Investment, R&D and Credit Constraints

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is my own work. Chapter 5 was undertaken as joint work with Professor John Van Reenen.

Carlos Daniel Rodrigues de Assunção Santos

Abstract

This thesis develops a dynamic industry equilibrium framework to be employed in situations where firms compete in a complex environment with either several firms in the industry or large state spaces. This model is employed to analyze the problems of Investment, R&D and Credit Constraints in situations where the 'curse of dimensionality' occurs. Chapter 1 introduces the problem and applications. Chapter 2 describes the model, assumptions and main results. Chapter 3 considers the problem of estimating production functions in a manner which is consistent with the model. Chapter 4 contains an application to estimate the Sunk Costs of R&D in the Portuguese Moulds Industry and estimate them to be about 2.6 million euros (1.7 times the average firm sales level). Finally Chapter 5 incorporates an application to the US Steel Industry to estimate the costs of external finance. We find that the average sunk cost of R&D for this industry is on the order of \$194m and the costs of external finance are about 35 cents per dollar raised.

In the second application (in joint work with John Van Reenen), we use a similar framework and introduce financial constraints which can affect investment and R&D decisions. By specifying a dynamic structural model and solving through numerical simulation we model adjustment costs, R&D decisions and financial constraints simultaneously. Applying the model to 35 years of firm-level panel data from the US iron and steel industry we provide evidence that costs of external finance are substantial, consistent with asymmetric information, even in a developed financial market like the US. The average sunk cost of R&D is on the order of \$194m - consistent with industry estimates of the typical costs of building an R&D lab.

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Chapter 1

Introduction

In this thesis I try to address two fundamental questions in economics. The first is the existence of sunk costs of R&D which, as emphasized by other authors, can significantly affect equilibrium market structure and innovation. The second question is the role of financial constraints for investment in general and innovation in particular. This question is one of the most debated issues in empirical economics. It is obviously important as investment and innovation are critical for economic growth, so financial market failures can have first order effects on welfare, and policies to address growth will depend on whether financial constraints are important.

To study these problems I develop a tractable model with dynamic competition where firms can decide to invest in physical capital and R&D. By assuming that firms' individual states are private information, the industry state is summarized by the aggregate (payoff relevant) state. This has two advantages for estimation purposes: (i) it avoids the 'curse of dimensionality', typical in dynamic industry models and; (ii) it deals with unobserved firms in the data, a problem neglected in the literature arising if one wants to estimate from the equilibrium conditions which depend on the whole (unobserved) industry state.

As a by-product, I address two problems in the production function estimation literature. The first problem is input endogeneity and the second is the use of deflated sales as a proxy for output when there is imperfect competition. Using a demand system and allowing input demand to depend on the individual state variables as well as on the industry equilibrium I explain how to jointly recover the production function parameters and demand elasticity.

In the first application I recover the sunk costs of R&D for the Portuguese Moulds Industry and estimate them to be about 2.6 million euros (1.7 times the average firm sales level). I also evaluate the impact of a reduction in the sunk costs of R&D on equilibrium market structure, productivity and capital stock. The results corroborate the idea that sunk costs of R&D have implications for policies which target at promoting R&D. Policy makers should be concerned with reducing the large sunk costs of R&D and promote R&D start-ups.

In the second application (in joint work with John Van Reenen), we use a similar framework and introduce financial constraints which can affect investment and R&D decisions. By specifying a dynamic structural model and solving through numerical simulation we model adjustment costs, R&D decisions and financial constraints simultaneously. Applying the model to 35 years of firm-level panel data from the US iron and steel industry we provide evidence that costs of external finance are substantial, consistent with asymmetric information, even in a developed financial market like the US. The average sunk cost of R&D is on the order of \$194m - consistent with industry estimates of the typical costs of building an R&D lab.

Chapter 2

Investment and R&D in a Dynamic Equilibrium with Incomplete Information

2.1 Introduction

In this chapter I develop a model which can be applied to the type of financial firm level datasets normally available and avoids the 'curse of dimensionality'. The framework is the following: firms can enter and exit the market, invest in physical capital and decide to engage in R&D by paying a setup sunk cost. There are both linear and quadratic costs with total irreversibility for physical capital investment. Productivity follows a first order Markov process which depends on whether the firm is an R&D performer or not. Finally, firms compete in the market where demand is modeled by a representative consumer Constant Elasticity of Substitution framework.

Most firm level datasets[1] contain information on financial variables (balance

[1]Examples of these are Standard & Poor's COMPUSTAT for US firms, Bureau Van Dijk's FAME (UK) and AMADEUS (Europe) or Thomson Financial's DATASTREAM (UK). Only

sheet, profits and losses, number of workers) for a subset of the total population of firms in the industry. However, estimating a game theoretic type of model where players' strategies depend on the state of all competitors, requires observing all players in the industry.[2] This becomes a problem because the equilibrium resulting from such a game depends on the state of all individual competitors. If some of these competitors are unobserved in the data, in principle, it becomes hard to estimate such an equilibrium model. To see this imagine that we want to estimate a policy function as a function of the state of all (N) competitors in the industry, $\sigma(s_1, ...s_N)$. If there is data on actions and individual states, this can be done non-parametrically. However, if some players are not observed we immediately face a problem of unobserved heterogeneity since some important variables are unobserved. So, either we control for this unobserved heterogeneity in some way or we face problems in estimating the equilibrium policy functions.

A second problem is the 'curse of dimensionality' which occurs when the state space grows exponentially, either by increasing the number of firms or the number of states per firm. This is in fact the main constraint on solving dynamic industry equilibrium models and other authors have tried to address (for example Weintraub, Benkard and Van Roy, 2007).

Most studies in empirical Industrial Organization have then focused in oligopolies or regulated industries where good information for a small number of players in the market is available. This leaves aside a large number of industries which are interesting cases to study. In this paper I propose a framework which allows us to estimate a structural model without facing these problems. Furthermore, for questions like the sunk costs of R&D, oligopolistic markets might be less interest-

census data would contain observations for all firms present in the industry and even in this case smaller firms are normally sampled.

[2]This can be relaxed if only the distribution of states is relevant, (for example, by imposing symmetry and anonymity). In this case the industry state distribution is a sufficient statistic for the industry state. In principle, if we know the sampling method for collecting the data, we can potentially recover the industry distribution from the observed sample.

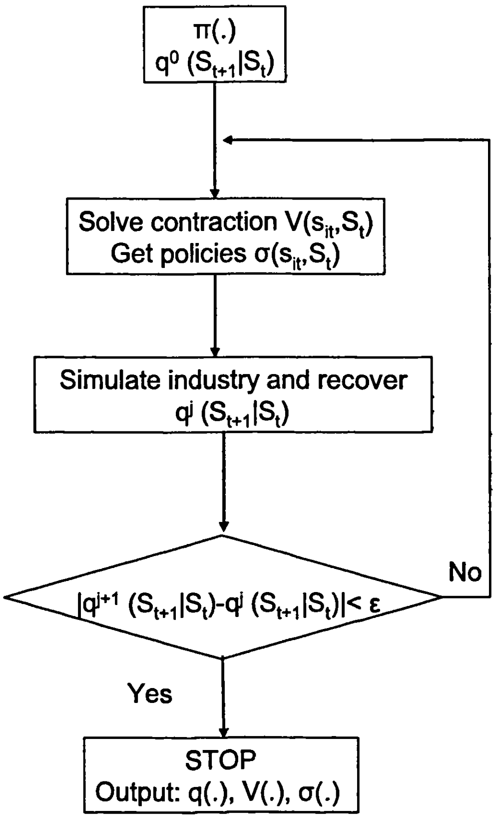
ing because in some of these industries firms are sufficiently large and the sunk cost of R&D are not binding. However, if firms are sufficiently large and sunk costs of R&D do not bind, the data would not show sufficient variation in R&D performance to allow identification of sunk costs because either all firms or no firm would do R&D.

To deal with the problems mentioned above, I introduce the assumption of incomplete information. By doing so the industry state, under some assumptions, can be summarized by the (payoff relevant) aggregate state. The equilibrium definition is then very intuitive. Agents behave optimally conditional on their beliefs about the evolution for the aggregate industry state. The beliefs about the evolution of the aggregate industry state are equilibrium beliefs, meaning that they are rational beliefs. The assumption addresses the two problems both avoiding the 'curse of dimensionality' by reducing the dimensionality of the state space and dealing with unobserved firms in the data since it only requires that the aggregate industry state is observed.[3]

I have also developed an algorithm to solve the model which resembles a nested fixed point where the inside loop solves the dynamic programing problem and the outside loop solves for equilibrium beliefs (Figure 2.1). I can use this algorithm to recalculate the model for different structural parameters and perform policy simulations. Due to the 'curse of dimensionality, this would not be computationally

[3] To better understand the "curse of dimensionality' problem, consider a model with several state variables per firm and/or large numbers of firms. Equilibria and policy rules are then computationally intractable since the size of the problem grows exponentially. For example, let $\mathbf{s}$ be the industry state (i.e. define s_{it} the state vector of firm i at time t, then the industry state at time t is $\mathbf{s}_t = (s_{1t}, ...s_{Nt})$), finding the industry state transition, $q(\mathbf{s}_{t+1}|\mathbf{s}_t)$, for an industry with 50 firms and 2 binary state variables would mean calculating a $4^{50} \times 4^{50}$ transition matrix. If one introduces the typical anonymity and symmetry assumptions (Pakes and McGuire, 2001) the problem will be greatly reduced but still intractable ($50^2 \times 50^2$). The 'curse of dimensionality' is not only a computational problem but will also arise in the estimation. As we will see ahead, since this industry state is very large, if one tries to estimate a flexible policy function on the whole state like proposed by Bajari, Benkard and Levin (2007), it will require a large amount of data (not available on most firm level dataset). The best one can do then is estimate the policies for some aggregation of the state space like implemented in Ryan (2006).

possible in the Full Information case for industries where the average number of firms reaches hundreds.



Notes: Algorithm is initialized at iteration 0. $\pi(.)$ are period returns. $q^{j+1}(S_{t+1}|S_t)$ is aggregate state transition at iteration j+1. $V(s_{it},S_t)$ is the Value function and $\sigma(s_{it},S_t)$ are the policy functions. The final output of the algorithm are the optimal value and policy function as well as the equilibrium industry state transition.

Figure 2.1: Algorithm for solving the model

In related research Weintraub, Benkard and Van Roy (2007) propose the use of a different equilibrium concept, the "Oblivious Equilibrium". In this type of equilibrium firms disregard the current state of the industry and base their decisions solely upon the (stationary) long run industry state. As the number of firms in the industry grows, they show that it converges to the Markov Perfect Nash Equilibrium (MPNE) provided the industry state distribution satisfies a 'light tail' condition. This result resembles Hopenhayn (1992) where, with no aggregate shocks, the equilibrium is deterministic when the number of firms grows large.

Introducing incomplete information has some potential drawbacks by implicitly imposing more structure on the type of strategic interactions since firms now react to the 'average' competitor (i.e. firm A's reaction to a market structure where both competitors B and C are very similar will be the same as when B is very large and C is very small). How well this approximates actual competition in the industry will vary from case to case. It is more likely that the assumption is not valid in oligopolistic industries where strategic interactions are very important. In other industries, competition might be well summarized by the aggregate variables. Some examples of this can be industries where there is a large number of players, no market leaders or products are differentiated, like Industrial Machinery Manufacturing or Metalworking Machinery Manufacturing (moulds, dies, machine tools). What these industries share in common is the fact that each firm sells specialized products, prices are contract specific and information is not publicly available.

The earlier dynamic models only accounted for the effects of entry and exit and did not allowed for investment or R&D (Jovanovic, 1982; Hopenhayn, 1992). Ericson and Pakes (1995) develop an attractive framework for modeling investment decisions where players use Markovian Strategies which result in a Markov Perfect Nash Equilibrium (MPNE) as defined by Maskin and Tirole (1988, 2001).

However, solving the MPNE brings with it two complications. One was the possibility of non-existence of equilibrium in pure strategies which Doraszelski and Satterthwaite (2007) addressed with the introduction of privately observed independent and identically distributed shocks. These shocks "smooth out" reaction functions reestablishing existence of equilibria. The second, is the 'curse of dimensionality' and the computational burden attached to solving the model. Recent algorithms (e.g. Pakes and McGuire (2001)) are successful in minimizing this second problem and can solve the model for up to 10-15 firms, by using stochastic algorithms similar to the artificial intelligence literature. However, they cannot solve problems where there is either a larger number of firms in the market or large state spaces per firm.

Other theoretical models exist that study the R&D decision in an industry framework. Vives (2004) for example, does this in a static setting, but since it does not incorporate any heterogeneity, it cannot explain some facts like the coexistence of R&D and non-R&D firms. Klette and Kortum (2004) use a dynamic framework with the advantage of providing an analytical solution. However, the simplification that allows the elegance of an analytical solution is also the constraint which prevents extensions to the model (for example accounting for R&D sunk costs and aggregate uncertainty).

The literature on dynamic industry models has received increased attention recently with the development of several alternative estimators (Aguirregabiria and Mira, 2007; Bajari, Benkard and Levin, 2007; Pakes, Ostrovsky and Berry, forthcoming; Pesendorfer and Schmidt-Dengler, forthcoming) and some successful applications to oligopolistic industries (Benkard, 2004; Ryan, 2005; Schmidt-Dengler, 2007).

2.2 The aggregate state dynamic model

2.2.1 States and actions

This section describes the elements of the general model. Time is discrete and every period, $t = 1, 2, ..., \infty$, there are N firms in the market (N_t incumbents and $N_t^* = N - N_t$ potential entrants) where a firm is denoted by $i \in \{1, ..., N\}$

States Agents are endowed with a continuous state $s_{it} \in \mathfrak{s}_i$[4] and a vector of payoff shocks $\varphi_{it} \in \mathfrak{J}$ both belonging to some compact set. Both the state and the payoff are privately observed by the players. The econometrician observes the states, s_{it}, but not the payoff shocks, φ_{it}.

The industry state is $\mathbf{s}_t = (s_{1t}, ..., s_{Nt}) \in \mathfrak{s}_i^N$. The vector of payoff shocks are independent and identically distributed and can depend on the actions of the players. This satisfies Rust's (1987) conditional independence assumption[5] and allows the value function to be written as a function of the state variables which keeps the number of payoff relevant state variables small.

Assumption 2.1 *(a) Individual states and actions are private information and;*

(b) $g(\mathbf{s}_t|S_t, ..., S_0) = g(\mathbf{s}_t|S_t)$

where $g(\mathbf{s}_t|S_t)$ is the density function for the industry state, $\mathbf{s}_t$, conditional on the aggregate state S_t.

Assumption 2.1 states that the only common information to all players is the aggregate state. Moreover, it implies that everything agents can learn about the state of the industry, $\mathbf{s}_t$, is contained in S_t and history $(S_{t-1}, ..., S_0)$ adds no more extra information.

Actions Incumbents choose $l = l^c + l^d$ actions that can be continuous $a_{it}^c \in \mathfrak{A}^c \subset \mathbb{R}^{l^c}$ or discrete (exit, R&D start-up) $a_{it}^d \in \{0,1\}^{l^d}$ and $a_{it} = \{a_{it}^c, a_{it}^d\} \in \mathfrak{A} \subset \mathbb{R}^{l^c} \times \{0,1\}^{l^d}$. Throughout the analysis I will restrict discrete actions to be binary for simplicity and I also use one continuous variable (investment) and one discrete variable (entry/exit). For example, if a_{it}^d represents 'status' and firms choose to

[4]The model can be extended to discrete states but I focus here in the continuous case to keep notation simple and possible to follow.

[5]Rust (1987) states the conditional independence assumption $p(s_{t+1}, \varepsilon_{t+1}|s_t, \varepsilon_t, a) = q(\varepsilon_{t+1}|s_{t+1})p(s_{t+1}|s_t, a)$ which allows the use of the ex-ante value function by integrating over ε_t, reducing the dimensionality of the problem.

exit the industry they set $a^d_{it} = 0$. Potential (short lived) entrants may choose to pay a privately observed entry cost and enter the industry.

State transition

Assumption 2.2 *(No Spillover) Conditional on current state and actions, own state evolves with transition function*

$$p(s_{it+1}|s_{it}, a_{it})$$

Per period payoff Time is discrete and firms receive per period returns which depend on the state of the industry, current actions and shocks ($\pi(a_{it}, \mathbf{s}_t, \varphi_{it})$) where the period returns are continuous and bounded.

Assumption 2.3 *(a) There exists a function ($S : \mathfrak{s}^N \to \mathfrak{S} \in \mathbb{R}$) which maps the vector of firm's individual states ($\mathbf{s}_t$) into an aggregate index ($S(s_{1t}, s_{2t}, ..., s_{Nt})$) and the aggregate state is observed with noise ($S_t = S(s_{1t}, s_{2t}, ..., s_{Nt}) + \varepsilon_t$, where ε_t is independent and identically distributed over time with cumulative function F_ε and bounded support).*

(b) Per period returns can be written as

$$\pi(a_{it}, \mathbf{s}_t, \varphi_{it}) = \pi(a_{it}, s_{it}, S_t, \varphi_{it})$$

Under this assumption, S_t is the payoff relevant variable commonly observed by all agents. The random shock, ε_t, guarantees that there is no perfectly informative state S_t from which agents could recover $(s_{1t}, ..., s_{Nt})$ exactly.[6] Note that the

[6] The intuition for this error term is the following, imagine s_{it} is marginal cost which affects pricing in the stage game so that the price is a function of the state $p(s_{it}, S_t)$. If players make pricing mistakes, imagine the actual price they set is $p(s_{it}, S_t) + \varepsilon^i_t$, where ε^i_t is independent and identically distributed over time and firms, the aggregate state (in this example the average price) is then $S_t = \frac{1}{N}\sum_{i=1}^{N} p(s_{it}, S_t) + \varepsilon^i_t = \frac{1}{N}\sum_{i=1}^{N} p_{it} + \varepsilon_t$, where $\varepsilon_t = \frac{1}{N}\sum_{i=1}^{N} \varepsilon^i_t$.

payoff relevant shocks (φ_{it}) have no impact on the stage game pricing. One type of demand which meets this assumption is the CES demand where the aggregate industry state is aggregate industry deflated sales.

The timing is the following:

1. States (s_{it}) and shocks (φ_{it}) are observed by firms

2. Firms compete in the market and collect period returns ($\pi(.)$)

3. Actions ($\mathbf{a}_t = (a_{1t}, .., a_{Nt})$ are taken simultaneously

4. New state is formed ($(\mathbf{s}_{t+1}, S_{t+1}, \varphi_{t+1}) \in \mathfrak{s}^N \times \mathfrak{S} \times \mathfrak{J}^N$))

2.2.2 Strategies

For each state firms can take actions in some compact set $a_{it} \in \mathfrak{A}$. I restrict to Symmetric Markovian Pure Strategies,[7] which map the set of states into the action space, $\sigma : \mathfrak{s} \times \mathfrak{S} \times \mathfrak{J} \rightarrow \mathfrak{A}$ $(\sigma_{it}(s_{it}, S_t, \varphi_{it}) = (\sigma^c_{it}(s_{it}, S_t, \varphi_{it}), \sigma^d_{it}(s_{it}, S_t, \varphi_{it})))$ where the action space defined by $\mathfrak{A}(s_{it}, S_t, \varphi_{it}) \subset \mathfrak{s} \times \mathfrak{S} \times \mathfrak{J} \times \mathbb{R}^{l^c} \times \{0,1\}^{l^d}$ can be a mixture of closed and compact discrete and continuous sets. Using symmetry we can drop the i subscript and imposing stationarity we can drop the t subscript:

$$\sigma_{it}(s_{it}, S_t, \varphi_{it}) = \sigma(s_{it}, S_t, \varphi_{it}).$$

Proposition 2.1 *Under Assumptions 2.1 to 2.3 the aggregate industry state conditional distribution takes the form $q(S_{t+1}|S_t)$.*

Proof. See appendix.

So while the industry state is a vector $\mathbf{s}_t = (s_{1t}, s_{2t}, ..., s_{Nt})$, S_t is a scalar variable which maps individual firm's states into an aggregate industry state $S_t =$

[7] Anonymity as defined in Ericson and Pakes (1995) is implicitly imposed by assuming that firms do not observe each others state.

$g(s_{1t}, ...s_{Nt}) + \varepsilon_t$. The validity of this result depends on the validity of the assumptions. I propose a method to test the assumptions which I will explain later but basically tests whether the transition for the aggregate state is a first-order Markov process by testing the significance of previous lags and moments of the individual states distribution.

When some actions and states are not observed, the firm has to condition its strategies on the expected actions and state of the competitors. When nothing is observed about the competitors, the firm will have the same expectation about the state and actions for all competitors. To understand the implications of this incomplete information assumption, recall that in the Ericson and Pakes framework with the symmetry and anonymity assumption firms "keep track" of the industry state distribution and not the whole industry state vector as it would be the case with no anonymity. This is because under anonymity, the industry state distribution is a sufficient statistic for the industry state vector. In the incomplete information case I propose, what matters is just one moment of this same distribution so this imposes slightly stronger conditions than the usual symmetry and anonymity. It implicitly imposes more structure in the type of strategic interactions since firms now react to the 'average' competitor (i.e., *ceteris paribus,* firm A's reaction to a market structure where both competitors B and C are very similar will be the same as when B is very large and C is very small provided the aggregate state is the same). Notice that I have assumed implicitly that knowledge about the own state is considered to have no impact on the evolution of the aggregate state conditional on knowing the current state, i.e., $q(S_{t+1}|s_{it}, S_t) = q(S_{t+1}|S_t)$.

Corollary 2.1 *Under assumptions 2.1 to 2.3 and when* $S_t = \sum_{i=1}^{N} h(s_{it}) + \varepsilon_t$, *as* N *becomes large* $q(S_{t+1}|S_t)$ *is approximately normally distributed with conditional mean* $\mu_{S_{t+1}|S_t} = (1-\rho_S)\mu_S + \rho_S S$ *and standard deviation* $\sigma_{S_{t+1}|S_t} = \sigma_S(1-\rho^2)^{1/2}$. *Where* $\mu_S, \sigma_S^2, \rho_s$ *are respectively the unconditional mean, variance and autocorre-*

lation for the S_t process.

Proof. By the Central Limit Theorem.

Corollary 2.2 *As N becomes large, three moments of the aggregate state distribution, $(\mu_S, \sigma_S, \rho_S)$ fully characterize $q(S_{t+1}|S_t)$.*

Proof. Follows directly from Corollary 2.1.

Value function Given Proposition 2.1 and Assumption 2.2, we can write the ex-ante value function defined as the discounted sum of future payoffs before player specific shocks are observed and actions taken, as

$$\begin{aligned}&W(s_{it}, S_t; f_{it}^a, q(S_{t+1}|S_t)) \\ =\ &\int_{\varphi_{it}} \int_{a_{it}^c} \sum_{a_{it}^d} \left[\pi_{it} + \rho \int_{s_{it+1}, S_t} W_{it+1} p(ds_{it+1}|s_{it}, a_{it}) q(dS_{t+1}|S_t) \right] f_{it}^a \phi_{it}^{\varphi} da_{it}^c d\varphi_{it}\end{aligned}$$

where $f_{it}^a = f(a_{it}|s_{it}, S_t)$ is the probability of choosing actions $a_{it} = (a_{it}^c, a_{it}^d)$ conditional on being at state (s_{it}, S_t), $\phi_{it}^{\varphi} = \phi(\varphi_{it})$ is the density function for payoff shocks (φ_{it}), $\pi_{it} = \pi(a_{it}, s_{it}, S_t, \varphi_{it})$ are period returns and $W_{it+1} = W(s_{it+1}, S_{t+1})$ is the ex-ante continuation value.

This value function depends on the beliefs about the transition of the aggregate state, $q(S_{t+1}|S_t)$. These beliefs depend on the equilibrium strategies played by all players. Notice that since firm i does not observe $s_{jt}, \forall j \neq i$, it can only form an expectation on its rivals actions conditional on the information available S_t, $p(a_{jt}|S_t) = \int_{s_j} f(a_{jt}|s_{jt}, S_t) g(s_{jt}|S_t) ds_{jt}$ where $g(s_{jt}|S_t)$ is the probability density function of firm j's state conditional on S_t and $f(a_{jt}|s_{jt}, S_t) = \int_{\varphi_j} \sigma(s_{jt}, S_t, \varphi_{jt}) \phi(\varphi_{jt}) d\varphi_{jt}$. The assumption has a similar effect to mixed strategies or privately observed information in Doraszelski and Satterthwaite (2007) which smooths out the continuation value and guarantees existence of equilibria.[8]

2.2.3 Equilibrium

The equilibrium concept is Markov Perfect Bayesian Equilibrium in the sense of Maskin and Tirole (1988, 2001). Since I restrict to Markovian pure strategies where the firm can take actions $a_{it} \in A(s_{it}, S_t, \varphi_{it})$, the problem can be represented as:

$$V(s_{it}, S_t, \varphi_{it}; q) = \sup_{a \in \mathfrak{A}(s,S,\varphi)} h(s, S, \varphi, a, V; q) \tag{2.1}$$

where

$$\begin{aligned} & h(s, S, \varphi, a, V; q) \\ = \quad & \{\pi(s_{it}, S_t, \varphi_{it}, a_{it}) + \rho E\{V(s_{it+1}, S_{t+1}, \varphi_{it+1}) | s_{it}, S_t, a_{it}; q\} \end{aligned}$$

and

$$E\left[V_{i,t+1} | s_{it}, S_t, \varphi_{it}\right] = \int_{s \in \mathfrak{s}, S \in \mathfrak{S}, \varphi \in \mathfrak{I}} V_{i,t+1} \tilde{q}(ds_{it+1}, dS_{t+1}, d\varphi_{it+1} | s_{it}, S_t, \varphi_{it})$$

$$\tilde{q}(s_{it+1}, S_{t+1}, \varphi_{it+1} | s_{it}, S_t, , \varphi_{it}) = q(S_{t+1} | S_t) p(s_{it+1} | s_{it}, a_{it}) \phi(\varphi_{it+1})$$

Definition 1 *A collection of Markovian strategies and beliefs $(\sigma, q())$ constitute a Markov perfect equilibrium if:*

[8]Doraszelski and Satterthwaite (2005) have shown that in some cases the original Ericson and Pakes framework did not have an equilibrium in pure strategies.

(i) Conditional on beliefs about industry evolution (q) firms' strategies ($\sigma_{it}=$ $\sigma^*(s_{it}, S_t, \varphi_{it}; q)$ maximize the value function $V(s_{it}, S_t, \varphi_{it}; q)$.

(ii) The industry transition ($q^*(S_{t+1}|S_t; \sigma^*(s_{it}, S_t, \varphi_{it}|q))$) resulting from optimal behavior (σ^*_{it}) defined above is consistent with beliefs $q(S_{t+1}|S_t)$

The solution to the dynamic programming problem conditional on q is the optimal strategy $\sigma^*(.|q)$ and a solution exists, under Blackwell's regularity conditions. These strategies will then characterize the industry conditional distribution $q(S_{t+1}|S_t;\sigma^*)$ and the equilibrium is the fixed point to a mapping from the beliefs used to obtain the strategies into this industry state transition

$$\Upsilon(q)(S_{t+1}|S_t) = q^*(S_{t+1}|S_t; \sigma^*(.|q))$$

where firm's follow optimal strategies $\sigma^*(.)$. An equilibrium exists when there is a fixed point to the mapping $\Upsilon(q) : \Omega \rightarrow \Omega$

Theorem 2.1 *An equilibrium q^* exists.*

Proof. See appendix.

Uniqueness

The problem of multiple equilibrium is recurrent in this type of games and has been widely discussed in the literature. One of the main concerns is the difficulty that arises in estimating the model when one cannot fully characterize the whole set of possible equilibria.

> *"However, discrete games with incomplete information have a very different equilibrium structure than games with complete information. For example, in a static coordination game Bajari, Hong, Krainer and Nekipelov (2006) show that the number of equilibria decreases as the*

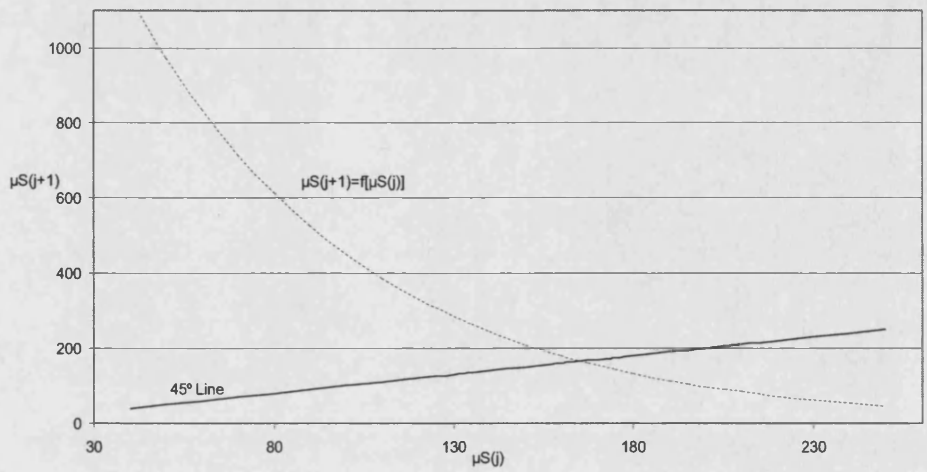
number of players in the game increase. In fact, the equilibrium is typically unique when there are more than four players. In a complete information game, by comparison, the average number of Nash equilibrium will increase as players are added to the game (see McKelvey and McLennan (1996)). Thus, the assumption of incomplete information appears to refine the equilibrium set." Bajari, Hong and Ryan (2007: 11)

Given the structure of the game developed above, I can compute a subset of equilibria. Using Corollary 2.2 the equilibrium is defined by a triple $(\mu_S, \sigma_S, \rho_S)$. Given this triple I can solve the model for any starting vector $(\mu_S^0, \sigma_S^0\, \rho_S^0)$ and compute the resulting equilibrium. Figure 2.2 represents the configuration for any starting value of (μ_S)[9] and corroborates the findings by Bajari et al (2007) supporting the idea of uniqueness of equilibrium for this model because there is single crossing. Whereas in general uniqueness is difficult to prove, with this framework it can be checked by looking at possible equilibrium configurations $(\mu_S, \sigma_S, \rho_S)$.

2.3 Final comments

Reducing the industry state into the payoff relevant aggregate state by introducing incomplete information avoids the 'curse of dimensionality'. As noted before, this imposes more structure on the type of strategic interactions by making strategic reactions identical to all competitors. In a sense this condition imposes slightly stronger restrictions than the usual anonymity and symmetry assumptions which are also fundamental to reduce the dimensionality of the state space. Symmetry and anonymity are a restriction that allows the state space to be char-

[9] (σ_S, ρ_S) are held constant only for simplicity in order to provide a visual representation.



Notes: μS(j+1)=f[μS(j)] is the function representing average industry state at iteration j+1, as a function of average industry state at iteration j. The point where this function crosses the 45° line represents the equilibrium. This figure represents several "outputs" at iteration j+1 for the expected industry state from different starting iteration j beliefs keeping variance and autocorrelation constant. There is evidence supporting a single crossing property and therefore uniqueness.

Figure 2.2: Uniqueness of equilibria

acterized more compactly as a set of "counting measures" (i.e. the industry state distribution).[10]

In a different area of research, Krusell and Smith (1998) explore a similar idea whereby the evolution of the aggregate variables in the economy is well approximated by some summary statistics even in the presence of substantial heterogeneity in the population.

Empirical applications can avoid the calculation of the equilibrium, and its computational burden, but they either require estimating $\Pr(\mathbf{s}_{t+1}|\mathbf{s}_t)$ from the data (Pakes, Ostrovsky and Berry, forthcoming) or estimating the policy functions $\sigma(\mathbf{s}, \varphi)$ (Bajari, Benkard and Levin, 2007). However, if the industry state is large, since it does not solve the 'curse of dimensionality', it will require a very large amount of data to flexibly estimate either $\Pr(\mathbf{s}_{t+1}|\mathbf{s}_t)$ or $\sigma(\mathbf{s}, \varphi)$. Estimating very flexible policies can lead to serious bias in the second stage estimates which

[10]Notice that the aggregate state is the payoff relevant variable and the role of the individual states is only to be informationally relevant.

arise because the first stage parameters enter nonlinearly in the second stage. Therefore any error in the first stage can be greatly magnified into the second stage (Aguirregabiria and Mira, 2007). In an empirical application to the Portland Cement Industry, Ryan (2005) used the sum of competitors capacities as the state variable rather than the individual capacities of competitors. While doing this for tractability reasons, it is using a similar approach to what I propose here, since players strategies are of the form $\sigma(s, S, \varphi)$ instead of $\sigma(\mathrm{s}, \varphi)$.

Assumptions 2.1 and 2.3 might be seen as restrictive in some settings.[11] The first is satisfied by most reduced form profit functions whenever S is payoff relevant. The algorithm is therefore flexible enough to allow different demand structures provided the aggregate state is the payoff relevant variable.

The second assumption is more restrictive as it imposes that firms do not observe each other's states (and actions) and also that history of the aggregate state is irrelevant conditional on the current state. For example, imagine the state variable is price, this means that firms observe industry aggregate prices (e.g. published by some entity) but they do not observe other firms individual prices because this would involve incurring in costly market research. This might not be restrictive since in some industries firms try to keep their prices secret.

