A Structural Empirical Model of R&D, Firm Heterogeneity, and Industry Evolution*

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Abstract

This paper develops and estimates a dynamic industry equilibrium model of R&D, R&D spill-overs, and productivity evolution of manufacturing plants in the Korean electric motor industry from 1991 to 1996. Plant-level decisions for R&D, physical capital investment, entry, and exit are integrated in an equilibrium model with imperfectly competitive product market. Estimates of the structural parameters explains observed heterogeneity in plant R&D choice, size, and turnover, and quantifies how R&D and R&D spill-overs drive the change of plant productivity and industry structure. Given the structural estimates, I study an important policy question: how does product market competition affect individual firm innovation and aggregate industry productivity?

The empirical model is estimated in two steps. In the first step, a model of static market competition is used to estimate the demand elasticity, returns to scale in production, and the process of plant level productivity. The initial productivity distribution for new entrants is also recovered. In the second step, I use a Simulated Method of Moments estimator to estimate the cost of R&D, the magnitude of the R&D spill-over, adjustment costs of physical investment, and the distribution of plant scrap values. To circumvent the computational burden of solving the industry equilibrium with a large number of plants in the second stage estimation, I apply the recent approximation method of Weintraub, Benkard and Van Roy (2005).

The industry equilibrium model provides a natural link from individual firm's R&D decisions to aggregate industry productivity. Counterfactual experiments of two policies are implemented. Increasing the elasticity of substitution between products increases plant innovation incentives and the plant turnover. In the long run, a 5% drop in price-cost margin improves industry productivity by 2.8%. In contrast, a lower entry cost, which increases total entry by 50%, does not change industry productivity. Although the market selection effect is strengthened by higher firm turnover, the plant's incentives to invest in R&D are reduced.

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1 Introduction

A large empirical literature has documented substantial and persistent firm productivity heterogeneity even within narrowly-defined industries.[1] Theoretical models of industry dynamics by Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995) have been developed to explain the patterns of individual firm size, success, and failure observed in longitudinal micro-level data. These existing theoretical models share a common feature: a stochastic process that changes a firm's productivity (or knowledge of its productivity) over time. This process of productivity evolution is a key component that drives the success and failure of individual firms and the overall evolution of industry structure.

In this paper, I study an important source of productivity evolution: the investment in R&D by individual firms. Specifically, using micro data for producers in the Korean electric motor industry for the period 1991 to 1996, I estimate how a firm's productivity is affected by its own R&D investment and spill-overs from the R&D investments of its competitors within the same industry. There exists strong empirical evidence that a firm's technological position does not just evolve exogenously. Griliches (1998) provides an extensive survey of the empirical literature linking own firm R&D spending, R&D spill-overs and productivity growth. I extend these previous studies by investigating the R&D decision of firms within a dynamic industry equilibrium model.

I contribute to the existing literature in several dimensions. First, it is widely observed that a large fraction of firms reporting no R&D activity in even high tech industries. I reconcile this observation with Gibrat's law by allowing firms to survive by imitation. Furthermore, solving the firm's dynamic optimization problem enables me to identify how firm investment, output, and exit decisions interact with its productivity change, which relates firm R&D directly to firm heterogeneity. Second, the equilibrium industry structure provides a natural link from individual firm performance to aggregate industry productivity and output by two mechanisms: the "market selection" mechanism, which operates through resource re-allocation from low efficiency to high efficiency firms or through entry and exit, and the active "firm learning" mechanism, which operates through individual firm's productivity improvement over time. Fi-

[1] See Bartlesman and Doms (2000) for an excellent survey of the micro productivity literature.

nally, following estimation of the model parameters, I am able to evaluate how pro-competition policies affect firm R&D, physical investment, entry, exit, and industry aggregates quantitatively.

The idea of investigating firm R&D, inter-firm spill-overs, and the evolution of industry structure simultaneously dates back to Dasgupta and Stiglitz (1980). Under imperfect product market competition, firms maximize their value of continuation given expectations about the evolution of their own and competitors' states. This implies that a firm's learning effort and investment decision are endogenously shaped by the level of product market competition as well as by pressure from potential entrants.[2] Yet, few previous empirical studies have attempted to estimate such a dynamic equilibrium model.[3] My estimation builds on the industry dynamics model pioneered by Ericson and Pakes (1995). I adapt it to an environment with both physical-capital and knowledge-capital investments. The firms make entry, exit, and investment decisions each period and improve their productivity as a result of their own investments in knowledge capital. Furthermore, I allow for a technological spill-over from more productive to less productive firms. Finally, firms experience technological setbacks due to idiosyncratic exogenous shocks.

Ericson and Pakes (1995) propose a Markov Perfect Equilibrium concept to characterize the evolution of an industry. To circumvent the well-known heavy computational burden of the Markov Perfect Equilibrium, I use the "oblivious equilibrium" concept proposed by Weintraub, Benkard, and Van Roy (2007) to solve the industry equilibrium of the theoretical model. When there are large number of firms within the industry, the "oblivious equilibrium", which assumes that firms ignore current information about competitors states and condition their choices on the knowledge of the long run average industry state, closely approximates a Markov Perfect Equilibrium.

The model is used to study the process of R&D and productivity growth for producers

[2]Spence (1984) shows that imperfect competition induces a free-rider problem in R&D effort given the existence of a spill-over. More recently, Bloom, Schankerman and Van Reenen (2004) use a panel of U.S. firms to empirically identify technological spill-over and product market rivalry.

[3]Some exceptions include Benkard (2004), Ryan (2005) and Collard-Wexler (2006), who use empirical dynamic oligopoly models to analyze industry pricing, industry performance, and optimal industry policy. Recently, Lentz and Mortensen (2005) estimate an equilibrium model of firm innovation developed by Klette and Kortum (2004) using a panel of Danish firms.

in the Korean electric motor industry. In the first step, I utilize the model specification for static market competition to estimate the demand elasticity, returns to scale in production, and the process of plant level productivity. I also recover the plant's entry decision and new entrant's initial productivity distribution. In the second step, I use a Simulated Method of Moments estimator to estimate the dynamic investment model to recover the cost of R&D, the magnitude of the spill-over, adjustment costs of investment, and the distribution of plant scrap values. I apply a recent approach by Chernozhukov and Hong (2005), which is based on the Markov Chain Monte Carlo (MCMC) method, to obtain point estimates and confidence intervals. By explicitly controlling for imperfect competition, productivity heterogeneity and both physical-capital and knowledge-capital investment, the model is rich enough to reproduce the observed market structure and industry turnover patterns.

Furthermore, the estimation results show that each element of the model is critical in explaining the observed pattern in the data. The empirical results show that: first, a firm's own R&D effort improves its future productivity while this process is subject to substantial idiosyncratic uncertainty. The within-industry R&D spill-over is significant and helps to explain the observed producer R&D spending and productivity evolution patterns. On average, one dollar of competitor's R&D expenditure can substitute for 1.6 cents of own R&D input. Taking into account that the total R&D spill-over pool is much larger relative to any producer's own spending and the R&D spill-over is a public good, spill-overs are quite important to the less productive producers. Second, each producer also incurs substantial adjustment costs for physical capital investment. Third, the mean random scrap value and entry cost equals four years and six years of average firm profit, respectively. The relatively narrow hysteresis band, defined as the difference between the entry cost and the mean scrap value, explains the high turnover rate observed in the industry data. Finally, there is a complementarity between a firm's physical capital investment and its innovation incentives. Not only does a firm's own R&D investment, but also its physical capital investment, responds to the spill-over.[4]

Using the point estimates of the parameters, I implement counter-factual experiments to study the effects of two different pro-competitive policies. In the first experiment, the compet-

[4] Bernstein and Nadiri (1989) report the same pattern using a dynamic duality approach.

itive pressure comes from the more elastic substitution between products within the industry. I investigate the case where there is a 5% reduction in the price-cost margin. In the second experiment, the entry cost is reduced to introduce 50% more entrants. As the simulations show, the two policies have very different implications for firm R&D effort, firm turnover, and industry productivity. Increasing the elasticity of substitution between products increases a firm's innovation incentive but slows firm turnover. In the long run, a 5% drop in price-cost margin improves industry productivity by 2.8%. On the other hand, lower entry cost doesn't change the industry productivity. Although the market selection is enforced by higher firm turnover, this is offset by a reduction in firm incentive to invest in R&D.

The paper is organized as follows. The following section highlights several interesting aspects of the data and motivates the modelling strategy. The related literature is also reviewed. The second section describes the economic environment and the industry equilibrium. The third section estimates and reports the model parameters. I implement counter-factual simulations of a set of policy changes and conclude in the final section.

1.1 Korean Electric Motor Industry

This paper will analyze a panel data set of Korean plants that manufacture electric motors (SIC31101) from 1991 to 1996.[5] The data is from the Korean Annual Mining and Manufacturing Survey, which is collected by Korean Statistical Office for all the establishments with more than 5 workers on an annual basis. Environmental concerns have put energy efficiency on high priority for a lot of governments, including Korea. As an intermediate input sector, electric motor industry is important in this respect.

