile purchases in the US, and finds that it is "strikingly" wide. With a controlled experiment he also investigates the behavior of the aggregate variables, and concludes that the *S-s* model can generate important features of aggregate dynamics.

As the main focus of this dissertation is on *investment* decisions, the next section discusses the evolution of *S-s* models in the context of the investment literature.

2.4. *S-s* Models in the Investment Literature

[15] In estimating the within-band distribution, he uses a method similar to that of *Caballero et al. (1997)*.
[16] The remaining households are found to behave according to a liquidity constraint when deciding about automobile purchases.

As discussed before in details, early investment models (focusing mainly on scale effects and linking the firms' investment activity to sales, see for example *Koyck (1954)*) were quite successful in explaining aggregate investment, but did not have an underlying theory of why exactly those variables were included into investment regressions. On the other hand, although later models (*Jorgensen (1963)*'s neoclassical model on capital adjustment, *Tobin (1969)*'s *Q*-theory, *Abel (1983)*'s neoclassical model with convex costs, for example) did provide an underlying theory of capital adjustment, they failed empirically. Recent empirical studies explain this failure by pointing out the absence of some important factors from the previous models: lumpiness (*Doms and Dunne (1998)*) and irreversibility (*Ramey and Shapiro (2001)*).

Abel and Eberly (1994), (among others, see also *Bertola and Caballero (1994)*) incorporate the empirical observations about lumpiness and (not perfect) irreversibility into a theoretical model of firm-level investment. They assume that the costs of (dis)investment have three distinct components. The first one is a purchase or sales costs, which is simply the buying cost when investment is positive, and the negative selling cost (or revenue) when investment is negative. In this context not perfect reversibility (or partial irreversibility) means that the selling price is smaller than the purchasing price per unit of capital, but still positive. (Perfect irreversibility would mean that the selling price is 0.) The second type of investment cost is size-dependent adjustment cost, for which it is generally assumed that it is a convex function of the size of (dis)investment. The idea here is that various types of costs (like learning costs, transportation costs, installment costs etc.) are not linearly increasing with the size of investment. And finally, the third type of investment cost is fixed cost, which is to be paid whenever investment is non-zero.

Abel and Eberly show that under this cost structure, the optimal investment behavior is an increasing function of the marginal q (this finding is similar to *Abel (1983)*'s result, where only convex adjustment costs were incorporated). But in this case the optimal investment function is discontinuous: under a certain threshold q_1, optimal investment is negative: $I(q) < 0$. Above a higher threshold $q_2 \geq q_1$, optimal investment is positive. Between these two thresholds the optimal investment is zero. The interval $q_1 \leq q \leq q_2$ is called the inaction range.

In one of their later study, *Abel and Eberly (1999)* empirically estimate the parameters of their theoretical model in a panel of US plants. They find that investment is increasing as q increases: for relatively low levels of q, responses to improvement in q are strong, indicating that many firms pass their thresholds from the inaction range to the positive investment range. On the other hand, if q is high, than the still positive response to a further improvement in q is much weaker. This represents the fact that the majority of the firms have already been in their positive investment range before the improvement. Therefore, the distribution of firms within their inaction ranges does have an impact on aggregate investment patterns.

Caballero and Engel (1999) generalize the Abel-Eberly model by assuming that the borders of the inaction range, q_1 and q_2 are stochastic. In this framework, they estimate the hazard function of a positive investment for US manufacturing plants, and find that the hazard function, in line with the theoretical results, is increasing in q.

Cooper et al. (1999) set up an alternative framework in which the hazard function of investment can be estimated. The variable under their focus is the age of capital, and the main question is the optimal timing for the individual firms to replace their old capital with new one. This model assumes constant rate of depreciation of capital goods, and fixed costs of adjustment. While it is not possible to solve the model analytically, Cooper et al. show that the hazard of machine replacement is an increasing function of the age of the capital goods, a similar result to *Caballero and Engel (1999)*.

The next three chapters of the dissertation will present empirical investigations about the determinants of firm-level investment behavior. In particular, in *Chapter 3* I will estimate the extent of irreversibility of investment (together with its determinants) based on a Hungarian data set. I will also examine how my results can be incorporated into the current line of investment models. In *Chapter 4*, based on a different data set, I will estimate directly and simultaneously the fix, convex and irreversibility costs of the firm-level investment decisions on a panel of US manufacturing firms. The main focus of *Chapter 5* is on aggregate implications. There I use a Hungarian panel to estimate the structural cost parameters, and concentrate on the aggregate effects of the results.

3. ESTIMATION OF IRREVERSIBILITY OF INVESTMENT

3.1. Literature: More on Irreversibility

Traditional investment models (by assuming that the sales price of new capital is 0) assume that any investment decision is perfectly irreversible. In contrast, *Ramey and Shapiro (2001)* estimate the average ratio of the sales price and replacement value of used capital to be 0.28,[17] so irreversibility is not perfect.

The assumption of perfect irreversibility may have emerged because negative investments are rarely observed empirically. The reason of this can be that a typical data set contains yearly data on firm- or plant-level investments. In these data sets, positive and negative investments are added up, and any disinvestment is likely to be hidden behind the positive investments in other types of capital by the firm or plant in the observed year. Moreover, as *Abel and Eberly (1994)* note, even if irreversibility is not perfect, it is still possible that it is never optimal for the firms to disinvest. This is the case when the lower threshold of the inaction range happens to be negative.

Despite the fact that negative investments are very rarely observed, it is still very important to investigate this problem, because the possibility of disinvestment can influence the costs of investment decisions and optimal investment rules. Besides the study of *Ramey and Shapiro (2001)*, *Goolsbee (1997)* considers this issue by investigating the retirement pattern of Boeing-707 airplanes. Based on a complete list of retired Boeing-707s, he finds that retirement and depreciation are endogenous decision variables: the retirement hazard is an increasing function of fuel costs, the aerospace-company’s cash-flow, while it is negatively related to the GDP-growth and cost of capital. This means that factors influencing investment decisions may also influence retirement decisions, so the effect of any shocks to gross investment may be different from their effect to net investment.

In this chapter I directly measure the extent of irreversibility at a discontinuing Hungarian manufacturing plant.

[17] This ratio depends on the specificity of the capital assets and several other factors. One of the main goals of Ramey and Shapiro is to investigate these determinants.

3.2. Estimation Strategy and Data

I examine a Hungarian data set that is similar to the data set of *Ramey and Shapiro (2001)*, and I also adopt a similar (though not identical) estimation framework to theirs. The starting point is the following equation:

$$S_i = \alpha + \beta R_i + \varepsilon_i , \qquad (3.1)$$

where S_i , R_i are the sales price and the current-dollar replacement price of the *i*-th item sold, respectively, ε_i is random noise, and α is the constant term. I will return to the measurement of these variables only in section 3.3, after the data description here.

Ramey and Shapiro do not motivate the above specification with some underlying theory, they just provide some verbal justification: "[…] To put the data on a current-cost basis, we reflate the original acquisition cost plus the cost of subsequent investment for rebuilds using implicit deflators for investment goods. […] In theory, these indexes should measure the change in price holding quality constant, so the reflated values represent *replacement cost*."[18]

Later, in the econometric specification that they actually use, they define the replacement cost as the "current-dollar (reflated), depreciated acquisition cost of initial investment",[19] claming that this "is the standard definition of the net capital stock from depreciated, current-dollar investment flows […]".[20] That is, the replacement cost (or replacement value) that they use for their econometric investigations accounts for *both* inflation of the capital items and the depreciation of them.

Despite the lack of any structural model behind equation (3.1), and the somewhat *ad hoc* nature of its specification, I use this equation as a *reduced form starting point* that relates observed auction sales prices to their estimated "replacement values". Another advantage of this approach is that it makes it easy to directly relate my findings to those of Ramey and Shapiro.

[18] *Ramey-Shapiro (2001)*, p. 970. (My emphasis.)
[19] *Ramey-Shapiro (2001)*, p. 972.
[20] *Ramey-Shapiro (2001)*, p. 972.

I collected data from a small Hungarian manufacturing plant that discontinued operation on July 1, 2001, due to the reorganization of the main firms' activities. As the entire product line was discontinued (despite yielding profits during the final years of operation), and because of the relatively large distance of the closing plant from other plants of the firm, all producing capacities were sold in an open asset auction. This, together with the exogenous nature of the discontinuation, excludes the possibility of any kind of endogeneity (due to decreasing industry-level demand or selection of capital items sold).

The asset auction took place in September 2001, after an extensive advertising campaign (local newspapers, Hungarian newspapers, Internet) run by the US-based auctioning company. Some advertising was also undertaken in Slovakia, Poland and the Czech Republic, but no bidders turned up from foreign countries. There were some individual bidders from the near proximity of the closing plant, but institutional bidders came from all regions of Hungary.

During the auction, all producing capacities of the plant were offered to sale. In the auction report there is a total number of 617 items, but because of the grouping of the various items, sometimes several closely related items were sold for a single price, and actually there are only 408 different auction price entries. The total sales value of the auction is more than HUF 61 million (then approximately 200,000 US dollars).

Besides the auction report, the list of all existing assets of the company at the time of discontinuation is also available, making it possible to match the items sold at the auction with items on the asset list. After careful examination, such matches could be identified in only 193 instances, comprising of less than half of the total number of items. But the total auction sales value for these matches still exceeds HUF 57 million, so the sales value based coverage of the final data set is well above 90%.[21] Once a match was found, it was also possible to identify the date of purchase and the purchase price of particular assets, together with the book value at the time of the asset listing. This is a unique feature of my data set: in *Ramey-Shapiro (2001)*, initial purchase prices are only available for a very small (and probably non-randomly selected) sub-sample of items sold.

[21] This fact indicates that the unidentifiable items are mainly those with very low sales price, and that mostly big-ticket items are present in the final sample.

Among the 193 identified matches, I make distinction between three major types of items: tools and machines (130), raw materials (25), and finished goods (38). *Table 3.1* summarizes the number of entries and the total sales price in each of these groups in our final sample.

	Tools and machines	*Raw materials*	*Finished goods*	*Unidentified match*	***TOTAL***
No. of items	130	25	38	215	**408**
Sales value	44,812,000	6,316,000	6,000,000	4,635,600	**61,763,600**
% of sales val.	72.55%	10.23%	9.71%	7.51%	**100.00%**

Table 3.1. The composition of the final auction sample.

The most interesting part of this data set is *tools and machines*, but it is also interesting to have a look at the basic characteristics of the data on raw materials and finished goods liquidations. In case of *raw materials* (25 items), it is reasonable to assume that the company purchased them not very long before the asset auction (say, within one year), so it is possible to compare nominal purchase prices to the nominal sales prices. For this subgroup, the total sales price was HUF 6,316,000, while the total purchase price was HUF 62,618,877, which means that on average the sales price was only 10% of the purchase price.[22] *Figure 3.1* illustrates the sales price – purchase price relationship of the different observations, and also a trend-line. (Note the difference between the scaling of the two axes.)

[22] This is not very surprising. The company knew well in advance that it will discontinue its operation on 1 July, 2001, so it had only those types of raw materials on stock that could be purchased by larger amounts, and were half-used at the moment of discontinuation.

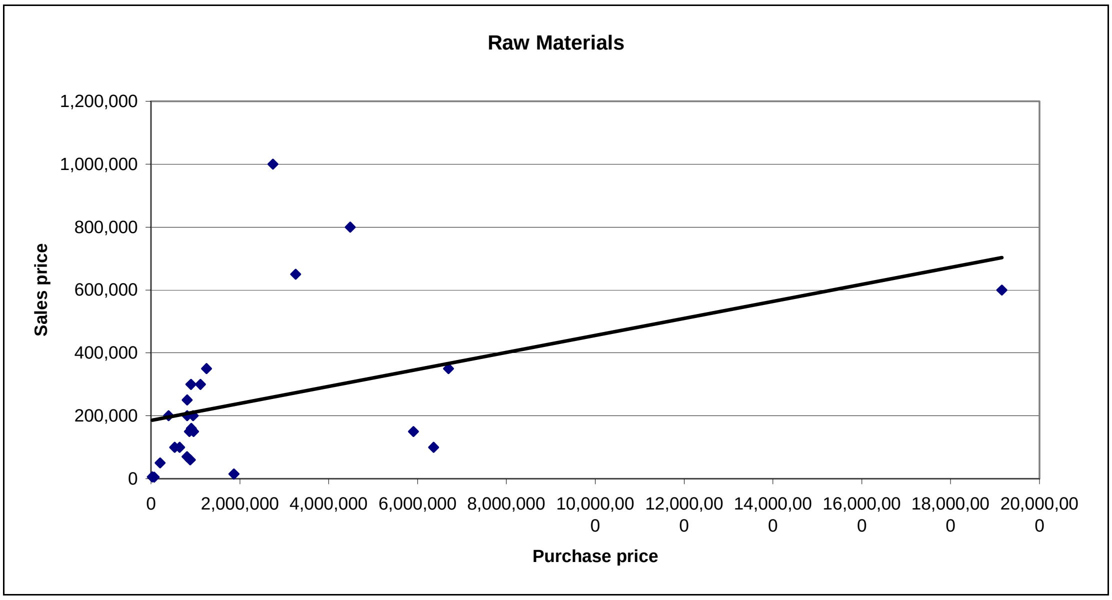

Figure 3.1. The sales price and the purchase price of raw materials.

There were 38 items on the auctions that belonged to the *finished goods*, and their total sales price (HUF 6,000,000) is about one-sixths of their total purchase (or production) price (HUF 35,791,472). Therefore the discount is smaller in this case, but it is still substantial. It is apparent from *Figure 3.2* that the variation of the sales price – purchase price ratio is much smaller in this case.

Figure 3.2. The sales price and purchase price of finished goods.

To answer the question of whether there are also large discounts in the most interesting subgroup of the data set, *tools and machinery* (130 items), further investigations are needed. The difficulty here is that the majority of the tools and machines were purchased several years, or in some cases several decades before the auction, therefore observed sales prices are not comparable to nominal purchase prices. Furthermore, depreciation also changes the replacement value of the various assets, and has to be estimated in order to obtain a meaningful comparison.

Before turning to this issue (in section 3.3), I present a further classification of the items belonging to this sub-group. First of all, a careful investigation of the data revealed that 17 observations of the data are unreliable.[23] As the total sales value associated to these observations is only about HUF 1 million, for the sake of reliability I decided not to include them into the final sample.

Among the remaining 113 items, there is one with a very high sales price (comprising more than 58% of total sales). This is a product-specific complex structure of machines. For the empirical investigations, I decided to drop this observation, as it is totally different from the other categories and is likely to influence the results to a large extent. Moreover, there are altogether 66 machine-type items, with more than 39% of total sales price, 4 forklift-type equipments and 33 hand-tools, with much less importance in terms of sales price. Machine supplements (4) and measuring items (5) have only minor importance (see *Table 3.2*).

Category	No of Items	Total Sales Value	%
General tools	25	HUF 201,000	0.46%
Industry-specific tools	8	HUF 222,000	0.51%
General machines	61	HUF 17,012,000	38.83%
Industry-specific machines	5	HUF 231,000	0.53%
Machine supplements	4	HUF 23,000	0.05%
Measuring items	5	HUF 39,000	0.09%
Forklifts	4	HUF 580,000	1.32%
Structures	1	HUF 25,500,000	58.21%
SUM	**113**	**HUF 43,808,000**	**100.00%**
Unreliable match	*17*	*HUF 1,004,026*	

Table 3.2. Further classification of tools and machines.

[23] I have several variables according to which matches between the auction report and the asset listing could be identified: item numbers, buyers' codes, asset descriptions. If one of these variables were not the same in the two data sources for a specific item (despite some others being identical), then I classified the match as being unreliable.

3.3. A Simple Model for Determining the Discount on Sales

Now I return to the measurement of the variables in equation (3.1) that serves as a starting point. The first task is to determine the replacement value of the assets in the sample, in which I adopt the method used by *Ramey-Shapiro (2001)*. In the current data set, entries in the auction report generally have several lots: that is, more than one asset may have been sold for a single price. For all the lots, I have information about their age and initial purchase price. This latter can be expressed easily in current HUF-s by using appropriately selected investment price indices.[24] I denote the current-forint price of the *v*-th lot in the *i*-th item by I_{iv}.

Next, following the empirical evidence about the quadratic nature of the economic depreciation function in *Ramey and Shapiro (2001)*, I assume a quadratic depreciation function: the value of assets at any age (relative to their initial value) is $\exp\left(-\delta_1 AGE_{iv} - \delta_2 AGE_{iv}^2\right)$. Therefore, the replacement value $\left(K_i\right)$ of item *i* in the auction report (in which the total number of lots is LOT_i) can be calculated in the following way:

$$K_i \equiv \sum_{v=1}^{LOT_i} I_{iv} \exp\left(-\delta_1 AGE_{iv} - \delta_2 AGE_{iv}^2\right). \tag{3.2}$$

The next step is to express the sales price $\left(S_i\right)$ as a function of this replacement value. For this I use a modified version of Ramey and Shapiro's equation (and also a modified version of (3.1)). Assuming that the proportion of sales price and replacement value, i.e. the "discount rate" is asset-specific (with respect to different type and specificity) and constant over time for each type of assets, the equation to be estimated is

$$\begin{aligned} S_i = \alpha + \beta_1 D_{GENTOOL} K_i + \beta_2 D_{SPECTOOL} K_i + \beta_3 D_{GENMACH} K_i + \beta_4 D_{SPECMACH} K_i + \\ + \beta_5 D_{SUPPLEMENT} K_i + \beta_6 D_{MEASURE} K_i + \beta_7 D_{FORKLIFT} K_i + \varepsilon_i , \end{aligned} \tag{3.3}$$

[24] The purchasing date of the oldest machine sold at the auction is 1952. I have investment price indices from that time, which is likely to be reliable as effectively there was no inflation in Hungary before 1965.

where D_j represents the dummy variables for the different types of assets.[25]

Equation (3.3) is estimated by OLS, with a grid-search for the depreciation parameters. I found that the variance of the error term is the smallest if $\delta_1 = 0.1168, \delta_2 = -0.00245$, and the estimated regression parameters in this case are

$$SALESPR_i = 118152 - 0.9663 D_{GENTOOL} K_i + 0.0058 D_{SPECTOOL} K_i +$$
$$+ 0.0941 D_{GENMACH} K_i + 0.0055 D_{SPECMACH} K_i - 0.8422 D_{SUPPLEMENT} K_i -$$
$$- 3.0524 D_{MEASURE} K_i + 0.2472 D_{FORKLIFT} K_i .$$

where parameters $\beta_2, \beta_4, \beta_7$ (on variables *SPECTOOL, SPECMACH* and *FORKLIFT*) are *not significant* at the 5% level.

There are several problems with this specification. First, some of the estimated parameters are negative, indicating that any *increase* in the replacement price is likely to *reduce* the sales price. Further, similarly to the results of *Ramey and Shapiro (2001)*, the constant term is significantly positive. Finally, the residual graph (*Figure 3.3.*) indicates that there are several outlier observations for which the model fits poorly.

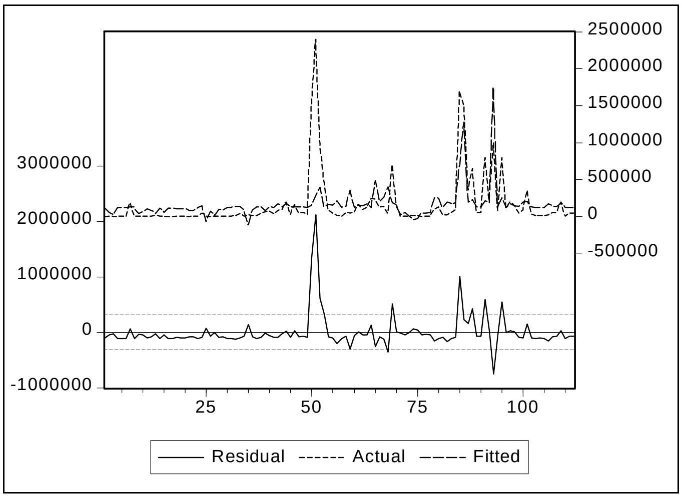

Figure 3.3. The residuals in the original (linear) model.

[25] These different types are classified as in *Table 3.2*: general tools (GENTOOL), special tools (SPECTOOL), general machines (GENMACH), special machines (SPECMACH), supplements (SUPPLEMENT), measuring items (MEASURE), forklifts (FORKLIFT).

To correct for these problems, I ran several modified regressions. First I estimated the same model with the omission of the outliers, but this did not help: the original outliers were those observations that had the highest sales price, and after the omission of these the observations the next few highest sales prices became outliers. Then I constrained the constant term to be zero. This helped a bit, as all the remaining estimated parameters became significantly positive (and all being below 1), but I still could not solve the outlier problem. *Table 3.3* summarizes the parameter estimates of some of the modifications.

	N=112	*N=112*	*N=110*	*N=112*	*N=110*
Delta1	0.1168	0.1572	0.1794	0.1551	0.1763
Delta2	-0.00245	-0.00359	-0.00401	-0.00355	-0.00396
Constant	118152	-	-	-	-
GENTOOL	-0.9663	0.1290	0.1476		
SPECTOOL	0.0058	0.1262	0.1352	0.1482	0.1708
GENMACH	0.0941	0.1517	0.1769		
SPECMACH	0.0055	0.0332	0.0377	0.0328	0.0370
SUPPLEMENT	-0.8422	0.0816	0.1033	0.0798	0.0999
MEASURE	-3.0524	0.3055	0.3444	0.3017	0.3390
FORKLIFT	0.2472	0.7588	0.9677	0.7390	0.9309

Table 3.3. The estimated parameters in the variants of the original model.
(Note: N=112 means that all observations except for the structural item are included into the sample. N=110 means that two observations with the highest sales prices are dropped. When there is no estimate for the constant term, it was imposed to be 0. The final two columns contain estimates for specifications where the $\beta_{GENTOOL} = \beta_{SPECTOOL} = \beta_{GENMACH}$ *restriction was imposed.)*

The parameter estimates in those specifications where the constant term is restricted to zero are quite meaningful (all the parameters in all the models are significant at the 5% level), because (1) all of them lie between 0 and 1; (2) specialized items generally have significantly higher discounts than general items, as expected (for example: the most general forklift-type items always have the largest estimated parameter, and hence the smallest discount).

These specifications, however, are still not satisfactory. First, the constant term, initially found to be significantly positive, is restricted to 0, making it inappropriate to apply the constant-discount model for these data. Moreover, the residuals are not normally distributed, but the biggest problem seems to be that the number of outliers is particularly high in all of the specifications.

The main problem with these specifications becomes apparent if one looks at the distribution of the dependent variable, S_i, depicted in *Figure 3.4*.

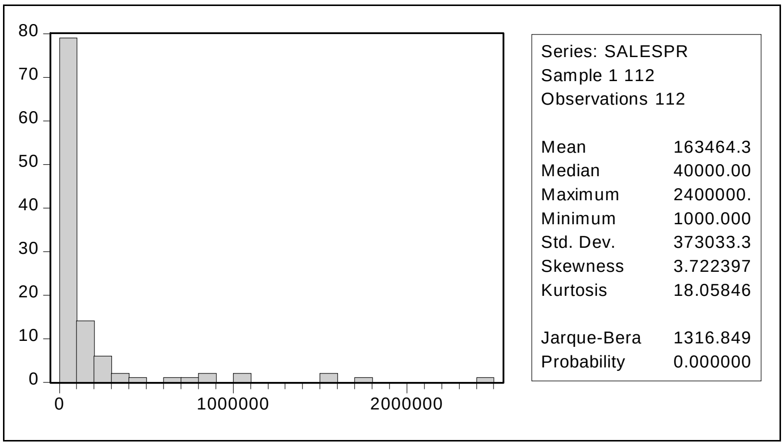

Figure 3.4. The distribution of the auction sales prices.

This distribution is clearly non-normal. So as a next step I tried to fit models in which the distribution of the residuals is non-normal, but the results were disappointing. Finally I took the logarithm of the sales price variable, and found that the null hypothesis that the auction sales prices are log-normally distributed cannot be rejected (*Figure 3.5.*).

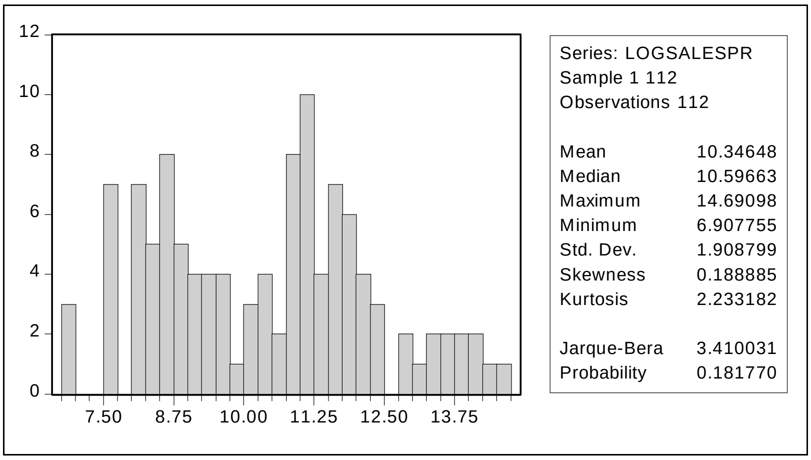

Figure 3.5. The distribution of the log of the sales price at the auction.

Therefore I estimated equation (3.3) for the logs of the variables instead of the levels. The estimated depreciation parameters are ($\delta_1 = 0.0536, \delta_2 = -0.00107$) in this case, while the estimated regression parameters are reported in *Table 3.4.*

	Estimated	*Std error*	*t-stat*
Constant	3.4298	0.9448	3.6302
GENTOOL	0.4689	0.0901	5.2042
SPECTOOL	0.4363	0.0816	5.3468
GENMACH	0.6098	0.0709	8.6008
SPECMACH	0.5213	0.0811	6.4279
SUPPLEMENT	0.4116	0.0885	4.6508
MEASURE	0.4938	0.0972	5.0802
FORKLIFT	0.6452	0.0860	7.5023

Table 3.4. Estimated parameters in the log-log model.

This model has several advantages, compared to the model on the levels: the residuals are normally distributed, the proportion of outliers is approximately 5% (in both directions), and all the estimated parameters are significantly positive.

As the model is estimated in logarithms, one can interpret the parameters as the elasticities of the sales prices of the different sub-groups with respect to their replacement value. As all the estimated parameters are significantly bigger than 0, and significantly smaller than 1, one can conclude that if the replacement value of any asset increases by 1%, its auction sales price will increase by less than 1%. In terms of the levels, the higher is the replacement value of an asset, the higher will be the discount at which it can be sold. This conclusion is consistent with the significantly positive constant term in the earlier specification for the levels, and also with the findings of *Ramey and Shapiro (2001)*.

Investigating the relative magnitude of the estimated parameters, the elasticity estimates are the highest for forklifts and general machinery; in fact, these two estimates are not significantly different from each other, so forklifts can be treated as machines for general purpose. This means that for these asset types when the size of investment increases, the corresponding increase of the discount is the smallest. On the other hand, the estimated parameters for the specialized items, together with the machine supplements (that are also special items if sold on their own) are significantly lower. So the discount on these items is likely to be substantial, which is a quite sensible result.

3.4. A By-Product of the Analysis

Besides the estimates of the selling discounts on various assets, I also have parameter estimates for the depreciation rates; these are that I examine briefly in this section. *Figure 3.6.* shows the estimated depreciation scheme in the log-log model, by depicting the graph of the function $\exp\left(-0.0536AGE + 0.00107AGE^2\right)$.

