Essays on Market Structure and Technological Innovation

DISSERTATION

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Abstract

In these essays, I examine the endogenous relationship between market structure and innovation within industries with product markets characterized by horizontal and vertical product differentiation and fixed costs which relate R&D investment and product quality. The theoretical and empirical models build upon Sutton's (1991, 1997, 1998, 2007) endogenous fixed cost (EFC) framework. In the first essay, I develop an EFC model under asymmetric R&D costs that incorporates an endogenous decision by firms to license or cross-license their technology. In the second essay, I examine whether a specific industry, agricultural biotechnology, is characterized by endogenous fixed costs associated with R&D investment.

The theoretical model presents a more general expression of Sutton's framework in the sense that Sutton's results are embedded in the endogenous licensing model when markets are sufficiently small, when transactions costs associated with licensing are sufficiently large, or when patent rights are sufficiently weak. For finitely-sized markets, the presence of multiple research trajectories and fixed transactions costs associated with licensing raises the lower bound to market concentration under licensing relative to the bound in which firms invest along a

single R&D trajectory or in which transactions costs associated with licensing are negligible. Moreover, I find that the lower bound to R&D intensity is strictly greater than the lower bound to market concentration under licensing whereas Sutton (1998) finds equivalent lower bounds. This implies a greater level of R&D intensity within industries in which licensing is prevalent as innovating firms are able to recoup more of the sunk costs associated with increased R&D expenditure. Sutton's (1998) EFC model predicts that as the size of the market increases, existing firms escalate the levels of quality they offer rather than permit additional entry of new firms. This primary result of quality escalation continues to hold when firms are permitted to license their technology to rivals, but low-cost innovators are able to increase the number of licenses to high-cost imitators as market size increases.

Prior to estimating the empirical model, I illustrate the theoretical lower bounds to market concentration implied by an endogenous fixed cost (EFC) model with vertical and horizontal product differentiation and derive the theoretical lower bound to R&D concentration from the same model. Using data on field trial applications of genetically modified (GM) crops, I empirically estimate the lower bound to R&D concentration in the agricultural biotechnology sector. I identify the lower bound to concentration using exogenous variation in market size across time, as adoption rates of GM crops increase, and across agricultural regions.

The results of the empirical estimations imply that the markets for GM corn, cotton, and soybean seeds are characterized by endogenous fixed costs associated with R&D investments. For the largest-sized markets in GM corn and cotton seed, single firm concentration ratios range from approximately .35 to .44 whereas three firm concentration ratios are approximately .78 to .82. The concentration ratios for GM soybean seeds are significantly lower relative to corn and cotton, despite greater levels of product homogeneity in soybeans. Moreover, adjusting for firm consolidation via mergers and acquisitions does not significantly change the lower bound estimations for the largest-sized markets in corn or cotton for either one or three firm concentration, but does increase the predicted lower bound for GM soybean seed significantly. These results imply that concentration in intellectual property in soybean varieties is differentially effected by mergers and acquisitions relative to corn and cotton varieties.

The empirical estimations imply that the agricultural biotechnology sector is characterized by endogenous fixed costs associated with R&D investments. As firms are able to increase their market shares by increasing the quality of products offered, there are incentives for firms to increase their R&D investments prior to competing in the product market. The lower bound to concentration implies that even as the acreage of GM crops planted increases, one would not expect a corresponding increase in firm entry. However, the results from the estimations for GM soybean seeds indicate that concerns for increased concentration of intellectual property arising from firm mergers and acquisitions may be justified, even though there is little evidence to support this claim from the corn and cotton seed markets.

Regulators and policymakers will find the results of the theoretical and empirical models particularly relevant across a variety of industries. The announcements of license and cross-license agreements between firms within the same industry are often accompanied by concerns of collusion and anti-competitive behavior. Moreover, there have been renewed concerns over concentration in agricultural inputs, and in particular agricultural biotechnology. However, the theoretical model implies that the ability of firms to license their technology increases the highest levels of quality offered by providing additional incentives to R&D for low-cost market leaders. The empirical estimations reveal that the agricultural biotechnology sector is characterized by endogenous fixed costs thus implying a greater level of firm concentration than what would be observed in perfectly competitive or exogenous fixed cost markets.

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CHAPTER 1: Introduction

In 1942, Joseph Schumpeter proposed that more concentrated markets encouraged additional technological innovation by firms. However, the relationship between market concentration and R&D intensity, defined respectively as the market share of the industry-leading firms and the ratio of R&D expenditure to sales, remains an open research question both theoretically and empirically. The presence of factors that affect both market structure and the incentives of firms to invest in R&D, such as differing consumer preferences, horizontal and vertical comparative advantages, product differentiation, and strategic alliances across firms, confound attempts to isolate the relationship between of concentration and R&D intensity.

I focus upon understanding the relationship between market concentration and technological innovation in two ways. First, I incorporate strategic interactions between firms in the form of technology licensing into a theoretical model in which market structure, R&D investment, and technology licensing occur endogenously. Second, I extend the existing literature by examining the theoretical lower bound to concentration of R&D activity in an endogenous framework and empirically estimate these lower bounds using data from the agricultural biotechnology market.

In the first essay, I develop a theoretical model of endogenous market structure and fixed (sunk) R&D investment, based on Sutton (1998; 2007), in which I allow firms to pursue license and cross-license agreements as an alternate form of market consolidation which is potentially less costly compared to firm integration via mergers or acquisitions. I argue that a firm's R&D investment decision is inseparable from its decision to pursue licensing agreements such that strategic alliances, market structure, and technological innovation are all determined endogenously within some equilibrium process. Additionally, by permitting firms to invest in R&D and license their technology to competitors without restricting the nature of product market competition, the theoretical model that I develop allows for a general, yet rich, examination of the relationship between R&D investments and market structure.

Allowing for licensing, I find that as market size increases, the market share of the quality leader and industry concentration converge to a lower bound that is strictly greater than the bound without licensing which is bounded away from the predictions of perfectly competitive markets. The model also implies that R&D intensity of market leaders is greater under licensing relative to the case without licensing as the innovating firms can escalate quality and recoup the additional sunk R&D costs via licensing to rivals. Taken together, these results imply that analyses of market concentration and innovation should not neglect the importance of strategic alliances between firms nor should models of licensing and innovation rely solely upon an exogenously determined market structure.

Anand and Khanna (2000) find that licensing and cross-licensing agreements are increasingly observed across R&D-intensive industries and constitute between 20-33% of all strategic alliances in R&D-intensive sectors such as: chemicals, biotechnology, and computers and semiconductors. Consider for instance, the flash memory industry which is both a heavily concentrated market (with a four firm concentration ratio upwards of 0.75) and characterized by extensive fixed cost investments in R&D. Recently, Samsung Electronics, the leader in flash memory chips, completed patent cross-license agreements with two of its primary competitors in this industry, Toshiba and SanDisk. As a general model, this analysis is relevant to any industry characterized by intensive R&D investments, concentrated market structures, and licensing agreements including the licensing of genetic traits in agricultural biotechnology between market-leading firms and the observed patterns of technology licensing between smaller R&D labs and larger pharmaceutical manufacturers. Generally, the model describes a relationship between firm concentration, incentives to invest in R&D, and the incentives of firms to pursue license agreements with competitors through an endogenous fixed cost framework.

This model adds to the literature on market structure and innovation by allowing for technology licensing, a form of firm consolidation, to be considered within an endogenous framework. Moreover, I contribute to the literature on technology licensing by incorporating the decision of firms to both license their innovations and choose their own level of R&D expenditure into an endogenously-determined market structure framework. Firms compete vertically in product quality and horizontally in product attributes, such that the model also provides an alternate framework that complements the existing literature concerning mixed models of vertical and horizontal differentiation (Irmen and Thisse, 1998; Ebina and Shimizu, 2008) and multiproduct competition (Johnson and Myatt, 2006). Moreover, I contribute to the literature on cross-licensing agreements between competitors by developing an endogenous model in which cross-licensing arises endogenously from complementary technologies across firms.

Sutton (1998; 2007) argues that R&D intensity alone is insufficient to capture all of the relevant aspects of an industry's technology and that a more general "bounds" model which permits a range of possible equilibrium configurations should be considered. However, Sutton's model does not differentiate between forms of consolidation between firms (i.e. licensing and cross-licensing agreements, R&D joint ventures, mergers and acquisitions, etc.) within an industry and the potential impact of these mechanisms upon market structure. Sutton's endogenous fixed cost (EFC) model predicts that in certain R&D-intensive industries, an escalation of fixed (sunk) cost expenditures by existing firms, rather than entry by new firms, will occur in response to exogenous changes in market size or available technology. The EFC model thus implies that there exists a lower "bound" such that as the size of the market increases, market concentration and R&D intensity do not converge to the levels prescribed by perfect competition. If firms engage in licensing and cross-licensing agreements, we cannot determine *a priori* if market concentration and R&D intensity remain bounded away from, or converge to, perfectly competitive levels.

I develop a model in which innovating low-cost firms have an incentive to offer licenses to high-cost rivals in order to deter entry by other low-cost firms escalating the market-leading level of quality. This is consistent with Gallini (1984) who finds that incumbent firms have a strategic incentive to license their technology to potential entrants in order to "share" the market and deter more aggressive entry via increased R&D expenditures. Moreover, the model is also consistent with Rockett (1990) who finds that incumbent firms utilize strategic licensing in order to sustain its comparative advantage past the expiration of its patents by facing an industry comprised of "weak" competitors. Additionally, I draw upon the findings of Gallini and Winter (1985) that there exist two contrasting effects of licensing: (i) there is the incentive which successful innovators have to license their technology out to competitors (originally pointed out by Salant (1984) in the comment on Gilbert and Newberry's (1982) preemption model); and (ii) the low-cost firm has an incentive to offer the high-cost firm a license in order to make additional research by the high-cost firm unattractive. Specifically, the EFC model under licensing is largely driven by the second effect which Reinganum (1989) identifies as "minimizing the erosion of the low-cost firm's market share while economizing on development expenditures" (p. 893, 1989).

Within the licensing literature, this analysis is most closely related to that of Arora and Fosfuri (2003) who develop a model of optimal licensing behavior under vertically-related markets. Specifically, they examine the role of licensing as a strategic behavior when multiple holders of a single technology compete not only in a final-stage product market, but also in a first-stage market for technology. Their results indicate that lower transactions costs, arising from stronger patent rights, increase the propensity of firms to license their technology; thereby lowering overall profits to innovators, reducing the incentives to engage in R&D, and decreasing the rates of innovation compared with what would be observed otherwise. Moreover, upon allowing for the number of firms to be endogenously determined, Arora and Fosfuri find that larger fixed costs associated with R&D reduce both the number of incumbent firms as well as the per-firm number of licenses. This model relaxes some of the assumptions of Arora and Fosfuri such that: (i) competitors in the product market engage in their own R&D activities; (ii) multiple technology trajectories exist within the industry; and (iii) an fully endogenous model for both market structure as well as the level of R&D investment is developed.

In the second essay, I empirically estimate the lower bound to R&D concentration for the agricultural biotechnology sector in order to determine whether the industry is characterized by endogenous fixed costs and if the observed pattern of firm consolidation is consistent with an EFC model. Over the past three decades, the agricultural biotechnology sector has been characterized by rapid innovation, market consolidation, and a more exhaustive definition of property rights. Concentration has occurred in both firm and patent ownership with the six-firm concentration ratios in patents reaching approximately 50% in the U.S. and the U.K. (Harhoff, Régibeau, and Rockett, 2001) However, increased concentration has had ambiguous effects on R&D investment as the ratio of R&D expenditure to industry sales (71.4%) remains relatively large (Lavoie, 2004). Using data on field trial applications for genetically modified (GM) crops, I exploit exogenous variation in technology and market size across time and submarkets to analyze whether the agricultural biotechnology is characterized by a lower bound to concentration consistent with an endogenous fixed cost (EFC) framework.

Prior to estimating the lower bound to R&D concentration for the agricultural biotechnology industry, I examine an illustrative model of endogenous fixed costs in an industry characterized by multiple submarkets. I then derive the theoretical lower bound to R&D concentration under both exogenous and endogenous fixed costs as implied by Sutton's (1998) EFC model in order to obtain the empirical predictions for testing for a lower bound to R&D concentration. Using cluster analysis, I define regional submarkets for each GM crop type (corn, cotton, and soybean) based upon observable data on farm characteristics and crop production practices at the state level.

Ultimately, this leads to a test of the hypothesis that the agricultural biotechnology sector is characterized by an EFC model through the examination of data on field trial applications for GM crop release. The Animal and Plant Health Inspection Service (APHIS) provides data on permit, notification, and petition applications for the importation, interstate movement, and release of genetically-modified organisms in the US for the years 1985-2010. By classifying the permit data according to type, I obtain estimates of concentration in intellectual property within distinct submarkets as a measure of (intermediate) R&D concentration. Results from the empirical estimations support the hypothesis that the agricultural biotechnology sector is characterized by endogenous fixed costs to R&D with the largest effects within the GM corn and cotton seed markets. However, the estimation results also indicate that within the soybean seed markets, firm merger and acquisition activity has significantly increased the observed levels of concentration in intellectual property. These results jointly reveal a difficulty associated with examinations of the agricultural biotechnology sector; namely, the nature of technology competition implies a level of concentration is to be expected, but the level of merger and acquisition activity remains an important determinate into examinations of concentration in intellectual property.

Rapid technological innovation and observed firm consolidation has led to several empirical examinations of market structure in the agricultural biotechnology industry. Fulton and Giannakas (2001) find that the agricultural biotechnology sector has undergone a restructuring in the form of both horizontal and vertical integration over the past ten years. The industry attributes consistently identified by the literature and that factor into the proposed analysis include: (i) endogenous sunk costs in the form of expenditures on R&D that may create economies of scale and scope within firms[1]; (ii) seed and agricultural chemical technologies that potentially act as complements within firms and substitutes across firms; and (iii) property rights governing plant and seed varieties that have become more clearly defined since the 1970s. This proposed research extends the stylized facts for the agricultural biotechnology industry by identifying the relevance of sunk costs investments in R&D in shaping the observed concentration and distribution of firms. As Sheldon (2008) identifies, the presence of endogenous sunk costs in R&D expenditures, high levels of market concentration, and high levels of R&D intensity in the agricultural biotechnology make this sector a likely candidate to be well-described by an EFC-type model such as that proposed by Sutton (1998).

In estimating an EFC-type model, this analysis extends the previous work by considering a more general framework in which concentration and innovation are jointly determined. Previously, Schimmelpfennig, Pray, and Brennan (2004) tested Schumpeterian hypotheses regarding the levels of industry concentration and innovation in biotechnology and found a negative and endogenous relationship between measures of industry concentration and R&D intensity. Additional stylized

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[1] In regards to economies of scale and/or economies of scope in agricultural biotechnology, Chen, Naseem, and Pray (2004) find evidence that supports economies of scope as well as internal and external spillover effects in R&D. However, they fail to find any conclusive results concerning economies of scale or correlation between the size of firms and the size of R&D in agricultural biotechnology.

examinations of the agricultural biotechnology industry have identified an endogenous, cyclical relationship between industry concentration and R&D intensity (Oehmke, Wolf, and Raper, 2005) and categorized the endogenous relationship between firm innovation strategies, including the role of complementary intellectual assets, and industry consolidation characteristics (Kalaitzandonakes and Bjornson, 1997). As a more general model, this analysis embeds previous results that observe an endogenous relationship between R&D investments and industry concentration. Moreover, I incorporate exogenous variations in total market size for each crop type as well as technological innovations, including the development of second- and third-generation GM crops, and changes in consumer preferences over the relevant time frame to provide a richer analysis of industry configurations. Whereas previous examinations have focused upon identifying the endogenous relationship between R&D intensity and concentration in agricultural biotechnology, I determine whether (sunk) R&D investments drive this relationship.

A related vein of research has focused upon the significant levels of merger and acquisition activity that have historically been observed in the agricultural biotechnology industry. The explanations behind the high levels of activity have included the role of patent rights in biotechnology (Marco and Rausser, 2008), complementarities in intellectual property in biotechnology (Graff, Rausser, and Small, 2003; Goodhue, Rausser, Scotchmer, and Simon, 2002), and strategic interactions between firms (Johnson and Melkonyan, 2003). This analysis extends previous examinations into merger and acquisition activity in agricultural biotechnology in estimating whether this firm consolidation has had a significant impact upon the observed patterns of R&D concentration while abstaining from addressing the possible causal mechanisms behind the consolidation activity.

The EFC model employed in this framework has been utilized to empirically examine a variety of other industries including chemical manufacturing (Marin and Siotis, 200)), supermarkets (Ellickson, 2007), banking (Dick, 2007), newspapers and restaurants (Berry and Waldfogel, 2003), and online book retailers (Latcovich and Smith, 2001). These previous analyses have focused upon examining the relationship between concentration, captured by the ratio of firm to industry sales, and investments in either capacity (Marin and Siotis, 2007), product quality (Ellickson, 2007; Berry and Waldfogel, 2003), or advertising (Latcovich and Smith, 2001). The model of endogenous market structure and R&D investment developed by Sutton (1998) predicts a lower bound to firm R&D intensity that is theoretically equivalent to the lower bound to firm concentration under significantly large markets. To our knowledge, ours is the first examination of a specific industry in the context of firm-level investments in R&D, although the empirical analysis of Marin and Siotis (2007) of chemical manufacturers does differentiate between product markets characterized by high and low R&D intensities. Moreover, I contribute to the industrial organization literature by applying an EFC model to a previously unexamined industry as well as derive and estimate the lower bound to R&D concentration under endogenous fixed costs.

In light of the recent Justice Department announcement regarding its investigations into anticompetitive practices in agriculture[2], this analysis is of interest to both regulators and policymakers concerned with the observed high levels of concentration in agricultural biotechnology. Specifically, if the agricultural biotechnology sector is characterized by endogenous fixed costs, the high levels of concentration, accompanied with high levels of innovative activity, are a natural outcome of technology competition and are not evidence of collusion among firms. However, the significant shift in the observed patterns of R&D concentration in cotton and soybean seed upon accounting for merger and acquisition activity imply that industry consolidation has increased concentration of intellectual property to levels greater than what is predicted under endogenous fixed costs alone.

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[2] Neuman, W. 2010. "Justice Dept. Tells Farmers It Will Press Agricultural Industry on Antitrust." *The New York Times*, March 13, pp. 7.

CHAPTER 2: Endogenous Market Structure, Innovation, and Licensing

In this chapter, I show that there are incentives for firms with cost advantages to escalate quality-enhancing investments in R&D and license the increased quality to high-cost competitors. I derive this result from a theoretical, three-stage model in which firms first face a market entry choice, and, upon entry, compete first in a technology market via R&D investment and technology licensing followed by product market competition given quality choices. The model is fully endogenous in the sense that market structure, R&D investment, and licensing decisions occur simultaneously and the model does not rely upon restrictions upon the number of entrants or the level of R&D investment. Given a set of reasonable assumptions on the structure of the technology licensing contracts, the model implies that in an endogenous fixed cost industry, firm concentration will be greater under licensing relative to the case without licensing and the quality level of the industry-leading firm will be greater under licensing.

Theoretical Model: Extending Sutton's Bounds Approach

Basic Framework and Notation

Sutton's (1998; 2007) bounds approach to the analysis of market structure and innovation considers firm concentration and R&D intensity to be jointly and endogenously determined in an equilibrium framework. As Van Cayseele (1998) identifies, the bounds approach incorporates several attractive features to the analysis of market structure and sunk cost investments; namely it provides empirically testable hypotheses while permitting a wide class of possible equilibrium configurations consistent with a diverse contingent of game-theoretic models. Thus, I adopt the basic endogenous sunk cost framework proposed by Sutton (1998) as the basis for the theoretical framework incorporating the ability of firms to license their technology to competitors.

The bounds approach considers firm concentration to be a function of endogenous sunk costs in R&D investment rather than as being deterministically driven by exogenous sunk costs. As the level of firm concentration will affect the incentives to innovate, the endogenous sunk cost framework provides the opportunity for some firms to outspend rivals in R&D and still profitably recover their sunk cost expenditures. The effectiveness with which firms can successfully recoup their sunk cost outlays depends upon demand side linkages across products, the patterns of technology and consumer preferences, and the nature of price competition. Moreover, the model allows for multiple technology holders to viably enter into the product market in equilibrium and successfully regain their sunken investments provided that the market size is sufficiently large.

In building on the framework developed by Sutton (1998), I am interested in examining an industry characterized by a product market consisting of goods differentiated both vertically in observable quality and horizontally in observable attributes. I am thus concerned with some industry consisting of K submarkets such that the quantity of a good in submarket k is identified by x_k. In developing an endogenous fixed cost (EFC) model, Sutton is primarily concerned with the concept of R&D trajectories and identifying the equilibrium configurations that result from firms' R&D activities. He assumes that the industry consists of M possible research trajectories, indexed by m, such that each is associated with a distinct submarket. Thus, each firm i invests in one or more research programs, each associated with a particular trajectory, and achieves a competence (i.e. quality or capability) defined by an index u_{im} to be associated with some good x_{im}.

The model developed here diverges from Sutton's (1998) with respect to the concepts of product quality and research trajectories primarily in two dimensions: first, in the definition of quality for some good k; and second, in the relationship between research trajectories and the associated levels of quality. I consider multiple attribute products in which the overall quality u_k of some good k is characterized as a function of the technical competencies achieved across all attributes M^k associated with the good. Specifically, some Firm i achieves quality u_{ik} according to:

$$u_{ik} = f_{ik}\left(v_{i1}, \dots, v_{im}, \dots, v_{iM^k}\right), \tag{2.1}$$

where v_{im} corresponds to the technical competence that Firm i achieves along research trajectory m. Therefore, I make the minor distinction between the quality of a product directly associated with a distinct research trajectory, as is the case in Sutton's (1998) model, and the quality of a product as a function of the qualities of its individual attributes which are directly associated with distinct research trajectories.[3]

A firm chooses some value $v_{im} \in \{0, [1, \infty)\}$ along each trajectory such that $v_{im} = 0$ corresponds to inactivity along trajectory m and $v_{im} = 1$ corresponds to a

[3] This distinction relates, in part, to the discussion on the possibilities of economies of scope across research trajectories as discussed by Sutton (1998) in Appendix 3.2. Implicit in the model proposed here is the assumption that once firms achieve a level of technical competency along some research trajectory, it can utilize this competency across a broad range of products without incurring additional R&D costs.

minimum level of quality required to offer attribute m. The quality function $f_k(\cdot)$ is a $M^k \rightarrow 1$ mapping for every product k such that the shape and characteristics of the quality function $f(\cdot)$ satisfy the following assumptions:

(i) Product quality is concave in individual attributes (i.e. $\frac{\partial f}{\partial v_m} \geq 0$, $\frac{\partial^2 f}{\partial {v_m}^2} \leq 0$, and $\frac{\partial^2 f}{\partial v_n \partial v_m} \geq 0$). Thus, firms are limited in their ability to increase the overall quality level of some product k by escalating the competency they acquire along a single trajectory;[4]

(ii) A firm that is inactive along any attribute for some product k achieves a capability equal to the zero (i.e. If ∃ ∈ , $= 0$, then $= 0$.). Thus, firms must achieve at least a minimum level of competency across all trajectories in order to enter the product market for good k; and

(iii) A capability equal to one, associated with a minimum level of quality, indicates that a firm has achieved a minimum level of competency across all trajectories for some product k. (i.e. If $\forall m \in M^k, v_{im} = 1$, then $u_{ik} = 1$.)

[4] In the case in which a product consists of only a single attribute, then the overall level of quality of the product may be increasing at a constant rate. This case is equivalent to the model proposed by Sutton (1998) in which each product is associated with a distinct research trajectory.

Thus, there are two possible alternatives with which overall capability achieved by Firm i can be defined: namely, as the K-tuple set of qualities that it achieves in each submarket such that $\mathbf{u}_i = (u_{i1}, \dots, u_{ik}, \dots u_{iK})$ or as the M-tuple set of competencies that it achieves in each trajectory such that $\mathbf{v}_i = (v_{i1}, \dots, v_{im}, \dots v_{iM})$. Within the product market, the primary concern is with the quality levels of the offered products and the resulting configuration of firms given these qualities. Thus, the analysis is confined to considering the overall capability that Firm i achieves as being represented by $\mathbf{u}_i = u(\mathbf{v}_i)$ such that $\mathbf{u}_i = \emptyset$ corresponds to the case in which Firm i is inactive in every product.

Let $\mathbf{u}$ be an equilibrium configuration of capabilities that is the outcome of the R&D process across all firms in an industry. Then $\mathbf{u} = (\mathbf{u}_1, \dots, \mathbf{u}_i, \dots, \mathbf{u}_N)$ is a KxN vector which consists of the set of capabilities across all active firms N. Moreover, let the industry consist of N_0 total firms, with N 'active' firms in equilibrium, indexed by i such that the costs of R&D investment vary across firms. It is useful to also specify several other notations regarding capabilities and configurations, specifically I denote $\mathbf{u}_{(-i)}$ as the set of capabilities of Firm i's rivals, define $\hat{u}_k(\mathbf{u}) = \max_i(u_{ik})$ as the maximum level of quality achieved across all firms for good k in some configuration $\mathbf{u}$, and define $\hat{v}_m = \max_i v_{im}$ and $\hat{v} = \max_m \hat{v}_m$ as the maximum level of competency achieved within some attribute m and across all attributes, respectively. Moreover, let the set of products offered in equilibrium be K, set of products offered by Firm i be $\mathrm{K}_i \subset \mathrm{K}$, the set of products offered by Firm i that contain attribute m be $\mathrm{K}_{im} \subset \mathrm{K}_i$, and the total set of attributes possessed by Firm i be V^i.

The profit function and sales revenue for Firm i are defined in terms of the set of firm competencies $\mathbf{u}_i$ and the equilibrium configuration $\mathbf{u}$. Total profit for Firm i, written in terms of the number of consumers in the market S and per consumer profit $\pi(\cdot)$, is specified as $S\pi_i(u(\mathbf{v}_i)|\mathbf{u})$. Let profit for Firm i from a single product market k be specified as $S\pi_{ik}(u(\mathbf{v}_i)|\mathbf{u})$. Additionally for some configuration $\mathbf{u}$, I specify the total sales revenue for Firm i within a single product market k as $Sr_{ik}(\mathbf{u})$, total industry sales summed across all active firms within a single product market k as $Sr_k(\mathbf{u}) = S\sum_{i\in N_k} r_{ik}(\mathbf{u})$, and the total industry sales revenue across all markets, $\mathrm{R}(\mathbf{u}) \equiv Sr(\mathbf{u}) = S\sum_k r_k(\mathbf{u})$.

Innovation and market structure are endogenous in Sutton's (1998) bounds model via the presence of sunk cost investments in technology. Sunk (fixed) costs are typically industry-specific and can include investments in research laboratories with a focus upon a specific technology discovery, the adoption of machinery that offers a cost-reducing process innovation, or marketing, advertising, and branding campaigns. The model developed here is primarily concerned with R&D

investments that lead to products that offer new characteristics and/or improved quality. Let the sunk (fixed) R&D outlay that achieves technical competency v_{im} by Firm i along trajectory m be expressed as:

$$F(v_{im}) = F_0 {v_{im}}^{\beta_{im}}, \quad \beta_{im} \geq 2 \ \forall i, m. \tag{2.2}$$

I assume that firms incur a minimum setup cost F_0 associated with entry in any R&D trajectory regardless of the level of competency. Moreover, I assume that the fixed cost schedule is convex (i.e. the elasticity of the fixed cost schedule β_{im} is greater than or equal to two) such that the costs of escalating quality increase at least as rapidly as profits for R&D expenditures above the minimum level; thereby restricting the ability of firms to infinitely increase the level of product quality they offer.

I relax the simplifying assumption that firms face symmetric costs (i.e. $\beta_{im} = \beta \ \forall i, m$) and thus allow for asymmetric costs schedules across firms and across trajectories, implying that there exist potential costs advantages in R&D. For simplicity, I assume that along each trajectory m there exist two types of firms; those with a "low" R&D cost parameter β_m^L within the trajectory and those with a "high" R&D cost parameter β_m^H such that $\beta_m^H > \beta_m^L \geq 2$. In equilibrium, there exist N_m^L firms with a "low" R&D cost parameter and N_m^H firms with a "high" R&D cost parameter for each trajectory m. Additionally, R&D cost parameters across trajectories are assumed to be independent such that the relationship between the R&D cost parameters of Firms i and j in trajectory m does not correlate with the relationship between the R&D cost parameters of the firms in trajectory n.

The total fixed costs for Firm i across all trajectories V^i in which the firm is active can be expressed as:

$$F(\mathbf{v}_\mathrm{i}) = F_0 \sum_{m \in \mathrm{V}^i} {v_{im}}^{\beta_{im}}. \tag{2.3}$$

Additionally, let the R&D spending by Firm i along trajectory $m,$ in excess of the minimum level of investment, be:

$$D(v_{im}) = F(v_{im}) - F_0 = F_0\left({v_{im}}^{\beta_{im}} - 1\right). \tag{2.4}$$

such that total R&D spending across all trajectories equals:

$$D(\mathbf{v}_\mathrm{i}) = F_0 \sum_{m \in \mathrm{V}^i} \left({v_{im}}^{\beta_{im}} - 1\right) = F(\mathbf{v}_\mathrm{i}) - n_i F_0. \tag{2.5}$$

where n_i is the total number of trajectories that Firm i enters.