The majority of previous studies of R&D investment and knowledge spill-overs use data from Compustat or various kinds of R&D surveys, which usually include a limited number of firms competing in multiple industries.[6] Therefore, it is not a data set that meets the need of

[5]SIC31101 is equivalent to NAICS 335312 (Motor and Generator Manufacturing) in U.S census. The establishments primarily engaged in manufacturing electric motors (except internal combustion engine starting motors), power generators (except battery charging alternators for internal combustion engines), and motor generator sets (except turbine generator set units).

[6]Griliches (1998) documents many studies using this data.

linking producer heterogeneity, industry structure and productivity dynamics. On the other hand, several features of the Korean electric motor industry data provide support for the estimation of my empirical model. First, each establishment reports detailed R&D expenditure on an annual basis, which provides us with a measure of its learning input. Second, electric motors is a manufacturing industry with a long history, mature technology and a large number of single-establishment firms.[7] Furthermore, the primary competition within this industry is based on producing motors with higher energy efficiency and lower cost. Firm R&D investment serves this purpose. Finally, industry incumbents usually engage in in-lab process innovation. So a firm's R&D activity affects its output through the reduction of cost for each efficiency unit of electric motors.

The plants in this industry are heterogenous in their underlying productivity and this is reflected in the pattern of their growth, investment and survival within the industry. To summarize this pattern, I focus on the plants present in the first year of the data, 1991, and follow them over the subsequent years. By tracking each of them over the years, I assign them into three groups: those who survive until the end of 1996 and increase their total value-added shares compared with the beginning of sample, those who survive until the end of 1996 but decrease their total value-added shares, and those who exit the sample before the end of 1996.

Table 1 summarizes the productivity change and investment patterns for each of three groups. Plant productivity is systematically correlated with plant expansion, decline and exit. Notice that the change in plant productivity, measured by differences in log TFP from 1991 to 1996 for expanding plants, is 0.029. The change is significantly higher than that of the other two groups.[8] The plants that expand also invest much more. After controlling for the scale of plants, the improving plants' investment to value-added ratio is on average 0.133, 50% more than those who exit and 300% more than those who deteriorate.

I also report the average R&D investment and R&D intensity of each plant over the sample period.[9] There is a strong positive relationship between average R&D intensity and the change in productivity over the years. The R&D intensity of expanding plants is four times more than

[7]On average 82% of the plants in the data are single-plant firms.
[8]The method of measuring plant level productivity is discussed in Section 3.
[9]For plants that exited, until the year of their exit.

that of the other two groups.

The model I use in this paper is in part motivated by these observations. It intends to reconcile the observed producer heterogeneity in size, growth, decline, capital intensity and R&D intensity with the theory of optimizing agents. At the heart of the model is a stochastic process of individual producer's productivity, which is driven by past R&D investment and idiosyncratic shocks. Meanwhile each producer also invests in physical capital based on their expectations about the evolution of their own productivity and industry structure. Thus R&D expenditure, physical investment, exit and entry are the policy functions of each producer's dynamic optimization problem. Given some initial industry state, some producers grow stronger and gain market share, while others become weaker and finally exit the industry. An equilibrium is defined when the industry evolution is consistent with individual producer's perception.

Table 1: Success and Failure of 1991 Establishments*

(Standard Deviations in Parentheses)

Different Life Path	Survive and Expand Output	Survive and Reduce Output	Exit by 96
LnTFP(end)-LnTFP91	0.029	0.021	−0.025
	(0.291)	(0.054)	(0.134)
Investment in Capital	668.790	48.954	80.459
	(1546.40)	(84.569)	(211.951)
Investment Intensity (I/Vadd)	0.133	0.031	0.085
	(0.152)	(0.027)	(0.171)
R&D	150.148	13.444	9.773
	(615.976)	(40.333)	(33.911)
R&D Intensity (R&D/Vadd)	0.027	0.006	0.006
	(0.093)	(0.017)	(0.02)

*R&D and investment in millions of won.

1.2 Related Literature

There are three separate but relevant lines of literature that are related to this paper. The first builds the link between market structure and productivity. There have been two mechanisms explored by recent work. A series of papers by Aghion et al (2001, 2005 and 2006) emphasize this link by considering firm innovation effort as the primary source of productivity improvement.[10] Either market competition or entry pressure affects industry productivity through the change in each firm's R&D decisions. Using micro-level panel data from the UK, Aghion et al (2006) show that an entry threat spurs innovation incentives in sectors close to the technological frontier while in lagging sectors it discourages innovation. A second mechanism that has been emphasized in the literature is the impact of market competition on the process of resource reallocation among firms. Hopenhayn (1992) and Melitz (2003) are two examples. They abstract from the endogenous innovation considerations by taking firm productivity as exogenous. The primary mechanism they emphasize is the role of more intense market competition on resource allocation from less to more productive firms or the selection of more productive firms to stay in operation. On the empirical side, Foster, Haltiwanger, Krizan (2000) tests this mechanism using U.S. census data. Aw, Chung and Roberts (2004) use various two-digit industries from Korea and Taiwan and find that impediments to exit or entry can explain the difference in productivity and turnover patterns between the same industry in those two countries. Tybout (2000) reviews evidences from previous studies on developing countries. In summary, both mechanisms, "active learning" and "market selection" are confirmed to play a role. In my empirical model, both these mechanisms are present as a result of individual firm's optimization decisions.

The second line of literature explains and substantiates firm innovation efforts, especially the production experience and ideas the firms can obtain from each other freely *within* one specific industry. There have been quite a few game theoretical papers that analyze firm technology innovation decisions when knowledge spill-overs are present. Specifically, Spence (1984) proposes a model of firms with Cournot competition in a homogeneous good. Each firm's cost depends on their accumulated industry knowledge. In a symmetric market equilibrium, he shows that with a positive spill-over, industry R&D is lower than the optimal level. However, as Jennifer Reinganum (1989) summarizes in her review article, "since it is largely restricted to special cases (e.g. deterministic innovations, drastic innovations, two firms, symmetric firms), this line of work has not yet had a significant impact on the applied literature in industrial organization; its usefulness for policy purposes should also be considered limited". In contrast, the empirical

[10] Earlier works start with Dasgupta and Stiglitz (1980) and Aghion and Howitt (1992).

studies have found enormous heterogeneity across firms in their R&D decisions. Cohen and Klepper (1992), for instance, show that the distribution of firm R&D intensities within industries tends to be uni-modal, positively skewed, with a long tail to the right and to include a large number of non-performers. To match the empirical observations, it will be crucial to have a model which can accommodate firm-level heterogeneity in the investment decision. In terms of empirical studies, both Jaffe (1988) and Bloom, Schankerman and Van Reenen (2004) use Compustat and U.S. patent data to derive the significance of these effects from a set of reduced form regressions using patent output, R&D or Tobin'q as dependent variables.[11] They find a significant "strategic effect" from product market competition and a "spill-over effect" from firms in close technological space. However, these previous studies don't look at the firm's R&D decisions using a dynamic industry equilibrium framework. Thus they are not able to provide predictions on the effect of firm's innovation effort on industry productivity and evolution.

Finally, the empirical model of this paper draws heavily from the fully-dynamic work-horse industry evolution models by Hopenhayn (1992) and Ericson and Pakes (1995). In particular, I adopt a recent simplification of the computational algorithm by Weintraub, Benkard, and Van Roy (2007). Weintraub, Benkard and Van Roy (2007) develop an algorithm for computing an "oblivious equilibrium", in which each firm is assumed to make decisions based on its own state and knowledge of the long run average industry state. They further prove that, if the industry is not highly concentrated, as the market becomes large the oblivious equilibrium closely approximates the Markov Perfect Equilibrium defined in Ericson and Pakes (1995).

[11] Jaffe (1988) used PICA database as additional source because product market information is provided by Compustat from 1993 onwards.

2 A Dynamic Model of R&D Investment

2.1 Sequence of Actions

In this section I extend the model of dynamic competition by Weintraub, Benkard and Van Roy (2007) to incorporate a knowledge spill-over and physical capital accumulation. Time is discrete and indexed by $t = 1, 2, 3, ..., \infty$. The firms within an industry are indexed by $i = 1, 2, 3, ...$ For each period t, each firm's state $\omega \in \Omega$ can be described by a pair of knowledge x and physical capital k, where x takes discrete values from the set $\mathbb{X} = \{x^1 < x^2 < x^3 <, ...\}$ and k takes discrete values from the set $\mathbb{K} = \{k^1 < k^2 < k^3 <, ...\}$. Accordingly $\Omega \in \mathbb{X} \times \mathbb{K}$ takes all the possible combinations of knowledge capital and physical capital, which is also a set of discrete values. The industry state at each period t is denoted s_t. Each of its element $s_t(\omega)$ is the total number of firms at state ω. The set of possible industry states is denoted by $\mathbb{S}$.

At the beginning of period t, all the incumbent firms engage in competition in the product market and simultaneously set their prices for each period t. A firm with state (x_t, k_t) earns profit $\pi(x_t, k_t; s_t)$. Then, incumbent firms and potential entrants make their exit and entry decisions simultaneously. Each incumbent firm observes an idiosyncratic scrap value ϕ_t, which is *i.i.d.* across different firms and time and has a well defined density function with support $\mathbb{R}_+$. Given the industry state s_t and its own state (x_t, k_t), the firm decides whether to exit. If it decides to exit, it can get the period profit plus the scrap value. The exit strategy $\chi_t = 1$ if a firm decides to exit and $\chi_t = 0$ otherwise. If it instead decides to remain in the industry, it can choose to invest in either knowledge capital or physical capital or both to improve its own state.