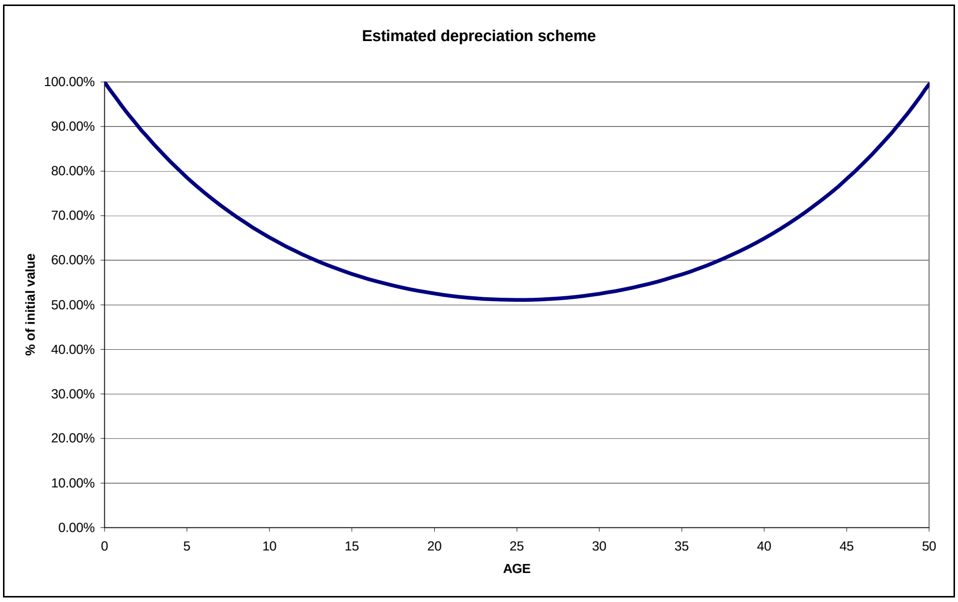

Figure 3.6. Estimated depreciation scheme in the log-log model.

In this respect, my results are similar to those obtained by *Ramey and Shapiro (2001)*. First, the quadratic term, $\hat{\delta}_2$ is significant in the sense that due to this term, the depreciation scheme is highly non-linear. The approximately 5% rate of depreciation in the first few years also matches the initial expectations one could have, and is in line with other empirical estimates (see, for example *Jorgenson (1996)*).

A further similarity is that for older assets, estimated depreciation rates become negative. This finding can be explained by two factors. First, old assets in any sample may suffer from selectivity bias: if a machine is still in operation after, say, 50 years, then it must be of very good quality (relative to their similar counterparts), otherwise it would have been retired earlier. Second, old machines become more and more valuable, as they are generally the only sources that contain supplements and parts which can be used to repair other machines of similar age. These supplements then become more and more scarce over time as the production of them is likely to be finished at some point.

3.5. Linking the Results to Theoretical Investment Models

I now examine how the result of increasing discounts on asset liquidation can be incorporated into theoretical investment models.

I found that even after controlling for the specificity of the various types of capital assets, the discount when selling used capital goods is increasing with the size of the replacement value.[26] The estimated equation in the preferred model was

$$\ln S = \alpha + \beta \ln I \qquad (3.4),$$

or equivalently, $S = AI^{\beta}$, with $A = \exp(\alpha)$. The estimated parameters were significantly positive at the 5% level, but the β-s for the different types of assets ranged between 0.4 and 0.6 (the lowest values referred to the most specific, while the highest values were obtained for the most general assets).

As discussed later in length, a general formulation of the investment cost function in theoretical investment models is the following:

$$\frac{C(I,K)}{K} = \begin{cases} 0, I = 0, \\ F + P\dfrac{I}{K} + \gamma_1(I/K), I > 0, \\ F + p\dfrac{I}{K} + \gamma_2(I/K), I < 0. \end{cases} \qquad (3.5)$$

In equation (3.5) F is the fixed cost of investment, and it has to be paid whenever investment is non-zero. (Note that the fixed cost is assumed to be proportional with the firm's capital, or size, a common assumption in the literature.) Then there is also a linear component in the cost structure, which comes from the buying (P) and selling (p) price of capital, with the buying price being at least as high as the selling price $(P \geq p \geq 0)$. Irreversibility then means that the selling price is strictly smaller than the buying price. Finally, $\gamma_i(I/K)$ are convex functions of the

[26] A similar finding can be deducted from the results of *Ramey and Shapiro (2001),* where the estimated constant term in the model for the levels of the variables is significantly positive, also indicating increasing discounts with size.

investment rate, I/K; it is usually assumed that γ_1 and γ_2 are quadratic and identical (and therefore the convex cost component is symmetric around 0).

To incorporate my result of increasing discounts when selling capital, one has to modify this formulation. Assuming that the estimated β in equation (3.4) is 0.5 (in fact we estimated it between 0.4 and 0.6 for the various types of assets), then the cost function becomes

$$\frac{C(I,K)}{K} = \begin{cases} 0, I = 0, \\ F + P\dfrac{I}{K} + \gamma_1(I/K), I > 0, \\ F - p\sqrt{\dfrac{-I}{K}} + \gamma_2(I/K), I < 0. \end{cases} \qquad (3.5')^{27}$$

Thus in equation (3.5') the lower part $(I < 0)$ of the function is the sum of two (weakly) convex functions, while in the usual specification (3.5) it is the sum of a linear and a weakly convex function; therefore, the only difference is that it has become "more convex". So the new specification is simply a special case of the original one, in which one chooses a different, more convex functional form for $\gamma_2(I/K)$. This means that the model with the alternative cost specification is qualitatively the same as the original one; only quantitative differences may arise as a result of a more convex $\gamma_2(I/K)$. (For example, the set of cost parameters for which disinvestment is never optimal may widen. For more details, see *section 4.2.*)

In the next chapter I use an alternative strategy to estimate the extent of irreversibility of investment decisions. The new method is different in two respects: first, it estimates the different cost components simultaneously, so irreversibility is estimated together with fixed and convex costs. Second, the cost parameters are estimated on a panel of firms, as opposed to estimating on data from a single firm.

[27] One has to write $-I$ under the square root as $I<0$, and to represent that this is a negative investment "cost" (i.e. sales revenue) the correct expression is $-p\sqrt{-I}$.

4. STRUCTURAL ESTIMATION OF THE DIFFERENT TYPES OF INVESTMENT COSTS

While in the previous chapter the main focus was on irreversibility costs, now I use a more general framework to investigate the various types of investment costs simultaneously. This chapter describes a method of structural estimation of various firm-level investment costs, and uses an unbalanced panel of US manufacturing firms between 1959-87, to estimate the structural investment cost parameters of a dynamic investment model. First, in *section 4.1*, I set up the basic investment model under my focus. This model is novel in the sense that it makes explicit distinction between new and replacement investment. I also investigate the theoretical implications of fixed, irreversibility and convex costs to the responsiveness of investment to shocks (or, in the terminology often used later, to the investment-shock relationships). This line of argument may seem straightforward, but it is still important as later I will identify the different cost components based on this investment-shock relationships. Then *section 4.2.* gives an overview of the estimation strategy, highlighting the new elements of my technique. *Section 4.3.* discusses the first stage of estimation: after describing the data, I present the estimation results. *Section 4.4.* discusses the second stage of estimation: it describes the steps of the simulation exercise, presents the results and discusses the estimated cost parameters. A short analysis of aggregate implications is also provided.

4.1. The Model

Let us consider a firm that maximizes the present value of its future profits net of future investment costs:[28]

$$V(A_0, K_0) = \max_{\{I_t\}_{t=0}^{\infty}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left[\Pi(A_t, K_t) - C(I_t, K_t) \right] \right\}, \qquad (4.1)$$

where profit at time *t* is given by $\Pi(A_t, K_t)$, with A_t and K_t denoting profit shock and capital stock at time t, respectively, the cost of investment I_t is $C(I_t, K_t)$, and

[28] This model is similar to the models presented by *Abel and Eberly (1994)* and *Stokey (2001)*.

β is a discount factor. The capital stock depreciates at a constant rate $\delta > 0$, and the profit shock is assumed to be a first-order Markov-process, so the transition equations are

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{4.2}$$

$$A_{t+1}\big|A_t \text{ is a random variable with known distribution.} \tag{4.3}$$

The firm then maximizes (4.1) with constraints (4.2) and (4.3). This is then a dynamic optimization problem with state variables (A, K) and control I. Omitting time indices, and denoting future values by primes, the solution entails solving the following maximization problem in each time period:

$$\max_I \left\{-C(I,K) + \beta E_{A'|A} V\left(A', K' = (1-\delta)K + I \big| A\right)\right\}, \qquad (4.4)^{29}$$

and the solution is

$$\beta E_{A'|A} \frac{\partial V(A', K')}{\partial K} = \beta E_{A'|A} V_K(A', K') = C_I(I, K). \tag{4.5}$$

This is a well-known optimum condition, stating that the (expected) discounted marginal value of capital for the firms (left-hand side) must be equal to the marginal cost of capital (right-hand side).[30]

Obviously, this solution depends crucially on the exact formulation of the cost function. In this chapter I use a general formulation of the investment cost function $C(I_t, K_t)$, and I assume that it has three components. In the following,

[29] More precisely, the value function of the solution is given by the Bellman equation
$V(A,K) = \max_I \left\{\Pi(A,K) - C(I,K) + E_{A'|A} V\left(A', K' \big| A\right)\right\}$

[30] The timing of the model is the following: firms have an initial capital stock K, and then they learn the value of the profitability shock A. This influences the expected discounted marginal value of capital (left-hand side of (4.5)). Finally, firms choose I to make the marginal cost (right-hand side) equal to the marginal value of capital (taking into account that the choice of I also influences the marginal value of capital through K'), and enter the next period with their new capital stock K'. Effectively, I will refer to this sequence of events with the "investment-shock relationship": in each time period, firms respond to profitability shock A with an optimal investment rate I or $I^*(A)$.

along the lines of *Stokey (2001)*, I examine these components one by one, with a special emphasis on their effect on investment decisions.

The first component of the investment cost function is the fixed cost F, which has to be paid whenever investment is non-zero:[31]

$$C(I,K)=\begin{cases} F+\Gamma(I,K), I\neq 0. \\ 0, I=0. \end{cases} \tag{4.6}$$

where $\Gamma(I,K)$ is the cost of investment other than fixed costs (time indices are dropped once again to ease exposition).

The second component of the investment cost function is a linear term, which represents the buying (*P*) and selling (*p*) price of capital $(P\geq p\geq 0)$. Thus $\Gamma(I,K)$ can be further divided as

$$\Gamma(I,K)=\begin{cases} PI+\gamma(I,K), I>0. \\ pI+\gamma(I,K), I<0. \end{cases} \tag{4.7}$$

Finally, the third component of the investment cost function is $\gamma(I,K)$, which is the usual convex adjustment cost. I adopt the general assumption that $\gamma(I,K)$ is a parabola-like function, with a minimum value of 0, and also a possible kink at $I=0$.[32] Therefore the partial derivative of this function with respect to I is non-decreasing, with negative values for $I<0$ and positive values for $I>0$, and this derivative may be discontinuous at $I=0$ if and only if there is a kink in the $\gamma(I,K)$ function there.

More specifically, in this chapter (and also in *Chapter 5*) I define the fixed component of the investment cost function as FK, and the convex component as

[31] This fixed cost is assumed to be independent from I, but not necessarily from K. In fact it is a common assumption in the literature that the investment cost function is homogenous of degree 1 in (I,K), and therefore the fixed cost is assumed to be proportional to K. To ease exposition, for the time being I simply use F instead of FK.

[32] Specifically, $\gamma(I,K)=0$ is assumed to be twice continuously differentiable except possibly at $I=0$, weakly convex, non-decreasing in $|I|$, with $\gamma(0,K)=0$.

$\gamma(I,K)=\frac{\gamma}{2}\left(\frac{I}{K}\right)^2 K$, so that the investment cost function is linearly homogenous in (I,K). I normalize the model to the buying cost of capital, and assume that $P=1$, from which it follows that for the selling cost of capital $0\leq p\leq 1$ must hold.[33]

Additionally, I will also distinguish between replacement investment and new investment, which has not been done in previous models. There are several reasons why replacement investment is not as costly as new investment: (1) when undertaking replacement investment, firms often have their tools and machines checked, certain parts exchanged or upgraded, and this entails contacting well-known suppliers at much lower costs; (2) learning costs are also likely to be much lower in this case. Though replacement investment may also entail adjustment costs, it seems to be a reasonable approximation to treat replacement investment cost-free, as opposed to costly new investment. More specifically, I assume that investments up to the size of δK (the depreciated part of capital) have no convex or fixed costs, and firms have to pay adjustment costs after that part of investment that exceeds this amount. (Of course, when undertaking replacement investment, firms still have to pay the unit purchase price of investment goods.)

Thus the final specification of the investment cost function is the following:

$$\frac{C(I,K)}{K}=\begin{cases}\frac{I}{K}, 0\leq\frac{I}{K}\leq\delta, \\ F+\frac{I}{K}+\frac{\gamma}{2}\left(\frac{I-\delta K}{K}\right)^2, \frac{I}{K}>\delta, \\ F+p\frac{I}{K}+\frac{\gamma}{2}\left(\frac{I}{K}\right)^2, \frac{I}{K}<0.\end{cases} \tag{4.8}$$

For the remaining part of this section I return to the general specification of the investment cost function (see expression (4.6)), and also neglect the distinction between replacement and new investment, with the purpose of investigating the

[33] So if $p=1$, then there is no irreversibility. Complete irreversibility will be characterized by $p=0$.

effects of each cost components.[34] A careful investigation of the effects of the various cost components is important because a full understanding of the role of the model's key parameters will ease their empirical identification.

Specifically, I examine the shape of $C_I(I,K)$ on the right-hand side of (4.5); I will do this by drawing a graph about the partial derivatives of each cost components. First, denote the limits of the partial derivative of $\gamma(I,K)$ (with respect to I) as $q_a = \lim_{I\to 0-0} \gamma_I(I,K)$ and $q_A = \lim_{I\to 0+0} \gamma_I(I,K)$ (as in *Figure 4.1*); my assumptions ensure that $q_a \le 0 \le q_A$.

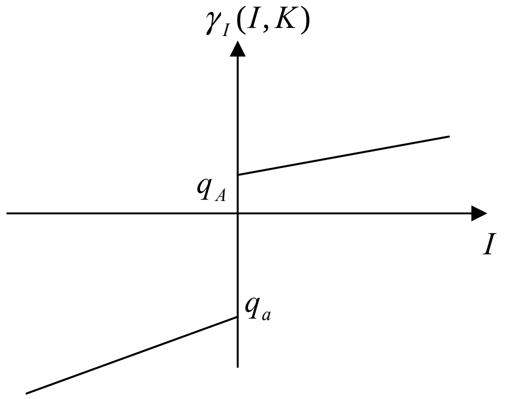

Figure 4.1. The general shape of the function $\gamma_I(I,K)$

Moreover, the partial derivative of $\Gamma(I,K)$ with respect to I is $P+\gamma_I(I,K)$ for $I>0$, and $p+\gamma_I(I,K)$ for $I<0$, so the shape of this function is as in *Figure 4.2*.[35]

---

[34] The effect of various cost components does not change if one allows for cost-free replacement investment, so I can neglect this distinction to ease exposition.

[35] Here $q_1 \ge q_2$ follows from $P \ge p$ and $q_A \ge q_a$.

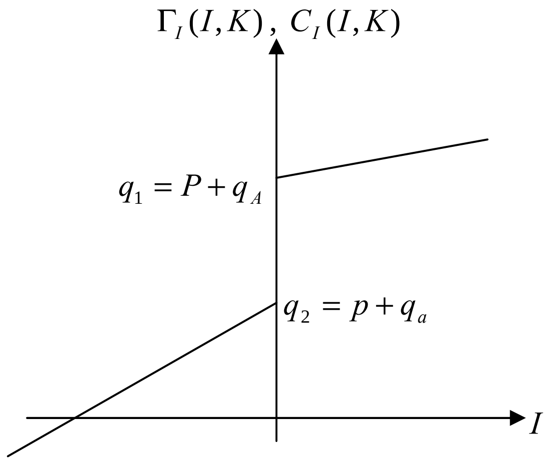

Figure 4.2. The general shape of the function $\Gamma_I(I,K)$ *and* $C_I(I,K)$

Finally, $C_I(I,K) = \Gamma_I(I,K)$ by the definition of the cost function.

Returning to the first order condition in (4.5), without fixed costs the solution is the following:

- if for the current capital stock K and profit shock A $E_{A'|A}V_K(A',(1-\delta)K) > q_1$,[36] then the optimal level of investment will be positive;
- if $E_{A'|A}V_K(A',(1-\delta)K) < q_2$, then the optimal investment will be negative;
- and if $q_1 \geq E_{A'|A}V_K(A',(1-\delta)K) \geq q_2$, then the optimal investment will be zero.

In this case there is an inaction region as long as $q_1 > q_2$ (i.e., either if there is a kink at $I = 0$ in the adjustment cost function $(q_A > q_a)$ or if there is no perfect reversibility $(P > p)$), so the investment function $I^*(q)$ (i.e. investment as a function of the underlying fundamental) is flat at $I^* = 0$ for q-s in a certain region (if $q \in [q_1; q_2]$), but it is continuous: even small investment episodes will occur.

---

[36] $E_{A'|A}V_K(A',(1-\delta)K)$ is the expected marginal value of capital when investment is zero; its value only depends on the current value of the state variables (A,K), and hence can be treated as given when firms decide about the control I. It is also obvious that $E_{A'|A}V_K(A',(1-\delta)K)$ increases as the profitability shock A increases, so the $I^*(q)$ function investigated here has the same shape as the $I^*(A)$ shock-investment relationships, which will be the key for identification.

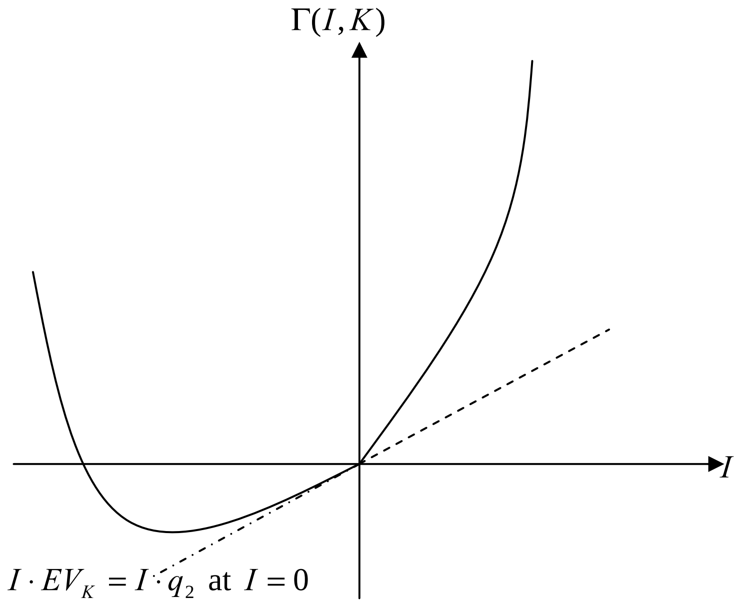

Figure 4.3. The firms' investment problem without fixed costs– graphically.

If there are fixed costs, there is a slight difference. To see this, consider the $\Gamma(I,K)$ function, which is the sum of a convex and a linear function, with $\Gamma(0,K)=0$, and a possible kink at $I=0$. Moreover, its derivative should be $\Gamma_I(I,K)$ as shown on *Figure 4.2*. Then *Figure 4.3* illustrates the possible shape of $\Gamma(I,K)$, with the additional assumption that currently $E_{A'|A}V_K(A',(1-\delta)K)=q_2$ (that is, there is no new investment, but the marginal value of the depreciated capital stock is the lowest possible to have no new investment: exactly q_2).

In a situation depicted on *Figure 4.3*, optimal investment is zero, but $EV_K = E_{A'|A}V_K(A',(1-\delta)K)$ has the smallest possible value (q_2) (or the slope of the dashed line is the smallest) so that in the absence of fixed costs investment is non-negative. If $E_{A'|A}V_K(A',(1-\delta)K)=EV_K$ decreases marginally, then, still assuming that fixed costs are 0, the optimal decision will be a marginal disinvestment, as the IV_K line, which represents the benefit from investment in terms of future profits, will be locally above the $\Gamma(I,K)$ function, the function representing the costs of investment. If there are positive fixed costs, however, then after a marginal decrease of $E_{A'|A}V_K(A',(1-\delta)K)=EV_K$, it will be the zero investment that would be still optimal: the expected marginal net benefit ($I \cdot EV_K - \Gamma(I,K)$) would be so small that it would not compensate for the fixed costs that would have to be paid.

Indeed, if $F > 0$, then in case of the situation illustrated on *Figure 4.3* there is only disinvestment if the value of $E_{A'|A} V_K(A',(1-\delta)K) = EV_K$ decreases well below q_2: so that the net benefit from disinvestment – the highest difference between $I \cdot EV_K$ and $\Gamma(I,K)$ in the graph – should be at least F (see *Figure 4.4*).

In *Figure 4.4* one can see that the highest q_2' for which the optimal investment is negative, is smaller than q_2 in *Figure 4.3*, because of the fixed cost F. With similar reasoning it is easy to see that the lowest q for which the optimal decision is to have positive investment (i.e., the upper bound of the inaction region) is $q_1' > q_1$.

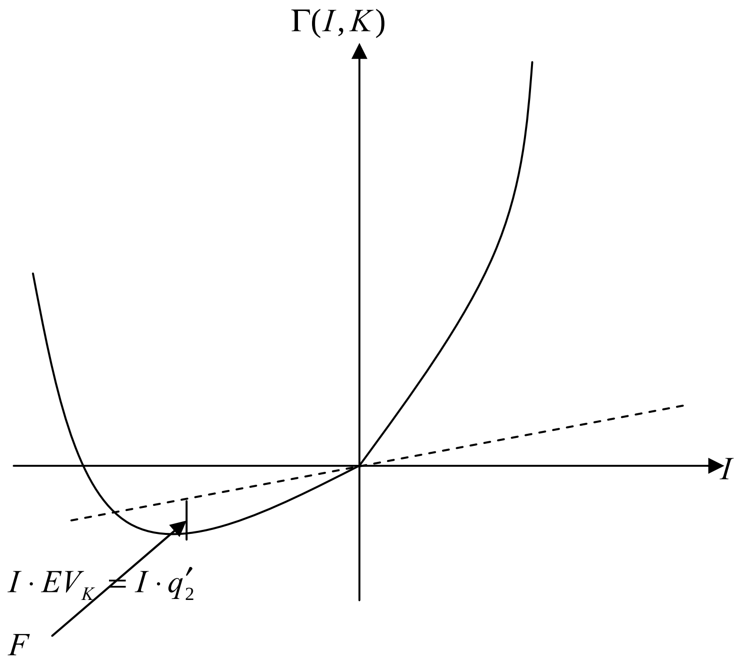

Figure 4.4. The firms' investment problem with fixed costs– graphically.

It should be obvious from *Figure 4.4.* that the presence of fixed costs generates discontinuities in the investment function: the threshold between the inaction region and the disinvestment region is q_2', but for q-s slightly below this, the optimal disinvestment is not marginal.

To conclude this section, it may be useful to summarize the role of the different cost parameters in the theoretical model. I have shown that:

- **irreversibility** generates an inaction region (i.e., if the marginal value of capital is inside a certain band, firms will neither invest nor disinvest), but leaves the investment function continuous;
- **fixed costs** also generate an inaction region (or in the presence of irreversibility costs they further widen it), and create discontinuities in the investment function (i.e., there will be no small investments undertaken).

To further illustrate this point, I solved numerically the model for some simple cost structures.[37] *Appendix A* contains the investment functions (investment as a function of *log(profitability shock)*) in various cases: when investment is cost-free, when there are only convex costs of investment, when there are only fixed costs of investment, and when there is irreversibility. The effects of the various cost components can also be observed on these figures.

4.2. Estimation of Cost Parameters: General Strategy

In this chapter, I use *indirect inference* (as described by *Gourieroux and Monfort (1996)*) to estimate structural investment cost parameters. The general idea behind the identification of the structural parameters is to match the investment-shock relationships obtained from the theoretical model to the observed investment-shock relationships. The "philosophy" of this approach is that we believe that we are able to observe the "true" investment-shock relationships fairly precisely; and then we choose those cost parameters in the theoretical model, for which the theoretical investment-shock relationships is very close to the observed one.

This identification strategy is an indirect one when compared to more conventional methods, which (for example) start out from the first-order conditions, and identify structural parameters on the basis that these conditions should be met

[37] For the numerical solution, I assumed that $\beta = 0.95$, $\delta = 0.07$, two common assumptions in the literature dealing with US data. I solved the dynamic optimization problem with parametric value function iteration as described by *Judd (1998)*, with a bi-variate cubic specification for the value function. (I also solved the problem with the more accurate value function iteration for appropriately discretised state space, and found that the cubic approximation of the value function was quite close to this more accurate solution.) I assume that the profitability shock behaves as estimated from real data (see *section 4.3*.).

empirically. This conventional method (or its variations), however, cannot be used directly in the context of our model, since the existence of an inaction region means that the conventional first-order conditions are not always equalities: for observations when there is inaction, we have only an inequality, stating that the current marginal value of capital, q is somewhere between the left-hand side derivative of the investment cost function, q_1 and the right-hand side derivative of the investment cost function, q_2. So I use an indirect method because the direct, first-order condition based approach cannot be used in the usual manner.[38]

However, my identification strategy is not straightforward either, as there is no closed-from solution of the model, and one can not derive analytically the theoretical investment-shock relationship as a function of structural cost parameters. As discussed in the previous sub-section and also in *Appendix A*, the theoretical investment-shock relationship is non-linear, and in case of positive fixed costs it is not even continuous. In recent literature using indirect inference (see for example *Bayraktar, Sakellaris, Vermeulen (2005)* and the initial version of *Cooper-Haltiwanger (2005)*), it has been very popular to identify the cost parameters based on a quadratic shock-investment relationships that captures non-linearity, but fails to capture discontinuity and inaction. Now I argue that though this method can be useful in identifying the convexity and irreversibility parameters, it is not sufficient to identify the fixed cost parameter.[39]

In recent literature, the usual quadratic reduced form regression (the “shock-investment relationship“, based on which the parameters are identified) applied when using indirect inference is the following:

$$\tilde{i}_{it} = \phi_0 + \phi_1 \tilde{a}_{it} + \phi_2 \tilde{a}_{it}^2 + \phi_3 \tilde{a}_{i,t-1} + \mu_t + u_{it}\,, \tag{4.9}$$

[38] *Cooper, Haltiwanger and Willis (2005)* investigate the possibility of modifying the usual first-order condition based approach so that it remains applicable in this context. Their modification solves the problem of inequality-type first-order conditions for inactive observations by using the data of the active firms only, together with the lengths of inaction spells of inactive firms. They also correct for the endogenous selection, which arises because of the exclusion of the inactive observations.

[39] This is not surprising: the fixed cost parameter is the one that creates discontinuity and inaction, none of which is present in the quadratic equation.

where *i* denotes the investment rate, *a* denotes the profitability shock, μ_t is a time-dummy, *u* is a well-behaving error term, and the variables with tildes denote deviations from plant-specific means. In this specification the parameter ϕ_2 is meant to capture the non-linearity of the investment-shock relationship (as higher profitability shocks are assumed to lead to proportionally higher investment activity in absolute value). According to the usual arguments, parameter ϕ_3 represents the lumpiness of investment: because of inaction, shocks sometimes lead to lagged effects – following a positive profitability shock, for example, the investment threshold may be passed only in later periods. (Or, alternatively, current shocks may trigger immediate investment, and then inaction for many periods.) The parameter ϕ_3 therefore is included to account for the possible inaction region, and captures both the effects of irreversibility and fixed costs.

For proper identification of the cost parameters, it is essential that the estimated coefficients of the reduced regression should be sensitive to the structural parameters. To investigate the effect of structural cost parameters to these regression parameters, I estimated the reduced regression parameters in certain simple cases. I have already referred to *Appendix A* to illustrate the investment-shock relationship under basic cost structures; now I examine the estimated reduced regression parameters for the same cases.

- In the **cost-free case** $(F = 0, \gamma = 0, p = 1)$, I have $\hat{\psi}_1 = 2.5233$, $\hat{\psi}_2 = 0.4384$, $\hat{\psi}_3 = -2.5151$. Here the significantly positive $\hat{\psi}_2$ represents the slight convexity of this relationship due to diminishing returns to capital (a further discussion of this is provided in *Appendix A*), and it is also obvious that investment is highly responsive for shocks: the absolute values of the estimated parameters are relatively high.
- When there are **only irreversibility costs** $(F = 0, \gamma = 0, p = 0.95)$, I estimated $\hat{\psi}_1 = 0.8520$, $\hat{\psi}_2 = 0.3928$, $\hat{\psi}_3 = -0.5564$. Because of the inaction region, the estimated shock-investment relationship became more convex, which is apparent from the increase in the relative magnitude of $\hat{\psi}_2$. On the other hand, investment is much less responsive to shocks, also

because of the inaction region; this is obvious from the smaller absolute values of the estimated reduced regression parameters.