In industries where there are market leaders, Assumption 2.1 will not hold. However, the model can be extended in these cases by enlarging the state space to include the state of the market leaders. Instead of one there are two problems to solve, one for the leader and one for all other firms and the state space becomes (s_{it}, S_t, s_{Lt}) where s_{Lt} is the state of the leader. Even though this seems logical, one would still need to check what the equilibrium resulting from players using these strategies looks like, which might not be a trivial extension of the work I

[11] Assumption 2.2 ('no spillover') is standard in the literature and it allows us to write down the transition for the individual state conditional on the firms' actions independently of the other firms' action/states.

presented here.

Once $q(S_{t+1}|S_t)$ is known the problem can be represented as a standard dynamic programming problem which can be estimated with available techniques for single agent models (Rust (1987), Hotz and Miller (1993), Aguirregabiria and Mira (2002)) or using estimators developed for dynamic games (Aguirregabiria and Mira, 2007; Bajari, Benkard and Levin, 2007; Pakes, Ostrovsky and Berry, forthcoming; Pesendorfer and Schmidt-Dengler, forthcoming).

2.A Appendix

2.A.1 Auxiliary Lemmas

Lemma 2.1 *$s_{it}|S_t$ is independently and identically distributed across firms with density function $g(s_{it}|S_t; q)$.*

Proof. By the independence assumption (no spillovers).

Lemma 2.2 *The distribution $g(s_{it}|S_t)$ is continuous in s_{it} with positive densities and bounded support.*

Proof. $S_t = S(s_{1t}, ..., s_{Nt}) + \varepsilon_t$ with ε_t independent and identically distributed with cumulative function F_ε and bounded support. Then S_t is never perfectly informative and therefore $g(s_{it}|S_t) > 0 \ \forall s_{it}, S_t$.

2.A.2 Proof of Proposition 2.1

Proof. Using Assumptions 2.1 to 2.3, S_t is the payoff relevant variable and $g(\mathbf{s}_t|S_{t,}...S_0) = g(\mathbf{s}_t|S_t)$ the aggregate (industry) state transition is

$$f(S_{t+1}|S_t, S_{t-1}, ...) = \int_{\varepsilon_{t+1}, \mathbf{s}_{t+1}: S_{t+1} = S(\mathbf{s}_{t+1}) + \varepsilon_{t+1}} f(\mathbf{s}_{t+1}|S_t, ..., S_0) d\mathbf{s}_{t+1} d\Phi(\varepsilon_{t+1})$$

$$
\begin{aligned}
&= \int_{\varepsilon_{t+1}, \mathbf{s}_{t+1}: S_{t+1}=S(\mathbf{s}_{t+1})+\varepsilon_{t+1}} \int_{\mathbf{s}_t} p(\mathbf{s}_{t+1}|\mathbf{s}_t) g(d\mathbf{s}_t|S_t, ...S_0) d\mathbf{s}_{t+1} d\Phi(\varepsilon_{t+1}) \\
&= \int_{\varepsilon_{t+1}, \mathbf{s}_{t+1}: S_{t+1}=S(\mathbf{s}_{t+1})+\varepsilon_{t+1}} \int_{\mathbf{s}_t} p(\mathbf{s}_{t+1}|\mathbf{s}_t) g(d\mathbf{s}_t|S_t) d\mathbf{s}_{t+1} d\Phi(\varepsilon_{t+1}) \\
&= \int_{\varepsilon_{t+1}, \mathbf{s}_{t+1}: S_{t+1}=S(\mathbf{s}_{t+1})+\varepsilon_{t+1}} f(\mathbf{s}_{t+1}|S_t) d\mathbf{s}_{t+1} d\Phi(\varepsilon_{t+1}) \\
&= q(S_{t+1}|S_t)
\end{aligned}
$$

2.A.3 Sketch proof of Theorem 2.1

Preliminary Lemmas:

Rewriting the state transition

$$
\begin{aligned}
q(S_{t+1}|S_t) &= \int_{\mathbf{s}_{t+1}: S_{t+1}=S(\mathbf{s}_{t+1})+\varepsilon_{t+1}} f(d\mathbf{s}_{t+1}|S_t; q) d\Phi(\varepsilon_{t+1}) \qquad (2.2) \\
&= \int_{(\mathbf{s}_{t+1}): S_{t+1}=S(\mathbf{s}_{t+1})+\varepsilon_{t+1}} p(ds_{1t+1}|S_t; q) ... p(ds_{Nt}|S_t; q) d\Phi(\varepsilon_{t+1})
\end{aligned}
$$

$$
\begin{aligned}
p(s_{it+1}|S_t; q) &= \int_{s_{it}} p(s_{i,t+1}|s_{it}, a^c(s_{it}, S_t), \chi(s_{it}, S_t)) g(ds_{it}|S_t; q) \qquad (2.3) \\
&= \int_{s_{it}} \sum_{\iota_i \in \{0,1\}} p(s_{i,t+1}|s_{it}, a_{it}, \iota_i) \xi(S)^{\iota_i} (1 - \xi(S)^{(1-\iota_i)}) g(ds_{it}|S_t; q)
\end{aligned}
$$

where $\xi(S) = \int_s \chi(s, S) g(ds|S)$.

Lemma 2.3 *$V(s_{it}, S_t)$ is continuous in q.*

Proof. Follows from the definition of the Value Function 2.1 and the Envelope Theorem.

Lemma 2.4 *$a^c(s_{it}, S_t)$ is continuous in q.*

Proof. Standard dynamic programming argument.

Lemma 2.5 *$\xi(S_t)$ is continuous in q.*

Proof. Since $\xi(S) = \int_s \chi(s, S) g(ds|S)$.

$$\chi(s, S; q) = \begin{cases} 1 & \text{if } c \leq \bar{c}(s, S; q) \\ 0 & \text{otherwise} \end{cases}$$

Where we can define

$$\begin{aligned}
\bar{c}(s, S; q)/\rho &= \{E[V(s_{t+1}, S_{t+1})|a_t, \chi_t = 1] - E[V(s_{t+1}, S_{t+1})|a_t, \chi_t = 0]|s_t, S_t\} \\
&= \begin{bmatrix} \int_S \int_s V(s_{t+1}, S_{t+1}) p(s_{t+1}|s_t, a_t, \chi_t = 1) q(S_{t+1}|S_t) ds_t dS_t \\ - \int_S \int_s V(s_{t+1}, S_{t+1}) p(s_{t+1}|s_t, a_t, \chi_t = 0) q(S_{t+1}|S_t) ds_t dS_t \end{bmatrix} \\
&= \int_S \begin{bmatrix} \int_s V(s_{t+1}, S_{t+1}) p(s_{t+1}|s_t, a^c(s_t, S_t), \chi_t = 1) ds_t \\ - \int_s V(s_{t+1}, S_{t+1}) p(s_{t+1}|s_t, a^c(s_t, S_t), \chi_t = 0) ds_t \end{bmatrix} q(S_{t+1}|S_t) dS_t
\end{aligned}$$

and since $\bar{c}(s, S; q)$ is continuous in q (because V is continuous in q and $a^c(s, S)$ is also continuous in q), then $\xi(S)$ will also be continuous in q.

Conjecture 1 *$g(s_{it}|S_t)$ is continuous in q.*

Since $\bar{c}$ is continuous in q as shown above, this means that for a small change in q, there is only a small fraction of firms affected by this as $\bar{c}$ also changes only slightly due to continuity (remind that $a^c(s_{it}, S_t)$ is also continuous in q). This means that the steady state distribution for s_{it} will not have any discrete jump and is continuous in q.

Proof of Theorem 2.1. From Lemmas 2.3-2.5 and conjecture 1, $q(S_{t+1}|S_t) \in \Omega$ as defined in 2.2 and 2.3, is a continuous self map on a non-empty compact and convex set $\Omega \in \mathcal{BC}[\underline{S}, \bar{S}]$ to which Schauder's Fixed Point Theorem can be applied. This proves the result.

Chapter 3

Production Functions with Imperfect Competition

In this chapter I address two common problems in the production function estimation literature. I will then use this to estimate Total Factor Productivity (TFP) in the remaining chapters. The first problem is input endogeneity and the second is the use of deflated sales as a proxy for output when there is imperfect competition. Using a demand system and allowing input demand to depend on the individual state variables as well as on the industry equilibrium I explain how to jointly recover the production function parameters and demand elasticity.

I analyze the effect of specifying a fully dynamic equilibrium model on estimating the production function. The main problem that arises in an imperfect competition setting is that demand elasticity can no longer be recovered in the first stage as proposed by Levinsohn and Melitz (2005) and De Loecker (2007). This is due to the fact that input demand (either investment or materials) are functions of aggregate market conditions. I present evidence of the biased demand elasticity estimates.

3.1 Estimating production functions

The traditional approach to estimating production functions dates back to Cobb and Douglas (1928) and some of its problems, namely the endogeneity problem, have been detected since Marschak and Andrews (1944). Currently there have been some attempts to solve the input endogeneity problem either via productivity control function (Olley and Pakes, 1995, henceforth O&P; Levinsohn and Petrin, 2003, henceforth L&P) or via dynamic panel data techniques (Bond and Soderbom, 2005, henceforth B&S). A second problem has been the use of revenues instead of physical output when markets are not perfectly competitive (Klette and Griliches, 1996). Recently De Loecker (2007) and Levinsohn and Melitz (2005) have proposed a framework which accounts for the two problems jointly. In this chapter I show that the methodology is inconsistent with a industry dynamic equilibrium framework similar to Ericson and Pakes (1996). The main problem is that the demand elasticity cannot be recovered in the first step. I propose a way to deal with this problem by recovering demand elasticity in the second step.

Finally Buettner (2005) and Doraszelski and Jaumandreu (2007) propose alternative ways to relax the exogenous Markov process for productivity by allowing this to be controlled by R&D expenditures. In my case I allow productivity to follow a controlled Markov process of a special form which depends only on whether firms are R&D performers or not.

3.1.1 Demand

Using the Dixit-Stiglitz monopolistic competition framework demand can be written as:

$$Q_i = \tilde{Y}\tilde{P}^{\eta-1}P_i^{-\eta} \tag{3.1}$$

Where $\left(\frac{\tilde{Y}}{\tilde{P}}\right) = \frac{\sum_{i=1}^{N_t} P_i Q_i}{\tilde{P}}$ is total industry deflated revenues.

3.1.2 Production function

The production technology is assumed to be Cobb-Douglas with inputs capital (K), labor (L) and a given productivity factor (ω)

$$Q_i = e^{\omega_i} L_i^{\alpha} K_i^{\beta} \tag{3.2}$$

3.1.3 Productivity

Productivity is not directly observed but there are methods[1] to estimate it as the residual from a production function estimation (Olley and Pakes, 1995; Levinsohn and Petrin, 2003; De Loecker, 2007). To be consistent with the theoretical model developed in chapter 2 I use a methodology similar to De Loecker (2007) which allows me to recover both the production function parameters and the demand elasticity when one uses deflated sales instead of quantities. The main problem with De Loecker (2007) is that it only works if input demand does not depend on market conditions which is true in a static or a single agent model. The reason for the inconsistency arises from the fact that input demand function depend on the industry state, more precisely on the aggregate industry state. This means that the elasticity of demand cannot be recovered in the first step since the input demand is also a function of the aggregate state and can only be recovered in the second step together with the capital coefficient. To see this notice that sales are $P.Q$ so taking the logs and using (3.1) and (3.2) from above (lowercase letters denote logs of their uppercase counterparts):

[1]Ackerberg et al. (forthcoming) provide a survey on the literature for estimating production functions.

$$y_{it} = p_{it} + q_{it} = \frac{1}{\eta}\tilde{y}_t + \frac{\eta - 1}{\eta}\tilde{p}_t + \frac{\eta - 1}{\eta}(\omega_{it} + \alpha_k k_{it} + \alpha_l l_{it}) + \varepsilon_{it}$$

or

$$y_{it} - \tilde{p}_t = \frac{1}{\eta}(\tilde{y}_t - \tilde{p}_t) + \frac{\eta - 1}{\eta}(\omega_{it} + \alpha_k k_{it} + \alpha_l l_{it}) + \varepsilon_{it} \tag{3.3}$$

Instead of following directly De Loecker (2007), I use a version of his proposed technique but recover demand elasticity only in the second step. This is also similar to Levinsohn and Petrin (2003) using materials to control for the unobservable. The method is as follows. First, input demand is a function of individual states and the aggregate state.

$$m_{it} = m(\omega_{it}, k_{it}, R_{it}, \tilde{y}_t) \tag{3.4}$$

where R_{it} is a binary variable which denotes whether the firm is an R&D perfomer or not. Assuming invertibility this can be expressed as[2]

$$\omega_{it} = \omega(k_{it}, R_{it}, \tilde{y}_t, m_{it}) \tag{3.5}$$

and the unobservable is now a function of observables. Note however that since productivity is also a function of market conditions ($\tilde{y}_t$) in 3.4, demand elasticity (η) cannot be recovered in the first stage, because it enters non-parametrically in the control function 3.5. This is the main difference from De Loecker (2007) where input demand depends solely on individual state variables ($m_{it} = m(\omega_{it}, k_{it}, R_{it})$).

Imposing that productivity is governed by a controlled first order Markov

[2]A slight concern with invertibility and imperfect competition is the fact that with imperfect competition an increase in productivity might not lead to a direct increase in output and therefore in materials usage. For the demand system specified, an increase in productivity is equivalent to a decrease in costs and it translates directly into a decrease in prices (equation 4.21 in the Appendix to chapter 4). This means total output goes up and therefore also does materials usage.

process we get

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, R_{it-1}] + \nu_{it}$$

where ν_{it} is an independent and identically distributed random shock to productivity.

Stage I

From above we can rewrite the production function as (deflating sales with the industry wide price $\tilde{p}_t$, $y^p_{it} = y_{it} - \tilde{p}_t$)

$$\begin{aligned} y^p_{it} &= \frac{1}{\eta}\tilde{y}^p_t + \frac{\eta-1}{\eta}(\alpha_k k_{it} + \alpha_l l_{it}) + \frac{\eta-1}{\eta}\omega_{it} + \varepsilon_{it} \\ &= \frac{\eta-1}{\eta}\alpha_l l_{it} + \phi(k_{it}, R_{it}, \tilde{y}^p_t, m_{it}) + \varepsilon_{it} \end{aligned}$$

where

$$\phi(k_{it}, R_{it}, \tilde{y}^p_t, m_{it}) = \frac{1}{\eta}\tilde{y}^p_t + \frac{\eta-1}{\eta}\alpha_k k_{it} + \frac{\eta-1}{\eta}\omega(k_{it}, R_{it}, \tilde{y}^p, m_{it})$$

And we can estimate this non-parametrically using an nth-order polynomial. This provides estimates $\widehat{\frac{\eta-1}{\eta}\alpha_l}$ and $\hat{\phi}$.

Stage II

For the second stage I use the estimated values to construct

$$\hat{\phi}_{it} = \hat{y}_{it} - \widehat{\frac{\eta-1}{\eta}\alpha_l} l_{it}$$

with this we can construct an estimate of $\frac{\eta-1}{\eta}\omega_{it}$ for a given candidate $\widetilde{\frac{\eta-1}{\eta}\alpha_k}$ and $\widetilde{\frac{1}{\eta}}$

$$\widehat{\frac{\eta-1}{\eta}}\omega_{it} = \hat{\phi}_{it} - \widetilde{\frac{1}{\eta}}\tilde{y}_t + \widetilde{\frac{\eta-1}{\eta}}\alpha_k k_{it}$$

and approximate non-parametrically $E[\omega_{it}|\omega_{it-1}, R_{it-1}]$ with an nth-order polynomial

$$\begin{aligned}
y_{it} - \widehat{\frac{\eta-1}{\eta}}\alpha_l l_{it} &= \frac{1}{\eta}\tilde{y}_t + \frac{\eta-1}{\eta}\alpha_k k_{it} + E[\omega_{it}|\omega_{it-1}, R_{it-1}] + \nu_{it} + \varepsilon_{it} \qquad (3.6) \\
&= \frac{1}{\eta}\tilde{y}_t + \frac{\eta-1}{\eta}\alpha_k k_{it} + \\
&+ \left[\begin{array}{c} \gamma_0^0 + \gamma_1^0\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right) \\ +... + \gamma_n^0\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right)^n \end{array}\right] \times 1\left[R_{it-1} = 0\right] \\
&+ \left[\begin{array}{c} \gamma_0^1 + \gamma_1^1\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right) \\ +... + \gamma_n^1\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right)^n \end{array}\right] \times 1\left[R_{it-1} = 1\right] \\
&+\nu_{it} + \varepsilon_{it}
\end{aligned}$$

Using non-linear least squares allows us to finally recover an estimate for $\frac{1}{\eta}$ and $\frac{\eta-1}{\eta}\alpha_k$.

Potential problems in the second stage For the second stage estimation to work, the error term of equation (3.6), $\nu_{it} + \varepsilon_{it}$, must be uncorrelated with k_{it} and $\tilde{y}_t$. While this might be a reasonable assumption for k_{it} due to the timing of investment that makes k_{it} independent from 'news' in period t, the same is not necessarily true for $\tilde{y}_t$ if in the productivity shock ν_{it} there is an aggregate time component ν_t not captured by $E[\omega_{it}|\omega_{it-1}, R_{it-1}]$. One potential instrument is the use of lagged $\tilde{y}_{t-1}$.

I also acknowledge the criticism by Ackerberg, Caves and Frazer (2006) on the potential multicollinearity problem between l_{it} and $(k_{it}, R_{it}, \tilde{y}_t, m_{it})$. I estimate the production function as proposed by Ackerberg et al. (2006) by recovering the labor coefficient in the second step and the results remain almost unchanged. The multicollinearity problem might actually not be severe if all we want is to recover an estimate for productivity and not for the production function coefficients.

A further problem is the sample selection due to exit. As explained by Olley and Pakes (1995), this selection problem arises if big firms are more likely to exit upon a negative shock which generates negative correlation between productivity and capital stock for the firms which remain in the industry. However, this fact is likely to be relevant in industries with severe exit behavior, but it is unlikely that this is true for industries with little exit.

3.1.4 Dynamic panel data literature (adjustment costs)

Somehow related, the dynamic panel data adjustment cost literature has evolved using advanced dynamic panel data specifications. Bond and Soderbom (2005) propose an adjustment cost model that can solve the multicollinearity problems between labor and materials has explained also in Ackerberg, Caves and Frazer (2006)[3]. Productivity is assumed to follow a particular first-order autoregressive Markov process. Since they do not specify R&D into their model, for comparison purposes I just assume two different AR(1) processes for R&D and non-R&D firms

$$\omega_{it} = \begin{cases} \rho^0 \omega_{i,t-1} + \nu_{it} & \text{if } R_{i,t-1} = 0 \\ \rho^1 \omega_{i,t-1} + \nu_{it} & \text{if } R_{i,t-1} = 1 \end{cases}$$

This way quasi-differencing equation 3.3 above we get (where superscript p denotes deflated values and subscript j denotes R&D status)

[3] Doraszelski and Jaumadreu (2005) propose the use of a parametric input demand specification to solve this problem. This parametric form arises naturally for the Cobb-Douglas production function case .

$$
\begin{aligned}
y_{it}^{p}-\rho^{j}y_{i,t-1}^{p} &= \frac{1}{\eta}\left(\tilde{y}_{t}^{p}-\rho^{j}\tilde{y}_{t-1}^{p}\right) \\
&+\frac{\eta-1}{\eta}\left(\left(\omega_{it}-\rho^{j}\omega_{i,t-1}\right)+\alpha_{k}\left(k_{it}-\rho^{j}k_{i,t-1}\right)+\alpha_{l}\left(l_{it}-\rho^{j}l_{i,t-1}\right)\right) \\
&+\varepsilon_{it}-\rho^{j}\varepsilon_{i,t-1} \text{ for } j=0,1
\end{aligned}
$$

Or

$$
\begin{aligned}
y_{it}^{p}-\rho^{j}y_{i,t-1}^{p} &= \frac{1}{\eta}\left(\tilde{y}_{t}^{p}-\rho^{j}\tilde{y}_{t-1}^{p}\right) \\
&+\frac{\eta-1}{\eta}\left(\alpha_{k}\left(k_{it}-\rho^{j}k_{i,t-1}\right)+\alpha_{l}\left(l_{it}-\rho^{j}l_{i,t-1}\right)\right) \\
&+\frac{\eta-1}{\eta}\nu_{it}+\varepsilon_{it}-\rho^{j}\varepsilon_{i,t-1}
\end{aligned} \tag{3.7}
$$

which I estimate using a system GMM estimator for dynamic panel models. I do this in two stages. In the first stage I estimate the full equation without imposing the constraint on the lagged variables for $k_{it-1}, l_{it-1}, \tilde{y}_{t-1}$

$$
y_{it}^{p}=\pi_{0}^{j}y_{i,t-1}^{p}+\pi_{1}^{j}\tilde{y}_{t}^{p}+\pi_{2}^{j}\tilde{y}_{t-1}^{p}+\pi_{3}^{j}k_{it}+\pi_{4}^{j}k_{i,t-1}+\pi_{5}^{j}l_{it}+\pi_{6}^{j}l_{i,t-1}+\tilde{\nu}_{it}
$$

I recover an estimate for $\hat{\rho}^{j}=\hat{\pi}_{0}^{j}$ and in the second stage reestimate the model imposing the constraints on the parameters π^{j} from equation 3.7. I run this separately for R&D and non-R&D firms.

Dependent Variable: log of deflated value added	OLS						Fixed Effects					
	(i)			(ii)			(iii)			(iv)		
	Coef.	SE	Pval	Coef.	SE	Pval	Coef.	SE	Pval	Coef.	SE	Pval
$ln(L_{it}$	0.74	0.03	0.00	0.76	0.03	0.00	0.69	0.04	0.00	0.70	0.04	0.00
$ln(K_{it})$	0.24	0.02	0.00	0.23	0.02	0.00	0.25	0.03	0.00	0.22	0.03	0.00
$ln(Y_t)$	0.08	0.02	0.00	-	-	-	0.07	0.03	0.01	-	-	-
Const	6.36	0.26	0.00	7.69	0.23	0.00	6.53	0.27	0.00	7.80	0.32	0.00
Observations	1038			1038			1038			1038		
Firms	227			227			227			227		
Year dummies	No			Yes			No			Yes		
Labor Coef	0.80			0.76			0.74			0.70		
Capital Coef	0.27			0.23			0.27			0.22		
Returns to scale	1.07			0.99			1.01			0.93		
Price Cost Margin	0.08			-			0.07			-		

Notes: Columns (i) and (iii) report results without time dummies and columns (ii) and (iv) include time dummies

Table 3.1: Production function estimates using OLS and Fixed effects.

3.2 Results

In this section I compare the results for the alternative methodologies using data for the Portuguese Moulds Industry over the period 1994-2003 from a dataset collected by the Bank of Portugal.[4]

Table 3.1 contains the results for a simple OLS and fixed effects specification. In Table 3.2 I estimate the original O&P model using investment to control for productivity, using the original specification without time dummies in column (i) and with time dummies in column (ii), and allowing for imperfect competition recovering demand elasticity in the first stage (column (iii)) or in the second stage (column (iv)). Finally column (v) addresses the multicollinearity problem by recovering all the parameters in stage II. In Table 3.3 I reestimate the model using materials input to control for productivity as proposed by Levinsohn and Petrin. As for the O&P specification, columns (i) and (ii) assumes perfect competition, column (iii) estimates demand elasticity in the first stage, column (iv) allows materials demand to be a function of the aggregate state and recovers demand elasticity in the second stage. Finally column (v) addresses again the multicollinearity problem by recovering all the parameters in stage II. In Table 3.4 I estimate the dynamic production function model as proposed by Bond and Soderbom. Finally

[4]See Appendix 4.A.3 and Section 4.5 for a description of the data and variable construction.

Dependent Variable: log of deflated value added	(i) Coef.	SE	Pval	(ii) Coef.	SE	Pval	(iii) Coef.	SE	Pval	(iv) Coef.	SE	Pval	(v) Coef.	SE	Pval
$ln(L_{it}$	0.62	0.03	0.00	0.84	0.03	0.00	0.62	0.03	0.00	0.63	0.03	0.00	0.65	0.06	0.00
$ln(K_{it})$	0.06	0.04	0.09	0.27	0.02	0.00	0.07	0.04	0.08	0.07	0.03	0.05	0.00	0.04	0.91
$ln(Y_t)$							0.05	0.02	0.04	0.23	0.07	0.00	0.26	0.08	0.00
γ_{00}	-195.67	104.03	0.06	109.08	73.36	0.14	19.34	59.33	0.75	-32.31	27.25	0.24	-25.32	19.64	0.20
γ_{01}	58.96	31.89	0.07	56.60	41.14	0.17	-4.86	18.84	0.80	14.55	11.15	0.19	11.41	7.11	0.11
γ_{02}	-5.72	3.27	0.08	10.47	7.70	0.17	0.58	1.99	0.77	-1.89	1.57	0.23	-1.42	0.89	0.11
γ_{03}	0.19	0.11	0.09	0.65	0.48	0.18	-0.02	0.07	0.79	0.09	0.08	0.24	0.06	0.04	0.11
γ_{10}	-252.17	295.32	0.39	-219.54	443.04	0.62	-115.33	206.48	0.58	-90.76	87.68	0.30	-49.14	49.03	0.32
γ_{11}	72.88	85.22	0.39	-119.35	233.11	0.61	34.36	63.23	0.59	38.06	35.96	0.29	20.59	18.79	0.27
γ_{12}	-6.84	8.20	0.41	-21.02	40.88	0.61	-3.22	6.45	0.62	-5.03	5.03	0.32	-2.59	2.47	0.30
γ_{13}	0.22	0.26	0.41	-1.24	2.39	0.61	0.10	0.22	0.64	0.23	0.24	0.34	0.11	0.11	0.31
Observations	1038			1038			1038			1038			1038		
Firms	227			227			227			227			227		
Price Cost Margin							0.05			0.23			0.26		
Labor Coef.	0.62			0.84			0.65			0.83			0.88		
Capital Coef	0.06			0.27			0.07			0.09			0.01		
Returns to scale	0.68			1.10			0.72			0.92			0.89		

Notes: Columns (i) and (ii) present the results for the simple OP estimator with and without time dummis. Column (iii) uses the method proposed by De Loecker (2007) that allows for imperfect competition. Column (iv) allows for imperfect competition but acknowledges that the aggregate state is part of the investment function. Finally in column (v) acknowledges the multicolinearity problem and recovers all parameters in the second stage.

Table 3.2: Production function estimates using investment control (Olley and Pakes).

Table 3.5 provides a comparison for the different specifications.

The results in columns (vii) and (xii) of Table 3.5 confirm the bias in the estimates if demand elasticity is recovered in the first stage. The sign of the bias is a priori undetermined, however, a negative bias is consistent with a negative correlation between the aggregate demand shock and productivity (or positive correlation between average prices and productivity). This would be the case if for instance productivity, which can also be interpreted as quality, has a time component which is positively correlated with industry wide prices.

Notice also the bias in the labor and capital coefficients of both O&P and L&P in columns (v) and (x) when time dummies are not used and imperfect competition effects are not controlled for.

I have a preference for the L&P approach over O&P because of the labor coefficient bias in the first stage if the conditions for investment invertibility fail and productivity is not well controlled. This could be the cause of the upward bias in the labor coefficient with the O&P approach. Curiously, the Fixed Effect specification with time dummies in column (iv) performs very well and gives similar results to the preferred specification in column (xiii).

Using the methodology proposed by B&S the results for the capital and labor coefficients are similar. The only problem seems to be the estimate for demand elasticity. As for columns (vii) and (xii) this could be due to aggregate shocks being negatively correlated with productivity. Splitting the sample into R&D and non-R&D firms in columns (xvi) and (xvii) seems to suggest a higher mark-up for the R&D firms.

Note that the potential problem of multicollinearity using L&P as pointed out by Ackerberg et al (2006) and Bond and Soderbom (2005) does not seem to be a major concern since the labor coefficients recovered in the first stage are not significantly different from the ones using B&S (column (xv)). Also, the correction

Dependent Variable: log of deflated value added	(i)			(ii)			(iii)			(iv)			(v)		
	Coef.	SE	Pval	Coef.	SE	Pval	Coef.	SE	Pval	Coef.	SE	Pval	Coef.	SE	Pval
$ln(L_{it}$	0.58	0.03	0.00	0.73	0.03	0.00	0.61	0.03	0.00	0.61	0.03	0.00	0.61	0.06	0.00
$ln(K_{it})$	0.25	0.03	0.00	0.39	0.02	0.00	0.21	0.03	0.00	0.19	0.03	0.00	0.20	0.04	0.00
$ln(Y_t)$							0.09	0.03	0.00	0.19	0.05	0.00	0.23	0.08	0.01
γ_{00}	53.34	23.53	0.02	95.15	54.52	0.08	31.80	14.54	0.03	21.85	10.68	0.04	1.14	7.13	0.87
γ_{01}	-19.00	9.61	0.05	38.44	24.87	0.12	-12.20	6.72	0.07	-11.24	4.95	0.02	-0.18	4.42	0.97
γ_{02}	2.46	1.30	0.06	5.54	3.78	0.14	1.78	1.03	0.08	2.21	0.80	0.01	0.32	0.90	0.73
γ_{03}	-0.10	0.06	0.09	0.27	0.19	0.16	-0.08	0.05	0.14	-0.13	0.05	0.01	-0.03	0.06	0.68
γ_{10}	-379.86	540.11	0.48	-49.86	274.49	0.86	-369.55	400.58	0.36	-261.88	191.99	0.17	-59.72	70.25	0.40
γ_{11}	132.66	196.84	0.50	-24.78	119.22	0.84	144.29	164.11	0.38	123.35	89.73	0.17	33.69	36.53	0.36
γ_{12}	-15.19	23.89	0.53	-3.69	17.25	0.83	-18.50	22.38	0.41	-19.01	14.32	0.19	-5.92	6.60	0.37
γ_{13}	0.58	0.97	0.55	-0.18	0.83	0.83	0.80	1.02	0.43	0.98	0.78	0.21	0.35	0.41	0.39
Observations	1038			1038			1038			1038			1038		
Firms	227			227			227			227			227		
Price Cost Margin							0.09			0.19			0.23		
Labor Coef.	0.58			0.73			0.67			0.75			0.79		
Capital Coef	0.25			0.39			0.23			0.23			0.26		
Returns to scale	0.83			1.11			0.89			0.99			1.06		

Notes: Columns (i) and (ii) present the results for the simple LP estimator with and without time dummis. Column (iii) uses the method proposed by De Loecker (2007) that allows for imperfect competition. Column (iv) allows for imperfect competition but acknowledges that the aggregate state is part of the material demand function. Finally in column (v) acknowledges the multicolinearity problem and recovers all parameters in the second stage.

Table 3.3: Production function estimates using materials control (Levinsohn and Petrin).

Dependent Variable: log of deflated value added	(i)			(ii)			(iii)		
	Coef.	SE	Pval	Coef.	SE	Pval	Coef.	SE	Pval
$ln(L_{it})$	0.85	0.11	0.00	0.94	0.17	0.00	0.73	0.13	0.00
$ln(K_{it})$	0.22	0.09	0.01	0.23	0.10	0.02	0.27	0.09	0.00
$ln(Y_t)$	0.03	0.08	0.68	0.11	0.05	0.02	0.05	0.06	0.43
Const	4.11	0.47	0.00	3.16	0.65	0.00	3.78	0.35	0.00
Labor Coef	0.88			1.06			0.77		
Capital Coef	0.23			0.26			0.28		
Returns to scale	1.11			1.32			1.06		
ρ	0.42			0.41			-		
AR1 test	-3.73	0.00		-1.57	0.12		-4.22	0.00	
AR2 test	-0.26	0.79		1.20	0.23		-0.02	0.99	

Notes: Column (i) presents the results for the non-RD firms and column (ii) for the RD firms. Column (iii) reports results imposing same production function and demand for both RD and non-RD firms.

Table 3.4: Dynamic production function estimates with AR1 productivity.

proposed by Ackerberg et al. (2006) where the labor coefficient is recovered in stage II does not change the overall results as we can see from columns (ix) and (xiv).

3.3 Final comments

In this chapter I have addressed two common problems in the production function literature. The first is very well know and has been widely studied in the literature, relates to input endogeneity. The second is the problem of estimating production functions when competition is imperfect. Even though the problem has been addressed by Levinsohn and Melitz (2005) and De Loecker (2007), both have done this assuming input demand does not depend on industry conditions. If one expands this to a dynamic industry model, input demand will be a function of market conditions and demand elasticity can only be recovered in the second stage. I presented evidence that supports the bias in demand elasticity. One curious result is the good performance of a simple fixed effects specification with time dummies. I also have a preference for the Levinsohn and Petrin approach as compared to Olley and Pakes. This is due to the potential problems with investment inversion.

Methodology	(i) OLS	(ii)	(iii) Fixed Effects	(iv)	(v)	(vi)	(vii) Olley and Pakes	(viii)	(ix)	(x)	(xi)	(xii) Levinsohn and Petrin	(xiii)	(xiv)	(xv) Bond and Soderbom	(xvi)	(xvii)
Labor Coef	0.80	0.76	0.74	0.70	0.62	0.84	0.65	0.83	0.88	0.58	0.73	0.67	0.75	0.79	0.77	0.88	1.06
Capital Coef	0.27	0.23	0.27	0.22	0.06	0.27	0.07	0.09	0.01	0.25	0.39	0.23	0.23	0.26	0.28	0.23	0.26
Price Cost Margin	0.08	-	0.07	-	-	-	0.05	0.23	0.26	-	-	0.09	0.19	0.23	0.05	0.03	0.11
Returns to scale	1.07	0.99	1.01	0.93	0.68	1.10	0.72	0.92	0.89	0.83	1.11	0.89	0.99	1.06	1.06	1.11	1.32
Time dummies	No	Yes	No	Yes	No	Yes	No	No	No	No	Yes	No	No	No	No	No	No
Notes							(a)	(b)	(c)			(a)	(b)	(c)		(d)	(e)

(a) Imperfect competition, input demand independent on aggregate shocks
(b) Imperfect competition, input demand dependent on aggregate shocks
(c) Imperfect competition, input demand dependent on aggregate shocks, Multicolinearity correction
(d) Non-RD firms
(e) RD firms

Table 3.5: Summary table for production function estimates of labor, capital and demand elasticity coefficients using alternative methodologies.