Finally, as Sutton (1998) identifies, it is necessary to make additional assumptions upon the size of the market in order to ensure that the level of sales sufficient to sustain some minimal configuration such that at least one firm can be supported in equilibrium. I restrict the domain for the total market size $S \in [1, \infty)$ and assume that the conditions defined by Sutton (1998) in Assumption 3.1 also hold for our model. Generally, this assumption implies: (i) for every nonempty configuration, industry sales revenue approaches infinity as market size approaches infinity; and (ii) there is some nonempty configuration that is viable for market sizes falling within the restricted domain.

Licensing in an Endogenous Model of R&D and Market Structure

In addition to the relaxation of the assumption on symmetric firms and the (somewhat trivial) clarification regarding the relationship between product quality, product attributes, and research trajectories, the primary extension of Sutton's (1998) model allows firms to acquire attributes either through their own R&D investments or via the licensing agreements with rivals. Specifically, I permit a single firm to possess a first-mover advantage in the quality choice decision within each research trajectory. Thus, the market leader (or "innovator") decides on the level of R&D investment that it commits in the given trajectory and whether or not it will license the technical competency that it attains. All other firms (or "imitators") face the decision to enter this research trajectory with their own R&D investment and incur the associated fixed cost or, if available, to pursue a license agreement to acquire the level of quality offered by the market leader.

For some research trajectory m, "imitating" licensee Firm i, and "innovating" licensor Firm j, I assume that Firm i and Firm j can credibly commit to a license contract that specifies the upfront, lump sum payment, , from Firm i to Firm j and the level of competence to be transferred . The assumption of lump sum payments is consistent with the licensing models developed by Katz and Shapiro (1985) and Arora and Fosfuri (2003). As Katz and Shapiro (1985) identify, the presence of information asymmetries over output or imitation of technological innovations implies that the use of a "fixed-fee" licensing contract is optimal.[5] Although the model is characterized by a lump sum, fixed-fee payment for the license, for tractability I assume that Firm j is able to specify this payment as a proportion of the sales revenue earned by Firm *i* along all products which incorporate the licensed competency along trajectory . The acquisition of a licensed technology is considered as an alternate to R&D investment while remaining a sunk cost expenditure such that the payment takes the form:

$$P_{im}^{j} = \rho\left(v_{jm}\right) S \sum_{k \in \mathrm{K}_m} r_{ik}(\mathbf{\acute{u}}), \tag{2.6}$$

[5] For a counter-argument regarding the feasibility of lump sum payments in licensing contracts, the reader is referred to Gallini and Winter (1985) who assume per unit royalty fees as lump sum payments and two-part tariffs are "institutionally infeasible" (p. 242, 1985). For a more thorough discussion of the pricing of license agreements, please refer to Gallini and Winter (1990).

where **ú** is the equilibrium configuration of qualities offered under licensing and $\rho(v_{jm}) \in [0,1]$ is the proportion of sales revenue across all products that incorporate capability v_{jm} that Firm i pays to Firm j.

Transactions costs associated with licensing are incorporated into the model in two ways: first, in the form of a fixed component associated with the formation of each license agreement; and second, in the imperfect transfer of technical competencies between firms. I assume that a firm that licenses technology from a competitor also incurs a fixed transactions cost T_0 associated with each license agreement that is irrecoverable to either contracting firm. This fixed fee can be thought of as the rents captured by some unrelated, third party intermediary negotiating the license agreement between the two firms. The fixed transactions cost and imperfect transfer of technologies introduce inefficiencies into the model under licensing. However, these inefficiencies are counterbalanced by efficiency gains as more firms capitalize upon the same R&D expenditures and as high-cost firms are reduce their inefficient R&D spending such that there is an overall ambiguous effect.

I account for the variable component of the transactions cost via an imperfect transfer of technologies between firms. Specifically, some Firm i that licenses competency v_{jm} from Firm j is only able to utilize a level of competency equal to

δv_{jm}, where $\delta \in [0,1]$, without incurring an additional fixed cost of R&D. This implies that for Firm i to achieve the full competency for which it contracted, it must also incur an additional R&D investment equal to $F_0(1-\delta)^{\beta_{im}} v_{jm}^{\beta_{im}}$. This imperfect transfer of technology permits a generalization of the case in which firms incur additional investments in order to incorporate the licensed competencies into their own set of offered products.

The total costs associated with Firm i licensing competency v_{jm} from Firm j along trajectory m, and incurring the additional R&D investment to accommodate the licensed technology, can thus be expressed as:

$$\begin{aligned} T(v_{jm}) &= T_0 + P_{im}^{j} + F\left((1-\delta)v_{jm}\right) \\ &= T_0 + \rho(v_{jm}) S \sum_{k \in \mathrm{K}_m} r_{ik}(\acute{\mathbf{u}}) + F_0(1-\delta)^{\beta_{im}} v_{jm}^{\beta_{im}}. \end{aligned} \tag{2.7}$$

In order to examine the feasibility of such license agreements, consider some Firm i that has a high cost to R&D along trajectory n such that $\beta_{in} = \beta^{H}$. Firm i faces the choice between licensing capability $\hat{v}_n$ from the market leader (and offering a product with quality $\hat{u}$) and producing some capability v_{in} by investing in its own R&D (and offering a product with quality u). Given some set of capabilities $\mathbf{v}_{i,(-n)}$ across all other trajectories $m \neq n$, Firm i will (weakly) prefer a license to incurring the total amount of R&D investment for some quality $\hat{v}_n$ iff:

$$S\pi(\hat{u}|\mathbf{\acute{u}}) - F\big(\mathbf{v}_{i,(-n)}\big) - T(\hat{v}_n) \geq S\pi(u|\mathbf{u}) - F(v_{in}) - F\big(\mathbf{v}_{i,(-n)}\big). \tag{2.8}$$

As firms enter endogenously in equilibrium, the right-hand side of expression (2.8) will be zero (i.e. additional firms enter the market until profit net of fixed R&D costs equals zero). Substituting for $T(\hat{v}_n)$ and simplifying, I derive an expression for the proportion of sales revenue accrued to licensor firms which must be satisfied for a firm with high R&D costs along trajectory n to prefer licensing to own R&D. Namely,

$$\rho(\hat{v}_n) \leq \frac{S\pi(\hat{u}|\mathbf{\acute{u}}) - F\big(\mathbf{v}_{i,(-n)}\big) - F_0(1-\delta)^{\beta^H}\hat{v}_n{}^{\beta^H} - T_0}{S\sum_{k\in \mathrm{K}_n} r_{ik}(\mathbf{\acute{u}})}. \tag{2.9}$$

For tractability in analysis, consider the special case in which marginal costs of production are equal to zero such that $S\pi(\hat{u}|\mathbf{\acute{u}}) = S\hat{r}$ and let the sales from products containing attribute $\hat{v}_n$ equal some proportion γ_n of total sales revenue $S\hat{r}$ across all goods. If licensor firms are able to appropriate all excess profits from licensees, the proportion of sales revenue specified in the licensing agreement can be specified as:

$$\rho(\hat{v}_n) = \frac{S\hat{r} - F\big(\mathbf{v}_{i,(-n)}\big) - F_0(1-\delta)^{\beta^H}\hat{v}_n{}^{\beta^H} - T_0}{\gamma_n S\hat{r}}. \tag{2.10}$$

Comparative statics reveal that the proportion of sales revenue that a licensor is able to capture is decreasing monotonically in the fixed transactions cost parameter T_0 (i.e. $\frac{\partial\rho(\hat{v}_n)}{\partial T_0} = \frac{-1}{S\sum_{k\in \mathrm{K}_n} r_{ik}(\mathbf{\acute{u}})} \leq 0$) while it is increasing and concave in the variable transactions cost parameter δ (i.e. $\frac{\partial\rho(\hat{v}_n)}{\partial\delta} = \frac{\beta^H F_0(1-\delta)^{\beta^H-1}\hat{v}_n{}^{\beta^H}}{\gamma_n S\hat{r}} \geq 0$ and $\frac{\partial^2\rho(\hat{v}_n)}{\partial^2\delta} =$

$\frac{-\beta^H(\beta^H-1)F_0(1-\delta)^{\beta^H-2}\hat{v}_n{}^{\beta^H}}{\gamma_n S\hat{r}} \leq 0$). As $\delta \to 1$, variable transactions costs approach zero (i.e. more perfect transfer of technology) such that comparative statics on both fixed and variable transactions costs imply that there is an upper bound on the proportion of sales revenue that a licensor firm can extract from licensee firms such that $\rho \to 0$ as transactions costs increase.

Moreover, the proportion of revenue that can be appropriated by licensor firms is also decreasing in the proportion of total licensee sales revenue from products associated with the licensed competency (i.e. $\frac{\partial\rho(\hat{v}_n)}{\partial\gamma_n} \leq 0$ and $\frac{\partial^2\rho(\hat{v}_n)}{\partial^2\gamma_n} \geq 0$). This implies that there is a trade-off between "major" innovations in attributes that can be applied across a broad class of products and the proportion of sales revenue that can be captured in the licensing of these innovations. This comparative static result is consistent with the first proposition of Katz and Shapiro (1985) regarding which innovations will be licensed by firms under a fixed licensing fee and Cournot competition in the product market. Their first proposition implies that firms will engage in licensing over minor (or arbitrarily small) innovations, but that major (or large) innovations will not be licensed. Thus, major innovations which contribute significantly to total sales revenue will be less likely to be licensed as licensees would prefer to pursue their own R&D investments in such innovations.

Equilibrium Configurations under Licensing

Now I define the conditions that must be satisfied for some configuration **u** to be an equilibrium without licensing as well as the conditions that must be satisfied for some configuration **ú** to be an equilibrium under licensing. For convenience, Tables 1 and 2 provide a notational summary of equilibrium definitions and firm, product, and trajectory sets, respectively.

Table 1: Summary of Equilibrium Definitions

Variable	Definition
u	Equilibrium configuration
ú	Equilibrium configurations under licensing
$\hat{u}$	Highest level of quality offered without licensing
$\hat{v}$	Highest competency attained without licensing
$\hat{u}'$	Highest level of quality offered under licensing
$\hat{v}'$	Highest competency attained under licensing

Table 2: Firm, Product, and Trajectory Sets

Variable	Definition
N	Total active firms in equilibrium
N_m^L	Active firms with a low-cost parameter along trajectory m
N_m^H	Active firms with a high-cost parameter along trajectory m
K_i	Products offered by Firm i
K_{im}	Products offered by Firm i that incorporate attribute m
L^m	Number of licenses granted for attribute m
V_l^i	Set of trajectories in which Firm i licenses technology
V_{-l}^i	Set of trajectories in which Firm i pursues own R&D

Sutton's viability condition, or "survivorship principle", implies that an active Firm i does not earn negative profits net of avoidable fixed costs in equilibrium. Specifically using the current notation, this condition can be specified as:

$$\forall i \in N \quad S\pi_i(u(\mathbf{v}_i)|\mathbf{u}) - F(\mathbf{v}_i) \geq 0. \qquad (V.1)$$

Sutton's (1998) stability condition, or "(no) arbitrage principle", implies that in equilibrium, there are no profitable opportunities remaining to permit entry by a new firm. Specifically, for an entrant firm indexed as Firm $N+1$, the condition can be written as:

$$S\pi_{N+1}(u(\mathbf{v}_{N+1})|\mathbf{u}) - F(\mathbf{v}_{N+1}) \leq 0. \qquad (S.1)$$

Sutton (1998) provides the proof that any outcome that can be supported as a (perfect) Nash equilibrium in pure strategies is also an equilibrium configuration and I forgo any further discussion of the comparability of these results with the results from purely game theoretic models.

These conditions must also hold for a low-cost Firm i producing the highest level of quality $\hat{u}$ that attains the highest level of competency $\hat{v}$ along some trajectory n. The viability condition implies that this firm earns non-negative profits such that:

$$S\pi(\hat{u}|\mathbf{u}) - F_0 \hat{v}_n{}^{\beta^L} - \sum_{m \neq n} F(v_{im}) \geq 0. \qquad (V.1')$$

The corresponding stability condition, which precludes a low-cost Firm i entering and escalating quality along trajectory n by a factor $\kappa > 1$, is specified as

$$S\pi(\kappa\hat{u}|\mathbf{u}) - F_0(\kappa\hat{v}_n)^{\beta^L} - \sum_{m \neq n} F(v_{im}) \leq 0, \quad \forall \kappa > 1. \qquad (S.1')$$

In order to make these conditions comparable, I assume that firms achieve the same level of competency v_m along all trajectories $m \neq n$. As I allow for asymmetry across firms in the R&D cost parameter, in equilibrium only firms facing a low-cost R&D parameter are able to attain the highest levels of competency within any trajectory. Without the assumption that low-cost firms offer the market-leading levels of quality in equilibrium, there would exist profitable opportunities for low-cost firms to enter and escalate quality along trajectories in which high-cost firms offered the highest level of quality.

The assumption of symmetric R&D costs across firms in Sutton (1998) provides for a tractable examination of market structure and R&D intensity, but is unable to explain why some industries are characterized by a subset of market leaders in quality. I relax the assumption of cost symmetry, but restrict the R&D cost function in two ways. First, if some equilibrium configuration satisfies the stability condition for all low R&D cost firms, it will also be satisfied for all high R&D cost firms. Second, a configuration in which a high-cost firm offers the market-leading quality is not stable to entry (and escalation) by a low-cost firm. One final point of interest is that the viability and stability conditions allowing for multiple-attribute products are equivalent to the conditions specified in Sutton (1998) for the subset of products consisting of a single quality attribute.

There exist stability and viability conditions which must be satisfied for some configuration **ú** to be an equilibrium under licensing.[6] For simplicity, I assume that licensing of competency $\hat{v}'$ occurs along trajectory n between a firm with a low R&D cost parameter and firms with high R&D cost parameters. Thus, competitor firms

[6] I differentiate these configurations and competencies from those specified by Sutton (1998) as there is no *a priori* reason to believe that there will be correspondence between the two sets of equilibrium configurations or between the sets of product attributes, although I do anticipate some overlap.

are able to cross-license their competencies if there are complementary R&D cost advantages such that the model predicts increased levels of concentration and ambiguous effects upon R&D as market-leading, low-cost firms are able to successfully sustain a “research cartels” across trajectories.

The viability condition for a firm that licenses its technology to rivals can be expressed as:

$$\forall i \in N \quad S\pi_i(u(\acute{\mathbf{v}}_i)|\acute{\mathbf{u}}) - F(\acute{\mathbf{v}}_i) + \sum_{m \in \mathrm{V}^i} \sum_{j \in N_m^i} P_{jm}^i \geq 0. \qquad (V.2)$$

Condition $(V.2)$ implies that every firm that licenses technology in equilibrium earns non-negative profits. Under licensing, firms may offer similar products which could lead to an increase in competition, a decrease in consumer prices, and a potential reduction in per-person consumer profit in the first term of equation $(V.2)$ (i.e. “rent dissipation effect”). On the other hand, the final term in equation $(V.2)$ is the licensing revenue earned by the innovating firm as summed over all R&D trajectories and over all firms that license within each trajectory (i.e. “revenue effect”). The corresponding stability condition for licensor firms is:

$$S\pi_{N+1}(u(\acute{\mathbf{v}}_{N+1})|\acute{\mathbf{u}}) - F(\acute{\mathbf{v}}_{N+1}) + \sum_{m \in \mathrm{V}^{N+1}} \sum_{j \in N_m^{N+1}} P_{jm}^{N+1} \leq 0. \qquad (S.2)$$

The stability condition precludes an additional firm from entering in equilibrium and recouping the fixed costs associated with entry via licensing its quality to rivals.

Similarly, the viability and stability conditions under licensing must hold for a low-cost licensor Firm i that produces the highest level of quality $\hat{u}'$ and attains the highest level of competency $\hat{v}'$ along some trajectory n. Assuming that the high-quality firm only licenses the competency $\hat{v}'$ that it attains along trajectory n and substituting for the lump-sum licensing payment P, the viability condition $(V.2)$ can be specified as:

$$S\pi(\hat{u}'|\mathbf{\acute{u}}) - F_0 \hat{v}'^{\beta^L} - \sum_{m \neq n} F(v_{im}) + \sum_{j \in N_n^i} \rho(\hat{v}') S \sum_{k \in \mathrm{K}_n} r_{jk}(\mathbf{\acute{u}}) \geq 0. \qquad (2.11)$$

Similarly, the stability condition for licensor firms can be expressed as:

$$S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}) - F_0 (\kappa\hat{v}')^{\beta^L} - \sum_{m \neq n} F(v_{im}) + \sum_{j \in N_n^i} \rho(\kappa\hat{v}') S \sum_{k \in \mathrm{K}_n} r_{jk}(\mathbf{\acute{u}}) \leq 0, \;\; \forall \kappa > 1. \; (2.12)$$

The stability condition under licensing (2.12) precludes entry by a low-cost innovating firm that escalates product quality by a factor of $\kappa > 1$ and recoups the additional fixed cost investments via licensing to high-cost rivals. Moreover, I also specify a stability condition for licensor firms which precludes entry by a low-cost innovating firm that escalates product quality and chooses not to license to high-cost rivals. Specifically,

$$S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}') - F_0 (\kappa\hat{v}')^{\beta^L} - \sum_{m \neq n} F(v_{im}) \leq 0, \quad \forall \kappa > 1. \qquad (2.13)$$

Equation (2.13) implies that, in equilibrium, an innovating firm cannot profitably enter via quality escalation and not licensing its higher quality when it observes licensing within the industry. The rent dissipation effect associated with the licensing of technology or quality to competitors implies that a firm escalating quality and entering without licensing to competitors earns greater profit relative to a firm that escalates and enters with licensing. Thus, $S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})$ is necessarily no greater than $S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')$ such that equation (2.12) does not cover all potential profitable opportunities for entry and equation (2.13) is also necessary.

Let the number of licenses of attribute n granted by Firm j be equal to L^{jn} and assume that a potential entrant firm that attempts to escalate quality chooses to grant the same number of licenses L^n. A firm that licenses technology to competitors chooses both its level of R&D expenditure and the number of licenses that it offers and thereby sets the number of rivals that it competes against. By symmetry of profit functions across firms, I assume that an entrant firm that attempts to establish a new technology standard along the same trajectory by escalating the capability by some positive factor κ will chose the same number of rivals as that chosen by original firm.

Finally, I make two trivial simplifying assumptions in order to provide clearer intuition over the viability and stability conditions under licensing. First, I assume that the sales from all of the products that incorporate a licensed attribute n can be expressed as a proportion $\gamma_n \in [0,1]$ of total firm sales. Second, I assume zero marginal costs of production such that firm profit functions and firm sales functions for some configuration $\mathbf{ú}$ are equivalent. Although zero marginal costs is a potentially strong assumption, many of the industries with which I am concerned, including pharmaceuticals, biotechnology, and semiconductors, are characterized by production processes with negligible or zero marginal costs to production.

Under these two assumptions, the proportion of sales revenue specified by the lump-sum transfer for the licensing of some attribute n with quality $\hat{v}'$ to Firm j can be specified as:

$$\rho(\hat{v}')S\sum_{k\in \mathrm{K}_n} r_{jk}(\mathbf{ú}) = \rho(\hat{v}')S\gamma_n r_j(\mathbf{ú}) = \rho(\hat{v}')\gamma_n S\pi(\hat{u}'|\mathbf{ú}). \tag{2.14}$$

Under these additional assumptions, the viability and stability conditions for all firms that license some attribute n with quality $\hat{v}'$ can now be characterized as:

$$[1 + L^n\rho(\hat{v}')\gamma_n]S\pi(\hat{u}'|\mathbf{ú}) - F_0\hat{v}'^{\beta^L} - \sum_{m\neq n} F(v_{jm}) \geq 0, \qquad (V.2')$$

$$[1 + L^n\rho(\kappa\hat{v}')\gamma_n]S\pi(\kappa\hat{u}'|\mathbf{ú}) - F_0(\kappa\hat{v}')^{\beta^L} - \sum_{m\neq n} F(v_{jm}) \leq 0, \quad \forall\kappa > 1, \quad (S.2')$$

$$S\pi(\kappa\hat{u}'|\mathbf{ú}') - F_0(\kappa\hat{v}')^{\beta^L} - \sum_{m\neq n} F(v_{jm}) \leq 0, \quad \forall\kappa > 1. \qquad (S.2'')$$

In order to specify the stability and viability conditions that must be satisfied by firms that license technology in equilibrium, let the set of trajectories along which Firm i licenses technology be V_l^i and the set of trajectories along which it invests in its own R&D be V_{-l}^i. The licensee viability condition ensures that high-cost firms that license technology from their low-cost rivals earn profits that cover the fixed R&D costs along all trajectories in which they do not license technology, the fixed R&D costs associated with the "catch-up" from the imperfect transfer of technology, the lump-sum license fee, and the fixed transactions costs associated with licensing. Thus, for all licensee firms i:

$$\forall i \in N \quad S\pi_i(u(\acute{\mathbf{v}}_i)|\acute{\mathbf{u}}) - \sum_{m \in \mathrm{V}_{-l}^i} F(v_{im}) - \sum_{m \in \mathrm{V}_l^i} \sum_{j \in N_{im}^j} T\left(v_{jm}\right) \geq 0. \qquad (V.3)$$

Similarly, the stability condition for licensee firms implies that a firm cannot enter via licensing, invest in its own R&D along the same trajectory, and recoup the costs associated with licensing and R&D. Namely,

$$S\pi_{N+1}(u(\acute{\mathbf{v}}_{N+1})|\acute{\mathbf{u}}) - \sum_{m \in \mathrm{V}_{-l}^{N+1}} F(v_{N+1m}) - \sum_{m \in \mathrm{V}_l^{N+1}} \sum_{j \in N_{N+1m}^j} T\left(v_{jm}\right) \leq 0. \qquad (S.3)$$

Again, consider the case in which high-cost firms license competency $\hat{v}'$ along a single trajectory n, produces quality $\hat{u}'$, and attains the same levels of competency along every other trajectory $m \neq n$. The viability condition can be expressed as:

$$S\pi(\hat{u}'|\acute{\mathbf{u}}) - \sum_{m\neq n} F(v_{im}) - \left[1-(1-\delta)^{\beta^H}\right]F_0\hat{v}'^{\beta^H} - \rho(\hat{v}')S\sum_{k\in \mathrm{K}_n} r_{ik}(\acute{\mathbf{u}}) - T_0 \geq 0. \quad (2.15)$$

In equilibrium, the stability condition for the licensee must hold such that a firm that licenses technology from the market leader cannot then escalate the level of quality provided by escalating its own R&D expenditure. Thus, equilibrium configurations preclude cases in which licensee firms can acquire technology "cheaply" from rivals and then pursue their own R&D to escalate the overall level of quality. The explicit expression of the stability condition in this case is:

$$\begin{aligned} S\pi(\kappa\hat{u}'|\acute{\mathbf{u}}') - \sum_{m\neq n} F(v_{im}) - \kappa^{\beta^H}\left[1-(1-\delta)^{\beta^H}\right]F_0\hat{v}'^{\beta^H} \\ -\rho(\hat{v}')S\sum_{k\in \mathrm{K}_n} r_{jk}(\acute{\mathbf{u}}) - T_0 \leq 0, \quad \forall\kappa > 1. \end{aligned} \quad (2.16)$$

I also specify a second stability condition such that a high-cost entrant that licenses the current maximum quality, escalates this quality through its own R&D, and then licenses to other high-cost firms is not a feasible equilibrium strategy. Explicitly, this stability condition can expressed as:

$$\begin{aligned} S\pi(\kappa\hat{u}'|\acute{\mathbf{u}}') - \sum_{m\neq n} F(v_{im}) - \kappa^{\beta^H}\left[1-(1-\delta)^{\beta^H}\right]F_0\hat{v}'^{\beta^H} - \rho(\hat{v}')S\sum_{k\in \mathrm{K}_n} r_{jk}(\acute{\mathbf{u}}) \\ -T_0 + \sum_{j\in N_n^i} \rho(\kappa\hat{v}')S\sum_{k\in \mathrm{K}_n} r_{jk}(\acute{\mathbf{u}}) \leq 0, \quad \forall\kappa > 1. \end{aligned} \quad (2.17)$$

Again, under the same assumptions of zero marginal costs and the specification of sales revenue from associated products as a percentage of total sales revenue, the viability and stability conditions can be specified as:

$$[1-\rho(\hat{v}')\gamma_n]S\pi(\hat{u}'|\acute{\mathbf{u}})-\sum_{m\neq n}F(v_{im})-\left[1-(1-\delta)^{\beta^H}\right]F_0\hat{v}'^{\beta^H}-T_0\geq 0, \quad (V.3')$$

$$\begin{aligned} S\pi(\kappa\hat{u}'|\acute{\mathbf{u}})-\rho(\hat{v}')\gamma_n S\pi(\hat{u}'|\acute{\mathbf{u}})-\sum_{m\neq n}F(v_{im}) \\ -\kappa^{\beta^H}\left[1-(1-\delta)^{\beta^H}\right]F_0\hat{v}'^{\beta^H}-T_0\leq 0, \quad \forall\kappa>1. \end{aligned} \quad (S.3')$$

$$\begin{aligned} [1+L^n\rho(\kappa\hat{v}')\gamma_n]S\pi(\kappa\hat{u}'|\acute{\mathbf{u}})-\rho(\hat{v}')\gamma_n S\pi(\hat{u}'|\acute{\mathbf{u}})-\sum_{m\neq n}F(v_{im}) \\ -\kappa^{\beta^H}\left[1-(1-\delta)^{\beta^H}\right]F_0\hat{v}'^{\beta^H}-T_0\leq 0, \quad \forall\kappa>1. \end{aligned} \quad (S.3'')$$

For a configuration to be an equilibrium configuration under licensing, the viability conditions for both licensors $(V.2')$ and licensees $(V.3')$ as well as the entire set of stability conditions $(S.2', S.2'', S.3', S.3'')$ must hold. These conditions must hold in order for there to be an equilibrium without firm entry and exit. If the first (second) viability condition is violated, then licensing is not profitable or sustainable for the innovating (imitating) firm. Moreover, if any of the three stability conditions does not hold, the equilibrium configuration is not stable to entry by a quality-escalating firm, with or without licensing.

Determining whether the licensor or the licensee conditions will provide the binding constraint upon the feasible set of equilibrium configurations requires either further restrictions upon the model (i.e. a specific functional form for the profit function) and/or specific parameter values. However, it is possible to derive a benchmark in which firms do not license their technology to rivals such that the relevant viability and stability conditions are $(V.1')$ and $(S.1')$. The feasible set of equilibrium configurations is defined by the profit function and escalation parameter $\kappa > 1$ such that:

$$S\pi(\hat{u}|\mathbf{u}) \geq \frac{1}{\kappa^{\beta^L}} S\pi(\kappa\hat{u}|\mathbf{u}) + \left(\frac{\kappa^{\beta^L}-1}{\kappa^{\beta^L}}\right) \sum_{m \neq n} F(v_{im}). \qquad (2.18)$$

This condition implies that allowing for quality differences in multiple attribute products decreases the set of feasible equilibrium configurations relative to the case of single attribute products. Similarly, combining the viability $(V.2')$ and stability $(S.2', S.2'')$ conditions that must hold for licensor firms yields the expressions:

$$S\pi(\hat{u}'|\acute{\mathbf{u}}) \geq \frac{1}{\kappa^{\beta^L}} \left[\frac{1 + L^n \rho(\kappa\hat{v}')\gamma_n}{1 + L^n \rho(\hat{v}')\gamma_n}\right] S\pi(\kappa\hat{u}'|\acute{\mathbf{u}}) + \left(\frac{\kappa^{\beta^L}-1}{\kappa^{\beta^L}}\right) \left[\frac{\sum_{m \neq n} F(v_{jm})}{1 + L^n \rho(\hat{v}')\gamma_n}\right]. \qquad (2.19)$$

$$S\pi(\hat{u}'|\acute{\mathbf{u}}) \geq \frac{1}{\kappa^{\beta^L}} \left[\frac{1}{1 + L^n \rho(\hat{v}')\gamma_n}\right] S\pi(\kappa\hat{u}'|\acute{\mathbf{u}}') + \left(\frac{\kappa^{\beta^L}-1}{\kappa^{\beta^L}}\right) \left[\frac{\sum_{m \neq n} F(v_{jm})}{1 + L^n \rho(\hat{v}')\gamma_n}\right]. \qquad (2.20)$$

It is important to note at this time that if $[1 + L^n \rho(\kappa\hat{v}')\gamma_n] S\pi(\kappa\hat{u}'|\acute{\mathbf{u}}) > S\pi(\kappa\hat{u}'|\acute{\mathbf{u}}')$, then equation (2.19) describes a more stringent definition of feasible equilibrium configurations compared to equation (2.20). The intuition behind this result is that in an industry in which firms license in equilibrium under significant rent dissipation effects, it is more profitable for quality-escalating entrants to license competencies to competitors rather than forgo licensing revenues.