- If there are **only convex costs** of adjustment $(F = 0, \gamma = 0.2, p = 1)$, then the estimated reduced regression parameters are $\hat{\psi}_1 = 0.4657$, $\hat{\psi}_2 = 0.0672$, $\hat{\psi}_3 = -0.2557$. As can be seen in *Figure A/3*, the only difference between this case and the cost-free case is that the investment-shock relationship became flatter, and this is apparent from the proportional decrease of the estimated reduced regression parameters.
- When there are **only fixed costs** of investment $(F = 0.001, \gamma = 0, p = 1)$, the shock-investment relationship is basically the same as in the frictionless case, with its middle part (when the absolute value of shocks is small) missing; see *Figure A/4*. It is not surprising, therefore, that the estimated regression coefficients are quite similar to the estimated regression coefficients in the cost-free case: now they are $\hat{\psi}_1 = 2.4475$, $\hat{\psi}_2 = 0.4423$, $\hat{\psi}_3 = -2.4165$.[40] This indicates that *changes in* F *do not lead to changes in the estimated reduced regression parameters*.

Thus the general responsiveness of investment to shocks (in other words, the absolute value of the estimated reduced regression parameters) identifies the convex component of the investment cost function (γ). Also, the relative magnitude of $\hat{\psi}_2$ identifies the irreversibility costs (p). However, *these regression parameters do not contain any information* based on which one could identify F, the fixed cost of investment.[41]

Therefore, while reduced form regression (4.9) is useful to estimate γ and p, one should look for a different type of information to also identify F. To do this, it seems to be obvious to use some property of the investment-shock relationship that is exclusively due to the presence of fixed costs.

[40] In the cost-free case they were $\hat{\psi}_1 = 2.5233$, $\hat{\psi}_2 = 0.4384$, $\hat{\psi}_3 = -2.5151$.

[41] While this result is obvious (and also intuitive) from the shock-investment relationship graphs in *Appendix A* when $F = 0, \gamma = 0, p = 1$, it still remains a question whether this result is only local, or it also holds globally. For a deeper investigation of this issue, see *Appendix D*.

In *section 4.2* I demonstrated that in the theoretical model, *increasing fixed costs* lead to wider inaction region *and* larger discontinuity in the investment-shock relationship, while *increasing irreversibility* leads to higher inaction *without* affecting the continuity of the investment-shock relationship. So it seems to be natural to think that matching theoretical discontinuity with empirically observed discontinuity in the investment-shock relationship could easily identify fixed costs. But given that this discontinuity is very hard to observe empirically (see observed gross and new investment rate distributions in *section 4.4*, both of which are continuous), this method does not work.[42]

Because of this, I chose a somewhat more indirect method to identify the fixed cost parameter: I try to match theoretical and observed inaction rates. (As discussed later, inaction is easily observable when we distinguish between new and replacement investment.) The general idea behind this is the following: inaction can emerge both because of fixed costs and irreversibility. But given that reduced regression (4.9) identifies irreversibility (and also irreversibility-induced inaction), from the observed inaction, together with the irreversibility-induced inaction, we can infer fixed cost-induced inaction and fixed costs themselves.

An alternative way to identify irreversibility separately from fixed costs is to investigate the asymmetry of the investment rate distribution. It seems to be obvious that irreversibility creates asymmetric behavior on the positive and negative ends at the micro level, while fixed costs do not lead to such an asymmetry. So when identifying the structural cost parameters, I will also control for the asymmetry of the theoretical investment distribution, hoping that the direct identification of the irreversibility parameter indirectly identifies fixed costs (through matching the inaction rates). Thus I also match the theoretical and observed asymmetry to each other.

To conclude this section, let me summarize in one sentence my estimation strategy. To identify the investment cost function's structural parameters, I will *match the estimated regression parameters of equation (4.9), along with the inaction rate and investment rate distribution skewness in the theoretical model to similar parameters observed in real data*.

[42] *Cooper and Haltiwanger (2005)* also report continuous investment distribution, based on a different establishment-level data set.

4.3. Data and empirical results

Data set and main variables

To estimate the structural parameters of the investment cost function, I use a panel data set about balance sheet and income statement data of publicly traded US manufacturing firms between 1959-1987, a part of the COMPUSTAT database.[43] This is a well-known data set, and for a detailed documentation I simply refer to *Hall (1990)*. Here I give only a brief description of the main features of the data.

The "Manufacturing Sector Master File" is a data set about 2,726 large US manufacturing firms between 1959-87. The unique feature of this data set is that it contains information about the reasons of exits, indicating any domestic/foreign acquisitions, privatizations, leveraged buyouts, bankruptcies, liquidations, reorganizations, and name changes. This makes it possible (by dropping only those firms who were acquisited, reorganized, bought out) to build a data set that contains companies with continuous operation together with companies that were either bankrupt or liquidated. Excluding also the bankrupt or liquidated firms could lead to selectivity bias by excluding many companies with presumably large negative profitability shocks and therefore negative investment activity.

The raw data set contains 49,225 year-observations about 2,726 companies. As a first step, I excluded all merged, acquired, privatized firms from the data set (along with those companies for which the reason of exit is unknown), and obtained a data set containing the continuously operating, bankrupt or liquidated firms. This reduced the size of the data set to 31,297 year-observations about 1,664 companies. I had to narrow the sample further as there are some companies for which I do not have any information about their net value of capital; due to this fact the size of the panel is decreased to 29,548 year-observations about 1,617 companies. Finally, at later stages I will use sales revenues as a weighting variable; in some cases this is missing, or it is unreasonably small.[44] After deleting these observations, the size of

[43] I am grateful to *Plutarchos Sakellaris* for giving me access to these data.
[44] This latter case includes newly created firms: in case of these the sales revenue is virtually zero, while having huge losses. I assume that this phenomenon is due to initial investment in the first (few)

the data set decreases to 29,500 year-observations about 1,616 firms. *Table 4.2.* contains information about the entry and exit dates of these 1,616 companies.

From now on, I will refer to these 29,500 year-observations about 1,616 companies as the "*full sample*". But for comparison purposes I also created a balanced sub-sample between 1972-87[45] of the entire data set, labeled thereafter as "*balanced*". This sub-sample contains 15,088 year-observations about 943 firms, and its composition is as in the shaded-striped area of *Table 4.2*.

The choice between the balanced and unbalanced samples is not straightforward. On the one hand, in the theoretical model I do not model entry and exit, so that model is only valid for continuously operating firms, and therefore it should be estimated on the balanced sub-sample. On the other hand, eliminating all newborn and discontinuing firms from the estimation would inevitably raise selectivity issues, as important information about these firms would be missing from the data set. So while the optimal solution would be to estimate a theoretical model with endogenous entry and exit on the unbalanced sample, modeling entry and exit would make the theoretical model much more complicated, and it would be even more difficult to estimate that model. Keeping in mind that it is necessary to make further steps into this direction, here I use the simple theoretical model without entry and exit, and I estimate it on both balanced and unbalanced sub-samples, and report the results of these. In any case, the differences between the results of these will give some insights about the importance to make distinction between continuously operating firms and firms that are subject of entry or exit.

To measure the capital stock of the firms, I use inflation-adjusted net plant value (NPLANT). This variable was calculated by "multiplying the book plant value by the ratio of the US GNP deflator for fixed nonresidential investment in the current year to the GNP deflator AA years ago"[46], where AA stands for the average age of the plant and equipment for this particular firm. Thus this variable is a corrected book plant value of the firms, where the correction was made to express all previous capital purchases at current prices.

---

years of operation, and therefore does not represent normal operation, so I deleted these few cases from the data set.

[45] *Cooper and Haltiwanger (2005)* use a balanced sub-sample of the Longitudinal Research Database (LRD) between 1972-88.

[46] *Hall (1990), page 18.*

To measure gross investment, I used the difference between gross capital expenditures (UFCAP) and sales of property, plant and equipment (SFPPE), both reported from firms' statements of changes. I preferred these variables to the main investment variable of the data set (INVEST) as this latter also includes the amount spent to acquisitions and other not strictly investment-related expenditures. (Note, however, that in the vast majority of the observations UFCAP = INVEST, so the results would not change dramatically if I used the other investment variable.)

		LAST OBSERVATION													
		75	76	77	78	79	80	81	82	83	84	85	86	87	SUM
	59				1	1	2	4						278	**286**
	60	1	3	2	2	2	2	3	1	2	1	2		124	**145**
	61		1		1	1	1	1		2				24	**31**
	62		1					1		1		1		60	**64**
	63					1				1	3	2		42	**49**
F	64			1	1			1		1		1		26	**31**
I	65					1				2		1		33	**37**
R	66				1						1			37	**39**
S	67	1		2		1	1			1		1	1	46	**54**
T	68		1		2	1	1	3	1	2	2	2	2	126	**143**
	69		1			1	2	3			1	1	1	38	**48**
	70		1					2			1			21	**25**
O	71		1	2	1	1	1	4	1				1	42	**54**
B	72					1	1	2			2	1		46	**53**
S	73								1		2	1		43	**47**
E	74						1	1	1	2	1	3		86	**95**
R	75							1						12	**13**
V	76										1	1		14	**16**
A	77						1	1						7	**9**
T	78													24	**24**
I	79						1		2	1				34	**38**
O	80							2		1		1	1	43	**48**
N	81												1	23	**24**
	82											1	1	65	**67**
	83										1		1	55	**57**
	84													37	**37**
	85													44	**44**
	86													38	**38**
	SUM	**2**	**9**	**7**	**9**	**11**	**14**	**29**	**7**	**16**	**16**	**19**	**9**	**1468**	**1616**

Table 4.2. Entry and exit dates of the companies in the sample

To calculate an investment rate variable I first subtracted the capital sales (SFPPE) from gross capital expenditures (UFCAP), and then divided this by the previous year's net plant value, and obtained the investment rate in year *t*:

$$INVRATE_t = \frac{UFCAP_t - SFPPE_t}{NPLANT_{t-1}} \,. \tag{4.10}$$

This observed investment rate, however, contains both new and replacement investments, while I am mainly interested – in line with the specification of the investment cost function in the theoretical model – in the costly new investment rate. Therefore I separated new investment and replacement investment based on the relationship between observed net capital expenditures $(UFCAP_t - SFPPE_t)$ and depreciation $(ADJDEP_t)$.[47]

- If $UFCAP_t - SFPPE_t > ADJDEP_t$, then net capital expenditures exceeded depreciation, so net capital stock increased. In this "expansionary" case I assume that firms undertake as much replacement investment as possible (as this is relatively cheap), and only the increase in the value of net capital stock is the result of the costly new investment activity. So in this case, $NEWINVRATE_t = \dfrac{(UFCAP_t - SFPPE_t) - ADJDEP_t}{NPLANT_{t-1}}$.
- If $ADJDEP_t \geq UFCAP_t - SFPPE_t \geq 0$, then the firm's net capital expenditures were positive, but since they did not entirely cover depreciation, the firm's former capital stock depreciated to some extent. In this case I assume that all capital expenditures were maintenance-type replacement expenditures with no adjustment costs (other than the purchase price), and therefore $NEWINVRATE_t = 0$.
- if $0 > UFCAP_t - SFPPE_t$, then the firm is obviously shrinking. It seems to be logical to assume in this case that no replacement investment was undertaken, as this could have been compensated for only by costly capital sales. In this case then I calculate the new investment rate as $NEWINVRATE_t = INVRATE_t = \dfrac{UFCAP_t - SFPPE_t}{NPLANT_{t-1}}$.

The distributions of the calculated gross and new investment rates in the full sample are depicted on *Figures 4.5-4.6*.

[47] ADJDEP is an adjusted measure of the depreciation, where (similarly to the correction of NPLANT) observed depreciation is deflated by an investment deflator AA (average age of capital) years ago, to get a measure of depreciation that is expressed in current prices (as opposed to historical purchase prices represented in the book value).

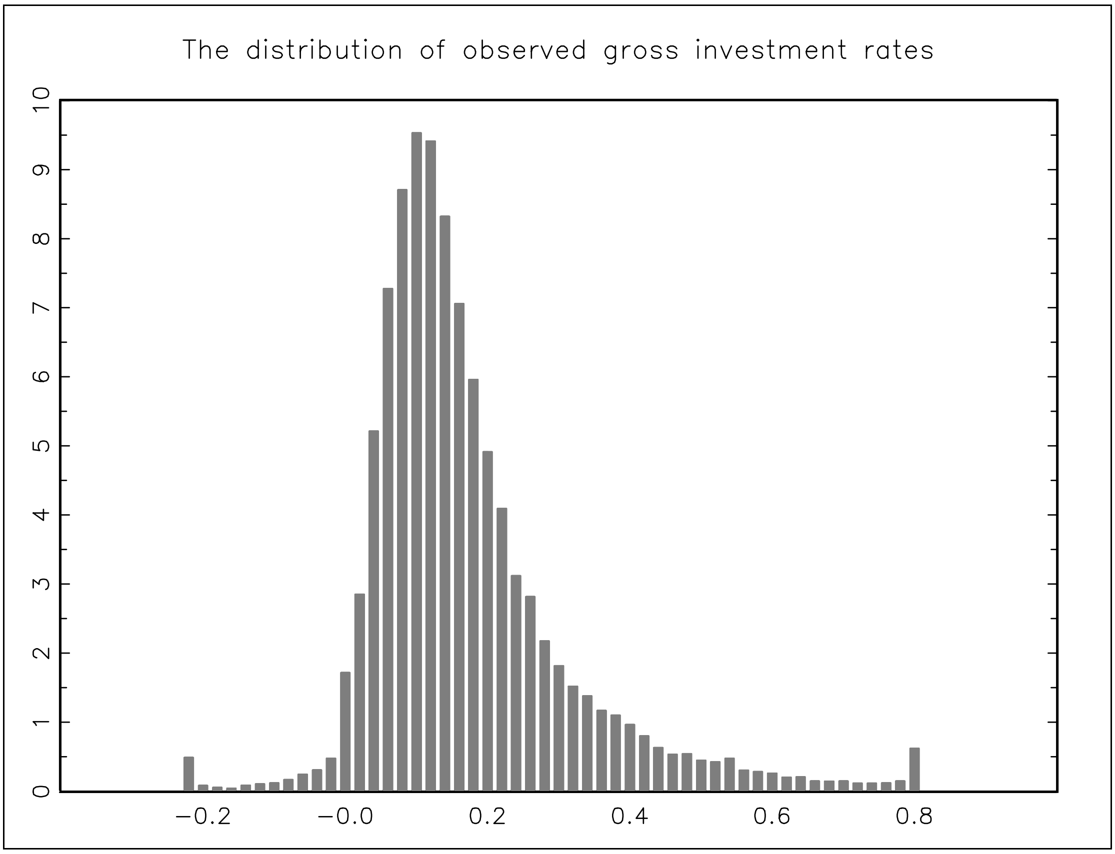

Figure 4.5. The distribution of observed gross investment rates, full sample.

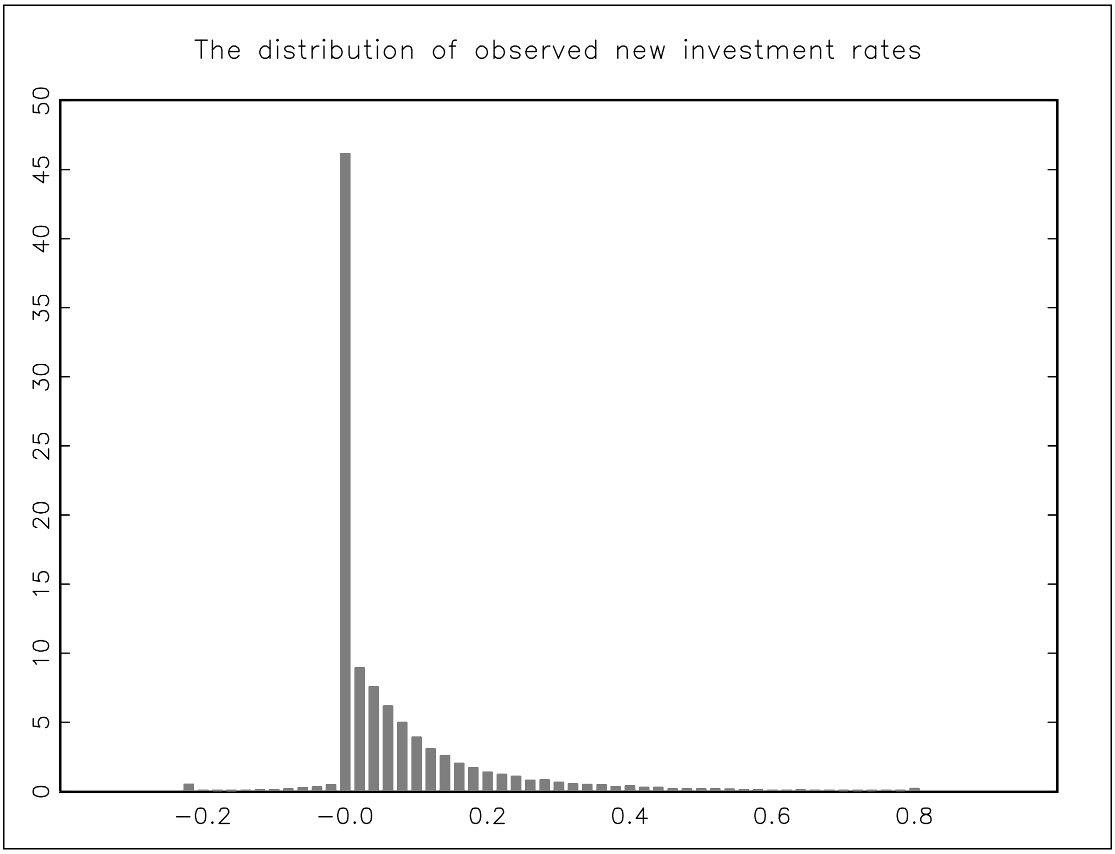

Figure 4.6. The distribution of observed new investment rates, full sample.

The shape of the gross investment rate distribution is very similar to what is reported in *Cooper and Haltiwanger (2005)*, even though I use firm-level (as opposed to establishment-level) data. The mode of the distribution is at about 8% investment rate, probably reflecting usual replacement investment activity. In the new investment rate distribution I have a large peak at zero, reflecting the fact that I had many observations with net investment expenditure between 0 and observed depreciation. Regarding non-zero investment rates, the mode of the distribution is at very low positive investment levels: further 12.51% of observed investment rates is in the [0;3%] range, while the proportion of rates in the [0;5%] range is 21.18%. Also, both observed distributions are apparently skewed to the left.

In certain steps of the analysis, I will also use the following variables: operating income before depreciation (OPINC), sales revenue (SALES), and employment (EMPLY). *Appendix C* contains a full description of variable definitions.

Estimating the reduced regression parameters from data

As discussed in *section 4.2*, I estimate the investment cost parameters (F, γ, p) by matching the observed reduced regression parameters, inaction rate and asymmetry of investment distribution with the same parameters calculated from theoretical investment models. Therefore, as a first step I estimate the reduced form regression parameters, calculate the inaction rate and asymmetry of investment distribution for the data set.

To estimate the reduced form regression (4.9) I first identify the yearly profitability shocks that hit the firms in our data. I do this by adopting the strategy of *Cooper and Haltiwanger (2005)*. First I assume that firms have identical, constant returns-to-scale Cobb-Douglas production functions:

$$Y_{it} = B_{it} L_{it}^{\alpha_L} K_{it}^{1-\alpha_L}, \tag{4.11}$$

where labor (L_{it}) can be adjusted in the short-run and can therefore be regarded in the yearly data set as being optimized out, but capital (K_{it}) cannot be adjusted in the short-run. In this expression Y_{it} denotes production, B_{it} is production shock,[48] α_L is labor share. I also assume that firms face a constant elasticity (ξ) demand curve $D(p)=p^{\xi}$, so the inverse demand curve is $p(y)=y^{1/\xi}$. Therefore the firms' problem is:[49]

$$\Pi_{it} = p_{it}(y_{it})y_{it} - wL_{it} = y_{it}^{\frac{1+\xi}{\xi}} - wL_{it} = B_{it}^{\frac{1+\xi}{\xi}} L_{it}^{\alpha_L \frac{1+\xi}{\xi}} K_{it}^{(1-\alpha_L)\frac{1+\xi}{\xi}} - wL_{it} \xrightarrow[L_{it}]{} \max , \quad (4.12)$$

where w denotes the wage rate (assumed to be constant). The first-order condition of this problem is $\alpha_L \dfrac{1+\xi}{\xi} B_{it}^{\frac{1+\xi}{\xi}} K_{it}^{(1-\alpha_L)\frac{1+\xi}{\xi}} L_{it}^{\alpha_L \frac{1+\xi}{\xi}-1} = w$, from which the optimal labor usage is

$$L_{it}^{*} = \left(\frac{\xi}{\alpha_L(1+\xi)}\right)^{\frac{\xi}{\alpha_L(1+\xi)-\xi}} w^{\frac{\xi}{\alpha_L(1+\xi)-\xi}} B_{it}^{\frac{1+\xi}{\xi-\alpha_L(1+\xi)}} K_{it}^{\frac{(1+\xi)(1-\alpha_L)}{\xi-\alpha_L(1+\xi)}} . \quad (4.13)$$

Substituting this back to the profit function (4.11), the optimal profit of the firm is

$$\Pi_{it}^{*} = B_{it}^{\frac{1+\xi}{\xi}} \left(L_{it}^{*}\right)^{\alpha_L \frac{1+\xi}{\xi}} K_{it}^{(1-\alpha_L)\frac{1+\xi}{\xi}} - wL_{it}^{*} =$$

$$= \left(\frac{\xi}{\alpha_L(1+\xi)}\right)^{\frac{-\xi}{\xi-\alpha_L(1+\xi)}} w^{\frac{-\alpha_L(1+\xi)}{\xi-\alpha_L(1+\xi)}} B_{it}^{\frac{1+\xi}{\xi-\alpha_L(1+\xi)}} K_{it}^{\frac{(1+\xi)(1-\alpha_L)}{\xi-\alpha_L(1+\xi)}} \left[\frac{\xi}{\alpha_L(1+\xi)} - 1\right]. \quad (4.14)$$

[48] Note that this is not the profitability shock that we have in reduced regression (4.9).
[49] To be consistent with the maximand in the theoretical model in (4.1), it is unnecessary to include here the cost of capital: it is already included into the capital adjustment cost function.

Hence if I write (4.14) as $\Pi^*_{it} = A_{it} K^{\theta}_{it}$, where A_{it} denotes the profitability shock[50] (as opposed to B_{it}, which was productivity shock), then $\theta = \frac{(1+\xi)(1-\alpha_L)}{\xi - \alpha_L (1+\xi)}$, a function of the demand elasticity and the labor share in the production function.

To identify firm-level profitability shocks, I simply calculate $A_{it} = \frac{\Pi^*_{it}}{K^{\theta}_{it}}$, which can be computed from the data set once having an estimate for θ.

As the estimation of parameter θ is not straightforward, I estimated it with four alternative methods. I also checked for robustness to different outlier-filters in each case. The four methods are:

(1) I assumed that the error term is additive, and estimated θ with non-linear least squares from the equation $\Pi^*_{it} = A_i K^{\theta}_{it} + \varepsilon_{it}$ (using fixed effects). To avoid the large impact of larger firms on the estimated θ, I weighted observations with their size (measured as sales revenue), so effectively I estimated the equation $\Pi^*_{it} / R_{it} = A_i K^{\theta}_{it} / R_{it} + \varepsilon_{it} / R_{it}$ (where R_{it} is sales revenues).[51]

(2) I shifted each Π^*_{it} / R_{it} by a constant C to be able to take the log of most observations, and used simple OLS to estimate the equation $\ln\left(\Pi^*_{it} / R_{it} + C\right) + \ln\left(R_{it}\right) = \ln\left(A_i\right) + \theta \ln\left(K_{it}\right) + \varepsilon_{it}$. Of course, in this case I had to drop all observations with $\Pi^*_{it} / R_{it} \leq -C$, so the choice of parameter C determines the outlier filtering rule. Also, the θ estimates for different values of C will be different, so it is essential to check the robustness of $\hat{\theta}$ to different values of the shifting parameter.[52]

[50] So the profitability shock consists of wages, demand elasticities, labor shares and productivity shocks. One could argue that wages are also changing over time, but as one can easily see, any aggregate time-series variation of wages is captured by the time dummies in the reduced form regression.

[51] For a more detailed description of the estimation method, see *Appendix B*.

[52] I chose parameter C to be between 1 and 15. The reason of this is that: (1) the number of firms with larger negative profits than their sales revenue is relatively small; (2) a careful investigation of these observations shows that these firms are usually either entering or leaving the market, and cannot be treated as firms under "normal operation". So for these parameter values I do not lose too much information when excluding the outliers.

(3) To account for the potential endogeneity of K_{it}, I estimated the same equation $\ln\left(\Pi_{it}^{*}/R_{it}+C\right)+\ln\left(R_{it}\right)=\ln\left(A_{i}\right)+\theta\ln\left(K_{it}\right)+\varepsilon_{it}$ with IV (with lagged capital as instrument).

(4) I estimated $\ln\left(\Pi_{it}^{*}/R_{it}+C\right)+\ln\left(R_{it}\right)=\ln\left(A_{i}\right)+\theta\ln\left(K_{it}\right)+\varepsilon_{it}$ by OLS on the same sub-sample as in case of IV estimation (I call this method as "sample corrected OLS").

As it turned out, the estimated parameter was robust to both different estimation techniques and different outlier filtering. (The estimated parameters were between 0.68-0.70 in each cases.) I accept the estimate based on the first method, and so the estimated parameter is $\theta=0.6911$ in the full sample. (In the balanced sub-sample the estimated θ is $\hat{\theta}=0.4641$; these estimates were also robust to the estimation method and outlier filtering.)

With this estimate, it is now possible to calculate firm-level profitability shocks. I call the profitability shock calculated this way $(A_{it}=\Pi_{it}^{*}/K_{it}^{\theta})$ as type 1 shock. But as the resulting variance of the profitability shocks appears to be implausibly large (see *Tables 4.3a-4.3b* later), replicating the method followed by *Cooper and Haltiwanger (2005)*, I also estimated the profitability shocks in an alternative way. A little algebra shows that the optimal profit in (4.14) can also be written as

$$\Pi_{it}^{*}=wL_{it}^{*}\left[\frac{\xi}{\alpha_{L}(1+\xi)}-1\right]=wL_{it}^{*}\frac{1}{\theta}\frac{1-\alpha_{L}}{\alpha_{L}}, \tag{4.15}$$

so the A_{it} profitability shock can also be calculated as

$$A_{it}=\frac{\Pi_{it}^{*}}{K_{it}^{\theta}}=\frac{wL_{it}^{*}(\xi-\alpha_{L}(1+\xi))}{K_{it}^{\theta}\alpha_{L}(1+\xi)}=\frac{wL_{it}^{*}}{\theta K_{it}^{\theta}}\frac{1-\alpha_{L}}{\alpha_{L}}. \tag{4.16}$$

To compute the profitability shock this way, one should have an estimate for the labor share α_{L}. But as I only need the deviation of the (log) profit shocks from their plant-specific means (see reduced regression (4.9)), the parameter α_{L} becomes unimportant: $\log(A_{it}) = \log\left(\frac{wL_{it}^*}{\theta K_{it}^{\theta}}\right) + \log\left(\frac{1-\alpha_L}{\alpha_L}\right)$, so when subtracting the plant-specific means, the time-invariant term disappears. Therefore it is enough to calculate $A_{it} = \frac{wL_{it}^*}{\theta K_{it}^{\theta}}$, for which there is data. I will call the profitability shock calculated this way as type 2 shock.[53]

With the calculated profitability shocks now it is possible to estimate reduced regression (4.9). But later, when the theoretical model is solved numerically, I will simulate the profitability shocks and draw random variables from the observed distribution of shocks, using the exact correlation structure. As this correlation structure is extremely rich (shocks are correlated both across individuals and through time), I decomposed the A_{it} profitability shocks (both types) into aggregate and idiosyncratic shocks.[54] Following *Cooper and Haltiwanger (2005)*, I define the aggregate shock simply as $A_t = \frac{\sum_{i=1}^{N_t} A_{it}}{N_t}$, where N_t stands for the number of observations in year *t*. The idiosyncratic shock is what remains: $\omega_{it} = \frac{A_{it}}{A_t}$.