Chapter 4

Recovering the Sunk Costs of R&D: The Moulds Industry Case

4.1 Introduction

Even in narrowly defined industries R&D firms coexist with non-R&D firms. Since most existing theories focus in the continuous R&D choice rather than the discrete decision, they predict that in general, either all or no firms perform R&D (e.g. Cohen and Klepper, 1996; Klette and Kortum, 2004; Vives, 2004). In this chapter I explore the discrete decision to become an R&D firm using the framework developed in chapter 2. This allows me to deal with the 'curse of dimensionality', typical of dynamic industry models. I achieve this by using an aggregate (payoff relevant) state to represent the state of the industry. This way, instead of keeping track of all individual competitors' state, each firm just observes individual state and the aggregate state, considerably reducing the size of the state space.

The *objective* in this chapter is quantifying the magnitude of R&D sunk costs and their implications for industry R&D and innovation. I will estimate the sunk costs of R&D in a fully dynamic setting and I find these to be of significant magnitude (about 1.7 times the yearly average sales of a firm in the industry) using a dynamic equilibrium framework for productivity and physical capital accumulation within a Monopolistic Competition setting.

In this area, several dynamic industry equilibrium models have been developed (Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Klette and Kortum, 2004). The most flexible of these models is the Ericson and Pakes (1995) since it allows for optimal R&D and investment choices. However, the model very easily becomes intractable due to the 'curse of dimensionality'. I will address this problem by summarizing the industry state in the aggregate (payoff relevant) state and estimate the model for a panel of firms in the Portuguese Moulds industry.

The literature on the estimation of dynamic industry models has received increased attention with alternative estimators developed (Aguirregabiria and Mira, 2007; Bajari, Benkard and Levin, 2007; Pakes, Ostrovsky and Berry, forthcoming; Pesendorfer and Schmidt-Dengler, forthcoming) and some successful applications to oligopolistic industries (Benkard, 2004; Ryan, 2005; Schmidt Dengler, 2007).

I use a forward simulation method similar to Hotz et al. (1994) as developed by Bajari, Benkard and Levin (2007) which allows for both continuous and discrete actions. The estimation is done in three steps. In the first two steps I recover the static parameters (production function, demand elasticity, policy function and transition functions). By assumption, estimated policies are profit maximizing conditional on the equilibrium being played, i.e. the equilibrium observed in the data. I can then estimate continuation values by simulating industry paths far enough in the future using the estimated policies and transitions. By slightly perturbing the estimated policy functions I "construct" non-optimal policies and simulate alternative (non-profit maximizing) continuation values. With these optimal and non-optimal simulated continuation values and exploring the property that the value function is linear in the dynamic parameters, I can recover the parameters by imposing the equilibrium condition, i.e., that optimal values must be larger than non-optimal values. The linearity of the value function in the dynamic parameters allows the forward simulation to be done only once and not for each parameter value. This greatly reduces the burden of computing continuation values for each parameter set speeding up the minimization routine.

The minimum distance estimator explores the optimality condition by searching for the parameters that minimize the cases where the values for the non-optimal policies are larger than the values for the estimated policies. These are the parameters which are consistent with actual behavior being near optimal.

One alternative I have not explored here is the possibility of using a nested fixed point estimator as proposed by Rust (1987). The reason why this is computationally feasible is because conditional on equilibrium beliefs for the evolution of the industry state, agents solve a simple dynamic programming problem with just a few state variables. The equilibrium beliefs can be directly recovered from the data and parameters estimated using a single agent approach.[1] However, contrary to the estimator I use here, the value function has to be solved for each parameter value, significantly increasing the estimation time from a few hours to some days or weeks of computations.

In order to implement the model, I directly test the validity of the assumptions. The main objective of introducing incomplete information into the model is to solve the 'curse of dimensionality' problem by summarizing the industry state distribution into the aggregate industry state. This allows the restriction to Markovian strategies on own state and aggregate (payoff relevant) industry state to work. Even restricting to these type of strategies, the aggregate state transition might, in general, be a higher order process. However, problems occur if the

[1] The main problem with such approach is its computational cost even for the single agent case when there are several individual state variables. The reason is because we have to recalculate the value function for each set of parameters.

(equilibrium) aggregate industry transition is not first order Markovian because we get history dependency and previous lags of the aggregate industry state add useful information about the expected future industry state. This can be checked by testing the significance of previous lags (t-2 and above) in predicting the aggregate state. An alternative I have also explored is to test the significance of further moments of the individual variables distribution in predicting the evolution of the aggregate state. If previous lags of the aggregate state and/or further moments of the individual variables distribution are not significant in predicting the aggregate industry state, the assumptions are valid and there is no evidence of model misspecification.

The data I use has been collected by the Bank of Portugal ("Central de Balanços") for the period 1994-2003. This industry competes in the international market and exports 90% of its production, mainly to the automotive industry. The strategy adopted by most players has been to reinforce strong links with clients, to develop new materials (product innovation) and minimize waste (process innovation). Given the state of the industry, to survive competition firms should perform R&D since according to the experts it is the only survival strategy in the long run. The sector has developed partnerships with universities to achieve this and has been quite successful internationally. However, only a fraction of firms (around 40% in my sample for the year 2003) report positive R&D expenditures. Some under reporting could be occurring because the accounting rules to qualify as R&D expenditures are quite restrictive. However, under reporting by itself cannot explain such large fraction of firms not reporting R&D. I argue that sunk costs of R&D are significant, especially in this industry populated by many micro firms. Since the industry is populated by many small firms and the products and prices are contract specific, it fits very well in the assumptions for the theoretical model outlined in chapter 2.

The Portuguese Moulds industry has been very successful and is recognized worldwide for its quality standards, technology and competitive prices. A 2002 report by the US international trade commission (USITC, 2002) emphasizes the fast delivery, technology, quality and competitive price as the main strengths of the Portuguese Moulds Industry. There has been also a considerable effort in moving upstream in the value chain by supplying design and prototyping services jointly with moulds making. Some firms have also developed new materials with specific properties for making the moulds. This creates value for the clients since it allows them to reduce the costs of producing the final product (both in terms of rejection of pieces with defects as well as speed of production). This upstream move and technology shift requires considerable investment in Research and Development and it significantly increases productivity. However, only 40% of the firms in my sample have reported to do this. Using the estimation approach explained above, I estimate the size of the Sunk Costs required to rationalize this wedge in productivity.

Firm evolution within the industry is very stylized. First, most are founded as spin-offs by ex-employees (managers and engineers) who launch their own business. This is normally done at a very small initial size (less than 10 workers). If the firm is successful and able to secure some client base, it grows by incremental investment in producing capacity. Later in the life cycle, it might decide to increase supply of services to design and prototyping and also develop new products and materials which can be achieved by performing R&D.

There is a considerable cost of becoming a pro-active firm who besides producing moulds, is also able to supply their clients with moulds conception and design skills, mould testing and development of new materials, all at a competitive price. A successful innovative firm should be able to produce not only the mould itself but also deliver all the pre and post production services required by their clients.

The costs can range from training and hiring of new employees, investment in new machinery and even the establishment of links with universities and public research agencies. These costs motivate the idea of sunkness since they cannot be recovered, particularly in this industry. Sunk costs can also easily explain why R&D firms are bigger than their non-R&D counterparts.

Sunk costs have for a long time been regarded as one potential source of inefficiency in the economy. The earlier literature puts most of the emphasis in the failure of the contestability theory in the presence of sunk entry costs. This results in market failures because the industry will not be competitive and firms can maintain some degree of market power (Baumol and Willig, 1981; Stiglitz, 1987). The issue is of great importance for policy makers and regulators since the existence of sunk costs results in a market failure which induces the need for policy intervention.

Sunk costs of R&D, in particular, have been widely studied in the industrial organization literature, especially following the work by Sutton (1991, 1998). The main purpose of this research was to explore the relationship between R&D and market structure. Particularly, firms can use R&D as a strategic tool to create barriers to entry and maintain a dominant position even for large market size. One question raised by Schmalensee (1992) is how can an incumbent firm maintain a dominant position. In the cases R&D does not guarantee a permanent advantage, other firms can still leapfrog the incumbent because the barrier to entry will not last forever. However, the study of more complex dynamics for the outcome of R&D requires a fully dynamic model that goes beyond the two period approach. This type of framework however, was at the time in an early development stage. Dixit (1988) acknowledges this in his work

"Perhaps the most important aspect ignored here is the possibility of partial progress (state variables) in the R&D race. That has so far

proved intractable at any reasonably general level, but remains an important problem for future research". Dixit (1988: 326)

Finally, in the last section of this chapter, I evaluate the impact on investment, productivity and market structure of a reduction in the sunk costs of R&D. The results show that a 25% reduction in the sunk cost of R&D results in an expected 11% increase in average productivity and 18% increase in average capital stock.

4.2 Recovering the sunk costs

To estimate the sunk costs of R&D, I use a model where firms sell differentiated products in a Constant Elasticity of Substitution demand environment. They can invest in both physical capital and decide to engage in R&D for which they have to pay a sunk cost. This sunk cost can go from building an R&D lab to the costs involved in internally changing the firm's organization or even credit constraints. Finally potential entrants can enter and incumbents can exit.

4.2.1 State and action space

The state space s_{it} for firm i at time t is represented by four variables: Physical capital (K), productivity (ω), R&D status (R, where $R = 1$ denotes that the firm has built the R&D lab and $R = 0$ otherwise) and operating status (χ, where $\chi = 1$ denotes that the firm has decided to continue operations and $\chi = 0$ denotes that it is not operating).

$$s_{it} = (K_{it}, \omega_{it}, R_{it}, \chi_{it})$$

where $\omega_{it} \in \Omega$, a compact set on the real number line and $K_{it} \in \mathfrak{K}$, a compact set bounded below by 0. For the discrete decisions, $R_{it} \in \{0, 1\}, \chi_{it} \in \{0, 1\}$.

There are also stochastic shocks (privately observed by the firm and unobserved by the econometrician) including shocks to investment φ_{it}^{I} , to the sunk cost of R&D φ_{it}^{R}, and the scrap value φ_{it}^{S}. The vector of payoff shocks $\varphi_{it} = (\varphi_{it}^{I}, \varphi_{it}^{R}, \varphi_{it}^{S})$ are independent and identically distributed standard normal random variables.

After entering the industry, firms can invest in physical capital, pay a sunk cost and engage in R&D and finally decide on exiting from the industry. I denote the action space as a, where a superscript denotes either a continuous decision (c) such as investment levels or a discrete decision (d) such as starting an R&D lab or exiting the industry.

$$a_{it} = (a_{it}^{c}, a_{it}^{d}) = (I_{it}, R_{it+1}, \chi_{it+1})$$

Investment, $I_{it} \in \mathfrak{I}$ can be any non-negative number.

This generates a law of motion for the state variables that depends on the previous state and actions with density function

$$p(s_{it+1}|s_{it}, a_{it})$$

As will be discussed below, this law of motion will be stochastic for productivity and deterministic for all other state variables.

4.2.2 Parametrization

Per period returns are a primitive of the model which I specify as π_{it}. S_t is the aggregate industry state (such as the industry price index), ξ_{it} is an independent and identically distributed random transitory cash flow shock and φ_{it} is a vector of other stochastic shocks including price shocks to investment φ_{it}^{I} , to the sunk cost of R&D φ_{it}^{R}, and the scrap value φ_{it}^{S}. The vector of payoff shocks $\varphi_{it} = (\varphi_{it}^{I}, \varphi_{it}^{R}, \varphi_{it}^{S})$ are independent and identically distributed standard normal random

random variables.

I first define the demand and production functions and then, assuming Bertrand pricing, I solve for the reduced form period returns. The period return function satisfies Rust's (1987) conditional independence and additive separability assumptions

$$\pi(s_{it}, S_t, a_{it}, \varphi_{it}) = \tilde{\pi}(s_{it}, S_t, a_{it}, \xi_{it}) + \varphi_{it}(a_{it})$$

Demand

I use the representative consumer Dixit-Stiglitz monopolistic competition framework [2]. There are N_t available varieties each supplied by a different firm so there are N_t firms in the market and $N - N_t$ potential entrants. Consumers choose quantities of each variety Q_i to consume and pay P_i with the following preferences:

$$U\left(\left(\sum_i Q_{it}{}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, Z_t\right)$$

where $U(.)$ is differentiable and quasi-concave and Z represents an aggregate industry utility shifter. Under these conditions the aggregate price index is

$$\tilde{P}_t = \left(\sum_{i=1}^{N_t} P_{it}^{-(\eta-1)}\right)^{-\frac{1}{\eta-1}} \tag{4.1}$$

and the firm's demand is [see Appendix 4.A.1]

$$Q_{it} = \tilde{Y}_t \tilde{P}_t^{\eta-1} P_i^{-\eta} \tag{4.2}$$

Where $\left(\frac{\tilde{Y}}{\tilde{P}}\right) = \frac{\sum_{i=1}^{N_t} P_{it} Q_{it}}{\tilde{P}}$ is total industry deflated revenues. If the goods were

[2] The model also works with other demand structures. A monopolistic competition framework is well adjusted for the cases when we do not observe firm level prices. More complex demand structures can be used when individual price data is available.

perfect substitutes (η is infinite), then there can be no variations in adjusted prices across firms, $P_i = \tilde{P}$ and $\frac{\tilde{Y}_i}{\tilde{P}} = Q_i$ for all firms.

Production function

The production technology is assumed to be Cobb-Douglas where L is labor input:

$$Q_i = e^{\omega_i} L_i^{\alpha} K_i^{\beta} \tag{4.3}$$

Since gross flow profits are $\tilde{\pi} = [P(Q_{it})Q_{it} - wL_{it}]\, \xi_{it}$ (w is the wage rate), so maximizing out for labor, this becomes:[3]

$$\tilde{\pi}(\omega_{it}, K_{it}, S_t; \eta, \beta) = \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\tilde{Y}_t \frac{\left(e^{\omega_{it}} K_{it}^{\beta}\right)^{\gamma}}{\sum_j \left[\omega_{jt} K_{jt}^{\beta}\right]^{\gamma}} \xi_{it} \tag{4.4}$$

where $\gamma = (\eta-1)/(\eta-\alpha(\eta-1))$. Notice that since in the short run, productivity and physical capital are fixed, the only way to adjust production is through labor which is assumed to be perfectly flexible. I log-linearize this equation and estimate

$$\ln \tilde{\pi}_{it} = \alpha_0 + \alpha_1 \omega_{it} + \alpha_2 \ln K_{it} + \alpha_3 \ln S_t + \ln \xi_{it} \tag{4.5}$$

Productivity and R&D

I assume that productivity evolves stochastically with a different distribution for R&D performing and non-R&D performing firms. Firms who have built an R&D lab draw a productivity distribution that stochastically dominates that (in a first-order sense) of non-R&D firms. In general, product and process innovation are difficult to disentangle from each other unless one has firm level price data

[3] See Appendix 4.A.2.

(e.g. Foster, Haltiwanger and Syverson, 2008). Since in my data I do not have firm level price data I consider them to be indistinguishable in the model and restrict the analysis to the effect on productivity, ω. The model can however be extended to allow for quality in the demand specification (see Melitz, 2000). This distinction would be important to model other type of phenomena like dynamic pricing, where the effects of product and process innovation would be qualitatively different.

This 'internal' source of uncertainty distinguishes R&D investment from other firm's decisions like capital investment, labor hiring, entry and exit which have deterministic outcomes and where the only source of uncertainty is 'external' to the company (e.g. due to the environment, to competition, to demand, etc.). This distinction is important since the stochastic R&D outcome will determine (together with entry and exit) the stochastic nature of the equilibrium.

I assume that productivity follows a controled Markov process.

$$\omega_{it+1} = E(\omega_{it+1}|\omega_{it}, R_{it}) + \nu_{it}$$

where v_{it} is independently and identically distributed across firms and time.

Cost functions

Investment cost Investment costs are allowed to have a quadratic component (Hayashi 1982) and total irreversibility. I assume that investment costs ($C^K(I_t, K_{it-1})$) take the following form:

$$C^K(I_t, K_{it-1}) = \left[\mu_1 I_{it} + \mu_2 \frac{I_{it}^2}{K_{it-1}}\right] + \varphi_{it}^I I_{it} \text{ if } I_{it} > 0 \tag{4.6}$$

where $\mu_2 > 0$ indexes the degree of convexity and the 'price' of investment is $\mu_1 + \varphi_{it}^I > 0$.

R&D costs The firm has the choice of building an R&D lab at a sunk cost of $\lambda + \varphi_{it}^R$ where φ_{it}^R is an i.i.d. standard normal random variable. As discussed above I abstract away from the continuous R&D choice after building the R&D lab and assume that after building an R&D lab, R&D costs are a fixed proportion of firm sales. This is mainly for tractability so I do not need to keep track of another continuous policy function. However, the empirical literature tends to find that R&D intensity (R&D to sales ratio) is highly serial correlated - indeed Klette and Kortum (2004) take this as a stylized fact that they try and fit with their model. I assume that the process that determined period to period R&D flows leads to R&D being proportional to sales.

Notice that under these assumptions productivity evolves stochastically depending on whether the R&D sunk cost have been paid or not, i.e.

$$p(\omega_{i,t+1}|\omega_{it}, R_{it}, \chi_{it})$$

where $p(.)$ is the conditional probability of $\omega_{i,t+1}$ given ω_{it}, R_{it} and χ_{it}.

Entry cost Potential entrants are short lived and cannot delay entry. Upon entry, firms must pay a (privately observed) sunk entry fee of $Ent + \varphi_{it}^E$ to get a draw of ω with distribution $p(\omega_{t+1}|\chi_t = 0)$ next period. The capital stock level upon entry is fixed $K = \underline{K}$ and $R = 0$, i.e., firms enter the market with a capital stock of $\underline{K}$ and no R&D. Active firms take a value $\chi = 1$ and inactive firms $\chi = 0$.

Exit value Every period the firm has the option of exiting the industry and collect a scrap exit value of $e + \varphi_{it}^{scrap}$.

Payoff shocks The vector of payoff shocks $\varphi = (\varphi^I, \varphi^R, \varphi^E, \varphi^S)$ are i.i.d. standard normal.

State transition

As explained above productivity follows a controled Markov process. The capital stock depreciates at rate δ and investment add to the stock:

$$K_{i,t+1} = (1-\delta)K_{it} + I_{it}$$

If a firm decides to start R&D, the sunk cost is paid only once and does not need to be paid ever again while the firm stays in the industry:

$$R_{i,t+1} = \begin{cases} 1 & \text{if } R_{it} = 1 \\ 0 & \text{otherwise} \end{cases}$$

If a firm exits it sets $\chi_{i,t+1} = 0$ and if it enters it sets $\chi_{i,t+1} = 1$

$$\chi_{i,t+1} = \begin{cases} 1 & \begin{array}{c}\text{if } \chi_{it} = 0 \text{ and firm } i \text{ enters OR,} \\ \chi_{it} = 1 \text{ and firm } i \text{ stays}\end{array} \\ 0 & \begin{array}{c}\text{if } \chi_{it} = 0 \text{ and firm } i \text{ does not enter OR,} \\ \chi_{it} = 1 \text{ and firm } i \text{ exits}\end{array} \end{cases}$$

Period returns

Using the above specification I can write the per period return function

$$\pi(\omega_{it}, K_{it}, R_{it}, \chi_{it}, R_{it+1}, \chi_{it+1}, I_{it}, S_t) =$$
$$= \left\{ \begin{array}{c} \chi_{it} \left(\begin{array}{c} \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\tilde{Y}_t \frac{\left(\omega_{it}K_{it}^{\beta}\right)^{\gamma}}{\sum_j \left[\omega_{jt}K_{jt}^{\beta}\right]^{\gamma}} - \mu_1 I_{it} - \mu_2 I_{it}^2 - \varphi_{it}^I I_{it} \\ -(\lambda + \varphi_{it}^R)(R_{it+1} - R_{it})R_{it+1} + (1-\chi_{it+1})(e + \varphi_{it}^S) \end{array} \right) \\ -(1-\chi_{it})\chi_{it+1}(Ent + \varphi_{it}^E) \end{array} \right\}$$

Using the demand specified above (4.2) there are two 'external' variables which affect company's revenues. One is market size ($\tilde{Y}$) and the other is competitors' adjusted price index ($\tilde{P}$). Since individual prices are determined by productivity and physical capital ($P_i^* = P(\omega_i, K_i, \tilde{P}, \tilde{Y})$, see appendix), the price index is a mapping from individual firms' productivity and capital stock onto a pricing function so that I get the final result for the aggregate state variable

$$S_t = \tilde{Y}_t / \sum_j \left[\omega_{jt} K_{jt}^{\beta}\right]^{\gamma} \tag{4.7}$$

It is important to recall that as explained before, firms adjust production to maximize short run profits through the only flexible input, labor.

4.2.3 Value function

The value function for the firm is

$$V(s_{it}, S_t, \varphi_{it}; q) = \sup_{a \in \mathfrak{A}} \; h(s_{it}, S_s, \varphi_{it}, a_{it}, V_{it}; q)$$

where

$$\begin{aligned} & h(s_{it}, S_t, \varphi_{it}, a_{it}, V_{it}; q) \\ = \; & \tilde{\pi}(s_{it}, S_t, a_{it}) + \varphi_{it}(a_{it}) + \rho E\{V(s_{it+1}, S_{t+1}) | s_{it}, S_t, a_{it}; q\} \end{aligned}$$

s_{it} and a_{it} have been defined above and the expectation $E[.|s_{it}, S_t, a_{it}; q]$ is taken over $p(\omega_{t+1}|\chi_t = 0)q(S_{t+1}|S_t)$ if $\chi = 0$ and $p(\omega_{t+1}|\omega_t, R_t)q(S_{t+1}|S_t)$ if $\chi = 1$. So the firms decide on next period capital investment (K_{t+1}), R&D start-up (R_{t+1}) and next period operating status, i.e. entry and exit (χ_{t+1}).

Firms optimally choose their entry, exit, R&D and investment given the knowledge about the evolution of the industry $q(S_{t+1}|S_t)$.

There are two different value functions depending on the firm being an incumbent ($\chi_{it} = 1$) or a potential entrant ($\chi_{it} = 0$). For incumbents, the value function is the sum of current returns and the expected continuation value which depends on current individual state (s_{it}), current industry state (S_t) and actions taken (a_{it}). For the potential entrant the value function is either zero if it chooses to remain outside ($\chi_{it+1} = 0$) or the sum of the entry cost with the continuation value which depends on the aggregate industry state (S_t) and the entry state distribution ($p(s_{it+1}|\chi_{it} = 0)$).

4.3 The estimation procedure

There are currently several proposed alternatives to estimate dynamic industry models in the recent surge of estimation techniques which extend the work of Hotz and Miller (1993) for single agent models (see Pesendorfer and Schmidt-Dengler, forthcoming; Aguirregabiria and Mira, 2007; Bajari, Benkard and Levin, 2007; and Pakes, Ostrovsky and Berry, 2007). I will follow the technique developed by Bajari, Benkard and Levin (2007) since this allows for both discrete and continuous choices and is easily applicable to the model outlined above. This framework has been applied by Ryan (2006) to study the impact of environmental regulation changes on capacity investment for the cement industry in the US. The industry state is the sum of competitors' capacities rather than the individual capacities of competitors and this resembles the model I am about to estimate.

The estimation proceeds in three steps. In the first step I recover the unobserved productivity (ω_{it}) via estimation of the production function. I consider a number of ways of estimating the production function (including Olley and Pakes, 1996; Levinsohn and Petrin, 2002; Ackerberg et al, 2008, and Bond and Soderbom, 2005), but I find these are broadly similar (see chapter 3). In the second step, I recover the profit function $(\pi(\omega_{it}, K_{it}, S_t)$ as well as the micro-level and industry-level state transitions, $(p(\omega_{it+1}|\omega_{it}, R_{it}, \chi_{it})$ and $q(S_{t+1}|S_t))$. I also estimate the equilibrium policy functions for investment, R&D and exit non-parametrically using a polynomial expansion in the state variables. Finally, in the third step, I impose the equilibrium conditions to estimate the linear and quadratic investment cost parameters, R&D sunk costs and exit costs i.e. the parameter vector $(\mu_1, \mu_2, \lambda, e)$.

By simulating actions and states from a starting configuration using the estimated policies and state transitions, and collecting these paths through time, I can calculate the present value for a given path and a given set of parameters. Slightly perturbing the policy functions allows me to generate alternative paths and different present-values for a given parameter vector. The observed policy functions were generated by profit-maximizing firms who chose the actions with the highest expected discounted value. This means that at the true parameters, the discounted value generated by the observed actions should be greater than those generated by any other set of actions. Particularly, at the true parameters, the perturbed actions should give a lower expected value and this is the equilibrium condition which identifies the structural parameters.

My main interest is recovering the R&D sunk costs, λ. Getting a good estimate of sunk costs of R&D is important because these will determine R&D performance and consequently innovation and productivity which are topics of extreme importance for policy makers. Second, these will have an effect on market structure and competition as explained by Sutton (1998).

For most industries, the R&D/Sales ratio is not very high (between 2% and 5%). This is puzzling if we recall that only a fraction of the firms actually perform R&D. The reason must then be that either the returns to R&D are too low or that there are very high costs involved which prevent firms from engaging in R&D

(credit constraints could also be a cause and I will investigate this in the next chapter). With all dynamic cost parameters recovered, I can then do some policy analysis to study changes in the amount of R&D and industry structure when the sunk costs of R&D change.

One hotly debated (and unsolved) issue is the link between competition and R&D performance. Aghion et al. (2005) provide a theoretical explanation and some empirical evidence arguing that there is an inverted U-shape relationship between these two, whereby innovation is higher for mid levels of competition but lower for either very competitive or weakly competitive industries. Blundell, Griffith and Van Reenen (1999), by contrast, find that the pre-innovation effect dominates. However, since both market structure and R&D performance are jointly determined in equilibrium, it is not easy to disentangle these effects without a dynamic model that addresses the market structure endogeneity issue.

4.3.1 Step 1: Productivity

In the first two steps I recover the static parameters (production function, demand, policies and transitions). This then allows me to compute the per period returns, simulate actions for a given state using the estimated policies and update the states using the transitions which will be the hearth of the third step.

Productivity is not directly observed but there are methods[4] to estimate it as the residual from a production function estimation (Olley and Pakes, 1995; Levinsohn and Petrin, 2003; De Loecker, 2007). To be consistent with the theoretical model developed in chapter 2 I use a methodology similar to De Loecker (2007) which allows me to recover both the production function parameters and the demand elasticity when one uses deflated sales instead of quantities. The main

[4] Ackerberg et al. (forthcoming) provide a survey on the literature for estimating production functions.

problem with using the De Loecker (2007) method naively is that it only works if input demand does not depend on market conditions which is true in a static or a single agent model. The reason for the inconsistency arises from the fact that input demand function depend on the industry state, more precisely on the aggregate industry state. This means that the elasticity of demand cannot be recovered in the first step since the input demand is also a function of the aggregate state and can only be recovered in the second step together with the capital coefficient. To see this notice that sales are $P.Q$ so taking the logs and using (4.2) and (4.3) from above (lowercase letter denote logs of their uppercase counterparts):

$$y_{it} = p_{it} + q_{it} = \frac{1}{\eta}\tilde{y}_t + \frac{\eta-1}{\eta}\tilde{p}_t + \frac{\eta-1}{\eta}\left(\omega_{it} + \alpha_k k_{it} + \alpha_l l_{it}\right)$$

or

$$y_{it} - \tilde{p}_t = \frac{1}{\eta}(\tilde{y}_t - \tilde{p}_t) + \frac{\eta-1}{\eta}\left(\omega_{it} + \alpha_k k_{it} + \alpha_l l_{it}\right)$$

Instead of following directly De Loecker (2007), I use a version of his proposed technique but recover demand elasticity only in the second step. This is also similar to Levinsohn and Petrin (2003) using materials to control for the unobservable. The method is as follows. First, input demand is a function of individual states and the aggregate state

$$m_{it} = m(\omega_{it}, k_{it}, R_{it}, \tilde{y}_t) \tag{4.8}$$

Assuming invertibility this can be expressed as[5]

[5] A slight concern with invertibility and imperfect competition is the fact that with imperfect competition an increase in productivity might not lead to a direct increase in output and therefore in materials usage. For the demand system specified, an increase in productivity is equivalent to a decrease in costs and it translates directly into a decrease in prices (equation 4.21 in appendix). This means total output goes up and therefore also does materials usage.

$$\omega_{it} = \omega(k_{it}, R_{it}, \tilde{y}_t, m_{it}) \tag{4.9}$$

and the unobservable is now a function of observables. Note however that since productivity is also a function of market conditions ($\tilde{y}_t$) in 4.8, demand elasticity (η) cannot be recovered in the first stage, because it enters non-parametrically in the control function 4.9. This is the main difference from De Loecker (2007) where input demand depends solely on individual state variables ($m_{it} = m(\omega_{it}, k_{it}, R_{it})$).

Imposing that productivity is governed by a controlled first order Markov process we get

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, R_{it-1}] + \nu_{it}$$

where ν_{it} is an independent and identically distributed random shock to productivity.

Stage I From above we can rewrite the production function as (deflating sales with the industry wide price $\tilde{p}_t$, $y^p_{it} = y_{it} - \tilde{p}_t$)

$$\begin{aligned} y^p_{it} &= \frac{1}{\eta}\tilde{y}^p_t + \frac{\eta-1}{\eta}(\alpha_k k_{it} + \alpha_l l_{it}) + \frac{\eta-1}{\eta}\omega_{it} + \varepsilon_{it} \\ &= \frac{\eta-1}{\eta}\alpha_l l_{it} + \phi(k_{it}, R_{it}, \tilde{y}^p_t, m_{it}) + \varepsilon_{it} \end{aligned}$$

where

$$\phi(k_{it}, R_{it}, \tilde{y}^p_t, m_{it}) = \frac{1}{\eta}\tilde{y}^p_t + \frac{\eta-1}{\eta}\alpha_k k_{it} + \frac{\eta-1}{\eta}\omega(k_{it}, R_{it}, \tilde{y}^p, m_{it})$$

And we can estimate this non-parametrically using an nth-order polynomial. This provides estimates $\widehat{\frac{\eta-1}{\eta}\alpha_l}$ and $\hat{\phi}$.

Stage II For the second stage I use the estimated values to construct

$$\hat{\phi}_{it} = \hat{y}_{it} - \widehat{\frac{\eta-1}{\eta}\alpha_l} l_{it}$$

with this we can construct an estimate of $\frac{\eta-1}{\eta}\omega_{it}$ for a given candidate $\widetilde{\frac{\eta-1}{\eta}\alpha_k}$ and $\widetilde{\frac{1}{\eta}}$

$$\widehat{\frac{\eta-1}{\eta}\omega_{it}} = \hat{\phi}_{it} - \widetilde{\frac{1}{\eta}}\tilde{y}_t - \widetilde{\frac{\eta-1}{\eta}\alpha_k}k_{it}$$

Using this we can approximate non-parametrically $E[\omega_{it}|\omega_{it-1}, R_{it-1}]$ with an nth-order polynomial

$$\begin{aligned}
y_{it} - \widehat{\frac{\eta-1}{\eta}\alpha_l}l_{it} &= \frac{1}{\eta}\tilde{y}_t + \frac{\eta-1}{\eta}\alpha_k k_{it} + E[\omega_{it}|\omega_{it-1}, R_{it-1}] + \nu_{it} + \varepsilon_{it} \qquad (4.10)\\
&= \frac{1}{\eta}\tilde{y}_t + \frac{\eta-1}{\eta}\alpha_k k_{it} + \\
&\quad + \left[\begin{array}{c} \gamma_0^0 + \gamma_1^0\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right) \\ +\ldots + \gamma_n^0\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right)^n \end{array}\right] \times 1\left[R_{it-1} = 0\right]\\
&\quad + \left[\begin{array}{c} \gamma_0^1 + \gamma_1^1\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right) \\ +\ldots + \gamma_n^1\left(\hat{\phi}_{it-1} - \frac{1}{\eta}\tilde{y}_{t-1} - \frac{\eta-1}{\eta}\alpha_k k_{it-1}\right)^n \end{array}\right] \times 1\left[R_{it-1} = 1\right]\\
&\quad +\nu_{it} + \varepsilon_{it}
\end{aligned}$$

Using non-linear least squares allows us to finally recover an estimate for $\frac{1}{\eta}$ and $\frac{\eta-1}{\eta}\alpha_k$.

Potential problems of the second stage For the second stage estimation to work, the error term of equation (4.10), $\nu_{it} + \varepsilon_{it}$, must be uncorrelated with k_{it} and $\tilde{y}_t$. While this might be a reasonable assumption for k_{it} due to the timing of investment that makes k_{it} independent from 'news' in period t, the same is not necessarily true for $\tilde{y}_t$ if in the productivity shock ν_{it} there is an aggregate time component ν_t not captured by $E[\omega_{it}|\omega_{it-1}, R_{it-1}]$. One potential instrument is the use of lagged $\tilde{y}_{t-1}$.