Meanwhile, there is also a pool of ex-ante identical potential entrants. To enter the industry, an entrant needs to pay a fixed amount of entry cost κ. Upon entry, the new entrants can draw their initial states from a distribution Φ^e. Each potential entrant compares its expected entry value with the entry cost to decide whether to become an incumbent next period. If it decides to enter, $\epsilon_t = 1$, otherwise $\epsilon_t = 0$. The number of firms entering at industry state s_t is a Poisson random variable, with mean $M(s_t)$.

In summary, the timing of events in each period is as follows:

1. Incumbent firms simultaneously set their prices to receive static period profit $\pi(x_t, k_t; s_t)$

2. Incumbent firms privately observe an idiosyncratic scrap value ϕ_t. If they exit, they get that value. If not, they make R&D and physical capital investment decisions.

3. Potential entrants decide whether to enter next period based on current industry state s_t. Each entrant pays a fixed entry cost κ.

4. Firms exit and receive their scrap values.

5. The investment outcome of each firm is realized, the new entrants enter and take their initial draws of x and k from a fixed distribution Φ_e.

2.2 Static Competition

I will first look at how firms interact with each other in the product market each period. We assume each firm within an industry has a standard Cobb-Douglas production function with returns to scale parameters γ.

$$q_t = exp(\bar{X}_t + x_t)(l_t^{\alpha}(k_t)^{1-\alpha})^{\gamma}, \tag{1}$$

where q_t is the output of the individual firm. A firm's efficiency is defined by its distance from the industry technological frontier $exp(\bar{X}_t)$. x_t captures how much a firm's knowledge lies behind the current frontier, so it has a maximum value of zero. k_t is physical capital input and l_t is labor input. Furthermore, we assume $\bar{X}_t$ has a deterministic exogenous growth process, which is determined by the world technological frontier.

Each firm produces a differentiated product and each one of them faces a demand function such that

$$q_t = Q_t(p_t/P_t)^{\eta} = \frac{I_t}{P_t}(\frac{p_t}{P_t})^{\eta} \tag{2}$$

where p_t is the price set by the firm, while Q_t and P_t are the industry-level output and price index. Accordingly, I_t is defined as the industry market size at time t. This demand function is from the widely-used monopolistic competition model by Dixit and Stiglitz (1977). The parameter η captures the elasticity of substitution between different products. Notice that since there is a limited number of firms within one single industry, we follow Yang and Heijdra (1993) and assume that each firm's output decision influences the aggregate industry price index.[12]

Thus each period, a firm takes quasi-fixed factors (k_t, x_t), exogenous variable factor prices w_t, aggregate market price P_t, and current frontier technology $exp(\bar{X}_t)$ as given and chooses variable inputs l_t to maximize its profit

$$\pi_t = p_t(I_t, P_t, q_t)q_t - w_t l_t. \tag{3}$$

We could rewrite this problem as

$$max_{l_t} P_t^{1+\frac{1}{\eta}} I^{-\frac{1}{\eta}} (exp(\bar{X}_t + x_t) k_t^{(1-\alpha)\gamma})^{1+\frac{1}{\eta}} (l_t^{\alpha\gamma})^{1+\frac{1}{\eta}} - w_t l_t. \tag{4}$$

Redefining the industry price index as

$$\hat{P}_t = P_t exp(\bar{X}_t),$$

allows us to write the optimal labor decision as

$$l_t^* = [\frac{w_t I^{\frac{1}{\eta}}}{(exp(x_t) k_t^{(1-\alpha)\gamma})^{1/\eta+1} \hat{P}_t^{1+\frac{1}{\eta}} (1+1/\eta)\alpha\gamma}]^{\frac{1}{(1+1/\eta)\alpha\gamma-1}}. \tag{5}$$

In equilibrium, the normalized industry price index $\hat{P}_t$ is determined by the industry state s_t. Let $\varphi_t = exp(x_t)k_t^{(1-\alpha)\gamma}$ and $s_t(\varphi)$ be the number of firms whose $\varphi_t = \varphi$, then

$$\hat{P}_t = I^{1-\alpha\gamma} (\frac{w}{(1+1/\eta)\alpha\gamma})^{\alpha\gamma} (\sum_{\varphi} s_t(\varphi)\varphi^{\sigma})^{-\frac{1}{\sigma}}. \tag{6}$$

where $\sigma = \frac{1+\eta}{\eta-(1+\eta)\alpha\gamma}$. Finally, the equilibrium maximized profit for firm with individual state $\varphi_t = exp(x_t)k_t^{(1-\alpha)\gamma}$ is

$$\pi(\varphi_t, s_t) = I(1-(1+\frac{1}{\eta})\alpha\gamma)\frac{\varphi_t^{\sigma}}{\sum_{\varphi} s_t(\varphi)\varphi^{\sigma}}. \tag{7}$$

In summary, the profit of each firm only depends on their relative magnitude of knowledge capital x_t and physical capital k_t. The technological frontier improves exogenously and each firm tries to keep up with it to maintain its relative technological position. Under competition the implied cost reductions show up in a decline of the aggregate price index.

[12] In the empirical application, we assume $I_t \equiv I$ is taken as exogenous to the model and time invariant. There have been recent interest in the interaction between aggregate uncertainty and firm responses (i.e., Bloom (2006)), which is out of the scope the current model.

2.3 Transition of States: Knowledge Production and Physical Investment

Each period, a firm can choose to invest in either knowledge capital or physical capital or both to improve its own state. There are major differences between the two types of investment. Consider a firm with state (x_t, k_t). The investment in physical capital has a deterministic outcome. It also involves an adjustment cost $c(k_t, k_{t+1})$. So a firm could directly choose the level of physical capital k_{t+1} for next period. In contrast, the improvement of knowledge capital involves uncertainty and depends on the firm's own R&D, competitor's R&D, and its current knowledge capital level.

For each period t, firms exert learning effort to keep up with or to close their gap with the current frontier technology. The input of knowledge production consists of two components. One part is the firm's own research and development $d_t = d(x_t, k_t; s_t)$. The other part is the R&D spill-over from other establishments competing in the same industry d_{-t}. So the transition of knowledge capital from x_t to x_{t+1} is determined jointly by d_t and d_{-t}, and also subject to uncertainty. We assume that within a narrowly defined industry, "technology space" and "product space" are reasonably well overlapping. Thus, the rival establishments' technological positions will affect a firm's knowledge production directly. So the "spill-over pool" for a firm with individual state (x_t, k_t) is defined as

$$\sum_{x>x_t} \sum_k \frac{d(x, k; s_t) s_t(x, k)}{N_t}$$

Recall that s_t is the industry state at time t, and N_t is defined as the total number of incumbents at time t. This "spill-over" pool is an average of the truncated sum R&D investment of firms within the industry. One thing to notice about this specification is that a firm gets the spill-over only from the firms which have higher knowledge capital than it has. This brings a backward advantage for the incumbents who are far from the technological frontier.[13] The composite term entering the knowledge production takes the following form:

$$D_t = [\frac{d(x_t, k_t) + \theta(\sum_{x>x_t} \sum_k d(x, k; s_t) s_t(x, k)/N_t)}{k_{t+1}}] \tag{8}$$

[13] Using UK plant-level data, Griffith, Redding, and Simpson (2005) shows that technology transfer plays an important role in productivity improvement of non-frontier establishment.

This specification assumes that an establishment can benefit freely from more productive firms and the parameter θ controls the size of this spill-over effect. This specification is related to Jovanovic and MacDonald (1994) in the sense that learning depends on the firm's state and actions, and on the state of the industry, including the distribution of know-how in use.[14] However, unlike Jovanovic and MacDonald (1994), the decision to invest in R&D doesn't preclude the opportunity to get the knowledge externality. The effectiveness of R&D in improving the next period productivity also depends on how big the firm builds itself into. This is also consistent with the empirical observations that while total R&D investment increases with the size of the firm, the R&D intensity is independent of firm size.[15]

Furthermore, like Weintraub, Benkard and Van Roy (2007), there is an idiosyncratic exogenous depreciation shock each firm will suffer with probability δ each period. In reality, it could capture two risks faced by individual firms. The first one is the firm level "organizational forgetting" documented by Benkard (2004), which causes the production process less efficient. The second one is the possibility that an individual firm has difficulty keeping up with the improvement in the industry frontier such that its relative position deteriorates. With all the pieces we described so far, we can now introduce the knowledge production function. Specifically, for $x_t = x^j \in \mathbb{X}$

$$x_{t+1} = \begin{cases} x^{j+1}, & \text{with probability } \frac{(1-\delta)D_t}{1+D_t}; \\ x^{j-1}, & \text{with probability } \frac{\delta}{1+D_t}; \\ x^{j}, & \text{with probability } \frac{1-\delta+\delta D_t}{1+D_t} \end{cases} \tag{9}$$

The firm needs to pay an extra investment cost $c(k_t, k_{t+1})$ for adjusting physical capital level from k_t to k_{t+1}. By normalizing the purchase price of capital $c_k = 1$, I specify the adjustment cost of each establishment as:

$$c(k_t, k_{t+1}) = c_a(i_t/k_t)^2 k_t, \tag{10}$$

[14] Jovanovic and MacDonald (1994) show that in a competitive industry, imitation by the firms that lag behind the frontier force some convergence of technology among establishments as the industry matures.