Tables 4.3a-4.3b contain the descriptive statistics of the identified type 1 and type 2 shocks in the full sample and balanced sub-sample.

Type 1 shocks	*Full sample*	*Balanced panel*
Aggregate shock standard deviation	0.1359	0.1196
Aggregate shock autocorrelation	0.6979	0.5297
Idiosyncratic shock standard deviation	1.8355	2.1477
Idiosyncratic shock autocorrelation	0.4004	0.4975

Table 4.3a. Standard deviations and autocorrelations of type 1 shocks.

[53] In fact I have data only on the size of labor force, not on labor costs. But similar considerations as in case of α_L leads to conclude that the value of w is unimportant.

[54] Thus the common aggregate shock captures between-firm correlation of shocks; the autocorrelation of the aggregate and idiosyncratic shocks captures the within-firm correlation of shocks.

Type 2 shocks	*Full sample*	*Balanced panel*
Aggregate shock standard deviation	0.0822	0.0407
Aggregate shock autocorrelation	0.9325	0.7449
Idiosyncratic shock standard deviation	0.2891	0.2482
Idiosyncratic shock autocorrelation	0.6410	0.7050

Table 4.3b. Standard deviations and autocorrelations of type 2 shocks.

It is apparent from *Tables 4.3a-b* that the type 2 shocks have much smaller variation than type 1 shocks, probably reflecting lower measurement error in the labor force variable than in the profit variable.[55] It is also intuitive that in case of the more reliable type 2 shocks if one identifies the profitability shocks in the full sample, as opposed to the balanced sub-sample, then the standard deviation of the shocks is significantly (25-30%) higher. This difference could be attributed to the variance-increasing effect of the large negative shocks that probably hit the liquidated and bankrupt firms mostly excluded from the balanced panel.

Having identified the profitability shocks, one can estimate the reduced form regression (4.9):

$$\tilde{i}_{it} = \psi_0 + \psi_1 \tilde{a}_{it} + \psi_2 (\tilde{a}_{it})^2 + \psi_3 \tilde{a}_{i,t-1} + \mu_t + u_{it}\,.^{56} \qquad (4.9)$$

Table 4.4 reports the estimated parameters of this regression for the full sample and balanced sub-sample. The estimated reduced regression coefficients are quite similar to each other, the only difference is in the estimated ψ_2 parameter, which is significant only at the 10% level in the balanced sub-sample.[57]

[55] *Cooper and Haltiwanger (2005)* have similar findings for a different data set.
[56] Firms were quite heterogeneous with respect to the variation of shocks that hit them. To deal with this kind of firm-level heterogeneity, and to avoid larger influence of more volatile firms for the estimated parameters, I weighted each observation by the inverse of the firm-level standard deviation of the identified shock. This makes the results more comparable to the results of the controlled experiments (see *section 4.4* and *Chapter 5*), as in the simulation exercise I also assumed that the standard deviation of the shocks is the same for each firm.
[57] This is probably because there are relatively few large shocks in the balanced sample, and therefore the reduced regression detects relatively modest non-linearity.

	Full sample	*Balanced sub-sample*
ψ_1	0.1150 (0.0085)	0.1032 (0.0099)
ψ_2	0.0822 (0.0147)	0.0310 (0.0289)
ψ_3	-0.0251 (0.0081)	-0.0368 (0.0092)
R-squared	0.0711	0.0528
No. of firms	1,554	941
No. of obs.	23,413	12,847

Table 4.4. Estimated reduced regression parameters. Standard errors are in parenthesis.

Estimating the inaction rate and asymmetry of investment distribution from data

As discussed in *section 4.2*, I also match theoretical inaction rate (the proportion of zero investments) to the observed inaction rate, because this way I can better identify the fixed cost parameter of the investment cost function. The observed inaction rate is 42.35% in the full sample, with a standard error of 0.29%.[58] Similar inaction rate is reported for the balanced sub-sample in *Table 4.5*.

As usual, I use skewness to measure the asymmetry of the investment rate distribution. As discussed earlier, only the irreversibility parameter is likely to influence the asymmetry of this distribution, so this may lead to better identification of the irreversibility parameter. *Table 4.5* contains the estimated skewness values of the investment rate distribution: it is 1.2182 for the full sample, and 0.9866 for the balanced sub-sample. (The corresponding standard errors of the estimated skewness figures[59] are 0.0146 for the full sample, and 0.0200 for the balanced sub-sample.)

---

[58] The standard errors of the estimated proportions are $\sqrt{\dfrac{p(1-p)}{n}}$, with p denoting the estimated proportion, and n is the number of observations. Inaction rate in *Figure4.6* is apparently larger, but that is actually the proportion of new investment rates between -1% and 1%.

[59] The standard error of estimated skewness is calculated as $\sqrt{\dfrac{6n(n-1)}{(n-2)(n+1)(n+3)}} \approx \sqrt{\dfrac{6}{n}}$, with n denoting the number of observations.

	Full sample	*Balanced sub-sample*
Skewness of investment rate distribution	1.2182 (0.0146)	0.9866 (0.0200)
Inaction rate	0.4235 (0.0029)	0.4625 (0.0041)

Table 4.5. Skewness of investment rates and observed inaction. Standard errors are in parenthesis.

From now on, I will work with the parameter estimates for the full sample as benchmark parameters. In the second step of the estimation procedure I will choose the structural parameters of the investment cost function in such a way, that the estimated reduced regression parameters from the theoretical model, along with the inaction rate and skewness of investment rate distribution, should be sufficiently close to these benchmark parameters.

Before finishing this section, it maybe useful to summarize those results that I will use to identify the theoretical cost parameters:

- *standard deviations and autocorrelations of the identified (type 2) aggregate and idiosyncratic shocks* (for the full sample, these are in column 2 in *Table 4.3b*). This information will be used to simulate aggregate and idiosyncratic shocks that are similar to observed shocks to solve numerically the theoretical model and simulate investment paths;
- *estimated parameters of the reduced form regression* from the full sample (column 2 in *Table 4.4*), and the estimated variance-covariance matrix $(\hat{W})$of the estimated parameters $\psi^{TRUE} = (\hat{\psi}_1, \hat{\psi}_2, \hat{\psi}_3)$;
- *estimated skewness* of the distribution of the investment rates in full sample, and the standard error of this (first entry of the 2nd column in *Table 4.5*);
- *observed inaction rate* in full sample, and the standard error of this (second entry of the 2nd column in *Table 4.5*).

4.4. Estimation Results

The estimation of structural cost parameters involves three steps.

Step 1. I specify the investment cost function according to (4.8):

$$\frac{C(I,K)}{K} = \begin{cases} \frac{I}{K}, 0 \le \frac{I}{K} \le \delta, \\ F + \frac{I}{K} + \frac{\gamma}{2}\left(\frac{I-\delta K}{K}\right)^2, \frac{I}{K} > \delta, \\ F + p\frac{I}{K} + \frac{\gamma}{2}\left(\frac{I}{K}\right)^2, \frac{I}{K} < 0. \end{cases} \tag{4.8}$$

Then I solve numerically the theoretical investment model for any cost parameter vector (F, γ, p). When solving the model, I assume that $\beta = \frac{1}{1+r} = 0.95$, $\delta = 0.07$, common assumptions in the literature using US data. For the numerical solution I use parametric value function iteration (as described by *Judd (1998)*), with the value function assumed to be a bivariate cubic function of (*A, K*).[60] During the solution I assume that the profitability shock A_{it} is the sum of aggregate and idiosyncratic shocks, where the aggregate shock is a 2-state Markov-process with standard deviation and autocorrelation estimated from real data (see *Table 4.3b*), and the idiosyncratic shock is an AR(1) process with normally distributed innovations (also matching the properties of idiosyncratic shocks reported in *Table 4.3b*).

Step 2. With the numerical solution of the theoretical model, I simulate capital and investment paths of hypothetical firms. To do this, first I simulate (aggregate and idiosyncratic) profitability shocks, using the descriptive statistics of the "true" (type-2) profitability shocks identified from the data (*Table 4.3b*). I also simulate the initial capital of the firms, then with the policy function obtained in Step1, along with the simulated shocks, I generate the capital and investment path of

[60] I solved the model initially with the more precise (but computationally more demanding) value function iteration, and chose the cubic functional form based on these results.

each firm.[61] Then I calculate the deviations from plant-specific means for both the investment rate and profitability shocks, and estimate the reduced form regression (4.9) on the simulated data set. I also calculate the skewness and the inaction rate in the simulated investment distribution. From now on, denote the estimated set of parameters by $\psi(F,\gamma,p)$, which expresses that these estimated parameters will depend on the structural cost parameters.[62]

Step 3. For any cost parameter vector (F,γ,p), I calculate the "distance" between $\psi(F,\gamma,p)$ and the parameter vector estimated from real data. The distance function is

$$D(F,\gamma,p)=\left(\psi(F,\gamma,p)-\psi^{TRUE}\right)'\cdot\hat{W}^{-1}\cdot\left(\psi(F,\gamma,p)-\psi^{TRUE}\right), \qquad (4.18)$$

where $\hat{W}$ is the variance-covariance matrix of ψ^{TRUE} estimated from the data.[63] That is, for any (F,γ,p) the distance is the weighted sum of squared deviation of the estimated parameters on simulated data from the "true" parameter set estimated on real data, with the weights being the inverse of the estimated variance-covariance matrix of the "true" parameters. [64]

I estimate the structural cost parameters (F,γ,p) by minimizing the distance function (4.18). The results for the "full sample" are in *Tables 4.6-4.7*.

Table 4.6 contains the estimated structural cost parameters.[65] The magnitude of the fixed costs seems to be very small, but the estimated parameter is about 4.69%

---

[61] To avoid problems arising from the misspecified distribution of the initial capital of the firms, we prepare the capital path of each firm for 129 periods (instead of 29), and only consider the data of the last 29 periods, which are not influenced by the initial level of the capital. The number of simulated firms is the same as the number of firms in our data, 1616.

[62] Note that here ψ is a vector containing 5 elements: (ψ_1,ψ_2,ψ_3) from the reduced form regression, and the skewness and the inaction rate in the investment rate distribution.

[63] $\hat{W}$ contains the estimated variance-covariance matrix of the reduced regression parameters, the estimated variance of the skewness of the investment distribution (0.0146^2), and the estimated variance of the observed inaction rate (0.0029^2). The pair-wise covariance between the estimated skewness, inaction rate and reduced regression parameters is assumed to be 0.

[64] So parameters estimated with smaller standard errors have larger weights.

[65] Standard errors are calculated as described by *Gourieroux and Monfort (1996)*.

of the "regular" purchase price of capital when investment rate is 1%.[66] Moreover, the estimated irreversibility parameter indicates substantial irreversibility, a more than 30% average discount on capital sales. The estimated convex cost parameter is 0.4464, which is in line with comparable estimates in the literature.

estimated F	0.000469 (0.000151)
estimated γ	0.4464 (0.0252)
estimated p	0.6962 (0.0923)
optimal LOSS	**193.4723**

Table 4.6. Estimated cost parameters from the full sample. Standard errors are in parenthesis

To further analyze the estimated cost parameters, suppose that a firm sells 1% of its existing capital stock. Then the fixed cost of this transaction is 0.000469, the convex cost is (0.4464/2)*(-0.01)*(-0.01) = 0.00002232, and the irreversibility cost is 0.3038*0.01 = 0.003038 (the product of the discount at which the firm can sell capital, and the quantity sold). So the total adjustment cost to be paid is 0.003529, which is 35.29% of the price the firm would receive for this capital sale in the frictionless case (0.01). The relative importance of the different cost components is the following: 13.3% of total adjustment costs is fixed cost, 0.6% of total adjustment costs is convex cost, and the remaining 86.1% is irreversibility cost.[67]

To take another example, the average positive investment rate in the data set is 6.34%; in this case the total adjustment costs are 2.15% of the purchase price, of which 34.3% are due to fixed costs, and 65.7% are due to convex costs. (Obviously, in case of positive investment rate there are no direct irreversibility costs.)

The estimated irreversibility parameter, $p = 0.6962$ (significantly smaller than 1) indicates that firms can sell their used capital at a 31% discount, or on

[66] Note that I normalized the model to the buying price of capital, and therefore when investment rate is 1%, the price of new capital is 0.01.
[67] For different investment rates, these proportions change. Larger new investment activity generally increases the importance of adjustment costs, mainly because of the relatively quickly increasing convex costs. Also, for larger investment projects convex costs will dominate fixed and irreversibility costs.

average 31% of any dollar spent on investment is sunk. This is quite far from the estimate of *Ramey and Shapiro (2001)*, who find that at a discontinuing US plant the average discount on used capital is 72% of the replacement value. This value is also far from the results in the previous chapter, where the average discount was approximately 50% on the capital sales of a discontinuing Hungarian manufacturing plant. However, the estimate of $p = 0.69$ is based on continuously operating plants, as opposed to the total sell-out of assets at discontinuing plants, so these results cannot be directly compared. On the other hand, this parameter estimate is much smaller (and therefore indicates much higher irreversibility) than those results in the literature that use similar techniques to ours. Based on indirect inference, with reduced form regression (4.9) in a somewhat modified model, the initial version of *Bayraktar, Sakellaris and Vermuelen (2005)* estimate $p = 0.902$ for German manufacturing plants between 1992-2000. Further, for a balanced panel of US manufacturing plants *Cooper and Haltiwanger (2005)* estimate $p = 0.975$ with a simulated maximum likelihood method. The latter two results are estimated from a balanced panel, which may lead to significantly different results than estimation from an unbalanced panel. Moreover, the result of substantial irreversibility is primarily due to the control for the skewness of investment rate distribution, which is missing from other studies.

	simulated	*"true"*
reduced regression parameter ψ_1	0.1971	0.1150
reduced regression parameter ψ_2	0.0778	0.0822
reduced regression parameter ψ_3	-0.0767	-0.025
inaction rate	0.4179	0.4235
skewness of investment distribution	1.2087	1.2182
total LOSS	**193.4723**	

Table 4.7. Estimated reduced regression parameters, inaction rate and skewness.

Table 4.7 reports the simulated reduced regression parameters, inaction rate and investment rate skewness, and also the observed values of the same parameters. It is apparent that the applied matching technique does quite well to match simulated regression parameters, inaction rate and skewness to their observed values.

4.5. Aggregate Implications

With the estimated cost parameters one can investigate the aggregate implications of the results. To do this, I simulated a panel of firms that have the investment cost function as estimated, and calculated the aggregate investment and aggregate shock over the years in the simulated data set. *Table 4.8* contains the main descriptive statistics of the simulated aggregate variables with the corresponding descriptive statistics of the individual variables.

	in plant-level data (real data)	*in plant-level data (simulation)*	*in aggregate data (real data)*	*in aggregate data (simulation)*
$st.dev.(i_t)$	0.1258	0.0704	0.0354	0.0224
$corr(i_t, i_{t-1})$	0.2248	0.1143	0.3707	0.5695
$corr(i_t, a_t)$	0.0890	0.5179	0.5227	0.6416

Table 4.8. Descriptive statistics of aggregate and plant-level investment and shocks.

It is apparent from *Table 4.8* that the standard deviation of the aggregate investment rate is naturally much smaller than that of the individual investment rate. Moreover, the autocorrelation of the investment rate is also much higher in the aggregate level, and the correlation between the investment rate and the profitability shock also increases. Aggregate investment behaves quite differently from individual investment.

I also estimated the investment-shock relationship on the aggregate level. Contrary to what was found on the plant-level, I could not detect any nonlinearity in this relationship. (The squared shock remained insignificant when I estimated a regression of investment on shocks.) I found that on the aggregate level there is a modest linear relationship between profitability shocks and investment – the estimated parameter of the profitability shock is 0.2392 in the real data, and 0.3394 in the simulated data (both of them are significant at the 5% level). *Chapter 5* contains further controlled experiments on the aggregate effects of profitability shocks.

5. AGGREGATE EFFECTS OF ESTIMATED FIRM-LEVEL INVESTMENT COSTS IN HUNGARY

In Hungary, corporate investment behavior has been mainly investigated on aggregate data (see, for example, *Darvas-Simon, 2000*, and *Pula, 2003*), and only few studies follow the new international trend of addressing this question at the firm level. Among these few studies, *Molnár-Skultéty (1999)* used the 1996 wave of the investment statistics survey of the Hungarian Central Statistical Office[68] to characterize the corporate investment behavior by such factors as size of investment costs, number of employees, sales revenues, and to make a correlation analysis of investment activity with various balance sheet measures. In another study, *Szanyi (1998)* uses a PHARE-ACE investment survey[69] to investigate the dynamics of investment activity, and reports the evolution of some simple descriptive statistics (investment relative to sales revenues and number of employees) between 1992-1995. Finally, *Kátay-Wolf (2004)* use the Hungarian Tax Agency's balance sheet data of all double entry book keeping firms between 1992-2002, and make a step beyond providing simple descriptive statistics of firm-level corporate investment behavior by addressing the question of how „changes in the user cost of capital – of which the interest rate is only a determinant – affect corporate investment behavior"[70] with econometric tools.

This chapter is a follow-up of the analysis of *Kátay-Wolf (2004)* in the sense that (1) it investigates the determinants of the investment behavior at the firm level; and (2) uses the same data set. However, there are several aspects according to which my approach is somewhat different:

(1) Similarly to the previous chapter, I use the "new investment models" set up by the post-1990 investment literature as a modeling framework, incorporating those characteristics of firm-level investment behavior that we have overwhelming empirical evidence about.[71] The main focus of these models is on different types of

---

[68] This survey contains all corporate investment activity that exceeded 10 million HUF-s in 1996 prices.

[69] Here data is available about 258 firms that voluntarily filled a questionnaire about their investment behavior between 1992-95. The data set is admittedly non representative.

[70] *Kátay-Wolf (2004),* p. 2.

[71] I refer again to *Doms-Dunne (1998)* about lumpiness, and *Ramey-Shapiro (2001)* about irreversibility.

firm-level investment costs, which may include fixed, convex, irreversibility and disruption costs that firms may have to pay when undertaking investment.[72]

(2) Another difference of my approach is that while in *Kátay-Wolf (2004)* the main driving force of investment is the appropriately defined "user cost of capital", I use a model as described in the previous chapter, in which one does not claim to know exactly which factors affect investment activity and which do not, but treats a "profitability shock" (that incorporates any influencing factor) as the main determinant of investment at the firm level. As a consequence, much emphasis is taken on the empirical identification of this profitability shock and its distribution.

(3) Most importantly, I extend the framework to investigate aggregate investment behavior, where aggregate investment is defined simply as the sum of firm-level behaviors.

So in this chapter I use the model set up in section 4.2, and the estimation strategy discussed in section 4.3 to analyze the investment decisions of Hungarian firms between 1992-2002. As a contribution to my earlier results, here the main focus is on aggregate investment dynamics. In particular, I investigate how a monetary policy shock can affect aggregate investment. In doing so, I assume that monetary policy affects the aggregate profitability shock that hits the firms, and the sum of the firm-level responses to this aggregate profitability shock will determine the aggregate effect on investment.

5.1. Data and Variables

I use the same data set that was also used by *Kátay-Wolf (2004)*: "corporate tax returns of double entry book keeping firms between 1992 and 2002",[73] with the only exception that I use only manufacturing firms for the analysis. Otherwise, the initial data filtering is the same, and in fact I mostly used the variables that were constructed by *Kátay-Wolf (2004)*.

[72] See *Stokey (2001)* for a taxonomy about these types of costs. For empirical estimation of the different cost components, see *Bayraktar et al (2005)* and *Cooper-Haltiwanger (2005)*.
[73] *Kátay-Wolf (2004)*, p. 28. The 1992 wave of the tax returns is excluded later because of low reliability and missing investment rate data, so in fact the panel starts in 1993 and ends in 2002.

As it is important to know the aspects of sample construction, let me briefly summarize the steps of initial data manipulation in *Kátay-Wolf (2004)*:

(1) observations with relevant missing data (number of employees, capital depreciation) were deleted;

(2) very small firms[74] were deleted;

(3) data was corrected when it was considered false;

(4) outliers (with respect to cash-flow, depreciation rate, user cost, investment rate, changes in capital stock, employment, sales, user cost) were excluded.

As a result of this, the original panel of 1,269,527 year-observations was reduced by *Kátay-Wolf (2004)* to 308,850 year-observations. Since I estimate the cost parameters only on manufacturing firms, the size of the sample further reduced to 110,808 year-observations. Also, I went on with the exclusion of missing observations and outliers with respect to my key variables (investment rate, sales revenue, capital stock, profit), so the final sample size of my data set is 92,293 year-observations.[75]

As in *Chapter 4*, the key variables investment rate, capital and profit. To measure *gross investment rate*, I adopted the investment rate variable also used in *Kátay-Wolf (2004)*, who constructed investment rates from accounting capital data. From the calculated gross investment levels and observed depreciations, *Kátay-Wolf (2004)* constructed a real *capital variable* with Perpetual Inventory Method (PIM); I used this variable to measure capital stock. Finally, we used *operating profit* to measure the profit of the firms.

5.2. Firm-Level Results

[74] Definition of very small firms: if the number of employees is smaller than 2 in a particular year, or if the number of employees is smaller than five during three consecutive years.

[75] Specifically, I deleted 18,308 year-observations because of missing investment rate. (These were mostly the observations of 1992, when initial capital stock was not available.) Then I deleted further 118 year-observations because of non-positive sales revenues. Next, I deleted those 35 year-observations for which capital stock was not observed. Finally, I deleted 54 year-observations with unobserved profit. These steps reduced the sample size to 110,808 – 18,308 – 118 – 35 – 54 = 92,293 year-observations.

In this section I describe the measurement of the profitability shock and inaction rate that will be used to identify the structural cost parameters. As discussed in the previous chapter, these will then be used to calculate the estimated parameters of the shock-investment relationship (or the reduced regression parameters), the inaction rate, and the skewness of the investment rate distribution.

For the reduced-form shock-investment relationship, it is necessray to have a profitability shock and an investment rate variable. This latter variable will also be used to determine the inaction rate and the investment rate distribution skewness. In what follows, I first describe the identification of profitability shocks, then discuss the measurement of new investment rates, and finally present the estimated statistics (to which matching will be done).

Identification of profitability shock

Again, I identify the profitability shock based on the methodology of *Cooper-Haltiwanger (2005)*. Following the same steps as in *section 4.5*, one can derive that the type-1 profitability shock can be calculated as $A_{it} = \frac{\Pi^*_{it}}{K^\theta_{it}}$, and type-2 shock is $A_{it} = \frac{\Pi^*_{it}}{K^\theta_{it}} = \frac{wL^*_{it}(\xi - \alpha_L(1+\xi))}{K^\theta_{it}\alpha_L(1+\xi)} = \frac{wL^*_{it}}{\theta K^\theta_{it}}\frac{1-\alpha_L}{\alpha_L}$, as derived in (4.16). As opposed to the US data used in the previous chapter, the estimation of θ was not entirely robust to different estimation techniques and outlier filtering,[76] so now I discuss the results of these estimations in more details. As I already discussed in *Chapter 4*, I used four alternative methods to estimate θ:

(1) I assumed that the error term is additive, and estimated θ with non-linear least squares from the equation $\Pi^*_{it} = A_i K^\theta_{it} + \varepsilon_{it}$ (using fixed

[76] This is probably because the Hungarian data is much more noisy than the COMPUSTAT data. One could argue that it would be advisable to explicitly take into account the potential measurement errors. One way of doing this could be the method developed by *Altonji-Devereux (1999)*, who model the measurement error of reported wages. However, in this case the measurement error problem is more difficult to solve, as in this data set there are several variables affected by the measurement error problem, while for Altonji-Devereux the only problematic variable is reported wages. So a systematic modeling of all types of measurement errors would make the model much more complicated, and is therefore beyond the scope of the dissertation. Instead, I check very carefully for the robustness of the results across different specifications.

effects). To avoid the large impact of larger firms on the estimated θ, I weighted observations with their size (measured as sales revenue), so effectively I estimated the equation $\Pi_{it}^{*} / R_{it} = A_i K_{it}^{\theta} / R_{it} + \varepsilon_{it} / R_{it}$ (where R_{it} is sales revenues).

(2) I shifted each Π_{it}^{*} / R_{it} by a constant C to be able to take the log of most observations, and estimated $\ln\left(\Pi_{it}^{*} / R_{it} + C\right) + \ln\left(R_{it}\right) = \ln\left(A_i\right) + \theta \ln\left(K_{it}\right) + \varepsilon_{it}$ by OLS.

(3) To account for the potential endogeneity of K_{it}, I estimated the same equation $\ln\left(\Pi_{it}^{*} / R_{it} + C\right) + \ln\left(R_{it}\right) = \ln\left(A_i\right) + \theta \ln\left(K_{it}\right) + \varepsilon_{it}$ with IV (with lagged capital as instrument).

(4) I estimated $\ln\left(\Pi_{it}^{*} / R_{it} + C\right) + \ln\left(R_{it}\right) = \ln\left(A_i\right) + \theta \ln\left(K_{it}\right) + \varepsilon_{it}$ by OLS on the same sub-sample as in case of IV estimation (I call this method as "sample corrected OLS").

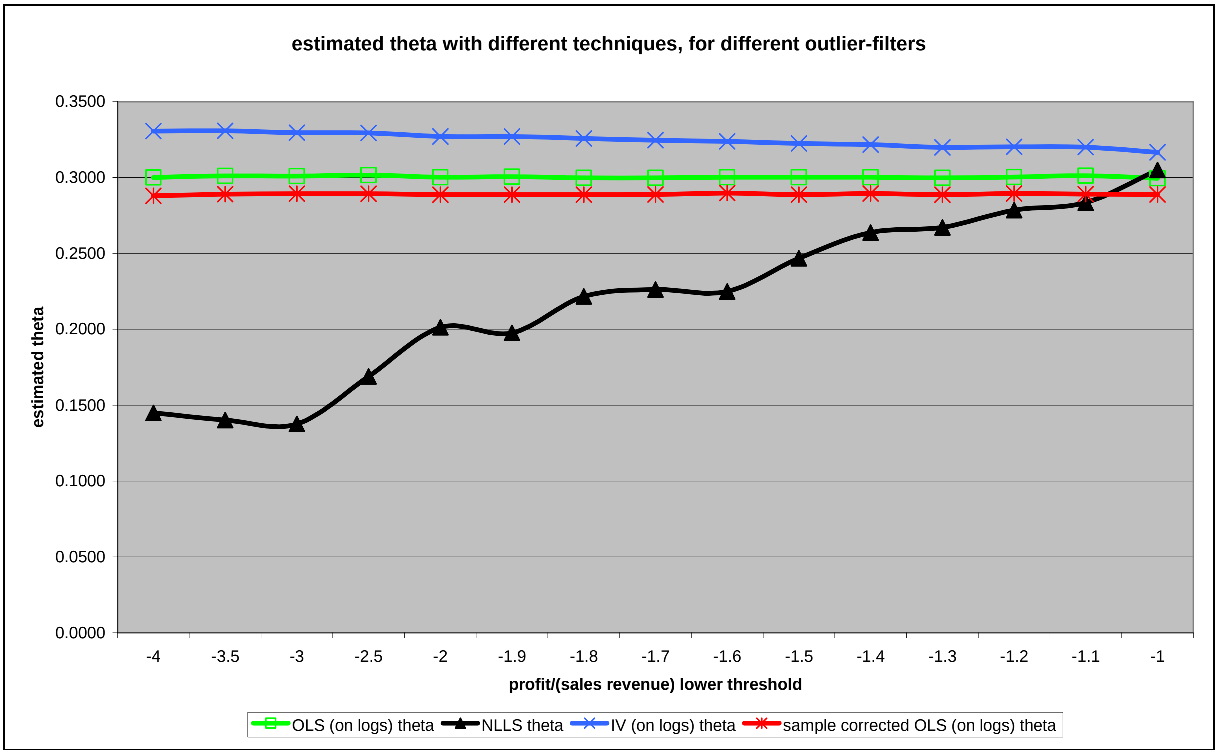

Figure 5.1. Estimates of parameter θ with different methods, as a function of different outlier filtering.