I also acknowledge the criticism by Ackerberg, Caves and Frazer (2006) on the potential multicollinearity problem between l_{it} and $(k_{it}, R_{it}, \tilde{y}_t, m_{it})$. I estimate the production function as proposed by Ackerberg et al. (2006) by recovering the labor coefficient in the second step and the results remain almost unchanged. The multicollinearity problem might actually not be severe if all we want is to recover an estimate for productivity and not for the production function coefficients. To address this multicolinearity problem I also use the method proposed by Bond and Soderbom (2005).

A further problem is the sample selection due to exit. As explained by Olley and Pakes (1995), this selection problem arises if big firms are more likely to exit upon a negative shock which generates negative correlation between productivity and capital stock for the firms which remain in the industry. However, this fact is likely to be relevant in industries with severe exit behavior, but it is unlikely that this is true for industries with little exit.

4.3.2 Step 2: Policies and transitions

Policies

With all state variables recovered $(\omega, K, \tilde{Y}, R)$, the policy functions can be easily estimated. The investment function which results as the solution to the dynamic problem is

$$I_{it} = \frac{1}{2\mu_2}\left(\rho \frac{\partial E(V(s_{it+1}, \tilde{Y}_{t+1}|s_{it}, \tilde{Y}_t, R_{it}, a_{it}))}{\partial I_{it}} - \mu_1\right) - \frac{1}{2\mu_2}\varphi^I_{it} \qquad (4.11)$$

which I estimate separately for R&D and non-R&D firms as

$$i_{it} = P^n(\omega_{it}, K_{it}, \tilde{Y}_t, R_{it}) + \tilde{\varphi}^I_{it} \tag{4.12}$$

where $P^n(.)$ is an n^{th}-order polynomial. I have tried different degrees for the polynomials and there is a clear preference over polynomials with smaller degrees because they produce policy functions with less noise. Since errors in the policy functions enter nonlinearly in the third step, this can significantly bias the estimates in small samples.

For the R&D equation, I estimate it with a probit model where firms will decide to start doing R&D if

$$(\lambda + \varphi^R_{it}) < \rho \begin{bmatrix} E\{V(s_{it+1}, \tilde{Y}_{t+1}) | s_{it}, \tilde{Y}_t, I_{it}, R_{it+1} = 1\} \\ -E\{V(s_{it+1}, \tilde{Y}_{t+1}) | s_{it}, \tilde{Y}_t, I_{it}, R_{it+1} = 0\} \end{bmatrix}$$

So the probability that the firm starts performing R&D is

$$\begin{aligned} \Pr(R_{it+1} &= 1 | R_{it} = 0, s_{it}, \tilde{Y}_t, I_{it}) = \\ &\Pr\left(\varphi^R_{it} < -\lambda + \rho \begin{bmatrix} E\{V(s_{it+1}, \tilde{Y}_{t+1}) | R_{it+1} = 1\} \\ -E\{V(s_{it+1}, \tilde{Y}_{t+1}) | R_{it+1} = 0\} \end{bmatrix}\right) \end{aligned}$$

or since φ^R_{it} is assumed to be a standard normal random variable

$$\Pr(R_{it+1} = 1 | R_{it} = 0) = \Phi\left(-\lambda + \rho \begin{bmatrix} E\{V(s_{it+1}, \tilde{Y}_{t+1}) | R_{it+1} = 1\} \\ -E\{V(s_{it+1}, \tilde{Y}_{t+1}) | R_{it+1} = 0\} \end{bmatrix}\right)$$

which I approximate by

$$\Pr(R_{it+1} = 1 | R_{it} = 0) = \Phi\left(P^n(\omega_{it}, K_{it}, \tilde{Y}_t, R_{it})\right) \tag{4.13}$$

where again $P^n(.)$ is again an n^{th}order polynomial.

The exit function can be treated in a similar way resulting in

$$\Pr(\chi_{it+1} = 0 | \chi_{it} = 1) = \Phi\left(P^n(\omega_{it}, K_{it}, \tilde{Y}_t, R_{it})\right) \tag{4.14}$$

The transition function

Aggregate state From Corollary 2.2 the observed aggregate state has a conditional normal distribution with mean $\mu_{S_{t+1}|S_t} = (1 - \rho_S)\mu_S + \rho_S S$ and variance $\sigma_{S_{t+1}|S_t} = \sigma_S(1 - \rho_S^2)^{1/2}$. Where $(\mu_S, \sigma_S, \rho_S)$ are respectively the unconditional mean, variance and autocorrelation for the S process and are easily estimated from the data.

Productivity Since the model does not impose any parametric restrictions on the transition for individual productivity, I estimate it separately for R&D and non-R&D firms using a polynomial on lagged productivity $(g^{RD}(\omega_{i,t-1}), g^{NRD}(\omega_{i,t-1}))$.

$$\omega_{i,t+1} = E(\omega_{i,t+1} | \omega_{it}, R_{it}) + \varepsilon^R_{it+1} = \alpha^R_0 + \alpha^R_1\omega_{it} + \alpha^R_3\omega^2_{it} + \alpha^R_3\omega^3_{it} + \varepsilon^r_{it+1} \tag{4.15}$$

which is estimated separately for R&D firms and non-R&D firms

4.3.3 Step 3: Minimum distance estimator

Assuming the policy and transition functions are consistently estimated, starting from a state configuration (s_0, S_0), I can draw vectors of payoff shocks $\varphi = (\varphi^I, \varphi^R, \varphi^S)$, simulate actions (a_0) by reading off the estimated policy functions and update states (s_1, S_1) by reading off the estimated transition functions. Doing this for long periods (each path has been simulated for $\bar{T}$ periods), I compute a sequence of actions and states $\{a_t(s_0, S_0, \varphi_0), s_t(s_0, S_0), S_t(s_0, S_0)\}_{t=1}^{\bar{T}}$ from a starting configuration (I have used n_s different starting configuration combinations for (s_0, S_0)). With this sequence of actions and states, I can compute the discounted stream of profits for a given parameter vector θ and a given second step estimate for the policy and transition function $(\tilde{\alpha})$, $\sum_{t=0}^{\bar{T}} \rho^t \pi(a_t, s_t, S_t, \varphi_t; \tilde{\alpha}, \theta)$ which gives me an estimate of the expected value from a starting configuration $EV(s_0, S_0; \tilde{\alpha}, \theta) = \sum_{t=0}^{\bar{T}} \rho^t \pi(a_t, s_t, S_t, \varphi_t; \tilde{\alpha}, \theta)$.[6] For each starting configuration I simulate n_J different paths to get an average estimate

$$EV(s_0, S_0; \tilde{\alpha}, \theta) = \frac{1}{n_J} \sum_{j=1}^{n_J} \sum_{t=0}^{\bar{T}} \rho^t \pi(a_t^j, s_t^j, S_t^j, \varphi_t^j; \tilde{\alpha}, \theta)$$

In order for a strategy, σ, to be an equilibrium it must be that for all $\sigma' \neq \sigma$

$$V(s, S; \sigma, q(S_{t+1}|S_t); \theta) \geq V(s, S; \sigma', q(S_{t+1}|S_t); \theta)$$

So the set of dynamic parameters θ, must rationalize the strategy profile σ. I just consider the case where θ is point identified whereas Bajari et al. (2007) also develop the method for (bounds) set identification on θ.

Given the linearity of the value function on the dynamic parameters I can write

$$V(s, S; \sigma, q(S_{t+1}|S_t); \theta) = W(s, S; \sigma, q(S_{t+1}|S_t)) * \theta$$

where $W(s_t, S_t; \sigma, q(S_{t+1}|S_t)) = E_{\sigma|s_t, S_t} \sum_{s=t}^{\infty} \rho^s w_t$ and $\theta = [1, \mu_1, \mu_2, \lambda, e]$, $w_t = \left[\pi(s_s, S_s; \eta), I_s, I_s^2, \mathbf{1}(R_{s+1} = 1, R_s = 0), \mathbf{1}(\chi_{s+1} = 0, \chi_s = 1)\right]$.

I construct alternative investment, R&D and exit policies (σ') by drawing a

[6] I set the discount factor at $\rho = 0.92$ which is in line with other studies. The estimate for the sunk costs is sensitive to the choice of the discount factor. The magnitude of this effect is insignificant for my purpose.

mean-zero normal error and adding it to the estimated second step policies. With these non-optimal policies I construct alternative expected value following the same procedure as before to get $W(s_0, S_0; \sigma', Q(.))$ (I calculate these values for n_σ alternative policies).

I then compute the differences between the optimal and non-optimal value functions for several (X_k) policies and states $(X_k, k = 1, ...n_I)$, where $n_I = n_\sigma * n_s$

$$\hat{g}(x; \theta, \tilde{\alpha}) = \left[\hat{W}(s, S; \hat{\sigma}, \hat{q}(S_{t+1}|S_t)) - \hat{W}(s, S; \hat{\sigma}', \hat{q}(S_{t+1}|S_t))\right] * \theta$$

Since the estimated policies should be optimal, the expected value when using σ should be bigger then using alternative σ'. The empirical minimum difference estimator minimizes the square of the violations $(g(x, \theta, \tilde{\alpha}) < 0)$

$$\hat{J}(\theta; \tilde{\alpha}) = \frac{1}{n_I} \sum_{k=1}^{n_I} (\min \{\hat{g}(X_k; \theta, \tilde{\alpha}), 0\})^2$$

and

$$\hat{\theta} = \arg \min_{\theta \in \Theta} \frac{1}{n_I} \sum_{k=1}^{n_I} (\min \{g(X_k; \theta, \tilde{\alpha}), 0\})^2$$

Notice that I set the length of each path $\bar{T} = 100$, the number of starting configurations $n_s = 100$, the number of simulations for each configuration $n_J = 150$ and the number of alternative policies $n_\sigma = 200$, so that I get the number of differences $n_I = 20,000$

Standard errors

Since the estimated parameters in the first two steps are used in the third step, the standard errors of the parameters are determined by the first stage standard errors. The easiest way to estimate them is to use sub-sampling or the bootstrap. An important remark is that there is simulation error. Since bootstrapping requires very intense computations, the bootstrapped standard errors are an upper bound to the true standard errors since they are a mixture of estimation and simulation error.

Optimization

When the objective functions lacks smoothness (e.g. problems with discontinuous, non-differentiable, or stochastic objective functions) using derivative based methods might produce inaccurate solutions. For this reason, to minimize the empirical minimum distance ($\hat{J}$) I use a derivative free optimization method (Nelder-Mead) which circumvents this problem. Non-smoothness might occur with finite n_I, because of the min operator in the objective function, $\hat{J}$, which takes only the negative values of $g(.)$ and this creates discontinuities even if $g()$ is continuous in θ.

4.3.4 Identification

Identification of the static parameters follows the identification strategy used in De Loecker (2007) with the main difference that the demand elasticity cannot be recovered in the first stage since it enters the input demand function (in order to be consistent with the model above). Therefore, as explained above, both the capital coefficient and demand elasticity are recovered in the second stage.

The sunk costs of R&D are identified from the observed R&D decisions. Under the assumption that observed actions are profit maximizing, the sunk costs of R&D are identified through the comparison between observed (optimal) behavior and alternative (non-optimal) behavior. Given the observed profits earned by R&D firms and non-R&D firms, we can recover the value of being an R&D firm and compare this with the R&D behavior observed in the data. Similarly, investment costs and exit values are estimated from the observation of optimal behavior and comparing with non-optimal behavior. So the identification of the dynamic parameters is achieved by comparing actual with alternative actions. Note that if policies are estimated with error, the parameters might be incorrectly estimated. Because of this I have chosen polynomials of lower degree (1st and 2nd) to approximate the policy functions.

A second potential problem is that the parameters are only identified provided there are no unobservable state variables. This is actually a potential concern and a reason why one might consider the use of a fixed effects specification in the first step, an issue currently under research.

4.4 The moulds industry

The Portuguese moulds industry is a case study of success and ability to compete in a global environment. The industry exports 90% of its production and supplies 60% of its production to the very competitive car manufacturing industry accounting for more than 1% of total Portuguese Exports (CEFAMOL, 2005). The main advantage of the industry is the ability to produce complex moulds which require advanced technology at a low cost and high quality (USITC, 2002).

> "Despite Portugal's small size, it has emerged as one of the world's leading exporters of industrial molds. In 2001, despite limited production of dies, Portugal was the eighth largest producer of dies and molds in the world and it exports to more than 70 countries. The Portuguese TDM industry's success in exporting, and in adoption of the latest computer technologies, has occurred despite the fact that Portugal has a small industrial base on which the TDM industry can depend. Since joining the EU in 1986, Portugal has focused on serving customers in the common market." (USITC, 2002)

There has been a considerable effort of improvement and investment over the last 15 years. There has been three ways how firms have successfully improved performance and developed new skills. Firstly, there has been an upstream move in the value chain. By supplying design and propotyping services, the firms have been able to provide valuable services which reduce the cost of production to their clients. Secondly there has been an orientation towards lean manufacturing and waste minimization which has been influenced by clients in the car manufacturing industry and management practices adopted by them. Finally some firms have been in close contact with universities and research labs for the development of new materials. Even though this upstream move and technology shift requires considerable investment in Research and Development, only 40% of firms in the industry perform R&D and these firms are also considerably more productive (more then 40%).

The history of the industry dates back to the 1930's and 1940's when the development of plastics created a great demand for plastics' moulds. The Portuguese moulds industry started to fill this need in the late 1950's as a major producer of moulds for the glass (where it inherited some of its expertise) and specially for the toy manufacturing industry. Figures 4.1 and 4.2 provide some examples of what moulds looked like during this period. From the late 1970's there was a dramatic increase in production mainly driven by the export market, as reported in Figure 4.3, with the sector currently representing around 1% of the total country's exports. In the late 1980's the production shifted from toy manufacturing towards the growing industries of automobiles and packaging. Figure 4.4 shows the export composition (share of total exports), by main client/product type between 1984 and 2004 and it is clear the increasing importance of the Car Manufacturing industry and decreasing importance of the Toys and Home Electricals industries. During the 1990's the biggest export markets started shifting from the US towards

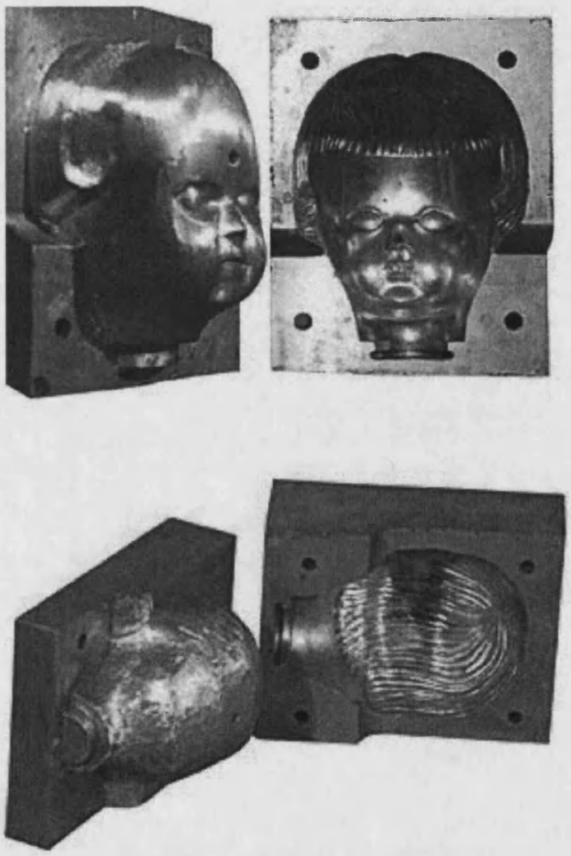


Figure 4.1: Plastics' moulds (1950's): Toy's head

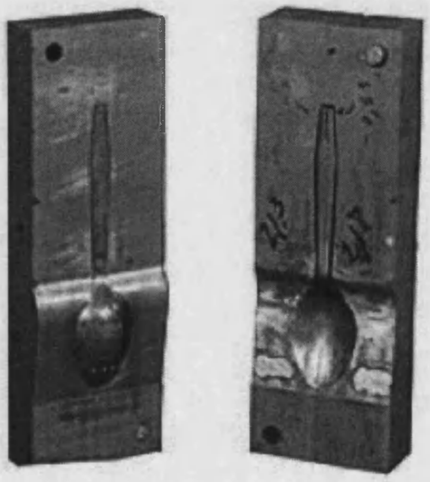


Figure 4.2: Metals' mould (1950's): Spoon

France, Germany and Spain. (IAPMEI, 2006).

During this period the industry suffered several changes both in terms of number of firms with a big increase in the early 1980's and a shift towards other main clients due to the boom of the plastics and packaging sectors. This put pressure for the introduction of new technologies (e.g. CAD, CAM, Complex process, In-mould Assembling) and an increasingly importance of innovation and R&D. For example, Figure 4.5 shows a computer operated machine for building moulds which is radically different from the techniques used in the 1970's and 1980's. This state of the art machinery allows flexibility at a low cost besides a close collaboration with the client in the pre mould construction phase. The design teams can work closely with the clients' engineers and produce 3D virtual versions of the mould which are then programed into the machine to start production.

The sector is mainly populated by small and medium firms as we can see from Figure 4.6. In 2004, Portugal was the 9th biggest world exporter and 3rd European exporter (Figure 4.7). The industry invests in R&D and has established close links

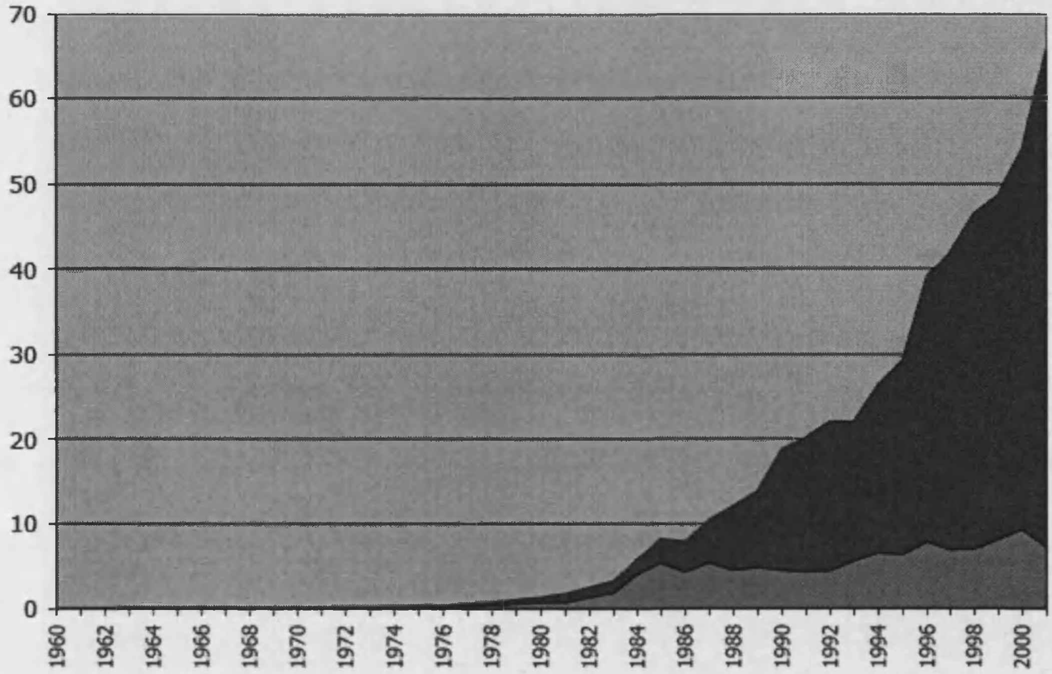


Figure 4.3: Portuguese moulds exports: World (blue) and US (green) totals 1960-2001 (millions of euros)

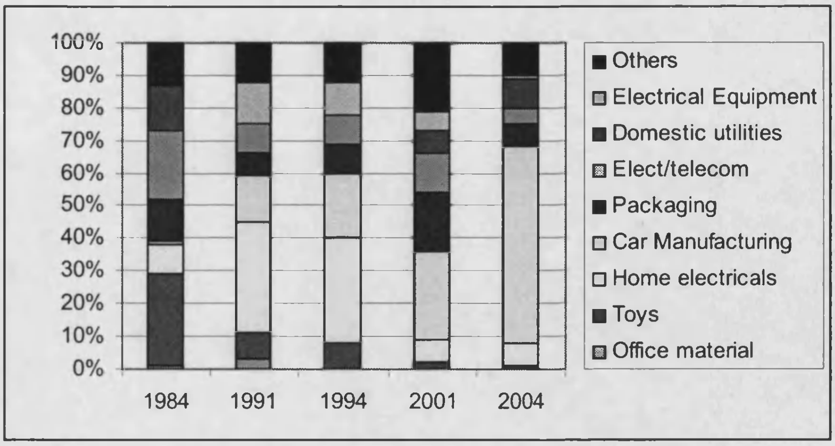


Figure 4.4: Portuguese moulds exports: Composition (share of total exports), by client/product type for 1984-2004

Figure 4.5: CNC (computer numerical control) machine used in production of moulds (2006)

with universities.

Wikipedia provides a quote about a Portuguese moulds manufacturer (SIMOLDES) which illustrates the importance of the industry:

> *Simoldes is a Portuguese mould maker company headquartered in Oliveira de Azeméis.*
>
> *Considered to be Europe's largest mould maker, Simoldes Group Mould* [redacted] *motive industry.* (http://en.wikipedia.org/wiki/Simoldes)

However, a puzzling fact about the Portuguese moulds industry (and most industries in general) is that only 40% of the firms in my sample in 2003 report positive R&D expenditures. With increasing competition from low wage countries.

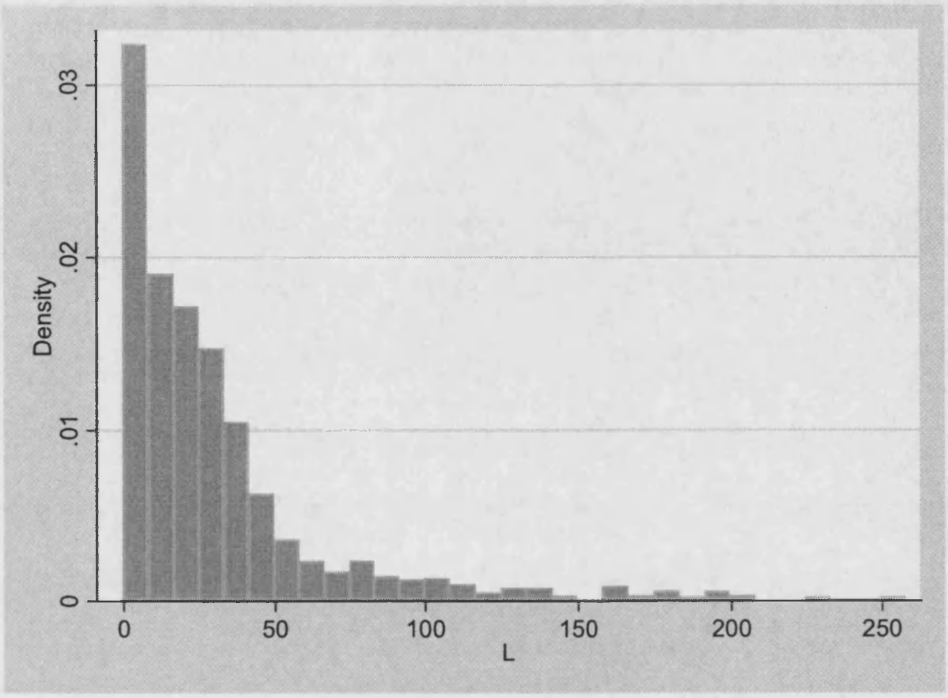


Figure 4.6: Firm size distribution: Number of workers per firm for the period 1994-2003

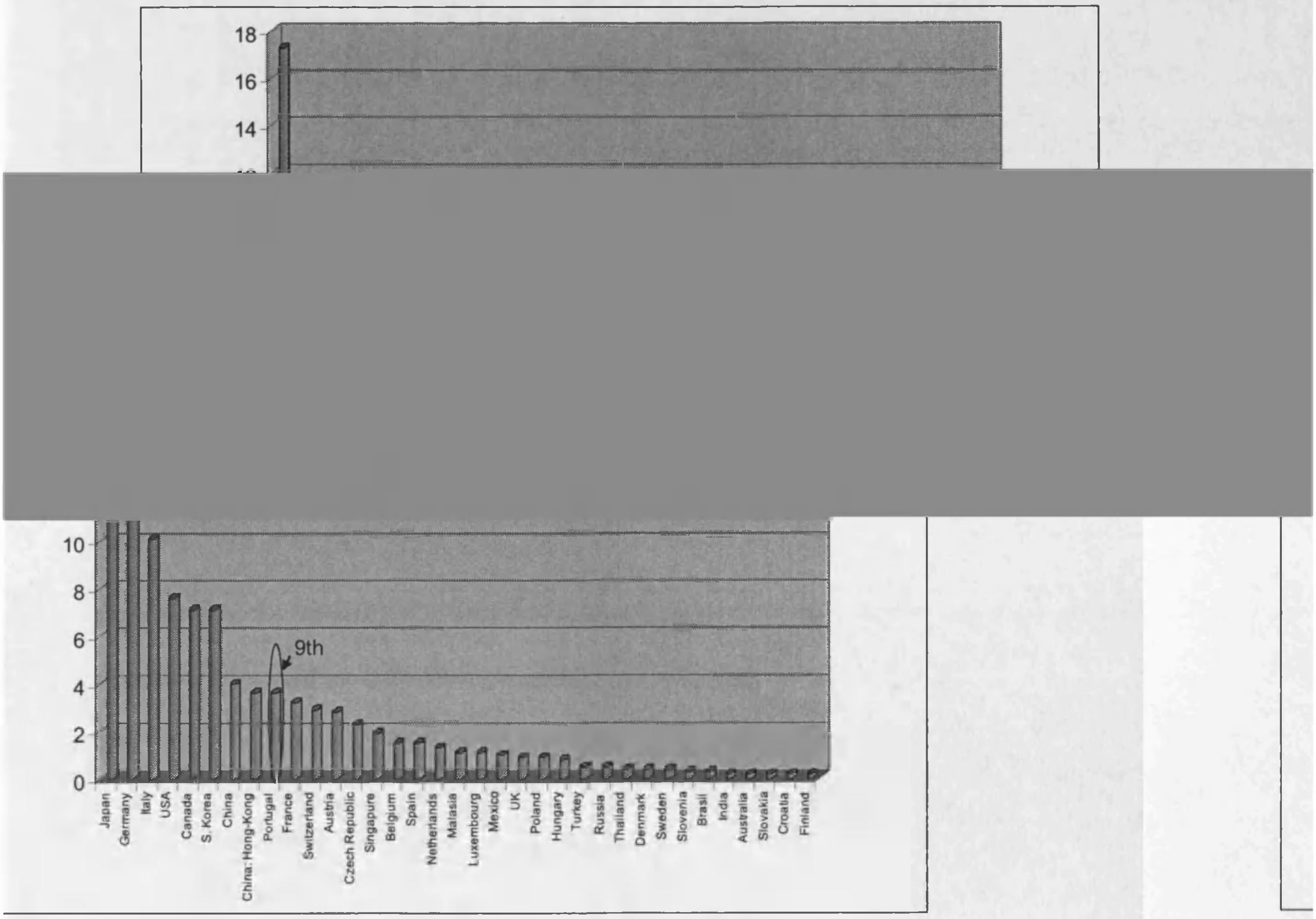


Figure 4.7: Moulds: World exports in 2004, % of total per country

firms not performing any R&D? The potential reason I will explore is the existence of R&D sunk costs.

Each mould is (quasi) unique, prices depend on the mould specification and are typically contract specific and agreed between the producer and the client. Therefore, individual prices are not observed but even if they were observable it would be difficult to compare them due to the product nature. Most firms establish close cooperative relations with their clients in order to improve product quality. Firms tend to specialize in a particular type of mould and therefore potential clients approach firms with the expertise in their product, but the technology is sufficiently flexible and allows them to produce most types of moulds. For this reason the industry fits very well within the monopolistic competition framework. This is appropriate since firms sell a differentiated product and along this product dimension they have some degree of market power. The assumption that firms react to aggregate movements in the industry and not to any particular competitor is not unreasonable because the market is quite fragmented. The incomplete information is not violated since firms do not directly observe their competitors prices or productivity. Because of all these facts, the industry fits very well in the framework developed in chapter 2.

I have observations for both large and small firms but I do not observe all firms in the market since the data is collected through a sampling procedure. These type of datasets are very common and as explained before the complete information model might have problems because of the non-observed players. However, for the incomplete information case, I just need to observe aggregate variables which are available from the National Statistics Office (INE). Another important advantage of the Portuguese Moulds Industry is the fact that I observe R&D behavior and this is what will identify the R&D sunk costs.

Year	Number of firms	Number of non RD firms	Number of RD firms	RD start-ups	Entry	Entry in the dataset	Exits
1994	144	134	10	-	2	3	0
1995	157	137	20	10	12	14	2
1996	165	141	24	4	8	14	0
1997	170	145	25	2	11	20	2
1998	164	135	29	7	9	33	0
1999	136	108	28	3	2	46	1
2000	92	68	24	7	2	8	0
2001	88	56	32	9	1	5	0
2002	88	53	35	4	1	2	0
2003	86	48	38	3	0	0	2
Total	1290	1025	265	49	48	145	7

Table 4.1: Firms, Entry, Exit and RD data, totals per year.

4.5 The data

The data is part of a database compiled yearly by the Portuguese Central Bank ("Central de Balanços"). I have extracted the observations for the period between 1994-2003 for the five-digit NACE (rev 1.1) industry, 29563. This database collects, financial information (balance sheet and P&L) together with other variables like number of workers, occupation of workers (5 levels), total exports, R&D, founding year and current operational status (e.g. operating, bankrupt, etc). I have also collected industry aggregate variables for sales, number of firms, employment and value added from the Portuguese National Statistics Office (INE, 2007) and industry price data from IAPMEI (2006).

4.5.1 Descriptive statistics

The dataset has 231 firms over the period 1994-2003 and 1,290 observations. There are 265 observations with positive R&D that corresponds to 59 firms. I observe 49 cases of R&D start-ups after 1994 (defined as a firm not reporting R&D ever before in the sample). On average, an R&D firm reports positive R&D for 2.5 consecutive years (Tables 4.1 and 4.2).

Due to the short nature of the panel, there are few observations on entry and exit. A further complication arises due to the way data has been collected. Since answering the questionnaire is not compulsory, some firms might not be reported in

Consecutive RD years	Number of firms
0	172
1	26
2	12
3	6
4	6
5	2
6	6
7	2
8	1

Table 4.2: RD spans: Number of consecutive years of positive reported RD.

the dataset but still be active in the industry. This complicates the identification of exiting firms and entrants since the firms might enter the dataset but could have been operating in the market before first appearing in the dataset. I address these problem with two variables that help to identify entry and exit. For entry, firms report their founding year so I match the founding year with the year the firm first appeared in the sample and if it is within a 2 year window I consider it to be a new entrant (this is reported in Table 4.1 under the column entry in the industry). Regarding exit, the central bank collects a variable that reports the "status" of the firm. The problem with this variable is that some firms that might have closed down are still reported as "active", so I can only capture a fraction of the total exits. Using this methodology I identify a total of 48 entries and 7 exits from the panel.

In Tables 4.3 and 4.4 I present some summary statistics for the main variables. The average firm in my sample sells 1.5 million Euros and employs 33 workers with an average labor productivity of 20,427 euros. Over the period 1994-2003, real sales have grown at an average 9.9% and labor productivity at 6%.

After a decline until 1998, the total number of firms in the industry has grown up to a maximum of 738 in 2003, employing 8,766 employees. The industry is populated by small and medium firms and there are no market leaders.

R&D performers are normally larger and older and their labour productivity is on average 20% higher.

Variable	Mean	P(50)	Std. Dev.	Min	Max
Sales (EUR)	1,575,080	699,394	2,869,985	3,292	34,700,000
Value Added (EUR)	795,083	390,753	1,439,538	494	15,200,000
Employment	33	20	39	1	258
Capital Stock (EUR)	785,655	296,575	1,551,721	135	15,500,000
Labor Productivity (EUR)	20,427	19,234	9,039	386	74,632
RD/Sales ratio	0.00	0.00	0.02	0.00	0.47
Sales growth	0.09	0.08	0.34	-1.69	4.69
Value added growth	0.10	0.07	0.39	-2.66	4.77
Labor productivity growth	0.06	0.05	0.35	-2.66	2.84
Non-RD firms					
Sales (EUR)	1,198,259	551,273	2,319,458	3,292	26,800,000
Value Added (EUR)	641,511	310,656	1,291,371	494	11,800,000
Employment	27	17	35	1	230
Capital Stock (EUR)	650,823	208,792	1,444,562	135	15,100,000
Labor Productivity (EUR)	19,663	18,239	9,178	386	74,632
RD/Sales ratio	0.00	0.00	0.00	0.00	0.00
Sales growth	0.10	0.09	0.37	-1.69	4.69
Value added growth	0.11	0.08	0.43	-2.66	4.77
Labor productivity growth	0.07	0.05	0.39	-2.66	2.84
RD firms					
Sales (EUR)	3,002,735	1,764,672	4,066,477	99,206	34,700,000
Value Added (EUR)	1,376,916	845,023	1,785,470	45,924	15,200,000
Employment	52	37	45	3	258
Capital Stock (EUR)	1,296,492	837,083	1,818,168	23,508	15,500,000
Labor Productivity (EUR)	23,321	22,462	7,861	7,148	59,923
RD/Sales ratio	0.01	0.00	0.03	0.00	0.47
Sales growth	0.06	0.06	0.20	-1.02	1.23
Value added growth	0.06	0.06	0.20	-1.13	1.02
Labor productivity growth	0.04	0.04	0.20	-0.87	1.17

Table 4.3: Summary statistics, all firms and by RD status.