By inspection, the stability condition $(S.3')$ is a special case of the second stability condition $(S.3'')$ in which the licensee entrant does not choose to license its escalated quality. Thus, I derive a similar condition for the feasible set of equilibrium configurations as determined by the viability $(V.3')$ and stability $(S.3'')$ conditions for licensee firms. Namely,

$$\begin{aligned} S\pi(\hat{u}'|\mathbf{\acute{u}}) \geq \tfrac{1}{\kappa^{\beta^H}} & \left[\frac{1 + L^n \rho(\kappa\hat{v}')\gamma_n}{1 - \left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right] S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}) \\ & + \left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\left[\frac{\sum_{m\neq n} F(v_{im}) + T_0}{1 - \left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right]. \end{aligned} \tag{2.21}$$

Prior to examining the condition on the feasible set of equilibrium configurations, it is important to recall that the viability and stability conditions for licensee firms are defined only over firms with high costs to R&D. For some quality escalation parameter $\kappa > 1$, the additional fixed cost incurred by firms with high R&D costs is greater than that incurred by firms with low R&D costs (i.e. $\forall\kappa > 1, \kappa^{\beta^H} > \kappa^{\beta^L}$) since $\beta^H > \beta^L$ by assumption. The R&D cost asymmetry and fixed transactions costs with licensing imply that the second term on the right-hand side of equation (2.21) is greater than the second term on the right-hand side of equations (2.19)-(2.20) and thus a more restrictive set of feasible equilibrium configurations when transactions costs are large relative to firm profit.

<u>Proposition 1</u>: (Determination of Equilibrium Configurations under Licensing)

Let $\kappa > 1$. If:

$(i)\ \ \rho(\kappa\hat{v}') > \frac{1}{L^n\gamma_n}\left[\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})} - 1\right], \quad \forall\kappa > 1$ and

$(ii)\ \ \rho(\hat{v}') \leq \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H} - \kappa^{\beta^L}}{\kappa^{\beta^L}L^n + \kappa^{\beta^H} - 1}\right], \quad \forall\kappa > 1,$

then the set of licensor conditions $(V.2')$ and $(S.2')$ bind. If (i) does not hold, but (ii) does, then either the licensor conditions $(V.2')$ and $(S.2'')$ bind. Otherwise, the licensee conditions $(V.3')$ and $(S.3'')$ bind.

Proof of Proposition 1: See Appendix A.

Proposition 1 implies that the relevant licensor stability condition for the binding set of feasible equilibria will be determined by the rent dissipation effect from licensing of technology which relates to the competitiveness of the product market. Rent dissipation from licensing refers to the assumption that the escalating firm's profit under licensing is no greater than the escalating firm's profit without licensing. Thus, the term in the braces on the right-hand side of the first equation is, by assumption, greater than or equal to 0. As the rent dissipation effect becomes smaller, the stability condition on a licensing, quality-escalating entrant are more likely to provide the binding constraint on equilibrium configurations (i.e. if $\rho(\kappa\hat{v}) \geq \frac{1}{L^n \gamma_n}\left[\frac{S\pi(\kappa\hat{u}\prime|\acute{\mathbf{u}}\prime)}{S\pi(\kappa\hat{u}\prime|\acute{\mathbf{u}})} - 1\right]$, then condition (2.19) characterizes the feasible equilibrium configurations).

By inspection of Proposition 1, the licensee viability $(V.3')$ and stability $(S.3'')$ conditions will define the feasible set of equilibrium configurations independently of the binding licensor conditions iff: $\rho(\hat{v}) \geq \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H} - \kappa^{\beta^L}}{\kappa^{\beta^L} L^n + \kappa^{\beta^H} - 1}\right]$, $\forall \kappa > 1$. Thus, it is possible to interpret when the licensee viability and stability conditions are likely to provide the binding set of feasible equilibrium strategies. First, for minor innovations or small escalations of quality (i.e. as $\kappa \rightarrow 1$ from the right-hand side), the right-hand side of condition on $\rho(\hat{v})$ approaches zero such that all fixed-fee royalty payments offered by licensors will be feasible. As $\rho(\hat{v}), \gamma_n \in [0,1]$, the proportion of total sales revenue from products associated with the licensed attribute becomes small (i.e. $\gamma_n \rightarrow 0$), the viability and stability conditions on licensee firms are less likely to be binding as quality-leading firms would require a fixed-fee royalty payment $\rho(\hat{v})$ that was excessively large.

Thus, attributes that are incorporated into products that contribute to a small proportion of total licensee sales revenues will be unlikely candidates for licensing as licensor firms would require high rates of royalty payments. However, as the proportion of total sales revenue increases, licensor firms require a smaller proportion of firm profits be appropriated under the licensing agreements. Finally, as the R&D cost differential between low- and high-cost firms becomes larger, licensor firms can appropriate a greater proportion of firm sales revenue from the licensed technology. Thus, as the cost differential between types of firms decreases such that innovators lose their R&D cost advantage, licensor firms require a smaller proportion of sales in equilibrium.

Finally, the analysis of the feasible set of equilibrium configurations was limited to the cases in which licensing occurs. As the configuration of capabilities with and without licensing, as well as the maximum quality offered, are not necessarily equivalent, a direct comparison between the feasible set of equilibrium configurations according to Sutton's (1998) model under asymmetric costs and multiple products is uninformative. However, it is important to note that the "No Licensing" case is implicitly embedded in each of the "Licensing" conditions by either setting the total number of licenses L^n or the fixed-fee royalty payment $\rho(\hat{v}')$ equal to zero.

Bounds to Concentration under Licensing

I follow Sutton (1998) in deriving a lower bound theorem under licensing to motive the analysis of market concentration and the escalation of sunk costs in R&D. The model without licensing implies a lower bound to market share and R&D/sales ratio independent of market size. Thus, as market size increases, the market share of the high quality firm in the endogenous sunk cost industry does not converge to zero, the result implied by industries characterized by exogenous sunk costs. Thus far, I have extended Sutton's (1998) model along three dimensions by incorporating multiple attribute products, relaxing the assumption on symmetry of R&D costs across firms, and allowing firms to acquire a product characteristic via licensing rather than R&D. Given these extensions, I formulate three propositions for the potential lower bound to concentration as I am unable to distinguish *a priori* which of the lower bounds to concentration will be binding.

I define the minimum ratio $a(\kappa)$ of firm profit to industry sales for every value of κ, independently of market size and capability configuration, such that:

$$a(\kappa) \equiv \inf_{\mathbf{u}} \frac{\pi(\kappa\hat{u}|\mathbf{u})}{r(\mathbf{u})}. \tag{2.22}$$

Moreover, I also define a corresponding minimum ratio $\acute{a}(\kappa)$ for equilibrium configurations under licensing for every value of κ such that:

$$\acute{a}(\kappa) \equiv \inf_{\acute{\mathbf{u}}} \frac{\pi(\kappa\hat{u}'|\acute{\mathbf{u}})}{r(\acute{\mathbf{u}})}. \tag{2.23}$$

Thus, for a given configuration under licensing $\acute{\mathbf{u}}$ and maximum quality $\hat{u}$, an entrant firm chooses to enter with capability $\kappa\hat{u}$ along the trajectory which yields greatest profit $S\pi(\kappa\hat{u}'|\acute{\mathbf{u}})$. From the definitions of $a(\kappa)$ and $\acute{a}(\kappa)$, this profit is at least $a(\kappa)Sr(\mathbf{u})$ and $\acute{a}(\kappa)Sr(\acute{\mathbf{u}})$, respectively, independently from a given configuration ($\acute{\mathbf{u}}$,$\mathbf{u}$) and market size S.

<u>Proposition 2</u>: (Lower Bound under Multiple Attribute Products) Fix any pair $\big(\kappa, a(\kappa)\big)$. If $\mathbf{u}$ is an equilibrium configuration, then the firm that offers the highest level of quality has market share exceeding exceeding $\frac{a(\kappa)}{\kappa\beta^L}$.

Proof of Proposition 2: See Appendix A.

Proposition 2 implies that as the market size becomes large, the presence of multiple attribute products and asymmetric R&D costs alone does not change the lower bound to the market share of the quality-leading firm relative to that found in Sutton (1998). For finitely-sized markets however, multiple attributes products raise the lower bound to concentration such that the share of the market leader is convergent in market size.

Proposition 3: (Lower Bound under Licensing-1) Fix any pair $\left(\kappa, \acute{a}(\kappa)\right)$. If **ú** is an equilibrium configuration under licensing, then the firm that offers the highest level of quality and licenses its competency to rivals has a share of industry revenue exceeding $\frac{\acute{a}(\kappa)}{\kappa\beta^{L}} \cdot \left[\frac{1+L^{n}\gamma_{n}\rho(\kappa\hat{v}')}{1+L^{n}\gamma_{n}\rho(\hat{v}')}\right]$ as the size of the market becomes large.

Proof of Proposition 3: See Appendix A.

Suppose the proportion of sales revenue that licensor firms can appropriate from licensee firms is decreasing in technical competency such that a low-cost entrant that escalates competency $\hat{v}$ along trajectory n earns a smaller proportion of licensee sales revenue. This implies that $\rho(\kappa\hat{v}') \leq \rho(\hat{v}')$ such that $\left[\frac{1+L^{n}\gamma_{n}\rho(\kappa\hat{v}')}{1+L^{n}\gamma_{n}\rho(\hat{v}')}\right] \leq 1$

and the lower bound to the market share of the quality-leader is lower under licensing compared to the case without licensing. Moreover, when $(S.2')$ is the relevant stability condition such that Proposition 3 holds, the lower bound to market share is increasing at a decreasing rate in the number of licenses if $\rho(\kappa\hat{v}') > \rho(\hat{v}')$ (i.e. $\frac{\partial}{\partial L^n} \geq 0$ and $\frac{\partial^2}{\partial {L^n}^2} \leq 0$). Additional comparative statics on the proportion of total firm revenue associated with the licensed technology also imply that the lower bound to market share of the quality leader is increasing at a decreasing rate in γ_n(i.e. $\frac{\partial}{\partial \gamma_n} \geq 0$ and $\frac{\partial^2}{\partial {\gamma_n}^2} \leq 0$).

<u>Proposition 4</u>: (Lower Bound under Licensing-2) Fix any pair $(\kappa, \acute{a}(\kappa))$. If **ú** is an equilibrium configuration under licensing, then the firm that offers the highest level of quality and licenses its competency to rivals has a share of industry revenue exceeding $\frac{\acute{a}(\kappa)}{\kappa\beta^H} \cdot \left[\frac{1+L^n\gamma_n\rho(\kappa\hat{v}\prime)}{1-\left(\frac{\kappa\beta^H-1}{\kappa\beta^H}\right)\gamma_n\rho(\hat{v}\prime)}\right]$ as the size of the market becomes large.

Proof of Proposition 4: See Appendix A.

Unlike the cases in which the licensor stability conditions were the binding constraints upon equilibrium configurations, the lower bound to market concentration derived from the licensee conditions is not straightforward to interpret. Specifically under asymmetric R&D costs, the first term in the lower bound condition in Proposition 4 is strictly less than the first term derived in the previous propositions as $\beta^H > \beta^L$. However, considering the special case in which the proportion of sales revenue accrued to the licensor is constant (i.e. $\rho(\kappa\hat{v}') = \rho(\hat{v}') = \rho$), I find that the lower bound under the licensee conditions is greater if $\rho \geq \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H} - \kappa^{\beta^L}}{\kappa^{\beta^L} L^n + \kappa^{\beta^H} - 1}\right], \kappa \geq 1$. Comparative statics reveal that this bound is increasing at a constant rate in the number of licenses (i.e. $\frac{\partial}{\partial L^n} \geq 0$) and increasing at an increasing rate in the proportion of total sales revenue associated with the licensed technology trajectory (i.e. $\frac{\partial}{\partial \gamma_n} \geq 0$ and $\frac{\partial^2}{\partial {\gamma_n}^2} \geq 0$). Given the lower bound to the share of industry revenue accrued to the market leader in quality varies if it is derived from the licensor and licensee stability conditions, I further analyze the potential embedding of Proposition 3 into Proposition 4 and derive a theorem of non-convergence under licensing.

Theorem 1: (Lower Bound under Licensing) Fix any pair $(\kappa, \acute{a}(\kappa))$ and some feasible[7] royalty payment $\rho(\hat{v}') \geq \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H} - \kappa^{\beta^L}}{\kappa^{\beta^L} L^n + \kappa^{\beta^H} - 1}\right], \forall \kappa \geq 1$. If $\acute{\mathbf{u}}$ is an equilibrium configuration under licensing, then the firm that offers the highest level of quality and licenses its competency to rivals has a share of industry revenue exceeding:

$$\frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1 + L^n \gamma_n \rho(\kappa \hat{v}')}{1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right) \gamma_n \rho(\hat{v}')}\right] + \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right)\left[\frac{\sum_{m \neq n} F(v_m) + T_0}{\left[1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right) \gamma_n \rho(\hat{v}')\right] S r(\acute{\mathbf{u}})}\right].$$

Corollary to Theorem 1: As $S \to \infty$, the lower bound to market share converges to $\frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1 + L^n \gamma_n \rho(\kappa \hat{v}')}{1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right) \gamma_n \rho(\hat{v}')}\right]$.

All equilibrium configurations with a finitely "small" market size are bounded away from the convergent threshold by some factor of the fixed transactions costs associated with licensing and R&D investment along all other trajectories. When products consist of multiple attributes and there is technology licensing in equilibrium, the lower bound to market concentration under licensing is greater

[7] Here, "feasible" implies that the licensee viability condition $(V.3')$ is satisfied such that: $\rho(\hat{v}') \leq \frac{1}{\gamma_n}\left[1 - \frac{\sum_{m \neq n} F(v_m) + \left[1 - (1-\delta)^{\beta^H}\right] F_0 \hat{v}'^{\beta^H} + T_0}{S \acute{r}}\right]$.

than the lower bound without licensing independently of the size of the market. For finitely-sized markets, the lower bound is not independent of the size of the market and strictly greater under positive transactions costs.

Proof of Theorem 1: See Appendix A.

In Theorem 1, I derive the lower bound to concentration under licensing given the set of propositions over the feasible set of equilibrium configurations and the respective lower bounds. In the limit as $\rho(\hat{v}')$ and $\rho(\kappa\hat{v}')$ both approach the lower bound (i.e. $\rho(\hat{v}'), \rho(\kappa\hat{v}') \to \frac{1}{\gamma n}\left[\frac{\kappa^{\beta^H} - \kappa^{\beta^L}}{\kappa^{\beta^L} L^n + \kappa^{\beta^H} - 1}\right]$), then the lower bound under licensing approaches the lower bound without licensing (if transactions costs are minimal or market size is large). Additionally, it is interesting to note that lower bound to market share of the quality leader under licensing embeds the lower bound found by Sutton (1998) in the case in which the proportion of revenue accrued to the licensor and the total number of licenses equal zero.

The royalty percentage that a low-cost quality leader can charge to a high-cost firm for some competency $\hat{v}'$ is decreasing at an increasing rate in the number of licenses granted (i.e. $\frac{\partial \rho(\hat{v}')}{\partial L^n} \leq 0$, $\frac{\partial^2 \rho(\hat{v}')}{\partial^2 L^n} \geq 0$) whereas the lower bound to concentration is increasing at a constant rate (i.e. $\frac{\partial \cdot}{\partial L^n} \geq 0$). The first comparative static implies that there is a trade-off in the market share of sales for firms offering the highest quality with the number of licenses that it grants. The comparative static on the lower bound to concentration illustrates licensor firms require greater levels of market concentration in exchange for each additional license.

The lower bound to the ratio of the sales of the high-quality firm to the industry sales motivates the definition of the escalation parameter alpha. For any value of $\kappa > 1$, alpha is defined as:

$$\alpha \equiv \sup_{\kappa} \frac{a(\kappa)}{\kappa^{\beta^L}}. \tag{2.25}$$

Subsequently, the one-firm sales concentration ratio C_1 cannot be less than the share of industry sales revenue of the high-quality firm. Thus, for any equilibrium configuration with high quality $\hat{u}$ and competency $\hat{v}$, C_1 is bounded from below by α. In the examination of multiple attribute products without licensing (Proposition 2), I found a lower bound to concentration that was equivalent to lower bound for single attribute products under large markets. By fixing the royalty payment and number of licenses to be zero in Propositions 3 and 4, the lower bound to concentration without licensing is embedded as a special case of the general model.

However, given that I have determined that the binding conditions on equilibrium configurations of capabilities under licensing is derived from the viability and stability conditions of high-cost licensee firms (Theorem 1), I must consider an alternate definition of alpha which incorporates the fixed royalty payment $\rho(\hat{v}')$, the total number of licenses L^n, the proportion of sales of products associated with the licensed competency γ_n, and the level of escalation κ. For a high-cost firm, I define the escalation parameter alpha as derived from equation (2.24) under sufficiently large market sizes such that:

$$\acute{\alpha} \equiv \sup_{\kappa} \frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1 + L^n \gamma_n \rho(\kappa \hat{v}')}{1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}} \right) \gamma_n \rho(\hat{v}')} \right]. \tag{2.26}$$

It is important to note that the definition of $\acute{\alpha}$ is determined by a licensee that potentially escalates competency (quality) to a level greater than that which has been licensed. The total number of licenses and the royalty payments are taken as exogenous to these potential entrants firms. This definition of $\acute{\alpha}$ can be used to determine a bound to concentration that holds in the limit under no licensing (i.e. $L^n = 0$ and $\rho(\hat{v}') = 0$) which is equivalent to the condition derived by Sutton (1998). The lower bound to the R&D/sales ratio for the quality leader for the case in which the quality leader produces maximum competency $\widehat{v}''$ along some trajectory n and given some level of competency across all other trajectories can be specified according to Theorem 2.

<u>Theorem 2</u>: (Lower Bound to R&D-Intensity) For any equilibrium configuration under licensing, the R&D/sales ratio for the low-cost market leader firm, offering maximum quality $\widehat{u'}'$ by achieving competency $\widehat{v'}'$ along a single trajectory, is bounded from below as the size of the market becomes large by: $\acute{\alpha}\kappa^{\beta^H-\beta^L}\left[1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\gamma_n\rho(\hat{v}')\right], \forall\kappa > 1.$

Proof of Theorem 2: See Appendix A.

Sutton's (1998) EFC model predicted an identical lower bound to market concentration and R&D intensity as the size of the market became large. In contrast, I find that when firms are able to license their technology to competitors, both the lower bound to market concentration and R&D intensity are greater relative to the case without licensing, but are no longer identical. Specifically, permitting low-cost firms to license their technology to high-cost rivals encourages more intensive R&D as "innovator" firms realize efficiency gains from licensing. Thus, greater market concentration and more intensive and efficient R&D would have ambiguous effects upon consumer welfare.

CHAPTER 3: R&D Concentration and Market Structure in Agricultural Biotechnology

In this chapter, I derive and empirically test a lower bound to R&D concentration upon the theoretical endogenous fixed cost (EFC) model of Sutton (1998). I first demonstrate the lower bounds to R&D concentration via an illustrative model and then characterize the empirical predictions from the formal model. I use data on R&D investments, in the form of field trial applications for genetically modified (GM) crops, to test for lower bounds to R&D concentration among agricultural biotechnology firms.

I exploit variation along two dimensions: (i) geographically as adoption rates for GM crop varieties varies by state and agricultural region; and (ii) intertemporally as adoption rates for GM crops has been steadily increasing over time. Moreover, the strengthening of property rights over GM crops over the past 20 years and increased incentives for farmers to plant corn seed, relative to soybean seed, arising from the subsidies to ethanol production serve as natural experiments and provide sources of exogenous variation in the market. I estimate the lower bounds to R&D concentration using a two-step procedure suggested by Smith

(1994) in order to test whether the single firm R&D concentration ratios follow an extreme value distribution.

The econometric results indicate that the markets for corn, cotton, and soybean seeds are characterized by endogenous fixed costs in R&D with the lower bound to R&D concentration being greatest for GM corn and cotton seed markets. Accounting for consolidation of intellectual property via merger and acquisition activity, the lower bounds to R&D concentration increase significantly for soybean seed markets. These results imply that the observed concentration in GM seed varieties can be explained by the nature of technology competition within the sector, but the patterns of firm consolidation can magnify these results.

What is Agricultural Biotechnology?

Prior to examining market structure and innovation in the agricultural biotechnology sector, it is important to clearly define what I mean when I use the term “agricultural biotechnology”. Gaisford, et al. (2001) define biotechnology, in general terms, as “the use of information on genetically controlled traits, combined with the technical ability to alter the expression of those traits, to provide enhanced biological organisms, which allow mankind to lessen the constraints imposed by the natural environment." For my purposes, I am interested in firms that develop genetically-modified organisms (GMOs) for commercialization purposes within agriculture and restrict ourselves primarily to discussion concerning genetically-modified (GM), or genetically-engineered (GE), crops. Prior to the 1970s, the development of new plant varieties was largely limited to Mendelian-type genetics involving selective breeding within crop types and hybridization of characteristics to produce the desired traits. Generally, it was impossible to observe whether the crops successfully displayed the selected traits until they had reached maturity implying a considerable time investment with each successive round of experimentation. If successful, additional rounds of selective breeding were often required in order to ensure that the desired characteristics would be stably expressed in subsequent generations. This process is inherently uncertain as crop scientists and breeders rely upon "hit-and-miss" experimentation, implying that achieving the desired outcome might require a not insubstantial amount of time and resources.

The expansion of cellular and molecular biology throughout the 1960s and 1970s, specifically the transplantation of genes between organisms by Cohen and Boyer in 1973, increased the ability of crop scientists to identify and isolate desired traits, modify the relevant genes, and to incorporate these traits into new crop varieties via transplantation with greater precision (Lavoie, 2004). These advances had two key implications for agricultural seed manufacturers and plant and animal scientists. First, the ability to identify and isolate the relevant genetic traits greatly facilitated the transference of desirable characteristics through selective breeding. Second, the ability to incorporate genetic material from one species into the DNA of another organism allowed for previously infeasible or inconceivable transfers of specific traits. Perhaps the most widely known example of this was the incorporation of a gene from the soil bacterium *Bacillus thuringiensis* (Bt) that produces the Bt toxin protein. This toxin is poisonous to a fraction of insects, including the corn borer, and acts as a "natural" insecticide. When the gene is incorporated into a plant variety, such as corn, cotton, and now soybeans, the plants are able to produce their own insecticides, thereby reducing the need for additional application of chemical insecticides.

GM crops are typically assigned into three broad classifications, termed "generations", depending upon the traits that they display and who benefits from these technological advancements (i.e. farmers, consumers, or other firms). The first generation consists of crops that display cost- and/or risk-reducing traits that primarily benefit the farmers, but which also may have important environmental and consumer impacts via decreased application of agricultural chemicals. Specific examples of first generation crops include herbicide tolerant varieties (i.e. Roundup Ready® crops), insect resistant varieties (i.e. Bt crops), or crop types that are particularly tolerant to environmental stresses including drought or flood (Fernandez-Cornejo and Caswell, 2006). Second generation crops, which are largely still in development, consist of crops whose final products will deliver some additional value-added benefits directly to consumers. Products derived from second generation crops might offer increased nutritional content or other characteristics that directly benefit the health of end consumers. The third generation classification captures biotechnology crops developed for pharmaceuticals, industrial inputs (i.e. specialized oils or fibers), or bio-based fuels. I focus almost exclusively upon crops within the "first generation" classification as these constitute the majority of all currently commercialized GM crops. However, my analysis is applicable to the biotechnology industry in a general sense to the extent that I identify how the industry has evolved in the past with implications for how market structure and innovation will evolve as subsequent generations of biotechnology are introduced.

Endogenous Market Structure and Innovation: The "Bounds" Approach

An Illustrative Model

I adapt the theoretical endogenous fixed cost model of market structure and sunk R&D investments developed by Sutton (1998) and empirically estimate the lower bounds to R&D concentration in agricultural biotechnology. The empirical specification that I adopt was developed in Sutton (1991) and has since been adapted and extended in Giorgetti (2003), Dick (2007), and Ellickson (2007). I illustrate that the characterization of a market into horizontally differentiated submarkets does not change the theoretical predictions for the lower bound to concentration in the largest submarket under endogenous fixed costs. Subsequently, I derive the theoretical lower bound to R&D concentration for endogenous and exogenous fixed cost industries and specify the empirically testable hypotheses.

The specification of the empirical model relies upon a set of assumptions regarding the nature of product differentiation in the agricultural biotechnology sector. First, I assume that there exist regional variations in the demand for specific seed traits, such as herbicide tolerance or insecticide resistance, and that these regional variations create geographically distinct submarkets. This assumption corresponds with the empirical findings of Stiegert, Shi, and Chavas (2011) of spatial price differentiation in GM corn. Secondly, I assume that farmers value higher quality products such that a firm competes within each submarket primarily via vertically differentiating the quality of its seed traits. Thus, I estimate a model of vertical product differentiation in the agricultural biotechnology sector while accounting for horizontal differentiation via the definition of geographically distinct product submarkets.

In order to derive the empirical predictions for the lower bound to R&D concentration, I adapt the illustrative model developed by Sutton (1991). I assume that within a regional submarket m, there are S_m identical farmers that have a quality-indexed demand function such that:

$$\mathrm{U}_m = (uq)^{\gamma_m} z^{1-\gamma_m}, \tag{3.1}$$

where z is some "outside" composite good (i.e. fertilizer, machinery, etc.) which is set as numeraire, q is the quantity of the "quality" good (i.e. seeds), u is the quality level associated with good q and preferences are captured by the parameter γ_m. I assume a level of quality $u \geq 1$ such that $u = 1$ corresponds to a minimum level of quality in the market and all farmers prefer higher quality for a given set of prices. The farmer in submarket m maximizes across all quality goods such that:

$$\begin{aligned} &\max_{\{q_{im}\},z} \ (u_{im}q_{im})^{\gamma_m} z^{1-\gamma_m} \\ &s.t. \quad p_{im}q_{im} + p_z z \le M_m \end{aligned}, \tag{3.2}$$

where M_m is the total income for the farmer in submarket m. Solving reveals that, independent of equilibrium prices or qualities, the farmer will spend a fraction γ_m of her total income upon the quality good.

I consider a three stage game consisting of: (i) a market entry decision into some submarket m; (ii) technology market competition in which firms make fixed R&D investments in product quality; and (iii) product market competition in quantities. In the second stage, given decisions to enter in the first stage, firms choose the levels of quality $u \geq 1$ they offer by making deterministic fixed (sunk) R&D investments within each submarket. In the final stage, firms engage in Cournot competition over quantities in the product market with the set of product quality levels $\{u_i\}$ taken as given. The farmer thus chooses the good that maximizes the quality-price ratio u_i/p_i such that all firms that have positive sales in equilibrium have proportionate quality-price ratios (i.e. $u_i/p_i = u_j/p_j, \forall i, j$).