Figure 5.1 illustrates the estimated θ-s for different outlier-thresholds. (I filtered out outliers according to the left-hand-side variable, Π^*_{it} / R_{it}.) It is apparent from the graph that the NLLS-method is very sensitive to the exact way of outlier filtering, while the log-model-based estimates do not have similar sensitivity (despite the estimates being different by definition because of the different shift parameter *C*). It is also apparent that IV-estimates are always higher than OLS-estimates, which indicates that capital is endogenous.[77] Also, there is a systematic difference between the original and the sample-corrected OLS-estimates, which is probably because the omitted part of the sample (mainly the 1993-observations that are used only as instruments for IV-estimation) behaves differently from the remaining part of the sample.

In what follows, I accept the IV-based estimate of parameter θ. It is apparent from *Figure 5.1* that the parameter estimates are quite robust for different shift parameters *C* (they fluctuate between 0.3372 and 0.3301), so I accepted the value that is estimated for the largest possible sub-sample (the one that excludes the lowest number of outliers): $\hat{\theta} = 0.3372$.

To further evaluate the estimated θ,[78] it is interesting to compare it to estimates on other (international) data sets. To my knowledge, there are three comparable estimates in the literature:

(1) On a balanced panel of US manufacturing firms, *Cooper-Haltiwanger (2005)* estimated $\theta = 0.5$.

(2) In the previous chapter, using US data, I estimated $\theta = 0.6911$, and $\theta = 0.46$ for the balanced sub-sample.

(3) *Bayraktar et al. (2005)* estimated $\theta = 0.34$ for an unbalanced panel of German manufacturing firms.

[77] The Hausman-test of endogeneity was significant at the 1% level in case of all specifications. This finding is reasonable: capital itself also depends positively on the profit.

[78] Since θ is a key parameter to identify profitability shocks, it is important to have a reliable estimate of it. Although shocks identified with different θ-s are strongly correlated, θ is important as it influences the variability of the profitability shock, and also the structural cost parameters themselves.

Therefore my estimate of parameter θ seems to be much below comparable estimates for US manufacturing firms, but is in line with the findings for Germany. It seems that profits are much more responsive to capital in the US. (The investigation of the reasons of this phenomenon is beyond the scope of this chapter.)

To further the estimated θ parameter, I also estimated it for the different manufacturing sub-sectors (this time I only used the IV method on the shifted log-log model). It is apparent on *Figure 5.2* that in those sectors that we think to be relatively more capital-intensive (chemical industry, machinery), I obtain somewhat larger estimates, with the interpretation that profit is more responsive to capital in these sectors. *Figure 5.2* also suggests that outliers do not have large impact on the relative size of estimated industry-specific θ-s, a similar finding that was also true for the whole manufacturing industry.

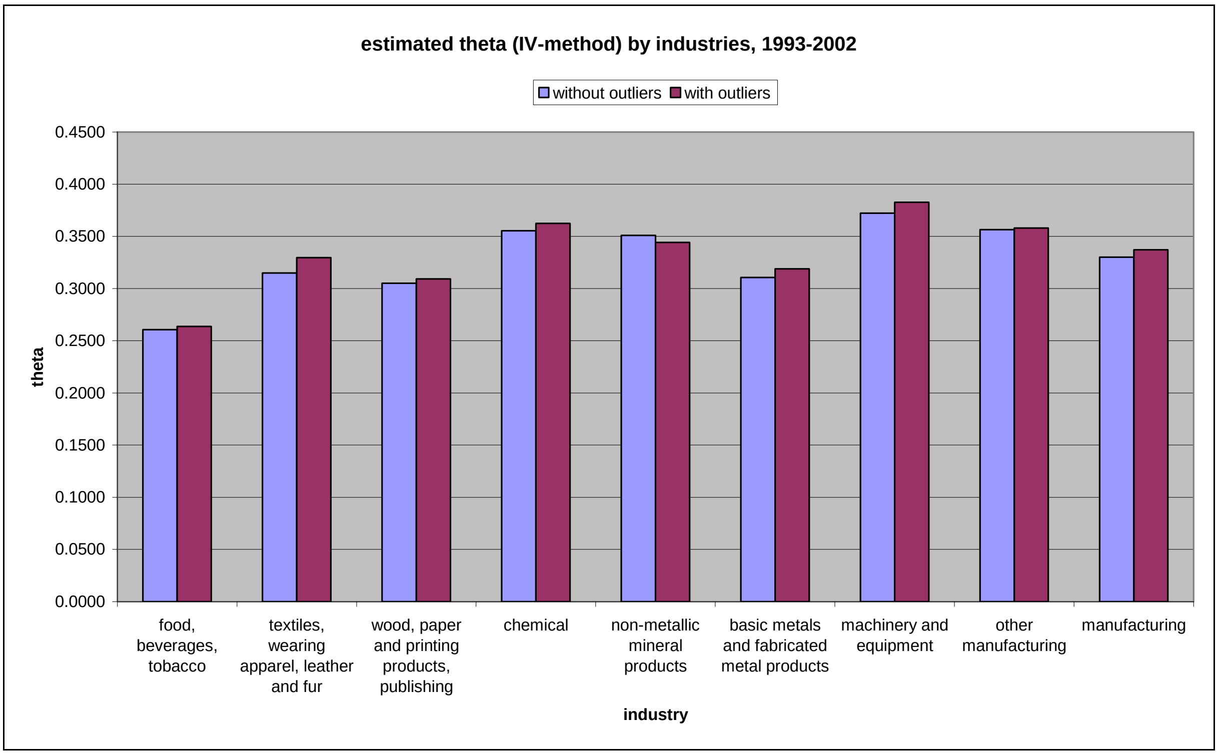

Figure 5.2. Estimated θ (IV-method) by industries.

To investigate the stability of the estimated parameters over time, I divided the data set to two further sub-samples: one early sub-sample containing observations between 1993-1997, and another sub-sample with observations between 1998-2002.

It is apparent on *Figure 5.3* that the estimates on the whole sample (1993-2002) are mainly driven by the estimates between 1998-2002, while the estimates based on the early period of 1993-97 are relatively more different. There are two possible explanations of this:

(1) Observations in the early years (1993, 1994) are noisy; a similar hypothesis was set up by *Kátay-Wolf (2004)*;[79]

(2) Firms behaved differently during the years of transition than later.

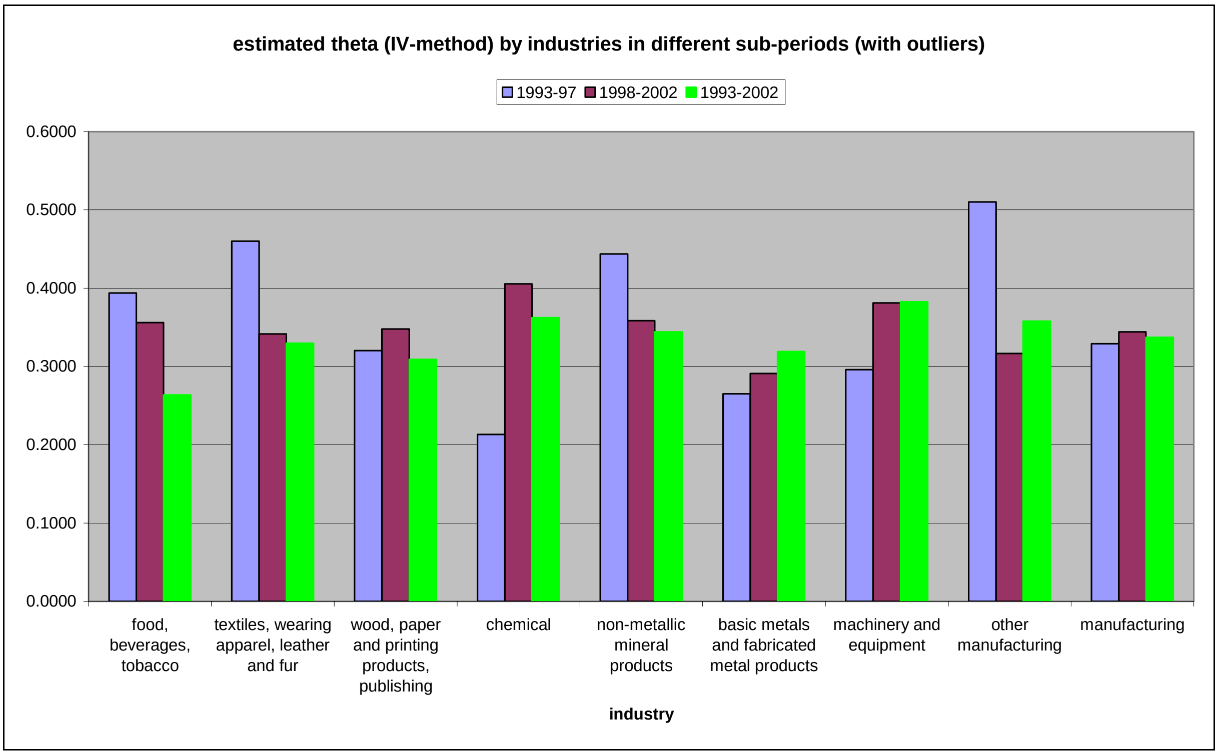

Figure 5.3. Estimated θ (IV-method) by industries in different sub-periods.

Based on all of these investigations, I accept the estimate of $\hat{\theta} = 0.3372$, and identify the profitability shocks accordingly. As profit, capital and wage bill variables are all available in the data set, I can now calculate both type-1 $\left(A_{it} = \frac{\Pi^*_{it}}{K^\theta_{it}} \right)$ and type-2 $\left(A_{it} = \frac{w_{it} L^*_{it}}{\theta K^\theta_{it}} \right)$ shocks.

Similarly to what I have done in *chapter 4*, and in order to mimic the rich correlation structure[80] of the identified profitability shocks, I decomposed them into

[79] *Kátay-Wolf (2004)* also concluded that early data is likely to be relatively less reliable.
[80] Shocks are correlated both over time and among firms.

aggregate and idiosyncratic shocks. Aggregate shock is defined as the average profitability shock in year *t*: $A_t = \frac{\sum_{i=1}^{N_t} A_{it}}{N_t}$ (here N_t is the number of observations in year *t*), while idiosyncratic shock is simply $\varepsilon_{it} = \frac{A_{it}}{A_t}$.

Table 5.1 contains the properties of the identified type-2 profitability shocks,[81] and for comparison purposes similar measures from the previous chapter are also reported. The results show that profitability shocks seem to be more volatile but less persistent in Hungary than in the US.

	Hungary	US (*Chapter 4*)
Aggregate shock standard deviation	0.1092	0.0822
Aggregate shock autocorrelation	0.6882	0.9325
Idiosyncratic shock standard deviation	0.3155	0.2891
Idiosyncratic shock autocorrelation	0.4033	0.6410

Table 5.1. Properties of identified type-2 profitability shocks.

Measurement of new investment rates

I measured new investment rates (as opposed to observed gross investment rates, the measurement of which is described in the previous section) in three alternative ways. Since exact measurement is impossible, all of these are only approximations that are based on (reasonable) assumptions.[82]

In the first method, I use an average depreciation rate (δ) to calculate new (as opposed to gross) investment rate:

[81] As type-1 shock is much more noisy, following my approach in *Chapter 4*, I work only with type-2 shocks in what follows.
[82] In *Chapter 4* I only used the third method to measure new investment rates. This will also be the preferred method here, but for comparison purposes I report the result with the two alternative measurement techniques.

- If the observed gross investment rate is bigger than δ, then I assume that firms engage in cheap replacement investment activity to reduce the need of costly new investment. So in this case there is δ replacement investment (replacing and/or renovating depreciated capital), and thus the new investment rate equals the gross investment rate less δ.
- Alternatively, if the observed gross investment rate is positive, but smaller than δ, then firms could make all their investment activities as replacement investment, which was in fact in their best interest, since this was cost-free. So in this case all investment is replacement investment, and new investment is 0.
- Finally, if the observed gross investment rate is negative, then I assume that there was no replacement investment. This is so because if firms did have some replacement investment, then their need of costly disinvestment (and also their costs) would have increased.

In the second measurement method I assume that firms always make replacement investment that is equal to their observed depreciation, irrespectively of whether their current situation is improving or deteriorating. So in this case new investment is calculated simply by taking the difference between gross investment and depreciation.

Finally, *the third measurement method* is a mixture of the previous two because it makes distinction between replacement investment activity in expansionary and contractionary periods,[83] but it does so on the basis of observed depreciation (as opposed to an average depreciation rate δ in method 1):

- If $INVEST_t > DEP_t$, then capital expenditures exceeded depreciation, so net capital stock increased. I assume that in this "expansionary" case firms undertake as much replacement investment as possible (as this is relatively cheap), and only the increase in the value of net capital stock is the result of the costly new investment activity. So in this case, $NEWINVRATE_t = \frac{INVEST_t - DEP_t}{CAPITAL_{t-1}}$.

[83] That is, when firms expend, they make as much replacement investment as possible, while when contracting, they let their capital depreciating.

- If $DEP_t \geq INVEST_t \geq 0$, then the firm's capital expenditures were positive, but since they did not entirely cover depreciation, the firm's former capital stock depreciated to some extent. I assume in this case that all capital expenditures were maintenance-type replacement expenditures, and therefore $NEWINVRATE_t = 0$.

- If $0 > INVEST_t$, then the firm is obviously shrinking. It seems to be logical to assume in this case that no replacement investment was undertaken, as this could have been compensated for only by costly capital sales. In this case $NEWINVRATE_t = INVRATE_t = \frac{INVEST_t}{CAPITAL_{t-1}}$.

Figures 5.4-5.6 illustrate the resulting new investment rate distributions, when new investment rates are defined according to the different measurement methods. In the following I will use the third measurement of new investment rates as a benchmark, since I think that the first method is only an approximation of method 3, and the second method leads to implausibly high negative investment rate proportions. However, to analyze robustness, in some cases I will also report the results that are obtained when using the alternative definitions.

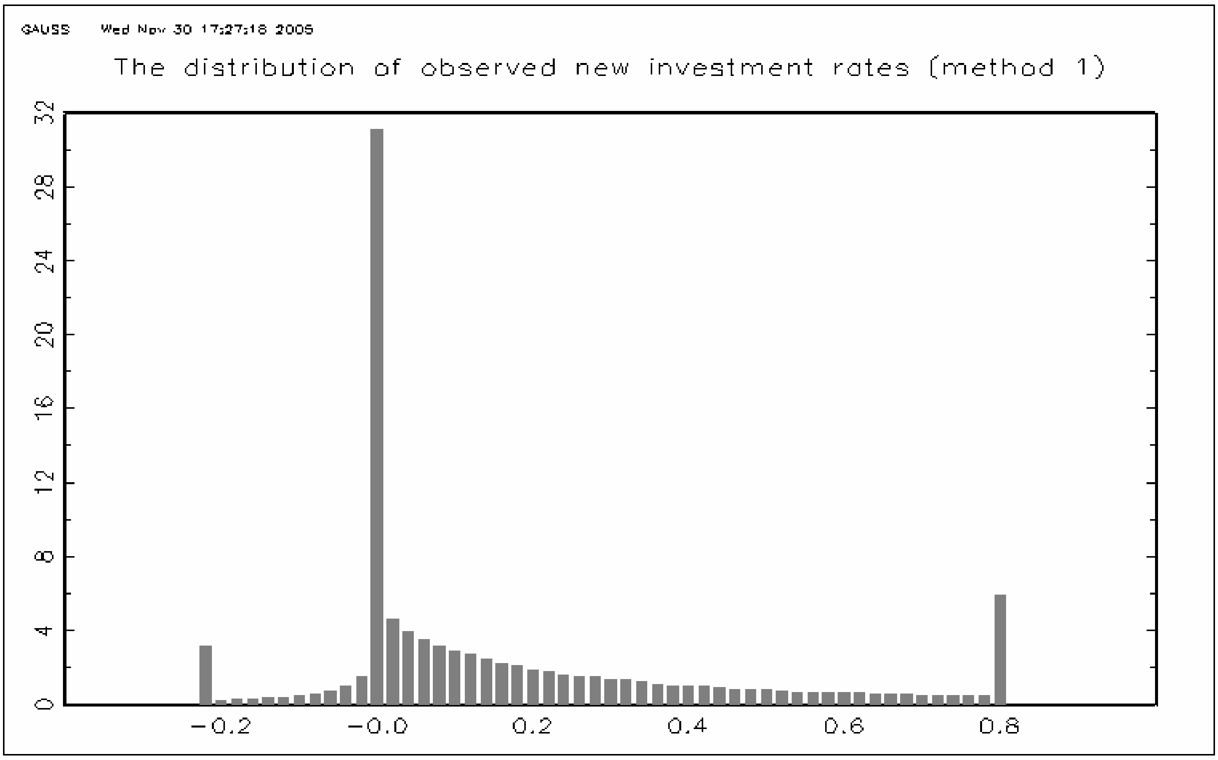

Figure 5.4. New investment rate distribution, method 1.

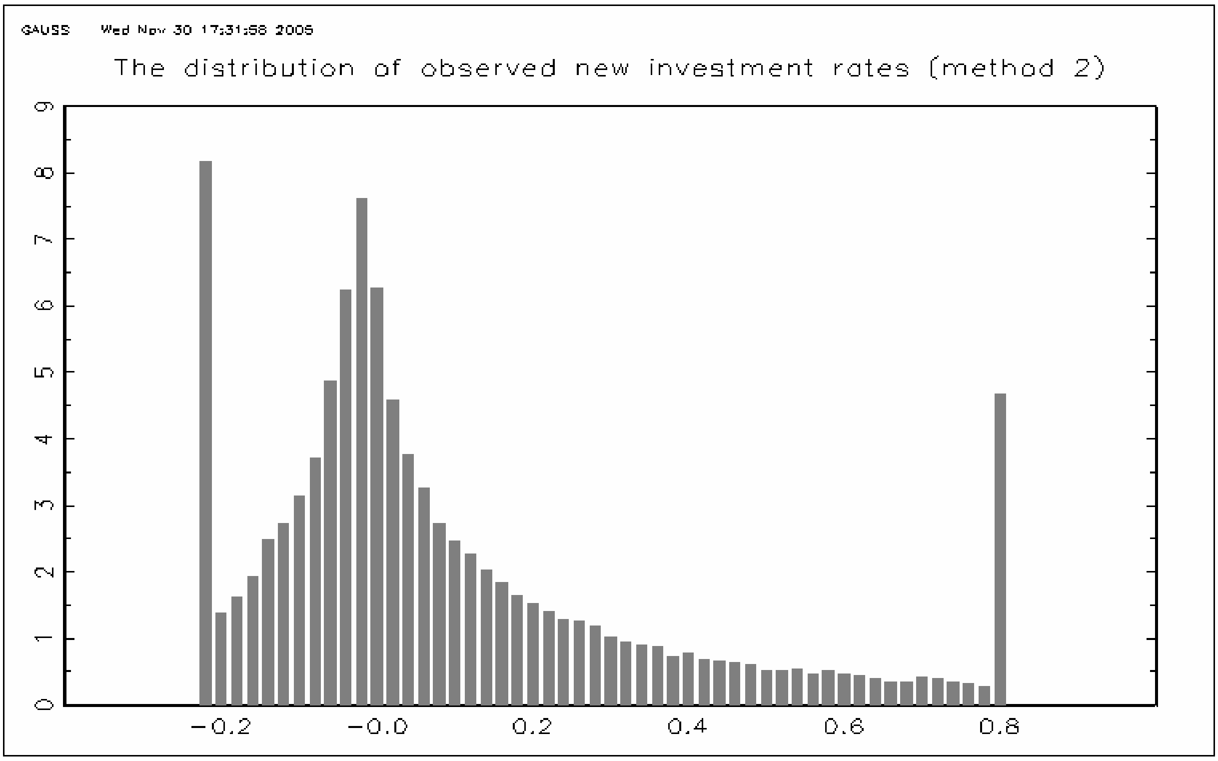

Figure 5.5. New investment rate distribution, method 2.

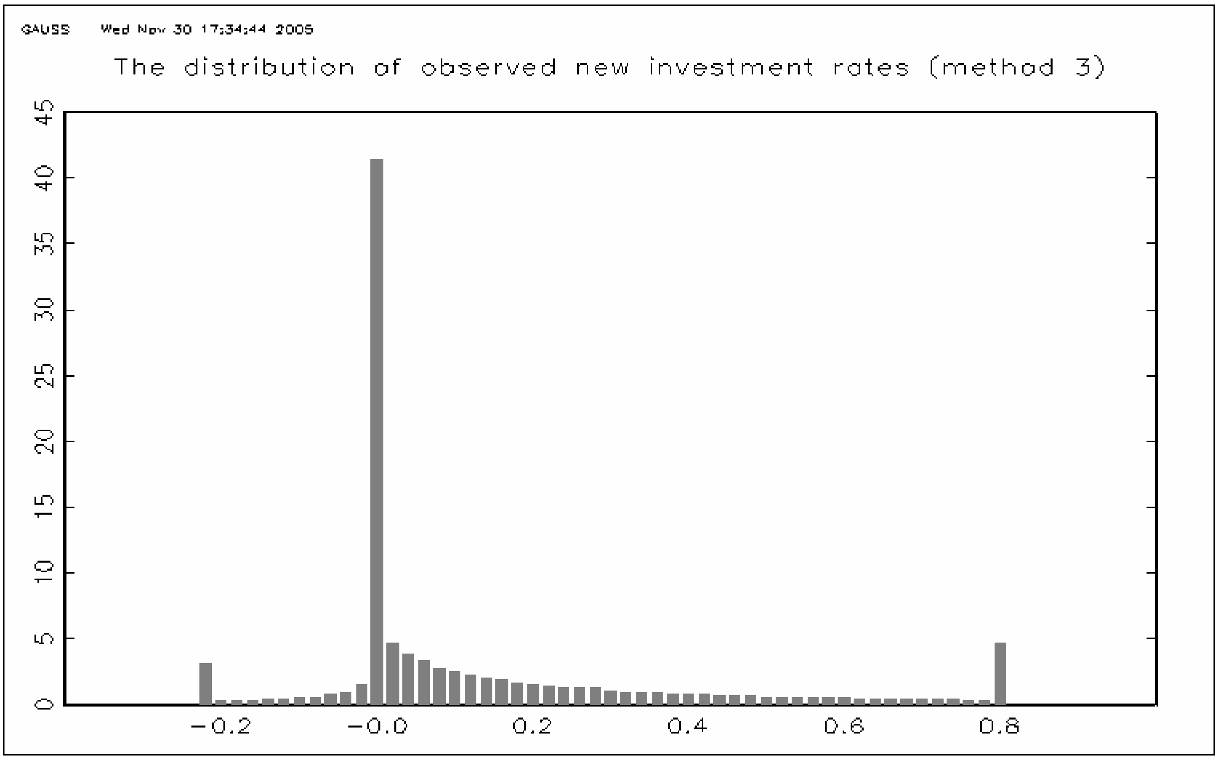

Figure 5.6. New investment rate distribution, method 3.

Table 5.2 contains some descriptive statistics of the measured new investment rate distribution (method 3). It is apparent that the dispersion of the observed investment rates is much higher in Hungary, and therefore the proportion of negative investment rates and investment spikes is naturally bigger. The higher inaction rate may be due to the higher observed depreciation rates. Nonetheless, all of these may simply indicate that the Hungarian data is much noisier.

	Hungary	US (*Chapter 4*)
Proportion of negative new investments	10.50%	2.45%
Proportion of inaction	49.64%	42.35%
Proportion of spikes (>20%)	27.73%	19.89%
Mean	13.39%	11.84%
Standard deviation	28.00%	15.10%
Skewness	1.4984	1.2182

Table 5.2. Descriptive statistics of the new investment rate distribution (method 3).

Estimation of the reduced-form shock-investment relationship

With the identified profitability shocks and investment rates, I can now estimate the reduced-form shock-investment relationship, which is the key to identify the structural cost parameters. According to equation (9), the specification that we estimate is a quadratic one between investment and profitability shocks, with lagged shocks also included. The quadratic term is included to capture fixed-cost- and irreversibility-induced non-linearity, while the lagged variable captures lumpiness (also due to either irreversibility or fixed costs). So the estimated regression is

$$\tilde{i}_{it} = \phi_0 + \phi_1 \tilde{a}_{it} + \phi_2 \tilde{a}_{it}^2 + \phi_3 \tilde{a}_{i,t-1} + \mu_t + u_{it} . \tag{4.9}$$

Table 5.3 contains the estimated parameters of this regression for alternative measurements of new investment rate. It is apparent from the table that estimated parameters are robust to the way of measurement of the new investment rate. The only exception is $\hat{\phi}_2$, which is much lower in case of method 1 than for alternative methods. This probably means that the assumption of an average depreciation rate (for calculating method 1 new investment rate) is not appropriate.

Table 5.3 also contains the estimated parameters of the same reduced-form regression for US data, as reported in *Chapter 4*. The structure of the estimated parameters is surprisingly similar.

I will use these estimated parameters (together with observed inaction rate and observed investment rate distribution skewness) to identify the structural cost parameters of the theoretical model.

	Method 1	Method 2	Method 3	US (*Chapter 4*)
Estimated ϕ_1	0.1343 (0.0099)	0.1466 (0.0106)	0.1354 (0.0097)	0.1150 (0.0085)
Estimated ϕ_2	0.0297 (0.0216)	0.0784 (0.0234)	0.0723 (0.0214)	0.0822 (0.0147)
Estimated ϕ_3	-0.0369 (0.0080)	-0.0368 (0.0084)	-0.0343 (0.0076)	-0.0251 (0.0081)
Number of firms	12,918	12,984	12,984	1,554
Number of observations[84]	50,470	51,485	51,485	23,413

Table 5.3. Estimated reduced regression parameters (with standard errors) for alternative new investment rate measurement methods.

5.3. Estimation of the structural cost parameters

As before, I identify the structural cost parameters by matching the parameters of the theoretical shock-investment relationship, the theoretical inaction rate and the theoretical investment rate distribution skewness to empirically observed values reported in the previous section. The parameters of the theoretical shock-investment relationship, the theoretical inaction rate and the theoretical investment rate distribution skewness are obtained by simulating the theoretical model for arbitrary cost parameters (F, γ, p). The simulation, as in *Chapter 4*, involves the following steps:

Step 1. Determine the value and policy functions of the theoretical model for arbitrary cost parameters (F, γ, p). I solve the model by value function iteration on fine grids with respect to the state variables (A, K), and assuming that shocks have the same distribution as observed from data.[85] I also assume that $\beta = 0.95$ and

[84] The number of observations is larger when we measure investment rate according to methods 2-3, based on observed depreciation (as opposed to an average depreciation rate δ). The reason of this is that in case of method 1, the number of investment outliers (defined as investment rates above 125%) is much larger.
[85] Here I used the rich correlation structure of the shocks, by assuming that overall shocks are the sum of aggregate and idiosyncratic shocks, with standard deviations and autocorrelations reported earlier.

$\delta = 0.07$, where the latter is an average depreciation rate reported by *Kátay-Wolf (2004)*.[86]

Step 2. With the policy functions obtained in *Step 1*, simulate artificial data sets of the same size as the original data set. As a starting point, I simulate profitability shocks, using again the observed distribution of shocks. Then I use the policy function obtained in *Step 1* to simulate the capital paths of the hypothetical firms in the artificial data set, and calculate the corresponding investment rates.

Step 3. Estimate the reduced-form shock-investment relationship in the simulated data set, and also the inaction rate and the investment rate distribution skewness.

Step 4. Choose a cost parameter vector (F, γ, p) for which the distance between simulated and observed reduced-regression parameters, inaction rate and investment rate distribution skewness is the smallest.