[15] See Klette and Kortum (2004) for a nice summary of the patterns of R&D investment and their relationship with productivity.

where $i_t = k_{t+1} - (1-\delta_c)k_t$ is the investment (divestment), c_a is the parameter for the component of convex cost of adjustment.[16]

2.4 Incumbent's Maximization Problem

Given the knowledge production technology described in the last section, for an establishment with (x_t, k_t) the value of continuation $V_c(x_t, k_t; s_t)$ is given by

$$V_c(x_t, k_t; s_t) = max_{d_t, k_{t+1}}\{-c_d d_t - c_k(k_{t+1} - (1-\delta_c)k_t)$$
$$-c(k_t, k_{t+1}) + \beta E_{s_{t+1}}[V(x_{t+1}, k_{t+1}; s_{t+1})|x_t, d_t, d_{-t}, s_t], \tag{11}$$

where $d_t(x_t, k_t; s_t)$ and $k_t(x_t, k_t; s_t)$ are associated policy functions. c_d is the cost of per unit of R&D input.

Let $V(x_t, k_t; s_t)$ be the establishment's value at the beginning of the current period. Each period, each incumbent establishment decides whether to stay or exit, so

$$V(x_t, k_t; s_t) = \pi^*(x_t, k_t; s_t) + E_{\phi_t}[max\{V_c(x_t, k_t; s_t), \phi_t\}], \tag{12}$$

where ϕ_t is the scrap value, which is assumed to be a random variable with distribution $U[0, u_b]$. The incumbent's decision rule $\chi(x_t, k_t; \phi_t, s_t) = 1$ if it decides to exit, $\chi(x_t, k_t; \phi_t, s_t) = 0$ otherwise.

2.5 Entrant's Problem

The potential entrants are ex-ante identical. Upon entry, they draw their initial endowment of x and k. It is assumed that each period's exogenous technological progress is embodied in the new generations of potential entrants to the industry. So their *relative* technological positions are drawn from a time invariant distribution Φ^e. Each potential entrant incurs entry cost κ. Potential entrants' decision $\epsilon = 1$ if

$$V_e(s_t) \equiv \beta E_{s_{t+1}}[\int V(x_e, k_e, s_{t+1}|a, \epsilon) d\Phi^e | s_t] \geqslant \kappa. \tag{13}$$

[16]The presence of irreversibility is emphasized by Abel and Eberly (1996). I also estimated the model using a slightly different version that incorporated a parameter for resale cost. All my results are robust with this change.

The mass of entrants for time t is a poisson random variable with mean $M(s_t)$.[17] The new entrants give additional competitive pressure to the incumbents' improvement. Any incumbent who can not keep up with the technological frontier's movement is going to be finally driven out of the business by superior "new generations".

2.6 Equilibrium

Following Ericson and Pakes (1995) and Weintraub, Benkard and Van Roy (2007), we define symmetric markov perfect strategies to be an action denoted by $a \in \mathbb{A}$ and entry decision $\epsilon \in \Lambda$. Specifically in our case, $a = \{d, k, \chi\}$, where $d : \Omega \times \mathbb{S} \times \mathbb{R}_+ \to R_+$ is each firm's R&D investment strategy, $k : \Omega \times \mathbb{S} \times \mathbb{R}_+ \to \mathbb{K}$ is its physical investment strategy and $\chi : \Omega \times \mathbb{S} \times \mathbb{R}_+ \to \mathbb{R}_+$ is its exit strategy. Similarly, define the entry strategy for potential entrants as: $\epsilon \in \Lambda : \mathbb{S} \to \mathbb{R}_+$. Define the value function $V(x, k, s|a', a, \epsilon)$ as the expected discounted payoffs for a firm at individual state (x, k) and industry state s playing strategy $a' \in \mathbb{A}$ while all rival firms follow strategy $a \in \mathbb{A}$ and potential entrants follow strategy ϵ. Then Markov Perfect Equilibrium strategies a and ϵ satisfy that:

1. for an incumbent $V(x, k, s|a, a, \epsilon) \geqslant V(x, k, s|a', a, \epsilon)$, $\forall a' \in \mathbb{A}$
2. entrants satisfy the zero profit condition such that $\beta E_{s'}[\int V(x, k, s'|a, \epsilon) d\Phi^e|s] \leqslant \kappa$, with equality if the mass of entrants $M(s) > 0$

2.7 Oblivious Equilibrium and Computation

In this section, I define an Oblivious Equilibrium. This equilibrium concept is based on Weintraub, Benkard and Van Roy (2007) who establish that when the number of establishments is large, oblivious strategies, which ignore current information about competitors states and are conditioned only on the knowledge of long run average industry state, can closely approximate a Markov Perfect Equilibrium. Let $\tilde{\mathbb{A}} \in \mathbb{A}$ and $\tilde{\Lambda} \in \Lambda$ be the set of oblivious strategies. Then for oblivious strategies $a = (d, k, \chi) \in \tilde{\mathbb{A}}$ and $\epsilon \in \tilde{\Lambda}$, the associated expected state of the industry

[17] The poisson random variable is justified by the following entry model: there are N potential entrants, $v_N(i)$ is the expected present value for each entering firm if i firms enter simultaneously. Each potential entrant employs the same strategy, the condition for a mixed strategy Nash Equilibrium is: $\sum_{i=0}^{N-1} C_{N-1}^i p_N^i (1-p_N)^{N-1-i} v_N(i+1) = \kappa$. The equation has a unique solution $p_N^* \in (0, 1)$, the number of firms entering is a binomial random variable Y_N with parameters (N, p_N^*). As $N \to \infty$, $Y_N \Rightarrow Z$, which is a poisson random variable with mean M.

in the long run is $S_{a,\epsilon}$. Define $\tilde{V}(x,k|a',a,\epsilon)$ as the expected payoff of an incumbent under the assumption that its competitors' state will be equal to $S_{a,\epsilon}$ in all future periods. Then oblivious equilibrium strategies a and ϵ satisfy, given self-generated $S_{a,\epsilon}$:

1. for an incumbent $\tilde{V}(x,k|a,a,\epsilon) \geqslant \tilde{V}(x,k|a',a,\epsilon)$, $\forall a' \in \mathbb{A}$

2. entrants satisfy the zero profit condition such that $\beta \int \tilde{V}(x,k|a,\epsilon) d\Phi^e \leqslant \kappa$, with equality if the mass of entrants $M > 0$

Weintraub, Benkard, and Van Roy (2007) proves that when incumbent's strategies and the entry rate function are oblivious, the industry state s_t is an irreducible, aperiodic and positive recurrent Markov Chain. Their key insight is that when there are a large number of firms and the market tends not to be concentrated, each individual firm can not benefit by unilaterally deviating to an optimal (non-oblivious) strategy by keeping track of the true industry state, *averaged over the invariant distribution of industry states.* In other words, in any industry state that has significant probability of occurrence, the oblivious strategy approximates the Markov Pefect Strategy.

The Oblivious Equilibrium provides an attractive alternative for my estimation and computation purpose. The Korean electric motor industry, which is already a detailed level 5-digit industry, still has on average 180 firms each year during my sample period. It's infeasible, and possibly unreasonable, to assume that each firm keeps track of industry state every single period and solves their optimization problem and computes the industry equilibrium. On the other hand, the model structure still allows for strategic interactions between heterogenous firms and can accommodate important industry aspects such as an imperfectly competitive product market and the R&D spill-overs across different producers.

Our procedure for calculating the equilibrium will follow the above definition closely. Given a set of parameters, the steps to compute the equilibrium are:

1. Initial guess of the mean number of entrants M

2. Initial guess of the average long run industry structure s_0

3. Solve the monopolistic competition equilibrium aggregate price P given s_0.

4. Solve the incumbent's maximization problem and recover their optimal investment policy and exit policy: $a = (d, k, \chi)$ given s_0.

5. Construct the transition matrix $T_{x,k,\chi}$ using the optimal policies. The long run average industry structure is calculated as $s_1 = M(I - T_{x,k,\chi})^{-1}\Phi^e$.

6. If $|s_0 - s_1|$ is not close enough, go back to step (2).

7. Check the free-entry condition of potential entrants. If it doesn't hold, go back to step (1).

3 Estimation of Model Preliminaries

3.1 Korean Electric Motor Industry Data

The Korean Annual Manufacturing Survey reports detailed information on each producer's physical investment, R&D investment, number of workers and value-added. In this section I will briefly review some key data patterns for the electric motor industry.

First, a considerable fraction of producers report zero R&D expenditure.[18] The R&D performers account for only 15% of the total observations during the sample years. The average R&D expenditure is 39.27 million won per year.[19] The major components of it are the wages for R&D workers and materials for R&D. As in Figure 1 and consistent with many previous empirical findings, the distribution of R&D intensity is positively skewed.[20] Among R&D performers, R&D intensity is negatively correlated with size, measured using either labor or capital.

[insert Figure 1 here]

[18] Doraszelski and Jaumandreu (2006) reports similar patterns of R&D expenditure using Spanish Manufacturing Survey data.