In order to derive the profit function for firms, consider the case in which all firms in a submarket are symmetric (i.e. $u_{im} = \bar{u}_m, \forall i$). It must be the case that the equilibrium level of prices $\bar{p}_m$ equals the share of expenditure over total industry output $\sum_i \bar{q}_{im}$ such that:

$$\bar{p}_m = \frac{S_m \gamma_m M_m}{\sum_i \bar{q}_{im}}. \tag{3.3}$$

Now suppose a single firm i deviates from the symmetric equilibrium by offering a quality level u_{im} such that it faces a price p_{im} equal to:

$$p_{im} = \frac{u_{im}}{\bar{u}_m} \bar{p}_m. \tag{3.4}$$

It follows that the equilibrium price $\bar{p}_m$ faced by all other firms can be expressed as:

$$\bar{p}_m = \frac{S_m \gamma_m M_m}{\sum_{j \neq i} \bar{q}_{jm} + \left(\frac{u_{im}}{\bar{u}_m}\right) q_{im}}, \tag{3.5}$$

where $\sum_{j \neq i} \bar{q}_{jm}$ is total industry output net the output of the deviating firm and q_{im} is the deviating firm output. Assuming that firms face a constant marginal cost c independent of the level of quality offered, the profit functions for the deviating firm i and any non-deviating firm j in submarket m can thus be expressed, respectively, as:

$$\pi_{im} = (p_{im} - c) q_{im} = \left(\frac{u_{im}}{\bar{u}_m} \cdot \frac{S_m \gamma_m M_m}{\sum_{j \neq i} \bar{q}_{jm} + \frac{u_{im}}{\bar{u}_m} q_{im}} - c \right) \cdot q_{im} \tag{3.6}$$

and

$$\bar{\pi}_{jm} = (\bar{p}_m - c) \bar{q}_{jm} = \left(\frac{S_m \gamma_m M_m}{\sum_{j \neq i} \bar{q}_{jm} + \frac{u_{im}}{\bar{u}_m} q_{im}} - c \right) \cdot \bar{q}_{jm}. \tag{3.7}$$

Differentiating and solving for the equilibrium levels of quantity yields the following expressions for the quantity produced for the deviating firm i and $(N_m - 1)$ non-deviating firms as a function of quality levels u_{im} and $\bar{u}_m$ such that:

$$q_{im}^* = \left[(N_m - 2) - \left(\frac{\bar{u}_m}{u_{im}}\right)(N_m - 1)\right] \cdot \bar{q}_m \tag{3.8}$$

and

$$\bar{q}_m = \frac{S_m \gamma_m M_m}{c}\left[\frac{\left(\frac{u_{im}}{\bar{u}_m}\right)(N_m - 1)}{\left[1 + \left(\frac{u_{im}}{\bar{u}_m}\right)(N_m - 1)\right]^2}\right]. \tag{3.9}$$

Substituting the expressions for the equilibrium levels of quantity (3.8) and (3.9) into the expressions for prices (3.4) and (3.5), I derive the equilibrium prices for the deviating firm i and $(N_m - 1)$ non-deviating firms such that:

$$p_{im} = c\left[\left(\frac{u_{im}}{\bar{u}_m}\right) + \frac{1}{(N_m - 1)}\right] \tag{3.10}$$

and

$$\bar{p}_m = c\left[1 + \frac{1}{\left(\frac{u_{im}}{\bar{u}_m}\right)(N_m - 1)}\right]. \tag{3.11}$$

Thus, the net final-stage profit for the deviating firm in submarket m can be expressed as:

$$\pi(u_{im}|\bar{u}_m, N_m) = S_m \gamma_m M_m \left[1 - \frac{1}{\left(\frac{u_{im}}{\bar{u}_m}\right) + \frac{1}{(N_m - 1)}}\right]^2. \tag{3.12}$$

This profit function allows for the examination of the case where all firms enter with symmetric quality (i.e. $u_{im} = \bar{u}_m$) and earn final-stage profits independent of quality (i.e. $\pi_m = \frac{S_m \gamma_m M_m}{N_m^2}$) as well as the case in which firms make fixed (sunk) R&D investments in quality. Letting the total market size (i.e. $S_m \gamma_m M_m$) in submarket m be Γ_m and summing across all submarkets in which firm i is active (i.e $m \in I$), firm i's total profit Π_i can be expressed as:

$$\Pi_i = \sum_{m \in I} \Gamma_m \left[1 - \frac{1}{\left(\frac{u_{im}}{\bar{u}_m}\right) + \frac{1}{(N_m - 1)}}\right]^2. \tag{3.13}$$

Sutton (1998) proposes a specification for product quality given the possibility of economies of scope across R&D trajectories. If agricultural biotechnology firms develop seed varieties that share attribute traits in adjoining geographic submarkets, then such a specification could capture technology spillovers between submarkets. Therefore, the quality level offered by some firm i in submarket m can be expressed as a function of the competencies that the firm achieves along all research trajectories such that:

$$u_{im} = v_{im} + \sigma \sum_{n \in I \setminus m} v_{in}, \tag{3.14}$$

where v_{im} is the competency that firm i achieves in submarket m and $\sigma \in [0,1]$ is a measure of economies of scope across competencies.

I assume a R&D cost function that consists of a minimum setup cost F_0 associated with entry in each submarket and a variable component that is increasing in the level of competency v. Thus for a given geographic submarket m (i.e. research trajectory), firm i chooses a competency v_{im} and incurs a sunk R&D cost $F(v_{im})$ equal to:

$$F(v_{im}) = F_0 v_{im}^{\beta}, \tag{3.15}$$

where β is the elasticity of the fixed cost schedule. I assume $\beta > 2$ such that R&D investment rises with quality at least as fast as profits for a given increase in quality. I obtain an expression for firm i's total R&D investment F_i by summing across geographic submarkets (i.e. research trajectories) such that:

$$F_i = \sum_{m \in I} F_0 \left(v_{im}^{\beta} - 1 \right) + n_i F_0, \tag{3.16}$$

where n_i corresponds to the total number of submarkets that firm i enters.

Given the expressions for firm profit (3.13) and firm R&D costs (3.16), the firm's payoff function (i.e. the profit function net of fixed R&D investments) for the second stage quality choice decision can be written as:

$$\Pi_i - F_i = \sum_{m \in I} \left\{ \Gamma_m \left[1 - \frac{1}{\left(\frac{u_{im}}{\bar{u}_m}\right) + \frac{1}{(N_m - 1)}} \right]^2 - F_0\left(v_{im}^{\beta} - 1\right) \right\} + n_i F_0, \qquad (3.17)$$

where firms take the number of entrants N_m in each submarket as given from the first-stage entry decision.

I assume that each submarket in which firms enter can support at least a single firm producing minimum quality such that:

$$\Gamma_m \geq F_0. \qquad (3.18)$$

Given that the assumption on the size of the market and minimum setup cost for entry holds, I identify two possible symmetric equilibrium outcomes by solving the quality choice condition in the second stage. The first case corresponds with a symmetric equilibrium in which all firms active firms in submarket m enter with minimum quality (i.e. $v_{im} = 1, \forall i$) and incur only the minimum setup cost F_0 such that:

$$\left.\frac{\partial \pi_{im}}{\partial v_{im}}\right|_{v_{im}=\bar{v}_m=1} \leq \left.\frac{dF}{dv_{im}}\right|_{v_{im}=\bar{v}_m=1}. \qquad (3.19)$$

Condition (3.19) is equivalent to the case of exogenous fixed costs in which all firms enter with minimum quality (i.e. $v_{im} = \bar{v}_m = 1, \forall i$).

I define symmetric free entry conditions for each submarket m such that firms enter in the first stage until additional entrants are unable to recoup their fixed R&D investments in the submarket such that:

$$\forall m \quad \pi(\bar{u}_m | \bar{u}_m, N_m) = F\left(\bar{v}_m^{\beta}\right). \tag{3.20}$$

I now derive the number of firms N_m^{EX} that enter in a symmetric equilibrium and incur only the R&D setup cost F_0 by investing in the minimum competency level ($\bar{v}_m = 1$) in submarket m. Therefore, the free entry condition (3.20) under exogenous fixed costs by can be expressed as:

$$\Gamma_m \left[1 - \frac{1}{1 + \frac{1}{(N_m - 1)}}\right]^2 = F_0. \tag{3.21}$$

Solving condition (3.21) explicitly for the equilibrium number of firms N_m^{EX} yields:

$$N_m^{EX} = \sqrt{\frac{\Gamma_m}{F_0}}, \tag{3.22}$$

which depends upon the market size of submarket m (i.e. the number of consumers S_m, the proportion of income spent on the "quality" good γ_m, and the income of consumers M_m) and the minimum setup cost F_0.

If condition (3.19) does not hold, then the quality choice condition for a symmetric equilibrium in which all firms enter with quality greater than the minimum (i.e. $v_{im} = \bar{v}_m > 1, \forall i$) can be expressed as:

$$\left.\frac{\partial \pi_{im}}{\partial v_{im}}\right|_{v_{im}=\bar{v}_m>1} = \left.\frac{dF}{dv_{im}}\right|_{v_{im}=\bar{v}_m>1}. \tag{3.22}$$

Condition (3.22) is the case in which firms make quality-enhancing investments in R&D such that fixed costs are endogenous. Expressing condition (3.22) explicitly yields:

$$\frac{2\Gamma_m}{\bar{u}_m} \cdot \left[\frac{(N_m - 1)^2}{N_m^3}\right] + 2\sigma \sum_{l \in I \setminus m} \frac{\Gamma_l}{\bar{u}_l} \cdot \left[\frac{(N_l - 1)^2}{N_l^3}\right] = \beta F_0 \bar{v}_m^{\beta-1}. \tag{3.23}$$

Adding and subtracting $\frac{2\sigma\Gamma_m}{\bar{u}_m} \cdot \left[\frac{(N_m-1)^2}{N_m^3}\right]$, we can express condition (3.23) as:

$$(1-\sigma)\frac{\Gamma_m}{\bar{u}_m} \cdot \left[\frac{(N_m - 1)^2}{N_m^3}\right] + \sigma \sum_{l \in I} \frac{\Gamma_l}{\bar{u}_l} \cdot \left[\frac{(N_l - 1)^2}{N_l^3}\right] = \frac{\beta}{2} F_0 \bar{v}_m^{\beta-1}.$$

Substituting equation (3.14) for $\bar{u}_m$ and adding and subtracting $\sigma\bar{v}_m$ yields:

$$\begin{aligned}(1-\sigma)\left[(1-\sigma)\bar{v}_m + \sigma \sum_{n \in I} \bar{v}_n\right]^{-1} &\left[\frac{\Gamma_m (N_m - 1)^2}{N_m^3}\right] \\ &+ \sigma \sum_{l \in I}\left[(1-\sigma)\bar{v}_l + \sigma \sum_{n \in I} \bar{v}_n\right]^{-1} \left[\frac{\Gamma_l (N_l - 1)^2}{N_l^3}\right] = \frac{\beta}{2} F_0 \bar{v}_m^{\beta-1}.\end{aligned}$$

Letting $v_i = \sum_{n \in I} \bar{v}_n$ and $\phi_m = \left[\frac{\Gamma_m (N_m-1)^2}{N_m^3}\right]$ and multiplying both sides by $\bar{v}_m$ yields:

$$(1-\sigma)\bar{v}_m[(1-\sigma)\bar{v}_m+\sigma v_i]^{-1}\phi_m \\ +\sigma\bar{v}_m\sum_{l\in I}[(1-\sigma)\bar{v}_l+\sigma v_i]^{-1}\phi_l=\frac{\beta}{2}F_0\bar{v}_m^{\beta}. \tag{3.24}$$

Summing equation (3.24) across all $m \in I$ such that:

$$(1-\sigma)\sum_{m\in I}\bar{v}_m[(1-\sigma)\bar{v}_m+\sigma v_i]^{-1}\phi_m \\ +\sigma\sum_{l\in I}[(1-\sigma)\bar{v}_l+\sigma v_i]^{-1}\phi_l\sum_{m\in I}\bar{v}_m=\frac{\beta}{2}F_0\bar{v}_m^{\beta}. \tag{3.25}$$

Since I am summing across all submarkets in which firm i is active, equation (3.25) can be simplified such that:

$$\sum_{m\in I}[(1-\sigma)\bar{v}_m[(1-\sigma)\bar{v}_m+\sigma v_i]^{-1}\phi_m+\sigma v_i[(1-\sigma)\bar{v}_m+\sigma v_i]^{-1}\phi_m]=\frac{\beta}{2}F_0\sum_{m\in I}\bar{v}_m^{\beta}.$$

Collecting terms, simplifying, and substituting for ϕ_m yields:

$$\sum_{m\in I}\left[\frac{\Gamma_m(N_m-1)^2}{N_m^3}\right]=\frac{\beta}{2}F_0\sum_{m\in I}\bar{v}_m^{\beta}. \tag{3.26}$$

I state the free entry condition, as characterized by equation (3.20), when firms enter symmetrically with competency $\bar{v}_m > 1$ in submarket m explicitly as:

$$\frac{\Gamma_m}{N_m^2}=F_0\bar{v}_m^{\beta}, \tag{3.27}$$

such that summing expression (3.27) across all submarkets in which some firm i is active (i.e. $m \in I$) yields:

$$\sum_{m\in I}\frac{\Gamma_m}{N_m^2}=F_0\sum_{m\in I}\bar{v}_m^{\beta}. \tag{3.28}$$

Dividing both sides of the quality choice condition (3.26) by both sides of the free entry condition (3.28) yields an expression for the equilibrium number of firms across submarkets such that:

$$\frac{\sum_{m\in I}\left[\frac{\Gamma_m(N_m-1)^2}{N_m^3}\right]}{\sum_{m\in I}\frac{\Gamma_m}{N_m^2}}=\frac{\beta}{2}. \tag{3.29}$$

Combining terms and rearranging yields:

$$\sum_{m\in I}\frac{\Gamma_m}{N_m^2}\left[\frac{(N_m-1)^2}{N_m}-\frac{\beta}{2}\right]=0. \tag{3.30}$$

Suppose the total market size Γ_m for each submarket are ranked from smallest to largest such that $\Gamma_0\le\Gamma_1\le\cdots\le\Gamma_M$. Then by summation by parts, equation (3.30) can be written as:

$$\left[\frac{(N_M-1)^2}{N_M}-\frac{\beta}{2}\right]\sum_{l=0}^{M}\frac{\Gamma_l}{N_l^2}-\sum_{l=0}^{M-1}\sum_{k=0}^{l}\frac{\Gamma_k}{N_k^2}\left[\frac{(N_{l+1}N_l-1)(N_{l+1}-N_l)}{N_{l+1}N_l}\right]=0. \tag{3.31}$$

Since $\sum_{l=0}^{M}\frac{\Gamma_l}{N_l^2}$ is equivalent to total firm profit, dividing equation (3.31) through by total profit obtains an expression in terms of the summation of the proportion ρ_m of total profit attributed to each submarket m such that: $\rho_m=\sum_{k=0}^{m}\frac{\Gamma_k}{N_k^2}$ Therefore, equation (3.31) can be written as:

$$\left[\frac{(N_M-1)^2}{N_M}-\frac{\beta}{2}\right]-\sum_{l=0}^{M-1}\rho_l\left[\frac{(N_{l+1}N_l-1)(N_{l+1}-N_l)}{N_{l+1}N_l}\right]=0. \qquad (3.32)$$

If fixed costs are exogenous, then the monotonocity of equation (3.22) implies that the number of firms that enter in equilibrium in each submarket maintains the same ordering. Thus, $N_{m+1} \geq N_m, \forall m$ and the second term in equation (3.32) is non-negative such that $\left[\frac{(N_M-1)^2}{N_M}-\frac{\beta}{2}\right] \geq 0$. On the other hand, Sutton's EFC model (1991; 1998) implies that the presence of endogenous sunk costs limits the equilibrium number of firms that can enter even as the market size becomes large. Therefore, for some critical value of market size Γ_{m^*}, industries switch from being characterized by exogenous fixed costs to endogenous fixed costs such that $N_{m+1} \leq N_m, \forall m > m^*$. Provided that the number, and size, of submarkets characterized by endogenous fixed costs are greater than those characterized by exogenous fixed costs, the second term in equation (3.32) is non-positive such that $\left[\frac{(N_M-1)^2}{N_M}-\frac{\beta}{2}\right] \leq 0$. Thus, if the largest submarket M is characterized by endogenous (exogenous) fixed costs, then solving $\left[\frac{(N_M^*-1)^2}{N_M^*}-\frac{\beta}{2}\right]=0$ for N_M^* yields the least upper bound (greatest lower bound) to the number of firms that enter in equilibrium.

The number of firms entering under endogenous fixed costs N_m^{EN} solves $\left[\frac{(N_m-1)^2}{N_m}-\frac{\beta}{2}\right]=0$ which can be expressed equivalently as:

$$N_m^2 - N_m\left(\frac{\beta}{2} + 2\right) - 1 = 0. \tag{3.33}$$

The roots to the quadratic equation (3.33) are equal to:

$$N_m^{EN} = \left(1 + \frac{\beta}{4}\right) \pm \frac{1}{4}\sqrt{\beta^2 + 4\beta}.$$

Given the assumption on the cost elasticity parameter $\beta > 2$, the smaller of the two roots is always less than one such that the equilibrium number of firms that enter under endogenous fixed costs equals:

$$N_m^{EN} = \frac{1}{4}(\beta + 4) + \frac{1}{4}\sqrt{\beta(\beta + 4)}. \tag{3.34}$$

Figure 1 illustrates the lower bound to concentration under exogenous ($\underline{C}_{EX}$) and endogenous ($\underline{C}_{EN}$) fixed costs for sets of parameter values $\{F_0, \beta\}$. As the R&D cost parameter β increases, the upper limit on the total number of firms that enter in equilibrium increases such that the lower bound to concentration $\underline{C}_{EN}$ under endogenous fixed costs decreases. Moreover, as the minimum setup cost F_0 increases, the total number of firms that enter in equilibrium decreases, hence shifting the lower bound to concentration $\underline{C}_{EX}$ under exogenous fixed costs outward.

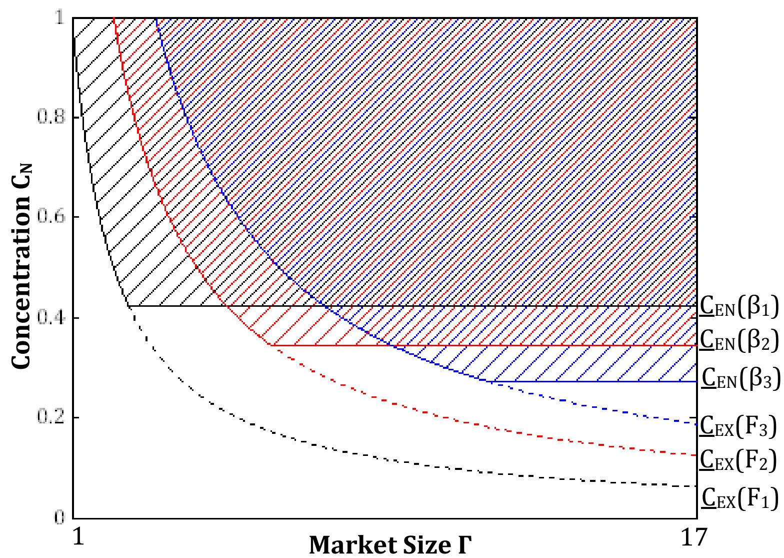


Figure 1: Illustrating equilibrium concentration and market size from the Cobb-Douglas demand example (under symmetric equilibrium and simultaneous entry). The R&D cost parameter $\beta_3 > \beta_2 > \beta_1$ illustrates the greater lower bound under lower R&D costs relative to the lower bound under higher R&D costs. The minimum setup cost $F_3 > F_2 > F_1$ illustrates the horizontal shift of firm entry associated with greater exogenous sunk costs.

Figure 1: Equilibrium Concentration Levels and Market Size

By equating the equilibrium number of firms from equations (3.22) and (3.34), I determine the threshold value for the market size Γ_{m^*} whereby a submarket m changes from being characterized by exogenous fixed costs to endogenous fixed costs. Specifically,

$$\Gamma_{m^*} = F_0 \left[\frac{1}{4}(\beta + 4) + \frac{1}{4}\sqrt{\beta^2 + 4\beta}\right]^2. \tag{3.35}$$

The upshot from this analysis is that for sufficiently sized markets, the ability of firms to increase quality via fixed (sunk) R&D investments precludes additional entry by new firms such that existing firms capture further expansions of market size via quality escalation. Thus, even as the size of the market grows large (i.e. $\Gamma_{m^*} \to \infty$) firm concentration levels remain bounded away from perfectly competitive levels (i.e. $C_1 \gg 0$).

A Lower Bound to R&D Concentration

The illustrative model developed in the previous section relates the number of firms that enter in equilibrium, hence industry concentration, to total market size and the endogeneity or exogeneity of sunk R&D expenditures. Sutton (1998) finds that the lower bound to R&D intensity, measured as the ratio of firm R&D to firm sales, is equivalent to the lower bound to concentration as markets become large. However, he does not address the implications of the EFC model upon concentration of R&D within these industries, which remains as a separate and additional concern in discussions regarding mergers and acquisitions, as well as patent pools, in agricultural biotechnology (Moschini, 2010; Dillon and Hubbard, 2010; Moss, 2009). I draw upon the results of Sutton (1998) in order to determine the empirical predictions of the EFC model regarding R&D concentration, defined as firm R&D

relative to industry R&D. The empirical predictions imply that: (i) the lower bound to R&D concentration is convergent in market size (i.e. the theoretical lower bound is not independent of the size of the market as is the case with sales concentration); and (ii) R&D concentration moves in an opposite direction from firm concentration with changes in market size such that larger markets are characterized by greater concentration in R&D.

Drawing upon the non-convergence results (Theorems 3.1-3.5) of Sutton (1998), the lower bound to the single firm concentration ratio C_{1m} for the quality-leading firm in submarket m can be stated as:

$$C_{1m} = \frac{\widehat{\Pi}_m}{\Pi_m} \geq \alpha(\sigma, \beta) \cdot h_m, \tag{3.36}$$

where α is some constant for a given set of parameter values (σ, β) and is independent of the size of the market in endogenous fixed cost industries. The value of alpha α depends upon industry technology, price competition, and consumer preferences and captures the extent that a firm can escalate quality via R&D investment and capture greater market share from rivals.

For simplicity of analysis, it will be beneficial to introduce notation for industry sales revenue and R&D expenditure. Following the notation for the sales revenue Π_{im} and R&D expenditure F_{im} for some firm i in submarket m, I define total industry sales revenue Π_m and R&D expenditure F_m in submarket m by summing across all firms such that $\Pi_m = \sum_{i \in m} \Pi_{im}$ and $F_m = \sum_{i \in m} F_{im}$. Additionally, I define the degree of market segmentation (or product heterogeneity) $h_m \in [0,1]$ as the share of industry sales revenue in submarket m accounted for by the largest product category such that:

$$h_m = \max_l \frac{\Pi_{lm}}{\Pi_m}, \tag{3.37}$$

where $h_m = 1$ corresponds with a submarket in which only a single product is offered.

Moreover, from Theorem 3.2 implies an equivalent expression for the lower bound to R&D-intensity $\hat{\mathrm{P}}_m$ for the quality-leading firm such that:

$$\hat{\mathrm{P}}_m = \frac{\hat{F}_m}{\hat{\Pi}_m} \geq \alpha(\sigma, \beta) \cdot h_m - \frac{F_0}{\Pi_m}. \tag{3.38}$$

Equation (3.38) implies that the R&D/sales ratio shares the same lower bound as the single firm concentration ratio as the size of the market becomes large (i.e. $\Pi_m \to \infty$). Multiplying both sides of equation (3.37) by $\hat{\Pi}_m$ yields:

$$\hat{F}_m \geq \alpha(\sigma, \beta) \cdot h_m \cdot \hat{\Pi}_m - F_0 \cdot \frac{\hat{\Pi}_m}{\Pi_m}. \tag{3.39}$$

Dividing both sides of equation (3.39) by total industry sales revenue in submarket m yields:

$$\frac{\hat{F}_m}{\Pi_m} \geq \left[\alpha(\sigma, \beta) \cdot h_m - \frac{F_0}{\Pi_m}\right] \cdot \frac{\hat{\Pi}_m}{\Pi_m}. \tag{3.40}$$

However, free entry in equilibrium implies that total industry sales revenue Π_m equals total industry R&D expenditure F_m such that equation (3.40) can be written as:

$$\frac{\hat{F}_m}{F_m} \geq \left[\alpha(\sigma,\beta)\cdot h_m - \frac{F_0}{\Pi_m}\right]\cdot\frac{\widehat{\Pi}_m}{\Pi_m}. \tag{3.41}$$

Defining the ratio of R&D concentration for the quality-leading firm as $R_{1m} = \frac{\hat{F}_m}{F_m}$, substituting for condition (3.36) on the lower bound to the single-firm concentration ratio, and substituting observable market size Γ_m for profit Π_m yields:

$$R_{1m} \geq \left[\alpha^2(\sigma,\beta)h_m^2 - \alpha(\sigma,\beta)h_m\frac{F_0}{\Gamma_m}\right]. \tag{3.42}$$

Equation (3.42) provides the empirically testable hypothesis for endogenous fixed costs relating the lower bound to concentration in R&D expenditure to market size, the minimum R&D setup cost, and the level of product heterogeneity. If sunk R&D costs are endogenous, there would be a nonlinear relationship between the degree of market segmentation (product homogeneity) h_m and the concentration of R&D R_{1m} for a given market. Moreover, equation (3.42) implies a lower bound to the ratio of R&D concentration that converges to some constant $\alpha^2(\sigma,\beta)h_m^2$ as the size of the market becomes large. For finitely sized markets though, the lower bound to R&D concentration is increasing in market size such that R&D expenditures are less concentrated in smaller sized markets.

If the industry is instead characterized by exogenous fixed costs, then the ratio of R&D concentration in submarket m can be expressed as:

$$R_{1m} = \frac{\hat{F}_m}{F_m} = \frac{F_0}{\Gamma_m}. \tag{3.43}$$

For some minimum fixed setup cost F_0, concentration in R&D investments is decreasing in market size and approaches 0 as market size becomes large and, contrary to the case of endogenous fixed costs, the R&D concentration under exogenous fixed costs is greatest in small markets. Figure 2 illustrates the relationship between R&D concentration and market size for both endogenous and exogenous fixed cost industries.

Figure 2 compares the lower bounds to R&D concentration for industries characterized by low and high levels of product heterogeneity h for a range of α parameters as market size Γ increases. If an industry is characterized by homogenous products (i.e. low h), there is no range of α such that firms invest more in R&D in excess of the minimum setup cost associated with entry. However, if an industry is characterized by differentiated products (i.e. high h) and sufficiently large α, then there is an incentive for firms to escalate R&D investment to increase product quality such that R&D concentration remains bounded away from zero as market size increases.

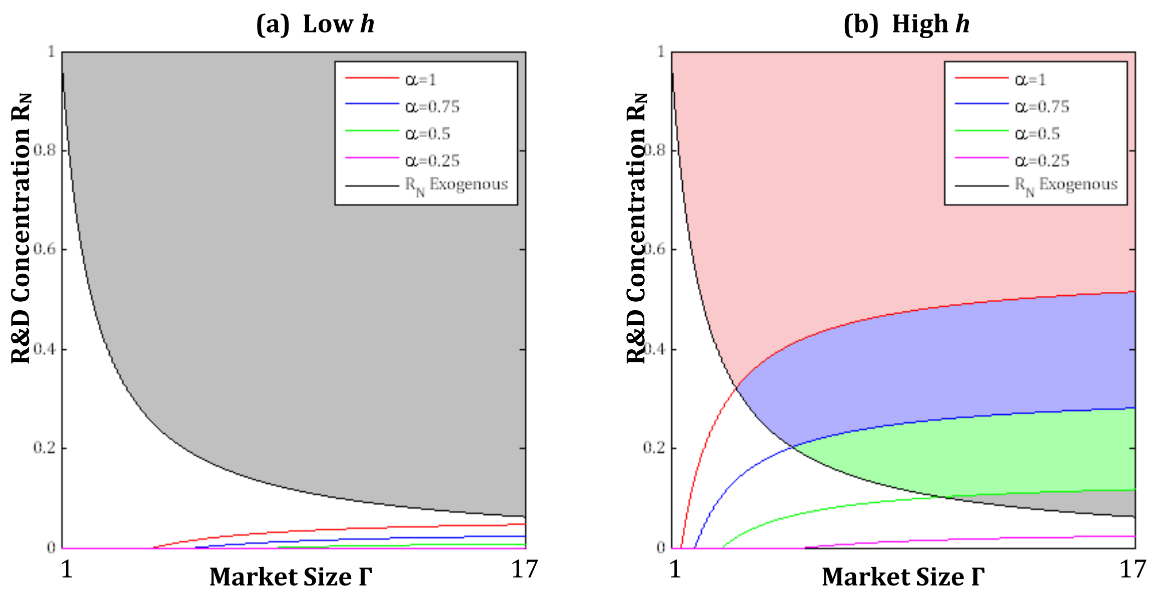


Figure 2: Equilibrium R&D Concentration Levels and Market Size

Figure 2: Illustrating equilibrium R&D concentration levels and market size for industries with low (2.a) and high (2.b) levels of product heterogeneity. For homogenous product industries (low *h*), no value of α would permit endogenous fixed costs such that R&D concentration decreases with market size. For heterogeneous product industries (high *h*), provided α is sufficiently large, R&D concentration will remain bounded away from zero as market size increases.

Empirical Specification

Equations (3.42) and (3.43) lead directly to the empirically testable hypotheses for the lower bound to R&D concentration. Specifically, an industry characterized by endogenous fixed costs in R&D should exhibit a lower bound to R&D concentration that is non-decreasing in market size whereas R&D concentration in exogenous fixed cost industries is decreasing in market size. Sutton (1991) derives a formal test for the estimation of the lower bound to concentration in an industry, based upon Smith (1985, 1994), in which the concentration ratio is characterized by the (extreme value) Weibull distribution. As Sutton (1991, 1998) identifies, it is necessary to transform the R&D concentration ratio R_1 such that the predicted concentration measures will lie between 0 and 1. Specifically, the R_n concentration measure is transformed according to:[8]

$$\tilde{R}_n = \ln \frac{1}{1 - R_n}. \tag{3.44}$$

I follow the functional form suggested by Sutton for the lower bound estimation such that for some submarket m, the R_n concentration ratio is characterized by:

$$\frac{\tilde{R}_{nm}}{h_m^2} = \theta_0 + \theta_1 \frac{1}{h_m \ln(\Gamma_m / F_0)} + \varepsilon_m, \tag{3.45}$$

where the residuals ε between the observed values of R&D concentration and the lower bound are distributed according the Weibull distribution such that:

$$F(\varepsilon) = 1 - \exp\left[-\left(\frac{\varepsilon - \mu}{\delta}\right)^{\gamma}\right], \quad \gamma > 0, \delta > 0 \tag{3.46}$$

[8] As the transformed R&D concentration is undefined for values of $R_{nm} = 1$, I monotonically shift the R&D concentration data by -0.01 prior to the transformation.

on the domain $\varepsilon \geq \mu$. The case of $\mu = 0$ corresponds to the two parameter Weibull distribution such that nonzero values of the shift parameter μ represent horizontal shifts of the distribution. The shape parameter γ corresponds to the degree of clustering of observations along the lower bound where as the scale parameter δ captures the dispersion of the distribution.