Table 5.4 illustrates that for cost parameters $F = 0.0001$, $\gamma = 0.22$, $p = 0.991$, the simulated reduced-regression parameters, inaction rate and investment rate distribution skewness are quite closed to their observed values. In fact I found that the distance between the simulated and observed values (weighted by the inverse of the standard deviation of each estimate) is the smallest for this vector of cost parameters, which means that this is my estimate for the structural cost parameters.

[86] In principle, these are also structural parameters of the model, so in fact one should estimate them jointly with the other structural parameters. But since the focus of this paper is on estimating the structural *cost parameters,* I decreased the dimension of the parameter vector to be estimated to 3. This leads to a considerable reduction computation time.

	Observed	Simulated $F = 0.0001$, $\gamma = 0.22$, $p = 0.991$
Reduced regression ϕ_1	0.1354	0.1207
Reduced regression ϕ_2	0.0723	0.0540
Reduced regression ϕ_3	-0.0324	-0.0669
Non-positive investments	60.15%	60.02%
Investment rate skewness	1.4984	1.4872

Table 5.4. Observed and simulated reduced regression parameters, non-positive investment rates and investment rate distribution skewness for "best" cost parameters.

Table 5.5 reports the estimated structural cost parameters and their standard errors for various cases. If I specify the cost function with only convex costs (*column 4*), the estimated convex cost is relatively high ($\hat{\gamma} = 0.7605$), but the distance of the simulated statistics from their observed counterparts is quite high (150.14).

Allowing for the existence of fixed costs (*column 3*), this distance decreases substantially (to 50.87), indicating that the match improved. The estimated convex cost parameter also declines (to $\hat{\gamma} = 0.479$), which may interpreted as increasing fixed costs compensate for decreasing convex costs.

If I further generalize the cost structure by allowing for irreversibility costs (*column 2*), then the distance decreases further (by approximately 16%). In this case increasing irreversibility costs compensate for decreasing fixed and convex costs, while improving the overall match.

	Fixed, convex and irreversibility costs	*Fixed and convex costs*	*Only convex costs*
F (fixed costs)	0.000100 (0.000018)	0.000119 (0.000007)	(0)
γ (convex costs)	0.220 (0.033322)	0.479 (0.039347)	0.7605 (0.001258)
p (irreversibility)	0.991 (0.002376)	(1)	(1)
DISTANCE	**42.61**	**50.87**	**150.14**

Table 5.5. Estimated structural cost parameters and standard errors.

As in *Chapter 4*, the estimated fixed cost parameter – though being significant – is numerically small, even if one compares it to similar estimates of *Cooper-Haltiwanger (2005)* $(F = 0.039)$ and *Bayrakhtar et al. (2005)* $(F = 0.031)$. This estimate means that the fixed cost is 1% of the purchase price of a 1% investment rate.[87]

The estimated convex cost parameter is in line with other results in the literature, with *Cooper-Haltiwanger (2005)* reporting an estimate of 0.049, while *Bayrakhtar et al. (2005)* estimate $\gamma = 0.532$. In *Chapter 4* I estimated $\gamma = 0.4462$ for US data.

The estimated irreversibility is significant, but indicates small degree of irreversibility, a similar phenomenon that was also observed by the other two comparable studies (*Cooper-Haltiwanger, 2005* had an estimate of 0.975, while the initial version of *Bayrakhtar et al., 2005* reported $p = 0.902$). This is in contrast of the relatively large irreversibility estimated for the US in *Chapter 4*. It is common in the literature that these types of estimates indicate much lower irreversibility than direct estimates (*Ramey-Shapiro, 2001* and Chapter 3 here).

[87] Again, as I normalize the model to the purchase price of capital, an investment rate of 1% costs 1*0.01=0.01.

In order to evaluate the relative significance of the different adjustment costs, I investigated the investment costs of certain investment episodes. For example, if a firm has a negative investment of -5%, then it has to pay a fixed cost of 0.0001, a convex cost of (0.22/2)*(-0.05)*(-0.05)=0.000275, and an irreversibility cost of 0.009*0.05=0.00045. So the total adjustment cost is 0.000825, or 1.65% of the total frictionless sales price (which is 1*0.05=0.05), out of which 12.1% is fixed cost, 33.3% is convex cost, and 54.6% is irreversibility cost.

On the other hand, if firms engage in an average investment project observed from data (when investment rate is 13.39%), then fixed costs are 0.0001, and the size of convex costs is (0.22/2)*0.1339*0.1339=0.001972, so of all adjustment costs, 95.2% is convex costs and 4.8% is fixed costs.[88]

5.4. Aggregate implications

In this section I analyze how shocks (from monetary policy, for example) affect aggregate investment. To do so, I assume that these monetary policy shocks (or other types of shocks) enter the model through the aggregate profitability shock. Monetary policy decisions translate to a profitability shock, because changing interest rates and/or exchange rates both affect the profitability of firms for obvious reasons. I also assume that monetary policy is an *aggregate* profitability shock because it has more or less similar effects on different firms.[89]

To fully understand the effect of monetary policy on aggregate investment, theoretically we should disentangle two effects: (1) to what extent monetary policy affects aggregate profitability;[90] and (2) how changes in aggregate profitability affect aggregate investment. Naturally, in the current modeling framework one can address the second question, and can not say much about the first one. Therefore in the

[88] For larger investments, convex costs obviously "take over". Also, for positive investments there are no direct irreversibility costs.
[89] One may argue that this is not necessarily true: firms with higher external financing needs may find that a certain increase in interest rates reduced their profitability more dramatically than others. Also, firms more exposed to foreign markets may feel exchange rate changes more influential than others. Still, I think that the assumption that monetary policy acts like an aggregate profitability shock is a good approximation.
[90] Optimally, the answer to this question should look like these statements: a 1 percentage point increase of the interest rate decreases aggregate profitability by ??? percents. Or: a 1-percent devaluation of the exchange rate changes aggregate profitability by ??? percents.

following I investigate the second question, and leave the first one to further research.[91]

I analyze the aggregate implications of the firm-level results along two dimensions. The first comparison is based on the differences between firm-level and aggregate behavior. This approach is similar to what I already presented in *Section 4.5*, which is in the sense of *Caballero (1992)*: what are the differences between micro- and macro-level behavior.[92] The second dimension of the comparison is based on the differences between the adjustment patterns for different cost structures: when there are only convex costs (so the adjustment is smooth), and when all kinds of adjustment costs are included into the analysis. So this approach tries to answer the question whether the existence of non-convex cost components has any important effects on aggregate variables. This analysis is similar to *Veracierto (2002)*, who compares the behavior of aggregate variables in two extreme cases: when there is complete irreversibility, and when there is no irreversibility.[93]

Comparison of firm-level and aggregate shock-investment relationship

To compare firm-level and aggregate investment dynamics, I estimated the reduced-form regressions (4.9) ($\tilde{i}_{it} = \phi_0 + \phi_1 \tilde{a}_{it} + \phi_2 \tilde{a}_{it}^2 + \phi_3 \tilde{a}_{i,t-1} + \mu_t + u_{it}$) for both firm-level and aggregate data, simulated for various cost structures.[94] The estimated parameters for the different scenarios are in *Table 5.6*.

[91] *Jakab-Vonnák-Várpalotai (2006)* investigate the effect of a monetary policy shock to aggregate investment in three alternative models for the Hungarian economy, and find that a 1% monetary policy shock (as they define) induces a cumulative change of approximately 0.2% in aggregate investment.

[92] The main result of that paper is that even if there is asymmetric adjustment at the micro-level, under general conditions (if shocks that hit the firms are not perfectly harmonized) this asymmetry vanishes at the macro-level because of aggregation.

[93] The main finding of this paper is that irreversibility is unimportant for the behavior of aggregate variables: the evolution of aggregate variables is the same, irrespectively from the degree of irreversibility. This result may seem a bit surprising, but it is a direct consequence of the relatively low variance of the production shock that hits the plants. For larger shocks, the irreversibility constraint would become effective at least in some cases, and also the aggregate behavior of the key variables would be different when there is irreversibility.

[94] Of course, while on the firm-level the reduced regression is estimated on a panel, on the aggregate level this can only be done on a time series (and for much smaller number of observations).

		Only convex costs (F=0, γ=0.7605, p=1)	*Convex and fixed costs* (F=0.000119, γ=0.479, p=1)	*All types of costs* (F=0.0001, γ=0.22, p=0.991)
Aggregate level	ϕ_1	0.0655 (0.0030)	0.0877 (0.0042)	0.1281 (0.0067)
	ϕ_2	0.5069 (0.3817)	0.8029 (0.5353)	1.3125 (0.8572)
	ϕ_3	-0.0195 (0.0030)	-0.0307 (0.0042)	-0.0554 (0.0067)
	N	28	28	28
Firm-level	ϕ_1	0.0613 (0.00010)	0.0822 (0.00013)	0.1207 (0.00017)
	ϕ_2	0.0224 (0.00023)	0.0357 (0.00030)	0.0540 (0.00045)
	ϕ_3	-0.0265 (0.00010)	-0.0389 (0.00013)	-0.0669 (0.00013)
	N	28*7000	28*7000	28*7000

Table 5.6. Aggregate and firm-level reduced regression parameters under different cost structures (estimated from simulated data sets). Standard errors are in parenthesis.

The results show that the parameters of the linear terms (ϕ_1 and ϕ_3) have similar patterns: they increase (in absolute terms) as we allow for fixed and irreversibility costs. Also, the parameter estimates are numerically close to each other in these cases. The major difference arises in case of the non-linear term (ϕ_2): despite being significant at the firm-level, it becomes insignificant at the aggregate level. This result is robust across different cost specifications.

Comparison of convex and non-convex investment cost structures

To analyze the aggregate implications of the non-convex costs of investment, I compare the behavior of aggregate variables after certain aggregate shocks for different cost structures.

The first case under my focus will be the one where fixed and irreversibility costs are excluded from the analysis, and all the adjustment costs are assumed to be convex costs. According to *Table 5.5*, the estimated convex cost parameter is $\gamma = 0.7605$ in this case (with $F = 0$ and $p = 1$ fixed).

The second scenario will be the one when there are convex and fixed costs, but no irreversibility cost. Under these assumptions I estimated the cost components as $\gamma = 0.479$ and $F = 0.000119$ in *Table 5.5*.[95] Intuitively, the effect of convex costs is partially taken on by the fixed cost component.

The third case investigated is the one when all cost components are allowed. Earlier I estimated the different cost parameters as $\gamma = 0.220$, $F = 0.0001$ and $p = 0.991$. Now the increasing irreversibility costs compensate for decreasing fixed and convex cost components.

To analyze the aggregate effects, I make three experiments for all of these three cost structures. In the first experiment, I simulate initial (aggregate + idiosyncratic) profitability shocks and corresponding capital paths for $N = 7000$ hypothetical firms, assuming that (log) aggregate shocks are 0 during periods 0-100, and equal to the standard deviation of the aggregate shock (0.1092, as measured empirically) from the 101st time period.[96] Idiosyncratic shocks are drawn from the same distribution that I observed empirically. So the assumption is that firms are hit by a permanent profitability shock at the 101st time period. For simplicity, in the following I index this 101st time period as $t = 1$.

Figure 5.7 illustrates the effect of this permanent profitability shock on the aggregate gross (replacement + new) investment rate.[97] The first thing to observe is that a permanent profitability shock of 10.92% immediately increases the aggregate gross investment rate by only 1.3-2.1%, a relatively moderate rate, and it has a cumulative effect of 4-5% during the next 5-6 periods (years).

It is also interesting to observe that in the presence of non-convex (fixed and irreversibility) costs, the aggregate response is higher. This is because if we have only convex costs, the estimated convex cost parameter is necessarily higher, which "punishes" relatively large investment episodes. On the other hand, in case of all

[95] And also noted that the fit of the model has increased dramatically: the "loss" decreased from 150.14 to 50.87.
[96] Allowing for 100 initial periods ensures that the results are not affected by the initial conditions.
[97] To ease interpretation, the deviation of steady state is depicted on the vertical axis. The steady state gross investment rate is equal to the average depreciation rate, and is therefore non-0.

types of costs convex costs are relatively lower and non-convex costs are relatively higher, so large investment episodes are relatively cheaper. So it is intuitive that in case of both convex and non-convex costs, the immediate response to the positive profitability shock is somewhat larger, and the impulse response function becomes zero relatively earlier.

So there is an apparent difference between the firm-level and aggregate effects of non-convex adjustment costs: while *fixed and irreversibility costs make investment lumpy at the firm level, aggregate investment is more flexible if we also have fixed and irreversibility cost components*.

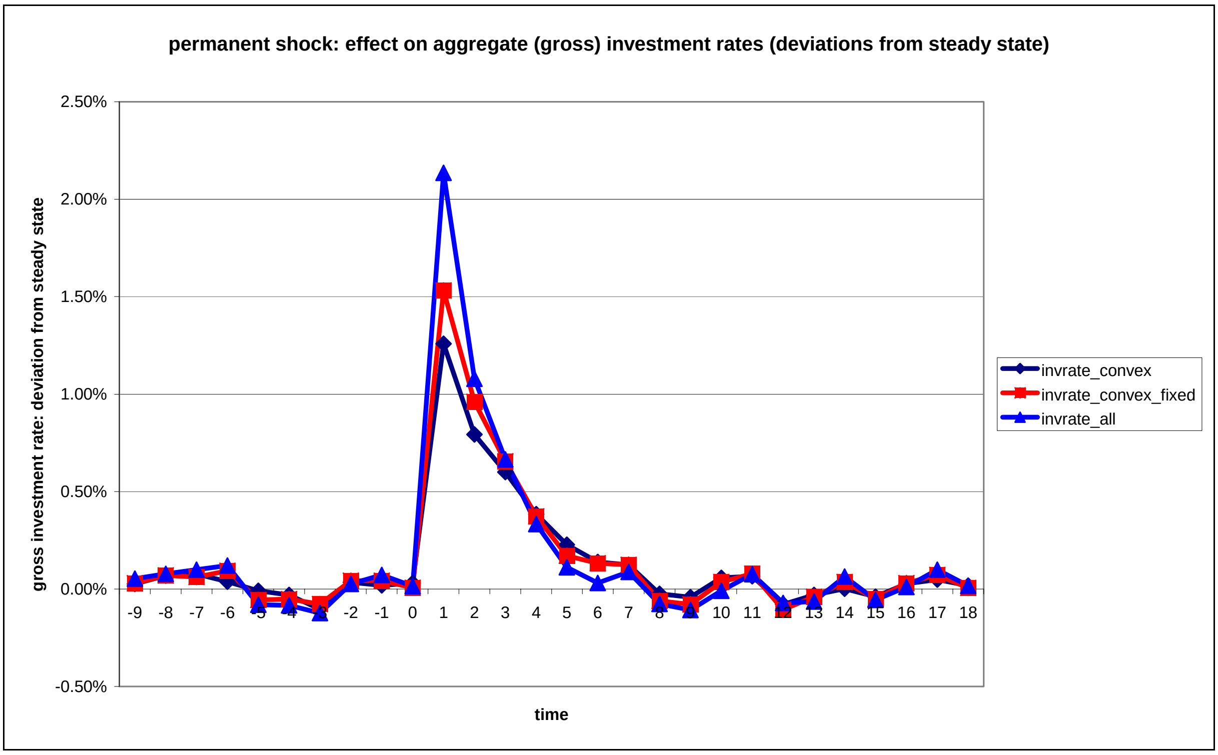

Figure 5.7. The effect of a permanent profitability shock on aggregate gross investment rate.

Figure 5.8 depicts the effect of the same permanent profitability shock to the aggregate new investment rate. It is apparent from the figure that there are differences between the various cases in the steady state aggregate new investment rates. Specifically, the steady-state new investment rate[98] is relatively larger when there are both convex and non-convex investment cost components. This is again

[98] The steady-state gross investment rate (which is the average depreciation rate) is held constant in the three cases.

because relatively lower convex costs and relatively larger non-convex costs make larger new investment episodes relatively cheaper.

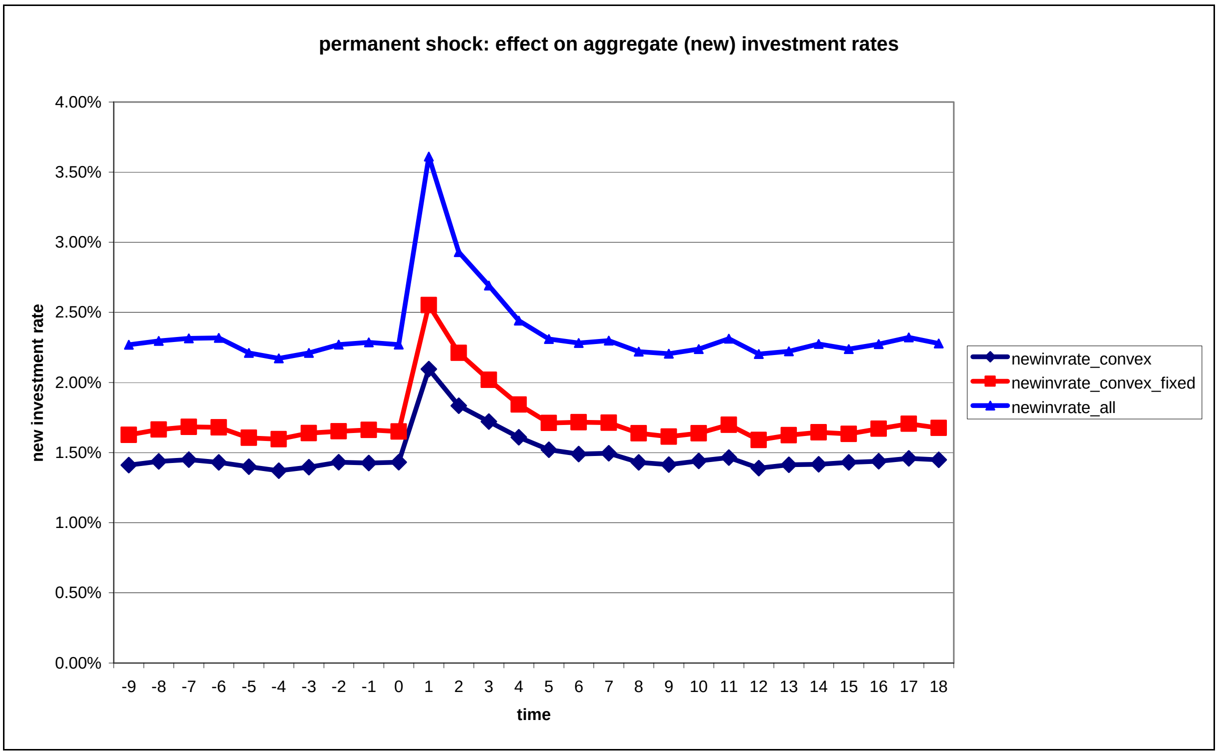

Figure 5.8. The effect of a permanent profitability shock on aggregate new investment rate.

In the second experiment I investigate the effect of a transitory profitability shock at $t = 1$ (again, to avoid initial value problems I simulate 100 initial periods). Now I assume that the (log) profitability shock is 0 during the initial 100 periods; it is 0.1092 (as measured from data) at $t = 1$, and is again 0 thereafter. *Figures 5.9-5.10* depict the effect of this one-standard-deviation transitory shock to the aggregate gross and new investment rates.[99] For the gross investment rates, the same story emerges as in case of permanent shocks: as convex costs punish large investments relatively more, the aggregate response is larger for relatively smaller convex cost components (that is, if we allow for all cost components). As for new investment rates, the steady state new investment rate is again the largest when convex costs are relatively lower; one can observe the largest response in this case.

[99] In case of gross (replacement + new) investment rate, I again depict deviations from steady-state.

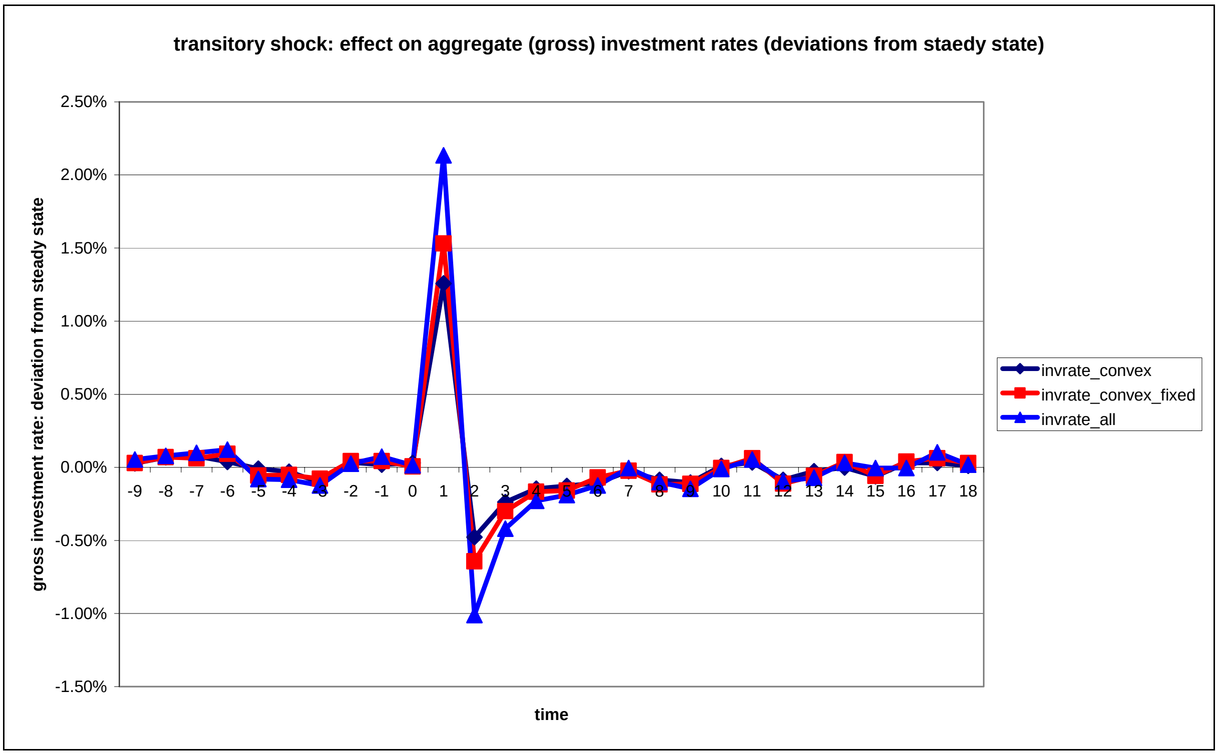

Figure 5.9. The effect of a transitory profitability shock on aggregate gross investment rate.

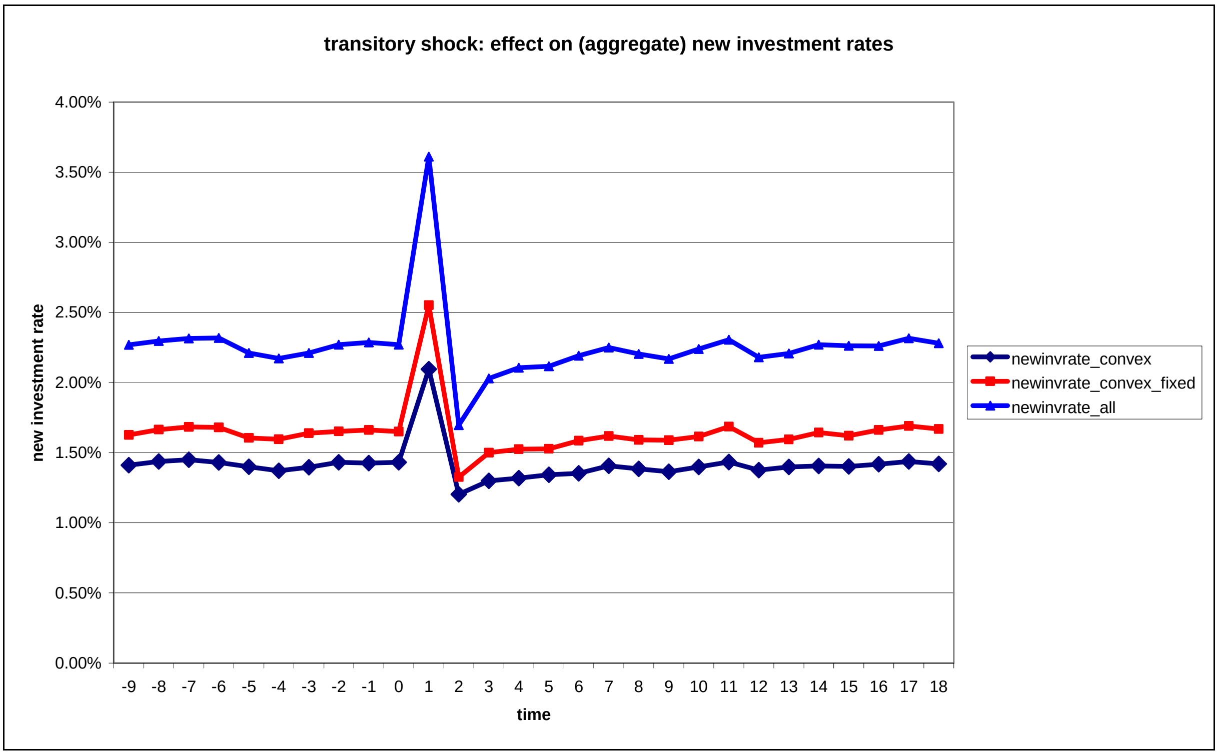

Figure 5.10. The effect of a transitory profitability shock on aggregate new investment rate.

While these experiments are important to improve our understanding of the effects of the different investment costs on the behavior of various aggregate investment rates, they are not too realistic in the sense that they assume that one can have a perfect control of the aggregate shock hitting the firms. In reality no institution can alone influence the aggregate profitability shock, so one should not assume this. To evaluate the impact of a certain policy (for example, if the central bank improves "aggregate profitability" by making the loans cheaper) it is more appropriate to assume that the profitability shock remains stochastic (in the sense it was stochastic in the previous sections), and the policy-induced permanent shock is in addition to this underlying stochastic profitability shock.

Therefore, as a third experiment, I simulated aggregate investment rates after a permanent profitability shock under these circumstances. The underlying stochastic aggregate profitability shock was as measured empirically,[100] and there is an additional positive aggregate profitability shock of 0.1092 from period 101 ($t = 1$). *Figure 5.11* depicts the behavior of the aggregate gross investment rate (deviation from steady state) after such a permanent shock. Obviously, the variance of the aggregate gross investment rate over time is much larger in this case than previously, as now it also depends on the evolution of the underlying aggregate shock that cannot be controlled. Otherwise, this figure is quite similar to the previous figures about aggregate gross investment rates: the largest responses occur when convex costs are relatively small (and other types of costs are relatively larger).

Figure 5.12 illustrates the effect of a similar permanent aggregate profitability shock to the new investment rates. It is apparent from the figure that while the absolute responses are still higher when convex costs are relatively small and fixed and irreversibility costs are relatively high, because of irreversibility, the aggregate new investment rate is less flexible downward than upward.[101]

[100] Its standard deviation and autocorrelation is 0.1092 and 0.6882, respectively.
[101] After clearly worsening aggregate profitability conditions, aggregate new investment rate is reluctant to go into the negative regions.