[19] The average exchange rate between won and U.S. dollar during the sample period is 786:1.

[20] For instance, Cohen and Klepper (1992) reports the R&D intensity in FTC Line of Business Data to be positively skewed, with a long tail extending to the right.

Table 2: Summary Statistics

variable	mean	std.	1%	99%
R&D expenditure	39.27	257.48	0	1143
R&D expenditure/Value-added	0.01	0.08	0	0.28
Physical capital	820.57	2434.89	4	14350.5
Physical investment	173.45	916.44	−40	3743
Value-added	1706.93	6630.42	46	33744
Number of workers	44.28	120.86	6	596

units of variables: millions of won

Second, we observe significant resource reallocation during the sample period. Physical investment at the establishment level, which includes net capital expenditures (purchase minus sales) on buildings, machinery/equipment, and transport vehicles, averages 173.45 million won per year. There is huge heterogeneity in plant investment decisions, ranging from −40 (1 percentile) to 6439 (99 percentile). The electric motor industry also features high turnover. The average annual entry rate of new establishments on average is .34 and the exit rate of incumbents is .28 over the sample years.

Finally, the data does not provide information on physical units of output. Establishments show large dispersion in their value-added and labor size. On the cost side, I also have the information on total material expenditure and total wage expenditure for each establishment per year. The ratio of total revenue and total cost is stable at approximately 1.22 over the years.

3.2 Estimating Production Function and Demand Elasticity

The first stage of estimation focuses on the static part of the model, the production function and the demand curve faced by the industry. The key parameters to be recovered from this stage are the demand elasticity η and the returns to scale γ. Furthermore, given consistent estimates of the production function, establishment level productivity for each time period can be constructed.

There are two well-known problems that must be addressed at this stage of estimation: the simultaneity bias for the coefficient of the variable input and the omitted price bias documented by Klette and Griliches (1996). The simultaneity bias is due to the fact that the unobserved productivity x_{it} is positively correlated with variable inputs in the production function. The omitted price bias is caused by the lack of firm-level price and quantity information. Essentially, if we proxy firm output by a firm's total revenue or value-added, the unobserved firm-level price deviation from the industry average price is correlated with variable inputs.[21] One additional difficulty is more closely related to the productivity estimates: there is large variation in the shares of variable inputs across different plants, which calls for a more flexible form of production function in order to estimate productivity more accurately at the plant level. In particular, I adapt the econometric framework proposed by Klette (1999) to the theoretical model. In this case, the expenditure share of labor is not assumed to be constant across plant.[22]

To be consistent with the theoretical model, I assume that labor is short-run variable input, while capital is quasi-fixed. The empirical production function for each establishment i at time t is assumed to take the following form

$$Q_{it} = L_{it}^{\alpha_{lit}} K_{it}^{\alpha_{kit}} exp(\alpha_0 + \bar{X}_t + x_{it} + u_{it}) \tag{14}$$

where $\alpha_0 + \bar{X}_t + x_{it}$ is the productivity and u_{it} is an i.i.d. idiosyncratic shock. Notice that α_{lt} and α_{kt} are not restricted to be constant over time. Equation (14) can be rewritten in logarithm terms as

$$q_{it} = \alpha_0 + \alpha_{lit} l_{it} + \alpha_{kit} k_{it} + \bar{X}_t + x_{it} + u_{it}. \tag{15}$$

Using the firm's profit maximization condition for labor, it is straightforward to show that

$$\alpha_{lit} = \frac{\eta}{1+\eta} s_{lit}, \tag{16}$$

where s_{lit} is the expenditure share of labor. The capital elasticity α_{kit} can be written as $\alpha_{kit} = \gamma - \alpha_{lit}$, where γ is defined as the returns to scale. It is assumed to be constant and estimated as a parameter. It follows that:

$$q_{it} = \alpha_0 + \frac{\eta}{1+\eta} s_{lit}(l_{it} - k_{it}) + \gamma k_{it} + \bar{X}_t + x_{it} + u_{it} \tag{17}$$

[21] De Loecker (2005) has a detailed discussion of the difficulties of introducing demand and product differentiation into the estimation. Recent papers on omitted price bias include Levinsohn and Melitz (2003) and Katayama, Lu and Tybout (2005).

[22] Klette (1999) draws heavily on Hall (1988), which is based on industry level data.

This is the equation that Klette (1999) used to estimate the mark-up, returns to scale and productivity jointly using instrumental variables. However, since real output is not observed, I will use the information from the demand structure to rewrite this equation in terms of deflated value-added.[23] The plant-level demand

$$Q_{it} = (Q_{It})(P_{it}/P_t)^{\eta}$$

can be written in logarithm terms as:

$$p_{it} - p_{It} = \frac{1}{\eta}(q_{it} - q_{It})$$

Combined with the fact that log total revenue is

$$r_{it} = p_{it} + q_{it}$$

we have the p_{It} deflated revenue $\tilde{r}_{it}$ as:

$$\tilde{r}_{it} = (1 + \frac{1}{\eta})q_{it} - \frac{1}{\eta}q_{It} \tag{18}$$

Finally, substituting the production function for q_{it} we defined in equation (17), we get an equation linking deflated plant revenue and the production function, demand parameters and plant productivity:

$$\tilde{r}_{it} = s_{lit}(l_{it} - k_{it}) + \frac{(1+\eta)\gamma}{\eta}k_{it} - \frac{1}{\eta}q_{It} + \frac{(1+\eta)}{\eta}(\alpha_0 + \bar{X}_t + x_{it} + u_{it}) \tag{19}$$

There are two key features of this equation. First, the first term on the right hand side is now observable using micro data on labor, capital and the cost of labor. Second, the returns to scale parameter γ can be directly estimated from the econometric model rather than inferred from the estimates of η and variable inputs' coefficients. The final estimating equation is given by:

$$\tilde{v}_{it} = \beta_0 + \beta_\gamma k_{it} + \beta_\eta q_{It} + \frac{(1+\eta)}{\eta}(x_{it} + \bar{X}_t) + \tilde{u}_{it} \tag{20}$$

where the dependent variable $\tilde{v}_{it} = \tilde{r}_{it} - s_{lit}(l_{it} - k_{it})$. $\beta_\eta = -\frac{1}{\eta}$ and $\beta_\gamma = \frac{(1+\eta)\gamma}{\eta}$. The error term is $\frac{(1+\eta)}{\eta}(x_{it} + \bar{X}_t) + \tilde{u}_{it}$, where $\tilde{u}_{it} = \frac{(1+\eta)}{\eta}u_{it}$. From the above specification, I avoid the

[23] I will need a quite restrictive demand structure (Dixit-Stiglitz). Considering the large number of firms in the industry, it is a reasonable approximation. Katayama, Lu and Tybout (2005) provide an alternative based on a nested-logit demand model.

hurdle of unobserved price. Another concern will be unobserved plant specific *i.i.d.* demand shocks. However, without price data, it's impossible to identify them separately from shocks on the production side x_{it}. So I assume $\tilde{u}_{it}$ captures both.

To estimate equation (20), now we need to consider the evolution of plant level productivity explicitly. In the model of section 2, the transition of firm's productivity x_{it} is a controlled Markov process, which depends positively on the plant's choice of innovation input D_{it-1}. It can also be derived from the model's first order condition that k_{it} depends on the previous period knowledge production input D_{it-1}. So k_{it} and x_{it} are correlated. This implies that equation (20) can't be estimated consistently with OLS. To handle this endogeneity problem, I apply the two-step procedure of Olley and Pakes (1996) and Levinsohn and Petrin (2003) to specify the first stage regression as

$$\tilde{v}_{it} = \beta_0 + \beta_\eta q_{It} + \varphi(m_{it}, k_{it}) + \tilde{u}_{it}, \tag{21}$$

where $\varphi(m_{it}, k_{it}) = \beta_\gamma k_{it} + h(m_{it}, k_{it}) + T_t$. We use the additional information on the plant's material input expenditure m_{it} and use the nonparametric function $h(m_{it}, k_{it})$ to proxy for plant i's productivity x_{it}. To capture the impact of $\bar{X}_t$ for each time period, we also include a time trend T_t to carry it through the estimation procedure. Estimation of equation (21) produces consistent estimates β_η and β_0 from the first stage. The second stage equation is defined as

$$\tilde{v}_{it} - \hat{\beta}_0 - \hat{\beta}_\eta q_{It} = \beta_\gamma k_{it} + g(\varphi_{it-1} - \beta_\gamma k_{it-1}, D_{it-1}) + e_{it}. \tag{22}$$