To test for a lower bound to R&D concentration, it is equivalent to test whether the residuals fit a two or three parameter Weibull distribution, that is to test whether $\mu = 0$. However, as Smith (1985) identifies, fitting equation (3.45) directly via maximum likelihood estimation is problematic for shape parameter values $\gamma \leq 2$.[9] Smith (1985, 1994) provides a two-step procedure for fitting the lower bound that is feasible over the entire range of shape parameter values.

Following the methodology of Giorgetti (2003), I first solve a linear programming problem using the simplex algorithm to obtain consistent estimators of $\{\theta_0, \theta_1\}$ in which the fitted residuals are non-negative. Therefore, $\{\hat{\theta}_0, \hat{\theta}_1\}$ solves:

$$\min_{\{\theta_0,\theta_1\}} \sum_{m=1}^{N} \left[\frac{\tilde{R}_{nm}}{h_m^2} - \left(\theta_0 + \theta_1 \frac{1}{h_m \ln(\Gamma_m/F_0)}\right)\right]$$

$$s.t. \quad \frac{\tilde{R}_{nm}}{h_m^2} \geq \left(\theta_0 + \theta_1 \frac{1}{h_m \ln(\Gamma_m/F_0)}\right), \forall m.$$

[9] Specifically, for $1 < \gamma \leq 2$, the maximum for the likelihood function exists, but it does not have the same asymptotic properties and may not be unique. Moreover, for $0 \leq \gamma \leq 1$, no local maximum of the likelihood function exists.

From the first step, I obtain parameter estimates for $\{\hat{\theta}_0, \hat{\theta}_1\}$ fitted residual values $\hat{\varepsilon}$ which can be used to estimate the parameters of the Weibull distribution via maximum likelihood. Specifically, as there are k parameters to be estimated in the first stage, there will be $N-k$ fitted residuals with positive values. By keeping only the fitted residuals with strictly greater than zero values, I maximize the log pseudo-likelihood function:

$$\max_{\{\gamma,\delta,\mu\}} \sum_{m=1}^{N-k} \ln\left[\left(\frac{\gamma}{\delta}\right)\left(\frac{\varepsilon-\mu}{\delta}\right)^{\gamma-1} \exp\left[-\left(\frac{\varepsilon-\mu}{\delta}\right)^{\gamma}\right]\right]$$

with respect to $\{\gamma, \delta, \mu\}$ in order to test whether $\mu = 0$, which is equivalent to testing the two parameter versus three parameter Weibull distribution via a likelihood ratio test. If the three parameter Weibull cannot be rejected, then this implies the presence of a horizontal shift in the distribution corresponding to an industry in which R&D is an exogenously determined sunk cost. In all cases, the likelihood ratio test fails to reject that the data fits the restricted, two parameter model such that $\mu = 0$. For each estimation, I report the likelihood ratio statistic which is distributed with a chi-squared distribution with one degree of freedom. Finally, I compute standard errors for the first-stage estimations via bootstrapping and standard errors for the second-stage estimations according to the asymptotic distributions defined in Smith (1994).

Data and Descriptive Statistics

In order to estimate an endogenous fixed cost model a la Sutton (1991, 1998), it is necessary to have both firm-level sales data and total market size for each market that is representative of the entirety of the industry. Although such data are of limited availability for the agricultural biotechnology sector, estimation of the endogenous lower bound to R&D concentration in agricultural biotechnology according to the proposed model is feasible using publicly available data. The model specifically requires four types of data for each crop type: (i) firm-level data on R&D investment, (ii) industry-level data on (sub-) market size, (iii) industry-level data on product heterogeneity, and (iv) industry-level data on the minimum setup costs for each (sub-) market. Moreover, additional data on agricultural characteristics at the state level are required in order to separate the agricultural biotechnology sector into distinct (sub-) markets for each crop type.

Sutton (1998) identifies the potential use of "natural experiments" in order to empirically identify the lower bound to concentration within a single industry. The natural experiments that allow for such an analysis occur when there is an exogenous shift in consumer preferences or an exogenous change in technology, although exogenous changes in market size also prove useful for analysis. For the empirical analysis of the agricultural biotechnology sector, I utilize two dimensions of variation in R&D investment and market size by estimating the lower bound across geographic submarkets as well as over time. In doing so, I am able to capitalize upon changes in consumer attitudes towards GM crops over time as well as advances in technology and/or regulation which decrease the fixed costs associated with R&D. Moreover, geographic and intertemporal variation in market size permits the theory to be tested across a variety of market sizes. Finally, I am able to utilize a "natural experiment", in the form of differential changes in demand for corn (positive) and soybean (negative) seed in response to an exogenous increase in the incentives for farmers to grow corn crops for use in ethanol.

The ideal data for the analysis of an endogenous lower bound to R&D concentration would be R&D expenditures for each product line for every firm in an industry. Although data at this level of detail is unavailable for the agricultural biotechnology sector, there is publicly available data that captures proxies for R&D investment at the firm and product level in the form of patent and/or field trial applications for GM crops. However, data on crop patent applications is not available for the years after 2000 and therefore is less useful for an estimation of lower bounds to concentration for an industry in which there has been considerable consolidation post-2000. Field trial application data are appropriate for the analysis as it captures an intermediate R&D process which is mandatory for firms that desire to bring a novel GM crop to market.

In accordance with the Federal Coordinated Framework for the Regulation of Biotechnology, the Animal and Plant Health Inspection Services (APHIS) regulates the release of any genetically engineered (GE) organism that potentially threatens the health of plant life. Specifically, prior to the release of any GE organism, the releasing agency, either firm or non-profit institution, must submit a permit application to the Biotechnology Regulatory Services (BRS). These Field Trial Applications are made publicly available by the BRS in a database that includes information on all permits, notification, and petition applications for the importation, interstate movement, and release of GE organisms in the US for the years 1985-2010. The database includes the institution applying for the permit, the status of the application, the plant (or "article") type, the dates in which the application was received, granted, and applicable, the states in which the crops will be released, transferred to or originated from, and the crop phenotypes and genotypes. As of October 2010, there are 33,440 permits or notifications of release included in the database for all types of crops. After restricting the sample to firms, by eliminating non-profit institutions, and permits or notification involving the release of GE crops, there are 9936 remaining observations in the database.

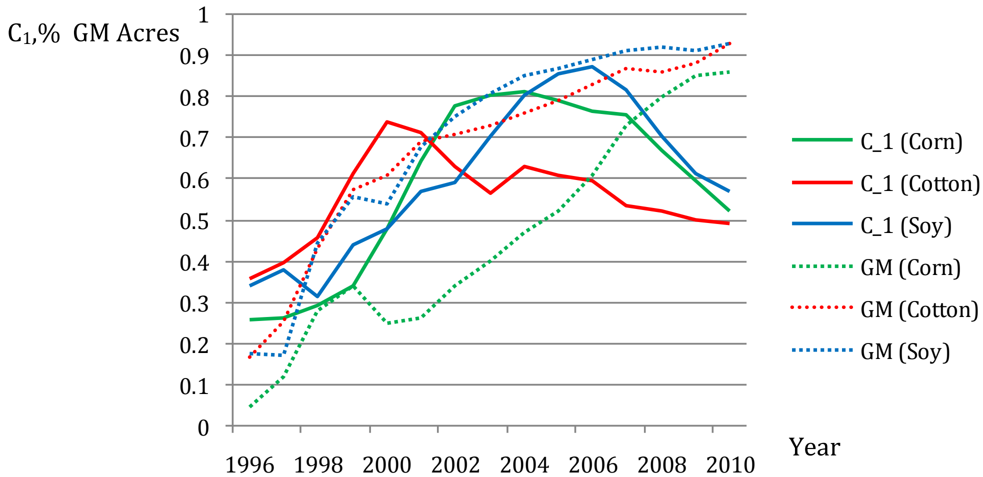
The National Agricultural Statistics Service (NASS), a division of the United States Department of Agriculture (USDA), conducts the annual June Agriculture Survey in order to obtain estimates of farm acreage for a variety of crops, including corn, cotton, and soybeans. The NASS reports data on total amount of acreage, both planted and harvested, in an annual *Acreage* report that is made publicly available. Moreover, the Economic Research Service (ERS) also computes yearly seed costs in dollars per acre based upon survey data collected by the USDA in the crop-specific Agricultural Resource Management Surveys (ARMS). After adjusting for inflation, these seed costs are multiplied by the total acres planted for each crop type to arrive at total market size.

Since 2000, the June Agricultural Survey has also sampled farmers regarding the adoption of GM seed varieties for corn, cotton, and soybeans across a subsample of states.[10] Using this survey data, ERS computes and reports estimates for the extent of GM adoption. GM adoption rates are used to obtain total GM acreage planted, as well as total market size after multiplying by the inflation adjusted dollar

[10] NASS estimates that the states reported in the GM adoption tables account for 81-86% of all corn acres planted, 87-90% of all soybean acres planted, and 81-93% of all upland cotton acres planted. For states without an adoption estimate, overall US adoption estimates are used to compute the size of the GM market. Provided rates of adoption or total planted acreage are not significantly greater among these "marginal" states, this imputation will not bias the estimates.

cost of seed, to arrive at a measure of GM market size for the lower bound estimation. Figure 3 plots three-year average one firm concentration ratios and adoption rates for GM crops for each crop type from 1996-2010. The graph illustrates two important trends: (i) increasing rates of adoption of GM seed varieties across time; and (ii) single firm concentration ratios that initially increased and have remained consistently high across time.

Additionally, the rates of adoption for 2000-2010, as well as the estimates of GM adoption for the years 1996-1999 from Fernandez-Cornejo and McBride (2002), are used to construct product heterogeneity indexes for each crop type that vary across time. By definition, the product heterogeneity index is meant to capture the percentage of industry sales of the largest product group. Therefore, I treat seed varieties as homogenous within product groups, defined as conventional, insect resistant (IR), herbicide tolerant (HT), and "stacked" varieties consisting of IR and HT traits, and equate the product heterogeneity index to the percentage of acres accounted for by the largest group.



Source: Author's calculations from APHIS and ERS GM crop adoption data.

Figure 3: Single-Firm R&D Concentration Ratios and GM Adoption

The final component required for the estimation of the lower bound to R&D concentration is the minimum setup cost associated with entry into the product market. I use data reported in the "National Plant Breeding Study" for 1994 and 2001 in order to obtain a proxy for the R&D setup cost for each crop type. The minimum setup cost is obtained by first summing the total number of public "scientist years" (SY), those reported by the State Agricultural Experiment Stations (SAES) and the Agricultural Research Service (ARS), and divide this sum by the total number of projects reported for both agencies in order to obtain average SY for a single crop.[11] Minimum setup costs are thus obtained by multiplying average SY by the private industry cost per SY ($148,000) and adjusting for inflation.[12] Table 3 reports summary statistics for field trial applications, crop acreage planted, seed costs, product heterogeneity, and minimum setup costs.

Table 3: Lower Bound Estimation Data Descriptive Statistics

Variable	Yearly Mean	Std. Dev.	Min.	Max.	Total
Field Trial Applications					
Corn	318.86	166.46	3.00	606.00	6696.00
Cotton	41.13	23.63	1.00	91.00	946.00
Soybeans	78.32	55.94	4.00	194.00	1723.00
Total Acres Planted (000 acre)					
Corn	79945.43	5176.88	71245.00	93600.00	1678854.00
Cotton	13434.61	1994.88	9149.50	16931.40	282126.90
Soybeans	69462.76	7287.88	57795.00	82018.00	1458718.00
Seed Costs ($/acre)					
Corn	25.13	7.10	15.65	49.15	-
Cotton	25.46	15.63	7.24	79.55	-
Soybeans	18.34	6.99	7.79	37.28	-
Product Heterogeneity					
Corn	0.69	0.24	0.35	1.00	-
Cotton	0.59	0.26	0.31	1.00	-
Soybeans	0.84	0.14	0.64	1.00	-
Minimum Setup Costs ($1000)					
Corn	182536.55	27275.81	147843.26	220132.27	-
Cotton	182019.44	27434.03	147424.44	219508.67	-
Soybeans	282336.98	42553.92	228675.42	340487.88	-

Source: Author's estimates

[11] A "scientist year" is defined as "work done by a person who has responsibility for designing, planning, administering (managing), and conducting (a) plant breeding research, (b) germplasm enhancement, and (c) cultivar development in one year (i.e. 2080 hours)."

[12] Results of the lower bound estimations are robust to an alternate definition based upon public sector cost per SY ($296,750).

The observable data used in the cluster analysis are from the period prior to the widespread adoption of GM varieties (1990-1995) and covers agricultural production in all lower, contiguous 48 states (except Nevada), although the extent of coverage varies by crop and state. The cluster analysis uses data (summarized in Table 4) that can be broadly classified into two types: (i) state level data that are constant across crops; and (ii) data that vary by state and crop level. The state level data include location data (longitude and latitude measured at the state's geometric center), climate data (mean monthly temperatures, mean monthly rainfall, and mean Palmer Drought Severity Index measured by the National Oceanic and Atmospheric Administration (NOAA) from 1971-2000), and public federal funding of agricultural R&D, including USDA and CSREES (NIFA) grants, reported by the Current Research Information System (CRIS) for the fiscal years 1990-1995. The state/crop level data analyzed include farm characteristics for each crop variety (i.e. acres planted, number of farms, average farm size, number of farms participating in the retail market, total sales, and average sales per farm) that are reported by the USDA in the 1987 and 1992 US Census of Agriculture. Additional data on the application of agricultural chemicals were collected by the USDA, NASS and ERS, and reported in the *Agricultural Chemical Usage: Field Crop Summary* for the years 1990-1995.

Table 4: Market Definition Data Descriptions

Observable Market Characteristics			
State Level			
Data	**Description**	**Years**	**Source**
Latitude	State geographic centroid	-	MaxMind®
Longitude	State geographic centroid	-	MaxMind®
Size	Total area (000s acres)	-	2000 Census of Population and Housing
Temperature	Monthly averages (°F)	1971-2000	NOAA
Rainfall	Monthly averages (inches)	1971-2000	NOAA
Drought Likelihood	Monthly averages (PDSI)	1971-2001	NOAA
R&D	Total public funds for agricultural R&D (1990 $000s)	1990-1995	CRIS
Cropland	Total cropland area (000s acres)	1987;1992	Census of Agriculture
State and Crop Level			
Data	**Description**	**Years**	**Source**
Acres Planted*	Total area planted (000s acres)	1987;1992	Census of Agriculture
Share of Cropland*	Percentage of cropland planted (%)	1987;1992	Census of Agriculture
Farms*	Total farms (farms)	1987;1992	Census of Agriculture
Average Farm Size*	Average farm size (000s acres)	1987;1992	Census of Agriculture
Farms with Sales*	Total farms selling (farms)	1987;1992	Census of Agriculture
Sales*	Total sales (1990 $000s)	1987;1992	Census of Agriculture
Average Farm Sales*	Average farm sales (1990 $000s)	1987;1992	Census of Agriculture
Fertilizer Usage (3 types)**	Percentage of planted acres treated (%)	1990-1995	Agricultural Chemical Usage
Herbicide Usage (All types)**	Percentage of planted acres treated (%)	1990-1995	Agricultural Chemical Usage
Insecticide Usage (All types)***	Percentage of planted acres treated (%)	1990-1995	Agricultural Chemical Usage

*: Corn - No NV; Cotton - Only AL, AZ, AR, CA, FL, GA, KS, LA, MS, MO, NM, NC, OK, SC, TN, TX, VA;
Soybean - No AZ, CA, CT, ID, ME, MA, MT, NV, NH, NM, NY, OR, RI, UT, WA, WY

**: Corn - No NV; Cotton - Only AZ, AR, CA, LA, MS, TX; Soybean - No AZ, CA, CO, CT, ID, ME, MA, MT, NV, NH, NM, NY, OR, RI, UT, VT, WA, WV, WY

***: Corn - No NV; Cotton - Only AZ, AR, CA, LA, MS, TX; Soybean - Only AR, GA, IL, IN, KY, LA, MS, MO, NE, NC, OH, SD

The Market for Agricultural Biotechnology

In estimating an EFC-type model for a single industry, an initial crucial step is the proper identification of the relevant product markets. The EFC model predicts an escalation of fixed-cost expenditures for existing firms as market size increases rather than entry by additional competitors. For the case of retail industries, such as those examined by Ellickson (2007) and Berry and Waldfogel (2003), markets are clearly delineated spatially. However, the identification of distinct markets in agricultural biotechnology is potentially more problematic as investments in R&D may be spread over multiple geographic retail markets. Moreover, as we only have data on firm concentration available at the state level, the difficulty associated with defining relevant markets is exacerbated.

In order to overcome issues associated with the correct market identification, I first assume that R&D expenditures on GM crops released domestically can only be recouped on sales within the US. Although somewhat innocuous for the market for corn seed, this assumption may be overly restrictive for other crop types including soybeans and cotton. However, disparate regulatory processes across countries, as well as the significant size of the US market, reveals the importance of the domestic market to seed manufacturers. Moreover, recent surveys of global agricultural biotechnology indicate that many of the varieties of GM crops adopted outside of the US have also been developed outside of the US. (ISAAA, 2010)

I consider a characterization of regional submarkets for each crop variety derived from statistical cluster analysis of observable characteristics of agricultural production within each state and crop variety. Cluster analysis is a useful tool in defining regional submarkets as it captures the "natural structure" of the data across multiple characteristics. I utilize K-means clustering by minimizing the Euclidean distance of the observable characteristics for each crop variety and arrive at ten corn clusters, six soybean clusters, and six cotton clusters.

The goal of cluster analysis is such that objects within a cluster (i.e. states within a regional submarket) are "close" in terms of observable characteristics while being "far" from objects in other clusters. Thus, the objective is to define distinct, exclusive submarkets in the agricultural seed sector by clustering states into non-overlapping partitions. I assume a "prototype-based" framework such that every state in some submarket is more similar to some prototype state that characterizes its own submarket relative to the prototype states that characterize other submarkets. Therefore, I utilize a K-means approach by defining the number of submarket clusters K for each crop type and minimizing the Euclidean distance between each state and the centroid of the corresponding cluster. For robustness, I vary the number of clusters K for each crop type and also consider alternate definitions for the distance function.

Although there is a considerable amount of observable data on market characteristics, I encounter an issue with the degrees of freedom required for the cluster analysis when we include all available data. Specifically, the number of explanatory variables for the cluster analysis is limited to $N - K$, where N is the number of observations (i.e. states with observable characteristics) and K is the number of clusters (i.e. submarkets). In order to reduce the problem of dimensionality in the cluster analysis, I use factor analysis, specifically principal-components factoring, to create indexes of variables that measure similar concepts (i.e. reduce monthly temperature averages to a single temperature index) and thereby reduce the number of explanatory variables.

The cluster analysis of the market for corn seed builds upon the spatial price discrimination analysis of Stiegert, Shi, and Chavas (2011) by separating the major corn production regions into "core" and "fringe" states and refining the classification of the other regions to better account for observed differences in the share of corn acres planted and proportion of acres with herbicide and pesticide applications prior to the introduction of GM crops. The resulting submarkets, summarized in Figure 3 with the submarket shares of total US production, reveals that corn production is heavily concentrated in only thirteen states with Illinois and Iowa alone accounting for approximately 30% of all production.

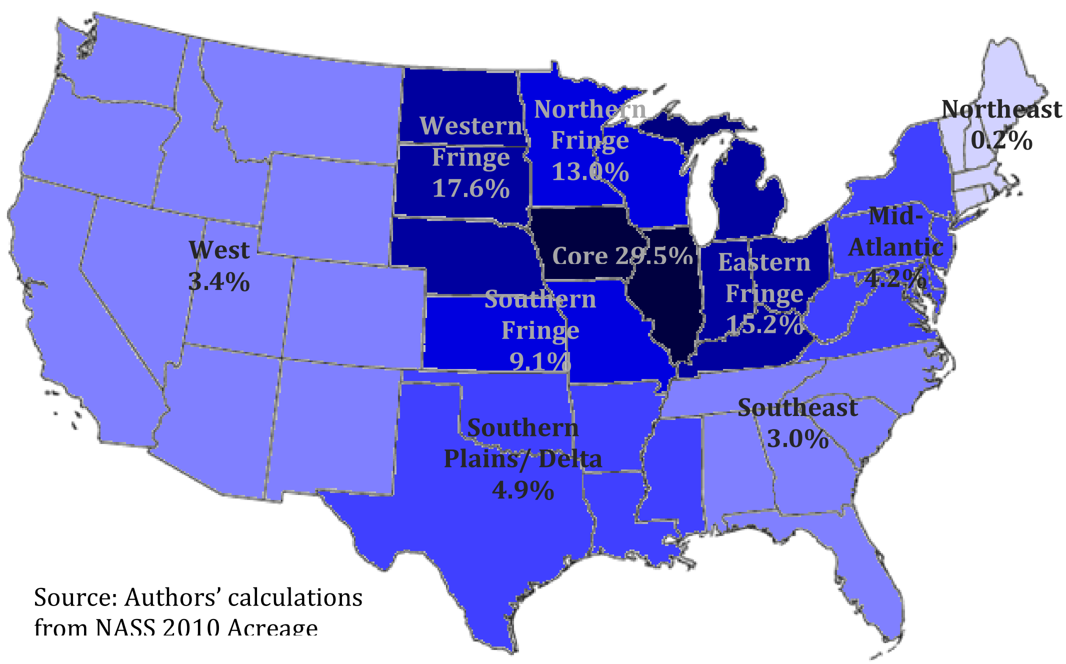


Figure 4: 2010 Submarket Shares of US Corn Acres Planted

The cluster analysis for cotton and soybean markets is slightly more problematic as fewer states farm these crops relative to corn. Regardless, the cluster analysis, along with robustness checks over the total number of clusters, reveals that the cotton and soybean markets can be reasonably divided into six submarkets apiece. However, there are large differences in the relative size of submarkets in cotton and soybean production as well as the regions in which production of each crop occurs. Texas accounts for over half of all planted acreage in cotton with the rest of the production primarily located in the Mississippi delta and southeast regions (Figure 5). Soybean production, on the other hand, primarily occurs in corn-producing regions with the significant overlap between the major corn and soybean producers (Figure 6).

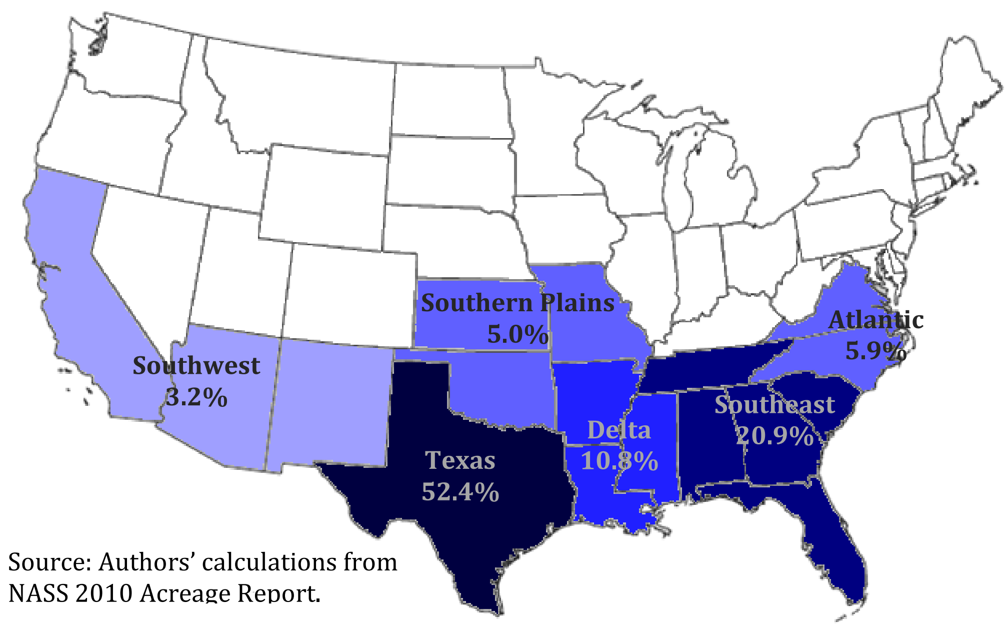


Figure 5: 2010 Submarket Shares of US Cotton Acres Planted

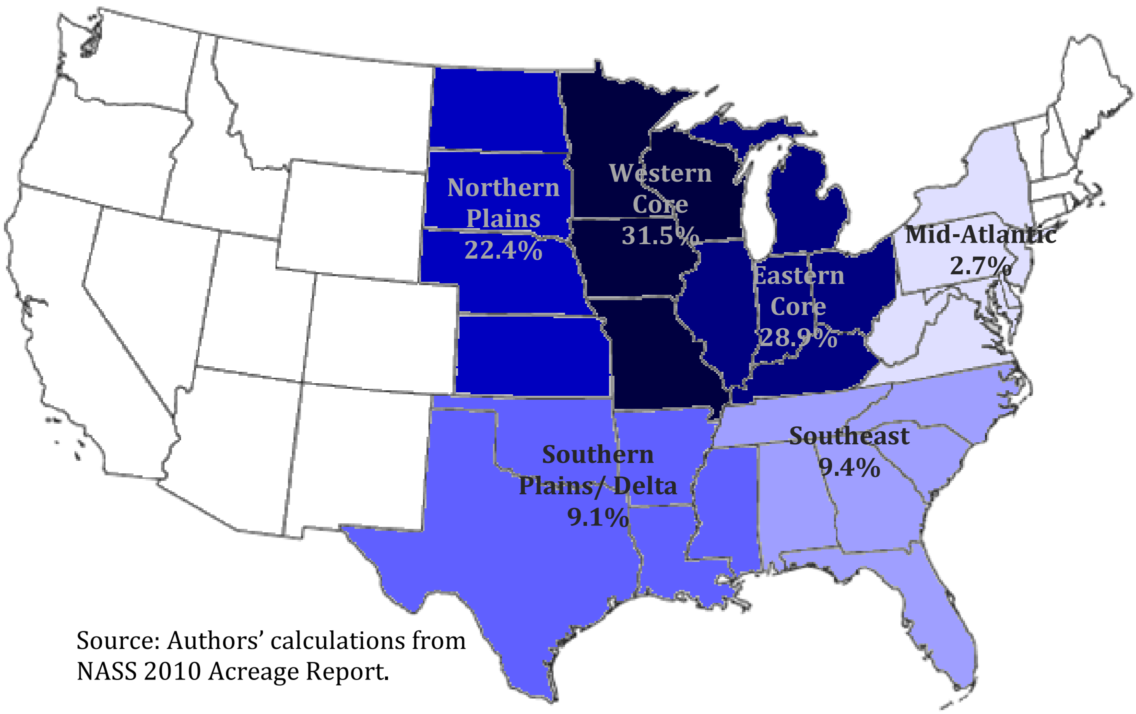
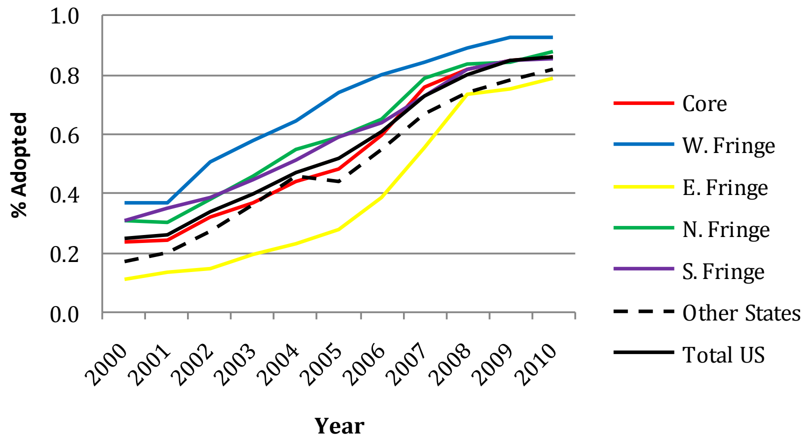


Figure 6: 2010 Submarket Shares of US Soybean Acres Planted

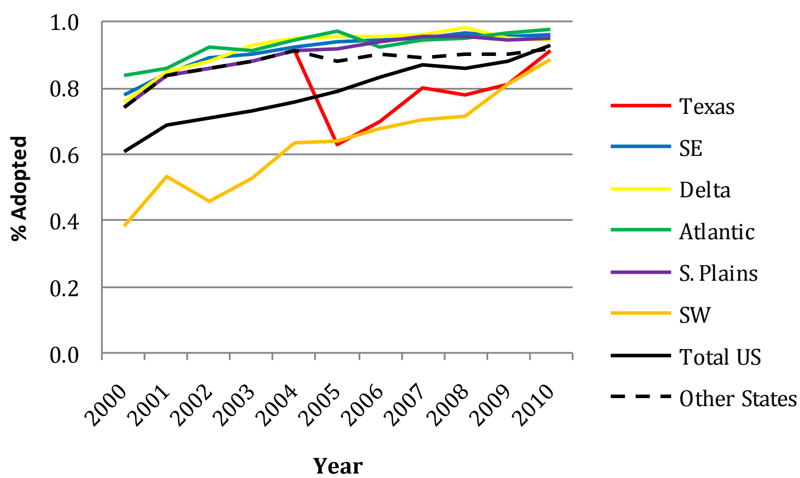
Examining rates of GM adoption across submarkets (Figures 7-9) reveals distinct differences across submarkets for GM corn and cotton seeds, but similar adoption rates for GM soybean. One possible explanation for the observed differences across crop types might be the relatively limited number of phenotypes of GM soybean released in this period such that all regions had a similar preference for insect resistance.[13] Although there is only limited number of states with available data on the percentage of farm acres planted with soybeans and treated with insecticide from 1990-1995, only two states (Georgia and Louisiana) reported percentage of acres treated at greater than 10% with the remaining states (Arkansas, Illinois, Indiana, Kentucky Mississippi, Missouri, Nebraska, North Carolina, Ohio, South Dakota) reporting rates that were typically less than 5% of acres treated. These descriptive statistics contrast greatly with those for cotton, which also had a limited number of phenotypes released in this period. Texas, which had the lowest rates of adoption of Bt Cotton, an insect resistant variety, also had the lowest rates of insecticide application from 1990-1995.