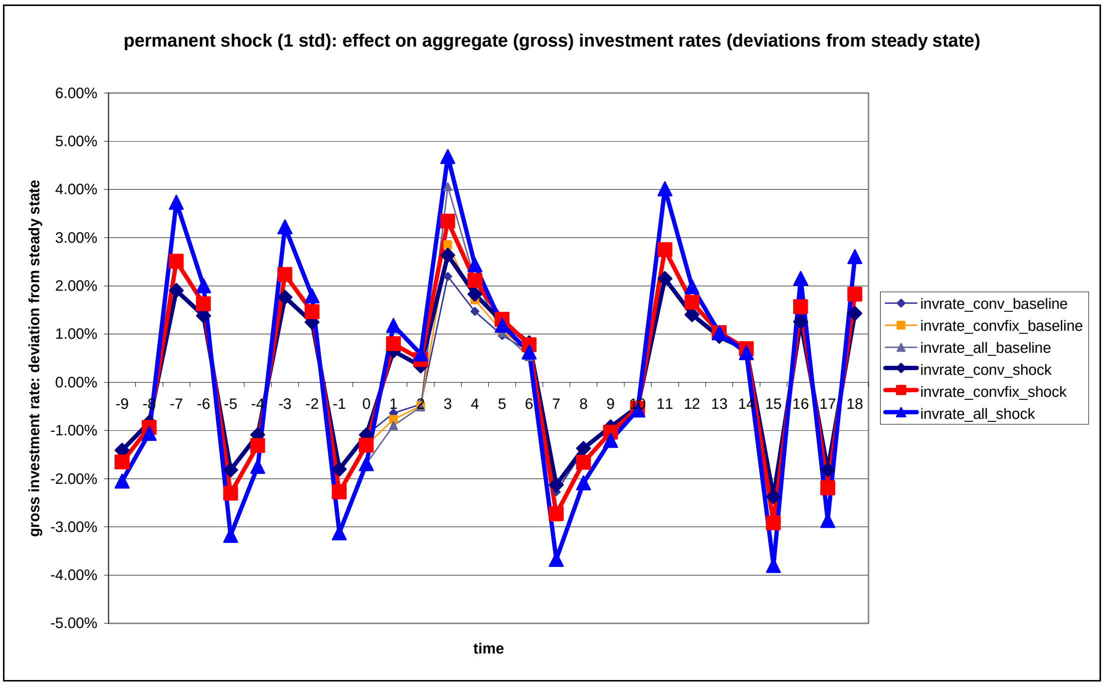

Figure 5.11. The effect of a permanent profitability shock (in addition to the regular profitability shock) on aggregate gross investment rate (deviation from steady state). For comparison purposes, I depict also what would have happened if there was no extra profitability shock (BASELINE).

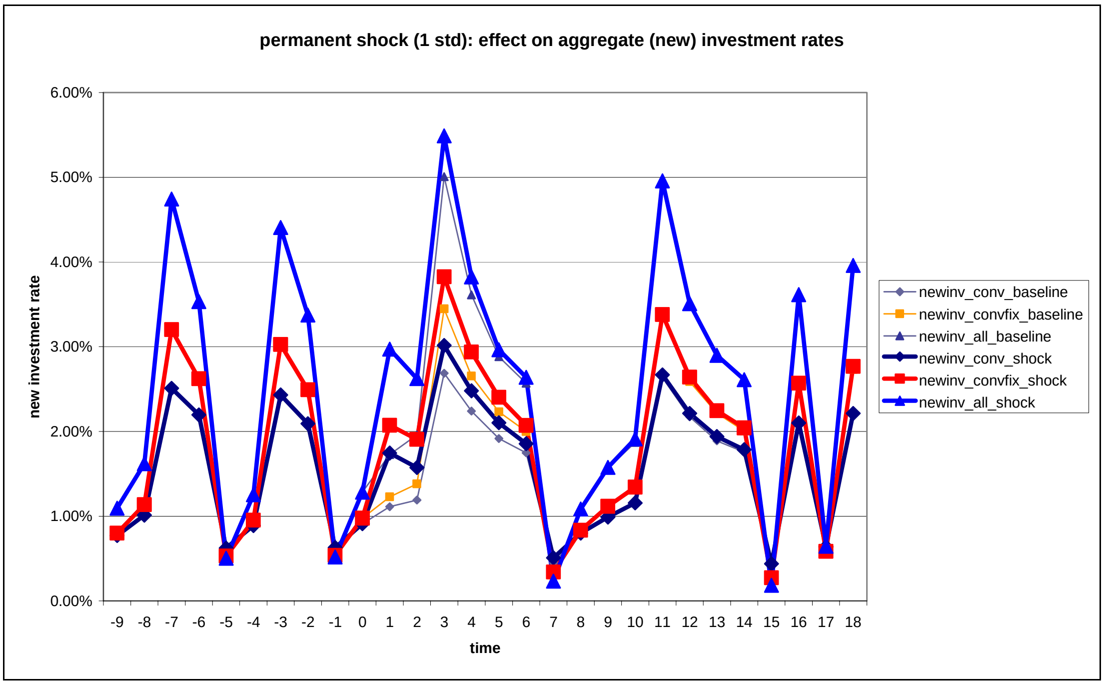

Figure 5.12. The effect of a permanent profitability shock (in addition to the regular profitability shock) on aggregate new investment rate. For comparison purposes, I depict also what would have happened if there was no extra profitability shock (BASELINE).

As a final experiment, I simulated the effect of the same set of permanent shocks when the permanent profitability shock is credible and foreseen. This means that once a shock (of 1 standard deviation) occurs in period 1, firms know that this shock will be permanent and form their expectations about future profitability condition accordingly.[102]

Figures 5.13-5.14 illustrate the case of a credible permanent profitability shock, when perfectly controlled by the authorities (so no aggregate shock that is independent from the authorities occurs); one should then relate these figures to *Figures 5.7-5.8*. It is apparent from *Figure 5.13* that if the positive permanent profitability shock is foreseen, and it enters into firms' expectations, then its effect is much bigger. I reported earlier that if the permanent shock is a surprise shock in each period, then the immediate effect of a 1 standard deviation positive permanent shock is 1.3-2.1%, and the cumulative effect is 4-5% during the following 5-6 periods. Now if the permanent profitability shock is anticipated, then its immediate effect is as high as 7.2-11.5%, while the cumulative effect is 24.1-24.3% during the next 10 periods. So if authorities can make the intended positive profitability shock foreseen and credible, then its effect can be much bigger.

Also, it is apparent (perhaps even more than before) from the figures that aggregate investment is the most responsive to profitability shocks if we have all types of investment costs, which is the same result that I reported earlier for unanticipated permanent profitability shocks.

[102] So far I had an implicit assumption that in case of a permanent shock, it was a "surprise shock" in each time period, in the sense that firms did not alter their expectations according to this permanent shock.

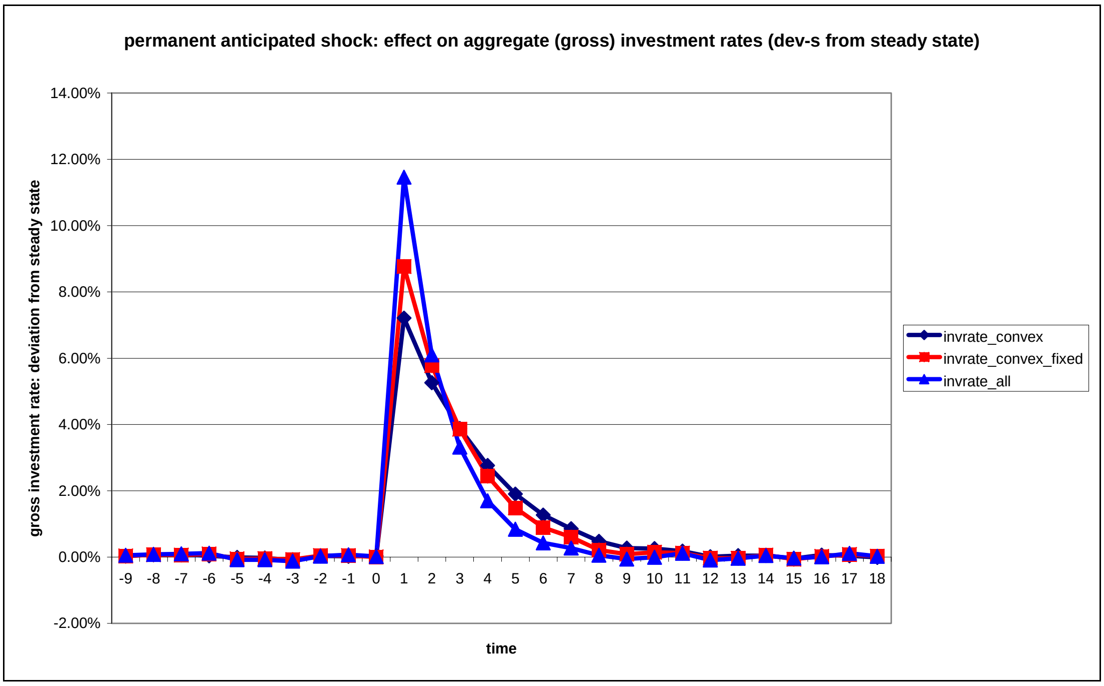

Figure 5.13. The effect of a permanent anticipated profitability shock on aggregate gross investment rate.

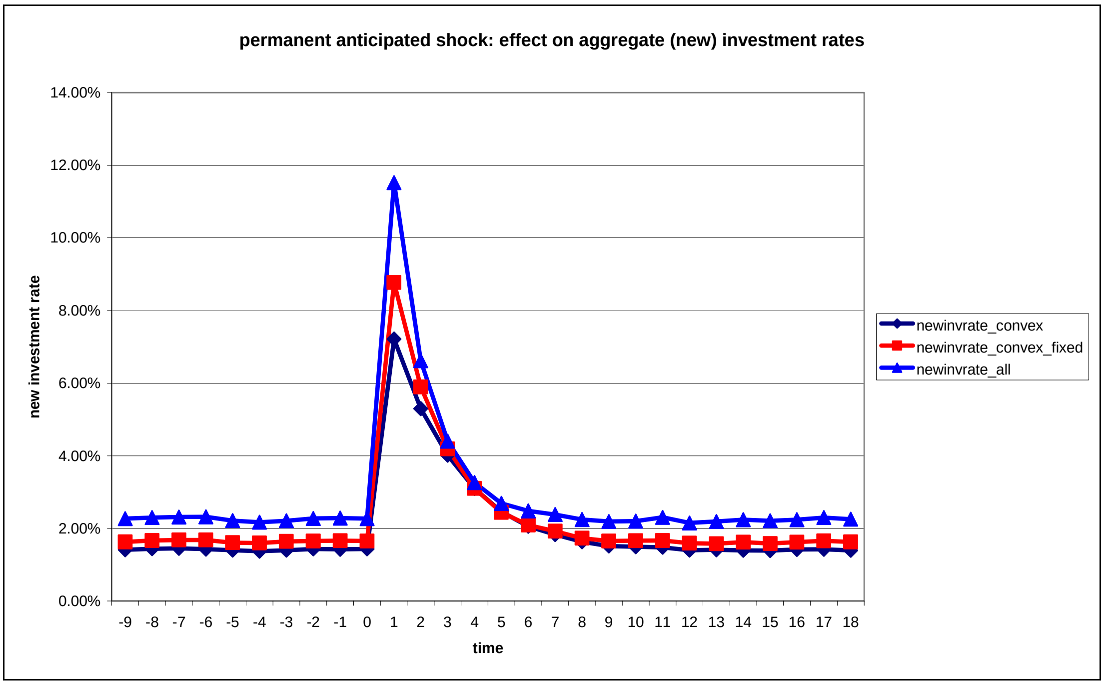

Figure 5.14. The effect of a permanent anticipated profitability shock on aggregate new investment rate.

In the most realistic case, when there is a permanent anticipated aggregate profitability shock *plus* an underlying profitability shock that cannot be controlled by the authorities, I found the same patterns: relative to what was reported on *Figures 5.11-5.12*, the effect of the extra profitability shock is higher. This is again a direct consequence that the firms now anticipate positive future profitability shocks and form their expectations accordingly. On the other hand, it still remains true that aggregate (gross and new) investment rates are the most responsive to shocks if there are both convex and non-convex cost components (relative to the case if there is only convex adjustment cost).

So the earlier finding is robust across different specifications of artificial shocks: the response of aggregate investment under both convex and non-convex investment costs to certain profitability shocks is more flexible than if there are only convex adjustment costs.

To further study the *dynamics* of investment adjustment under different cost structures, it may be useful to track the distribution of firm-level adjustments after a profitability shock. The observed inaction rate can be particularly interesting after such a hypothetical profitability shock. *Figure 5.15* illustrates the inaction rate (the proportion of firms that stay inactive) after a permanent profitability shock.[103] As I already demonstrated on *Figure 5.7*, adjustment is quicker (that is, aggregate investment rate is higher in the first 3-5 periods after the shock) when all types of adjustment costs arte present, as opposed to having only convex costs. It is also apparent on *Figure 5.15* that this quicker adjustment takes place mainly on the intensive margin: higher aggregate investment rates occur at similar inaction rates, from which one can infer: (1) if all types of adjustment costs are present, those firms that adjust must make relatively larger adjustments than in case of only convex costs,[104] and (2) those firms that remain inactive when there are only convex costs, also tend to remain inactive if we have all types of adjustment costs. Experimenting with the other types of aggregate profitability shocks investigated earlier (transitory

[103] In this case I assume that there are no other sources of aggregate uncertainty: aggregate profitability increases by exactly one standard deviation from $t=1$. So in terms of shock structure, *Figure 5.13* corresponds to *Figure 5.7*.

[104] In fact, it is apparent from *Figure 5.13* that when we have all types of adjustment costs, the larger aggregate adjustment (illustrated on *Figure 5.7*) takes place at a slightly higher inaction rate.

and extra profitability shocks, both surprise and anticipated case) leads to the same conclusion: adjustment takes place at the similar inaction rates under the different cost specifications, so adjustment takes place on the intensive margin also in these cases.[105] These are all further pieces of evidence that non-convex adjustment costs have important effects on aggregate dynamics.

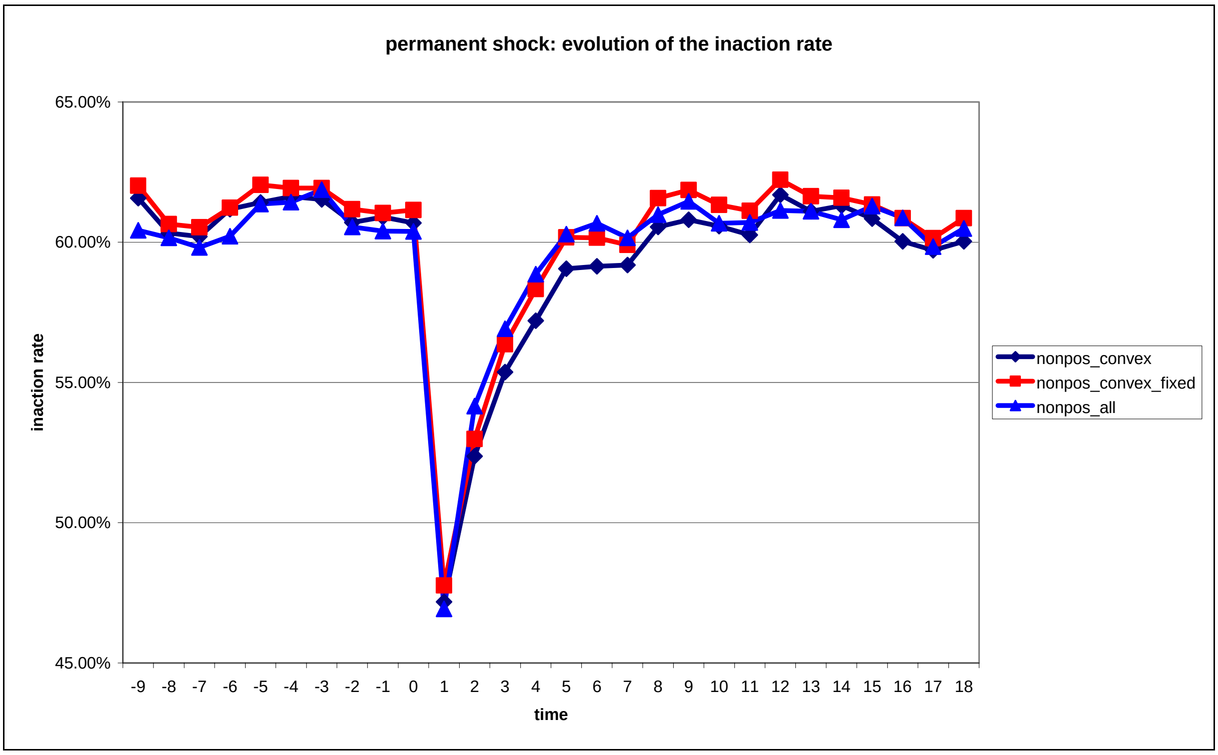

Figure 5.15. The effect of a permanent profitability shock on aggregate the proportion of inactive firms.

When tracking the inaction rates under different cost structures, one may ask how inaction occurs at all when there are only convex costs of adjustment. Indeed, standard investment models with convex adjustment cost suggest that in this case there is no inaction at all. However, if one makes distinction between replacement investment and new investment, then *inaction in new investment* can emerge easily, especially if the convex cost component is high. The reason of this is that convex costs make the shock-investment relationship flat, and therefore for a large interval

[105] An interesting result is that when aggregate profitability shocks are anticipated, then the inaction rate decreases to less than 5% (under all types of cost structures). So in this case basically all firms adjust in the light of much their favorable future profitability conditions.

of shocks the optimal *gross* investment rate will be between 0 and the depreciation rate, meaning that the *new* investment rate is zero in these cases. This phenomenon is also observable on *Figure A/4*. in *Appendix A*, where the optimal shock-investment relationship is depicted for the case of “only convex costs”. With a relatively modest convex cost parameter (in that figure $\gamma = 0.2$), the inaction rate of new investments is already visible. The case that is discussed here has much higher convex cost parameter: $\gamma = 0.7605$, therefore the shock-investment relationship is much flatter, so it is not a surprise that the inaction in *new* investment rates is as high as 60% in steady state.

All of these simulations suggest that there are important aggregate implications of the non-convex investment costs. This statement contradicts the main conclusion of *Veracierto (2002)*, who found that there is no aggregate implication of investment irreversibility at the plant level. But this difference can be fully explained with the difference between the magnitudes of identified profitability shocks. In this paper, the standard deviations of the aggregate and idiosyncratic profitability shocks are 0.1092 and 0.3155, much larger than the standard deviation of the productivity shock in *Veracierto (2002)*: 0.0063.[106] As a consequence of this, the irreversibility constraint is effective for many observations in the simulations, while it is never binding for Veracierto; as he notes, this is the ultimate reason of the opposite conclusions. Studies with comparable shock standard deviations (*Coleman, 1997, Faig, 1997*, and *Ramey-Shapiro, 1997*) all find important aggregate effects of irreversible investment.

[106] There are important differences between the identification of these standard deviations. First and most importantly, Veracierto (2002) deals with *productivity* shocks, and identifies them from observed Solow-residuals. On the other hand, our key concept is the *profitability* shock, which incorporates Veracierto’s productivity shock, and many other sources of shocks: labor shares, demand elasticities, wages.

6. SUMMARY

The focus of this dissertation is on various costs components associated with investment activity at the firm level, with a special emphasis on the non-convex investment costs. In *Chapters 3-5* I presented empirical investigations about these components, and now I summarize the main innovations and findings of these.

In *Chapter 3* I use a complete asset auction data collected at a discontinuing manufacturing firm, to measure the extent of irreversibility at the firm level. Though the estimation strategy that I follow is due to *Ramey and Shapiro (2001)*, the results indicate some novel elements that have not been discussed previously. In particular, I find that an alternative specification (a different from the one used by Ramey-Shapiro) of the discount structure is more appropriate: the log-log specification of the sales price–replacement value equation indicates that the size of discount (in percentage terms) to be paid at capital sales is increasing with the size of the capital item being sold.[107] Further, incorporating this result into theoretical models of investment with more general adjustment cost functions, this finding indicates that the investment adjustment cost function is asymmetric. This, however, does not have qualitative implications on the investment behavior; the model with an asymmetric adjustment cost function is only quantitatively different from the one with a symmetric cost function.[108]

Otherwise, the results of the analysis of firm-level irreversibilities in *Chapter 3* are similar to the results of comparable studies in the literature, in the sense that I find that various capital items can only be sold at significant discounts, and that this discount is influenced by the specificity of the assets. The more specific items sell at higher discounts on average.

In contrast to *Chapter 3*, where I focus exclusively on the irreversibility costs of investment, the goal of *Chapter 4* is to simultaneously estimate the most important cost components of investment by the structural estimation of the key cost parameters of a dynamic investment model. The approach of *Chapter 4* is novel in

[107] Ramey and Shapiro noticed this, but they left it unexplained. One can interpret this result by noting that size itself can be a means of specificity: a larger capital item is inherently more specific than a smaller one.

[108] As we explained in *Chapter 3*, size-dependent discount rates lead to “more convex” adjustment cost function at the negative side, which in turn does not have dramatic effects on firm-level investment behavior, but changes the firms’ responses quantitatively (by widening the inaction band, for example).

two respects. First, I modify the standard firm-level investment model with adjustment costs (see *Abel and Eberly, 1994* and *Bertola and Caballero, 1994*) by making explicit distinction between "cheap" replacement investment and "costly" new investment. As I argue, this is necessary as one can only observe the sum of these two types of investments empirically, and it may not be appropriate to treat all empirically observed investment as costly new investment. (If one did so, then it would be impossible to reject the models of fixed costs and hence also lumpy investment at the firm level right away, by observing that the mode of the empirical investment rate distributions is generally around at an investment rate of 6-10%.)

The second innovation in *Chapter 4* is that I estimate the structural parameters of this "modified" model of firm-level investment by an altered version of the usual indirect inference technique. As I argue in *section 4.2*, this modification is necessary as the traditional estimation strategy (based on the traditional reduced regression presented there) does not lead to a full identification of all structural model parameters.[109]

So in the estimation part of *Chapter 4*, I use an unbalanced panel of US manufacturing plants between 1959-87. According to my modified estimation strategy, I estimate a reduced form shock-investment regression that captures the effects (nonlinearity, lumpiness) of the fixed, convex and irreversibility cost components, and I also match the proportion of non-positive investment rate and skewness of investment distribution in real and simulated data.

My results in *Chapter 4* indicate that fixed costs may be an economically significant factor for the firms' investment activity, although their magnitude is relatively small if compared to the firms' capital stock. On the other hand, I find evidence of non-perfect reversibility: I estimate that firms in our panel data set (that are not necessarily closing firms, as in *Ramey and Shapiro (2001)* and also in *Chapter 3* of this dissertation) can sell their used capital at significantly lower prices than the purchase price. The estimated irreversibility parameter is somewhat smaller than in comparable studies (*Bayraktar, Sakellaris and Vermeulen (2005)*, and *Cooper and Haltiwanger (2005)*), indicating that the extent of irreversibility may be higher than thought earlier. Overall, my parameter estimates support the generally

[109] In particular, I argue that the traditional method does not identify the fixed cost parameter of the investment cost function.

accepted view about firm-level investment activity: there are investment peaks followed by periods of inactivity.

In *Chapter 4* I also presented some evidence that firm-level investment behavior is different from what one observes on the aggregate level: if one estimates similar shock-investment regressions at the firm- and on the aggregate level at the same time, the main difference is that the firm-level non-linearity is averaged out at the macro level. Simple descriptive statistics (persistence, volatility, correlation with shocks) also indicate important differences in the two cases.

The main goal of *Chapter 5* is to elaborate on the aggregate effects and importance of different firm-level investment costs, and investigate the policy implications of the earlier results. In particular, I address the question of how certain shocks (stemming from monetary policy, for example) translate into changes in aggregate investment. To do this, I use another panel on Hungarian manufacturing firms between 1992-2002 to estimate the structural parameters of the earlier model, and then simulate hypothetical investment paths following certain types of shocks. In particular, I argue that as in my modeling framework changes in monetary policy (for example) influence the aggregate profitability of the firms, it is necessary to investigate how changes in aggregate profitability influence aggregate investment. I find that in Hungary, aggregate investment responses are moderate to unanticipated aggregate profitability shocks. But if the aggregate profitability shock is anticipated and fully credible, then the aggregate investment response can be significant. Further, these aggregate responses are different under different cost structures: the transition to the new steady state is quicker if there are both convex and non-convex adjustment costs. This is exactly the opposite of what happens at the firm level, where non-convex adjustment costs make investment more lumpy. The main reason of this is that if we do have non-convex adjustment costs, then (according to the controlled experiments) the proportion of inactive firms is roughly the same as in case of convex adjustment costs, but the average size of investment of those active firms is higher (exactly because the non-convex adjustment costs “punish” relatively large investments less).

REFERENCES

Abel, Andrew B. (1983): "Optimal Investment under Uncertainty". *In: The American Economic Review, Vol. 73, Issue 1, pp. 228-233.*

Abel, Andrew B. and Janice Eberly (1994): "A Unified Model of Investment Under Uncertainty". *In: The American Economic Review, Vol. 84, Issue 5, December 1994, pp. 1369-1384.*

Abel, Andrew B. and Janice Eberly (1999): "Investment and q with Fixed Costs: An Empirical Analysis". *Manuscript.*

Akerlof, George A. (1979): "Irving Fisher on His Head: The Consequences of Constant Threshold-Target Monitoring of Money Holdings". *In: The Quarterly Journal of Economics, Vol. 93, Issue 2, May 1979, pp. 169-187.*

Altonji, Joseph G. and Deveroux, Paul J. (1999): "The Extent and Consequences of Downward Nominal Wage Rigidity". *In: National Bureau of Economic Research Working Paper No. 7236, http://www.nber.org/papers/w7236*.

Álvarez, Luis J., Emmanuel Dhyne, Marco M. Hoeberichts, Claudia Kwapil, Hervé Le Bihan, Patrick Lünnemann, Fernando Martins, Roberto Sabbatini, Harald Stahl, Philip Vermeulen, Jouko Vilmunen: "Sticky Prices in the Euro Area. A Summary of New Micro Evidence." *In: European Central Bank Working Paper No. 563, Dec 2005*.

Arrow, Kenneth J., Theodore Harris, Jacob Marschak (1951): "Optimal Inventory Policy". *In: Econometrica, Vol. 19, Issue 3, July 1951, pp. 250-272.*

Attanasio, Orazio P. (2000): "Consumer Durables and Inertial Behavior: Estimation and Aggregation of *S-s* Rules for Automobile Purchases". *In: Review of Economic Studies, Vol. 67, 2000, pp. 667-696.*

Ball, Laurence and Gregory Mankiw (1994): "Asymmetric Price Adjustment and Economic Fluctuations". *In: The Economic Journal, March 1994, pp. 247-261.*

Baumol, W. J. (1952): “The Transactions Demand for Cash: An Inventory Theoretic Approach”. *In: The Quarterly Journal of Economics, Vol. 66, November 1952, pp. 545-556.*

Bayraktar, Nihal, Plutarchos Sakellaris and Philip Vermeulen (2005): “Real versus Financial Frictions to Capital Investment”. *ECB Working Paper*, No. 566, December 2005.

Bertola, Giuseppe and Ricardo J. Caballero (1990): “Kinked Adjustment Costs and Aggregate Dynamics”. *NBER Macro Annual, 1990.*

Bertola, Giuseppe and Ricardo J. Caballero (1994): “Irreversibility and Aggregate Investment”. *In: Review of Economic Studies* 61:2, (April 1994, No. 207), pp. 223-246.

Bils, Mark and Peter J. Klenow (2004): “Some Evidence on the Importance of Sticky Prices”. *In: Journal of Political Economy, Vol. 112, no. 5, 2004, pp. 947-985.*

Blinder, Alan S. (1981): “Retail Inventory Behavior and Business Fluctuations”. *In: Brookings Papers on Economic Activity, Vol. 1981, Issue 2, pp. 443-505.*

Caballero, Ricardo J. (1992): “A Fallacy of Composition”. *In: The American Economic Review, Vol. 82, No. 5, December 1992, pp. 1279-1292.*

Caballero, Ricardo J. (1999): “Aggregate Investment”. *In: The Handbook of Macroeconomics, Vol. 1B, Chapter 12, pp. 813-862. Eds: Taylor, John B. and Michael Woodford. Elsevier 1999.*

Caballero, Ricardo J. and Eduardo M. R. A. Engel (1999): “Explaining Investment Dynamics in US Manufacturing: A Generalized (S,s) Approach”. *In: Econometrica, Vol. 67, Issue 4, July 1999, pp. 783-826.*

Caballero, Ricardo J., Eduardo M. R. A. Engel, John Haltiwanger (1997): “Aggregate Employment Dynamics: Building from Microeconomic Evidence”. *In: The American Economic Review, Vol. 87, No. 1, March 1997, pp. 115-137.*

Campbell, Jeffrey R. and Jonas D. M. Fisher (2000): “Aggregate Employment Fluctuations with Microeconomic Asymmetries”. *In: The American Economic Review, Vol. 90, No. 5, December 2000, pp. 1323-1345.*

Caplin, Andrew S. (1985): “The Variability of Aggregate Demand with (S, s) Inventory Policies”. *In: Econometrica, Vol. 53, Issue 6, November 1985, pp. 1395-1410.*

Coleman, Wilbur J. II. (1997): “Behavior of Interest Rates in a General Equilibrium Multisector Model with Irreversible Investment”. *Macroeconomic Dynamics*, March 1997, I(1), pp. 206-227.