A few comments are in order about this second stage equation. First, note that the knowledge production function differs from the one used by Olley and Pakes (1996) because firms are actively learning. The knowledge production function can be represented as $x_{it} = g(\varphi_{it-1} - \beta_\gamma k_{it-1}, D_{it-1}) + \zeta_{it}$, where ζ_{it} is the idiosyncratic uncertainty. The plants productivity depends on the lagged innovation input D_{it-1}. The new error term e_{it} includes both $\tilde{u}_{it}$ and ζ_{it}. Second, as assumed in equation (8), D_{it-1} depends on both plant's own R&D input d_{it-1} as well as the R&D spill-over from competitors $\sum_{x>x_{it}} \sum_k \frac{d(x,k;s_{t-1})s_{t-1}(x,k)}{N_{t-1}}$. Since I do not observe plant level productivity, let d_{-it-1} be firm i's competitor's R&D, I use the interaction between $\varphi_{it-1} - \beta_\gamma k_{it-1}$ and $\sum \frac{d_{-it-1}}{N_{t-1}}$ to capture the direction of the R&D spill-over. Consequently, we can instead write the second stage equation as

$$\tilde{v}_{it} - \hat{\beta}_0 - \hat{\beta}_\eta q_{It} = \beta_\gamma k_{it} + \tilde{g}(\varphi_{it-1} - \beta_\gamma k_{it-1}, d_{it-1}, \sum \frac{d_{-it-1}}{N_{t-1}}) + e_{it}. \tag{23}$$

Doraszelski and Jaumandreu (2006) develops an estimator for production functions in the presence of endogenous productivity change that allows them to retrieve productivity and its relationship with R&D at the firm level. They allow for different unknown knowledge production functions for the firm who adopts the corner solution of zero R&D and when it chooses positive R&D expenditures. In my application, I restrict the knowledge production functions of both cases to be the same. Following Doraszelski and Jaumandreu (2006), I use a third-order polynomial of all the elements to approximate the unknown function $\tilde{g}(.)$. Finally, the plant level productivity can be recovered from equation (20) as

$$\widehat{lnTFP}_{it} = (\tilde{v}_{it} - \hat{\beta}_0 - \hat{\beta}_\gamma k_{it} - \hat{\beta}_\eta q_{It} - \hat{u}_{it})\frac{\hat{\eta}}{\hat{\eta}+1}. \tag{24}$$

The estimation results are reported in the following table. The first column reports the OLS regression of deflated value-added minus weighted labor-capital ratio on capital and industry output. The regression shows a significant coefficient on the industry output. The implied demand elasticity is approximately -5.3 and the estimated mark-up is approximately 1.23. The second column reports the regression of an augmented model controlling for both omitted price variable and simultaneity bias following Olley and Pakes (1996). The coefficient on capital drops slightly once we control for serially-correlated productivity shocks. This could result from the fact that we are using the full sample rather than a balanced panel to estimate the coefficient, while both capital and productivity are positively correlated with lagged R&D investment. In addition, the estimated coefficient on industry output decreases, implying a lower mark-up.

At this stage, although I have not recovered structural parameters governing exactly how R&D and spill-over affects future productivity, I can test the significance of the plant's lagged own R&D expenditure d_{it-1} and the R&D expenditure of rival plants $\sum \frac{d_{-it-1}}{N_{t-1}}$ in the conditional expectation function $g(.)$ in equation (22). As shown in Table 3, the null hypothesis that there is no R&D spill-over is clearly rejected. On the other hand, the $p-value$ for own R&D investment d_{it} is around 0.07. This is partly due to the fact that I only have a small proportion of observations spending a positive amount on R&D each year. It also indicates the own innovation effort itself, by its nature, has a great deal of uncertainty in outcomes such that the idiosyncratic shock term is not negligible.

Table 3: Production Function Parameters
(Standard Errors in Parentheses)

	OLS	OP
β_γ	0.823*	0.793*
	(0.008)	(0.026)
β_η	0.187*	0.186*
	(0.041)	(0.039)
implied γ	1.012	0.975
implied mark-up	1.230	1.229
R&D test (p value)		0.07
Spill-over test (p value)		0.01

*significant at the 5% level

3.3 Measured Productivity

Using the estimation results, each plant's productivity for every sample year can be recovered as shown in equation (24). Examining the pattern of plant-level productivity reveal several patterns that have been discussed in previous studies. The productivity dispersion is very large. The 5 percentile value of $lnTFP$ distribution is 0.839, only roughly half the 95 percentile value 1.674. The ranking of establishment-level productivity is very persistent. Correlation between period t and period $t+1$ productivity is 0.83. We report the industry productivity distribution from year 1991 to year 1996 in Figure 2, where the dotted line is from 1996.

[insert Figure 2 here]

I define the frontier technology $\bar{X}_t$ as the average Total Factor Productivity of the top 5 percent plants in the industry for year t. The relative position x_t is calculated as the difference between each plant's estimated TFP and the frontier technology. Subsequently, $exp(x_t)$ ranges from 0 to 1 and indicates each plant's relative technological position within the industry at time t. The distribution of $exp(x_t)$ is right skewed and its dispersion is similar for different sample years. I discretize them into 10 categories based on the deciles of the productivity distribution.

In addition, the initial distribution on $exp(x_t)$ of the new entrants can be calculated by pooling the observations of entrants from year 1992 to year 1996. A close look at the new entrants reveals substantial heterogeneity in productivity within each group of the same year. In addition, the initial distribution of the new entrants are not systematically better than that of the incumbents. I use the same initial probabilities to solve and simulate the industry equilibrium in my second stage estimation.

Finally, one important feature of plant productivity evolution is that the probability of improvement depends on the current productivity level. As shown in Table 4, producers further behind the frontier have a higher probability of improvement in future efficiency. This is one of the data patterns that need to be reproduced from my model simulations.

TABLE 4: FRACTION OF IMPROVEMENT FOR DIFFERENT QUARTILES

quantile	improving	non-improving
1	0.433	0.569
2	0.352	0.648
3	0.295	0.705
4	0.132	0.868

4 Estimation of Dynamic Parameters

Given the first stage estimates of production function coefficients β_0, β_k and the demand elasticity η, I estimate the set of dynamic parameters $\Theta_0 = [\theta, c_d, c_a, u_b, \delta]$ in the second stage. The first parameter θ is the spill-over parameter that captures the contributions of rival plants' R&D to each plant's knowledge level. c_d is the effectiveness of R&D inputs to improve plant knowledge capital. c_a is the physical capital adjustment cost. u_b is the parameter of plant's scrap value distribution. Finally, δ represents the idiosyncratic uncertainty of the change in plant-level knowledge capital. Since the estimation involves solving a complicated dynamic industry equilibrium with no closed form solutions, I use the method of simulated moments approach, which minimizes a distance criterion between key moments from the actual data and the simulated data.

Recent empirical techniques have been proposed to estimate the dynamic industry equilibrium model without solving the equilibrium. Especially related to this study is the estimation procedure proposed by Bajari, Benkard and Levin (2006), which handles both continuous and discrete control variables. Their approach breaks the estimation into two stages. In the first stage, firm policy functions are recovered by regressing observed actions on the observed state variables. The probability distribution which defines the evolution of the state of the industry is also recovered at this stage. In the second stage, the structural parameters which make these observed policies optimal are estimated. The major breakthrough of their approach is to avoid the computational burden of Markov Perfect Equilibrium, with trade-off of the precise calculation of agent's value function and policy function.

I only have the plant-level data for one single industry over a six year period, while the possible state space is very large. It makes the sampling error of estimating the policy functions a major concern if I were to adopt the strategy of Bajari, Benkard and Levin (2006). On the other hand, the large number of firms and low industry concentration make the weaker notion of equilibrium-Oblivious Equilibrium especially attractive, since it is proved to be a good approximation of MPE in this case.

However, there is also a cost of using Simulated Method of Moments at this stage compared with Bejari, Benkard, Levin (2006). The industry evolution model I use is not proved to have a unique equilibrium in general. Although the profit function, production technology, and the entrant's initial distribution are estimated without computing the model, there is a risk that the computational algorithm might select a different equilibria than that observed in the data. On the other hand, since we are only focusing on one single industry, this problem is alleviated by matching a full set of moments on policies and transition of states from observed and simulated data, which allow the data to confirm the correct equilibrium. Nevertheless, the uniqueness of the computed equilibrium is a strong assumption.

4.1 Moments

In this section, I describe the set of data moments utilized and how they are relevant for the identification of key parameters. The sample I use to estimate the dynamic parameters is an unbalanced panel of plants in the electric motor industry at year 1991 and their subsequent annual observations through 1996. All the entrants in subsequent years are only used to construct a frequency estimate of the initial state distribution Ψ^e and are excluded from the construction of moments.

Table 5 report the moments I use in my estimation. The first set of moments captures the key features of optimal plant R&D investment behavior in equilibrium. The R&D investment cost c_d affects plant's R&D investment intensity. It is also the driving force behind the productivity improvement of R&D performers. On the other hand, the scale of technological transfer θ is shaped by non-frontier plant's "free-riding" incentives. Given its own technological position and expectation on industry productivity evolution, a plant makes an optimal decision on whether to stick with the "corner solution" of investing zero R&D. Thus, the fraction of R&D performers is affected by θ. Furthermore, what distinguish θ from the exogenous idiosyncratic shock δ is the backward advantage we observe in the data. When θ is larger, we will tend to see that the firms that lag behind will more easily improve their efficiency levels. Notice here that all moments of the change of firm productivity overtime are constructed conditional on survival. So they are also affected by the industry competition and turnovers.