Year	Number of firms	Employment	Sales (EUR)	VA (EUR)	Price Index	Price Variation	Sales Growth	VA growth
1994	644	5,133	171,300,000	152,600,000	96.7	-	-	-
1995	570	5,796	193,400,000	172,300,000	100.0	0.03	0.13	0.13
1996	452	7,316	244,200,000	217,500,000	101.8	0.02	0.26	0.26
1997	477	7,821	292,700,000	246,200,000	101.9	0.00	0.20	0.13
1998	461	7,740	322,400,000	258,800,000	97.5	-0.04	0.10	0.05
1999	549	8,429	362,200,000	277,300,000	99.9	0.02	0.12	0.07
2000	604	8,879	411,800,000	299,300,000	104.9	0.05	0.14	0.08
2001	612	8,919	421,000,000	368,800,000	105.9	0.01	0.02	0.23
2002	722	9,312	378,000,000	359,200,000	98.9	-0.07	-0.10	-0.03
2003	738	8,766	402,800,000	358,600,000	90.5	-0.08	0.07	0.00

Table 4.4: Aggregate variables, totals per year.

4.6 Results

4.6.1 Production function

Table 4.5 reports the results for the production function estimates using the methodology defined above. Because of problems that could arise in the first stage, and bias the estimates of α_L due to potential unobserved state variables, I have also tried using a fixed effects specification with no overall impact on the results.

The estimated labor and capital coefficients imply constant returns to scale while the estimated demand elasticity implies a price-cost margin of 19%. These values are at a reasonable level and within the range of parameters found in the literature for other industries. To test the method I also report the results using a range of specifications. The evidence seem to corroborate some of the findings by Bond and Soderbom (2005) according to which, in the presence of adjustment costs for the inputs and autocorrelation in productivity, consistent estimation of production functions parameters becomes possible by quasi-first differencing and using lagged levels of inputs as instruments. The only problem seems to be the estimates for demand elasticity.

In order for the firms to be willing to pay a sunk cost for R&D, it must be that they expect a higher productivity. To check if the productivity distribution for R&D firms stochastically dominates the distribution of productivity for the non-R&D firms I plot in Figure 4.8 the two distributions. As we can see, there is evidence that R&D firms have better productivity draws. TFP is on average 40% higher for R&D firms.

Methodology	(i) OLS	(ii)	(iii) Fixed Effects	(iv)	(v) Olley and Pakes	(vi)	(vii)	(viii)	(ix)	(x) Levinsohn and Petrin	(xi)	(xii)	(xiii)	(xiv)	(xv) Bond and Soderbom	(xvi)	(xvii)
Labor Coef	0.80	0.76	0.74	0.70	0.62	0.84	0.65	0.83	0.88	0.58	0.73	0.67	0.75	0.79	0.77	0.88	1.06
Capital Coef	0.27	0.23	0.27	0.22	0.06	0.27	0.07	0.09	0.01	0.25	0.39	0.23	0.23	0.26	0.28	0.23	0.26
Price Cost Margin	0.08	-	0.07	-	-	-	0.05	0.23	0.26	-	-	0.09	0.19	0.23	0.05	0.03	0.11
Returns to scale	1.07	0.99	1.01	0.93	0.68	1.10	0.72	0.92	0.89	0.83	1.11	0.89	0.99	1.06	1.06	1.11	1.32
Time dummies	No	Yes	No	Yes	No	Yes	No	No	No	No	Yes	No	No	No	No	No	No
Notes							(a)	(b)	(c)			(a)	(b)	(c)		(d)	(e)

(a) Imperfect competition, input demand independent on aggregate shocks
(b) Imperfect competition, input demand dependent on aggregate shocks
(c) Imperfect competition, input demand dependent on aggregate shocks, multicolinearity correction (Ackerberg, Caves and Frazer)
(d) Non-RD firms
(e) RD firms

Table 4.5: Summary table for production function estimates of labor, capital and demand elasticity coefficients using alternative methodologies.

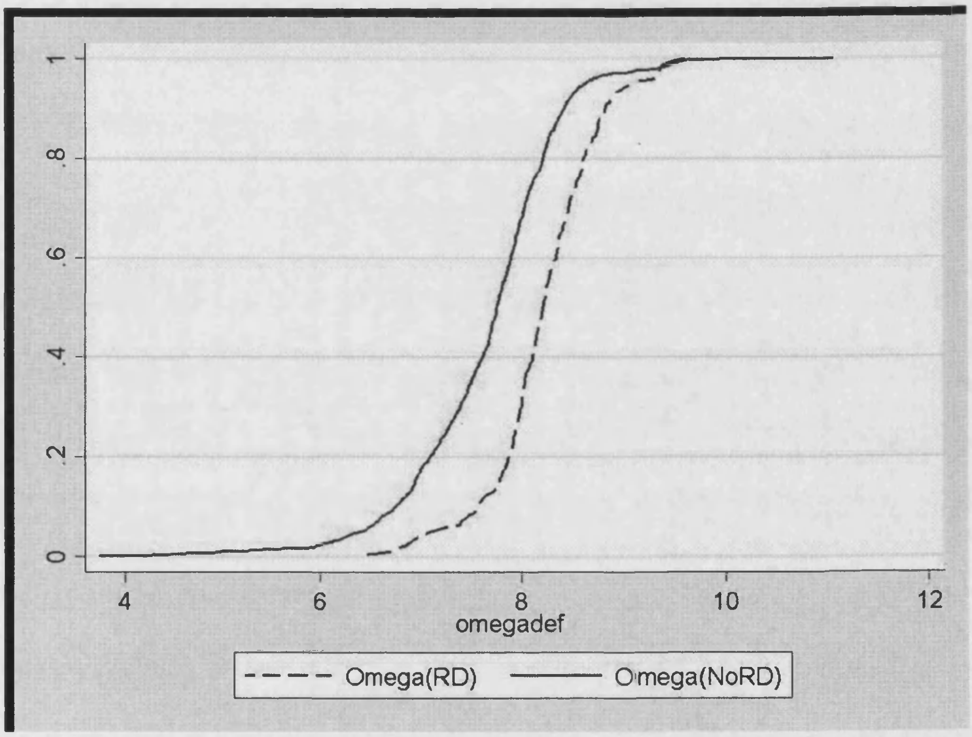


Figure 4.8: TFP distribution (CDF) for R&D and non-R&D firms

Dependent Variable: Aggregate State $ln(S)$	(i) Coef.	s.e.	(ii) Coef.	s.e.	(iii) Coef.	s.e.	(iv) Coef.	s.e.
$ln(S_{t-1})$	0.95	0.08	1.25	0.34	-2.33	7.34	570.85	598.06
$ln(S_{t-2})$			-0.35	0.32				
$ln(S_{t-1})^2$					0.10	0.23	-34.94	36.56
$ln(S_{t-1})^3$							0.71	0.74
Constant	1.01	1.23	1.76	1.50	27.66	59.81	-3096.74	3260.35
Observations	11		10		11		11	
Adjusted R Squared	0.946		0.9335		0.9474		0.9535	
Mean $ln(S)$	16.43							
St. Dev $ln(S)$	0.39							
Autocorrelation $ln(S)$	0.97							

Notes: Column (i) specifies a linear first order markov process and column (ii) a second order Markov process. Column (iii) and (iv) present results for a second and third degree polynomial.

Table 4.6: Tests on the aggregate state variable.

4.6.2 Transition function

Aggregate state

For the aggregate state, I calculate the mean, variance and autocorrelation and use Corollary 2.2 to specify the aggregate state transition. These are estimated at: $\hat{\mu}_S = 16.43$, $\hat{\sigma}_S = 0.39$, $\hat{\rho}_S = 0.97$.

Alternatively, we might not impose normality and estimate the transition, $q(S_{t+1}|S_t)$ directly. In Table 4.6 I report these results for a non-parametric approximation using a polynomial expansion.

Specification test Proposition 2.1 in chapter 2 contains the result that under some assumptions, the resulting equilibrium evolution for the aggregate state is Markovian. In this section I test the validity of this result. This is important to confirm (or reject) the model's assumption that allow using the aggregate state representation. The problem arises because even if players use Markovian strategies, the resulting equilibrium might not be first order Markovian. If Assumption 2.1 is violated, the use of one period lagged values of the aggregate variable is insufficient and potentially all history could matter leading to a time dependency problem. This is an important specification test of the model since the idea that the industry state can be summarized by the aggregate state is a crucial result to resolve the 'curse of dimensionality' problem.

In Table 4.7, I test the significance of previous lags of the state variable (which would constitute a violation of a first order Markovian process). I directly perform a test of the following implication of Proposition 2.1 in chapter 2

$$p(S_{t+1}|S_t, S_{t-1}, ...S_0) = p(S_{t+1}|S_t)$$

The results support the first order Markovian process for the industry state. I further investigate this by testing whether further moments of the state variables $(\ln(Y), \omega, \ln(K))$ are statistically significant conditional on S_t. This is actually a stronger test. To see this remember that the aggregate state is the payoff relevant variable. However, the individual competitors' states might be informationally relevant variables in the complete information model. Therefore testing their significance is similar to testing how far the aggregate state model is from the complete full information model. I test the following restriction

$$p(S_{t+1}|g(\mathrm{s}_t), S_t) = p(S_{t+1}|S_t)$$

In Table 4.7 we the results show that the second and third moments of the productivity, capital stock and sales distribution are not statistically significant, conditional on S_t,which again confirms the previous result. This gives me confidence in using the aggregate state model.

Productivity

For the individual productivity, I estimate a third order polynomial for ω separately for R&D and non R&D firms (equation 4.15) and results are shown in Table 4.8. R&D firms are on average 40% more productive and their productivity dispersion is also considerably smaller.

Dependent Variable: $ln[S_{t+1}]$	(i) Coef.	(i) *s.e.*	(ii) Coef.	(ii) *s.e.*	(iii) Coef.	(iii) *s.e.*	(iv) Coef.	(iv) *s.e.*	(v) Coef.	(v) *s.e.*	(vi) Coef.	(vi) *s.e.*	(vii) Coef.	(vii) *s.e.*	(viii) Coef.	(viii) *s.e.*
$ln[S]$	0.95	*0.08*	0.90	*0.09*	0.84	*0.09*	0.79	*0.10*	0.68	*0.18*	0.88	*0.07*	0.83	*0.08*	0.69	*0.20*
std($ln(Y)$)	-	-	-0.62	*0.59*	-	-	-	-	-	-	-	-	-	-	-1.77	*0.87*
skew($ln(Y)$)	-	-	-	-	-0.02	*0.18*	-	-	-	-	-	-	-	-	-0.68	*0.28*
std($ln(K)$)	-	-	-	-	-	-	0.49	*0.47*	-	-	-	-	-	-	-0.25	*0.83*
skew($ln(K)$)	-	-	-	-	-	-	-	-	-0.15	*0.15*	-	-	-	-	0.07	*0.13*
std(ω)	-	-	-	-	-	-	-	-	-	-	-0.58	*0.28*	-	-	0.07	*0.26*
skew(ω)	-	-	-	-	-	-	-	-	-	-	-	-	0.04	*0.05*	-0.12	*0.10*
const	1.01	*1.23*	2.64	*1.27*	2.65	*1.51*	2.81	*1.29*	5.14	*2.85*	2.50	*1.06*	2.83	*1.36*	7.46	*3.49*
Obs.	11		9		9		9		9		9		9		9	
R^2	94%		94%		92%		94%		94%		96%		93%		99%	

Notes: Column (i) specifies a linear first order markov process and columns (ii)-(viii) test the significance of further moments (standard deviation and skewness) of the distribution of log sales ($ln(Y)$), capital stock ($ln(K)$) and TFP (ω).

Table 4.7: Further tests on the aggregate state variable.

	(i) Non-RD firms		(ii) RD firms	
	Coef.	*s.e.*	Coef.	*s.e.*
$[\omega_{t-1}]$	0.72	*0.03*	0.75	*0.09*
$[\omega_{t-1}]^2$	0.16	*0.01*	0.07	*0.10*
$[\omega_{t-1}]^3$	-0.03	*0.01*	-0.01	*0.03*
constant	0.14	*0.03*	0.24	*0.05*
R-squared	67%		80%	
Obs.	784		254	
Firms	198		59	
S.E. Resid.	0.40		0.26	

Note: Results for the productivity transition using a 3rd degree polynomial

Table 4.8: Transition function for productivity, OLS results.

Investment, R&D and exit policies

The final part of the second step involves the estimation of the investment and R&D policy functions. These will be at the heart of the third step where it is imposed that they represent optimal behavior. I have used different degrees for the polynomials (1st, 2nd and 3rd) and opted for a 2nd order polynomial. The reason for doing so is because higher order polynomials can create more noise in the estimates and this is magnified in the third step as these variables enter non-linearly in the minimum distance estimator (Aguirregabiria and Mira, 2007).

The R&D policy function (equation 4.13) was estimated using a probit model whereas the investment policy function (equation 4.12) was estimated using OLS. For the exit policies due to data limitations, I have adopted a probit model only on productivity and aggregate sales.

The results are presented in Table 4.9. The probability of doing R&D is increasing in both productivity and capital stock, meaning that larger and more productive firms are more likely to pay the sunk cost probably because they are also able to extract a higher benefit from doing R&D. Regarding investment decisions, more productive firms tend to invest more and they are also less likely to exit the industry. This is all in line with previous findings.

	(i)		(ii)		(iii)		(iv)	
Dep. Var.	Investment				RD start-up		Exit Probit	
	RD firms		Non RD firms					
	Coef.	*s.e.*	Coef.	*s.e.*	Coef.	*s.e.*	Coef.	*s.e.*
$ln(S_{t-1})$	-0.36	*0.27*	-0.16	*0.20*	0.26	*0.25*	-0.02	*0.53*
$ln(K_{t-1})$	-2.08	*1.13*	1.20	*0.37*	0.16	*0.06*		
$ln(K_{t-1})^2$	0.10	*0.04*	-0.02	*0.02*	-	-	-	-
$[\omega_{t-1}]$	1.17	*0.37*	0.25	*0.10*	0.07	*0.14*	-0.17	*0.20*
$[\omega_{t-1}]^2$	-0.25	*0.13*	0.17	*0.06*	-	-	-	-
Constant	26.67	*8.90*	1.90	*3.98*	-7.90	*4.05*	-2.07	*8.66*
R Squared	53%		30%		4%		1%	
Observations	206		832		1038	832	1038	
Firms	51		213		264	213	224	

Notes: Columns (i) and (ii) contain results for the invesment OLS results for the non-RD and RD firms. Column (iii) contains results for the RD start-up probit regression. Finally column (iv) contains results for the exit probit regression.

Table 4.9: Estimated policy functions.

4.6.3 Main results

In the third step I use the minimum distance estimator outlined above to recover the linear and quadratic investment cost, R&D sunk cost and exit value, reported in Table 4.10. Standard errors were estimated using the bootstrap. As mentioned above, the bootstrapped standard errors are an upper bound to the true standard errors because they also incorporate simulation error which is present because of computational constraints. I have introduced per period R&D expenditures for firms who decide to do R&D at 1% of their sales level. This is a fixed cost component for any firm who choose to do R&D and has to be paid every period to keep the "R&D lab" operating. As explained above, this is consistent with some models where R&D is optimally chosen as a fixed proportion of total sales (e.g. Klette and Kortum, 2004).

The values are estimated with the expected signs. Specially, investment has positive quadratic adjustment costs. The exit value is positive and estimated at around 534,000 euros which is slightly higher then the average capital stock of exiting firms (420,684 EUR). Finally for the parameter we are interested in, the R&D sunk costs are estimated at about 2.6 million euros which is 1.7 times the average firm level sales in the industry and 87% the average sales of an R&D firm.

As explained above, bias in the policy function estimates will translate non-

	μ_1	μ_2	λ	e
Coefs	-0.46	5.77	2,598,000	-534,000
s.e.	*1.61*	*7.17*	*1,020,524*	*1,020,162*

Notes: Estimates for the dynamic parameters and bootstraped standard errors. These include simulation error and are an upper bound on true ones.

Table 4.10: Investment cost, RD sunk cost and exit value.

linearly in the dynamic parameter estimates. I have tried alternative specifications for the policy functions using different degrees for the polynomials. The estimated dynamic parameters are relatively robust to these alternative polynomials. One issue not addressed here and currently under research is the existence of unobserved state variables. This is a significant problem which might bias the estimates but the literature with methods for properly addressing it is still at an early stage.

4.7 Counterfactual experiments

In this section I perform a policy experiment where the sunk cost of R&D is exogenously decreased by 25% and access the impact of this change in industry R&D, productivity and investment. The simplest example of such a policy would be a direct R&D start-up subsidy but could be more broad like the creation of public research agency dedicated to advise firms during R&D start-ups or the supply of training to workers with very specific skills required to do R&D. These are probably more effective because some of the sunk costs might be duplication costs and a research agency would explore the economies of scale.

To achieve this I now need to solve the model. Particularly I have to find the new equilibrium industry evolution, $q(S_{t+1}|S_t)$. This requires defining entry costs and specifying the productivity distribution for entrants. I match these to the actual mean and variance for the productivity of entrants in my dataset and calibrate an entry value to get a consistent equilibrium average number of firms in the industry.

	$\lambda = 2,598,000$	$\lambda = 1,948,500$	change
Market size	*4,228,255*	*6,514,233*	*43%*
Number of firms	*267*	*227*	*-15%*
% of RD firms	*16%*	*33%*	*16%*
Average Productivity	*2.92*	*3.24*	*11%*
Average Capital Stock	*77,637*	*92,865*	*18%*
Entry Rate	*4%*	*5%*	*1%*
Exit Rate	*4%*	*5%*	*1%*

Notes: Simulated results for the impact on market structure of a 25% reduction in RD sunk costs

Table 4.11: Counterfactual results for a 25 percent reduction in sunk costs of RD.

After setting these I use the algorithm in Figure 2.1 to calculate the equilibrium for the model using the estimated structural parameters. Notice that these experiments could not be performed without using the aggregate state instead of the full industry state model. To solve the model in the complete information case with 300 firms in the market would be computationally impossible, but it is feasible and relatively fast in the "aggregate state" case.[7]

Results are presented in Table 4.11. The first point to notice is the decrease in the equilibrium number of firms. This happens because with lower sunk costs of R&D, more firms perform R&D and since R&D firms are larger, the average firm size increases and so the entry condition is met with less firms in the market. Secondly, there is an increase in the percentage of firms performing R&D, which doubles. This increase in the number of R&D firms translates into an increase in aggregate R&D, average productivity of 11% and average capital stock of 18%.

4.8 Final comments

In this chapter I have estimated the sunk costs of R&D for the Portuguese Moulds Industry using a model which is computationally tractable and possible to implement empirically with the most common firm level datasets. The model both avoids the 'curse of dimensionality' and the existence of unobserved firms in the data.

[7] Solving the model takes about 100 minutes of computer time on a 2.0 Ghz Pentium Core2 Duo with 2GB Memory RAM.

The idea I explored was to summarize the industry state into the payoff relevant aggregate state by introducing incomplete information in the model. As explained in chapter 2, this implicitly imposes more structure in terms of strategic interactions, specifically the firms react symmetrically to all its competitors. This is not restrictive for the moulds manufacturing industry because each firm specializes in a particular product, they do not observe what their competitors offer, firms produce almost per piece and prices are contract specific. This means that demand can be reasonably well approximated with a constant demand elasticity framework.

Finally I apply this setup to recover the sunk cost of R&D for the Portuguese moulds industry. I have estimated these to be about 2.6 million euros (or 1.7 times the average yearly firm sales level). The magnitude of the sunk costs suggest that policies cannot disregard the discreteness of the R&D decision. Particularly, policies targeted at reducing the sunk costs and increasing R&D start-ups will be effective at increasing industry productivity.

I have not explored two ways of making alternative use of the simplification introduced by the aggregate state model. First, since given the beliefs about the aggregate state evolution, the problem can be almost represented as a single agent one, I can apply the Nested Fixed Point Algorithm as developed in Rust (1987). The disadvantage is that the value function has to be solved for each parameter value, θ greatly increasing computational time.

Second, the existence of serially correlated unobserved variables might bias the second step estimates. This bias can be magnified in the third step because of the nonlinear relationship between the second and third step parameters. Aguirregabiria and Mira (2007) propose a method to deal with this which makes use of the equilibrium conditions. I have not explored the fact that since my model avoids the curse of dimensionality, I can recalculate the equilibrium for a given parameter set and use the equilibrium conditions in a similar way. A future line of research is to make use of these alternatives to increase the efficiency of the estimator.

4.A Appendix

4.A.1 Demand derivation

Assuming individuals have the following utility

$$U\left(\left(\sum_i Q_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, Z\right)$$

With $U(.)$ differentiable and quasi-concave and Z represents aggregate industry shifters.

Setting up the Lagrangian for $i = 1, ..., N$ $\left(\left(\sum_i Q_i^{\frac{\eta-1}{\eta}}\right) = \tilde{Q}\right)$

$$L = U\left(\left(\sum_i Q_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, Z\right) - \varpi\left(\sum P_i Q_i - \tilde{Y}\right)$$

Take the First Order Conditions

$$U_1^{\frac{1}{\eta-1}}\left(\sum_i Q_i^{\frac{\eta-1}{\eta}}\right) Q_i^{\frac{\eta-1}{\eta}} Q_i^{-1} = P_i \varpi \tag{4.16}$$

Rearranging

$$\left(\varpi^{-1} U_1^{\frac{1}{\eta-1}}\left(\sum_i Q_i^{\frac{\eta-1}{\eta}}\right)\right)^{\eta} P_i^{-\eta} = Q_i$$

$\left(\varpi^{-1} U_1 \tilde{Q}^{\frac{1}{\eta-1}}\right) Q_i^{-1/\eta} = P_i$

Using the budget constraint $\tilde{Y} = \sum P_i Q_i$ and (4.16) from above

$$\tilde{Y} = \varpi^{-1} U_1^{\frac{1}{\eta-1}} \left(\sum_i Q_i^{\frac{\eta-1}{\eta}} \right) \sum Q_i^{\frac{\eta-1}{\eta}} \tag{4.17}$$

Using (4.17) from above and replacing for Q_i

$$\tilde{Y} = \left(\varpi^{-1} U_1^{\frac{1}{\eta-1}} \left(\sum_i (Q_i)^{\frac{\eta-1}{\eta}} \right) \right)^{\eta} \sum P_i^{-(\eta-1)}$$

Finally replacing back in the first order condition and rearranging, demand is

$$Q_i = \frac{\tilde{Y}}{\sum P_i^{-(\eta-1)}} P_i^{-\eta}$$

4.A.2 Derivation of the reduced form profit function

Since ω_i and K_i are fixed factors, the only adjustable factor is labor: $\pi = P[Q(L_i)]Q(L_i) - wL_i$ where w is the wage rate. Using equations 4.3 and 4.2 the first order conditions are

$$\frac{\eta-1}{\eta} \alpha P\left[Q(L_i)\right] \frac{Q(L_i)}{L_i} = w \tag{4.18}$$

Rewriting we get

$$L_i^* = \left[\left[\frac{(\eta-1)\alpha}{\eta w} \right]^{\eta} \tilde{Y} (\tilde{P} \omega_i K_i^{\beta})^{(\eta-1)} \right]^{1/[\eta-\alpha(\eta-1)]} \tag{4.19}$$

Replacing back in the production function (4.3)

$$Q_i^* = \omega_i L_i^{\alpha} K_i^{\beta} = \left[\left(\omega_i K_i^{\beta} \right) \left(\frac{(\eta-1)\alpha}{\eta w} \left(\tilde{P}^{(\eta-1)} \tilde{Y} \right)^{1/\eta} \right)^{\alpha} \right]^{\eta/[\eta-\alpha(\eta-1)]} \tag{4.20}$$

Prices can be written from the Demand Function (4.2)

$$P_i^* = \left[\omega_i K_i^\beta \left(\frac{(\eta-1)\alpha}{\eta w}\right)^\alpha \left(\left(\frac{\tilde{Y}}{\tilde{P}}\right)^{1/\eta} \tilde{P}\right)^{-\eta(1-\alpha)}\right]^{-1/[\eta-\alpha(\eta-1)]} \tag{4.21}$$

Finally sales are

$$P_i Q_i = \left[\left(\frac{(\eta-1)\alpha}{\eta w}\right)^{\alpha(\eta-1)} \tilde{Y} \left(\tilde{P}\omega_i K_i^\beta\right)^{(\eta-1)}\right]^{1/[\eta-\alpha(\eta-1)]} \tag{4.22}$$

The price index is

$$\tilde{P} = \left(\sum P_i^{-(\eta-1)}\right)^{-\frac{1}{\eta-1}} \tag{4.23}$$

From (4.21) above we can express this as

$$(P_i^*)^{-1} = \left[\omega_i K_i^\beta \left(\frac{(\eta-1)\alpha}{\eta w}\right)^\alpha \left(\tilde{Y}\tilde{P}^{(\eta-1)}\right)^{-(1-\alpha)}\right]^{1/[\eta-\alpha(\eta-1)]} \tag{4.24}$$

So that the price index is

$$\tilde{P} = \left[\left(\frac{(\eta-1)\alpha}{\eta w}\right)^\alpha \tilde{Y}^{-(1-\alpha)}\right]^{-1} \left(\sum \left[\omega_i K_i^\beta\right]^{(\eta-1)/[\eta-\alpha(\eta-1)]}\right)^{-(\eta-\alpha(\eta-1))/(\eta-1)} \tag{4.25}$$

Using this in the equation for profit

$$\tilde{\pi}(\omega_i, K_i, S; \eta, \beta) = P(Q_i)Q_i - wL_i =$$

$$= \left(\frac{\eta-\alpha(\eta-1)}{\eta}\right)\left[\left(\frac{(\eta-1)\alpha}{\eta w}\right)^{\alpha(\eta-1)} \tilde{Y}\left(\tilde{P}\omega_i K_i^\beta\right)^{(\eta-1)}\right]^{1/[\eta-\alpha(\eta-1)]}$$

Writing $\gamma = (\eta - 1)/(\eta - \alpha(\eta - 1))$

$$\tilde{\pi}(\omega_i, K_i, S; \eta, \beta) = \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\left(w\frac{\eta}{(\eta-1)\alpha}\right)^{-\alpha\gamma}\tilde{Y}^{\gamma/(\eta-1)}\left(\omega_i K_i^{\beta}\tilde{P}\right)^{\gamma} \tag{4.26}$$

or

$$\frac{\tilde{\pi}(\omega_i, K_i, S; \eta, \beta)}{\tilde{P}} = \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\left(\frac{w}{\tilde{P}}\frac{\eta}{(\eta-1)\alpha}\right)^{-\alpha\gamma}\left(\frac{\tilde{Y}}{\tilde{P}}\right)^{\gamma/(\eta-1)}\left(\omega_i K_i^{\beta}\right)^{\gamma} \tag{4.27}$$

Using the expression for $\tilde{P}$, (4.25) we finally get the period returns

$$\tilde{\pi}(\omega_i, K_i, S; \eta, \beta) = \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\tilde{Y}\frac{\left(\omega_i K_i^{\beta}\right)^{\gamma}}{\sum\left[\omega_i K_i^{\beta}\right]^{\gamma}} \tag{4.28}$$

4.A.3 Data and sample construction

I have collected data for the aggregate variables from the Portuguese National Statistics Office (INE), together with data on industry price deflators (from IAPMEI, 2006). I have merged these aggregate variables with the sample for the 5 digit NACE code industry 29563 (Moulds Industry). The capital stock was calculated using the perpetual inventory formula and a depreciation rate of 8%. Value added was constructed as total sales subtracted from materials and services. Both aggregate and individual sales and value added were deflated with the industry price deflator.

In 11 observations the number of workers reported was zero which occurs mostly in the year the firms enter or exit the industry. Since the owner of the firm is never reported as a worker I add one to all firms with zero reported workers. The results are robust to dropping these observations.

I identified 9 holes in the sample (firms that interrupt reporting for 1 or more consecutive years). In these cases either the earlier or later periods are dropped, minimizing the total number of observations lost.

Entry and exit are difficult to identify since it is not compulsory for firms to report to the central bank. However, the dataset has information on the founding year and current firm "status" (i.e. active, bankrupt, merged, etc). Using this information I identify 48 actual entries and 7 exits.

I have winsorized at 1% (0.5% on each tail) the variables for ln(K), I, ln(Materials), ln(Value Added), value added growth, sales growth.

Chapter 5

Identifying Financial Constraints in a Dynamic Structural Model of R&D and Investment: The US Iron and Steel Industry

5.1 Introduction

The question of the role of financial constraints for investment in general and innovation in particular is one of the most debated issues in empirical economics. It is obviously important as investment and innovation are critical for economic growth, so financial market failures can have first order effects on welfare and policies to address growth will depend on whether one thinks financial constraints are a problem or not (e.g. Banerjee, 2004; Banerjee and Duflo, 2008).

Given this interest, the current state of the empirical literature is rather disappointing (see Bond and Van Reenen, 2008 for a survey). Our main structural econometric models of investment assume away financial constraints even though there is a general feeling that they are important[1]. Unfortunately, empirical strategies to test for the presence and magnitude of financial constraints have floundered for at least two reasons. First, we do not have a good structural econometric model of investment decisions in the presence of financial constraints. Second, the key tests for the presence of financial constraints is the significance of a measure of cash flow on investment, but the cash flow measure could signal future profitable investment opportunities rather than the "deep pockets" of firms.

This chapter seeks to address these problems by exploiting recent methodological advances in estimating dynamic structural models through numerical simulation (e.g. Bajari, Benkard and Levin, 2007; Santos, 2008; Bloom, 2008). We do this by building an explicit structural model of investment and R&D in a world with costs of external finance and estimating this on a panel of firms from the U.S. steel industry. We uncover evidence of significant financial constraints (a premium of 35 cents on the dollar) and quantitatively large and important sunk costs of R&D (an estimated sunk cost of $194m for "building an R&D lab").

The classic way to examine financial constraints is to include some measure of cash flow in an investment equation, generally allowing for some ex ante separation of the sample into regimes where we think financial constraints may be more important (e.g. Fazzari, Hubbard and Peterson, 1988). Much criticism has been levelled at this approach because of the ambiguity of the interpretation of the larger coefficient on cash flows in the allegedly financially constrained regime (e.g. younger firms, smaller firms, those with worse bond ratings, etc.) given that the investment models tend to be somewhat ad hoc and cash flow is usually significant in both regimes (e.g. Kaplan and Zingales, 1997). An alternative approach is to estimate a structural model of investment and then include cash flow as a specification test. Bond and Meghir (1994) estimate an Euler equation

[1]There are many theoretical models of financial constraints, of course, but these have not proven to be empirically tractable.

and Hayashi (1982) a Q-equation. Both found evidence that cash flow was significant (at least for some sub-groups). However, the performance of the Euler equation and Q model for investment is questionable, not least because of the assumption that adjustment costs are convex. There is much recent evidence of non-convexities due to partial irreversibilities (e.g. Bloom, Bond and Van Reenen, 2008). Additionally, stock market based measures of Q are subject to large measurement errors due to bubbles and the like (e.g. Bond and Cummins, 1999). If these models are incorrectly specified, the significance of cash flow may still be reflecting misspecification rather than positive evidence of financing constraints.

The approach we take here starts with a structural model that allows for the presence of financing constraints where raising finance from external sources is more expensive than from internal funds. We then estimate the parameters of this model, which includes the null that the cost of external finance may be equal to that of internal finance.

The information asymmetries between borrowers and lenders that lie at the heart of the financing problem are likely to affect investment in innovation more than other forms of investment. Several papers have investigated this. For example, Bond, Harhoff and Van Reenen (2008) argue that these financing constraints are most likely to bind for firms when they choose to start up an R&D lab. This is because there is a substantial sunk cost involved in starting an R&D program (e.g. Sutton, 1998) and this irrecoverable cost might be the hardest to convince external investors to cover (e.g. there is no collateral to reclaim if the project fails). In chapter 2 I have examined a dynamic structural model with sunk R&D costs and investment in a world with perfect financial markets. This chapter builds on this framework where we add financial frictions. We find that this addition considerably enriches the predictions of the model in terms of productivity and entry dynamics.

The application of the chapter is to the US iron and steel industry. We believe that it is useful to focus on a particular sector where we can more credibly outline the main industrial features rather than pooling across a large number of very heterogenous sectors - this by itself should reduce some of the potential sources of endogeneity from unobserved shocks that plague the literature. The sector has many attractive features from our perspective. First there has been substantial technical change (such as the mini-mill revolution of the 1980s). Second, there is a mixture of firms who have R&D labs and those who do not (and some who switch status in our 35 year sample). This is a feature of many industries that has puzzled some writers, but emerges naturally as an equilibrium phenomenon in a world of firm heterogeneity in productivity and cash flow shocks.

Our chapter relates to many others (see the next section for a brief literature review). First, the structural model of financial constraints we use builds on Gomes (2001) approach but extends it to allow for R&D and imperfect competition. Furthermore, our implementation is on micro data rather than macro data. Second, we work with models in the spirit of heterogeneous firm models of Hopenhayn (1992), Ericson and Pakes (1995) or Melitz (2003) but with a firm-level IO orientation.

The structure of the chapter is as follows. Section 5.2 offers a brief overview of the literature and Section 5.3 gives an overview of the industry. Section 5.4 outlines the model, Section 5.5 the estimation strategy and section 5.6 provides a brief description of the data. Section 5.7 and 5.8 detail the results and robustness tests and finally Section 5.9 concludes. Details are left to Appendices.