Cooper, Russell W. and John C. Haltiwanger (2002): “On the Nature of Capital Adjustment Costs”. *Manuscript, February 2002.*

Cooper, Russell W. and John C. Haltiwanger (2005): “On the Nature of Capital Adjustment Costs - revised”. *Manuscript, January 2005.*

Cooper, Russell W., John C. Haltiwanger and Jonathan Willis (2005): “GMM for Discrete Choice Models: A Capital Accumulation Application”. *Paper presented at the Society for Economic Dynamics Annual Meeting in Budapest, June 2005.*

Darvas, Zsolt and András Simon (2000): “Capital Stock and Economic Development in Hungary”. *The Economics of Transition*, Vol. 8, No. 1.

Doms, Mark and Timothy Dunne (1998): “Capital Adjustment Patterns in Manufacturing Plants”. *In: Review of Economic Dynamics, Vol. 1, Issue 2, April 1998, pp. 409-429.*

Eberly, Janice S. (1994): “Adjustment of Consumers’ Durables Stocks: Evidence from Automobile Purchases”. *In: Journal of Political Economy, Vol. 102, No. 3, 1994, pp. 403-436.*

Ehrhardt, R. A. (1979): “The Power Approximation for Computing (S, s) Inventory Policies”. *In: Management Science, Vol. 25, 1979, pp. 777-786.*

Faig, Miguel (1997): “Investment Irreversibility in General Equilibrium: Capital Accumulation, Interest Rates, and the Risk Premium”. Mimeo, University of Toronto, 1997.

Foote, Christopher L. (1998): “Trend Employment Growth and the Bunching of Job Creation and Destruction”. *Website: http://post.economics.harvard.edu/faculty/foote/ papers/Final2.pdf.*

Gourieroux, C. and A. Monfort (1996): “Simulation Based Econometric Methods”. *Oxford University Press.*

Hall, Brownyn H. (1990): “The Manufacturing Sector Master File: 1959-1987”. *National Bureau of Economic Research Working Paper No. 3366, May 1990.*

Ireland, Peter N. (1997): “Stopping Inflations, Big and Small”. *In: Journal of Money, Credit and Banking, Vol. 29, No. 4, November 1997, pp. 759-775.*

Jakab, Zoltán M., Viktor Várpalotai and Balázs Vonnák (2006): “How does Monetary Policy Affect Aggregate Demand? A Multimodel Approach for Hungary”. *MNB Working Paper (forthcoming)*.

Jorgenson, Dale W. (1963): “Capital Theory and Investment Behavior”. *In: The American Economic Review, Vol. 53, Issue 2, May 1963, pp. 247-259.*

Jorgenson, Dale W. (1996): “Empirical Studies of Depreciation”. *In: Economic Inquiry, Vol. 34, January 1996, pp. 24-42.* Judd, Kenneth L. (1998): “Numerical Methods in Economics”. *Cambridge, Mass.: MIT Press, 1998.*

Judd, Kenneth L. (1998): “Numerical Methods in Economics”. *Cambridge, Mass.: MIT Press, 1998.*

Kátay, Gábor and Zoltán Wolf (2004): “Investment Behavior, User Cost and Monetary Policy Transmission – the Case of Hungary”. *MNB Working Paper 2004/12*.

Klenow, Peter J. and Jonathan L. Willis (2006): “Real Rigidities and Nominal Price Changes”. *Manuscript, March 2006.*

Koyck, L. M. (1954): “Distributed Lags and Investment Analysis”. *North-Holland, Amsterdam.*

Levy, Daniel, Mark Bergen, Shantanu Dutta, Robert Venable (1998): “The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains”. *In: Quarterly Journal of Economics, 1997, pp. 791-825.*

Molnár, László and László Skultéty (1999): “A beruházások alakulása 1992-1998 között” (Investments in Hungary between 1992-1998, available only in Hungarian). *Közgazdasági Szemle*, XLVI. évf., 1999. december, 1041-1058. o.

Pula, Gábor (2003): “Capital Stock Estimation in Hungary: A Brief Description of Methodology and Results”. *MNB Working Paper 2003/7*.

Ramey, Valerie A. and Matthew D. Shapiro (1997): “Costly Capital Reallocation and the Effects of Government Spending”. NBER Working Paper No. 6283, November 1997. http://www.nber.org/papers/w6283.pdf.

Ramey, Valerie A. and Matthew D. Shapiro (2001): “Displaced Capital: A Study of Aerospace Plant Closings”. *In: Journal of Political Economy, Vol. 109, No. 5, October 2001, pp. 958-992.*

Rátfai, Attila (2002): “Linking Individual and Aggregate Price Changes”. *Manuscript, July 2002.*

Scarf, H. E. (1959): “The Optimality of (S, s) Policies in the Dynamic Inventory Problem”. *In: Mathematical Methods in the Social Sciences, ed. by K. J. Arrow, S. Karlin and P. Suppes, Chapter 13. Stanford: Stanford University Press, 1959.*

Stokey, Nancy L. (2001): “Brownian Models in Economics” Chapter 11: Investment. *Lecture notes from web-page http://www.spc.uchicago.edu/users/stoke/toc.pdf.*

Szanyi, Miklós (1998): “Ipari beruházások az átalakuló országokban” (Industrial investment in transition countries, available only in Hungarian). *Közgazdasági Szemle*, XLV. évf., 1998. szeptember, 851-868. o.

Tobin, J. (1956): “The Interest Elasticity of the Transaction Demand for Cash”. *In: Review of Economics and Statistics, Vol. 38, August 1956, pp. 241-247.*

Tobin, J. (1969): “A General Equilibrium Approach to Monetary Theory”. *In: Journal of Money, Credit and Banking 1, pp. 15-29.*

Veracierto, Marcelo L. (2002): “Plant-Level Irreversible Investment and Equilibrium Business Cycles”. *The American Economic Review*, Vol. 92, No. 1 (Mar., 2002), pp. 181-197.

Wynne, Mark A. (1995): “Sticky Prices: What is the Evidence?” *In: Fed of Dallas Economic Review, First Quarter 1995, pp. 1-12.*

Appendix A

Investment functions with different simple cost structures

Figure A/1 illustrates the investment-shock relationship in the **cost-free case**. $(F = 0, \gamma = 0, p = 1)$. We see that investment is non-zero whenever the shock is non-zero, that is, we have instantaneous adjustment. We see that this function is slightly convex even in this case. This reflects the law of diminishing returns for the capital: when a large shock increases the marginal value of capital (q), we need a proportionally higher increase in the capital stock to restore the optimality condition of $q = 1/\beta$; therefore the shock-investment relationship is slightly convex: $\hat{\psi}_1 = 2.5233$, $\hat{\psi}_2 = 0.4384$, $\hat{\psi}_3 = -2.5151$. We also see that as investment is cost-free, investment rates are relatively high even for small shocks: a typical profitability shock (of one standard deviation, $\tilde{a} = 0.0822$) triggers a 21.04% (2.5233*0.0822 + 0.4384*0.0822*0.0822) investment rate.

Figure A/2: the case of **partially irreversible** investment $(F = 0, \gamma = 0, p = 0.95)$. Observe that irreversibility creates an inaction region, but the investment function remains continuous: small investments are still possible. Because of the inaction region, the shock-investment relationship became more convex, and as capital sales became more expensive, we need very large negative shocks (<-60%) to induce negative investments. The estimated parameters of the usual reduced form regression $\hat{\psi}_1 = 0.8520$, $\hat{\psi}_2 = 0.3928$, $\hat{\psi}_3 = -0.5564$. Convexity is stronger (the relative size of $\hat{\psi}_2$ increased), and the absolute value of the parameters decreased, so effect of profitability shocks is much smaller (a 1 standard deviation profitability shock, $\tilde{a} = 0.0822$ leads to 7.27% = 0.8520*0.0822 + 0.3928*0.0822*0.0822 investment).

Figure A/3: we have **convex cost** of investment $(F = 0, \gamma = 0.2, p = 1)$. We see that investment is instantaneous (any shock leads to investment activity), but as the marginal cost increased, it is of smaller magnitude (the function became flatter). Estimated reduced regression parameters: $\hat{\psi}_1 = 0.4657$, $\hat{\psi}_2 = 0.0672$, $\hat{\psi}_3 = -0.2557$, so a 1 standard deviation profitability shock leads to an investment rate of 3.87% (0.4657*0.0822 + 0.0672*0.0822*0.0822), which is much smaller than in the frictionless case.

Figure A/4: investment function with **fixed costs** $(F = 0.001, \gamma = 0, p = 1)$. This is basically the same as in the frictionless case, but firms do not undertake small investments, when the net gain is smaller than fixed costs. So fixed costs create an inaction region, and also lead to discontinuity (as no small investment activity is observed). The estimated parameters of the reduced form regression (9) are: $\hat{\psi}_1 = 2.4475$, $\hat{\psi}_2 = 0.4423$, $\hat{\psi}_3 = -2.4165$, which is very similar to the frictionless case. This result is intuitive, as the graph of the investment function has not changed dramatically. A 1 standard deviation profitability shock leads to an investment rate of 20.42% (2.4475*0.0822 + 0.4423*0.0822*0.0822), which is also similar to the frictionless case.

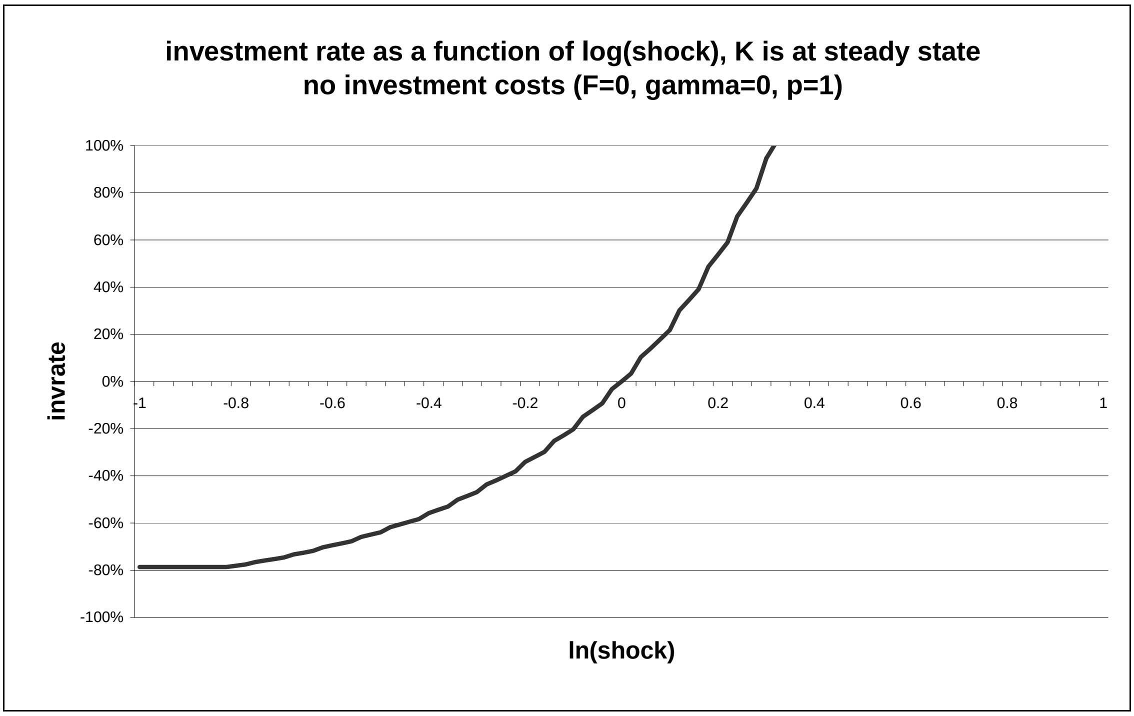

Figure A/1. The investment function in the costless case

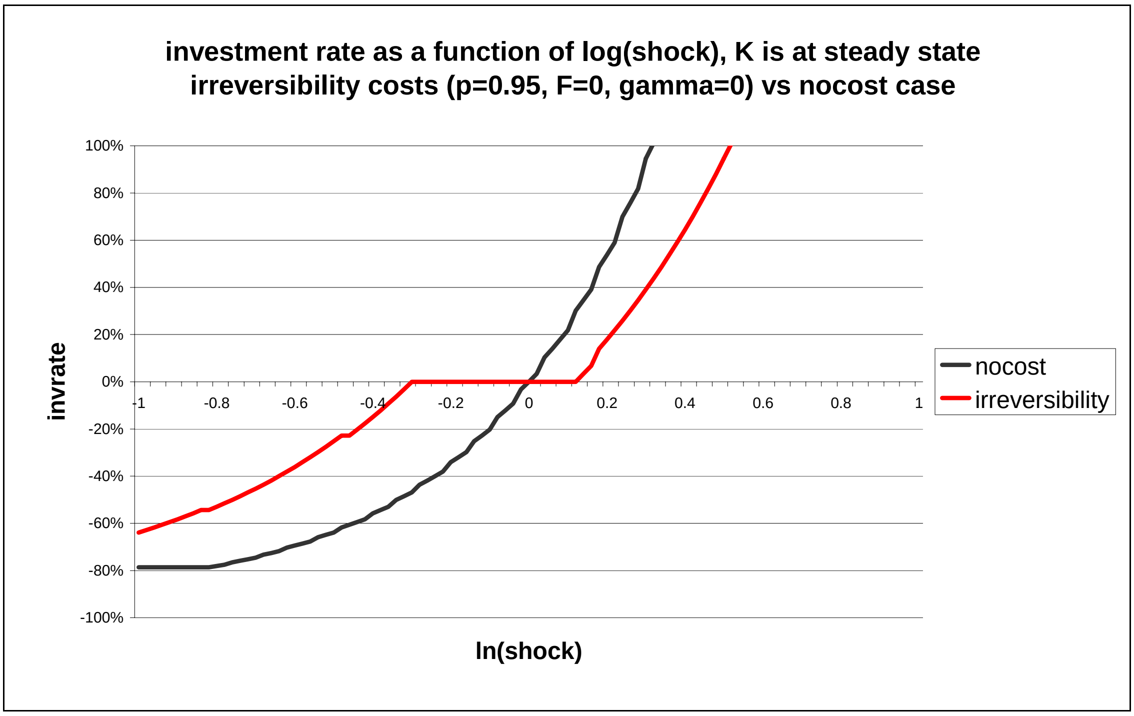

Figure A/2. The investment function if there is (partial) irreversibility

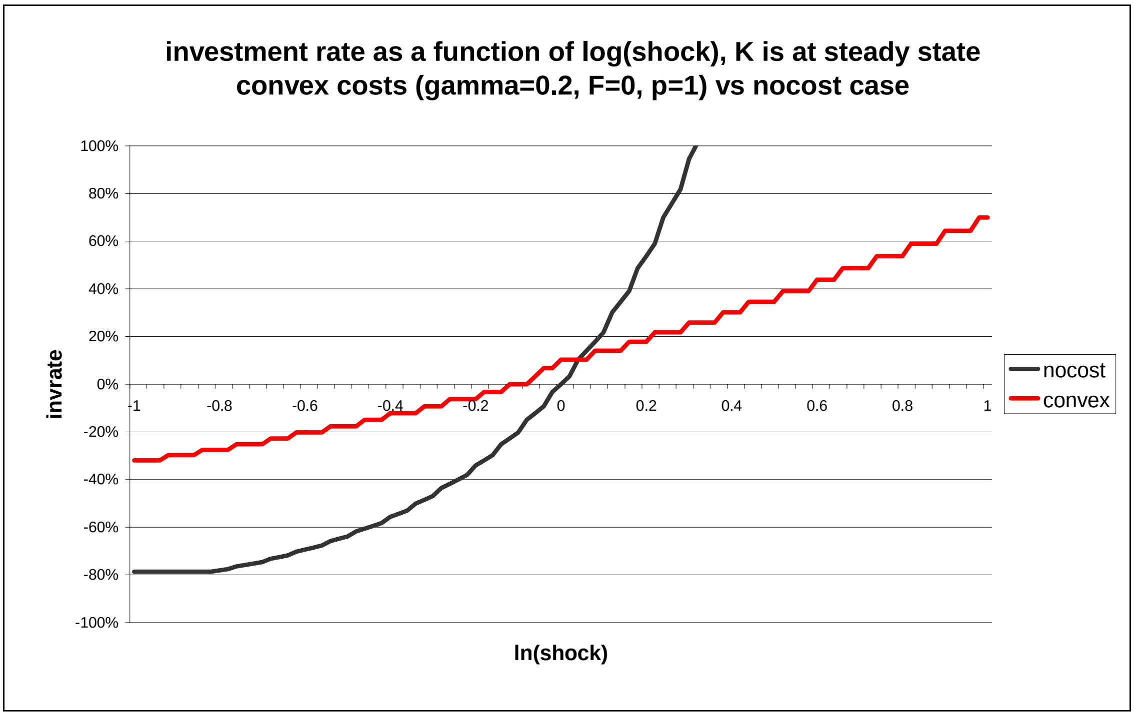

Figure A/3. The investment function if there is a convex cost of investment

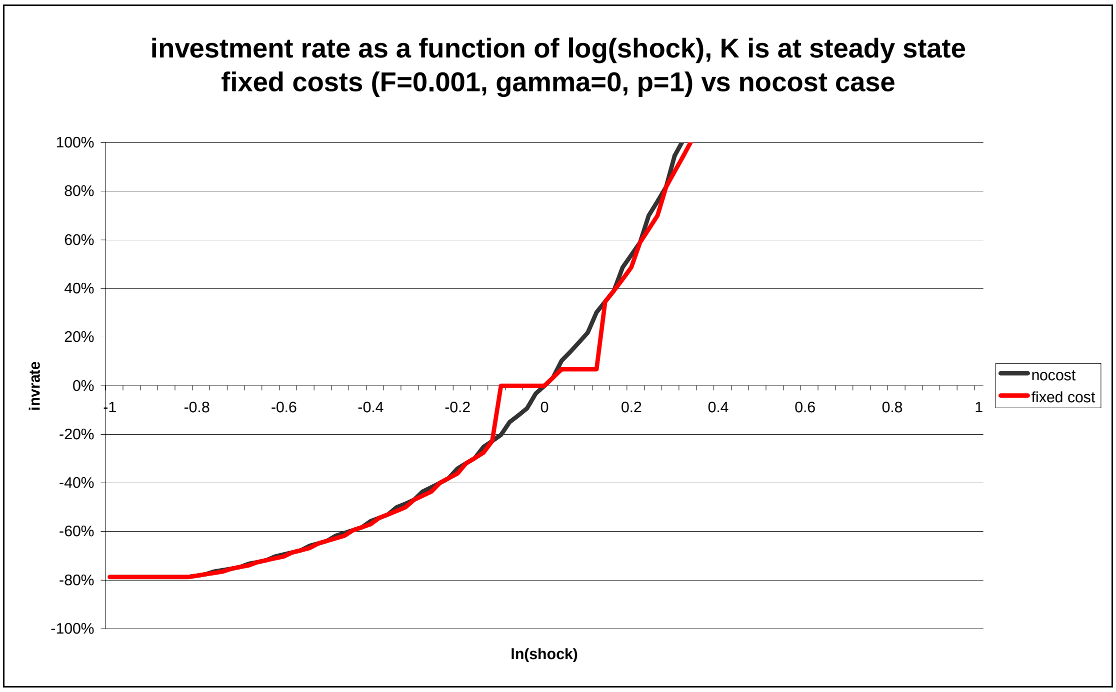

Figure A/4. The investment function if there is a fixed cost of investment

Appendix B

Methodology to estimate the curvature of the profit function

We want to estimate θ in the profit function:

$$\Pi_{it} = A_i K_{it}^{\theta} + \varepsilon_{it}, \tag{A1}$$

where Π_{it} and K_{it} are the profit and capital of firm *i* at year *t*, respectively, A_i is a firm-specific scaling parameter of the profit function, and ε_{it} is a well-behaving error term. To estimate parameter θ, we have to solve

$$\sum_i \sum_t \left(\Pi_{it} - A_i K_{it}^{\theta}\right)^2 \xrightarrow[\theta, A_i]{} \min . \tag{A2}$$

First-order condition with respect to θ:

$$\sum_i \sum_t 2\left(\Pi_{it} - A_i K_{it}^{\theta}\right)\left(- A_i \theta K_{it}^{\theta-1}\right) = 0, \tag{A3}$$

that is,

$$\sum_i A_i \sum_t \Pi_{it} K_{it}^{\theta-1} = \sum_i A_i^2 \sum_t K_{it}^{2\theta-1} . \tag{A3'}$$

First-order condition with respect to A_i:

$$\sum_{t=1}^{T_i} 2\left(\Pi_{it} - A_i K_{it}^{\theta}\right)\left(- K_{it}^{\theta}\right) = 0, \tag{A4}$$

or

$$\sum_t \Pi_{it} K_{it}^{\theta} = A_i \sum_t K_{it}^{2\theta}, \tag{A4'}$$

therefore

$$A_i = \frac{\sum_t \Pi_{it} K_{it}^{\theta}}{\sum_t K_{it}^{2\theta}} . \tag{A5}$$

If we substitute (A5) back to (A3'), then we obtain an equation for $\hat{\theta}$.

Appendix C

Variable definitions♦

NPLANT: capital stock. "The net value of the plant adjusted for inflation. This quantity is obtained by multiplying the book plant value by the ratio of the GNP deflator for fixed nonresidential investment in the current year to GNP deflator AA years ago. AA is the average age of the plant and equipment for this firm which is deduced in the following manner: an average age series is obtained as the ratio of accumulated depreciation (gross plant minus net plant) to depreciation this year. This assumes straight-line depreciation…"

UFCAP: capital purchases. "Compustat data item #128, capital expenditures (from statement of changes)."

SFPPE: capital sales. "Compustat data item #107, sale of plant, property and equipment (from statement of changes)."

INVEST: alternative investment measure, not used because we want to exclude acquisitions. "Compustat data item #30, capital expenditures (gross investment). The amount spent for the construction and/or acquisition of property, plant and equipment, including that of purchased companies (acquisition)."

ADJDEP: depreciation (to calculate new investment rate). "This year's depreciation adjusted for the effects of inflation. This variable is DEPREC deflated by the ratio of the GNP deflator for fixed nonresidential investment AA (see NPLANT for a definition of AA, average age) years ago to the current GNP deflator."

OPINC: profit variable, before depreciation, which is consistent with expression (12). "Compustat data item #13, operating income before depreciation."

SALES: sales revenue, a weighting variable for NLLS-estimation of parameter θ in *Appendix B*. "Compustat data item #12, net sales. This is the amount of actual billings to customers for regular sales completed during the period, reduced by cash discounts, trade discounts, and returned sales for which credit is given to customers. Interest and equity income from unconsolidated subsidiaries, non-operating income, and income from discontinued operations are excluded."

EMPLY: number of employees. (Wage bill is unavailable.) "Compustat data item #29, number of employees. This is the number of company workers as reported to shareholders. It may be an average throughout the year or an end-of-year number; the latter is reported if both are given. It includes part-time employees and the employees of consolidated subsidiaries."

♦ Variable definitions are quoted from *Hall (1990), pp. 13-22*.

Appendix D

The responsiveness of matched parameters to the structural cost parameters

In *Section 4.2* it is claimed that the reduced-regression parameters do not contain any information based on which one could identify F, the fixed cost of investment. The main argument behind this is that in the frictionless case (when $F = 0, \gamma = 0, p = 1$), changing F does not lead to changes in the estimated reduced regression parameters. This claim is also intuitive from *Figure A/4* in *Appendix A*.

This is, however, only a "local" finding for the frictionless case, and it still remains to be seen that something similar happens for changes in the fixed cost parameter when the other types of costs (convex, irreversibility costs) are non-zero. To investigate this, my focus is on the following matrix:

$$B = \begin{bmatrix} \frac{\partial \phi_1}{\partial F} & \frac{\partial \phi_1}{\partial \gamma} & \frac{\partial \phi_1}{\partial p} \\ \frac{\partial \phi_2}{\partial F} & \frac{\partial \phi_2}{\partial \gamma} & \frac{\partial \phi_2}{\partial p} \\ \frac{\partial \phi_3}{\partial F} & \frac{\partial \phi_3}{\partial \gamma} & \frac{\partial \phi_3}{\partial p} \end{bmatrix}.$$

When using indirect inference, it is common to refer to this matrix as the *binding matrix*. It shows how sensitive are the matching parameters to the structural parameters to be estimated. In fact, as *Gourieroux et al. (1996)* show, the variance-covariance matrix of the estimated structural parameters is proportional to $\left[B'\hat{\Omega}^{-1}B\right]^{-1}$, where $\hat{\Omega}$ is simply the variance-covariance matrix of the matching parameters (reduced-regression parameters in our case), as estimated from the data.

Now it is easy to see why it is a problem if the reduced regression parameters are not sensitive to one of the structural parameters. In the frictionless case, I find (locally) that $\frac{\partial \phi_1}{\partial F}, \frac{\partial \phi_2}{\partial F}, \frac{\partial \phi_3}{\partial F}$ are zero (or they are very close to that when calculated numerically), so the first column of the binding matrix is zero, so the estimated standard error of the fixed cost parameter is infinite.

Since it is impossible to prove globally that one particular column of the binding matrix is (sufficiently close to) zero, I numerically investigated this binding matrix for some triplets of the structural cost parameters. For example, for $F = 0.0001, \gamma = 0.22, p = 0.991$ (this is the estimated cost structure for the Hungarian data in *Chapter 5*) the binding matrix is

$$\begin{bmatrix} -35 & -0.315 & 1.85 \\ 75 & -0.050 & -2.05 \\ 30 & 0.245 & -1.50 \end{bmatrix}.$$

These numbers have to be compared according to the scaling of the model. For example, one would think that $\frac{\partial \phi_1}{\partial F} = -35$ is relatively high (in absolute terms), but taking into account the scaling, a typical change in F is very small: a 1% increase in F (0.000001) would decrease ϕ_1 by 0.000035 (approximately). In contrast, as a result of a 1% increase in γ (0.0022), ϕ_1 would decrease by 0.000690 (approximately), a 20-times bigger effect. And also, a 1% increase in the extent of irreversibility (i.e. the change of p from 0.991 to 0.99091, by 0.00009) would decrease ϕ_1 by 0.000167, a 5-times bigger effect again.

In other words, while the entries in the first column of the binding matrix seem to be bigger (in absolute terms), they are not sufficiently bigger to bring down the estimated standard error of F to such a low level so that the estimated F would become significant. Indeed, if I try to estimate the structural cost parameters only on the basis of the reduced regression, then the estimated fixed cost parameter is insignificant.

In this case, the introduction of the inaction rate (and skewness) ensures the identification. If we include these into the set of the matching parameters, then the first column of the binding matrix (whose shape is now *5x3*) is

$$\begin{bmatrix} -35 \\ 75 \\ 30 \\ 45000 \\ 680 \end{bmatrix}.$$

It is intuitive that $\frac{\partial inaction}{\partial F}$ is positive: increasing fixed costs obviously increase the inaction rate. But now the magnitude of this positive parameter is enough to bring down the estimated standard error of the fixed cost to a level when the estimated fixed cost becomes significant.

I did these numerical calculations for a wide range of structural parameter sets (including all parameter sets that are reported as estimated cost parameters anywhere in the paper), and I found that the results were as I explained here for $F = 0.0001, \gamma = 0.22, p = 0.991$. So it seems to be the case that it is a global phenomenon that the reduced regression alone does not identify (or at least poorly identifies) the fixed cost parameter, and it is the inaction rate (and skewness) that brings identification to this type of cost parameter.