The second set of moments described in Table 5 relate to the plant's physical investment behavior. Following Cooper and Haltiwanger (2005), the cost parameters c_a help to capture the nonlinear relationship between plant-level investment and profitability. The level of the investment ratio and the spike rate of plant's positve investment depend critically on its magnitude. On the other hand, since we model firm's investment behavior within an industry equilibrium, the investment moments also help to pin down other key model parameters such as intensity of competition, technological spill-over and R&D costs. I include the correlation between productivity and investment, which not only responds to one's endogenous R&D effort but also to the industry spill-overs. Recent empirical investment literature also emphasized the role of partial irreversibility in describing micro-level plant investment behavior, i.e. if the plant has to incur a significant loss by selling its existing asset, then it takes more caution to invest during periods of high productivity shocks. On the other hand, when there is a negative shock plants tend to hold on to capital. I estimated a slightly more complicated model of incorporating this feature and the estimation results on all other parameters turn out to be robust to this extension.

Finally, the long run exit pattern helps to identify the scrap value distribution parameter.[24]

Table 5: Key Data Moments

R&D Investment and Productivity Improvement	
fraction of R&D performers	13%
R&D intensity of performers (R&D/Value-added)	0.06
mean relative productivity	0.60
std relative productivity level	0.17
fraction of productivity staying same (lower 50% firms)	46%
fraction of productivity staying same (higher 50% firms)	56%
fraction of productivity improving (lower 50% firms)	33%
fraction of productivity improving (higher 50% firms)	20%
Physical Capital Investment	
mean investment ratio ($\frac{i}{k}_{it}$)	.23
spike rate of positive investment ($\geqslant$ 30%)	21%
fraction of observations with positive investment	59%
corr between productivity shock and investment	37%
Firm Turnover	
mean exit rate	18%

4.2 Empirical Implementation

The estimation of the dynamic parameters Θ_0 is implemented according to the following procedures. First, denote the set of data moments in table 5 as Γ^d, which is a 13 by 1 vector. Second, for a given set of parameters Θ, the industry equilibrium is solved and optimal policy functions for R&D expenditure, physical investment and survival (d^*, k^*, χ^*) are generated. Third, initialized by the observed data in 1991, we use the optimal policy functions to simulate the path for each plant. Notice that for a single simulation, each plant's behavior and subsequently their investment outcomes need to be updated simultaneously for each time period. We are able to calculate $\Gamma^s(\Theta)$ for simulation s. Finally, the simulated moments are defined as:

$$\Gamma^S(\Theta) = \frac{1}{S}\sum_{s=1}^{S}\Gamma^s(\Theta)$$

The MSM estimate $\hat{\Theta}$ minimizes the weighted distance between data and simulated moments:

$$L(\Theta) = min_{\Theta}[\Gamma^d - \Gamma^S(\Theta)]'W[\Gamma^d - \Gamma^S(\Theta)]$$

[24]Obviously, the other moments are also affected by the exit pattern of incumbent firms in an industry equilibrium setting.

where W is a positive definite matrix.

The objective function $L(\Theta)$ is from a complicated dynamic problem, thus is non-smooth and with many local optima. To handle this, I apply a recent approach proposed by Chernozhukov and Hong (2005), which develops a class of Laplace Type Estimators (LTE) to circumvent this problem in the computation of the classical extremum estimators. Their estimation procedure focuses on LTE, which are functions of integral transformations of the criterion function $L(\Theta)$ and can be computed using Markov Chain Monte Carlo. In addition, I use their inference procedures to calculate confidence intervals from the quartiles of the Quasi-posterior distribution.

4.3 Estimation Results

Several of the model parameters are directly calculated from the data. The aggregate market size I is calculated as the average of industry total value-added over the sample period $I = 543,525$ mil won. We also follow Cooper and Haltiwanger (2005) to set annual discounting rate β at 0.95 and annual rate of depreciation δ_c at 0.06. Finally, labor's share parameter is calculated as the average of sample observation's labor expenditure share α_{lit}. It has a value of 0.65.

The following table reports the point estimates and their 90% confidence interval. The point estimates are the mean of random draws from the posterior distribution using Markov Chain Monte Carlo.

TABLE 6: DYNAMIC PARAMETER ESTIMATES

	Point Estimate	90% confidence interval
c_d	0.2889	$[0.2472, 0.3296]$
θ	2.7476	$[2.1354, 3.2748]$
c_a	0.0441	$[0.0367, 0.0537]$
u_b	12999	$[10069, 16488]$
δ	0.4312	$[0.3965, 0.4755]$

By solving the industry equilibrium using the reported point estimates Θ, we can also infer the fixed entry cost κ using the model's free entry condition, equation (13). To further evaluate the overall fit of the estimation, I also report the simulated moments at the point estimates in Table 7.

Table 7: Model Fit

	Data Moments	Simulated Moments
R&D Investment and Productivity Improvement		
fraction of R&D performers	13%	13%
R&D intensity of performers (R&D/Value-added)	0.06	0.05
mean relative productivity	0.61	0.61
std relative productivity level	0.17	0.13
fraction of productivity staying same (lower 50% firms)	46%	52%
fraction of productivity staying same (higher 50% firms)	56%	54%
fraction of productivity improving (lower 50% firms)	33%	32%
fraction of productivity improving (higher 50% firms)	20%	19%
Physical Capital Investment		
mean investment ratio ($\frac{i}{k}_{it}$)	.23	.23
spike rate of positive investment ($\geqslant 30\%$)	21%	21%
fraction of observations with positive investment	59%	56%
corr between productivity shock and investment	37%	36%
Firm Turnover		
mean exit rate	18%	19%

*Simulated moments are generated with the point estimates using 50 simulations.

The simulated data does a good job of repeating the pattern of R&D investment and the productivity evolution, which is the core piece of this model. It is relatively less accurate on the proportion of firms who stay at the same productivity level. One of reasons could be that there are different knowledge depreciation rate for firms at the higher half and lower half of the knowledge capital level.

4.4 Evaluation of Results

How do the magnitude of the point estimates compare with previous studies? First, examine the R&D spill-over parameter θ, which has a value of 2.7476. Evaluating at the mean number of producers of the sample, it implies that 1 dollar of the sum of one producer's competitors' R&D can substitute for 1.6 cents of its own R&D. This may seem like a tiny amount at first glance, however, the total R&D spill-over pool is much larger relative to any producer's own spending. Taking into account that the R&D spill-over is a public good and affects the knowledge capital improvement of every producer, including those who do not perform R&D by themselves, spill-overs are important even though the magnitude of θ is small. Bloom, Schankerman and Van Reenen (2005) report that the private value of 1 dollar of spill-over is worth about 3 cents of own R&D in terms of the effect on market-value. Jaffe (1986) gets a similar number considering the effect on firm patents. Both of these studies use patent information to construct the "true" relevant R&D for each firm. Thus it is not surprising that their estimate of θ is about 2 times larger than what I find for the Korean electric motor industry. But without further information to link my data with Korean patent data, it's infeasible for me narrow the range of firms in the pool like they do. Second, the idiosyncratic depreciation probability δ equals 0.4312. It captures the two forces that erode the plant-specific knowledge, both because of the improvement of the industry frontier and because the loss of its own knowledge.

In terms of quadratic adjustment cost, Cooper and Haltiwager (2005) reports a value of 0.225 while not controlling for fixed cost and 0.025 while controlling for fixed cost. Bloom (2006) reports a quadratic adjustment coefficient of 4.743 on a monthly basis, which implies a yearly value of 0.39. Our estimate of c_a, which equals .044, is slightly lower. It indicates that it is less costly to acquire or sell physical capital in the Korean electric motor industry. Another reason could be that a fixed investment cost is not included in the model due to computational burden, thus a low c_a is needed to be consistent with freqent investment spikes in our data.

The estimated upper bound of scrap value distribution u_b implies an unconditional mean of 6500 mil won, which is around four times of the industry average profit. On the other hand, the entry cost implied from free-entry condition is 10695 mil won. These values results in a quite narrow hysteresis band, which is driven by the high turnover rate observed in the data.

5 Policy Simulation: Competition, Innovation and Productivity

Korean industries are long believed to be less competitive relative to other OECD countries, because of their history of government intervention and the influence from business conglomerates.[25] Previous studies have shown mixed evidence about the relationship between product market competition and innovation. In theoretical papers, Dasgupta and Stiglitz (1980) and Spence (1984) concluded that more competition reduces innovation effort. Recently, empirical

[25] A recent summary is provided by Baek, Jones and Wise (2004).

studies of Nickell (1996) and Blundell, Griffith and Van Reenen (1999) have found a positive effect from competitive pressure on innovation.

This relationship is not analytically clear given the heterogeneity of firms in my model and data. However, using the structural estimates from Table 6, I am able to simulate the producer and industrial response from more intensified competitive pressure. The increase in competitive pressure can be introduced in two ways in the model: an increase in product substitutability η, or an decrease in the entry cost κ.[26] It's straight-forward in the model to express each parameter in terms of an observable outcome: the price-cost margin is equal to $\frac{\eta}{1+\eta}$, so the competitive effect of a 5% decline in price-cost margin can be simulated by altering η. Second, the number of entrants is determined by the entry cost κ and this can be adjusted to simulate change in competition resulting from of a 50% increase in the mean number of entrants.

Notice that the oblivious equilibrium concept provides a nice way to summarize the average long run industry state $s_{a\epsilon}$, which is based on the equilibrium strategies of the plants. Statistics can be constructed from $s_{a\epsilon}$ to reflect the policy effect over a relatively long period. In addition, the industry evolution patterns before and after the policy change can also be simulated. These will highlight the short run transitory dynamic effects.