5.2 Literature review

The literature on credit constraints has in the past presented strong econometric evidence of an important role for cash flows in predicting investment decisions.[2] Simulation methods of fully structural models emphasize that Tobin's Q should incorporate all information needed regarding investment profitability and cash flow significance should not be taken as a signal of constraints but either misspecification or measurement error (Gomes, 2001). However, these results crucially depend on the assumption that there are no unanticipated temporary shocks to cash flow and if one could observe permanent and temporary shocks to cash flow, we would be able to separately identify the effect of cash flows on profitability (permanent) and the effect of cash flows on relaxing financial constraints (temporary).

Below, we present some evidence that when cash flows are affected by temporary shocks, cash flow is still a significant variable for credit constrained firms, even after controlling for investment opportunities. Since the central question is how can we separately identify investment opportunities and financial constraints we aim at shedding some light on this. We adopt a structural estimation approach and carefully provide an explanation for what drives identification of the relevant parameters. There has been some recent work on structural estimation of financial constraints (Schulden, 2008; Hennessy and Whited, 2007) but this has mostly been done in a single agent context and ignores the impacts of financial constraints on industry equilibrium and market structure.

5.2.1 Investment and financial constraints

Financial frictions have for a long time been regarded as one potential barrier to capital accumulation and growth, and a potential impairment to competition.

[2] See Bond and Van Reenen (2008) for a survey.

The correct assessment of their existence (or not) therefore seems to be of utmost importance for several branches of economics. The issue is really an empirical rather than theoretical problem and most results seem to indicate a significance importance for credit constraints. These results do not go without problems and have been object of several criticisms which we hope to address.

Fazzari, Hubbard and Petersen (1988) pioneered the empirical research on investment and credit constraints by investigating the validity of the Modigliani-Miller Theorem due to the effects of tax treatments, asymmetric information and agency costs of external and internal finance. Using various models, they argue that cash flow should not be a relevant explanatory variable once you control for investment opportunities (e.g. Tobin's Q). This well known "excess sensitivity" could then be taken as a signal of credit constraints.

The failure of Tobin's Q framework has raised doubts about the cash flow results on the grounds that the basic framework is misspecified and cash flows are good predictors for future profitability that do not necessarily reflect credit constraints. Kaplan and Zingales (1997) criticize the sample splitting procedure normally used by showing that higher cash flow coefficients are not necessarily a signal of bigger credit problems. Cooper and Haltiwanger's (2006) criticisms, along the same lines, are based on the fact that the measurement error introduced by the use of average Q instead of marginal Q would make conclusions hard to establish. Gomes (2001) for example, shows that Tobin's Q already reflects credit constraints so that additional variables should only be relevant if they capture nonlinearities of Q or measurement error problems.

The poor performance of the basic Tobin's Q framework has driven the investment literature to follow alternative paths to solve the misspecification and measurement error problems. The first approach was to build a better Q measure.

Abel and Blanchard (1986)[3] build it using a VAR of discount rates and average productivity of capital to proxy for marginal profit. They find that marginal Q variation is mainly driven by discount rate volatility but it is the profitability that better explains investment variation. Bond and Cummins (1999) suggest using analysts forecast as a proxy for marginal Q and find that with this methodology cash flow is no longer significant and the size of adjustment costs is more reasonably estimated.[4]

The second approach to deal with the Q problem was taken by relaxing the assumptions on the cost function, allowing for fixed costs, irreversibilities and non-convexities. Cooper and Haltiwanger (2006) introduce imperfect competition in a model with non-convexities and irreversibilities. They point that i) non convexities and irreversibilities play a central role in the investment process and; ii) non-convexities are less important at the aggregate level. In the same line of research Dixit and Pindyck's option theory is derived in the case of irreversibilities that create an option value for investment delay. Naive Net Present Value formulations forget to take into account the existence of options arising from reversibility and expandability. Firms can disinvest, but resale price may be lower and can continue to invest later but acquisition price may be higher. When future returns are uncertain, these features yield two options: a put option for installed capital and a call option for opportunity to invest. Generally, the option to expand reduces the incentive to invest, while the option to disinvest raises it. Both the option value approach and the Q-theory approach will correctly characterize optimal behavior, yet each offers its own set of distinctive insights about the investment decision.

Allowing for a different specification of the profit function (Abel and Eberly (2002)) show that average Q and marginal Q are not the same in a model with

[3]Gilchrist and Himmelberg (1995) use the same approach

[4]The validity of using the coefficient in Q as the size of adjustment costs depends very strongly on the parametric assumption of the cost function.

monopoly power and no credit constraints where cash flows are relevant because they help to predict non-observables or poorly measured variables like growth rates or depreciation. It is also shown that the effect of cash flows should be stronger for small, fast growing or volatile firms (since they should have higher depreciation rates) even though there are no credit constraints.

Finally Bloom, Bond and Van Reenen (2008) show how investment reacts at the firm level in a model where there is lumpiness and inaction at the single capital single plant level. They try to explain how the investment rate at the firm level will react to uncertainty and show that an increase in demand uncertainty will move the upper (investment) threshold up and the lower (disinvestment) threshold down such that it reduces reaction to shocks and increases the region of inaction. Basically this means that higher uncertainty increases the value of the options and so it increases the value of waiting.

5.2.2 R&D and financial constraints

Authors since Schumpeter (1942) have pointed to difficulties in financing R&D that can lead to underinvestment (e.g. Nelson, 1959; Arrow, 1962). The nature of R&D (intangible assets, mostly constituted by wages, high uncertainty) makes it very difficult for firms to offer good collateral and for lenders to "control" the investment. Also, firms might not want to reveal confidential information to the lenders as this might result in leakages of secret information to rival competitors.

Himmelberg and Petersen (1994) argue that firm's R&D expenditure in high technology sectors should react to permanent cash flow movements but not to transitory ones. Since costs are mainly wages paid to highly qualified people, hiring and firing costs are very high, R&D expenditures tend to be smooth and highly autocorrelated.

Hall (2002) and Aghion et al. (2004) study the problem of R&D financing and present evidence that R&D performers have a different financing structure. Firms choice of financial structure may be different for R&D performers due to bankruptcy costs (intangibility of R&D), greater degree of asymmetric information or control rights (more attractive investment opportunities for more innovative firms). Aghion et al. (2004) find that use of debt is higher for R&D performers but decreases with R&D intensity and, use of equity is higher for performers and increases with R&D intensity.

We analyze the impact of financial constraints on the decision to start R&D. Particularly we focus on the effect of internal availability of funds on the R&D start-up decision. We model the outcome of R&D, innovations, as a stochastic increase in productivity (TFP) which could incorporate both process and product innovations.[5] The firm faces a discrete decision in that first decides on whether or not to start an R&D project and after that it sets its optimal R&D expenditure levels. We will abstract from this second decision for simplicity. The reason why we can separate the (binary) decision to start the R&D project from the continuous R&D amounts to set is because data suggests that the R&D to sales ratio is highly autocorrelated. In a sense we assume that firms set the R&D to sales ratio at an optimal level like in Klette and Kortum (2004).

5.3 The U.S. iron and steel industry

We use data for the US Iron and Steel Mills industry (NAICS 331111) for the period 1970-2005.[6] The Steel industry was one of the engines of growth for the United States during the 1950's and is still considered as a "strategic" sector by

[5]The productivity index can be shown to be a mixture of both quality and costs. These cannot be easily disentagled unless price data is available.

[6]For a detailed description of the data see the Data Appendix.

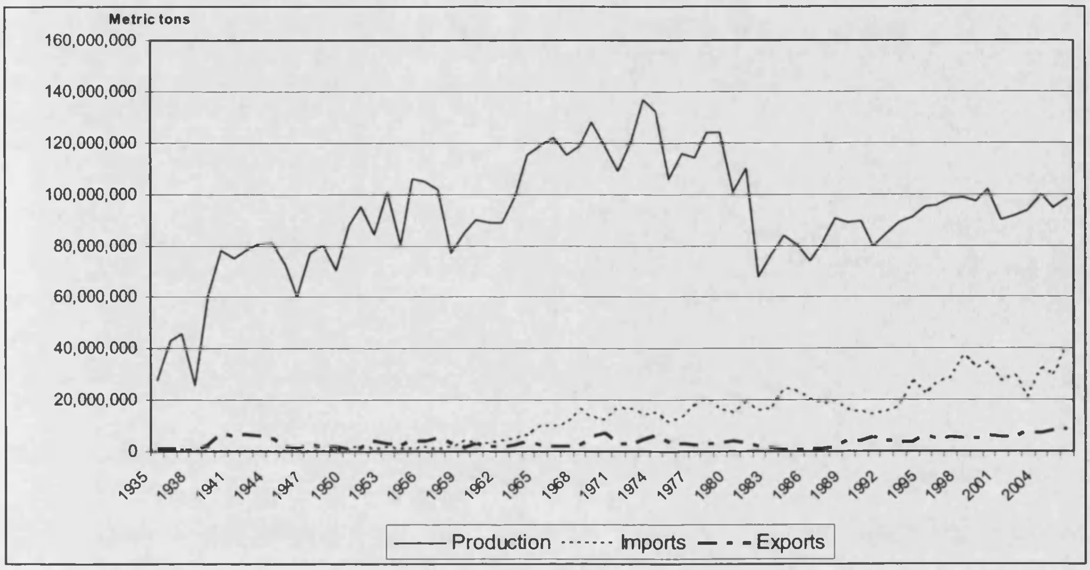


Figure 5.1: US Steel production, imports and exports in million tons: 1935-2006 (source: US Geological Survey)

the US government.[7] However, the sector suffered substantial turmoil over the last three decades. In the 1980's the industry went through a severe crisis leading to falls in production (Figure 5.1) with two industry leaders - U.S. Steel and the LTV Corporation - undergoing severe problems in 1986. Since the industry

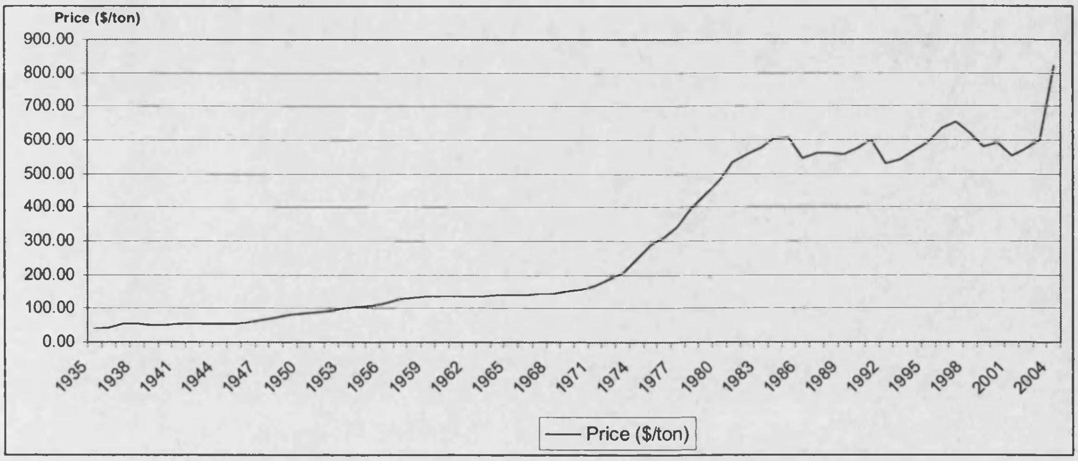


Figure 5.2: US Price of Steel in dollars per ton: 1935-2005 (source: US Geological Survey)

in the mid 1980's which allowed an increase in competitiveness. One of the main drivers of this change was the entry of the so-called mini-mills (or electric arc furnaces) as opposed to the traditional integrated producers (open hearth or basic oxygen furnaces). Mini-mills produce lower quality steel from scrap metal while the integrated producers can use pig iron and supply high quality steel. There was also a recent "import crisis" event in 1998, where several foreign countries were accused of dumping steel prices and import penetration reached a peak maximum of 30%. This was related to the Asian financial crisis and the drastic decline in demand for steel in the region which resulted in a world overcapacity problem.

Summarizing, there is evidence that the industry is very reactive to the business cycle and demand for steel from main clients (e.g. automotive sector) . The high capital investment necessary for production requires a minimum production capacity. This implies that it is hard to reduce capacity when demand is low and the result is the strong cyclicality observed with record losses during crisis and high profits in good times. The two types of firm organization and the success of the mini-mills vs integrated producers is also related with their higher flexibility

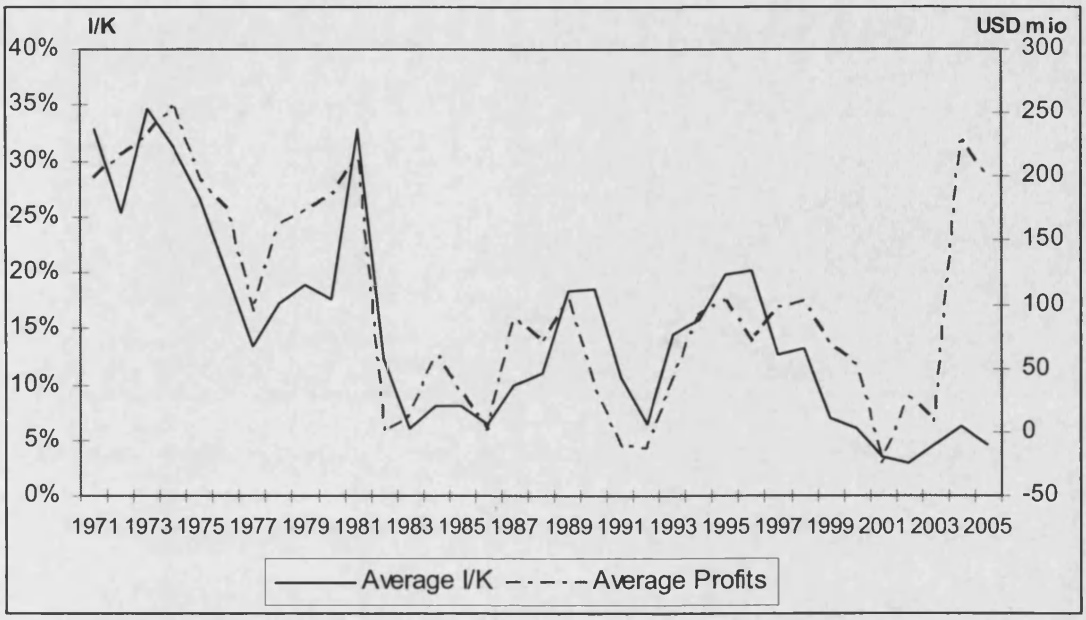


Figure 5.3: Average firm level profits and investment rate per year (COMPUSTAT data): 1970-2005.

in terms of costs and production and lower investment requirements (capital costs for the integrated mills are normally much higher then for mini-mills). However, since the mini-mills use scrap metal and cannot produce the highest quality steel, the integrated producers are still able to partly survive the competition. We try used by firms as a strategic variable compared to other industries like Biotech or Semiconductors. This is important because it allows us to abstract away from all different sorts of motives behind the R&D decisions typical of high tech industries and focus mainly on sunk costs and financial constraints.

A feature of the industry is that average firm profits and the investment rate are highly correlated. Since current profits could potentially be a signal of future profitability as well as an indicator of the internal availability of funds, we cannot immediately identify whether firms in the Steel industry are credit constrained. But since this industry is capital intensive, the existence of financial frictions that prevent firms from investing might be a large source of inefficient capital allocation.

5.4 The Model

We develop a model in which firms invest in physical capital and decide on whether or not to set up an R&D lab. We allow R&D into the model because of its importance for innovation and growth. Production is done with a Cobb-Douglas technology and goods are sold in the market in a monopolistically competitive framework. If firms do not have sufficient funds to finance investment internally (via cash flow), they have to incur a financial cost which is increasing in the total amount borrowed. The specification of a dynamic equilibrium framework is important due to the fact that investment is very sensitive to the business cycle. This is the reason why we adopt a similar framework to the one in chapter 4 where industry competition is summarized by the aggregate state. This allows us to estimate an otherwise intractable model.[8] We build and expand on that framework by introducing the possibility of higher costs for external funds (debt or equity). We model them by adding a cost which depends on whether the firm

[8] See chapter 2 for a discussion of the advantages and disadvantes of using the aggregate state model.

has sufficient internal funds to finance its investment or not.

We note here that the model is restrictive in several dimensions. First, we do not investigate the firms' optimal financing structure but simply assume that external funds are more costly then internal funds. This is because we are mostly interested in the magnitude (if any) of the costs of external financing. Second, R&D is modelled as a single sunk cost ("building an R&D lab") rather than a continuous decision of how much R&D to spend each period. We discuss how this assumption can be relaxed, but regard it as a reasonable first step. Bloom, Harhoff and Van Reenen (2008) argue that financial constraints may be particularly important at the point when firms decide whether to set up an R&D lab. The theory literature also focuses on the sunk cost nature of R&D (e.g. Sutton, 1991 and 1998). Third, we have a simple imperfect competition model in the product market whereas we could potentially enrich the menu of strategic interactions.

5.4.1 State and action space

The state space s_{it} for firm i at time t is represented by four variables: Physical capital (K), productivity (ω), R&D status (R, where $R = 1$ denotes that the firm has built the R&D lab and $R = 0$ otherwise) and operating status (χ, where $\chi = 1$ denotes that the firm has decided to continue operations and $\chi = 0$ denotes that it is not operating).

$$s_{it} = (K_{it}, \omega_{it}, R_{it}, \chi_{it})$$

where $\omega_{it} \in \Omega$, a compact set on the real number line and $K_{it} \in \mathfrak{K}$, a compact set bounded below by 0. For the discrete decisions, $R_{it} \in \{0, 1\}, \chi_{it} \in \{0, 1\}$.

There are also stochastic shocks (privately observed by the firm and unobserved by the econometrician) including shocks to investment φ^{I}_{it} , to the sunk cost of

R&D φ_{it}^R, and the scrap value φ_{it}^S. The vector of payoff shocks $\varphi_{it} = (\varphi_{it}^I, \varphi_{it}^R, \varphi_{it}^S)$ are independent and identically distributed standard normal random variables.

After entering the industry, firms can invest in physical capital, pay a sunk cost and engage in R&D and finally decide on exiting from the industry. We denote the action space as a, where a superscript denotes either a continuous decision (c) such as investment levels or a discrete decision (d) such as starting an R&D lab or exiting the industry.

$$a_{it} = (a_{it}^c, a_{it}^d) = (I_{it}, R_{it+1}, \chi_{it+1})$$

Investment, $I_{it} \in \mathfrak{I}$ can be any non-negative number. We do not allow for disinvestment for simplicity reasons. They could be added to the framework and estimated in a straightforward way but we think in our data it would be difficult to identify them because there are no significant disinvestment observations (for example, less then 30 observations in the our sample reported a disinvestment of more then 5% of total capital).

This generates a law of motion for the state variables that depends on the previous state space and actions with density function

$$p(s_{it+1}|s_{it}, a_{it})$$

As will be discussed below, this law of motion will be stochastic for productivity and deterministic for all other state variables.

5.4.2 The aggregate state model

There is a set of assumptions explained in chapter 2 that allow the model to be represented by the aggregate state model. The main advantage of this is that it allows to break the 'curse of dimensionality'. The players in the industry are assumed to use Markovian strategies, individual states are private information and players observe own states and the aggregate state, which is also the payoff relevant state (e.g. the average price in the monopolistic competition framework, as explained below).

The main advantage is that instead of solving the full industry state transition, i.e. $\Pr(\mathbf{s}_{t+1}|\mathbf{s}_t)$ where $\mathbf{s}_t$ is the industry state vector $\mathbf{s}_t = (s_{1t}, s_{2t}, ..., s_{Nt})$ one only needs to solve the aggregate state transition $q(S_{t+1}|S_t)$ where S_t is the aggregate state variable. This results in solving a dynamic problem with a smaller dimensionality then the original problem.[9] This implicitly imposes more structure in the type of strategic interactions since firms now react to the 'average' competitor (i.e., *ceteris paribus,* firm A's reaction to a market structure where both competitors B and C are very similar will be the same as when B is very large and C is very small).

5.4.3 Equilibrium

The equilibrium concept is Markov Perfect Bayesian Equilibrium in the sense of Maskin and Tirole (1988, 2001). Since we restrict to Markovian pure strategies where the firm can take actions $a_{it} \in A(s_{it}, S_t, \varphi_{it})$ the problem can be represented as:

$$V(s_{it}, S_t, \varphi_{it}; q) = \sup_{a_{it}} \; h(s_{it}, S_t, \varphi_{it}, a_{it}, V_{it}; q)$$

where

[9] To better understand the "curse of dimensionality' problem, consider a model with several state variables per firm and/or large numbers of firms. Equilibria and policy rules are then computationally intractable since the size of the problem grows exponentially. For example, let s be the industry state (i.e. define s_{it} the state vector of firm i at time t, then the industry state at time t is $\mathbf{s}_t = (s_{1t}, ...s_{Nt})$), finding the industry state transition, $q(\mathbf{s}_{t+1}|\mathbf{s}_t)$, for an industry with 50 firms and 2 binary state variables would mean calculating a $4^{50} \times 4^{50}$ transition matrix. If one assumes the typical anonymity and symmetry (Pakes and McGuire, 2001) the problem will be greatly reduced but still intractable ($50^2 \times 50^2$).

$$
\begin{aligned}
& h(s_{it}, S_t, \varphi_{it}, a_{it}, V_{it}; q) && (5.1)\\
= \quad & \tilde{\pi}(s_{it}, S_t, a_{it}) + \varphi_{it}(a_{it}) + \rho E\{V(s_{it+1}, S_{t+1})|s_{it}, S_t, a_{it}; q\} && (5.2)
\end{aligned}
$$

where ρ is the discount factor and $q(.)$ are equilibrium beliefs about aggregate state evolution. The s_{it} and a_{it} have been defined above and the expectation $E[.|s_{it}, S_t, a_{it}; q]$ is taken over $p(\omega_{it+1}|\chi_{it} = 0)q(S_{t+1}|S_t)$ if $\chi_{it} = 0$ and $p(\omega_{it+1}|\omega_{it}, R_{it})q(S_{t+1}|S_t)$ if $\chi_{it} = 1$. Notice that $q(S_{t+1}|S_t)$ is the equilibrium transition probability for the aggregate state. So the firms decide on next period's capital investment, whether to start up an R&D lab, and next period's operating status. Firms optimally choose their entry, exit, R&D and investment given the knowledge about the evolution of the industry $q(S_{t+1}|S_t)$.

The value function depends on whether the firm is an incumbent ($\chi_{it} = 1$) or the firm is a potential entrant ($\chi_{it} = 0$). For incumbents, the value function is the sum of current returns and the expected continuation value which depends on current individual state (s_{it}), current industry state (S_t) and actions taken (a_{it}). For the potential entrant the value function is either zero if it chooses to remain outside ($\chi_{it+1} = 0$) or the sum of the entry cost with the continuation value which depends on the aggregate industry state (S_t) and the entry state distribution ($p(\omega_{it+1}|\chi_{it} = 0)$).

Definition 2 *A collection of Markovian strategies and beliefs* $(\sigma, q())$ *constitute a Markov perfect equilibrium if:*

(i) Conditional on beliefs about industry evolution (q) firms' strategies $(\sigma_{it} = \sigma^*(s_{it}, S_t, \varphi_{it}; q)$ *maximize the value function* $V(s_{it}, S_t, \varphi_{it}; q)$.

(ii) The industry transition $(q^*(S_{t+1}|S_t; \sigma^*(s_{it}, S_t|q))$ *resulting from optimal behavior* (σ^*_{it}) *defined above is consistent with beliefs* $q(S_{t+1}|S_t)$

The solution to the dynamic programming problem conditional on q is the optimal strategy $\sigma^*(.|q)$ and a solution exists, under Blackwell's regularity conditions. These strategies will then characterize the industry conditional distribution $q(S_{t+1}|S_t;\sigma^*)$ and the equilibrium is the fixed point to a mapping from the beliefs used to obtain the strategies into this industry state transition

$$\Upsilon(q)(S_{t+1}|S_t) = q^*(S_{t+1}|S_t;\sigma^*(.|q))$$

where firm's follow optimal strategies $\sigma^*(.)$. An equilibrium exists when there is a fixed point to the mapping $\Upsilon(q) : \Omega \to \Omega$.

5.4.4 Parametrization

Per period returns are a primitive of the model which we specify as π_{it}. S_t is the aggregate industry state (such as the industry price index), ξ_{it} is an independent and identically distributed random transitory cash flow shock and φ_{it} is a vector of other stochastic shocks including price shocks to investment φ_{it}^I , to the sunk cost of R&D φ_{it}^R, and the scrap value φ_{it}^S (if the firm exits the market). The vector of payoff shocks $\varphi_{it} = (\varphi_{it}^I, \varphi_{it}^R, \varphi_{it}^S)$ are independent and identically distributed standard normal random random variables.

We first define the demand and production functions and then, assuming Bertrand pricing, we solve for the reduced form period returns. The period return function satisfies Rust's (1987) conditional independence and additive separability assumptions

$$\pi(s_{it}, S_t, a_{it}, \varphi_{it}) = \tilde{\pi}(s_{it}, S_t, a_{it}, \xi_{it}) + \varphi_{it}(a_{it})$$

Demand

We use the representative consumer Dixit-Stiglitz monopolistic competition framework [10]. There are N_t available varieties each supplied by a different firm so there are N_t firms in the market and $N - N_t$ potential entrants. Consumers choose quantities of each variety Q_i to consume and pay P_i with the following preferences:

$$U\left(\left(\sum_i Q_{it}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, Z_t\right)$$

where $U(.)$ is differentiable and quasi-concave and Z represents an aggregate industry utility shifter. Under these conditions the aggregate price index is

$$\tilde{P}_t = \left(\sum_{i=1}^{N_t} P_{it}^{-(\eta-1)}\right)^{-\frac{1}{\eta-1}} \tag{5.3}$$

and the firm's demand is [see Appendix 4.A.1]

$$Q_{it} = \tilde{Y}_t \tilde{P}_t^{\eta-1} P_i^{-\eta} \tag{5.4}$$

Where $\left(\frac{\tilde{Y}}{\tilde{P}}\right) = \frac{\sum_{i=1}^{N_t} P_{it}Q_{it}}{\tilde{P}}$ is total industry deflated revenues.

Production function

The production technology is assumed to be Cobb-Douglas where L is labor input:

$$Q_{it} = e^{\omega_{it}} L_{it}^{\alpha} K_{it}^{\beta} \tag{5.5}$$

Since gross flow profits are $\tilde{\pi} = [P(Q_{it})Q_{it} - wL_{it}]\,\xi_{it}$ (w is the wage rate), so maximizing out for labor, this becomes:

[10] The model also works with other demand structures. A monopolistic competition framework is well adjusted for the cases when we do not observe firm level prices. More complex demand structures can be used when individual price data is available.

$$\tilde{\pi}(\omega_{it}, K_{it}, S_t; \eta, \beta) = \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\tilde{Y}_t \frac{\left(e^{\omega_{it}} K_{it}^{\beta}\right)^{\gamma}}{\sum_j \left[\omega_{jt} K_{jt}^{\beta}\right]^{\gamma}} \xi_{it} \tag{5.6}$$

where $\gamma = (\eta-1)/(\eta-\alpha(\eta-1))$. Notice that since in the short run, productivity and physical capital are fixed, the only way to adjust production is through labor which is assumed to be perfectly flexible. We log-linearize this equation and estimate

$$\ln \tilde{\pi}_{it} = \alpha_0 + \alpha_1 \omega_{it} + \alpha_2 \ln K_{it} + \alpha_3 \ln S_t + \ln \xi_{it} \tag{5.7}$$

where $S_t = \tilde{Y}_t / \tilde{P}_t$. Capital accumulation follows the perpetual inventory method depreciating at rate δ:

$$K_{it+1} = (1-\delta)K_{it} + I_{it}$$

Productivity and R&D

We assume that productivity evolves stochastically with a different distribution for R&D performing and non-R&D performing firms. Firms who have built an R&D lab draw a productivity distribution that stochastically dominates that (in a first-order sense) of non-R&D firms. In general, product and process innovation are difficult to disentangle from each other unless one has firm level price data (e.g. Foster, Haltiwanger and Syverson, 2008). Since in our data we do not have price data we consider them to be indistinguishable in the model and restrict the analysis to the effect on productivity, ω. The model can however be extended to allow for quality in the demand specification (see Melitz, 2000). This distinction would be important to model other type of phenomena like dynamic pricing, where the effects of product and process innovation would be qualitatively different.

This 'internal' source of uncertainty distinguishes R&D investment from other firm's decisions like capital investment, labor hiring, entry and exit which have deterministic outcomes and where the only source of uncertainty is 'external' to the company (e.g. due to the environment, to competition, to demand, etc.). This distinction is important since the stochastic R&D outcome will determine (together with entry and exit) the stochastic nature of the equilibrium.

We assume that productivity follows a controled Markov process.

$$\omega_{it+1} = E(\omega_{it+1}|\omega_{it}, R_{it}) + \nu_{it}$$

where v_{it} is independently and identically distributed across firms and time.

Cost functions

Investment cost Investment costs have a quadratic component (Hayashi 1982) and total irreversibility (no disinvestment). We assume that investment costs $(C^K(I_t, K_{it-1}))$ take the following form:

$$C^K(I_t, K_{it-1}) = \left[\mu_1 I_{it} + \mu_2 \frac{I_{it}^2}{K_{it-1}}\right] + \varphi_{it}^I I_{it} \text{ if } I_{it} > 0 \tag{5.8}$$

where $\mu_2 > 0$ indexes the degree of convexity and the 'price' of investment is $\mu_1 + \varphi_{it}^I > 0$.

R&D costs The firm has the choice of building an R&D lab at a sunk cost of $\lambda + \varphi_{it}^R$ where φ_{it}^R is an i.i.d. standard normal random variable. As discussed above we abstract away from the continuous R&D choice after building the R&D lab and assume that after building an R&D lab, R&D costs are a fixed proportion of firm sales (we also consider a model where R&D is simply a fixed cost paid every period after the lab is built). This is mainly for tractability so we do not need to keep track of another continuous policy function. However, the empirical literature tends to find that R&D intensity (R&D to sales ratio) is highly serially correlated - indeed Klette and Kortum (2004) take this as a stylized fact that they try and fit with their model. We assume that the process that determines period to period R&D flows leads to R&D being proportional to sales. We report in Table 5.11 in the Appendix some evidence that this does not seem to be a restrictive assumption. In future work we will try to make this an equilibrium outcome of our structural model.

Notice that under these assumptions productivity evolves stochastically depending on whether the R&D sunk cost have been paid or not, i.e.

$$p(\omega_{i,t+1}|\omega_{it}, R_{it}, \chi_{it})$$

where $p(.)$ is the conditional probability of $\omega_{i,t+1}$ given ω_{it}, R_{it} and χ_{it}.

Financial Costs The assumption we will use is that firms face a financial cost increasing in the amount borrowed. We allow financial constraints to vary for firms who decide to start R&D. Following Gomes (2001) the specification is the following for the financial cost (FC) of external finance (EXT)

$$FC(EXT_{it}) = \begin{cases} \kappa_1^R EXT_{it} \times \mathbf{1}(EXT_{it} > 0) & \text{if } R_{it+1} = 1 \text{ and } R_{it} = 0 \\ \kappa_1^{NR} EXT_{it} \times \mathbf{1}(EXT_{it} > 0) & \text{otherwise} \end{cases} \tag{5.9}$$

where

$$EXT_{it} = I_{it} - CF_{it}$$

So the firm needs to borrow money to finance any amount invested above current cash flow (CF_{it}) and the cost of external finance might vary from R&D to non-R&D firms. We implicitly impose two assumptions. First, firms exhaust all internal funds before borrowing (pecking order theory) and second, firms can only have two sources of funds internal or external.

Notice that we implicitly assume that the sunk costs of R&D are present in the company accounts as investment but we cannot identify them separately from other forms of investment. Also setting up an R&D lab could cause production disruption which would reduce profits and therefore cash flows. So the sunk costs of R&D are accounted by increasing the needs for external finance, EXT_{it}.

Exit value Every period the firm has the option of exiting the industry and collect a scrap exit value of $e + \varphi_{it}^S$.

Period returns

Using the above specification the per period return function for an incumbent is

$$
\begin{aligned}
&\pi(\omega_{it}, K_{it}, R_{it}, \chi_{it}, R_{it+1}, \chi_{it+1}, I_{it}, EXT_{it}, S_t) \\
= \;& \frac{1}{\gamma}\left(\frac{\eta-1}{\eta}\right)\tilde{Y}_t \frac{\left(\omega_{it}K_{it}^{\beta}\right)^{\gamma}}{\sum_j\left[\omega_{jt}K_{jt}^{\beta}\right]^{\gamma}}\xi_{it} - C^K(I_t, K_{it-1}) - FC(EXT_{it}) \\
&-(\lambda + \varphi_{it}^R)(R_{it+1} - R_{it})R_{it+1} + (1 - \chi_{it+1})(e + \varphi_{it}^S)
\end{aligned}
\tag{5.10}
$$

Using the demand specified above (5.4) there are two 'external' variables that affect company's revenues. One is market size ($\tilde{Y}$) and the other is competitors' adjusted price index ($\tilde{P}$). Since individual prices are determined by productivity and physical capital, the price index is a mapping from individual firms' productivity and capital stock onto a pricing function so we get the aggregate state variable

$$S_t = \tilde{Y}_t / \tilde{P}_t \tag{5.11}$$

It is important to recall that as explained before, firms adjust production to maximize short run profits through the only flexible input, labor.