[13] For additional descriptive analysis of the geographically distinct submarkets, please refer to "Appendix B: (Sub-)Market Analysis for GM Crops". Specifically, Appendix B contains maps illustrating the geographical differences in climate and market size for each crop type as well as differences in the application of fertilizers, herbicides, and insecticides by crop.



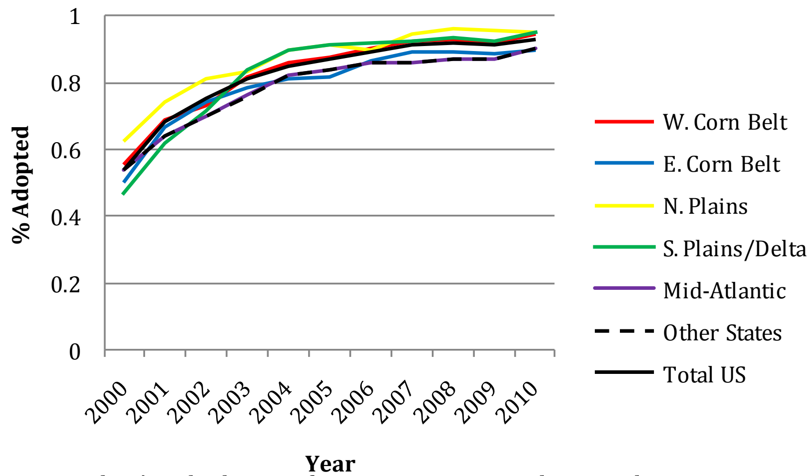
Source: Author's calculations from ERS GM crop adoption data.

Figure 7: Adoption Rates of GM Corn Across Submarkets



Source: Author's calculations from ERS GM crop adoption data.

Figure 8: Adoption Rates of GM Cotton Across Submarkets



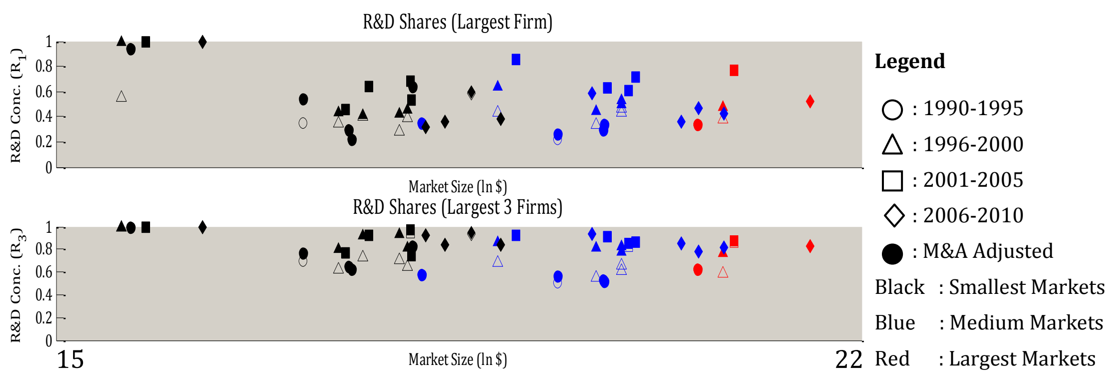
Source: Author's calculations from ERS GM crop adoption data.

Figure 9: Adoption Rates of GM Soybean Across Submarkets

Empirical Results and Discussion

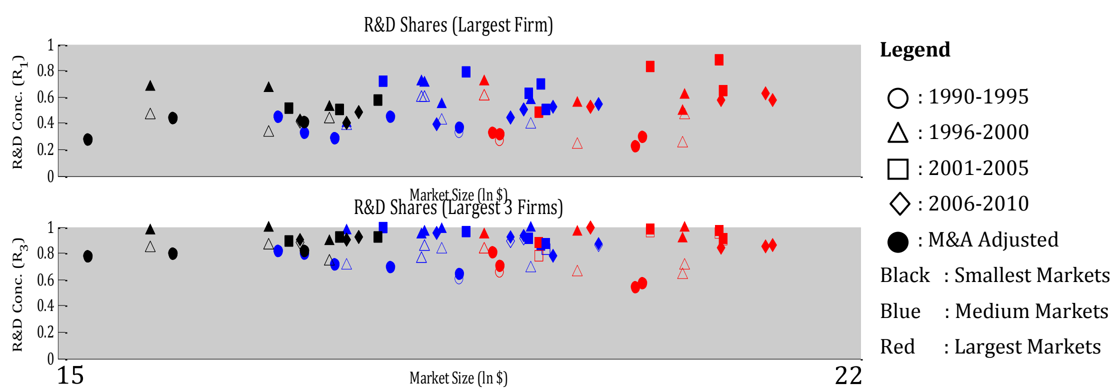
Estimating the Lower Bounds to R&D Concentration

Prior to estimating the lower bounds to R&D concentration, it is useful to illustrate why one would expect the agricultural biotechnology sector to be characterized by endogenous lower bounds. Specifically, Figures 7-9 illustrate the one- and three-firm R&D concentration ratios relative to market size for each crop type with and without adjustments for merger and acquisition activity.



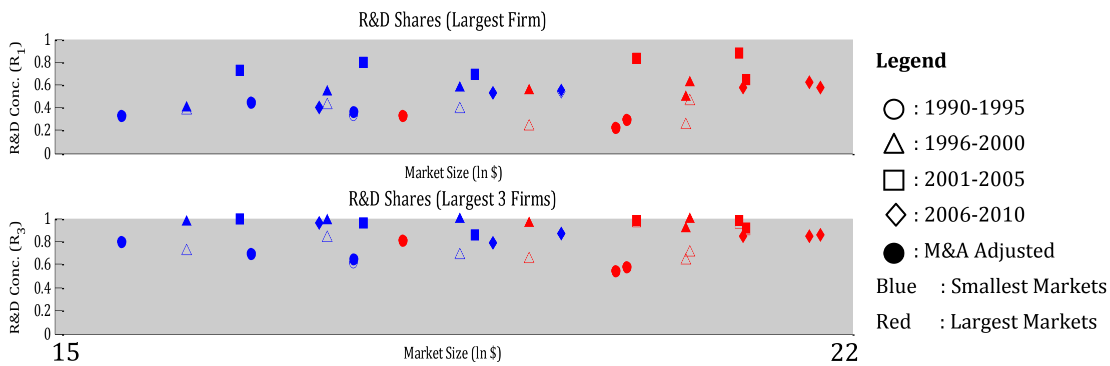
Source: Authors' calculations.

Figure 10: Corn R&D Concentration and Market Size



Source: Authors' calculations.

Figure 11: Cotton R&D Concentration and Market Size



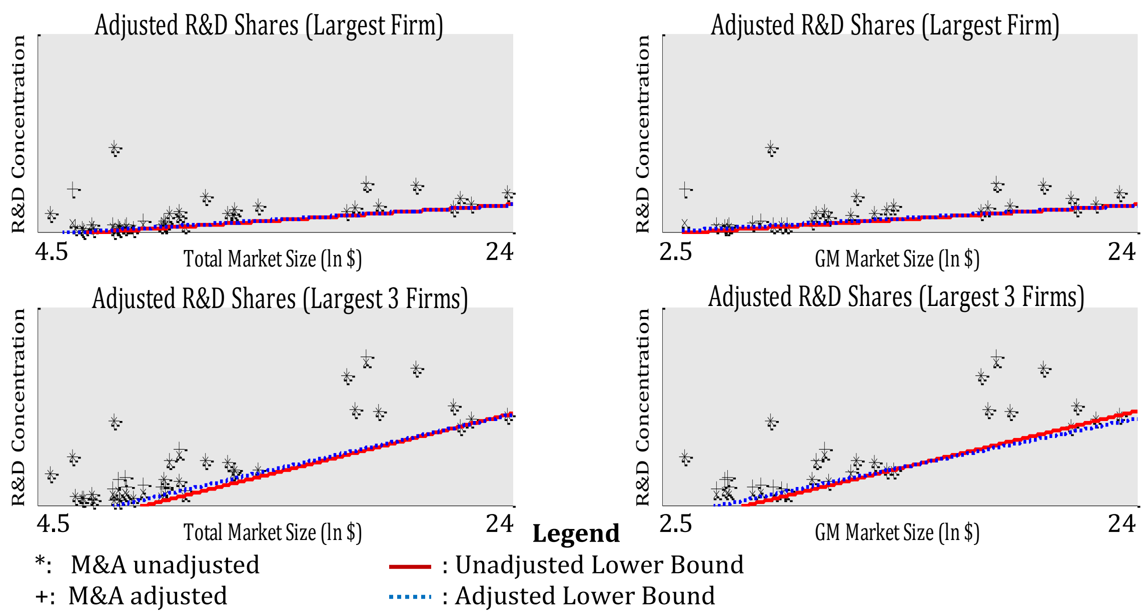
Source: Authors' calculations.

Figure 12: Soybean R&D Concentration and Market Size

Figures 10-12 illustrate that R&D concentration ratios are non-decreasing in market size for each type of crop regardless of the measure of R&D concentration, therefore implying a lower bound. However, these descriptive illustrations do not account for differing levels of product heterogeneity across time and therefore it is not possible to reconcile these illustrations with the lower bound to R&D concentration implied by the theory. As such, the following analysis considers eight variations for each crop type by analyzing both the single and three-firm concentration, concentration adjusted and unadjusted for merger and acquisition of intellectual property, and both total market size for each crop as well as the market size for genetically engineered crops (1996-2000, 2001-2005, 2006-2010). The two-stage estimation results as well as illustrative figures are presented for each crop type.

R&D Concentration in GM Corn Seed

The lower bounds to concentration for corn seed are illustrated in Figure 13 and the estimation results are presented in Table 5. The results indicate a lower bound to R&D concentration that is increasing in the size of the market, independent of the definitions of R&D concentration and market size. These results are consistent with an endogenous lower bound to R&D concentration as illustrated in Figure 2 in which concentration is very low in small-sized markets and increasing in market size, which contrasts with the exogenous lower bound to R&D concentration which is strictly decreasing in market size. Moreover, factoring merger and acquisition activity into the measurement of R&D concentration does not significantly change the estimates for the lower bound to concentration in corn seed. These results imply that increased concentration of intellectual property in corn seed occur not as a consequence of merger and acquisition activity, but rather are inherent in the nature of technological competition.



Source: Author's calculations

Figure 13: Lower Bounds to R&D Concentration in GM Corn Seed

When interpreting the results of the lower bound estimation, it is important to recall that the R&D concentration data have been adjusted according to equation (3.44) and for the level of product heterogeneity. For large markets, the predicted lower bound converges to 1 whereas for very small markets, the predicted lower bound converges to some negative number (i.e. 0). This result can be explained by what we observe in Figures 2 and 10. According to the theory, I am attempting to fit a lower bound to an industry that is characterized by exogenous fixed costs in smaller-sized markets and endogenous fixed costs in larger-sized markets such that there is a structural break for some unidentified level of market size. A more accurate estimation based upon the observed data could fit a non-linear lower bound to the data to account for this structural break, although it is difficult *a priori* to reconcile such an analysis with the theoretical predictions. Moreover, Figure 13, which plots the adjusted data, does not necessarily indicate that a non-linear lower bound would provide a better fit.

In order to interpret the coefficient estimates over the range of possible market sizes, I consider 10% changes in the market size for both the largest and smallest submarkets and report the predicted lower bound results in Table 8. In the largest submarket (Iowa and Illinois), the predicted lower bound of the single firm R&D concentration ratio ranges from .3776 to .3909 and a 10% increase in market size increases the lower bound in the range of .0035 to .0049. For the smallest submarket (Northeast states), the range of predicted single firm R&D concentration ratios range from .1122 to .2178 and a 10% increase in market size increases the lower bound by a range from about .0044-.0071. The predicted values of the three firm R&D concentration ratios range from .7887 to .8152 in large markets and .2409 to .5062 for small markets. A 10% increase in market size increases the lower bound in small markets between .0102-.0226 and increases the lower bound in large markets between .0044-.0055.

Table 5: Lower Bound Estimations for GM Corn Seed

Concentration	Market Size	M&A	First-Stage θ_0		First-Stage θ_1		Second-Stage γ		Second-Stage δ		LR $(\chi^2=1)$
R_1	Total	Unadjusted	-1.714	**	0.240	**	0.747	**	1.925	**	0.161
			0.060		0.006		0.080		0.445		
		Adjusted	-1.444	**	0.228	**	0.718	**	1.913	**	0.117
			0.042		0.005		0.079		0.459		
	GM	Unadjusted	-0.443	**	0.186	**	0.710	**	2.126	**	-0.006
			0.034		0.004		0.091		0.601		
		Adjusted	-0.069	*	0.168	**	0.690	**	2.118	**	0.034
			0.030		0.004		0.090		0.617		
R_3	Total	Unadjusted	-7.804	**	0.901	**	1.007	**	4.975	**	-0.020
			0.148		0.011		0.119		0.846		
		Adjusted	-6.244	**	0.830	**	0.946	**	4.403	**	0.016
			0.119		0.010		0.111		0.801		
	GM	Unadjusted	-3.211	**	0.725	**	0.770	**	4.007	**	0.022
			0.083		0.007		0.112		1.038		
		Adjusted	-1.923	**	0.625	**	0.813	**	4.273	**	-0.030
			0.139		0.012		0.116		1.026		

Source: Author's estimates.

**,*: Significance at the 99% and 95% levels, respectively.

R&D Concentration in GM Cotton Seed

As with the market for corn seed, the estimation of a lower bound to R&D concentration in cotton seed implies an industry characterized by endogenous fixed costs to R&D. Figure 14 illustrates lower bounds to R&D concentration that are again increasing in market size in each estimation. The results, reported in Table 6, imply a significant and increasing lower bound to R&D concentration that is not independent of the size of the market (i.e. $\theta_1 > 0$). However, when merger and acquisition activity are accounted for in R&D concentration, the predicted lower bound for the cotton seed market changes significantly in the three-firm concentration estimations, thus implying some of the observed concentration in intellectual property in cotton seed has occurred as a result of firm mergers and acquisitions and cannot necessarily be attributed to the nature of technology competition.

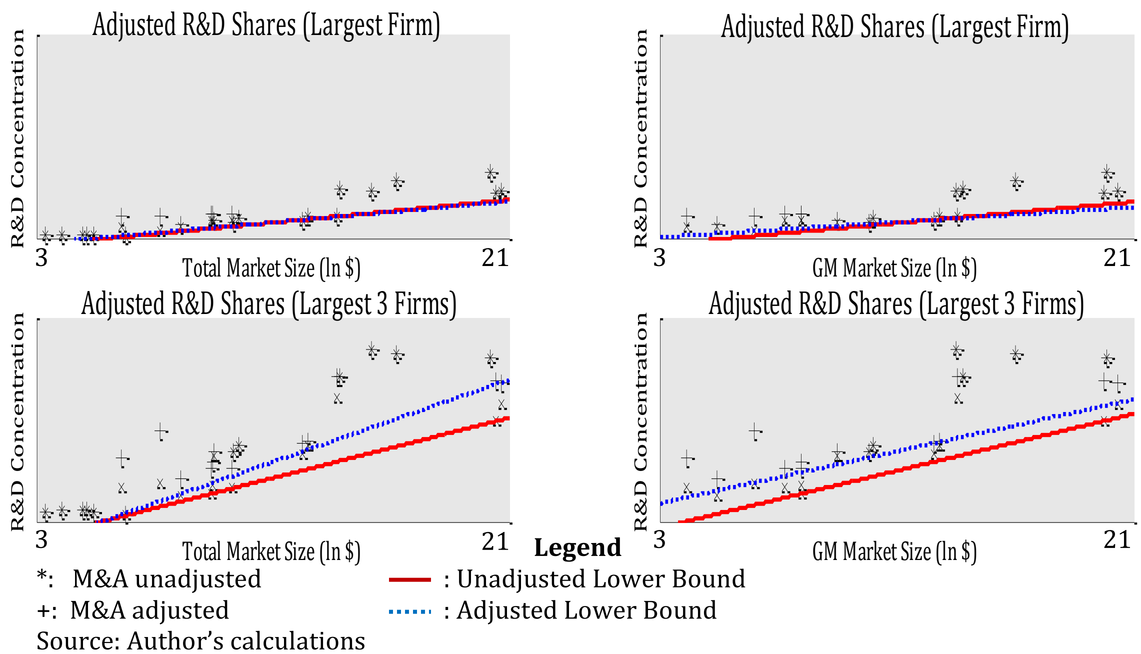


Figure 14: Lower Bounds to R&D Concentration in GM Cotton Seed

The predicted lower bound to single firm R&D concentration for GM cotton seed range from .3539 to .4302 for the largest sized market (Texas) and from .2388 to .2662 for the smallest sized market (Southwest states). A 10% increase in market size increases the lower bound to concentration from between .0045 to .0081 regardless of the size of the market. Furthermore, the predicted lower bound for the three firm R&D concentration ratios range from .7811 to .8767 in the largest market with a 10% increase in market size raising the predicted lower bound by .0042-

.0063. In the smallest-sized market, the predicted lower bound to the three firm R&D concentration ratio ranges from .5765 to .6917 and a 10% increase in market size increases the predicted lower bound by .0074 to .0123.

Table 6: Lower Bound Estimations for GM Cotton Seed

			First-Stage				Second-Stage				LR
Concentration	Market Size	M&A	θ_0		θ_1		γ		δ		$(\chi^2=1)$
R_1	Total	Unadjusted	-2.203	**	0.372	**	1.260	**	1.579	**	0.028
			0.121		0.010		0.195		0.277		
		Adjusted	-1.822	**	0.343	**	1.405	**	1.947	**	0.066
			0.123		0.010		0.231		0.313		
	GM	Unadjusted	-1.606	**	0.328	**	1.492	**	2.277	**	0.058
			0.287		0.022		0.281		0.391		
		Adjusted	-0.366		0.233	**	1.474	**	2.551	**	0.010
			0.335		0.026		0.289		0.442		
R_3	Total	Unadjusted	-5.459	**	0.986	**	1.114	**	5.166	**	-0.008
			0.432		0.042		0.188		1.040		
		Adjusted	-7.426	**	1.347	**	1.400	**	5.101	**	0.008
			0.268		0.019		0.234		0.821		
	GM	Unadjusted	-2.715	**	0.881	**	1.328	**	6.181	**	0.114
			0.428		0.040		0.255		1.234		
		Adjusted	1.037	*	0.803	**	1.022	**	4.656	**	-0.018
			0.507		0.041		0.203		1.160		

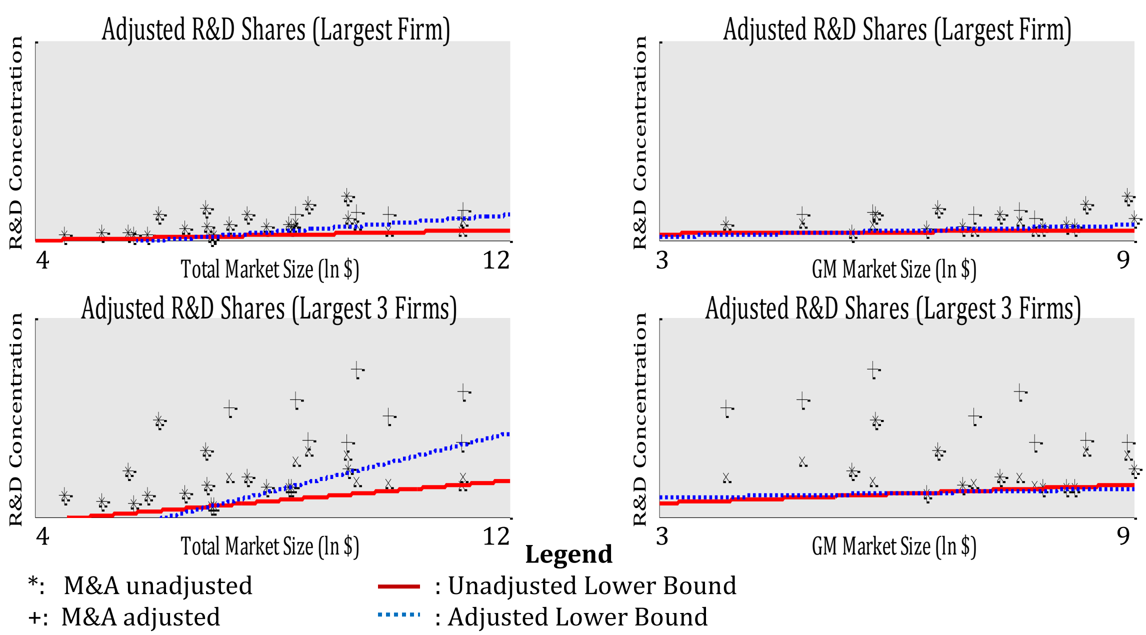
Source: Author's estimates.

**,*: Significance at the 99% and 95% levels, respectively.

Comparing the predicted lower bounds of the corn and cotton seed markets, it is evident that the lower bound to R&D concentration in cotton seed increases somewhat more rapidly relative to corn seed. This result can be explained in part by the proliferation of products in the GM corn seed market (29 GM seed varieties) relative to the number of GM cotton seeds marketed (11 GM seed varieties). (Howell, et al., 2009) As the h-index decreases with the level of product heterogeneity, the R&D concentration for GM cotton seed is more likely to be characterized by endogenous fixed costs.

R&D Concentration in GM Soybean Seed

Unlike the estimations for GM corn and GM cotton seed, the lower bound estimations for R&D concentration in GM soybean seed, reported in Figure 15 and Table 10, are more ambiguous. Although six of eight lower bound estimations are indicative of endogenous fixed costs in R&D with R&D concentration increasing with market size, the estimations for the GM market are relatively flat and it is not evident that these estimations are significantly different from zero for feasible market sizes. Moreover, from the estimations for total market size, the results indicate that even though the market appears to be characterized by endogenous fixed costs, much of the concentration has occurred as a result of merger and acquisition activity. Despite relatively high levels of product homogeneity (5 GM soybean varieties) and data points that imply a lower bound to R&D concentration in Figure 12, the empirical results provide only partial evidence that the market for GM soybeans is characterized by endogenous fixed costs. (Howell, et al., 2009)



Source: Author's calculations

Figure 15: Lower Bounds to R&D Concentration in GM Soybean Seed

The predicted lower bound to R&D concentration for GM soybean seeds reveals the increase in R&D concentration resulting from mergers and acquisitions more clearly than either the estimations for GM corn or GM cotton seed. Whereas the lower bound to single firm R&D concentration ranges from .2625-.2998 in the unadjusted estimations for the largest-sized market, after adjusting for merger and acquisition activity the predicted lower bound increases to .4616-.5264. Moreover, a 10% increase in market size increases the predicted lower bound twice as rapidly when consolidation of intellectual property via mergers and acquisitions is considered. The estimations for the three firm R&D concentration ratios imply predicted lower bounds that range from .3539 for the smallest-sized market to .9187 for the largest-sized market. Contrary to the results for the single firm R&D concentration ratio, the predicted lower bound when considering mergers and acquisitions is lower.

It is also important to address the similarities and differences in the second-stage estimations for GM corn, cotton, and soybean seeds. Recall that the parameter γ corresponds to the shape of the Weibull distribution such that a lower value of γ corresponds to a higher degree of clustering around the lower bound. Additionally, the scale parameter δ describes the dispersion of the data. Most interesting are the results on the shape parameter γ which imply a high degree of clustering on the lower bound for all crop types, with cotton being characterized by the least clustering and corn the most. Moreover, γ is less than two in all 24 estimations implying that the two-step procedure of Smith (1985, 1994) is appropriate. Finally, the estimations of the scale parameter δ indicate a wider dispersion of R&D concentration in the three-firm estimations relative to the one-firm estimations.

Table 7: Lower Bound Estimations for GM Soybean Seed

			First-Stage				Second-Stage				LR
Concentration	Market Size	M&A	θ_0		θ_1		γ		δ		$(\chi^2=1)$
R_1	Total	Unadjusted	-0.450	**	0.100	**	1.325	**	1.015	**	0.006
			0.105		0.014		0.217		0.172		
		Adjusted	-1.990	**	0.321	**	1.674	**	1.092	**	-0.035
			0.137		0.017		0.272		0.147		
	GM	Unadjusted	0.302		0.048		1.261	**	0.963	**	-0.029
			0.191		0.027		0.249		0.201		
		Adjusted	-0.197		0.145	**	1.410	**	1.067	**	-0.060
			0.127		0.017		0.303		0.198		
R_3	Total	Unadjusted	-1.892	**	0.383	**	1.317	**	2.093	**	-0.033
			0.188		0.024		0.213		0.357		
		Adjusted	-6.835	**	1.091	**	0.913	**	2.888	**	-0.053
			0.332		0.041		0.168		0.699		
	GM	Unadjusted	0.317		0.232	**	1.009	**	1.609	**	-0.057
			0.371		0.049		0.205		0.418		
		Adjusted	1.048		0.117		1.082	**	3.727	**	-0.029
			0.863		0.119		0.221		0.876		

Source: Author's estimates.

**,*: Significance at the 99% and 95% levels, respectively.

Table 8: Predicted Lower Bounds for GM Corn, Cotton, and Soybean Seeds

			1 Firm R&D Concentration				3 Firm R&D Concentration			
			Total Market		GM Market		Total Market		GM Market	
			Merger & Acquisition		Merger & Acquisition		Merger & Acquisition		Merger & Acquisition	
			Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Corn	Largest Market	Bound	0.3909	0.3888	0.3807	0.3776	0.8152	0.8125	0.8141	0.7887
		10% Change	0.0049	0.0046	0.0039	0.0035	0.0055	0.0051	0.0045	0.0044
	Smallest Market	Bound	0.1122	0.1264	0.2025	0.2178	0.2409	0.3103	0.5023	0.5062
		10% Change	0.0071	0.0066	0.0050	0.0044	0.0226	0.0189	0.0120	0.0102
Cotton	Largest Market	Bound	0.4302	0.4166	0.3983	0.3539	0.7835	0.8767	0.7811	0.8228
		10% Change	0.0063	0.0060	0.0059	0.0045	0.0063	0.0049	0.0057	0.0042
	Smallest Market	Bound	0.2662	0.2635	0.2419	0.2388	0.5765	0.6917	0.5933	0.6884
		10% Change	0.0081	0.0075	0.0074	0.0053	0.0123	0.0122	0.0106	0.0074
Soybean	Largest Market	Bound	0.2625	0.5264	0.2998	0.4616	0.6631	0.9187	0.7140	0.6323
		10% Change	0.0045	0.0092	0.0021	0.0048	0.0078	0.0053	0.0040	0.0026
	Smallest Market	Bound	0.1251	0.1818	0.2422	0.3162	0.3539	0.4790	0.5808	0.5539
		10% Change	0.0128	0.0378	0.0022	0.0060	0.0354	0.0773	0.0059	0.0032

Source: Author's estimates

CHAPTER 4: Conclusions

In these essays, I examine the endogenous relationship between market structure and innovation within industries with product markets characterized by horizontal and vertical product differentiation and fixed costs which relate R&D investment and product quality. The theoretical and empirical models build upon Sutton's (1991, 1997, 1998, 2007) endogenous fixed cost (EFC) framework.