In the long run, the two different pro-competitive policies have very different outcomes. The difference comes from the interaction of two very different (sometimes offsetting) mechanisms. First, consider the case where there is an increase in product substitutability that reduces the price-cost margin by 5%. In the long run, since competition is tougher within the industry, there are more exits. Subsequently, the mean number of plants declines. Column 2 in table 8 shows that the exit rate increases from 16.22% to 17.44%, so the "market selection" from exit is stronger in this scenario. On the other hand, the smaller number of plants in the industry generates higher output and innovation effort per plant. The average R&D intensity of plant increases from 2.63% to 3.45%. With the presence of the R&D spill-over, the producers within the industry improve as a whole.

The effect of more entrants, resulting from a reduction in entry cost, are reported in column 3 in the table 8. With more plants in the industry and a lower aggregate price, incumbents

[26]The closeness of product substitution and its role in industry productivity dispersion was emphasized in Syverson (2004).

reduce both their physical capital investment and R&D intensity. The "market selection" effect is much more pronounced in this case. The exit rate is 18.65%, a 15 percentage increase. With the two mechanisms offsetting each other, there is no overall effect on industry productivity.

Table 8: Long Run Effects of Enhanced Competitive Pressure

	Benchmark	5% drop in PCM	50% increase in entrants
average R&D intensity			
-all firms	2.63%	3.45%	2.07%
-top 10% (TFP) firms	4.86%	5.90%	4.07%
output share: top 10% (TFP) firms	21.91%	26.76%	22.35%
industry (weighted) productivity	0.754	0.775	0.754
mean investment ratio	0.258	0.310	0.212
mean number of firms	437	407	571
mean exit rate	16.22%	17.44%	18.65%

6 Conclusion

This paper develops and estimates a structural model of R&D investment and productivity evolution by manufacturing plants in the Korean electric motor industry from 1991 to 1996. Plant-level decisions on R&D investment, physical capital investment, entry, and exit are developed using an equilibrium industry evolution model. Plant productivity is affected by its own R&D and by spill-overs from the R&D of its competitors. The model provides a detailed set of pathways connecting R&D investment, plant productivity, plant physical investment and industry turnover patterns observed in the data.

The structural parameter estimates show that a plant's own R&D expenditure has a positive effect on its future productivity. There is also a small spill-over effect with one dollar of competitor's R&D expenditure substituting for 1.6 cents of own R&D input. The public externality of R&D is important given the large number of firms within the same industry. A narrow difference between the entry cost and the mean scrap value explains the high turnover rate in this industry. Finally, the industry equilibrium model provides a natural link from individual plant R&D decisions to aggregate industry productivity and output. This feature of the model provides us with a powerful tool to evaluate various industry or innovation policies. As our example experiments show: increasing the elasticity of substitution between products increases plant innovation incentives but slows plant turnover. In the long run, a 5% drop in price-cost margin improves industry productivity by 2.8%. On the other hand, a lower entry cost, which increases total entry by 50%, does not change industry productivity.

There are quite a few possible extensions to the current framework. An interesting one will be to look at the interaction of firm's decision to export, R&D, and the overall industry evolution. Given the fact that trade and innovation policy are considered to be among the most important institutional settings of emerging economies such as Korea, it will be important to provide a general framework to evalute how they interact and affect long run industry performance.

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7 Appendix

7.1 Profit from Static Competition

The static competition model of heterogenous firms is built on Melitz (2003). We assume that firm i within an industry has a standard Cobb-Douglas production function with returns to scale parameters γ. I will describe individual firm's problem by abstracting from the notation i for convenience.

$$q_t = exp(\bar{X}_t + x_t)(l_t^{\alpha}(k_t)^{1-\alpha})^{\gamma}, \tag{25}$$

where q_t is the output for firm i. Firm's efficiency is defined by its distance from the industry technological frontier $exp(\bar{X}_t)$. x_t captures how much a firm's knowledge lies behind current frontier, so it has a maximum value of zero. k_t is physical capital input and l_t is labor input. Furthermore, we assume $\bar{X}_t$ follows a deterministic exogenous process, which is determined by the world technological frontier.

Each firm produces a differentiated product and each one of them faces a demand function such that

$$q_t = Q_t(p_t/P_t)^{\eta} = \frac{I_t}{P_t}(\frac{p_t}{P_t})^{\eta} \tag{26}$$

where p_t is the price set by firm i, while Q_t and P_t are industry level output and price index. Accordingly, I_t is defined as the industry market size at time t. This demand function is from the widely-used monopolistic competition model by Dixit and Stiglitz (1977). The parameter η captures the elasticity of substitution between different products.

Thus each period, a firm takes quasi-fixed factors (k_t, x_t), exogenous variable factor prices w_t, aggregate market price P_t, and current frontier technology $exp(\bar{X}_t)$ as given and chooses variable inputs l_t to maximize its profit

$$\pi_t = p_t(I_t, P_t, q_t)q_t - w_t l_t \tag{27}$$

We could rewrite this problem as:

$$max_{l_t} P_t^{1+\frac{1}{\eta}} I^{-\frac{1}{\eta}} (exp(\bar{X}_t + x_t) k_t^{(1-\alpha)\gamma})^{1+\frac{1}{\eta}} (l_t^{\alpha\gamma})^{1+\frac{1}{\eta}} - w_t l_t. \tag{28}$$

Let's redefine industry price index as

$$\hat{P}_t = P_t exp(\bar{X}_t),$$

which allows us to write the optimal labor decision as

$$l_t^* = [\frac{w_t I^{\frac{1}{\eta}}}{(exp(x_t)k_t^{(1-\alpha)\gamma})^{1/\eta+1} \hat{P}_t^{1+\frac{1}{\eta}} (1+1/\eta)\alpha\gamma}]^{\frac{1}{(1+1/\eta)\alpha\gamma-1}}. \tag{29}$$

Let $\varphi_t = exp(x_t)k_t^{(1-\alpha)\gamma}$, $\sigma = \frac{1+\eta}{\eta-(1+\eta)\alpha\gamma}$, then $\frac{1}{(1+1/\eta)\alpha\gamma-1} = \frac{-\eta\sigma}{1+\eta}$. Substitute the optimal labor decision into the individual price equation $p(\hat{P}_t, q_t)$

$$\hat{p}(\hat{P}_t, \varphi_t) = p(\hat{P}_t, \varphi_t)exp(\bar{X}_t) = [\hat{P}_t^{(1+\frac{1}{\eta})(\alpha\gamma-1)} I^{\frac{1}{\eta}(1-\alpha\gamma)} (\frac{w}{(1+1/\eta)\alpha\gamma})^{\frac{1}{\eta}\alpha\gamma} \varphi_t^{-\frac{1}{\eta}}]^{\frac{-\eta\sigma}{1+\eta}}. \tag{30}$$

Furthermore $s_t(\varphi)$ is defined as the number of firms whose $\varphi_t = \varphi$. In equilibrium, normalized industry price index $\hat{P}_t$ is determined by the industry state s_t

$$\hat{P}_t = [\sum_{\varphi} s_t(\varphi)\hat{p}(\hat{P}_t, \varphi)^{1+\eta}]^{\frac{1}{1+\eta}}. \tag{31}$$

Substitute individual price equation $\hat{p}(\hat{P}_t, \varphi)$ into equilibrium industry price index

$$\hat{P}_t = I^{1-\alpha\gamma}(\frac{w}{(1+1/\eta)\alpha\gamma})^{\alpha\gamma}(\sum_{\varphi} s_t(\varphi)\varphi^{\sigma})^{-\frac{1}{\sigma}}. \tag{32}$$

Finally, we have the equilibrium maximized profit for firm with individual state $\varphi_t = exp(x_t)k_t^{(1-\alpha)\gamma}$ as

$$\pi(\varphi_t, s_t) = I(1-(1+\frac{1}{\eta})\alpha\gamma)\frac{\varphi_t^{\sigma}}{\sum_{\varphi} s_t(\varphi)\varphi^{\sigma}}. \tag{33}$$

8 Figures

Figure 1

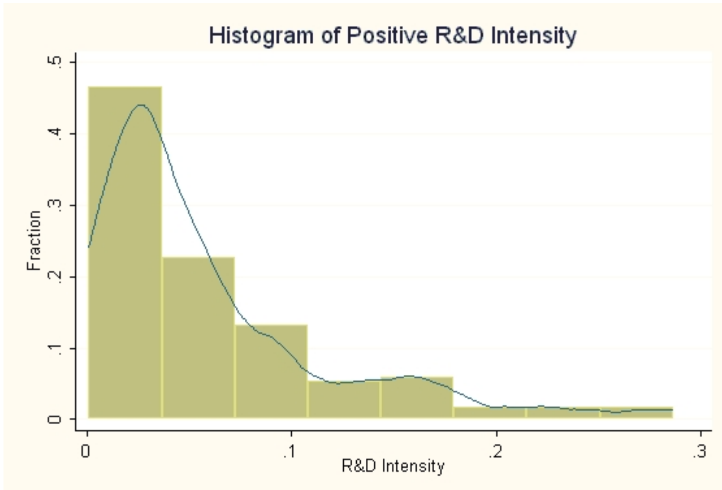

Figure 2