5.5 The estimation procedure

5.5.1 General approach

There are currently several proposed alternatives to estimate dynamic industry models in the recent surge of estimation techniques which extend the work of Hotz and Miller (1993) for single agent models to dynamic games (see Pesendorfer and Schmidt-Dengler, forthcoming; Aguirregabiria and Mira, 2007; Bajari, Benkard and Levin, 2007; and Pakes, Ostrovsky and Berry, 2007). We follow closely the approach proposed by Bajari, Benkard and Levin (2007) since this allows for both discrete and continuous choices and is easily applicable to the model outlined above. This framework has been applied by Ryan (2006) to study the impact of environmental regulation changes on capacity investment for the cement industry in the US. The industry state is the sum of competitors' capacities rather than the individual capacities of competitors and this resembles the model we are about to estimate. This is because players' strategies are approximated by a function on individual and aggregate capacities, just like in the model developed in chapter 2.

The estimation proceeds in three steps. In the first step we recover the unobserved productivity (ω_{it}) via estimation of the production function. We consider a number of ways for estimating the production function (including Olley and Pakes, 1996; Ackerberg et al, 2008, and Bond and Soderbom, 2005), but we find these are broadly similar (see chapter 3). In the second step, we recover the profit function $(\pi(\omega_{it}, K_{it}, S_t)$ as well as the micro-level and industry-level state transitions, $(p(\omega_{it+1}|\omega_{it}, R_{it}, \chi_{it})$ and $q(S_{t+1}|S_t))$. We also estimate the equilibrium policy functions for investment, R&D and exit non-parametrically using a polynomial expansion in the state variables. Finally, in the third step, we impose the equilibrium conditions to estimate the linear and quadratic investment cost parameters, R&D sunk costs, exit costs and financing costs i.e. the parameter vector $(\mu_1, \mu_2, \lambda, e, \kappa_1^R, \kappa_1^{NR})$.

By simulating actions and states from a starting configuration using the estimated policies and state transitions, and collecting these paths through time, we can calculate the present-value for a given path and a given set of parameters. Slightly perturbing the policy functions allows us to generate alternative paths and different present-values for a given parameter vector. The observed policy functions were generated by profit-maximizing firms who chose the actions with the highest expected discounted value. This means that at the true parameters, the discounted value generated by the observed actions should be greater than those generated by any other set of actions. Particularly, at the true parameters, the perturbed actions should give a lower expected value and this is the equilibrium condition which identifies the structural parameters.

5.5.2 Identification

Adjustment costs for investment are identified off the observed investment behavior and profits earned. Using the estimated profits and state transition, we can recover an estimate of the marginal value of investment (or the continuation value). Once the marginal value is known, we can recover the marginal costs by choosing the adjustment cost parameters (μ_1, μ_2) which are consistent with observed investment being optimally chosen.

R&D sunk costs are identified from the observed R&D start-up decisions.

Given the observed profits earned by R&D firms and non-R&D firms, we can recover the value of being an R&D firm and compare this with the R&D behavior observed in the data. The sunk costs are the ones which rationalize observed behavior.

Financial costs are identified from the variation in investment at similar states when there are sufficient internal funds and when there are not sufficient funds. By comparing investment decisions when internal funds are available and when they are not available, we can therefore estimate the implied costs of external finance. Notice that due to the fact that identification arises from investment behavior like adjustment costs, there are potential problems for the separate identification of the two parameters. To see this note that equations (5.8) and (5.9) are potentially collinear:

$$
\begin{aligned}
&FC(EXT_{it}) + C^K(I_{it}, K_{it-1}) \qquad (5.12)\\
&= \begin{cases} \left[(\mu_1 + \varphi^I_{it})I_{it} + \mu_2 \frac{I^2_{it}}{K_{it-1}}\right] & \text{if } EXT_{it} \leq 0 \\ (\mu_1 + \varphi^I_{it})I_{it} + \mu_2 \frac{I^2_{it}}{K_{it-1}} + \kappa^R_1(EXT_{it}) & \text{if } EXT_{it} > 0,\ R_{it+1} = 1 \text{ and } R_{it} = 0 \\ (\mu_1 + \varphi^I_{it})I_{it} + \mu_2 \frac{I^2_{it}}{K_{it-1}} + \kappa^{NR}_1(EXT_{it}) & \text{otherwise} \end{cases}
\end{aligned}
$$

As seen above, if all investment is financially constrained, it becomes difficult to separately identify μ_1 and κ^{NR}_1 (or κ^R_1) because CF_{it} and I_{it} are both functions of the same state variables and potentially multicollinear. Because of this we rely on two sources of identification: (i) the existence of variation between firms who are credit constrained ($I_{it} > CF_{it}$) and firms who are not ($I_{it} \leq CF_{it}$) which allows us to back-out μ_1 and μ_2 from the first row of equation 5.12 and then recover κ^R_1 (κ^{NR}_1) in the second (third) row even with collinearity between the cash flow and investment variables; (ii) temporary cash flow shocks ξ_{it} which affect the availability of internal funds but not the profitability of investment, can be used as an exclusion restriction that allows the identification of κ_1^R and κ_1^{NR}. The unobserved payoff shocks, φ_{it}^I, are the structural error terms that allow us to "fit the data" and are assumed to enter additively as in Rust (1987).

5.5.3 Policy functions

Investment

The investment function which results as the solution to [5.1] is

$$\frac{I_{it}}{K_{it-1}} = \frac{1}{2\mu_2}\left(\rho\frac{\partial E(V(s_{it+1}, S_{t+1}|s_{it}, S_t, a_{it}))}{\partial I_{it}} - \left(\mu_1 + \varphi_{it}^I\right)\right) - \frac{1}{2\mu_2}\left[\frac{\partial FC(EXT_{it})}{\partial I_{it}}\right] \tag{5.13}$$

which we estimate separately for R&D and non-R&D firms as:

$$\ln I_{it} = \alpha_0 + \alpha_1 \ln K_{it-1} + \alpha_2(\ln K_{it-1})^2 + \alpha_3 \ln S_t + \alpha_4 \dot{\omega}_{it} + \alpha_5 \ln \xi_{it} + \varphi_{it}^I \tag{5.14}$$

We can immediately see the typical problem of identification in reduced form models from equation 5.13. The same variables which determine the first term on the right hand side (marginal Q) are also the variables which determine the second term (the financial constraints function) and the two effects are difficult to separately identify.

We have also tried several specifications with different degrees for the polynomials on the state variables. Notice the role of the temporary cash flow shock, $\ln \xi_{it}$ (recovered from 5.7) which has no effect on the returns to investment $\frac{\partial E(V(s_{it+1},S_{t+1}|s_{it},S_t,a_{it}))}{\partial I_{it}}$ but plays a role in relaxing the need for external funds $\frac{\partial FC(EXT_{it})}{\partial I_{it}}$ and is therefore a relevant state variable for investment when firms need to raise external finance.

R&D

Firms will decide to build an R&D lab if the expected future benefit of building (relative to not building) exceeds the sunk cost, i.e.

$$(\lambda + \varphi_{it}^{R}) < \rho \left[\begin{array}{c} E\{V(s_{it+1}, S_{t+1}) | s_{it}, S_t, I_{it}, R_{it+1} = 1\} \\ -E\{V(s_{it+1}, S_{t+1}) | s_{it}, S_t, I_{it}, R_{it+1} = 0\} \end{array} \right]$$

So the probability that the firm starts performing R&D is:

$$\begin{aligned} \Pr(R_{it+1} &= 1 | R_{it} = 0, s_{it}, S_t, I_{it}) = \\ & \Pr\left(\varphi_{it}^{R} < -\lambda + \rho \left[\begin{array}{c} E\{V(s_{it+1}, S_{t+1}) | R_{it+1} = 1\} \\ -E\{V(s_{it+1}, S_{t+1}) | R_{it+1} = 0\} \end{array} \right] \right) \end{aligned}$$

or

$$\Pr(R_{it+1} = 1 | R_{it} = 0) = \Phi \left(-\lambda + \rho \left[\begin{array}{c} E\{V(s_{it+1}, S_{t+1}) | R_{it+1} = 1\} \\ -E\{V(s_{it+1}, S_{t+1}) | R_{it+1} = 0\} \end{array} \right] \right)$$

which we parametrize with a first order approximation:

$$\Pr(R_{it+1} = 1 | R_{it} = 0) = \Phi\left(\alpha_0 + \alpha_1 \ln K_{it-1} + \alpha_2 \ln S_t + \alpha_3 \omega_{it}\right) \tag{5.15}$$

where $\Phi\left(.\right)$ is the cumulative normal density function.

5.5.4 Minimum distance estimator

We use the Minimum Distance Estimator proposed by Bajari, Benkard and Levin (2007). Assuming the policy and transition functions are consistently estimated, starting from a state configuration (s_0, S_0), we can draw vectors of payoff shocks $\varphi = (\varphi^I, \varphi^R, \varphi^S)$, simulate actions (a_0) by reading off the policy functions and update states (s_1, S_1) by reading off the transition functions. Doing this for long enough periods (each path has been simulated for $\bar{T}$ periods), we compute a sequence of actions and states $\{a_t(s_0, S_0, \varphi_0), s_t(s_0, S_0), S_t(s_0, S_0)\}_{t=1}^{\bar{T}}$ from a starting configuration (we have used n_s different starting configuration combinations for (s_0, S_0)). With this sequence of actions and states, we can compute the discounted stream of profits for a given parameter vector θ and a given second step estimate for the policy and transition function $(\tilde{\alpha})$, $\sum_{t=0}^{\bar{T}} \rho^t \pi(a_t, s_t, S_t, \varphi_t; \tilde{\alpha}, \theta)$ which gives us an estimate of the expected value from a starting configuration $EV(s_0, S_0; \tilde{\alpha}, \theta) = \sum_{t=0}^{\bar{T}} \rho^t \pi(a_t, s_t, S_t, \varphi_t; \tilde{\alpha}, \theta)$.[11] For each starting configuration we simulate n_J different path to get an average estimate

$$EV(s_0, S_0; \tilde{\alpha}, \theta) = \frac{1}{n_J} \sum_{j=1}^{n_J} \sum_{t=0}^{\bar{T}} \rho^t \pi(a_t^j, s_t^j, S_t^j, \varphi_t^j; \tilde{\alpha}, \theta)$$

In order for a strategy, σ, to be an equilibrium it must be that for all $\sigma' \neq \sigma$

$$V(s, S; \sigma, q(S_{t+1}|S_t); \theta) \geq V(s, S; \sigma', q(S_{t+1}|S_t); \theta)$$

So the set of dynamic parameters θ, must rationalize the strategy profile σ. We just consider the case where θ is point identified whereas Bajari et al. (2007) also develop the method for (bounds) set identification on θ.

Given the linearity of the value function on the dynamic parameters we can write

[11] We set the discount factor at $\rho = 0.88$.

$$V(s,S;\sigma,q(S_{t+1}|S_t);\theta) = W(s,S;\sigma,q(S_{t+1}|S_t)) * \theta$$

where $W(s_t,S_t;\sigma,q(S_{t+1}|S_t)) = E_{\sigma|s_t,S_t}\sum_{s=t}^{\infty}\rho^s w_t$ and $\theta = [1,\mu_1,\mu_2,\lambda,e,\kappa_1^R,\kappa_1^{NR}]$, $w_t = \left[\pi(s_s,S_s;\sigma), I_s, I_s^2, \mathbf{1}(R_{s+1}=1,R_s=0), \mathbf{1}(\chi_{s+1}=0,\chi_s=1)\right]$.

We construct alternative investment, R&D and exit policies (σ') by drawing a mean-zero normal error and adding it to the estimated first stage policies. With these non-optimal policies we construct alternative expected values following the same procedure as before to get $W(s_0,S_0;\sigma',q(.))$ (we calculate these values for n_σ alternative policies).

We then compute the differences between the optimal and non-optimal value functions for several (X_k) policies and states ($X_k, k=1,...n_I$), where $n_I = n_\sigma * n_s$

$$\hat{g}(x;\theta,\tilde{\alpha}) = \left[\hat{W}(s,S;\hat{\sigma},\hat{q}(S_{t+1}|S_t)) - \hat{W}(s,S;\hat{\sigma}',\hat{q}(S_{t+1}|S_t))\right] * \theta$$

Since the estimated policies should be optimal, the expected value when using σ should be bigger then using alternative σ'. The empirical minimum difference estimator minimizes the square of the empirical violations ($\hat{g}(x,\theta,\tilde{\alpha}) < 0$)

$$\hat{J}(\theta;\tilde{\alpha}) = \frac{1}{n_I}\sum_{k=1}^{n_I}\left(\min\left\{\hat{g}(X_k;\theta,\tilde{\alpha}),0\right\}\right)^2$$

and

$$\hat{\theta} = \arg\min_{\theta\in\Theta}\frac{1}{n_I}\sum_{k=1}^{n_I}\left(\min\left\{\hat{g}(X_k;\theta,\tilde{\alpha}),0\right\}\right)^2$$

Notice that we set the length of each path $\bar{T} = 100$, the number of starting configurations $n_s = 350$, the number of simulations for each configuration $n_J = 150$ and the number of alternative policies $n_\sigma = 500$, so that we get the number of differences $n_I = 175,000$

5.6 Data

We discuss the Data in more detail in the Data Appendix, but sketch the main details here. The data was collected from Standard and Poor's COMPUSTAT dataset. We have selected all US firms in industry "Iron and Steel Mills", NAICS 331111 for the period 1970-2005. We also get aggregate data from the Bureau of Economic Analysis (BEA) for total shipments, value added, and deflators (sales, materials and investment). Finally we get data from the US Geological Survey for total US production, shipments, imports, exports, price and total world production. We drop observations with missing values for sales, value added, number of workers and investment. We interpolate some of these missing values when they were missing for only one intermediate year. We winsorize the data at 0.5% on each tail of the distribution for the variables cash flow, log of sales, log of capital stock, log of labor and log of TFP. From an initial sample of 1,263 observations we are left with an unbalanced panel with 1,069 observations over the 25 year period. Only less then half of the firms report positive R&D expenditures. We set the discount factor $\rho = 0.88$.

The capital stock is generated using the perpetual inventory method and we use a 6% depreciation rate. We recover total factor productivity (ω_{it}) using a methodology similar to Levinsohn and Melitz (2004) and De Loecker (2007) to control for endogeneity as in Olley and Pakes (1996) but also incorporate imperfect competition in a similar way to Klette and Griliches (1996).

Our 25 years of data cover an average sample of 30 firms per year. Size distribution is skewed with the average firm being 3 times as large as the median firm. Investment rates over the whole period are around 15% per year with an average real sales growth of 2% per year and a decline in employment of 1% per year. R&D firms have however, reduced its labor force more heavily than their non-R&D counterparts. We also note that an R&D firm is on average more then three times as large.

As explained before, the industry is very reactive to the business cycle due to the fluctuations in demand for steel products. This can be seen in Table 5.2 where yearly investment rates varied from a maximum of 25% in 1995 and 1996 to a minimum of 4% in 2002. The same picture arises in the sales growth rates and cash flows. Total employment has been steadily decreasing with an increase in labor productivity which more then tripled in the 25 year period.

5.7 Results

5.7.1 Preliminary evidence

We start with a brief analysis of the investment sensitivity to cash flows. For this we use a simple Error Correction Model (see Bond and Van Reenen, 2008 for a description of these reduced form approaches).

$$\begin{aligned}\frac{I}{K}_{it} &= \alpha_0^{ECM} + \alpha_1^{ECM}\frac{I}{K}_{it-1} + \alpha_2^{ECM} dy_{it} + \alpha_3^{ECM} dy_{it-1} + \alpha_4^{ECM}(k-y)_{it-2} + \alpha_5^{ECM} y_{it-2} \\ &+\alpha_6^{ECM}\frac{CF}{K}_{it} + \alpha_7^{ECM}\frac{CF}{K}_{it-1} + \alpha_8^{ECM}\frac{CF}{K}_{it-2} + \varepsilon_{it}^{ECM}\end{aligned}$$

where $\frac{I}{K}$ is investment rate, dy sales growth, $(k-y)$ log of capital minus log of sales (error correction term), y log of sales and $\frac{CF}{K}$ cash flow to capital ratio.

The results in Table 5.3 show that cash flows have a very strong effect on investment and that this effect was stronger in the period pre 1994 in columns (iv) and (v). This suggests that credit constraints where stronger in the period before 1994, before the two waves of financial deregulation happened in the US (see Cunat and Guadalupe, 2005 for a discussion of the US financial deregulation

Variable (USD mio)	Obs.	Mean	Std dev.	P(10)	Median	P(90)
Sales	1,069	1,343	1,987	105	507	4,151
Capital Stock	1,069	1,072	2,023	47	290	3,192
Employees (1,000's)	1,069	11	24	1	3	35
RD/Sales	1,069	0%	4%	0%	0%	1%
Investment/Capital	1,002	15%	23%	2%	8%	31%
Cash Flow/Capital	1,000	14%	27%	-4%	13%	36%
Real Sales growth	1,002	2%	32%	-20%	2%	23%
Employment Growth	1,002	-1%	17%	-14%	-1%	12%
Labor Productivity	1,069	207	132	92	168	380
Non-RD firms						
Sales	560	736	1,252	80	343	1,906
Capital Stock	560	516	1,189	29	156	1,355
Employees (1,000's)	560	6	17	0	2	9
RD/Sales	560	0%	0%	0%	0%	0%
Investment/Capital	506	17%	27%	2%	9%	38%
Cash Flow/Capital	504	16%	32%	-7%	13%	42%
Real Sales growth	506	5%	41%	-21%	4%	26%
Employment Growth	506	1%	17%	-13%	0%	15%
Labor Productivity	560	238	152	108	188	444
RD firms						
Sales	509	2,011	2,393	195	979	5,251
Capital Stock	509	1,685	2,516	116	533	5,610
Employees (1,000's)	509	18	29	2	6	48
RD/Sales	509	1%	6%	0%	0%	2%
Investment/Capital	496	12%	19%	2%	8%	21%
Cash Flow/Capital	496	12%	21%	-4%	12%	29%
Real Sales growth	496	0%	20%	-19%	0%	16%
Employment Growth	496	-3%	17%	-15%	-2%	9%
Labor Productivity	509	171	94	84	145	292

Table 5.1: Summary statistics for the Iron and Steel Mills Industry (NAICS 331111): 1970-2005.

year	Obs	RD (count)	RD start (count)	RD (USD mio)	sales (USD mio)	Capital Stock (USD mio)	Employees (1,000's)	RD/Sales	Investment /Capital	Cash Flow /Capital	Real Sales growth	Employment growth	Labor Prod. (USD mio)
1970	20	6	-	57	874	1375	31.7	0.6%	.	.	.	.	122
1971	20	9	3	78	871	1425	28.7	0.6%	13%	27%	3%	-3%	116
1972	20	11	2	80	946	1441	27.9	0.9%	12%	28%	11%	1%	116
1973	21	12	1	122	1141	1406	27.9	0.7%	18%	28%	20%	2%	131
1974	22	13	1	123	1415	1411	27.2	0.5%	19%	37%	28%	1%	149
1975	22	13	0	134	1295	1525	24.9	0.6%	18%	26%	-6%	-10%	127
1976	22	14	1	179	1363	1608	24.2	0.6%	14%	17%	2%	1%	116
1977	23	14	0	172	1427	1582	22.9	0.6%	10%	14%	8%	0%	114
1978	23	14	0	174	1656	1635	23.8	0.5%	14%	18%	18%	5%	112
1979	24	15	1	219	2111	1811	25.7	0.5%	16%	18%	18%	3%	117
1980	25	15	0	245	2082	1792	23.4	0.5%	15%	15%	5%	-3%	123
1981	25	15	0	269	2322	1838	23.0	0.4%	28%	20%	13%	0%	136
1982	24	14	0	165	1415	1402	13.8	0.5%	12%	4%	-29%	-26%	128
1983	25	14	0	180	1364	1384	13.5	0.6%	6%	4%	-12%	-5%	113
1984	25	13	0	196	1482	1289	13.4	0.6%	9%	7%	15%	-3%	130
1985	25	13	0	207	1198	1019	10.0	0.6%	9%	3%	-3%	-4%	124
1986	28	12	0	172	1052	945	8.5	0.6%	7%	3%	-10%	-10%	143
1987	35	13	1	183	949	781	7.1	0.6%	11%	13%	12%	5%	166
1988	37	15	2	187	1109	755	6.8	5.8%	13%	25%	23%	1%	206
1989	40	17	2	202	1157	780	6.7	4.2%	21%	17%	6%	0%	217
1990	41	19	2	204	1083	790	6.1	4.6%	21%	5%	-2%	-3%	205
1991	40	18	0	196	1020	822	5.8	0.5%	13%	4%	-7%	-5%	197
1992	41	18	1	188	908	788	4.8	0.7%	8%	-3%	-2%	-5%	234
1993	42	17	0	165	975	776	4.7	0.9%	18%	13%	8%	4%	247
1994	43	19	2	197	1111	785	4.7	1.0%	20%	23%	13%	1%	247
1995	45	19	0	187	1143	774	4.5	0.9%	25%	30%	15%	5%	251
1996	44	17	0	163	1178	802	4.6	0.4%	25%	20%	24%	2%	255
1997	42	17	0	157	1277	856	4.7	0.4%	16%	16%	7%	1%	256
1998	37	15	0	151	1368	985	5.0	0.4%	17%	12%	-1%	-2%	280
1999	36	14	0	107	1253	968	4.8	0.4%	10%	3%	-9%	-2%	276
2000	34	14	0	92	1430	1024	5.5	0.4%	9%	1%	7%	2%	290
2001	28	13	0	78	1385	983	5.7	0.3%	5%	-8%	-10%	-8%	298
2002	27	13	0	71	1546	1013	5.7	0.3%	4%	3%	1%	-2%	328
2003	23	13	2	62	1808	823	6.3	0.3%	7%	1%	14%	3%	333
2004	22	12	0	53	2893	857	6.6	0.2%	9%	30%	40%	3%	364
2005	18	9	0	32	2960	892	6.7	0.2%	8%	24%	13%	4%	348

Table 5.2: Summary statistics for the Iron and Steel Mills Industry (NAICS 331111), totals per year.

Dependent Variable: I/K	(i)			(ii)			(iii)		
	All Years			Pre-1994			Post-1994		
	Coef.	S.E.	Pval	Coef.	S.E.	Pval	Coef.	S.E.	Pval
I/K(t-1)	0.19	0.07	0.00	0.29	0.09	0.00	0.11	0.07	0.13
dy(t)	-0.05	0.03	0.10	-0.07	0.05	0.16	-0.03	0.04	0.51
dy(t-1)	-0.03	0.03	0.38	-0.02	0.04	0.65	0.00	0.04	0.94
k-y(t-2)	-0.01	0.01	0.26	-0.02	0.02	0.34	-0.01	0.01	0.47
y(t-2)	0.00	0.00	0.50	0.00	0.01	0.67	-0.01	0.00	0.28
CF/K(t)	0.06	0.04	0.17	0.20	0.06	0.00	0.04	0.04	0.31
CF/K(t-1)	0.22	0.04	0.00	0.20	0.06	0.00	0.19	0.03	0.00
CF/K(t-2)	0.08	0.05	0.07	-0.04	0.05	0.43	0.20	0.05	0.00
Constant	0.07	0.04	0.12	0.06	0.04	0.12	0.07	0.03	0.06
Observations	864			513			351		
Groups	59			46			46		
AR(1)	-3.87	0.00		-3.28	0.00		-3.45	0.00	
AR(2)	-2.59	0.01		-1.06	0.29		-1.76	0.08	
CF significance	0.36	0.05	0.00	0.36	0.06	0.00	0.43	0.08	0.00

Dependent Variable: I/K	(iv)			(v)			(vi)		
	All years			All years			OLS/All years		
	Coef.	S.E.	Pval	Coef.	S.E.	Pval	Coef.	S.E.	Pval
I/K(t-1)	0.20	0.07	0.00	0.15	0.08	0.06	0.29	0.03	0.00
dy(t)	-0.05	0.04	0.18	-0.01	0.04	0.88	0.01	0.02	0.68
dy(t-1)	-0.02	0.03	0.66	0.02	0.03	0.63	0.05	0.02	0.02
k-y(t-2)	-0.01	0.01	0.26	-0.03	0.01	0.01	-0.03	0.01	0.00
y(t-2)	0.00	0.00	0.53	0.00	0.00	0.42	0.00	0.00	0.11
CF/K(t)*1(year<=1994)	0.16	0.06	0.01	0.24	0.07	0.00	0.13	0.03	0.33
CF/K(t-1)*1(year<=1994)	0.19	0.06	0.00	0.12	0.07	0.08	0.12	0.04	0.00
CF/K(t-2)*1(year<=1994)	0.05	0.05	0.36	0.03	0.06	0.65	0.03	0.03	0.36
CF/K(t)*1(year>1994)	0.01	0.04	0.75	0.05	0.04	0.23	-0.02	0.03	0.57
CF/K(t-1)*1(year>1994)	0.24	0.06	0.00	0.17	0.07	0.01	0.24	0.04	0.00
CF/K(t-2)*1(year>1994)	0.09	0.07	0.22	0.08	0.07	0.28	-0.05	0.03	0.13
Constant	0.06	0.04	0.21	0.05	0.04	0.18	0.03	0.03	0.31
Observations	864			864			864		
Groups	59			59			59		
AR(1)	-3.85	0.00		-3.50	0.00		-		
AR(2)	-2.29	0.02		-2.30	0.02		-		
CF*1(year<=1994)	0.40	0.06	0.00	0.39	0.08	0.00	0.28	0.03	0.00
CF*1(year>1994)	0.34	0.07	0.00	0.29	0.06	0.00	0.18	0.04	0.00

Notes: The reported results are for the system GMM estimator. In columns (i)-(iv) levels from periods t-2 and t-3 have been used as instruments for the difference equations and differences at t-2 and t-3 as instruments for the levels equations. In column (v) the lags used where t-3 and t-4. Column (vi) reports OLS results. Time dummies.

Table 5.3: ECM investment regressions: system GMM and OLS results.

waves).

Finally in Table 5.4 we split the cash flow into the predicted (CFf) and the random component (CFe), $\ln(\xi_{it})$ which is recovered by estimating equation 5.7 above. The random cash flow component is significant and stronger in the period pre-1994. Notice that this component is the cash flow residual after controlling for size and productivity, so it should in principle have no effect on investment, unless firms are financially constrained.

We acknowledge that the dynamic panel data GMM methods' asymptotic results are valid for large N, and in our sample we have an unbalanced panel of 59 firms over a period of 35 years. We have used alternative estimators with very

Dependent Variable: I/K	(i) All Years Coef.	S.E.	Pval	(ii) Pre-1994 Coef.	S.E.	Pval	(iii) Post-1994 Coef.	S.E.	Pval
I/K(t-1)	0.23	0.06	0.00	0.23	0.09	0.01	0.20	0.09	0.02
dy(t)	0.04	0.04	0.35	0.03	0.05	0.55	0.06	0.04	0.15
dy(t-1)	-0.02	0.05	0.74	-0.02	0.06	0.79	0.11	0.05	0.02
k-y(t-2)	-0.01	0.02	0.71	-0.02	0.02	0.39	-0.06	0.03	0.03
y(t-2)	0.00	0.01	0.95	0.00	0.01	0.68	0.01	0.01	0.44
CFf/K(t)	-0.15	0.12	0.19	-0.10	0.17	0.56	-0.19	0.11	0.09
CFf/K(t-1)	0.35	0.22	0.12	0.41	0.23	0.07	0.08	0.15	0.59
CFf/K(t-2)	0.05	0.07	0.46	0.00	0.09	0.97	0.04	0.11	0.74
CFe/K(t)	0.68	0.67	0.31	1.03	1.45	0.48	0.50	0.59	0.40
CFe/K(t-1)	0.38	0.58	0.51	2.73	1.53	0.08	0.11	0.42	0.79
CFe/K(t-2)	-0.27	0.23	0.24	-2.08	0.87	0.02	-0.02	0.18	0.91
Constant	0.09	0.07	0.24	0.10	0.05	0.03	-0.04	0.09	0.61
Observations	597			370			227		
Groups	54			40			42		
AR(1)	-3.85	0.00		-3.16	0.00		-2.44	0.01	
AR(2)	-2.23	0.03		-0.96	0.33		-1.89	0.06	
CFf significance	0.25	0.12	0.04	0.30	0.15	0.04	-0.07	0.15	0.65
Cfe significance	0.78	0.64	0.22	1.67	0.97	0.08	0.59	0.59	0.32

Notes: In collumns (i)-(iii) levels from periods t-2 and t-3 have been used as instruments for the difference equations and differences at t-2 and t-3 as instruments for the levels equations. Time dummies included. CFf and CFe are predicted and the error component of the CF variable

Table 5.4: ECM investment regression with cash flow shocks, before and after 1994: system GMM results.

similar results. For example, in column (vi) of table 5.3 we report some results using a simple OLS estimator.

We now structurally estimate the model to recover the size of financial constraints consistent with observed behavior.

5.7.2 Step 1: Productivity (TFP) estimates

In Table 5.5 we present production function estimates using alternative methodologies (OLS, Fixed Effects (FE), Olley and Pakes, 1996 (O&P), Ackerberg, Caves and Frazer, 2005 (ACF) and Bond and Soderbom, 2005 (B&S)). Since we do not have firm level price deflators, we account for imperfect competition and recover demand elasticity as proposed by Klette and Griliches (1996). We have used the same methodology as in chapter 3.

Our preferred specification in column (viii) controls for input endogeneity using the investment function inversion as proposed by Olley and Pakes (1996). We note that the labor and capital coefficients using either Fixed Effects or the dynamic

Methodology	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
	OLS		Fixed Effects				Olley and Pakes			Bond and Soderbom		
Labor Coef	0.51	0.62	0.69	0.86	0.58	0.71	0.63	0.65	0.61	0.69	0.79	0.78
Capital Coef	0.34	0.29	0.36	0.13	0.33	-0.12	0.36	0.43	0.74	0.37	0.28	0.29
Price Cost Margin	-0.06	-	0.03	-	-	-	0.09	0.18	0.46	-	-	-
Returns to scale	0.85	0.92	1.05	0.98	0.91	0.60	1.00	1.07	1.35	1.06	1.08	1.06
Time dummies	No	Yes	No	Yes	No	Yes	No	No	No	No	No	No
Notes							(a)	(b)	(c)		(d)	(e)

(a) Imperfect competition, input demand independent on aggregate shocks
(b) Imperfect competition, input demand dependent on aggregate shocks
(c) Imperfect competition, input demand dependent on aggregate shocks, multicollinearity correction (Ackerberg, Caves and Frazer)
(d) Non-RD firms
(e) RD firms

Table 5.5: Production function estimates.

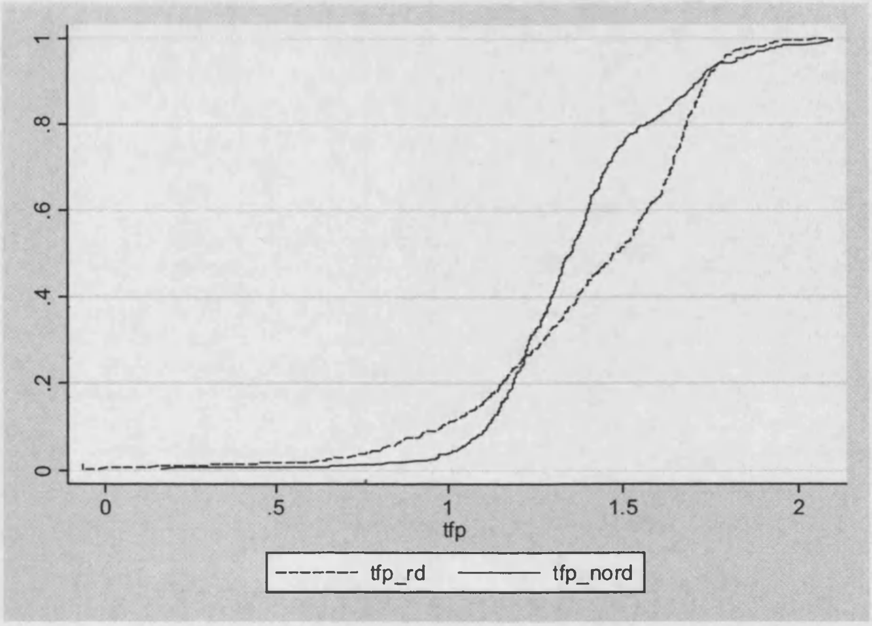


Figure 5.4: TFP distribution (CDF) for R&D and non-R&D firms

production function proposed by Bond and Soderbom are very similar. We find an estimate of demand elasticity for the Steel industry with implied "price-cost margins" of around 18%.

With these production function estimates we recover unobserved productivity. Figure 5.4 reports the productivity distribution, where R&D firms are on average 3.5% more productive than non-R&D firms.

5.7.3 Step 2: Period returns, state transitions and policy functions

Period returns

Using the estimated productivity, ω_{it}, we can estimate the profit function using observed cash flows to substitute in equation 5.6. Our estimate for $\ln(\xi_{it})$ is used as the unanticipated and temporary cash flow shock which will, as discussed above, bring in additional identification power to estimate the financial constraints parameters. As seen in equation 5.12, investment decisions when cash flows are not sufficient to cover investment might not be sufficient to separately identify adjustment and financial costs. The profit function results are reported in column (i) of Table 5.6 and profits are increasing in productivity, capital stock and market size.

Policy functions

In this section we present the results for the estimated investment and R&D policy functions using equations 5.14 and 5.15.