In the first essay, I develop an EFC model under asymmetric R&D costs that incorporates an endogenous decision by firms to license or cross-license their technology. The model presents a more general expression of Sutton's framework in the sense that Sutton's results are embedded in the endogenous licensing model when markets are sufficiently small, when transactions costs associated with licensing are sufficiently large, or when patent rights are sufficiently weak. For finitely-sized markets, the presence of multiple research trajectories and fixed transactions costs associated with licensing raises the lower bound to market concentration under licensing relative to the bound in which firms invest along a single R&D trajectory or in which transactions costs associated with licensing are negligible. Moreover, I find that the lower bound to R&D intensity is strictly greater than the lower bound to market concentration under licensing whereas Sutton

(1998) finds equivalent lower bounds. This implies a greater level of R&D intensity within industries in which licensing is prevalent as innovating firms are able to recoup more of the sunk costs associated increased R&D expenditure and higher quality.

The results of the theoretical model are consistent with previous models of strategic licensing between competitors in which the availability of licensing creates incentives for firms to choose their competition as well as economize on R&D expenditures. Namely, I find that given sufficiently strong patent protection, it can be profitable for low-cost "innovating" firms to increase R&D expenditure and license the higher level of quality to a fewer number of high-cost "imitating" firms than would enter endogenously without licensing. Sutton's (1998) EFC model predicts that as the size of the market increases, existing firms escalate the levels of quality they offer rather than permit additional entry of new firms. This primary result of quality escalation continues to hold when firms are permitted to license their technology to rivals, but low-cost innovators are able to increase the number of licenses to high-cost imitators as market size increases.

Regulators and policymakers will find these results particularly relevant as the announcements of license and cross-license agreements between firms within the same industry are often accompanied by concerns of collusion and anticompetitive behavior. As I have shown however, the ability of firms to license their technology increases the highest levels of quality offered by providing additional incentives to R&D for low-cost market leaders. Without an explicit expression of the functional form of the utility function, I am unable to determine the welfare effects of higher market concentration, accompanied by higher levels of R&D investment and product quality. Thus, the consumer welfare effects of an endogenous market structure and innovation under asymmetric R&D costs and licensing remains an open area for future research.

In the second essay, I examine whether a specific industry, agricultural biotechnology, is characterized by endogenous fixed costs associated with R&D investment. In a mixed model of vertical and horizontal product differentiation, I illustrate the theoretical lower bounds to market concentration implied by an endogenous fixed cost (EFC) model and derive the theoretical lower bound to R&D concentration from the same model. Using data on field trial applications of genetically modified (GM) crops, I estimate the lower bound to R&D concentration in the agricultural biotechnology sector. I identify the lower bound to concentration using exogenous variation in market size across time, as adoption rates of GM crops increase, and across agricultural regions.

The results of the empirical estimations imply that the markets for GM corn, cotton, and soybean seeds are characterized by endogenous fixed costs associated with R&D investments. For the largest-sized markets in GM corn and cotton seed, single firm concentration ratios range from approximately .35 to .44 whereas three firm concentration ratios are approximately .78 to .82. The concentration ratios for GM soybean seeds are significantly lower relative to corn and cotton, despite greater levels of product homogeneity in soybeans. Moreover, adjusting for firm consolidation via mergers and acquisitions does not significantly change the lower bound estimations for the largest-sized markets in corn or cotton for either one or three firm concentration, but does increase the predicted lower bound for GM soybean seed significantly. These results imply that concerns of concentration of intellectual property resulting from mergers and acquisitions in agricultural biotechnology are more important for some crop types relative to others.

The empirical estimations imply that the agricultural biotechnology sector is characterized by endogenous fixed costs associated with R&D investments. As firms are able to increase their market shares by increasing the quality of products offered, there are incentives for firms to increase their R&D investments prior to competing in the product market. The lower bound to concentration implies that even as the acreage of GM crops planted increases, one would not expect a corresponding increase in firm entry. However, the results from the estimations for GM soybean seeds indicate that concerns for increased concentration of intellectual property arising from firm mergers and acquisitions may be justified, even though there is little evidence to support this claim from the corn and cotton seed markets.

Given the increased concerns over concentration in agricultural inputs, and in particular in agricultural biotechnology, regulators and policymakers alike will find these results of particular interest. Whereas increased levels of concentration are often associated with an anticompetitive industry, the presence of endogenous fixed costs and the nature of technology competition in agricultural biotechnology imply a certain level of concentration is to be expected. Specifically, R&D activity is concentrated within three to four firms across corn, cotton, and soybeans and the ratios of concentration have been changing little over the past 20 years. Moreover, the empirical model leaves open the possibility that the introduction of second and third generation GM varieties, the opening of foreign markets to GM crops, future exogenous shocks to technology, or reductions in regulatory cost could lead to additional entry, exit, or consolidation in the industry.

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Appendix A: Chapter 2 Proofs

Proof to Proposition 1: In order to derive the first condition in Proposition 1, I compare the conditions on the feasible set of equilibrium as characterized by equations (2.19) and (2.20). As the left-hand side and fixed-cost term on the right-hand side are equivalent across equations, I focus upon the relationship between $[1 + L^n \rho(\kappa \hat{v}')\gamma_n] S\pi(\kappa \hat{u}'|\mathbf{\acute{u}})$ and $S\pi(\kappa \hat{u}'|\mathbf{\acute{u}}')$. The larger of these two terms will determine which of the stability conditions will be binding upon low-cost firms. As these relationships hold for all values of the escalation parameter $\kappa > 1$, I can derive an expression for the proportion of sales revenues accrued to innovating firms in licensing agreements. Specifically this depends upon:

$$\rho(\kappa \hat{v}) \gtreqless \frac{1}{L^n \gamma_n} \left[\frac{S\pi(\kappa \hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa \hat{u}'|\mathbf{\acute{u}})} - 1 \right], \quad \forall \kappa > 1. \qquad (A.1.1)$$

The expression on the right-hand side of equation $(A.1.1)$ is non-negative for any positive rent dissipation effect. The rent dissipation effect falls directly out of the profit function such that equation $(A.1.1)$ implies the first licensor stability condition $(S.2')$ will bind over the second licensor stability condition $(S.2'')$ if the right-hand side is less than or equal to $\rho(\kappa \hat{v})$.

Without the assumption of either an explicit functional form on the per-consumer profit function or the nature of competition in the product market, I cannot determine if the rent dissipation effect will be large or small. However, if product market competition is intense such that the rent dissipation effect is large, it can be inferred that $\rho(\kappa\hat{v}) \leq \frac{1}{L^n \gamma_n}\left[\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})} - 1\right]$ is likely to be observed as $\rho(\kappa\hat{v})$ is bounded between 0 and 1. If the product market competition is not strong such that rent dissipation is weak, the converse likely holds such that first licensor stability condition $(S.2')$ will be binding.

If the second stability condition on licensor firms is to bind, then equation (2.20) specifies the feasible set of equilibrium configurations as the first term on the right-hand side is no less than the first right-hand side term in equation (2.19). This condition will be binding under intense product market competition and large rent dissipation effects.

The second part of Proposition 1 is derived by comparing condition (2.19) and (2.21). Assuming that market size and firm profits are sufficiently large relative to fixed cost expenditures along other trajectories and fixed transactions costs associated with licensing, comparing the coefficients on the first terms yields the following relationship:

$$\frac{1}{\kappa^{\beta^L}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1+L^n\rho(\hat{v}')\gamma_n}\right] \gtreqless \frac{1}{\kappa^{\beta^H}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right], \quad \forall\kappa > 1. \qquad (A.1.2)$$

If the left-hand side is greater than or equal to the right-hand side, then the licensor viability and stability conditions provide a more restrictive set of feasible equilibrium configurations independently of fixed costs associated with R&D investment in other attributes or transactions costs associated with licensing. Similarly, if the right-hand side is greater than left-hand side, then the licensee viability and stability conditions provide the relevant constraints upon the feasible set of equilibrium. Simplifying yields the proportion of sales revenues that licensees can earn given some level of quality:

$$\rho(\hat{v}') \lesseqgtr \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right], \quad \forall\kappa > 1. \qquad (A.1.3)$$

As I have assumed $\beta^H > \beta^L$, the right-hand side of this condition is nonnegative for all $\kappa > 1$. Thus, the set of equilibrium configurations derived from the licensor viability and stability conditions $(V.2')$ and $(S.2')$ will be the binding to the feasible set of equilibrium configurations if: $\rho(\hat{v}) \leq \frac{1}{\gamma n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right], \quad \forall\kappa > 1.$

Comparing equation (2.20) to equation (2.21) under the assumption that market size is sufficiently large or fixed R&D and transactions costs are sufficiently small. The relationship can be specified as:

$$\frac{1}{\kappa^{\beta^L}}\left[\frac{1}{1+L^n\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}') \gtreqless \frac{1}{\kappa^{\beta^H}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}), \quad \forall\kappa > 1. \tag{A.1.4}$$

Re-arranging:

$$\left[1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n\right]\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})} \gtreqless \frac{\kappa^{\beta^L}}{\kappa^{\beta^H}}[1+L^n\rho(\kappa\hat{v}')\gamma_n][1+L^n\rho(\hat{v}')\gamma_n], \quad \forall\kappa > 1. \tag{A.1.5}$$

As I have already determined that $\rho(\kappa\hat{v}') \leq \frac{1}{L^n\gamma_n}\left[\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})}-1\right]$ for condition (2.20) to provide the binding set of feasible equilibrium configurations, I know that the right-hand side of expression $(A.1.5)$ will be greatest for $\rho(\kappa\hat{v}') = \frac{1}{L^n\gamma_n}\left[\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})}-1\right]$. Substituting and simplifying yields:

$$\rho(\hat{v}') \lesseqgtr \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right], \quad \forall\kappa > 1. \tag{A.1.6}$$

As was the case for Proposition 1, the set of equilibrium configurations derived from the licensor viability and stability conditions $(V.2')$ and $(S.2'')$ will be the binding to the feasible set of equilibrium configurations if: $\rho(\hat{v}) \leq \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right], \quad \forall\kappa > 1.$ ■

Proof of Proposition 2: Consider some equilibrium configuration $\mathbf{u}$ without licensing in which the market-leading firm produces maximum quality $\hat{u}$ by attaining maximum competency $\hat{v}$ along some trajectory n while producing an "industry standard" level of competency across all other trajectories. Let the sales revenue from the associated products be denoted $S\hat{r}$ such that its share of industry sales revenue is $S\hat{r}/Sr(\mathbf{u})$. Suppose the high-spending, low-cost entrant produces quality $\kappa\hat{u}$ by attaining capability $\kappa\hat{v}$ along trajectory n and achieves the "industry standard" level of competency $\overline{v}$ across all other trajectories.[14] By definition of $a(\kappa)$, the high-spending entrant obtains a profit net of sunk costs of at least: $a(\kappa)Sr(\mathbf{u}) - F_0(\kappa\hat{v})^{\beta^L} - \sum_{m\neq n} F(\overline{v}_m)$.

Recall that the relevant stability condition $(S.1)$ implies that the profit of an escalating entrant is non-positive such that:

$$F_0(\hat{v})^{\beta^L} \geq \frac{a(\kappa)}{\kappa^{\beta^L}} Sr(\mathbf{u}) - \frac{1}{\kappa^{\beta^L}} \sum_{m\neq n} F(\overline{v}_m), \quad \kappa \geq 1. \qquad (A.2.1)$$

The viability condition $(V.1)$ necessitates the current market-leader in quality has profits that cover its fixed outlays. Thus, regardless of the marginal costs of production (assumed to be zero here for simplicity and congruency with subsequent

[14] The assumption that there is an "industry standard" level of quality offered on all other trajectories is consistent with the results of Irmen and Thisse (1998). They show that maximum differentiation along a single characteristic, and minimum differentiation across all other characteristics, is sufficient to relax price competition, regardless of whether there exists a "dominant" attribute or all attributes are weighted evenly.

results), the sales and licensing revenue of the market-leading firm must at least be as large as its sunk R&D expenditures which implies:

$$S\hat{r} - \sum_{m \neq n} F(\overline{v}_m) \geq F_0(\hat{v})^{\beta^L}. \qquad (A.2.2)$$

Combining these conditions yields:

$$S\hat{r} - \sum_{m \neq n} F(\overline{v}_m) \geq F_0(\hat{v})^{\beta^L} \geq \frac{a(\kappa)}{\kappa^{\beta^L}} Sr(\mathbf{u}) - \frac{1}{\kappa^{\beta^L}} \sum_{m \neq n} F(\overline{v}_m), \quad \kappa \geq 1. \qquad (A.2.3)$$

Therefore, the market share of sales along the highest-quality trajectory is:

$$\frac{S\hat{r}}{Sr(\mathbf{u})} \geq \frac{a(\kappa)}{\kappa^{\beta^L}} + \left(\frac{\kappa^{\beta^L} - 1}{\kappa^{\beta^L}}\right) \left[\frac{\sum_{m \neq n} F(\overline{v}_m)}{Sr(\mathbf{u})}\right]. \qquad (A.2.4)$$

Condition $(A.2.4)$ implies that as the market size becomes large (i.e. $S \to \infty$), the second term approaches zero and the market share of the quality-leading firm is bounded away from zero by $\frac{a(\kappa)}{\kappa^{\beta^L}}$. ■

Proof of Proposition 3: Consider the case of a high-spending entrant that achieves competency $\kappa\hat{v}'$ along some trajectory n (with overall quality of $\kappa\hat{u}'$) and licenses this competency to high-cost rivals. Let the current market leader produce quality $\hat{u}'$ by achieving competency $\hat{v}'$ along trajectory n, earn sales revenue of the market leader as $S\hat{r}'$, and achieve a share of the industry sales revenue equal to $S\hat{r}'/Sr(\acute{\mathbf{u}})$. By definition of $\acute{a}(\kappa)$, the high-spending entrant obtains a profit with licensing revenue net of sunk costs of at least: $\acute{a}(\kappa)Sr(\acute{\mathbf{u}}) - F_0(\kappa\hat{v}')^{\beta^L} - \sum_{m\neq n} F(\overline{v}_m) + L^n\gamma_n\rho(\kappa\hat{v}')\acute{a}(\kappa)Sr(\acute{\mathbf{u}})$.

The stability condition $(S.2')$ for licensor firms implies that the profit of an escalating entrant is non-positive such that:

$$F_0(\hat{v}')^{\beta^L} \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^L}}[1 + L^n\gamma_n\rho(\kappa\hat{v}')]Sr(\acute{\mathbf{u}}) - \frac{1}{\kappa^{\beta^L}}\sum_{m\neq n} F(\overline{v}_m), \quad \kappa \geq 1. \quad (A.3.1)$$

Moreover, the relevant viability condition $(V.2')$ implies that the current quality leader that licenses its competency to rivals has profits and licensing revenues that are greater than its fixed R&D costs. The viability condition can be specified as:

$$[1 + L^n\gamma_n\rho(\hat{v}')]S\hat{r}' - \sum_{m\neq n} F^L(\overline{v}_m) \geq F_0(\hat{v}')^{\beta^L}. \qquad (A.3.2)$$

Combining equations $(A.3.1)$ and $(A.3.2)$ and simplifying yields:

$$\begin{aligned}[1 + L^n\gamma_n\rho(\hat{v}')]S\hat{r}' \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^L}}&[1 + L^n\gamma_n\rho(\kappa\hat{v}')]Sr(\acute{\mathbf{u}}) \\ &+ \left(\frac{\kappa^{\beta^L} - 1}{\kappa^{\beta^L}}\right)\sum_{m\neq n} F(\overline{v}_m), \quad \forall\kappa > 1.\end{aligned} \qquad (A.3.3)$$

The market share of sales for firm producing the highest level of quality and licensing its competency to high-cost rivals can be expressed as:

$$\frac{S\hat{r}'}{Sr(\acute{\mathbf{u}})} \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^L}} \cdot \left[\frac{1 + L^n\gamma_n\rho(\kappa\hat{v}')}{1 + L^n\gamma_n\rho(\hat{v}')}\right] + \left(\frac{\kappa^{\beta^L} - 1}{\kappa^{\beta^L}}\right)\left[\frac{\sum_{m\neq n} F(\overline{v}_m)}{[1 + L^n\gamma_n\rho(\hat{v}')]Sr(\acute{\mathbf{u}})}\right]. \qquad (A.3.4)$$

As the size of the market becomes large, the second term in equation $(A.3.4)$ approaches zero and the lower bound to market concentration derived from the equilibrium conditions for licensor firms is: $\frac{\acute{a}(\kappa)}{\kappa^{\beta^L}} \cdot \left[\frac{1+L^n\gamma_n\rho(\kappa\hat{v}')}{1+L^n\gamma_n\rho(\hat{v}')}\right]$. ■

Proof of Proposition 4: Consider the case of a high-spending entrant that licenses competence $\hat{v}'$ from the market leader and then escalates its competence by a factor $\kappa > 1$ to attain an overall quality level of $\kappa\hat{u}'$. From the definition of $\acute{a}(\kappa)$, the profits net of sunk costs and transactions costs associated with licensing for this firm can be specified as being greater than or equal to: $\acute{a}(\kappa)Sr(\mathbf{\acute{u}}) - \gamma_n\rho(\hat{v}')S\hat{r}' + L^n\gamma_n\rho(\kappa\hat{v}')\acute{a}(\kappa)Sr(\mathbf{\acute{u}}) - \left[1-(1-\delta)^{\beta^H}\right]F_0(\kappa\hat{v}')^{\beta^H} - \sum_{m\neq n}F(\overline{v}_m) - T_0$.

From the stability condition for licensee firms $(S.3'')$, the profit of an escalating entrant that licenses competency $\hat{v}$ from the market leader and then licenses its escalated competency to rivals is non-positive such that:

$$\begin{aligned}\left[1-(1-\delta)^{\beta^H}\right]F_0(\hat{v}')^{\beta^H} \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^H}}&[1+L^n\gamma_n\rho(\kappa\hat{v}')]Sr(\mathbf{\acute{u}}) \\ &-\frac{\gamma_n\rho(\hat{v}')}{\kappa^{\beta^H}}S\hat{r}' - \frac{1}{\kappa^{\beta^H}}\left[\sum_{m\neq n}F(\overline{v}_m) - T_0\right], \quad \kappa \geq 1.\end{aligned} \tag{A.4.1}$$

The viability condition for licensee firms $(V.3')$ implies that a licensee of the market-leading competency $\hat{v}'$ earns profits that are greater than both the "catch-up" R&D from the imperfect transfer of technologies across firms and the transactions costs associated with the license T_0. Therefore, sales revenue of the licensee firm is such that:

$$[1-\rho(\hat{v}')\gamma_n]S\hat{r}' - \sum_{m\neq n} F(\overline{v}_m) - T_0$$
$$\geq \left[1-(1-\delta)^{\beta^H}\right]F_0(\hat{v}')^{\beta^H}. \qquad (A.4.2)$$

Combining the conditions $(A.4.1)$ and $(A.4.2)$ yields the expression:

$$\left[1-\rho(\hat{v}')\gamma_n + \frac{\gamma_n\rho(\hat{v}')}{\kappa^{\beta^H}}\right]S\hat{r}' \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^H}}[1+L^n\gamma_n\rho(\kappa\hat{v}')]Sr(\acute{\mathbf{u}}) + \left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\left[\sum_{m\neq n} F(\overline{v}_m) + T_0\right], \quad \kappa \geq 1. \qquad (A.4.3)$$

Therefore, the market share of any firm producing the market-leading level of quality and the maximum competency $\hat{v}'$ in equilibrium must satisfy:

$$\frac{S\hat{r}'}{Sr(\acute{\mathbf{u}})} \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1+L^n\gamma_n\rho(\kappa\hat{v}')}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\gamma_n\rho(\hat{v}')}\right] + \left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\left[\frac{\sum_{m\neq n} F(\overline{v}_m) + T_0}{\left[1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\gamma_n\rho(\hat{v}')\right]Sr(\acute{\mathbf{u}})}\right], \quad \kappa \geq 1. \qquad (A.4.4)$$

As the size of the market becomes large, the second term approaches zero and the lower bound to concentration as derived from the equilibrium conditions on licensee firms is: $\frac{\acute{a}(\kappa)}{\kappa\beta^{H}} \cdot \left[\frac{1+L^{n}\gamma_{n}\rho(\kappa\hat{v}\prime)}{1-\left(\frac{\kappa\beta^{H}-1}{\kappa\beta^{H}}\right)\gamma_{n}\rho(\hat{v}\prime)}\right]$. ■

Proof of Theorem 1: (Proof by Transposition) Prior to commencing the proof, it is useful to recall the three conditions (2.19)-(2.21) that were specified in order to determine which viability and stability conditions characterized the feasible set of equilibrium configurations. The two licensor conditions can be expressed as:

$$S\pi(\hat{u}'|\mathbf{\acute{u}}) \geq \tfrac{1}{\kappa^{\beta^L}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1+L^n\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}) + \left(\tfrac{\kappa^{\beta^L}-1}{\kappa^{\beta^L}}\right)\left[\frac{\sum_{m\neq n}F(v_m)}{1+L^n\rho(\hat{v}')\gamma_n}\right] \tag{2.19}$$

$$S\pi(\hat{u}'|\mathbf{\acute{u}}) \geq \tfrac{1}{\kappa^{\beta^L}}\left[\frac{1}{1+L^n\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}') + \left(\tfrac{\kappa^{\beta^L}-1}{\kappa^{\beta^L}}\right)\left[\frac{\sum_{m\neq n}F(v_m)}{1+L^n\rho(\hat{v}')\gamma_n}\right] \tag{2.20}$$

whereas the licensee condition can be expressed as:

$$\begin{aligned} S\pi(\hat{u}'|\mathbf{\acute{u}}) \geq \tfrac{1}{\kappa^{\beta^H}}&\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}) \\ &+\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\left[\frac{\sum_{m\neq n}F(v_m)+T_0}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right]. \end{aligned} \tag{2.21}$$

Suppose that the licensee viability $(V.3')$ and stability $(S.3'')$ conditions are not the relevant conditions in defining equilibrium configurations implying that equation (2.21) does not bind the feasible set of configurations. If equilibrium configurations are not determined by the licensee conditions, then they must be determined by the licensor viability $(V.2')$ condition and one of the licensor stability $(S.2', S.2'')$ conditions, hence either equation (2.19) or (2.20).

First, consider the case in which a quality-escalating entrant also licenses its technology to rivals such that equation (2.19) is binding. If equation (2.19) provides the relevant condition on the binding set of equilibrium configurations, then it must be that for sufficiently large markets, the right-hand side of (2.19) is greater than the right-hand side of (2.21). Specifically,

$$\tfrac{1}{\kappa^{\beta^L}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1+L^n\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}) > \tfrac{1}{\kappa^{\beta^H}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}). \qquad (A.5.1)$$

Simplifying equation $(A.5.1)$ yields the following expression in which the licensee conditions are not binding:

$$\rho(\hat{v}') < \tfrac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right], \quad \forall\kappa > 1. \qquad (A.5.2)$$

Now considering the case in which a quality-escalating entrant does not license its technology to rivals, equation (2.20) will define the binding set of feasible equilibrium configurations. The equivalent expression to equation $(A.5.1)$ assuming sufficiently-sized markets can be specified as:

$$\tfrac{1}{\kappa^{\beta^L}}\left[\frac{1}{1+L^n\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}') > \tfrac{1}{\kappa^{\beta^H}}\left[\frac{1+L^n\rho(\kappa\hat{v}')\gamma_n}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\rho(\hat{v}')\gamma_n}\right]S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}). \qquad (A.5.3)$$

Dividing both sides by $S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})$ and re-arranging yields the expression:

$$\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})} > \kappa^{\beta^L}\left[\frac{[1+L^n\rho(\kappa\hat{v}')\gamma_n][1+L^n\rho(\hat{v}')\gamma_n]}{\kappa^{\beta^H}-\left(\kappa^{\beta^H}-1\right)\rho(\hat{v}')\gamma_n}\right]. \qquad (A.5.4)$$

In the Proposition 1, I determined that in order for equation (2.20) to be binding relative to equation (2.19), it must be that: $\rho(\kappa\hat{v}') \le \frac{1}{L^n\gamma_n}\left[\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})} - 1\right]$. Thus, the right-hand side of equation $(A.5.4)$ is no less than: $\kappa^{\beta^L}\left[\frac{1+L^n\rho(\hat{v}')\gamma_n}{\kappa^{\beta^H}-\left(\kappa^{\beta^H}-1\right)\rho(\hat{v}')\gamma_n}\right]\frac{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}}')}{S\pi(\kappa\hat{u}'|\mathbf{\acute{u}})}$. Simplifying and re-arranging yields the following expression in which the licensee conditions are not binding:

$$\rho(\hat{v}') < \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right], \quad \forall\kappa > 1. \qquad (A.5.5)$$

If the licensee viability and stability conditions are not binding in the definition of the feasible set of equilibrium configurations, it must be $\rho(\hat{v}') < \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right]$ regardless of which licensor conditions are specified. This is the contra positive to Theorem 1 implying that if $\rho(\hat{v}') \ge \frac{1}{\gamma_n}\left[\frac{\kappa^{\beta^H}-\kappa^{\beta^L}}{\kappa^{\beta^L}L^n+\kappa^{\beta^H}-1}\right]$, it must be that equation (2.21) defines the binding set of feasible equilibrium configurations. Moreover, from Proposition 4 the lower bound to market concentration from the licensee viability and stability conditions was derived. As these conditions determine the most restricted set of feasible equilibrium configurations, one can determine that the market share of any firm producing the market-leading level of quality and the maximum competency $\hat{v}'$ in equilibrium must satisfy:

$$\frac{S\hat{r}'}{Sr(\acute{\mathbf{u}})} \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1 + L^n \gamma_n \rho(\kappa \hat{v}')}{1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right) \gamma_n \rho(\hat{v}')}\right] + \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right)\left[\frac{\sum_{m \neq n} F^H(\overline{v}_m) + T_0}{\left[1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right) \gamma_n \rho(\hat{v}')\right] Sr(\acute{\mathbf{u}})}\right]. \qquad (A.5.6)$$

As the size of the market becomes large, the second term approaches zero and the lower bound to concentration as derived from the equilibrium conditions on licensee firms is: $\frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1 + L^n \gamma_n \rho(\kappa \hat{v}')}{1 - \left(\frac{\kappa^{\beta^H} - 1}{\kappa^{\beta^H}}\right) \gamma_n \rho(\hat{v}')}\right]$. ■

Proof of Theorem 2: Consider the quality-escalating entrant's profit derived from the licensor stability condition $(S.2')$ is at least:

$$\begin{aligned} &[1 + L^n \gamma_n \rho(\kappa \hat{v}')]\acute{a}(\kappa) Sr(\acute{\mathbf{u}}) - \kappa^{\beta^L} F^L(\hat{v}') - (n_i - 1)F_0 \\ &\quad = [1 + L^n \gamma_n \rho(\kappa \hat{v}')]\acute{a}(\kappa) Sr(\acute{\mathbf{u}}) - \kappa^{\beta^L} D^L(\hat{v}') - \left(n_i + \left(\kappa^{\beta^L} - 1\right)\right) F_0, \end{aligned} \qquad (A.6.1)$$

where n_i is the total number of research trajectories pursued by the innovating quality leader. The R&D spending of the low-cost quality leader is at least $D^L(\hat{v}')$ and it earns sales revenue, separate from licensing revenue, equal to $S\hat{r}'$ such that the R&D/sales ratio must be at least $D^L(\hat{v}')/S\hat{r}'$. We substitute for R&D costs in equation $(A.6.1)$ according to:

$$D^L(\hat{v}') = \frac{D^L(\hat{v}')}{S\hat{r}'} \cdot S\hat{r}' \leq \frac{D^L(\hat{v}')}{S\hat{r}'} \cdot Sr(\mathbf{ú}). \qquad (A.6.2)$$

Thus, combining inequality $(A.6.2)$ with equation $(A.6.1)$ yields entrant's net profit such that:

$$[1 + L^n\gamma_n\rho(\kappa\hat{v}')]\acute{a}(\kappa)Sr(\mathbf{ú}) - \kappa^{\beta^L}\frac{D^L(\hat{v}')}{S\hat{r}'} \cdot Sr(\mathbf{ú}) - \left(n_i + \left(\kappa^{\beta^L} - 1\right)\right)F_0. \quad (A.6.3)$$

The licensor stability condition $(S.2')$ implies that equation $(A.6.3)$ is non-positive. Re-arranging yields the expression:

$$\frac{D^L(\hat{v}')}{S\hat{r}'} \geq \frac{\acute{a}(\kappa)}{\kappa^{\beta^L}}[1 + L^n\gamma_n\rho(\kappa\hat{v}')] - \frac{\left(n_i + \left(\kappa^{\beta^L} - 1\right)\right)F_0}{\kappa^{\beta^L}Sr(\mathbf{ú})}. \qquad (A.6.4)$$

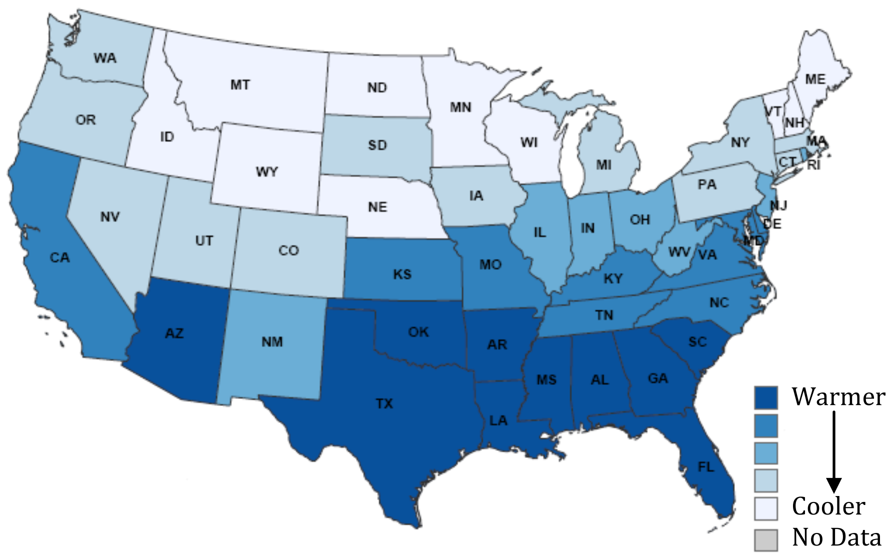
From the analysis on the concentration ratios, the sales of the market leader in quality is at least $\frac{\acute{a}(\kappa)}{\kappa^{\beta^H}} \cdot \left[\frac{1+L^n\gamma_n\rho(\kappa\hat{v}\prime)}{1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\gamma_n\rho(\hat{v}\prime)}\right]$, $\forall\kappa > 1$. Thus, one can compare the coefficient of the first term in expression $(A.6.4)$ in order to determine if one would expect the lower bound to R&D/sales ratio of the quality leader is greater than, equal to, or less than the lower bound on market concentration. By inspection, the lower bound on R&D/sales ratio is greater than the lower bound to market concentration. Substituting for $\acute{\alpha}$:

$$\frac{D^L(\hat{v}')}{S\hat{r}'} \geq \acute{\alpha}\kappa^{\beta^H-\beta^L}\left[1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\gamma_n\rho(\hat{v}')\right]-\frac{\left(n_i+\left(\kappa^{\beta^L}-1\right)\right)F_0}{\kappa^{\beta^L}Sr(\acute{\mathbf{u}})}. \qquad (A.6.5)$$

Thus, as the market size becomes large, the R&D/sales ratio is bounded from below by $\acute{\alpha}\kappa^{\beta^H-\beta^L}\left[1-\left(\frac{\kappa^{\beta^H}-1}{\kappa^{\beta^H}}\right)\gamma_n\rho(\hat{v}')\right], \forall\kappa > 1$. Under the assumptions over the fixed-fee royalty payment, $\kappa > 1$, and $\beta^H > \beta^L > 2$, the lower bound to the R&D/sales ratio is strictly greater than the lower bound to market concentration in sales.

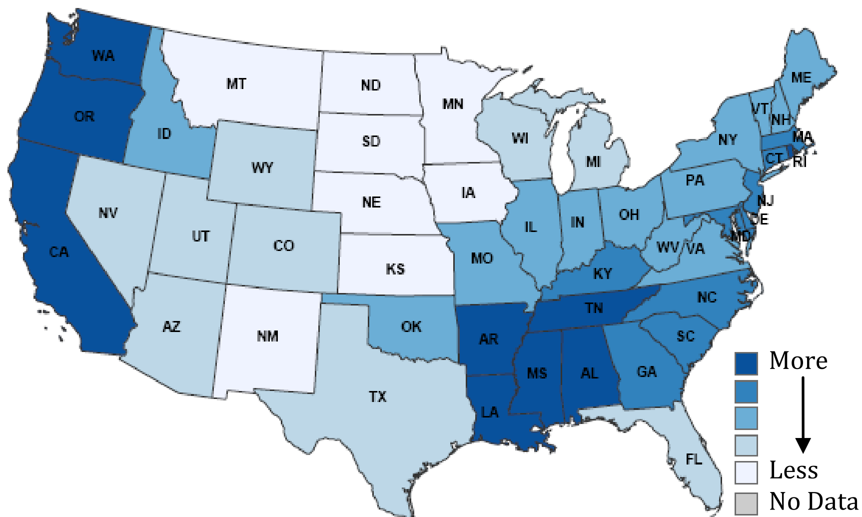
Appendix B: (Sub-)Market Analysis for GM Crops

Submarket Analysis: State-Level Climate



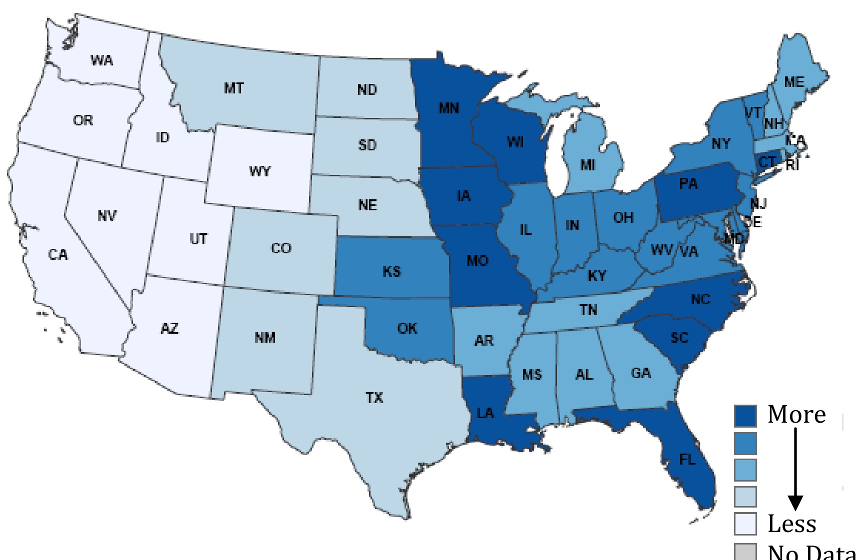
Source: Author's calculations from NOAA data (1970-2000).

Figure 16: Average Monthly Temperatures Factor Analysis



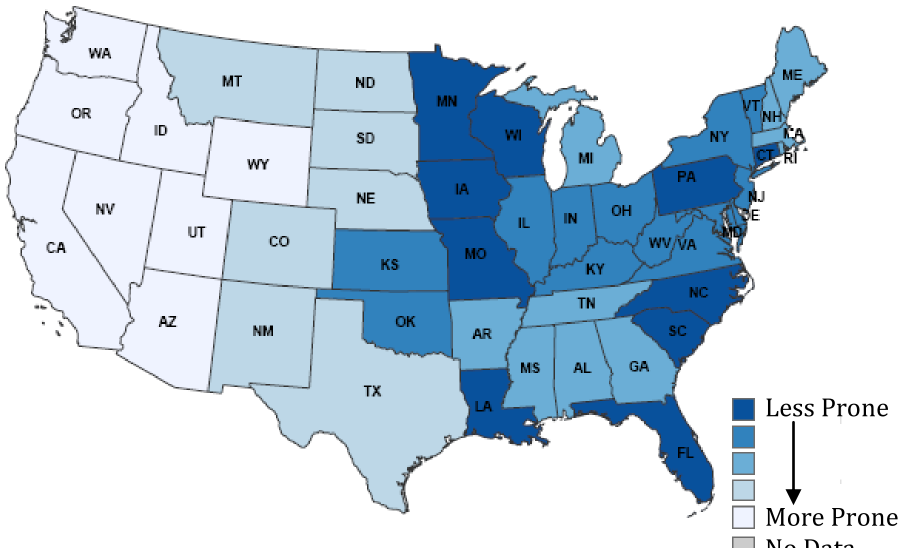
Source: Author's calculations from NOAA data (1970-2000).

Figure 17: Average Monthly Precipitation Factor Analysis (1)



Source: Author's calculations from NOAA data (1970-2000).

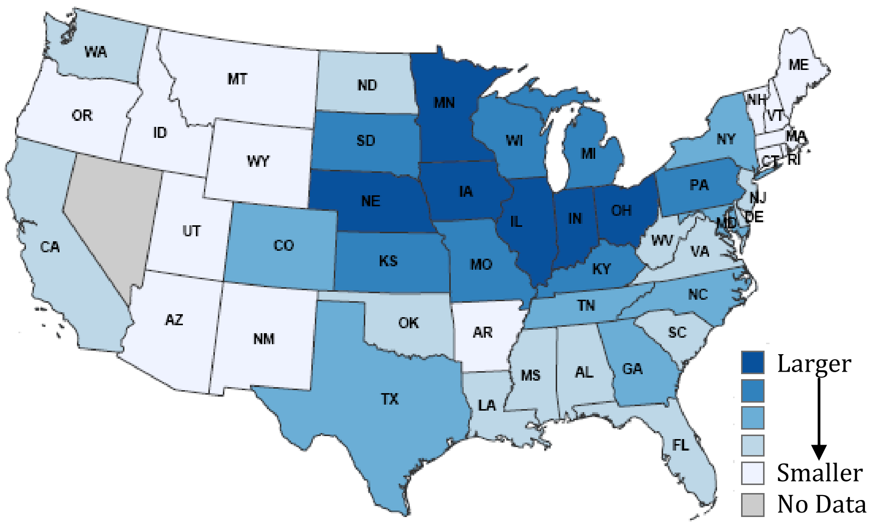
Figure 18: Average Monthly Precipitation Factor Analysis (2)



Source: Author's calculations from NOAA data (1970-2000).

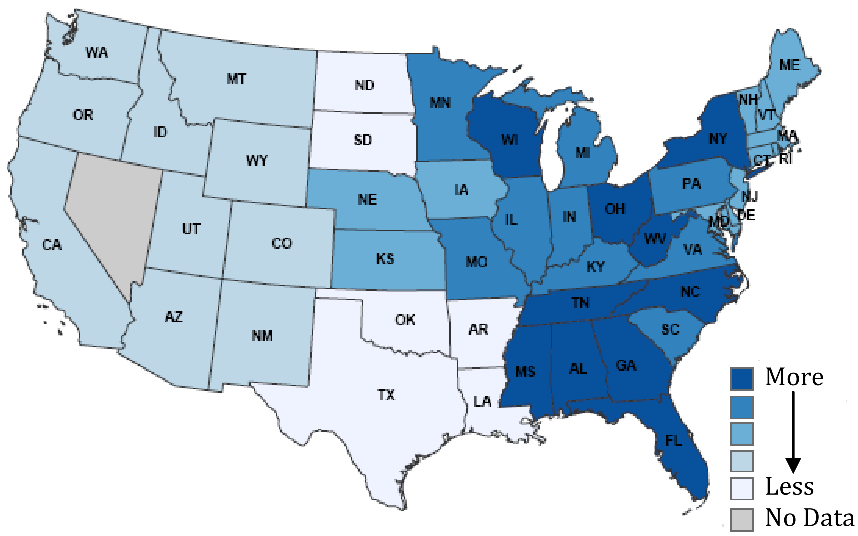
Figure 19: Average Monthly Drought Likelihood Factor Analysis

Submarket Analysis: Corn



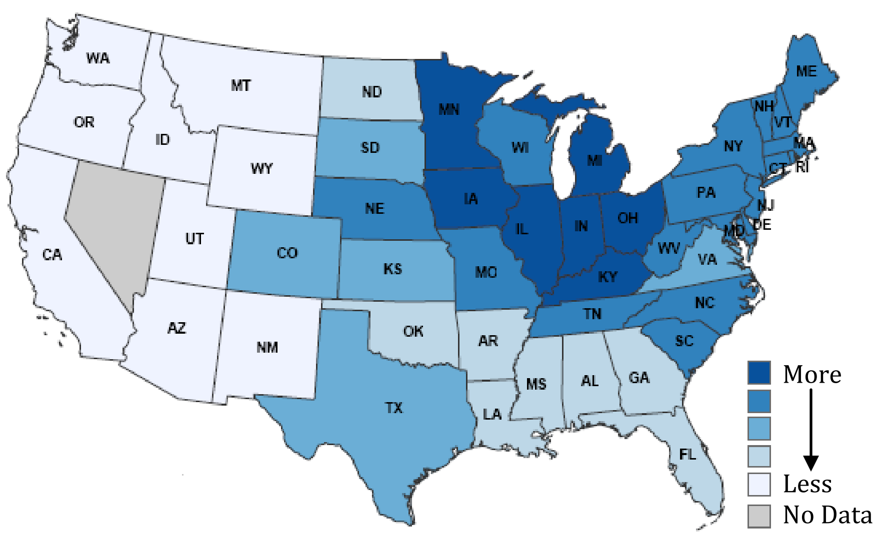
Source: Author's calculations from Census of Agriculture (1987, 1992).

Figure 20: Corn Seed Market Size Factor Analysis



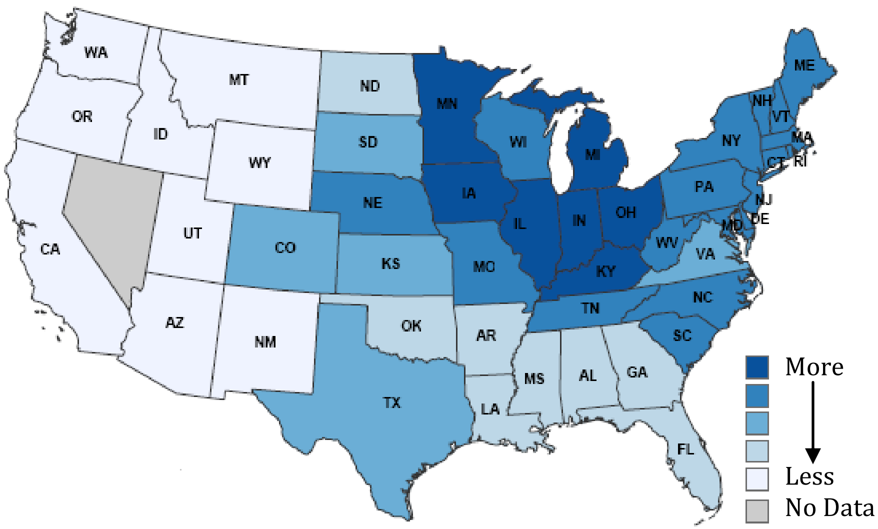
Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

Figure 21: Percentage of Planted Corn Acres Treated with Fertilizer



Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

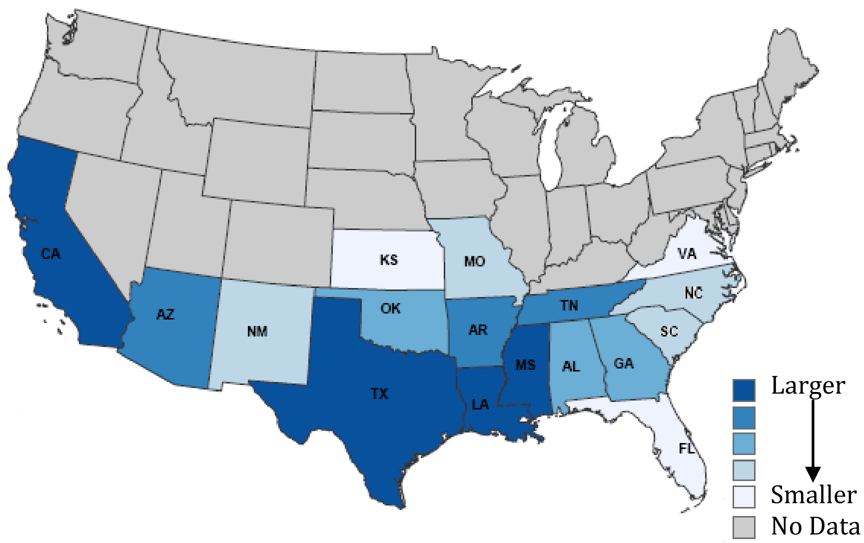
Figure 22: Percentage of Planted Corn Acres Treated with Herbicide



Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

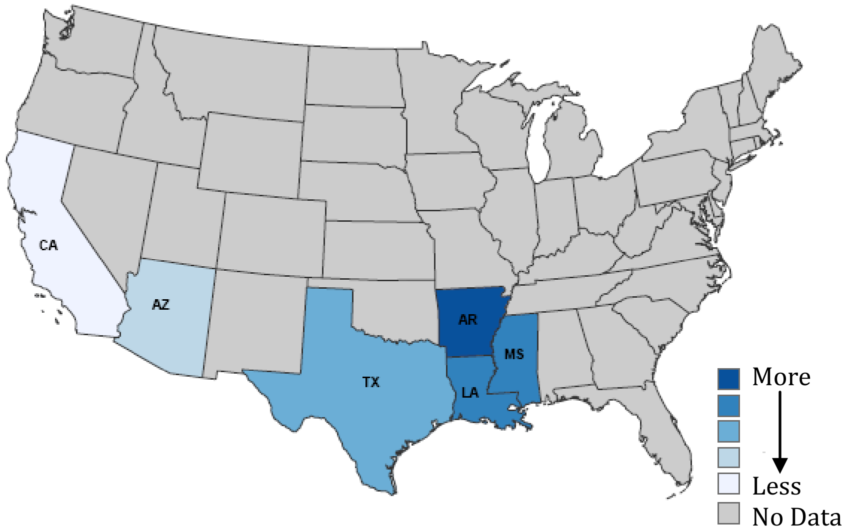
Figure 23: Percentage of Planted Corn Acres Treated with Insecticide

Submarket Analysis: Cotton



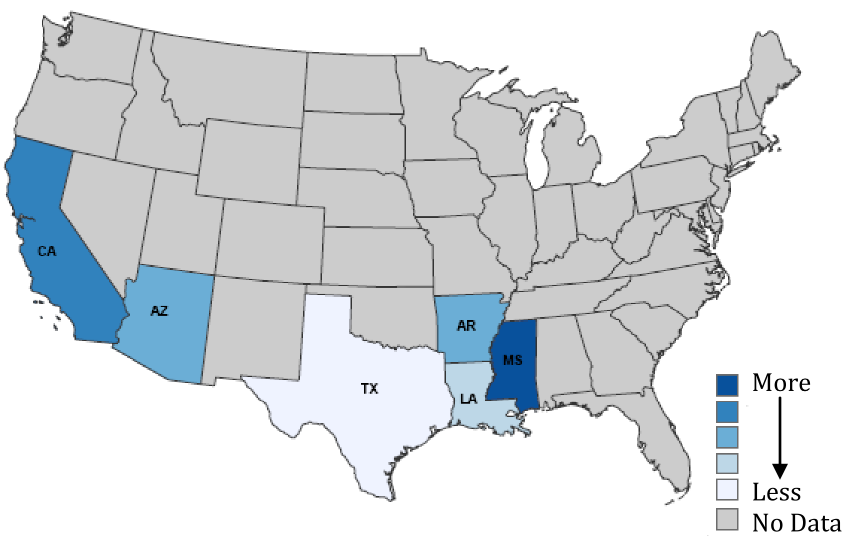
Source: Author's calculations from Census of Agriculture (1987, 1992).

Figure 24: Cotton Seed Market Size Factor Analysis



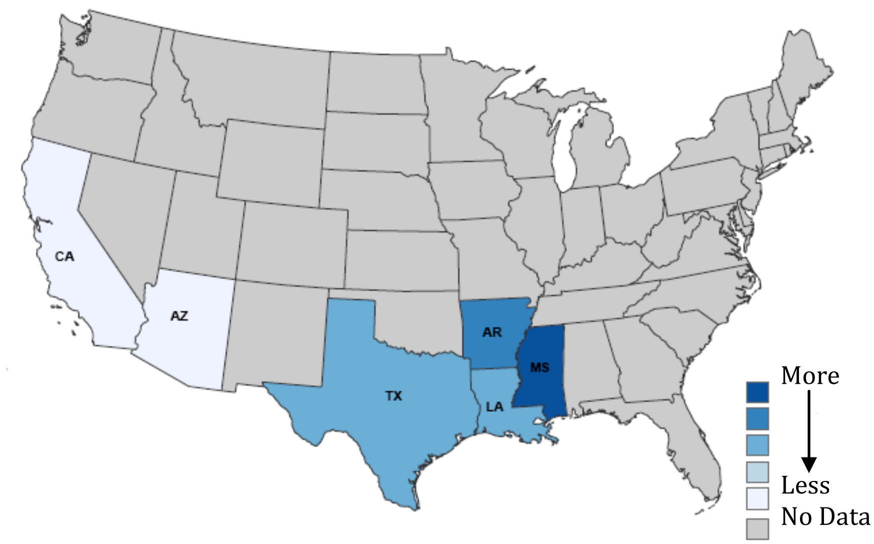
Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

Figure 25: Percentage of Planted Cotton Acres Treated with Fertilizer (1)



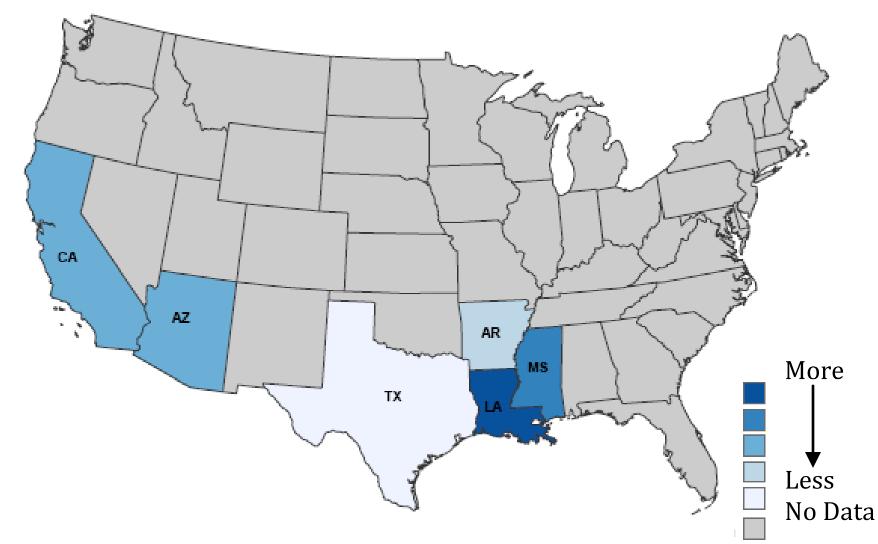
Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

Figure 26: Percentage of Planted Cotton Acres Treated with Fertilizer (2)



Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

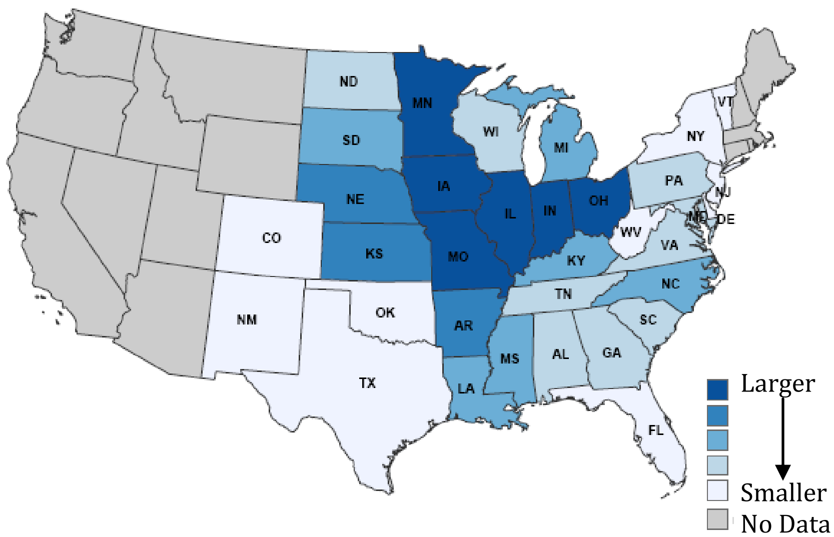
Figure 27: Percentage of Planted Cotton Acres Treated with Herbicide



Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

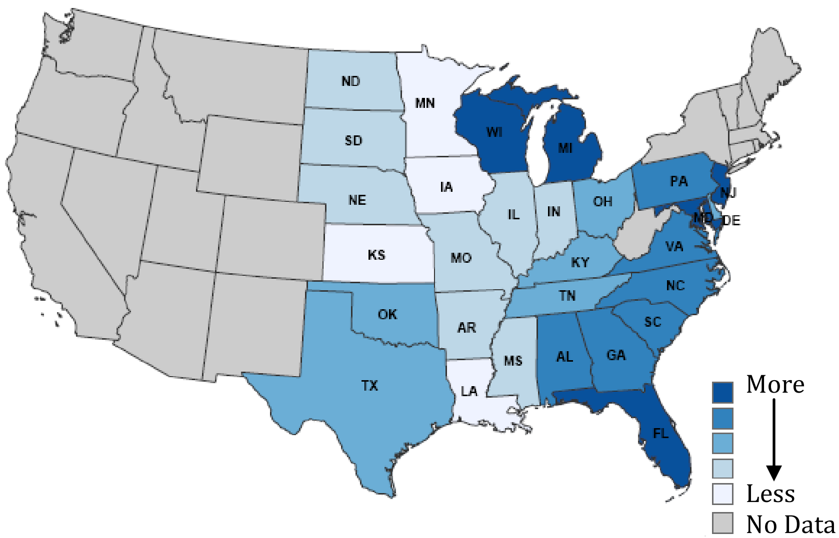
Figure 28: Percentage of Planted Cotton Acres Treated with Insecticide

Submarket Analysis: Soybean



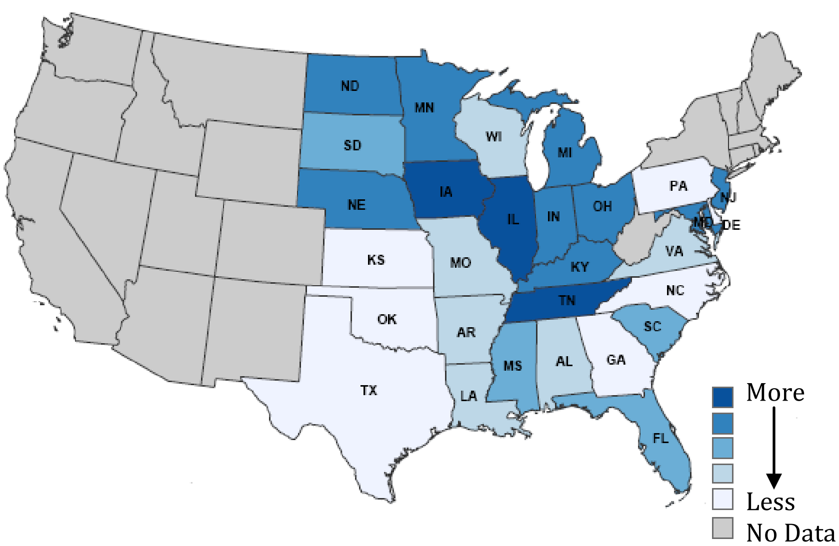
Source: Author's calculations from Census of Agriculture (1987, 1992).

Figure 29: Soybean Seed Market Size Factor Analysis



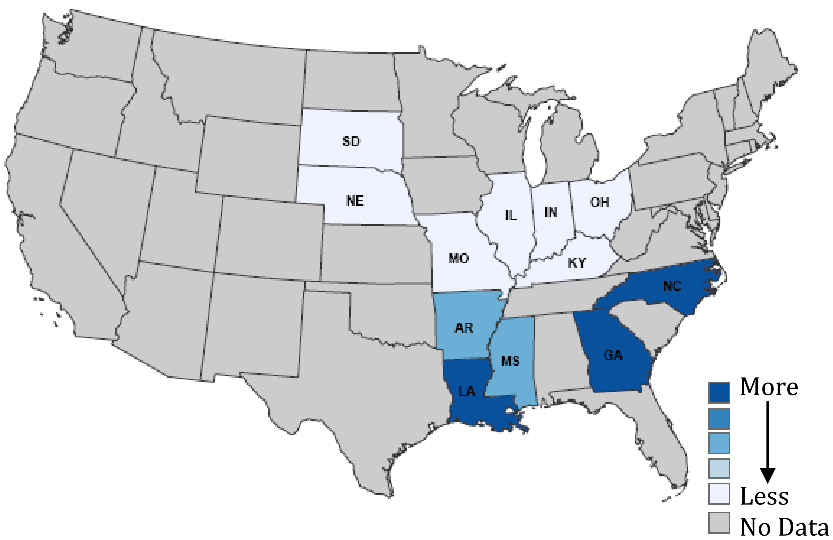
Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

Figure 30: Percentage of Planted Soybean Acres Treated with Fertilizer



Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

Figure 31: Percentage of Planted Soybean Acres Treated with Herbicide



Source: Author's calculations from Agricultural Chemical Usage (1990-1995).

Figure 32: Percentage of Planted Soybean Acres Treated with Insecticide