Investment The results in Table 5.6 show that investment is increasing in all state variables. More interestingly, temporary cash flow shocks $\ln \xi_{it}$ are positive and statistically significant and stronger for the R&D firms which is consistent with the previous literature on excess sensitivity to cash flows. Since these shocks increase internal funds available but should not affect future profitability of investment because they are constructed after removing the predictable part of cash flow, $\alpha_0 + \alpha_1 \omega_{it} + \alpha_2 \ln K_{it} + \alpha_3 \ln S_t$, its significance can be taken as a first signal that financial costs are binding and therefore $\frac{\partial FC(EF_{it})}{\partial I_{it}} \neq 0$.

R&D Regarding R&D start-up decisions, from Table 5.6 we can see that larger and more productive firms are more likely to start performing R&D. Also, firms are more likely to start performing R&D when the state of the market (in terms of productivity and/or demand) is strong.

State transition

Productivity As discussed above, productivity is recovered via production function estimation under the assumption that it follows a first order Markovian

Dependent Variable:	(i) $ln(CF_it)$			(ii) $ln(I_{it})$ Non-RD firms			(iii) RD firms			(iv) $ln(RD_it)$		
	Coef.	S.E.	Pval.	Coef.	S.E.	Pval.	Coef.	S.E.	Pval.	Coef.	S.E.	Pval.
$ln(K_{it-1})$	0.65	0.02	0.00	0.78	0.13	0.00	-0.01	0.31	0.98	0.10	0.11	0.36
$ln(K_{it-1})^2$	-	-	-	0.00	0.01	0.77	0.06	0.02	0.01	-	-	-
$ln(S_t)$	0.61	0.09	0.00	-0.05	0.13	0.68	0.21	0.11	0.07	0.88	0.36	0.01
ω_{it}	1.15	0.15	0.00	1.06	0.29	0.00	0.51	0.28	0.07	0.25	0.66	0.70
ξ_{it}	-	-	-	0.36	0.05	0.00	0.42	0.04	0.00	-	-	-
Constant	-10.60	1.40	0.00	-1.60	2.09	0.45	-2.39	1.90	0.21	-15.92	5.36	0.00
R^2	0.69			0.73			0.73			0.09		
Observations	836			433			403			520		

Notes: Estimates for the profit function (i), investment policy functions for RD and non-RD firms (ii) and (iii) and RD start-up probit (iv).

Table 5.6: Profit function and policy function for investment and RD, OLS estimates.

Dep. Variable			ω			
	Non-RD firms			RD firms		
	Coef.	S.E.	Pval.	Coef.	S.E.	Pval.
$[\omega_{t-1}]$	1.13	0.41	0.01	0.69	0.15	0.00
$[\omega_{t-1}]^2$	-0.13	0.32	0.67	0.42	0.15	0.01
$[\omega_{t-1}]^3$	0.02	0.08	0.83	-0.16	0.05	0.00
constant	0.03	0.18	0.86	0.06	0.05	0.25
S.E.(residuals)	0.13			0.12		
R^2	0.73			0.87		
Observations	467			469		
Long run distribution						
$E(\omega)$	1.36			1.39		
$std(\omega)$	0.26			0.46		
Data moments						
$E(\omega)$	1.37			1.41		
$std(\omega)$	0.25			0.34		

Note: Results for the productivity transition using a 3rd degree polynomial.

Table 5.7: Transition function for productivity, OLS results.

process

$$\omega_{it+1} = E(\omega_{it+1}|\omega_{it}, R_{it}) + \nu_{it}$$

which we estimate using a third order polynomial separately for R&D and non-R&D firms

$$\omega_{it+1} = \eta_0^R + \eta_1^R \omega_{it} + \eta_2^R \omega_{it}^2 + \eta_3^R \omega_{it}^3 + \nu_{it}$$

With these estimated coefficients we can generate the steady-state distribution for R&D and non-R&D firms implied by these coefficients and compare them with the productivity distribution in the data. The estimated coefficients presented in Table 5.7 imply a steady state distribution for productivity which is 3% larger for R&D performing firms. Comparing with the actual moments for productivity in the data, the implied long run distribution for productivity matches closely actual productivity distribution.

Aggregate state One of the main results of the framework proposed in chapter 2 is that one can use the aggregate state to represent the industry evolution. Under some assumptions, the resulting equilibrium evolution for the aggregate state is Markovian. In this section we test whether this is a valid model. This is important to confirm (or reject) the model's assumption that allow the use of the aggregate state. We do this by checking in Table 5.8 the significance of previous lags of the state variable (which would constitute a violation of a first order Markovian process) and we do not reject the null hypothesis that the assumption is valid. We further investigate this by testing whether further moments of the state variables (ω, K) are statistically significant conditional on S_{t-1}. Particularly, the first and second moments of the productivity and capital stock distribution are not statistically significant, conditional on S_{t-1},which again confirms our previous result.

5.7.4 Step 3: Main results

In step 3 we use the minimum distance estimator outlined above to recover the linear and quadratic investment cost (μ_1, μ_2), R&D sunk cost (λ), exit value (e) and costs of external finance $(\kappa_1^R, \kappa_1^{NR})$. Given the estimated period returns, policy functions, and state transitions we can simulate industry paths, which allows to recover an estimate of the value function conditional on the dynamic parameters $(V_{\sigma^*}^E(\mu_1, \mu_2, \lambda, e, \kappa_1^R, \kappa_1^{NR}))$. By slightly perturbing the estimated policies (for investment, R&D and exit) we can obtain an estimate of the value function for these alternative policies $(V_{\sigma'}^E(\mu_1, \mu_2, \lambda, e, \kappa_1^R, \kappa_1^{NR}))$. The estimator then searches for the parameters, $(\mu_1, \mu_2, \lambda, e, \kappa_1^R, \kappa_1^{NR})$, which rationalize the observed actions as being optimal.

For the R&D firms we have assumed that firms incur a fixed cost every period, equivalent to 1% of total sales in order to keep the R&D lab running. The value of 1% is the average R&D to sales ratio observed in the data for R&D firms. Standard errors were estimated using the bootstrap.

The results in Table 5.9 reveal that adjustment costs for investment are increas-

Dep. Variable	(i) Coef.	(i) S.E.	(i) Pval.	(ii) Coef.	(ii) S.E.	(ii) Pval.	(iii) Coef.	(iii) S.E.	(iii) Pval.	(iv) $ln(S_t)$ Coef.	(iv) S.E.	(iv) Pval.	(v) Coef.	(v) S.E.	(v) Pval.	(vi) Coef.	(vi) S.E.	(vi) Pval.	(vii) Coef.	(vii) S.E.	(vii) Pval.
$ln(S_{t-1})$	0.92	0.07	0.00	3.34	6.98	0.64	0.89	0.18	0.00	0.94	0.09	0.00	-	-	-	-	-	-	0.93	0.12	0.00
$ln(S_{t-1})^2$	-	-	-	-0.08	0.24	0.73	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$ln(S_{t-2})$	-	-	-	-	-	-	0.03	0.18	0.87	-	-	-	-	-	-	-	-	-	-	-	-
$E(ln(K_{it}))$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.09	0.13	0.51	0.11	0.08	0.17
$E(ln(K_{it-1}))$	-	-	-	-	-	-	-	-	-	0.13	0.07	0.08	0.00	0.14	0.99	-	-	-	-	-	-
$\text{std}(ln(K_{it})$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.84	0.30	0.01	0.06	0.19	0.76
$\text{std}(ln(K_{it-1})$	-	-	-	-	-	-	-	-	-	-0.01	0.17	0.98	-0.73	0.32	0.03	-	-	-	-	-	-
$E(\omega_{it})$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.20	0.11	0.09	0.00	0.07	0.99
$E(\omega_{it-1})$	-	-	-	-	-	-	-	-	-	0.09	0.06	0.13	-0.10	0.12	0.38	-	-	-	-	-	-
$\text{std}(\omega_{it})$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.54	0.18	0.01	-0.04	0.13	0.74
$\text{std}(\omega_{it-1})$	-	-	-	-	-	-	-	-	-	0.01	0.10	0.92	-0.47	0.19	0.02	-	-	-	-	-	-
Constant	1.22	1.10	0.28	-16.69	51.62	0.75	1.16	1.20	0.34	1.35	1.61	0.41	15.44	1.71	0.00	15.10	1.63	0.00	0.42	1.88	0.83
R^2	0.82			0.82			0.81			0.85			0.34			0.40			0.83		
Observations	35			35			34			35			35			35			35		

Notes: Estimates for the aggregate state law of motion. Columns (i) and (ii) using a linear and quadratic approximation. Column (iii) tests the first order markov assumption. Columns (iv)-(vii) further test the significance of moments for productivity and capital.

Table 5.8: Aggregate state transition and tests, OLS results.

	Investment Cost		RD cost	Exit Value	Financial Cost				
	μ_1	μ_2	λ	e	κ_1^{NR}	κ_1^{R}	κ_0	κ_2	κ_3
Coefficients	-0.19	3.09	194	-588	0.37	1.20	-	-	-
Standard Errors	*0.18*	*1.09*	*62*	*63*	*0.48*	*0.64*	-	-	-
Coefficients	-0.16	3.07	194	-597	-	-	-	0.35	-
Standard Errors	*0.17*	*1.06*	*61*	*63*	-	-	-	*0.46*	-
Coefficients	-0.14	3.64	182	-560	-	-	-	-0.80	0.01
Standard Errors	*0.16*	*1.02*	*65*	*64*	-	-	-	*0.39*	*0.01*
Coefficients	-0.26	4.65	169	-632	-	-	-22.5	0.36	-
Standard Errors	*0.17*	*1.18*	*62*	*71*	-	-	*8.4*	*0.56*	-
Coefficients	-0.21	4.38	173	-590	-	-	-12.6	-0.45	0.01
Standard Errors	*0.16*	*1.10*	*58*	*65*	-	-	*7.3*	*0.40*	*0.01*

Notes: Dynamic parameter coefficient estimates. Bootstrapped standard errors

Table 5.9: Investment cost, RD sunk cost, exit value and financial costs.

ing in the amount invested. The R&D sunk costs are estimated at \$194 million dollars (in 1987 USD) which represents around 10% of average annual sales and 70% of average annual profits.

Finally our main parameter of interest, the costs of external finance, are significant since for each dollar raised in external finance, there is an estimated additional financial cost of 37 cents for non-R&D firms and 1.20 dollars for firms who start R&D. This reflects substantial external financial costs, particularly for firms who want to start R&D suggesting that some firms might be prevented from starting R&D if they do not have sufficient internal funds.

5.8 Robustness of the results

5.8.1 Fixed and quadratic costs of finance

Because of the identification reasons outlined above we have adopted the simplest specification but we have also estimated more flexible parametrization for financing costs introducing both a fixed and a quadratic component in the following way

$$FC(EXT_{it}) = \left[\kappa_0 + \kappa_2 EXT_{it} + \kappa_3 EXT_{it}^2\right] * \mathbf{1}(EXT_{it} > 0)$$

The overall results emerging from Table 5.9 are that the costs of external finance are increasing in the total amount borrowed.

5.8.2 Pre and post 1994

Our error correction model results suggested higher financial constraints in the period before 1994 due to deregulation in the financial sector. We investigate this by estimating the model separately for the two sub-periods. The results in

Pre 1994	Investment Cost		RD cost	Exit Value	Financial Cost				
	μ_1	μ_2	λ	e	κ_1^{NR}	κ_1^{R}	κ_0	κ_2	κ_3
Coefficients	-0.32	3.52	149	-638	0.34	0.72			
Standard Errors	*0.18*	*1.05*	*84*	*74*	*0.72*	*0.65*			
Coefficients	-0.34	3.72	168	-639				0.46	
Standard Errors	*0.18*	*1.09*	*89*	*74*				*0.69*	
Coefficients	-0.30	4.16	143	-596				-0.75	0.01
Standard Errors	*0.19*	*1.35*	*82*	*80*				*0.95*	*0.00*
Coefficients	-0.41	5.03	154	-665			-25.0	0.33	
Standard Errors	*0.19*	*1.53*	*85*	*74*			*13.9*	*0.73*	
Coefficients	-0.31	4.38	141	-603			-4.4	-0.70	0.01
Standard Errors	*0.24*	*1.76*	*95*	*77*			*11.1*	*0.98*	*0.00*

Pos 1994	Investment Cost		RD cost	Exit Value	Financial Cost				
	μ_1	μ_2	λ	e	κ_1^{NR}	κ_1^{R}	κ_0	κ_2	κ_3
Coefficients	-0.07	3.65	138	-501	-0.60	-0.57			
Standard Errors	*0.20*	*1.39*	*58*	*71*	*0.62*	*0.61*			
Coefficients	-0.17	4.48	193	-486				-0.65	
Standard Errors	*0.20*	*1.10*	*49*	*69*				*0.18*	
Coefficients	-0.10	5.07	177	-450				-1.30	0.00
Standard Errors	*0.18*	*1.11*	*105*	*77*				*0.23*	*0.00*
Coefficients	-0.19	6.19	177	-512			-29.6	-1.07	
Standard Errors	*0.16*	*1.27*	*52*	*67*			*11.8*	*0.17*	
Coefficients	-0.07	5.31	120	-486			-18.8	-1.29	0.00
Standard Errors	*0.16*	*1.35*	*131*	*108*			*17.1*	*0.24*	*0.00*

Notes: Dynamic parameter coefficient estimates. Bootstrapped standard errors

Table 5.10: Investment cost, RD sunk cost, exit value and financial costs: sample split before and after 1994.

Table 5.10 confirm the previous evidence with the costs of external finance being substantially higher in the period before 1994.

5.9 Final comments

In this chapter we have presented a dynamic structural model of investment and R&D where there are financial frictions (external finance is more costly than internal finance). We have fitted the parameters of this model to 35 years of firm-level data from the US iron and steel industry. We find that there is evidence of financial constraints as external financing is much costlier than internal financing with a premium of 35 cents to the dollar. Furthermore, we estimate there are substantial sunk costs for R&D - on the order of $194m.

Given the difficulties in credibly identifying the effects of financing constraints we believe that our structural approach offers a promising way forward in investigating their importance. As in any structural model, we have had to make several assumptions and although we have tried to test many of them, there is surely much more robustness testing to be done.

In terms of future work there are several avenues. First, we have abstracted away from ongoing R&D costs and focused on the discrete decision over whether or not to build an R&D lab. This makes the analysis more tractable, but is clearly unsatisfactory. Second, it would be good to have some more "external instruments" for cash flow, such as using the fact that firms are often multidivisional and a cash flow shock in one division should affect investment in unrelated divisions if there are financing constraints. These quasi-experimental treatment effects could be combined with the structural model to generate better identification of the costs of external financing. Thirdly, we have not used the structure of external financing - debt vs. equity for example, to further pin down the model. Finally, we would like to investigate the adequacy of the model in a wider range of sectors. This work is all in progress.

5.A Appendix

5.A.1 Data and sample construction

The data was collected from Standard and Poor's COMPUSTAT dataset. We have selected all US firms in industry "Iron and Steel Mills", NAICS 331111 for the period 1970-2005. We use aggregate data from the Bureau of Economic Analysis (BEA) for total shipments, value added and deflators (sales, materials and investment). Finally we get data from the US Geological Survey for total US production, shipments, imports, exports, price and total world production. We drop observations with missing values for sales, number of workers and Investment. We interpolate some of these missing values when they were missing for only one intermediate year. We winsorize the data at the 0.5% on each tail of the distribution for the variables cash flow, log of sales, log of materials, log of capital stock, log of labor and log of TFP. From a initial sample of 1,263 observations we are left with an unbalanced panel with 1,069 observations over the 25 year period. Our sample covers around 88% of total industry sales varying from a minimum of 73% in 1972 to a maximum of 103% in 1980.

The capital stock is generated using the perpetual inventory method and we use a 6% depreciation rate. We use the following variables (all in US $millions unless otherwise stated).

VA_{it} - Value Added

CF_{it} - Cash Flow

K_{it} - Capital Stock

L_{it} - Number of Workers ('000)

Dep. Variable	OLS			Fixed Effects		
	$RD_{it}/Sales_{it}$					
	Coef.	s.e.	Pval	Coef.	s.e.	Pval
$RD_{it-1}/Sales_{it-1}$	0.96	0.01	0.00	0.136	0.035	0.00
Constant	0.00	0.00	0.39	0.00	0.00	0.00
R^2	0.95			0.95		

Notes: Evidence of constant firm level RD to sales ratio.

Table 5.11: RD to sales ratio, AR1.

Y_{it} - Sales

S_t - Total US Shipments (metric tons)

IMP_t - Total US Imports (metric tons)

EX_t - Total US Exports (metric tons)

$\tilde{Y}_t$ - Total US Production (metric tons)

WP_t - Total World Production (USD billion)

δ_t - Physical Capital deflator

P_t^S - Sales deflator (USD per ton)

P_t^I - Investment deflator (1987=100)

RD_{it} - Research and Development expenditures

We recover total factor productivity (ω_{it}) using a methodology similar to Levinsohn and Melitz (2004) and De Loecker (2007) to control for endogeneity as in Olley and Pakes (1996) but also incorporate imperfect competition in a similar way to Klette and Griliches (1996).

Bibliography

[1] Abel, A., and Blanchard,O. (1986) "The Present Value of Profits and Cyclical Movements in Investment", Econometrica 54, 249-73.v

[2] Abel, A and Eberly, J. (2002) "Q Theory without adjustment costs and cash flow effects withou financing constraints" University of Pennsylvania mimeo

[3] Ackerberg, D., Benkard, L., Berry, S., and Pakes, A. (2003) "Econometric Tools for Analyzing Market Outcomes", Forthcoming chapter in Handbook of Econometrics, Volume 6

[4] Ackerberg, D., Caves, K and Frazer, G. (2006) "Structural Identification of Production Functions", mimeo

[5] Adda, J. and Cooper, R. (2003) "Dynamic Economics", MIT Press

[6] Aghion, P., Bloom, N., Blundell, R., Grifith, R., and Howitt, P. (2005) "On Competition and Innovation: An Inverted U Relationship"; QJE; 120 (2), 701-728

[7] Aghion, P., Klemm,P., Marinescu,I., Bond, S. (2004) "Technology and Financial Structure: Are Innovative Firms Different?," Journal of the European Economic Association vol. 2 (2), 277-288

[8] Aguirregabiria, V. and Mira, P. (2002) "Swapping the Nested Fixed Point Algorithm: A Class of Estimators for Discrete Markov Decision Models"; Econometrica; 70 (4) 1519-1543

[9] Aguirregabiria, V. and Pedro Mira (2007) "Sequential Estimation of Dynamic Discrete Games", Econometrica, 75(1), 1-53.

[10] Arellano, M. and Bond, S. (1991) "Some tests of specifications for panel data: Monte Carlo evidence and an application to employment equations", Review of Economic Studies, 58

[11] Arellano, M. and Bover, O. (1995) "Another look at the instrumental-variable estimation of error component models", Journal of Econometrics 68, 29-52

[12] Arellano, M. and Bond, S. (1998) " Dynamic panel data estimation using DPD98: a guide for users", University of Oxford mimeo

[13] Arrow, Kenneth J. (1962), "Economic Welfare and the Allocation of Resources for Invention," In Richard Nelson (ed.), The Rate and Direction of Inventive Activity. Princeton, N. J.: Princeton University Press.

[14] Bajari, P. Benkard, C. and Levin, J. (2007) "Estimating Dynamic Models of Imperfect Competition", Econometrica

[15] Bajari, P., Hong, H., Krainer, J. and Denis Nekipelov (2006) "Estimating Static Models of Strategic Interaction" NBER WP12013

[16] Bajari, P., Hong, H., and Steve Ryan (2007) "Identification and Estimation of A Discrete Game of Complete Information", Working Paper, MIT

[17] Banerjee, A. (2004) "Inequality and Investment", mimeo

[18] Banerjee, A. and Ester Duflo (2008) "Do Firms Want to Borrow More? Testing Credit Constraints Using a Direct Lending Program", mimeo

[19] Baumol, W. and Robert Willig (1981) "Fixed Cost, Sunk Cost, Entry Barriers and Sustainability of Monopoly ", Quarterly Journal of Economics 95, 405-431

[20] Beira, E., Crespo, C., Gomes, N. and Menezes, J. (2003) "Dos moldes à engenharia do produto, a trajectória de um cluster", in M. Heitor, J.M.B. Brito e M.F. Rollo (eds) "Momentos de Inovação e Engenharia em Portugal no seculo XX", Lisboa: Dom Quixote

[21] Berry, S. (1994) "Estimating Discrete-Choice Models of Product Differentiation"; RAND Journal of Economics; 25 (2)

[22] Besanko, D., Perry, M. and Spady, R. (1990) "The Logit Model of Monopolistic Competition: Brand Diversity", The Journal of Industrial Economics, 38 (4), 397-415

[23] Benkard, L. (2004) "A Dynamic Analysis of the Market for Wide-Bodied Commercial Aircraft", Review of Economic Studies, 71(3), 581-611

[24] Bloom, N. (2008) "The Impact of Uncertainty Shocks", mimeo

[25] Bloom, N., Bond, S. and John Van Reenen (2007) "Uncertainty and Investment Dynamics", Review of Economic Studies, vol 74, 391-415

[26] Bloom, N., Griffith, R. and John Van Reenen. (2002) "Do R&D Tax Credits Work?" Journal of Public Economics, 85, pp. 1-31

[27] Bloom, N., Criscuolo C., Hall, B. and John Van Reenen. (2008) "Innovation outputs and R&D Tax Credits: Panel data evidence from U.S. firms" LSE mimeo

[28] Blundell, R. and Bond, S. (1998) "Initial conditions and moment restrictions in dynamic panel data models", Journal of Econometrics 87, 115-143

[29] Blundell, R. Griffith, R. and Van Reenen, J. (1999) "Market share, market value and Innovation: Evidence from British Manufacturing Firms", Review of Economic Studies, 66(3), 529-554

[30] Bond, S. and Cummins, J. (1999) "Noisy Share Prices and the Q Model of Investment", IFS Working Paper

[31] Bond, S., Harhoff, D and Van Reenen, J. (2008) "Investment, R&D and Financial Constraints in Britain and Germany", Annales d'Économie et de Statistique

[32] Bond, S. and Costas Meghir (1994) "Dynamic Investment Models and the Firm's Financial Policy", Review of Economic Studies, 61, 197-222

[33] Bond, S. and Måns Söderbom, (2005) "Adjustment costs and the identification of Cobb Douglas production functions", IFS Working Papers, W05/04.

[34] Bond, S. and Van Reenen, J. (2008) "Microeconometric models of investment and employment" forthcoming in J.J. Heckman and E.E. Leamer (eds.) Handbook of Econometrics, Volume 6

[35] Buettner, T. (2004) "The Dynamics of Firm Profitability, Growth and Exit", LSE Phd dissertation

[36] Cabral, L. and Mata, J (2003) "On the evolution of Firm Size Distribution: Facts and Theory", American Economic Review, 93:4, 1075-1090

[37] Caplin, A. and Nalebuff, B. (1991) "Aggregation and Imperfect Competition: On the Existence of Equilibrium", Econometrica, 59 (1), 25-59

[38] CEFAMOL, (2005) "Situação Actual da Indústria Portuguesa de Moldes", http://www.cefamol.pt/

[39] Cobb, C.and P. H. Douglas (1928) "A Theory of Production", American Economic Review, 18 (Supplement), 139-165.

[40] Cohen, W. and S. Klepper; (1996) "Firm size and the nature of innovation within industries: the case of process and product R&D", Review of Economic Studies

[41] Cooper, R. and John Haltiwanger (2006) "On the Nature of Capital Adjustment Costs", Review of Economic Studies, 73 (3),611-633

[42] Cooper R., Haltiwanger, J. and Laura Power (1999) "Machine Replacement and the Business Cycle: Lumps and Bumps", American Economic Review 89 (4), 921-946

[43] Cunat, V. and Maria Guadalupe (2005) "Executive Compensation in the Banking and Financial Sectors", mimeo

[44] Cyert, R. and R. Fruehan (1996) "The Basic Steel Industry", US Department of Commerce, Office of Technology Policy

[45] De Loecker, J. (2007) "Product Differentiation, Multi-product Firms and Estimating the Impact of Trade Liberalization on Productivity", NBER WP13155

[46] Dixit, A. (1988) "A General Model of R&D and Competition Policy", Rand Journal of Economics, 19 (3), 317-326

[47] Doraszelski, U. and Jaumandreu, J. (2007) "R&D and Productivity: Estimating Production Functions when Productivity is Endogenous", mimeo

[48] Doraszelski, U. and Satterthwaite, M. (2007) "Foundations of Markov-Perfect Industry Dynamics: Existence, Purification, and Multiplicity", CEPR Discussion Papers, DP6212

[49] Ericson, R. and Pakes, A. (1995) "Markov-Perfect Industry Dynamics: A Framework for Empirical Work"; Review of Economic Studies; 62 (1); 53-82

[50] Evans, D. and Jovanovic, B. (1989) "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints", Journal of Political Economy 97 (4), 808-827

[51] Fazzari, S.M., R.G.Hubbard and B.C.Petersen (1988) "Financing constraints and corporate investment", Brooking Papers on Economic Policy, 141-195

[52] Foster, Haltiwanger, J. and Chad Syverson (2008) "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?", American Economic Review

[53] Gilchrist, S. and Himmelberg, C. (1995) "Evidence of the role of cash flow for investment", Journal of Monetary Economics 36, 541-572

[54] Gomes, J. (2001) "Financing Investment", American Economic Review, 91:, 1263-1285

[55] Hall, B (2002) " Financing of R&D", Oxford Review of Economic Policy

[56] Hayashi, F. (1982) "Tobin's Marginal q and Average q: A Neoclassical Interpretation", Econometrica 50, 213-224

[57] Hekman, J. (1978) "An Analysis of the Changing Location of Iron and Steel Prodution in the Twentieth Century", The American Economic Review, vol. 68 (1), pp. 123-133

[58] Hennessy, C. and Toni Whited (2007) "How Costly is External Financing: Evidence from a Structural Estimation", The Journal of Finance, vol. 62, no. 4, 1705-1745

[59] Himmelberg, C. and Petersen, C. (1994), "R&D and Internal Finance: a Panel Study of Small Firms in High-Tech Industries, The Review of Economics and Statistics, 76 (1)

[60] Hopenhayn, H. (1992) "Entry, Exit and Firm Dynamics in Long Run Equilibrium", Econometrica, 60(5), 1127-1150

[61] Hotz, V. and Miller, R. (1993) "Conditional Choice Probabilities and the Estimation of Dynamic Models"; Review of Economic Studies 60 (3); pp 497-529

[62] Hotz, V. J., Miller, R. A., Sanders, S., and J. Smith (1994), "A Simulation Estimator for Dynamic Models of Discrete Choice," Review of Economic Studies, 61:2, 265-289.

[63] Hubbard, R Glenn & Kashyap, Anil K & Whited, Toni M (1995) "International Finance and Firm Investment," Journal of Money, Credit and Banking, Ohio State University Press, vol. 27(3), pages 683-701, August

[64] IAPMEI, (2006) "A Industria Portuguesa de Moldes no Contexto Internacional - contributos para o conhecimento da actividade", www.iapmei.pt

[65] Jovanovic, B. (1982) "Selection and the Evolution of Industry", Econometrica, 50(3), 649-670

[66] Jovanovic, B. and Saul Lach (1989): "Entry, Exit and Diffusion with Learning by Doing", The American Economic Review, 79 (4), 690-699

[67] Kaplan, S. and Zingales, L. (1997) " Do investment - cash flow sensitivities provide useful measures of financing constraints?", Quarterly Journal of Economics CXII, 1, 169-216

[68] Karlson, S. (1983) "Modeling Location and Production: An Application to U.S. Fully Integrated Steel Plants", The Review of Economics and Statistics, Vol 65 (1), pp. 41-50

[69] Klepper, S. (1996) "Entry, exit, growth and innovation over the product life cycle" American Economic Review, 86, pp. 562-83

[70] Klette, T. and Zvi Griliches (1996) "The Inconsistency of Common Scale Estimators When Output Prices Are Unobserved and Endogenous," Journal of Applied Econometrics 11(4), 343-61

[71] Klette, T. and Griliches, Z., (2000) "Empirical Patterns of Firm Growth and R&D Investment: A Quality Ladder Model Interpretation", The Economic Journal, 110, 363-387

[72] Klette, T. and Kortum, S. (2004) "Innovating Firms and Aggregate Innovation", Journal of Political Economy 112 (5), 986-1018

[73] Krusell, P. and A. Smith (1998) "Income and Wealth Heterogeneity in the Macroeconomy", Journal of Political Economy 106(5), 867-896

[74] Lach, S. and Mark Schankerman (1989): "Dynamics of R&D and Investment in the Scientific Sector", The Journal of Political Economy, 97 (4)

[75] Leahy, John V & Whited, Toni M (1996) "The Effect of Uncertainty on Investment: Some Stylized Facts," Journal of Money, Credit and Banking, Ohio State University Press, vol. 28(1), pages 64-83, February.

[76] Lentz, R. and Mortensen, D. (2005) "An Empirical Model of Growth Through Product Innovation" NBER WP11546

[77] Levinsohn, J. and Melitz, M. (2004) "Productivity in a Diferentiated Products Market Equilibrium", mimeo

[78] Levinsohn, J and Amil Petrin, (2003) "Estimating Production Functions Using Inputs to Control for Unobservables", Review of Economic Studies, 317-342.

[79] Macieira, J. (2006) "Extending the Frontier: A Structural Model of Investment and Technological Competition in the Supercomputer Industry"; mimeo, Virginia Tech

[80] Marschak, J. and W.H. Andrews (1944) "Random Simultaneous Equations and the Theory of Production", 1944, Econometric, vol 12, No 3 and 4, 143-205

[81] Maskin, E., and Tirole, J. (1988), A Theory of Dyamic Oligopoly, I: Overview and Quantity Competition with Large Fixed Costs, Econometrica 56(3), 549-569

[82] Maskin, Eric and Tirole, Jean; (2001) "Markov Perfect Equilibrium: I. Observable Actions"; Journal of Economic Theory; 100 (2); 191-219

[83] Melitz, M. (2000) "Estimating Firm-Level Productivity in Differentiated Product Industries"; Harvard University

[84] Melitz, M. (2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity"; Econometrica; 71 (6); 1695-1725

[85] Nelson, Richard R. (1959), "The Simple Economics of Basic Scientific Research," Journal of Political Economy 49: 297-306

[86] Olley, S. and Ariel Pakes, (1996); "The Dynamics of Productivity in the Telecommunications Equipment Industry," Econometrica, vol. 64, no. 6, 1263-98.

[87] Pakes, A. and McGuire, P. (1994) "Computing Markov-perfet Nash Equilibria: Numerical Implications of a Dynamic differentiated Product Model"; RAND Journal of Economics 25(4)

[88] Pakes, A. and McGuire, P. (2001) "Stochastic Algorithms, Symetric Markov Perfect Equilibrium, and the 'Curse' of Dimensionality"; Econometrica; 69 (5); 1261-1281

[89] Pakes, A., Ostrovsky, M. and Steve Berry (forthcoming) "Simple Estimators for the Parameters of Discrete Dynamic Games", RAND Journal of Economics

[90] Pesendorfer, M. and Philipp Schmidt-Dengler (forthcoming): "Asymptotic Least Squares Estimators for Dynamic Games", Review of Economic Studies

[91] Pesendorfer, M. and Philipp Schmidt-Dengler (2003): "Identification and Estimation of Dynamic Games", NBER Working Paper No. 9726

[92] Raith, M. (2003) "Competition, Risk and Managerial Incentives", American Economic Review, 93 (4), 1425-1436

[93] Ryan, S. (2006): "The Costs of Environmental Regulation in a Concentrated Industry", Working Paper, MIT

[94] Rust, J. (1987) "Optimal replacement of GMC bus engines: an empirical model of Harold Zurcher", Econometrica 55 (5); 999-1033

[95] Santos, C. (2008) "Recovering the Sunk Costs of R&D: The Moulds Industry Case", mimeo

[96] Schmalensee, R. (1992) "Sunk Costs and Market Structure: A Review Article", The Journal of Industrial Economics, 40 (2), 125-134

[97] Schmidt-Dengler, P. (2007) "The Timing of New Technology Adoption: The Case of MRI", manuscript

[98] Schumpeter, J. A. (1942), Capitalism, Socialism and Democracy, New York: Harper and Row

[99] Schundeln, M. (2008) "Modeling Firm Dynamics to Identify the Cost of Financing Constraints in Ghanaian Manufacturing", mimeo

[100] Stiglitz, J. (1987) "Technological Change, Sunk Costs and Competition", Brooking Papers on Economic Activity, 3, 883-947

[101] Sutton, J. (1991): Sunk Costs and Market Structure, MIT Press

[102] Sutton, J. (1998): Technology and Market Structure, MIT Press

[103] USITC, United States International Trade Comission, (2002) ; "Tools, dies and industrial molds: competitive conditions in the United States and selected foreign markets", Investigation no. 332-435, USITC Publication 3556

[104] Vives, X. (2004) "Innovation and Competitive Pressure", CEPR DP 4369

[105] Weintraub, G. Benkard, L. Van Roy, B. (2007) "Markov Perfect Industry Dynamics with Many Firms", mimeo, Stanford University

[106] Whited, T.M. (1992) "Debt, liquidity constraints and corporate investment: evidence from panel data", Journal of Finance 47: 1425-1460

[107] Whited, Toni M (1998) "Why Do Investment Euler Equations Fail?," Journal of Business and Economic Statistics, American Statistical Association, vol. 16(4), pp. 479-88